Axelrod Documentation

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Contents

Here is quick overview of the current capabilities of the library:

- Over 100 strategies from the literature and some exciting original contributions
  - Classic strategies like TiT-For-Tat, WSLS, and variants
  - Zero-Determinant and other Memory-One strategies
  - Many generic strategies that can be used to define an array of popular strategies, including finite state machines, strategies that hunt for patterns in other strategies, and strategies that combine the effects of many others
  - Strategy transformers that augment the abilities of any strategy
- Head-to-Head matches
- Round Robin tournaments with a variety of options, including:
  - noisy environments
  - spatial tournaments
  - probabilistically chosen match lengths
- Population dynamics
  - The Moran process
  - An ecological model
- Multi-processor support (not currently supported on Windows), caching for deterministic interactions, automatically generate figures and statistics

Every strategy is categorized on a number of dimensions, including:

- Deterministic or Stochastic
- How many rounds of history used
- Whether the strategy makes use of the game matrix, the length of the match, etc.

Furthermore the library is extensively tested with 99%+ coverage, ensuring validity and reproducibility of results!

CHAPTER 1

Quick start

Create matches between two players:

```
>>> import axelrod as axl
>>> players = (axl.Alternator(), axl.TitForTat())
>>> match = axl.Match(players, 5)
>>> interactions = match.play()
>>> interactions
[('C', 'C'), ('D', 'C'), ('C', 'D'), ('D', 'C'), ('C', 'D')]
```

Build full tournaments between groups of players:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator(), axl.TitForTat())
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
>>> results.ranked_names
['Alternator', 'Tit For Tat', 'Cooperator']
```

Study the evolutionary process using a Moran process:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator(), axl.TitForTat())
>>> mp = axl.MoranProcess(players)
>>> populations = mp.play()
>>> populations
[Counter({'Alternator': 1, 'Cooperator': 1, 'Tit For Tat': 1}),
 Counter({'Alternator': 1, 'Cooperator': 1, 'Tit For Tat': 1}),
 Counter({'Cooperator': 1, 'Tit For Tat': 2}),
 Counter({'Cooperator': 1, 'Tit For Tat': 2}),
 Counter({'Tit For Tat': 3})]
```

As well as this, the library has a growing collection of strategies. The *Strategies index* gives a description of them.

For further details there is a library of *Tutorials* available and a *Community* page with information about how to get support and/or make contributions.

CHAPTER 2

Table of Contents

Tutorials

This section contains a variety of tutorials related to the Axelrod library.

Contents:

New to Game Theory and/or Python

This section contains a variety of tutorials that should help get you started with the Axelrod library.

Contents:

Installation

The simplest way to install the package is to obtain it from the PyPi repository:

```
$ pip install axelrod
```

You can also build it from source if you would like to:

```
$ git clone https://github.com/Axelrod-Python/Axelrod.git
$ cd Axelrod
$ python setup.py install
```

Creating Matches

You can create your own match between two players using the `Match` class. This is often useful when designing new strategies in order to study how they perform against specific opponents.

For example, to create a 5 turn match between `Cooperator` and `Alternator`:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator())
>>> match = axl.Match(players, 5)
>>> match.play()
[('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C')]
```

By default, a match will not be noisy, but you can introduce noise if you wish. Noise is the probability with which any action dictated by a strategy will be swapped:

```
>>> match = axl.Match(players=players, turns=5, noise=0.2)
>>> match.play()
[('D', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('D', 'D')]
```

The result of the match is held as an attribute within the `Match` class. Each time `play()` is called, it will overwrite the content of that attribute:

```
>>> match.result
[('D', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('D', 'D')]
>>> match.play()
[('C', 'C'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'C')]
>>> match.result
[('C', 'C'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'C')]
```

The result of the match can also be viewed as sparklines where cooperation is shown as a solid block and defection as a space. Sparklines are a very concise way to view the result and can be useful for spotting patterns:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator())
>>> match = axl.Match(players, 25)
>>> match.play()
[('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), (
↪'C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C')]
>>> print(match.sparklines())


```

The character for cooperation and a space for defection are default values but you can use any characters you like:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator())
>>> match = axl.Match(players, 25)
>>> match.play()
[('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), (
↪'C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C')]
>>> print(match.sparklines(c_symbol='|', d_symbol='-'))
|||||||||||||||||||||||||
|-|-|-|-|-|-|-|-|-|-|-|-|
```

A *Match* class can also score the individual turns of a match. Just call *match.scores()* after play:

```
>>> import axelrod as axl
>>> players = (axl.Cooperator(), axl.Alternator())
>>> match = axl.Match(players, 25)
>>> match.play()
```

```
[('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), (
↪'C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C'), (
↪'C', 'D'), ('C', 'C'), ('C', 'D'), ('C', 'C')]
>>> match.scores()
[(3, 3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3,␣
↪3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3, 3), (0, 5), (3, 3),␣
↪(0, 5), (3, 3), (0, 5), (3, 3)]
```

There are various further methods:

```
>>> match.final_score()
(39, 99)
>>> match.final_score_per_turn()
(1.56, 3.96)
>>> match.winner()
Alternator
>>> match.cooperation()  # The count of cooperations
(25, 13)
>>> match.normalised_cooperation()  # The count of cooperations per turn
(1.0, 0.52)
```

Creating and running a simple tournament

The following lines of code creates a list players playing simple strategies:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> players
[Cooperator, Defector, Tit For Tat, Grudger]
```

We can now create a tournament, play it, save the results and view the rank of each player:

```
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
>>> results.ranked_names
['Defector', 'Tit For Tat', 'Grudger', 'Cooperator']
```

We can also plot these results:

```
>>> plot = axl.Plot(results)
>>> p = plot.boxplot()
>>> p.show()
```

Note that in this case none of our strategies are stochastic so the boxplot shows that there is no variation. Take a look at the *Visualising results* section to see plots showing a stochastic effect.

Summarising tournament results

As shown in *Creating and running a simple tournament* let us create a tournament:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> tournament = axl.Tournament(players, turns=10, repetitions=3)
>>> results = tournament.play()
```

The results set can return a list of named tuples, ordered by strategy rank that summarises the results of the tournament:

```
>>> summary = results.summarise()
>>> import pprint
>>> pprint.pprint(summary)
[Player(Rank=0, Name='Defector', Median_score=2.6..., Cooperation_rating=0.0, Wins=3.
↪0, Initial_C_rate=0.0, CC_rate=...),
 Player(Rank=1, Name='Tit For Tat', Median_score=2.3..., Cooperation_rating=0.7,␣
↪Wins=0.0, Initial_C_rate=1.0, CC_rate=...),
 Player(Rank=2, Name='Grudger', Median_score=2.3..., Cooperation_rating=0.7, Wins=0.0,
↪ Initial_C_rate=1.0, CC_rate=...),
 Player(Rank=3, Name='Cooperator', Median_score=2.0..., Cooperation_rating=1.0,␣
↪Wins=0.0, Initial_C_rate=1.0, CC_rate=...)]
```

It is also possible to write this data directly to a csv file using the *write_summary* method:

```
>>> results.write_summary('summary.csv')
>>> import csv
>>> with open('summary.csv', 'r') as outfile:
...     csvreader = csv.reader(outfile)
...     for row in csvreader:
...         print(row)
['Rank', 'Name', 'Median_score', 'Cooperation_rating', 'Wins', 'Initial_C_rate', 'CC_
↪rate', 'CD_rate', 'DC_rate', 'DD_rate', 'CC_to_C_rate', 'CD_to_C_rate', 'DC_to_C_
↪rate', 'DD_to_C_rate']
['0', 'Defector', '2.6...', '0.0', '3.0', '0.0', '0.0', '0.0', '0.4...', '0.6...', '0
↪', '0', '0', '0']
['1', 'Tit For Tat', '2.3...', '0.7', '0.0', '1.0', '0.66...', '0.03...', '0.0', '0.3.
↪..', '1.0', '0', '0', '0']
['2', 'Grudger', '2.3...', '0.7', '0.0', '1.0', '0.66...', '0.03...', '0.0', '0.3...',
↪ '1.0', '0', '0', '0']
['3', 'Cooperator', '2.0...', '1.0', '0.0', '1.0', '0.66...', '0.33...', '0.0', '0.0',
↪ '1.0', '1.0', '0', '0']
```

The result set class computes a large number of detailed outcomes read about those in *Accessing tournament results*.

Accessing the interactions

This tutorial will show you briefly how to access the detailed interaction results corresponding to the tournament.

To access the detailed interaction results we create a tournament as usual (see *Creating and running a simple tournament*) but indicate that we want to keep track of the interactions:

```
>>> import axelrod as axl
>>> players = [
...     axl.Cooperator(), axl.Defector(),
...     axl.TitForTat(), axl.Grudger()]
>>> tournament = axl.Tournament(players, turns=3, repetitions=1)
>>> results = tournament.play(keep_interactions=True)
```

If the play method is called with `keep_interactions=True`, the result set object will have an `interactions` attribute which contains all the interactions between the players. These can be used to view the history of the interactions:

```
>>> for index_pair, interaction in results.interactions.items():
...     player1 = tournament.players[index_pair[0]]
...     player2 = tournament.players[index_pair[1]]
...     print('%s vs %s: %s' % (player1, player2, interaction))
Cooperator vs Defector: [('C', 'D'), ('C', 'D'), ('C', 'D')]
Defector vs Tit For Tat: [('D', 'C'), ('D', 'D'), ('D', 'D')]
Cooperator vs Cooperator: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Tit For Tat vs Grudger: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Grudger vs Grudger: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Tit For Tat vs Tit For Tat: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Defector vs Grudger: [('D', 'C'), ('D', 'D'), ('D', 'D')]
Cooperator vs Grudger: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Cooperator vs Tit For Tat: [('C', 'C'), ('C', 'C'), ('C', 'C')]
Defector vs Defector: [('D', 'D'), ('D', 'D'), ('D', 'D')]
```

We can use these interactions to reconstruct `axelrod.Match` objects which have a variety of available methods for analysis (more information can be found in *Creating Matches*):

```
>>> matches = []
>>> for index_pair, interaction in results.interactions.items():
...     player1 = tournament.players[index_pair[0]]
...     player2 = tournament.players[index_pair[1]]
...     match = axl.Match([player1, player2], turns=3)
...     match.result = interaction
...     matches.append(match)
>>> len(matches)
10
```

As an example let us view all winners of each match (`False` indicates a tie):

```
>>> for match in matches:
...     print("{} v {}, winner: {}".format(match.players[0], match.players[1], match.
↪winner()))
Cooperator v Defector, winner: Defector
Defector v Tit For Tat, winner: Defector
Cooperator v Cooperator, winner: False
Tit For Tat v Grudger, winner: False
Grudger v Grudger, winner: False
Tit For Tat v Tit For Tat, winner: False
Defector v Grudger, winner: Defector
Cooperator v Grudger, winner: False
Cooperator v Tit For Tat, winner: False
Defector v Defector, winner: False
```

Visualising results

This tutorial will show you briefly how to visualise some basic results

Visualising the results of the tournament

As shown in *Creating and running a simple tournament*, let us create a tournament, but this time we will include a player that acts randomly:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> players.append(axl.Random())
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
```

We can view these results (which helps visualise the stochastic effects):

```
>>> plot = axl.Plot(results)
>>> p = plot.boxplot()
>>> p.show()
```

Visualising the distributions of wins

We can view the distributions of wins for each strategy:

```
>>> p = plot.winplot()
>>> p.show()
```

Visualising the payoff matrix

We can also easily view the payoff matrix described in *Accessing tournament results*, this becomes particularly useful when viewing the outputs of tournaments with a large number of strategies:

```
>>> p = plot.payoff()
>>> p.show()
```

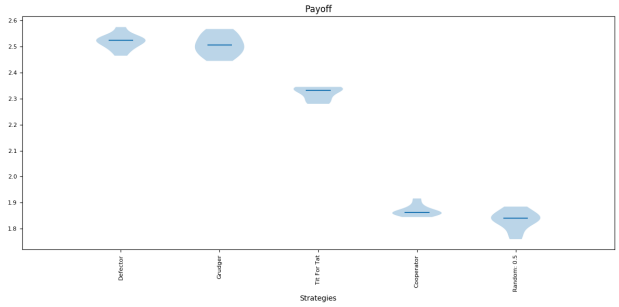
Saving all plots

The `axelrod.Plot` class has a method: `save_all_plots` that will save all the above plots to file.

Passing various objects to plot

The library give access to underlying matplotlib axes objects of each plot, thus the user can easily modify various aspects of a plot:

```
>>> import matplotlib.pyplot as plt
>>> _, ax = plt.subplots()
>>> title = ax.set_title('Payoff')
>>> xlabel = ax.set_xlabel('Strategies')
>>> p = plot.boxplot(ax=ax)
>>> p.show()
```



Moran Process

The strategies in the library can be pitted against one another in the Moran process, a population process simulating natural selection.

The process works as follows. Given an initial population of players, the population is iterated in rounds consisting of:

- matches played between each pair of players, with the cumulative total scores recorded
- a player is chosen to reproduce proportional to the player's score in the round
- a player is chosen at random to be replaced

The process proceeds in rounds until the population consists of a single player type. That type is declared the winner. To run an instance of the process with the library, proceed as follows:

```
>>> import axelrod as axl
>>> axl.seed(0)
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> mp = axl.MoranProcess(players)
>>> populations = mp.play()
>>> mp.winning_strategy_name
'Grudger'
```

You can access some attributes of the process, such as the number of rounds:

```
>>> len(mp)
14
```

The sequence of populations:

```
>>> import pprint
>>> pprint.pprint(populations)
[Counter({'Grudger': 1, 'Cooperator': 1, 'Defector': 1, 'Tit For Tat': 1}),
 Counter({'Grudger': 1, 'Cooperator': 1, 'Defector': 1, 'Tit For Tat': 1}),
 Counter({'Grudger': 1, 'Cooperator': 1, 'Defector': 1, 'Tit For Tat': 1}),
 Counter({'Tit For Tat': 2, 'Grudger': 1, 'Cooperator': 1}),
 Counter({'Grudger': 2, 'Cooperator': 1, 'Tit For Tat': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 3, 'Cooperator': 1}),
```

```
 Counter({'Grudger': 3, 'Cooperator': 1}),
 Counter({'Grudger': 4})]
```

The scores in each round:

```
>>> for row in mp.score_history:
...     print([round(element, 1) for element in row])
[6.0, 7.1, 7.0, 7.0]
[6.0, 7.1, 7.0, 7.0]
[6.0, 7.1, 7.0, 7.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
[9.0, 9.0, 9.0, 9.0]
```

The `MoranProcess` class also accepts an argument for a mutation rate. Nonzero mutation changes the Markov process so that it no longer has absorbing states, and will iterate forever. To prevent this, iterate with a loop (or function like `takewhile` from `itertools`):

```
>>> import axelrod as axl
>>> axl.seed(4) # for reproducible example
>>> players = [axl.Cooperator(), axl.Defector(),
...                axl.TitForTat(), axl.Grudger()]
>>> mp = axl.MoranProcess(players, mutation_rate=0.1)
>>> for _ in mp:
...     if len(mp.population_distribution()) == 1:
...         break
>>> mp.population_distribution()
Counter({'Cooperator': 4})
```

Other types of implemented Moran processes:

- *Moran Process on Graphs*
- *Approximate Moran Process*

Human Interaction

It is possible to play interactively using the Human strategy:

```
>>> import axelrod as axl
>>> me = axl.Human(name='me')
>>> players = [axl.TitForTat(), me]
>>> match = axl.Match(players, turns=3)
>>> match.play()
```

You will be prompted for the action to play at each turn:

```
Starting new match
Turn 1 action [C or D] for me: C
```

```
Turn 1: me played C, opponent played C
Turn 2 action [C or D] for me: D

Turn 2: me played D, opponent played C
Turn 3 action [C or D] for me: C
[('C', 'C'), ('C', 'D'), ('D', 'C')]
```

after this, the `match` object can be manipulated as described in *Creating Matches*

Research topics

This section contains descriptions of particular tools of interest to those doing game theoretic research.

Contents:

Noisy tournaments

A common variation on iterated prisoner's dilemma tournaments is to add stochasticity in the choice of actions, simply called noise. This noise is introduced by flipping plays between 'C' and 'D' with some probability that is applied to all plays after they are delivered by the player *[Bendor1993]*.

The presence of this persistent background noise causes some strategies to behave substantially differently. For example, `TitForTat` can fall into defection loops with itself when there is noise. While `TitForTat` would usually cooperate well with itself:

```
C C C C C ...
C C C C C ...
```

Noise can cause a C to flip to a D (or vice versa), disrupting the cooperative chain:

```
C C C D C D C D D D ...
C C C C D C D D D D ...
```

To create a noisy tournament you simply need to add the *noise* argument:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> noise = 0.1
>>> tournament = axl.Tournament(players, noise=noise)
>>> results = tournament.play()
>>> plot = axl.Plot(results)
>>> p = plot.boxplot()
>>> p.show()
```

Here is how the distribution of wins now looks:

```
>>> p = plot.winplot()
>>> p.show()
```

Probabilistic Ending Tournaments

It is possible to create a tournament where the length of each Match is not constant for all encounters: after each turn the Match ends with a given probability, *[Axelrod1980b]*:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> tournament = axl.ProbEndTournament(players, prob_end=0.5)
```

We can view the results in a similar way as described in *Accessing tournament results*:

```
>>> results = tournament.play()
>>> m = results.payoff_matrix
>>> for row in m:
...     print([round(ele, 1) for ele in row]) # Rounding output

[3.0, 0.0, 3.0, 3.0]
[5.0, 1.0, 3.7, 3.6]
[3.0, 0.3, 3.0, 3.0]
[3.0, 0.4, 3.0, 3.0]
```

We see that `Cooperator` always scores 0 against `Defector` but other scores seem variable as they are effected by the length of each match.

We can (as before) obtain the ranks for our players:

```
>>> results.ranked_names
['Defector', 'Tit For Tat', 'Grudger', 'Cooperator']
```

We can plot the results:

```
>>> plot = axl.Plot(results)
>>> p = plot.boxplot()
>>> p.show()
```

We can also view the length of the matches played by each player. The plot shows that the length of each match (for each player) is not the same. The median length is 4 which is the expected value with the probability of a match ending being `0.5`.

```
>>> p = plot.lengthplot()
>>> p.show()
```

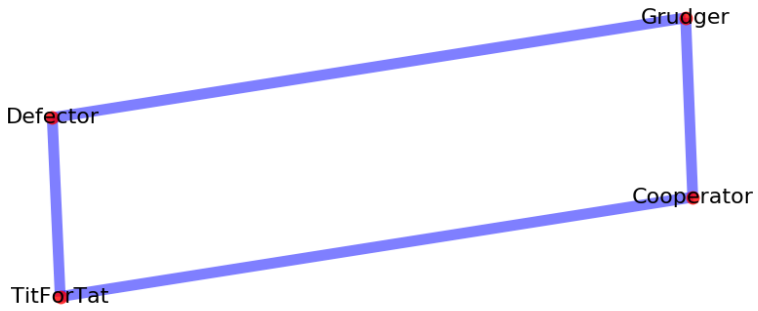
Spatial tournaments

A spatial tournament is defined on a graph where the nodes correspond to players and edges define whether or not a given player pair will have a match.

The initial work on spatial tournaments was done by Nowak and May in a 1992 paper: *[Nowak1992]*.

Additionally, Szabó and Fáth in their 2007 paper *[Szabo2007]* consider a variety of graphs, such as lattices, small world, scale-free graphs and evolving networks.

Let's create a tournament where `Cooperator` and `Defector` do not play each other and neither do `TitForTat` and `Grudger` :



Note that the edges have to be given as a list of tuples of player indices:

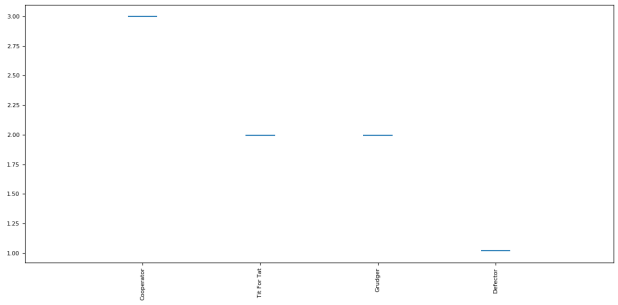
```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> edges = [(0, 2), (0, 3), (1, 2), (1, 3)]
```

To create a spatial tournament you call the `SpatialTournamnent` class:

```
>>> spatial_tournament = axl.SpatialTournament(players, edges=edges)
>>> results = spatial_tournament.play(keep_interactions=True)
```

We can plot the results:

```
>>> plot = axl.Plot(results)
>>> p = plot.boxplot()
>>> p.show()
```



We can, like any other tournament, obtain the ranks for our players:

```
>>> results.ranked_names
['Cooperator', 'Tit For Tat', 'Grudger', 'Defector']
```

Let's run a small tournament of 2 `turns` and 5 `repetitions` and obtain the interactions:

```
>>> spatial_tournament = axl.SpatialTournament(players ,turns=2, repetitions=2,␣
↪edges=edges)
>>> results = spatial_tournament.play(keep_interactions=True)
>>> for index_pair, interaction in sorted(results.interactions.items()):
...     player1 = spatial_tournament.players[index_pair[0]]
...     player2 = spatial_tournament.players[index_pair[1]]
...     print('%s vs %s: %s' % (player1, player2, interaction))
```

```
Cooperator vs Tit For Tat: [[('C', 'C'), ('C', 'C')], [('C', 'C'), ('C', 'C')]]
Cooperator vs Grudger: [[('C', 'C'), ('C', 'C')], [('C', 'C'), ('C', 'C')]]
Defector vs Tit For Tat: [[('D', 'C'), ('D', 'D')], [('D', 'C'), ('D', 'D')]]
Defector vs Grudger: [[('D', 'C'), ('D', 'D')], [('D', 'C'), ('D', 'D')]]
```

As anticipated `Cooperator` does not interact with `Defector` neither `TitForTat` with `Grudger`.

It is also possible to create a probabilistic ending spatial tournament with the `ProbEndSpatialTournament` class:

```
>>> prob_end_spatial_tournament = axl.ProbEndSpatialTournament(players, edges=edges,␣
↪prob_end=.1, repetitions=1)
>>> prob_end_results = prob_end_spatial_tournament.play(keep_interactions=True)
```

We see that the match lengths are no longer all equal:

```
>>> axl.seed(0)
>>> lengths = []
>>> for interaction in prob_end_results.interactions.values():
...     lengths.append(len(interaction[0]))
>>> min(lengths) != max(lengths)
True
```

Moran Process on Graphs

The library also provides a graph-based Moran process *[Shakarian2013]* with `MoranProcessGraph`. To use this class you must supply at least one `Axelrod.graph.Graph` object, which can be initialized with just a list of edges:

```
edges = [(source_1, target1), (source2, target2), ...]
```

The nodes can be any hashable object (integers, strings, etc.). For example:

```
>>> import axelrod as axl
>>> from axelrod.graph import Graph
>>> edges = [(0, 1), (1, 2), (2, 3), (3, 1)]
>>> graph = Graph(edges)
```

Graphs are undirected by default. Various intermediates such as the list of neighbors are cached for efficiency by the graph object.

A Moran process can be invoked with one or two graphs. The first graph, the *interaction graph*, dictates how players are matched up in the scoring phase. Each player plays a match with each neighbor. The second graph dictates how players replace another during reproduction. When an individual is selected to reproduce, it replaces one of its neighbors in the *reproduction graph*. If only one graph is supplied to the process, the two graphs are assumed to be the same.

To create a graph-based Moran process, use a graph as follows:

```
>>> from axelrod.graph import Graph
>>> axl.seed(40)
>>> edges = [(0, 1), (1, 2), (2, 3), (3, 1)]
>>> graph = Graph(edges)
>>> players = [axl.Cooperator(), axl.Cooperator(), axl.Cooperator(), axl.Defector()]
>>> mp = axl.MoranProcessGraph(players, interaction_graph=graph)
>>> results = mp.play()
>>> mp.population_distribution()
Counter({'Cooperator': 4})
```

You can supply the *reproduction_graph* as a keyword argument. The standard Moran process is equivalent to using a complete graph for both graphs.

Approximate Moran Process

Due to the high computational cost of a single Moran process, an approximate Moran process is implemented that can make use of cached outcomes of games. The following code snippet will generate a Moran process in which the outcomes of the matches played by a `Random: 0.5` are sampled from one possible outcome against each opponent (`Defector` and `Random: 0.5`). First the cache is built by passing counter objects of outcomes:

```
>>> import axelrod as axl
>>> from collections import Counter
>>> cached_outcomes = {}
>>> cached_outcomes[("Random: 0.5", "Defector")] = axl.Pdf(Counter([(1, 1)]))
>>> cached_outcomes[("Random: 0.5", "Random: 0.5")] = axl.Pdf(Counter([(3, 3)]))
>>> cached_outcomes[("Defector", "Defector")] = axl.Pdf(Counter([(1, 1)]))
```

Now let us create an Approximate Moran Process:

```
>>> axl.seed(2)
>>> players = [axl.Defector(), axl.Random(), axl.Random()]
>>> amp = axl.ApproximateMoranProcess(players, cached_outcomes)
>>> results = amp.play()
>>> amp.population_distribution()
Counter({'Random: 0.5': 3})
```

We see that, for this random seed, the `Random: 0.5` won this Moran process. This is not what happens in a standard Moran process where the `Random: 0.5` player will not win:

```
>>> axl.seed(2)
>>> amp = axl.MoranProcess(players)
>>> results = amp.play()
>>> amp.population_distribution()
Counter({'Defector': 3})
```

Morality Metrics

Tyler Singer-Clark's June 2014 paper, "Morality Metrics On Iterated Prisoner's Dilemma Players" *[Singer-Clark2014]*), describes several interesting metrics which may be used to analyse IPD tournaments all of which are available within the ResultSet class. (Tyler's paper is available here: http://www.scottaaronson.com/morality.pdf).

Each metric depends upon the cooperation rate of the players, defined by Tyler Singer-Clark as:

$$CR(b) = \frac{C(b)}{TT}$$

where C(b) is the total number of turns where a player chose to cooperate and TT is the total number of turns played.

A matrix of cooperation rates is available within a tournament's ResultSet:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
>>> [[round(float(ele), 3) for ele in row] for row in results.normalised_cooperation]
[[1.0, 1.0, 1.0, 1.0], [0.0, 0.0, 0.0, 0.0], [1.0, 0.005, 1.0, 1.0], [1.0, 0.005, 1.0,
↪ 1.0]]
```

There is also a 'good partner' matrix showing how often a player cooperated at least as much as its opponent:

```
>>> results.good_partner_matrix
[[0, 10, 10, 10], [0, 0, 0, 0], [10, 10, 0, 10], [10, 10, 10, 0]]
```

Each of the metrics described in Tyler's paper is available as follows (here they are rounded to 2 digits):

```
>>> [round(ele, 2) for ele in results.cooperating_rating]
[1.0, 0.0, 0.67, 0.67]
>>> [round(ele, 2) for ele in results.good_partner_rating]
[1.0, 0.0, 1.0, 1.0]
>>> [round(ele, 2) for ele in results.eigenjesus_rating]
[0.58, 0.0, 0.58, 0.58]
>>> [round(ele, 2) for ele in results.eigenmoses_rating]
[0.37, -0.37, 0.6, 0.6]
```

Ecological Variant

In Axelrod's original work an ecological approach based on the payoff matrix of the tournament was used to study the evolutionary stability of each strategy. Whilst this bears some comparison to the *Moran Process*, the latter is much more widely used in the literature.

To study the evolutionary stability of each strategy it is possible to create an ecosystem based on the payoff matrix of a tournament:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger(),
...            axl.Random()]
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
>>> eco = axl.Ecosystem(results)
>>> eco.reproduce(100) # Evolve the population over 100 time steps
```

Here is how we obtain a nice stackplot of the system evolving over time:

```
>>> plot = axl.Plot(results)
>>> p = plot.stackplot(eco)
>>> p.show()
```

Fingerprinting

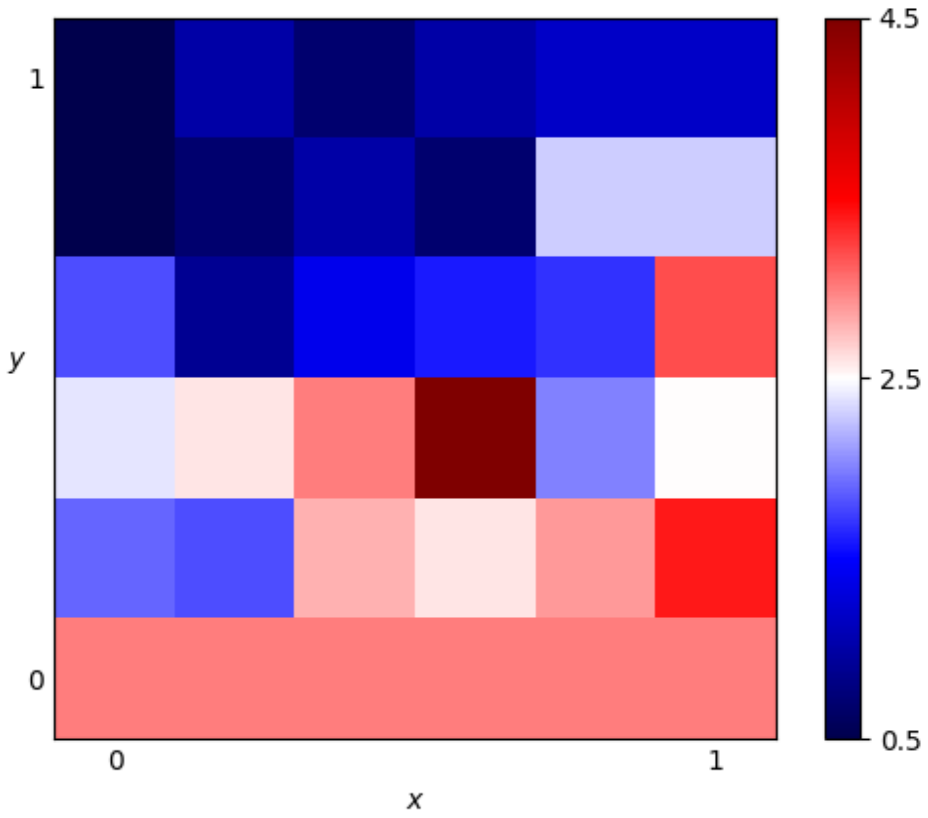
In *[Ashlock2008]*, *[Ashlock2009]* a methodology for obtaining visual representation of a strategy's behaviour is described. The basic method is to play the strategy against a probe strategy with varying noise parameters. These noise parameters are implemented through the `JossAnnTransformer`. The Joss-Ann of a strategy is a new strategy which has a probability `x` of cooperating, a probability `y` of defecting, and otherwise uses the response appropriate to the original strategy. We can then plot the expected score of the strategy against `x` and `y` and obtain a heat plot over the unit square. When `x + y >= 1` the `JossAnn` is created with parameters `(1-y, 1-x)` and plays against the Dual of the probe instead. A full definition and explanation is given in *[Ashlock2008]*, *[Ashlock2009]*.

Here is how to create a fingerprint of `WinStayLoseShift` using `TitForTat` as a probe:

```
>>> import axelrod as axl
>>> axl.seed(0)  # Fingerprinting is a random process
>>> strategy = axl.WinStayLoseShift
>>> probe = axl.TitForTat
>>> af = axl.AshlockFingerprint(strategy, probe)
>>> data = af.fingerprint(turns=10, repetitions=2, step=0.2)
>>> data
{...
>>> data[(0, 0)]
3.0
```

The `fingerprint` method returns a dictionary mapping coordinates of the form `(x, y)` to the mean score for the corresponding interactions. We can then plot the above to get:

```
>>> p = af.plot()
>>> p.show()
```

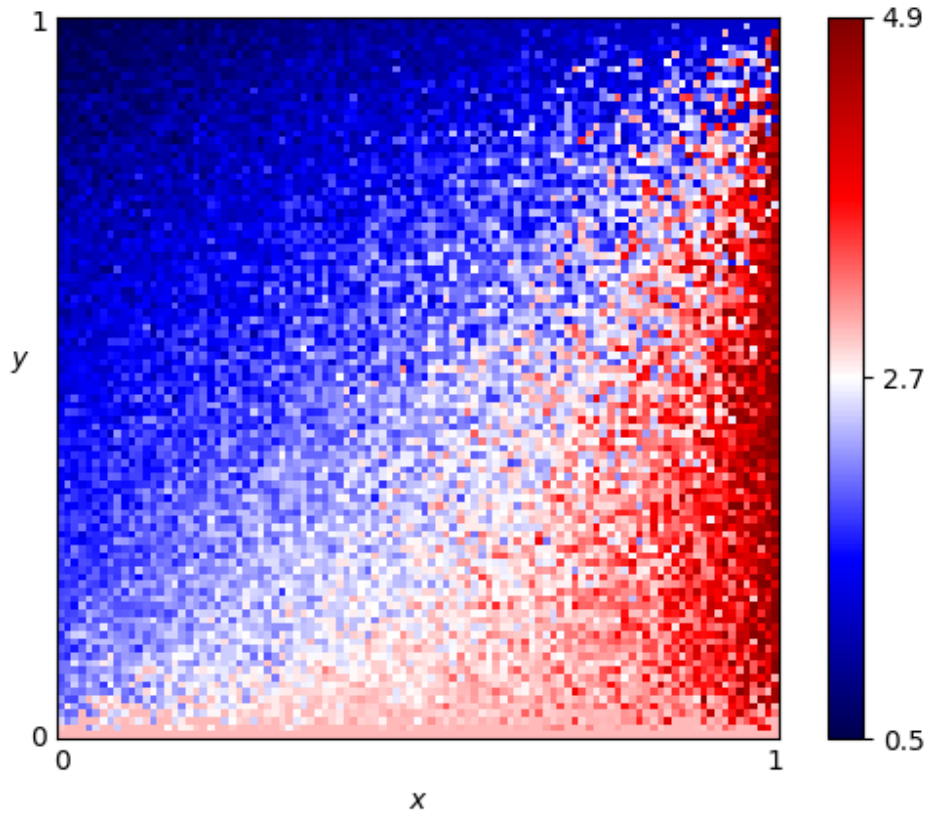


In reality we would need much more detail to make this plot useful.

Running the above with the following parameters:

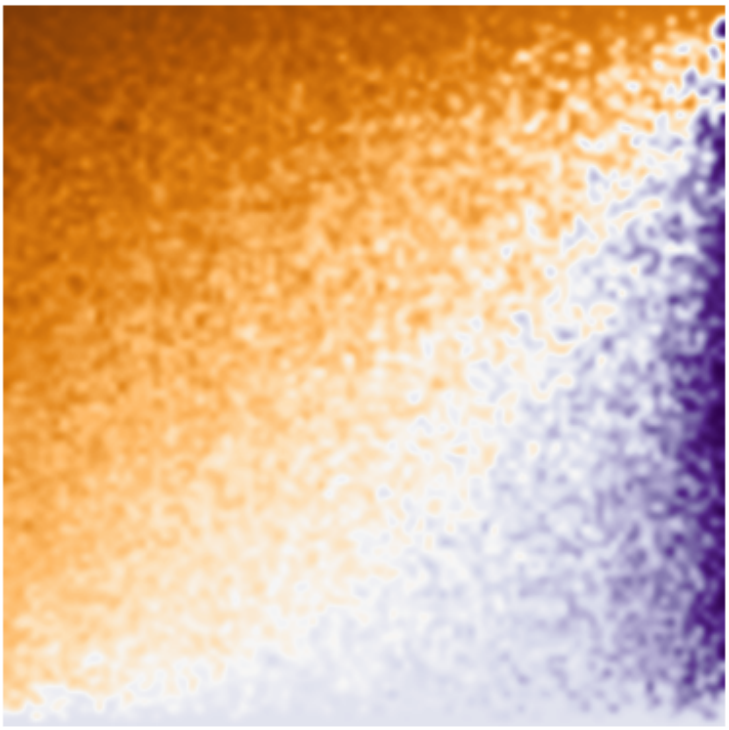
```
>>> af.fingerprint(turns=50, repetitions=2, step=0.01)
```

We get the plot:



We are also able to specify a matplotlib colour map, interpolation and can remove the colorbar and axis labels:

```
>>> p = af.plot(col_map='PuOr', interpolation='bicubic', colorbar=False, labels=False)
>>> p.show()
```



Note that it is also possible to pass a player instance to be fingerprinted and/or as a probe. This allows for the fingerprinting of parametrized strategies:

```
>>> axl.seed(0)
>>> player = axl.Random(p=.1)
>>> probe = axl.GTFT(p=.9)
>>> af = axl.AshlockFingerprint(player, probe)
>>> data = af.fingerprint(turns=10, repetitions=2, step=0.2)
>>> data
{...
>>> data[(0, 0)]
4.4...
```

Ashlock's fingerprint is currently the only fingerprint implemented in the library.

Further capabilities in the library

This section shows some of the more intricate capabilities of the library.

Contents:

Accessing strategies

All of the strategies are accessible from the main name space of the library. For example:

```
>>> import axelrod as axl
>>> axl.TitForTat()
Tit For Tat
>>> axl.Cooperator()
Cooperator
```

The **main strategies** which obey the rules of Axelrod's original tournament can be found in a list: *axelrod.strategies*:

```
>>> axl.strategies
[...
```

This makes creating a full tournament very straightforward:

```
>>> players = [s() for s in axl.strategies]
>>> tournament = axl.Tournament(players)
```

There are a list of various other strategies in the library to make it easier to create a variety of tournaments:

```
>>> axl.demo_strategies  # 5 simple strategies useful for demonstration.
[...
>>> axl.basic_strategies  # A set of basic strategies.
[...
>>> axl.long_run_time_strategies  # These have a high computational cost
[...
```

Furthermore there are some strategies that 'cheat' (for example by modifying their opponents source code). These can be found in `axelrod.cheating_strategies`:

```
>>> axl.cheating_strategies
[...
```

All of the strategies in the library are contained in: `axelrod.all_strategies`:

```
>>> axl.all_strategies
[...
```

All strategies are also classified, you can read more about that in *Classification of strategies*.

Classification of strategies

Due to the large number of strategies, every class and instance of the class has a `classifier` attribute which classifies that strategy according to various dimensions.

Here is the `classifier` for the `Cooperator` strategy:

```
>>> import axelrod as axl
>>> expected_dictionary = {
...     'manipulates_state': False,
...     'makes_use_of': set([]),
...     'long_run_time': False,
...     'stochastic': False,
...     'manipulates_source': False,
...     'inspects_source': False,
...     'memory_depth': 0
... }  # Order of this dictionary might be different on your machine
>>> axl.Cooperator.classifier == expected_dictionary
True
```

Note that instances of the class also have this classifier:

```
>>> s = axl.Cooperator()
>>> s.classifier == expected_dictionary
True
```

and that we can retrieve individual entries from that `classifier` dictionary:

```
>>> s = axl.TitForTat
>>> s.classifier['memory_depth']
1
>>> s = axl.Random
>>> s.classifier['stochastic']
True
```

We can use this classification to generate sets of strategies according to filters which we define in a 'filterset' dictionary and then pass to the 'filtered_strategies' function. For example, to identify all the stochastic strategies:

```
>>> filterset = {
...     'stochastic': True
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
66
```

Or, to find out how many strategies only use 1 turn worth of memory to make a decision:

```
>>> filterset = {
...     'memory_depth': 1
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
27
```

Multiple filters can be specified within the filterset dictionary. To specify a range of memory_depth values, we can use the 'min_memory_depth' and 'max_memory_depth' filters:

```
>>> filterset = {
...     'min_memory_depth': 1,
...     'max_memory_depth': 4
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
49
```

We can also identify strategies that make use of particular properties of the tournament. For example, here is the number of strategies that make use of the length of each match of the tournament:

```
>>> filterset = {
...     'makes_use_of': ['length']
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
27
```

Note that in the filterset dictionary, the value for the 'makes_use_of' key must be a list. Here is how we might identify the number of strategies that use both the length of the tournament and the game being played:

```
>>> filterset = {
...     'makes_use_of': ['length', 'game']
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
21
```

Some strategies have been classified as having a particularly long run time:

```
>>> filterset = {
...     'long_run_time': True
... }
>>> strategies = axl.filtered_strategies(filterset)
>>> len(strategies)
17
```

Strategies that `manipulate_source`, `manipulate_state` and/or `inspect_source` return `False` for the `obey_axelrod` function:

```
>>> s = axl.MindBender()
>>> axl.obey_axelrod(s)
False
>>> s = axl.TitForTat()
>>> axl.obey_axelrod(s)
True
```

Strategy Transformers

What is a Strategy Transformer?

A strategy transformer is a function that modifies an existing strategy. For example, `FlipTransformer` takes a strategy and flips the actions from C to D and D to C:

```
>>> import axelrod as axl
>>> from axelrod.strategy_transformers import *
>>> FlippedCooperator = FlipTransformer()(axl.Cooperator)
>>> player = FlippedCooperator()
>>> opponent = axl.Cooperator()
>>> player.strategy(opponent)
'D'
>>> opponent.strategy(player)
'C'
```

Our player was switched from a `Cooperator` to a `Defector` when we applied the transformer. The transformer also changed the name of the class and player:

```
>>> player.name
'Flipped Cooperator'
>>> FlippedCooperator.name
'Flipped Cooperator'
```

This behavior can be suppressed by setting the `name_prefix` argument:

```
>>> FlippedCooperator = FlipTransformer(name_prefix=None)(axl.Cooperator)
>>> player = FlippedCooperator()
```

```
>>> player.name
'Cooperator'
```

Note carefully that the transformer returns a class, not an instance of a class. This means that you need to use the Transformed class as you would normally to create a new instance:

```
>>> from axelrod.strategy_transformers import NoisyTransformer
>>> player = NoisyTransformer(0.5)(axl.Cooperator)()
```

rather than `NoisyTransformer(0.5)(axl.Cooperator())` or just `NoisyTransformer(0.5)(axl.Cooperator)`.

Included Transformers

The library includes the following transformers:

- `ApologizingTransformer`: Apologizes after a round of `(D, C)`:

```
 >>> ApologizingDefector = ApologyTransformer([D], [C])(axl.Defector)
 >>> player = ApologizingDefector()

You can pass any two sequences in. In this example the player would apologize
after two consequtive rounds of `(D, C)`::

    >>> ApologizingDefector = ApologyTransformer([D, D], [C, C])(axl.Defector)
    >>> player = ApologizingDefector()
```

- `DeadlockBreakingTransformer`: Attempts to break `(D, C) -> (C, D)` deadlocks by cooperating:

```
>>> DeadlockBreakingTFT = DeadlockBreakingTransformer()(axl.TitForTat)
>>> player = DeadlockBreakingTFT()
```

- `DualTransformer`: The Dual of a strategy will return the exact opposite set of moves to the original strategy when both are faced with the same history. *[Ashlock2008]*:

```
>>> DualWSLS = DualTransformer()(axl.WinStayLoseShift)
>>> player = DualWSLS()
```

- `FlipTransformer`: Flips all actions:

```
>>> FlippedCooperator = FlipTransformer()(axl.Cooperator)
>>> player = FlippedCooperator()
```

- `FinalTransformer(seq=None)`: Ends the tournament with the moves in the sequence `seq`, if the tournament_length is known. For example, to obtain a cooperator that defects on the last two rounds:

```
>>> FinallyDefectingCooperator = FinalTransformer([D, D])(axl.Cooperator)
>>> player = FinallyDefectingCooperator()
```

- `ForgiverTransformer(p)`: Flips defections with probability `p`:

```
>>> ForgivinDefector = ForgiverTransformer(0.1)(axl.Defector)
>>> player = ForgivinDefector()
```

- `GrudgeTransformer(N)`: Defections unconditionally after more than N defections:

```
>>> GrudgingCooperator = GrudgeTransformer(2)(axl.Cooperator)
>>> player = GrudgingCooperator()
```

- `InitialTransformer(seq=None)`: First plays the moves in the sequence `seq`, then plays as usual. For example, to obtain a defector that cooperates on the first two rounds:

```
>>> InitiallyCooperatingDefector = InitialTransformer([C, C])(axl.Defector)
>>> player = InitiallyCooperatingDefector()
```

- `JossAnnTransformer(probability)`: Where `probability = (x, y)`, the Joss-Ann of a strategy is a new strategy which has a probability `x` of choosing the move C, a probability `y` of choosing the move D, and otherwise uses the response appropriate to the original strategy. *[Ashlock2008]*:

```
>>> JossAnnTFT = JossAnnTransformer((0.2, 0.3))(axl.TitForTat)
>>> player = JossAnnTFT()
```

- `MixedTransformer`: Randomly plays a mutation to another strategy (or set of strategies. Here is the syntax to do this with a set of strategies:

```
>>> strategies = [axl.Grudger, axl.TitForTat]
>>> probability = [.2, .3]  # .5 chance of mutated to one of above
>>> player =  MixedTransformer(probability, strategies)(axl.Cooperator)
```

  Here is the syntax when passing a single strategy:

```
>>> strategy = axl.Grudger
>>> probability = .2
>>> player =  MixedTransformer(probability, strategy)(axl.Cooperator)
```

- `NiceTransformer()`: Prevents a strategy from defecting if the opponent has not yet defected:

```
>>> NiceDefector = NiceTransformer()(axl.Defector)
>>> player = NiceDefector()
```

- `NoisyTransformer(noise)`: Flips actions with probability `noise`:

```
>>> NoisyCooperator = NoisyTransformer(0.5)(axl.Cooperator)
>>> player = NoisyCooperator()
```

- `RetaliateTransformer(N)`: Retaliation N times after a defection:

```
>>> TwoTitsForTat = RetaliationTransformer(2)(axl.Cooperator)
>>> player = TwoTitsForTat()
```

- `RetaliateUntilApologyTransformer()`: adds TitForTat-style retaliation:

```
>>> TFT = RetaliateUntilApologyTransformer()(axl.Cooperator)
>>> player = TFT()
```

- `TrackHistoryTransformer`: Tracks History internally in the `Player` instance in a variable `_recorded_history`. This allows a player to e.g. detect noise.:

```
>>> player = TrackHistoryTransformer()(axl.Random)()
```

Composing Transformers

Transformers can be composed to form new composers, in two ways. You can simply chain together multiple transformers:

```
>>> cls1 = FinalTransformer([D,D])(InitialTransformer([D,D])(axl.Cooperator))
>>> p1 = cls1()
```

This defines a strategy that cooperates except on the first two and last two rounds. Alternatively, you can make a new class using `compose_transformers`:

```
>>> cls1 = compose_transformers(FinalTransformer([D, D]), InitialTransformer([D, D]))
>>> p1 = cls1(axl.Cooperator)()
>>> p2 = cls1(axl.Defector)()
```

Usage as Class Decorators

Transformers can also be used to decorate existing strategies. For example, the strategy `BackStabber` defects on the last two rounds. We can encode this behavior with a transformer as a class decorator:

```
@FinalTransformer([D, D]) # End with two defections
class BackStabber(Player):
    """
    Forgives the first 3 defections but on the fourth
    will defect forever. Defects on the last 2 rounds unconditionally.
    """

    name = 'BackStabber'
    classifier = {
        'memory_depth': float('inf'),
        'stochastic': False,
        'inspects_source': False,
        'manipulates_source': False,
        'manipulates_state': False
    }

    def strategy(self, opponent):
        if not opponent.history:
            return C
        if opponent.defections > 3:
            return D
        return C
```

Writing New Transformers

To make a new transformer, you need to define a strategy wrapping function with the following signature:

```
def strategy_wrapper(player, opponent, proposed_action, *args, **kwargs):
    """
    Strategy wrapper functions should be of the following form.

    Parameters
    ----------
    player: Player object or subclass (self)
```

```
    opponent: Player object or subclass
    proposed_action: an axelrod.Action, C or D
        The proposed action by the wrapped strategy
        proposed_action = Player.strategy(...)
    args, kwargs:
        Any additional arguments that you need.

    Returns
    -------
    action: an axelrod.Action, C or D

    """

    # This example just passes through the proposed_action
    return proposed_action
```

The proposed action will be the outcome of:

```
self.strategy(player)
```

in the underlying class (the one that is transformed). The strategy_wrapper still has full access to the player and the opponent objects and can have arguments.

To make a transformer from the `strategy_wrapper` function, use `StrategyTransformerFactory`, which has signature:

```
def StrategyTransformerFactory(strategy_wrapper, name_prefix=""):
    """Modify an existing strategy dynamically by wrapping the strategy
    method with the argument `strategy_wrapper`.

    Parameters
    ----------
    strategy_wrapper: function
        A function of the form `strategy_wrapper(player, opponent, proposed_action,␣
↪*args, **kwargs)`
        Can also use a class that implements
            def __call__(self, player, opponent, action)
    name_prefix: string, "Transformed "
        A string to prepend to the strategy and class name
    """
```

So we use `StrategyTransformerFactory` with `strategy_wrapper`:

```
TransformedClass = StrategyTransformerFactory(generic_strategy_wrapper)
Cooperator2 = TransformedClass(*args, **kwargs)(axl.Cooperator)
```

If your wrapper requires no arguments, you can simply proceed as follows:

```
>>> TransformedClass = StrategyTransformerFactory(generic_strategy_wrapper)()
>>> Cooperator2 = TransformedClass(axl.Cooperator)
```

For more examples, see `axelrod/strategy_transformers.py`.

Build new types of tournaments

It is possible to create new tournaments not yet implemented in the library itself. There are two tools that make up a tournament:

- The `MatchGenerator` class: this class is responsible for generating the required matches.
- The `Tournament` class: this class is responsible for playing the matches generated.

Let us aim to create a round robin tournament of matches with 5 turns each with the modification that two players only play each other with .5 probability.

To do this let us create a new class to generate matches:

```
>>> import axelrod as axl
>>> import random
>>> axl.seed(0)  # Setting a seed.
>>> class StochasticMatchups(axl.RoundRobinMatches):
...     """Inherit from the `axelrod.match_generator.RoundRobinMatches` class"""
...
...     def build_match_chunks(self):
...         """
...         A generator that yields match parameters only with a given probability.
...
...         This over writes the
...         `axelrod.match_generator.RoundRobinMatches.build_match_chunks` method.
...         """
...         for player1_index in range(len(self.players)):
...             for player2_index in range(player1_index, len(self.players)):
...                 if random.random() < 0.5:  # This is the modification
...                     match_params = self.build_single_match_params()
...                     index_pair = (player1_index, player2_index)
...                     yield (index_pair, match_params, self.repetitions)
```

Using this class we can create a tournament with little effort:

```
>>> players = [axl.Cooperator(), axl.Defector(), axl.TitForTat(),
...            axl.Grudger(), axl.Alternator()]
>>> tournament = axl.Tournament(players, match_generator=StochasticMatchups, turns=2,␣
↪repetitions=2)
>>> results = tournament.play(keep_interactions=True)
```

We can then look at the interactions (results may differ based on random seed) for the first repetition:

```
>>> for index_pair, interaction in results.interactions.items():
...     player1 = tournament.players[index_pair[0]]
...     player2 = tournament.players[index_pair[1]]
...     print('%s vs %s: %s' % (player1, player2, interaction))
Cooperator vs Defector: [[('C', 'D'), ('C', 'D')], [('C', 'D'), ('C', 'D')]]
Alternator vs Alternator: [[('C', 'C'), ('D', 'D')], [('C', 'C'), ('D', 'D')]]
Tit For Tat vs Grudger: [[('C', 'C'), ('C', 'C')], [('C', 'C'), ('C', 'C')]]
Grudger vs Grudger: [[('C', 'C'), ('C', 'C')], [('C', 'C'), ('C', 'C')]]
Tit For Tat vs Tit For Tat: [[('C', 'C'), ('C', 'C')], [('C', 'C'), ('C', 'C')]]
Cooperator vs Alternator: [[('C', 'C'), ('C', 'D')], [('C', 'C'), ('C', 'D')]]
Defector vs Defector: [[('D', 'D'), ('D', 'D')], [('D', 'D'), ('D', 'D')]]
```

We see that not all possible matches were played (for example *Cooperator* has not played *TitForTat*). The results can be viewed as before:

```
>>> results.ranked_names
['Cooperator', 'Defector', 'Tit For Tat', 'Grudger', 'Alternator']
```

Note: the `axelrod.MatchGenerator` also has a `build_single_match` method which can be overwritten (similarly to above) if the type of a particular match should be changed.

For example the following could be used to create a tournament that randomly builds matches that were either 200 turns or single 1 shot games:

```
>>> class OneShotOrRepetitionMatchups(axl.RoundRobinMatches):
...     """Inherit from the `axelrod.match_generator.RoundRobinMatches` class"""
...
...
...     def build_single_match_params(self):
...         """Create a single set of match parameters"""
...         turns = 1
...         if random.random() < 0.5:
...             turns = 200
...         return (turns, self.game, None, self.noise)
```

We can take a look at the match lengths when using this generator:

```
>>> players = [axl.Cooperator(), axl.Defector(), axl.TitForTat(),
...            axl.Grudger(), axl.Alternator()]
>>> tournament = axl.Tournament(players, match_generator=OneShotOrRepetitionMatchups,
...                             turns=float("inf"), repetitions=1)
>>> results = tournament.play(keep_interactions=True)
>>> sorted(list(set([len(matches[0]) for matches in results.interactions.values()])))
[1, 200]
```

Accessing tournament results

This tutorial will show you how to access the various results of a tournament:

- Wins: the number of matches won by each player
- Match lengths: the number of turns of each match played by each player (relevant for tournaments with probabilistic ending).
- Scores: the total scores of each player.
- Normalised scores: the scores normalised by matches played and turns.
- Ranking: ranking of players based on median score.
- Ranked names: names of players in ranked order.
- Payoffs: average payoff per turn of each player.
- Payoff matrix: the payoff matrix showing the payoffs of each row player against each column player.
- Payoff standard deviation: the standard deviation of the payoffs matrix.
- Score differences: the score difference between each player.
- Payoff difference means: the mean score differences.
- Cooperation counts: the number of times each player cooperated.
- Normalised cooperation: cooperation count per turn.
- Normalised cooperation: cooperation count per turn.
- State distribution: the count of each type of state of a match
- Normalised state distribution: the normalised count of each type of state of a match
- State to action distribution: the count of each type of state to action pair of a match
- Normalised state distribution: the normalised count of each type of state to action pair of a match

- Initial cooperation count: the count of initial cooperation by each player.
- Initial cooperation rate: the rate of initial cooperation by each player.
- Cooperation rating: cooperation rating of each player
- Vengeful cooperation: a morality metric from the literature (see *Morality Metrics*).
- Good partner matrix: a morality metric from *[Singer-Clark2014]*.
- Good partner rating: a morality metric from *[Singer-Clark2014]*.
- Eigenmoses rating: a morality metric from *[Singer-Clark2014]*.
- Eigenjesus rating: a morality metric from *[Singer-Clark2014]*.

As shown in *Creating and running a simple tournament* let us create a tournament:

```
>>> import axelrod as axl
>>> players = [axl.Cooperator(), axl.Defector(),
...            axl.TitForTat(), axl.Grudger()]
>>> tournament = axl.Tournament(players, turns=10, repetitions=3)
>>> results = tournament.play()
```

Wins

This gives the number of wins obtained by each player:

```
>>> results.wins
[[0, 0, 0], [3, 3, 3], [0, 0, 0], [0, 0, 0]]
```

The `Defector` is the only player to win any matches (all other matches are ties).

Match lengths

This gives the length of the matches played by each player:

```
>>> import pprint  # Nicer formatting of output
>>> pprint.pprint(results.match_lengths)
[[[10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10]],
 [[10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10]],
 [[10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10], [10, 10, 10, 10]]]
```

Every player plays 10 turns against every other player (including themselves) for every repetition of the tournament.

Scores

This gives all the total tournament scores (per player and per repetition):

```
>>> results.scores
[[60, 60, 60], [78, 78, 78], [69, 69, 69], [69, 69, 69]]
```

Normalised scores

This gives the scores, averaged per opponent and turns:

```
>>> results.normalised_scores
[[2.0, 2.0, 2.0], [2.6, 2.6, 2.6], [2.3, 2.3, 2.3], [2.3, 2.3, 2.3]]
```

We see that Cooperator got on average a score of 2 per turn per opponent:

```
>>> results.normalised_scores[0]
[2.0, 2.0, 2.0]
```

Ranking

This gives the ranked index of each player:

```
>>> results.ranking
[1, 2, 3, 0]
```

The first player has index 1 (`Defector`) and the last has index 0 (`Cooperator`).

Ranked names

This gives the player names in ranked order:

```
>>> results.ranked_names
['Defector', 'Tit For Tat', 'Grudger', 'Cooperator']
```

Payoffs

This gives for each player, against each opponent every payoff received for each repetition:

```
>>> pprint.pprint(results.payoffs)
[[[3.0, 3.0, 3.0], [0.0, 0.0, 0.0], [3.0, 3.0, 3.0], [3.0, 3.0, 3.0]],
 [[5.0, 5.0, 5.0], [1.0, 1.0, 1.0], [1.4, 1.4, 1.4], [1.4, 1.4, 1.4]],
 [[3.0, 3.0, 3.0], [0.9, 0.9, 0.9], [3.0, 3.0, 3.0], [3.0, 3.0, 3.0]],
 [[3.0, 3.0, 3.0], [0.9, 0.9, 0.9], [3.0, 3.0, 3.0], [3.0, 3.0, 3.0]]]
```

Payoff matrix

This gives the mean payoff of each player against every opponent:

```
>>> pprint.pprint(results.payoff_matrix)
[[3.0, 0.0, 3.0, 3.0],
 [5.0, 1.0, 1.4, 1.4],
 [3.0, 0.9, 3.0, 3.0],
 [3.0, 0.9, 3.0, 3.0]]
```

We see that the `Cooperator` gets a mean score of 3 against all players except the `Defector`:

```
>>> results.payoff_matrix[0]
[3.0, 0.0, 3.0, 3.0]
```

Payoff standard deviation

This gives the standard deviation of the payoff of each player against every opponent:

```
>>> pprint.pprint(results.payoff_stddevs)
[[0.0, 0.0, 0.0, 0.0],
 [0.0, 0.0, 2.2, 2.2],
 [0.0, 0.0, 0.0, 0.0],
 [0.0, 0.0, 0.0, 0.0]]
```

We see that there is no variation for the payoff for `Cooperator`:

```
>>> results.payoff_stddevs[0]
[0.0, 0.0, 0.0, 0.0]
```

Score differences

This gives the score difference for each player against each opponent for every repetition:

```
>>> pprint.pprint(results.score_diffs)
[[[0.0, 0.0, 0.0], [-5.0, -5.0, -5.0], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0]],
 [[5.0, 5.0, 5.0], [0.0, 0.0, 0.0], [0.5, 0.5, 0.5], [0.5, 0.5, 0.5]],
 [[0.0, 0.0, 0.0], [-0.5, -0.5, -0.5], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0]],
 [[0.0, 0.0, 0.0], [-0.5, -0.5, -0.5], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0]]]
```

We see that `Cooperator` has no difference in score with all players except against the `Defector`:

```
>>> results.score_diffs[0][1]
[-5.0, -5.0, -5.0]
```

Payoff difference means

This gives the mean payoff differences over each repetition:

```
>>> pprint.pprint(results.payoff_diffs_means)
[[0.0, -5.0, 0.0, 0.0],
 [5.0, 0.0, 0.49999999999999983, 0.49999999999999983],
 [0.0, -0.49999999999999983, 0.0, 0.0],
 [0.0, -0.49999999999999983, 0.0, 0.0]]
```

Here is the mean payoff difference for the `Cooperator` strategy, shows that it has no difference with all players except against the `Defector`:

```
>>> results.payoff_diffs_means[0]
[0.0, -5.0, 0.0, 0.0]
```

Cooperation counts

This gives a total count of cooperation for each player against each opponent:

```
>>> results.cooperation
[[0, 30, 30, 30], [0, 0, 0, 0], [30, 3, 0, 30], [30, 3, 30, 0]]
```

Normalised cooperation

This gives the average rate of cooperation against each opponent:

```
>>> pprint.pprint(results.normalised_cooperation)
[[1.0, 1.0, 1.0, 1.0],
 [0.0, 0.0, 0.0, 0.0],
 [1.0, 0.1, 1.0, 1.0],
 [1.0, 0.1, 1.0, 1.0]]
```

We see that `Cooperator` for all the rounds (as expected):

```
>>> results.normalised_cooperation[0]
[1.0, 1.0, 1.0, 1.0]
```

State distribution counts

This gives a total state count against each opponent. A state corresponds to 1 turn of a match and can be one of `('C', 'C')`, `('C', 'D')`, `('D', 'C')`, `('D', 'D')` where the first element is the action of the player in question and the second the action of the opponent:

```
>>> pprint.pprint(results.state_distribution)
[[Counter(),
  Counter({('C', 'D'): 30}),
  Counter({('C', 'C'): 30}),
  Counter({('C', 'C'): 30})],
 [Counter({('D', 'C'): 30}),
  Counter(),
  Counter({('D', 'D'): 27, ('D', 'C'): 3}),
  Counter({('D', 'D'): 27, ('D', 'C'): 3})],
 [Counter({('C', 'C'): 30}),
  Counter({('D', 'D'): 27, ('C', 'D'): 3}),
  Counter(),
  Counter({('C', 'C'): 30})],
 [Counter({('C', 'C'): 30}),
  Counter({('D', 'D'): 27, ('C', 'D'): 3}),
  Counter({('C', 'C'): 30}),
  Counter()]]
```

Normalised state distribution

This gives the average rate state distribution against each opponent. A state corresponds to 1 turn of a match and can be one of `('C', 'C')`, `('C', 'D')`, `('D', 'C')`, `('D', 'D')` where the first element is the action of the player in question and the second the action of the opponent:

```
>>> pprint.pprint(results.normalised_state_distribution)
[[Counter(),
  Counter({('C', 'D'): 1.0}),
  Counter({('C', 'C'): 1.0}),
  Counter({('C', 'C'): 1.0})],
 [Counter({('D', 'C'): 1.0}),
  Counter(),
  Counter({('D', 'D'): 0.9, ('D', 'C'): 0.1}),
  Counter({('D', 'D'): 0.9, ('D', 'C'): 0.1})],
 [Counter({('C', 'C'): 1.0}),
  Counter({('D', 'D'): 0.9, ('C', 'D'): 0.1}),
  Counter(),
  Counter({('C', 'C'): 1.0})],
 [Counter({('C', 'C'): 1.0}),
  Counter({('D', 'D'): 0.9, ('C', 'D'): 0.1}),
  Counter({('C', 'C'): 1.0}),
  Counter()]]
```

State to action distribution counts

This gives a total state action pair count against each opponent. A state corresponds to 1 turn of a match and can be one of `('C', 'C')`, `('C', 'D')`, `('D', 'C')`, `('D', 'D')` where the first element is the action of the player in question and the second the action of the opponent:

```
>>> pprint.pprint(results.state_to_action_distribution)
[[Counter(),
  Counter({(('C', 'D'), 'C'): 27}),
  Counter({(('C', 'C'), 'C'): 27}),
  Counter({(('C', 'C'), 'C'): 27})],
 [Counter({(('D', 'C'), 'D'): 27}),
  Counter(),
  Counter({(('D', 'D'), 'D'): 24, (('D', 'C'), 'D'): 3}),
  Counter({(('D', 'D'), 'D'): 24, (('D', 'C'), 'D'): 3})],
 [Counter({(('C', 'C'), 'C'): 27}),
  Counter({(('D', 'D'), 'D'): 24, (('C', 'D'), 'D'): 3}),
  Counter(),
  Counter({(('C', 'C'), 'C'): 27})],
 [Counter({(('C', 'C'), 'C'): 27}),
  Counter({(('D', 'D'), 'D'): 24, (('C', 'D'), 'D'): 3}),
  Counter({(('C', 'C'), 'C'): 27}),
  Counter()]]
```

Normalised state to action distribution

This gives the average rate state to action pair distribution against each opponent. A state corresponds to 1 turn of a match and can be one of `('C', 'C')`, `('C', 'D')`, `('D', 'C')`, `('D', 'D')` where the first element is the action of the player in question and the second the action of the opponent:

```
>>> pprint.pprint(results.normalised_state_to_action_distribution)
[[Counter(),
  Counter({(('C', 'D'), 'C'): 1.0}),
  Counter({(('C', 'C'), 'C'): 1.0}),
  Counter({(('C', 'C'), 'C'): 1.0})],
 [Counter({(('D', 'C'), 'D'): 1.0}),
```

```
  Counter(),
  Counter({(('D', 'C'), 'D'): 1.0, (('D', 'D'), 'D'): 1.0}),
  Counter({(('D', 'C'), 'D'): 1.0, (('D', 'D'), 'D'): 1.0})],
 [Counter({(('C', 'C'), 'C'): 1.0}),
  Counter({(('C', 'D'), 'D'): 1.0, (('D', 'D'), 'D'): 1.0}),
  Counter(),
  Counter({(('C', 'C'), 'C'): 1.0})],
 [Counter({(('C', 'C'), 'C'): 1.0}),
  Counter({(('C', 'D'), 'D'): 1.0, (('D', 'D'), 'D'): 1.0}),
  Counter({(('C', 'C'), 'C'): 1.0}),
  Counter()]]
```

Initial cooperation counts

This gives the count of cooperations made by each player during the first turn of every match:

```
>>> results.initial_cooperation_count
[9, 0, 9, 9]
```

Each player plays an opponent a total of 9 times (3 opponents and 3 repetitions). Apart from the `Defector`, they all cooperate on the first turn.

Initial cooperation rates

This gives the rate of which a strategy cooperates during the first turn:

```
>>> results.initial_cooperation_rate
[1.0, 0.0, 1.0, 1.0]
```

Morality Metrics

The following morality metrics are available, they are calculated as a function of the cooperation rating:

```
>>> results.cooperating_rating
[1.0, 0.0, 0.7, 0.7]
>>> pprint.pprint(results.vengeful_cooperation)
[[1.0, 1.0, 1.0, 1.0],
 [-1.0, -1.0, -1.0, -1.0],
 [1.0, -0.8, 1.0, 1.0],
 [1.0, -0.78 1.0, 1.0]]
>>> pprint.pprint(results.good_partner_matrix)
[[0, 3, 3, 3], [0, 0, 0, 0], [3, 3, 0, 3], [3, 3, 3, 0]]
>>> pprint.pprint(results.good_partner_rating)
[1.0, 0.0, 1.0, 1.0]
>>> results.eigenmoses_rating
[0.37..., -0.37..., 0.59..., 0.59...]
>>> results.eigenjesus_rating
[0.57..., 0.0, 0.57..., 0.57...]
```

For more information about these see *Morality Metrics*.

Reading and writing interactions from/to file

When dealing with large tournaments it might be desirable to separate the analysis from the actual running of the tournaments. This can be done by passing a `filename` argument to the `play` method of a tournament:

```
>>> import axelrod as axl
>>> players = [s() for s in axl.basic_strategies]
>>> tournament = axl.Tournament(players, turns=4, repetitions=2)
>>> results = tournament.play(filename="basic_tournament.csv")
```

This will create a file *basic_tournament.csv* with data that looks something like:

```
0,0,Alternator,Alternator,CDCD,CDCD
0,0,Alternator,Alternator,CDCD,CDCD
0,1,Alternator,Anti Tit For Tat,CDCD,CDCD
0,1,Alternator,Anti Tit For Tat,CDCD,CDCD
0,2,Alternator,Bully,CDCD,DDCD
0,2,Alternator,Bully,CDCD,DDCD
0,3,Alternator,Cooperator,CDCD,CCCC
0,3,Alternator,Cooperator,CDCD,CCCC
0,4,Alternator,Defector,CDCD,DDDD
0,4,Alternator,Defector,CDCD,DDDD
0,5,Alternator,Suspicious Tit For Tat,CDCD,DCDC
0,5,Alternator,Suspicious Tit For Tat,CDCD,DCDC
0,6,Alternator,Tit For Tat,CDCD,CCDC
0,6,Alternator,Tit For Tat,CDCD,CCDC
0,7,Alternator,Win-Stay Lose-Shift,CDCD,CCDD
0,7,Alternator,Win-Stay Lose-Shift,CDCD,CCDD
1,1,Anti Tit For Tat,Anti Tit For Tat,CDCD,CDCD
1,1,Anti Tit For Tat,Anti Tit For Tat,CDCD,CDCD
1,2,Anti Tit For Tat,Bully,CCCC,DDDD
1,2,Anti Tit For Tat,Bully,CCCC,DDDD
1,3,Anti Tit For Tat,Cooperator,CDDD,CCCC
1,3,Anti Tit For Tat,Cooperator,CDDD,CCCC
1,4,Anti Tit For Tat,Defector,CCCC,DDDD
1,4,Anti Tit For Tat,Defector,CCCC,DDDD
1,5,Anti Tit For Tat,Suspicious Tit For Tat,CCDD,DCCD
1,5,Anti Tit For Tat,Suspicious Tit For Tat,CCDD,DCCD
1,6,Anti Tit For Tat,Tit For Tat,CDDC,CCDD
1,6,Anti Tit For Tat,Tit For Tat,CDDC,CCDD
1,7,Anti Tit For Tat,Win-Stay Lose-Shift,CDDC,CCDC
1,7,Anti Tit For Tat,Win-Stay Lose-Shift,CDDC,CCDC
2,2,Bully,Bully,DCDC,DCDC
2,2,Bully,Bully,DCDC,DCDC
2,3,Bully,Cooperator,DDDD,CCCC
2,3,Bully,Cooperator,DDDD,CCCC
2,4,Bully,Defector,DCCC,DDDD
2,4,Bully,Defector,DCCC,DDDD
2,5,Bully,Suspicious Tit For Tat,DCCD,DDCC
2,5,Bully,Suspicious Tit For Tat,DCCD,DDCC
2,6,Bully,Tit For Tat,DDCC,CDDC
2,6,Bully,Tit For Tat,DDCC,CDDC
2,7,Bully,Win-Stay Lose-Shift,DDCD,CDCC
2,7,Bully,Win-Stay Lose-Shift,DDCD,CDCC
3,3,Cooperator,Cooperator,CCCC,CCCC
3,3,Cooperator,Cooperator,CCCC,CCCC
3,4,Cooperator,Defector,CCCC,DDDD
3,4,Cooperator,Defector,CCCC,DDDD
```

```
3,5,Cooperator,Suspicious Tit For Tat,CCCC,DCCC
3,5,Cooperator,Suspicious Tit For Tat,CCCC,DCCC
3,6,Cooperator,Tit For Tat,CCCC,CCCC
3,6,Cooperator,Tit For Tat,CCCC,CCCC
3,7,Cooperator,Win-Stay Lose-Shift,CCCC,CCCC
3,7,Cooperator,Win-Stay Lose-Shift,CCCC,CCCC
4,4,Defector,Defector,DDDD,DDDD
4,4,Defector,Defector,DDDD,DDDD
4,5,Defector,Suspicious Tit For Tat,DDDD,DDDD
4,5,Defector,Suspicious Tit For Tat,DDDD,DDDD
4,6,Defector,Tit For Tat,DDDD,CDDD
4,6,Defector,Tit For Tat,DDDD,CDDD
4,7,Defector,Win-Stay Lose-Shift,DDDD,CDCD
4,7,Defector,Win-Stay Lose-Shift,DDDD,CDCD
5,5,Suspicious Tit For Tat,Suspicious Tit For Tat,DDDD,DDDD
5,5,Suspicious Tit For Tat,Suspicious Tit For Tat,DDDD,DDDD
5,6,Suspicious Tit For Tat,Tit For Tat,DCDC,CDCD
5,6,Suspicious Tit For Tat,Tit For Tat,DCDC,CDCD
5,7,Suspicious Tit For Tat,Win-Stay Lose-Shift,DCDD,CDDC
5,7,Suspicious Tit For Tat,Win-Stay Lose-Shift,DCDD,CDDC
6,6,Tit For Tat,Tit For Tat,CCCC,CCCC
6,6,Tit For Tat,Tit For Tat,CCCC,CCCC
6,7,Tit For Tat,Win-Stay Lose-Shift,CCCC,CCCC
6,7,Tit For Tat,Win-Stay Lose-Shift,CCCC,CCCC
7,7,Win-Stay Lose-Shift,Win-Stay Lose-Shift,CCCC,CCCC
7,7,Win-Stay Lose-Shift,Win-Stay Lose-Shift,CCCC,CCCC
```

The columns of this file are of the form:

1. Index of first player
2. Index of second player
3. Name of first player
4. Name of second player
5. History of play of the first player
6. History of play of the second player

Note that depending on the order in which the matches have been played, the rows could also be in a different order.

`Alternator` versus `TitForTat` has the following interactions: `CCDC, CDCD`:

- First turn: `C` versus `C` (the first two letters)
- Second turn: `D` versus `C` (the second pair of letters)
- Third turn: `C` versus `D` (the third pair of letters)
- Fourth turn: `D` versus `C` (the fourth pair of letters)

This can be transformed in to the usual interactions by zipping:

```
>>> list(zip("CCDC", "CDCD"))
[('C', 'C'), ('C', 'D'), ('D', 'C'), ('C', 'D')]
```

This should allow for easy manipulation of data outside of the capabilities within the library. Note that you can supply *build_results=False* as a keyword argument to *tournament.play()* to prevent keeping or loading interactions in memory, since the total memory footprint can be large for various combinations of parameters. The memory usage scales as $O(\text{players}^2 * \text{turns} * \text{repetitions})$.

It is also possible to generate a standard result set from a datafile:

```
>>> results = axl.ResultSetFromFile(filename="basic_tournament.csv")
>>> results.ranked_names
['Defector',
 'Bully',
 'Suspicious Tit For Tat',
 'Alternator',
 'Tit For Tat',
 'Anti Tit For Tat',
 'Win-Stay Lose-Shift',
 'Cooperator']
```

Parallel processing

When dealing with large tournaments on a multi core machine it is possible to run the tournament in parallel **although this is not currently supported on Windows**. Using `processes=0` will simply use all available cores:

```
>>> import axelrod as axl
>>> players = [s() for s in axl.basic_strategies]
>>> tournament = axl.Tournament(players, turns=4, repetitions=2)
>>> results = tournament.play(processes=0)
```

Using the cache

Whilst for stochastic strategies, every repetition of a Match will give a different result, for deterministic strategies, when there is no noise there is no need to re run the match. The library has a `DeterministicCache` class that allows us to quickly replay matches.

Caching a Match

To illustrate this, let us time the play of a match **without** a cache:

```
>>> import axelrod as axl
>>> import timeit
>>> def run_match():
...     p1, p2 = axl.GoByMajority(), axl.Alternator()
...     match = axl.Match((p1, p2), turns=200)
...     return match.play()
>>> time_with_no_cache = timeit.timeit(run_match, number=500)
>>> time_with_no_cache
2.2295279502868652
```

Here is how to create a new empty cache:

```
>>> cache = axl.DeterministicCache()
>>> len(cache)
0
```

Let us rerun the above match but using the cache:

```
>>> p1, p2 = axl.GoByMajority(), axl.Alternator()
>>> match = axl.Match((p1, p2), turns=200, deterministic_cache=cache)
```

```
>>> match.play()
[('C', 'C'), ..., ('C', 'D')]
```

We can take a look at the cache:

```
>>> cache
{('Soft Go By Majority', 'Alternator', 200): [('C', 'C'), ..., ('C', 'D')]}
>>> len(cache)
1
```

This maps a triplet of 2 player names and the match length to the resulting interactions. We can rerun the code and compare the timing:

```
>>> def run_match_with_cache():
...     p1, p2 = axl.GoByMajority(), axl.Alternator()
...     match = axl.Match((p1, p2), turns=200, deterministic_cache=cache)
...     return match.play()
>>> time_with_cache = timeit.timeit(run_match_with_cache, number=500)
>>> time_with_cache
0.04215192794799805
>>> time_with_cache < time_with_no_cache
True
```

We can write the cache to file:

```
>>> cache.save("cache.txt")
True
```

Caching a Tournament

Tournaments will automatically create caches as needed on a match by match basis.

Caching a Moran Process

A prebuilt cache can also be used in a Moran process (by default a new cache is used):

```
>>> cache = axl.DeterministicCache("cache.txt")
>>> players = [axl.GoByMajority(), axl.Alternator(),
...            axl.Cooperator(), axl.Grudger()]
>>> mp = axl.MoranProcess(players, deterministic_cache=cache)
>>> populations = mp.play()
>>> mp.winning_strategy_name
Defector
```

We see that the cache has been augmented, although note that this particular number will depend on the stochastic behaviour of the Moran process:

```
>>> len(cache)
18
```

Although, in this case the length of matches are not all the same (the default match length in the Moran process is 100):

```
>>> list(set([length for p1, p2, length in cache.keys()]))
[200, 100]
```

Setting a random seed

The library has a variety of strategies whose behaviour is stochastic. To ensure reproducible results a random seed should be set. As both Numpy and the standard library are used for random number generation, both seeds need to be set. To do this we can use the *seed* function:

```
>>> import axelrod as axl
>>> players = (axl.Random(), axl.MetaMixer())  # Two stochastic strategies
>>> axl.seed(0)
>>> results = axl.Match(players, turns=3).play()
```

We obtain the same results if it is played with the same seed:

```
>>> axl.seed(0)
>>> results == axl.Match(players, turns=3).play()
True
```

Note that this is equivalent to:

```
>>> import numpy
>>> import random
>>> players = (axl.Random(), axl.MetaMixer())
>>> random.seed(0)
>>> numpy.random.seed(0)
>>> results = axl.Match(players, turns=3).play()
>>> numpy.random.seed(0)
>>> random.seed(0)
>>> results == axl.Match(players, turns=3).play()
True
```

Player equality

It is possible to test for player equality using ==:

```
>>> import axelrod as axl
>>> p1, p2, p3 = axl.Alternator(), axl.Alternator(), axl.TitForTat()
>>> p1 == p2
True
>>> p1 == p3
False
```

Note that this checks all the attributes of an instance:

```
>>> p1.name = "John Nash"
>>> p1 == p2
False
```

This however does not check if the players will behave in the same way. For example here are two equivalent players:

```
>>> p1 = axl.Alternator()
>>> p2 = axl.Cycler((axl.Actions.C, axl.Actions.D))
```

```
>>> p1 == p2
False
```

To check if player strategies are equivalent you can use *Fingerprinting*.

Using and playing different stage games

As described in *Play Contexts and Generic Prisoner's Dilemma* the default game used for the Prisoner's Dilemma is given by:

```
>>> import axelrod as axl
>>> pd = axl.game.Game()
>>> pd
Axelrod game: (R,P,S,T) = (3, 1, 0, 5)
>>> pd.RPST()
(3, 1, 0, 5)
```

These `Game` objects are used to score *matches*, *tournaments* and *Moran processes*:

```
>>> pd.score((axl.Actions.C, axl.Actions.C))
(3, 3)
>>> pd.score((axl.Actions.C, axl.Actions.D))
(0, 5)
>>> pd.score((axl.Actions.D, axl.Actions.C))
(5, 0)
>>> pd.score((axl.Actions.D, axl.Actions.D))
(1, 1)
```

It is possible to run a matches, tournaments and Moran processes with a different game. For example here is the game of chicken:

```
>>> chicken = axl.game.Game(r=0, s=-1, t=1, p=-10)
>>> chicken
Axelrod game: (R,P,S,T) = (0, -10, -1, 1)
>>> chicken.RPST()
(0, -10, -1, 1)
```

Here is a simple tournament run with this game:

```
>>> players = [axl.Cooperator(), axl.Defector(), axl.TitForTat()]
>>> tournament = axl.Tournament(players, game=chicken)
>>> results = tournament.play()
>>> results.ranked_names
['Cooperator', 'Defector', 'Tit For Tat']
```

The default Prisoner's dilemma has different results:

```
>>> tournament = axl.Tournament(players)
>>> results = tournament.play()
>>> results.ranked_names
['Defector', 'Tit For Tat', 'Cooperator']
```

Contributing

This section contains a variety of tutorials that should help you contribute to the library.

Contents:

Guidelines

All contributions to this repository are welcome via pull request on the github repository.

The project follows the following guidelines:

1. Use the base Python library unless completely necessary. A few external libraries (such as numpy) have been included in requirements.txt – feel free to use these as needed.
2. Try as best as possible to follow PEP8 which includes **using descriptive variable names**.
3. Commits: Please try to use commit messages that give a meaningful history for anyone using git's log features. Try to use messages that complete sentence, "This commit will..." There is some excellent guidance on the subject from Chris Beams
4. Testing: the project uses the unittest library and has a nice testing suite that makes some things very easy to write tests for. Please try to increase the test coverage on pull requests.
5. Merging pull-requests: We require two of the (currently three) core-team maintainers to merge. Opening a PR for early feedback or to check test coverage is OK, just indicate that the PR is not ready to merge (and update when it is).

By submitting a pull request, you are agreeing that your work may be distributed under the terms of the project's licence and you will become one of the project's joint copyright holders.

Contributing a strategy

This section contains a variety of tutorials that should help you contribute a new strategy to the library.

Contents:

Instructions

Here is the file structure for the Axelrod repository:

```
.
- axelrod
|   - __init__.py
|   - ecosystem.py
|   - game.py
|   - player.py
|   - plot.py
|   - result_set.py
|   - round_robin.py
|   - tournament.py
|   - /strategies/
|       - __init__.py
|       - _strategies.py
|       - cooperator.py
|       - defector.py
|       - grudger.py
|       - titfortat.py
|       - gobymajority.py
|       - ...
|   - /tests/
```

```
|       - integration
|       - strategies
|       - unit
|           - test_*.py
- README.md
```

To contribute a strategy you need to follow as many of the following steps as possible:

1. Fork the github repository.
2. Add a `<strategy>.py` file to the strategies directory or add a strategy to a pre existing `<strategy>.py` file.
3. Update the `./axelrod/strategies/_strategies.py` file.
4. If you created a new `<strategy>.py` file add it to `.docs/reference/all_strategies.rst`.
5. Write some unit tests in the `./axelrod/tests/strategies/` directory.
6. This one is also optional: ping us a message and we'll add you to the Contributors team. This would add an Axelrod-Python organisation badge to your profile.
7. Send us a pull request.

If you would like a hand with any of the above please do get in touch: we're always delighted to have new strategies.

Writing the new strategy

Identify a new strategy

If you're not sure if you have a strategy that has already been implemented, you can search the *Strategies index* to see if they are implemented. If you are still unsure please get in touch: via the gitter room or open an issue.

Several strategies are special cases of other strategies. For example, both `Cooperator` and `Defector` are special cases of `Random`, `Random(1)` and `Random(0)` respectively. While we could eliminate `Cooperator` in its current form, these strategies are intentionally left as is as simple examples for new users and contributors. Nevertheless, please feel free to update the docstrings of strategies like `Random` to point out such cases.

The code

There are a couple of things that need to be created in a strategy.py file. Let us take a look at the `TitForTat` class (located in the `axelrod/strategies/titfortat.py` file):

```
class TitForTat(Player):
    """
    A player starts by cooperating and then mimics previous move by
    opponent.

    Note that the code for this strategy is written in a fairly verbose
    way. This is done so that it can serve as an example strategy for
    those who might be new to Python.

    Names

    - Rapoport's strategy: [Axelrod1980]_
    - TitForTat: [Axelrod1980]_
```

```
    """

    # These are various properties for the strategy
    name = 'Tit For Tat'
    classifier = {
        'memory_depth': 1,  # Four-Vector = (1.,0.,1.,0.)
        'stochastic': False,
        'inspects_source': False,
        'manipulates_source': False,
        'manipulates_state': False
    }

    def strategy(self, opponent):
        """This is the actual strategy"""
        # First move
        if len(self.history) == 0:
            return C
        # React to the opponent's last move
        if opponent.history[-1] == D:
            return D
        return C
```

The first thing that is needed is a docstring that explains what the strategy does:

```
"""A player starts by cooperating and then mimics previous move by opponent."""
```

Secondly, any alternate names should be included and if possible references provided (this helps when trying to identify if a strategy has already been implemented or not):

```
- Rapoport's strategy: [Axelrod1980]_
- TitForTat: [Axelrod1980]_
```

These references can be found in the *Bibliography*. If a required references is not there please feel free to add it or just get in touch and we'd be happy to help.

After that simply add in the string that will appear as the name of the strategy:

```
name = 'Tit For Tat'
```

Note that this is mainly used in plots by `matplotlib` so you can use LaTeX if you want to. For example there is strategy with π as a name:

```
name = '$\pi$'
```

Following that you can add in the `classifier` dictionary:

```
classifier = {
    'memory_depth': 1,  # Four-Vector = (1.,0.,1.,0.)
    'stochastic': False,
    'inspects_source': False,
    'manipulates_source': False,
    'manipulates_state': False
}
```

This helps classify the strategy as described in *Classification of strategies*.

After that the only thing required is to write the `strategy` method which takes an opponent as an argument. In the case of `TitForTat` the strategy checks if it has any history (`if len(self.history) == 0`). If it does not

(ie this is the first play of the match) then it returns `C`. If not, the strategy simply repeats the opponent's last move (`return opponent.history[-1]`):

```
def strategy(opponent):
    """This is the actual strategy"""
    # First move
    if len(self.history) == 0:
        return C
    # Repeat the opponent's last move
    return opponent.history[-1]
```

The variables `C` and `D` represent the cooperate and defect actions respectively.

If your strategy creates any particular attribute along the way you need to make sure that there is a `reset` method that takes account of it. An example of this is the `ForgetfulGrudger` strategy.

You can also modify the name of the strategy with the `__repr__` method, which is invoked when `str` is applied to a player instance. For example, the `Random` strategy takes a parameter `p` for how often it cooperates, and the `__repr__` method adds the value of this parameter to the name:

```
def __repr__(self):
    return "%s: %s" % (self.name, round(self.p, 2))
```

Now we have separate names for different instantiations:

```
>>> import axelrod
>>> player1 = axelrod.Random(p=0.5)
>>> player2 = axelrod.Random(p=0.1)
>>> player1
Random: 0.5
>>> player2
Random: 0.1
```

This helps distinguish players in tournaments that have multiple instances of the same strategy. If you modify the `__repr__` method of player, be sure to add an appropriate test.

There are various examples of helpful functions and properties that make writing strategies easier. Do not hesitate to get in touch with the Axelrod-Python team for guidance.

Writing docstrings

The project takes pride in its documentation for the strategies and its corresponding bibliography. The docstring is a string which describes a method, module or class. The docstrings help the user in understanding the working of the strategy and the source of the strategy. The docstring must be written in the following way, i.e.:

```
 """This is a docstring.

It can be written over multiple lines.

"""
```

Sections

The Sections of the docstring are:

1. **Working of the strategy**

   A brief summary on how the strategy works, E.g.:

```
class TitForTat(Player):
"""
A player starts by cooperating and then mimics the
previous action of the opponent.
"""
```

2. **Bibliography/Source of the strategy**

   A section to mention the source of the strategy or the paper from which the strategy was taken. The section must start with the Names section. For E.g.:

```
class TitForTat(Player):
"""
A player starts by cooperating and then mimics the
previous action of the opponent.

Names:

- Rapoport's strategy: [Axelrod1980]_
- TitForTat: [Axelrod1980]_
"""
```

   Here, the info written under the Names section tells about the source of the TitforTat strategy. `[Axelrod1980]_` corresponds to the bibliographic item in `docs/reference/bibliography.rst`. If you are using a source that is not in the bibliography please add it.

Adding the new strategy

To get the strategy to be recognised by the library we need to add it to the files that initialise when someone types `import axelrod`. This is done in the `axelrod/strategies/_strategies.py` file.

If you have added your strategy to a file that already existed (perhaps you added a new variant of `titfortat` to the `titfortat.py` file), simply add your strategy to the list of strategies already imported from `<file_name>.py`:

```
from <file_name> import <list-of-strategies>
```

If you have added your strategy to a new file then simply add a line similar to above with your new strategy.

Once you have done that, you need to add the class itself to the `all_strategies` list (in `axelrod/strategies/_strategies.py`).

Finally, if you have created a new module (a new `<strategy.py>` file) please add it to the `docs/references/all_strategies.rst` file so that it will automatically be documented.

Classifying the new strategy

Every strategy class has a classifier dictionary that gives some classification of the strategy according to certain dimensions.

Let us take a look at the dimensions available by looking at `TitForTat`:

```
>>> import axelrod
>>> classifier = axelrod.TitForTat.classifier
>>> for key in sorted(classifier.keys()):
...     print(key)
inspects_source
long_run_time
makes_use_of
manipulates_source
manipulates_state
memory_depth
stochastic
```

You can read more about this in the *Classification of strategies* section but here are some tips about filling this part in correctly.

Note that when an instance of a class is created it gets it's own copy of the default classifier dictionary from the class. This might sometimes be modified by the initialisation depending on input parameters. A good example of this is the `Joss` strategy:

```
>>> joss = axelrod.Joss()
>>> boring_joss = axelrod.Joss(p=1)
>>> joss.classifier['stochastic'], boring_joss.classifier['stochastic']
(True, False)
```

Dimensions that are not classified have value `None` in the dictionary.

There are currently three important dimensions that help identify if a strategy obeys axelrod's original tournament rules.

1. `inspects_source` - does the strategy 'read' any source code that it would not normally have access to. An example of this is `Geller`.
2. `manipulates_source` - does the strategy 'write' any source code that it would not normally be able to. An example of this is `Mind Bender`.
3. `manipulates_state` - does the strategy 'change' any attributes that it would not normally be able to. An example of this is `Mind Reader`.

These dimensions are currently relevant to the *obey_axelrod* function which checks if a strategy obeys Axelrod's original rules.

Writing tests for the new strategy

To write tests you either need to create a file called `test_<library>.py` where `<library>.py` is the name of the file you have created or similarly add tests to the test file that is already present in the `axelrod/tests/strategies/` directory.

Typically we want to test the following:

- That the strategy behaves as intended on the first move and subsequent moves, triggering any expected actions
- That the strategy initializes correctly

A `TestPlayer` class has been written that has a number of convenience methods to help write tests efficiently for how a strategy plays. It has three helpful methods. All three of these functions can take an optional keyword argument `seed` (useful and necessary for stochastic strategies, `None` by default).

1. The member function `first_play_test` tests the first strategy, e.g.:

```
self.first_play_test(play=C, seed=None)
```

This is equivalent to:

```
P1 = axelrod.TitForTat() # Or whatever player is in your test class
P2 = axelrod.Player()
self.assertEqual(P1.strategy(P2), C)
```

2. The member function `second_play_test` takes a list of four plays, each following one round of CC, CD, DC, and DD respectively. So for example here we test that Tit for tat will cooperate if and only if the opponent cooperates in the previous round:

```
self.second_play_test(rCC=C, rCD=D, rDC=C, rDD=D, seed=None)
```

This is equivalent to choosing if an opponent will play `C` or `D` following the last round of play and checking the player's subsequent action.

3. The member function `versus_test` can be used to test how the player plays against a given opponent:

```
self.versus_test(opponent=axelrod.MockPlayer(actions=[C, D]),
                 expected_actions=[(D, C), (C, D), (C, C)], seed=None)
```

In this case the player is tested against an opponent that will cycle through `C, D`. The `expected_actions` are the actions player by both the tested player and the opponent in the match. In this case we see that the player is expected to play `D, C, C` against `C, D, C`.

Note that you can either user a `MockPlayer` that will cycle through a given sequence or you can use another strategy from the Axelrod library.

The function `versus_test` also accepts a dictionary parameter of attributes to check at the end of the match. For example this test checks if the player's internal variable `opponent_class` is set to `"Cooperative"`:

```
actions = [(C, C)] * 6
self.versus_test(axelrod.Cooperator(), expected_actions=actions
                 attrs={"opponent_class": "Cooperative"})
```

Note here that instead of passing a sequence of actions as an opponent we are passing an actual player from the axelrod library.

The function `versus_test` also accepts a dictionary parameter of match attributes that dictate the knowledge of the players. For example this test assumes that players do not know the length of the match:

```
actions = [(C, C), (C, D), (D, C), (C, D)]
self.versus_test(axelrod.Alternator(), expected_actions=actions,
                 match_attributes={"length": -1})
```

The function `versus_test` also accepts a dictionary parameter of keyword arguments that dictate how the player is initiated. For example this test how the player plays when initialised with `p=1`:

```
actions = [(C, C), (C, D), (C, C), (C, D)]
self.versus_test(axelrod.Alternator(), expected_actions=actions,
                 init_kwargs={"p": 1})
```

As an example, the tests for Tit-For-Tat are as follows:

```
import axelrod
from test_player import TestPlayer
```

```
C, D = axelrod.Actions.C, axelrod.Actions.D

class TestTitForTat(TestPlayer):
    """
    Note that this test is referred to in the documentation as an example on
    writing tests.  If you modify the tests here please also modify the
    documentation.
    """

    name = "Tit For Tat"
    player = axelrod.TitForTat
    expected_classifier = {
        'memory_depth': 1,
        'stochastic': False,
        'makes_use_of': set(),
        'inspects_source': False,
        'manipulates_source': False,
        'manipulates_state': False
    }

    def test_strategy(self):
        self.first_play_test(C)
        self.second_play_test(rCC=C, rCD=D, rDC=C, rDD=D)

        # Play against opponents
        actions = [(C, C), (C, D), (D, C), (C, D)]
        self.versus_test(axelrod.Alternator(), expected_actions=actions)

        actions = [(C, C), (C, C), (C, C), (C, C)]
        self.versus_test(axelrod.Cooperator(), expected_actions=actions)

        actions = [(C, D), (D, D), (D, D), (D, D)]
        self.versus_test(axelrod.Defector(), expected_actions=actions)

        # This behaviour is independent of knowledge of the Match length
        actions = [(C, C), (C, D), (D, C), (C, D)]
        self.versus_test(axelrod.Alternator(), expected_actions=actions,
                         match_attributes={"length": -1})

        # We can also test against random strategies
        actions = [(C, D), (D, D), (D, C), (C, C)]
        self.versus_test(axelrod.Random(), expected_actions=actions,
                         seed=0)

        actions = [(C, C), (C, D), (D, D), (D, C)]
        self.versus_test(axelrod.Random(), expected_actions=actions,
                         seed=1)

        #  If you would like to test against a sequence of moves you should use
        #  a MockPlayer
        opponent = axelrod.MockPlayer(actions=[C, D])
        actions = [(C, C), (C, D), (D, C), (C, D)]
        self.versus_test(opponent, expected_actions=actions)

        opponent = axelrod.MockPlayer(actions=[C, C, D, D, C, D])
        actions = [(C, C), (C, C), (C, D), (D, D), (D, C), (C, D)]
        self.versus_test(opponent, expected_actions=actions)
```

There are other examples of using this testing framework in `axelrod/tests/strategies/test_titfortat.py`.

The `expected_classifier` dictionary tests that the classification of the strategy is as expected (the tests for this is inherited in the `init` method). Please be sure to classify new strategies according to the already present dimensions but if you create a new dimension you do not **need** to re classify all the other strategies (but feel free to! :)), but please do add it to the `default_classifier` in the `axelrod/player.py` parent class.

Contributing to the library

All contributions (docs, tests, etc) are very welcome, if there is a specific functionality that you would like to add then please open an issue (or indeed take a look at the ones already there and jump in the conversation!).

If you want to work on documentation please keep in mind that doctests are encouraged to help keep the documentation up to date.

Running tests

Basic test runners

The project has an extensive test suite which is run each time a new contribution is made to the repository. If you want to check that all the tests pass before you submit a pull request you can run the tests yourself:

```
$ python -m unittest discover
```

If you are developing new tests for the suite, it is useful to run a single test file so that you don't have to wait for the entire suite each time. For example, to run only the tests for the Grudger strategy:

```
$ python -m unittest axelrod.tests.strategies.test_grudger
```

The test suite is divided into three categories: strategy tests, unit tests and integration tests. Each can be run individually:

```
$ python -m unittest discover -s axelrod.tests.strategies
$ python -m unittest discover -s axelrod.tests.unit
$ python -m unittest discover -s axelrod.tests.integration
```

Testing coverage of tests

The library has 100% test coverage. This can be tested using the Python `coverage` package. Once installed (`pip install coverage`), to run the tests and check the coverage for the entire library:

```
$ coverage run --source=axelrod -m unittest discover
```

You can then view a report of the coverage:

```
$ coverage report -m
```

You can also run the coverage on a subset of the tests. For example, to run the tests with coverage for the Grudger strategy:

```
$ coverage run --source=axelrod -m unittest axelrod.tests.strategies.test_grudger
```

Testing the documentation

The documentation is doctested, to run those tests you can run the script:

```
$ python doctests.py
```

You can also run the doctests on any given file. For example, to run the doctests for the `docs/tutorials/getting_started/match.rst` file:

```
$ python -m doctest docs/tutorials/getting_started/match.rst
```

Type checking

The library makes use of type hinting, this can be checked using the Python `mypy` package. Once installed (`pip install mypy`), to run the type checker:

```
$ python run_mypy.py
```

You can also run the type checker on a given file. For example, to run the type checker on the Grudger strategy:

```
$ mypy --ignore-missing-imports --follow-imports skip axelrod/strategies/grudger.py
```

Continuous integration

This project is being taken care of by travis-ci, so all tests will be run automatically when opening a pull request. You can see the latest build status here.

Reference

This section is the reference guide for the various components of the library.

Contents:

Background to Axelrod's Tournament

In the 1980s, professor of Political Science Robert Axelrod ran a tournament inviting strategies from collaborators all over the world for the Iterated Prisoner's Dilemma.

Another nice write up of Axelrod's work and this tournament on github was put together by Artem Kaznatcheev here.

The Prisoner's Dilemma

The Prisoner's dilemma is the simple two player game shown below:

	Cooperate	Defect
Cooperate	(3,3)	(0,5)
Defect	(5,0)	(1,1)

If both players cooperate they will each go to prison for 2 years and receive an equivalent utility of 3. If one cooperates and the other defects: the defector does not go to prison and the cooperator goes to prison for 5 years, the cooperator

receives a utility of 0 and the defector a utility of 5. If both defect: they both go to prison for 4 years and receive an equivalent utility of 1.

Note: Years in prison doesn't equal to utility directly. The formula is U = 5 - Y for Y in [0, 5], where `U` is the utility, `Y` are years in prison. The reason is to follow the original Axelrod's scoring.

By simply investigating the best responses against both possible actions of each player it is immediate to see that the Nash equilibrium for this game is for both players to defect.

The Iterated Prisoner's Dilemma

We can use the basic Prisoner's Dilemma as a *stage* game in a repeated game. Players now aim to maximise the utility (corresponding to years in prison) over a repetition of the game. Strategies can take in to account both players history and so can take the form:

> "I will cooperate unless you defect 3 times in a row at which point I will defect forever."

Axelrod ran such a tournament (twice) and invited strategies from anyone who would contribute. The tournament was a round robin and the winner was the strategy who had the lowest total amount of time in prison.

This tournament has been used to study how cooperation can evolve from a very simple set of rules. This is mainly because the winner of both tournaments was 'tit for tat': a strategy that would never defect first (referred to as a 'nice' strategy).

Play Contexts and Generic Prisoner's Dilemma

There are four possible round outcomes:

- Mutual cooperation: (C, C)
- Defection: (C, D) or (D, C)
- Mutual defection: (D, D)

Each of these corresponds to one particular set of payoffs in the following generic Prisoner's dilemma:

	Cooperate	Defect
Cooperate	(R,R)	(S,T)
Defect	(T,S)	(P,P)

For the above to constitute a Prisoner's dilemma, the following must hold: $T > R > P > S$.

These payoffs are commonly referred to as:

- R: the **Reward** payoff (default value in the library: 3)
- P: the **Punishment** payoff (default value in the library: 1)
- S: the **Sucker** payoff (default value in the library: 0)
- T: the **Temptation** payoff (default value in the library: 5)

A particular Prisoner's Dilemma is often described by the 4-tuple: (R, P, S, T):

```
>>> import axelrod
>>> axelrod.game.DefaultGame.RPST()
(3, 1, 0, 5)
```

Tournaments

Axelrod's first tournament

Axelrod's first tournament is described in his 1980 paper entitled 'Effective choice in the Prisoner's Dilemma' *[Axelrod1980]*. This tournament included 14 strategies (plus a random "strategy") and they are listed below, (ranked in the order in which they appeared).

An indication is given as to whether or not this strategy is implemented in the `axelrod` library. If this strategy is not implemented please do send us a pull request.

Strategies in the Axelrod's first tournament:

Name	Long name	Axelrod Library Name
Tit For Tat	Tit For Tat	`TitForTat`
Tideman and Chieruzzi	Tideman and Chieruzzi (authors' names)	Not Implemented
Nydegger	Nydegger (author's name)	`Nydegger`
Grofman	Grofman (author's name)	`Grofman`
Shubik	Shubik (author's name)	`Shubik`
Stein and Rapoport	Stein and Rapoport (authors' names)	`SteinAndRapoport`
Grudger	Grudger (by Friedman)	`Grudger`
Davis	Davis (author's name)	`Davis`
Graaskamp	Graaskamp (author's name)	Not Implemented
Downing	Downing (author's name)	`RevisedDowning`
Feld	Feld (author's name)	`Feld`
Joss	Joss (author's name)	`Joss`
Tullock	Tullock (author's name)	`Tullock`
Unnamed Strategy	Unnamed Strategy (by a Grad Student in Political Science)	`UnnamedStrategy`
Random	Random	`Random`

Tit for Tat

This strategy was referred to as the *'simplest'* strategy submitted. It begins by cooperating and then simply repeats the last moves made by the opponent.

Tit for Tat came 1st in Axelrod's original tournament.

Tideman and Chieruzzi

Not implemented yet

This strategy begins by playing Tit For Tat and then things get slightly complicated:

1. Every run of defections played by the opponent increases the number of defections that this strategy retaliates with by 1.
2. The opponent is given a 'fresh start' if:
   - it is 10 points behind this strategy
   - **and** it has not just started a run of defections
   - **and** it has been at least 20 rounds since the last 'fresh start'
   - **and** there are more than 10 rounds remaining in the tournament
   - **and** the total number of defections differs from a 50-50 random sample by at least 3.0 standard deviations.

A 'fresh start' is a sequence of two cooperations followed by an assumption that the game has just started (everything is forgotten).

This strategy came 2nd in Axelrod's original tournament.

Nydegger

This strategy begins by playing Tit For Tat for the first 3 rounds with the following modifications:

If it is the only strategy to cooperate in the first round and the only strategy to defect on the second round then it defects on the 3 round (despite the fact that Tit For Tat would now cooperate).

After these first 3 rounds the next move is made depending on the previous 3 rounds. A score is given to these rounds according to the following calculation:

$$A = 16a_1 + 4a_2 + a_3$$

Where a_i is dependent on the outcome of the previous i th round. If both strategies defect, $a_i = 3$, if the opponent only defects: $a_i = 2$ and finally if it is only this strategy that defects then $a_i = 1$.

Finally this strategy defects if and only if:

$$A \in \{1, 6, 7, 17, 22, 23, 26, 29, 30, 31, 33, 38, 39, 45, 49, 54, 55, 58, 61\}$$

This strategy came 3rd in Axelrod's original tournament.

Grofman

This is a pretty simple strategy: it cooperates on the first two rounds and returns the opponent's last action for the next 5. For the rest of the game Grofman cooperates if both players selected the same action in the previous round, and otherwise cooperates randomly with probability $\frac{2}{7}$.

This strategy came 4th in Axelrod's original tournament.

Shubik

This strategy plays a modification of Tit For Tat. It starts by retaliating with a single defection but the number of defections increases by 1 each time the opponent defects when this strategy cooperates.

This strategy came 5th in Axelrod's original tournament.

Stein and Rapoport

Not implemented yet

This strategy plays a modification of Tit For Tat.

1. It cooperates for the first 4 moves.
2. It defects on the last 2 moves.
3. Every 15 moves it makes use of a chi-squared test to check if the opponent is playing randomly.

This strategy came 6th in Axelrod's original tournament.

Grudger

This strategy cooperates until the opponent defects and then defects forever.

This strategy came 7th in Axelrod's original tournament.

Davis

This strategy is a modification of Grudger. It starts by cooperating for the first 10 moves and then plays Grudger.

This strategy came 8th in Axelrod's original tournament.

Graaskamp

Not implemented yet

This strategy follows the following rules:

1. Play Tit For Tat for the first 50 rounds;
2. Defects on round 51;
3. Plays 5 further rounds of Tit For Tat;
4. A check is then made to see if the opponent is playing randomly in which case it defects for the rest of the game;
5. The strategy also checks to see if the opponent is playing Tit For Tat or another strategy from a preliminary tournament called 'Analogy'. If so it plays Tit For Tat. If not it cooperates and randomly defects every 5 to 15 moves.

This strategy came 9th in Axelrod's original tournament.

Downing

This strategy attempts to estimate the next move of the opponent by estimating the probability of cooperating given that they defected ($p(C|D)$) or cooperated on the previous round ($p(C|C)$). These probabilities are continuously updated during play and the strategy attempts to maximise the long term play. Note that the initial values are $p(C|C) = p(C|D) = .5$.

Downing is implemented as *RevisedDowning*. Apparently in the first tournament the strategy was implemented incorrectly and defected on the first two rounds. This can be controlled by setting *revised=True* to prevent the initial defections.

This strategy came 10th in Axelrod's original tournament.

Feld

This strategy plays Tit For Tat, always defecting if the opponent defects but cooperating when the opponent cooperates with a gradually decreasing probability until it is only .5.

This strategy came 11th in Axelrod's original tournament.

Joss

This strategy plays Tit For Tat, always defecting if the opponent defects but cooperating when the opponent cooperates with probability .9.

This strategy came 12th in Axelrod's original tournament.

Tullock

This strategy cooperates for the first 11 rounds and then (randomly) cooperates 10% less often than the opponent has in the previous 10 rounds.

This strategy came 13th in Axelrod's original tournament.

Unnamed Strategy

Apparently written by a grad student in political science whose name was withheld, this strategy cooperates with a given probability P. This probability (which has initial value .3) is updated every 10 rounds based on whether the opponent seems to be random, very cooperative or very uncooperative. Furthermore, if after round 130 the strategy is losing then P is also adjusted.

Since the original code is not available and was apparently complicated, we have implemented this strategy based on published descriptions. The strategy cooperates with a random probability between 0.3 and 0.7.

This strategy came 14th in Axelrod's original tournament.

Random

This strategy plays randomly (disregarding the history of play).

This strategy came 15th in Axelrod's original tournament.

Axelrod's second tournament

Work in progress.

EATHERLEY

This strategy was submitted by Graham Eatherley to Axelrod's second tournament and generally cooperates unless the opponent defects, in which case Eatherley defects with a probability equal to the proportion of rounds that the opponent has defected.

This strategy came in Axelrod's second tournament.

CHAMPION

This strategy was submitted by Danny Champion to Axelrod's second tournament and operates in three phases. The first phase lasts for the first 1/20-th of the rounds and Champion always cooperates. In the second phase, lasting until 4/50-th of the rounds have passed, Champion mirrors its opponent's last move. In the last phase, Champion cooperates unless - the opponent defected on the last round, and - the opponent has cooperated less than 60% of the rounds, and - a random number is greater than the proportion of rounds defected

TESTER

This strategy is a TFT variant that attempts to exploit certain strategies. It defects on the first move. If the opponent ever defects, TESTER 'apologies' by cooperating and then plays TFT for the rest of the game. Otherwise TESTER alternates cooperation and defection.

This strategy came 46th in Axelrod's second tournament.

Stewart and Plotkin's Tournament (2012)

In 2012, Alexander Stewart and Joshua Plotkin ran a variant of Axelrod's tournament with 19 strategies to test the effectiveness of the then newly discovered Zero-Determinant strategies.

The paper is identified as *doi: 10.1073/pnas.1208087109* and referred to as *[Stewart2012]* below. Unfortunately the details of the tournament and the implementation of strategies is not clear in the manuscript. We can, however, make reasonable guesses to the implementation of many strategies based on their names and classical definitions.

The following classical strategies are included in the library:

S&P Name	Long name	Axelrod Library Name
ALLC	Always Cooperate	`Cooperator`
ALLD	Always Defect	`Defector`
EXTORT-2	Extort-2	`ZDExtort2`
HARD_MAJO	Hard majority	`HardGoByMajority`
HARD_JOSS	Hard Joss	`Joss`
HARD_TFT	Hard tit for tat	`HardTitForTat`
HARD_TF2T	Hard tit for 2 tats	`HardTitFor2Tats`
TFT	Tit-For-Tat	`TitForTat`
GRIM	Grim	`Grudger`
GTFT	Generous Tit-For-Tat	`GTFT`
TF2T	Tit-For-Two-Tats	`TitFor2Tats`
WSLS	Win-Stay-Lose-Shift	`WinStayLoseShift`
RANDOM	Random	`Random`
ZDGTFT-2	ZDGTFT-2	`ZDGTFT2`

ALLC, ALLD, TFT and RANDOM are defined above. The remaining classical strategies are defined below. The tournament also included two Zero Determinant strategies, both implemented in the library. The full table of strategies and results is available online.

Memory one strategies

In 2012 Press and Dyson *[Press2012]* showed interesting results with regards to so called memory one strategies. Stewart and Plotkin implemented a number of these. A memory one strategy is simply a probabilistic strategy that is defined by 4 parameters. These four parameters dictate the probability of cooperating given 1 of 4 possible outcomes of the previous round:

- $P(C \mid CC) = p_1$
- $P(C \mid CD) = p_2$
- $P(C \mid DC) = p_3$
- $P(C \mid DD) = p_4$

The memory one strategy class is used to define a number of strategies below.

GTFT

Generous-Tit-For-Tat plays Tit-For-Tat with occasional forgiveness, which prevents cycling defections against itself.

GTFT is defined as a memory-one strategy as follows:

- $P(C \mid CC) = 1$
- $P(C \mid CD) = p$
- $P(C \mid DC) = 1$
- $P(C \mid DD) = p$

where $p = \min\left(1 - \frac{T-R}{R-S}, \frac{R-P}{T-P}\right)$.

GTFT came 2nd in average score and 18th in wins in S&P's tournament.

TF2T

Tit-For-Two-Tats is like Tit-For-Tat but only retaliates after two defections rather than one. This is not a memory-one strategy.

TF2T came 3rd in average score and last (?) in wins in S&P's tournament.

WSLS

Win-Stay-Lose-Shift is a strategy that shifts if the highest payoff was not earned in the previous round. WSLS is also known as "Win-Stay-Lose-Switch" and "Pavlov". It can be seen as a memory-one strategy as follows:

- $P(C \mid CC) = 1$
- $P(C \mid CD) = 0$
- $P(C \mid DC) = 0$
- $P(C \mid DD) = 1$

TF2T came 7th in average score and 13th in wins in S&P's tournament.

RANDOM

Random is a strategy that was defined in *Axelrod's first tournament*, note that this is also a memory-one strategy:

- $P(C \mid CC) = 0.5$
- $P(C \mid CD) = 0.5$
- $P(C \mid DC) = 0.5$
- $P(C \mid DD) = 0.5$

RANDOM came 8th in average score and 8th in wins in S&P's tournament.

ZDGTFT-2

This memory-one strategy is defined by the following four conditional probabilities based on the last round of play:

- $P(C \mid CC) = 1$
- $P(C \mid CD) = 1/8$
- $P(C \mid DC) = 1$
- $P(C \mid DD) = 1/4$

This strategy came 1st in average score and 16th in wins in S&P's tournament.

EXTORT-2

This memory-one strategy is defined by the following four conditional probabilities based on the last round of play:

- $P(C \mid CC) = 8/9$
- $P(C \mid CD) = 1/2$
- $P(C \mid DC) = 1/3$
- $P(C \mid DD) = 0$

This strategy came 18th in average score and 2nd in wins in S&P's tournament.

GRIM

Grim is not defined in *[Stewart2012]* but it is defined elsewhere as follows. GRIM (also called "Grim trigger"), cooperates until the opponent defects and then always defects thereafter. In the library this strategy is called *Grudger*.

GRIM came 10th in average score and 11th in wins in S&P's tournament.

HARD_JOSS

HARD_JOSS is not defined in *[Stewart2012]* but is otherwise defined as a strategy that plays like TitForTat but cooperates only with probability 0.9. This is a memory-one strategy with the following probabilities:

- $P(C \mid CC) = 0.9$
- $P(C \mid CD) = 0$
- $P(C \mid DC) = 1$
- $P(C \mid DD) = 0$

HARD_JOSS came 16th in average score and 4th in wins in S&P's tournament.

HARD_JOSS as described above is implemented in the library as *Joss* and is the same as the Joss strategy from *Axelrod's first tournament*.

HARD_MAJO

HARD_MAJO is not defined in *[Stewart2012]* and is presumably the same as "Go by Majority", defined as follows: the strategy defects on the first move, defects if the number of defections of the opponent is greater than or equal to the number of times it has cooperated, and otherwise cooperates,

HARD_MAJO came 13th in average score and 5th in wins in S&P's tournament.

HARD_TFT

Hard TFT is not defined in *[Stewart2012]* but is [elsewhere](http://www.prisoners-dilemma.com/strategies.html) defined as follows. The strategy cooperates on the first move, defects if the opponent has defected on any of the previous three rounds, and otherwise cooperates.

HARD_TFT came 12th in average score and 10th in wins in S&P's tournament.

HARD_TF2T

Hard TF2T is not defined in *[Stewart2012]* but is elsewhere defined as follows. The strategy cooperates on the first move, defects if the opponent has defected twice (successively) of the previous three rounds, and otherwise cooperates.

HARD_TF2T came 6th in average score and 17th in wins in S&P's tournament.

Calculator

This strategy is not unambiguously defined in *[Stewart2012]* but is defined elsewhere. Calculator plays like Joss for 20 rounds. On the 21 round, Calculator attempts to detect a cycle in the opponents history, and defects unconditionally thereafter if a cycle is found. Otherwise Calculator plays like TFT for the remaining rounds.

Prober

PROBE is not unambiguously defined in *[Stewart2012]* but is defined elsewhere as Prober. The strategy starts by playing D, C, C on the first three rounds and then defects forever if the opponent cooperates on rounds two and three. Otherwise Prober plays as TitForTat would.

Prober came 15th in average score and 9th in wins in S&P's tournament.

Prober2

PROBE2 is not unambiguously defined in *[Stewart2012]* but is defined elsewhere as Prober2. The strategy starts by playing D, C, C on the first three rounds and then cooperates forever if the opponent played D then C on rounds two and three. Otherwise Prober2 plays as TitForTat would.

Prober2 came 9th in average score and 12th in wins in S&P's tournament.

Prober3

PROBE3 is not unambiguously defined in *[Stewart2012]* but is defined elsewhere as Prober3. The strategy starts by playing D, C on the first two rounds and then defects forever if the opponent cooperated on round two. Otherwise Prober3 plays as TitForTat would.

Prober3 came 17th in average score and 7th in wins in S&P's tournament.

HardProber

HARD_PROBE is not unambiguously defined in *[Stewart2012]* but is defined elsewhere as HardProber. The strategy starts by playing D, D, C, C on the first four rounds and then defects forever if the opponent cooperates on rounds two and three. Otherwise Prober plays as TitForTat would.

Prober2 came 5th in average score and 6th in wins in S&P's tournament.

NaiveProber

NAIVE_PROBER is a modification of Tit For Tat strategy which with a small probability randomly defects. Default value for a probability of defection is 0.1.

Strategies index

Here are the docstrings of all the strategies in the library.

class axelrod.strategies.adaptive.**Adaptive**(*initial_plays: typing.List[str] = None*) → None
Start with a specific sequence of C and D, then play the strategy that has worked best, recalculated each turn.

Names:

•Adaptive: *[Li2011]*

classifier = {'manipulates_source': False, 'makes_use_of': {'game'}, 'memory_depth': inf, 'stochastic': False, 'mani

name = 'Adaptive'

reset()

score_last_round(*opponent: axelrod.player.Player*)

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.alternator.**Alternator**
A player who alternates between cooperating and defecting.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Alternator'

strategy(*opponent: axelrod.player.Player*) → str

Artificial Neural Network based strategy.

Original Source: https://gist.github.com/mojones/550b32c46a8169bb3cd89d917b73111a#file-ann-strategy-test-L60 # Original Author: Martin Jones, @mojones

class axelrod.strategies.ann.**ANN**(*weights: typing.List[float], num_features: int, num_hidden: int*) → None
A single layer neural network based strategy, with the following features: * Opponent's first move is C * Opponent's first move is D * Opponent's second move is C * Opponent's second move is D * Player's previous move is C * Player's previous move is D * Player's second previous move is C * Player's second previous move is D * Opponent's previous move is C * Opponent's previous move is D * Opponent's second previous move is C * Opponent's second previous move is D * Total opponent cooperations * Total opponent defections * Total player cooperations * Total player defections * Round number

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'ANN'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.ann.**EvolvedANN** → None
A strategy based on a pre-trained neural network with 17 features and a hidden layer of size 10.

Names:

•Evolved ANN: Original name by Martin Jones.

name = 'Evolved ANN'

class axelrod.strategies.ann.**EvolvedANN5** → None
A strategy based on a pre-trained neural network with 17 features and a hidden layer of size 5.

Names:

•Evolved ANN 5: Original name by Marc Harper.

name = 'Evolved ANN 5'

class axelrod.strategies.ann.**EvolvedANNNoise05** → None
A strategy based on a pre-trained neural network with a hidden layer of size 10, trained with noise=0.05.

Names:

•Evolved ANN Noise 05: Original name by Marc Harper.

name = 'Evolved ANN 5 Noise 05'

axelrod.strategies.ann.**activate**(*bias: typing.List[float], hidden: typing.List[float], output: typing.List[float], inputs: typing.List[int]*) → float

Compute the output of the neural network: output = relu(inputs * hidden_weights + bias) * output_weights

axelrod.strategies.ann.**compute_features**(*player: axelrod.player.Player*, *opponent: axelrod.player.Player*) → typing.List[int]
Compute history features for Neural Network: * Opponent's first move is C * Opponent's first move is D * Opponent's second move is C * Opponent's second move is D * Player's previous move is C * Player's previous move is D * Player's second previous move is C * Player's second previous move is D * Opponent's previous move is C * Opponent's previous move is D * Opponent's second previous move is C * Opponent's second previous move is D * Total opponent cooperations * Total opponent defections * Total player cooperations * Total player defections * Round number

axelrod.strategies.ann.**split_weights**(*weights: typing.List[float], num_features: int, num_hidden: int*) → typing.Tuple[typing.List[typing.List[float]], typing.List[float], typing.List[float]]
Splits the input vector into the the NN bias weights and layer parameters.

class axelrod.strategies.apavlov.**APavlov2006** → None
APavlov as defined in http://www.cs.nott.ac.uk/~pszjl/index_files/chapter4.pdf (pages 10-11).

APavlov attempts to classify its opponent as one of five strategies: Cooperative, ALLD, STFT, PavlovD, or Random. APavlov then responds in a manner intended to achieve mutual cooperation or to defect against uncooperative opponents.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipula

name = 'Adaptive Pavlov 2006'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.apavlov.**APavlov2011** → None
APavlov as defined in http://www.graham-kendall.com/papers/lhk2011.pdf, as closely as can be determined.

APavlov attempts to classify its opponent as one of four strategies: Cooperative, ALLD, STFT, or Random. APavlov then responds in a manner intended to achieve mutual cooperation or to defect against uncooperative opponents.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Adaptive Pavlov 2011'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.appeaser.**Appeaser**
A player who tries to guess what the opponent wants.

Switch the classifier every time the opponent plays 'D'. Start with 'C', switch between 'C' and 'D' when opponent plays 'D'.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Appeaser'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.averagecopier.**AverageCopier**
The player will cooperate with probability p if the opponent's cooperation ratio is p. Starts with random decision.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Average Copier'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.averagecopier.**NiceAverageCopier**
Same as Average Copier, but always starts by cooperating.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Nice Average Copier'

strategy(*opponent: axelrod.player.Player*) → str

Additional strategies from Axelrod's first tournament.

class axelrod.strategies.axelrod_first.**Davis**(*rounds_to_cooperate: int = 10*) → None
Submitted to Axelrod's first tournament by Morton Davis.

A player starts by cooperating for 10 rounds then plays Grudger, defecting if at any point the opponent has defected.

Names:

- Davis: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Davis'

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for the remaining rounds if the opponent ever plays D.

class axelrod.strategies.axelrod_first.**Feld**(*start_coop_prob: float = 1.0*, *end_coop_prob: float = 0.5*, *rounds_of_decay: int = 200*) → None
Submitted to Axelrod's first tournament by Scott Feld.

Defects when opponent defects. Cooperates with a probability that decreases to 0.5 at round 200.

Names:

•Feld: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 200, 'stochastic': True, 'manipula

name = 'Feld'

strategy (*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**Grofman**
Submitted to Axelrod's first tournament by Bernard Grofman.

Cooperate on the first 2 moves. Return opponent's move for the next 5. Then cooperate if the last round's moves were the same, otherwise cooperate with probability 2/7.

Names:

•Grofman: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Grofman'

strategy (*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**Joss** (*p: float = 0.9*) → None
Submitted to Axelrod's first tournament by Johann Joss.

Cooperates with probability 0.9 when the opponent cooperates, otherwise emulates Tit-For-Tat.

Names:

•Joss *[Axelrod1980]*

•Hard Joss *[Stewart2012]*

name = 'Joss'

class axelrod.strategies.axelrod_first.**Nydegger** → None
Submitted to Axelrod's first tournament by Rudy Nydegger.

The program begins with tit for tat for the first three moves, except that if it was the only one to cooperate on the first move and the only one to defect on the second move, it defects on the third move. After the third move, its choice is determined from the 3 preceding outcomes in the following manner.

Let A be the sum formed by counting the other's defection as 2 points and one's own as 1 point, and giving weights of 16, 4, and 1 to the preceding three moves in chronological order. The choice can be described as defecting only when A equals 1, 6, 7, 17, 22, 23, 26, 29, 30, 31, 33, 38, 39, 45, 49, 54, 55, 58, or 61.

Thus if all three preceding moves are mutual defection, A = 63 and the rule cooperates. This rule was designed for use in laboratory experiments as a stooge which had a memory and appeared to be trustworthy, potentially cooperative, but not gullible.

Names:

•Nydegger: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Nydegger'

static score_history (*my_history: typing.List[str], opponent_history: typing.List[str], score_map: typing.Dict[typing.Tuple[str, str], int]*) → int
Implements the Nydegger formula A = 16 a_1 + 4 a_2 + a_3

strategy (*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**RevisedDowning**(*revised: bool = True*) → None
Revised Downing attempts to determine if players are cooperative or not. If so, it cooperates with them. This strategy would have won Axelrod's first tournament.

Names:

•Revised Downing: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Revised Downing'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**Shubik** → None
Submitted to Axelrod's first tournament by Martin Shubik.

Plays like Tit-For-Tat with the following modification. After each retaliation, the number of rounds that Shubik retaliates increases by 1.

Names:

•Shubik: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Shubik'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**SteinAndRapoport**(*alpha: float = 0.05*) → None
A player who plays according to statistic methods. Begins by playing C for the first four (4) rounds, then it plays tit for tat and at the last 2 round it Defects. Every 15 turns it runs a chi-squared test to check whether the opponent behaves randomly or not. In case the opponent behaves randomly then Stein and Rapoport Defects until the next 15 round (where we check again), otherwise it still plays TitForTat.0

Names:

•SteinAndRapoport *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': 15, 'stochastic': False, 'mani

name = 'Stein and Rapoport'

original_class
alias of *SteinAndRapoport*

strategy(*opponent*)

class axelrod.strategies.axelrod_first.**Tullock**(*rounds_to_cooperate: int = 11*) → None
Submitted to Axelrod's first tournament by Gordon Tullock.

Cooperates for the first 11 rounds then randomly cooperates 10% less often than the opponent has in previous rounds.

Names:

•Tullock: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 11, 'stochastic': True, 'manipulat

name = 'Tullock'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_first.**UnnamedStrategy**

Apparently written by a grad student in political science whose name was withheld, this strategy cooperates with a given probability P. This probability (which has initial value .3) is updated every 10 rounds based on whether the opponent seems to be random, very cooperative or very uncooperative. Furthermore, if after round 130 the strategy is losing then P is also adjusted.

Fourteenth Place with 282.2 points is a 77-line program by a graduate student of political science whose dissertation is in game theory. This rule has a probability of cooperating, P, which is initially 30% and is updated every 10 moves. P is adjusted if the other player seems random, very cooperative, or very uncooperative. P is also adjusted after move 130 if the rule has a lower score than the other player. Unfortunately, the complex process of adjustment frequently left the probability of cooperation in the 30% to 70% range, and therefore the rule appeared random to many other players.

Names:

•Unnamed Strategy: *[Axelrod1980]*

Warning: This strategy is not identical to the original strategy (source unavailable) and was written based on published descriptions.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 0, 'stochastic': True, 'manipulates

name = 'Unnamed Strategy'

static strategy(*opponent: axelrod.player.Player*) → str

Additional strategies from Axelrod's second tournament.

class axelrod.strategies.axelrod_second.**Champion**

Strategy submitted to Axelrod's second tournament by Danny Champion.

This player cooperates on the first 10 moves and plays Tit for Tat for the next 15 more moves. After 25 moves, the program cooperates unless all the following are true: the other player defected on the previous move, the other player cooperated less than 60% and the random number between 0 and 1 is greater that the other player's cooperation rate.

Names:

•Champion: *[Axelrod1980b]*

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': inf, 'stochastic': True, 'mani

name = 'Champion'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_second.**Eatherley**

Strategy submitted to Axelrod's second tournament by Graham Eatherley.

A player that keeps track of how many times in the game the other player defected. After the other player defects, it defects with a probability equal to the ratio of the other's total defections to the total moves to that point.

Names:

•Eatherley: *[Axelrod1980b]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Eatherley'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.axelrod_second.**Tester** → None

Submitted to Axelrod's second tournament by David Gladstein.

Defects on the first move and plays Tit For Tat if the opponent ever defects (after one apology cooperation round). Otherwise alternate cooperation and defection.

Names:

•Tester: *[Axelrod1980b]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Tester'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.backstabber.**BackStabber**
Forgives the first 3 defections but on the fourth will defect forever. Defects on the last 2 rounds unconditionally.

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': inf, 'stochastic': False, 'man

name = 'BackStabber'

original_class
alias of *BackStabber*

strategy(*opponent*)

class axelrod.strategies.backstabber.**DoubleCrosser**
Forgives the first 3 defections but on the fourth will defect forever. Defects on the last 2 rounds unconditionally.

If 8 <= current round <= 180, if the opponent did not defect in the first 7 rounds, the player will only defect after the opponent has defected twice in-a-row.

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': inf, 'stochastic': False, 'man

name = 'DoubleCrosser'

original_class
alias of *DoubleCrosser*

strategy(*opponent*)

class axelrod.strategies.better_and_better.**BetterAndBetter**
Defects with probability of '(1000 - current turn) / 1000'. Therefore it is less and less likely to defect as the round goes on.

Names:

- Better and Better: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Better and Better'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.calculator.**Calculator** → None
Plays like (Hard) Joss for the first 20 rounds. If periodic behavior is detected, defect forever. Otherwise play TFT.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

extended_strategy(*opponent: axelrod.player.Player*) → str

name = 'Calculator'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.cooperator.**Cooperator**
A player who only ever cooperates.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 0, 'stochastic': False, 'manipulate

name = 'Cooperator'

static **strategy**(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.cooperator.**TrickyCooperator**
A cooperator that is trying to be tricky.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 10, 'stochastic': False, 'manipulat

name = 'Tricky Cooperator'

strategy(*opponent: axelrod.player.Player*) → str
Almost always cooperates, but will try to trick the opponent by defecting.

Defect once in a while in order to get a better payout. After 3 rounds, if opponent has not defected to a max history depth of 10, Defect.

class axelrod.strategies.cycler.**AntiCycler** → None
A player that follows a sequence of plays that contains no cycles: CDD CD CCD CCCD CCCCD ...

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'AntiCycler'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.cycler.**Cycler**(*cycle: str = 'CCD'*) → None
A player that repeats a given sequence indefinitely.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

get_new_itertools_cycle()

name = 'Cycler'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.cycler.**CyclerCCCCCD** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'Cycler CCCCCD'

class axelrod.strategies.cycler.**CyclerCCCD** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Cycler CCCD'

class axelrod.strategies.cycler.**CyclerCCCDCD** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'Cycler CCCDCD'

class axelrod.strategies.cycler.**CyclerCCD** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Cycler CCD'

class axelrod.strategies.cycler.**CyclerDC** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Cycler DC'

class axelrod.strategies.cycler.**CyclerDDC** → None

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Cycler DDC'

The player class in this module does not obey standard rules of the IPD (as indicated by their classifier). We do not recommend putting a lot of time in to optimising it.

class axelrod.strategies.darwin.**Darwin** → None

A strategy which accumulates a record (the 'genome') of what the most favourable response in the previous round should have been, and naively assumes that this will remain the correct response at the same round of future trials.

This 'genome' is preserved between opponents, rounds and repetitions of the tournament. It becomes a characteristic of the type and so a single version of this is shared by all instances for each loading of the class.

As this results in information being preserved between tournaments, this is classified as a cheating strategy!

If no record yet exists, the opponent's response from the previous round is returned.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

static foil_strategy_inspection() → str

Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

genome = ['C']

mutate(*outcome: tuple*, *trial: int*) → None

Select response according to outcome.

name = 'Darwin'

receive_match_attributes()

reset()

Reset instance properties.

static reset_genome() → None

For use in testing methods.

strategy(*opponent: axelrod.player.Player*) → str

valid_callers = ['play']

class axelrod.strategies.dbs.**DBS**(*discount_factor=0.75*, *promotion_threshold=3*, *violation_threshold=4*, *reject_threshold=3*, *tree_depth=5*)

Desired Belief Strategy as described in *[Au2006]* http://www.cs.utexas.edu/%7Echiu/papers/Au06NoisyIPD.pdf

A strategy that learns the opponent's strategy, and uses symbolic noise detection for detecting whether anomalies in player's behavior are deliberate or accidental, hence increasing performance in noisy tournaments.

From the learned opponent's strategy, a tree search is used to choose the best move

Default values for the parameters are the suggested values in the article. When noise increases you can try to diminish violation_threshold and rejection_threshold

Parameters

discount_factor [float, optional] used when computing discounted frequencies to learn opponent's strategy. Must be between 0 and 1. The default is 0.75

promotion_threshold [int, optional] number of successive observations needed to promote an opponent behavior as a deterministic rule. The default is 3.

violation_threshold [int, optional] number of observations needed to considerate opponent's strategy has changed. You can lower it when noise increases. The default is 4, which is good for a noise level of .1

reject_threshold [int, optional] number of observations before forgetting opponent's previous strategy. You can lower it when noise increases. The default is 3, which is good for a noise level of .1

tree_depth: int, optional depth of the tree for the tree-search algorithm. Higher depth means more time to compute the move. The default is 5

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipula

compute_prob_rule(*outcome*, *alpha=1*)

Uses the game history to compute the probability of the opponent playing C, in the outcome situation (exemple : outcome = (C, C)). When alpha = 1, the results is approximately equal to the frequency of the occurence of outcome -> C. alpha is a discount factor that allows to give more weight to recent events than earlier ones.

Parameters

outcome [tuple of two actions.Actions] in {(C, C), (C, D), (D, C), (D, D)} We want to compute the probability that the opponent plays C following this outcome in the game

alpha [int, optionnal] Discount factor. Default is 1.

name = 'DBS'

reset()

Reset instance properties.

should_demote(*r_minus*, *violation_threshold=4*)

Checks if the number of successive violations of a deterministic rule (in the opponent's behavior) exceeds the user-defined violation_threshold

should_promote(*r_plus*, *promotion_threshold=3*)

This function determines if the move r_plus is a deterministic behavior of the opponent, and then returns True, or if r_plus is due to a random behavior (or noise) which would require a probabilistic rule, in which case it returns False

To do so it looks into the game history : if the K last times when the opponent was in the same situation than in r_plus, he played the same thing, then then r_plus is considered as a deterministic rule (where K is the user-defined promotion_threshold)

Parameters

r_plus [tuple of (tuple of actions.Actions, actions.Actions)] exemple: ((C, C), D) r_plus represents one outcome of the history, and the following move played by the opponent

promotion_threshold [int, optionnal] number of successive observations needed to promote an opponent behavior as a deterministic rule. Default is 3.

strategy(*opponent: axelrod.player.Player*) → str

update_history_by_cond(*opponent_history*)
Updates self.history_by_cond, between each turns of the game.

class axelrod.strategies.dbs.**DeterministicNode**(*action1*, *action2*, *depth*)
Nodes (C, C), (C, D), (D, C), or (D, D) with deterministic choice for siblings

get_siblings(*policy*)
Returns the siblings node of the current DeterministicNode Builds 2 siblings (C, X) and (D, X) that are StochasticNodes Those siblings are of the same depth as the current node Their probability pC are defined by the policy argument

get_value()

is_stochastic()
Returns True if self is a StochasticNode

axelrod.strategies.dbs.**MoveGen**(*outcome*, *policy*, *depth_search_tree=5*)
Returns the best move considering opponent's policy and last move, using tree-search procedure

class axelrod.strategies.dbs.**Node**
Nodes used to build a tree for the tree-search procedure The tree has Deterministic ans Stochastic nodes, as the opponent's strategy is learned as a probability distribution

get_siblings()

is_stochastic()

class axelrod.strategies.dbs.**StochasticNode**(*own_action*, *pC*, *depth*)
Node that have a probability pC to get to each sibling A StochasticNode can be written (C, X) or (D, X), with X = C with a probability pC, else X = D

get_siblings()
Returns the siblings node of the current StochasticNode There are two sibling which are DeterministicNodes, their depth is equal to current node depth's + 1 This function allows to build the tree

is_stochastic()
Returns True if self is a StochasticNode

axelrod.strategies.dbs.**action_to_int**(*action*)

axelrod.strategies.dbs.**create_policy**(*pCC*, *pCD*, *pDC*, *pDD*)
Creates a dict that represents a Policy. As defined in the reference, a Policy is a set of (prev_move, p) where p is the probability to cooperate after prev_move, where prev_move can be (C, C), (C, D), (D, C) or (D, D)

Parameters

pCC, pCD, pDC, pDD [float] Must be between 0 and 1

axelrod.strategies.dbs.**minimax_tree_search**(*begin_node*, *policy*, *max_depth*)
Tree search function (minimax search procedure) build by recursion the tree corresponding to a game against opponent's policy, and solve it Returns a tuple of two float, that are the utility of playing C, and the utility of playing D

class axelrod.strategies.defector.**Defector**
A player who only ever defects.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 0, 'stochastic': False, 'manipulate

name = 'Defector'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.defector.**TrickyDefector**
A defector that is trying to be tricky.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Tricky Defector'

strategy(*opponent: axelrod.player.Player*) → str
Almost always defects, but will try to trick the opponent into cooperating.

Defect if opponent has cooperated at least once in the past and has defected for the last 3 turns in a row.

class axelrod.strategies.doubler.**Doubler**
Cooperates except when the opponent has defected and the opponent's cooperation count is less than twice their defection count.

Names:

•Doubler: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Doubler'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.finite_state_machines.**EvolvedFSM16** → None
A 16 state FSM player trained with an evolutionary algorithm.

Names:

•Evolved FSM 16: Original name by Marc Harper

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 16, 'stochastic': False, 'manipulat

name = 'Evolved FSM 16'

class axelrod.strategies.finite_state_machines.**EvolvedFSM16Noise05** → None
A 16 state FSM player trained with an evolutionary algorithm with noisy matches (noise=0.05).

Names:

•Evolved FSM 16 Noise 05: Original name by Marc Harper

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 16, 'stochastic': False, 'manipulat

name = 'Evolved FSM 16 Noise 05'

class axelrod.strategies.finite_state_machines.**EvolvedFSM4** → None
A 4 state FSM player trained with an evolutionary algorithm.

Names:

•Evolved FSM 4: Original name by Marc Harper

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 4, 'stochastic': False, 'manipulate

name = 'Evolved FSM 4'

class axelrod.strategies.finite_state_machines.**FSMPlayer**(*transitions: tuple = ((1, 'C', 1, 'C'), (1, 'D', 1, 'D'))*, *initial_state: int = 1*, *initial_action: str = 'C'*) → None
Abstract base class for finite state machine players.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'FSM Player'

reset() → None

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.finite_state_machines.**Fortress3** → None
Finite state machine player specified in http://DOI.org/10.1109/CEC.2006.1688322.

Note that the description in http://www.graham-kendall.com/papers/lhk2011.pdf is not correct.

Names:

•Fortress 3: *[Ashlock2006b]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Fortress3'

class axelrod.strategies.finite_state_machines.**Fortress4** → None
Finite state machine player specified in http://DOI.org/10.1109/CEC.2006.1688322.

Note that the description in http://www.graham-kendall.com/papers/lhk2011.pdf is not correct.

Names:

•Fortress 4: *[Ashlock2006b]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 4, 'stochastic': False, 'manipulate

name = 'Fortress4'

class axelrod.strategies.finite_state_machines.**Predator** → None
Finite state machine player specified in http://DOI.org/10.1109/CEC.2006.1688322

Names:

•Predator: *[Ashlock2006b]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 9, 'stochastic': False, 'manipulate

name = 'Predator'

class axelrod.strategies.finite_state_machines.**Pun1** → None
FSM player described in [Ashlock2006].

Names:

- Pun1 *[Ashlock2006]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Pun1'

class axelrod.strategies.finite_state_machines.**Raider** → None
FSM player described in http://DOI.org/10.1109/FOCI.2014.7007818

Names

•Raider: *[Ashlock2014]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Raider'

class axelrod.strategies.finite_state_machines.**Ripoff** → None
FSM player described in http://DOI.org/10.1109/TEVC.2008.920675.

Names

•Ripoff: *[Ashlock2008]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Ripoff'

class axelrod.strategies.finite_state_machines.**SimpleFSM**(*transitions: tuple*, *initial_state: int*) → None
Simple implementation of a finite state machine that transitions between states based on the last round of play.

https://en.wikipedia.org/wiki/Finite-state_machine

move(*opponent_action: str*) → str
Computes the response move and changes state.

state

state_transitions

class axelrod.strategies.finite_state_machines.**SolutionB1** → None
FSM player described in http://DOI.org/10.1109/TCIAIG.2014.2326012.

Names

•Solution B1: *[Ashlock2015]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'SolutionB1'

class axelrod.strategies.finite_state_machines.**SolutionB5** → None
FSM player described in http://DOI.org/10.1109/TCIAIG.2014.2326012.

Names

•Solution B5: *[Ashlock2015]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'SolutionB5'

class axelrod.strategies.finite_state_machines.**Thumper** → None
FSM player described in http://DOI.org/10.1109/TEVC.2008.920675.

Names

•Thumper: *[Ashlock2008]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Thumper'

class axelrod.strategies.forgiver.**Forgiver**
A player starts by cooperating however will defect if at any point the opponent has defected more than 10 percent of the time

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Forgiver'

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D if the opponent has defected more than 10 percent of the time

class axelrod.strategies.forgiver.**ForgivingTitForTat**
A player starts by cooperating however will defect if at any point, the opponent has defected more than 10 percent of the time, and their most recent decision was defect.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Forgiving Tit For Tat'

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D if, the opponent has defected more than 10 percent of the time, and their most recent decision was defect.

Stochastic variants of Lookup table based-strategies, trained with particle swarm algorithms.

For the original see: https://gist.github.com/GDKO/60c3d0fd423598f3c4e4

class axelrod.strategies.gambler.**Gambler**(*lookup_dict: dict = None*, *initial_actions: tuple = None*, *pattern: typing.Any = None*, *parameters: axelrod.strategies.lookerup.Plays = None*) → None
A stochastic version of LookerUp which will select randomly an action in some cases.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Gambler'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.gambler.**PSOGambler1_1_1** → None
A 1x1x1 PSOGambler trained with pyswarm.

Names:

- PSO Gambler 1_1_1: Original name by Marc Harper

name = 'PSO Gambler 1_1_1'

class axelrod.strategies.gambler.**PSOGambler2_2_2** → None
A 2x2x2 PSOGambler trained with pyswarm. Original version by @GDKO.

Names:

- PSO Gambler 2_2_2: Original name by Marc Harper

name = 'PSO Gambler 2_2_2'

class axelrod.strategies.gambler.**PSOGambler2_2_2_Noise05** → None
A 2x2x2 PSOGambler trained with pyswarm with noise=0.05.

Names:

- PSO Gambler 2_2_2 Noise 05: Original name by Marc Harper

name = 'PSO Gambler 2_2_2 Noise 05'

class axelrod.strategies.gambler.**PSOGamblerMem1** → None
A 1x1x0 PSOGambler trained with pyswarm. This is the 'optimal' memory one strategy trained against the set of short run time strategies in the Axelrod library.

Names:

- PSO Gambler Mem1: Original name by Marc Harper

name = 'PSO Gambler Mem1'

The player classes in this module do not obey standard rules of the IPD (as indicated by their classifier). We do not recommend putting a lot of time in to optimising them.

class axelrod.strategies.geller.**Geller**
Observes what the player will do in the next round and adjust.

If unable to do this: will play randomly.

Geller - by Martin Chorley (@martinjc), heavily inspired by Matthew Williams (@voxmjw)

This code is inspired by Matthew Williams' talk "Cheating at rock-paper-scissors — meta-programming in Python" given at Django Weekend Cardiff in February 2014.

His code is here: https://github.com/mattjw/rps_metaprogramming and there's some more info here: http://www.mattjw.net/2014/02/rps-metaprogramming/

This code is **way** simpler than Matt's, as in this exercise we already have access to the opponent instance, so don't need to go hunting for it in the stack. Instead we can just call it to see what it's going to play, and return a result based on that

This is almost certainly cheating, and more than likely against the spirit of the 'competition' :-)

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': -1, 'stochastic': True, 'manipulate

static foil_strategy_inspection() → str
Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

name = 'Geller'

strategy(*opponent: axelrod.player.Player*) → str
Look at what the opponent will play in the next round and choose a strategy that gives the least jail time, which is is equivalent to playing the same strategy as that which the opponent will play.

class axelrod.strategies.geller.**GellerCooperator**
Observes what the payer will do (like Geller) but if unable to will cooperate.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': -1, 'stochastic': False, 'manipulat

static foil_strategy_inspection() → str
Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

name = 'Geller Cooperator'

class axelrod.strategies.geller.**GellerDefector**
Observes what the payer will do (like Geller) but if unable to will defect.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': -1, 'stochastic': False, 'manipulat

static foil_strategy_inspection() → str
Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

name = 'Geller Defector'

class axelrod.strategies.gobymajority.**GoByMajority**(*memory_depth: typing.Union[int, float] = inf*, *soft: bool = True*) → None
A player examines the history of the opponent: if the opponent has more defections than cooperations then the player defects.

In case of equal number of defections and cooperations this player will Cooperate. Passing the *soft=False* keyword argument when initialising will create a HardGoByMajority which Defects in case of equality.

An optional memory attribute will limit the number of turns remembered (by default this is 0)

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Go By Majority'

strategy(*opponent: axelrod.player.Player*) → str
This is affected by the history of the opponent.

As long as the opponent cooperates at least as often as they defect then the player will cooperate. If at any point the opponent has more defections than cooperations in memory the player defects.

class axelrod.strategies.gobymajority.**GoByMajority10** → None
GoByMajority player with a memory of 10.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 10, 'stochastic': False, 'manipulat

name = 'Go By Majority 10'

class axelrod.strategies.gobymajority.**GoByMajority20** → None
GoByMajority player with a memory of 20.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 20, 'stochastic': False, 'manipulat

name = 'Go By Majority 20'

class axelrod.strategies.gobymajority.**GoByMajority40** → None
GoByMajority player with a memory of 40.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 40, 'stochastic': False, 'manipulat

name = 'Go By Majority 40'

class axelrod.strategies.gobymajority.**GoByMajority5** → None
GoByMajority player with a memory of 5.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'Go By Majority 5'

class axelrod.strategies.gobymajority.**HardGoByMajority**(*memory_depth: typing.Union[int, float] = inf*) → None
A player examines the history of the opponent: if the opponent has more defections than cooperations then the player defects. In case of equal number of defections and cooperations this player will Defect.

An optional memory attribute will limit the number of turns remembered (by default this is 0)

name = 'Hard Go By Majority'

class axelrod.strategies.gobymajority.**HardGoByMajority10** → None
HardGoByMajority player with a memory of 10.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 10, 'stochastic': False, 'manipulat

name = 'Hard Go By Majority 10'

class axelrod.strategies.gobymajority.**HardGoByMajority20** → None
HardGoByMajority player with a memory of 20.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 20, 'stochastic': False, 'manipulat

name = 'Hard Go By Majority 20'

class axelrod.strategies.gobymajority.**HardGoByMajority40** → None
HardGoByMajority player with a memory of 40.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 40, 'stochastic': False, 'manipulat

name = 'Hard Go By Majority 40'

class axelrod.strategies.gobymajority.**HardGoByMajority5** → None
HardGoByMajority player with a memory of 5.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'Hard Go By Majority 5'

class axelrod.strategies.gradualkiller.**GradualKiller**
It begins by defecting in the first five moves, then cooperates two times. It then defects all the time if the opponent has defected in move 6 and 7, else cooperates all the time. Initially designed to stop Gradual from defeating TitForTat in a 3 Player tournament.

Names

•Gradual Killer: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Gradual Killer'

original_class
alias of *GradualKiller*

strategy(*opponent*)

class axelrod.strategies.grudger.**Aggravater**
Grudger, except that it defects on the first 3 turns

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Aggravater'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.grudger.**EasyGo**
A player starts by defecting however will cooperate if at any point the opponent has defected.

Names:

•Easy Go *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'EasyGo'

static strategy(*opponent: axelrod.player.Player*) → str
Begins by playing D, then plays C for the remaining rounds if the opponent ever plays D.

class axelrod.strategies.grudger.**ForgetfulGrudger** → None
A player starts by cooperating however will defect if at any point the opponent has defected, but forgets after mem_length matches.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 10, 'stochastic': False, 'manipulat

name = 'Forgetful Grudger'

reset()
Resets scores and history.

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for mem_length rounds if the opponent ever plays D.

class axelrod.strategies.grudger.**GeneralSoftGrudger**(*n: int = 1*, *d: int = 4*, *c: int = 2*) → None
A generalization of the SoftGrudger strategy. SoftGrudger punishes by playing: D, D, D, D, C, C. after a defection by the opponent. GeneralSoftGrudger only punishes after its opponent defects a specified amount of times consecutively. The punishment is in the form of a series of defections followed by a 'penance' of a series of consecutive cooperations.

Names:

•General Soft Grudger: Original Name by J. Taylor Smith

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'General Soft Grudger'

reset()
Resets scores and history.

strategy(*opponent: axelrod.player.Player*) → str
Punishes after its opponent defects 'n' times consecutively. The punishment is in the form of 'd' defections followed by a penance of 'c' consecutive cooperations.

class axelrod.strategies.grudger.**Grudger**
A player starts by cooperating however will defect if at any point the opponent has defected.

Names:

•Friedman's strategy: *[Axelrod1980]*

•Grudger: *[Li2011]*

•Grim: *[Berg2015]*

•Grim Trigger: *[Banks1980]*

•Spite: *[Beaufils1997]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Grudger'

static strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for the remaining rounds if the opponent ever plays D.

class axelrod.strategies.grudger.**GrudgerAlternator**
A player starts by cooperating until the first opponents defection, then alternates D-C.

Names:

•c_then_per_dc: *[Prison1998]*

•Grudger Alternator: Original name by Geraint Palmer

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'GrudgerAlternator'

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays Alternator for the remaining rounds if the opponent ever plays D.

class axelrod.strategies.grudger.**OppositeGrudger**
A player starts by defecting however will cooperate if at any point the opponent has cooperated.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Opposite Grudger'

static strategy(*opponent: axelrod.player.Player*) → str
Begins by playing D, then plays C for the remaining rounds if the opponent ever plays C.

class axelrod.strategies.grudger.**SoftGrudger** → None
A modification of the Grudger strategy. Instead of punishing by always defecting: punishes by playing: D, D, D, D, C, C. (Will continue to cooperate afterwards).

For reference see: "Engineering Design of Strategies for Winning Iterated Prisoner's Dilemma Competitions" by Jiawei Li, Philip Hingston, and Graham Kendall. IEEE TRANSACTIONS ON COMPUTATIONAL INTELLIGENCE AND AI IN GAMES, VOL. 3, NO. 4, DECEMBER 2011

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 6, 'stochastic': False, 'manipulate

name = 'Soft Grudger'

reset()
Resets scores and history.

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D, D, D, D, C, C against a defection

class axelrod.strategies.grumpy.**Grumpy**(*starting_state: str = 'Nice', grumpy_threshold: int = 10, nice_threshold: int = -10*) → None
A player that defects after a certain level of grumpiness. Grumpiness increases when the opponent defects and decreases when the opponent co-operates.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Grumpy'

reset()
Resets score, history and state for the next round of the tournament.

strategy(*opponent: axelrod.player.Player*) → str
A player that gets grumpier the more the opposition defects, and nicer the more they cooperate.

Starts off Nice, but becomes grumpy once the grumpiness threshold is hit. Won't become nice once that grumpy threshold is hit, but must reach a much lower threshold before it becomes nice again.

class axelrod.strategies.handshake.**Handshake**(*initial_plays: typing.List[str] = None*) → None
Starts with C, D. If the opponent plays the same way, cooperate forever, else defect forever.

Names:

•Handshake: *[Robson1989]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Handshake'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hmm.**EvolvedHMM5** → None
An HMM-based player with five hidden states trained with an evolutionary algorithm.

Names:

•Evolved HMM 5

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': True, 'manipulates

name = 'Evolved HMM 5'

class axelrod.strategies.hmm.**HMMPlayer**(*transitions_C=None, transitions_D=None, emission_probabilities=None, initial_state=0, initial_action='C'*) → None
Abstract base class for Hidden Markov Model players.

Names

•HMM Player

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

is_stochastic() → bool
Determines if the player is stochastic.

name = 'HMM Player'

reset() → None

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hmm.**SimpleHMM**(*transitions_C*, *transitions_D*, *emission_probabilities*, *initial_state*) → None

Implementation of a basic Hidden Markov Model. We assume that the transition matrix is conditioned on the opponent's last action, so there are two transition matrices. Emission distributions are stored as Bernoulli probabilities for each state. This is essentially a stochastic FSM.

https://en.wikipedia.org/wiki/Hidden_Markov_model

is_well_formed() → bool

Determines if the HMM parameters are well-formed:

- Both matrices are stochastic
- Emissions probabilities are in [0, 1]
- The initial state is valid.

move(*opponent_action: str*) → str

Changes state and computes the response action.

Parameters

opponent_action: Axelrod.Action The opponent's last action.

axelrod.strategies.hmm.**is_stochastic_matrix**(*m*, *ep=1e-08*) → bool

Checks that the matrix m (a list of lists) is a stochastic matrix.

class axelrod.strategies.hunter.**AlternatorHunter** → None

A player who hunts for alternators.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Alternator Hunter'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hunter.**CooperatorHunter**

A player who hunts for cooperators.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Cooperator Hunter'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hunter.**CycleHunter** → None

Hunts strategies that play cyclically, like any of the Cyclers, Alternator, etc.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Cycle Hunter'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hunter.**DefectorHunter**

A player who hunts for defectors.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Defector Hunter'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.hunter.**EventualCycleHunter** → None
Hunts strategies that eventually play cyclically.

name = 'Eventual Cycle Hunter'

strategy(*opponent: axelrod.player.Player*) → None

class axelrod.strategies.hunter.**MathConstantHunter**
A player who hunts for mathematical constant players.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Math Constant Hunter'

strategy(*opponent: axelrod.player.Player*) → str
Check whether the number of cooperations in the first and second halves of the history are close. The variance of the uniform distribution (1/4) is a reasonable delta but use something lower for certainty and avoiding false positives. This approach will also detect a lot of random players.

class axelrod.strategies.hunter.**RandomHunter** → None
A player who hunts for random players.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Random Hunter'

reset()

strategy(*opponent: axelrod.player.Player*) → str
A random player is unpredictable, which means the conditional frequency of cooperation after cooperation, and defection after defections, should be close to 50%... although how close is debatable.

axelrod.strategies.hunter.**is_alternator**(*history: typing.List[str]*) → bool

class axelrod.strategies.inverse.**Inverse**
A player who defects with a probability that diminishes relative to how long ago the opponent defected.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Inverse'

static strategy(*opponent: axelrod.player.Player*) → str
Looks at opponent history to see if they have defected.

If so, player defection is inversely proportional to when this occurred.

class axelrod.strategies.lookerup.**EvolvedLookerUp1_1_1** → None
A 1 1 1 Lookerup trained with an evolutionary algorithm.

Names:

- Evolved Lookerup 1 1 1: Original name by Marc Harper

name = 'EvolvedLookerUp1_1_1'

class axelrod.strategies.lookerup.**EvolvedLookerUp2_2_2** → None
A 2 2 2 Lookerup trained with an evolutionary algorithm.

Names:

- Evolved Lookerup 2 2 2: Original name by Marc Harper

name = 'EvolvedLookerUp2_2_2'

class axelrod.strategies.lookerup.**LookerUp**(*lookup_dict: dict = None*, *initial_actions: tuple = None*, *pattern: typing.Any = None*, *parameters: axelrod.strategies.lookerup.Plays = None*) → None

This strategy uses a LookupTable to decide its next action. If there is not enough history to use the table, it calls from a list of self.initial_actions.

if self_depth=2, op_depth=3, op_openings_depth=5, LookerUp finds the last 2 plays of self, the last 3 plays of opponent and the opening 5 plays of opponent. It then looks those up on the LookupTable and returns the appropriate action. If 5 rounds have not been played (the minimum required for op_openings_depth), it calls from self.initial_actions.

LookerUp can be instantiated with a dictionary. The dictionary uses tuple(tuple, tuple, tuple) or Plays as keys. for example.

- self_plays: depth=2
- op_plays: depth=1
- op_openings: depth=0:

```
{Plays((C, C), (C), ()): C,
 Plays((C, C), (D), ()): D,
 Plays((C, D), (C), ()): D,  <- example below
 Plays((C, D), (D), ()): D,
 Plays((D, C), (C), ()): C,
 Plays((D, C), (D), ()): D,
 Plays((D, D), (C), ()): C,
 Plays((D, D), (D), ()): D}
```

From the above table, if the player last played C, D and the opponent last played C (here the initial opponent play is ignored) then this round, the player would play D.

The dictionary must contain all possible permutations of C's and D's.

LookerUp can also be instantiated with *pattern=str/tuple* of actions, and:

```
parameters=Plays(
    self_plays=player_depth: int,
    op_plays=op_depth: int,
    op_openings=op_openings_depth: int)
```

It will create keys of len=2 ** (sum(parameters)) and map the pattern to the keys.

initial_actions is a tuple such as (C, C, D). A table needs initial actions equal to max(self_plays depth, opponent_plays depth, opponent_initial_plays depth). If provided initial_actions is too long, the extra will be ignored. If provided initial_actions is too short, the shortfall will be made up with C's.

Some well-known strategies can be expressed as special cases; for example Cooperator is given by the dict (All history is ignored and always play C):

```
{Plays((), (), ()) : C}
```

Tit-For-Tat is given by (The only history that is important is the opponent's last play.):

```
{Plays((), (D,), ()): D,
 Plays((), (C,), ()): C}
```

LookerUp's LookupTable defaults to Tit-For-Tat. The initial_actions defaults to playing C.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

default_tft_lookup_table = {Plays(self_plays=(), op_plays=('C',), op_openings=()): 'C', Plays(self_plays=(), op_pl

lookup_dict

lookup_table_display(*sort_by: tuple = ('op_openings', 'self_plays', 'op_plays')*) → str
Returns a string for printing lookup_table info in specified order.

Parameters **sort_by** – only_elements='self_plays', 'op_plays', 'op_openings'

name = 'LookerUp'

reset() → None

strategy(*opponent: axelrod.player.Player*) → Reaction

class axelrod.strategies.lookerup.**LookupTable**(*lookup_dict: dict*) → None
LookerUp and its children use this object to determine their next actions.

It is an object that creates a table of all possible plays to a specified depth and the action to be returned for each combination of plays. The "get" method returns the appropriate response. For the table containing:

```
....
Plays(self_plays=(C, C), op_plays=(C, D), op_openings=(D, C): D
Plays(self_plays=(C, C), op_plays=(C, D), op_openings=(D, D): C
...
```

with: player.history[-2:]=[C, C] and opponent.history[-2:]=[C, D] and opponent.history[:2]=[D, D], calling LookupTable.get(plays=(C, C), op_plays=(C, D), op_openings=(D, D)) will return C.

Instantiate the table with a lookup_dict. This is {(self_plays_tuple, op_plays_tuple, op_openings_tuple): action, ...}. It must contain every possible permutation with C's and D's of the above tuple. so:

```
good_dict = {((C,), (C,), ()): C,
             ((C,), (D,), ()): C,
             ((D,), (C,), ()): D,
             ((D,), (D,), ()): C}

bad_dict = {((C,), (C,), ()): C,
            ((C,), (D,), ()): C,
            ((D,), (C,), ()): D}
```

LookupTable.from_pattern() creates an ordered list of keys for you and maps the pattern to the keys.:

```
LookupTable.from_pattern(pattern=(C, D, D, C),
    player_depth=0, op_depth=1, op_openings_depth=1
)
```

creates the dictionary:

```
{Plays(self_plays=(), op_plays=(C), op_openings=(C)): C,
 Plays(self_plays=(), op_plays=(C), op_openings=(D)): D,
 Plays(self_plays=(), op_plays=(D), op_openings=(C)): D,
 Plays(self_plays=(), op_plays=(D), op_openings=(D)): C,}
```

and then returns a LookupTable with that dictionary.

dictionary

display(*sort_by: tuple = ('op_openings', 'self_plays', 'op_plays')*) → str
Returns a string for printing lookup_table info in specified order.

Parameters **sort_by** – only_elements='self_plays', 'op_plays', 'op_openings'

classmethod from_pattern(*pattern: tuple*, *player_depth: int*, *op_depth: int*, *op_openings_depth: int*)

get(*plays: tuple*, *op_plays: tuple*, *op_openings: tuple*) → typing.Any

op_depth

op_openings_depth

player_depth

table_depth

class axelrod.strategies.lookerup.**Plays**(*self_plays*, *op_plays*, *op_openings*)

op_openings
Alias for field number 2

op_plays
Alias for field number 1

self_plays
Alias for field number 0

class axelrod.strategies.lookerup.**Winner12** → None
A lookup table based strategy.

Names:

- Winner12 *[Mathieu2015]*

name = 'Winner12'

class axelrod.strategies.lookerup.**Winner21** → None
A lookup table based strategy.

Names:

- Winner21 *[Mathieu2015]*

name = 'Winner21'

axelrod.strategies.lookerup.**create_lookup_table_keys**(*player_depth: int*, *op_depth: int*, *op_openings_depth: int*) → list
Returns a list of Plays that has all possible permutations of C's and D's for each specified depth. the list is in order, C < D sorted by ((player_tuple), (op_tuple), (op_openings_tuple)). create_lookup_keys(2, 1, 0) returns:

```
[Plays(self_plays=(C, C), op_plays=(C,), op_openings=()),
 Plays(self_plays=(C, C), op_plays=(D,), op_openings=()),
 Plays(self_plays=(C, D), op_plays=(C,), op_openings=()),
 Plays(self_plays=(C, D), op_plays=(D,), op_openings=()),
 Plays(self_plays=(D, C), op_plays=(C,), op_openings=()),
 Plays(self_plays=(D, C), op_plays=(D,), op_openings=()),
 Plays(self_plays=(D, D), op_plays=(C,), op_openings=()),
 Plays(self_plays=(D, D), op_plays=(D,), op_openings=())]
```

axelrod.strategies.lookerup.**get_last_n_plays**(*player: axelrod.player.Player*, *depth: int*) → tuple
Returns the last N plays of player as a tuple.

axelrod.strategies.lookerup.**make_keys_into_plays**(*lookup_table: dict*) → dict
Returns a dict where all keys are Plays.

class axelrod.strategies.mathematicalconstants.**CotoDeRatio**
The player will always aim to bring the ratio of co-operations to defections closer to the ratio as given in a sub class

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipula

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.mathematicalconstants.**Golden**
The player will always aim to bring the ratio of co-operations to defections closer to the golden mean

name = '$\\phi$'

ratio = 1.618033988749895

class axelrod.strategies.mathematicalconstants.**Pi**
The player will always aim to bring the ratio of co-operations to defections closer to the pi

name = '$\\pi$'

ratio = 3.141592653589793

class axelrod.strategies.mathematicalconstants.**e**
The player will always aim to bring the ratio of co-operations to defections closer to the e

name = 'e'

ratio = 2.718281828459045

class axelrod.strategies.memorytwo.**MEM2** → None
A memory-two player that switches between TFT, TFTT, and ALLD.

Note that the reference claims that this is a memory two strategy but in fact it is infinite memory. This is because the player plays as ALLD if ALLD has ever been selected twice, which can only be known if the entire history of play is accessible.

Names:

- MEM2 *[Li2016]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipula

name = 'MEM2'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.memoryone.**ALLCorALLD**
This strategy is at the parameter extreme of the ZD strategies (phi = 0). It simply repeats its last move, and so mimics ALLC or ALLD after round one. If the tournament is noisy, there will be long runs of C and D.

For now starting choice is random of 0.6, but that was an arbitrary choice at implementation time.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'ALLCorALLD'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.memoryone.**FirmButFair** → None
A strategy that cooperates on the first move, and cooperates except after receiving a sucker payoff.

Names:

- Firm But Fair: *[Frean1994]*

name = 'Firm But Fair'

class axelrod.strategies.memoryone.**GTFT**(*p: float = None*) → None
Generous Tit For Tat Strategy.

Names:

•Generous Tit For Tat: *[Nowak1993]*

classifier = {'manipulates_source': False, 'makes_use_of': {'game'}, 'memory_depth': 1, 'stochastic': True, 'manipu

name = 'GTFT'

receive_match_attributes()

class axelrod.strategies.memoryone.**LRPlayer**(*four_vector: typing.Union[typing.List[float], typing.Tuple[float, float, float, float]] = None, initial: str = 'C'*) → None
Abstraction for Linear Relation players. These players enforce a linear difference in stationary payoffs s * (S_xy - l) = S_yx - l, with 0 <= l <= R. The parameter *s* is called the slope and the parameter *l* the baseline payoff. For extortionate strategies, the extortion factor is the inverse of the slope.

This parameterization is Equation 14 in http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0077886. See Figure 2 of the article for a more in-depth explanation.

classifier = {'manipulates_source': False, 'makes_use_of': {'game'}, 'memory_depth': 1, 'stochastic': True, 'manipu

name = 'LinearRelation'

receive_match_attributes(*phi: float = 0*, *s: float = None*, *l: float = None*)
Parameters

phi, s, l: floats Parameter used to compute the four-vector according to the parameterization of the strategies below.

class axelrod.strategies.memoryone.**MemoryOnePlayer**(*four_vector: typing.Union[typing.List[float], typing.Tuple[float, float, float, float]] = None, initial: str = 'C'*) → None
Uses a four-vector for strategies based on the last round of play, (P(C|CC), P(C|CD), P(C|DC), P(C|DD)), defaults to Win-Stay Lose-Shift. Intended to be used as an abstract base class or to at least be supplied with a initializing four_vector.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Generic Memory One Player'

set_four_vector(*four_vector: typing.Union[typing.List[float], typing.Tuple[float, float, float, float]]*)

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.memoryone.**SoftJoss**(*q: float = 0.9*) → None
Defects with probability 0.9 when the opponent defects, otherwise emulates Tit-For-Tat.

name = 'Soft Joss'

class axelrod.strategies.memoryone.**StochasticCooperator** → None
Stochastic Cooperator, http://www.nature.com/ncomms/2013/130801/ncomms3193/full/ncomms3193.html.

name = 'Stochastic Cooperator'

class axelrod.strategies.memoryone.**StochasticWSLS**(*ep: float = 0.05*) → None
Stochastic WSLS, similar to Generous TFT

name = 'Stochastic WSLS'

class axelrod.strategies.memoryone.**WinShiftLoseStay**(*initial: str = 'D'*) → None
Win-Shift Lose-Stay, also called Reverse Pavlov.

Names:

•WSLS: *[Li2011]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Win-Shift Lose-Stay'

class axelrod.strategies.memoryone.**WinStayLoseShift**(*initial: str = 'C'*) → None
Win-Stay Lose-Shift, also called Pavlov.

Names:

•WSLS: *[Stewart2012]*

•Win Stay Lose Shift: *[Nowak1993]*

•Pavlov: *[Kraines1989]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Win-Stay Lose-Shift'

class axelrod.strategies.memoryone.**ZDExtort2**(*phi: float = 0.1111111111111111*, *s: float = 0.5*) → None
An Extortionate Zero Determinant Strategy with l=P.

name = 'ZD-Extort-2'

receive_match_attributes()

class axelrod.strategies.memoryone.**ZDExtort2v2**(*phi: float = 0.125*, *s: float = 0.5*, *l: float = 1*) → None
An Extortionate Zero Determinant Strategy with l=1.

name = 'ZD-Extort-2 v2'

receive_match_attributes()

class axelrod.strategies.memoryone.**ZDExtort4**(*phi: float = 0.23529411764705882*, *s: float = 0.25*, *l: float = 1*) → None
An Extortionate Zero Determinant Strategy with l=1, s=1/4. TFT is the other extreme (with l=3, s=1)

name = 'ZD-Extort-4'

receive_match_attributes()

class axelrod.strategies.memoryone.**ZDGTFT2**(*phi: float = 0.25*, *s: float = 0.5*) → None
A Generous Zero Determinant Strategy with l=R.

name = 'ZD-GTFT-2'

receive_match_attributes()

class axelrod.strategies.memoryone.**ZDGen2**(*phi: float = 0.125*, *s: float = 0.5*, *l: float = 3*) → None
A Generous Zero Determinant Strategy with l=3.

name = 'ZD-GEN-2'

receive_match_attributes()

class axelrod.strategies.memoryone.**ZDSet2**(*phi: float = 0.25*, *s: float = 0.0*, *l: float = 2*) → None
A Generous Zero Determinant Strategy with l=2.

name = 'ZD-SET-2'

receive_match_attributes()

class axelrod.strategies.meta.**MetaHunter**
A player who uses a selection of hunters.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

static meta_strategy(*results*, *opponent*)

name = 'Meta Hunter'

class axelrod.strategies.meta.**MetaHunterAggressive**(*team=None*)
A player who uses a selection of hunters.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

static meta_strategy(*results*, *opponent*)

name = 'Meta Hunter Aggressive'

class axelrod.strategies.meta.**MetaMajority**(*team=None*)
A player who goes by the majority vote of all other non-meta players.

static meta_strategy(*results*, *opponent*)

name = 'Meta Majority'

class axelrod.strategies.meta.**MetaMajorityFiniteMemory**
MetaMajority with the team of Finite Memory Players

name = 'Meta Majority Finite Memory'

class axelrod.strategies.meta.**MetaMajorityLongMemory**
MetaMajority with the team of Long (infinite) Memory Players

name = 'Meta Majority Long Memory'

class axelrod.strategies.meta.**MetaMajorityMemoryOne**
MetaMajority with the team of Memory One players

name = 'Meta Majority Memory One'

class axelrod.strategies.meta.**MetaMinority**(*team=None*)
A player who goes by the minority vote of all other non-meta players.

static meta_strategy(*results*, *opponent*)

name = 'Meta Minority'

class axelrod.strategies.meta.**MetaMixer**(*team=None*, *distribution=None*)
A player who randomly switches between a team of players. If no distribution is passed then the player will uniformly choose between sub players.

In essence this is creating a Mixed strategy.

Parameters

team [list of strategy classes, optional] Team of strategies that are to be randomly played If none is passed will select the ordinary strategies.

distribution [list representing a probability distribution, optional] This gives the distribution from which to select the players. If none is passed will select uniformly.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

meta_strategy(*results*, *opponent*)
Using the numpy.random choice function to sample with weights

name = 'Meta Mixer'

class axelrod.strategies.meta.**MetaPlayer**(*team=None*)
A generic player that has its own team of players.

classifier = {'manipulates_source': False, 'makes_use_of': {'length', 'game'}, 'memory_depth': inf, 'stochastic': Tru

meta_strategy(*results*, *opponent*)
Determine the meta result based on results of all players. Override this function in child classes.

name = 'Meta Player'

reset()

strategy(*opponent*)

class axelrod.strategies.meta.**MetaWinner**(*team=None*)
A player who goes by the strategy of the current winner.

meta_strategy(*results*, *opponent*)

name = 'Meta Winner'

reset()

class axelrod.strategies.meta.**MetaWinnerDeterministic**
Meta Winner with the team of Deterministic Players.

name = 'Meta Winner Deterministic'

class axelrod.strategies.meta.**MetaWinnerEnsemble**(*team=None*)
A variant of MetaWinner that chooses one of the top scoring strategies at random against each opponent. Note this strategy is always stochastic regardless of the team.

Names:

Meta Winner Ensemble: Original name by Marc Harper

meta_strategy(*results*, *opponent*)

name = 'Meta Winner Ensemble'

class axelrod.strategies.meta.**MetaWinnerFiniteMemory**
MetaWinner with the team of Finite Memory Players

name = 'Meta Winner Finite Memory'

class axelrod.strategies.meta.**MetaWinnerLongMemory**
MetaWinner with the team of Long (infinite) Memory Players

name = 'Meta Winner Long Memory'

class axelrod.strategies.meta.**MetaWinnerMemoryOne**
MetaWinner with the team of Memory One players

name = 'Meta Winner Memory One'

class axelrod.strategies.meta.**MetaWinnerStochastic**
Meta Winner with the team of Stochastic Players.

name = 'Meta Winner Stochastic'

class axelrod.strategies.meta.**NMWEDeterministic**
Nice Meta Winner Ensemble with the team of Deterministic Players.

name = 'NMWE Deterministic'

class axelrod.strategies.meta.**NMWEFiniteMemory**
Nice Meta Winner Ensemble with the team of Finite Memory Players.

name = 'NMWE Finite Memory'

class axelrod.strategies.meta.**NMWELongMemory**
Nice Meta Winner Ensemble with the team of Long Memory Players.

name = 'NMWE Long Memory'

class axelrod.strategies.meta.**NMWEMemoryOne**
Nice Meta Winner Ensemble with the team of Memory One Players.

name = 'NMWE Memory One'

class axelrod.strategies.meta.**NMWEStochastic**
Nice Meta Winner Ensemble with the team of Stochastic Players.

name = 'NMWE Stochastic'

class axelrod.strategies.meta.**NiceMetaWinner**(*team=None*)
A player who goes by the strategy of the current winner.

classifier = {'manipulates_source': False, 'makes_use_of': {'length', 'game'}, 'memory_depth': inf, 'stochastic': Tru

name = 'Nice Meta Winner'

original_class
alias of *MetaWinner*

strategy(*opponent*)

class axelrod.strategies.meta.**NiceMetaWinnerEnsemble**(*team=None*)
A variant of MetaWinner that chooses one of the top scoring strategies at random against each opponent. Note this strategy is always stochastic regardless of the team.

Names:

Meta Winner Ensemble: Original name by Marc Harper

classifier = {'manipulates_source': False, 'makes_use_of': {'length', 'game'}, 'memory_depth': inf, 'stochastic': Tru

name = 'Nice Meta Winner Ensemble'

original_class
alias of *MetaWinnerEnsemble*

strategy(*opponent*)

class axelrod.strategies.mindcontrol.**MindBender**
A player that changes the opponent's strategy by modifying the internal dictionary.

classifier = {'manipulates_source': True, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

name = 'Mind Bender'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.mindcontrol.**MindController**
A player that changes the opponents strategy to cooperate.

classifier = {'manipulates_source': True, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

name = 'Mind Controller'

static strategy(*opponent: axelrod.player.Player*) → str
Alters the opponents strategy method to be a lambda function which always returns C. This player will then always return D to take advantage of this

class axelrod.strategies.mindcontrol.**MindWarper**
A player that changes the opponent's strategy but blocks changes to its own.

classifier = {'manipulates_source': True, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

name = 'Mind Warper'

static strategy(*opponent: axelrod.player.Player*) → str

The player classes in this module do not obey standard rules of the IPD (as indicated by their classifier). We do not recommend putting a lot of time in to optimising them.

class axelrod.strategies.mindreader.**MindReader**
A player that looks ahead at what the opponent will do and decides what to do.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

static foil_strategy_inspection() → str
Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

name = 'Mind Reader'

strategy(*opponent: axelrod.player.Player*) → str
Pretends to play the opponent a number of times before each match. The primary purpose is to look far enough ahead to see if a defect will be punished by the opponent.

class axelrod.strategies.mindreader.**MirrorMindReader**
A player that will mirror whatever strategy it is playing against by cheating and calling the opponent's strategy function instead of its own.

classifier = {'manipulates_source': True, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

static foil_strategy_inspection() → str
Foils _strategy_utils.inspect_strategy and _strategy_utils.look_ahead

name = 'Mirror Mind Reader'

strategy(*opponent: axelrod.player.Player*) → str
Will read the mind of the opponent and play the opponent's strategy.

class axelrod.strategies.mindreader.**ProtectedMindReader**
A player that looks ahead at what the opponent will do and decides what to do. It is also protected from mind control strategies

classifier = {'manipulates_source': True, 'makes_use_of': set(), 'memory_depth': -10, 'stochastic': False, 'manipula

name = 'Protected Mind Reader'

class axelrod.strategies.mutual.**Desperate**
A player that only cooperates after mutual defection.

Names:

•Desperate: *[Berg2015]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Desperate'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.mutual.**Hopeless**
A player that only defects after mutual cooperation.

Names:

•Hopeless: *[Berg2015]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Hopeless'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.mutual.**Willing**
A player that only defects after mutual defection.

Names:

•Willing: *[Berg2015]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Willing'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.negation.**Negation**
A player starts by cooperating or defecting randomly if it's their first move, then simply doing the opposite of the opponents last move thereafter.

Names:

Negation - [http://www.prisoners-dilemma.com/competition.html]

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Negation'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.oncebitten.**FoolMeForever**
Fool me once, shame on me. Teach a man to fool me and I'll be fooled for the rest of my life.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Fool Me Forever'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.oncebitten.**FoolMeOnce**
Forgives one D then retaliates forever on a second D.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Fool Me Once'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.oncebitten.**ForgetfulFoolMeOnce**(*forget_probability: float = 0.05*) → None
Forgives one D then retaliates forever on a second D. Sometimes randomly forgets the defection count, and so keeps a secondary count separate from the standard count in Player.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Forgetful Fool Me Once'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.oncebitten.**OnceBitten** → None
Cooperates once when the opponent defects, but if they defect twice in a row defaults to forgetful grudger for 10 turns defecting.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 12, 'stochastic': False, 'manipulat

name = 'Once Bitten'

reset()
Resets grudge memory and history.

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for mem_length rounds if the opponent ever plays D twice in a row.

class axelrod.strategies.prober.**CollectiveStrategy**
Defined in [Li2009]. 'It always cooperates in the first move and defects in the second move. If the opponent also cooperates in the first move and defects in the second move, CS will cooperate until the opponent defects. Otherwise, CS will always defect.'

Names:

•Collective Strategy *[Li2009]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'CollectiveStrategy'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**HardProber**
Plays D, D, C, C initially. Defects forever if opponent cooperated in moves 2 and 3. Otherwise plays TFT.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Hard Prober'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**NaiveProber**(*p: float = 0.1*) → None
Like tit-for-tat, but it occasionally defects with a small probability.

For reference see: "Engineering Design of Strategies for Winning Iterated Prisoner's Dilemma Competitions" by Jiawei Li, Philip Hingston, and Graham Kendall. IEEE TRANSACTIONS ON COMPUTATIONAL INTELLIGENCE AND AI IN GAMES, VOL. 3, NO. 4, DECEMBER 2011

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': True, 'manipulates

name = 'Naive Prober'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**Prober**
Plays D, C, C initially. Defects forever if opponent cooperated in moves 2 and 3. Otherwise plays TFT.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Prober'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**Prober2**
Plays D, C, C initially. Cooperates forever if opponent played D then C in moves 2 and 3. Otherwise plays TFT.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Prober 2'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**Prober3**
Plays D, C initially. Defects forever if opponent played C in moves 2. Otherwise plays TFT.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Prober 3'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**Prober4** → None
Plays C, C, D, C, D, D, D, C, C, D, C, D, C, C, D, C, D, D, C, D initially. Counts retaliating and provocative defections of the opponent. If the absolute difference between the counts is smaller or equal to 2, defects forever. Otherwise plays C for the next 5 turns and TFT for the rest of the game.

Names:

•prober4: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Prober 4'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.prober.**RemorsefulProber**(*p: float = 0.1*) → None
Like Naive Prober, but it remembers if the opponent responds to a random defection with a defection by being remorseful and cooperating.

For reference see: "Engineering Design of Strategies for Winning Iterated Prisoner's Dilemma Competitions" by Jiawei Li, Philip Hingston, and Graham Kendall. IEEE TRANSACTIONS ON COMPUTATIONAL INTELLIGENCE AND AI IN GAMES, VOL. 3, NO. 4, DECEMBER 2011

A more complete description is given in "The Selfish Gene" (https://books.google.co.uk/books?id=ekonDAAAQBAJ):

"Remorseful Prober remembers whether it has just spontaneously defected, and whether the result was prompt retaliation. If so, it 'remorsefully' allows its opponent 'one free hit' without retaliating."

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': True, 'manipulates

name = 'Remorseful Prober'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.punisher.**InversePunisher** → None
An inverted version of Punisher. The player starts by cooperating however will defect if at any point the opponent has defected, and forgets after mem_length matches, with 1 <= mem_length <= 20. This time mem_length is proportional to the amount of time the opponent has played C.

Names:

•Inverse Punisher: Original by Geraint Palmer

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Inverse Punisher'

reset()
Resets internal variables and history

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for an amount of rounds proportional to the opponents historical '%' of playing C if the opponent ever plays D.

class axelrod.strategies.punisher.**LevelPunisher**
A player starts by cooperating however, after 10 rounds will defect if at any point the number of defections by an opponent is greater than 20%.

Names:

•Level Punisher: Name from CoopSim https://github.com/jecki/CoopSim

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Level Punisher'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.punisher.**Punisher** → None
A player starts by cooperating however will defect if at any point the opponent has defected, but forgets after meme_length matches, with 1<=mem_length<=20 proportional to the amount of time the opponent has played D, punishing that player for playing D too often.

Names:

•Punisher: Original by Geraint Palmer

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Punisher'

reset()
Resets scores and history

strategy(*opponent: axelrod.player.Player*) → str
Begins by playing C, then plays D for an amount of rounds proportional to the opponents historical '%' of playing D if the opponent ever plays D

class axelrod.strategies.qlearner.**ArrogantQLearner** → None
A player who learns the best strategies through the q-learning algorithm.

This Q learner jumps to quick conclusions and cares about the future.

Names:

•Arrogant Q Learner: Original strategy by Geraint Palmer

discount_rate = 0.1

learning_rate = 0.9

name = 'Arrogant QLearner'

class axelrod.strategies.qlearner.**CautiousQLearner** → None
A player who learns the best strategies through the q-learning algorithm.

This Q learner is slower to come to conclusions and wants to look ahead more.

Names:

•Cautious Q Learner: Original strategy by Geraint Palmer

discount_rate = 0.1

learning_rate = 0.1

name = 'Cautious QLearner'

class axelrod.strategies.qlearner.**HesitantQLearner** → None
A player who learns the best strategies through the q-learning algorithm.

This Q learner is slower to come to conclusions and does not look ahead much.

Names:

•Hesitant Q Learner: Original strategy by Geraint Palmer

discount_rate = 0.9

learning_rate = 0.1

name = 'Hesitant QLearner'

class axelrod.strategies.qlearner.**RiskyQLearner** → None
A player who learns the best strategies through the q-learning algorithm.

This Q learner is quick to come to conclusions and doesn't care about the future.

Names:

•Risky Q Learner: Original strategy by Geraint Palmer

action_selection_parameter = 0.1

classifier = {'manipulates_source': False, 'makes_use_of': {'game'}, 'memory_depth': inf, 'stochastic': True, 'manip

discount_rate = 0.9

find_reward(*opponent: axelrod.player.Player*) → typing.Dict[str, typing.Dict[str, typing.Union[int, float]]]
Finds the reward gained on the last iteration

find_state(*opponent: axelrod.player.Player*) → str
Finds the my_state (the opponents last n moves + its previous proportion of playing C) as a hashable state

learning_rate = 0.9

memory_length = 12

name = 'Risky QLearner'

perform_q_learning(*prev_state: str*, *state: str*, *action: str*, *reward*)
Performs the qlearning algorithm

receive_match_attributes()

reset()
Resets scores and history

select_action(*state: str*) → str
Selects the action based on the epsilon-soft policy

strategy(*opponent: axelrod.player.Player*) → str
Runs a qlearn algorithm while the tournament is running.

class axelrod.strategies.rand.**Random**(*p: float = 0.5*) → None
A player who randomly chooses between cooperating and defecting.

Names:

•Random: *[Axelrod1980]*

•Lunatic: *[Tzafestas2000]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 0, 'stochastic': True, 'manipulates

name = 'Random'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.resurrection.**DoubleResurrection**

A player starts by cooperating and defects if the number of rounds played by the player is greater than five and the last five rounds are cooperations.

If the last five rounds were defections, the player cooperates.

Names: - DoubleResurrection: Name from CoopSim https://github.com/jecki/CoopSim

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'DoubleResurrection'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.resurrection.**Resurrection**

A player starts by cooperating and defects if the number of rounds played by the player is greater than five and the last five rounds are defections.

Otherwise, the strategy plays like Tit-for-tat.

Names: - Resurrection: Name from CoopSim https://github.com/jecki/CoopSim

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 5, 'stochastic': False, 'manipulate

name = 'Resurrection'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.retaliate.**LimitedRetaliate**(*retaliation_threshold: float = 0.1*, *retaliation_limit: int = 20*) → None

A player that co-operates unless the opponent defects and wins. It will then retaliate by defecting. It stops when either, it has beaten the opponent 10 times more often that it has lost or it reaches the retaliation limit (20 defections).

Names:

•LimitedRetaliate: Original strategy by Owen Campbell

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipula

name = 'Limited Retaliate'

reset()

strategy(*opponent: axelrod.player.Player*) → str

If the opponent has played D to my C more often than x% of the time that I've done the same to him, retaliate by playing D but stop doing so once I've hit the retaliation limit.

class axelrod.strategies.retaliate.**LimitedRetaliate2**(*retaliation_threshold: float = 0.08*, *retaliation_limit: int = 15*) → None

LimitedRetaliate player with a threshold of 8 percent and a retaliation limit of 15.

Names:

•LimitedRetaliate2: Original strategy by Owen Campbell

name = 'Limited Retaliate 2'

class axelrod.strategies.retaliate.**LimitedRetaliate3**(*retaliation_threshold: float = 0.05*, *retaliation_limit: int = 20*) → None

LimitedRetaliate player with a threshold of 5 percent and a retaliation limit of 20.

Names:

•LimitedRetaliate3: Original strategy by Owen Campbell

name = 'Limited Retaliate 3'

class axelrod.strategies.retaliate.**Retaliate**(*retaliation_threshold: float = 0.1*) → None
A player starts by cooperating but will retaliate once the opponent has won more than 10 percent times the number of defections the player has.

Names:

•Retaliate: Original strategy by Owen Campbell

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Retaliate'

reset()

strategy(*opponent: axelrod.player.Player*) → str
If the opponent has played D to my C more often than x% of the time that I've done the same to him, play D. Otherwise, play C.

class axelrod.strategies.retaliate.**Retaliate2**(*retaliation_threshold: float = 0.08*) → None
Retaliate player with a threshold of 8 percent.

Names:

•Retaliate2: Original strategy by Owen Campbell

name = 'Retaliate 2'

class axelrod.strategies.retaliate.**Retaliate3**(*retaliation_threshold: float = 0.05*) → None
Retaliate player with a threshold of 5 percent.

Names:

•Retaliate3: Original strategy by Owen Campbell

name = 'Retaliate 3'

class axelrod.strategies.sequence_player.**SequencePlayer**(*generator_function: function*, *generator_args: typing.Tuple = ()*) → None
Abstract base class for players that use a generated sequence to determine their plays.

meta_strategy(*value: int*) → None
Determines how to map the sequence value to cooperate or defect. By default, treat values like python truth values. Override in child classes for alternate behaviors.

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.sequence_player.**ThueMorse** → None
A player who cooperates or defects according to the Thue-Morse sequence. The first few terms of the Thue-Morse sequence are: 0 1 1 0 1 0 0 1 1 0 0 1 0 1 1 0 . . .

Thue-Morse sequence: http://mathworld.wolfram.com/Thue-MorseSequence.html

Names:

•Thue Morse: Original by Geraint Palmer

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'ThueMorse'

class axelrod.strategies.sequence_player.**ThueMorseInverse** → None
A player who plays the inverse of the Thue-Morse sequence.

Names:

•Inverse Thue Morse: Original by Geraint Palmer

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

meta_strategy(*value: int*) → str

name = 'ThueMorseInverse'

class axelrod.strategies.shortmem.**ShortMem**
A player starts by always cooperating for the first 10 moves.

From the tenth round on, the player analyzes the last ten actions, and compare the number of defects and cooperates of the opponent, based in percentage. If cooperation occurs 30% more than defection, it will cooperate. If defection occurs 30% more than cooperation, the program will defect. Otherwise, the program follows the TitForTat algorithm.

Names:

•ShortMem: *[Andre2013]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 10, 'stochastic': False, 'manipulat

name = 'ShortMem'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.selfsteem.**SelfSteem**
This strategy is based on the feeling with the same name. It is modeled on the sine curve(f = sin(2* pi * n / 10)), which varies with the current iteration.

If f > 0.95, 'ego' of the algorithm is inflated; always defects. If 0.95 > abs(f) > 0.3, rational behavior; follows TitForTat algortithm. If 0.3 > f > -0.3; random behavior. If f < -0.95, algorithm is at rock bottom; always cooperates.

Futhermore, the algorithm implements a retaliation policy, if the opponent defects; the sin curve is shifted. But due to lack of further information, this implementation does not include a sin phase change. Names:

•SelfSteem: *[Andre2013]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'SelfSteem'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.stalker.**Stalker** → None
This is a strategy which is only influenced by the score. Its behavior is based on three values: the very_bad_score (all rounds in defection) very_good_score (all rounds in cooperation) wish_score (average between bad and very_good score)

It starts with cooperation.

•If current_average_score > very_good_score, it defects

•If current_average_score lies in (wish_score, very_good_score) it cooperates

•If current_average_score > 2, it cooperates

•If current_average_score lies in (1, 2)

•The remaining case, current_average_score < 1, it behaves randomly.

•It defects in the last round

Names:

•Stalker: *[Andre2013]*

classifier = {'manipulates_source': False, 'makes_use_of': {'game', 'length'}, 'memory_depth': inf, 'stochastic': Tru

name = 'Stalker'

original_class
alias of *Stalker*

strategy(*opponent*)

class axelrod.strategies.titfortat.**AdaptiveTitForTat**(*rate: float = 0.5*) → None
ATFT - Adaptive Tit For Tat (Basic Model)

Algorithm

if (opponent played C in the last cycle) then world = world + r*(1-world) else world = world + r*(0-world) If (world >= 0.5) play C, else play D

Attributes

world [float [0.0, 1.0], set to 0.5] continuous variable representing the world's image 1.0 - total cooperation 0.0 - total defection other values - something in between of the above updated every round, starting value shouldn't matter as long as it's >= 0.5

Parameters

rate [float [0.0, 1.0], default=0.5] adaptation rate - r in Algorithm above smaller value means more gradual and robust to perturbations behaviour

Names:

•Adaptive Tit For Tat: *[Tzafestas2000]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Adaptive Tit For Tat'

reset()

strategy(*opponent: axelrod.player.Player*) → str

world = 0.5

class axelrod.strategies.titfortat.**Alexei**
Plays similar to Tit-for-Tat, but always defect on last turn.

Names:

•Alexei's Strategy: *[LessWrong2011]*

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': inf, 'stochastic': False, 'man

name = 'Alexei'

original_class
alias of *Alexei*

strategy(*opponent*)

class axelrod.strategies.titfortat.**AntiTitForTat**
A strategy that plays the opposite of the opponents previous move. This is similar to Bully, except that the first move is cooperation.

Names:

•Anti Tit For Tat: *[Hilde2013]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Anti Tit For Tat'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**Bully**
A player that behaves opposite to Tit For Tat, including first move.

Starts by defecting and then does the opposite of opponent's previous move. This is the complete opposite of Tit For Tat, also called Bully in the literature.

Names:

•Reverse Tit For Tat: *[Nachbar1992]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Bully'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**ContriteTitForTat**
A player that corresponds to Tit For Tat if there is no noise. In the case of a noisy match: if the opponent defects as a result of a noisy defection then ContriteTitForTat will become 'contrite' until it successfully cooperates.

Names:

•Contrite Tit For Tat: *[Axelrod1995]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Contrite Tit For Tat'

original_class
alias of *ContriteTitForTat*

strategy(*opponent*)

class axelrod.strategies.titfortat.**Gradual** → None
A player that punishes defections with a growing number of defections but after punishing enters a calming state and cooperates no matter what the opponent does for two rounds.

Names:

•Gradual: *[Beaufils1997]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Gradual'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**HardTitFor2Tats**
A variant of Tit For Two Tats that uses a longer history for retaliation.

Names:

•Hard Tit For Two Tats: Reference Required

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Hard Tit For 2 Tats'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**HardTitForTat**
A variant of Tit For Tat that uses a longer history for retaliation.

Names:

•Hard Tit For Tat: Reference Required

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 3, 'stochastic': False, 'manipulate

name = 'Hard Tit For Tat'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**OmegaTFT**(*deadlock_threshold: int = 3, randomness_threshold: int = 8*) → None
OmegaTFT modifies Tit For Tat in two ways: - checks for deadlock loops of alternating rounds of (C, D) and (D, C), and attempting to break them - uses a more sophisticated retaliation mechanism that is noise tolerant

Names:

•OmegaTFT: *[Slany2007]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Omega TFT'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**SlowTitForTwoTats**
A player plays C twice, then if the opponent plays the same move twice, plays that move.

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Slow Tit For Two Tats'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**SlowTitForTwoTats2**
A player plays C twice, then if the opponent plays the same move twice, plays that move, otherwise plays previous move.

Names:

•Slow Tit For Tat *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Slow Tit For Two Tats 2'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**SneakyTitForTat**
Tries defecting once and repents if punished.

Names:

•Sneaky Tit For Tat: Reference Required

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Sneaky Tit For Tat'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**SpitefulTitForTat** → None
A player starts by cooperating and then mimics the previous action of the opponent until opponent defects twice in a row, at which point player always defects

Names:

•Spiteful Tit For Tat *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'Spiteful Tit For Tat'

reset()

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**SuspiciousTitForTat**
A variant of Tit For Tat that starts off with a defection.

Names:

•Suspicious Tit For Tat: *[Hilde2013]*

•Mistrust: *[Beaufils1997]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Suspicious Tit For Tat'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**TitFor2Tats**
A player starts by cooperating and then defects only after two defects by opponent.

Names:

•Tit for two Tats: *[Axelrod1984]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Tit For 2 Tats'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.titfortat.**TitForTat**
A player starts by cooperating and then mimics the previous action of the opponent.

Note that the code for this strategy is written in a fairly verbose way. This is done so that it can serve as an example strategy for those who might be new to Python.

Names:

•Rapoport's strategy: *[Axelrod1980]*

•TitForTat: *[Axelrod1980]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 1, 'stochastic': False, 'manipulate

name = 'Tit For Tat'

strategy(*opponent: axelrod.player.Player*) → str
This is the actual strategy

class axelrod.strategies.titfortat.**TwoTitsForTat**
A player starts by cooperating and replies to each defect by two defections.

Names:

•Two Tits for Tats: *[Axelrod1984]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': 2, 'stochastic': False, 'manipulate

name = 'Two Tits For Tat'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.verybad.**VeryBad**
It cooperates in the first three rounds, and uses probability (it implements a memory, which stores the opponent's moves) to decide for cooperating or defecting. Due to a lack of information as to what that probability refers to in this context, probability(P(X)) refers to (Count(X)/Total_Moves) in this implementation P(C) = Cooperations / Total_Moves P(D) = Defections / Total_Moves = 1 - P(C)

Names:

•VeryBad: *[Andre2013]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': False, 'manipulat

name = 'VeryBad'

static strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.worse_and_worse.**KnowledgeableWorseAndWorse**
This strategy is based on 'Worse And Worse' but will defect with probability of 'current turn / total no. of turns'.

Names:

- Knowledgeable Worse and Worse: Original name by Adam Pohl

classifier = {'manipulates_source': False, 'makes_use_of': {'length'}, 'memory_depth': inf, 'stochastic': True, 'mani

name = 'Knowledgeable Worse and Worse'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.worse_and_worse.**WorseAndWorse**
Defects with probability of 'current turn / 1000'. Therefore it is more and more likely to defect as the round goes on.

Source code available at the download tab of *[Prison1998]*

Names:

- Worse and Worse: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Worse and Worse'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.worse_and_worse.**WorseAndWorse2**
Plays as tit for tat during the first 20 moves. Then defects with probability (current turn - 20) / current turn. Therefore it is more and more likely to defect as the round goes on.

Names:

- Worse and Worse 2: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Worse and Worse 2'

strategy(*opponent: axelrod.player.Player*) → str

class axelrod.strategies.worse_and_worse.**WorseAndWorse3**
Cooperates in the first turn. Then defects with probability no. of opponent defects / (current turn - 1). Therefore it is more likely to defect when the opponent defects for a larger proportion of the turns.

Names:

- Worse and Worse 3: *[Prison1998]*

classifier = {'manipulates_source': False, 'makes_use_of': set(), 'memory_depth': inf, 'stochastic': True, 'manipulat

name = 'Worse and Worse 3'

strategy(*opponent: axelrod.player.Player*) → str

Bibliography

This is a collection of various bibliographic items referenced in the documentation.

Glossary

There are a variety of terms used in the documentation and throughout the library. Here is an overview:

An action

An **action** is either `C` or `D`. You can access these actions as follows but should not really have a reason to:

```
>>> import axelrod as axl
>>> axl.Actions.C
'C'
>>> axl.Actions.D
'D'
```

A play

A **play** is a single player choosing an **action**. In terms of code this is equivalent to:

```
>>> p1, p2 = axl.Cooperator(), axl.Defector()
>>> p1.play(p2)  # This constitues two 'plays' (p1 plays and p2 plays).
```

This is equivalent to `p2.play(p1)`. Either function invokes both `p1.strategy(p2)` and `p2.strategy(p1)`.

A turn

A **turn** is a 1 shot interaction between two players. It is in effect a composition of two **plays**.

Each turn has four possible outcomes of a play: `(C, C)`, `(C, D)`, `(D, C)`, or `(D, D)`.

A match

A **match** is a consecutive number of **turns**. The default number of turns used in the tournament is 200. Here is a single match between two players over 10 turns:

```
>>> p1, p2 = axl.Cooperator(), axl.Defector()
>>> for turn in range(10):
...     p1.play(p2)
>>> p1.history, p2.history
(['C', 'C', 'C', 'C', 'C', 'C', 'C', 'C', 'C', 'C'], ['D', 'D', 'D', 'D', 'D', 'D', 'D
↪', 'D', 'D', 'D'])
```

A win

A **win** is attributed to the player who has the higher total score at the end of a match. For the example above, `Defector` would win that match.

A strategy

A **strategy** is a set of instructions that dictate how to play given one's own strategy and the strategy of an opponent. In the library these correspond to the strategy classes: *TitForTat*, *Grudger*, *Cooperator* etc...

When appropriate to do so this will be used interchangeable with *A player*.

A player

A **player** is a single agent using a given strategy. Players are the participants of tournament, usually they each represent one strategy but of course you can have multiple players choosing the same strategy. In the library these correspond to __instances__ of classes:

```
>>> p1, p2 = axl.Cooperator(), axl.Defector()
>>> p1
Cooperator
>>> p2
Defector
```

When appropriate to do so this will be used interchangeable with *A strategy*.

A round robin

A **round robin** is the set of all potential (order invariant) matches between a given collection of players.

A tournament

A **tournament** is a repetition of round robins so as to smooth out stochastic effects.

Noise

A match or tournament can be played with **noise**: this is the probability that indicates the chance of an action dictated by a strategy being swapped.

Community

Contents:

Part of the team

If you're reading this you're probably interested in contributing to and/or using the Axelrod library! Firstly: **thank you** and **welcome**!

We are proud of the library and the environment that surrounds it. A primary goal of the project is to cultivate an open and welcoming community, considerate and respectful to newcomers to python and game theory.

The Axelrod library has been a first contribution to open source software for many, and this is in large part due to the fact that we all aim to help and encourage all levels of contribution. If you're a beginner, that's awesome! You're very welcome and don't hesitate to ask for help.

With regards to any contribution, please do not feel the need to wait until your contribution is perfectly polished and complete: we're happy to offer early feedback, help with git, and anything else that you need to have a positive experience.

If you are using the library for your own work and there's anything in the documentation that is unclear: we want to know so that we can fix it. We also want to help so please don't hesitate to get in touch.

Communication

There are various ways of communicating with the team:

- Gitter: a web based chat client, you can talk directly to the users and maintainers of the library.
- Irc: we have an irc channel. It's #axelrod-python on freenode.
- Email forum.
- Issues: you are also very welcome to open an issue on github
- Twitter. This account periodically tweets out random match and tournament results; you're welcome to get in touch through twitter as well.

Code of Conduct

Our Pledge

In the interest of fostering an open and welcoming environment, we as contributors and maintainers pledge to making participation in our project and our community a harassment-free experience for everyone, regardless of age, body size, disability, ethnicity, gender identity and expression, level of experience, nationality, personal appearance, race, religion, or sexual identity and orientation.

Our Standards

Examples of behavior that contributes to creating a positive environment include:

- Using welcoming and inclusive language
- Being respectful of differing viewpoints and experiences
- Gracefully accepting constructive criticism
- Focusing on what is best for the community
- Showing empathy towards other community members

Examples of unacceptable behavior by participants include:

- The use of sexualized language or imagery and unwelcome sexual attention or advances
- Trolling, insulting/derogatory comments, and personal or political attacks
- Public or private harassment
- Publishing others' private information, such as a physical or electronic address, without explicit permission
- Other conduct which could reasonably be considered inappropriate in a professional setting

Our Responsibilities

Project maintainers are responsible for clarifying the standards of acceptable behavior and are expected to take appropriate and fair corrective action in response to any instances of unacceptable behavior.

Project maintainers have the right and responsibility to remove, edit, or reject comments, commits, code, wiki edits, issues, and other contributions that are not aligned to this Code of Conduct, or to ban temporarily or permanently any contributor for other behaviors that they deem inappropriate, threatening, offensive, or harmful.

Scope

This Code of Conduct applies both within project spaces and in public spaces when an individual is representing the project or its community. Examples of representing a project or community include using an official project e-mail address, posting via an official social media account, or acting as an appointed representative at an online or offline event. Representation of a project may be further defined and clarified by project maintainers.

Enforcement

Instances of abusive, harassing, or otherwise unacceptable behavior may be reported by contacting a member of the core team. All complaints will be reviewed and investigated and will result in a response that is deemed necessary and appropriate to the circumstances. The project team is obligated to maintain confidentiality with regard to the reporter of an incident. Further details of specific enforcement policies may be posted separately.

Project maintainers who do not follow or enforce the Code of Conduct in good faith may face temporary or permanent repercussions as determined by other members of the project's leadership.

Attribution

This Code of Conduct is adapted from the Contributor Covenant, version 1.4, available at http://contributor-covenant.org/version/1/4

Citing the library

We would be delighted if anyone wanted to use and/or reference this library for their own research.

If you do please let us know and reference the library: as described in the CITATION.rst file on the library repository.

CHAPTER 3

Indices and tables

- genindex
- modindex
- search

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