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The *quantecon* python library consists of a number of modules which includes game theory (game_theory), markov chains (markov), random generation utilities (random), a collection of tools (tools), and other utilities (util) which are mainly used by developers internal to the package.
1.1 lemke_howson

Compute mixed Nash equilibria of a 2-player normal form game by the Lemke-Howson algorithm.

```python
quantecon.game_theory.lemke_howson.lemke_howson(g, init_pivot=0, max_iter=1000000, capping=None, full_output=False)
```

Find one mixed-action Nash equilibrium of a 2-player normal form game by the Lemke-Howson algorithm [2], implemented with “complementary pivoting” (see, e.g., von Stengel [3] for details).

**Parameters**

- `g` [NormalFormGame] NormalFormGame instance with 2 players.
- `init_pivot` [scalar(int), optional(default=0)] Initial pivot, an integer k such that 0 <= k <= m+n, where integers 0, ..., m-1 and m, ..., m+n-1 correspond to the actions of players 0 and 1, respectively.
- `max_iter` [scalar(int), optional(default=10**6)] Maximum number of pivoting steps.
- `capping` [scalar(int), optional(default=None)] If supplied, the routine is executed with the heuristics proposed by Codenotti et al. [1]; see Notes below for details.
- `full_output` [bool, optional(default=False)] If False, only the computed Nash equilibrium is returned. If True, the return value is `(NE, res)`, where `NE` is the Nash equilibrium and `res` is a `NashResult` object.

**Returns**

- `NE` [tuple(ndarray(float, ndim=1))] Tuple of computed Nash equilibrium mixed actions.
- `res` [NashResult] Object containing information about the computation. Returned only when `full_output` is True. See `NashResult` for details.

**Notes**

- This routine is implemented with floating point arithmetic and thus is subject to numerical instability.
• If \( capping \) is set to a positive integer, the routine is executed with the heuristics proposed by [1]:
  
  – For \( k = init\_pivot, init\_pivot + 1, \ldots, init\_pivot + (m+n-2), \mod (m+n) \), the Lemke-Howson algorithm is executed with \( k \) as the initial pivot and \( capping \) as the maximum number of pivoting steps. If the algorithm converges during this loop, then the Nash equilibrium found is returned.

  – Otherwise, the Lemke-Howson algorithm is executed with \( init\_pivot + (m+n-1) \mod (m+n) \) as the initial pivot, with a limit \( max\_iter \) on the total number of pivoting steps.

According to the simulation results for uniformly random games, for medium- to large-size games this heuristics outperforms the basic Lemke-Howson algorithm with a fixed initial pivot, where [1] suggests that \( capping \) be set to 10.

**References**

[1], [2], [3]

**Examples**

Consider the following game from von Stengel [3]:

```python
>>> np.set_printoptions(precision=4)  # Reduce the digits printed
>>> bimatrix = [[[3, 3], [3, 2]],
              [[2, 2], [5, 6]],
              [[0, 3], [6, 1]]]
>>> g = NormalFormGame(bimatrix)
```

Obtain a Nash equilibrium of this game by `lemke_howson` with player 0’s action 1 (out of the three actions 0, 1, and 2) as the initial pivot:

```python
>>> lemke_howson(g, init_pivot=1)
(array([ 0. , 0.3333, 0.6667]), array([ 0.3333, 0.6667]))
>>> g.is_nash(_)
True
```

Additional information is returned if `full_output` is set True:

```python
>>> NE, res = lemke_howson(g, init_pivot=1, full_output=True)
>>> res.converged  # Whether the routine has converged
True
>>> res.num_iter  # Number of pivoting steps performed
4
```

### 1.2 mclennan_tourky

Compute mixed Nash equilibria of an N-player normal form game by applying the imitation game algorithm by McLennan and Tourky to the best response correspondence.

```python
quantecon.game_theory.mclennan_tourky.mclennan_tourky(g, init=None, epsilon=0.001, max_iter=200, full_output=False)
```

Find one mixed-action epsilon-Nash equilibrium of an N-player normal form game by the fixed point computation algorithm by McLennan and Tourky [1].

**Parameters**
QuantEcon Documentation, Release 0.4.5

`g` [NormalFormGame] NormalFormGame instance.

`init` [array_like(int or array_like(float, ndim=1)), optional] Initial action profile, an array of N objects, where each object must be an integer (pure action) or an array of floats (mixed action). If None, default to an array of zeros (the zero-th action for each player).

`epsilon` [scalar(float), optional(default=1e-3)] Value of epsilon-optimality.

`max_iter` [scalar(int), optional(default=100)] Maximum number of iterations.

`full_output` [bool, optional(default=False)] If False, only the computed Nash equilibrium is returned. If True, the return value is (NE, res), where NE is the Nash equilibrium and res is a NashResult object.

Returns

NE [tuple(ndarray(float, ndim=1))] Tuple of computed Nash equilibrium mixed actions.

res [NashResult] Object containing information about the computation. Returned only when full_output is True. See NashResult for details.

References

[1]

Examples

Consider the following version of 3-player “anti-coordination” game, where action 0 is a safe action which yields payoff 1, while action 1 yields payoff $v$ if no other player plays 1 and payoff 0 otherwise:

```python
>>> N = 3
>>> v = 2
>>> payoff_array = np.empty((2,)*n)
>>> payoff_array[0, :] = 1
>>> payoff_array[1, :] = 0
>>> payoff_array[1].flat[0] = v
>>> g = NormalFormGame((Player(payoff_array,),)*N)
>>> print(g)
3-player NormalFormGame with payoff profile array:
[[[ 1., 1., 1.], [ 1., 1., 2.]],
 [[ 1., 2., 1.], [ 1., 0., 0.]]],
[[[ 2., 1., 1.], [ 0., 1., 0.]],
 [[ 0., 0., 1.], [ 0., 0., 0.]]]
```

This game has a unique symmetric Nash equilibrium, where the equilibrium action is given by $(p^*, 1 - p^*)$ with $p^* = 1/v^{1/(N-1)}$:

```python
>>> p_star = 1/(v**(1/(N-1)))
>>> [p_star, 1 - p_star]
[0.7071067811865475, 0.29289321881345254]
```

Obtain an approximate Nash equilibrium of this game by `mclennan_tourky`:

```python
>>> epsilon = 1e-5  # Value of epsilon-optimality
>>> NE = mclennan_tourky(g, epsilon=epsilon)
>>> print(NE[0], NE[1], NE[2], sep='\n')
[ 0.70710754 0.29289246]
[ 0.70710754 0.29289246]
```

(continues on next page)
[0.70710754 0.29289246]
>>> g.is_nash(NE, tol=epsilon)
True

Additional information is returned if full_output is set True:

```python
>>> NE, res = mclennan_tourky(g, epsilon=epsilon, full_output=True)
>>> res.converged
True
>>> res.num_iter
18
```

### 1.3 normal_form_game

Tools for normal form games.

#### 1.3.1 Definitions and Basic Concepts

An $N$-player normal form game $g = (I, (A_i)_{i \in I}, (u_i)_{i \in I})$ consists of

- the set of players $I = \{0, \ldots, N-1\}$,
- the set of actions $A_i = \{0, \ldots, n_i - 1\}$ for each player $i \in I$, and
- the payoff function $u_i : A_i \times A_{i+1} \times \cdots \times A_{i+N-1} \to \mathbb{R}$ for each player $i \in I$,

where $i + j$ is understood modulo $N$. Note that we adopt the convention that the 0-th argument of the payoff function $u_i$ is player $i$’s own action and the $j$-th argument is player $(i + j)$’s action (modulo $N$). A mixed action for player $i$ is a probability distribution on $A_i$ (while an element of $A_i$ is referred to as a pure action). A pure action $a_i \in A_i$ is identified with the mixed action that assigns probability one to $a_i$. Denote the set of mixed actions of player $i$ by $X_i$.

We also denote $A_{-i} = A_{i+1} \times \cdots \times A_{i+N-1}$ and $X_{-i} = X_{i+1} \times \cdots \times X_{i+N-1}$.

The (pure-action) best response correspondence $b_i : X_{-i} \to A_i$ for each player $i$ is defined by

$$b_i(x_{-i}) = \{a_i \in A_i \mid u_i(a_i, x_{-i}) \geq u_i(a'_i, x_{-i}) \forall a'_i \in A_i\},$$

where $u_i(a_i, x_{-i}) = \sum_{a_{-i} \in A_{-i}} u_i(a_i, a_{-i}) \prod_{j=1}^{N-1} x_{i+j}(a_j)$ is the expected payoff to action $a_i$ against mixed actions $x_{-i}$. A profile of mixed actions $x^* \in X_0 \times \cdots \times X_{N-1}$ is a Nash equilibrium if for all $i \in I$ and $a_i \in A_i$,

$$x^*_i(a_i) > 0 \Rightarrow a_i \in b_i(x^*_{-i}),$$

or equivalently, $x^*_i \cdot v_i(x^*_{-i}) \geq x_i \cdot v_i(x^*_{-i})$ for all $x_i \in X_i$, where $v_i(x_{-i})$ is the vector of player $i$’s payoffs when the opponent players play mixed actions $x_{-i}$.

#### 1.3.2 Creating a NormalFormGame

There are three ways to construct a `NormalFormGame` instance.

The first is to pass an array of payoffs for all the players:
>>> matching_pennies_bimatrix = [[(1, -1), (-1, 1)], [(-1, 1), (1, -1)]]
>>> g = NormalFormGame(matching_pennies_bimatrix)
>>> print(g.players[0])
Player in a 2-player normal form game with payoff array:
[[ 1, -1],
 [-1, 1]]
>>> print(g.players[1])
Player in a 2-player normal form game with payoff array:
[[-1, 1],
 [ 1, -1]]

If a square matrix (2-dimensional array) is given, then it is considered to be a symmetric two-player game:

>>> coordination_game_matrix = [[4, 0], [3, 2]]
>>> g = NormalFormGame(coordination_game_matrix)
>>> print(g)
2-player NormalFormGame with payoff profile array:
[[[4, 4], [0, 3]],
 [[3, 0], [2, 2]]]

The second is to specify the sizes of the action sets of the players, which gives a NormalFormGame instance filled with payoff zeros, and then set the payoff values to each entry:

>>> g = NormalFormGame((2, 2))
>>> print(g)
2-player NormalFormGame with payoff profile array:
[[[ 0., 0.], [ 0., 0.]],
 [[ 0., 0.], [ 0., 0.]]]
>>> g[0, 0] = 1, 1
>>> g[0, 1] = -2, 3
>>> g[1, 0] = 3, -2
>>> print(g)
2-player NormalFormGame with payoff profile array:
[[[ 1., 1.], [-2., 3.]],
 [[ 3., -2.], [ 0., 0.]]]

The third is to pass an array of Player instances, as explained in the next section.

### 1.3.3 Creating a Player

A Player instance is created by passing a payoff array:

```python
>>> player0 = Player([[3, 1], [0, 2]])
>>> player0.payoff_array
array([[3, 1],
       [0, 2]])
```

Passing an array of Player instances is the third way to create a NormalFormGame instance.

```python
>>> player1 = Player([[2, 0], [1, 3]])
>>> player1.payoff_array
array([[2, 0],
       [1, 3]])
>>> g = NormalFormGame((player0, player1))
>>> print(g)
2-player NormalFormGame with payoff profile array:
```
Beware that in `payoff_array[h, k]`, \( h \) refers to the player’s own action, while \( k \) refers to the opponent player’s action.

```python
class quantecon.game_theory.normal_form_game.NormalFormGame(data, dtype=None)
Bases: object

Class representing an N-player normal form game.

Parameters

data [array_like of Player, int (ndim=1), or float (ndim=2 or N+1)] Data to initialize a NormalFormGame. `data`  may be an array of Players, in which case the shapes of the Players’ payoff arrays must be consistent. If `data`  is an array of N integers, then these integers are treated as the numbers of actions of the N players and a NormalFormGame is created consisting of payoffs all 0 with `data[i]` actions for each player \( i \). `data` may also be an (N+1)-dimensional array representing payoff profiles. If `data` is a square matrix (2-dimensional array), then the game will be a symmetric two-player game where the payoff matrix of each player is given by the input matrix.

dtype [data-type, optional(default=None)] Relevant only when `data` is an array of integers. Data type of the players’ payoff arrays. If not supplied, default to numpy.float64.

Attributes

players [tuple(Player)] Tuple of the Player instances of the game.

N [scalar(int)] The number of players.

nums_actions [tuple(int)] Tuple of the numbers of actions, one for each player.

payoff_arrays [tuple(ndarray(float, ndim=N))] Tuple of the payoff arrays, one for each player.

Methods

delete_action(self, player_idx, action) Return a new NormalFormGame instance with the action(s) specified by `action` deleted from the action set of the player specified by `player_idx`.

is_nash(self, action_profile[, tol]) Return True if `action_profile` is a Nash equilibrium.

delete_action (self, player_idx, action)
Return a new NormalFormGame instance with the action(s) specified by `action` deleted from the action set of the player specified by `player_idx`. Deletion is not performed in place.

Parameters

player_idx [scalar(int)] Index of the player to delete action(s) for.

action [scalar(int) or array_like(int)] Integer or array like of integers representing the action(s) to be deleted.

Returns

NormalFormGame Copy of `self` with the action(s) deleted as specified.
Examples

```python
>>> g = NormalFormGame(
    ... 
    [(3, 0), (0, 1)], [(0, 0), (3, 1)], [(1, 1), (1, 0)]
    ...
)
>>> print(g)
2-player NormalFormGame with payoff profile array:
[[3, 0], [0, 1]],
[[0, 0], [3, 1]],
[[1, 1], [1, 0]]
```

Delete player 0’s action 2 from g:

```python
>>> g1 = g.delete_action(0, 2)
>>> print(g1)
2-player NormalFormGame with payoff profile array:
[[3, 0], [0, 1]],
[[0, 0], [3, 1]]
```

Then delete player 1’s action 0 from g1:

```python
>>> g2 = g1.delete_action(1, 0)
>>> print(g2)
2-player NormalFormGame with payoff profile array:
[[0, 1]],
[[3, 1]]
```

`is_nash(self, action_profile, tol=None)`

Return True if `action_profile` is a Nash equilibrium.

Parameters

- `action_profile` [array_like(int or array_like(float))] An array of N objects, where each object must be an integer (pure action) or an array of floats (mixed action).
- `tol` [scalar(float)] Tolerance level used in determining best responses. If None, default to each player’s `tol` attribute value.

Returns

- `bool` True if `action_profile` is a Nash equilibrium; False otherwise.

`payoff_profile_array`

`class quantecon.game_theory.normal_form_game.Player(payoff_array)`

Bases: object

Class representing a player in an N-player normal form game.

Parameters

- `payoff_array` [array_like(float)] Array representing the player’s payoff function, where `payoff_array[a_0, a_1, ..., a_(N-1)]` is the payoff to the player when the player plays action `a_0` while his N-1 opponents play actions `a_1, ..., a_(N-1)`, respectively.

Attributes

- `payoff_array` [ndarray(float, ndim=N)] See Parameters.
- `num_actions` [scalar(int)] The number of actions available to the player.
- `num_opponents` [scalar(int)] The number of opponent players.
**dtype** [dtype] Data type of the elements of `payoff_array`.

**tol** [scalar(float), default=1e-8] Default tolerance value used in determining best responses.

### Methods

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<td><code>delete_action</code></td>
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<td><code>dominated_actions</code></td>
<td>Return a list of actions that are strictly dominated by some mixed actions.</td>
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<td><code>payoff_vector</code></td>
<td>Return an array of payoff values, one for each own action, given a profile of the opponents’ actions.</td>
</tr>
<tr>
<td><code>random_choice</code></td>
<td>Return a pure action chosen randomly from <code>actions</code>.</td>
</tr>
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</table>

#### best_response

```python
best_response(self, opponents_actions[, ...])
```

Return the best response action(s) to `opponents_actions`.

**Parameters**

- **opponents_actions** [scalar(int) or array_like] A profile of N-1 opponents’ actions, represented by either scalar(int), array_like(float), array_like(int), or array_like(array_like(float)). If N=2, then it must be a scalar of integer (in which case it is treated as the opponent’s pure action) or a 1-dimensional array of floats (in which case it is treated as the opponent’s mixed action). If N>2, then it must be an array of N-1 objects, where each object must be an integer (pure action) or an array of floats (mixed action).

- **tie_breaking** [str, optional/default=‘smallest’) str in {‘smallest’, ‘random’, False}. Control how, or whether, to break a tie (see Returns for details).

- **payoff_perturbation** [array_like(float), optional/default=None] Array of length equal to the number of actions of the player containing the values (“noises”) to be added to the payoffs in determining the best response.

- **tol** [scalar(float), optional/default=None] Tolerance level used in determining best responses. If None, default to the value of the `tol` attribute.

- **random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used. Relevant only when `tie_breaking=‘random’`.

#### Returns

- **scalar(int) or ndarray(int, ndim=1)** If `tie_breaking=False`, returns an array containing all the best response pure actions. If `tie_breaking=‘smallest’`, returns the best response action with the smallest index; if `tie_breaking=‘random’`, returns an action randomly chosen from the best response actions.
delete_action (self, action, player_idx=0)
Return a new Player instance with the action(s) specified by action deleted from the action set of the player specified by player_idx. Deletion is not performed in place.

Parameters

action [scalar(int) or array_like(int)] Integer or array like of integers representing the action(s) to be deleted.

player_idx [scalar(int), optional(default=0)] Index of the player to delete action(s) for.

Returns

Player Copy of self with the action(s) deleted as specified.

Examples

```python
>>> player = Player([[3, 0], [0, 3], [1, 1]])
>>> player
Player([[3, 0],
        [0, 3],
        [1, 1]])
>>> player.delete_action(2)
Player([[3, 0],
        [0, 3]])
>>> player.delete_action(0, player_idx=1)
Player([[0],
        [3],
        [1]])
```

dominated_actions (self, tol=None, method=None)
Return a list of actions that are strictly dominated by some mixed actions.

Parameters

tol [scalar(float), optional(default=None)] Tolerance level used in determining domination. If None, default to the value of the tol attribute.

method [str, optional(default=None)] If None, lemke_howson from quantecon.game_theory is used to solve for a Nash equilibrium of an auxiliary zero-sum game. If method is set to 'simplex' or 'interior-point', scipy.optimize.linprog is used with the method as specified by method.

Returns

list(int) List of integers representing pure actions, each of which is strictly dominated by some mixed action.

is_best_response (self, own_action, opponents_actions, tol=None)
Return True if own_action is a best response to opponents_actions.

Parameters

own_action [scalar(int) or array_like(float, ndim=1)] An integer representing a pure action, or an array of floats representing a mixed action.

opponents_actions [see best_response]

tol [scalar(float), optional(default=None)] Tolerance level used in determining best responses. If None, default to the value of the tol attribute.

Returns
is dominated (self, action, tol=None, method=None)
Determine whether action is strictly dominated by some mixed action.

Parameters

action [scalar(int)] Integer representing a pure action.

tol [scalar(float), optional(default=None)] Tolerance level used in determining domination. If None, default to the value of the tol attribute.

method [str, optional(default=None)] If None, lemke_howson from quantecon.game_theory is used to solve for a Nash equilibrium of an auxiliary zero-sum game. If method is set to 'simplex' or 'interior-point', scipy.optimize.linprog is used with the method as specified by method.

Returns

bool True if action is strictly dominated by some mixed action; False otherwise.

payoff_vector (self, opponents_actions)
Return an array of payoff values, one for each own action, given a profile of the opponents’ actions.

Parameters

opponents_actions [see best_response.]

Returns

payoff_vector [ndarray(float, ndim=1)] An array representing the player’s payoff vector given the profile of the opponents’ actions.

random_choice (self, actions=None, random_state=None)
Return a pure action chosen randomly from actions.

Parameters

actions [array_like(int), optional(default=None)] An array of integers representing pure actions.

random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

scalar(int) If actions is given, returns an integer representing a pure action chosen randomly from actions; if not, an action is chosen randomly from the player’s all actions.

quantecon.game_theory.normal_form_game.best_response_2p (payoff_matrix, opponent_mixed_action, tol=1e-08)
Numba-optimized version of Player.best_response compiled in nopython mode, specialized for 2-player games (where there is only one opponent).

Return the best response action (with the smallest index if more than one) to opponent_mixed_action under payoff_matrix.

Parameters

payoff_matrix [ndarray(float, ndim=2)] Payoff matrix.

opponent_mixed_action [ndarray(float, ndim=1)] Opponent’s mixed action. Its length must be equal to payoff_matrix.shape[1].
tol [scalar(float), optional(default=None)] Tolerance level used in determining best responses.

Returns
scalar(int) Best response action.

quantecon.game_theory.normal_form_game.pure2mixed(num_actions, action)
Convert a pure action to the corresponding mixed action.

Parameters
num_actions [scalar(int)] The number of the pure actions (= the length of a mixed action).
action [scalar(int)] The pure action to convert to the corresponding mixed action.

Returns
ndarray(float, ndim=1) The mixed action representation of the given pure action.

1.4 pure_nash

Methods for computing pure Nash equilibria of a normal form game. (For now, only brute force method is supported)
quantecon.game_theory.pure_nash.pure_nash_brute(g, tol=None)
Find all pure Nash equilibria of a normal form game by brute force.

Parameters
g [NormalFormGame]
tol [scalar(float), optional(default=None)] Tolerance level used in determining best responses.
If None, default to the value of the tol attribute of g.

Returns
NEs [list(tuple(int))] List of tuples of Nash equilibrium pure actions. If no pure Nash equilibrium is found, return empty list.

Examples
Consider the “Prisoners’ Dilemma” game:

```python
>>> PD_bimatrix = [[(1, 1), (-2, 3)],
                 ...               [(3, -2), (0, 0)]
>>> g_PD = NormalFormGame(PD_bimatrix)
>>> pure_nash_brute(g_PD)
[(1, 1)]
```

If we consider the “Matching Pennies” game, which has no pure nash equilibrium:

```python
>>> MP_bimatrix = [[(1, -1), (-1, 1)],
                 ...               [(1, -1), (1, -1)]
>>> g_MP = NormalFormGame(MP_bimatrix)
>>> pure_nash_brute(g_MP)
[]
```

quantecon.game_theory.pure_nash.pure_nash_brute_gen(g, tol=None)
Generator version of pure_nash_brute.

Parameters
g  [NormalFormGame]

    tol  [scalar(float), optional(default=None)] Tolerance level used in determining best responses.
    If None, default to the value of the tol attribute of g.

Yields

    out  [tuple(int)] Tuple of Nash equilibrium pure actions.

1.5 random

Generate random NormalFormGame instances.

    quantecon.game_theory.random.covariance_game(nums_actions, rho, random_state=None)

    Return a random NormalFormGame instance where the payoff profiles are drawn independently from the standard multi-normal with the covariance of any pair of payoffs equal to rho, as studied in [1].

Parameters

    nums_actions  [tuple(int)] Tuple of the numbers of actions, one for each player.
    rho  [scalar(float)] Covariance of a pair of payoff values. Must be in [-1/(N-1), 1], where N is the number of players.
    random_state  [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

    g  [NormalFormGame]

References

[1]

    quantecon.game_theory.random.random_game(nums_actions, random_state=None)

    Return a random NormalFormGame instance where the payoffs are drawn independently from the uniform distribution on [0, 1).

Parameters

    nums_actions  [tuple(int)] Tuple of the numbers of actions, one for each player.
    random_state  [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

    g  [NormalFormGame]

    quantecon.game_theory.random.random_mixed_actions(nums_actions, random_state=None)

    Return a tuple of random mixed actions (vectors of floats).

Parameters

    nums_actions  [tuple(int)] Tuple of the numbers of actions, one for each player.
random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns
action_profile [tuple(ndarray(float, ndim=1))] Tuple of mixed_actions, one for each player.

quantecon.game_theory.random.random_pure_actions (nums_actions, random_state=None)
Return a tuple of random pure actions (integers).

Parameters
nums_actions [tuple(int)] Tuple of the numbers of actions, one for each player.
random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns
action_profile [Tuple(int)] Tuple of actions, one for each player.

1.6 repeated_game

Tools for repeated game.

class quantecon.game_theory.repeated_game.RepeatedGame (stage_game, delta)
Bases: object

Class representing an N-player repeated game.

Parameters
stage_game [NormalFormGame] The stage game used to create the repeated game.
delta [scalar(float)] The common discount rate at which all players discount the future.

Attributes
sg [NormalFormGame] The stage game. See Parameters.
delta [scalar(float)] See Parameters.
N [scalar(int)] The number of players.
nums_actions [tuple(int)] Tuple of the numbers of actions, one for each player.

Methods

equilibrium_payoffs (self[, method, options])
Compute the set of payoff pairs of all pure-strategy subgame-perfect equilibria with public randomization for any repeated two-player games with perfect monitoring and discounting.

equilibrium_payoffs (self, method=None, options=None)
Compute the set of payoff pairs of all pure-strategy subgame-perfect equilibria with public randomization for any repeated two-player games with perfect monitoring and discounting.

Parameters
**method** [str, optional] The method for solving the equilibrium payoff set.

**options** [dict, optional] A dictionary of method options. For example, ‘abreu_sannikov’ method accepts the following options:

- **tol** [scalar(float)] Tolerance for convergence checking.
- **max_iter** [scalar(int)] Maximum number of iterations.
- **u_init** [ndarray(float, ndim=1)] The initial guess of threat points.

**Notes**

Here lists all the implemented methods. The default method is ‘abreu_sannikov’.

1. ‘abreu_sannikov’

### 1.7 support enumeration

Compute all mixed Nash equilibria of a 2-player (non-degenerate) normal form game by support enumeration.

#### 1.7.1 References


quantecon.game_theory.support_enumeration.**support_enumeration**(*g*)

Compute mixed-action Nash equilibria with equal support size for a 2-player normal form game by support enumeration. For a non-degenerate game input, these are all the Nash equilibria.

- The algorithm checks all the equal-size support pairs; if the players have the same number n of actions, there are 2n choose n minus 1 such pairs. This should thus be used only for small games.

**Parameters**

- **g** [NormalFormGame] NormalFormGame instance with 2 players.

**Returns**

- list(tuple(ndarray(float, ndim=1))) List containing tuples of Nash equilibrium mixed actions.

quantecon.game_theory.support_enumeration.**support_enumeration_gen**(*g*)

Generator version of support_enumeration.

**Parameters**

- **g** [NormalFormGame] NormalFormGame instance with 2 players.

**Yields**

- tuple(ndarray(float, ndim=1)) Tuple of Nash equilibrium mixed actions.

### 1.8 utilities

Utility routines for the game_theory submodule
class quantecon.game_theory.utilities.NashResult
    Bases: dict

    Contain the information about the result of Nash equilibrium computation.

    Notes

    This is sourced from `scipy.optimize.OptimizeResult`.
    There may be additional attributes not listed above depending of the routine.

    Attributes

    NE \[\text{tuple(ndarray(float, ndim=1))}\] Computed Nash equilibrium.
    converged [bool] Whether the routine has converged.
    num_iter [int] Number of iterations.
    max_iter [int] Maximum number of iterations.
    init [scalar or array_like] Initial condition used.

    Methods

    clear()
    copy()
    fromkeys(iterable[, value]) Returns a new dict with keys from iterable and values equal to value.
    get()
    items()
    keys()
    pop() If key is not found, d is returned if given, otherwise KeyError is raised
    popitem() 2-tuple; but raise KeyError if D is empty.
    setdefault()
    update() If E is present and has a .keys() method, then does: for k in E: D[k] = E[k] If E is present and lacks a .keys() method, then does: for k, v in E: D[k] = v In either case, this is followed by: for k in F: D[k] = F[k]
    values()

1.9 vertex_enumeration

Compute all mixed Nash equilibria of a 2-player normal form game by vertex enumeration.

1.9.1 References


quantecon.game_theory.vertex_enumeration.vertex_enumeration(g, qhull_options=None)
Compute mixed-action Nash equilibria of a 2-player normal form game by enumeration and matching of vertices of the best response polytopes. For a non-degenerate game input, these are all the Nash equilibria.

Internally, `scipy.spatial.ConvexHull` is used to compute vertex enumeration of the best response polytopes, or equivalently, facet enumeration of their polar polytopes. Then, for each vertex of the polytope for player 0, vertices of the polytope for player 1 are searched to find a completely labeled pair.

**Parameters**

- `g` ([NormalFormGame](#)) NormalFormGame instance with 2 players.
- `qhull_options` ([str, optional(default=None)]) Options to pass to `scipy.spatial.ConvexHull`. See the [Qhull manual](https://docs.qhull.org/) for details.

**Returns**

- `list(tuple(ndarray(float, ndim=1)))` List containing tuples of Nash equilibrium mixed actions.

```python
quantecon.game_theory.vertex_enumeration.vertex_enumeration_gen(g, qhull_options=None)
```

Generator version of `vertex_enumeration`.

**Parameters**

- `g` ([NormalFormGame](#)) NormalFormGame instance with 2 players.
- `qhull_options` ([str, optional(default=None)]) Options to pass to `scipy.spatial.ConvexHull`. See the [Qhull manual](https://docs.qhull.org/) for details.

**Yields**

- `tuple(ndarray(float, ndim=1))` Tuple of Nash equilibrium mixed actions.

### 1.10 `bimatrix_generators`

This module contains functions that generate NormalFormGame instances of the 2-player games studied by Fearnley, Igwe, and Savani (2015):

- **Colonel Blotto Games** ([blotto_game](#)): A non-zero sum extension of the Blotto game as studied by Hortala-Vallve and Llorente-Saguer (2012), where opposing parties have asymmetric and heterogeneous battlefield valuations.

- **Ranking Games** ([ranking_game](#)): In these games, as studied by Goldberg et al. (2013), each player chooses an effort level associated with a cost and a score. The players are ranked according to their scores, and the player with the higher score wins the prize. Each player’s payoff is given by the value of the prize minus the cost of the effort.

- **SGC Games** ([sgc_game](#)): These games were introduced by Sandholm, Gilpin, and Conitzer (2005) as a worst case scenario for support enumeration as it has a unique equilibrium where each player uses half of his actions in his support.

- **Tournament Games** ([tournament_game](#)): These games are constructed by Anbalagan et al. (2013) as games that do not have interim epsilon-Nash equilibria with constant cardinality supports for epsilon smaller than a certain threshold.

- **Unit Vector Games** ([unit_vector_game](#)): These games are games where the payoff matrix of one player consists of unit (column) vectors, used by Savani and von Stengel (2016) to construct instances that are hard, in terms of computational complexity, both for the Lemke-Howson and support enumeration algorithms.

Large part of the code here is based on the C code available at [https://github.com/bimatrix-games/bimatrix-generators](https://github.com/bimatrix-games/bimatrix-generators) distributed under BSD 3-Clause License.
1.10.1 References


quantecon.game_theory.game_generators.bimatrix_generators.blotto_game(h, t, rho, mu=0, random_state=None)

Return a NormalFormGame instance of a 2-player non-zero sum Colonel Blotto game (Hortala-Vallve and Llorente-Saguer, 2012), where the players have an equal number t of troops to assign to h hills (so that the number of actions for each player is equal to \((t+h-1)\choose(h-1) = \frac{(t+h-1)!}{t!*(h-1)!}\)). Each player has a value for each hill that he receives if he assigns strictly more troops to the hill than his opponent (ties are broken uniformly at random), where the values are drawn from a multivariate normal distribution with covariance \(\rho\). Each player’s payoff is the sum of the values of the hills won by that player.

**Parameters**

- \(h\) [scalar(int)] Number of hills.
- \(t\) [scalar(int)] Number of troops.
- \(\rho\) [scalar(float)] Covariance of the players’ values of each hill. Must be in \([-1, 1]\).
- \(\mu\) [scalar(float), optional(default=0)] Mean of the players’ values of each hill.
- \(\text{random\_state}\) [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

**Returns**

- \(g\) [NormalFormGame]

**Examples**

```python
>>> g = blotto_game(2, 3, 0.5, random_state=1234)
>>> g.players[0]
Player([[[-0.44861083, -1.08443468, -1.08443468, -1.08443468],
          [0.18721302, -0.44861083, -1.08443468, -1.08443468],
          [0.18721302, 0.18721302, -0.44861083, -1.08443468],
          [0.18721302, 0.18721302, 0.18721302, -0.44861083]])
>>> g.players[1]
Player([[-1.20042463, -1.39708658, -1.39708658, -1.39708658],
          [-1.00376268, -1.20042463, -1.39708658, -1.39708658],
          [-1.00376268, -1.00376268, -1.20042463, -1.39708658],
          [-1.00376268, -1.00376268, -1.00376268, -1.20042463]])
```

(continues on next page)
quantecon.game_theory.game_generators.bimatrix_generators.ranking_game(n, steps=10, random_state=None)

Return a NormalFormGame instance of (the 2-player version of) the “ranking game” studied by Goldberg et al. (2013), where each player chooses an effort level associated with a score and a cost which are both increasing functions with randomly generated step sizes. The player with the higher score wins the first prize, whose value is 1, and the other player obtains the “second prize” of value 0; in the case of a tie, the first prize is split and each player receives a value of 0.5. The payoff of a player is given by the value of the prize minus the cost of the effort.

Parameters

n [scalar(int)] Number of actions, i.e, number of possible effort levels.

steps [scalar(int), optional(default=10)] Parameter determining the upper bound for the size of the random steps for the scores and costs for each player: The step sizes for the scores are drawn from 1, ..., steps, while those for the costs are multiples of 1/(n*steps), where the cost of effort level 0 is 0, and the maximum possible cost of effort level n-1 is less than or equal to 1.

random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

g [NormalFormGame]

Examples

>>> g = ranking_game(5, random_state=1234)
>>> g.players[0]
Player([[ 0. , 0. , 0. , 0. , 0. ],
[ 0.82, -0.18, -0.18, -0.18, -0.18],
[ 0.8 , 0.8 , -0.2 , -0.2 , -0.2 ],
[ 0.68, 0.68, 0.68, -0.32, -0.32],
[ 0.66, 0.66, 0.66, 0.66, -0.34]])
>>> g.players[1]
Player([[ 1. , 0. , 0. , 0. , 0. ],
[ 0.8 , 0.8 , -0.2 , -0.2 , -0.2 ],
[ 0.66, 0.66, 0.66, -0.34, -0.34],
[ 0.6 , 0.6 , 0.6 , 0.6 , -0.4 ],
[ 0.58, 0.58, 0.58, 0.58, 0.58]])

quantecon.game_theory.game_generators.bimatrix_generators.sgc_game(k)

Return a NormalFormGame instance of the 2-player game introduced by Sandholm, Gilpin, and Conitzer (2005), which has a unique Nash equilibrium, where each player plays half of the actions with positive probabilities. Payoffs are normalized so that the minimum and the maximum payoffs are 0 and 1, respectively.

Parameters

k [scalar(int)] Positive integer determining the number of actions. The returned game will have 4*k-1 actions for each player.
QuantEcon Documentation, Release 0.4.5

Returns

\[ g \text{ [NormalFormGame]} \]

Examples

```python
>>> g = sgc_game(2)
>>> g.players[0]
Player([[ 0.75, 0.5 , 1. , 0.5 , 0.5 , 0.5 , 0.5 ],
[ 1. , 0.75, 0.5 , 0.5 , 0.5 , 0.5 , 0.5 ],
[ 0.5 , 1. , 0.75, 0.5 , 0.5 , 0.5 , 0.5 ],
[ 0. , 0. , 0. , 0.75, 0. , 0. , 0. ],
[ 0. , 0. , 0. , 0. , 0.75, 0. , 0. ],
[ 0. , 0. , 0. , 0. , 0. , 0. , 0.75],
[ 0. , 0. , 0. , 0. , 0. , 0.75, 0. ]])
>>> g.players[1]
Player([[ 0.75, 0.5 , 1. , 0.5 , 0.5 , 0.5 , 0.5 ],
[ 1. , 0.75, 0.5 , 0.5 , 0.5 , 0.5 , 0.5 ],
[ 0.5 , 1. , 0.75, 0.5 , 0.5 , 0.5 , 0.5 ],
[ 0. , 0. , 0. , 0. , 0.75, 0. , 0. ],
[ 0. , 0. , 0. , 0. , 0. , 0. , 0.75],
[ 0. , 0. , 0. , 0. , 0. , 0.75, 0. ]])
```

Return a NormalFormGame instance of the 2-player win-lose game, whose payoffs are either 0 or 1, introduced by Anbalagan et al. (2013). Player 0 has \( n \) actions, which constitute the set of nodes \{0, \ldots, n-1\}, while player 1 has \( \binom{n}{k} \) actions, each corresponding to a subset of \( k \) elements of the set of \( n \) nodes. Given a randomly generated tournament graph on the \( n \) nodes, the payoff for player 0 is 1 if, in the tournament, the node chosen by player 0 dominates all the nodes in the \( k \)-subset chosen by player 1. The payoff for player 1 is 1 if player 1’s \( k \)-subset contains player 0’s chosen node.

Parameters

- \( n \text{ [scalar(int)] Number of nodes in the tournament graph.} \)
- \( k \text{ [scalar(int)] Size of subsets of nodes in the tournament graph.} \)
- \( \text{random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.} \)

Returns

- \( g \text{ [NormalFormGame]} \)

Notes

The actions of player 1 are ordered according to the combinatorial number system \[1\], which is different from the order used in the original library in C.

References

\[1\]
Returns a NormalFormGame instance of the 2-player game “unit vector game” (Savani and von Stengel, 2016). Payoffs for player 1 are chosen randomly from the \([0, 1)\) range. For player 0, each column contains exactly one payoff and the rest is 0.

Parameters

- **n** [scalar(int)] Number of actions.

- **avoid_pure_nash** [bool, optional(default=False)] If True, player 0’s payoffs will be placed in order to avoid pure Nash equilibria. (If necessary, the payoffs for player 1 are redrawn so as not to have a dominant action.)

- **random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

- **g** [NormalFormGame]

Examples

```python
>>> g = unit_vector_game(4, random_state=1234)
>>> g.players[0]
Player([[ 1. ],
[ 0. ],
[ 0. ],
[ 0. ]])
>>> g.players[1]
Player([[ 0.19151945, 0.62210877, 0.43772774, 0.78535858],
[ 0.77997581, 0.27259261, 0.27646426, 0.80187218],
[ 0.95813935, 0.87593263, 0.35781727, 0.50099513],
[ 0.68346294, 0.71270203, 0.37025075, 0.56119619]])
```
With `avoid_pure_nash=True`:

```python
>>> g = unit_vector_game(4, avoid_pure_nash=True, random_state=1234)
>>> g.players[0]
Player([[ 1.,  1.,  0.,  0.],
       [ 0.,  0.,  0.,  0.],
       [ 0.,  0.,  1.,  1.],
       [ 0.,  0.,  0.,  0.]])
>>> g.players[1]
Player([[ 0.19151945,  0.62210877,  0.43772774,  0.78535858],
       [ 0.77997581,  0.27259261,  0.27646426,  0.80187218],
       [ 0.95813935,  0.87593263,  0.35781727,  0.50099513],
       [ 0.68346294,  0.71270203,  0.37025075,  0.56119619]])
>>> pure_nash_brute(g)
[]
```
2.1 approximation

2.1.1 tauchen

Discretizes Gaussian linear AR(1) processes via Tauchen’s method

`quantecon.markov.approximation.rouwenhorst(n, ybar, sigma, rho)`

Takes as inputs n, p, q, psi. It will then construct a markov chain that estimates an AR(1) process of: 

\[ y_t = \bar{y} + \rho y_{t-1} + \varepsilon_t \]

where \( \varepsilon_t \) is i.i.d. normal of mean 0, std dev of sigma

The Rouwenhorst approximation uses the following recursive definition for approximating a distribution:

\[
\theta_2 = \begin{bmatrix}
    p & 1 - p \\
    1 - q & q
\end{bmatrix}
\]

\[
\theta_{n+1} = p \begin{bmatrix}
    \theta_n & 0 \\
    0 & 0
\end{bmatrix} + (1 - p) \begin{bmatrix}
    0 & \theta_n \\
    0 & 0
\end{bmatrix} + q \begin{bmatrix}
    0 & 0 \\
    \theta_n & 0
\end{bmatrix} + (1 - q) \begin{bmatrix}
    0 & 0 \\
    0 & \theta_n
\end{bmatrix}
\]

**Parameters**

- `n` [int] The number of points to approximate the distribution
- `ybar` [float] The value \( \bar{y} \) in the process. Note that the mean of this AR(1) process, \( y \), is simply \( \bar{y}/(1 - \rho) \)
- `sigma` [float] The value of the standard deviation of the \( \varepsilon \) process
- `rho` [float] By default this will be 0, but if you are approximating an AR(1) process then this is the autocorrelation across periods

**Returns**

- `mc` [MarkovChain] An instance of the MarkovChain class that stores the transition matrix and state values returned by the discretization method

`quantecon.markov.approximation.std_norm_cdf(x)`
Computes a Markov chain associated with a discretized version of the linear Gaussian AR(1) process

\[ y_{t+1} = b + \rho y_t + u_{t+1} \]

using Tauchen’s method. Here \( u_t \) is an i.i.d. Gaussian process with zero mean.

**Parameters**
- \( b \) [scalar(float)] The constant term of \( y_t \)
- \( \rho \) [scalar(float)] The autocorrelation coefficient
- \( \sigma_u \) [scalar(float)] The standard deviation of the random process
- \( m \) [scalar(int), optional(default=3)] The number of standard deviations to approximate out to
- \( n \) [scalar(int), optional(default=7)] The number of states to use in the approximation

**Returns**
- \( mc \) [MarkovChain] An instance of the MarkovChain class that stores the transition matrix and state values returned by the discretization method

### 2.2 core

This file contains some useful objects for handling a finite-state discrete-time Markov chain.

#### 2.2.1 Definitions and Some Basic Facts about Markov Chains

Let \( \{X_t\} \) be a Markov chain represented by an \( n \times n \) stochastic matrix \( P \). State \( i \) has access to state \( j \), denoted \( i \to j \), if \( i = j \) or \( P^k[i,j] > 0 \) for some \( k = 1, 2, \ldots \); \( i \) and \( j \) communicate, denoted \( i \leftrightarrow j \), if \( i \to j \) and \( j \to i \). The binary relation \( \leftrightarrow \) is an equivalent relation. A **communication class** of the Markov chain \( \{X_t\} \), or of the stochastic matrix \( P \), is an equivalent class of \( \leftrightarrow \). Equivalently, a communication class is a **strongly connected component** (SCC) in the associated directed graph \( \Gamma(P) \), a directed graph with \( n \) nodes where there is an edge from \( i \) to \( j \) if and only if \( P[i,j] > 0 \). The Markov chain, or the stochastic matrix, is **irreducible** if it admits only one communication class, or equivalently, if \( \Gamma(P) \) is strongly connected.

A state \( i \) is **recurrent** if \( i \to j \) implies \( j \to i \); it is **transient** if it is not recurrent. For any \( i, j \) contained in a communication class, \( i \) is recurrent if and only if \( j \) is recurrent. Therefore, recurrence is a property of a communication class. Thus, a communication class is a **recurrent class** if it contains a recurrent state. Equivalently, a recurrent class is a SCC that corresponds to a sink node in the condensation of the directed graph \( \Gamma(P) \), where the condensation of \( \Gamma(P) \) is a directed graph in which each SCC is replaced with a single node and there is an edge from one SCC \( C \) to another SCC \( C' \) if \( C \neq C' \) and there is an edge from some node in \( C \) to some node in \( C' \). A recurrent class is also called a **closed communication class**. The condensation is acyclic, so that there exists at least one recurrent class.

For example, if the entries of \( P \) are all strictly positive, then the whole state space is a communication class as well as a recurrent class. (More generally, if there is only one communication class, then it is a recurrent class.) As another example, consider the stochastic matrix \( P = \begin{bmatrix} 1, 0, 0 \end{bmatrix} \). This has two communication classes, \{0\} and \{1\}, and \{0\} is the only recurrent class.

A **stationary distribution** of the Markov chain \( \{X_t\} \), or of the stochastic matrix \( P \), is a nonnegative vector \( x \) such that \( x'P = x' \) and \( x'1 = 1 \), where \( 1 \) is the vector of ones. The Markov chain has a unique stationary distribution if and only if it has a unique recurrent class. More generally, each recurrent class has a unique stationary distribution whose support equals that recurrent class. The set of all stationary distributions is given by the convex hull of these unique stationary distributions for the recurrent classes.
A natural number $d$ is the period of state $i$ if it is the greatest common divisor of all $k$’s such that $P^k[i,i] > 0$; equivalently, it is the GCD of the lengths of the cycles in $\Gamma(P)$ passing through $i$. For any $i, j$ contained in a communication class, $i$ has period $d$ if and only if $j$ has period $d$. The period of an irreducible Markov chain (or of an irreducible stochastic matrix) is the period of any state. We define the period of a general (not necessarily irreducible) Markov chain to be the least common multiple of the periods of its recurrent classes, where the period of a recurrent class is the period of any state in that class. A Markov chain is aperiodic if its period is one. A Markov chain is irreducible and aperiodic if and only if it is uniformly ergodic, i.e., there exists some $m$ such that $P^m[i,j] > 0$ for all $i, j$ (in this case, $P$ is also called primitive).

Suppose that an irreducible Markov chain has period $d$. Fix any state, say state 0. For each $m = 0, \ldots, d - 1$, let $S_m$ be the set of states $i$ such that $P^{kd+m}[0,i] > 0$ for some $k$. These sets $S_0, \ldots, S_{d-1}$ constitute a partition of the state space and are called the cyclic classes. For each $S_m$ and each $i \in S_m$, we have $\sum_{j \in S_{m+1}} P[i,j] = 1$, where $S_d = S_0$.

```python
class quantecon.markov.core.MarkovChain (P, state_values=None)
    Bases: object

    Class for a finite-state discrete-time Markov chain. It stores useful information such as the stationary distributions, and communication, recurrent, and cyclic classes, and allows simulation of state transitions.

    Parameters

    P [array_like or scipy sparse matrix (float, ndim=2)] The transition matrix. Must be of shape n x n.

    state_values [array_like(default=None)] Array_like of length n containing the values associated with the states, which must be homogeneous in type. If None, the values default to integers 0 through n-1.

    Notes

    In computing stationary distributions, if the input matrix is a sparse matrix, internally it is converted to a dense matrix.

    Attributes

    P [ndarray or scipy.sparse.csr_matrix (float, ndim=2)] See Parameters

    stationary_distributions [array_like(float, ndim=2)] Array containing stationary distributions, one for each recurrent class, as rows.

    is_irreducible [bool] Indicate whether the Markov chain is irreducible.

    num_communication_classes [int] The number of the communication classes.

    communication_classes_indices [list(ndarray(int))] List of numpy arrays containing the indices of the communication classes.

    communication_classes [list(ndarray)] List of numpy arrays containing the communication classes, where the states are annotated with their values (if state_values is not None).

    num_recurrent_classes [int] The number of the recurrent classes.

    recurrent_classes_indices [list(ndarray(int))] List of numpy arrays containing the indices of the recurrent classes.

    recurrent_classes [list(ndarray)] List of numpy arrays containing the recurrent classes, where the states are annotated with their values (if state_values is not None).

    is_aperiodic [bool] Indicate whether the Markov chain is aperiodic.

    period [int] The period of the Markov chain.
```
cyclic_classes_indices [list(ndarray(int))] List of numpy arrays containing the indices of the cyclic classes. Defined only when the Markov chain is irreducible.

cyclic_classes [list(ndarray)] List of numpy arrays containing the cyclic classes, where the states are annotated with their values (if state_values is not None). Defined only when the Markov chain is irreducible.

Methods

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<th>Method</th>
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<tr>
<td>get_index(self, value)</td>
<td>Return the index (or indices) of the given value (or values) in state_values.</td>
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<tr>
<td>simulate(self, ts_length[, init, num_reps, ...])</td>
<td>Simulate time series of state transitions, where the states are annotated with their values (if state_values is not None).</td>
</tr>
<tr>
<td>simulate_indices(self, ts_length[, init, ...])</td>
<td>Simulate time series of state transitions, where state indices are returned.</td>
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- cdfs
- cdfs1d
- communication_classes
- communication_classes_indices
- cyclic_classes
- cyclic_classes_indices
- digraph
- get_index (self, value)
  Return the index (or indices) of the given value (or values) in state_values.

  Parameters

  value Value(s) to get the index (indices) for.

  Returns

  idx [int or ndarray(int)] Index of value if value is a single state value; array of indices if value is an array_like of state values.

- is_aperiodic
- is_irreducible
- num_communication_classes
- num_recurrent_classes
- period
- recurrent_classes
- recurrent_classes_indices
- simulate (self, ts_length, init=None, num_reps=None, random_state=None)
  Simulate time series of state transitions, where the states are annotated with their values (if state_values is not None).

  Parameters

  ts_length
  init
  num_reps
  random_state
**ts_length** [scalar(int)] Length of each simulation.

**init** [scalar or array_like, optional(default=None)] Initial state values(s). If None, the initial state is randomly drawn.

**num_reps** [scalar(int), optional(default=None)] Number of repetitions of simulation.

**random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

**Returns**

X [ndarray(ndim=1 or 2)] Array containing the sample path(s), of shape (ts_length,) if init is a scalar (integer) or None and num_reps is None; otherwise, where k = len(init) if (init, num_reps) = (array, None), k = num_reps if (init, num_reps) = (int or None, int), and k = len(init)*num_reps if (init, num_reps) = (array, int).

**simulate_indices** (self, ts_length, init=None, num_reps=None, random_state=None)

Simulate time series of state transitions, where state indices are returned.

**Parameters**

**ts_length** [scalar(int)] Length of each simulation.

**init** [int or array_like(int, ndim=1), optional] Initial state(s). If None, the initial state is randomly drawn.

**num_reps** [scalar(int), optional(default=None)] Number of repetitions of simulation.

**random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

**Returns**

X [ndarray(ndim=1 or 2)] Array containing the state values of the sample path(s). See the `simulate` method for more information.

**state_values**

**stationary_distributions**

**quantecon.markov.core.mc_compute_stationary** (P)

Computes stationary distributions of P, one for each recurrent class. Any stationary distribution is written as a convex combination of these distributions.

**Returns**

stationary_dists [array_like(float, ndim=2)] Array containing the stationary distributions as its rows.

**quantecon.markov.core.mc_sample_path** (P, init=0, sample_size=1000, random_state=None)

Generates one sample path from the Markov chain represented by (n x n) transition matrix P on state space S = \{0,...,n-1\}.

**Parameters**

**P** [array_like(float, ndim=2)] A Markov transition matrix.

**init** [array_like(float ndim=1) or scalar(int), optional(default=0)] If init is an array_like, then it is treated as the initial distribution across states. If init is a scalar, then it treated as the deterministic initial state.
For a policy function \( \sigma \) defined by the Bellman equation, or the unique fixed point of the Bellman operator, and that \( \sigma^* \) is an optimal policy function if and only if it is \( \nu^* \)-greedy, i.e., it satisfies \( T v^* = T_{\sigma^*} v^* \).

2.3 ddp

Module for solving dynamic programs (also known as Markov decision processes) with finite states and actions.

2.3.1 Discrete Dynamic Programming

A discrete dynamic program consists of the following components:

- finite set of states \( S = \{0, \ldots, n - 1\} \);
- finite set of available actions \( A(s) \) for each state \( s \in S \) with \( A = \bigcup_{s \in S} A(s) = \{0, \ldots, m - 1\} \), where \( SA = \{(s, a) \in S \times A | a \in A(s)\} \) is the set of feasible state-action pairs;
- reward function \( r : SA \to \mathbb{R} \), where \( r(s, a) \) is the reward when the current state is \( s \) and the action chosen is \( a \);
- transition probability function \( q : SA \to \Delta(S) \), where \( q(s'|s, a) \) is the probability that the state in the next period is \( s' \) when the current state is \( s \) and the action chosen is \( a \); and
- discount factor \( 0 \leq \beta < 1 \).

For a policy function \( \sigma \), let \( r_\sigma \) and \( Q_\sigma \) be the reward vector and the transition probability matrix for \( \sigma \), which are defined by \( r_\sigma(s) = r(s, \sigma(s)) \) and \( Q_\sigma(s, s') = q(s'|s, \sigma(s)) \), respectively. The policy value function \( v_\sigma \) for \( \sigma \) is defined by

\[
v_\sigma(s) = \sum_{t=0}^{\infty} \beta^t (Q_\sigma^t r_\sigma)(s) \quad (s \in S).
\]

The optimal value function \( v^* \) is the function such that \( v^*(s) = \max_{\sigma} v_\sigma(s) \) for all \( s \in S \). A policy function \( \sigma^* \) is optimal if \( v_{\sigma^*}(s) = v^*(s) \) for all \( s \in S \).

The Bellman equation is written as

\[
v(s) = \max_{a \in A(s)} r(s, a) + \beta \sum_{s' \in S} q(s'|s, a) v(s') \quad (s \in S).
\]

The Bellman operator \( T \) is defined by the right hand side of the Bellman equation:

\[
(Tv)(s) = \max_{a \in A(s)} r(s, a) + \beta \sum_{s' \in S} q(s'|s, a) v(s') \quad (s \in S).
\]

For a policy function \( \sigma \), the operator \( T_{\sigma} \) is defined by

\[
(T_{\sigma}v)(s) = r(s, \sigma(s)) + \beta \sum_{s' \in S} q(s'|s, \sigma(s)) v(s') \quad (s \in S),
\]
or \( T_{\sigma}v = r_\sigma + \beta Q_\sigma v \).

The main result of the theory of dynamic programming states that the optimal value function \( v^* \) is the unique solution to the Bellman equation, or the unique fixed point of the Bellman operator, and that \( \sigma^* \) is an optimal policy function if and only if it is \( \nu^* \)-greedy, i.e., it satisfies \( T v^* = T_{\sigma^*} v^* \).
2.3.2 Solution Algorithms

The `DiscreteDP` class currently implements the following solution algorithms:

- value iteration;
- policy iteration;
- modified policy iteration.

Policy iteration computes an exact optimal policy in finitely many iterations, while value iteration and modified policy iteration return an $\varepsilon$-optimal policy and an $\varepsilon/2$-approximation of the optimal value function for a prespecified value of $\varepsilon$.

Our implementations of value iteration and modified policy iteration employ the norm-based and span-based termination rules, respectively.

- Value iteration is terminated when the condition $\|Tv - v\| < [(1 - \beta)/(2\beta)]\varepsilon$ is satisfied.
- Modified policy iteration is terminated when the condition $\text{span}(Tv - v) < [(1 - \beta)/\beta]\varepsilon$ is satisfied, where $\text{span}(z) = \max(z) - \min(z)$.

2.3.3 References


class quantecon.markov.ddp.DPSolveResult
    Bases: dict

    Contain the information about the dynamic programming result.

    Attributes
    v [ndarray(float, ndim=1)] Computed optimal value function
    sigma [ndarray(int, ndim=1)] Computed optimal policy function
    num_iter [int] Number of iterations
    mc [MarkovChain] Controlled Markov chain
    method [str] Method employed
    epsilon [float] Value of epsilon
    max_iter [int] Maximum number of iterations

    Methods
    clear()
    copy()
    fromkeys(iterable[, value]) Returns a new dict with keys from iterable and values equal to value.
    get()
    items()
    keys()
    pop() If key is not found, d is returned if given, otherwise KeyError is raised
    popitem() 2-tuple; but raise KeyError if D is empty.

Continued on next page
If E is present and has a .keys() method, then does:
for k in E: D[k] = E[k] If E is present and lacks a
.keys() method, then does: for k, v in E: D[k] = v In
either case, this is followed by: for k in F: D[k] =
F[k]

### values()

```python
class quantecon.markov.ddp.DiscreteDP (R, Q, beta, s_indices=None, a_indices=None)
Bases: object
```

Class for dealing with a discrete dynamic program.

There are two ways to represent the data for instantiating a `DiscreteDP` object. Let n, m, and L denote the numbers of states, actions, and feasible state-action pairs, respectively.

1. `DiscreteDP(R, Q, beta)`
   with parameters:
   - `n x m` reward array R,
   - `n x m x n` transition probability array Q, and
   - discount factor beta,

   where $R[s, a]$ is the reward for action $a$ when the state is $s$ and $Q[s, a, s_{next}]$ is the probability that the state in the next period is $s_{next}$ when the current state is $s$ and the action chosen is $a$.

2. `DiscreteDP(R, Q, beta, s_indices, a_indices)`
   with parameters:
   - length L reward vector R,
   - L x n transition probability array Q,
   - discount factor beta,
   - length L array `s_indices`, and
   - length L array `a_indices`,

   where the pairs $(s_{indices}[0], a_{indices}[0]), \ldots, (s_{indices}[L-1], a_{indices}[L-1])$ enumerate feasible state-action pairs, and $R[i]$ is the reward for action $a_{indices}[i]$ when the state is $s_{indices}[i]$ and $Q[i, s_{next}]$ is the probability that the state in the next period is $s_{next}$ when the current state is $s_{indices}[i]$ and the action chosen is $a_{indices}[i]$. With this formulation, Q may be represented by a scipy.sparse matrix.

#### Parameters

- `R` [array_like(float, ndim=2 or 1)] Reward array.
- `Q` [array_like(float, ndim=3 or 2) or scipy.sparse matrix] Transition probability array.
- `beta` [scalar(float)] Discount factor. Must be in [0, 1].
- `s_indices` [array_like(int, ndim=1), optional(default=None)] Array containing the indices of the states.
- `a_indices` [array_like(int, ndim=1), optional(default=None)] Array containing the indices of the actions.
**Notes**

DiscreteDP accepts beta=1 for convenience. In this case, infinite horizon solution methods are disabled, and the instance is then seen as merely an object carrying the Bellman operator, which may be used for backward induction for finite horizon problems.

**Examples**

Consider the following example, taken from Puterman (2005), Section 3.1, pp.33-35.

- Set of states $S = \{0, 1\}$
- Set of actions $A = \{0, 1\}$
- Set of feasible state-action pairs $SA = \{(0, 0), (0, 1), (1, 0)\}$
- Rewards $r(s, a)$:
  - $r(0, 0) = 5$, $r(0, 1) = 10$, $r(1, 0) = -1$
- Transition probabilities $q(s_{next}, a)$:
  - $q(0|0, 0) = 0.5$, $q(1|0, 0) = 0.5$, $q(0|0, 1) = 0$, $q(1|0, 1) = 1$, $q(0|1, 0) = 0$, $q(1|1, 0) = 1$
- Discount factor 0.95

**Creating a ‘DiscreteDP’ instance**

*Product formulation*

This approach uses the product set $S \times A$ as the domain by treating action 1 as yielding a reward negative infinity at state 1.

```python
>>> R = [[5, 10], [-1, float('inf')]]
>>> Q = [[(0.5, 0.5), (0, 1)], [(0, 1), (0.5, 0.5)]]
>>> beta = 0.95
>>> ddp = DiscreteDP(R, Q, beta)
```

($Q[1, 1]$ is an arbitrary probability vector.)

*State-action pairs formulation*

This approach takes the set of feasible state-action pairs $SA$ as given.

```python
>>> s_indices = [0, 0, 1]  # State indices
>>> a_indices = [0, 1, 0]  # Action indices
>>> R = [5, 10, -1]
>>> Q = [(0.5, 0.5), (0, 1), (0, 1)]
>>> beta = 0.95
>>> ddp = DiscreteDP(R, Q, beta, s_indices, a_indices)
```

**Solving the model**

*Policy iteration*

```python
>>> res = ddp.solve(method='policy_iteration', v_init=[0, 0])
>>> res.sigma  # Optimal policy function
array([0, 0])
>>> res.v  # Optimal value function
array([-8.57142857, -20.])
>>> res.num_iter  # Number of iterations
2
```
Value iteration

```python
>>> res = ddp.solve(method='value_iteration', v_init=[0, 0],
... epsilon=0.01)
>>> res.sigma  # (Approximate) optimal policy function
array([0, 0])
>>> res.v    # (Approximate) optimal value function
array([-8.5665053 , -19.99507673])
>>> res.num_iter  # Number of iterations
162
```

Modified policy iteration

```python
>>> res = ddp.solve(method='modified_policy_iteration',
... v_init=[0, 0], epsilon=0.01)
>>> res.sigma  # (Approximate) optimal policy function
array([0, 0])
>>> res.v    # (Approximate) optimal value function
array([-8.57142826, -19.99999965])
>>> res.num_iter  # Number of iterations
3
```

Attributes

- **R, Q, beta**  [see Parameters.]
- **num_states**  [scalar(int)] Number of states.
- **num_sa_pairs**  [scalar(int)] Number of feasible state-action pairs (or those that yield finite rewards).
- **epsilon**  [scalar(float), default=1e-3] Default value for epsilon-optimality.
- **max_iter**  [scalar(int), default=250] Default value for the maximum number of iterations.

Methods

- **RQ_sigma(self, sigma)**  Given a policy `sigma`, return the reward vector `R_sigma` and the transition probability matrix `Q_sigma`.
- **T_sigma(self, sigma)**  Given a policy `sigma`, return the `T_sigma` operator.
- **bellman_operator(self, v[, Tv, sigma])**  The Bellman operator, which computes and returns the updated value function `Tv` for a value function `v`.
- **compute_greedy(self, v[, sigma])**  Compute the `v`-greedy policy.
- **controlled_mc(self, sigma)**  Returns the controlled Markov chain for a given policy `sigma`.
- **evaluate_policy(self, sigma)**  Compute the value of a policy.
- **modified_policy_iteration(self[, v_init, ...])**  Solve the optimization problem by modified policy iteration.
- **operator_iteration(self, T, v, max_iter[, tol])**  Iteratively apply the operator `T` to `v`.
- **policy_iteration(self[, v_init, max_iter])**  Solve the optimization problem by policy iteration.
- **solve(self[, method, v_init, epsilon, ...])**  Solve the dynamic programming problem.
- **to_product_form(self)**  Convert this instance of `DiscreteDP` to the “product” form.
- **to_sa_pair_form(self[, sparse])**  Convert this instance of `DiscreteDP` to SA-pair form.

Continued on next page
**Table 3 – continued from previous page**

| value_iteration(self[, v_init, epsilon, ...]) | Solve the optimization problem by value iteration. |

**RQ_sigma** (self, sigma)
Given a policy sigma, return the reward vector R_sigma and the transition probability matrix Q_sigma.

**Parameters**

- **sigma** [array_like(int, ndim=1)] Policy vector, of length n.

**Returns**

- **R_sigma** [ndarray(float, ndim=1)] Reward vector for sigma, of length n.
- **Q_sigma** [ndarray(float, ndim=2)] Transition probability matrix for sigma, of shape (n, n).

**T_sigma** (self, sigma)
Given a policy sigma, return the T_sigma operator.

**Parameters**

- **sigma** [array_like(int, ndim=1)] Policy vector, of length n.

**Returns**

- **callable** The T_sigma operator.

**bellman_operator** (self, v, Tv=None, sigma=None)
The Bellman operator, which computes and returns the updated value function Tv for a value function v.

**Parameters**

- **v** [array_like(float, ndim=1)] Value function vector, of length n.
- **Tv** [ndarray(float, ndim=1), optional(default=None)] Optional output array for Tv.
- **sigma** [ndarray(int, ndim=1), optional(default=None)] If not None, the v-greedy policy vector is stored in this array. Must be of length n.

**Returns**

- **Tv** [ndarray(float, ndim=1)] Updated value function vector, of length n.

**compute_greedy** (self, v, sigma=None)
Compute the v-greedy policy.

**Parameters**

- **v** [array_like(float, ndim=1)] Value function vector, of length n.
- **sigma** [ndarray(int, ndim=1), optional(default=None)] Optional output array for sigma.

**Returns**

- **sigma** [ndarray(int, ndim=1)] v-greedy policy vector, of length n.

**controlled_mc** (self, sigma)
Returns the controlled Markov chain for a given policy sigma.

**Parameters**

- **sigma** [array_like(int, ndim=1)] Policy vector, of length n.

**Returns**

- **mc** [MarkovChain] Controlled Markov chain.
evaluate_policy (self, sigma)
Compute the value of a policy.

Parameters

    sigma [array_like(int, ndim=1)] Policy vector, of length n.

Returns

    v_sigma [ndarray(float, ndim=1)] Value vector of sigma, of length n.

modified_policy_iteration (self, v_init=None, epsilon=None, max_iter=None, k=20)
Solve the optimization problem by modified policy iteration. See the solve method.

operator_iteration (self, T, v, max_iter, tol=None, *args, **kwargs)
Iteratively apply the operator T to v. Modify v in-place. Iteration is performed for at most a number max_iter of times. If tol is specified, it is terminated once the distance of T(v) from v (in the max norm) is less than tol.

Parameters

    T [callable] Operator that acts on v.
    v [ndarray] Object on which T acts. Modified in-place.
    max_iter [scalar(int)] Maximum number of iterations.
    tol [scalar(float), optional(default=None)] Error tolerance.
    args, kwargs : Other arguments and keyword arguments that are passed directly to the function T each time it is called.

Returns

    num_iter [scalar(int)] Number of iterations performed.

policy_iteration (self, v_init=None, max_iter=None)
Solve the optimization problem by policy iteration. See the solve method.

solve (self, method='policy_iteration', v_init=None, epsilon=None, max_iter=None, k=20)
Solve the dynamic programming problem.

Parameters

    method [str, optional(default='policy_iteration')] Solution method, str in {'value_iteration', 'vi', 'policy_iteration', 'pi', 'modified_policy_iteration', 'mpi'}.
    v_init [array_like(float, ndim=1), optional(default=None)] Initial value function, of length n. If None, v_init is set such that v_init(s) = max_a r(s, a) for value iteration and policy iteration; for modified policy iteration, v_init(s) = min_(s_next, a) r(s_next, a)/(1 - beta) to guarantee convergence.
    epsilon [scalar(float), optional(default=None)] Value for epsilon-optimality. If None, the value stored in the attribute epsilon is used.
    max_iter [scalar(int), optional(default=None)] Maximum number of iterations. If None, the value stored in the attribute max_iter is used.
    k [scalar(int), optional(default=20)] Number of iterations for partial policy evaluation in modified policy iteration (irrelevant for other methods).

Returns

    res [DPSolveResult] Optimization result represented as a DPSolveResult. See DPSolveResult for details.
to_product_form(self)

Convert this instance of DiscreteDP to the “product” form.

The product form uses the version of the init method taking \( R, Q \) and \( \beta \).

Returns

**ddp_sa** [DiscreteDP] The corresponding DiscreteDP instance in product form

Notes

If this instance is already in product form then it is returned un-modified

to_sa_pair_form(self, sparse=True)

Convert this instance of DiscreteDP to SA-pair form

Parameters

**sparse** [bool, optional(default=True)] Should the \( Q \) matrix be stored as a sparse matrix?

If true the CSR format is used

Returns

**ddp_sa** [DiscreteDP] The corresponding DiscreteDP instance in SA-pair form

Notes

If this instance is already in SA-pair form then it is returned un-modified

value_iteration(self, v_init=None, epsilon=None, max_iter=None)

Solve the optimization problem by value iteration. See the solve method.

quant_econ.markov.ddp.backward_induction(ddp, T, v_term=None)

Solve by backward induction a \( T \)-period finite horizon discrete dynamic program with stationary reward and transition probability functions \( r \) and \( q \) and discount factor \( \beta \in [0, 1] \).

The optimal value functions \( v_T^*, \ldots, v_0^* \) and policy functions \( \sigma_T^*, \ldots, \sigma_0^* \) are obtained by \( v_T^* = v_T \), and

\[
v_{t-1}^*(s) = \max_{a \in A(s)} r(s, a) + \beta \sum_{s' \in S} q(s'|s, a) v_t^*(s') \quad (s \in S)
\]

and

\[
\sigma_{t-1}^*(s) \in \arg \max_{a \in A(s)} r(s, a) + \beta \sum_{s' \in S} q(s'|s, a) v_t^*(s') \quad (s \in S)
\]

for \( t = T, \ldots, 1 \), where the terminal value function \( v_T \) is exogenously given.

Parameters

**ddp** [DiscreteDP] DiscreteDP instance storing reward array \( R \), transition probability array \( Q \), and discount factor \( \beta \).

**T** [scalar(int)] Number of decision periods.

**v_term** [array_like(float, ndim=1), optional(default=None)] Terminal value function, of length equal to \( n \) (the number of states). If None, it defaults to the vector of zeros.

Returns

**vs** [ndarray(float, ndim=2)] Array of shape \((T+1, n)\) where \( vs[t] \) contains the optimal value function at period \( t = 0, \ldots, T \).
sigmas [ndarray(int, ndim=2)] Array of shape (T, n) where sigmas[t] contains the optimal policy function at period t = 0, ..., T-1.

2.4 gth_solve

Routine to compute the stationary distribution of an irreducible Markov chain by the Grassmann-Taksar-Heyman (GTH) algorithm.

quantecon.markov.gth_solve.gth_solve(A, overwrite=False, use_jit=True)

This routine computes the stationary distribution of an irreducible Markov transition matrix (stochastic matrix) or transition rate matrix (generator matrix) $A$.

More generally, given a Metzler matrix (square matrix whose off-diagonal entries are all nonnegative) $A$, this routine solves for a nonzero solution $x$ to $x (A - D) = 0$, where $D$ is the diagonal matrix for which the rows of $A - D$ sum to zero (i.e., $D_{ii} = \sum_j A_{ij}$ for all $i$). One (and only one, up to normalization) nonzero solution exists corresponding to each recurrent class of $A$, and in particular, if $A$ is irreducible, there is a unique solution; when there are more than one solution, the routine returns the solution that contains in its support the first index $i$ such that no path connects $i$ to any index larger than $i$. The solution is normalized so that its 1-norm equals one. This routine implements the Grassmann-Taksar-Heyman (GTH) algorithm [1], a numerically stable variant of Gaussian elimination, where only the off-diagonal entries of $A$ are used as the input data. For a nice exposition of the algorithm, see Stewart [2], Chapter 10.

Parameters

- **A** [array_like(float, ndim=2)] Stochastic matrix or generator matrix. Must be of shape n x n.

Returns

- **x** [numpy.ndarray(float, ndim=1)] Stationary distribution of $A$.
- **overwrite** [bool, optional(default=False)] Whether to overwrite $A$.

References

[1], [2]

2.5 random

Generate MarkovChain and DiscreteDP instances randomly.

quantecon.markov.random.random_discrete_dp(num_states, num_actions, beta=None, k=None, scale=1, sparse=False, sa_pair=False, random_state=None)

Generate a DiscreteDP randomly. The reward values are drawn from the normal distribution with mean 0 and standard deviation $scale$.

Parameters

- **num_states** [scalar(int)] Number of states.
- **num_actions** [scalar(int)] Number of actions.
- **beta** [scalar(float), optional(default=None)] Discount factor. Randomly chosen from [0, 1) if not specified.
- **k** [scalar(int), optional(default=None)] Number of possible next states for each state-action pair. Equal to num_states if not specified.
scale  [scalar(float), optional(default=1)] Standard deviation of the normal distribution for the 
reward values.

sparse  [bool, optional(default=False)] Whether to store the transition probability array in 
sparse matrix form.

sa_pair  [bool, optional(default=False)] Whether to represent the data in the state-action pairs 
formulation. (If sparse=True, automatically set True.)

random_state  [int or np.random.RandomState, optional] Random seed (integer) or 
np.random.RandomState instance to set the initial state of the random number genera-
tor for reproducibility. If None, a randomly initialized RandomState is used.

Returns

ddp  [DiscreteDP] An instance of DiscreteDP.

quantecon.markov.random.random_markov_chain(n, k=None, sparse=False, random_state=None)

Return a randomly sampled MarkovChain instance with n states, where each state has k states with positive 
transition probability.

Parameters

n  [scalar(int)] Number of states.

k  [scalar(int), optional(default=None)] Number of states that may be reached from each state 
with positive probability. Set to n if not specified.

sparse  [bool, optional(default=False)] Whether to store the transition probability matrix in 
sparse matrix form.

random_state  [int or np.random.RandomState, optional] Random seed (integer) or 
np.random.RandomState instance to set the initial state of the random number genera-
tor for reproducibility. If None, a randomly initialized RandomState is used.

Returns

mc  [MarkovChain]

Examples

```python
>>> mc = qe.markov.random.random_markov_chain(3, random_state=1234)
>>> mc.P
array([[ 0.19151945, 0.43058932, 0.37789123],
       [ 0.43772774, 0.34763084, 0.21464142],
       [ 0.27259261, 0.5073832 , 0.43772774]])
```

quantecon.markov.random.random_stochastic_matrix(n, k=None, sparse=False, format='csr', random_state=None)

Return a randomly sampled n x n stochastic matrix with k nonzero entries for each row.

Parameters

n  [scalar(int)] Number of states.
k [scalar(int), optional(default=None)] Number of nonzero entries in each row of the matrix. Set to n if not specified.

sparse [bool, optional(default=False)] Whether to generate the matrix in sparse matrix form.


random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

P [numpy ndarray or scipy sparse matrix (float, ndim=2)] Stochastic matrix.

See also:

random_markov_chain Return a random MarkovChain instance.

2.6 utilities

Utility routines for the markov submodule

quantecon.markov.utilities.sa_indices (num_states, num_actions)

Generate s_indices and a_indices for DiscreteDP, for the case where all the actions are feasible at every state.

Parameters

num_states [scalar(int)] Number of states.

num_actions [scalar(int)] Number of actions.

Returns

s_indices [ndarray(int, ndim=1)] Array containing the state indices.

a_indices [ndarray(int, ndim=1)] Array containing the action indices.

Examples

```python
>>> s_indices, a_indices = qe.markov.sa_indices(4, 3)
>>> s_indices
array([0, 0, 0, 1, 1, 1, 2, 2, 2, 3, 3, 3])
>>> a_indices
array([0, 1, 2, 0, 1, 2, 0, 1, 2, 0, 1, 2])
```
3.1 nelder_mead

Implements the Nelder-Mead algorithm for maximizing a function with one or more variables.

```python
quantecon.optimize.nelder_mead.nelder_mead(fun, x0, bounds=array([], shape=(0, 2), dtype=float64), args=(), tol_f=1e-10, tol_x=1e-10, max_iter=1000)
```

Maximize a scalar-valued function with one or more variables using the Nelder-Mead method.

This function is JIT-compiled in `nopython` mode using Numba.

**Parameters**

- `fun` [callable] The objective function to be maximized: `fun(x, *args) -> float` where `x` is an 1-D array with shape `(n,)` and `args` is a tuple of the fixed parameters needed to completely specify the function. This function must be JIT-compiled in `nopython` mode using Numba.

- `x0` [ndarray(float, ndim=1)] Initial guess. Array of real elements of size `(n,)`, where `n` is the number of independent variables.

- `bounds` [ndarray(float, ndim=2), optional] Bounds for each variable for proposed solution, encoded as a sequence of (min, max) pairs for each element in `x`. The default option is used to specify no bounds on `x`.

- `args` [tuple, optional] Extra arguments passed to the objective function.

- `tol_f` [scalar(float), optional(default=1e-10)] Tolerance to be used for the function value convergence test.

- `tol_x` [scalar(float), optional(default=1e-10)] Tolerance to be used for the function domain convergence test.

- `max_iter` [scalar(float), optional(default=1000)] The maximum number of allowed iterations.

**Returns**
**results** [namedtuple] A namedtuple containing the following items:

- "x": Approximate local maximizer
- "fun": Approximate local maximum value
- "success": 1 if the algorithm successfully terminated, 0 otherwise
- "nit": Number of iterations
- "final_simplex": Vertices of the final simplex

**Notes**

This algorithm has a long history of successful use in applications, but it will usually be slower than an algorithm that uses first or second derivative information. In practice, it can have poor performance in high-dimensional problems and is not robust to minimizing complicated functions. Additionally, there currently is no complete theory describing when the algorithm will successfully converge to the minimum, or how fast it will if it does.

**References**

[1], [2], [3], [4], [5], [6], [7], [8]

**Examples**

```python
>>> @njit
... def rosenbrock(x):
...     return -(100 * (x[1] - x[0]**2)**2 + (1 - x[0])**2)
...
>>> x0 = np.array([-2, 1])
>>> qe.optimize.nelder_mead(rosenbrock, x0)
results(x=array([0.99999814, 0.99999756]), fun=-1.6936258239463265e-10,
    success=True, nit=110,
    final_simplex=array([[0.99998652, 0.9999727],
                         [1.00000218, 1.00000301],
                         [0.99999814, 0.99999756]])
```

**class** `quantecon.optimize.nelder_mead.results(x, fun, success, nit, final_simplex)`

**Bases:** `tuple`

**Attributes**

- `final_simplex` Alias for field number 4
- `fun` Alias for field number 1
- `nit` Alias for field number 3
- `success` Alias for field number 2
- `x` Alias for field number 0

**Methods**

- `count()`
- `index()` Raises ValueError if the value is not present.
3.2 root_finding

quantecon.optimize.root_finding.newton (func, x0, fprime, args=(), tol=1.48e-08, maxiter=50, disp=True)

Find a zero from the Newton-Raphson method using the jitted version of Scipy’s newton for scalars. Note that this does not provide an alternative method such as secant. Thus, it is important that fprime can be provided.

Note that func and fprime must be jitted via Numba. They are recommended to be njit for performance.

Parameters

func [callable and jitted] The function whose zero is wanted. It must be a function of a single variable of the form f(x,a,b,c,...), where a,b,c... are extra arguments that can be passed in the args parameter.

x0 [float] An initial estimate of the zero that should be somewhere near the actual zero.

fprime [callable and jitted] The derivative of the function (when available and convenient).

args [tuple, optional(default=())] Extra arguments to be used in the function call.

tol [float, optional(default=1.48e-8)] The allowable error of the zero value.

maxiter [int, optional(default=50)] Maximum number of iterations.

disp [bool, optional(default=True)] If True, raise a RuntimeError if the algorithm didn’t converge

Returns

results [namedtuple] A namedtuple containing the following items:

- root - Estimated location where function is zero.
- function_calls - Number of times the function was called.
- iterations - Number of iterations needed to find the root.
- converged - True if the routine converged

quantecon.optimize.root_finding.newton_halley (func, x0, fprime, fprime2, args=(), tol=1.48e-08, maxiter=50, disp=True)

Find a zero from Halley’s method using the jitted version of Scipy’s.

func, fprime, fprime2 must be jitted via Numba.

Parameters
func [callable and jitted] The function whose zero is wanted. It must be a function of a single variable of the form $f(x,a,b,c...)$, where $a,b,c...$ are extra arguments that can be passed in the `args` parameter.

x0 [float] An initial estimate of the zero that should be somewhere near the actual zero.

fprime [callable and jitted] The derivative of the function (when available and convenient).

fprime2 [callable and jitted] The second order derivative of the function

args [tuple, optional(default=())] Extra arguments to be used in the function call.

tol [float, optional(default=1.48e-8)] The allowable error of the zero value.

maxiter [int, optional(default=50)] Maximum number of iterations.

disp [bool, optional(default=True)] If True, raise a RuntimeError if the algorithm didn’t converge.

Returns

results [namedtuple] A namedtuple containing the following items:

- root - Estimated location where function is zero.
- function_calls - Number of times the function was called.
- iterations - Number of iterations needed to find the root.
- converged - True if the routine converged.

quantecon.optimize.root_finding.newton_secant (func, x0, args=(), tol=1.48e-08, maxiter=50, disp=True)

Find a zero from the secant method using the jitted version of Scipy’s secant method.

Note that `func` must be jitted via Numba.

Parameters

- func [callable and jitted] The function whose zero is wanted. It must be a function of a single variable of the form $f(x,a,b,c...)$, where $a,b,c...$ are extra arguments that can be passed in the `args` parameter.
- x0 [float] An initial estimate of the zero that should be somewhere near the actual zero.
- args [tuple, optional(default=())] Extra arguments to be used in the function call.
- tol [float, optional(default=1.48e-8)] The allowable error of the zero value.
- maxiter [int, optional(default=50)] Maximum number of iterations.
- disp [bool, optional(default=True)] If True, raise a RuntimeError if the algorithm didn’t converge.

Returns

results [namedtuple] A namedtuple containing the following items:

- root - Estimated location where function is zero.
- function_calls - Number of times the function was called.
- iterations - Number of iterations needed to find the root.
- converged - True if the routine converged.

quantecon.optimize.root_finding.bisect (f, a, b, args=(), xtol=2e-12, rtol=8.881784197001252e-16, maxiter=100, disp=True)

Find root of a function within an interval adapted from Scipy’s bisect.
Basic bisection routine to find a zero of the function \( f \) between the arguments \( a \) and \( b \). \( f(a) \) and \( f(b) \) cannot have the same signs.

\( f \) must be jitted via numba.

**Parameters**

- \( f \) ([jitted and callable] Python function returning a number.) \( f \) must be continuous.
  - \( a \) ([number] One end of the bracketing interval \([a,b]\)).
  - \( b \) ([number] The other end of the bracketing interval \([a,b]\)).
  - \( \text{args} \) ([tuple, optional(default=())] Extra arguments to be used in the function call.)
  - \( \text{xtol} \) ([number, optional(default=2e-12)] The computed root \( x_0 \) will satisfy
    \( \text{np. allclose}(x, x_0, \text{atol}=\text{xtol}, \text{rtol}=\text{rtol}) \), where \( x \) is the exact root.
    The parameter must be nonnegative.
  - \( \text{rtol} \) ([number, optional(default=4*\text{np.finfo(float).eps})] The computed root \( x_0 \) will satisfy
    \( \text{np. allclose}(x, x_0, \text{atol}=\text{xtol}, \text{rtol}=\text{rtol}) \), where \( x \) is the exact root.
  - \( \text{maxiter} \) ([number, optional(default=100)] Maximum number of iterations.)
  - \( \text{disp} \) ([bool, optional(default=True)] If True, raise a RuntimeError if the algorithm didn’t converge.)

**Returns**

- \( \text{results} \) ([namedtuple])

\[
\text{quantecon.optimize.root_finding.brentq}(f, a, b, \text{args}(), \text{xtol}=2e-12, \\
\text{rtol}=8.881784197001252e-16, \text{maxiter}=100, \\
\text{disp}=\text{True})
\]

Find a root of a function in a bracketing interval using Brent’s method adapted from Scipy’s brentq.

Uses the classic Brent’s method to find a zero of the function \( f \) on the sign changing interval \([a, b]\).

\( f \) must be jitted via numba.
3.3 scalar_maximization

quantecon.optimize.scalar_maximization.brent_max(func, a, b, args=(), xtol=1e-05, maxiter=500)

Uses a jitted version of the maximization routine from SciPy’s fminbound. The algorithm is identical except that it’s been switched to maximization rather than minimization, and the tests for convergence have been stripped out to allow for jit compilation.

Note that the input function func must be jitted or the call will fail.

Parameters

- **func** [jitted function]
- **a** [scalar] Lower bound for search
- **b** [scalar] Upper bound for search
- **args** [tuple, optional] Extra arguments passed to the objective function.
- **maxiter** [int, optional] Maximum number of iterations to perform.
- **xtol** [float, optional] Absolute error in solution xopt acceptable for convergence.

Returns

- **xf** [float] The maximizer
- **fval** [float] The maximum value attained
- **info** [tuple] A tuple of the form (status_flag, num_iter). Here status_flag indicates whether or not the maximum number of function calls was attained. A value of 0 implies that the maximum was not hit. The value num_iter is the number of function calls.

Examples

```python
>>> @njit
def f(x):
...    return -(x + 2.0)**2 + 1.0
...>>> xf, fval, info = brent_max(f, -2, 2)
```
4.1 utilities

Utilities to Support Random Operations and Generating Vectors and Matrices

quantecon.random.utilities.draw(cdf, size=None)
Generate a random sample according to the cumulative distribution given by cdf. Jit-complied by Numba in nopython mode.

Parameters

cdf [array_like(float, ndim=1)] Array containing the cumulative distribution.

size [scalar(int), optional(default=None)] Size of the sample. If an integer is supplied, an
ndarray of size independent draws is returned; otherwise, a single draw is returned as a scalar.

Returns

scalar(int) or ndarray(int, ndim=1)

Examples

```python
>>> cdf = np.cumsum([0.4, 0.6])
>>> qe.random.draw(cdf)
1
>>> qe.random.draw(cdf, 10)
array([1, 0, 1, 0, 1, 0, 0, 1, 0, 0])
```

quantecon.random.utilities.probvec(m, k, random_state=None, parallel=True)
Return m randomly sampled probability vectors of dimension k.

Parameters

m [scalar(int)] Number of probability vectors.
k [scalar(int)] Dimension of each probability vectors.

random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

parallel [bool(default=True)] Whether to use multi-core CPU (parallel=True) or single-threaded CPU (parallel=False). (Internally the code is executed through Numba.guvectorize.)

Returns

x [ndarray(float, ndim=2)] Array of shape (m, k) containing probability vectors as rows.

Examples

```python
>>> qe.random.probvec(2, 3, random_state=1234)
array([[ 0.19151945, 0.43058932, 0.37789123],
   [ 0.43772774, 0.34763084, 0.21464142]])
```

quantecon.random.utilities.sample_without_replacement(n, k, num_trials=None, random_state=None)

Randomly choose k integers without replacement from 0, . . . , n-1.

Parameters

n [scalar(int)] Number of integers, 0, . . . , n-1, to sample from.

k [scalar(int)] Number of integers to sample.

num_trials [scalar(int), optional(default=None)] Number of trials.

random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

result [ndarray(int, ndim=1 or 2)] Array of shape (k,) if num_trials is None, or of shape (num_trials, k) otherwise, (each row of) which contains k unique random elements chosen from 0, . . . , n-1.

Examples

```python
>>> qe.random.sample_without_replacement(5, 3, random_state=1234)
array([0, 2, 1])
>>> qe.random.sample_without_replacement(5, 3, num_trials=4, random_state=1234)
array([[0, 2, 1],
   [3, 4, 0],
   [1, 3, 2],
   [4, 1, 3]])
```
CHAPTER 5

Tools

5.1 arma

Provides functions for working with and visualizing scalar ARMA processes.

TODO: 1. Fix warnings concerning casting complex variables back to floats

class quantecon.arma.ARMA(phi, theta=0, sigma=1)

Bases: object

This class represents scalar ARMA(p, q) processes.

If phi and theta are scalars, then the model is understood to be

\[ X_t = \phi X_{t-1} + \epsilon_t + \theta \epsilon_{t-1} \]

where \( \epsilon_t \) is a white noise process with standard deviation \( \sigma \). If phi and theta are arrays or sequences, then the interpretation is the ARMA(p, q) model

\[ X_t = \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} \]

where

- \( \phi = (\phi_1, \phi_2, \ldots, \phi_p) \)
- \( \theta = (\theta_1, \theta_2, \ldots, \theta_q) \)
- \( \sigma \) is a scalar, the standard deviation of the white noise

Parameters

phi [scalar or iterable or array_like(float)] Autocorrelation values for the autocorrelated variable. See above for explanation.

theta [scalar or iterable or array_like(float)] Autocorrelation values for the white noise of the model. See above for explanation
**Attributes**

- **phi, theta, sigma** [see Parameters]

- **ar_poly** [array_like(float)] The polynomial form that is needed by scipy.signal to do the processing we desire. Corresponds with the phi values

- **ma_poly** [array_like(float)] The polynomial form that is needed by scipy.signal to do the processing we desire. Corresponds with the theta values

**Methods**

- **autocovariance**
  
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>self</td>
<td>Compute the autocovariance function from the ARMA parameters over the integers range(num_autocov) using the spectral density and the inverse Fourier transform.</td>
</tr>
</tbody>
</table>

- **impulse_response**
  
<table>
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<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>self</td>
<td>Get the impulse response corresponding to our model.</td>
</tr>
</tbody>
</table>

- **set_params**
  
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>self</td>
<td>Internally, scipy.signal works with systems of the form</td>
</tr>
</tbody>
</table>

- **simulation**
  
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>self</td>
<td>Compute a simulated sample path assuming Gaussian shocks.</td>
</tr>
</tbody>
</table>

- **spectral_density**
  
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>self</td>
<td>Compute the spectral density function.</td>
</tr>
</tbody>
</table>

**autocovariance** *(self, num_autocov=16)*

Compute the autocovariance function from the ARMA parameters over the integers range(num_autocov) using the spectral density and the inverse Fourier transform.

**Parameters**

- **num_autocov** [scalar(int), optional(default=16)] The number of autocovariances to calculate

**impulse_response** *(self, impulse_length=30)*

Get the impulse response corresponding to our model.

**Returns**

- **psi** [array_like(float)] psi[j] is the response at lag j of the impulse response. We take psi[0] as unity.

**phi**

**set_params** *(self)*

Internally, scipy.signal works with systems of the form

\[
\text{ar}_\text{poly}(L)X_t = \text{ma}_\text{poly}(L)e_t
\]

where L is the lag operator. To match this, we set

\[
\text{ar}_\text{poly} = (1, -\phi_1, -\phi_2, \ldots, -\phi_p) \\
\text{ma}_\text{poly} = (1, \theta_1, \theta_2, \ldots, \theta_q)
\]

In addition, ar_poly must be at least as long as ma_poly. This can be achieved by padding it out with zeros when required.
simulation (self, ts_length=90, random_state=None)

Compute a simulated sample path assuming Gaussian shocks.

Parameters

- **ts_length** [scalar(int), optional(default=90)] Number of periods to simulate for
- **random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

- **vals** [array_like(float)] A simulation of the model that corresponds to this class

spectral_density (self, two_pi=True, res=1200)

Compute the spectral density function. The spectral density is the discrete time Fourier transform of the autocovariance function. In particular,

\[ f(w) = \sum_k \gamma(k) \exp(-ikw) \]

where gamma is the autocovariance function and the sum is over the set of all integers.

Parameters

- **two_pi** [Boolean, optional] Compute the spectral density function over \([0, \pi]\) if two_pi is False and \([0, 2\pi]\) otherwise. Default value is True
- **res** [scalar or array_like(int), optional(default=1200)] If res is a scalar then the spectral density is computed at res frequencies evenly spaced around the unit circle, but if res is an array then the function computes the response at the frequencies given by the array

Returns

- **w** [array_like(float)] The normalized frequencies at which h was computed, in radians/sample
- **spect** [array_like(float)] The frequency response

5.2 ce_util

Utility functions used in CompEcon
Based routines found in the CompEcon toolbox by Miranda and Fackler.

5.2.1 References


quantecon.ce_util.ckron (*arrays)

Repeatedly applies the np.kron function to an arbitrary number of input arrays

Parameters

- **arrays** [tuple/list of np.ndarray]

Returns
out [np.ndarray] The result of repeated kronecker products.

Notes

Based of original function *ckron* in CompEcon toolbox by Miranda and Fackler.

References


quantecan.ce_util.gridmake(*arrays)

Expands one or more vectors (or matrices) into a matrix where rows span the cartesian product of combinations of the input arrays. Each column of the input arrays will correspond to one column of the output matrix.

Parameters

*arrays [tuple/list of np.ndarray] Tuple/list of vectors to be expanded.

Returns

out [np.ndarray] The cartesian product of combinations of the input arrays.

Notes

Based of original function *gridmake* in CompEcon toolbox by Miranda and Fackler

References


5.3 compute_fp

Compute an approximate fixed point of a given operator T, starting from specified initial condition v.

quantecan.compute_fp.compute_fixed_point(T, v, error_tol=0.001, max_iter=50, verbose=2, print_skip=5, method='iteration', *args, **kwargs)

Computes and returns an approximate fixed point of the function T.

The default method ‘iteration’ simply iterates the function given an initial condition v and returns $T^k v$ when the condition $\|T^k v - T^{k-1} v\| \leq error\_tol$ is satisfied or the number of iterations $k$ reaches max_iter. Provided that $T$ is a contraction mapping or similar, $T^k v$ will be an approximation to the fixed point.

The method ‘imitation_game’ uses the “imitation game algorithm” developed by McLennan and Tourky [1], which internally constructs a sequence of two-player games called imitation games and utilizes their Nash equilibria, computed by the Lemke-Howson algorithm routine. It finds an approximate fixed point of $T$, a point $v^*$ such that $\|T(v) - v\| \leq error\_tol$, provided $T$ is a function that satisfies the assumptions of Brouwer’s fixed point theorem, i.e., a continuous function that maps a compact and convex set to itself.

Parameters

T [callable] A callable object (e.g., function) that acts on v

v [object] An object such that T(v) is defined; modified in place if method=‘iteration’ and ‘v is an array
error_tol  [scalar(float), optional(default=1e-3)] Error tolerance
max_iter  [scalar(int), optional(default=50)] Maximum number of iterations
verbose  [scalar(int), optional(default=2)] Level of feedback (0 for no output, 1 for warnings only, 2 for warning and residual error reports during iteration)
print_skip  [scalar(int), optional(default=5)] How many iterations to apply between print messages (effective only when verbose=2)
method  [str, optional(default='iteration')] str in {'iteration', 'imitation_game'}. Method of computing an approximate fixed point
args, kwags : Other arguments and keyword arguments that are passed directly to the function T each time it is called

Returns

ev  [object] The approximate fixed point

References

[1]

5.4 discrete_rv

Generates an array of draws from a discrete random variable with a specified vector of probabilities.

class quantecon.discrete_rv.DiscreteRV(q)
Bases: object

Generates an array of draws from a discrete random variable with vector of probabilities given by q.

Parameters

q  [array_like(float)] Nonnegative numbers that sum to 1.

Attributes

q  [see Parameters.] Getter method for q.
Q  [array_like(float)] The cumulative sum of q.

Methods

\[\text{draw}(\text{self}, k, \text{random\_state})\] Returns k draws from q.

\[\text{draw} (\text{self}, k=1, \text{random\_state}=\text{None})\]
Returns k draws from q.

For each such draw, the value i is returned with probability q[i].

Parameters

k  [scalar(int), optional] Number of draws to be returned
random_state  [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.
Returns

array_like(int) An array of k independent draws from q

q

Getter method for q.

5.5 distributions

Probability distributions useful in economics.

5.5.1 References


class quant econ. distributions. BetaBinomial (n, a, b)
Bases: object

The Beta-Binomial distribution

Parameters

n [scalar(int)] First parameter to the Beta-binomial distribution
a [scalar(float)] Second parameter to the Beta-binomial distribution
b [scalar(float)] Third parameter to the Beta-binomial distribution

Attributes

n, a, b [see Parameters]

Methods

pdf(self) Generate the vector of probabilities for the Beta-binomial (n, a, b) distribution.

mean

pdf (self)

Generate the vector of probabilities for the Beta-binomial (n, a, b) distribution.

The Beta-binomial distribution takes the form

\[ p(k \mid n, a, b) = \binom{n}{k} \frac{B(k + a, n - k + b)}{B(a, b)}, \quad k = 0, \ldots, n, \]

where \( B \) is the beta function.

Parameters

n [scalar(int)] First parameter to the Beta-binomial distribution
a [scalar(float)] Second parameter to the Beta-binomial distribution
b [scalar(float)] Third parameter to the Beta-binomial distribution

Returns

probs: array_like(float) Vector of probabilities over k
5.6 dle

Provides a class called DLE to convert and solve dynamic linear economics (as set out in Hansen & Sargent (2013)) as LQ problems.

class quantecon.dle.DLE (information, technology, preferences)

This class is for analyzing dynamic linear economies, as set out in Hansen & Sargent (2013). The planner’s problem is to choose \{c_t, s_t, i_t, h_t, k_t, g_t\}_{t=0}^{\infty} to maximize

\[
\max -\left(\frac{1}{2}\right) \mathbb{E} \sum_{t=0}^{\infty} \beta^t \left( (s_t - b_t) \cdot (s_t - b_t) + g_t \cdot g_t \right)
\]

subject to the linear constraints

\[
\begin{align*}
\Phi_c c_t + \Phi_g g_t + \Phi_i i_t &= \Gamma k_{t-1} + d_t \\
\Delta_k k_{t-1} + \Theta_k i_t &= \Delta_h h_{t-1} + \Theta_h c_t \\
-1 &\leq s_t \leq 1
\end{align*}
\]

and

\[
\begin{align*}
z_{t+1} &= A_{22} z_t + C_2 w_{t+1} \\
b_t &= U_b z_t \\
d_t &= U_d z_t
\end{align*}
\]

where \(h_{-1}, k_{-1}, \text{ and } z_0\) are given as initial conditions.

Section 5.5 of HS2013 describes how to map these matrices into those of a LQ problem.

HS2013 sort the matrices defining the problem into three groups:

- Information: \(A_{22}, C_2, U_b, \text{ and } U_d\) characterize the motion of information sets and of taste and technology shocks
- Technology: \(\Phi_c, \Phi_g, \Phi_i, \Gamma, \Delta_k, \text{ and } \Theta_k\) determine the technology for producing consumption goods
- Preferences: \(\Delta_h, \Theta_h, \Lambda, \text{ and } \Pi\) determine the technology for producing consumption services from consumer goods. A scalar discount factor \(\beta\) determines the preference ordering over consumption services.

**Parameters**

- **Information** [tuple] Information is a tuple containing the matrices \(A_{22}, C_2, U_b, \text{ and } U_d\)
- **Technology** [tuple] Technology is a tuple containing the matrices \(\Phi_c, \Phi_g, \Phi_i, \Gamma, \Delta_k, \text{ and } \Theta_k\)
- **Preferences** [tuple] Preferences is a tuple containing the matrices \(\Delta_h, \Theta_h, \Lambda, \Pi, \text{ and the scalar } \beta\)

**Methods**
### QuantEcon Documentation, Release 0.4.5

#### Methods

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<td><strong>canonical</strong> (self)</td>
<td>Compute canonical preference representation. Uses auxiliary problem of 9.4.2, with the preference shock process reintroduced. Calculates ( \pihat ), ( \llambdahat ) and ( \ubhat ) for the equivalent canonical household technology.</td>
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**canonical** (self)

Compute canonical preference representation. Uses auxiliary problem of 9.4.2, with the preference shock process reintroduced. Calculates \( \pihat \), \( \llambdahat \) and \( \ubhat \) for the equivalent canonical household technology.

**compute_sequence** (self, x0[, ts_length, Pay])

Simulate quantities and prices for the economy.

**Parameters**

- **x0** [array_like(float)] The initial state
- **ts_length** [scalar(int)] Length of the simulation
- **Pay** [array_like(float)] Vector to price an asset whose payout is \( \text{Pay} \times t \)

**compute_steadystate** (self[, nnc=2])

Computes the non-stochastic steady-state of the economy.

**Parameters**

- **nnc** [array_like(float)] \( \text{nnc} \) is the location of the constant in the state vector \( x_t \)

**irf** (self[, ts_length=100, shock=None])

Create Impulse Response Functions.

**Parameters**

- **ts_length** [scalar(int)] Number of periods to calculate IRF
- **Shocks** [array_like(float)] Vector of shocks to calculate IRF to. Default is first element of \( \text{w} \)

### 5.7 ecdf

Implements the empirical cumulative distribution function given an array of observations.

#### Class

```python
class quantecon.ecdf.ECDF (observations)
```

One-dimensional empirical distribution function given a vector of observations.

**Parameters**

- **observations** [array_like] An array of observations

**Attributes**

- **observations** [see Parameters]
5.8 estspec

Functions for working with periodograms of scalar data.

quantecon.estspec.ar_periodogram(x, window='hanning', window_len=7)

Compute periodogram from data x, using prewhitening, smoothing and recoloring. The data is fitted to an AR(1) model for prewhitening, and the residuals are used to compute a first-pass periodogram with smoothing. The fitted coefficients are then used for recoloring.

Parameters

- x [array_like(float)] A flat NumPy array containing the data to smooth
- window_len [scalar(int), optional] An odd integer giving the length of the window. Defaults to 7.
- window [string] A string giving the window type. Possible values are ‘flat’, ‘hanning’, ‘hamming’, ‘bartlett’ or ‘blackman’

Returns

- w [array_like(float)] Fourier frequencies at which periodogram is evaluated
- I_w [array_like(float)] Values of periodogram at the Fourier frequencies

quantecon.estspec.periodogram(x, window=None, window_len=7)

Computes the periodogram

\[ I(w) = \frac{1}{n} \left( \sum_{t=0}^{n-1} x_t e^{itw} \right)^2 \]

at the Fourier frequencies \( w_j := \frac{2\pi j}{n}, j = 0, \ldots, n-1 \), using the fast Fourier transform. Only the frequencies \( w_j \) in \([0, \pi]\) and corresponding values \( I(w_j) \) are returned. If a window type is given then smoothing is performed.

Parameters

- x [array_like(float)] A flat NumPy array containing the data to smooth
- window_len [scalar(int), optional(default=7)] An odd integer giving the length of the window. Defaults to 7.
- window [string] A string giving the window type. Possible values are ‘flat’, ‘hanning’, ‘hamming’, ‘bartlett’ or ‘blackman’

Returns

- w [array_like(float)] Fourier frequencies at which periodogram is evaluated
- I_w [array_like(float)] Values of periodogram at the Fourier frequencies

quantecon.estspec.smooth(x, window_len=7, window='hanning')

Smooth the data in x using convolution with a window of requested size and type.

Parameters

- x [array_like(float)] A flat NumPy array containing the data to smooth
window_len [scalar(int), optional] An odd integer giving the length of the window. Defaults to 7.

window [string] A string giving the window type. Possible values are 'flat', 'hanning', 'hamming', 'bartlett' or 'blackman'

Returns

array_like(float) The smoothed values

Notes

Application of the smoothing window at the top and bottom of x is done by reflecting x around these points to extend it sufficiently in each direction.

5.9 filter

function for filtering

quantecon.filter.hamilton_filter(data, h, *args)

This function applies “Hamilton filter” to the data

http://econweb.ucsd.edu/~jhamilto/hp.pdf

Parameters

data [array or dataframe]

h [integer] Time horizon that we are likely to predict incorrectly. Original paper recommends 2 for annual data, 8 for quarterly data, 24 for monthly data.

*args [integer] If supplied, it is p in the paper. Number of lags in regression. Must be greater than h. If not supplied, random walk process is assumed.

Note: For seasonal data, it’s desirable for p and h to be integer multiples of the number of observations in a year. e.g. For quarterly data, h = 8 and p = 4 are recommended.

Returns

cycle [array of cyclical component]

trend [trend component]

5.10 graph_tools

Tools for dealing with a directed graph.

class quantecon.graph_tools.DiGraph(adj_matrix, weighted=False, node_labels=None)

Bases: object

Class for a directed graph. It stores useful information about the graph structure such as strong connectivity [Rbad921e459e7-1] and periodicity [Rbad921e459e7-2].

Parameters

adj_matrix [array_like(ndim=2)] Adjacency matrix representing a directed graph. Must be of shape n x n.
weighted [bool, optional(default=False)] Whether to treat adj_matrix as a weighted adjacency matrix.
	node_labels [array_like(default=None)] Array_like of length n containing the labels associated with the nodes, which must be homogeneous in type. If None, the labels default to integers 0 through n-1.

Attributes

csgraph [scipy.sparse.csr_matrix] Compressed sparse representation of the digraph.

is_strongly_connected [bool] Indicate whether the digraph is strongly connected.

num_strongly_connected_components [int] The number of the strongly connected components.

strongly_connected_components_indices [list(ndarray(int))]] List of numpy arrays containing the indices of the strongly connected components.

strongly_connected_components [list(ndarray)] List of numpy arrays containing the strongly connected components, where the nodes are annotated with their labels (if node_labels is not None).

num_sink_strongly_connected_components [int] The number of the sink strongly connected components.

sink_strongly_connected_components_indices [list(ndarray(int))]] List of numpy arrays containing the indices of the sink strongly connected components.

sink_strongly_connected_components [list(ndarray)] List of numpy arrays containing the sink strongly connected components, where the nodes are annotated with their labels (if node_labels is not None).

is_aperiodic [bool] Indicate whether the digraph is aperiodic.

period [int] The period of the digraph. Defined only for a strongly connected digraph.

cyclic_components_indices [list(ndarray(int))]] List of numpy arrays containing the indices of the cyclic components.

cyclic_components [list(ndarray)] List of numpy arrays containing the cyclic components, where the nodes are annotated with their labels (if node_labels is not None).

Methods

subgraph(self, nodes) Return the subgraph consisting of the given nodes and edges between these nodes.

cyclic_components
cyclic_components_indices
is_aperiodic
is_strongly_connected
node_labels
num_sink_strongly_connected_components
num_strongly_connected_components
period
csc_proj
sink_scc_labels
sink_strongly_connected_components
sink_strongly_connected_components_indices
strongly_connected_components
strongly_connected_components_indices
subgraph (self, nodes)
    Return the subgraph consisting of the given nodes and edges between these nodes.

    Parameters
    
    nodes [array_like(int, ndim=1)] Array of node indices.

    Returns
    
    DiGraph A DiGraph representing the subgraph.

quantecon.graph_tools.annotate_nodes (func)
quantecon.graph_tools.random_tournament_graph (n, random_state=None)
    Return a random tournament graph [1] with n nodes.

    Parameters
    
    n [scalar(int)] Number of nodes.

    random_state [int or np.random.RandomState, optional] Random seed (integer) or
    np.random.RandomState instance to set the initial state of the random number genera-
    tor for reproducibility. If None, a randomly initialized RandomState is used.

    Returns
    
    DiGraph A DiGraph representing the tournament graph.

References

[1]

5.11 gridtools

Implements cartesian products and regular cartesian grids, and provides a function that constructs a grid for a simplex
as well as one that determines the index of a point in the simplex.
quantecon.gridtools.cartesian (nodes, order='C')
    Cartesian product of a list of arrays

    Parameters
    
    nodes [list(array_like(ndim=1))]
order  [str, optional(default='C')] (‘C’ or ‘F’) order in which the product is enumerated

Returns

out  [ndarray(ndim=2)] each line corresponds to one point of the product space

quantecon.gridtools.mlinspace(a, b, nums, order='C')
Constructs a regular cartesian grid

Parameters

a  [array_like(ndim=1)] lower bounds in each dimension
b  [array_like(ndim=1)] upper bounds in each dimension
nums  [array_like(ndim=1)] number of nodes along each dimension
order  [str, optional(default='C')] (‘C’ or ‘F’) order in which the product is enumerated

Returns

out  [ndarray(ndim=2)] each line corresponds to one point of the product space

quantecon.gridtools.num_compositions(m, n)
The total number of m-part compositions of n, which is equal to (n+m-1) choose (m-1).

Parameters

m  [scalar(int)] Number of parts of composition.
n  [scalar(int)] Integer to decompose.

Returns

scalar(int) Total number of m-part compositions of n.

quantecon.gridtools.num_compositions_jit(m, n)
Numba jit version of num_compositions. Return 0 if the outcome exceeds the maximum value of np.intp.

quantecon.gridtools.simplex_grid(m, n)
Construct an array consisting of the integer points in the (m-1)-dimensional simplex \{x | x_0 + \cdots + x_{m-1} = n\}, or equivalently, the m-part compositions of n, which are listed in lexicographic order. The total number of the points (hence the length of the output array) is L = (n+m-1)!/(n!*(m-1)!) (i.e., (n+m-1) choose (m-1)).

Parameters

m  [scalar(int)] Dimension of each point. Must be a positive integer.
n  [scalar(int)] Number which the coordinates of each point sum to. Must be a nonnegative integer.

Returns

out  [ndarray(int, ndim=2)] Array of shape (L, m) containing the integer points in the simplex, aligned in lexicographic order.

Notes

A grid of the (m-1)-dimensional unit simplex with n subdivisions along each dimension can be obtained by simplex_grid(m, n) / n.

References

5.12 inequality

Implements inequality and segregation measures such as Gini, Lorenz Curve
quantecon.inequality.gini_coefficient(y)

Implements the Gini inequality index

Parameters

y [array_like(float)] Array of income/wealth for each individual. Ordered or unordered is fine

Returns

Gini index: float The gini index describing the inequality of the array of income/wealth

References

https://en.wikipedia.org/wiki/Gini_coefficient

quantecon.inequality.lorenz_curve(y)

Calculates the Lorenz Curve, a graphical representation of the distribution of income or wealth.
It returns the cumulative share of people (x-axis) and the cumulative share of income earned

Parameters

y [array_like(float or int, ndim=1)] Array of income/wealth for each individual. Unordered or ordered is fine.

Returns

cum_people [array_like(float, ndim=1)] Cumulative share of people for each person index (i/n)
cum_income [array_like(float, ndim=1)] Cumulative share of income for each person index

References

[1]

Examples

```python
>>> a_val, n = 3, 10_000
>>> y = np.random.pareto(a_val, size=n)
>>> f_vals, l_vals = lorenz(y)
```

quantecon.inequality.shorrocks_index(A)

Implements Shorrocks mobility index

Parameters

A [array_like(float)] Square matrix with transition probabilities (mobility matrix) of dimension m

Returns

Shorrocks index: float The Shorrocks mobility index calculated as

$$s(A) = \frac{m - \sum_j a_{jj}}{m - 1} \in (0, 1)$$

An index equal to 0 indicates complete immobility.
References

[1]

5.13 ivp

Base class for solving initial value problems (IVPs) of the form:

\[
\frac{dy}{dt} = f(t, y), \quad y(t_0) = y_0
\]

using finite difference methods. The `quantecon.ivp` class uses various integrators from the `scipy.integrate.ode` module to perform the integration (i.e., solve the ODE) and parametric B-spline interpolation from `scipy.interpolate` to approximate the value of the solution between grid points. The `quantecon.ivp` module also provides a method for computing the residual of the solution which can be used for assessing the overall accuracy of the approximated solution.

```python
class quantecon.ivp.IVP(f, jac=None)
    Bases: scipy.integrate._ode.ode

    Creates an instance of the IVP class.

    Parameters

    f [callable f(t, y, *f_args)] Right hand side of the system of equations defining the ODE. The independent variable, t, is a scalar; y is an `ndarray` of dependent variables with `y.shape == (n,)`. The function `f` should return a scalar, `ndarray` or `list` (but not a `tuple`).

    jac [callable jac(t, y, *jac_args), optional(default=None)] Jacobian of the right hand side of the system of equations defining the ODE.

    Attributes

    y

    Methods

    compute_residual(self, traj, ti[, k, ext]) The residual is the difference between the derivative of the B-spline approximation of the solution trajectory and the right-hand side of the original ODE evaluated along the approximated solution trajectory.

    get_return_code(self) Extracts the return code for the integration to enable better control if the integration fails.

    integrate(self, t[, step, relax]) Find y = y(t), set y as an initial condition, and return y.

    interpolate(self, traj, ti[, k, der, ext]) Parametric B-spline interpolation in N-dimensions.

    set_f_params(self, *args) Set extra parameters for user-supplied function f.

    set_initial_value(self, y[, t]) Set initial conditions y(t) = y.

    set_integrator(self, name, *integrator_params) Set integrator by name.

    set_jac_params(self, *args) Set extra parameters for user-supplied function jac.

    set_solout(self, solout) Set callable to be called at every successful integration step.
```

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<th>Function</th>
<th>Description</th>
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<td>solve</td>
<td>Solve the IVP by integrating the ODE given some initial condition.</td>
</tr>
<tr>
<td>successful</td>
<td>Check if integration was successful.</td>
</tr>
<tr>
<td>compute_residual</td>
<td>The residual is the difference between the derivative of the B-spline approximation of the solution trajectory and the right-hand side of the original ODE evaluated along the approximated solution trajectory.</td>
</tr>
<tr>
<td>Parameters</td>
<td></td>
</tr>
<tr>
<td>traj</td>
<td>Solution trajectory providing the data points for constructing the B-spline representation.</td>
</tr>
<tr>
<td>ti</td>
<td>Array of values for the independent variable at which to interpolate the value of the B-spline.</td>
</tr>
<tr>
<td>k</td>
<td>Degree of the desired B-spline. Degree must satisfy $1 \leq k \leq 5$.</td>
</tr>
<tr>
<td>ext</td>
<td>Controls the value of returned elements for outside the original knot sequence provided by traj. For extrapolation, set ext=0; ext=1 returns zero; ext=2 raises a ValueError.</td>
</tr>
<tr>
<td>Returns</td>
<td></td>
</tr>
<tr>
<td>residual</td>
<td>Difference between the derivative of the B-spline approximation of the solution trajectory and the right-hand side of the ODE evaluated along the approximated solution trajectory.</td>
</tr>
<tr>
<td>interpolate</td>
<td>Parametric B-spline interpolation in N-dimensions.</td>
</tr>
<tr>
<td>Parameters</td>
<td></td>
</tr>
<tr>
<td>traj</td>
<td>Solution trajectory providing the data points for constructing the B-spline representation.</td>
</tr>
<tr>
<td>ti</td>
<td>Array of values for the independent variable at which to interpolate the value of the B-spline.</td>
</tr>
<tr>
<td>k</td>
<td>Degree of the desired B-spline. Degree must satisfy $1 \leq k \leq 5$.</td>
</tr>
<tr>
<td>der</td>
<td>The order of derivative of the spline to compute (must be less than or equal to k).</td>
</tr>
<tr>
<td>ext</td>
<td>Controls the value of returned elements for outside the original knot sequence provided by traj. For extrapolation, set ext=0; ext=1 returns zero; ext=2 raises a ValueError.</td>
</tr>
<tr>
<td>Returns</td>
<td></td>
</tr>
<tr>
<td>interp_traj: ndarray</td>
<td>The interpolated trajectory.</td>
</tr>
<tr>
<td>solve</td>
<td>Solve the IVP by integrating the ODE given some initial condition.</td>
</tr>
<tr>
<td>Parameters</td>
<td></td>
</tr>
<tr>
<td>t0</td>
<td>Initial condition for the independent variable.</td>
</tr>
<tr>
<td>y0</td>
<td>Initial condition for the dependent variables.</td>
</tr>
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</table>

5.13. ivp 65
**h** [float, optional(default=1.0)] Step-size for computing the solution. Can be positive or negative depending on the desired direction of integration.

**T** [int, optional(default=None)] Terminal value for the independent variable. One of either T or g must be specified.

**g** [callable g(t, y, f_args), optional(default=None)] Provides a stopping condition for the integration. If specified user must also specify a stopping tolerance, **tol**.

**tol** [float, optional (default=None)] Stopping tolerance for the integration. Only required if **g** is also specified.

**integrator** [str, optional(default='dopri5')] Must be one of ‘vode’, ‘lsoda’, ‘dopri5’, or ‘dop853’

**step** [bool, optional(default=False)] Allows access to internal steps for those solvers that use adaptive step size routines. Currently only ‘vode’, ‘zvode’, and ‘lsoda’ support **step=True**.

**relax** [bool, optional(default=False)] Currently only ‘vode’, ‘zvode’, and ‘lsoda’ support **relax=True**.

**kwargs** [dict, optional(default=None)] Dictionary of integrator specific keyword arguments. See the Notes section of the docstring for scipy.integrate.ode for a complete description of solver specific keyword arguments.

**Returns**

**solution**: ndarray (float) Simulated solution trajectory.

## 5.14 kalman

Implements the Kalman filter for a linear Gaussian state space model.

### 5.14.1 References

https://lectures.quantecon.org/py/kalman.html

**class** quantecon.kalman.Kalman (ss, x_hat=None, Sigma=None)

**Bases**: object

Implements the Kalman filter for the Gaussian state space model

\[
x_{t+1} = Ax_t + Cw_{t+1} \\
y_t = Gx_t + Hv_t
\]

Here \(x_t\) is the hidden state and \(y_t\) is the measurement. The shocks \(w_t\) and \(v_t\) are iid standard normals. Below we use the notation

\[
Q := CC'R := HH'
\]

**Parameters**

**ss** [instance of LinearStateSpace] An instance of the quantecon.lss.LinearStateSpace class

**x_hat** [scalar(float) or array_like(float), optional(default=None)] An n x 1 array representing the mean \(x_{\text{hat}}\) of the prior/predictive density. Set to zero if not supplied.
Sigma [scalar(float) or array_like(float), optional(default=None)] An n x n array representing the covariance matrix Sigma of the prior/predictive density. Must be positive definite. Set to the identity if not supplied.

References
https://lectures.quantecon.org/py/kalman.html

Attributes

Sigma, x_hat [as above]
Sigma_infinity [array_like or scalar(float)] The infinite limit of Sigma_t
K_infinity [array_like or scalar(float)] The stationary Kalman gain.

Methods

filtered_to_forecast(self) Updates the moments of the time t filtering distribution to the moments of the predictive distribution, which becomes the time t+1 prior
prior_to_filtered(self, y) Updates the moments (x_hat, Sigma) of the time t prior to the time t filtering distribution, using current measurement \( y_t \).
stationary_coefficients(self, j[, coeff_type]) Wold representation moving average or VAR coefficients for the steady state Kalman filter.
stationary_values(self[, method]) Computes the limit of \( \Sigma_t \) as t goes to infinity by solving the associated Riccati equation.
update(self, y) Updates x_hat and Sigma given k x 1 ndarray y.
whitener_lss(self) This function takes the linear state space system that is an input to the Kalman class and it converts that system to the time-invariant whitener representation given by

\[
\hat{x}^F = \hat{x} + \Sigma G'(G\Sigma G' + R)^{-1}(y - G\hat{x})
\]

\[
\Sigma^F = \Sigma - \Sigma G'(G\Sigma G' + R)^{-1}G\Sigma
\]

Parameters
y [scalar or array_like(float)] The current measurement

**set_state** *(self, x_hat, Sigma)*

**stationary_coefficients** *(self, j, coeff_type='ma')*
Wold representation moving average or VAR coefficients for the steady state Kalman filter.

**Parameters**

- **j** [int] The lag length
- **coeff_type** [string, either ‘ma’ or ‘var’ (default=’ma’)] The type of coefficient sequence to compute. Either ‘ma’ for moving average or ‘var’ for VAR.

**stationary_innovation_covar** *(self)*

**stationary_values** *(self, method='doubling')*
Computes the limit of $\Sigma_t$ as $t$ goes to infinity by solving the associated Riccati equation. The outputs are stored in the attributes $K_{\infty}$ and $\Sigma_{\infty}$. Computation is via the doubling algorithm (default) or a QZ decomposition method (see the documentation in *matrix_eqn.solve_discrete_riccati*).

**Parameters**

- **method** [str, optional(default=“doubling”)] Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}.

**Returns**

- **Sigma_infinity** [array_like or scalar(float)] The infinite limit of $\Sigma_t$
- **K_infinity** [array_like or scalar(float)] The stationary Kalman gain.

**update** *(self, y)*
Updates $x_{\hat{\cdot}}$ and $\Sigma$ given $k \times 1$ ndarray $y$. The full update, from one period to the next

**Parameters**

- **y** [np.ndarray] A $k \times 1$ ndarray $y$ representing the current measurement

**whitener_lss** *(self)*
This function takes the linear state space system that is an input to the Kalman class and it converts that system to the time-invariant whitener representation given by

$$\tilde{x}_{t+1}^* = \tilde{A}\tilde{x} + \tilde{C}v_{a} = \tilde{G}\tilde{x}$$

where

$$\tilde{x}_t = [x + t, \hat{x}_t, v_t]$$

and

$$\tilde{A} = \begin{bmatrix} A & 0 & 0 \\ KG & A - KG & KH \\ 0 & 0 & 0 \end{bmatrix}$$

$$\tilde{C} = \begin{bmatrix} C \\ 0 \\ 0 \end{bmatrix}$$

$$\tilde{G} = \begin{bmatrix} G & -G & H \end{bmatrix}$$

with $A, C, G, H$ coming from the linear state space system that defines the Kalman instance

**Returns**

- **whitened_lss** [LinearStateSpace] This is the linear state space system that represents the whitened system
5.15 lae

Computes a sequence of marginal densities for a continuous state space Markov chain $X_t$ where the transition probabilities can be represented as densities. The estimate of the marginal density of $X_t$ is

$$\frac{1}{n} \sum_{i=0}^{n} p(X_{t-1}^i, y)$$

This is a density in $y$.

5.15.1 References

https://lectures.quantecon.org/py/stationary_densities.html

class quantecon.lae.LAE(p, X)

An instance is a representation of a look ahead estimator associated with a given stochastic kernel $p$ and a vector of observations $X$.

Parameters

- $p$ [function] The stochastic kernel. A function $p(x, y)$ that is vectorized in both x and y
- $X$ [array_like(float)] A vector containing observations

Examples

```python
>>> psi = LAE(p, X)
>>> y = np.linspace(0, 1, 100)
>>> psi(y)  # Evaluate look ahead estimate at grid of points y
```

Attributes

- $p$, $X$ [see Parameters]

Methods

- `__call__`(self, y) A vectorized function that returns the value of the look ahead estimate at the values in the array y.

5.16 lqcontrol

Provides a class called LQ for solving linear quadratic control problems, and a class called LQMarkov for solving Markov jump linear quadratic control problems.

class quantecon.lqcontrol.LQ(Q, R, A, B, C=None, N=None, beta=1, T=None, Rf=None)

Bases: object
This class is for analyzing linear quadratic optimal control problems of either the infinite horizon form

$$\min \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t r(x_t, u_t) \right]$$

with

$$r(x_t, u_t) := x_t'Rx_t + u_t'Qu_t + 2u_t'Nx_t$$

or the finite horizon form

$$\min \mathbb{E} \left[ \sum_{t=0}^{T-1} \beta^t r(x_t, u_t) + \beta^T x_T' R_f x_T \right]$$

Both are minimized subject to the law of motion

$$x_{t+1} = Ax_t + Bu_t + Cw_{t+1}$$

Here $x$ is $n \times 1$, $u$ is $k \times 1$, $w$ is $j \times 1$ and the matrices are conformable for these dimensions. The sequence $w_t$ is assumed to be white noise, with zero mean and $\mathbb{E}[w_t'w_t] = I$, the $j \times j$ identity.

If $C$ is not supplied as a parameter, the model is assumed to be deterministic (and $C$ is set to a zero matrix of appropriate dimension).

For this model, the time $t$ value (i.e., cost-to-go) function $V_t$ takes the form

$$x_t'P_Tx_t + d_T$$

and the optimal policy is of the form $u_T = -F_T x_T$. In the infinite horizon case, $V, P, d$ and $F$ are all stationary.

**Parameters**

- **Q** [array_like(float)] Q is the payoff (or cost) matrix that corresponds with the control variable $u$ and is $k \times k$. Should be symmetric and non-negative definite
- **R** [array_like(float)] R is the payoff (or cost) matrix that corresponds with the state variable $x$ and is $n \times n$. Should be symmetric and non-negative definite
- **A** [array_like(float)] A is part of the state transition as described above. It should be $n \times n$
- **B** [array_like(float)] B is part of the state transition as described above. It should be $n \times k$
- **C** [array_like(float), optional=default=None] C is part of the state transition as described above and corresponds to the random variable today. If the model is deterministic then C should take default value of None
- **N** [array_like(float), optional=default=None] N is the cross product term in the payoff, as above. It should be $k \times n$.
- **beta** [scalar(float), optional=default=1]] beta is the discount parameter
- **T** [scalar(int), optional=default=None] T is the number of periods in a finite horizon problem.
- **Rf** [array_like(float), optional=default=None] Rf is the final (in a finite horizon model) pay-off(or cost) matrix that corresponds with the control variable $u$ and is $n \times n$. Should be symmetric and non-negative definite

**Attributes**

- **Q, R, N, A, B, C, beta, T, Rf** [see Parameters]
- **P** [array_like(float)] P is part of the value function representation of $V(x) = x'Px + d$
d [array_like(float)] d is part of the value function representation of \( V(x) = x'Px + d \)

F [array_like(float)] F is the policy rule that determines the choice of control in each period.

k, n, j [scalar(int)] The dimensions of the matrices as presented above

**Methods**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td><strong>compute_sequence</strong> (self, x0[, ts_length, ...])</td>
<td>Compute and return the optimal state and control sequences ( x_0, ..., x_T ) and ( u_0, ..., u_T ) under the assumption that ( w_t ) is iid and ( N(0, 1) ).</td>
</tr>
<tr>
<td><strong>stationary_values</strong> (self[, method])</td>
<td>Computes the matrix ( P ) and scalar ( d ) that represent the value function</td>
</tr>
<tr>
<td><strong>update_values</strong> (self)</td>
<td>This method is for updating in the finite horizon case.</td>
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</table>

**compute_sequence** (self, x0, ts_length=None, method='doubling', random_state=None)  
Compute and return the optimal state and control sequences \( x_0, ..., x_T \) and \( u_0, ..., u_T \) under the assumption that \( w_t \) is iid and \( N(0, 1) \).

**Parameters**

- **x0** [array_like(float)] The initial state, a vector of length \( n \)
- **ts_length** [scalar(int)] Length of the simulation – defaults to \( T \) in finite case
- **method** [str, optional(default='doubling')] Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}. Only relevant when the \( T \) attribute is None (i.e., the horizon is infinite).
- **random_state** [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

**Returns**

- **x_path** [array_like(float)] An \( n \times T+1 \) matrix, where the \( t \)-th column represents \( x_t \)
- **u_path** [array_like(float)] A \( k \times T \) matrix, where the \( t \)-th column represents \( u_t \)
- **w_path** [array_like(float)] A \( j \times T+1 \) matrix, where the \( t \)-th column represents \( w_t \)

**stationary_values** (self, method='doubling')  
Computes the matrix \( P \) and scalar \( d \) that represent the value function \( V(x) = x'Px + d \) in the infinite horizon case. Also computes the control matrix \( F \) from \( u = -Fx \). Computation is via the solution algorithm as specified by the method option (default to the doubling algorithm) (see the documentation in `matrix_eqn.solve_discrete_riccati`).

**Parameters**

- **method** [str, optional(default='doubling')] Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}.

**Returns**

- **P** [array_like(float)] P is part of the value function representation of \( V(x) = x'Px + d \)
- **F** [array_like(float)] F is the policy rule that determines the choice of control in each period.

---

5.16. lqcontrol
\( d \) \[\text{array_like(float)}\] \( d \) is part of the value function representation of \( V(x) = x'P_x + d \)

**update_values** *(self)*

This method is for updating in the finite horizon case. It shifts the current value function

\[
V_t(x) = x'P_t x + d_t
\]

and the optimal policy \( F_t \) one step back in time, replacing the pair \( P_t \) and \( d_t \) with \( P_{t-1} \) and \( d_{t-1} \), and \( F_t \) with \( F_{t-1} \)

**class quantecon.lqcontrol.LQMarkov** *(\( \Pi, Qs, Rs, As, Bs, Cs=None, Ns=None, beta=1 \))*

**Bases:** object

This class is for analyzing Markov jump linear quadratic optimal control problems of the infinite horizon form

\[
\min \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t r(x_t, s_t, u_t) \right]
\]

with

\[
r(x_t, s_t, u_t) := (x_t'R(s_t)x_t + u_t'Q(s_t)u_t + 2u_t'N(s_t)x_t)
\]

subject to the law of motion

\[
x_{t+1} = A(s_t)x_t + B(s_t)u_t + C(s_t)w_{t+1}
\]

Here \( x \) is \( n \times 1 \), \( u \) is \( k \times 1 \), \( w \) is \( j \times 1 \) and the matrices are conformable for these dimensions. The sequence \( w_t \) is assumed to be white noise, with zero mean and \( \mathbb{E}[w_t'w_t] = I \), the \( j \times j \) identity.

If \( C \) is not supplied as a parameter, the model is assumed to be deterministic (and \( C \) is set to a zero matrix of appropriate dimension).

The optimal value function \( V(x_t, s_t) \) takes the form

\[
x_t'P(s_t)x_t + d(s_t)
\]

and the optimal policy is of the form \( u_t = -F(s_t)x_t \).

**Parameters**

- \( \Pi \) \[\text{array_like(float, ndim=2)}\] The Markov chain transition matrix with dimension \( m \times m \).
- \( Qs \) \[\text{array_like(float)}\] Consists of \( m \) symmetric and non-negative definite payoff matrices \( Q(s) \) with dimension \( k \times k \) that corresponds with the control variable \( u \) for each Markov state \( s \)
- \( Rs \) \[\text{array_like(float)}\] Consists of \( m \) symmetric and non-negative definite payoff matrices \( R(s) \) with dimension \( n \times n \) that corresponds with the state variable \( x \) for each Markov state \( s \)
- \( As \) \[\text{array_like(float)}\] Consists of \( m \) state transition matrices \( A(s) \) with dimension \( n \times n \) for each Markov state \( s \)
- \( Bs \) \[\text{array_like(float)}\] Consists of \( m \) state transition matrices \( B(s) \) with dimension \( n \times k \) for each Markov state \( s \)
- \( Cs \) \[\text{array_like(float), optional[default=None]}\] Consists of \( m \) state transition matrices \( C(s) \) with dimension \( n \times j \) for each Markov state \( s \). If the model is deterministic then \( Cs \) should take default value of None
- \( Ns \) \[\text{array_like(float), optional[default=None]}\] Consists of \( m \) cross product term matrices \( N(s) \) with dimension \( k \times n \) for each Markov state,
beta [scalar(float), optional(default=1)] beta is the discount parameter

Attributes

Π, Qs, Rs, Ns, As, Bs, Cs, beta  [see Parameters]

Ps [array_like(float)] Ps is part of the value function representation of $V(x, s) = x'P(s)x + d(s)$

ds [array_like(float)] ds is part of the value function representation of $V(x, s) = x'P(s)x + d(s)$

Fs [array_like(float)] Fs is the policy rule that determines the choice of control in each period at each Markov state

m [scalar(int)] The number of Markov states

k, n, j [scalar(int)] The dimensions of the matrices as presented above

Methods

```
compute_sequence(self, x0[, ts_length, . . .])  Compute and return the optimal state and control sequences $x_0, ..., x_T$ and $u_0, ..., u_T$ under the assumption that $w_t$ is iid and $N(0, 1)$, with Markov states sequence $s_0, ..., s_T$
stationary_values(self)  Computes the matrix $P(s)$ and scalar $d(s)$ that represent the value function
```

```
compute_sequence (self, x0, ts_length=None, random_state=None)  Computes the matrix $P(s)$ and scalar $d(s)$ that represent the value function in the infinite horizon case. Also computes the control matrix $F$ from $u = -F(s)x$.
```

Parameters

x0  [array_like(float)] The initial state, a vector of length n

hs_length  [scalar(int), optional(default=None)] Length of the simulation. If None, T is set to be 100

random_state  [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

x_path  [array_like(float)] An n x T+1 matrix, where the t-th column represents $x_t$

u_path  [array_like(float)] A k x T matrix, where the t-th column represents $u_t$

w_path  [array_like(float)] A j x T+1 matrix, where the t-th column represent $w_t$

state  [array_like(int)] Array containing the state values $s_t$ of the sample path

stationary_values (self)  Computes the matrix $P(s)$ and scalar $d(s)$ that represent the value function

in the infinite horizon case.
\[ \text{Ps} \quad \text{[array_like(float)]} \quad \text{Ps} \text{ is part of the value function representation of } V(x, s) = x' P(s) x + d(s) \]

\[ \text{ds} \quad \text{[array_like(float)]} \quad \text{ds} \text{ is part of the value function representation of } V(x, s) = x' P(s) x + d(s) \]

\[ \text{Fs} \quad \text{[array_like(float)]} \quad \text{Fs} \text{ is the policy rule that determines the choice of control in each period at each Markov state} \]

### 5.17 lqnash

The solution computed in this routine is the \( f_i \) and \( p_i \) of the associated double optimal linear regulator problem.

**Parameters**

- **A** [scalar(float) or array_like(float)] Corresponds to the above equation, should be of size \((n, n)\)
- **B1** [scalar(float) or array_like(float)] As above, size \((n, k_1)\)
- **B2** [scalar(float) or array_like(float)] As above, size \((n, k_2)\)
- **R1** [scalar(float) or array_like(float)] As above, size \((n, n)\)
- **R2** [scalar(float) or array_like(float)] As above, size \((n, n)\)
- **Q1** [scalar(float) or array_like(float)] As above, size \((k_1, k_1)\)
- **Q2** [scalar(float) or array_like(float)] As above, size \((k_2, k_2)\)
- **S1** [scalar(float) or array_like(float)] As above, size \((k_1, k_1)\)
- **S2** [scalar(float) or array_like(float)] As above, size \((k_2, k_2)\)
- **W1** [scalar(float) or array_like(float)] As above, size \((n, k_1)\)
- **W2** [scalar(float) or array_like(float)] As above, size \((n, k_2)\)
- **M1** [scalar(float) or array_like(float)] As above, size \((k_2, k_1)\)
- **M2** [scalar(float) or array_like(float)] As above, size \((k_1, k_2)\)
- **beta** [scalar(float), optional(default=1.0)] Discount rate
- **tol** [scalar(float), optional(default=1e-8)] This is the tolerance level for convergence
- **max_iter** [scalar(int), optional(default=1000)] This is the maximum number of iterations allowed
random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

F1 [array_like, dtype=float, shape=(k_1, n)] Feedback law for agent 1
F2 [array_like, dtype=float, shape=(k_2, n)] Feedback law for agent 2
P1 [array_like, dtype=float, shape=(n, n)] The steady-state solution to the associated discrete matrix Riccati equation for agent 1
P2 [array_like, dtype=float, shape=(n, n)] The steady-state solution to the associated discrete matrix Riccati equation for agent 2

5.18 lss

Computes quantities associated with the Gaussian linear state space model.

5.18.1 References

https://lectures.quantecon.org/py/linear_models.html

class quantecon.lss.LinearStateSpace (A, C, G=H=None, mu_0=None, Sigma_0=None)
Bases: object

A class that describes a Gaussian linear state space model of the form:

\[ x_{t+1} = Ax_t + Cw_{t+1} \]
\[ y_t = Gx_t + Hv_t \]

where \( w_t \) and \( v_t \) are independent and standard normal with dimensions k and l respectively. The initial conditions are \( \mu_0 \) and \( \Sigma_0 \) for \( x_0 \sim N(\mu_0, \Sigma_0) \). When \( \Sigma_0 = 0 \), the draw of \( x_0 \) is exactly \( \mu_0 \).

Parameters

A [array_like or scalar(float)] Part of the state transition equation. It should be \( n \times n \)
C [array_like or scalar(float)] Part of the state transition equation. It should be \( n \times m \)
G [array_like or scalar(float)] Part of the observation equation. It should be \( k \times n \)
H [array_like or scalar(float), optional(default=None)] Part of the observation equation. It should be \( k \times l \)
mu_0 [array_like or scalar(float), optional(default=None)] This is the mean of initial draw and is \( n \times 1 \)
Sigma_0 [array_like or scalar(float), optional(default=None)] This is the variance of the initial draw and is \( n \times n \) and also should be positive definite and symmetric

Attributes

A, C, G, H, mu_0, Sigma_0 [see Parameters]
n, k, m, l [scalar(int)] The dimensions of \( x_t, y_t, w_t \) and \( v_t \) respectively
Methods

**convert** (self, x)
Convert array_like objects (lists of lists, floats, etc.) into well formed 2D NumPy arrays

**geometric_sums** (self, beta, x_t)
Forecast the geometric sums

**impulse_response** (self, j)
Pulls off the impulse response coefficients to a shock in \( w_t \) for \( x \) and \( y \)

**moment_sequence** (self)
Create a generator to calculate the population mean and variance-covariance matrix for both \( x_t \) and \( y_t \) starting at the initial condition (self.mu_0, self.Sigma_0).

**replicate** (self, T, num_reps, random_state)
Simulate num_reps observations of \( x_T \) and \( y_T \) given \( x_0 \sim N(\mu_0, \Sigma_0) \).

**simulate** (self, ts_length, random_state)
Simulate a time series of length ts_length, first drawing stationary_distributions:

**stationary_distributions** (self, max_iter, tol)
Compute the moments of the stationary distributions of \( x_t \) and \( y_t \) if possible.

---

**convert** (self, x)
Convert array_like objects (lists of lists, floats, etc.) into well formed 2D NumPy arrays

**geometric_sums** (self, beta, x_t)
Forecast the geometric sums

\[
S_x := E \left[ \sum_{j=0}^{\infty} \beta^j x_{t+j} | x_t \right]
\]

\[
S_y := E \left[ \sum_{j=0}^{\infty} \beta^j y_{t+j} | x_t \right]
\]

**Parameters**

- **beta** [scalar(float)] Discount factor, in [0, 1)
- **beta** [array_like(float)] The term x_t for conditioning

**Returns**

- **S_x** [array_like(float)] Geometric sum as defined above
- **S_y** [array_like(float)] Geometric sum as defined above

**impulse_response** (self, j=5)
Pulls off the impulse response coefficients to a shock in \( w_t \) for \( x \) and \( y \)

Important to note: We are uninterested in the shocks to \( v \) for this method

- \( x \) coefficients are \( C, AC, A^2C \ldots \)
- \( y \) coefficients are \( GC, GAC, GA^2C \ldots \)

**Parameters**

- **j** [Scalar(int)] Number of coefficients that we want

**Returns**

- **xcoef** [list(array_like(float, 2))] The coefficients for \( x \)
- **ycoef** [list(array_like(float, 2))] The coefficients for \( y \)
moment_sequence (self)
Create a generator to calculate the population mean and variance-convariance matrix for both \(x_t\) and \(y_t\) starting at the initial condition \((self.mu_0, self.Sigma_0)\). Each iteration produces a 4-tuple of items \((mu_x, mu_y, Sigma_x, Sigma_y)\) for the next period.

Yields

- **mu_x**: \([\text{array_like(float)}]\) An \(n \times 1\) array representing the population mean of \(x_t\)
- **mu_y**: \([\text{array_like(float)}]\) A \(k \times 1\) array representing the population mean of \(y_t\)
- **Sigma_x**: \([\text{array_like(float)}]\) An \(n \times n\) array representing the variance-covariance matrix of \(x_t\)
- **Sigma_y**: \([\text{array_like(float)}]\) A \(k \times k\) array representing the variance-covariance matrix of \(y_t\)

replicate (self, T=10, num_reps=100, random_state=None)
Simulate num_reps observations of \(x_T\) and \(y_T\) given \(x_0 \sim N(\mu_0, \Sigma_0)\).

Parameters

- **T**: \([\text{scalar(int)}, \text{optional}(default=10)]\) The period that we want to replicate values for
- **num_reps**: \([\text{scalar(int)}, \text{optional}(default=100)]\) The number of replications that we want
- **random_state**: \([\text{int or np.random.RandomState, optional}]\) Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

- **x**: \([\text{array_like(float)}]\) An \(n \times \text{num_reps}\) array, where the \(j\)-th column is the \(j\_th\) observation of \(x_T\)
- **y**: \([\text{array_like(float)}]\) A \(k \times \text{num_reps}\) array, where the \(j\)-th column is the \(j\_th\) observation of \(y_T\)

simulate (self, ts_length=100, random_state=None)
Simulate a time series of length ts_length, first drawing \(x_0 \sim N(\mu_0, \Sigma_0)\)

Parameters

- **ts_length**: \([\text{scalar(int)}, \text{optional}(default=100)]\) The length of the simulation
- **random_state**: \([\text{int or np.random.RandomState, optional}]\) Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

- **x**: \([\text{array_like(float)}]\) An \(n \times \text{ts_length}\) array, where the \(t\)-th column is \(x_t\)
- **y**: \([\text{array_like(float)}]\) A \(k \times \text{ts_length}\) array, where the \(t\)-th column is \(y_t\)

stationary_distributions (self, max_iter=200, tol=1e-05)
Compute the moments of the stationary distributions of \(x_t\) and \(y_t\) if possible. Computation is by iteration, starting from the initial conditions \(self.mu_0\) and \(self.Sigma_0\)

Parameters

- **max_iter**: \([\text{scalar(int)}, \text{optional}(default=200)]\) The maximum number of iterations allowed
tol [scalar(float), optional(default=1e-5)] The tolerance level that one wishes to achieve

Returns

mu_x_star [array_like(float)] An n x 1 array representing the stationary mean of \( x_t \)
mu_y_star [array_like(float)] An k x 1 array representing the stationary mean of \( y_t \)
Sigma_x_star [array_like(float)] An n x n array representing the stationary var-cov matrix of \( x_t \)
Sigma_y_star [array_like(float)] An k x k array representing the stationary var-cov matrix of \( y_t \)

quantecon.lss.multivariate_normal (mean, cov[, size, check_valid, tol])

Draw random samples from a multivariate normal distribution.

The multivariate normal, multinormal or Gaussian distribution is a generalization of the one-dimensional normal distribution to higher dimensions. Such a distribution is specified by its mean and covariance matrix. These parameters are analogous to the mean (average or “center”) and variance (standard deviation, or “width,” squared) of the one-dimensional normal distribution.

Parameters

mean [1-D array_like, of length N] Mean of the N-dimensional distribution.
cov [2-D array_like, of shape (N, N)] Covariance matrix of the distribution. It must be symmetric and positive-semidefinite for proper sampling.
size [int or tuple of ints, optional] Given a shape of, for example, \((m, n, k)\), \(m\times n\times k\) samples are generated, and packed in an \(m\)-by-\(n\)-by-\(k\) arrangement. Because each sample is \(N\)-dimensional, the output shape is \((n, n, k, N)\). If no shape is specified, a single \((N-D)\) sample is returned.
check_valid [{‘warn’, ‘raise’, ‘ignore’}, optional] Behavior when the covariance matrix is not positive semidefinite.
tol [float, optional] Tolerance when checking the singular values in covariance matrix. cov is cast to double before the check.

Returns

out [ndarray] The drawn samples, of shape size, if that was provided. If not, the shape is \((N,)\).

In other words, each entry \(\text{out}[i, j, \ldots, :]\) is an N-dimensional value drawn from the distribution.

Notes

The mean is a coordinate in N-dimensional space, which represents the location where samples are most likely to be generated. This is analogous to the peak of the bell curve for the one-dimensional or univariate normal distribution.

Covariance indicates the level to which two variables vary together. From the multivariate normal distribution, we draw N-dimensional samples, \(X = [x_1, x_2, \ldots x_N]\). The covariance matrix element \(C_{ij}\) is the covariance of \(x_i\) and \(x_j\). The element \(C_{ii}\) is the variance of \(x_i\) (i.e. its “spread”).

Instead of specifying the full covariance matrix, popular approximations include:

- Spherical covariance (\(cov\) is a multiple of the identity matrix)
- Diagonal covariance (\(cov\) has non-negative elements, and only on the diagonal)
This geometrical property can be seen in two dimensions by plotting generated data-points:

```python
>>> mean = [0, 0]
>>> cov = [[1, 0], [0, 100]]  # diagonal covariance
```

Diagonal covariance means that points are oriented along x or y-axis:

```python
>>> import matplotlib.pyplot as plt
>>> x, y = np.random.multivariate_normal(mean, cov, 5000).T
>>> plt.plot(x, y, 'x')
>>> plt.axis('equal')
>>> plt.show()
```

Note that the covariance matrix must be positive semidefinite (a.k.a. nonnegative-definite). Otherwise, the behavior of this method is undefined and backwards compatibility is not guaranteed.

**References**

[1], [2]

**Examples**

```python
>>> mean = (1, 2)
>>> cov = [[1, 0], [0, 1]]
>>> x = np.random.multivariate_normal(mean, cov, (3, 3))
>>> x.shape
(3, 3, 2)
```

The following is probably true, given that 0.6 is roughly twice the standard deviation:

```python
>>> list((x[0,0,0] - mean) < 0.6)
[True, True]
```

```python
quantEcon.lss.simulate_linear_model(A, x0, v, ts_length)
```

This is a separate function for simulating a vector linear system of the form

\[ x_{t+1} = Ax_t + v_t \]

given \( x_0 = x0 \)

Here \( x_t \) and \( v_t \) are both n x 1 and \( A \) is n x n.

The purpose of separating this functionality out is to target it for optimization by Numba. For the same reason, matrix multiplication is broken down into for loops.

**Parameters**

- \( A \) [array_like or scalar(float)] Should be n x n
- \( x0 \) [array_like] Should be n x 1. Initial condition
- \( v \) [np.ndarray] Should be n x ts_length-1. Its t-th column is used as the time t shock \( v_t \)
- \( ts\_length \) [int] The length of the time series

**Returns**

- \( x \) [np.ndarray] Time series with ts_length columns, the t-th column being \( x_t \)
5.19 matrix_eqn

This file holds several functions that are used to solve matrix equations. Currently has functionality to solve:

- Lyapunov Equations
- Riccati Equations

**TODO:** 1. See issue 47 on github repository, should add support for Sylvester equations
2. Fix warnings from checking conditioning of matrices

```python
def solve_discrete_lyapunov(A, B, max_it=50, method='doubling')
    Computes the solution to the discrete lyapunov equation
    \[ AXA' - X + B = 0 \]
    \( X \) is computed by using a doubling algorithm. In particular, we iterate to convergence on \( X_j \) with the following recursions for \( j = 1, 2, \ldots \) starting from \( X_0 = B, a_0 = A \):
    \[ a_j = a_{j-1}a_{j-1} \]
    \[ X_j = X_{j-1} + a_{j-1}X_{j-1}a_{j-1}' \]
```

**Parameters**

- `A` [array_like(float, ndim=2)] An \( n \times n \) matrix as described above. We assume in order for convergence that the eigenvalues of \( A \) have moduli bounded by unity
- `B` [array_like(float, ndim=2)] An \( n \times n \) matrix as described above. We assume in order for convergence that the eigenvalues of \( A \) have moduli bounded by unity
- `max_it` [scalar(int), optional(default=50)] The maximum number of iterations
- `method` [string, optional(default="doubling")] Describes the solution method to use. If it is "doubling" then uses the doubling algorithm to solve, if it is "bartels-stewart" then it uses scpy’s implementation of the Bartels-Stewart approach.

**Returns**

- `gamma1`: array_like(float, ndim=2) Represents the value \( X \)

```python
def solve_discrete_riccati(A, B, Q, R, N=None, tolerance=1e-10, max_iter=500, method='doubling')
    Solves the discrete-time algebraic Riccati equation
    \[ X = A'XA - (N + B'XB + R)^{-1}(N + B'XB + R)(N + B'XA) + Q \]
    Computation is via a modified structured doubling algorithm, an explanation of which can be found in the reference below, if `method`="doubling" (default), and via a QZ decomposition method by calling `scipy.linalg.solve_discrete_are` if `method"="qz".
```

**Parameters**

- `A` [array_like(float, ndim=2)] \( k \times k \) array.
- `B` [array_like(float, ndim=2)] \( k \times n \) array
- `Q` [array_like(float, ndim=2)] \( k \times k \), should be symmetric and non-negative definite
- `R` [array_like(float, ndim=2)] \( n \times n \), should be symmetric and positive definite
- `N` [array_like(float, ndim=2)] \( n \times k \) array
- `tolerance` [scalar(float), optional(default=1e-10)] The tolerance level for convergence
max_iter  [scalar(int), optional=default=500]) The maximum number of iterations allowed

method  [string, optional=default="doubling")] Describes the solution method to use. If it is “doubling” then uses the doubling algorithm to solve, if it is “qz” then it uses scipy.linalg.solve_discrete_are (in which case tolerance and max_iter are irrelevant).

Returns

X  [array_like(float, ndim=2)] The fixed point of the Riccati equation; a k x k array representing the approximate solution

References


quantecol.matrix_eqn.solve_discrete_riccati_system(Π, As, Bs, Cs, Qs, Rs,
Ns, beta, tolerance=1e-10,
max_iter=1000)

Solves the stacked system of algebraic matrix Riccati equations in the Markov Jump linear quadratic control problems, by iterating Ps matrices until convergence.

Parameters

Π  [array_like(float, ndim=2)] The Markov chain transition matrix with dimension m x m.

As  [array_like(float)] Consists of m state transition matrices A(s) with dimension n x n for each Markov state s

Bs  [array_like(float)] Consists of m state transition matrices B(s) with dimension n x k for each Markov state s

Cs  [array_like(float), optional=default=None] Consists of m state transition matrices C(s) with dimension n x j for each Markov state s. If the model is deterministic then Cs should take default value of None

Qs  [array_like(float)] Consists of m symmetric and non-negative definite payoff matrices Q(s) with dimension k x k that corresponds with the control variable u for each Markov state s

Rs  [array_like(float)] Consists of m symmetric and non-negative definite payoff matrices R(s) with dimension n x n that corresponds with the state variable x for each Markov state s

Ns  [array_like(float), optional=default=None] Consists of m cross product term matrices N(s) with dimension k x n for each Markov state,

beta  [scalar(float), optional=default=1)] beta is the discount parameter

tolerance  [scalar(float), optional=default=1e-10)] The tolerance level for convergence

max_iter  [scalar(int), optional=default=500)] The maximum number of iterations allowed

Returns

Ps  [array_like(float, ndim=2)] The fixed point of the stacked system of algebraic matrix Riccati equations, consists of m n x n P(s) matrices
5.20 quad

Defining various quadrature routines.
Based on the quadrature routines found in the CompEcon toolbox by Miranda and Fackler.

5.20.1 References


```
quantecon.quad.qnwcheb(n, a=1, b=1)
```
Computes multivariate Guass-Chebyshev quadrature nodes and weights.

**Parameters**

- `n` [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- `a` [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- `b` [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

**Returns**

- `nodes` [np.ndarray(dtype=float)] Quadrature nodes
- `weights` [np.ndarray(dtype=float)] Weights for quadrature nodes

**Notes**

Based of original function qnwcheb in CompEcon toolbox by Miranda and Fackler

**References**


```
quantecon.quad.qnwequi(n, a, b, kind='N', equidist_pp=None, random_state=None)
```
Generates equidistributed sequences with property that averages value of integrable function evaluated over the sequence converges to the integral as n goes to infinity.

**Parameters**

- `n` [int] Number of sequence points
- `a` [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- `b` [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- `kind` [string, optional(default="N")] One of the following:
  - N - Neiderreiter (default)
  - W - Weyl
  - H - Haber
  - R - pseudo Random
equidist_pp [array_like, optional\((default=None)\)] TODO: I don’t know what this does

random_state [int or np.random.RandomState, optional] Random seed (integer) or np.random.RandomState instance to set the initial state of the random number generator for reproducibility. If None, a randomly initialized RandomState is used.

Returns

nodes [np.ndarray\(\text{dtype}=\float\)] Quadrature nodes

weights [np.ndarray\(\text{dtype}=\float\)] Weights for quadrature nodes

Notes

Based of original function qnwequi in CompEcon toolbox by Miranda and Fackler

References


quantecon.quad.qnwequi \((n, a, b)\)
Computes multivariate Guass-Legendre quadrature nodes and weights.

Parameters

n [int or array_like\(\text{float}\)] A length-d iterable of the number of nodes in each dimension

a [scalar or array_like\(\text{float}\)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

b [scalar or array_like\(\text{float}\)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

Returns

nodes [np.ndarray\(\text{dtype}=\float\)] Quadrature nodes

weights [np.ndarray\(\text{dtype}=\float\)] Weights for quadrature nodes

Notes

Based of original function qnwequi in CompEcon toolbox by Miranda and Fackler

References


quantecon.quad.qnwnorm \((n, \mu=None, \sigma^2=None, usesqrtm=False)\)
Computes nodes and weights for multivariate normal distribution

Parameters

n [int or array_like\(\text{float}\)] A length-d iterable of the number of nodes in each dimension

\(\mu\) [scalar or array_like\(\text{float}\), optional\((\text{default}=\text{zeros}(d))\)] The means of each dimension of the random variable. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

\(\sigma^2\) [array_like\(\text{float}\), optional\((\text{default}=\text{eye}(d))\)] A d x d array representing the variance-covariance matrix of the multivariate normal distribution.
Returns

- **nodes** [np.ndarray(dtype=float)] Quadrature nodes
- **weights** [np.ndarray(dtype=float)] Weights for quadrature nodes

Notes

Based of original function `qnwnorm` in CompEcon toolbox by Miranda and Fackler

References


**quantecon.quad.qnwlgn** (*n*, *mu=None*, *sig2=None*)
Computes nodes and weights for multivariate lognormal distribution

Parameters

- **n** [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- **mu** [scalar or array_like(float), optional(default=zeros(d))] The means of each dimension of the random variable. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- **sig2** [array_like(float), optional(default=eye(d))] A d x d array representing the variance-covariance matrix of the multivariate normal distribution.

Returns

- **nodes** [np.ndarray(dtype=float)] Quadrature nodes
- **weights** [np.ndarray(dtype=float)] Weights for quadrature nodes

Notes

Based of original function `qnwlgn` in CompEcon toolbox by Miranda and Fackler

References


**quantecon.quad.qnwsimp** (*n*, *a*, *b*)
Computes multivariate Simpson quadrature nodes and weights.

Parameters

- **n** [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- **a** [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- **b** [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

Returns

- **nodes** [np.ndarray(dtype=float)] Quadrature nodes
- **weights** [np.ndarray(dtype=float)] Weights for quadrature nodes
Notes

Based of original function qnwsimp in CompEcon toolbox by Miranda and Fackler

References


quantecon.quad.qnwtrap(n, a, b)
Computes multivariate trapezoid rule quadrature nodes and weights.

Parameters

- **n** [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- **a** [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- **b** [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

Returns

- **nodes** [np.ndarray(dtype=float)] Quadrature nodes
- **weights** [np.ndarray(dtype=float)] Weights for quadrature nodes

Notes

Based of original function qnwtrap in CompEcon toolbox by Miranda and Fackler

References


quantecon.quad.qnwunif(n, a, b)
Computes quadrature nodes and weights for multivariate uniform distribution

Parameters

- **n** [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- **a** [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions
- **b** [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated d times, where d is the number of dimensions

Returns

- **nodes** [np.ndarray(dtype=float)] Quadrature nodes
- **weights** [np.ndarray(dtype=float)] Weights for quadrature nodes

Notes

Based of original function qnwunif in CompEcon toolbox by Miranda and Fackler
References


quantecon.quad.quadrect \( (f, n, a, b, \text{kind}='\text{lege}', *\text{args}, **\text{kwargs}) \)

Integrate the d-dimensional function \( f \) on a rectangle with lower and upper bound for dimension \( i \) defined by \( a[i] \) and \( b[i] \), respectively; using \( n[i] \) points.

**Parameters**

- \( f \) [function] The function to integrate over. This should be a function that accepts as its first argument a matrix representing points along each dimension (each dimension is a column). Other arguments that need to be passed to the function are caught by \( *\text{args} \) and \( **\text{kwargs} \).
- \( n \) [int or array_like(float)] A length-d iterable of the number of nodes in each dimension.
- \( a \) [scalar or array_like(float)] A length-d iterable of lower endpoints. If a scalar is given, that constant is repeated \( d \) times, where \( d \) is the number of dimensions.
- \( b \) [scalar or array_like(float)] A length-d iterable of upper endpoints. If a scalar is given, that constant is repeated \( d \) times, where \( d \) is the number of dimensions.
- \( \text{kind} \) [string, optional(default='lege')] Specifies which type of integration to perform. Valid values are:
  - 'lege' - Gauss-Legendre
  - 'cheb' - Gauss-Chebyshev
  - 'trap' - Trapezoid rule
  - 'simp' - Simpson rule
  - 'N' - Neiderreiter equidistributed sequence
  - 'W' - Weyl equidistributed sequence
  - 'H' - Haber equidistributed sequence
  - 'R' - Monte Carlo
- \( *\text{args}, **\text{kwargs} \): Other arguments passed to the function \( f \).

**Returns**

- \( \text{out} \) [scalar (float)] The value of the integral on the region \([a, b]\).

Notes

Based of original function quadrect in CompEcon toolbox by Miranda and Fackler

References


quantecon.quad.qnwbeta \( (n, a=1.0, b=1.0) \)

Computes nodes and weights for beta distribution

**Parameters**

- \( n \) [int or array_like(float)] A length-d iterable of the number of nodes in each dimension.
- \( a \) [scalar or array_like(float), optional(default=1.0)] A length-d.
- \( b \) [array_like(float), optional(default=1.0)] A \( d \times d \) array representing the variance-covariance matrix of the multivariate normal distribution.

**Returns**

- \( \text{nodes} \) [np.ndarray(dtype=float)] Quadrature nodes.
- \( \text{weights} \) [np.ndarray(dtype=float)] Weights for quadrature nodes.
Notes

Based of original function \texttt{qnwbeta} in CompEcon toolbox by Miranda and Fackler

References


\texttt{quantecon.quad.qnwgamma}\,(n, a=1.0, b=1.0, tol=3e-14)
Computes nodes and weights for gamma distribution

Parameters

- \texttt{n} [int or array_like(float)] A length-d iterable of the number of nodes in each dimension
- \texttt{a} [scalar or array_like(float)] Shape parameter of the gamma distribution parameter. Must be positive
- \texttt{b} [scalar or array_like(float)] Scale parameter of the gamma distribution parameter. Must be positive
- \texttt{tol} [scalar or array_like(float)] Tolerance parameter for newton iterations for each node

Returns

- \texttt{nodes} [np.ndarray(dtype=float)] Quadrature nodes
- \texttt{weights} [np.ndarray(dtype=float)] Weights for quadrature nodes

Notes

Based of original function \texttt{qnwgamma} in CompEcon toolbox by Miranda and Fackler

References


5.21 quadsums

This module provides functions to compute quadratic sums of the form described in the docstrings.

\texttt{quantecon.quadsums.m_quadratic_sum}\,(A, B, max_it=50)
Computes the quadratic sum

\[ V = \sum_{j=0}^{\infty} A^jBA^j \]

V is computed by solving the corresponding discrete lyapunov equation using the doubling algorithm. See the documentation of \texttt{util.solve_discrete_lyapunov} for more information.

Parameters

- \texttt{A} [array_like(float, ndim=2)] An n x n matrix as described above. We assume in order for convergence that the eigenvalues of A have moduli bounded by unity
- \texttt{B} [array_like(float, ndim=2)] An n x n matrix as described above. We assume in order for convergence that the eigenvalues of A have moduli bounded by unity
max_it [scalar(int), optional(default=50)] The maximum number of iterations

Returns

gamma1: array_like(float, ndim=2) Represents the value $V$

quantecon.quadsums.var_quadratic_sum($A$, $H$, $beta$, $x0$)
Computes the expected discounted quadratic sum

$$q(x_0) = E \left[ \sum_{t=0}^{\infty} \beta^t x_t' H x_t \right]$$

Here $x_t$ is the VAR process $x_{t+1} = Ax_t + Cw_t$ with $x_t$ standard normal and $x_0$ the initial condition.

Parameters

$A$ [array_like(float, ndim=2)] The matrix described above in description. Should be n x n
$C$ [array_like(float, ndim=2)] The matrix described above in description. Should be n x n
$H$ [array_like(float, ndim=2)] The matrix described above in description. Should be n x n
$beta$: scalar(float) Should take a value in (0, 1)
$x_0$: array_like(float, ndim=1) The initial condition. A conformable array (of length n, or with n rows)

Returns

$q0$: scalar(float) Represents the value $q(x_0)$

Remarks: The formula for computing $q(x_0)$ is

$$q(x_0) = x_0' Q x_0 + v$$

where

- $Q$ is the solution to $Q = H + \beta A' Q A$, and
- $v = \frac{trace(C' Q C) \beta}{(1-\beta)}$

### 5.22 rank_nullspace

quantecon.rank_nullspace.nullspace($A$, atol=1e-13, rtol=0)
Compute an approximate basis for the nullspace of $A$.

The algorithm used by this function is based on the singular value decomposition of $A$.

Parameters

$A$ [array_like(float, ndim=1 or 2)] $A$ should be at most 2-D. A 1-D array with length k will be treated as a 2-D with shape (1, k)
atol [scalar(float), optional(default=1e-13)] The absolute tolerance for a zero singular value.
Singular values smaller than atol are considered to be zero.
rtol [scalar(float), optional(default=0)] The relative tolerance. Singular values less than rtol*smax are considered to be zero, where smax is the largest singular value.

Returns
ns [array_like(float, ndim=2)] If \( A \) is an array with shape \((m, k)\), then \( ns \) will be an array with shape \((k, n)\), where \( n \) is the estimated dimension of the nullspace of \( A \). The columns of \( ns \) are a basis for the nullspace; each element in \( \text{numpy.dot}(A, ns) \) will be approximately zero.

**Note:** If both \( atol \) and \( rtol \) are positive, the combined tolerance is the maximum of the two; that is: \( \text{tol} = \max(atol, rtol * \text{smax}) \)

**Note:** Singular values smaller than \( tol \) are considered to be zero.

\[
\text{numpy.linalg.matrix_rank} \quad \text{matrix_rank} \text{ is basically the same as this function, but it does not provide the option of the absolute tolerance.}
\]

### 5.23 robustlq

Solves robust LQ control problems.

**class** `quantecon.robustlq.RBLQ(Q, R, A, B, C, beta, theta)`

**Bases:** `object`

Provides methods for analysing infinite horizon robust LQ control problems of the form

\[
\min_{u_t} \sum_t \beta^t x_t' R x_t + u_t' Q u_t
\]

subject to

\[
x_{t+1} = A x_t + B u_t + C w_{t+1}
\]

and with model misspecification parameter \( \theta \).

**Parameters**
Q [array_like(float, ndim=2)] The cost (payoff) matrix for the controls. See above for more. Q should be k x k and symmetric and positive definite

R [array_like(float, ndim=2)] The cost (payoff) matrix for the state. See above for more. R should be n x n and symmetric and non-negative definite

A [array_like(float, ndim=2)] The matrix that corresponds with the state in the state space system. A should be n x n

B [array_like(float, ndim=2)] The matrix that corresponds with the control in the state space system. B should be n x k

C [array_like(float, ndim=2)] The matrix that corresponds with the random process in the state space system. C should be n x j

beta [scalar(float)] The discount factor in the robust control problem

theta [scalar(float)] The robustness factor in the robust control problem

Attributes

Q, R, A, B, C, beta, theta [see Parameters]

k, n, j [scalar(int)] The dimensions of the matrices

Methods

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<td>robust_rule(self[, method])</td>
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F_to_K(self, F, method='doubling')

Compute agent 2’s best cost-minimizing response K, given F.

Parameters

F [array_like(float, ndim=2)] A k x n array

method [str, optional(default='doubling')] Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}.

Returns
K: array_like(float, ndim=2) Agent’s best cost minimizing response for a given F
P: array_like(float, ndim=2) The value function for a given F

K_to_F(self, K, method='doubling')
Compute agent 1’s best value-maximizing response F, given K.

Parameters
K: array_like(float, ndim=2) A j x n array
   method: str, optional(default='doubling') Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}.

Returns
F: array_like(float, ndim=2) The policy function for a given K
P: array_like(float, ndim=2) The value function for a given K

b_operator(self, P)
The B operator, mapping P into

\[ B(P) := R - \beta^2 A'PB(Q + \beta B'PB)^{-1}B'PA + \beta A'PA \]

and also returning

\[ F := (Q + \beta B'PB)^{-1}\beta B'PA \]

Parameters
P: array_like(float, ndim=2) A matrix that should be n x n

Returns
F: array_like(float, ndim=2) The F matrix as defined above
new_p: array_like(float, ndim=2) The matrix P after applying the B operator

compute_deterministic_entropy(self, F, K, x0)
Given K and F, compute the value of deterministic entropy, which is

\[ \sum_t \beta^t x_t'K'Kx_t' \]

with

\[ x_{t+1} = (A - BF + CK)x_t \]

Parameters
F: array_like(float, ndim=2) The policy function, a k x n array
K: array_like(float, ndim=2) The worst case matrix, a j x n array
x0: array_like(float, ndim=1) The initial condition for state

Returns
e: scalar(int) The deterministic entropy

d_operator(self, P)
The D operator, mapping P into

\[ D(P) := P + PC(\theta I - C'PC)^{-1}C'P. \]
Parameters

- **P** [array_like(float, ndim=2)] A matrix that should be n x n

Returns

- **dP** [array_like(float, ndim=2)] The matrix P after applying the D operator

**evaluate_F** *(self, F)*

Given a fixed policy F, with the interpretation \( u = -Fx \), this function computes the matrix \( P_F \) and constant \( d_F \) associated with discounted cost \( J_F(x) = x'P_Fx + d_F \).

Parameters

- **F** [array_like(float, ndim=2)] The policy function, a k x n array

Returns

- **P_F** [array_like(float, ndim=2)] Matrix for discounted cost
- **d_F** [scalar(float)] Constant for discounted cost
- **K_F** [array_like(float, ndim=2)] Worst case policy
- **O_F** [array_like(float, ndim=2)] Matrix for discounted entropy
- **o_F** [scalar(float)] Constant for discounted entropy

**robust_rule** *(self, method='doubling')*

This method solves the robust control problem by tricking it into a stacked LQ problem, as described in chapter 2 of Hansen-Sargent’s text “Robustness.” The optimal control with observed state is

\[
 u_t = -Fx_t
\]

And the value function is \( -x'Px \).

Parameters

- **method** [str, optional(default='doubling')] Solution method used in solving the associated Riccati equation, str in {'doubling', 'qz'}.

Returns

- **F** [array_like(float, ndim=2)] The optimal control matrix from above
- **P** [array_like(float, ndim=2)] The positive semi-definite matrix defining the value function
- **K** [array_like(float, ndim=2)] the worst-case shock matrix K, where \( w_{t+1} = Kx_t \) is the worst case shock

**robust_rule_simple** *(self, P_init=None, max_iter=80, tol=1e-08)*

A simple algorithm for computing the robust policy F and the corresponding value function P, based around straightforward iteration with the robust Bellman operator. This function is easier to understand but one or two orders of magnitude slower than self.robust_rule(). For more information see the docstring of that method.

Parameters

- **P_init** [array_like(float, ndim=2), optional(default=None)] The initial guess for the value function matrix. It will be a matrix of zeros if no guess is given
- **max_iter** [scalar(int), optional(default=80)] The maximum number of iterations that are allowed
- **tol** [scalar(float), optional(default=1e-8)] The tolerance for convergence
Returns

- **F** [array_like(float, ndim=2)] The optimal control matrix from above
- **P** [array_like(float, ndim=2)] The positive semi-definite matrix defining the value function
- **K** [array_like(float, ndim=2)] the worst-case shock matrix K, where $w_{t+1} = K x_t$ is the worst case shock
6.1 array

6.1.1 Array Utilities

Array

searchsorted

quantecon.util.array.searchsorted(a, v)

Custom version of np.searchsorted. Return the largest index $i$ such that $a[i-1] <= v < a[i]$ (for $i = 0$, $v < a[0]$); if $v[n-1] <= v < v$, return $n$, where $n = len(a)$.

Parameters

- **a** [ndarray(float, ndim=1)] Input array. Must be sorted in ascending order.
- **v** [scalar(float)] Value to be compared with elements of $a$.

Returns

- **scalar(int)** Largest index $i$ such that $a[i-1] <= v < a[i]$, or len(a) if no such index exists.

Notes

This routine is jit-complied if the module Numba is vailable; if not, it is an alias of np.searchsorted(a, v, side='right').

Examples
6.2 combinatorics

Useful routines for combinatorics

```python
>>> a = np.array([0.2, 0.4, 1.0])
>>> searchsorted(a, 0.1)
0
>>> searchsorted(a, 0.4)
2
>>> searchsorted(a, 2)
3
```

**quant econ.util.combinatorics.k_array_rank** *(a)*

Given an array a of k distinct nonnegative integers, sorted in ascending order, return its ranking in the lexicographic ordering of the descending sequences of the elements [1].

**Parameters**

- **a** [ndarray(int, ndim=1)] Array of length k.

**Returns**

- **idx** [scalar(int)] Ranking of a.

**References**

[1]

**quant econ.util.combinatorics.k_array_rank_jit** *(a)*

Numba jit version of k_array_rank.

**Notes**

An incorrect value will be returned without warning or error if overflow occurs during the computation. It is the user’s responsibility to ensure that the rank of the input array fits within the range of possible values of np.intp; a sufficient condition for it is scipy.special.comb(a[-1]+1, len(a), exact=True) <= np.iinfo(np.intp).max.

**quant econ.util.combinatorics.next_k_array** *(a)*

Given an array a of k distinct nonnegative integers, sorted in ascending order, return the next k-array in the lexicographic ordering of the descending sequences of the elements [1]. a is modified in place.

**Parameters**

- **a** [ndarray(int, ndim=1)] Array of length k.

**Returns**

- **a** [ndarray(int, ndim=1)] View of a.

**References**

[1]
Examples

Enumerate all the subsets with $k$ elements of the set $\{0, \ldots, n-1\}$.

```python
>>> n, k = 4, 2
>>> a = np.arange(k)
>>> while a[-1] < n:
...    print(a)
...    a = next_k_array(a)
...
[0 1]
[0 2]
[1 2]
[0 3]
[1 3]
[2 3]
```

6.3 common_messages

6.3.1 Warnings Module

Contains a collection of warning messages for consistent package wide notifications

6.4 notebooks

Support functions to Support QuantEcon.notebooks

The purpose of these utilities is to implement simple support functions to allow for automatic downloading of any support files (python modules, or data) that may be required to run demonstration notebooks.

6.4.1 Note

Files on the REMOTE Github Server can be organised into folders but they will end up at the root level of when downloaded as a support File

```
“https://github.com/QuantEcon/QuantEcon.notebooks/raw/master/dependencies/mpi/something.py” -> ./something.py
```

6.4.2 TODO

1. Write Style guide for QuantEcon.notebook contributions
2. Write an interface for Dat Server
3. Platform Agnostic (replace wget usage)

```python
quantecon.util.notebooks.fetch_nb_dependencies(files, repo='https://github.com/QuantEcon/QuantEcon.notebooks',
                                              raw='raw', branch='master',
                                              folder='dependencies',
                                              overwrite=False, verbose=True)
```

Retrieve raw files from QuantEcon.notebooks or other Github repo
Parameters

- **file_list** list or dict: A list of files to specify a collection of filenames. A dict of dir: list(files) to specify a directory.
- **repo** str, optional (default=REPO)
- **raw** str, optional (default=RAW): This is here in case Github changes access to their raw files through web links.
- **branch** str, optional (default=BRANCH)
- **folder** str, optional (default=FOLDER)
- **overwrite** bool, optional (default=False)
- **verbose** bool, optional (default=True)

Examples

Consider a notebook that is dependent on a csv file to execute. If this file is located in a Github repository then it can be fetched using this utility.

Assuming the file is at the root level in the master branch then:

```python
>>> from quantecon.util import fetch_nb_dependencies
>>> status = fetch_nb_dependencies(['test.csv'], repo="https://<github_address>")
```

More than one file may be requested in the list provided:

```python
>>> status = fetch_nb_dependencies(['test.csv', 'data.csv'], repo="https://<github_address>")
```

A folder location can be added using **folder=**

```python
>>> status = fetch_nb_dependencies('test.csv', repo="https://<github_address>", folder="data")
```

You can also specify a specific branch using **branch=** keyword argument.

This will download the requested file(s) to your local working directory. The default behaviour is **not** to overwrite a local file if it is present. This can be switched off by setting **overwrite=True**.

### 6.5 numba

Utilities to support Numba jitted functions

```python
quantecon.util.numba.comb_jit(N, k)
```

Numba jitted function that computes N choose k. Return 0 if the outcome exceeds the maximum value of `np.intp` or if N < 0, k < 0, or k > N.

**Parameters**

- **N** [scalar(int)]
- **k** [scalar(int)]

**Returns**

- **val** [scalar(int)]
6.6 random

Utilities to Support Random State Infrastructure

```python
quantecon.util.random.check_random_state(seed)
```

Check the random state of a given seed.

- If seed is None, return the RandomState singleton used by np.random.
- If seed is an int, return a new RandomState instance seeded with seed.
- If seed is already a RandomState instance, return it.
- Otherwise raise ValueError.

6.7 timing

Provides Matlab-like tic, tac and toc functions.

```python
quantecon.util.timing.loop_timer(n, function, args=None, verbose=True, digits=2, best_of=3)
```

Return and print the total and average time elapsed for n runs of function.

- **Parameters**
  - `n` [scalar(int)] Number of runs.
  - `function` [function] Function to be timed.
  - `args` [list, optional(default=None)] Arguments of the function.
  - `verbose` [bool, optional(default=True)] If True, then prints average time.
  - `digits` [scalar(int), optional(default=2)] Number of digits printed for time elapsed.
  - `best_of` [scalar(int), optional(default=3)] Average time over best_of runs.

- **Returns**
  - `average_time` [scalar(float)] Average time elapsed for n runs of function.
  - `average_of_best` [scalar(float)] Average of best_of times for n runs of function.

```python
quantecon.util.timing.tac(verbos=True, digits=2)
```

Return and print elapsed time since last `tic()`, `tac()`, or `toc()`.

- **Parameters**
  - `verbose` [bool, optional(default=True)] If True, then prints time.
  - `digits` [scalar(int), optional(default=2)] Number of digits printed for time elapsed.

- **Returns**
  - `elapsed` [scalar(float)] Time elapsed since last `tic()`, `tac()`, or `toc()`.

```python
quantecon.util.timing.tic()
```

Save time for future use with `tac()` or `toc()`.

```python
quantecon.util.timing.toc(verbos=True, digits=2)
```

Return and print time elapsed since last `tic()`.

- **Parameters**
  - `verbose` [bool, optional(default=True)] If True, then prints time.
  - `digits` [scalar(int), optional(default=2)] Number of digits printed for time elapsed.

- **Returns**
elapsed  scalar(float) Time elapsed since last tic().
CHAPTER 7

Indices and tables

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- modindex
- search
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