1 ARLO: Automated Reinforcement Learning Optimizer

This library allows modular pipeline creation to solve RL problems. Two ways:

- Create an AutoRLPipeline block: I expect all the pipelines in the automatic block to end with a model generation block.
 - Jointly optimise the pipelines with no Automatic Blocks.
 - Jointly optimise the pipelines with Automatic Blocks.
- Create a RLPipeline block: A pipeline can end with any block.
 - You do not use Automatic Blocks: you perform some DataGeneration, DataPreparation, FeatureEngineering,
 ModelGeneration. You specify every hyper-parameter.

This can be used to test new blocks: take a benchmarked pipeline and swap a block with a new block. You see the impact on the pipeline.

 You do use Automatic Blocks: you can singly optimise a block of the pipeline between FeatureEngineering and ModelGeneration.

You can move from doing automated RL to hand-crafted RL:

- You can decide what to optimise and how
- You can benchmark new blocks
- You can find promising hyper-parameters configurations for new environments, or new RL algorithms. Create the heatmap of the hyper-parameters and see possible trends in the configuration space.
- You can fine-tune already well performing hyper-parameters configurations.
- Use everything implemented in this library with some of your custom blocks simply wrapping your custom block.
- Work on the blocks and don't worry how to piece everything together: focus on what's important. You want to test a new DataPreparation blocks: simply create a Class for it and instantiate a RL pipeline with the blocks already present in the library. Then benchmark your result with a pipeline that does not have your new DataPreparation block.

Units of the library:

• DataGeneration blocks: an environment enters the block and a dataset exits the block. This dataset will be used for learning a RL algorithm.

These blocks can only be inserted in an Offline RL pipeline.

• DataPreparation blocks: a dataset enters the block and a dataset exits the block. You can impute missing data, shuffle data, augment data.

These blocks can only be inserted in an Offline RL pipeline.

• FeatureEngineering blocks: a dataset and-or an environment enter the block and a dataset and-or an environment exit the block. You can discretise the state-action spaces, perform reward shaping, wrap the environment, apply transformations to the state-action spaces. Automated hyper-parameter tuning and algorithm selection can be applied.

- ModelGeneration blocks: a dataset and-or an environment enters the block and a policy exits: an RL algorithm is applied. Automated hyper-parameter tuning and algorithm selection can be applied.
- RLPipeline blocks: you can put together various blocks to perform tasks or sub-tasks in RL. You can just have a DataGeneration and DataPreparation blocks, or you can have an entire pipeline with a block from each of the possible Classes of blocks. Automated hyper-parameter tuning and algorithm selection can be applied.
- Tuner blocks: these blocks are used to perform hyper-parameter tuning. These can be used onto FeatureEngineering blocks, ModelGeneration blocks or RLPipeline blocks.

Specify your wanted Tuner and your wanted Metric and InputLoader.

- Metric blocks: these are used to measure the goodness of a certain block. For example it can compute the DiscountedReward of an agent acting in an environment.
- InputLoader blocks: these are used to decide how to transform the data to pass to each trial in the tuning procedure. For example you may have a selection of environments and you want to train on the randomly.

You can specify any custom unit you want.

Note that the hyper-parameters of all blocks must be specified as *HyperParameter* objects.

This library makes use of the following libraries:

- abc, numpy, scipy, pandas, cloudpickle, joblib, math, copy, os, datetime, itertools, matplotlib
- optuna
- plotly
- torch, gym, xgboost, catboost, MushroomRL, sklearn

List of implemented Classes for each unit:

DataGeneration:

- DataGenerationRandomUniformPolicy
- DataGenerationMEPOL

• Data Preparation:

- DataPreparationIdentity
- DataPreparation1NNImputation
- DataPreparationMeanImputation

• Feature Engineering:

- FeatureEngineeringIdentity
- FeatureEngineeringRFS
- FeatureEngineeringFSCMI
- FeatureEngineeringNystroemMap

Model Generation:

- ModelGenerationMushroomOnlineDQN

- ModelGenerationMushroomOnlinePPO
- ModelGenerationMushroomOnlineSAC
- ModelGenerationMushroomOnlineDDPG
- ModelGenerationMushroomOnlineGPOMDP
- ModelGenerationMushroomOfflineFQI
- ModelGenerationMushroomOfflineDoubleFQI
- ModelGenerationMushroomOfflineLSPI

• Environment:

- BaseGridWorld
- BaseCarOnHill
- BaseCartPole
- BaseInvertedPendulum
- LQG
- BaseHalfCheetah
- BaseAnt
- BaseHopper
- BaseHumanoid
- BaseSwimmer
- BaseWalker2d

• Input Loader:

- LoadSameEnv
- LoadSameTrainData
- LoadUniformSubSampleWithReplacement
- LoadUniformSubSampleWithReplacementAndEnv
- LoadDifferentSizeForEachBlock
- LoadDifferentSizeForEachBlockAndEnv

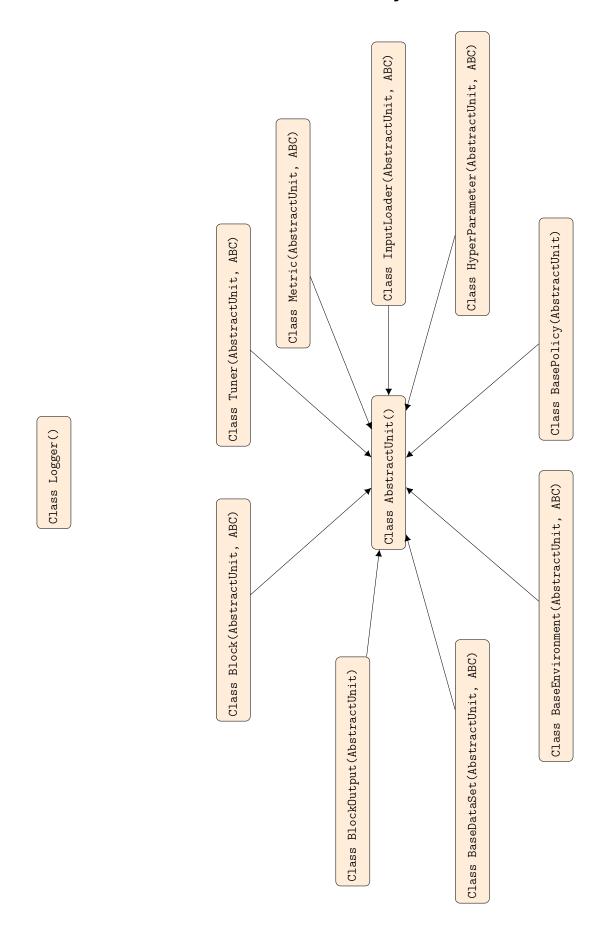
• Metric:

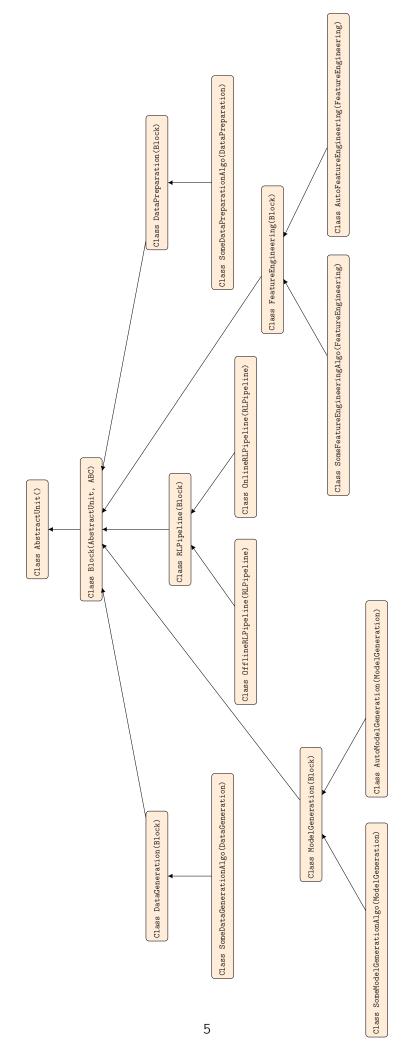
- TDError
- DiscountedReward
- $\ {\sf TimeSeriesRollingAverageDiscountedReward}$
- SomeSpecificMetric

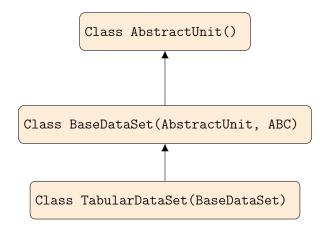
• Tuner:

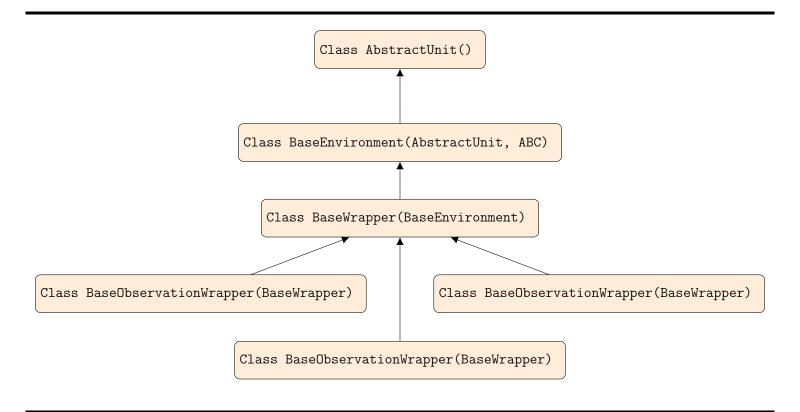
- TunerOptuna
- TunerGenetic

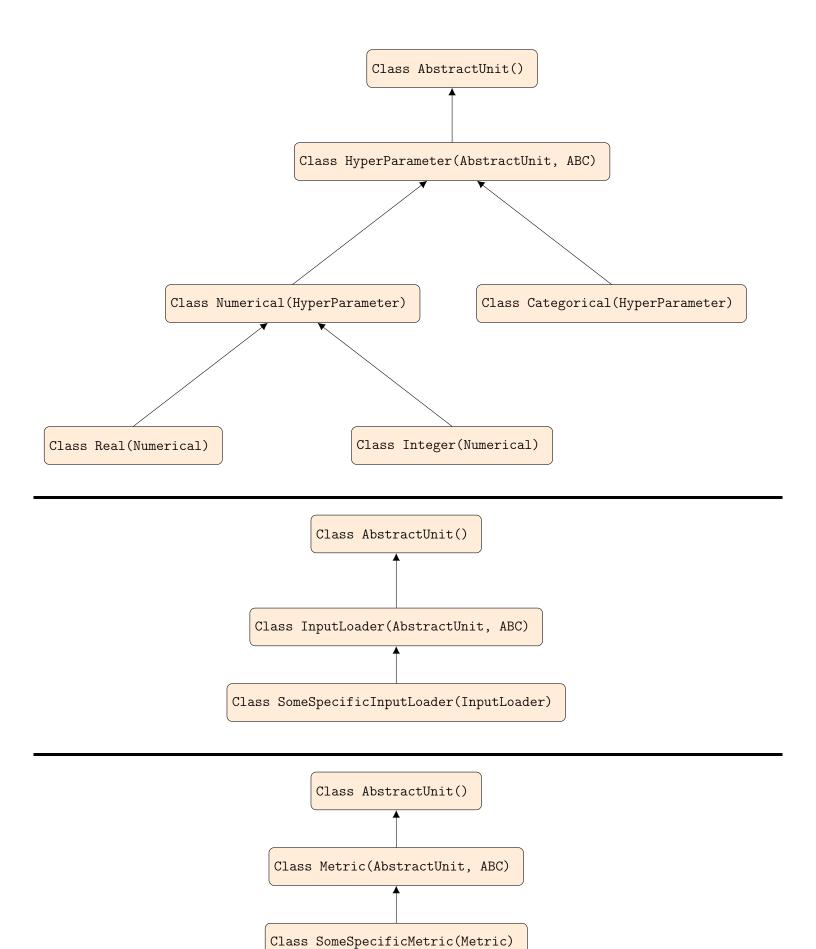
2 High level view of the class structure of the library

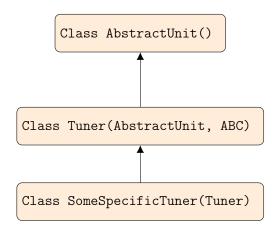












3 logger.py

In the module *logger.py* the Class *Logger* is implemented.

3.1 Logger

This Class is used in all the library to perform logging. The Class *Logger* is the only one in the library that does not inherit from the Class *AbstractUnit*.

Initialiser:

```
__init__(name_obj_logging, verbosity=3, mode='console', log_path=None)
```

Parameters:

- name obj logging (str) This is the name of the object that is being logged.
- **verbosity** (*int*, 3) This is a positive integer representing the verbosity level. There are 5 different levels of verbosity:
 - If verbosity = 0 then only exceptions are logged.
 - If verbosity ≥ 1 then also informations are logged.
 - If verbosity ≥ 2 then also warnings are logged.
 - If verbosity ≥ 3 then also errors are logged.
 - If verbosity ≥ 4 then also debug comments are logged.
- **mode** (*str*, 'console') This is a string and can assume three valid values:
 - If mode = 'console' then everything is printed to the console
 - If mode = 'file' then a file is created. The name of the files is given by: ARLO plus the current date and time appended at the end of the name, while the extension is log (e.g. ARLO 16 39 48 18 12 2021.log).
 - If mode = 'both' then everything is printed to the console but also saved in the log file.
- **log_path** (*str*, *None*) This is a string and it must be the path where to save the log file. If not specified the log file will not be saved.

Methods:

• _to_console(msg, log_level) - This method prints to console the log with the logging level and with the name of the object that has called the logging. An example of what could be logged is the following: [18-12-2021, 16:39:48][INFO, OnlinePipeline]: Learning the online RL pipeline...

Parameters:

- msg (str) This is a string and it represents the message to be logged to console.
- log_level (str) This is a string representing the log level which can be: 'INFO', 'WARNING', 'ERROR',
 'DEBUG' or 'EXCEPTION'.
- _to_file(msg, log_level) This method write to file the log with the logging level and with the name of the object that has called the logging. An example of what could be logged is the following: [18-12-2021, 16:39:48][INFO, OnlinePipeline]: Learning the online RL pipeline...

Parameters:

- msg (str) This is a string and it represents the message to be logged to file.
- log_level (str) This is a string representing the log level which can be: 'INFO', 'WARNING', 'ERROR',
 'DEBUG' or 'EXCEPTION'.
- _log(msg, log_level) This method, based on the *mode* parameter of the object of Class Logger, either calls the method: _to_console(msg, log_level), _to_file(msg, log_level) or both.

Parameters:

- msg (str) This is a string and it represents the message to be logged, either to console or to file.
- log_level (str) This is a string representing the log level which can be: 'INFO', 'WARNING', 'ERROR', 'DEBUG' or 'EXCEPTION'.
- info(msg) This method logs the message with logging level 'INFO'.

Parameters:

- **msg** (*str*) This is a string and it represents the message to be logged.
- warning(msg) This method logs the message with logging level 'WARNING'.

Parameters:

- **msg** (*str*) This is a string and it represents the message to be logged.
- error(msq) This method logs the message with logging level 'ERROR'.

Parameters:

- msg (str) This is a string and it represents the message to be logged.
- **debug(msg)** This method logs the message with logging level 'DEBUG'.

Parameters:

- msq (str) This is a string and it represents the message to be logged.
- exception(msg) This method logs the message with logging level 'EXCEPTION'.

Parameters:

– msg (*str*) - This is a string and it represents the message to be logged.

4 abstract unit.py

In the module abstract_unit.py the Class AbstractUnit is implemented. Moreover in this same module the **load()** method is present to load a saved object.

4.1 AbstractUnit

Every Class in this library, except for the Class Logger, inherits from this Class. This Class contains some common parameters, the possibility to update the verbosity of an object, the possibility to save an object via *cloudpickle* and the possibility to set a new seeder and creating a new local PRNG.

This is a base Class.

Initialiser:

Parameters:

- **obj_name** (*str*) This is a string representing the name of the object. This is used as name of the pickle file where the object will be saved to.
- **seeder** (*int*, 2) This must be a non-negative integer for seeding: this will be used for setting the state of the local pseudo random number generator (PRNG).
- log mode (str, 'console') This is a string and can assume three valid values:
 - If log mode = 'console' then everything is printed to the console
 - If log _mode = 'file' then a file is created. The name of the files is given by: ARLO plus the current date and time appended at the end of the name, while the extension is log (e.g. ARLO 16 39 48 18 12 2021.log).
 - If log mode = 'both' then everything is printed to the console but also saved in the log file.
- **checkpoint_log_path** (*str*, None) This is the path where the file containing all logging is saved to. If it is not specified no log file will be saved.

This is also the path where the object will be saved to. If the path is not specified the object will not be saved. Note that the object will be saved to a pickle file in binary form.

- **verbosity** (*int*, 3) This is an integer which can be: 0, 1, 2, 3, 4. The higher its value the more informations are logged.
- **n_jobs** (*int*, 1) This is the number of jobs to be used to run some parts of the code of the various Classes in parallel. The jobs can be processes or threads: to pick between these there is the parameter **job type**.

It must be a number greater than or equal to 1, since it may be used for deciding how to parallelise the code, hence the value -1 is not supported.

• **job_type** (*str*, 'process') - This is a string and it is either 'process' or 'thread': if 'process' then multiple processes will be created, else if 'thread' then multiple threads will be created.

Threads can be used to parallelise some parts of the code that release the GIL (running non-Python code): If the GIL is not released then it is best to use processes:

Non-Parameters Members:

- **local_prng** (numpy.random.default_rng) This is the local pseudo random number generator (PRNG). It is an object of Class numpy.random.default_rng and it is seeded using the **seeder**.
- logger (Logger) This is an object of Class Logger that will do the logging.
- **backend** (*str*) This is a string and it is used in *Joblib* to parallelise the code. It can be: 'multiprocessing', 'loky' or 'threading'. This is assigned based on the value of the parameter **job type**.
- **prefer** (*str*) This is a string and it is used in *Joblib* to parallelise the code. It can be: 'processes' or 'threads'. This is assigned based on the value of the parameter **job type**.

Methods:

• **set_local_prng(new_seeder)** - This method updates the seeder and creates a new local PRNG seeded with the new given seeder.

Parameters:

new_seeder (int) - This is a non-negative integer and it represents the new seeder to be used for creating a
new local PRNG.

Without this *numpy.random* is not always safe to use on concurrent threads or processes:

- * cf. https://numpy.org/doc/stable/reference/random/parallel.html
- * cf. https://albertcthomas.github.io/good-practices-random-number-generators/
- save() This method saves the object in a pickle file in binary form. The name of the file is equal to the name given to the object that is trying to be saved, plus the current time and date.

Note that if **checkpoint log path** is not specified then no file will be saved.

• update_verbosity(new_verbosity) - This method updates the verbosity of this object and the verbosity of the Logger object in the logger parameter of this object.

Parameters:

- **new verbosity** (*int*) - This is a positive integer and it represents the new verbosity.

4.2 load() method

load(pickled file path) - This method loads a pickled object and returns the loaded object.

Parameters:

• **pickled_file_path** (*str*) - This must be a string containing the absolute path to the pickled file that you want to load.

Returns:

• **loaded_class_obj** (AbstractUnit) - This is the loaded object: it will be an object of a Class inheriting from the Class AbstractUnit.

5 block.py

In the module *block.py* the Class *Block* is implemented.

5.1 Block

This Class is used to represent a generic block: these blocks can make up the pipeline, it can be an automatic block or it can be a pipeline itself. The Class *Block* is an abstract Class, and so it inherits from *ABC*, but it also inherits from the Class *AbstractUnit*.

Initialiser:

```
___init___(eval__metric, obj__name, seeder=2, log__mode='console', checkpoint__log__path=None, verbosity=3, n__jobs=1, job__type='process')
```

Parameters:

• **eval_metric** (*Metric*) - This is the metric by which the specific block will be ranked. It must be an object of a Class inheriting from the Class *Metric*.

Non-Parameters Members:

- works_on_online_rl (bool) This is either *True* or *False*. It is *True* if the block works on online reinforcement learning, while it is *False* otherwise.
- works_on_offline_rl (bool) This is either *True* or *False*. It is *True* if the block works on offline reinforcement learning, while it is **False** otherwise.
- works_on_box_action_space (bool) This is either *True* or *False*. It is *True* if the block works on box action spaces, while it is *False* otherwise.
- works_on_discrete_action_space (bool) This is either *True* or *False*. It is *True* if the block works on discrete action spaces, while it is *False* otherwise.
- works_on_box_observation_space (bool) This is either *True* or *False*. It is *True* if the block works on box observation spaces, while it is *False* otherwise.
- works_on_discrete_observation_space (bool) This is either *True* or *False*. It is *True* if the block works on discrete observation spaces, while it is *False* otherwise.
- **pipeline_type** (*str*) This is either 'online' or 'offline' and it represents the type of pipeline in which the current block is present. This is needed to know in each block the type of pipeline it is being inserted in.
- is learn successful (bool, False) This is *True* if the block was learnt properly, *False* otherwise.
- is_parametrised (bool) This is either *True* or *False*. It is *True* if the block is parametrised, meaning that it has parameters that can be optimised. One can also create a block with is_parametrised equal to *False*: this tells the Class *Tuner* not to do anything with such a block.
- **block_eval** (*float*, None) This is used by the Class *Tuner* to save the evaluation of the block corresponding to a specific set of hyper parameters with respect to the evaluation metric that is being used in the Class *Tuner*.

This is useful for having the information about the block evaluation even after the Class Tuner method tune is called (i.e. we can access this information in automatic blocks).

Methods:

• pre_learn_check(train_data=None, env=None) - Before learning a block it must be checked that the selected block works on the chosen problem: it must be checked that the block works in offline and-or online reinforcement learning, that it works in continuous and-or discrete, action and-or observation spaces.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the block can work with the given offline and-or online reinforcement learning problem and environment spaces this method returns *True*, else it returns *False*.
- learn(train_data=None, env=None) This method checks that the pipeline_type of every block is either 'on-line' or 'offline' and that at least one of train data and env are not None and that they are of the appropriate type.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) This method returns an object of Class BlockOutput in one of the three cases below:
 - * The **pipeline type** is neither 'online' nor 'offline'.
 - * train data and env are both None.
 - * **train_data** is not *None* and **train_data** is not an object of a Class inheriting from the Class *BaseDataSet*, or **env** is not **None** and **env** is not an object of a Class inheriting from the Class *BaseEnvironment*.

Otherwise this method does not return anything.

• **get_metric()** - This method is used to extract the evaluation metric (or KPI) used by the block to assess the quality of the learnt algorithm present in the block.

Returns:

- (*Metric*) The evaluation metric (or KPI) used by the block to assess the quality of the learnt algorithm present in the block. It is an object of a Class inheriting from the Class *Metric*.
- set metric(new metric) This method changes the evaluation metric of the block.

Parameters:

- **new metric** (*Metric*) - This must be an object of a Class inheriting from the Class *Metric*.

Returns:

- (bool) This method returns True if **new_metric** was set successfully, else it returns False.
- update_verbosity(new_verbosity) This method calls the base method update_verbosity() implemented in the Class AbstractUnit that updates the verbosity of the block and also the verbosity of the logger present in the block. Then this method calls the method update_verbosity() of the eval_metric present in the block.

Parameters:

 new_verbosity (int) - This must be a positive integer representing the new verbosity. 	

6 rl pipeline.py

In the module *rl pipeline.py* the Class *RLPipeline* is implemented.

6.1 RLPipeline

This Class serves as base Class for the Classes OnlineRLPipeline and OfflineRLPipeline.

The Class RLPipeline inherits from the Class Block. This is an Abstract Class.

A pipeline is a collection of blocks: it can contain user defined blocks, specific blocks or automatic blocks.

Initialiser:

```
__init__(list_of_block_objects, eval_metric, obj_name, seeder=2, log_mode='console', checkpoint log path=None, verbosity=3, n jobs=1, job type='process')
```

Parameters:

• **list_of_block_objects** (*list*) - This is the list of the block objects that make up the pipeline. Every block in the list must be an object of a Class inheriting from the Class *Block*.

Non-Parameters Members:

• list_of_block_objects_upon_instantiation (list, None) - This a deep copy of the original value of list_of_block_objects.

Methods:

• pre_learn_check(train_data=None, env=None) - This method calls the base method pre_learn_check() implemented in the Class Block that checks that the selected block works on the chosen problem: it must be checked that the pipeline works in offline and-or online reinforcement learning, that it works in continuous and-or discrete, action and-or observation spaces.

Moreover this method sets <code>list_of_block_objects</code> equal to <code>list_of_block_objects_upon_instantiation</code>. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the pipeline can work with the given offline and-or online reinforcement learning problem and environment spaces this method returns *True*, else it returns *False*.
- get_params() This method calls the get_params() method of every block in list_of_block_objects, that has is parametrised equal to True.

In order to keep track of which parameter is of which block every time we call the **get_params()** method of a block we modify the non-parameter member **block_owner_flag**. In particular every parameter of the block in

position k in the **list of block objects** will have **block owner flag** equal to k.

Returns:

- entire_dict (dict) This is a flat dictionary containing all the parameters of all the blocks in the list of block objects that have is parametrised equal to True.
- set_params(new_params) This method calls the set_params() method of every block in the
 list_of_block_objects passing to the set_params() method of every block the appropriate dictionary of parameters

Note that only blocks that have **is parametrised** equal to **True** are considered.

To make sure to pass to each block its correct parameters, every call to the **get_params()** method of the pipeline will modify the non-parameter member **block_owner_flag** of the objects of Classes inheriting from the Class *HyperParameter*, to keep track of which parameter is of which block.

Parameters:

new_params (dict) - This is a flat dictionary containing all the parameters to be used in all the blocks that have is parametrised equal to True.

It must be a dictionary that does not contain any dictionaries (i.e. all parameters must be at the same level).

Returns:

- (bool) This is *True* if **new params** was set successfully, and it is *False* otherwise.
- consistency_check(train_data=None, env=None) This method checks that the pipeline is consistent, namely it checks that:
 - Every block in the list_of_block_objects is an object of a Class inheriting from one of the following Classes:
 DataGeneration, DataPreparation, FeatureEngineering, ModelGeneration.
 - The **list of block objects** is not of length zero.
 - There is no more than one *DataGeneration* block, as it would not make sense to have more.
 - There is no more than one *ModelGeneration* block, as it would not make sense to have more.
 - The **list_of_block_objects** is ordered, namely: *DataGeneration* blocks must come before *DataPreparation* blocks, that must come before *FeatureEngineering* blocks, that must come before *ModelGeneration* blocks.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) This is *True* if the pipeline is consistent, else it is *False*.
- update_verbosity(new_verbosity) This method calls the *base* method update_verbosity() implemented in the Class *Block* that updates the verbosity of the pipeline, the verbosity of the *logger* present in the pipeline and the verbosity of the eval metric present in the pipeline.

Then this method calls the **update verbosity()** method of every block contained in **list of block objects**.

Parameters:

 new_verbosity (int) - This must be a positive integer representing the new verbosity. 	

7 online rl pipeline.py

In the module *online rl pipeline.py* the Class *OnlineRLPipeline* is implemented.

7.1 OnlineRLPipeline

An OnlineRLPipeline is used to solve an online reinforcement learning problem.

The Class OnlineRLPipeline inherits from the Class RLPipeline.

Note that in this Class:

- works on online rl is equal to True.
- works on offline rl is equal to False.
- works_on_box_action_space is equal to *True*: This means that the blocks inside **list_of_block_objects** can be of any type.
- works_on_discrete_action_space is equal to *True*: This means that the blocks inside list_of_block_objects can be of any type.
- works_on_box_observation_space is equal to *True*: This means that the blocks inside **list_of_block_objects** can be of any type.
- works_on_discrete_observation_space is equal to *True*: This means that the blocks inside list_of_block_objects can be of any type.
- pipeline type is equal to 'online'.

Moreover each block in this pipeline will have **pipeline type** equal to 'online'.

• is_parametrised is equal to *True*, hence the library expects that at least one of the blocks in the pipeline has is parametrised equal to *True*.

It is however up to the user to make sure to have the proper blocks that can work with the problem at hand: if this is not the case the **pre_learn_check()** method of a block of the wrong type will return *False*, and hence the **pre_learn_check()** method of the pipeline will return *False* and hence no learning can occur: it will not be possible to successfully call the *learn()* method of the pipeline.

Initialiser:

```
__init__(list_of_block_objects, eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Methods:

• learn(train_data=None, env=None) - This method calls the learn method learn() implemented in the Class *Block* that checks the pipeline type and that makes sure that not both train data and env are *None*.

Then the method **consistency_check()** is called: If this returns *True* then we cycle through each block present in the **list_of_block_objects** and for each block we call its method **pre_learn_check()** and then we call its method **learn()**.

For blocks that are objects of a Class inheriting from the Class ModelGeneration between the call to the method

pre learn check() and the method learn(), a third method is called: the method full block instantiation().

After having called the method **learn()** of a block if everything was successful we update the local variables **env**, **policy** and **policy_eval**. These will go on to be inserted in an object inheriting from the Class *BlockOutput*, that will be the return value of this method.

Note that **policy_eval** is a dictionary containing the mean of the evaluation and the variance of the evaluation: it follows that the Classes *Metric* that are used with *ModelGeneration* blocks must have two members: **eval_mean** and **eval_var**. These are used in this method to construct the **policy_eval**.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (*BlockOutput*) If the pipeline was learnt successfully this object contains: **env**, **policy**_**eval**. Else this object will have *None* values for the members: **env**, **policy**, **policy eval**.
- consistency_check(train_data=None, env=None) This method first calls the method consistency_check of the Class RLPipeline. Then it makes sure that there are no blocks of a Class inheriting from the Classes DataGeneration and DataPreparation, as it would not make sense to have these kind of blocks since this is an online pipeline.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) This is *True* if the pipeline is consistent, else it is *False*.
- analyse() This method calls the analyse() method of every block present in the list_of_block_objects. Note that this method can be called only once the learn() method of the pipeline has been called.
- **get_info_MDP(latest_env)** This method given an environment it extracts the member info of such object which contains the observation space, the action space, gamma and the horizon of the environment.

This is needed for fully instantiating object of a Class inheriting from the Class *ModelGeneration*: indeed these objects undergo a two-step initialisation.

Parameters:

- latest env (BaseEnvironment) - This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (mushroom_rl.environment.MDPInfo) This is an object of Class mushroom_rl.environment.MDPInfo which is a Class implemented in MushroomRL in the module environment.py. It contains the observation space, the action space, gamma and the horizon of the environment.
 - cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/core/environment.py

8 offline rl pipeline.py

In the module offline rl pipeline.py the Class OfflineRLPipeline is implemented.

8.1 OfflineRLPipeline

An OfflineRLPipeline is used to solve an offline reinforcement learning problem.

The Class OfflineRLPipeline inherits from the Class RLPipeline.

Note that in this Class:

- works on online rl is equal to False.
- works on offline rl is equal to True.
- works_on_box_action_space is equal to *True*: This means that the blocks inside **list_of_block_objects** can be of any type.
- works_on_discrete_action_space is equal to *True*: This means that the blocks inside list_of_block_objects can be of any type.
- works_on_box_observation_space is equal to *True*: This means that the blocks inside **list_of_block_objects** can be of any type.
- works_on_discrete_observation_space is equal to *True*: This means that the blocks inside list_of_block_objects can be of any type.
- pipeline type is equal to 'offline'.

Moreover each block in this pipeline will have **pipeline type** equal to 'offline'.

• is_parametrised is equal to *True*, hence the library expects that at least one of the blocks in the pipeline has is parametrised equal to *True*.

It is however up to the user to make sure to have the proper blocks that can work with the problem at hand: if this is not the case the **pre_learn_check()** method of a block of the wrong type will return *False*, and hence the **pre_learn_check()** method of the pipeline will return *False* and hence no learning can occur: it will not be possible to successfully call the *learn()* method of the pipeline.

Initialiser:

```
__init__(list_of_block_objects, eval_metric, obj_name, seeder=2, log_mode='console', checkpoint log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Methods:

• learn(train_data=None, env=None) - This method calls the learn method learn() implemented in the Class *Block* that checks the pipeline type and that makes sure that not both train data and env are *None*.

Then the method **consistency_check()** is called: If this returns *True* then we cycle through each block present in the **list_of_block_objects** and for each block we call its method **pre_learn_check()** and then we call its method **learn()**.

For blocks that are objects of a Class inheriting from the Class ModelGeneration between the call to the method

pre learn check() and the method learn(), a third method is called: the method full block instantiation().

After having called the method **learn()** of a block if everything was successful we update the local variables **train_data**, **env**, **policy** and **policy_eval**. These will go on to be inserted in an object inheriting from the Class *BlockOutput*, that will be the return value of this method.

Note that **policy_eval** is a dictionary containing the mean of the evaluation and the variance of the evaluation: it follows that the Classes *Metric* that are used with *ModelGeneration* blocks must have two members: **eval_mean** and **eval_var**. These are used in this method to construct the **policy_eval**.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) If the pipeline was learnt successfully this object contains: train_data, env, policy, policy_eval. Else this object will have None values for the members: train_data, env, policy_eval.
- consistency_check(train_data=None, env=None) This method first calls the method consistency_check of the Class *RLPipeline*. Then it makes sure that not both train data and env are *None*. Moreover:
 - If both the train_data and the env are not None then it checks that there are no blocks of a Class inheriting from the Class DataGeneration: since the train_data is provided there is no need to extract a dataset from the env.
 - If the train_data is not None, while the env is None then it checks that there are no blocks of a Class inheriting from the Class DataGeneration: since the train data is provided there is no need to extract a dataset.
 - If the train_data is None, while the env is not None then it checks that there are is a block of a Class inheriting from the Class DataGeneration: since the train_data is not provided we have to extract a dataset from the given env.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) This is *True* if the pipeline is consistent, else it is *False*.
- analyse() This method calls the analyse() method of every block present in the list_of_block_objects. Note that this method can be called only once the learn() method of the pipeline has been called.
- **get_info_MDP(latest_dataset)** This method given a dataset it extracts the member info of such object which contains the observation space, the action space, gamma and the horizon of the environment.

This is needed for fully instantiating object of a Class inheriting from the Class *ModelGeneration*: indeed these objects undergo a two-step initialisation.

Parameters:

- latest dataset (BaseDataSet) - This must be an object of a Class inheriting from the Class BaseDataSet.

Returns:

- (mushroom_rl.environment.MDPInfo) This is an object of Class mushroom_rl.environment.MDPInfo which is a Class implemented in MushroomRL in the module environment.py. It contains the observation space, the action space, gamma and the horizon of the environment.
 - cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/core/environment.py

9 rl pipeline automatic.py

In the module rl pipeline automatic.py the Class AutoRLPipeline is implemented.

9.1 AutoRLPipeline

This Class implements automatic reinforcement learning: given a metric and a list of pipelines this block picks the best reinforcement learning pipeline among the possible ones.

The Class AutoRLPipeline inherits from the Class Block.

Note that in this Class:

- works on online rl is equal to *True* if online task is *True*, else it is *False*.
- works on offline rl is equal to True if online task is False, else it is False.
- works on box action space is equal to *True*.
- works on discrete action space is equal to True.
- works on box observation space is equal to *True*.
- works_on_discrete_observation_space is equal to *True*.
- pipeline type is equal to 'online' if works on online rl is equal to True, else it is 'offline'.
- **is_parametrised** is equal to *False*, hence this block cannot go in a *Tuner* object. Indeed it makes no sense to have **is parametrised** is equal to *True* because this block is already performing joint-optimisation of the pipeline.

Note that the members works_on_box_action_space, works_on_discrete_action_space, works_on_box_observation_space and works_on_discrete_observation_space are *True* so that one can specify the right pipelines for the problem at hand.

If the pipelines provided in the **tuner_blocks_dict** are incompatible with the problem at hand then no tuner will be tuned and the method **learn()** of the *AutoRLPipeline* block will fail.

Initialiser:

```
__init__(eval_metric, obj_name, online_task=False, seeder=2, tuner_blocks_dict=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

- tuner_blocks_dict (dict) This must be a dictionary where the key is a string while the value is an object of a Class inheriting from the Class *Tuner*.
- **online_task** (*bool*) This must be *True* if the task is an online RL problem, otherwise if the task is an offline RL problem it must be *False*.

Non-Parameters Members:

• tuner_blocks_dict_upon_instantiation (dict, None) - This is a deep copy of the original value of tuner blocks dict.

Methods:

• pre_learn_check(train_data=None, env=None) - This method simply returns *True* and updates the value of tuner blocks dict to tuner blocks dict upon instantiation. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) - This method overrides the one of the base Class Block and it always returns True. Why is this needed?
 Because there is only one default dictionary for tuner_blocks_dict therefore it contains both online and offline pipelines.

We do not want to stop learning an automatic block only because it contains an online pipeline while the problem is an offline problem: we just want to skip over it.

• learn(train_data=None, env=None) - This method calls the learn method learn() implemented in the Class *Block* that checks the pipeline_type and that makes sure that not both train_data and env are *None*.

Then the method **consistency_check()** is called: If this returns *True* then we cycle through each tuner present in the **tuner blocks dict** and for each tuner we call its method **tune()**.

Before calling the method tune() of a tuner:

- We assign the **pipeline type** to the **block to opt** present in the tuner.
- We call the method pre_learn_check() of the block_to_opt present in the tuner. If this returns False then
 the currently selected tuner will be skipped.

Note that we skip over tuners that have input loader and metric not consistent with each other: this is checked by calling the method is _metric _consistent _with _input _loader() of the tuner.

After having called the method **tune()** of a tuner if everything was successful we update the local variables **best pipeline** and **best pipeline** eval.

If after having gone through each tuner at least one was successfully tuned then the best pipeline found overall will be learnt over the original starting input given to the *AutoRLPipeline* block, and the corresponding object of Class *BlockOutput* is returned.

Otherwise if no tuner was tuned successfully, out of the ones present in the **tuner_blocks_dict** an empty object of Class *BlockOutput* is returned.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (*BlockOutput*) - If this block was learnt successfully this object contains: **train_data**, **env**, **policy**, **policy eval**. Else this object will have *None* values for the members: **train_data**, **env**, **policy**, **policy eval**.

- **consistency_check(train_data=None, env=None)** This method checks that the *AutoRLPipeline* block is consistent, namely it checks that:
 - All the pipelines terminate with a block of the same type: this is important since we cannot compare pipelines
 (and it makes no sense) that end with a block of different type.
 - All pipelines satisfy the call to their method **consistency check()**.

Note that all the tuners present in the **tuner_blocks_dict** must have the same metric as it does not make sense to compare different tuners with different metrics. This is not checked in the library, so it is up to the user to provide sensible metrics.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) This is *True* if the *AutoRLPipeline* block is consistent, else it is *False*.
- get params() This method returns a deep copy of tuner blocks dict.

Returns:

- (dict) This is a deep copy of tuner blocks dict.
- set_params(new_params_dict) This method replaces the current tuner_blocks_dict and updates tuner blocks dict upon instantiation to new params dict.

Parameters:

new_params_dict (dict) - This must be a flat dictionary for the parameters of all pipelines present in this automatic block: it replaces the current tuner_blocks_dict.

Returns:

- (bool) This is *True* if **new params dict** was set successfully, else it is *False*.
- analyse() This method is not yet implemented. It should analyse the learnt *AutoRLPipeline* block, namely it should evaluate it according to the provided **eval metric**.
- update_verbosity(new_verbosity) This method calls the base method update_verbosity() implemented in the Class Block. Then for all Tuner object in the tuner_blocks_dict it calls the corresponding method update_verbosity().

Parameters:

- new_verbosity (int) - This must be a positive integer representing the new verbosity.

10 data generation.py

In the module data_generation.py the Classes DataGeneration, DataGenerationRandomUniformPolicy and DataGenerationMEPOL are implemented.

10.1 DataGeneration

This Class is an abstract class and it is used as generic base class for all data generation blocks.

The Class DataGeneration inherits from the Class Block. This is an Abstract Class.

Initialiser:

```
\label{eq:console} $$\_\_init\_\_(eval\_metric, obj\_name, seeder=2, log\_mode='console', checkpoint\_log\_path=None, verbosity=3, \\ n\_jobs=1, job\_type='process')
```

Methods:

• _get_sample(env, state, episode_steps, discrete_actions, policy=None) - This method collects a single sample from the environment made of: the current state, the current taken action, the current obtained reward, the next state (reached by taking the current action in the current state), the done (absorbing) flag and the last (episode terminal) flag.

A sample of this particular kind is sampled because it is what is required by MushroomRL.

If the **policy** is *None* then this method first samples an action:

- If the action space is *Discrete* we call the method integers() of the local_prng, passing to it the number of actions in the action space.
 - In this case a *numpy.array* containing the action is added to the sample that will later be returned. This is done as it is required by MushroomRL algorithms. Moreover the *numpy.array* containing the action is also used to interact with the environment, and so it is passed to the method **step()** of the **env**. Therefore the **env**, even if with a discrete action space must expect a *numpy.array* containing the action. To learn more about this see the sub-section **On environments** of the section **Further Details** at the end of this documentation.
- If the action space is Box we call the method sample from box action space() of the env.

Otherwise the the **policy** is not *None* we call the method **draw_action()** of the **policy** to get the action to use in the current state.

Parameters:

- env (BaseEnvironment) This must be an object of a Class inheriting from the Class BaseEnvironment.
- state (numpy.array) This must be a numpy array containing the current state.
- discrete actions (bool) This is *True* if the environment has discrete actions, else it is *False*.
- policy (None) This can be provided if the dataset needs to be extracted using a specified policy different from
 the random uniform policy. It must be an object of a Class that has the method draw_action() accepting as
 only parameter a state.

Returns:

- (numpy.array) This is a numpy.array containing: the current state, the current taken action, the current obtained reward, the next state (reached by taking the current action in the current state), the done (absorbing) flag and the last (episode terminal) flag.
- _generate_a_dataset(env, n_samples, discrete_actions, policy=None) This method extracts a dataset: a collections of samples, by calling the method _get _sample() of this block.

Parameters:

- env (BaseEnvironment) This must be an object of a Class inheriting from the Class BaseEnvironment.
- n_samples (int) This must be a positive integer representing the number of samples to extract from the environment.
- discrete actions (bool) This is True if the environment has discrete actions, else it is False.
- policy (None) This can be provided if the dataset needs to be extracted using a specified policy different from
 the random uniform policy. It must be an object of a Class that has the method draw_action() accepting as
 only parameter a state.

Returns:

- new_dataset (list) This is one dataset with a number of samples equal to n_samples: it is a list where each component is a numpy.array.
- pre_learn_check(train_data=None, env=None) This method calls the base method pre_learn_check() implemented in the Class Block.

Moreover this method sets **algo_params** to **algo_params_upon_instantiation**. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the block can work with the given offline and-or online reinforcement learning problem and environment spaces this method returns *True*, else it returns *False*.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class Block that checks the pipeline_type and that makes sure that not both train_data and env are None.

Then since a *DataGeneration* block in order to work needs an **env** it is checked that **env** is not *None*: if the **env** is *None* the call to the method **learn()** fails.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) - This method returns an empty object of Class BlockOutput if the call to the base method learn() implemented in the Class Block was not successful.

Otherwise it returns the **env**: this is going to be passed onto a specific *DataGeneration* block.

• get params() - This method returns a deep copy of algo params.

Returns:

- (dict) This is a dictionary and it corresponds to a deep copy of algo params.
- set_params(new_params) This method changes the value of algo_params and of algo params upon instantiation, to that of new params.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) This is True if **new params** was set successfully, else it is False.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided eval metric.

10.2 DataGenerationRandomUniformPolicy

This Class implements a specific data generation algorithm: it uses a random uniform policy to pick an action with which we probe the environment.

The Class DataGenerationRandomUniformPolicy inherits from the Class DataGeneration.

Note that in this Class:

- works on online rl is equal to False: indeed DataGeneration blocks are only needed in an offline RL problem.
- works on offline rl is equal to *True*.
- works on box action space is equal to *True*.
- works on discrete action space is equal to True.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'offline'.
- is parametrised is equal to *True*, indeed this block has one parameter that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, algo_params=None, log_mode='console',
checkpoint log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then 10000 samples will be collected from the environment, thus the following parameters will be used:

- 'n samples': 10000, this is the number of samples to extract.

Non-Parameters Members:

• algo params upon instantiation (dict, None) - This is a deep copy of the original value of algo params.

Methods:

• learn(train_data=None, env=None) - This method calls the base method learn() implemented in the Class Data-Generation. Then an object of Class TabularDataSet is created and its dataset member is filled by repeatedly calling the method generate a dataset(), implemented in the base Class DataGeneration.

Since we want to extract a dataset using a random uniform policy we set **policy** equal to *None* when calling the method **_generate_a_dataset()**, implemented in the *base* Class *DataGeneration*.

This can be done in parallel: multiple environments are created and from each environment a dataset is extracted, and these are then concatenated into a single list.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

res (BlockOutput) - This is an object of Class BlockOutput which contains the dataset generated in the train_data member, which is an object of Class TabularDataSet.

If the procedure was not successful this method returns an object of Class *BlockOutput* but all its members are *None*.

10.3 DataGenerationMEPOL

This Class implements a specific data generation algorithm: it implements Task-Agnostic Exploration via Policy Gradient of a Non-Parametric State Entropy Estimate as described in cf. https://arxiv.org/abs/2007.04640

The implementation is a readaptation of the code present in the GitHub repository associated with the above paper, namely cf. https://github.com/muttimirco/mepol

The Class DataGenerationMEPOL inherits from the Class DataGeneration.

Note that in this Class:

- works on online rl is equal to False: indeed DataGeneration blocks are only needed in an offline RL problem.
- works on offline rl is equal to *True*.
- works on box action space is equal to True.
- works on discrete action space is equal to False.
- works on box observation space is equal to True.
- works on discrete observation space is equal to False.
- pipeline type is equal to 'offline'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, algo_params=None, log_mode='console', checkpoint log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then 10000 samples will be collected from the environment, thus the following parameters will be used:

```
- 'n samples': 10000, this is the number of samples to extract.
```

```
- 'train steps': 100
```

- 'batch size': 5000

- 'create policy learning rate': 0.00025

- 'state filter': None

- 'zero mean start': 1

- 'hidden_sizes': [300, 300]

- 'activation': ReLU

- 'log_std_init': -0.5

- 'eps': 1*e* − 15

- 'k': 30

- 'kl threshold': 0.1

- 'max_off_iters': 20

```
'use_backtracking': 1
'backtrack_coeff': 2
'max_backtrack_try': 10
'learning_rate': 1e - 3
'num_traj': 20
'traj_len': 500
'num_epochs': 100
'optimizer': Adam
'full_entropy_traj_scale': 2
```

Non-Parameters Members:

- 'full entropy k': 4

• algo params upon instantiation (dict, None) - This is a deep copy of the original value of algo params.

Methods:

• <u>__extract__dataset__using__policy(env)</u> - This method extracts a dataset from the provided **env** using the **policy** learnt in the previous steps of this block (the one obtained by calling the method **mepol()** of this block).

This method calls extracts a dataset by repeatedly calling the method **__generate__a_dataset** implemented in the *base* Class *DataGeneration*.

Since we want to extract a dataset using the learnt policy we set **policy** equal to the one we found, when calling the method **_generate_a_dataset()**, implemented in the *base* Class *DataGeneration*.

This can be done in parallel: multiple environments are created and from each environment a dataset is extracted, and these are then concatenated into a single list.

Parameters:

- env (BaseEnvironment, None) - This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- **stacked_dataset** (*list*) This is a dataset in the from that can be used by MushrromRL algorithms, that is: it is a list of list where each list contains a sample from the environment containing the current state, the current action, the reward, the next state, the absorbing state flag and the episode terminal flag.
- **learn(train_data=None, env=None)** This method calls the *base* method **learn()** implemented in the Class *Data-Generation*.

Then the method **_mepol()** is called: this produces a policy. Then this policy is going to be used to extract a dataset.

An object of Class *TabularDataSet* is created and its **dataset** member is filled by calling the method **_extract_dataset_using_policy()**.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

res (BlockOutput) - This is an object of Class BlockOutput which contains the dataset generated in the train data member, which is an object of Class TabularDataSet.

If the procedure was not successful this method returns an object of Class *BlockOutput* but all its members are *None*.

To see more details about the meaning of the parameters used in this block and the functioning of the methods see the paper https://arxiv.org/abs/2007.04640 and the code associated with it.

11 data preparation.py

In the module data_preparation.py the Classes DataPreparation, DataPreparationIdentity, DataPreparationImputation, DataPreparation1NNImputation and DataPreparationMeanImputation are implemented.

11.1 DataPreparation

This Class is an abstract class and it is used as generic base class for all data preparation blocks.

The Class DataPreparation inherits from the Class Block. This is an Abstract Class.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Methods:

• pre_learn_check(train_data=None, env=None) - This method calls the base method pre_learn_check() implemented in the Class Block.

Moreover this method sets **algo_params** to **algo_params_upon_instantiation**. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the block can work with the given offline and-or online reinforcement learning problem and environment spaces this method returns *True*, else it returns *False*.
- learn(train_data=None, env=None) This method calls the learn method learn() implemented in the Class *Block* that checks the pipeline_type and that makes sure that not both train_data and env are *None*.

Then since a *DataPreparation* block in order to work needs the **train_data** it is checked that **train_data** is not *None*: if the **train_data** is *None* the call to the method **learn()** fails.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (*BlockOutput*) - This method returns an empty object of Class *BlockOutput* if the call to the *base* method **learn()** implemented in the Class *Block* was not successful.

Otherwise it returns the **train data**: this is going to be passed onto a specific *DataPreparation* block.

11.2 DataPreparationIdentity

This Class implements a specific data preparation algorithm: it is an identity block meaning that it will not do anything on the input **train data**. This can be useful when jointly optimising the pipeline.

The Class DataPreparationIdentity inherits from the Class DataPreparation.

Note that in this Class:

- works on online rl is equal to False: indeed DataPreparation blocks are only needed in an offline RL problem.
- works on offline rl is equal to *True*.
- works on box action space is equal to True.
- works_on_discrete_action_space is equal to *True*.
- works on box observation space is equal to True.
- works on discrete observation space is equal to *True*.
- pipeline type is equal to 'offline'.
- is parametrised is equal to False, indeed this block has no parameters.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3,
n_jobs=1, job_type='process')
```

Methods:

• learn(train_data=None, env=None) - This method calls the base method learn() implemented in the Class DataPreparation. Then since this is an identity block the entering train_data is inserted, as is, in an object of Class BlockOutput which is then returned.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- res (BlockOutput) This is an object of Class BlockOutput which contains the dataset, as it entered this block, in the train_data member, which is an object of Class BaseDataSet.
- **get_params()** This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Returns:

- (None) This is always None: this block has no parameters.
- set_params(new_params) This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Parameters:

- **new params** (*dict*) - This must be a dictionary containing all the parameters needed for this block to work.

- (bool) This is always False: this block has no parameters.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided **eval_metric**.

11.3 DataPreparationImputation

This Class is used to group together common operations for the imputation blocks.

The Class DataPreparationImputation inherits from the Class DataPreparation. This is an Abstract Class.

Initialiser:

__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')

Methods:

• _transform_data_for_imputation(train_data) - This method assumes to have a vector of data that is of the proper length, and some of its members are *numpy.nan*. This method construct a *numpy.ndarray* from the **dataset** member of the **train_data**.

Parameters:

- train data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- **stacked_dataset** (*numpy.ndarray*) This is a *numpy.ndarray* containing all the samples of the dataset where the features are the current state, the action, the reward and the next state.
- **get_params()** This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Returns:

- (None) This is always None: this block has no parameters.
- set_params(new_params) This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Parameters:

- **new params** (*dict*) - This must be a dictionary containing all the parameters needed for this block to work.

- (bool) This is always False: this block has no parameters.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided eval _ metric.

11.4 DataPreparation1NNImputation

This Class implements a specific data preparation algorithm: it preforms imputation of the data using 1-NN. Specifically an object of Class *sklearn.imputed.KNNImputer* is created. Note that only non-boolean data of the dataset can be imputed by this method.

The Class DataPreparation1NNImputation inherits from the Class DataPreparationImputation.

Note that in this Class:

- works on online rl is equal to False: indeed DataPreparation blocks are only needed in an offline RL problem.
- works on offline rl is equal to True.
- works on box action space is equal to *True*.
- works on discrete action space is equal to *True*.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to *True*.
- pipeline type is equal to 'offline'.
- is parametrised is equal to False, indeed this block has no parameters.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n jobs=1, job type='process')
```

Methods:

• _impute_data(train_data) - The method assumes that there are missing values and that there are no missing values in the episode terminal flags, nor in the absorbing state flags.

This method imputes the missing data using an object of Class *sklearn.imputed.KNNImputer* and returns an updated dataset.

Parameters:

- train_data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- new_tabular_dataset (TabularDataSet) This is a new object of Class TabularDataSet containing the imputed dataset.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class DataPreparation. Then the method _impute_data() is called and an object of Class BlockOutput, containing the imputed dataset, is returned.

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

res (BlockOutput) - This is an object of Class BlockOutput which contains the imputed dataset, in the train_data member, which is an object of Class TabularDataSet.

11.5 DataPreparationMeanImputation

This Class implements a specific data preparation algorithm: it preforms mean imputation of the data. Note that only non-boolean data of the dataset can be imputed by this method. Moreover this method works only when both the action space and the observation space are continuous (i.e. Box).

The Class DataPreparationMeanImputation inherits from the Class DataPreparationImputation.

Note that in this Class:

- works on online rl is equal to False: indeed DataPreparation blocks are only needed in an offline RL problem.
- works on offline rl is equal to True.
- works on box action space is equal to *True*.
- works on discrete action space is equal to False.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to False.
- pipeline type is equal to 'offline'.
- is parametrised is equal to False, indeed this block has no parameters.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n jobs=1, job type='process')
```

Methods:

• _impute_data(train_data) - The method assumes that there are missing values and that there are no missing values in the episode terminal flags, nor in the absorbing state flags.

This method imputes the missing data using the mean across the relevant feature and returns an updated dataset.

Parameters:

- train data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- new_tabular_dataset (TabularDataSet) This is a new object of Class TabularDataSet containing the imputed dataset.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class DataPreparation. Then the method _impute_data() is called and an object of Class BlockOutput, containing the imputed dataset, is returned.

Parameters:

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.



12 feature engineering.py

In the module feature_engineering.py the Classes FeatureEengineering, FeatureEngineeringIdentity, FeatureEngineeringRFS, FeatureEngineeringFSCMI and FeatureEngineeringNystroemMap are implemented.

12.1 Feature Eengineering

This Class is an abstract class and it is used as generic base class for all feature engineering blocks.

The Class FeatureEngineering inherits from the Class Block. This is an Abstract Class.

Note that feature engineering blocks are both *online* and *offline* blocks: what they return depends on what enters these blocks:

- If only the **env** enters, then only a modified **env** will be returned.
- If only the **train** data enters, then only a modified **train** data will be returned.
- If both env and train data enters, then both a modified env and a modified train data will be returned.

Remark: When an **env** goes into a *FeatureEngineering* block a wrapped **env** will be returned, but there is a problem. Suppose the *FeatureEngineering* blocks applies Principal Components Analysis (PCA): in the standard offline setting we simply fit the PCA onto the dataset and then apply the learnt transformation on the dataset itself.

If we only have an environment however this cannot be done: we could call both fit and transform of the PCA onto a single sample obtained by the **env** but then this would mean that two samples of the **env** could have different principal components and hence we would have different features across different samples of the **env**.

To overcome this, when an **env** enters a *FeatureEngineering* block, first a dataset is sampled from the **env**: on this dataset the *FeatureEngineering* block is fit, and then in the wrapped **env** we simply apply the learnt transformation without re-fitting the *FeatureEngineering* block every time.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Methods:

• __select__current__actual__value__from__hp__classes(params__objects__dict) - This method given a dictionary made of objects of a Class inheriting from the Class *HyperParameter* it constructs a dictionary where the keys are the same as the ones in params__objects__dict but the values are the value of the member current__actual__value of the *HyperParameter* objects in params__objects__dict.

This method is needed in order to pass appropriate values to objects of other libraries which we need to wrap. For example this method is called before creating an object of Class *sklearn.kernel_approximation.Nystroem*.

Parameters:

params_objects_dict (dict) - This must be a dictionary where the key is a string and the value is an object
of a Class inheriting from the Class HyperParameter.

- algo_params_values (dict) This is a dictionary with the same keys as the input dictionary but as values the value of the member current_actual_value of the HyperParameter objects in params_objects_dict.
- pre_learn_check(train_data=None, env=None) This method calls the base method pre_learn_check() implemented in the Class Block.

Moreover this method sets algo_params to algo_params_upon_instantiation. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the block can work with the given offline and-or online reinforcement learning problem and environment spaces this method returns *True*, else it returns *False*.
- **learn(train_data=None, env=None)** This method calls the *base* method **learn()** implemented in the Class *Block*. Then it makes sure that:
 - If this block has **pipeline type** equal to 'online' then **env** is not None.
 - If this block has **pipeline type** equal to 'offline' then **train data** is not None.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) - This method returns an empty object of Class BlockOutput if the call to the base method learn() implemented in the Class Block was not successful.

Otherwise it returns the **train_data** and the **env**: these are going to be passed onto a specific *FeatureEngineering* block.

• get params() - This method returns a deep copy of algo params.

Returns:

- (dict) This is a dictionary and it corresponds to a deep copy of algo_params.
- set_params(new_params) This method changes the value of algo_params and of algo_params_upon_instantiation, to that of new_params.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) - This is *True* if **new params** was set successfully, else it is *False*.

12.2 Feature Eengineering Identity

This Class implements a specific feature engineering algorithm: it provides the identity block. This simply returns the **env** and the **train data** as is without changing anything.

The Class FeatureEengineeringIdentity inherits from the Class FeatureEengineering.

Note that in this Class:

- works on online rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on offline rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on box action space is equal to *True*.
- works on discrete action space is equal to True.
- works on box observation space is equal to True.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'online' if works on online rl is equal to True, else it is False.
- is parametrised is equal to False, indeed this block has no parameters.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n jobs=1, job type='process')
```

Methods:

• **feature engineer env(old env)** - This method wraps the **env**.

Parameters:

- old env (BaseEnvironment) - This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- new_env (BaseEnvironment) This is an object of a Class inheriting from the Class BaseEnvironment. In
 this case since this is an identity block this is equal to old env.
- **feature engineer data(old data)** This method modifies the **train data**.

Parameters:

- old data (BaseDataSet) - This must be an object of a Class inheriting from the Class BaseDataSet.

- new_data (BaseDataSet) This is an object of a Class inheriting from the Class BaseDataSet. In this case since this is an identity block this is equal to old_data.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class FeatureEngineering. Then:
 - If train_data is not None the method _feature_engineer_data() is called: since this is an identity block the entering train data is not changed.

If env is not None the method _feature_engineer_env() is called: since this is an identity block the entering env is not changed.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- res (BlockOutput) This is an object of Class BlockOutput which contains the dataset, as it entered this block, in the train_data member, which is an object of Class BaseDataSet, and the environment, as it entered this block, in the env member, which is an object of Class BaseEnvironment.
- **get_params()** This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Returns:

- (None) This is always None: this block has no parameters.
- **set_params(new_params)** This method does nothing since in this block there are no parameters. This method is kept for having a consistent interface across all blocks.

Parameters:

- **new params** (*dict*) - This must be a dictionary containing all the parameters needed for this block to work.

- (bool) This is always False: this block has no parameters.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided eval metric.

12.3 FeatureEngineeringRFS

This Class implements a specific feature engineering algorithm: it provides a recursive feature selection algorithm for RL.

First an *XGBRegressor* is fitted on a dataset where the target is the reward and the features are the current state and actions. Then a threshold value is picked and only the meaningful features are kept: this is done via the member feature_importances_ of the *XGBRegressor*.

We continue applying the above procedure recursively taking as target all the next-states. We stop when all the states have been explained, that is when the only variable deemed important for a next state variable is the previous state variable itself.

At the end the list of states that are selected are the ones that appears as important variables at least once in the procedure.

The Class FeatureEngineeringRFS inherits from the Class FeatureEngineering.

Note that in this Class:

- works on online rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on offline rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on box action space is equal to *True*.
- works on discrete action space is equal to *True*.

Even though this member is *True* if the action space is discrete no feature selection will be applied to the actions. This is done so that this block can be used on Box Observation Space and any type of Action Space.

- works_on_box_observation_space is equal to *True*.
- works_on_discrete_observation_space is equal to False: this can only be applied to continuous observation spaces.
- pipeline type is equal to 'online' if works on online rl is equal to True, else it is False.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
___init___(eval_metric, obj_name, seeder=2, algo_params=None, data_gen_block_for_env_wrap=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'threshold': 0.1- 'n recursions': 100
- 'feature selector': XGBRegressor()
- data_gen_block_for_env_wrap (DataGeneration, None) This must be an object of a Class inheriting from the Class DataGeneration. This is used to extract a dataset from the environment and this dataset will be used for fitting the feature engineering algorithm.

This must extract an object of a Class inheriting from the Class *TabularDataSet*.

Note that this is only used if the method **learn()** receives an **env** but not the **train** data.

If this is not provided an object of Class *DataGenerationRandomUniformPolicy* collecting 100000 samples will be used.

To see more in detail why this is needed see the **Remark** before the **Initialiser** of the Class *FeatureEngineering*.

Non-Parameters Members:

- algo params upon instantiation (*dict*, None) This is a deep copy of the original value of algo params.
- **count** (*int*, 0) This is needed to make sure to stop the recursive feature elimination after the prescribed number.

This is a non-negative integer: after the method _recursive_call() has been called more than n_recursion times we stop the feature selection procedure.

Methods:

• _from_tabular_dataset_extract_y(original_train_data, idx_target) - This method loops over the dataset contained in an object of a Class inheriting from the Class *TabularDataSet* and it extracts the element at index idx target.

Parameters:

- original_train_data (TabularDataSet) This is the original train_data and it must be an object of a Class inheriting from the Class TabularDataSet.
- idx target (list) This is a list containing the index of the target variable.

Returns:

- y (numpy.array) This is a numpy.array containing the values of the target variable. This is the y parameter used in the method fit() of XGBRegressor.
- _recursive_call(original_train_data, list_of_selected_state_features, list_of_selected_action_features, list_of_states_not_explained)
 - This method is recursive:
 - Each call to this method increments **count** by one.
 - We exit the method if we are done: either when count reaches n_recursions or when list_of_states_not_explained is empty.
 - For each call to this method:
 - * We extract the target from the **train_data** using the method **_from_tabular_dataset_extract_y()**, then we fit the **feature selector**.
 - * From the **feature_selector** we extract the **feature_importances_** and by using the **threshold** we select the meaningful state and action variables.
 - * If there is only one meaningful state selected and it coincides with the target then we end, otherwise we recursively call this method on the remaining selected meaningful states.

- original_train_data (TabularDataSet) This is the original train_data and it must be an object of a Class inheriting from the Class TabularDataSet.
- list_of_selected_state_features (list) This is the list containing all the state features that appeared at least once throughout all the recursive calls of this method.
- list_of_selected_action_features (list) This is the list containing all the action features that appeared at least once throughout all the recursive calls of this method.
- list_of_states_not_explained (list) This is the list used to determine when to stop: it contains the states variables that are deemed not explained: those for which the target next state variable is not explained just by its previous value but by also other state variables.
- __recursive__feature__selection(original__train__data) This method calls the first step of the feature selection procedure: it uses the reward as target and it uses all the current states and action as features.

Once the important state are selected the method **recursive call()** is called on the renaming states.

If no states are selected the **list_of_selected_state_features** will be *None*, and if no actions are selected the **list of selected action features** will be *None*.

Parameters:

original_train_data (TabularDataSet) - This is the original train_data and it must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- list_of_selected_state_features (list) This is the list containing all the state features that have been deemed important. It can be None.
- list_of_selected_action_features (list) This is the list containing all the action features that have been deemed important. It can be None.
- **feature engineer env(old env)** This method wraps the **env**, specifically:
 - A TabularDataSet is extracted using the data gen block for env wrap.
 - Then the method **_recursive_feature_selection()** is called onto the extracted dataset. We now have the list of selected features. Then:
 - * If **list_of_selected_state_features** is not *None* a Class *Wrapper* inheriting from the Class *BaseObservationWrapper* is created: the observation space is modified by selecting only the important states present in **list_of_selected_state_features**.

Moreover the method **observation()** is **overridden**: we call the old **observation()** method and then we select only the important states present in **list of selected state features**.

An object, **new env**, of Class *Wrapper* is created, passing to the initialiser the **old env**.

Furthermore if the action_space is continuous and if list_of_selected_action_features is not *None* a Class *Wrapper* inheriting from the Class *BaseActionWrapper* is created: the action space is modified by selecting only the important actions present in list of selected action features.

Moreover the method action() is overridden: we call the old action() method and then we select only the important actions present in list_of_selected_action_features.

An object, **new env**, of Class *Wrapper* is created, passing to the initialiser the **old env**.

* If **list_of_selected_state_features** is *None* we return the original **old_env**: the feature selection procedure failed.

Parameters:

- **old env** (BaseEnvironment) - This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- new_env (BaseEnvironment) This is an object of a Class inheriting from the Class BaseEnvironment. It is
 the wrapped env.
- **feature engineer data(old data)** This method modifies the **train data**, specifically:
 - The method **recursive feature selection()** is called onto the **old data**. Then:
 - * If list_of_selected_state_features is not None the observation_space, the current states, and the next states present in old_data are modified by selecting only the important states present in list_of_selected_

Moreover if the action_space is continuous and if <code>list_of_selected_action_features</code> is not <code>None</code> the action_space and the current actions are modified by selecting only the important actions present in <code>list_of_selected_action_features</code>.

* If **list_of_selected_state_features** is *None* we return the original **old_data**: the feature selection procedure failed.

Parameters:

- old data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- new_data (TabularDataSet) This is an object of a Class inheriting from the Class TabularDataSet. It is the modified train data.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class FeatureEngineering. Then:
 - If train_data is not None and if the observation_space is not one dimensional the method _feature_engineer_data() is called.

Otherwise if the **observation space** is one dimensional the original **train data** is returned as is.

If env is not None and if the observation_space is not one dimensional the method _feature_engineer_env() is called.

Otherwise if the **observation** space is one dimensional the original **env** is returned as is.

Parameters:

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

res (BlockOutput) - This is an object of Class BlockOutput which contains the new dataset in the train_data member, which is an object of Class BaseDataSet, and the new environment in the env member, which is an object of Class BaseEnvironment.

• analyse() - This method is not yet implemented	. It should evaluate this block according to the provided eval_metric

12.4 FeatureEngineeringFSCMI

This Class implements a specific feature engineering algorithm: it performs forward feature selection of the observation space using as metric the mutual information as proposed in Feature Selection via Mutual Information: New Theoretical Insights.

cf.https://arxiv.org/abs/1907.07384

The implementation of this block is based on the implementation associated with the cited paper.

This can be applied only to continuous spaces: it has no effect on discrete spaces.

The Class FeatureEngineeringFSCMI inherits from the Class FeatureEngineering.

Note that in this Class:

- works on online rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on offline rl is equal to *True*: indeed *FeatureEngineering* blocks are both *online* and *offline* blocks.
- works on box action space is equal to *True*.
- works on discrete action space is equal to True.

Even though this member is *True* if the action space is discrete no feature selection will be applied to the actions. This is done so that this block can be used on Box Observation Space and any type of Action Space.

- works on box observation space is equal to *True*.
- works_on_discrete_observation_space is equal to False: this can only be applied to continuous observation spaces.
- pipeline type is equal to 'online' if works on online rl is equal to True, else it is False.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
___init___(eval_metric, obj_name, seeder=2, algo_params=None, data_gen_block_for_env_wrap=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'threshold': 0.1
- 'k': 5
- data gen_block for env wrap (DataGeneration, None) This must be an object of a Class inheriting from the Class DataGeneration. This is used to extract a dataset from the environment and this dataset will be used for fitting the feature engineering algorithm.

This must extract an object of a Class inheriting from the Class *TabularDataSet*.

Note that this is only used if the method **learn()** receives an **env** but not the **train data**.

If this is not provided an object of Class *DataGenerationRandomUniformPolicy* collecting 100000 samples will be used.

To see more in detail why this is needed see the **Remark** before the **Initialiser** of the Class *FeatureEngineering*.

Non-Parameters Members:

• algo params upon instantiation (dict, None) - This is a deep copy of the original value of algo params.

Methods:

• <u>__mixed__mutual__info__forward__fs(features, target)</u> - This method computes an ordering of the features via Forward Feature Selection, by ranking the features based on the Mutual Information. We discard all the features that have a Mutual Information below the provided *threshold*.

Parameters:

- **features** (*numpy.ndarray*) This is a multi-dimensional *numpy.ndarray* representing the features: this is the current state.
- **target** (*numpy.ndarray*) This is a multi-dimensional *numpy.ndarray* representing the target: this is the next state and the reward.

Returns:

- sorted_ids (list) This is a list of non-negative integers and it corresponds to the selected ordering of the state features.
- **feature engineer env(old env)** This method wraps the **env**, specifically:
 - A **TabularDataSet** is extracted using the **data gen block for env wrap**.
 - Then the method _mixed_mutual_info_forward_fs() is called onto the extracted dataset. We now have the list of selected state features. Then:
 - * If **list_of_selected_state_features** is not *None* a Class *Wrapper* inheriting from the Class *BaseObservationWrapper* is created: the observation space is modified by selecting only the important states present in **list_of_selected_state_features**.

Moreover the method **observation()** is **overridden**: we call the old **observation()** method and then we select only the important states present in **list of selected state features**.

An object, **new env**, of Class *Wrapper* is created, passing to the initialiser the **old env**.

* If **list_of_selected_state_features** is *None* we return the original **old_env**: the feature selection procedure failed.

Parameters:

- old env (BaseEnvironment) - This must be an object of a Class inheriting from the Class BaseEnvironment.

- new_env (BaseEnvironment) This is an object of a Class inheriting from the Class BaseEnvironment. It is the wrapped env.
- _feature_engineer_data(old_data) This method modifies the train_data, specifically:

- The method **mixed mutual info forward fs()** is called onto the **old data**. Then:
 - * If list_of_selected_state_features is not *None* the observation_space, the current states, and the next states present in old data are modified by selecting only the important states present in list of selected
 - * If **list_of_selected_state_features** is *None* we return the original **old_data**: the feature selection procedure failed.

Parameters:

- old data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- new_data (TabularDataSet) This is an object of a Class inheriting from the Class TabularDataSet. It is the modified train data.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class FeatureEngineering. Then:
 - If train_data is not None and if the observation_space is not one dimensional the method feature engineer data() is called.

Otherwise if the **observation space** is one dimensional the original **train data** is returned as is.

If env is not None and if the observation_space is not one dimensional the method _feature_engineer_env() is called.

Otherwise if the **observation** space is one dimensional the original **env** is returned as is.

Parameters:

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- res (BlockOutput) This is an object of Class BlockOutput which contains the new dataset in the train_data member, which is an object of Class BaseDataSet, and the new environment in the env member, which is an object of Class BaseEnvironment.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided eval metric.

To see more details about the meaning of the parameters used in this block and the functioning of the methods see the paper https://arxiv.org/abs/1907.07384 and the code associated with it.

12.5 FeatureEngineeringNystroemMap

This Class implements a specific feature engineering algorithm: it constructs an approximate feature map for an arbitrary kernel using a subset of the data as basis.

cf. https://scikit-learn.org/stable/modules/generated/sklearn.kernel_approximation.Nystroem.html

The Class FeatureEngineeringNystroemMap inherits from the Class FeatureEngineering.

Note that in this Class:

- works on online rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works on offline rl is equal to True: indeed FeatureEngineering blocks are both online and offline blocks.
- works_on_box_action_space is equal to *True*.
- works on discrete action space is equal to True.
- works on box observation space is equal to True.
- works_on_discrete_observation_space is equal to False: this can only be applied to continuous observation spaces.
- **pipeline type** is equal to 'online' if **works** on **online** rl is equal to True, else it is False.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, algo_params=None, data_gen_block_for_env_wrap=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then a Radial Basis Function Kernel is going to be used with a value of gamma equal to 0.1 and 100 components will be created, using as the members **seeder** and **n_jobs** of this block to specify the random state and the number of jobs to use for parallelism, thus the following parameters will be used:

```
'kernel': 'rbf'
'gamma': 0.1
'n_components': 100
'random_state': seeder
'n of jobs': n jobs
```

• data _gen__block__for__env__wrap (DataGeneration, None) - This must be an object of a Class inheriting from the Class DataGeneration. This is used to extract a dataset from the environment and this dataset will be used for fitting the feature engineering algorithm.

This must extract an object of a Class inheriting from the Class *TabularDataSet*.

Note that this is only used if the method **learn()** receives an **env** but not the **train data**.

If this is not provided an object of Class *DataGenerationRandomUniformPolicy* collecting 100000 samples will be used.

To see more in detail why this is needed see the **Remark** before the **Initialiser** of the Class *FeatureEngineering*.

Non-Parameters Members:

- **algo_object** (None) This is the object containing the actual feature engineering algorithm. In this case it is an object of Class *sklearn.kernel approximation.Nystroem*.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.

Methods:

- feature engineer env(old env) This method wraps the env, specifically:
 - A Class Wrapper inheriting from the Class BaseObservationWrapper is created: the observation space is modified by calling the transform method of the algo_object (an object of Class sklearn.kernel_approximation.Nystroem in this case).

Moreover the method **observation()** is **overridden**: we call the old **observation()** method and then we apply the **transform** method of the **algo_object** (an object of Class *sklearn.kernel_approximation.Nystroem* in this case).

- An object, **new env**, of Class *Wrapper* is created, passing to the initialiser the **old env**.

Parameters:

- old env (BaseEnvironment) - This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- new_env (BaseEnvironment) This is an object of a Class inheriting from the Class BaseEnvironment. It is
 the wrapped env.
- feature engineer data(old data) This method modifies the train data, specifically:
 - The **transform** method of the **algo_object** (an object of Class *sklearn.kernel_approximation.Nystroem* in this case) is called onto the current states, and onto the next states present in **old data**.
 - A new object of Class *TabularDataSet* is created with the transformed data, and states.

Parameters:

- old data (TabularDataSet) - This must be an object of a Class inheriting from the Class TabularDataSet.

Returns:

- new_data (TabularDataSet) This is an object of a Class inheriting from the Class TabularDataSet. It is the modified train data.
- learn(train_data=None, env=None) This method calls the base method learn() implemented in the Class FeatureEngineering. Then:
 - If train data is not None the method feature engineer data() is called.
 - If **env** is not *None* then the **data gen block for env wrap** is learnt to extract a dataset from the **env**.

Then the **fit** method of the **algo_object** (an object of Class *sklearn.kernel_approximation.Nystroem* in this case) is called onto the extracted dataset.

Finally the method **feature engineer env()** is called.

Parameters:

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- res (BlockOutput) This is an object of Class BlockOutput which contains the new dataset in the train_data member, which is an object of Class BaseDataSet, and the new environment in the env member, which is an object of Class BaseEnvironment.
- analyse() This method is not yet implemented. It should evaluate this block according to the provided eval_metric.

13 model generation.py

In the module *model generation.py* the Class *ModelGeneration* is implemented.

13.1 ModelGeneration

This Class used to group all Classes that do ModelGeneration: this includes also AutoModelGeneration.

The Class ModelGeneration inherits from the Class Block. This is an Abstract Class.

Initialiser:

```
___init___(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n jobs=1, job type='process')
```

Methods:

• construct_policy(policy, regressor_type, approximator=None) - This method constructs an object of Class BasePolicy from the provided parameters.

Parameters:

 policy (mushroom_rl.policy.Policy) - This is the policy used in the RL algorithm implemented in the current ModelGeneration block.

Note that the **policy** alternatively can also be an object of any Class that exposes the method **draw_action()** taking as parameter just a single state.

- **regressor_type** (*str*) This is a string and it represents the regressor used in the policy, and it is either: 'action regressor', 'q regressor' or 'generic regressor'.
- approximator (mushroom_rl.approximators.regressor.Regressor, None) This represents the approximator used in the policy in the RL algorithm implemented in the current ModelGeneration block.

This is optional since all the relevant information are contained already in the **policy**, however this is used to discriminate between different policies and it plays a role in which *Metric* can be applied to which **policy**. To learn more about this read the documentation about the Class *DiscountedRewardMetric*.

Note that the **approximator** alternatively can also be an object of any Class that exposes the method **predict()** taking as parameter either a single sample, or multiple samples.

Returns:

- (BasePolicy) This is an object of Class BasePolicy in which the policy and the approximator are the ones give as parameters to this method.
- _walk_dict_to_select_current_actual_value(dict_of_hyperparams) This method is a recursive method that visits every sub-dictionary in the main dictionary with the aim to create a single flat dictionary from the original one. In doing so it also extracts the member current actual value from the *HyperParamter* object.

Parameters:

dict_of_hyperparams (dict) - This is a dictionary that can contain several sub-dictionary, where each value of each dictionary is an object of a Class inheriting from the Class HyperParameter.

- dict_of_hyperparams (dict) This is a flat dictionary where each value in the dictionary is a value: the value of the member current actual value of the corresponding HyperParameter object.
- __select__current__actual__value__from__hp__classes(params__structured__dict) This method flattens the original dictionary, that can contain multiple sub-dictionaries, and it extracts the member current__actual__value from the starting dictionary, that contains HyperParameter objects.

This is achieved by calling the method walk dict to select current actual value.

Parameters:

- params structured dict (dict) - This is a dictionary which can contain several sub-dictionaries.

Returns:

- algo_params_values (dict) This is a flat dictionary that contains the value of the member
 current_actual_value extracted from the original dictionary that contained HyperParameter objects.
- pre_learn_check(train_data=None, env=None) This method resets to False the member fully_instantiated: this means that the block has not been fully instantiated. Then:
 - It calls the base method **pre** learn **check()** implemented in the Class Block.
 - This method sets **algo** params to **algo** params upon instantiation. This is needed for re-loading objects.
 - It checks that the regressor_type is either one of: 'action_regressor', 'q_regressor' or 'generic_regressor'. These are the three types of regressor supported by MushroomRL for RL. cf. https://mushroomrl.readthedocs.io/en/latest/source/tutorials/tutorials.2_approximator. html

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) If the block satisfies the conditions indicated above this is *True*, else it is *False*.
- learn(train_data=None, env=None) This method first calls the base method learn() implemented in the Class Block. Then it checks that:
 - The current block was fully instantiated: ModelGeneration blocks undergo two-stage initialisation and therefore
 the method learn() of a ModelGeneration block can be called only once the method full_block_instantiation
 has been called.

Why is this needed? Because in a pipeline the environment may change and thus also the observation and action space of a RL environment may change, and therefore we don't know the specifics of the environment with which we are working with at the start of the pipeline but only once we reach the *ModelGeneration* block.

Furthermore the specifics of the environment with which we are working with are needed in order to instantiate MushroomRL algorithms objects.

- If the **pipeline type** is 'offline' the **train data** must not be None.
- If the **pipeline type** is 'online' the **env** must not be None.

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) - This method returns an empty object of Class BlockOutput if the call to the base method learn() implemented in the Class Block was not successful.

Otherwise it returns the **train_data** and the **env**: these are going to be passed onto a specific *ModelGeneration* block.

• _walk_dict_to_flatten_it(structured_dict, dict_to_fill) - This method is a recursive method that visits every sub-dictionary in the main dictionary with the aim to create a single flat dictionary from the original one.

Parameters:

- **structured dict** (*dict*) This is the original starting dictionary: it can contain several sub-dictionaries.
- dict_to_fill (dict) This is a variable that is passed to every recursive call of this method. At the first call to this method it is an empty dictionary.

Returns:

- **dict** to **fill** (*dict*) This is the filled flat dictionary.
- get_params() This method first extracts the algo_params: this can be a structured dictionary (i.e: the main dictionary can contain sub-dictionaries), therefore first it is rendered flat. This is achieved by calling the method _walk_dict_to_flatten_it().

Then a deep copy of this flat dictionary is returned.

Returns:

- flat dict (dict) - This is a flat dictionary containing a deep copy of the elements present in algo params.

14 model generation online.py

In the module model_generation_online.py the Classes ModelGenerationMushroomOnline, ModelGenerationMushroomOnlineDQN, ModelGenerationMushroomOnlineAC, ModelGenerationMushroomOnlinePPO, ModelGenerationMushroomOnlineSAC, ModelGenerationMushroomOnlineDDPG and ModelGenerationMushroomOnlineGPOMDP are implemented.

14.1 ModelGenerationMushroomOnline

This Class is used to contain all the common methods for the online model generation algorithms that are implemented in MushroomRL.

The Class ModelGenerationMushroomOnline inherits from the Class ModelGeneration. This is an Abstract Class.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', deterministic_output_policy=True)
```

Methods:

- **learn(train_data=None, env=None)** This method first calls the *base* method **learn()** implemented in the Class *ModelGeneration*. Then:
 - If the call to the *base* method **learn()** implemented in the Class *ModelGeneration* was not successful we return an empty object of Class *BlockOutput*.
 - If the call to the base method **learn()** implemented in the Class *ModelGeneration* was successful:
 - * If PyTorch is being used the number of threads of PyTorch is set.

To determine whether *PyTorch* is being used or not I simply check if the current block has the method **__default__network()**: this is not problematic indeed in MushroomRL you can only use *PyTorch* and not other deep learning frameworks.

- * The core is created by calling the method create core().
- * The **dict_of_evals** is created and initialised as empty dictionary: this will contain all the evaluation of the RL algorithm performed throughout training.
- * if the parameter **deterministic_output_policy** is equal to *True* then we call the method **make_policy_determ** onto the output block. If this calls happens it will be possible to use the batch evaluation in the metric *DiscountedReward*.
- * The RL algorithm is evaluated on the environment according to the provided **eval metric**.
- * If the RL algorithm has a replay buffer it is filled with random dataset and the **dict_of_evals** is updated by calling the method **update dict of evals()**.
- * Now we proceed as it is usually done and we perform **n epochs** in each of which we alternate between:
 - · Learning the RL algorithm, by calling the method learn() of the member core
 - · if the parameter **deterministic _output _policy** is equal to *True* then we call the method **make _policy _det** onto the output block. If this calls happens it will be possible to use the batch evaluation in the metric *DiscountedReward*.
 - · Evaluating the RL algorithm according to the provided **eval metric**.

Here the dict of evals is updated by calling the method update dict of evals().

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) - This method returns an empty object of Class BlockOutput if the call to the base method learn() implemented in the Class ModelGeneration was not successful.

Otherwise the object of Class *BlockOutput* contains the **policy** which is constructed by calling the method **construct policy()**.

If **deterministic_output_policy** is equal to *True* it will be possible to use the batch evaluation in the metric *DiscountedReward*, otherwise the *DiscountedReward* Class can only use non-batch evaluation.

To see more about what this means see the Class DiscountedReward.

- plot_dict_of_evals() This method generates a plot representing how the average discounted reward changes as the agent interacts with more environment steps. It uses the dict_of_evals to make the plot. The standard deviation and the mean across the episodes are plotted.
- update_dict_of_evals(current_epoch, single_episodes_eval, env) This method update the dict_of_evals which is a dictionary containing as key the current step and as value the average discounted reward of the agent over a number of episodes equal to that specified in the eval metric.

This is used to keep track of the evolution of the agent evaluation as learning progresses. This method does not use the trajectories that were extracted by the algorithm as part of the learning procedure, but interacts with the environment.

This method adds a new entry to the dictionary with key given by the number of interactions with the environment happened so far and value equal to the list **single episodes eval**.

The user should not call this method as it is called by the method **learn()** of online model generation blocks.

Parameters:

- **current_epoch** (*int*) This is a non-negative integer and it represents the current epoch: this is used to make the plot, indeed for each epoch we plots the mean evaluation and the standard deviation of the evaluation.
- **single_episodes_eval** (*list*) This is a list of floats containing the evaluation of the agent over the single episodes, for as many episodes as specified by the **eval metric**.
- env (BaseEnvironment) This must be an object of a Class inheriting from the Class BaseEnvironment.
- _create_core(env) This method create an object of Class mushroom_rl.core.Core and it assigns it to the core member of the online ModelGeneration object. This is needed in order to run online RL algorithms implemented in MushroomRL.

- env (BaseEnvironment) This must be an object of a Class inheriting from the Class BaseEnvironment.
- analyse() This method is not yet implemented. It should analyse the learnt online *ModelGeneration* block, namely it should evaluate it according to the provided eval metric.
- save() This method saves the block to a *pickle* file. This method deep copies the current block and then it removes from the deep copy the members core and algo object, then it calls the method save() of the deep copied object.

This is done because many online *ModelGeneration* blocks have a replay buffer which may contain a lot of data thus causing the *pickle* object obtained from calling the method **save()** be very heavy. This might result problematic when saving several thousand objects in a *Tuner*.

It is the deep copy of the block that is modified and then saved, indeed we cannot modify directly the object itself because the member <code>algo_object</code> is not restored in the call of the method <code>learn()</code>: the member <code>algo_object</code> is restored in the call of the method <code>set_params()</code> hence we would not be able to call twice in a row the method <code>learn()</code> if we were to modify directly the object itself, as we would not have the right value for <code>algo_object</code>.

14.2 ModelGenerationMushroomOnlineDQN

This Class implements a specific online model generation algorithm: DQN. This Class wraps the DQN method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/value/dqn/dqn.py

The Class ModelGenerationMushroomOnlineDQN inherits from the Class ModelGenerationMushroomOnline.

Note that in this Class:

- works_on_online_rl is equal to *True*.
- works on offline rl is equal to False.
- works on box action space is equal to False.
- works on discrete action space is equal to *True*.
- works on box observation space is equal to True.
- works on discrete observation space is equal to *True*.
- pipeline type is equal to 'online'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='q_regressor', seeder=2, algo_params=None,
log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process',
deterministic output policy=True)
```

Parameters:

- regressor_type (str, 'q_regressor') This is a string and it used to pick between the three possible regressors that can be used in MushroomRL. For more information about the different regressor see the link in the explanation of method pre learn check() of the ModelGeneration Class.
- algo params (dict, None) This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'epsilon': mushroom rl.utils.parameters.LinearParameter(value=1, threshold value=0.01, n=1000000)
- 'policy': mushroom rl.policy.EpsGreedy(epsilon='epsilon')
- 'approximator': mushroom rl.approximators.parametric.TorchApproximator
- 'network': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'optimizer': torch.optim.Adam
- 'lr': 0.0001
- 'critic loss': torch.nn.functional.smooth | 1 | loss
- 'batch size': 32
- 'target update frequency': 250
- 'replay memory': mushroom rl.utils.replay memory.ReplayMemory
- 'initial replay size': 50000
- 'max replay size': 1000000

```
'clip_reward': False
'n_epochs': 10
'n_steps': None
'n_steps_per_fit': None
'n_episodes': 500
'n episodes per fit': 50
```

• **deterministic_output_policy** (*bool*, True) - This is a boolean and if *True* the method **make_policy_deterministic()**, of the Class *BlockOutput*, will be called before the evaluation step through the method **learn()** of this block. This turns the policy contained in an object of Class *BlockOutput* into a deterministic policy.

If this happens then the mode **batch** evaluation can be used in the Class *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- **algo_object** (None) This is the object containing the actual RL online algorithm. In this case it is an object of Class *mushroom rl.algorithms.value.dqn.DQN*.
- algo_params_upon_instantiation (*dict*, None) This is a deep copy of the original value of algo_params.
- **model** This contains the *Class* of the actual RL online algorithm. In this case it contains the Class *mush-room rl.algorithms.value.dqn.DQN*.
- **core** (*mushroom_rl.core.Core*, None) This contains the **Core** object of MushroomRL that is needed in order to run an online RL algorithm.
- **dict_of_evals** (*dict*) This is a dictionary containing as key the current step and as value the average reward of the agent over the last 10 episodes ending at said step. This is used to keep track of the evolution of the agent evaluation as learning progresses.

Methods:

• _default_network() - This method creates a Class inheriting from the Class torch.nn.Module that has one hidden layer made up of 16 neurons with activation function ReLU.

This network will be used in DQN.

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in DQN is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo_params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom_rl.core.Core.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- set_params(new_params) This method changes the value of algo_params and of algo_params_upon _instantiation to that of new params. Moreover:
 - The policy, input_shape, output_shape and n_actions variables are created: these are needed for instantiating a core object from MushroomRL.

The **policy** is an epsilon greedy policy, while the other variables are created according to the choice of **regressor_type**. To see how read through the web page linked in the explanation of the method **pre_learn_check()** of the Class *ModelGeneration*.

- A structured dictionary is created: this is needed in order to properly instantiate a MushroomRL agent object.
 Moreover in order to instantiate such an object we also need to extract the current _actual _value from the new params dictionary, which is made of *HyperParameter* objects.
- An object of Class mushroom_rl.algorithms.value.dqn.DQN is created passing to it the structured dictionary created in the previous step. This is saved in the member algo object.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) - This is *True* if **new params** was set successfully, else it is *False*.

14.3 ModelGenerationMushroomOnlineAC

This Class is used as base Class for actor-critic methods implemented in MushroomRL. Specifically is used to contain some common methods that would have the same implementation across different actor critic methods.

The Class *ModelGenerationMushroomOnlineAC* inherits from the Class *ModelGenerationMushroomOnline*. This is an *Abstract Class*.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', deterministic_output_policy=True)
```

Methods:

- set_params(new_params) This method changes the value of algo_params and of algo_params_upon _instantiation to that of new_params. Moreover:
 - The input_shape, output_shape and n_actions variables are created: these are needed for instantiating a core object from MushroomRL.

These variables are created according to the choice of **regressor_type**. To see how read through the web page linked in the explanation of the method **pre learn check()** of the Class *ModelGeneration*.

- The method **model_specific_set_params()** is called: this method is implemented in Classes that inherit from this Class. This method:
 - * Returns a structured dictionary: this is needed in order to properly instantiate a MushroomRL **agent** object. Moreover in order to instantiate such an object we also need to extract the **current_actual_value** from the **new params** dictionary, which is made of *HyperParameter* objects.
 - * An object of Class **model** is created passing to it the structured dictionary created in the previous step. This is saved in the member **algo object**.

The Class **model** is specified in Class that inherit from this Class.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) - This is *True* if **new params** was set successfully, else it is *False*.

14.4 ModelGenerationMushroomOnlinePPO

This Class implements a specific online model generation algorithm: PPO. This Class wraps the PPO method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/actor_critic/deep_actor_critic/ppo.py

The Class ModelGenerationMushroomOnlinePPO inherits from the Class ModelGenerationMushroomOnlineAC.

Note that in this Class:

- works on online rl is equal to *True*.
- works on offline rl is equal to False.
- works on box action space is equal to True.
- works_on_discrete_action_space is equal to *True*.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'online'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='generic_regressor', seeder=2, algo_params=None,
log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process',
deterministic output policy=True)
```

Parameters:

- **regressor_type** (*str*, 'generic_regressor') This is a string and it used to pick between the three possible regressors that can be used in MushroomRL. For more information about the different regressor see the link in the explanation of method **pre learn check()** of the *ModelGeneration* Class.
- algo params (dict, None) This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'policy':
 - * For Box action spaces: mushroom rl.policy.GaussianTorchPolicy(std 0=1)
 - * For Discrete action spaces: mushroom rl.policy.BoltzmannTorchPolicy(beta=0.001)
- 'network': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'actor class': torch.optim.Adam
- 'actor Ir': 0.0003
- 'critic class': torch.optim.Adam
- 'critic Ir': 0.0003
- 'loss': torch.nn.functional.mse loss
- 'n epochs policy': 10
- 'batch size': 64

```
- 'eps_ppo': 0.2
- 'lam': 0.95
- 'ent_coeff': 0
- 'n_epochs': 10
- 'n_steps': None
- 'n_steps_per_fit': None
- 'n_episodes': 500
- 'n episodes per_fit': 50
```

• **deterministic_output_policy** (*bool*, True) - This is a boolean and if *True* the method **make_policy_deterministic()**, of the Class *BlockOutput*, will be called before the evaluation step through the method **learn()** of this block. This turns the policy contained in an object of Class *BlockOutput* into a deterministic policy.

If this happens then the mode **batch** evaluation can be used in the Class *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- algo_object (None) This is the object containing the actual RL online algorithm. In this case it is an object of Class mushroom_rl.algorithms.actor_critic.deep_actor_critic.PPO.
- algo_params_upon_instantiation (dict, None) This is a deep copy of the original value of algo_params.
- **model** This contains the *Class* of the actual RL online algorithm. In this case it contains the Class *mush-room_rl.algorithms.actor_critic.deep_actor_critic.PPO*.
- **core** (*mushroom_rl.core.Core*, None) This contains the **Core** object of MushroomRL that is needed in order to run an online RL algorithm.
- **dict_of_evals** (*dict*) This is a dictionary containing as key the current step and as value the average reward of the agent over the last 10 episodes ending at said step. This is used to keep track of the evolution of the agent evaluation as learning progresses.

Methods:

• _default_network() - This method creates a Class inheriting from the Class *torch.nn.Module* that has one hidden layer made up of 16 neurons with activation function ReLU.

This network will be used in PPO.

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in PPO is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo_params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom_rl.core.Core.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- model_specific_set_params(new_params, mdp_info, input_shape, output_shape, n_actions) This method is called by the method set params() in the common parent Class ModelGenerationMushroomOnlineAC.

This method:

- Selects the type of **policy** based on the action space, as described above in the **Parameters** section under the voice **algo params**.
- Starting from the flat dictionary new_params it constructs the proper structured dictionary that MushroomRL expects.

This structured dictionary is made up of *HyperParameter* objects: in order to instantiate a MushroomRL **agent** object we need to extract the **current actual value** from the newly created structured dictionary.

- An object of Class *mushroom_rl.algorithms.actor_critic.deep_actor_critic.PPO* is created passing to it the structured dictionary created in the previous step. This is saved in the member **algo object**.

This method should not be called by the user: it is called in the parent Class ModelGenerationMushroomOnlineAC.

Parameters:

- new_params (dict) This must be a flat dictionary containing all the parameters needed for this block to work.
- mdp_info (mushroom_rl.environment.MDPInfo) This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for selecting the policy to use: from mdp_info the action space is extracted so that we know if it is Box or Discrete.
- input shape (HyperParameter) This is an object of a Class inheriting from the Class HyperParameter.

This is the input shape of the environment, namely the shape of the observation space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- **output** shape (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

This is the output shape of the environment, namely the shape of the action space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- **n** actions (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

In case the environment has *Discrete* action space this is used to represent the number of actions. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- **tmp_structured_algo_params** (*dict*) This is a structured dictionary containing *HyperParameter* objects: it compromises all the parameters needed to instantiate a MushroomRL **agent** object.
- dict_to_add (dict) This is a dictionary is a flat dictionary containing more parameters that are not needed for the MushroomRL agent object but that are needed for the overall ModelGeneration block. Examples are:

- * The number of episodes and the number of episodes per fit.
- * The number of epochs: for how many times do we need to alternate between learning the agent and evaluating it?

14.5 ModelGenerationMushroomOnlineSAC

This Class implements a specific online model generation algorithm: SAC. This Class wraps the SAC method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/actor_critic/deep_actor_critic/sac.py

The Class ModelGenerationMushroomOnlineSAC inherits from the Class ModelGenerationMushroomOnlineAC.

Note that in this Class:

- works on online rl is equal to *True*.
- works on offline rl is equal to False.
- works on box action space is equal to True.
- works on discrete action space is equal to False.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'online'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='generic_regressor', seeder=2, algo_params=None,
log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process',
deterministic output policy=True)
```

Parameters:

- regressor_type (str, 'generic_regressor') This is a string and it used to pick between the three possible regressors that can be used in MushroomRL. For more information about the different regressor see the link in the explanation of method pre learn check() of the ModelGeneration Class.
- algo params (dict, None) This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'actor network mu': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'actor network sigma': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'critic network': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'actor class': torch.optim.Adam
- 'actor Ir': 0.0003
- 'critic class': torch.optim.Adam
- 'critic Ir': 0.0003
- 'loss': torch.nn.functional.mse loss
- 'batch size': 256
- 'initial replay size': 50000
- 'max replay size': 1000000

```
- 'warmup transitions': 100
```

- 'tau': 0.005

- 'lr_alpha': 0.0003

- 'log_std_min': -20

- 'log std max': 2

- 'target entropy': None

- 'n epochs': 10

- 'n steps': None

- 'n_steps_per_fit': None

- 'n episodes': 500

- 'n episodes per fit': 50

• **deterministic_output_policy** (*bool*, True) - This is a boolean and if *True* the method **make_policy_deterministic()**, of the Class *BlockOutput*, will be called before the evaluation step through the method **learn()** of this block. This turns the policy contained in an object of Class *BlockOutput* into a deterministic policy.

If this happens then the mode **batch** evaluation can be used in the Class *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- **algo_object** (None) This is the object containing the actual RL online algorithm. In this case it is an object of Class mushroom_rl.algorithms.actor_critic.deep_actor_critic.SAC.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL online algorithm. In this case it contains the Class *mush-room_rl.algorithms.actor_critic.deep_actor_critic.SAC*.
- **core** (*mushroom_rl.core.Core*, None) This contains the **Core** object of MushroomRL that is needed in order to run an online RL algorithm.
- **dict_of_evals** (*dict*) This is a dictionary containing as key the current step and as value the average reward of the agent over the last 10 episodes ending at said step. This is used to keep track of the evolution of the agent evaluation as learning progresses.

Methods:

• _default_network() - This method creates two Classes, both inheriting from the Class *torch.nn.Module*: one is the critic network, the other is the actor network.

Both networks have one hidden layer made up of 16 neurons with activation function ReLU.

These networks will be used in SAC.

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in SAC is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Core.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- model_specific_set_params(new_params, mdp_info, input_shape, output_shape, n_actions) This method is called by the method set params() in the common parent Class ModelGenerationMushroomOnlineAC.

This method:

Starting from the flat dictionary new_params it constructs the proper structured dictionary that MushroomRL expects.

This structured dictionary is made up of *HyperParameter* objects: in order to instantiate a MushroomRL **agent** object we need to extract the **current actual value** from the newly created structured dictionary.

 An object of Class mushroom_rl.algorithms.actor_critic.deep_actor_critic.SAC is created passing to it the structured dictionary created in the previous step. This is saved in the member algo_object.

This method should not be called by the user: it is called in the parent Class ModelGenerationMushroomOnlineAC.

Parameters:

- new_params (dict) This must be a flat dictionary containing all the parameters needed for this block to work.
- mdp_info (mushroom_rl.environment.MDPInfo) This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for selecting the policy to use: from mdp_info the action space is extracted so that we know if it is Box or Discrete.
- input_shape (HyperParameter) This is an object of a Class inheriting from the Class HyperParameter.

This is the input shape of the environment, namely the shape of the observation space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- **output_shape** (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

This is the output shape of the environment, namely the shape of the action space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- n actions (HyperParameter) - This is an object of a Class inheriting from the Class HyperParameter.

In case the environment has *Discrete* action space this is used to represent the number of actions. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

Returns:

- tmp_structured_algo_params (dict) This is a structured dictionary containing HyperParameter objects: it compromises all the parameters needed to instantiate a MushroomRL agent object.
- dict_to_add (dict) This is a dictionary is a flat dictionary containing more parameters that are not needed for the MushroomRL agent object but that are needed for the overall ModelGeneration block. Examples are:
 - * The number of episodes and the number of episodes per fit.
 - * The number of epochs: for how many times do we need to alternate between learning the agent and evaluating it?

14.6 ModelGenerationMushroomOnlineDDPG

This Class implements a specific online model generation algorithm: DDPG. This Class wraps the DDPG method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/actor_critic/deep_actor_critic/ddpg.py

The Class ModelGenerationMushroomOnlineDDPG inherits from the Class ModelGenerationMushroomOnlineAC.

Note that in this Class:

- works on online rl is equal to *True*.
- works on offline rl is equal to False.
- works on box action space is equal to True.
- works on discrete action space is equal to False.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'online'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='generic_regressor', seeder=2, algo_params=None,
log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process',
deterministic output policy=True)
```

Parameters:

- **regressor_type** (*str*, 'generic_regressor') This is a string and it used to pick between the three possible regressors that can be used in MushroomRL. For more information about the different regressor see the link in the explanation of method **pre learn check()** of the *ModelGeneration* Class.
- algo params (dict, None) This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'policy': mushroom rl.policy.noise policy.OrnsteinUhlenbeckPolicy(sigma, theta, dt) where:
 - * sigma = 0.2*np.ones(1)
 - * theta = 0.15
 - * dt = 1e-2
- 'actor network': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'critic network': one hidden layer made up of 16 neurons and ReLU as activation function.
- 'actor class': torch.optim.Adam
- 'actor Ir': 0.001
- 'critic class': torch.optim.Adam
- 'critic Ir': 0.001
- 'loss': torch.nn.functional.mse loss

```
- 'batch_size': 100
```

- 'initial_replay_size': 50000

- 'max replay size': 1000000

- 'tau': 0.005

- 'policy_delay': 1

- 'n_epochs': 10

- 'n steps': None

- 'n_steps_per_fit': None

- 'n episodes': 500

- 'n episodes per fit': 50

• **deterministic_output_policy** (*bool*, True) - This is a boolean and if *True* the method **make_policy_deterministic()**, of the Class *BlockOutput*, will be called before the evaluation step through the method **learn()** of this block. This turns the policy contained in an object of Class *BlockOutput* into a deterministic policy.

If this happens then the mode **batch** evaluation can be used in the Class *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- **algo_object** (None) This is the object containing the actual RL online algorithm. In this case it is an object of Class mushroom rl.algorithms.actor critic.deep actor critic.DDPG.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL online algorithm. In this case it contains the Class *mush-room_rl.algorithms.actor_critic.deep_actor_critic.DDPG*.
- **core** (*mushroom_rl.core.Core*, None) This contains the **Core** object of MushroomRL that is needed in order to run an online RL algorithm.
- **dict_of_evals** (*dict*) This is a dictionary containing as key the current step and as value the average reward of the agent over the last 10 episodes ending at said step. This is used to keep track of the evolution of the agent evaluation as learning progresses.

Methods:

• _default_network() - This method creates two Classes, both inheriting from the Class *torch.nn.Module*: one is the critic network, the other is the actor network.

Both networks have one hidden layer made up of 16 neurons with activation function ReLU.

These networks will be used in DDPG.

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in DDPG is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Core.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- model_specific_set_params(new_params, mdp_info, input_shape, output_shape, n_actions) This method is called by the method set_params() in the common parent Class ModelGenerationMushroomOnlineAC.

This method:

Starting from the flat dictionary new_params it constructs the proper structured dictionary that MushroomRL expects.

This structured dictionary is made up of *HyperParameter* objects: in order to instantiate a MushroomRL **agent** object we need to extract the **current actual value** from the newly created structured dictionary.

 An object of Class mushroom_rl.algorithms.actor_critic.deep_actor_critic.DDPG is created passing to it the structured dictionary created in the previous step. This is saved in the member algo_object.

This method should not be called by the user: it is called in the parent Class ModelGenerationMushroomOnlineAC.

Parameters:

- new_params (dict) This must be a flat dictionary containing all the parameters needed for this block to work.
- mdp_info (mushroom_rl.environment.MDPInfo) This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for selecting the policy to use: from mdp_info the action space is extracted so that we know if it is Box or Discrete.
- input shape (HyperParameter) This is an object of a Class inheriting from the Class HyperParameter.

This is the input shape of the environment, namely the shape of the observation space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- **output** shape (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

This is the output shape of the environment, namely the shape of the action space. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

- n actions (HyperParameter) - This is an object of a Class inheriting from the Class HyperParameter.

In case the environment has *Discrete* action space this is used to represent the number of actions. This parameter is set in the parent Class *ModelGenerationMushroomOnlineAC* based on the value of **regressor type**.

Returns:

- tmp_structured_algo_params (dict) This is a structured dictionary containing HyperParameter objects: it compromises all the parameters needed to instantiate a MushroomRL agent object.
- dict_to_add (dict) This is a dictionary is a flat dictionary containing more parameters that are not needed for the MushroomRL agent object but that are needed for the overall ModelGeneration block. Examples are:
 - * The number of episodes and the number of episodes per fit.
 - * The number of epochs: for how many times do we need to alternate between learning the agent and evaluating it?

14.7 ModelGenerationMushroomOnlineGPOMDP

This Class implements a specific online model generation algorithm: GPOMDP. This Class wraps the GPOMDP method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/policy_search/policy_gradient/gpomdp.py

The Class ModelGenerationMushroomOnlineGPOMDP inherits from the Class ModelGenerationMushroomOnline.

Initialiser:

```
___init___(eval_metric, obj_name, regressor_type='generic_regressor', seeder=2, algo_params=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', deterministic output policy=True)
```

Parameters:

- **regressor_type** (*str*, 'generic_regressor') This is a string and it used to pick between the three possible regressors that can be used in MushroomRL. For more information about the different regressor see the link in the explanation of method **pre_learn_check()** of the *ModelGeneration* Class.
- algo params (dict, None) This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'policy': mushroom rl.policy.gaussian policy.StateStdGaussianPolicy
- 'approximator': mushroom rl.approximators.parametric.linear.LinearApproximator
- 'optimizer': mushroom rl.utils.optimizers.AdaptiveOptimizer
- 'eps': 1e-2
- 'n epochs': 10
- 'n steps': None
- 'n steps per fit': None
- 'n episodes': 500
- 'n episodes per fit': 50
- **deterministic_output_policy** (*bool*, True) This is a boolean and if *True* the method **make_policy_deterministic()**, of the Class *BlockOutput*, will be called before the evaluation step through the method **learn()** of this block. This turns the policy contained in an object of Class *BlockOutput* into a deterministic policy.

If this happens then the mode **batch** evaluation can be used in the Class *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- algo_object (None) This is the object containing the actual RL online algorithm. In this case it is an object of Class mushroom rl.algorithms.policy search.policy gradient.GPOMDP.

- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL online algorithm. In this case it contains the Class *mush-room rl.algorithms.policy search.policy gradient.GPOMDP.*
- **core** (*mushroom_rl.core.Core*, None) This contains the **Core** object of MushroomRL that is needed in order to run an online RL algorithm.
- dict_of_evals (dict) This is a dictionary containing as key the current step and as value the average reward of the agent over the last 10 episodes ending at said step. This is used to keep track of the evolution of the agent evaluation as learning progresses.

Methods:

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in GPOMDP is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class mushroom_rl.environment.MDPInfo containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Core.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- __create__policy(input__shape, n__actions, output__shape) This method create the default policy: a policy of Class mushroom rl.policy.gaussian policy.StateStdGaussianPolicy.

You can create a Class inheriting from this Class and override this method to create a custom policy. The policy cannot be specified via a parameter because it can only be constructed at run time: we don't have the input parameters of this method when an object of this Class is initialised.

Parameters:

- input shape (HyperParameter) - This is an object of a Class inheriting from the Class HyperParameter.

This is the input shape of the environment, namely the shape of the observation space.

- **output** shape (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

This is the output shape of the environment, namely the shape of the action space.

- **n** actions (*HyperParameter*) - This is an object of a Class inheriting from the Class *HyperParameter*.

In case the environment has *Discrete* action space this is used to represent the number of actions.

Returns:

- **policy** (*Categorical*) - This is an object of Class *Categorical* and it contains the policy: an object of a Class inheriting from the Class *mushroom rl.policy.Policy.*

- set_params(new_params) This method changes the value of algo_params and of algo_params_upon _instantiation to that of new params. Moreover:
 - The **policy**, **input_shape**, **output_shape** and **n_actions** variables are created: these are needed for instantiating a **core** object from MushroomRL.

The **policy** is create by calling the method **_create_policy()**, while the other variables are created according to the choice of **regressor_type**. To see how read through the web page linked in the explanation of the method **pre learn check()** of the Class *ModelGeneration*.

- A structured dictionary is created: this is needed in order to properly instantiate a MushroomRL agent object.
 Moreover in order to instantiate such an object we also need to extract the current_actual_value from the new_params dictionary, which is made of HyperParameter objects.
- An object of Class *mushroom_rl.algorithms.policy_search.policy_gradient.GPOMDP* is created passing to it the structured dictionary created in the previous step. This is saved in the member **algo object**.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) - This is *True* if **new params** was set successfully, else it is *False*.

15 model generation offline.py

In the module model_generation_offline.py the Classes ModelGenerationMushroomOffline, ModelGenerationMushroomOfflineFQI, ModelGenerationMushroomOfflineDoubleFQI and ModelGenerationMushroomOfflineLSPI are implemented.

15.1 ModelGenerationMushroomOffline

This Class is used to contain all the common methods for the offline model generation algorithms that are implemented in MushroomRL.

The Class ModelGenerationMushroomOffline inherits from the Class ModelGeneration. This is an Abstract Class.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Methods:

- learn(train_data=None, env=None) This method first calls the base method learn() implemented in the Class ModelGeneration. Then:
 - If the call to the *base* method **learn()** implemented in the Class *ModelGeneration* was not successful we return an empty object of Class *BlockOutput*.
 - If the call to the *base* method **learn()** implemented in the Class *ModelGeneration* was successful we call the method **fit()** of the **algo object** on the member **dataset** of the **train data**.

Parameters:

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- This method returns an empty object of Class *BlockOutput* if the call to the *base* method **learn()** implemented in the Class *ModelGeneration* was not successful.

Otherwise the object of Class *BlockOutput* contains the **policy** which is constructed by calling the method **construct policy()**.

Here the **approximator** parameter is passed to the method **construct_policy()** therefore the *Discounte-dReward* Class can use both batch and non-batch evaluation on blocks of a Class inheriting from this Class.

To see more about what this means see the Class DiscountedReward.

- **set_params(new_params)** This method changes the value of **algo_params** and of **algo_params_upon_instantiation** to that of **new_params**. Moreover:
 - The policy, input_shape, output_shape and n_actions variables are created: these are needed for instantiating the actual offline RL algorithm from MushroomRL.

The **policy** is an epsilon greedy policy, while the other variables are created according to the choice of **regressor_type**. To see how read the web page linked in the explanation of the method **pre_learn_check()** of the Class *ModelGeneration*.

- A structured dictionary is created: this is needed in order to properly instantiate a MushroomRL agent object.
 Moreover in order to instantiate such an object we also need to extract the current_actual_value from the new params dictionary, which is made of *HyperParameter* objects.
- An object of Class mushroom_rl.core.Agent (based on the value of the member model) is created passing to
 it the structured dictionary created in the previous step. This is saved in the member algo object.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) This is *True* if **new params** was set successfully, else it is *False*.
- analyse() This method is not yet implemented. It should analyse the learnt offline *ModelGeneration* block, namely it should evaluate it according to the provided eval metric.
- save() This method saves the block to a *pickle* file. This method deep copies the current block and then it removes from the deep copy the member algo object, then it calls the method save() of the deep copied object.

This is done because the **algo_object** may contain a lot of data thus causing the *pickle* object obtained from calling the method **save()** be very heavy. This might result problematic when saving several thousand objects in a *Tuner*.

It is the deep copy of the block that is modified and then saved, indeed we cannot modify directly the object itself because the member algo_object is not restored in the call of the method learn(): the member algo_object is restored in the call of the method set_params() hence we would not be able to call twice in a row the method learn() if we were to modify directly the object itself, as we would not have the right value for algo object.

15.2 ModelGenerationMushroomOfflineFQI

This Class implements a specific offline model generation algorithm: FQI. This class wraps the Fitted Q-Iteration method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/value/batch_td/fqi.py

The Class ModelGenerationMushroomOfflineFQI inherits from the Class ModelGenerationMushroomOffline.

Note that in this Class:

- works on online rl is equal to False.
- works on offline rl is equal to *True*.
- works on box action space is equal to False.
- works on discrete action space is equal to *True*.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'offline'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='action_regressor', n_train_samples=None, seeder=2,
algo_params=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1,
job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

```
- 'policy': mushroom rl.policy.EpsGreedy(value=0)
```

- 'approximator': XGBRegressor

- 'n iterations': 10

- 'n estimators': 300

- 'subsample': 0.8

- 'colsample bytree': 0.3

- 'colsample bylevel': 0.7

- 'learning_rate': 0.08

- 'verbosity': 0

- 'random state': 3

- 'n jobs': 1

• regressor_type (str, 'action_regressor') - This is a string and it can either be: 'action_regressor', 'q_regressor' or 'generic regressor'. This is used to pick one of the 3 possible kind of regressor made available by MushroomRL.

Note that if you want to use a $'q_regressor'$ then the picked regressor must be able to perform multi-target regression, as a single regressor is used for all actions.

• n_train_samples (Integer, None) - This must be an object of Class Integer (sub-Class of HyperParameter) and it represents a tunable parameter. This has effect only when using the input loader: LoadDifferentSizeForEachBlock and LoadDifferentSizeForEachBlockAndEnv.

For this to work the block must have **is_parametrised** equal to *True*, otherwise it does not reach the method **tune()** of the *Tuner*!

If *None* then an *Integer* object is created with **current_actual_value** equal to 10000 and with **range_of_values** equal to [100, 1000000]

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full_block_instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- **algo_object** (None) This is the object containing the actual RL offline algorithm. In this case it is an object of Class *mushroom rl.algorithms.value.batch td.fqi.FQI*.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL offline algorithm. In this case it contains the Class *mush-room rl.algorithms.value.batch td.fqi.FQI*.

Methods:

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in FQI is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Agent.

Returns:

- (bool) - This is *True* if the block was successfully fully instantiated, else it is *False*.

15.3 ModelGenerationMushroomOfflineDoubleFQI

This Class implements a specific offline model generation algorithm: DoubleFQI. This class wraps the Double Fitted Q-Iteration method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/value/batch_td/double_fqi.py

The Class ModelGenerationMushroomOfflineDoubleFQI inherits from the Class ModelGenerationMushroomOffline.

Note that in this Class:

- works on online rl is equal to False.
- works on offline rl is equal to *True*.
- works on box action space is equal to False.
- works on discrete action space is equal to True.
- works on box observation space is equal to True.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'offline'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init__(eval_metric, obj_name, regressor_type='action_regressor', n_train_samples=None, seeder=2,
algo_params=None, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1,
job_type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

```
- 'policy': mushroom rl.policy.EpsGreedy(value=0)
```

- 'approximator': XGBRegressor

- 'n_iterations': 10

- 'n estimators': 300

- 'subsample': 0.8

- 'colsample bytree': 0.3

- 'colsample bylevel': 0.7

- 'learning rate': 0.08

- 'verbosity': 0

- 'random state': 3

- 'n jobs': 1

• regressor_type (str, 'action_regressor') - This is a string and it can either be: 'action_regressor', 'q_regressor' or 'generic regressor'. This is used to pick one of the 3 possible kind of regressor made available by MushroomRL.

Note that if you want to use a $'q_regressor'$ then the picked regressor must be able to perform multi-target regression, as a single regressor is used for all actions.

• n_train_samples (Integer, None) - This must be an object of Class Integer (sub-Class of HyperParameter) and it represents a tunable parameter. This has effect only when using the input loader: LoadDifferentSizeForEachBlock and LoadDifferentSizeForEachBlockAndEnv.

For this to work the block must have **is_parametrised** equal to *True*, otherwise it does not reach the method **tune()** of the *Tuner*!

If *None* then an *Integer* object is created with **current_actual_value** equal to 10000 and with **range_of_values** equal to [100, 1000000]

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full_block_instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- **algo_object** (None) This is the object containing the actual RL offline algorithm. In this case it is an object of Class *mushroom rl.algorithms.value.batch td.double fqi.DoubleFQI*.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL offline algorithm. In this case it contains the Class *mush-room rl.algorithms.value.batch td.double fqi.DoubleFQI*.

Methods:

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in DoubleFQI is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Agent.

Returns:

- (bool) - This is *True* if the block was successfully fully instantiated, else it is *False*.

15.4 ModelGenerationMushroomOfflineLSPI

This Class implements a specific offline model generation algorithm: LSPI. This class wraps the Least-Squares Policy Iteration method implemented in MushroomRL.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/algorithms/value/batch_td/lspi.py

The Class ModelGenerationMushroomOfflineLSPI inherits from the Class ModelGenerationMushroomOffline.

Note that in this Class:

- works on online rl is equal to False.
- works on offline rl is equal to *True*.
- works on box action space is equal to False.
- works on discrete action space is equal to *True*.
- works on box observation space is equal to True.
- works on discrete observation space is equal to *True*.
- **pipeline type** is equal to 'offline'.
- is parametrised is equal to *True*, indeed this block has several parameters that can be tuned.

Initialiser:

```
__init___(eval__metric, obj__name, regressor__type='action__regressor', n__train__samples=None, seeder=2,
algo__params=None, log__mode='console', checkpoint__log__path=None, verbosity=3, n__jobs=1,
job__type='process')
```

Parameters:

• algo params (dict, None) - This must be a flat dictionary containing all the parameters needed for this block.

If *None* is provided then the following parameters will be used:

- 'policy': mushroom_rl.policy.EpsGreedy(value=0)
- 'epsilon': 1e-2
- regressor_type (str, 'action_regressor') This is a string and it can either be: 'action_regressor', 'q_regressor' or 'generic_regressor'. This is used to pick one of the 3 possible kind of regressor made available by MushroomRL.

Note that if you want to use a $'q_regressor'$ then the picked regressor must be able to perform multi-target regression, as a single regressor is used for all actions.

• n_train_samples (Integer, None) - This must be an object of Class Integer (sub-Class of HyperParameter) and it represents a tunable parameter. This has effect only when using the input loader: LoadDifferentSizeForEachBlock and LoadDifferentSizeForEachBlockAndEnv.

For this to work the block must have **is_parametrised** equal to *True*, otherwise it does not reach the method **tune()** of the *Tuner*!

If *None* then an *Integer* object is created with **current_actual_value** equal to 10000 and with **range_of_values** equal to [100, 1000000]

Non-Parameters Members:

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.
- algo_object (None) This is the object containing the actual RL offline algorithm. In this case it is an object of Class mushroom rl.algorithms.value.batch td.lspi.LSPI.
- algo params upon instantiation (dict, None) This is a deep copy of the original value of algo params.
- **model** This contains the *Class* of the actual RL offline algorithm. In this case it contains the Class *mush-room_rl.algorithms.value.batch_td.lspi.LSPI*.

Methods:

• full_block_instantiation(info_MDP) - This method sets info_MDP equal to info_MDP. Then if algo_params is *None* the default dictionary of parameters to be used in LSPI is created (as specified above in the **Parameters** section) and this default dictionary is assigned to algo params.

Now the method **set_params()** is called by passing the member **algo_params**. If the parameters were set successfully this method returns *True*, else it returns *False*.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom_rl.core.Agent.

Returns:

- (bool) This is *True* if the block was successfully fully instantiated, else it is *False*.
- set_params(new_params) This method changes the value of algo_params and of algo params upon instantiation to that of new params. Moreover:
 - The **policy**, **input_shape**, **output_shape** and **n_actions** variables are created: these are needed for instantiating the actual offline RL algorithm from MushroomRL.

The **policy** is an epsilon greedy policy, while the other variables are created according to the choice of **regressor_type**. To see how read the web page linked in the explanation of the method **pre_learn_check()** of the Class *ModelGeneration*.

- A structured dictionary is created: this is needed in order to properly instantiate a MushroomRL agent object.
 Moreover in order to instantiate such an object we also need to extract the current_actual_value from the new_params dictionary, which is made of HyperParameter objects.
- An object of Class mushroom_rl.core.Agent (based on the value of the member model) is created passing to
 it the structured dictionary created in the previous step. This is saved in the member algo object.

Parameters:

 new_params (dict) - This must be a flat dictionary containing all the parameters needed for this block to work.

Returns:

- (bool) - This is *True* if **new_params** was set successfully, else it is *False*.

16 model generation default.py

In the module *model generation default.py* the dictionary *automatic model generation default* is present.

This is used as default setting in the Block *AutoModelGeneration* when the user does not want to specify anything. The default setting is given by:

- For the offline RL case when an environment is present we use a block of Class *ModelGenerationMushroomOfflineFQI* with default hyper-parameters, evaluated using the metric Class *DiscountedReward* for 10 episodes, tuned with the tuner Class *TunerGenetic*. The input loader Class is *LoadUniformSubSampleWithReplacementAndEnv* with each dataset being 10000 steps long.
- For the offline RL case when an environment is not present we use a block of Class *ModelGenerationMushroomOf-flineFQI* with default hyper-parameters, evaluated using the metric Class *TDError*, tuned with the tuner Class *TunerGenetic*. The input loader Class is *LoadUniformSubSampleWithReplacement* with each dataset being 10000 steps long.
- A block of Class *ModelGenerationMushroomOnlinePPO* with default hyper-parameters, evaluated using the metric Class *DiscountedReward* for 10 episodes, tuned with the tuner Class *TunerGenetic*. The input loader Class is *LoadSameEnv*.

17 model generation automatic.py

In the module model generation automatic.py the Class AutoModelGeneration is implemented.

17.1 AutoModelGeneration

This Class optimises over the proposed algorithms: it calls a Tuner on each proposed algorithm and picks the most performing one according to some metric.

The Class AutoModelGeneration inherits from the Class ModelGeneration.

Note that in this Class:

- works on online rl is equal to *True*.
- works_on_offline_rl is equal to *True*.
- works on box action space is equal to *True*.
- works_on_discrete_action_space is equal to *True*.
- works on box observation space is equal to *True*.
- works on discrete observation space is equal to True.
- pipeline type is equal to 'online' if works on online rl is equal to True, else it is 'offline'.
- **is_parametrised** is equal to *False*, hence this block cannot go in a *Tuner* object. Indeed it makes no sense to have **is parametrised** is equal to *True* because this block is already performing optimisation of the hyper-parameters.

Note that the members works_on_online_rl, works_on_offline_rl, works_on_box_action_space, works_on_discrete_action_space, works_on_box_observation_space and works_on_discrete_observation_space are *True* so that one can specify the right tuners for the problem at hand.

If the tuners provided in the **tuner_blocks_dict** are incompatible with the problem at hand then no tuner will be tuned and the method **learn()** of the *AutoModelGeneration* block will fail.

Initialiser:

```
__init__(eval_metric, obj_name, seeder=2, tuner_blocks_dict=None, log_mode='console',
checkpoint log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• tuner_blocks_dict (dict, None) - This must be a dictionary where the key is a string while the value is an object of a Class inheriting from the Class *Tuner*.

If *None* is provided then the default dictionary **automatic_model_generation_default** present in the module **model_generation_default.py** will be used.

Non-Parameters Members:

• tuner_blocks_dict_upon_instantiation (dict, None) - This is a deep copy of the original value of tuner_blocks_dict.

- **fully_instantiated** (*bool*, False) This is set to *True* once the block is fully instantiated, that is when the method **full block instantiation()** has been called.
- **info_MDP** (mushroom_rl.environment.MDPInfo, None) This is an object of a Class implemented in MushroomRL. It contains the observation space, the action space, gamma and the horizon of the environment.

Methods:

• full block instantiation(info MDP) - This method always returns True and sets the member info MDP.

This method does not call the methods **full_block_instantiation()** of all blocks present in **tuner_blocks_dict** because the default of such member, setted via **automatic_model_generation_default**, may contain several blocks that do not work on the problem at hand: we just want to skip over such blocks. This is taken care of in the method **learn()**.

Parameters:

- info_MDP (mushroom_rl.environment.MDPInfo) - This must be an object of Class containing the observation space, the action space, gamma and the horizon of the environment. This is needed for instantiating an object of Class mushroom rl.core.Agent.

Returns:

- (bool) This method always returns True.
- pre_learn_check(train_data=None, env=None) This method simply returns *True* and updates the value of tuner blocks dict to tuner blocks dict upon instantiation. This is needed for re-loading objects.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (bool) - This method overrides the one of the base Class ModelGeneration and it always returns True. Why
is this needed? Because there is only one default dictionary for tuner_blocks_dict therefore it contains a
variety of blocks.

We do not want to stop learning an automatic block only because it contains a block that only works on *Box* observation spaces, while the problem has *Discrete* observation space: we just want to skip over it.

• **learn(train_data=None, env=None)** - This method calls the learn method **learn()** implemented in the Class *ModelGeneration*.

Before calling the method **tune()** of a tuner:

- We assign the pipeline type to the block to opt present in the tuner.
- We call the method **pre_learn_check()** of the **block_to_opt** present in the tuner. If this returns *False* then the currently selected tuner will be skipped.
- If the call to the method pre_learn_check() of the block_to_opt present in the tuner, was successful then we call the method full_block_instantiation() of the block_to_opt present in the tuner.

If this returns *False* then the currently selected tuner will be skipped.

Note that we skip over tuners that have input loader and metric not consistent with each other: this is checked by calling the method is **metric consistent with input loader()** of the tuner.

After having called the method **tune()** of a tuner if everything was successful we update the local variables **best agent** and **best agent eval**.

If after having gone through each tuner at least one was successfully tuned then the best agent found overall will be learnt over the original starting input given to the *AutoModelGeneration* block, and the corresponding object of Class *BlockOutput* is returned.

Otherwise if no tuner was tuned successfully, out of the ones present in the **tuner_blocks_dict** an empty object of Class *BlockOutput* is returned.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (BlockOutput) If this block was learnt successfully this object contains: train_data, env, policy, policy_eval.
 Else this object will have None values for the members: train_data, env, policy_eval.
- get params() This method returns a deep copy of tuner blocks dict.

Returns:

- (dict) This is a deep copy of tuner blocks dict.
- set_params(new_params_dict) This method replaces the current tuner_blocks_dict and updates tuner blocks dict upon instantiation to new params dict.

Parameters:

new_params_dict (dict) - This must be a flat dictionary for the parameters of all model generation blocks present in this automatic block: it replaces the current tuner_blocks_dict.

Returns:

- (bool) This is True if new params dict was set successfully, else it is False.
- analyse() This method is not yet implemented. It should analyse the learnt *AutoModelGeneration* block, namely it should evaluate it according to the provided **eval** metric.
- update_verbosity(new_verbosity) This method calls the base method update_verbosity() implemented in the Class Block. Then for all Tuner object in the tuner_blocks_dict it calls the corresponding method update verbosity().

Parameters:

- new verbosity (int) - This must be a positive integer representing the new verbosity.

18 block output.py

In the module block output.py the Class BlockOutput is implemented.

18.1 BlockOutput

This Class is used to represent the output of a generic block of a Class inheriting from the Class *Block*.

The Class BlockOutput inherits from the Class AbstractUnit.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', train_data=None, env=None, policy=None, policy_eval=None)
```

Parameters:

- **train_data** (BaseDataSet, None) If specified this must be an object of a Class inheriting from the Class Base-DataSet.
- **env** (BaseEnvironment, None) If specified this must be an object of a Class inheriting from the Class BaseEnvironment.
- policy (BasePolicy, None) If specified this must be an object of a Class inheriting from the Class BasePolicy.
- **policy_eval** (*float*, None) If specified this must represent the evaluation, or KPI, of the **policy**. This is a dictionary containing the mean of the evaluation and the variance of the evaluation.

Note that the Classes *Metric* that are used with *ModelGeneration* blocks must have two members: **eval_mean** and **eval_var**. These are used in the method **learn()** of the Classes *OfflineRLPipeline* and *OnlineRLPipeline* to construct the **policy eval**.

Non-Parameters Members:

• **n_outputs** (*int*) - This is a positive integer and it represents the number of actual outputs that a block wants to save in an object of this Class.

Methods:

• make_policy_deterministic() - This method renders the policy deterministic: the approximator is extracted and added to the member approximator of the policy and the member policy of the policy is turned into an object of Class mushroom_rl.policy.DeterministicPolicy.

Note that this means that you can call batch evaluation in the metric *DiscountedReward*: to see more about what this means see the Class *DiscountedReward*.

19 dataset.py

In the module dataset.py the Classes BaseDataSet and TabularDataSet are implemented.

19.1 BaseDataSet

The Class *BaseDataSet* is an abstract Class used as base class for all types of data one can have: tabular data, image data, text data.

The Class BaseDataSet is an abstract Class, and so it inherits from ABC, but it also inherits from the Class AbstractUnit.

Initialiser:

Parameters:

• **observation_space** (Box/Discrete) - This is an object of either Class Box or Class Discrete: if the **observation_space** is discrete then it will be an object inheriting from the Class Discrete, else it will be an object inheriting from the Class Box.

```
Both of these Classes are implemented in the spaces.py module in MushroomRL. cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/utils/spaces.py
```

Since the RL algorithms available in this library are wrappers of those implemented in MushroomRL, and since in MushroomRL, as of now, only *Box* and *Discrete* spaces are supported, then also in this library we only support *Box* and *Discrete* spaces.

For example MultiDiscrete or Dict spaces are not currently supported.

• action_space (Box/Discrete) - This is an object of either Class Box or Class Discrete: if the action_space is discrete then it will be an object inheriting from the Class Discrete, else it will be an object inheriting from the Class Box.

```
Both of these Classes are implemented in the spaces.py module in MushroomRL. cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/utils/spaces.py
```

Since the RL algorithms available in this library are wrappers of those implemented in MushroomRL, and since in MushroomRL, as of now, only *Box* and *Discrete* spaces are supported, then also in this library we only support *Box* and *Discrete* spaces.

For example *MultiDiscrete* or *Dict* spaces are not currently supported.

- **discrete** actions (bool) This is *True* if the environment has discrete actions. Else it is *False*.
- **discrete observations** (bool) This is *True* if the environment has discrete observations. Else it is *False*.
- gamma (float) This is a real value in [0, 1] and it represents the discount factor of the MDP.
- **horizon** (*int*) This is a positive integer and it represents the horizon of the MDP.

• **info()** - This method is a *property* and it is used for compatibility with MushroomRL algorithms. This method returns an object inheriting from the Class *MDPInfo*, which is a Class implemented in MushroomRL in the module *environment.py*.

cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/core/environment.py

Returns:

- (mushroom_rl.environment.MDPInfo) - This object contains the observation_space, the action_space, the discount factor gamma and the horizon.

19.2 TabularDataSet

The Class TabularDataSet is used as base class for all tabular data: it has a member containing tabular data.

The Class TabularDataSet inherits from the Class BaseDataSet.

Initialiser:

```
___init___(dataset, observation_space, action_space, discrete_actions, discrete_observations, gamma, horizon, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• **dataset** (*list*) - This must be a list where each entry of the list is made up of: the current state, the drawn action, the reward, the next state, the absorbing state flag and the episode terminal flag.

This is needed in order to use MushroomRL algorithms.

Methods:

- **tuples_to_lists()** This method transforms a list of tuples into a list of lists. This is needed since tuples are immutable. This method is called in the **Initialiser** only when the **dataset** parameter is not *None*.
- arrays_as_data(states, actions, rewards, next_states, absorbings, lasts) This method constructs a dataset that can be passed to MushroomRL offline agents. Specifically it constructs a list of lists in which each list contains: the current state, the current action, the current reward, the next state, the absorbing state flag and the episode terminal flag.

This method simply calls the method **mushroom rl.utils.dataset.arrays as dataset()**.

This is a static method.

Parameters:

- states (numpy.array) This must be a numpy.array containing the states. Each state refers to a single time step.
- actions (numpy.array) This must be a numpy.array containing the actions. Each action refers to a single time step.
- rewards (numpy.array) This must be a numpy.array containing the rewards. Each reward refers to a single time step.
- next_states (numpy.array) This must be a numpy.array containing the next state the agent reaches by taking
 the sampled action in the current state.
- **absorbings** (*numpy.array*) This must be a *numpy.array* containing the flags indicating absorbing states.
- lasts (numpy.array) This must be a numpy.array containing the flags indicating end of episodes states.

Returns:

- **created dataset** (*list*) This is a list of lists constructed as described above.
- parse_data() This method simply calls the method mushroom_rl.utils.dataset.parse_dataset().

Returns:

- (numpy.array, numpy.array, numpy.array, numpy.array, numpy.array, numpy.array)
 The six numpy.array that are obtained by parsing the dataset: states, actions, rewards, next_states, absorbing state flags, episode terminals flags.
- get states() This method calls the method parse data() and selects the first numpy.array.

Returns:

- (numpy.array) The array of current states.
- get actions() This method calls the method parse data() and selects the second *numpy.array*.

Returns:

- (numpy.array) The array of actions.
- get rewards() This method calls the method parse data() and selects the third numpy.array.

Returns:

- (numpy.array) The array of rewards.
- get next states() This method calls the method parse data() and selects the fourth numpy.array.

Returns:

- (numpy.array) The array of the next states.
- get absorbing() This method calls the method parse data() and selects the fifth numpy.array.

Returns:

- (numpy.array) The array of absorbing states flags.
- get episode terminals() This method calls the method parse data() and selects the sixth numpy.array.

Returns:

- (numpy.array) - The array of episode terminal states flags.

20 environment.py

In the module environment.py the Classes BaseEnvironment, BaseWrapper, BaseObservationWrapper, BaseActionWrapper, BaseRewardWrapper are implemented.

Wrappers of actual environments that can be used are also implemented: BaseGridWorld, BaseCarOnHill, BaseCart-Pole, BaseInvertedPendulum, LQG, BaseMujoco, BaseHalfCheetah, BaseAnt, BaseHopper, BaseHumanoid, BaseSwimmer, BaseWalker2d.

20.1 BaseEnvironment

This is the base environment Class based on the OpenAl Gym class. Part of this class is a re-adaptation of code copied from:

- OpenAl gym: cf. https://github.com/openai/gym/blob/master/gym/core.py
- MushroomRL: cf. https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/core/environment.py

This can be sub-classed by the user to create their own specific environment. You must sub-class from this Class in order to use this library.

You must use Box and Discrete environment spaces from MushroomRL.

The Class *BaseEnvironment* is an abstract Class, and so it inherits from *ABC*, but it also inherits from the Class *AbstractUnit*.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

- **observation_space** (Box/Discrete, None) This must be a space from MushroomRL, either Box or Discrete: it must be an object inheriting from one of following two the Classes: mushroom_rl.utils.spaces.Box or mushroom_rl.utils.spaces.Discrete.
- action space (Box/Discrete, None) This must be a space from MushroomRL, either Box or Discrete.
- gamma (float, None) This is the value of the gamma of the MDP.
- **horizon** (*int*, None) This is the horizon of the MDP.

Methods:

• step(action) - This method is an abstract method and it must be implemented in a sub-Class of this Class.

Parameters:

- action (object) - This is an action to be applied on the environment.

Returns:

- **observation** (*object*) - This is the current observation returned to the agent by the environment.

- reward (float) This is the reward obtained by calling the previous action.
- done (bool) This is True if an episode has ended, else it is False.
- info (dict) This dictionary contains auxiliary diagnostic information about the environment.
- reset(state=None) This method is an abstract method and it must be implemented in a sub-Class of this Class.

Note that all methods **reset** in all environments must have this signature otherwise MushroomRL RL algorithms are going to fail!

- render(mode='human') This method is an abstract method and it must be implemented in a sub-Class of this Class.
- close() If needed, this method can be implemented in a sub-Class of this Class.
- seed(seed=None) If needed, this method can be implemented in a sub-Class of this Class.
- stop() This method is used to stop an MDP. This is needed for backward compatibility with MushroomRL.

If needed, this method can be implemented in a sub-Class of this Class.

• unwrapped() - This method completely unwraps the environment contained in the Class.

Returns:

- (BaseEnvironment) This is the base non-wrapped environment instance.
- info() This method is a property method and it is used to extract information about the environment.

Returns:

- (mushroom_rl.environment.MDPInfo) This method returns an object of Class mushroom_rl.environment.MDPInfo: it contains the observation space, the action space, gamma and the horizon of the environment.
- _sample _from _box(space) This method generates a single random sample inside of the *Box* space. It can only be called when the space is a *Box* (i.e: continuous).

This method was copied from OpenAI gym: cf. https://github.com/openai/gym/blob/master/gym/spaces/box.py

Parameters:

- space (Box) - This must be a Box space from MushroomRL. This is the space from which to sample from.

Returns:

- sample (numpy.array) This is a random sample from the Box space.
- sample_from_box_action_space() This method generates a single random sample inside of the *Box* action space. It can only be called when the action space is a *Box* (i.e. continuous). This method simply calls the method _sample_from_box() passing to it the action_space.

Returns:

- sample (numpy.array) - This is a random sample from the Box action space.

• sample_from_box_observation_space() - This method generates a single random sample inside of the Box observation space. It can only be called when the observation space is a Box (i.e. continuous). This method simply calls the method sample from box() passing to it the observation space.

Returns:

- sample (numpy.array) This is a random sample from the Box observation space.
- **set_params(params_dict)** This method is used to set the parameters of an environment. By passing a dictionary containing as keys the correct string member name of an environment it can be used to set a value to such members, according to the value provided in the **params dict**.

Parameters:

- params_dict (dict) This is a dictionary containing as keys the correct string member name for which we want to set a new value, and as value the new value to which we want to set the members.
- get_params(params_names) This method is used to obtain the value for certain members of an environment. It generates a dictionary with keys the same keys provided as input and as values the current value of the corresponding members.

Parameters:

- params_names (*list*) - This is a list containing, as string, the name of the members for which we want to retrieve their current value.

Returns:

params_dict (dict) - This is a dictionary containing as keys the correct string member name and as value the
corresponding member current value.

20.2 BaseWrapper

This is the base wrapper Class based on the OpenAl Wrapper Class. Part of this class is a re-adaptation of code copied from OpenAl gym:

cf. https://github.com/openai/gym/blob/master/gym/core.py

This is used as base Class for observation wrappers, action wrappers and reward wrappers.

Other kind of wrappers can be created inheriting from this Class.

The Class BaseWrapper inherits from the Class BaseEnvironment. This is an Abstract Class.

Initialiser:

```
__init__(env, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• **env** (BaseEnvironment) - This is the environment that needs to be wrapped. It must be an object of a Class inheriting from the Class BaseEnvironment.

Non-Parameters Members:

- **observation space** (Box/Discrete) This is set equal to the value of **observation space** of the **env**.
- action_space (Box/Discrete, None) This is set equal to the value of action_space of the env.
- gamma (float) This is set equal to the value of gamma of the env.
- **horizon** (*int*) This is set equal to the value of **horizon** of the **env**.

Methods:

• unwrapped() - This method simply calls the method unwrapped() of the env.

Returns:

- (BaseEnvironment) The base non-wrapped environment instance.
- stop() This method simply calls the method stop() of the env.
- **step(action)** This method simply calls the method **step()** of the **env**.
- reset(state=None) This method simply calls the method reset() of the env.
- render(mode='human') This method simply calls the method render() of the env.
- close() This method simply calls the method close() of the env.
- seed(seed=None) This method simply calls the method seed() of the env.

20.3 BaseObservationWrapper

To create an observation wrapper you must create a new Class inheriting from this Class. You must override the method **observation()** and in the **Initialiser** you must:

- Call the **Initialiser** of *BaseWrapper* via: super(). init (env)
- Properly modify the observation space.

Part of this Class is a re-adaptation of code copied from OpenAl gym: cf. https://github.com/openai/gym/blob/master/gym/core.py

The Class BaseObservationWrapper inherits from the Class BaseWrapper. This is an Abstract Class.

Initialiser:

```
__init__(env, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

- reset(state=None) This method calls the method observation(), that must be implemented in a sub-Class of this Class, onto the output of the method reset() of the env.
- **step(action)** This method calls the method **observation()**, that must be implemented in a sub-Class of this Class, onto the observation that is part of the output of the method **step()** of the **env**.
- **observation(observation)** This method is an abstract method and it must be implemented in a sub-Class of this Class. By implementing this method an observation wrapper is effectively constructed.

20.4 BaseActionWrapper

To create an action wrapper you must create a new Class inheriting from this Class. You must override the method **action()** and in the **Initialiser** you must:

- Call the **Initialiser** of *BaseWrapper* via: super(). init (env)
- Properly modify the action space.

Part of this Class is a re-adaptation of code copied from OpenAI gym: cf. https://github.com/openai/gym/blob/master/gym/core.py

The Class BaseActionWrapper inherits from the Class BaseWrapper. This is an Abstract Class.

Initialiser:

```
___init___(env, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

- **step(action)** This method calls the method **step()** of the **env**, on the output of the method **action()** that must be implemented in a sub-Class of this Class.
- action(action) This method is an abstract method and it must be implemented in a sub-Class of this Class. By implementing this method an action wrapper is effectively constructed.

20.5 BaseRewardWrapper

To create a reward wrapper you must create a new Class inheriting from this Class. You must override the method reward() and in the **Initialiser** you must:

• Call the **Initialiser** of *BaseWrapper* via: super(). init (env)

Part of this Class is a re-adaptation of code copied from OpenAl gym: cf. https://github.com/openai/gym/blob/master/gym/core.py

The Class BaseRewardWrapper inherits from the Class BaseWrapper. This is an Abstract Class.

Initialiser:

- **step(action)** This method calls the method **step()** of the **env**. Then the reward contained in the output of such call is modified by calling on it the method **reward()**, that must be implemented in a sub-Class of this Class.
- reward(reward) This method is an abstract method and it must be implemented in a sub-Class of this Class. By implementing this method a reward wrapper is effectively constructed.

20.6 BaseGridWorld

This Class wraps the GridWorld Class from MushroomRL: this is needed for the correct working of this library.

The Class BaseGridWorld inherits from the Class BaseEnvironment and from the MushroomRL Class GridWorld.

Initialiser:

```
__init__(height, width, goal, obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', start=(0,0))
```

To see the specifics of this Class see the documentation about the Class *BaseEnvironment* and the documentation of *MushroomRL* about the Class *GridWorld*.

cf. https://mushroomrl.readthedocs.io/en/latest/source/mushroom_rl.environments.html#module-mushroom_rl.environments.grid_world

20.7 BaseCarOnHill

This Class wraps the CarOnHill Class from MushroomRL: this is needed for the correct working of this library.

The Class BaseCarOnHill inherits from the Class BaseEnvironment and from the MushroomRL Class CarOnHill.

Initialiser:

```
\label{eq:console} $$\_\__{init}_{obj\_name, seeder=2, log\_mode='console', checkpoint\_log\_path=None, verbosity=3, n\_jobs=1, job\_type='process', horizon=100, gamma=0.95)$
```

To see the specifics of this Class see the documentation about the Class *BaseEnvironment* and the documentation of *MushroomRL* about the Class *CarOnHill*.

cf. https://mushroomrl.readthedocs.io/en/latest/source/mushroom_rl.environments.html#module-mushroom_rl.environments.car_on_hill

20.8 BaseCartPole

This Class wraps the CartPole Class from MushroomRL: this is needed for the correct working of this library.

The Class BaseCartPole inherits from the Class BaseEnvironment and from the MushroomRL Class CartPole.

Initialiser:

```
\label{eq:console} $$\_\_init\_\_(obj\_name, seeder=2, log\_mode='console', checkpoint\_log\_path=None, verbosity=3, n\_jobs=1, job\_type='process', m=2, M=8, l=0.5, g=9.8, mu=1e-2, max\_u=50, noise\_u=10, horizon=3000, gamma=0.95)
```

To see the specifics of this Class see the documentation about the Class *BaseEnvironment* and the documentation of *MushroomRL* about the Class *CartPole*.

cf. https://mushroomrl.readthedocs.io/en/latest/source/mushroom_rl.environments.html#module-mushroom_rl.environments.cart_pole

20.9 BaseInvertedPendulum

This Class wraps the InvertedPendulum Class from MushroomRL: this is needed for the correct working of this library.

The Class BaseInvertedPendulum inherits from the Class BaseEnvironment and from the MushroomRL Class InvertedPendulum.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', m=1, l=1, g=9.8, mu=1e-2, max_u=5, horizon=5000, gamma=0.99)
```

To see the specifics of this Class see the documentation about the Class *BaseEnvironment* and the documentation of *MushroomRL* about the Class *InvertedPendulum*.

cf. https://mushroomrl.readthedocs.io/en/latest/source/mushroom_rl.environments.html#module-mushroom_rl.environments.inverted_pendulum

20.10 LQG

This Class implements an LQG environment (i.e. a Linear-Quadratic Gaussian control (LQG) problem). The code for this Class is based on the following code:

cf. https://github.com/T3p/potion/blob/master/potion/envs/lq.py

The Class *LQG* inherits from the Class *BaseEnvironment*.

Initialiser:

```
___init___(obj_name, A=np.eye(1), B=np.eye(1), Q=np.eye(1), R=np.eye(1), max_pos=1.0, max_action=1.0, env_noise=np.eye(1), controller_noise=np.eye(1), horizon=10, gamma=0.9, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

- A (numpy.ndarray, np.eye(1)) This is the state dynamics matrix.
- **B** (numpy.ndarray, np.eye(1)) This is the action dynamics matrix.
- **Q** (numpy.ndarray, np.eye(1)) This is the cost weight matrix for the state. It must be a positive-definite matrix (to always have a negative reward).
- **R** (numpy.ndarray, np.eye(1)) This is the cost weight matrix for the action. It must be a positive-definite matrix (to always have a negative reward).
- max pos (float, 1.0) This is the maximum value that the state can reach.
- max action (float, 1.0) -This is the maximum value that the action can reach.
- env_noise (numpy.ndarray, np.eye(1)) This is the covariance matrix representing the Gaussian environment noise.
- **controller_noise** (*numpy.ndarray*, np.eye(1)) This is the covariance matrix representing the Gaussian controller noise.
- **horizon** (*int*, 10) This is the horizon of the MDP.
- gamma (float, 0.9) This is the discount factor of the MDP.

Non-Parameters Members:

• is _eval _phase (bool, False) - This is *True* if the environment is used for evaluating a policy: what happens is that the **controller noise** is added to the action selected by the policy, and then fed to the simulator.

Otherwise it is False.

This is used to represent the fact that even if we have learnt a theoretically optimal policy, in practice to execute it there is going to be some noise and so the resulting action taken in the real world will be different from the one selected by the policy.

This parameter can be set automatically by the evaluation metric.

Methods:

• **step(action)** - This method is used to run one step of the environment dynamics. As always it returns observation, reward, done and info. For more information see the documentation of the Class *BaseEnvironment*.

• **reset(state=None)** - This method is used to reset the environment: by default, random uniform initialisation. If the **state** is not *None* then the provided **state** is used for re-setting the environment.

Parameters:

- state (numpy.array, None) - This is a vector representing the new state for the environment.

Returns:

- state (numpy.array, None) This is a vector representing the new state for the environment.
- **seed(seed=None)** This method is used to seed the environment. This method calls the method **set_local_prng()** passing to it the provided **seed**.

Parameters:

- seed (int, None) This is a positive integer representing the new seed to use.
- render(mode='human', close=False) This method is used to render the environment.
- **get_optimal_K()** This method computes the optimal gain K and returns the optimal policy given by: -K * s where s is the state. To do so the discrete ARE is solved using *scipy*.

Returns:

- -K (numpy.ndarray) - This is the optimal gain matrix.

20.11 BaseMujoco

This Class wraps the Mujoco environments: every Mujoco environment inherits from this Class.

The Class BaseMujoco inherits from the Class BaseEnvironment. This is an Abstract Class.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• mujoco_env (gym.envs.mujoco.mujoco_env.MujocoEnv, None) - This is a Mujoco environment instance: an object of a Class inheriting from OpenAI gym Class: gym.envs.mujoco.mujoco env.MujocoEnv.

This is set in sub-Classes of this Class.

• **n_steps** (*int*, 0) - This is a counter for the horizon of the environment. It is the number of total steps that have happened so far.

Methods:

• _update_counter(out_step) - This method keeps track of how many steps the agent has interacted with the environment for, and if needed it sets **done** equal to *True* in the output obtained from the call of the method **step()** of the Mujoco environment (i.e. an object of a Class inheriting from the Class *gym.envs.mujoco.mujoco env.MujocoEnv*).

Parameters:

out_step (tuple) - This is the output from the call to the method step() of the Mujoco environment (i.e. an object of a Class inheriting from the Class gym.envs.mujoco.mujoco env.MujocoEnv).

Returns:

- tuple(out_step) (tuple) This is the new output of the call to the method step() of a Class inheriting from this Class: in case n steps reached horizon we set done equal to True.
- step(action) This method calls the method step() of the object mujoco_env and then it calls the method _up-date_counter().

Parameters:

action (object) - This is an action to be applied on the environment.

Returns:

- **out** (*tuple*) This is the usual tuple containing observation, reward done and info.
- reset(state=None) This method calls the method reset() of mujoco_env and it sets n_steps to 0. It returns the observation that is where the environment starts.

The signature contains a useless **state=None** since this is needed for compatibility with MushroomRL RL algorithms.

- seed(seed=None) This method simply calls the method seed() of the mujoco env.
- render(mode='human') This method calls the method render() of the mujoco env.

• set_local_prng(new_seeder) - This method overrides the method implemented in the Class AbstractUnit. This method calls the method seed() of this Class, passing to it the new_seeder. This method is used to adjust to the fact that OpenAl does not use the system of using the local_prng, defined in the Class AbstractUnit, but have their own way of doing it.

Without this method by calling the original method **set_local_prng()** implemented in the Class *AbstractUnit* I would have no effect on the environment: the method **set_local_prng()** is called in the Classes *Metric* and in some of the *DataGeneration* Classes so this method needs to work properly.

To learn more about this see the implementation of the method **set_local_prng()** implemented in the Class *AbstractUnit* or see the chapter **On environments** in the section **Further Details**.

Parameters:

- new_seeder (int) This is a non-negative integer and it represents the new seeder to be used for creating a
 new local PRNG.
- __initialise__mdp__properties(gamma, horizon) This method sets the MDP properties: the discount factor and the horizon. Moreover it converts the spaces contained in mujoco__env to use those implemented in MushroomRL.

Indeed all environments must use the spaces *Box* and *Discrete* implemented in MushroomRL, otherwise it will not be possible to use the RL algorithms in MushroomRL.

Parameters:

- gamma (float) This is the discount factor of the MDP.
- **horizon** (*int*) This is the horizon of the MDP.

To see some more specifics of this Class see the documentation about the Class *gym.envs.mujoco.mujoco_env.MujocoEnv.* cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/mujoco_env.py

20.12 BaseHalfCheetah

This Class wraps the HalfCheetahEnv Mujoco environment.

The Class BaseHalfCheetah inherits from the Class BaseMujoco.

Initialiser:

```
___init___(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', gamma=0.99, horizon=1000, xml_file='half_cheetah.xml', forward_reward_weight=1.0, ctrl_cost_weight=0.1, reset_noise_scale=0.1, exclude_current_positions_from_observation=True)
```

Parameters:

- gamma (float, 0.99) This is the discount factor of the MDP.
- horizon (int, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.half* cheetah v3.HalfCheetahEnv.

To see some more specifics of this Class see the documentation about the Mujoco Class *HalfCheetahEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/half_cheetah_v3.py

20.13 BaseAnt

This Class wraps the AntEnv Mujoco environment.

The Class BaseAnt inherits from the Class BaseMujoco.

Initialiser:

Parameters:

- gamma (float, 0.99) This is the discount factor of the MDP.
- horizon (int, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.ant_v3.AntEnv*.

To see some more specifics of this Class see the documentation about the Mujoco Class *AntEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/ant_v3.py

20.14 BaseHopper

This Class wraps the HopperEnv Mujoco environment.

The Class BaseHopper inherits from the Class BaseMujoco.

Initialiser:

Parameters:

- gamma (float, 0.99) This is the discount factor of the MDP.
- **horizon** (*int*, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.hopper v3.HopperEnv*.

To see some more specifics of this Class see the documentation about the Mujoco Class *HopperEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/hopper_v3.py

20.15 BaseHumanoid

This Class wraps the HumanoidEnv Mujoco environment.

The Class BaseHumanoid inherits from the Class BaseMujoco.

Initialiser:

Parameters:

- gamma (float, 0.99) This is the discount factor of the MDP.
- **horizon** (*int*, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.humanoid v3.HumanoidEnv*.

To see some more specifics of this Class see the documentation about the Mujoco Class *HumanoidEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/humanoid_v3.py

20.16 BaseSwimmer

This Class wraps the SwimmerEnv Mujoco environment.

The Class BaseSwimmer inherits from the Class BaseMujoco.

Initialiser:

```
___init___(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', gamma=0.99, horizon=1000, xml_file="swimmer.xml", forward_reward_weight=1.0, ctrl_cost_weight=1e-4, reset_noise_scale=0.1, exclude_current_positions_from_observation=True)
```

Parameters:

- gamma (float, 0.99) This is the discount factor of the MDP.
- horizon (int, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.swimmer v3.SwimmerEnv*.

To see some more specifics of this Class see the documentation about the Mujoco Class *SwimmerEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/swimmer_v3.py

20.17 BaseWalker2d

This Class wraps the Walker2dEnv Mujoco environment.

The Class BaseWalker2d inherits from the Class BaseMujoco.

Initialiser:

Parameters:

- qamma (float, 0.99) This is the discount factor of the MDP.
- horizon (int, 1000) This is the horizon of the MDP.

Note that in this Class **mujoco env** is an instance of *gym.envs.mujoco.walker2d_v3.Walker2dEnv*.

To see some more specifics of this Class see the documentation about the Mujoco Class *Walker2dEnv*. cf. https://github.com/openai/gym/blob/master/gym/envs/mujoco/walker2d_v3.py

21 policy.py

In the module *policy.py* the Class *BasePolicy* is implemented.

21.1 BasePolicy

This Class is used as container for the output of any *ModelGeneration* block. The Class *BasePolicy* inherits from the Class *AbstractUnit*.

Initialiser:

Parameters:

• **policy** (*mushroom_rl.policy*.*Policy*) - This is the **policy** used in the RL algorithm implemented in the *ModelGeneration* block.

Note that the **policy** alternatively can also be an object of any Class that exposes the method **draw_action()** taking as parameter just a single state.

• regressor_type (str) - This is a string and it can either be: 'action_regressor', 'q_regressor' or 'generic_regressor'. This is used to specify which one of the 3 possible kind of regressor, made available by MushroomRL, has been picked.

This is needed in the Metric Classes: depending on the **regressor_type** we handle the evaluation phase differently. To see an example of how **regressor_type** is used see the implementation of the Class *DiscountedReward*.

• **approximator** (*mushroom_rl.approximators.regressor.Regressor*, None) - This represents the **approximator** used in the **policy** in the RL algorithm implemented in the *ModelGeneration* block.

This is optional since all the relevant information are contained already in the **policy**, however this is used to discriminate between different policies and it plays a role in which *Metric* can be applied to which **policy**. To learn more about this read the documentation about the Class *DiscountedRewardMetric*.

Note that the **approximator** alternatively can also be an object of any Class that exposes the method **predict()** taking as parameter either a single sample, or multiple samples.

22 hyperparameter.py

In the module hyperparamter.py the Classes HyperParameter, Numerical, Integer, Real and Categorical are implemented.

22.1 HyperParameter

This Class is used as generic base Class for all hyper-parameters. These are used to ease the hyper-parameters tuning process.

The Class *HyperParameter* is an abstract Class, and so it inherits from *ABC*, but it also inherits from the Class *AbstractUnit*.

Initialiser:

```
__init__(hp_name, current_actual_value, obj_name, seeder=2, log_mode='console',
checkpoint log path=None, verbosity=3, n jobs=1, job type='process', to mutate=False)
```

Parameters:

• **hp_name** (*str*) - This is a string with the exact name of the hyper-parameter described by this class.

Why this since there is already **obj_name**? **obj_name** can be personalised while **hp_name** must match exactly the name of the parameter used in a specific block.

- **current actual value** (*object*) This is the current actual value of the parameter. It can be anything.
- **to mutate** (*bool*) This is either *True* or *False*. It is *True* if we want the *Tuner* to tune this hyper-parameter. It is *False* otherwise.

Non-Parameters Members:

• **block_owner_flag** (*int*, None) - This is an integer and it is used as flag to mark that a certain hyper-parameter belongs to some specific block. This is needed for assigning the correct hyper-parameters in the method **set_params()** of the Class *RLPipeline*.

What happens is that in the *Tuner* Class I extract the parameters of a block with the method **get_params()** of that block, I mutate the hyper-parameters, and then I call the method **set params()** of that block.

Now if that block is a pipeline it will be composed of multiple blocks. The member **block_owner_flag** allows the method **set_params()** of a pipeline block to set the right hyper-parameters in the right blocks.

For more see the documentation (or the implementation) of the **set_params()** and **get_params()** methods of the Class *RLPipeline*.

22.2 Numerical

This Class is the base Class for all numerical (both floats and integers) hyper-parameters.

The Class Numerical inherits from the Class HyperParameter. This is an Abstract Class.

Initialiser:

Parameters:

- range_of_values (list, None) This must be a list of two, containing the lower bound and the upper bound of the range of values that the hyper-parameter can assume.
- **type_of_mutation** (*str*, 'perturbation') This must be a string and it can either be:
 - 'perturbation': In this case the next possible values, occurring as a result of a mutation, can only be those in the range: current actual value \cdot [0.8, 1.2]
 - Selecting 'perturbation' we have less dramatic changes in the hyper-parameters from one step to the next: we must be between 0.8 times, and 1.2 times, of the current value.
 - 'mutation': In this case the next possible values, occurring as a result of a mutation, can be in the entire range of the possible values of the hyper-parameter.

22.3 Real

This is the Class representing all Numerical and Real (i.e. Continuous) hyper-parameters.

The Class *Real* inherits from the Class *Numerical*.

Initialiser:

Methods:

- mutate(first_mutation) This method mutates the current hyper-parameter value by sampling from a continuous uniform distribution. Note that:
 - If type_of_mutation is 'mutation' the sampling distribution is defined over the range_of_values.
 - If **type of mutation** is 'perturbation" the sampling is defined:
 - * Over the range of values, if first mutation is *True*.
 - * Over the range current actual value $\cdot [0.8, 1.2]$, clipped to range of values, if first mutation is False.

This method directly changes the value of **current actual value**.

Note that a call to this method is successful only when **to mutate** is equal to *True*.

Parameters:

- **first_mutation** (bool) - This is *True* if this is the first time we are mutating the hyper-parameter, else it is False.

22.4 Integer

This is the Class representing all Numerical and Integer (i.e. Discrete) hyper-parameters.

The Class *Integer* inherits from the Class *Numerical*.

Initialiser:

Methods:

- mutate(first_mutation) This method mutates the current hyper-parameter value by sampling from a discrete uniform distribution. Note that:
 - If type_of_mutation is 'mutation' the sampling distribution is defined over the range_of_values.
 - If **type of mutation** is 'perturbation" the sampling is defined:
 - * Over the range of values, if first mutation is True.
 - * Over the range current _actual _value \cdot [0.8, 1.2], clipped to range of values, if first mutation is False.

Since the hyper-parameter here is an integer we cast the range of the mutation to *int* to make sure that we get out an integer.

This method directly changes the value of **current_actual_value**.

Note that a call to this method is successful only when **to mutate** is equal to *True*.

Parameters:

- **first_mutation** (*bool*) - This is *True* if this is the first time we are mutating the hyper-parameter, else it is *False*.

22.5 Categorical

This is the Class representing all Categorical hyper-parameters.

The Class *Categorical* inherits from the Class *HyperParameter*.

Initialiser:

Parameters:

• **possible_values** (*list*, None) - This must be an exhaustive list containing all the possible values the hyper-parameter can assume.

Methods:

• mutate(first_mutation) - This method mutates the current hyper-parameter value by sampling a random value from the list of possible_values.

This method directly changes the value of **current actual value**.

Note that a call to this method is successful only when **to mutate** is equal to *True*.

Parameters:

- first mutation (bool) - This is *True* if this is the first time we are mutating the hyper-parameter, else it is *False*.

In this Class this member is useless: it is just kept to have the same interface across all *HyperParameter* objects.

23 input loader.py

In the module <code>input_loader.py</code> the Classes <code>InputLoader</code>, <code>LoadSameEnv</code>, <code>LoadSameTrainData</code>, <code>LoadUniformSubSampleWithReplacementAndEnv</code>, <code>LoadDifferentSizeForEachBlock</code> and <code>LoadDifferentSizeForEachBlockAndEnv</code> are implemented.

23.1 InputLoader

This Class is used as generic base class for all input loaders. These are used to generate the right input to the different blocks that are trained by the *Tuner*. These Classes are needed because the *Tuner* are block agnostic and so we need a way to generate the right input for whichever automatic block might have called the *Tuner*.

The Class InputLoader is an Abstract Class, and so it inherits from ABC, but it also inherits from the Class AbstractUnit.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• returns_dataset (bool, None) - This is True if the input loader returns a dataset, otherwise it is False.

This is needed for checking the consistency of the *Metric* with an *InputLoader*: this check is done in the *Tuner* via the method is _metric _consistent _with _input_loader().

To learn more about this check the documentation about the method **is __metric __consistent __with __input __loader()** of the Class *Tuner*.

• returns env (bool, None) - This is True if the input loader returns an environment, otherwise it is False.

This is needed for checking the consistency of the *Metric* with an *InputLoader*: this check is done in the *Tuner* via the method is metric consistent with input loader().

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

23.2 LoadSameEnv

This particular Class simply returns **n_inputs_to_load** times the copy of the input **env**: indeed for online model generation we just have an environment so we can keep using it, anyway the trajectory followed by the agents depends by the particular action taken by each agent.

The Class LoadSameEnv inherits from the Class InputLoader.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• returns dataset (bool, False) - This is False since this input loader does not generate a dataset.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• **returns env** (*bool*, True) - This is *True* since this input loader generates multiple copies of the original environment.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

• get_input(blocks, n_inputs_to_load, train_data=None, env=None) - This method generates a list containing a number of environments equal to n_inputs_to_load. Each environment is a deep copy of env.

Parameters:

- blocks (list) This is a list containing the blocks for which we need to load the input. This is used only in some InputLoader. In this InputLoader it is not used.
- **n inputs to load** (*int*) This is the number of environments that will be deep copied.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- None This indicates that no datasets were generated by this InputLoader.
- copied_envs (list) This is a list containing deep copies of the original environment env.

23.3 LoadSameTrainData

This particular Class simply returns **n** inputs to load times the copy of the input train data.

The Class LoadSameTrainData inherits from the Class InputLoader.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• returns dataset (bool, True) - This is True since this input loader does generate a list of datasets.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• returns env (bool, False) - This is False since this input loader does not generate an environment.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

• get_input(blocks, n_inputs_to_load, train_data=None, env=None) - This method generates a list containing a number of datasets equal to n inputs to load. Each dataset is a deep copy of the original train data.

Parameters:

- **blocks** (*list*) This is a list containing the blocks for which we need to load the input. This is used only in some *InputLoader*. In this *InputLoader* it is not used.
- **n** inputs to load (int) This is the number of environments that will be deep copied.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- copied train data (list) This is a list containing deep copies of the original train data.
- None This indicates that no environments were generated by this InputLoader.

23.4 LoadUniformSubSampleWithReplacement

This particular Class sub-samples with replacement the given dataset by using a uniform distribution. In the end a list of objects of Class *TabularDataSet* is created where each object has in its member dataset the new sub-sampled dataset.

The Class LoadUniformSubSampleWithReplacement inherits from the Class InputLoader.

Initialiser:

```
__init__(obj_name, single_split_length, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n jobs=1, job type='process')
```

Parameters:

• **single_split_length** (*int*) - This is the length of each new sub-sampled dataset: it is the number of samples that are contained in each *TabularDataSet* object.

Non-Parameters Members:

• returns dataset (bool, True) - This is True since this input loader does generate a list of datasets.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• returns env (bool, False) - This is False since this input loader does not generate environments.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

• get_input(blocks, n_inputs_to_load, train_data=None, env=None) - This method generates a list containing a number of *TabularDataSet* equal to n_inputs_to_load. Each dataset is sub-sampled with replacement using a uniform distribution from the given train_data.

Parameters:

- **blocks** (*list*) This is a list containing the blocks for which we need to load the input. This is used only in some *InputLoader*. In this *InputLoader* it is not used.
- **n inputs to load** (*int*) This is the number of datasets that will be sub-sampled.
- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- **splitted** datasets (*list*) This is a list containing objects of Class *TabularDataSet*.
- None This indicates that no environments were generated by this *InputLoader*.

23.5 LoadUniformSubSampleWithReplacementAndEnv

This particular Class sub-samples with replacement the given dataset by using a uniform distribution. In the end a list of objects of Class *TabularDataSet* is created where each object has in its member dataset the new sub-sampled dataset.

Moreover also a list of environments is returned so that this input loader can be used with metrics that use the environment, such as the *DiscountedReward* (to learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*).

The Class LoadUniformSubSampleWithReplacementAndEnv inherits from the Class InputLoader.

Initialiser:

```
___init___(obj_name, single_split_length, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

• **single_split_length** (*int*) - This is the length of each new sub-sampled dataset: it is the number of samples that are contained in each *TabularDataSet* object.

Non-Parameters Members:

• returns dataset (bool, True) - This is *True* since this input loader does generate a list of datasets.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• returns_env (bool, True) - This is *True* since this input loader does generate a list of environments.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

- get_input(blocks, n_inputs_to_load, train_data=None, env=None) This method generates two lists:
 - A list containing a number of *TabularDataSet* equal to n_inputs_to_load. Each dataset is sub-sampled with replacement using a uniform distribution from the given train data.
 - A list containing a number of environments equal to n_inputs_to_load. Each environment is a deep copy of env.

Note that this method simply creates two objects: one of Class *LoadUniformSubSampleWithReplacement* and one of Class *LoadSameEnv*.

Then it proceeds just to call the method **get input()** of these two objects.

Parameters:

- **blocks** (*list*) This is a list containing the blocks for which we need to load the input. This is used only in some *InputLoader*. In this *InputLoader* it is not used.
- n_inputs_to_load (int) This is the number of datasets that will be sub-sampled, which also equals the number of deep copied environments.
- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.

- env (BaseEnvironment, None) - This must be an object of a Class inheriting from the Class BaseEnvironment.

- splitted datasets (list) This is a list containing objects of Class TabularDataSet.
- copied envs (list) This is a list containing deep copies of the original environment env.

23.6 LoadDifferentSizeForEachBlock

This particular Class sub-samples with replacement the given dataset by using a uniform distribution, but it extracts for each block a different number of samples. In the end a list of objects of Class *TabularDataSet* is created where each object has in its member dataset the new sub-sampled dataset.

The Class LoadDifferentSizeForEachBlock inherits from the Class InputLoader.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• returns dataset (bool, True) - This is True since this input loader does generate a list of datasets.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• returns env (bool, False) - This is False since this input loader does not generate a list of environments.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

• get_input(blocks, n_inputs_to_load, train_data=None, env=None) - This method generates a list containing a number of *TabularDataSet* equal to n_inputs_to_load. Each dataset is sub-sampled with replacement using a uniform distribution from the given train_data.

Note that in this case each dataset is made up of a different number of samples: this value is selected according to the value of **n_train_samples** present in each block. This parameter is an object of Class *HyperParameter* and thus can be mutated (i.e. it can be optimised by a *Tuner*).

Note that the parameter **n** train samples is only present in offline model generation blocks.

Parameters:

- **blocks** (*list*) This is a list containing the blocks for which we need to load the input. This is used only in some *InputLoader*. In this *InputLoader* it is used.
- **n** inputs to load (int) This is the number of datasets that will be sub-sampled.
- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- **splitted** datasets (*list*) This is a list containing objects of Class *TabularDataSet*.
- None This indicates that no environments were generated by this *InputLoader*.

23.7 LoadDifferentSizeForEachBlockAndEnv

This particular Class sub-samples with replacement the given dataset by using a uniform distribution, but it extracts for each block a different number of samples. In the end a list of objects of Class *TabularDataSet* is created where each object has in its member dataset the new sub-sampled dataset.

Moreover also a list of environments is returned so that this input loader can be used with metrics that use the environment, such as the *DiscountedReward* (to learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*).

The Class LoadDifferentSizeForEachBlockAndEnv inherits from the Class InputLoader.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• returns dataset (bool, True) - This is True since this input loader does generate a list of datasets.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

• returns env (bool, True) - This is *True* since this input loader does generate a list of environments.

To learn more about this check the documentation about the **Non-Parameters Members** of the Class *InputLoader*.

Methods:

- get_input(blocks, n_inputs_to_load, train_data=None, env=None) This method generates two lists:
 - A list containing a number of *TabularDataSet* equal to n_inputs_to_load. Each dataset is sub-sampled with replacement using a uniform distribution from the given train data.

Note that in this case each dataset is made up of a different number of samples: this value is selected according to the value of **n_train_samples** present in each block. This parameter is an object of Class *HyperParameter* and thus can be mutated (i.e. it can be optimised by a *Tuner*).

Note that the parameter **n train samples** is only present in offline model generation blocks.

A list containing a number of environments equal to n_inputs_to_load. Each environment is a deep copy of env.

Note that this method simply creates two objects: one of Class *LoadDifferentSizeForEachBlock* and one of Class *LoadSameEnv*.

Then it proceeds just to call the method **get input()** of these two objects.

Parameters:

- blocks (list) This is a list containing the blocks for which we need to load the input. This is used only in some InputLoader. In this InputLoader it is used.
- n_inputs_to_load (int) This is the number of datasets that will be sub-sampled, which also equals the number of deep copied environments.

- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

- splitted datasets (list) This is a list containing objects of Class TabularDataSet.
- copied envs (list) This is a list containing deep copies of the original environment env.

24 metric.py

In the module *metric.py* the Classes *Metric*, *TDError*, *DiscountedReward*, *TimeSeriesRollingAverageDiscountedReward* and **SomeSpecificMetric** are implemented.

24.1 Metric

This Class is used as generic base class for all metrics. These are used to evaluate the good-ness of what was learnt in any block of a pipeline. These are also used in the *Tuner* for guiding the tuning procedure.

The *Metric* Classes check whether what they get as input is of the correct type: for example the *TDError* metric should check that **train** data is an object of Class *TabularDataSet*.

The Class *Metric* is an *Abstract Class*, and so it inherits from *ABC*, but it also inherits from the Class *AbstractU-nit*.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• requires dataset (bool, None) - This is *True* if the metric requires a dataset to work.

This is needed for checking the consistency of the consistency of the *Metric* with an *InputLoader*: this check is done in the *Tuner* via the method is **metric** consistent with input loader().

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

• requires env (bool, None) - This is *True* if the metric requires an environment to work.

This is needed for checking the consistency of the consistency of the *Metric* with an *InputLoader*: this check is done in the *Tuner* via the method **is metric consistent with input loader()**.

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

24.2 TDError

This Class implements a specific metric: given a dataset on which the model generation algorithm was learnt on it computes the TD error.

For each episode we compute the TD error, then from the TD error we compute its square. In the end we average over all the episodes.

Here smaller is better.

Note that the TDError can only be used for policies that have **regressor_type** different from *'generic_regressor'*, indeed an approximator of the Q-function is needed to compute the TDError.

The Class *TDError* inherits from the Class *Metric*.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

Non-Parameters Members:

• requires dataset (bool, True) - This is True since in this metric we need a dataset to compute the TD error.

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

• requires env (bool, False) - This is False since in this metric we do not need an environment.

To learn more about this check the documentation about the method is __metric__consistent__with__input__loader() of the Class *Tuner*.

- eval mean (float, None) This is the mean of the evaluation across the episodes.
- eval var (float, None) This is the variance of the evaluation across the episodes.

Methods:

• evaluate(block_res, block=None, train_data=None, env=None) - This method computes the TD error of the block res over the provided train_data.

This method computes for each episode the squared TD error and then returns the mean of the evaluations.

Note that in this case the parameter **n jobs** has no effect: the computation of the metric is vectorised.

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- **block** (*Block*, None) This must be an object of a Class inheriting from the Class *Block*.
- train_data (TabularDataSet, None) This must be an object of a Class inheriting from the Class Tabular-DataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- ag eval (float) This is the mean TD Error across the provided episodes.
- which _ one _ is _ better(block _ 1 _ eval, block _ 2 _ eval) This method is needed to decide which of the two blocks is best. Since this metric (*TDError*) is better if minimised then the best block is the one with the lowest evaluation.

This method compares the value of the member **block eval**, which are the two values provided as parameters.

This is needed in the Class *Tuner* and in the automatic blocks (e.g. *AutoModelGeneration*) to decide among best tuned blocks, without having to distinguish between a maximisation problem or a minimisation problem.

Parameters:

- block_1_eval (float) This is the value of the member block_eval of an object of a Class inheriting from the Class Block.
- block_2_eval (float) This is the value of the member block_eval of an object of a Class inheriting from the Class Block.

Returns:

- (int) - This is 0 if the first block is the best one (i.e. it has the lowest evaluation), else it is 1.

24.3 DiscountedReward

This Class implements a specific metric: given an environment and a policy (i.e. the output of a model generation block) it computes the average discounted reward.

For each episode we compute the discounted reward and then we average over the episodes.

Here bigger is better.

The Class DiscountedReward inherits from the Class Metric.

Initialiser:

```
___init___(obj_name, n_episodes, env_dict_of_params=None, batch=False, seeder=2, log_mode='console', checkpoint log path=None, verbosity=3, n_jobs=1, job_type='process')
```

Parameters:

- **n_episodes** (*int*) This must be a positive a positive integer and it is the number of episodes for which to evaluate the agent.
- env_dict_of_params (dict, None) This is a dictionary containing some members of the environment that you may want to modify only for the evaluation phase. The key must be the name of the member of the environment and the value must be the new value to be assigned to such member.

For example if you have an LQG environment you may want to include a noise on the controller only for testing, to simulate real world situations.

To understand how this work look at the documentation of the methods **set_params()** and **get_params()** of the Class *BaseEnvironment*.

- batch (bool, False) This is a boolean:
 - If True then the discounted reward is computed in batch mode, namely we copy the environment for a number of times equal to n episodes, and we make one step of advance at the time for all episodes.

If **n_jobs** is greater than 1 then also the call to the method **step()** of the environment **env** is performed in parallel. Note that this may slow things down if a single call to the method **step()** is not enough computationally expensive.

Remark: The batch mode cannot be applied on all model generation blocks: it can be applied only to those model generation blocks whose policy has a non *None* value for the member **approximator**.

Indeed the method **draw_action()** of a MushroomRL policy can only be called on a single state at the time. Instead the method **predict()** of the **approximator** can be called on as many states as we like.

This happens for all Classes inheriting from the Class *ModelGenerationMushroomOffline* and for the Classes inheriting from the Class *ModelGenerationMushroomOffline* that have **deterministic_output_policy** equal to *True*.

- If *False* then the discounted reward is computed either in serial or in parallel: if serial then we go through one single episode at the time, if parallel we divide the episodes over the selected number of jobs.

Non-Parameters Members:

• requires _dataset (bool, False) - This is False since in this metric we do need a dataset to compute the discounted reward.

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

• **requires_env** (*bool*, True) - This is *True* since in this metric we need an environment to compute the discounted reward.

To learn more about this check the documentation about the method is __metric __consistent __with __input __loader() of the Class *Tuner*.

- eval mean (float, None) This is the mean of the evaluation across the episodes.
- eval var (float, None) This is the variance of the evaluation across the episodes.

Methods:

• _evaluate_some_episodes(block_res, local_n_episodes, env=None) - This method computes the average discounted reward for a number of episodes equal to local n episodes.

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- local **n** episodes (*int*) This is the number of episodes for which we need to evaluate block res.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- total_rew (list) This is a list containing a number of elements equal to local_n_episodes. Each element is the average discounted reward over one episode.
- __non__batch__eval(block__res, train__data=None, env=None) We create a number of environments equal to the n__jobs (by deep copy of the original environment). Then the method __evaluate__some__episodes() is called in parallel: in particular each call is associated with one of the deep copied environments and each call has to do a number of evaluations equal for a certain number of episodes, namely:
 - From the first to the second last call of this method we have to evaluate for a number of episodes equal to the integer part of:

- For the last call of this method we have to evaluate for a number of episodes equal to:

$$1 - \left((n_{jobs} -1) \left\lfloor \frac{n_{episodes}}{n_{jobs}} \right\rfloor \right)$$

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- unlisted _evals (list) This is a list containing n _episodes elements: each element is the average discounted reward over one episode.
- _batch_eval_parallel_step(block_res, train_data=None, env=None) This method computes the discounted reward for n_episodes. A number of episodes equal to n_episodes is created (by deep copy of the original environment) and then trajectories are rolled out in batch (i.e: for all environments at the same time, one step at the time).

Moreover this method calls in parallel the method **step()** of each of the **n_episodes**. This may slow things down if a single call to the method **step()** is not enough computationally expensive.

For more information on the batch evaluation see the **Remark** about the **batch** parameter in the **Parameters** section of the Class *DiscountedReward*.

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- train_data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- tmp_rew (numpy.array) This is an array that has n_episodes components: in each component the average discounted reward over an episode is contained.
- _batch_eval_no_parallel(block_res, train_data=None, env=None) This method computes the discounted reward for n_episodes. A number of episodes equal to n_episodes is created (by deep copy of the original environment) and then trajectories are rolled out in batch (i.e. for all environments at the same time, one step at the time).

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- tmp_rew (numpy.array) This is an array that has n_episodes components: in each component the average discounted reward over an episode is contained.
- evaluate(block_res, block=None, train_data=None, env=None) This method computes the discounted reward of the block_res using the provided env.

First the **env** parameters are modified according to the provided **env_dict_of_params**. Then this method computes for each episode the discounted reward and then returns the mean of the evaluations.

This method computes the evaluations calling 3 other methods, namely:

- If batch is True and n jobs is 1 then the method batch eval no parallel() is called.
- If **batch** is *True* and **n jobs** is greater than 1 then the method **batch eval parallel step()** is called.
- If batch is False then the method non batch eval() is called.

Note that **n jobs** cannot be higher than **n episodes**: if higher it will be lowered to the same value of **n episodes**.

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- block (Block, None) This must be an object of a Class inheriting from the Class Block.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- ag eval (float) This is the mean discounted reward across the provided episodes.
- which _one _is _better(block _1 _eval, block _2 _eval) This method is needed to decide which of the two blocks is best. Since this metric (*DiscountedReward*) is better if maximised then the best block is the one with the highest evaluation.

This method compares the value of the member **block eval**, which are the two values provided as parameters.

This is needed in the Class *Tuner* and in the automatic blocks (e.g. *AutoModelGeneration*) to decide among best tuned blocks, without having to distinguish between a maximisation problem or a minimisation problem.

Parameters:

- block_1_eval (float) This is the value of the member block_eval of an object of a Class inheriting from the Class Block.
- block_2_eval (float) This is the value of the member block_eval of an object of a Class inheriting from the Class Block.

Returns:

- (int) - This is 0 if the first block is the best one (i.e. it has the highest evaluation), else it is 1.

24.4 TimeSeriesRollingAverageDiscountedReward

This Class implements a specific metric: given an environment and a policy (i.e: the output of a model generation block) it computes the rolling average discounted reward. Suppose we have an environment in which each horizon is made up of one day, then:

- We learn the block on the first N days and evaluate it from the (N+1)-th day to the (N+M)-th day.
- We learn the block on the first N+M days and evaluate it from the (N+M)-th day to the (N+2M)-th day.
- We learn the block on the first N + 2M days and evaluate it from the (N + 2M)-th day to the (N+3M)-th day.
- And so on and so forth...

The final result is the average of the result of the above steps.

In order to be able to use this metric the provided environment must have an attribute for selecting the time step at which to start the episode.

The environment must have two members:

- min time step for time series evaluation
- max time step for time series evaluation

These two members must limit the values the time step can take when calling the method **reset()** of the environment.

Here bigger is better.

The Class TimeSeriesRollingAverageDiscountedReward inherits from the Class Metric.

Initialiser:

```
__init__(obj_name, n_episodes_train, n_evaluations, n_episodes_eval, n_episodes_per_fit=None,
data_gen_block=None, env_dict_of_params=None, batch=False, seeder=2, log_mode='console',
checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

- n_episodes_train (int) This is a number and it is the starting number of episodes to use. We train the block on n_episodes and we evaluate it on n_episodes_eval, then we train the block on (n_episodes_train + n episodes eval) and we evaluate it on n episodes eval, and so on and so forth.
- **n_evaluations** (*int*) This is a number and it is the total number of evaluations to perform: it is the number of rolling windows.
- n_episodes_eval (int) This is a number and it is the number of episodes for evaluation to use in each rolling window.
- n_episodes_per_fit (int, None) This is a parameter needed for learning the online ModelGeneration block, and it must be less than n episodes. It is not used if the block to be evaluated is an offline model generation block.
- data_gen_block (DataGeneration, None) This must be an object of a Class inheriting from the Class DataGeneration. This is used if the block to evaluate is an offline ModelGeneration block in which case we need a way to extract data from the given environment.

• env_dict_of_params (dict, None) - This is a dictionary containing some members of the environment that you may want to modify only for the evaluation phase. The key must be the name of the member of the environment and the value must be the new value to be assigned to such member.

For example if you have an LQG environment you may want to include a noise on the controller only for testing, to simulate real world situations.

To understand how this work look at the documentation of the methods **set_params()** and **get_params()** of the Class *BaseEnvironment*.

Non-Parameters Members:

• requires_dataset (bool, False) - This is False since in this metric we do need a dataset to compute the rolling average discounted reward.

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

• **requires _env** (*bool*, True) - This is *True* since in this metric we need an environment to compute the rolling average discounted reward.

To learn more about this check the documentation about the method **is _metric _consistent _with _input _loader()** of the Class *Tuner*.

- eval mean (float, None) This is the mean of the evaluation across the rolling windows.
- eval var (float, None) This is the variance of the evaluation across the rolling windows.

Methods:

- __online__blocks__time__series__rolling__eval(block, rolling__window__idx, original__lower__bound, train__data=None, env=None)
 - This method only works on online *ModelGeneration* blocks and as such I might be calling methods that are only present in those blocks.

This method computes the discounted reward over a single rolling window:

- Since this method works on online *ModelGeneration* blocks we directly learn the **block** over the provided **env**.
- Finally the environment is used to compute the average discounted reward of the learnt block. The evaluation is performed on unseen data.

To make sure we use different data between training and testing we set appropriately in each call to this method the value of the parameters min_time_step_for_time_series_evaluation and max_time_step_for_time_series_evaluation of the env.

- block (Block, None) This must be an object of a Class inheriting from the Class Block.
- rolling_window_idx (int) This is an integer and it represent the current rolling window. It is used to set min time step for time series evaluation and max time step for time series evaluation.

original_lower_bound (int) - This is an integer and it represent the original value of
min_time_step_for_time_series_evaluation, that is: the value of such member at the start of the call of
the method evaluate().

This may be used by the user to restrict the evaluation only to some time steps. For example one may want to only consider time steps that come after the 100th time step, in which case this parameter would assume the value of 101.

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (float) This is the mean discounted reward across the provided episodes of a single rolling window.
- (float) This is the variance of the discounted reward across the provided episodes of a single rolling window.

_offline_blocks_time_series_rolling_eval(block, rolling_window_idx, original_lower_bound, train_data=None, env=None)

- This method only works on offline *ModelGeneration* blocks and as such I might be calling methods that are only present in those blocks.

This method computes the discounted reward over a single rolling window:

- Since this method works on offline ModelGeneration blocks then we need to extract a dataset from the environment. This is done via the parameter data_gen_block of the TimeSeriesRollingAverageDiscountedReward object.
- After the dataset is extracted the **block** is learnt over the extracted dataset.
- Finally the environment is used to compute the average discounted reward of the learnt block. The evaluation is performed on unseen data.

To make sure we use different data between training and testing we set appropriately in each call to this method the value of the parameters min_time_step_for_time_series_evaluation and max_time_step_for_time_series_evaluation of the env.

Parameters:

- **block** (*Block*, None) This must be an object of a Class inheriting from the Class *Block*.
- rolling_window_idx (int) This is an integer and it represent the current rolling window. It is used to set
 min time step for time series evaluation and max time step for time series evaluation.
- original_lower_bound (int) This is an integer and it represent the original value of
 min_time_step_for_time_series_evaluation, that is: the value of such member at the start of the call of
 the method evaluate().

This may be used by the user to restrict the evaluation only to some time steps. For example one may want to only consider time steps that come after the 100th time step, in which case this parameter would assume the value of 101.

- train_data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- (float) - This is the mean discounted reward across the provided episodes of a single rolling window.

- (float) This is the variance of the discounted reward across the provided episodes of a single rolling window.
- evaluate(block_res, block=None, train_data=None, env=None) This method computes the rolling average discounted reward of the block using the provided env.

Here **block_res** is not used since for each rolling window the **block** needs to be learnt from scratch.

This method calls either the method _online_blocks_time_series_rolling_eval() or the method _offline_blocks_time_series_rolling_eval(), depending on the pipeline_type of the block.

For each rolling window a different environment is created: this is done by deep copying the original env.

If **n_jobs** is greater than 1 this method calls one of the aforementioned methods in parallel: indeed each rolling window can be evaluated in parallel.

Inside each of the two aforementioned methods an object of Class *DiscountedReward* is created: the call to this inner metric is not done in parallel to avoid a parallel loop inside a parallel loop, as it could cause some issues. For example a process fork of a process fork is not possible.

Parameters:

- block res (BlockOutput) This must be an object of a Class inheriting from the Class BlockOutput.
- **block** (*Block*, None) This must be an object of a Class inheriting from the Class *Block*.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- ag eval (float) This is the mean rolling average discounted reward across the rolling windows.
- which one is better(block 1 eval, block 2 eval) This method is needed to decide which of the two blocks is best. Since this metric (*TimeSeriesRollingAverageDiscountedReward*) is better if maximised then the best block is the one with the highest evaluation.

This method compares the value of the member **block eval**, which are the two values provided as parameters.

This is needed in the Class *Tuner* and in the automatic blocks (e.g. *AutoModelGeneration*) to decide among best tuned blocks, without having to distinguish between a maximisation problem or a minimisation problem.

Parameters:

- block_1_eval (float) This is the value of the member block_eval of an object of a Class inheriting from the Class Block.
- block 2 _eval (float) This is the value of the member block _eval of an object of a Class inheriting from the Class Block.

Returns:

- (int) - This is 0 if the first block is the best one (i.e. it has the highest evaluation), else it is 1.

24.5 SomeSpecificMetric

This Class implements a specific metric: this is a placeholder to use in blocks for which there are no metrics, or for which you do not need a metric.

The Class SomeSpecificMetric inherits from the Class Metric.

Initialiser:

```
__init__(obj_name, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process')
```

25 tuner.py

In the module *tuner.py* the Class *Tuner* is implemented.

25.1 Tuner

This Class is used as base for all block tuning: the specific tuning algorithms inherit from this Class. Any block that wants to be tuned needs to use a tuner: starting from a generic configuration of hyper-parameters *Tuner* objects find a better hyper-parameters configuration that provides a better metric evaluation.

Tuner objects can be applied to blocks that inherit from the Classes:

- ModelGeneration
- RLPipeline

Tuner objects can only be applied to blocks inheriting from the Classes mentioned above, but there is one more restriction: such blocks must have the parameter **is parametrised** equal to *True*.

The Class Tuner is an Abstract Class, and so it inherits from ABC, but it also inherits from the Class AbstractUnit.

Initialiser:

```
__init__(block_to_opt, eval_metric, input_loader, obj_name, create_explanatory_heatmap=False, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', output_save_periodicity=25)
```

Parameters:

• **block_to_opt** (*Block*) - This must be an object inheriting from the Class *Block*. In particular it can only be a FeatureEngineering block, or a ModelGeneration block, or a RLPipeline block.

This block moreover must have the parameter **is parametrised** equal to *True*.

This is the block whose hyper-parameters are going to be tuned.

• **eval_metric** (*Metric*) - This must be an object inheriting from the Class *Metric*. This is the metric that is going to be used to rank the different tuned blocks in the tuner.

The user must make sure that the provided metric is a sensible choice for the provided block.

• input_loader (InputLoader) - This must be an object inheriting from the Class InputLoader. This object is going to generate the right train data and-or env for each block, in the tuning procedure.

The user must make sure that the provided input loader is a sensible choice for the provided block.

• **output_save_periodicity** (*int*, 25) - This is a positive integer and it represents the frequency with which to save the blocks as the tuning procedure takes place.

Note that if the member **checkpoint** log path is not set then nothing will be saved.

This is fundamental in order to create the explanatory heatmap of the hyper-parameters, which is generated by the method **create_explanatory_heatmap_hyperparameters()** at the end of the tuning procedure. If too few blocks are saved throughout the tuning procedure, then the same few blocks will go in input to the method **create explanatory heatmap hyperparameters()** and so the resulting heatmap quality might be low.

• **create_explanatory_heatmap** (*bool*, False) - This is a boolean and if *True* then at the end of the call of the method **tune()** the method **create_explanatory_heatmap_hyperparameters()** is going to be called: this creates an explanatory heatmap of the hyper-parameters.

To obtain the best possible result with the heatmap you should only create when **output_save_periodicity** is equal to 1.

Non-Parameters Members:

• is tune successful (bool, False) - This is used to know whether or not the tuner finished with no errors. If everything went smooth then it will be set to *True* before the end of the method tune().

Methods:

• is __metric _ consistent _ with _ input _ loader() - This method returns *True* if the eval __metric and the input _ loader are consistent.

These two are consistent when the metric requires in input something that the input loader will return. More precisely:

- If eval_metric has requires_dataset equal to True then input_loader must have returns_dataset equal to True.
- If eval metric has requires env equal to *True* then input loader must have returns env equal to *True*.

If this method returns False then the tuning procedure cannot take place.

Returns:

- (bool) This is *True* if the **eval** metric and the input loader are consistent, else it is *False*.
- tune(train_data=None, env=None) This method first checks that the eval_metric and the input_loader are consistent, by calling the method is _metric_consistent_with _input_loader().

Then it checks that the **block_to_opt** has the parameter **is_parametrised** equal to *True*. Note that one can set **is_parametrised** equal to *False* in two cases:

- When one doesn't want to tune the hyper-parameters of such block.
- When such block cannot be tuned since it has no hyper-parameters.

If **block_to_opt** has the parameter **is_parametrised** equal to *False*: The **block_to_opt** is learnt over the entire provided **train data** and **env**. Then:

- If the **block to opt** was learnt successfully: this agent, and its evaluation, are returned by this method.
- If the block_to_opt was not learnt successfully: this method returns value None both for the agent and for its evaluation.

If **block_to_opt** has the parameter **is_parametrised** equal to *True*: nothing is returned, hence the computation will proceed in a specific *Tuner* object which will inherit from the Class *Tuner*.

Note that in this case a folder for saving the tuned agents, and their result, is created: the folder name is given by the concatenation of the **obj name** of the *Tuner* object followed by the current time and date.

If a folder with such a same name already exists the computation stops and does not proceed any further.

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- If **is parametrised** is equal to *True*: nothing is returned.
- If **is parametrised** is equal to *False*:
 - * **best_agent** (*Block*), **best_agent_eval** (*float*) This is the return value in case the call to the method **learn()** of the **block to opt** succeeds.
 - * (None, None) This is the return value in case the call to the method learn() of the block to opt fails.
- update_verbosity(new_verbosity) This method calls the base method update_verbosity() implemented in the Class AbstractUnit. Then it calls the method update verbosity() for block to opt and input loader.

Parameters:

- **new verbosity** (*int*) This must be a positive integer representing the new **verbosity**.
- **create_explanatory_heatmap_hyperparameters()** This method is called at the end of the call of the method **tune()** only when **create explanatory heatmap** is set to *True*.

Starting from the result of the tuning procedure constructs a heatmap in which we can see the evaluation of an agent, when changing the value of two of its hyper-parameters, while keeping the other hyper-parameters value fixed to the value of the optimal agent obtained in the tuning procedure.

The agent evaluation seen on the heatmap is the predicted value for the new hyper-parameters configuration measured according to the **eval metric** provided in the tuner.

Specifically this method:

- Loads the data saved by the method **tune()**.
- Loads the best agent obtained by the tuning procedure.
- From the loaded agents it extracts a dataset where the features are the hyper-parameters configurations and the target is the obtained block evaluation.
- It fits a CatBoostRegressor on such dataset.
- For each pair of hyper-parameters that were tuned a 2-D grid is constructed and it is used to generate a new dataset. A new dataset is generated for each pair of hyper-parameters that were tuned.

Each dataset has fixed values for the hyper-parameters that were not tuned, equal to the values of the optimal found hyper-parameters overall, whereas for the hyper-parameters that are in the current pair the values change over a grid of points.

Each dataset is passed to the method **predict()** of the previously fitted *CatBoostRegressor*.

A heatmap is created by plotting such prediction. To do this the **plotly** library is used: an *html* file is generated containing the interactive heatmap where the effect of changing the value of the hyper-parameters pairs can be observed.

Part of the code that creates the heatmap is a re-adaptation of the following code:

cf. https://plotly.com/python/custom-buttons/

At the end an *html* file, containing the heatmap, is saved.

26 tuner optuna.py

In the module tuner optuna.py the Class TunerOptuna is implemented.

26.1 TunerOptuna

This Class implements an hyper-parameter optimisation algorithm, namely it provides access to the *Optuna* library. cf. https://optuna.readthedocs.io/en/stable/index.html cf. https://arxiv.org/abs/1907.10902

The Class *TunerOptuna* inherits from the Class *Tuner*.

Initialiser:

```
___init___(block_to_opt, eval_metric, input_loader, obj_name, create_explanatory _heatmap=False sampler='TPE', n_trials=100, max_time_seconds=3600, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_jobs=1, job_type='process', output_save_periodicity=25)
```

Parameters:

- **sampler** (*str*, 'TPE') This is a string representing the sampler to use out of the ones provided by *Optuna*. It can be:
 - 'CMA-ES', in which case th covariance matrix adaptation evolution strategy is used.
 - 'TPE', in which case the tree parzen estimator is used.
 - 'RANDOM', in which case random search is used.
 - 'GRID', in which case grid search is used.

Note that some samplers have some requirements: for example the 'CMA-ES' sampler does not work on categorical parameters.

cf. https://optuna.readthedocs.io/en/stable/tutorial/10_key_features/003_efficient_optimization_algorithms.html#sampling-algorithms

- **n trials** (*int*, 100) This must be a positive integer representing the number of trials to do.
- max_time_seconds (int, 3600) This must be a positive integer representing the maximum allowed time in seconds.

Non-Parameters Members:

- **optuna_object_sampler** (*optuna.samplers.sampler._base.BaseSampler*) This is a sampler object from the *Optuna* library. It is an object constructed by using the parameter **sampler**.
- **opt direction** (*str*) This is a string and it is either 'maximize' or 'minimize'.

It is 'maximize' if the metric of the block needs to be maximised, else it is 'minimize'.

Methods:

• _objective(trial) - This method is called by *Optuna* throughout the study. This method takes the current agent and it updates its hyper-parameters according to the **trial** suggested values.

Then the new agent is learnt over the current **train** data and **env** and it is evaluated according to the **eval** metric.

Note that if the block to be evaluate is an object of a Class inheriting from the Class *RLPipeline* and such pipeline ends with an object of a Class inheriting from the Class *ModelGeneration* then the **train_data** and the **env** used in the evaluation are those situated in the object obtained in output from the method **learn()** of the pipeline. Why is this done? Because if we performed feature engineering then the learnt policy cannot be evaluated in the old **train_data** and **env** as the observation space and the action space are different, and so we need the latest version of the **train_data** and **env**.

After each number of trials equal to **output** save **periodicity** we save the agent and its result in a *pickle* file.

Moreover also every new best agent, and its result, are saved.

Finally at the end of this method the new train data and env, obtained from the input loader, are constructed.

If everything went smoothly the new agent evaluation is returned, else *None* is returned.

Note that here, unless **verbosity** is greater than or equal to 4 we silence the agents: otherwise if we are in debug mode we print everything.

Parameters:

- **trial** (*optuna.trial.Trial*) - This object provides interfaces to get suggestions for the new values of the hyper-parameters.

cf. https://optuna.readthedocs.io/en/stable/reference/generated/optuna.trial.Trial.html

This is used by Optuna.

Returns:

- If the new agent was **not** learnt properly: *None* is returned.
- If the new agent was learnt properly the return value is: **tmp_agent_eval** (*float*) -This is the evaluation, according to **eval metric**, of the new agent.
- tune(train_data=None, env=None) This method calls the *base* method tune() implemented in the Class *Tuner*. Then we check the result of such call:
 - If what we get is *None*, it means that such method did not return anything, and so we are free to proceed.
 - Else we return immediately the results we got passed down from such method.

First the **input_loader** generates the data for the first agent and then an *Optuna* study is created: this is an object of Class *optuna.study.Study* and it coordinates the tuning procedure.

Now the method **optimize()** of such study is called: this takes care of the whole hyper-parameter optimisation procedure.

After this we can extract the best trial, according to the **eval_metric**, and create the final agent with the best set of hyper-parameters that was found. This new agent is also saved to a *pickle* file.

Now if **create_explanatory_heatmap** is equal to *True*, the heatmap explaining the impact of the hyper-parameters on the evaluation of **block_to_opt** is created by calling the method **create_explanatory_heatmap_hyperparameters(**

Finally the best agent and its evaluation are returned.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- If everything went smoothly we return: **best_agent** (*Block*), **best_agent_eval** (*float*) These are the best agent and its evaluation.
- If there was an error we return: None, None.

27 tuner genetic.py

In the module tuner genetic.py the Class TunerGenetic is implemented.

27.1 TunerGenetic

This Class implements a population based tuner, namely it implements a Genetic Algorithm.

The Class *TunerGenetic* inherits from the Class *Tuner*.

Initialiser:

```
___init___(block_to_opt, eval_metric, input_loader, obj_name, create_explanatory_heatmap=False, seeder=2, log_mode='console', checkpoint_log_path=None, verbosity=3, n_agents=10, n_generations=100, prob_point_mutation=0.5, tuning_mode='best_performant_elitism', pool_size=None, n_jobs=1, job_type='process', output_save_periodicity=25)
```

Parameters:

- n agents (int, 10) This must be a positive integer representing the number of agents in each generation.
- n_generations (int, 100) This must be a positive integer representing the number of generations of the genetic algorithm.
- **prob_point_mutation** (*float*, 0.5) This is the probability of mutating a certain hyper-parameter of **block_to_opt**.
- **tuning_mode** (*str*, 'best_performant_elitism') This is a string and it represents the tuning mode. It can assume one of three values:
 - If 'no_elitism' is selected then the best agent of each generation is not kept as is across generations but it undergoes mutation.
 - If 'best_performant_elitism' is selected then the best agent so far is added to each generation both as is and also mutated.
 - If 'pool_elitism' is selected then the most performant pool_size agents are kept across generations and are used to generate the new offspring by mutating them.

In the first two cases we perform tournament selection (note that we always reserve a spot for the best agent of the previous generation (which will be mutated)).

• **pool_size** (*int*, None) - This is a positive integer and it represents the number of best agents to use in each generation as starting point for obtaining the next generation.

This is only needed when **tuning mode** is equal to 'pool elitism'.

Note that **pool size** must divided exactly **n agents**: otherwise an exception is raised.

Non-Parameters Members:

• trial number (int, 0) - This is an integer used for keeping track of how many trials (agents) are being done.

Methods:

• _get_agent_data(current_agent, train_data=None, env=None) - This method creates the appropriate train_data and-or env for the provided current_agent by using the input_loader.

Parameters:

- current_agent (Block) This is the block for which we need to construct the train_data and-or env which will be used by the block for learning.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner.
- **env** (BaseEnvironment, None) This is the original **env** as passed in input to the method **tune()** of the Tuner.

Returns:

- tmp_agent_train_data (BaseDataSet) - This can be None (in case no dataset was needed to be extracted for the provided block current_agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseDataSet*.

- tmp_agent_env (BaseEnvironment) - This can be None (in case no environment was needed to be extracted for the provided block current agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseEnvironment*.

Note that all the above values are equal to *None* if something went wrong in the execution of this method.

- _mutate_gather_data_and_env(current_gen_n, current_gen_length, tmp_agent_to_tune, train_data=None, env=None, first_mutation=False)
 - -This method takes as input an agent, it deep copies it, then:
 - The agent hyper-parameters are mutate by calling the method mutate()
 - The agent is seeded with a different seed by calling its method **set local prng()**.
 - The train_data and-or env needed to learn the newly mutated agent are extracted by calling the method _get_agent_data()

Note that here, unless **verbosity** is greater than or equal to 4 we silence the agents: otherwise if we are in debug mode we print everything.

- current_gen_n (int) This the number of the current generation. It is solely used for re-naming each newly mutated agent.
- current_gen_length (int) This is the current generation length: it is the number of agents in the current generation. This is used for re-naming each newly mutated agent and for setting a different seed for each agent.
- tmp_agent_to_tune (Block) This must be an object of a Class inheriting from the Class Block. We deep copy this agent, and mutate its hyper-parameters.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner. It is used to generate the new train data for the newly mutated agent.
- env (BaseEnvironment, None) This is the original env as passed in input to the method tune() of the Tuner.
 It is used to generate the new env for the newly mutated agent.

first_mutation (bool, False) - This is a boolean and it is used to decide how to mutate the hyper-parameters of the agent. This is passed to the method mutate().

To see its effect see the documentation about the Class *Integer*, *Real*, *Categorical* in the section explaining about the parameter **type of mutation**.

Returns:

- tmp agent (Block) This is the newly mutated agent.
- tmp_agent_train_data (BaseDataSet) This can be None (in case no dataset was needed to be extracted for the newly mutated agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseDataSet*: this is used in the method **learn()** of the newly mutated agent.

- tmp_agent_env (BaseEnvironment) - This can be None (in case no environment was needed to be extracted for the newly mutated agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseEnvironment*: this is used in the method **learn()** of the newly mutated agent.

Note that all the above values are equal to *None* if something went wrong in the execution of this method.

_learn_and_evaluate(tmp_agent, tmp_agent_train_data, tmp_agent_env) - This method calls the method learn() of tmp agent by passing to it tmp agent train data and tmp agent env.

Then if the learning was not successful the **tmp_agent** is returned. Else if the learning was successful: the learn agent is evaluated by calling the method **_evaluate()**. This evaluation is added to the parameter **block_eval** of **tmp_agent**.

Note that if the block to be evaluate is an object of a Class inheriting from the Class *RLPipeline* and such pipeline ends with an object of a Class inheriting from the Class *ModelGeneration* then the **train_data** and the **env** used in the evaluation are those situated in the object obtained in output from the method **learn()** of the pipeline. Why is this done? Because if we performed feature engineering then the learnt policy cannot be evaluated in the old **train_data** and **env** as the observation space and the action space are different, and so we need the latest version of the **train_data** and **env**.

Now if **trial number** divides **output save periodicity** the learnt agent and its result are saved as *pickle* files.

A check here is also made to update the best agent found so far: we compare the new **block_eval** with that of the best agent found so far.

Finally **tmp agent** is returned.

Parameters:

- tmp agent (*Block*) This is the newly mutated agent which we need to learn.
- tmp_agent_train_data (BaseDataSet) This can be None (in case no dataset was needed to be extracted for the newly mutated agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseDataSet*: this is used in the method **learn()** of the newly mutated agent.

- tmp_agent_env (BaseEnvironment) - This can be None (in case no environment was needed to be extracted for the newly mutated agent).

Otherwise if it is not *None* it will be an object of a Class inheriting from the Class *BaseEnvironment*: this is used in the method **learn()** of the newly mutated agent.

Returns:

tmp_agent (Block) - This is the agent that was learnt: it is the same object as the one provided as parameter except that its parameter block eval has been changed.

This has value *None* if something went wrong in the execution of this method.

- _no_elitism_or_best_performant_elitism_common(agents_population, preserve_best_agent, train_data=None, env=None)
 - This method is used when **tuning** mode is not 'pool elitism'.

This method performs the tuning from the second to the last generation: it takes as input the first generation and then it returns as output the last generation.

For each generation the new agents population is constructed by tournament selection by repeatedly calling the method _select(): we take subsets of 3 agents and pick the best among the three agents. We reserve one spot for the best performing agent of the previous generation.

Once the new generation is constructed:

- The train data and-or env are created, by repeatedly calling the method mutate gather data and env().
- The agents are learnt and evaluated, by repeatedly calling the method _learn_and_evaluate().

Parameters:

- agents population (list) This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the first generation.
- preserve_best_agent (bool) This is a boolean and it is True if tuning_mode is equal to 'best performant elitism', else it is False.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner. It is used to generate the new train data for the generation.
- env (BaseEnvironment, None) This is the original env as passed in input to the method tune() of the Tuner.
 It is used to generate the new env for the generation.

Returns:

agents population (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the last generation.

This has value *None* if something went wrong in the execution of this method.

• __no__elitism(agents__population, train__data=None, env=None) - This method is used when tuning__mode is equal to 'no elitism'.

This method simply calls the method _no_elitism_or_best_performant_elitism_common() with preserve best agent equal to False.

- agents population (list) This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the first generation.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner. It is used to generate the new train_data for the generation.
- env (BaseEnvironment, None) This is the original env as passed in input to the method tune() of the Tuner.
 It is used to generate the new env for the generation.

Returns:

agents population (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the last generation.

This has value *None* if something went wrong in the execution of this method.

• _best_performant_elitism(agents_population, train_data=None, env=None) - This method is used when tuning mode is equal to 'best_performant_elitism'.

This method simply calls the method _no_elitism_or_best_performant_elitism_common() with preserve best agent equal to *True*.

Parameters:

- agents population (list) This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the first generation.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner. It is used to generate the new train data for the generation.
- env (BaseEnvironment, None) This is the original env as passed in input to the method tune() of the Tuner.
 It is used to generate the new env for the generation.

Returns:

agents population (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the last generation.

This has value *None* if something went wrong in the execution of this method.

• _pool_elitism(agents_population, train_data=None, env=None) - This method is used when tuning_mode is equal to 'pool_elitism'.

This method selects the top **pool_size** agents from each generation and it constructs the new generation by deep copying an equal amount of times each of the **pool_size** best agents. Then we proceed like in the previous two methods:

- The train_data and-or env are created, by repeatedly calling the method _mutate_gather_data_and_env().
- The agents are learnt and evaluated, by repeatedly calling the method learn and evaluate().

- agents population (list) This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the first generation.
- train_data (BaseDataSet, None) This is the original train_data as passed in input to the method tune() of the Tuner. It is used to generate the new train data for the generation.

env (BaseEnvironment, None) - This is the original env as passed in input to the method tune() of the Tuner.
 It is used to generate the new env for the generation.

Returns:

agents population (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the last generation.

This has value None if something went wrong in the execution of this method.

- tune(train_data=None, env=None) This method calls the *base* method tune() implemented in the Class *Tuner*. Then we check the result of such call:
 - If what we get is *None*, it means that such method did not return anything, and so we are free to proceed.
 - Else we return immediately the results we got passed down from such method.

Now based on the value of **tuning mode** we call the appropriate method:

- If 'no elitism' is selected then the method **no elitism()** is called.
- If 'best_performant_elitism' is selected then the method best performant elitism() is called.
- If 'pool elitism' is selected then the method **pool elitism()** is called.

After this we extract the best agent overall, according to the **eval metric**. This best agent is saved to a *pickle* file.

Now if **create_explanatory_heatmap** is equal to *True*, the heatmap explaining the impact of the hyper-parameters on the evaluation of **block_to_opt** is created by calling the method **create_explanatory_heatmap_hyperparameters(**

Finally the best agent and its evaluation are returned.

Parameters:

- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- If everything went smoothly we return: **best_agent** (*Block*), **best_agent_eval** (*float*) These are the best agent and its evaluation.
- If there was an error we return: None, None.
- _mutate(agent, first_mutation=False) This method mutates the hyper-parameters of the provided agent. Precisely:
 - The method **get params()** of the **agent** is called to extract its hyper-parameters.
 - We loop over all the hyper-parameters and we mutate those that have the member **to mutate** equal to *True*.

A mutation of a specific hyper-parameter takes place with probability **prob point mutation**.

- We call the method **set params()** of the **agent**: this way the new hyper-parameters are set.

Parameters:

 agent (Block) - This is the agent whose hyper-parameters needs to be mutated. It must be an object of a Class inheriting from the Class Block. - first_mutation (bool, False) - This is a boolean and it used to decide how to perform the mutation. This is going to be passed down to the method mutate() of a specific hyper-parameter. To understand precisely the impact of this parameter see the documentation about the method mutate() of the Classes Real and Integer.

Returns:

– agent (*Block*) - This is the mutated agent.

This has value *None* if something went wrong in the execution of this method.

_evaluate(agent_res, agent=None, train_data=None, env=None) - This method evaluates the provided agent res on the provided train data and-or env.

This method simply calls the method **evaluate()** of the **eval metric** of the *Tuner*.

Parameters:

- agent_res (BlockOutput) This is the output block produced by the call of the method learn() of the agent.
- agent (Block, None) This is the agent that was learnt.
- train data (BaseDataSet, None) This must be an object of a Class inheriting from the Class BaseDataSet.
- env (BaseEnvironment, None) This must be an object of a Class inheriting from the Class BaseEnvironment.

Returns:

- tmp_single_agent_eval (float) This is the evaluation of the provided agent_res.
- _select(agents_pop) This method selects an agent from the current population: this agent will be passed onto the next generation. How is the agent selected?
 - A random subset of 3 agents is selected from **agents pop**.
 - The best agent out of the three is selected.

Parameters:

agents_pop (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents the previous generation.

Returns:

- selected ag (Block) This is the selected agent that will be mutated and be part of the new generation.
- _evaluate_a_generation(gen) This method orders the agents of the provided gen according to their evaluation (which is contained in the member block_eval).

From the **gen** I extract the evaluation of the agents and then I use *numpy.argsort()*. In doing this I take into consideration whether the metric is to be maximised, or minimised.

Parameters:

gen (list) - This is a list of agents, namely of objects of a Class inheriting from the Class Block. This represents
a generation.

Returns:

- **best agent** (*Block*) This is the best agent.
- best_agent_eval (float) This is the best agent evaluation.

28 Further Details

The following are some facts that might be useful for using this library:

On Python version: You must use Python3.7 or above.

On policies: A policy *HyperParameter* object cannot have **to_mutate** equal to *True*: policies cannot be mutated. You can always create a *AutoModelGeneration* blocks and compare two different policies, while keeping the other things constant.

Note that not all RL algorithms work with all possible policies: to see which works with which see MushroomRL documentation. For example in deep actor critic method you can only use a *TorchPolicy*.

The **regressor_type** of a policy (and so of *ModelGeneration* blocks) has to be 'generic_regressor' when the action space is continuous (i.e. Box).

On metrics: The Classes *Metric* that are used with *ModelGeneration* blocks must have two members: **eval_mean** and **eval_var**. These are used in the method **learn()** of the Classes *OfflineRLPipeline* and *OnlineRLPipeline* to construct the **policy eval**.

To fill in **eval_metric** for block for which you do not care-need about the evaluation you can use the Class *Some-SpecificMetric*.

On blocks: If you follow the structure of the implemented blocks it is possible to implement any block and use it together with all the other things implemented in this library.

If you create a new tuner you can create a new Class inheriting from the Class *Tuner*, and then you can create an *AutoModelGeneration* block using your new tuner. You can then compare it with existing tuners.

If you create an automatic block make sure that the **block_to_opt** have the same metric: it does not make sense to rank them on different metrics.

On pipelines: The evaluation metric of an RL pipeline must be equal to the evaluation metric of the last block contained in the pipeline.

If you create a AutoRLPipeline block:

- Make sure that the pipelines have the same metric: it does not make sens to rank them on different metrics.
- You can have an automatic block (e.g. a *AutoModelGeneration* block): this is not going to be mutated as **is parametrised** is equal to *False*.
- You must pick the task type: online or offline by setting **online task** either to *True* or *False*.

On hyper-parameters:

- The hyper-parameters of all blocks must be specified as *HyperParameter* objects.
- At the moment the parameters of the data generation blocks used in feature engineering blocks can't be tuned.

On environments:

• MushroomRL dataset need *numpy.array* for all elements, except for the reward, hence even if the action space is *Discrete* we need a *numpy.array* for the action. Moreover MushroomRL policies predict numpy.array([action]) even if the action space is discrete. It is for this reason also that in *DataGenerationRandomUniformPolicy* passes numpy.array([action]) to all environments when extracting datasets.

Thus the environment must assume to use np.array([action]), even if it is a Discrete Action space. To go around this you can just extract the number at the top of the method **step()** of your environment.

- All methods **reset** in all environments must have the signature described in the documentation of the Class *BaseEnvironment* otherwise MushroomRL RL algorithms are going to fail!
- All environments must inherit from the Class *BaseEnvironment*, else they cannot be used in this library. Moreover you must use the spaces *Box* and *Discrete* from MushroomRL and not those from OpenAl gym.

No other space types are supported due to limitation of the current MushroomRL release.

• To be sure not to mess up parallel computation the method **seed()** should call the method **set_local_prng()** and also all source of randomness in the environment should use the **local_prng** provided by the *AbstractUnit*. This is because *numpy.random* is not safe to use on concurrent threads or processes.

```
cf. https://numpy.org/doc/stable/reference/random/parallel.html
cf. https://albertcthomas.github.io/good-practices-random-number-generators/
```

Moreover do not use *numpy.random* for sampling in an environment but use the **local_prng** provided by the *AbstractUnit*.

This is very important indeed in the Classes *Metric* and in some *DataGeneration* Classes the method **set_local_prng()** of the environments is called while the method **seed()** of the environment is never called!

You should seed the environment yourself upon creation of the environment object!

On performance:

• If the evaluation seems slow you may not be using the right metric. If you are using a RL algorithm with an Epsilon Greedy policy make sure to set **batch eval** equal to *True* in the *DiscountedReward* metric.

Why is the **non_batch_eval** slow? Because the method **draw_action()** of object of a Class inheriting from the Class *mushroom_rl.policy.Policy* only accept in input a single sample, therefore to predict 1000 samples we need to call 1000 times the method **draw action()**.

Instead with **batch eval** we can call just once the method predict.

• Make sure not to mix up too many parallelisation techniques: for example in python a fork of a fork is not possible so if you set two nested blocks to perform multi-processing this is not going to work. Moreover the fact that it is not going to work can be silent: the program may just freeze.

Moreover keep in mind that python has the GIL therefore only one thread at the time has control of the interpreter, as such if you perform multi-threading on *pure* python is going to be slower. This is not the case for python wrapper libraries for C or C++ code (e.g. PyTorch, xgboost).

```
cf. https://stackoverflow.com/questions/1912557/a-question-on-python-gil
```

On this note PyTorch only allows multi-threading therefore in deep actor critic methods, where PyTorch is used, specifying **job_type** is useless.

On the method: set_params() - When setting new parameters, for any block, all the previous parameters are lost: this is to ease the tuning procedure.

Therefore you can never partially specify hyper-parameters.

On algo params upon instantiation: If algo params is *None* then this is set to a structured default dictionary. Now if you stop the method learn() without algo params upon instantiation you would get an error since now algo params is a structured dictionary but the method set params() expects a flat dictionary.

The same reasoning holds for **tuner blocks dict upon instantiation**.

Things to consider when extending the library and library code styles:

- Methods starting with underscore are supposed to be private (as it is practice in python). This is however just a convention.
- Check type of a parameter also in the initialiser and not just in setter and getter methods.
- When reporting logs and messages write members and class names between single quotes like so: \'train data\'
- When calling a method use always keyword arguments and not positional arguments, that is: write also the name of method parameter, as in the prototype of the method, and not just the value passed to such method.
- Keep each row less than 130 characters.
- In comments and messages write the word Class with a capital C.
- Use as little as possible the raising of exception and raise the proper type of exceptions.
- When calling methods **get params()** check that you get something that is not *None*.
- When calling methods **set params()** you have to set also **params upon instantiation**.
- Set quiet equal to *True* in MushroomRL agents and core if you were to add a new wrapper Class for new algorithms.
- Sometimes I favour repetition of code if that helps avoiding increasing the cyclomatic complexity.

29 Known compatibility issues

- Completely reproducible results are not guaranteed in PyTorch. cf. https://pytorch.org/docs/stable/notes/randomness.html
- MushroomRL has no **kwargs in the method reset() and there is nothing in the mushroom_rl.core.Core Class that could make use of them hence I remove them from the method reset() of BaseEnvironment.
- If you use a server to run a script, with Python3.8, and then you use a PC with Python3.7 to checkout the results it will not be possible: You cannot load a pickled file in Python3.7 that was pickled by Python3.8.

Indeed there is a new attribute of **inspect** added in Python3.8 called **co_posonlyargcount**: in Python3.8 this attribute is serialised, but when de-serialising Python3.7 does not expect this value and it raises an exception.

You can see the differences in the definitions here:

- Python3.8 and above: https://docs.python.org/3/library/inspect.html
- Python 3.7: https://docs.python.org/3.7/library/inspect.html
- For pickling *cloudpickle* is used and not *dill* since *dill* can not serialise ABC data objects in Python greater than 3.7.
- A RL Algorithm may return NaN which may break the environment. See:
 - https://github.com/hill-a/stable-baselines/issues/340
 - https://stable-baselines.readthedocs.io/en/master/guide/checking_nan.html

This means that a trial in a tuner may fail for some strange hyper-parameters configurations.

I check this and catch the exception: in the Class *TunerOptuna* exceptions are handled natively.

In the Class $TunerGenetic\ I$ pass onto the next generation the agent with the hyper-parameters that returned NaN and I assign to it a $\pm\infty$ evaluation ($+\infty$ if the metric should be minimised, $-\infty$ if the metric should be maximised). It may happen that this agent is going to be picked to pass onto the next generation: indeed tournament selection is performed. This is not an issue indeed when handling the exception I also mutate its hyper-parameters using **first mutation=True**.

• When using 'CMA-ES' in TunerOptuna it may raise a warning telling yout that is using independent sampling because 'CMA-ES' does not support dynamic search space and-or categorical hyper-parameters.

This is a bug in Optuna.

• You cannot pickle a Class that is not Global: therefore for *ModelGeneration* blocks where I have the method __default_network() it will not be possible to pickle that network class hence it will not be possible to perform multi-processing.

Note that this is not an issue for multi-threading!

• MushroomRL is directly compatible only with sklearn. It is also compatible with xgboost (but this is due to xgboost design): this is rather an exception than a rule. Indeed it does not work with catboost.

This can be seen in lines 69 - 71 of the following link: https://github.com/MushroomRL/mushroom-rl/blob/dev/mushroom_rl/approximators/regressor.py

The problem is that **input_shape** is passed down to the approximator: xgboost can filter it, but catboost cannot. Therefore you will not be able to use catboost out-of-the-box.

You can always wrap the CatBoostRegressor Class to solve this issue.

• If you extract from a *Tuner* object the **eval_metric** this is different from the **eval_metric** that yu can extract from the **tuner blocks dict** of an automatic block.

This is not a bug, it is simply because in the method **pre_learn_check()** of automatic blocks I deep copy to **tuner_blocks_dict** the value of **tuner_blocksdict_upon_instantiation**.

The same holds for non automatic blocks in which I deep copy to **algo_params** the value of **algo_params upon instantiation**.