CS7646 ML4T
Machine Learning
for Trading

PROJECT 3: ASSESS LEARNERS

REVISIONS

This assignment is subject to change up until 3 weeks prior to the due date. We do not anticipate changes; any changes will be logged in this section.

- 5/27/2021 Updated typo in the script command 'Instanbul' to 'Istanbul'
- 6/1/2021 Updated the **Task & Requirements** section to further clarify the files necessary to submit
- 6/1/2021 Updated **Your Implementation**, **Implement the DT and RT Learners**, **Implement BagLearner**, and **Implement InsaneLearner** sections to further clarify the API and necessary changes.
- 6/3/2021 Updated **Task & Requirements** bullet point on BagLearner

OVERVIEW

In this assignment, you will implement four supervised learning machine learning algorithms from an algorithmic family called Classification and Regression Trees (CARTs). You will also conduct several experiments to evaluate the behavior and performance of the learners as you vary one of its hyperparameters. You will submit the code for the project in Gradescope SUBMISSION. You will also submit to Canvas a report where you discuss your experimental findings.

ABOUT THE PROJECT

Implement and evaluate four CART regression algorithms in object-oriented Python: a "classic" Decision Tree learner, a Random Tree learner, a Bootstrap Aggregating learner (i.e, a "bag learner"), and an Insane Learner. As regression learners, the goal for your learner is to return a continuous numerical result (not a discrete result). You will use techniques introduced in the course lectures. However, this project may require readings or additional research to ensure an understanding of supervised learning, linear regression, learner performance, performance metrics, and CARTs (i.e., decision trees).

YOUR IMPLEMENTATION

You will implement four CART learners as regression learners: DTLearner, RTLearner, BagLearner, and InsaneLearner. Each of the learners must implement this API specification, where LinRegLearner is replaced by DTLearner, RTLearner, BagLearner, or InsaneLearner, as necessary. In addition, each learner's constructor will need to be revised to align with the instantiation examples provided below.

This project has two main components: First, you will write code for each of the learners and for the experiments required for the report. You must write your own code for this project. You are NOT allowed to use other people's code or packages to implement these learners. Second, you will produce a report that summarizes the observation and analysis of several experiments. The experiments, analysis, and report should leverage the experimental techniques introduced in Project 1.

For the task below, you will mainly be working with the Istanbul datafile. This file includes the returns of multiple worldwide indexes for several days in history. In this task, the overall objective is to predict what the return for the MSCI Emerging Markets (EM) index will be based on the other index returns. Y in this case is the last column to the right of the Istanbul.csv file while the X values are the remaining columns to the left (except the first column). As part of reading the data file, your code should handle any data cleaning that is required. This includes the dropping of header rows and date-time columns (i.e., the first column of data in the Istanbul file, which should be ignored). Note that the local test script does this automatically for you, but you will have to handle it yourself when working on your report.

When the grading script tests your code, it randomly selects 60% of the data to train on and uses the other 40% for testing.

The other files, besides Istanbul.csv are there as alternative sets for you to test your code on. Each data file contains N+1 columns: X1, X2, ... XN, and Y.

The Istanbul data is also available here: File:Istanbul.csv

Task & Requirements

You will implement the following files:

- DTLearner.py – Contains the code for the regression Decision Tree class.
- RTLearner.py – Contains the code for the regression Random Tree class.
- BagLearner.py – Contains the code for the regression Bag Learner (i.e., a BagLearner containing Random Trees).
- InsaneLearner.py – Contains the code for the regression Insane Learner of Bag Learners.
- testlearner.py – Contains the code necessary to run your experiments and perform additional independent testing.

~~All your code will be placed into one of the four files (above). No other code files will be accepted. These files must remain and run from within the assess_learners directory. The testlearner.py file used to conduct your experiments is run using the following command:~~

All of your code must be placed into one of the above files. No other code files will be accepted. The four learner files (i.e., DTLearner.py, RTLearner.py, BagLearner.py, InsaneLearner.py) must reside in the assess_learners folder. The testlearner.py file that is used to conduct your experiments must also reside in the assess_learners folder and is run using the following command:

```
PYTHONPATH=../:. python testlearner.py Data/Istanbul.csv
```

Implement the DT and RT Learners (15 points each)

Implement a Decision Tree learner class named DTLearner in the file DTLearner.py. For this part of the project, your code should build a single tree only (not a forest). You should follow the algorithm outlined in the presentation here: decision tree slides.

- We define “best feature to split on” as the feature (Xi) that has the highest absolute value correlation with Y.

The algorithm outlined in those slides is based on the paper by JR Quinlan which you may also want to review as a reference. Note that Quinlan’s paper is focused on creating classification trees, while we are creating regression trees here, so you will need to consider the differences.

You will also implement a Random Tree learner class named RTLearner in the file RTLearner.py. This learner should be implemented exactly like your DTLearner, except that the choice of feature to split on should be made randomly. You should be able to accomplish this by revising a few lines from DTLearner (those that compute the correlation) and replacing the line that selects the feature with a call to a random number generator.

The DTLearner and RTLearners will be evaluated against 4 test cases (4 using Istanbul.csv and 1 using another data set from the assess_learners/Data folder). We will assess the absolute correlation between the predicted and actual results for the in-sample data and out-of-sample data with a leaf size of 1, and in-sample data with a leaf size of 50.

Example

The following example illustrates how the DTLearner class methods will be called:

```
import DTLearner as dt
learner = dt.DTLearner(leaf_size = 1, verbose = False) # constructor
learner.add_evidence(Xtrain, Ytrain) # training step
Y = learner.query(Xtest) # query
```

The following example illustrates how the RTLearner class methods will be called:

```
import RTLearner as rt
learner = rt.RTLearner(leaf_size = 1, verbose = False) # constructor
learner.add_evidence(Xtrain, Ytrain) # training step
Y = learner.query(Xtest) # query
```

The DTLearner and RTLearner constructors take two arguments: leaf_size and verbose. “leaf_size” is a hyperparameter that defines the maximum number of samples to be aggregated at a leaf. If verbose is True, your code can generate output; otherwise, the code should be silent. When the tree is constructed recursively, if there are leaf_size or fewer elements at the time of the recursive call, the data should be aggregated into a leaf. Xtrain and Xtest should be NDArrays (Numpy objects) where each row represents an X1, X2, X3... XN set of feature values. The columns are the features and the rows are the individual example instances. Y and Ytrain are single dimension NDArrays that indicate the value we are attempting to predict with X.

Implement BagLearner (20 points)

Implement Bootstrap Aggregating as a Python class named BagLearner. Your BagLearner class should be implemented in the file BagLearner.py. It should support EXACTLY, as illustrated in the example below. This API is designed so that BagLearner can accept any learner (e.g., RTLearner, LinRegLearner, even another BagLearner) as input and use it to generate a learner ensemble. Your BagLearner should support the following function/method prototypes:

```
import BagLearner as bl
learner = bl.BagLearner(learner = al.ArbitraryLearner, kwargs = {"argument1
learner.add_evidence(Xtrain, Ytrain)
Y = learner.query(Xtest)
```

The BagLearner constructor takes five arguments: learner, kwargs, bags, boost, and verbose. The learner points to the learning class that will be used in the BagLearner. The BagLearner should support any learner that aligns with the API specification. The "kwargs" are keyword arguments that are passed on to the learner's constructor and they can vary according to the learner (see example below). The "bags" argument is the number of learners you should train using Bootstrap Aggregation. If boost is true, then you should implement boosting (optional implementation). If verbose is True, your code can generate output; otherwise, the code should be silent.

~~Where learner is the learning class to use with bagging. You should be able to support any learning class that obeys the API defined above for DTLearner and RTLearner. "kwargs" are keyword arguments to be passed on to the learner's constructor and they vary according to the learner (see example below). The "bags" argument is the number of learners you should train using Bootstrap Aggregation. If boost is true, then you should implement boosting (optional). If verbose is True, your code can generate output. Otherwise, the code should be silent.~~

As an example, if we wanted to make a random forest of 20 Decision Trees with leaf_size 1 we might call BagLearner as follows:

```
import BagLearner as bl
learner = bl.BagLearner(learner = dt.DTLearner, kwargs = {"leaf_size":1}, b
learner.add_evidence(Xtrain, Ytrain)
Y = learner.query(Xtest)
```

As another example, if we wanted to build a bagged learner composed of 10 LinRegLearners we might call BagLearner as follows:

```
import BagLearner as bl
learner = bl.BagLearner(learner = lrl.LinRegLearner, kwargs = {}, bags = 10
learner.add_evidence(Xtrain, Ytrain)
Y = learner.query(Xtest)
```

Note that each bag should be trained on a different subset of the data. You will be penalized if this is not the case.

Boosting is an optional topic and not required. There is a citation in the Resources section that outlines a method of implementing boosting.

If the training set contains n data items, each bag should contain n items as well. Note that because you should sample with replacement, some of the data items will be repeated.

This code should not generate statistics or charts. If you want to create charts and statistics, you can modify testlearner.py.

You can use code like the below to instantiate several learners with the parameters listed in kwargs:

```
learners = []
kwargs = {"k":10}
for i in range(0,bags):
 learners.append(learner(**kwargs))
```

Implement InsaneLearner (Up to 10 point penalty)

Your BagLearner should be able to accept any learner object so long as the learner obeys the API defined above. We will test this in two ways: 1) By calling your BagLearner with an arbitrarily named class and 2) By having you implement InsaneLearner as described below. If your code dies in either case, you will lose 10 points. Note, the grading script only does a rudimentary check thus we will also manually inspect your code for correct implementation and grade accordingly.

Using your BagLearner class and the provided LinRegLearner class; implement InsaneLearner as follows:

- InsaneLearner should contain 20 BagLearner instances where each instance is composed of 20 LinRegLearner instances.

We should be able to call your InsaneLearner using the following API:

```
import InsaneLearner as it
learner = it.InsaneLearner(verbose = False) # constructor
learner.add_evidence(Xtrain, Ytrain) # training step
Y = learner.query(Xtest) # query
```

The InsaneLearner constructor takes one argument: verbose. If verbose is True, your code can generate output; otherwise, the code should be silent. The code for InsaneLearner must be 20 lines or less. Each “;” in the code counts as one line. Every line that appears in the file ~~All lines~~ (except comments and empty lines) will be counted. There is no credit for this, but a penalty if it is not implemented correctly. Comment, if included, must appear at the end of the file.

Implement author() (Up to 10 point penalty)

For all learners you submit (DT, RT, Bag, Insane) must implement a method called author() that returns your Georgia Tech user ID as a string. This must be implemented within each individual file even if using inheritance. It is not your 9 digit student number. Here is an example of how you might implement author() within a learner object:

```
class LinRegLearner(object):
 def __init__(self):
 pass # move along, these aren't the drones you're looking for
 def author(self):
 return 'tb34' # replace tb34 with your Georgia Tech user id.
```

And here’s an example of how it could be called from a testing program:

```
# create a learner and train it
learner = lrl.LinRegLearner() # create a LinRegLearner
learner.add_evidence(trainX, trainY) # train it
print(learner.author())
```

Note that no points are awarded for implementing the author function, but a penalty will be applied if not present.

Boosting (Optional Learning Activity – 0 Points)

Implement boosting as part of BagLearner. How does boosting affect performance compared to not boosting? Does overfitting occur as the number of bags with boosting increases? Create your own dataset for which overfitting occurs as the number of bags with boosting increases.

- Submit your report regarding boosting as report-boosting.pdf

Implement testlearner.py

Implement testlearner.py to perform the experiment and report analysis as required. This is intended to give a central location to complete the experiments, produce all necessary outputs, in a single standardized point.

- ONLY file submitted that produces outputs (e.g. charts, stats, calculations).
- ONLY allowed to read data with the provided data reading routine (not allowed to use util.py data reading).
- MUST run in under 10 minutes.
- MUST execute all experiments, charts, and data used for the report in a single run.

Able to use a dataset other than Istanbul.csv if not explicitly stated but must adhere to the following run command EXACTLY regardless of the dataset used (you will have to read the other datasets internally):

```
PYTHONPATH=../:. python testlearner.py Data/Istanbul.csv
```

TECHNICAL REQUIREMENTS

You must use a NumPy array (i.e., NDArray()), as shown in the course videos, to represent the decision tree. **You may not use another data structure (e.g., node-based trees) to represent the decision tree.**

You may not cast a variable of another data type (e.g., python list, Pandas data frame) into an NDArray.

Although Istanbul.csv is time-series data, you should ignore the date column and treat the dataset as a non-time series dataset. In this project, we are ignoring the time order aspect of the data and treating it as if it is static data and time does not matter. In a later project, we will make the transition to considering time-series data.

Files must be read using one of two approaches: 1) The open/readline functions, an example of which is provided in the testlearner.py file, or 2) using NumPy's genfromtxt function, an example of which is used in the grade_learners.py file.

The charts must be generated as .png files (when executed using the command given above in these instructions) and should include any desired annotations. Charts must be properly annotated with legible and appropriately named labels, titles, and legends. Image files cannot be post-processed to add annotations or otherwise change the image prior to their inclusion into the report. The learner code files (DT, RT, etc.) you submit should NOT generate any output: No prints, no charts, etc. testlearner.py is the only file that should generate charts.

Watermarked Charts (i.e., where the GT Username appears over the line studies) can be shared in the designated pinned (e.g., "Project 3- Student Charts") thread alone. Charts contained in reports or submitted for grading should not contain watermarks.

Your learners should be able to handle any number of feature dimensions in X from 2 to N.

Performance:

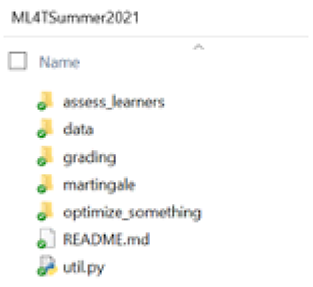
- DTLearner tests must complete in 10 seconds each (e.g., 50 seconds for 5 tests)
- RTLearner tests must complete in 3 seconds each (e.g., 15 seconds for 5 tests
- BagLearner tests must complete in 10 seconds each (e.g., 100 seconds for 10 tests)
- InsaneLearner must complete in 10 seconds each

If the "verbose" argument is True, your code can print out the information for debugging. If verbose = False your code must not generate ANY output other than the required charts. When we test your code, verbose will be False. The implementation must not display any text (except for "warning" messages) on the screen/console/terminal when executed in Gradescope SUBMISSION.

STARTER CODE

To make it easier to get started on the project and focus on the concepts involved, you will be given a starter framework. This framework assumes you have already set up the local environment and ML4T Software. The framework for Project 3 can be obtained from: Assess_Learners2021Summer.zip.

Extract its contents into the base directory (e.g., ML4T_2021Summer). This will add a new folder called "assess_learners" to the course directly structure:



Within the assess_learners folder are a folder and several files:

- ./Data (folder)
- LinRegLearner.py
- testlearner.py
- grade_learners.py

The data files that your learners will use for this project are contained in the Data folder. (Note the distinction between the "data" folder created as part of the local environment and the "Data" folder within the assess_learners folder that will be used in this assignment.) LinRegLearner is available for your use and must not be modified. However, you can use it as a template for implementing your learner classes. The testlearners.py file contains a simple testing scaffold that you can use to test your learners, which is useful for debugging. It must also be modified to run the experiments. The grade_learners.py file is a local pre-validation script that mirrors the script used in the Gradescope TESTING environment.

You will need to create the learners using the following names:

- DTLearner.py
- RTLearner.py
- BagLearner.py
- InsaneLearner.py

In the assess_learners/Data/ directory you will find a number of datasets:

- 3_groups.csv
- ripple_.csv
- simple.csv
- winequality-red.csv
- winequality-white.csv

- winequality.names.txt
- Istanbul.csv

In these files, we have provided test data for you to use in determining the correctness of the output of your learners. Each data file contains N+1 columns: X1, X2, ... XN, and Y.

HINTS & RESOURCES

“Official” course-based materials:

- How to use a decision tree if you have one (Balch Youtube video)
- How to build a decision tree & Random Trees (Balch Youtube video)
- Media:How-to-learn-a-decision-tree.pdf Balch slides on decision trees
- Decision-tree-example.xlsx Example tabular version of decision tree

Additional supporting materials:

- You may be interested in looking at Andrew Moore’s slides on instance-based learning.
- A definition of correlation is used to assess the quality of the learning.
- Bootstrap Aggregating
- AdaBoost
- numpy corrcoef
- numpy argsort
- RMS error

CONTENTS OF REPORT

The **report.pdf** file will consist of a report (of a maximum of 7 pages, excluding references), written in JDF Format. Any content beyond 7 pages will not be considered for a grade. At a minimum, the report must contain the following sections:

Abstract

First, include an abstract that briefly introduces your work and gives context behind your investigation. Ideally, the abstract will fit into 50 words, but should not be more than 100 words.

Introduction

The report should briefly describe the paper's justification. While the introduction may assume that the reader has some domain knowledge, it should assume that the reader is unfamiliar with the specifics of the assignment. The introduction should also present an initial hypothesis (or hypotheses).

Methods:

Discuss the setup of the experiment(s) in sufficient detail that **an informed reader (someone with the familiarity of the field, but not the assignment) could set up and repeat the experiment(s)** you performed.

Discussion:

Experiment 1

Research and discuss overfitting as observed in the experiment. (Use the dataset Istanbul.csv with DTLearner). Support your assertion with graphs/charts. (Do not use bagging in Experiment 1). At a minimum, the following question(s) that must be answered in the discussion:

- Does overfitting occur with respect to leaf_size?
- For which values of leaf_size does overfitting occur? Indicate the starting point and the direction of overfitting. Support your answer in the discussion or analysis. Use RMSE as your metric for assessing overfitting.

Experiment 2

Research and discuss the use of bagging and its effect on overfitting. (Again, use the dataset Istanbul.csv with DTLearner.) Provide charts to validate your conclusions. Use RMSE as your metric. At a minimum, the following questions(s) must be answered in the discussion.

- Can bagging reduce overfitting with respect to leaf_size?
- Can bagging eliminate overfitting with respect to leaf_size?

To investigate these questions, choose a fixed number of bags to use and vary leaf_size to evaluate. If there is overfitting, indicate the starting point and the direction of overfitting. Support your answer in the discussion or analysis.

Experiment 3

Quantitatively compare "classic" decision trees (DTLearner) versus random trees (RTLearner). For this part of the report, you must conduct new experiments; do not use the results of Experiment 1. Importantly, RMSE and correlation are not allowed as metrics for this experiment.

Provide at least two new quantitative measures in the comparison.

- Using two similar measures that illustrate the same broader metric does not count as two separate measures.
- Note: Do not use two measures for the accuracy or use the same measurement for two different attributes – e.g., **time** to train and **time** to query are both time.)
- Provide charts to support your conclusions.
- At a minimum, the following question(s) must be answered in the discussion.
- In which ways is one method better than the other?
- Which learner had better performance (based on your selected measures) and why do you think that was the case?
- Is one learner likely to always be superior to another (why or why not)?

Summary

The summary is an opportunity to synthesize and summarize the experiments. Ideally, it presents key findings and insights discovered during the research. It may also identify interesting areas for future investigation.

TESTING

To test your code, we will invoke each of the functions. We will also run the testlearner.py file to run your experiments. You are encouraged to perform any tests necessary to instill confidence that the code will run properly when submitted for grading and will produce the required results. You should confirm that testlearner.py runs as expected from the assess_learners folder since the following command illustrates how we will run your experiments:

```
PYTHONPATH=../:. python testlearner.py Data/Istanbul.csv
```

Note: Once submitted for grading, we will use the above command to call the "__main__" section only. The program should run in its entirety and produce the necessary output and chart.

Additionally, we have provided the grade_learners.py file that can be used for your tests. This file is the same script that will be run when the code is submitted to GradeScope TESTING. This file is not a complete test suite and does not match the more stringent private grader that is used in Gradescope SUBMISSION. To run and test that the file will run from within the assess_learners directory, use the command:

```
PYTHONPATH=../:. python grade_learners.py
```

You are encouraged to submit your files to Gradescope TESTING, where some basic pre-validation tests will be performed against the code. Gradescope TESTING does not grade your assignment. No credit will be given for coding assignments that does not pass this pre-validation.

You are allowed **unlimited** resubmissions to Gradescope **TESTING**. Please refer to the Gradescope Instructions for more information.

SUBMISSION INSTRUCTIONS

This is an individual assignment. All work you submit should be your own. Make sure to cite any sources you reference and use quotes and in-line citations to mark any direct quotes. Citations within code should be captured as comments.

Late work is not accepted without advanced agreement except in cases of medical or family emergencies. In the case of such an emergency, please contact the Dean of Students.

Report Submission

Complete your assignment using the JDF format, then save your submission as a PDF. The report is to be submitted as **report.pdf.** Assignments should be submitted to the corresponding assignment submission page in Canvas. You should submit a single PDF for this assignment. Please submit the following file to Canvas in PDF format only:

- **report.pdf**

Do not submit any other files. All charts must be included in the report, not submitted as separate files. Also note that when we run your submitted code, it should generate the charts contained in the report. Not submitting a report will result in a penalty.

You are allowed unlimited submissions of the report.pdf file to Canvas.

Code Submission

This class uses Gradescope, a server-side auto-grader, to evaluate your code submission. No credit will be given for code that does not run in this environment and students are encouraged to leverage Gradescope TESTING prior to submitting an assignment for grading.

Please submit the following files to Gradescope SUBMISSION:

- **RTLearner.py**
- **DTLearner.py**
- **InsaneLearner.py**
- **BagLearner.py**
- **testlearner.py**

Do not submit any other files.

You are allowed a MAXIMUM of three (3) code submissions to Gradescope SUBMISSION.

GRADING INFORMATION

Your report is worth 50% of your grade. As such, it will be graded on a 50-point scale coinciding with a rubric design to mirror the questions above. Make sure to answer those questions. The submitted code (which is worth 50% of your grade) is run as a batch job after the project deadline. The code will be graded using a 5-point scale coinciding with a rubric design to mirror the implantation details above. Deductions will be applied for unmet implementation requirements or code that fails to run.

We do not provide an explicit set timeline for returning grades, except that everything will be graded before the institute deadline (end of the term). As will be the case throughout the term, the grading team will work as quickly as possible to provide project feedback and grades. Once grades are released, any grade-related matters must follow the Assignment Follow-Up guidelines and process.

RUBRIC

Report [50 Points]

- Is the report neat and well organized? (-5 points if not)

- Is the experimental methodology and setup well described (up to -5 points per question if not)
- Does the chart properly reflect the intent of the assignment? (up to -10 points if not)
- Does the chart include a properly labeled axis and legend? (up to -5 points if not)

- Overfitting / leaf_size question:

- Are one or more charts provided to support the argument? (up to -5 points if not)
- Does the student state where the region of overfitting occurs (or state that there is no overfitting)? (up to -5 points if not)
- Are the starting point and direction of overfitting identified supported by the data (or if the student states that there is no overfitting, is that supported by the data)? (up to -5 points if not)

- Does bagging reduce or eliminate overfitting?:

- Is a chart provided to support the argument? (-5 points if not)
- Does the student state where the region of overfitting occurs (or state that there is no overfitting)? (up to -5 points if not)
- Are the starting point and direction of overfitting identified supported by the data (or if the student states that there is no overfitting, is that supported by the data)? (up to -5 points if not)

- Comparison of DT and RT learning

- Is each quantitative experiment explained well enough that someone else could reproduce it (up to -5 points if not)

- Are there at least two new quantitative properties that are compared (do not use RMSE or correlation)? (-5 points if only one, -10 if none)
- Is each conclusion regarding each comparison supported well with charts? (up to -10 points if not)

- Was the report exceptionally well done? (up to +2 points)
- Does the student’s response indicate a lack of understanding of overfitting? (up to -10 points)

- Were all charts provided generated in Python? (up to -20 points if not)

Code

- Is the author() method correctly implemented for all files: DTLearner, InsaneLearner, BagLearner and RTLearner? (-10 points for each if not)
- Is InsaneLearner correctly implemented in 20 lines or less **Please remove all blank lines and comments** (-10 points if not)
- Does BagLearner work correctly with an arbitrarily named class (-10 points if not)
- Does BagLearner generate a different learner in each bag? (-10 points if not)
- Are the learners implemented using a NumPy array (NDArray)? ***No casting to an NDArray*** (-20 points if not)
- Does the implemented code properly reflect the intent of the assignment? (-20 points if not)
- Does the testlearner.py file run using PYTHONPATH=../:. python testlearner.py Data/Istanbul.csv? (-20 points if not)
- Does testlearner.py run in under 10 minutes? (-20 points if not)
- Does the code generate appropriate charts written to png files? DO NOT display charts on the screen. Do not use plt.show() and manually save your charts. The charts should be created and saved using Python code (-20 points if not)

Auto-Grader [50 Points]

- DTLearner in sample/out of sample test, auto-grade 5 test cases (4 using istanbul.csv, 1 using another data set), 3 points each: 15 points.
- For each test 60% of the data will be selected at random for training and 40% will be selected for testing.
- Success criteria for each of the 5 tests:
    - Does the correlation between predicted and actual results for **in-sample data** exceed 0.95 with leaf_size = 1?
    - Does the correlation between predicted and actual results for **out-of-sample data** exceed 0.15 with leaf_size=1?
    - Is the correlation between predicted and actual results for **in-sample data** below 0.95 with leaf_size = 50?

    - Does the test complete in less than 10 seconds (i.e. 50 seconds for all 5 tests)?

- RTLearner in sample/out of sample test, auto-grade 5 test cases (4 using istanbul.csv, 1 using another data set), 3 points each: 15 points.
- For each test 60% of the data will be selected at random for training and 40% will be selected for testing.
- Success criteria for each of the 5 tests:
    - Does the correlation between predicted and actual results for **in-sample data** exceed 0.95 with leaf_size = 1?
    - Does the correlation between predicted and actual results for **out-of-sample data** exceed 0.15 with leaf_size=1?
    - Is the correlation between predicted and actual results for **in-sample data** below 0.95 with leaf_size = 50?
    - Does the test complete in less than 3 seconds (i.e. 15 seconds for all 5 tests)?

- BagLearner, auto-grade 10 test cases (8 using istanbul.csv, 2 using another data set), 2 points each 20 points
- For each test 60% of the data will be selected at random for training and 40% will be selected for testing.
- leaf_size = 20
- Success criteria for each run of the 10 tests:
    - For out-of-sample data is a correlation with 1 bag lower than the correlation for 20 bags?
    - Does the test complete in less than 10 seconds (i.e. 100 seconds for all 10 tests)?

ALLOWED

- You may set a specific random seed for this assignment. If a specific random seed is used, it must only be called once within the test_code() function and it must use your GT ID as the numeric value.

- You may use code written in other GT OMS courses if the following three conditions are met: 1) you are the 100% sole author of the code, 2) the code fully meets the requirements of this assignment, and 3) the code is properly cited and referenced.
- All libraries provided on the Local Environment setup page.
- All standard Python libraries (except the os library, which is prohibited)
- Code provided by the instructor or allowed by the instructor to be shared.

- Cheese.

PROHIBITED

- Any other method of reading data besides testlearner.py
- Any libraries not listed in the “allowed” section above.
- Any code you did not write yourself.

- Any Classes (other than Random) that create their own instance variables for later use (e.g., learners like kdtree).
- Code that includes any data reading routines. The provided testlearner.py code reads data for you.
- Code that generates any output to the screen/console/terminal (other run-time “warning” messages) when verbose = False: No prints, no charts, etc.
- Extra directories (manually or code created)
- Use of the Python os library/module.

- Use of global variables.
- Use of any Machine Learning package of the library as the implementation.
- Code that results in a window or chart being displayed (an example of which is Matplotlib’s plt.show() function)
- Code that creates any directories
- Any code that you did not write yourself (except for properly cited code provided by the instructor).

- Absolute import statements, such as: *from folder_name import optimization*, where “folder_name” is the path/name of a folder or directory.

- Any libraries not included as part of the Local Environment as provided on the Local Environment Setup page.
- Editing (i.e., adding, changing, or deleting) above the line that reads: "—–do not edit anything above this line—".
- Textual output "printed" to the terminal/console.
- Sharing of tables and statistics.

RELEVANT RESOURCES

You may find the following resources useful in completing the project or in providing an in-depth discussion of the material.

Martelli, A. Ravenscroft, and S. Holden (2017), Python in a Nutshell, 3rd Edition

James, D. Witten, T. Hastie, R. Tibshirani (2017), An Introduction to Statistical Learning (Chapters 2, 3, and 8)

Murphy, (2021), Probabilistic Machine Learning: An Introduction (Chapters 1, 11, and 18)
Videos:

- Decision Tree Videos, Charles Isbell and Michael Littman, Georgia Tech ML 7641
- Decision Tree Video (Part 1, staring around 0:40 minutes), Tom Mitchell, CMU 601
- Decision Tree Video (Part 2), Tom Mitchell, CMU 601

ACKNOWLEDGMENTS AND CITATIONS

The data used in this assignment was provided by UCI's ML Datasets.