Manufacturing Data Science 製造數據科學 Assignment 3

Manufacturing Data Science

Instructor: Chia-Yen Lee, Ph.D.

Due Date: Nov. 17, 2023, 5pm

Please solve the following questions and justify your answer. Show all your analysis result including equation/calculation or Python code in your report. Upload your "zip" file including (1) MS Word/LaTeX pdf report (answering each question and its sub-questions) and Python code; or (2) notebook (including answer and code), with file name: "MDS Assignment2 ID Name.zip" to NTU COOL by due. The late submission is not allowed.

1. (40%) Decision Tree Algorithms

Data Source: https://www.kaggle.com/uciml/faulty-steel-plates

Dataset provided by Semeion, Research Center of Sciences of Communication, Via Sersale 117, 00128, Rome, Italy. www.semeion.it

This dataset comes from research by Semeion, Research Center of Sciences of Communication. The original aim of the research was to correctly classify the type of surface defects in stainless steel plates, with six types of possible defects (plus "other"). The Input vector was made up of 27 indicators that approximately describe the geometric shape of the defect and its outline.

There are 1941 plates with 34 variables. The first 27 columns (i.e. independent variables) describe some kind of steel plate faults seen in images, i.e., X1-X27, as {X Minimum, X Maximum, Y Minimum, Y Maximum, Pixels Areas, X Perimeter,

{X_Minimum, X_Maximum, Y_Minimum, Y_Maximum, Pixels_Areas, X_Perimeter Y_Perimeter

SumofLuminosity, MinimumofLuminosity, MaximumofLuminosity, LengthofConveyer, TypeOfSteel_A300, TypeOfSteel_A400, SteelPlateThickness, Edges_Index,Empty_Index, Square_Index, OutsideXIndex, EdgesXIndex, EdgesYIndex, OutsideGlobalIndex, LogOfAreas, LogXIndex, LogYIndex, Orientation_Index, Luminosity_Index, SigmoidOfAreas}

The last seven columns (i.e. dependent variables) are one hot encoded classes, i.e. if the plate fault is classified as "Stains" there will be a 1 in that column and 0's in the other columns. {Pastry, Z Scratch, K Scatch, Stains, Dirtiness, Bumps, Other Faults}

These data can be found in http://archive.ics.uci.edu/ml/datasets/steel+plates+faults, and are attached in the file https://archive.ics.uci.edu/ml/datasets/steel+plates+faults, and are attached in the file https://archive.ics.uci.edu/ml/datasets/steel+plates+faults.

- (a) (5%) Construct a data science framework and show the data summary
- (b) (5%) What is the problem about the dataset? Any identical column? Any redundant column? Any missing value? How to handle these issues?

(c) (5%) After data preprocessing, based on the **prepared dataset**, use the classification and regression tree (CART) to analyze the prepared dataset. Show the classification results by 10-fold cross validation with several metrics (eg. accuracy, area under ROC curve (AUC), and F1-score), and also list the hyperparameters you adjust.

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- (d) (5%) Suggest a method to address the data imbalance issue. Build a new balanced dataset. (hint: undersampling or oversampling)
- (e) (5%) Based on the **balanced dataset**, use the classification and regression tree (CART) to analyze the balanced dataset. Show the classification results by 10-fold cross validation with several metrics (eg. accuracy, area under ROC curve (AUC), and F1-score), and also list the hyperparameters you adjust.
- (f) (5%) Give a comparison between (c) and (e). Any suggestion or insight?
- (g) (5%) Use "Random Forest" to solve both prepared dataset and balanced dataset, respectively. Give a comparison and provide your insight.
- (h) (5%) Use "Gradient Boosting Decision Tree (GBDT)" to solve both prepared dataset and balanced dataset, respectively. Give a comparison and provide your insight.

2. (45%) Feature Selection and Regularization-Ridge, Lasso, and Elastic Net

Data Source: a flotation plant in a mining process

<u>https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-process</u> and are attached in the file **MDS_Assignment3_Mining.zip**.

Dataset provided by EduardoMagalhãesOliveira. Data collection methodology is shown as follows.

Hardware sensors, like temperature, pH, flow, density and all continuous process variables, where data were collected every 20s with no transformation (the dataset here shows raw data). Quality variables, like % of silica content, % of iron ore content and so on are quality measurements made by laboratory analysis. A sample of the iron ore pulp is collected in the field/shop floor, every 15 minutes. Those samples are sent to lab for analysis. So, on every two hours, lab give a feedback of quality analysis, in other words, only every two hours you have a lab/quality measurement of the product stream (iron ore concentrate), which gives you a sense of the quality of the product (iron ore pulp concentrate).

The main goal is to use this data to predict how much impurity is in the ore concentrate. As this impurity is measured every hour, if we can predict how much silica (impurity) is in the ore concentrate, we can help the engineers, giving them early information to take actions (empowering!). Hence, they will be able to take corrective actions in advance (reduce impurity, if it is the case) and also help the environment (reducing the amount of ore that goes to tailings as you reduce silica in the ore concentrate).

Content

The first column shows time and date range (from march of 2017 until september of 2017). Some columns were sampled every 20 second. Others were sampled on a hourly base.

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The second and third columns are quality measures of the iron ore pulp right before it is fed into the flotation plant. Column 4 until column 8 are the most important variables that impact in the ore quality in the end of the process. From column 9 until column 22, we can see process data (level and air flow inside the flotation columns, which also impact in ore quality. The last two columns are the final iron ore pulp quality measurement from the lab.

Target is to predict the last column, which is the % of silica in the iron ore concentrate.

Inspiration

Is it possible to predict % Silica Concentrate every minute?

How many steps (hours) ahead can we predict % Silica in Concentrate? This would help engineers to act in predictive and optimized way, mitigating the % of iron that could have gone to tailings.

Also, for the Amina Flow, Ore Pulp Flow, and Flotation Column, etc. data are the "commas" in those cells supposed to be "decimals" as shown in the csv file. For example, given the column "% Silica Concentrate"="1,31", it means that the concentrate is 1.31%.

According to the description mentioned above, if the factor "% Silica Concentrate" is regarded as the response variable (y) and all factors (except the date and % Iron Concentrate) are independent variables, how to identify the importance variable which significantly affects the "% Silica Concentrate" (y)?

- (a) (5%) Identify the important variable by **linear regression** with ordinary least squares (OLS) (i.e. ranked by p-value). Identify the important variable by **stepwise regression**. (hint: you can select forward selection, backward elimination, or both)
- (b) (5%) Give a comparison between (a) and (b). The results are consistent?
- (c) (5%) From a methodology aspect, what's the difference between Ridge regression and Lasso? Why does Lasso support the variables selection rather than ridge? (hint: answer with description or formulation. No computation needed.)
- (d) (5%) What's the benefit to use the Elastic Net? (hint: answer with description or formulation. No computation needed.)
- (e) (5%) Identify the important variable by ridge regression, lasso, and elastic net.
- (f) (5%) Give a comparison in (e). The results are consistent? If no, what's the difference?
- (g) (5%) What is "adaptive elastic net"? Why we need it? How to build it? Please simply describe or formulate it. (No computation needed.)
- (h) (5%) Which columns are highly-correlated? Show the table of the coefficient estimation by

using linear regression. Any multicollinearity problem?

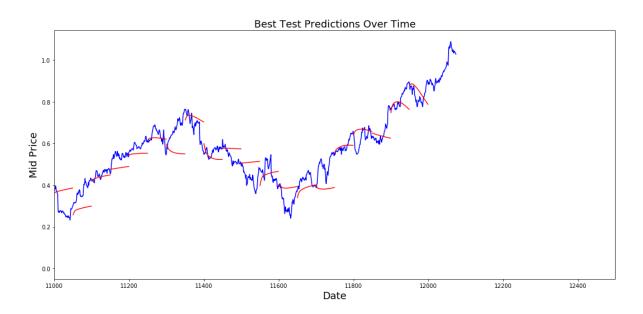
(i) (5%) Is it possible to predict % Silica in Concentrate with using % Iron Concentrate column (as they are highly correlated)? Why? What's the potential issue? How to address it?

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3. (15%) Deep Learning

Use Python to build up long short-term memory (LSTM), which is one type of recurrent neural network (RNN). Collect the dataset related to **weekly** raw material price **OR** consumption (i.e. demand). Build a price/demand forecast. Don't use STOCK PRICE for prediction. You may read the tutorial: https://www.datacamp.com/community/tutorials/lstm-python-stock-market. Note that, you only have price/demand data as response variable Y and it should be a **time-rolling prediction**, that is, for example, use the past 8 weeks dataset for 8-week ahead prediction. Thus, the prediction should be like the following diagram.



Dataset could be found as follows.

eg. Brent oil price: https://www.investing.com/commodities/brent-oil-historical-data

Commodity prices: https://fred.stlouisfed.org/categories/32217

Commodity prices: https://sdw.ecb.europa.eu/browse.do?node=9691219

The summary table of raw materials, https://just2.entrust.com.tw/z/ze/zeq/zeq.djhtm

Pick one raw material and collect its dataset. The collection period should be as long as possible (eg. from 2000 to 2022) to guarantee the sufficient samples for LSTM training.

- (a) (10%) Prepare and transform the data to appropriate format (eg. use Data Generator in https://www.datacamp.com/community/tutorials/lstm-python-stock-market). Build LSTM model and show the prediction results via Time-series (Nested) Cross Validation.
- (b) (5%) Visualize the time-rolling prediction as above diagram.

Note

- 1. Show all your work in detail. **Innovative** idea is encouraged.
- 2. If your answer refers to any external source, please "must" give an academic citation. Any "plagiarism" is not allowed.

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