assignment 1A

by Jerome Huang

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Assignment 1A

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Problem 1. Regression

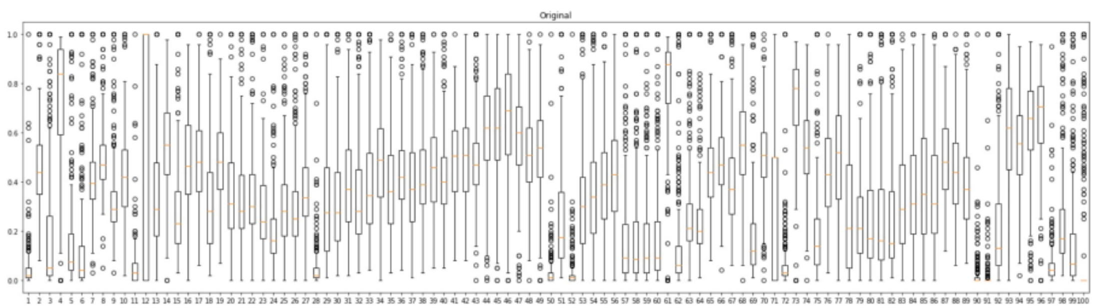
The purpose of the data is to explore the link between the various socio-economic factors and crime.

Data Characteristics

Data Split

The split of train, validation and test set is not ideal. Normally we want them to be roughly 70/15/15.

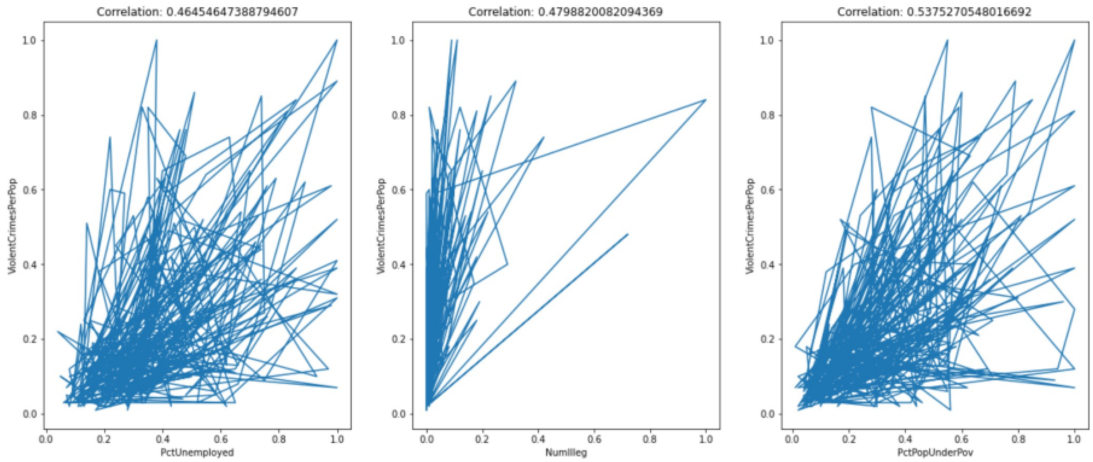
Variable Range



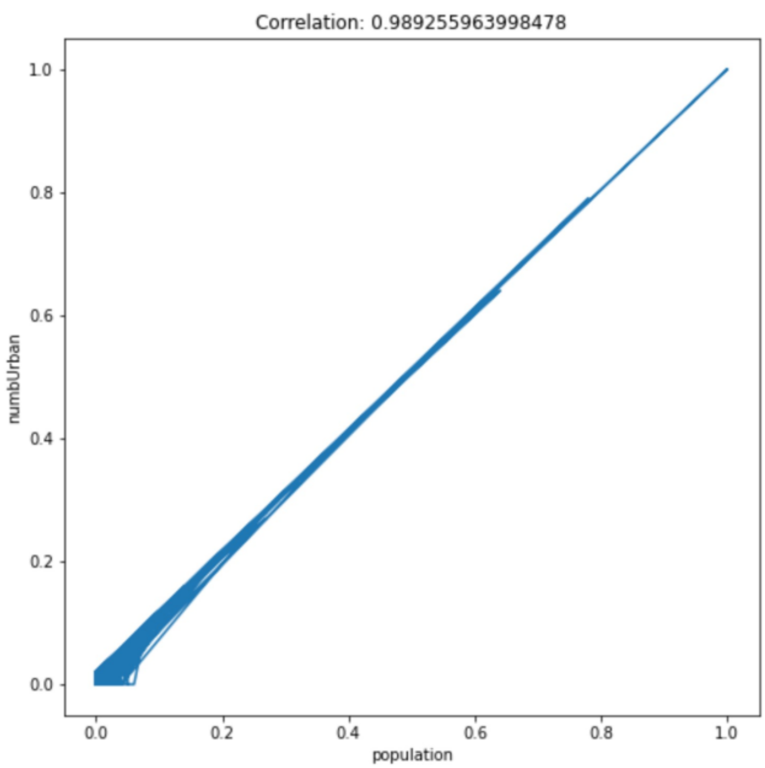
Let's explore the distribution of the training data by drawing A boxplot over input variables. By analyzing the plot above, we can see that all the variables have the same range 0~1. But they have different mean and standard deviation.

1

Correlation



Some variables are correlated with the response `ViolentCrimesPerPop`. For example, `PctUnemployed`, `NumIlleg`, and `PctPopUnderPov`. And these values are far away from 0, which indicates that there is a linear association between the response variable and the input variables.



Good justification.

In linear regression, predictors are expected to be **uncorrelated** with each other, since each predictor models a different aspect of the overall relationship. If they are correlated, we can end up with redundancy in the model.

Consider the graph above, it is clear that `population` and `numbUrban` are correlated and the correlation is 0.98, and thus the relationship between these two variables and the response (`ViolentCrimesPerPop`) will be (to some extent) captured twice in a linear regression model. In addition, it would also cause the `p-value` to be less important.

Pre-processing

Standardization

Because regularized linear regression models like `Ridge` and `Lasso` will be trained later. And to help regularization to penalize all weights equally. Standardization will be performed as one pre-processing step.

Good justification.

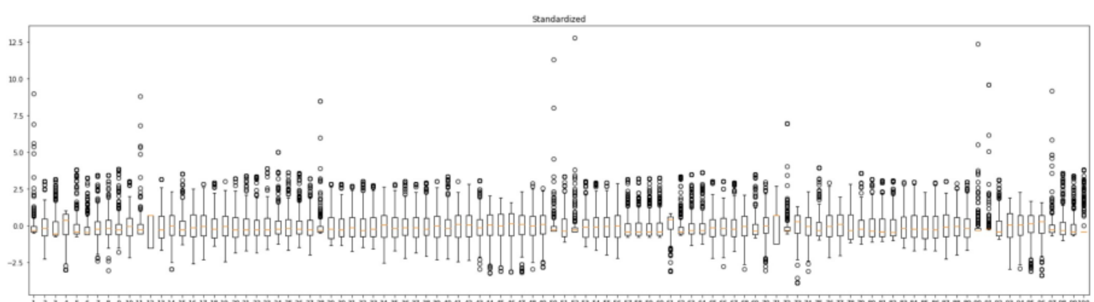
The standardization is achieved by $\hat{x} = \frac{x-\mu}{\sigma}$.

- $\hat{x}$ is the standardized result.
- x is the original data.
- μ is the mean of the data.
- σ is the standard deviation of the data.

Here is the python code that standardizes the input data including train, validation, and test set.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)

s_X_train =pd.DataFrame(scaler.transform(X_train), columns=X_train.columns,
index=X_train.index)
s_X_val =pd.DataFrame(scaler.transform(X_val), columns=X_val.columns,
index=X_val.index)
s_X_test =pd.DataFrame(scaler.transform(X_test), columns=X_test.columns,
index=X_test.index)
```

Avoid using screenshoots.



The above graph shows the data distribution after standardization. All variables have a mean of 0, and a standard deviation of 1. This enables regularized regression treat variables equally.

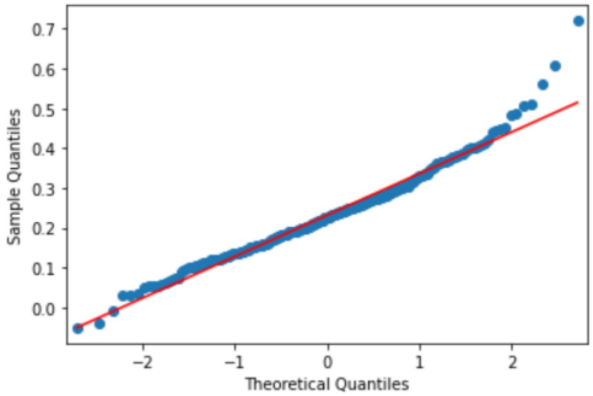
Linear Model

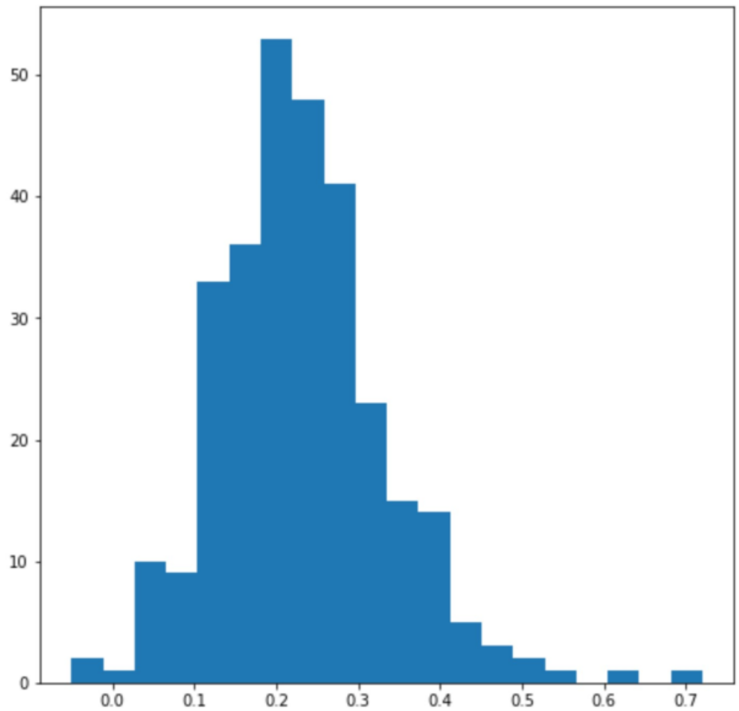
Model Development

Below is the python code for training a **linear regression model** to predict the number of violent crimes per captia from the socio-economic data.

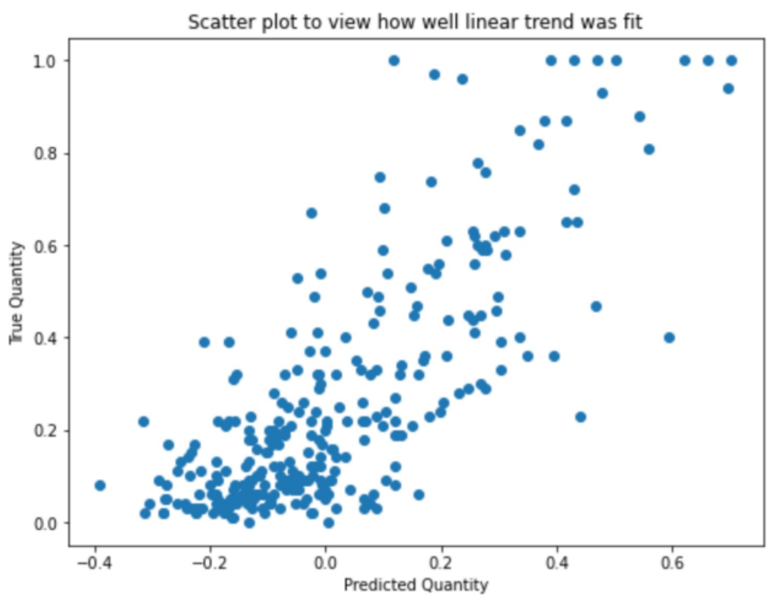
Unnecessary details.

```
import statsmodels.api as sm

# s_X_truth the standardized data
linear_model = sm.OLS(Y_train, s_X_train).fit()

# Draw a qqplot for residuals.
statsmodels.api.qqplot(linear_model.resid, line="s")
```





Residuals form a gaussian/normal distribution. Consider the qq-plot above, it forms straight line. And for the histogram, it is represented as a bell curve. 2



The scatter plot shows that the model fits the training data in a certain degree.

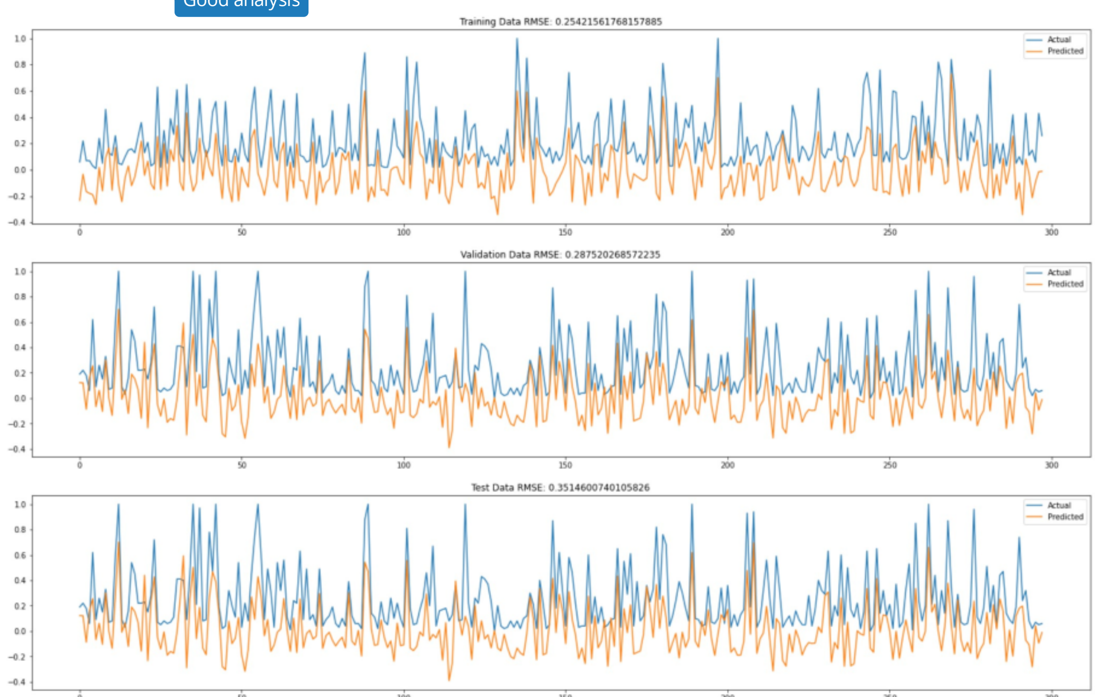
Analysis of Results

```
                              OLS Regression Results
==============================================================================
Dep. Variable:      ViolentCrimesPerPop   R-squared (uncentered):         0.346
                       coef    std err          t      P>|t|
------------------------------------------------------------------
population           0.0988      0.313      0.315      0.753
householdsize       -0.0767      0.119     -0.646      0.519
racepctblack         0.0102      0.098      0.104      0.917
racePctWhite        -0.0260      0.095     -0.274      0.784
racePctAsian        -0.0185      0.050     -0.371      0.711
racePctHisp         -0.0982      0.097     -1.012      0.313
agePct12t21         -0.0398      0.127     -0.313      0.755
agePct12t29          0.1069      0.174      0.614      0.540
agePct16t24         -0.0256      0.214     -0.120      0.905
agePct65up           0.0216      0.125      0.173      0.863
numbUrban           -0.0957      0.304     -0.314      0.753
...
```

Many predictors have a high p-value. This means that those predictors are not significant.

One possible reason is that some predictors are correlated with other predictor. see correlation section above. Therefore, the relationship between that variable and the response is captured twice in the model.

Good analysis

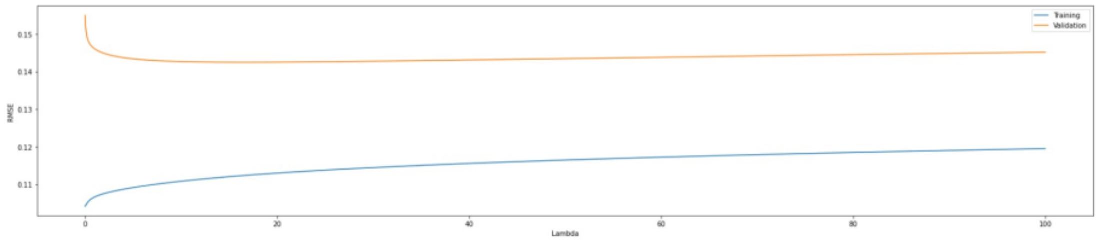


The **RMSE** for the training set is 0.25. And the **RMSE** for the validation set is 0.28. The model has a reasonable low value of RMSE, the smaller the better. In addition, the **RMSE** for the validation set is also small. This indicates that there is no sign of **overfitting** in this model.

Analyze the performance on test set: the **RMSE** for test set is 0.35. The performance might increase if we simplify the model by removing less significant terms.

Ridge Regression Model

Model Development & Hyper-parameter Selection



Initially, I train a series of Ridge regression model with the lambda given by `np.arange(0, 100, 0.01)` on validation set and discovered that the best lambda is 16.6 which result in a validation RMSE of 0.142.

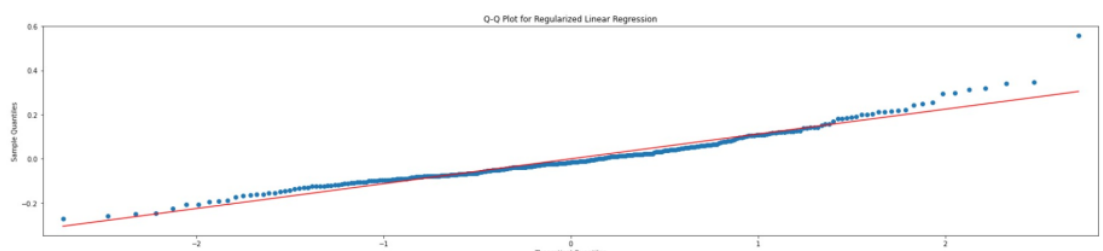
Correct

In order to get a better result, I then I start another search using `np.arange(0, 30, 0.005)` as the lambda list. Finally, the best lambda is 16.599 and the validation RMSE is 0.142. This is similar to the result of the first training.

Correct

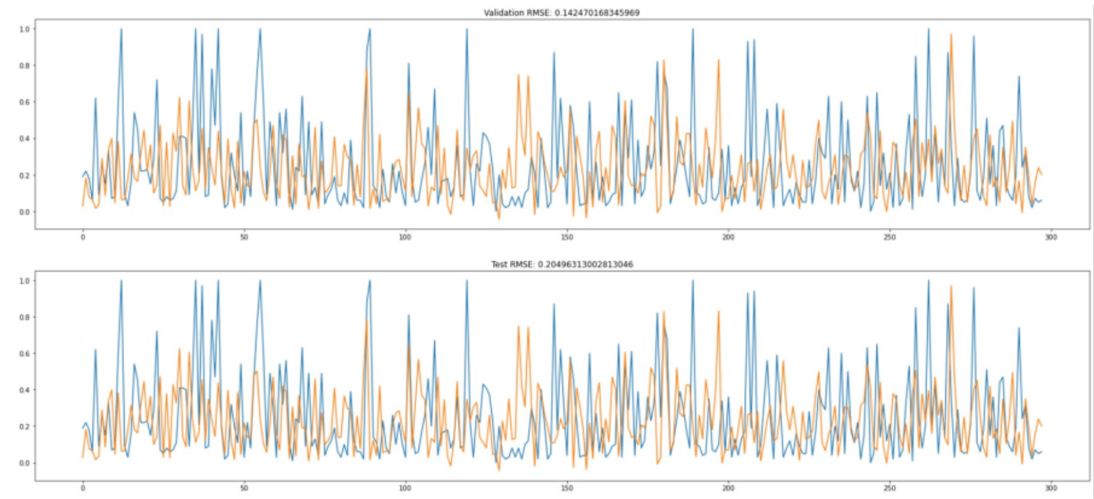
Analysis of Results

Validity



The Q-Q plot of the model's residual form a straight line. This means that the residuals are normally distributed which meet the assumption of linear model. So the model is valid.

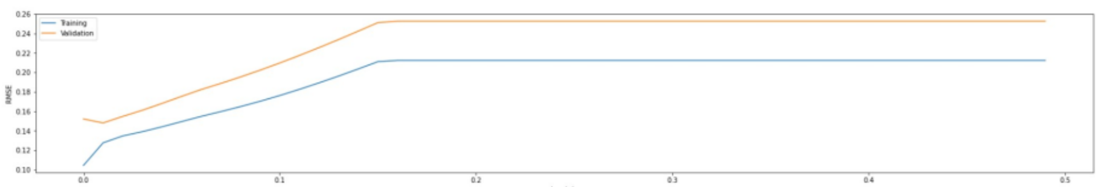
Accuracy



The **RMSE** for validation set is 0.14. And the **RMSE** for the test set is 0.2. indicates that the Ridge model fit the data quite well and can generalize well on unseen data.

LASSO Regression Model

Model Development & Hyper-parameter Selection

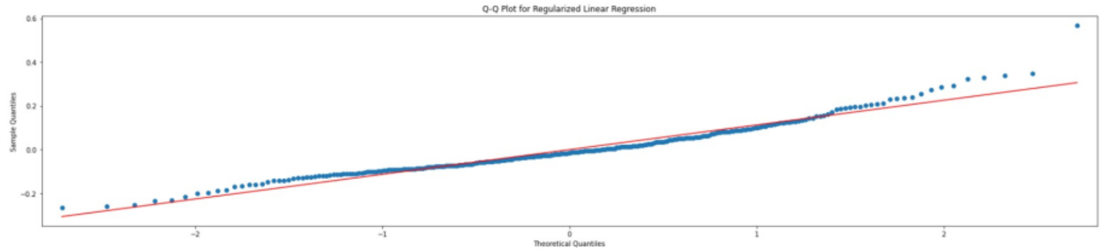


Initially, I trained LASSO model with different lambda given by `np.arange(0, 0.5, 0.01)` on the validation set and discovered the best lambda is 0.01 with RMSE of 0.148. And after this point, the **RMSE** goes up in graph. So I expect the best lambda will exist near the point.

I start another search using `np.arange(0, 0.2, 0.0001)` as the lambda list. Finally, the best lambda is 0.001 and has RMSE of 0.1431.

Analysis of Results

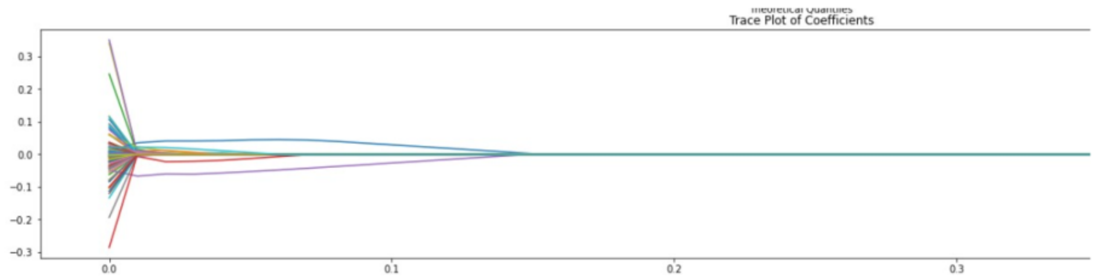
Validity



The Q-Q plot of the model's residual form a straight line. This means that the residuals are normally distributed which meet the assumption of linear model. So the model is valid.

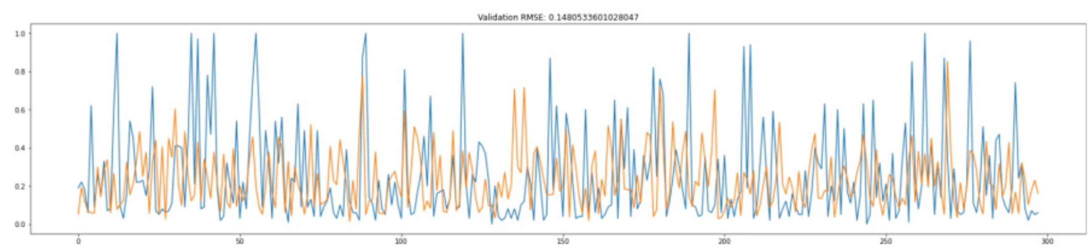
Good analysis

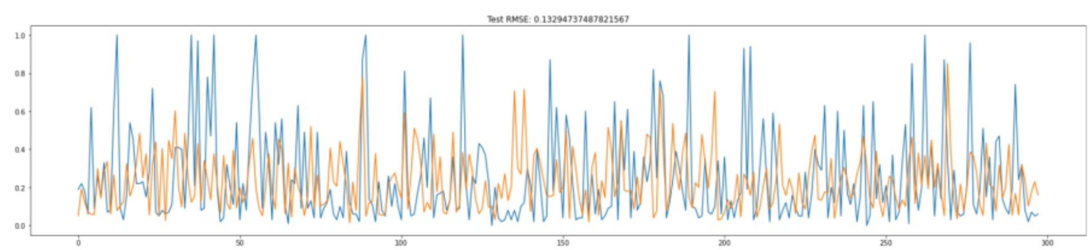
Accuracy



L1 regularization forces some of the coefficients to be **zero** and results a simpler model. It can help reduce the impact caused by the correlation between predictors.

Good analysis





The **RMSE** for the validation set is 0.14. And the **RMSE** for the test set is 0.13. This indicates that the LASSO model fit the data quite well and can generalize well on unseen data.

Comparison of Models

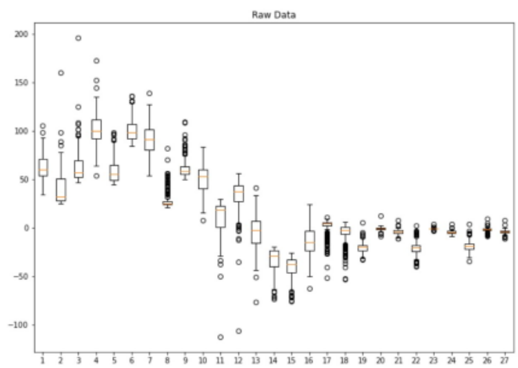
- Linear Model: test set RMSE is 0.35
- Ridge Regression Model: test set RMSE 0.2
- LASSO Regression Model: test set RMSE 0.13 Correct

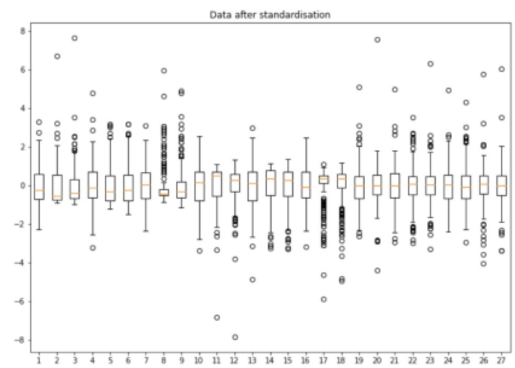
By comparing the RMSE on test set, it is clear that LASSO regression model performs best.

Problem 2. Classification

Data Characteristics

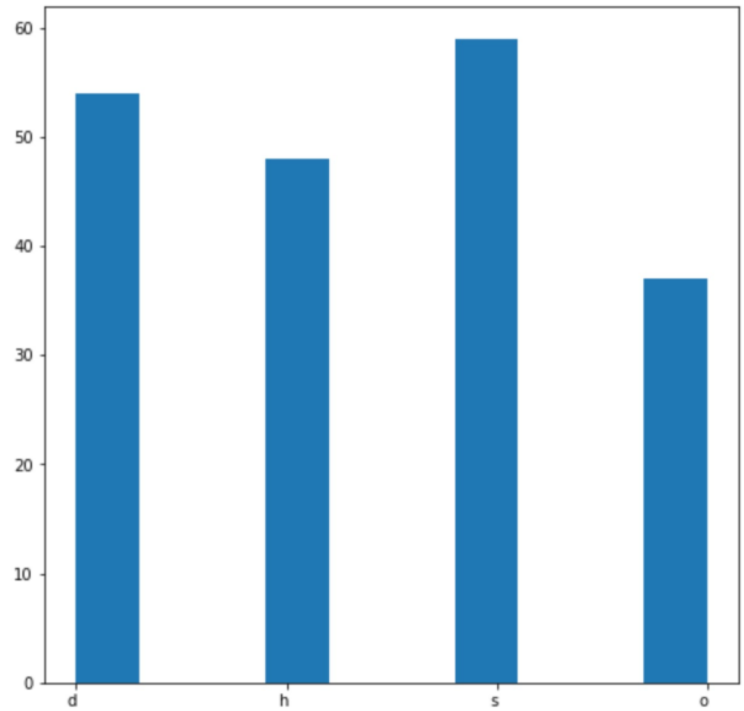
Different Range





Given the box plot above, it is clear that variables are in different scales.

Class Imbalance



Good analysis

The histogram shows that class "o" has the smallest number of samples in training set and it is significant smaller than other classes, which might cause class imbalance. While class "s" has the largest number of samples.

Pre-processing

Standardization

Because input variables are in different scales. Standardization is applied to make sure input data have the same mean and standard deviation.

Good analysis

K-Nearest Neighbors Classifier

Model Developer & Hyper-parameter Selection

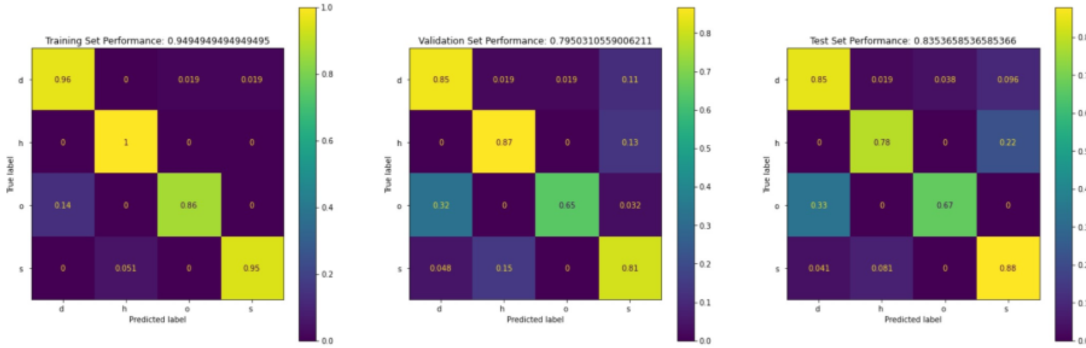
A randomized search is performed to search for optimal hyper-parameters.

- Number of neighbors: Hyperparameter selection
- weights: ['uniform', 'distance']

Use sk-learn's `RandomizedSearchCV(knn, params)` to search for hyper-parameters. Obtain the hyper-parameters from `RandomizedSearchCV` and evaluate it on validation set to improve `accuracy`

$A = \frac{TP+TN}{N}$ as well as $F1$ score.

Analysis of Results



From above we can see that:

- The model is quite accurate (~83%)
- The model cannot classify "h" and "o" very well. Because in the training set, class "h" and "o" have the smallest number of samples. (class imbalance).

Good analysis

Random Forest

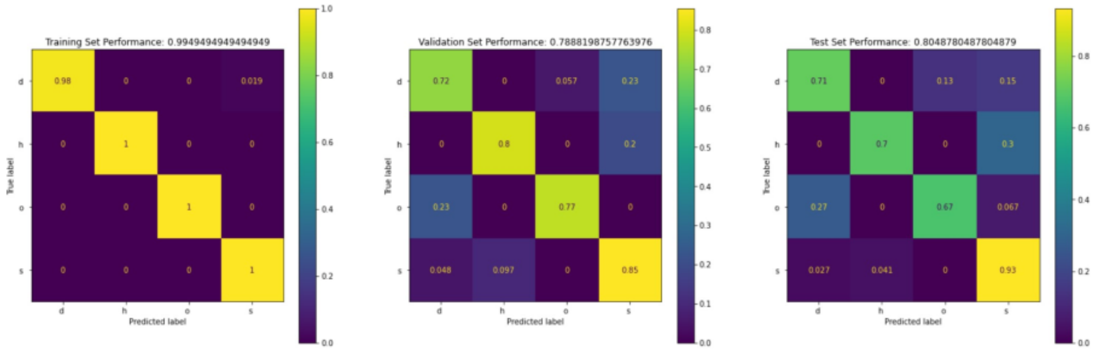
Model Developer & Hyper-parameter Selection

Use the Halving Grid Search method to search for optimal hyper-parameters. It will start by evaluating all systems on a small sample of data. It will then take only the best half of the systems and evaluate them on a larger sample. (lecture notebook) After obtaining the best hyper-parameter, I then evaluate it on validation set to improve **accuracy** as well as $F1$ score.

```
rf = RandomForestClassifier(random_state=42)
param_grid = {'max_depth': [2, 4, None], 'min_samples_split': [5, 10],
'n_estimators' : [25, 50,
halving_search = HalvingGridSearchCV(rf, param_grid, random_state=0).fit(X_train,
Y_train)
```

Hyperparameter selection

Analysis of Results




```
              precision    recall  f1-score   support

           d       0.86      0.71      0.78        52
           h       0.84      0.70      0.76        23
           o       0.59      0.67      0.62        15
           s       0.81      0.93      0.87        74

    accuracy                           0.80       164
   macro avg       0.78      0.75      0.76       164
weighted avg       0.81      0.80      0.80       164
```

From above we can see that :

- The model is doing a great job on training set. However, it cannot classify "d", "h", and "o" very well in test set.
- Class "o" has the lowest precision, recall, and f1-score. This might due to the fact that it has the smallest number of samples.\ Good analysis

Support Vector Machines

Model Developer & Hyper-parameter Selection

Use a grid search to search over the hyper-parameter space for SVM:

- Values of C
- Different kernels
- Kernel parameters

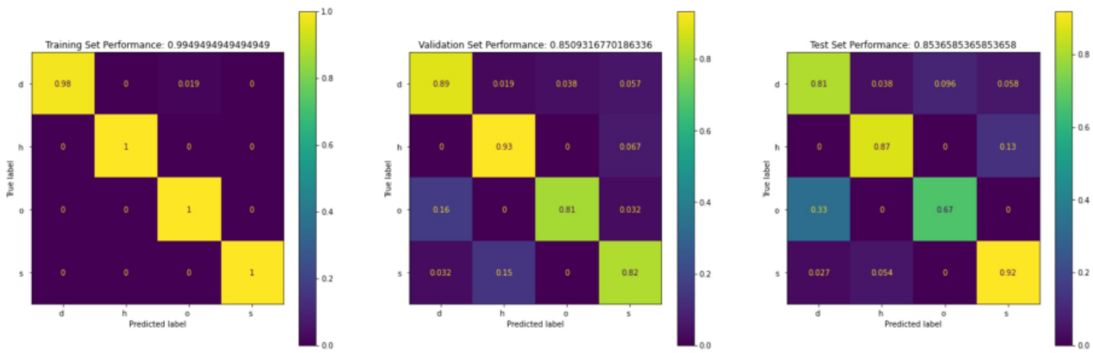
In my example, 3 grids are created and passed to sk-learn's `GridSearchCV()` to search for the optimal hyper-parameters.

```
param_grid = [
```

```
  {'C': [0.1, 1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [0.1, 1, 10, 100, 1000], 'gamma': [0.1, 0.01, 0.001, 0.0001], 'kernel':
['rbf']},
  {'C': [0.1, 1, 10, 100, 1000], 'degree': [3, 4, 5, 6], 'kernel': ['poly']},
 ]
svm = SVC()
grid_search = GridSearchCV(svm, param_grid)
grid_search.fit(X_train, Y_train)
```

After finding the best hyper-parameters using a grid search. I then create a model using the hyper-parameter and evaluate it on **validation set**. Finally, tune the parameters in the `param_grid` to improve validation set **accuracy** $A = \frac{TP+TN}{N}$ as well as $F1$ score.

Analysis of Results



From the above we can see:

- The SVM model is quite accurate (85%)
- The model is not great at classifying class "o" and "s".

Comparisons of Models

- K-Nearest Neighbors Classifier: Test Accuracy: 0.83
- Random Forest Classifier: Test Accuracy: 0.8 (only good at one class).
- SVM: Test Accuracy: 0.85

These three models are all bad at classifying class "o". The SVM classifier is the best model.

Appendix

- Jupyter Notebook for Q1 https://github.com/xiaohai-huang/cab420-workspace/blob/master/work/machine-learning/a1/Q1/q1.ipynb

- Jupyter Notebook for Q2 https://github.com/xiaohai-huang/cab420-workspace/blob/master/work/machine-learning/a1/Q2/q2.ipynb

Edit this page

*Last updated on **2018/10/14** by **Author***

(Simulated during dev for better perf)

assignment 1A

GRADEMARK REPORT

FINAL GRADE

5/8

GENERAL COMMENTS

Instructor

PAGE 1

Comment 1 | Criterion 1

so, are you performing standardisation?

PAGE 2

QM **Good justification.**

Good justification.

PAGE 3

QM **Good justification.** | Criterion 1

Good justification.

QM **Avoid using screenshoots.**

Avoid using screenshoots.

PAGE 4

QM **Unnecessary details.**

Unnecessary Implementation details.

When writing reports avoid referring to code segments or outputs returned by models in raw forms.

PAGE 5

Comment 2 | Criterion 3

vague/

qq-plot forms a straight line, you need to say what it implies!

it is represented as a bell curve, **and therefore the model ......**

PAGE 6

QM

Good analysis | Criterion 3

Good analysis

PAGE 7

Comment 3 | Criterion 3

The method you've followed for obtaining the value seems correct, yet the value seems to differ from the expected answer.

QM

Correct | Criterion 3

correct answer.

QM

Correct | Criterion 2

correct answer.

Comment 4 | Criterion 3

this is a correct analysis, you have discuss what you see in the figure, and then you've concluded something.

Strikethrough.

PAGE 8

Comment 6 | Criterion 3

a bit far from the expected value.

Comment 7 | Criterion 2

this is close to the expected value.

PAGE 9

QM **Good analysis** | Criterion 3

Good analysis

QM **Good analysis** | Criterion 3

Good analysis

PAGE 10

Comment 8 | Criterion 3

these values are a bit off

QM **Correct** | Criterion 3

correct answer.

Comment 9 | Criterion 3

too short discussion.

You need to compare and contrast the models. Look at the validation/test performance of the models.

look at the p-value.

compare the validities/residuals of the models.

I can see that you have discussed model specific performance in each section. but you need to summarise everything in this section.

PAGE 11

QM **Good analysis** | Criterion 4

Good analysis

QM **Good analysis**

Good analysis

QM **Hyperparameter selection** | Criterion 5

You need to specifically mention and justify the hyperparameter ranges used (lower and upper bounds in case real/int variables.).

PAGE 12

QM **Good analysis** | Criterion 6

Good analysis

QM **Hyperparameter selection** | Criterion 5

You need to specifically mention and justify the hyperparameter ranges used (lower and upper bounds in case real/int variables.).

PAGE 13

QM **Good analysis** | Criterion 6

Good analysis

PAGE 14

QM **Hyperparameter selection** | Criterion 5

You need to specifically mention and justify the hyperparameter ranges used (lower and upper bounds in case real/int variables.).

QM **Good analysis** | Criterion 6

Good analysis

Comment 10 | Criterion 6

use other performance matrices F1, precision and recall. You have not computed them for all three models.

Comment 11 | Criterion 6

Too short discussion.

1. You need to add a result table with all considered performance matrices.

2. Also you need to compare/contrast class-level performance of the three models.

CRITERION 1 (5%) 5 / 5

Q1 Discussion of Data Characteristics and Pre-processing

5 (5)	Clear and concise discussion of data characteristics, all issues present in the data are clearly identified, appropriate pre-processing is performed with strong justification.
4 (4)	Identifies all issues in the data and performs appropriate pre-processing.
3 (3)	Identifies any major issues within the data and performs appropriate pre-processing. Limited justification given.
2 (2)	Discussion present but limited. Pre-processing inappropriate and/or unjustified.
1 (1)	Failure to consider relevant characteristics in the data. Pre-processing not considered or incorrect.
0 (0)	Failure to consider relevant characteristics in the data. Pre-processing not considered or incorrect, or section missing.

CRITERION 2 (20%) 3 / 5

Q1 Model Development and Hyper-parameter Selection

5 (5)	Clearly and concisely describes the developed models and their hyper-parameters. Clear and correct justification for hyper-parameters, supported by figures/tables as/when appropriate. Correct use of data for model training and development.
4 (4)	Developed models and hyper-parameters are presented and justified with partial support by figures/tables as/when appropriate. Correct use of data for model training and development.
3 (3)	Provides basic justification for hyper-parameters, with limited/no support from figures and/or tables. Correct use of data for model training and development.
2 (2)	Weak model development approach. Limited/incorrect justification for hyper-parameter selections.
1 (1)	Flawed model development approach, with no clear justification for hyper-parameters, and/or incorrect use of data.
0 (0)	Flawed model development approach, with no clear justification for hyper-parameters, and/or incorrect use of data, or section missing.

CRITERION 3 (25%) 3 / 5

Q1 Analysis of Results

5 (5)	Excellent and insightful analysis of results, drawing on theoretical knowledge of the models and relevant characteristics of the data. Analysis considers the nature of the data in combination with the accuracy. Analysis is supported and enhanced by appropriate metrics and/or figures.
4 (4)	Sound analysis of results, relating key theoretical knowledge to observed results, with some consideration given to the nature of the data. Appropriate metrics and/or figures present and used to enhance discussion.
3 (3)	Provides basic analysis, with limited theoretical insights. Appropriate metrics and/or figures present.
2 (2)	Limited and/or superficial analysis of results. Weak/incorrect discussion of theoretical knowledge in relation to results. Poor use of metrics and/or figures.
1 (1)	Flawed analysis. No discussion relating theoretical knowledge to observed results. Incorrect and/or inappropriate use of metrics and/or figures.
0 (0)	Flawed analysis. No discussion relating theoretical knowledge to observed results. Incorrect and/or inappropriate use of metrics and/or figures, or section missing.

CRITERION 4 (5%) 5 / 5

Q2 Discussion of Data Characteristics and Pre-processing

5 (5)	Clear and concise discussion of data characteristics, all issues present in the data are clearly identified, appropriate pre-processing is performed with strong justification.
4 (4)	Identifies all issues in the data and performs appropriate pre-processing.
3 (3)	Identifies any major issues within the data and performs appropriate pre-processing. Limited justification given.
2 (2)	Discussion present but limited. Pre-processing inappropriate and/or unjustified.
1 (1)	Failure to consider relevant characteristics in the data. Pre-processing not considered or incorrect.
0 (0)	Failure to consider relevant characteristics in the data. Pre-processing not considered or incorrect, or section missing.

CRITERION 5 (20%) 3 / 5

Q2 Model Development and Hyper-parameter Selection

5 (5)	Clearly and concisely describes the developed models and their hyper-parameters. Clear and correct justification for hyper-parameters, supported by figures/tables as/when appropriate. Correct use of data for model training and development.

4 (4)	Developed models and hyper-parameters are presented and justified with partial support by figures/tables as/when appropriate. Correct use of data for model training and development.
3 (3)	Provides basic justification for hyper-parameters, with limited/no support from figures and/or tables. Correct use of data for model training and development.
2 (2)	Weak model development approach. Limited/incorrect justification for hyper-parameter selections.
1 (1)	Flawed model development approach, with no clear justification for hyper-parameters, and/or incorrect use of data.
0 (0)	Flawed model development approach, with no clear justification for hyper-parameters, and/or incorrect use of data, or section missing.

CRITERION 6 (25%) 3 / 5

Q2 Analysis of Results

5 (5)	Excellent and insightful analysis of results, drawing on theoretical knowledge of the models and relevant characteristics of the data. Analysis is supported and enhanced by appropriate metrics and/or figures.
4 (4)	Sound analysis of results, relating key theoretical knowledge to observed results. Appropriate metrics and/or figures present and used to enhance discussion.
3 (3)	Provides basic analysis, with limited theoretical insights. Appropriate metrics and/or figures present.
2 (2)	Limited and/or superficial analysis of results. Weak/incorrect discussion of theoretical knowledge in relation to results. Poor use of metrics and/or figures.
1 (1)	Flawed analysis. No discussion relating theoretical knowledge to observed results. Incorrect and/or inappropriate use of metrics and/or figures.
0 (0)	Flawed analysis. No discussion relating theoretical knowledge to observed results. Incorrect and/or inappropriate use of metrics and/or figures, or section missing.