Introduction to Machine Learning - Assignment 1 Report

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1 Practical

1.1 Preprocessing

1.1.1 Encoding categorical values

Encode var 3 using target encoding

$$\eta = \text{MinMaxScaler}\left(\frac{\#\text{ of occurrence of target of a country} + \text{my\_noise(country)}}{\#\text{ of occurrence of a country}}\right)$$

Encode var 6 using ordinary encoding

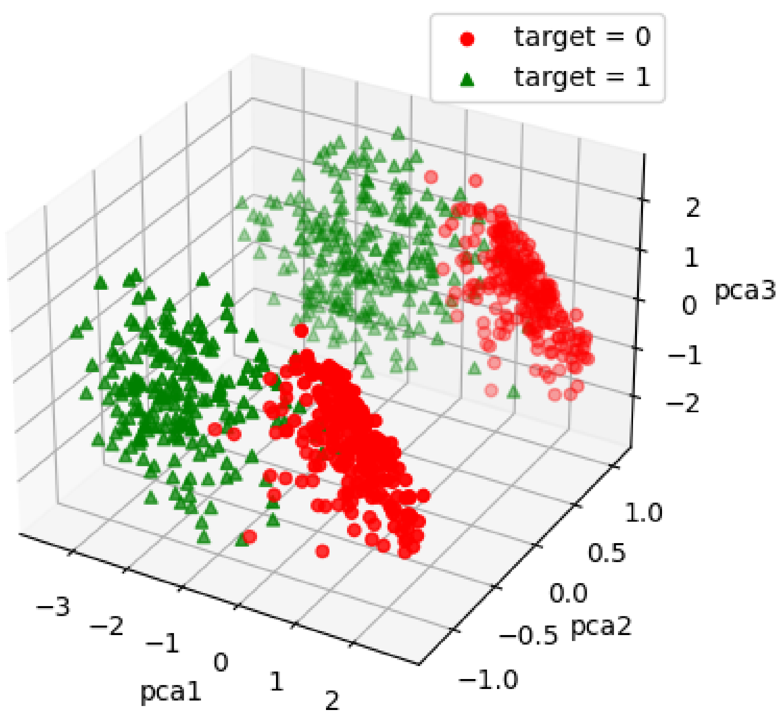
Did not encode var 7

1.1.2 Data imputation

Imputed the data using ridge regression

1.1.3 Implementing the PCA technique

Used PCA with the dimensionality of 3. It resulted in the following:



1.2 Training

1.2.1 Model without PCA

Naïve Bayes:

- Testing accuracy: 0.972972972972973
- Testing precision = 0.9666666666666667
- Testing recall = 0.9775280898876404

Logistic Regression:

- Testing accuracy: 0.9621621621621622
- Testing precision = 0.9555555555555556
- Testing recall = 0.9662921348314607

KNN:

- Testing accuracy: 0.9513513513513514
- Testing precision = 0.9761904761904762
- Testing recall = 0.9213483146067416

1.2.2 Models with PCA (d=4)

Naïve Bayes:

- Testing accuracy: 0.972972972972973
- Testing precision = 0.9772727272727273
- Testing recall = 0.9662921348314607

Logistic Regression:

- Testing accuracy: 0.9621621621621622
- Testing precision = 0.9555555555555556
- Testing recall = 0.9662921348314607

KNN:

- Testing accuracy: 0.972972972972973
- Testing precision = 0.9883720930232558
- Testing recall = 0.9550561797752809

2 Theoretical

2.1 Regarding the Preprocessing

2.1.1 Which regression model was the most effective for the missing values, and why?

The polynomial model yielded more accurate result

- Linear regression with polynomial coefficients
  - Mean Absolute Percentage Error: 0.14921567818592088
  - Mean Absolute Error: 15.436999813574154
  - Mean Squared Error: 495.9008222581229
  - Root Mean Squared Error: 22.268830733968116

compared to ridge regression

- Ridge regression
  - Mean Absolute Percentage Error: 0.20860892513670884
  - Mean Absolute Error: 20.069495142515294
  - Mean Squared Error: 583.4407476014106

– Root Mean Squared Error: 24.15451816123457

nonetheless I opted for using a ridge regression model with linear parameters for imputing the data of *var4*

2.1.2 What encoding technique did you use for encoding the categorical features, and why?

I used target encoding for encoding my categorical features since using one hot was proven to be suboptimal. My target encoding was implemented using the following formula:

$$\eta = \text{MinMaxScaler}\left(\frac{\#\text{ of occurrence of target of a country} + \text{my\_noise(country)}}{\#\text{ of occurrence of a country}}\right)$$

2.2 Regarding the training process

2.2.1 Which classification model performed best, and why? (30 %)

Overall the Naïve Bayes proved to be a reliable baseline of performance fo the classification models

Naïve Bayes without PCA:

- Testing accuracy: 0.972972972972973
- Testing precision = 0.9666666666666667
- Testing recall = 0.9775280898876404

The only model that got comparably better results was

KNN with PCA:

- Testing accuracy: 0.972972972972973
- Testing precision = 0.9883720930232558
- Testing recall = 0.9550561797752809

Somehow Logistic Regression did not achieve better results that Naïve Bayes

Logistic Regression with PCA:

- Testing accuracy: 0.9621621621621622
- Testing precision = 0.9555555555555556
- Testing recall = 0.9662921348314607

2.2.2 What were the most critical features with regards to the classification, and why? (20 %)

var1, *var2* and *var5* turned out to be the most impactful features

2.2.3 What features might be redundant or are not useful, and why? (20 %)

It turned out that *var3* can be counted as a redundant feature. Removing it results in only $< 5\%$ reduction in accuracy of the model

var7 is also a redundant feature

2.2.4 Did the dimensionality reduction by the PCA improve the model performance, and why? (20 %)

Yes it did. In my case it increased the testing precision of every model.

Dimensionality reduction can remove effectless columns that only introduce noise and result in overfitting

2.2.5 Additional research:

(a) what is a multi-label learning problem?

(b) suggest an example in which you can transform the given problem into a multi-label problem? Will the models work as it is in that case, or would some changes be required? (10 %))