Project-I by Group CITYNAME

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Abstract

In this report we summarize the results we obtained for the first machine learning of the EPFL machine learning course. Facing two datasets, we fit linear models and perform linear regression on the first one, and perform data classification using logistic regression on the second one. For the first dataset, we find that simple linear regression and ridge regression gives decent results, but that we can get better results by isolating one simple feature and performing transformations on that feature.

1 Linear Regression

1.1 Data Description

Our first data set consisted of a train set, with an input and an output variable respectively $\mathbf{X}$ and $\mathbf{y}$, composed of $N = 2800$ data samples, and a test set with only $\mathbf{X}$ variable observed and $N = 1200$ data samples. $\mathbf{X}$ spans over $D = 77$ features, among which 9 of them are categorical, with number of categories ranging from 2 to 4, 2 of them are binary and the other are real-valued.

Our goal is to produce linear predictions for test examples and approximate the test error.

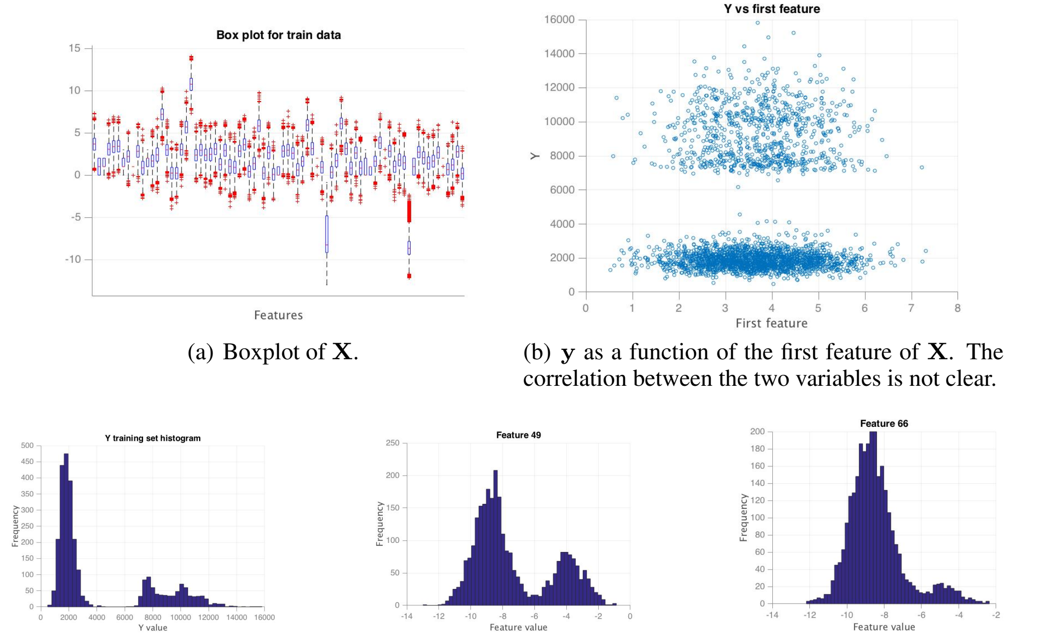
1.2 Data visualization and cleaning

The first tasks we performed on the data was to visualize it. The first thing we did was to obtain a visualization of the data, showed in 1(a) and 1(c). Those two figures led us to normalize both the input and the output variable (normalizing the output variable allow us to have results that are easier to interpret, as they are to be compared to values close to 1). No obvious outliers are noticeable on the $\mathbf{y}$ histogram.

We performed featurewise analysis to notice that most of our real valued variables have nearly gaussian distributions (or at least unimodal distributions), which is not the case of our output variable. Figure 1(b) shows how the output variable evolves as a function of the first feature. This behaviour is what we notice on most variables, and thus shows no clear correlations.

Although for variables 49 and 66 we notice a multimodal distribution that is closer to the behaviour of our output variable, as seen in Figure 1(d)and Figure 1(e). We thus chose to try and predict $\mathbf{y}$ using only those two features, transformed through polynomial transformation.

The categorical variables were encoded using dummy encoding, what led to a total feature number of 100. As the rank of our dataset is below 100 (it is 70), simple linear regression is likely to fail, and we use ridge regression to cope for the rank deficiency.



(a) Boxplot of $\mathbf{X}$.

(b) $\mathbf{y}$ as a function of the first feature of $\mathbf{X}$. The correlation between the two variables is not clear.

(c) Histogram of $\mathbf{y}$. The output distribution is bimodal.

(d) Histogram of feature 49 of $\mathbf{X}$. We see that the distribution is bimodal, as the output.

(e) Histogram of feature 66 of $\mathbf{X}$. Again, the distribution is bimodal.

Figure 1:

1.3 Ridge regression

As the dimension of the data is inferior to the number of feature, we expect least-squares to work quite poorly, and thus decided to apply mostly ridge regression.

For our first attempt at predicting the data, we simply used the initial features and used kFold with $k = 4$ to display the evolution of the RMSE as a function of the regularizing lambda both for the training and test data. The lambda we used ranged from 10^{-4} to 10^{3}, with 500 points. The results of the ridge regression are already satisfactory, with an error of approximately 0.32 ± 0.005 on the training set and 0.34 ± 0.005 on the test set, that is approximately one third of the standard deviation of the output variable.

We see that for sufficiently low lambda, both the training and test errors do not vary much (there is indeed only a very slight variation of test RMSE, with a nearly unnoticeable minimum between $\lambda = 10$ and $\lambda = 100$).

The results described here are summerized in the Figure 2(a).

1.4 Feature transformations

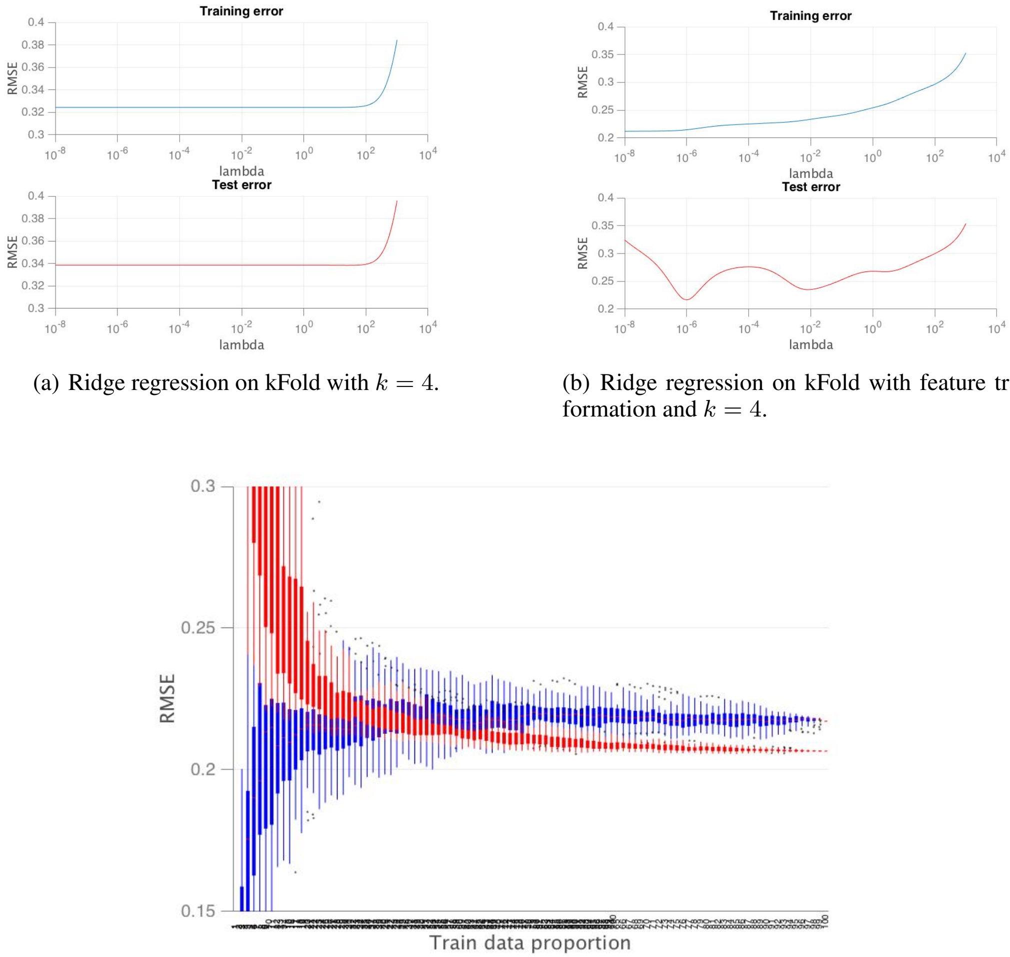
As notified in a previous section, among all the feature at our disposal, features 49 and 66 show distributions that ressemble the ditribution of the output variable.

This led us to try and regress only on thos two features and polynomial transformations of them. Using only those two features, we get an RMSE error that is quite close to the one we notified when all the features are used. When using polynomial features (up to degree 10), we basically get half the error that we got using all the features. Those results were obtained using ridge regression. As in the previous section, we obtained the RMSE as a function of lambda, calculating both training and test errors using a kFold procedure with $k = 4$. The results are summarized in Figure 2(b), where, as previously mentionned, we used as features only the two features and their polynomial transformation with degree ranging from 1 to 10.

This time, the test error varies much more as a function of lambda, and, given our curve, the best lambda possible seems to be around 10^{-6}.

Finally to evaluate our performances more accurately, we plotted learning curves for our model, with 20 features obtained by polynomial transformations and a lambda of 10^{-6}. The learning curve is obtained by using 20% of the training data to perform tests, while learning the model on a progressively increasing portion of the 80% remaining. We monitor the test and training error as functions of the proportion of data used to train. The results are summarized in Figure 2(c).

As expected, both training error and test error decrease as the proportion of training data increases. The test error obtained seems to exhibit a quite satisfactory behaviour.



(a) Ridge regression on kFold with $k = 4$.

(b) Ridge regression on kFold with feature transformation and $k = 4$.

(c) Learning curve. Blue is training data and red is test data.

Figure 2:

1.5 Regression Summary

While simple ridge regression with an appropriately optimized lambda already gave decent results on our dataset, we obtained better results using polynomial transformations of well chosen features. Doing so, we obtain an error that is approximately one fifth of the standard deviation.