

Exercise 0 Dataset description

e12045110 Maria de Ronde
eXXXXXXXXX Quentin Andre
e11921655 Fabian Holzberger

April 24, 2021

Classification Dataset: Email-Spam ([link to dataset](#))

Bridges Dataset([link to dataset](#))

Kaggle: Amazon review

Dataset Description

The Amazon review dataset is a text dataset translated into vectors. There are 50 classes, which represent authors of different reviews. The goal of the classification is to predict the author of reviews. The dataset contains 750 instances with 100002 vectors, a nominal attribute representing a unique ID, 10000 numerical vectors and a nominal vector representing the class.

In the figure 2 below we can see how many instances belong to each class. We can see that the dataset is not balanced. As some classes have 20 instances where other classes have only 10 instances.

In tabel 1 one can see the distribution of the sum of the vectors. On average a word appears 309 times in all reviews, however there is a word which appears 187520 times, from 49 to 410 times in a review.

	0
count	10000.000000
mean	308.859700
std	2419.468303
min	0.000000
25%	9.000000
50%	21.000000
75%	220.000000
max	187520.000000

Figure 1: Distribution sum of vectors

Pre-Processing

There are no missing values in the dataset. The unique ID has been deleted from the data set as has no relevance to the class. The text vectors have values differentiating of a mean of 250 occurrences per instance to 1 occurrence in the entire dataset. With 250 occurrences per instance it appears as though stop words have not been deleted from the dataset, however as we do not have the raw data available we cannot be certain.

We sort the vectors from highest number of total occurrences to the smallest number of total occurrences. Words which only occur in one instance can be seen as unique identifier to one author. By sorting the data we enable, to train our model leaving some of the first and last columns out and test whether this improve the model.

In tabel X one can see the distribution of the sum of the vectors. On average a word appears 309 times in all reviews, however there is a word which appears 187520 times, from 49 to 410 times in a review.

In order to flatten the weight of words which occur more often in one instance we will also train the model on the natural logarithm of the original dataset. The dataset will be transferred into $\ln(X) + 1$.

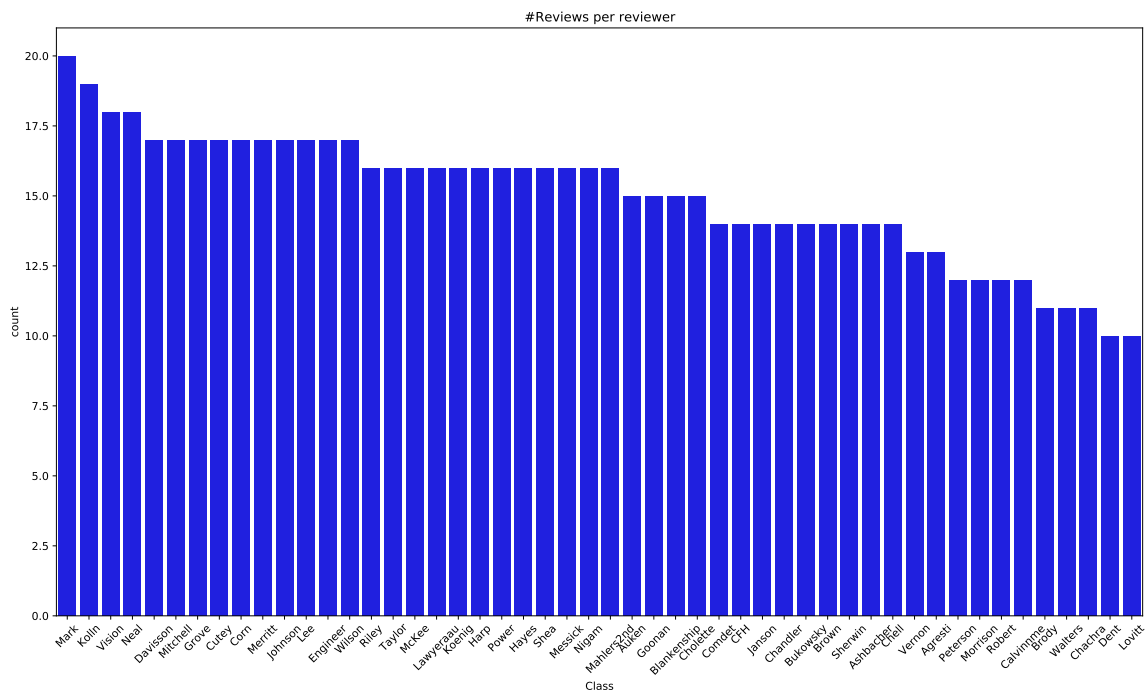


Figure 2: Instances per class

Sum of vector	
count	10000.000000
mean	308.859700
std	2419.468303
min	0.000000
25%	9.000000
50%	21.000000
75%	220.000000
max	187520.000000

Scenario	Scenario description
0 10000	Select all 10000 attributes
1 8000	select the first 8000 attributes
2 6000	select the first 6000 attributes
3 50:10000	select the 50th till the 10000th attribute
4 50:8000	select the 50th till the 8000th attribute
5 50:6000	select the 50th till the 6000th attribute
6 100:10000	select the 100th till the 10000th attribute
7 100:8000	select the 100th till the 8000th attribute
8 100:6000	select the 100th till the 6000th attribute

We create 9 scenarios, which are shown in table X for which we train the three classifiers: Perceptron, Random forest and Naive Bayes with the multi-nominal distribution.

text

Parameter-Tuning

First we will split the data in two parts. One part for training the model and one part for validating the models afterwards, we use the hold out strategy here. The training dataset is split into a training and test set, this is done with the hold out strategy as well as the cross validation. The results of the model on the test sets are used to tune the parameters on the model.

Perceptron

We determine the base parameters for the perceptron, alpha as 0.0005, eta as 1 penalty='none' and the max iterations are equal to 100.

All train set of the $\ln(X) + 1$ have an accuracy of a 100, for X , we could not obtain a perfect score when high occurring words were deleted. Comparing the accuracy of the test set of X to $\ln(X) + 1$, we see that the logarithmic dataset performs better when we do not delete the words with high occurrences. After removing the top 100 words the accuracy of the X dataset is higher than the $\ln(X) + 1$ dataset. Taking the logarithmic values has the highest effect on the words which occur most often.

A clear difference can be seen between the performance of the hold out and the cross validation runs. The cross validation run clearly out performs the hold out run. Due to the high amount of classes, 50, and the relative low amount of instances it can happen that classes are not represented in the test set, some classes only appear 10 times in the entire dataset. The accuracy is sensitive to the chosen test and train set. With using the cross validation the entire dataset is used and the influence of chance decreases. In order to the hyper parameters we will use cross validation and look at the results of the test set. For the parameter tuning scenario 4 of the untransformed dataset is chosen. Scenario performed slightly better. The vectors with very low occurrences might have unique identifiers to classes, which increases over fitting.

Overfitting....??? What to do

	Scenario	Basic test	Basic train	LN test	LN train
0	10000	37.777778	91.666667	40.000000	100.0
1	8000	39.259259	91.296296	41.481481	100.0
2	6000	40.000000	88.148148	47.407407	100.0
3	50:10000	40.740741	100.000000	34.074074	100.0
4	50:8000	40.740741	100.000000	36.296296	100.0
5	50:6000	40.000000	100.000000	41.481481	100.0
6	100:10000	40.000000	100.000000	43.703704	100.0
7	100:8000	40.000000	100.000000	42.962963	100.0
8	100:6000	37.037037	100.000000	41.481481	100.0

	Scenario	Basic test	Basic train	LN test	LN train
0	10000	40.133333	93.229630	50.133333	100.0
1	8000	40.000000	93.585185	50.266667	100.0
2	6000	39.466667	92.340741	51.200000	100.0
3	50:10000	51.600000	100.000000	50.666667	100.0
4	50:8000	51.200000	100.000000	50.266667	100.0
5	50:6000	49.066667	100.000000	50.400000	100.0
6	100:10000	50.800000	100.000000	49.333333	100.0
7	100:8000	50.533333	100.000000	50.133333	100.0
8	100:6000	50.266667	100.000000	48.933333	100.0

Parameter tuning

The first parameter we tune is the maximum number of iteration max_iter . We test for values $max_iter \in \{2, 3, 4, 5, 10, 50, 100\}$. It can be seen that after 10 iterations the training set has a perfect fit, and the test set has the highest accuracy, as well as precision and recall. Therefore, we take $max_iter = 10$ for the next parameter test.

Following the model has been ran for different learning rates ($eta0$), where $eta0 \in \{1^{-4}, 1^{-3}, 0.01, 0.1, 0.2, 0.3, 0.4, 0.6, 0.8, 1\}$. The model is indifferent for the learning rate and always obtains the same accuracy, precision and recall values. This means that the same weights are obtained.

Since the model is over fitting a regularization term has been introduced. At first α was set to be $\in \{1^{-4}, 1^{-3}, 0.01, 0.5, 1\}$. The accuracy for both the training set as well as the test set dropped rapidly after 1^{-3} . Therefore, a second run with $\alpha \in \{1e-5, 1e-4, 0.0002, 0.0004, 0.0006, 0.0008, 1e-3\}$ has been done. For $\alpha = 0.0002$, the test set performs best with 49.16%.

	Scenario	Basic test	Basic train
0	0.00001	47.258560	100.000000
1	0.00010	47.532924	99.983526
2	0.00020	49.163740	99.473169
3	0.00040	41.922739	98.616470
4	0.00060	39.078139	94.471517
5	0.00080	41.027217	96.558869
6	0.00100	42.811677	96.806311

Validation

Finally we run our final model with the following parameter settings, maximum number of iterations is 10, $eta0 = 1$, the regularization term is 11, with an α of 0.0002 against the validation set. This results in an accuracy of 50.4%. In the confusion matrix we can see that some names are never predicted and some names are predicted too often, like Brown.

Random forest

The second classifier is the random forest classifier. First it is checked which data pre-process steps will be applied to the model. The base parameter settings are the following: $ccp\alpha = 0$

$maxleaf = 50$

$maxdepth = 10$

$numberofestimators = 100$

The best scenario is scenario 1 on the natural logarithmic dataset with an accuracy of 49.17% in the cross validation. This model is less sensitive for the extreme values of words with an high occurrence as the results of $X\%$ and $LN(X) + 1$ are closer to each other, as well as the model taking the first attributes into account scoring highest on accuracy. Using cross validation the $LN(X) + 1$ always out performs the dataset X , where in the hold out run there is not pattern to be seen.

The following hyper parameters have been tested: number of estimators, the maximum depth, maximum leafs and the ccp alpha. Starting with the number of estimators, also the number of trees, given n estimators $\in \{1, 5, 10, 50, 70, 100, 200\}$.

Both the train set and the test set achieve an higher accuracy whenever the number of estimators increases. The number of estimators will be set to 200. The second hyper parameter is the maximum number of leafs per branch, we test $maxleafs \in \{5, 10, 20, 50, 100\}$ The accuracy increases when the number of leafs increase

to 50, with 100 the accuracy, precision and recall do increase for the training set, but not for the test set. The maximum number of leafs is set to 50.

After the number of trees and the leafs per branch, the depth of each tree is determined. where $maxdepth \in \{2, 3, 4, 5, 8, 10, 50, 100\}$. The accuracy for the training set is highest with a maximum depth of 10. The accuracy for the test set is highest with a maximum depth of 50 or a 100, the same scores are obtained. The maximum depth is set to 50.

Finally we will include some minimal cost complexity pruning. We test for $ccp\alpha \in \{1e-5, 2e-5, 1e-4, 2e-4, 1e-3, 5e-3, 75e-4, 1e-2\}$. It can be seen that for $ccp\alpha < 0.005$ no pruning has been done. However, for $ccp\alpha > 0.005$ both the train and the test have reduced scores. Therefor, we will set $ccp\alpha = 0.005$.

	Scenario	Basic test	Basic train	LN test	LN train
0	10000	42.222222	99.814815	43.703704	99.814815
1	8000	39.259259	99.814815	39.259259	99.814815
2	6000	39.259259	99.814815	38.518519	99.814815
3	50:10000	37.037037	99.814815	37.777778	99.814815
4	50:8000	37.777778	100.000000	36.296296	100.000000
5	50:6000	41.481481	99.814815	38.518519	99.814815
6	100:10000	37.037037	99.629630	36.296296	99.629630
7	100:8000	35.555556	99.444444	34.814815	99.444444
8	100:6000	37.037037	99.444444	37.777778	99.444444

	Scenario	Basic test	Basic train	LN test	LN train
0	10000	46.222564	99.703812	46.808604	99.720259
1	8000	48.432836	99.703731	49.174715	99.736652
2	6000	46.804214	99.868340	47.098332	99.851892
3	50:10000	47.245391	99.325143	47.396839	99.341618
4	50:8000	45.037313	99.489644	45.041703	99.506145
5	50:6000	46.661545	99.720286	47.695347	99.720286
6	100:10000	45.610184	99.193429	46.341089	99.176954
7	100:8000	46.501317	99.226215	46.652766	99.226215
8	100:6000	44.721247	99.374404	44.725637	99.374404

Validation

The final model is now tested on the validation data with the following parameter settings: $ccp\alpha = 0.005$

$maxleaf = 50$

$maxdepth = 50$

$nestimators = 200$

This gives a accuracy of

Performance-Analysis