Natural Language Processing 2020/21
Project Report

University *of Ljubljana*
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IMapBook Collaborative Discussion Classification

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Abstract

Automatic text classification has been considered as a vital method to manage and process a vast amount of documents in digital form, which is widespread and continuously increasing. That brought a wave of new tools for student education, such as the IMapBook platform. It gives students a way to communicate and discuss the books they are reading. In our assignment, we will try to classify those discussions based on the book it's relevant to, and the type of message.

Keywords
IMapBook, Text Classification, TF-IDF, Handcrafted Features, BERT, Logistic Regression

Advisors : Slavko Žitnik

Introduction

With the rapid development of the internet and big data, digital information is increasing at a high rate. With this technologies and applications such as IMapBook [1], a web-based application that allows for discussions on reading materials as well as interactive games, also started emerging.

In our assignment, we will look at some IMapBook collaborative discussions on different books. For that, we first need to look at some vital information, that we extracted from the discussions and the book texts. We will create two different message classifications, based on :

- Book ID (3-class),
- Code Preliminary (16-class).

From the message types we can say that not all are important to the discussions of the books, and only the content discussion and content question are directly related to the books.

With this we where also provided with a (1) dataset that contains all message types and (2) dataset that contains only massages important to the discussion. With this we will be able to further compare how much noise impacts the classifiers and prediction.

By checking the manual classifications in the dataset, we noticed some were misspelled and some were incorrectly written. Therefore, we applied some fixes to the manual classifications. The errors such as excess whitespace, lower and upper case, etc... were removed. Classifications where there were multiple classes, were simplified into one class, to simplify the classification process. The final fixed distribution is not intraclass uniform as can be seen in figures 1 and 2.

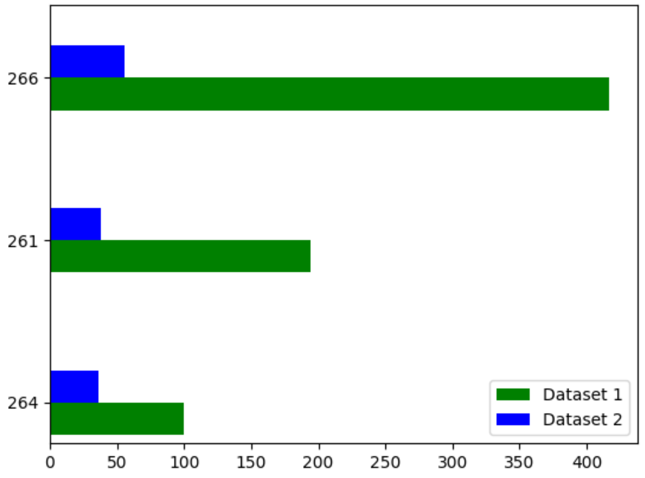


Figure 1. The distribution of book IDs in the dataset.

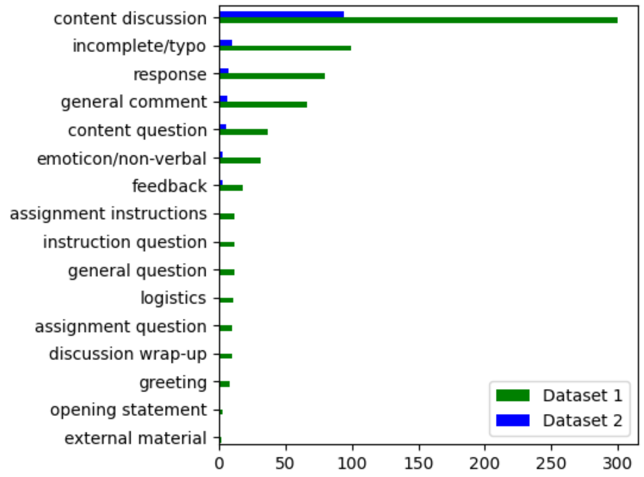


Figure 2. The distribution of message types in the dataset.

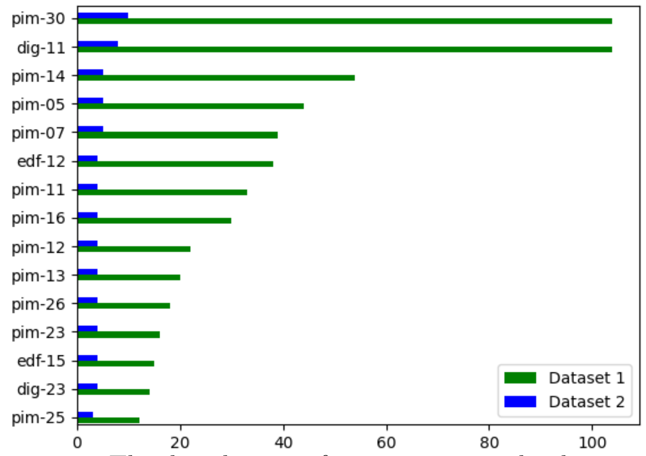
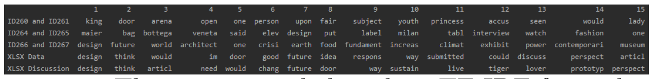


Figure 3. The distribution of active users in the dataset.

From all the graphs above we can see that in dataset 2, where there are messages concerning the discussion, we get a more uniform distribution of users as well as books. While the distribution of message types is dominated by the content discussion.

To better understand the contents we are trying to classify, we checked the top unigrams of the book texts. We also calculated the TF-IDF of the books as well as the collaborative discussions (as a whole) and displayed the top 15 stemmed words for each (see figure 4). This gives us a quick insight into the most important words of each book.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ID260 and ID261	king	door	arena	open	one	person	upon	fair	subject	youth	princess	accus	seen	would	lady
ID264 and ID265	maier	bag	bottega	veneta	said	elev	design	put	label	milan	tabl	interview	watch	fashion	one
ID266 and ID267	design	future	world	architect	one	crisi	earth	food	fundament	increas	climat	exhibit	power	contemporari	museum
XLSX Data	design	think	would	im	door	good	future	idea	respons	way	submitted	could	discuss	perspect	articl
XLSX Discussion	design	think	articl	need	would	chang	future	door	way	sustain	live	tiger	lover	prototyp	perspect

Figure 4. The top 15 words based on TF-IDF for each set.

From this we can say that the texts are contextually different, aside from a few words such as 'one', the top frequent words are more or less unique to their books.

Existing solutions

There are many approaches to automatic NLP text classification, which fall into three types of systems :

- rule-based systems,
- machine learning-based systems,
- hybrid systems.

Rule-based systems classify text into organized groups by using a set of handcrafted rules. But these systems require deep knowledge of the domain they are trying to classify. On the other hand, machine learning-based systems can learn the different associations between pieces of text by using pre-labeled examples as training data. Some of the more popular text classification algorithms [2] inlcude Naive Bayes, Support Vector Machines, and deep learning. While hybrid systems apply both handcrafted rules and machine learning approaches. The current state-of-the-art consists of approaches such as BERT [3] or ELMo [4].

Handcrafted features

We decided to create handcrafted features as well and compare them to the performance of other feature extractors such as tf-idf and countvec. Unlike the other two we will ot preprocess the text beforehand, meaning we will keep it as it is.

For our features we simply processed each message and created a vector of numbers, where the numbers in order represent :

- number of sentences,
- number of words,
- number of non-white characters,
- number of unique words,

- number of digits,
- number of stop words,
- number of interrogative words,
- the maximum word length,
- the average word length,
- the number of exclamation marks '!',
- the number of question marks '?',
- the number of commas ',',
- the number of dots '.',
- the number of dashes '-',
- the number of closing brackets ')',
- the number of opening brackets '(',
- the number of colons ':',
- the number of capital letters,
- the number of non-ascii characters.

Results

We then tested the all the combinations of models and extractors, in order to get a more in-depth analysis of the results. Note that RF is Random Forest, NB is Naive Bayes, LR is Logistic Regression, KNN is k-Nearest Neighbor and MV is Majority Voting.

Table 1. $CodePreliminary$ with $tfidf$ on dataset 1.

Model	Extractor	F1 Score	Accuracy
LR	**countvec**	**0.52 ± 0.07**	**0.58 ± 0.06**
NB	countvec	0.45 ± 0.08	0.52 ± 0.07
LR	handcrafted	0.44 ± 0.07	0.51 ± 0.06
RF	handcrafted	0.42 ± 0.07	0.51 ± 0.06
MV	handcrafted	0.42 ± 0.07	0.51 ± 0.06
LR	tfidf	0.39 ± 0.07	0.51 ± 0.06
RF	tfidf	0.39 ± 0.06	0.50 ± 0.05
MV	tfidf	0.39 ± 0.06	0.50 ± 0.05
KNN	handcrafted	0.39 ± 0.07	0.48 ± 0.07
NB	tfidf	0.34 ± 0.07	0.47 ± 0.06
RF	countvec	0.34 ± 0.07	0.47 ± 0.06
MV	countvec	0.34 ± 0.07	0.47 ± 0.06
NB	handcrafted	0.42 ± 0.06	0.46 ± 0.05
BERT	none	0.41 ± 0.21	0.42 ± 0.21
KNN	countvec	0.15 ± 0.07	0.13 ± 0.05
KNN	tfidf	0.07 ± 0.03	0.07 ± 0.03

Table 2. $Topic$ with $tfidf$ on dataset 1.

Model	Extractor	F1 Score	Accuracy
BERT	**none**	**0.93 ± 0.07**	**0.92 ± 0.08**
LR	countvec	0.77 ± 0.07	0.79 ± 0.05
NB	countvec	0.76 ± 0.06	0.77 ± 0.06
NB	tfidf	0.70 ± 0.06	0.75 ± 0.05
LR	tfidf	0.70 ± 0.05	0.74 ± 0.04
RF	tfidf	0.66 ± 0.07	0.71 ± 0.06
MV	tfidf	0.66 ± 0.07	0.71 ± 0.06
RF	countvec	0.64 ± 0.06	0.71 ± 0.05
MV	countvec	0.64 ± 0.06	0.71 ± 0.05
RF	handcrafted	0.57 ± 0.04	0.63 ± 0.04
MV	handcrafted	0.57 ± 0.04	0.63 ± 0.04
LR	handcrafted	0.55 ± 0.06	0.61 ± 0.06
KNN	countvec	0.50 ± 0.06	0.61 ± 0.05
KNN	tfidf	0.45 ± 0.05	0.59 ± 0.04
NB	handcrafted	0.56 ± 0.05	0.58 ± 0.04
KNN	handcrafted	0.50 ± 0.04	0.56 ± 0.04

Table 3. $BookID$ with $tfidf$ on dataset 1.

Model	Extractor	F1 Score	Accuracy
BERT	**none**	**0.92 ± 0.07**	**0.92 ± 0.07**
LR	countvec	0.77 ± 0.07	0.79 ± 0.05
NB	countvec	0.76 ± 0.06	0.77 ± 0.06
NB	tfidf	0.70 ± 0.06	0.75 ± 0.05
LR	tfidf	0.70 ± 0.05	0.74 ± 0.04
RF	tfidf	0.66 ± 0.07	0.71 ± 0.06
MV	tfidf	0.66 ± 0.07	0.71 ± 0.06
RF	countvec	0.64 ± 0.06	0.71 ± 0.05
MV	countvec	0.64 ± 0.06	0.71 ± 0.05
RF	handcrafted	0.57 ± 0.04	0.63 ± 0.04
MV	handcrafted	0.57 ± 0.04	0.63 ± 0.04
KNN	countvec	0.51 ± 0.06	0.62 ± 0.05
LR	handcrafted	0.55 ± 0.06	0.61 ± 0.05
KNN	tfidf	0.46 ± 0.04	0.59 ± 0.04
NB	handcrafted	0.56 ± 0.05	0.58 ± 0.04
KNN	handcrafted	0.50 ± 0.05	0.54 ± 0.05

Now on the second dataset, witch contains only comments related to the books.

Table 4. *CodePreliminary* with *tfidf* on dataset 2.

Model	Extractor	F1 Score	Accuracy
NB	**handcrafted**	**0.81 ± 0.11**	**0.82 ± 0.12**
LR	countvec	0.79 ± 0.08	0.82 ± 0.10
LR	handcrafted	0.82 ± 0.09	0.82 ± 0.09
RF	handcrafted	0.79 ± 0.08	0.82 ± 0.07
MV	handcrafted	0.79 ± 0.08	0.82 ± 0.07
KNN	handcrafted	0.76 ± 0.10	0.80 ± 0.10
KNN	tfidf	0.67 ± 0.10	0.77 ± 0.08
RF	tfidf	0.61 ± 0.11	0.72 ± 0.09
NB	tfidf	0.61 ± 0.11	0.72 ± 0.09
MV	tfidf	0.61 ± 0.11	0.72 ± 0.09
LR	tfidf	0.61 ± 0.11	0.72 ± 0.09
RF	countvec	0.61 ± 0.11	0.72 ± 0.09
MV	countvec	0.61 ± 0.11	0.72 ± 0.09
NB	countvec	0.58 ± 0.09	0.62 ± 0.10
KNN	countvec	0.34 ± 0.15	0.29 ± 0.11
BERT	none	0.07 ± 0.17	0.12 ± 0.17

Table 5. *Topic* with *tfidf* on dataset 2.

Model	Extractor	F1 Score	Accuracy
LR	**countvec**	**0.82 ± 0.11**	**0.82 ± 0.10**
NB	countvec	0.81 ± 0.11	0.82 ± 0.11
LR	tfidf	0.80 ± 0.15	0.81 ± 0.13
BERT	none	0.79 ± 0.09	0.79 ± 0.07
NB	tfidf	0.77 ± 0.14	0.78 ± 0.13
RF	tfidf	0.71 ± 0.14	0.72 ± 0.14
MV	tfidf	0.71 ± 0.14	0.72 ± 0.14
RF	countvec	0.71 ± 0.14	0.72 ± 0.14
MV	countvec	0.71 ± 0.14	0.72 ± 0.14
KNN	tfidf	0.69 ± 0.18	0.70 ± 0.17
LR	handcrafted	0.55 ± 0.15	0.58 ± 0.13
RF	handcrafted	0.55 ± 0.14	0.57 ± 0.12
MV	handcrafted	0.55 ± 0.14	0.57 ± 0.12
NB	handcrafted	0.52 ± 0.15	0.52 ± 0.13
KNN	handcrafted	0.45 ± 0.16	0.46 ± 0.18
KNN	countvec	0.39 ± 0.17	0.45 ± 0.17

Table 6. *BookID* with *tfidf* on dataset 2.

Model	Extractor	F1 Score	Accuracy
NB	**countvec**	**0.81 ± 0.11**	**0.82 ± 0.11**
LR	countvec	0.82 ± 0.11	0.82 ± 0.10
BERT	none	0.81 ± 0.11	0.82 ± 0.10
LR	tfidf	0.80 ± 0.15	0.81 ± 0.13
NB	tfidf	0.77 ± 0.14	0.78 ± 0.13
RF	tfidf	0.71 ± 0.14	0.72 ± 0.14
MV	tfidf	0.71 ± 0.14	0.72 ± 0.14
RF	countvec	0.71 ± 0.14	0.72 ± 0.14
MV	countvec	0.71 ± 0.14	0.72 ± 0.14
KNN	tfidf	0.67 ± 0.18	0.68 ± 0.18
LR	handcrafted	0.55 ± 0.15	0.58 ± 0.13
RF	handcrafted	0.55 ± 0.14	0.57 ± 0.12
MV	handcrafted	0.55 ± 0.14	0.57 ± 0.12
NB	handcrafted	0.52 ± 0.15	0.52 ± 0.13
KNN	handcrafted	0.44 ± 0.15	0.44 ± 0.17
KNN	countvec	0.37 ± 0.16	0.44 ± 0.15

Conclusion

In our assignment we compared multiple classifiers and models in IMapBooks discussion classifiction.

When comparing the different extractors we came to a conclusion that the countvec performed the best, and then depending on the classification target handcrafted and tf-idf. When we classfied CodePreliminary the handcrafted features performed better than the tf-idf, but performed worse when we classified Book ID and Topic. This is due to the fact that our handcrafted features only take account the structure of the messages, which would make more sense for CodePreliminary.

Overall BERT performed great with an accuracy of 92 % on the first dataset. An interesting observation is that for some reason BERT performed very poorly when predicting the CodePreliminary. Unfortuanatelly we ran out of time to do a more in-depth analysis there. It is important to also note that BERT's accuracy droped in the second dataset, while the accuracy of other classifers increased. This is due to a small dataset, which is not appropriate to use for learning deeper models. It still performed decent on Book ID and Topic, but due to the time complexity it took to predict, simpler classifiers, which take almost no time are more appropriate here.

The results also showed that most of the time Logistic Regression performed best out of the classifiers. An important result was also that KNN performed significantly better on the dataset continaing only messages pertaining to the discussion.

All this means that proper filtering is important when using text classification, as any unwanted or not relevant data will result in significant losses to the accuracy. Also if we use deeper networks, we definitly need enough data to train it, otherwise the results will not be good, due to overfitting or not learning at all.

References

[1] Grandon Gill and Glenn Smith. Imapbook: Engaging young readers with games. *Journal of Information Technology Education: Discussion Cases*, 2:10, 01 2013.

[2] Tomas Pranckevicius and V. Marcinkevicius. Comparison of naive bayes, random forest, decision tree, support vector machines, and logistic regression classifiers for text reviews classification. *Balt. J. Mod. Comput.*, 5, 2017.

[3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. 2019.

[4] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations, 2018.