# 20NewsGroup Project Report

**By Wei Yang**

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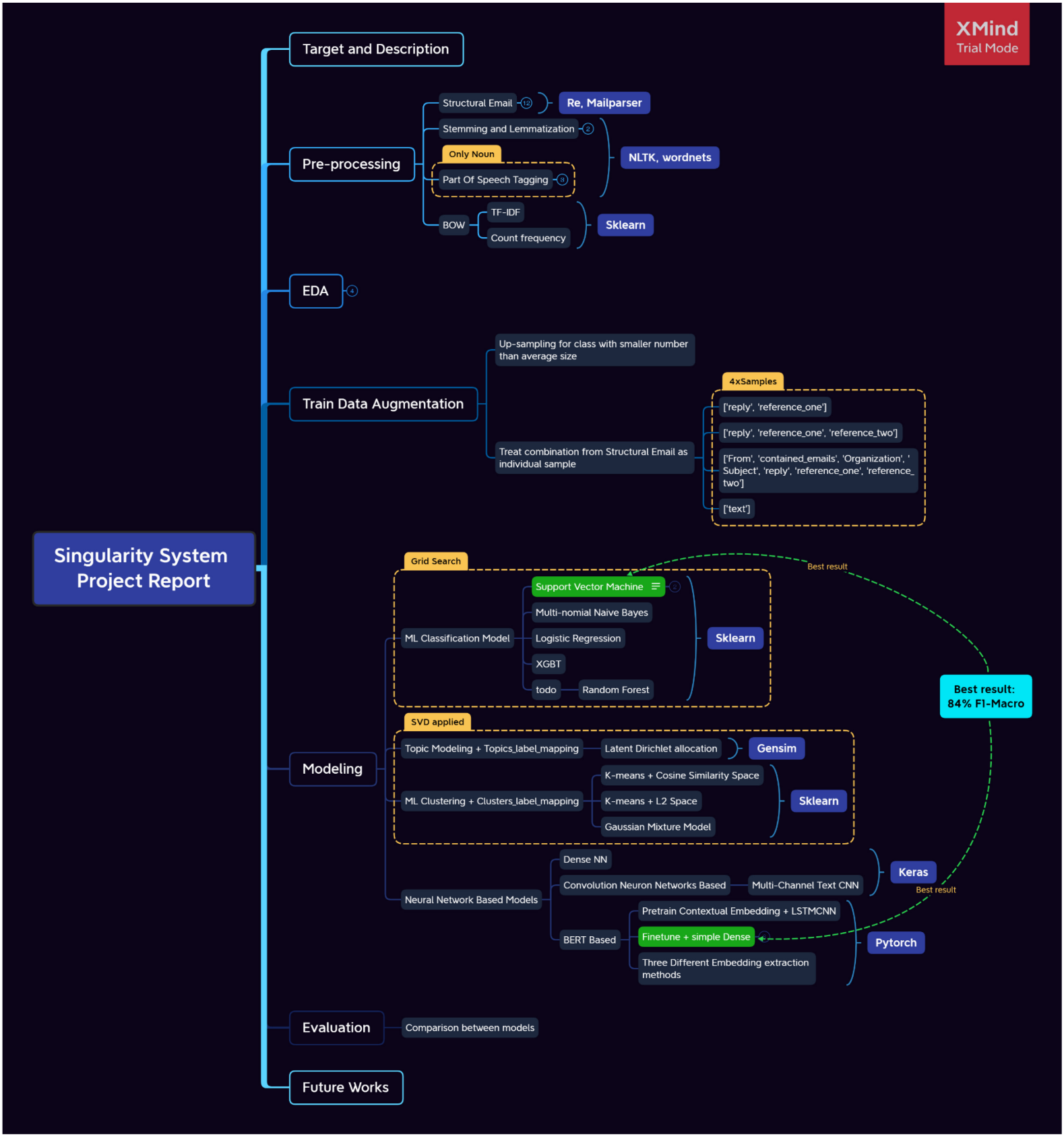


## Summary

After exploration of machine learning models, probability topic modeling, and deep learning models, this project makes a comparison between 10 different models. The best preprocessing procedure is also explored for better performance on each model. With making experiments on data augmentation, up-sampling for small samples, lemmatization, stemming, and feature selection, this project used grid search, cross-validation to find the best setting, and preprocessing path for machine learning models. In addition, clustering, topic modeling, Deep Neural Networks, and multi-channel text CNN are implemented and explored in this project. However, the performance is not that acceptable in such models. At last, this project also explores the performance of finetuning and pretrained BERT stacked with dense neural networks. The best performance has 0.84 macro F1 average scores, which is obtained by both SVM and finetune BERT with a specific preprocessed input.

In the future experiment on the similar dataset, considering the exploration cost, SVM should be tested at first to know the baseline of the model's performance in the dataset. It is well implemented by Sklearn and can be quickly trained with sparse matrix form input, which will reduce the risk of OOM as well. If further exploration is needed, the BERT-related model should be explored. With more detailed hyper-parameters tuning tricks and experience, the BERT model could have even better performance than 84% in this dataset. Furthermore, the finetuned model can also be transferred to other similar datasets to finish the classification task. For future reference, all the utils are wrapped and uploaded into the GitHub repository.


## 1. Introduction

This project is mainly focused on the exploration of the Machine learning model and Deep learning model performance on the 20 News Group (20NG) dataset. Besides, with organized the related tools in Natural Language Processing (NLP) field, the related python packages are wrapped as a higher level utils function in the GitHub for personal future references, such as the utils for preprocessing, clustering, classification, neural networks, and Bidirectional Encoder Representations from Transformers (BERT). With such utils, similar tasks could be easily implemented and tested in the future. With the wrapped utils, the computational expensive training task related to Neural Networks was trained by GPU in Google Colab. The exploration of the model is implemented and demonstrated in the Jupyter notebook.

## 2. Project Framework

To make the accurate prediction on the 20 labeled classes, this project explores the following models:

- Machine learning based models: K-means, Logistic Regression, Multinomial Naive Bayes, Support Vector Machine (SVM), gradient boost tree.
- Topic models: Latent Dirichlet allocation (LDA).
- Deep Learning based models: Fully connected Deep Neural Networks, Multi-channel Convolutional Neural Network, pretrained BERT with LSTM-CNN, finetune BERT with two linear dense layers.

Other parts of the project are showed as the previous mind map page and will be discussed in detail in the Experimental Evaluation part of this report.

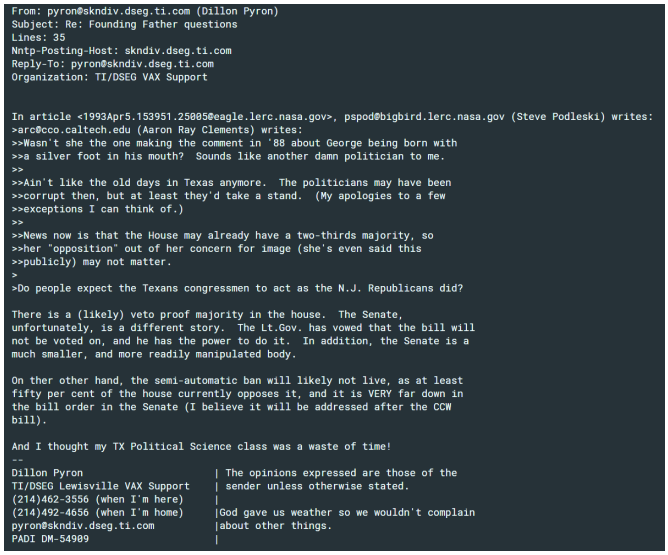
# 3. Data Description and Preprocessing

## 3.1 Data Description

The dataset in this project contains 11,083 training samples and 7,761 test samples. In this dataset, the 1060 and 770 indexes of files are duplicated in training and test samples. For future sample checking and further analysis, the global unique index is created along with the dataset. The graphs below show the basic summary statistics of the dataset and the basic content in one document.

| | label | count_train | percentage_train | count_test | percentage_test |
|---|---|---|---|---|---|
| 0 | alt.atheism | 480 | 0.043310 | 319 | 0.041103 |
| 1 | comp.graphics | 584 | 0.052693 | 389 | 0.050122 |
| 2 | comp.os.ms-windows.misc | 591 | 0.053325 | 394 | 0.050767 |
| 3 | comp.sys.ibm.pc.hardware | 590 | 0.053235 | 392 | 0.050509 |
| 4 | comp.sys.mac.hardware | 578 | 0.052152 | 385 | 0.049607 |
| 5 | comp.windows.x | 593 | 0.053505 | 395 | 0.050896 |
| 6 | misc.forsale | 585 | 0.052784 | 390 | 0.050251 |
| 7 | rec.autos | 593 | 0.053505 | 395 | 0.050896 |
| 8 | rec.motorcycles | 598 | 0.053957 | 398 | 0.051282 |
| 9 | rec.sport.baseball | 597 | 0.053866 | 397 | 0.051153 |
| 10 | rec.sport.hockey | 172 | 0.015519 | 827 | 0.106558 |
| 11 | sci.crypt | 595 | 0.053686 | 396 | 0.051024 |
| 12 | sci.electronics | 591 | 0.053325 | 393 | 0.050638 |
| 13 | sci.med | 792 | 0.071461 | 198 | 0.025512 |
| 14 | sci.space | 593 | 0.053505 | 394 | 0.050767 |
| 15 | soc.religion.christian | 599 | 0.054047 | 398 | 0.051282 |
| 16 | talk.politics.guns | 546 | 0.049265 | 364 | 0.046901 |
| 17 | talk.politics.mideast | 564 | 0.050889 | 376 | 0.048447 |
| 18 | talk.politics.misc | 465 | 0.041956 | 310 | 0.039943 |
| 19 | talk.religion.misc | 377 | 0.034016 | 251 | 0.032341 |

**Table 1: dataset summary statistics**



```
From: pyron@skndiv.dseg.ti.com (Dillon Pyron)
Subject: Re: Founding Father questions
Lines: 35
Nntp-Posting-Host: skndiv.dseg.ti.com
Reply-To: pyron@skndiv.dseg.ti.com
Organization: TI/DSEG VAX Support


In article <1993Apr5.153951.25085@eagle.lerc.nasa.gov>, pspod@bigbird.lerc.nasa.gov (Steve Podleski) writes:
>arc@cco.caltech.edu (Aaron Ray Clements) writes:
>>Wasn't she the one making the comment in '88 about George being born with
>>a silver foot in his mouth?  Sounds like another damn politician to me.
>>
>>Ain't like the old days in Texas anymore.  The politicians may have been
>>corrupt then, but at least they'd take a stand.  (My apologies to a few
>>exceptions I can think of.)
>>
>>News now is that the House may already have a two-thirds majority, so
>>her "opposition" out of her concern for image (she's even said this
>>publicly) may not matter.
>
>Do people expect the Texans congressmen to act as the N.J. Republicans did?

There is a (likely) veto proof majority in the house.  The Senate,
unfortunately, is a different story.  The Lt.Gov. has vowed that the bill will
not be voted on, and he has the power to do it.  In addition, the Senate is a
much smaller, and more readily manipulated body.

On ther other hand, the semi-automatic ban will likely not live, as at least
fifty per cent of the house currently opposes it, and it is VERY far down in
the bill order in the Senate (I believe it will be addressed after the CCW
bill).

And I thought my TX Political Science class was a waste of time!
--
Dillon Pyron                    | The opinions expressed are those of the
TI/DSEG Lewisville VAX Support  | sender unless otherwise stated.
(214)462-3556 (when I'm here)   |
(214)492-4656 (when I'm home)   |God gave us weather so we wouldn't complain
pyron@skndiv.dseg.ti.com        |about other things.
PADI DM-54909                   |
```

**Fig 1: sample document before parsing**

The samples are imbalanced in classes including rec.sport.hockey and sci.med. For better performance on the test set, the weights for them may need to be adjusted. Or, we can just up-sampling the rec.sport.hockey class to make sure our model will equally fit the features underlying each class. This project chooses the latter one as the option in the program.

## 3.2 Preprocessing

The preprocessing mainly works in two different directions depending on the models. The first direction is treated as a sequence with order information, which means more patterns could be recognized. The second direction is to treat the words in the document as a bag of words, which means the order of words is not important.

### 3.2.1 Data Cleaning

The original unstructured corpus contains lots of noise in the dataset. By utilizing the mail parser, the email can be separated into the main body and header parts. The header can be quite clearly separated and extracted, but for the main body of the email, some noise still existed. For example:

- Due to the reference of the previous emails, the reply of the email is not separated by the reference with the “>” symbol before the line of sentence.  And the email address also exists before every reference.
- Some of them contain binary data, which is image attachment that cannot be decoded by utf-8. To parse such binary data, some rules-based method implemented with regular expression.

After using multiple regular expressions strategically, two previous problems are fixed. For the previous sample, the program can generate the following structural json file:


```
{
    "From": { "0": "pyron@skndiv.dseg.ti.com (Dillon Pyron)" },
    "Subject": { "0": "Re: Founding Father questions" },
    "Lines": { "0": "35" },
    "Nntp-Posting-Host": { "0": "skndiv.dseg.ti.com" },
    "Reply-To": { "0": "pyron@skndiv.dseg.ti.com" },
    "Organization": { "0": "TI/DSEG VAX Support" },
    "reply": {"0": "There is a veto proof majority in the house. The Senate, unfortunately, is a different story. The Lt. Gov.
    "reference_one": { "0": "Do people expect the Texans congressmen to act as the N.J. Republicans did?" },
    "reference_two": {"0": "Wasn't she the one making the comment in '88 about George being born with a silver foot in his mou
    "date": { "0": null },
    "delivered_to": { "0": [] },
    "to_domains": { "0": ["skndiv.dseg.ti.com"] },
    "error_message": { "0": null },
    "contained_emails": {"0": [" <1993Apr5.153951.25005@eagle.lerc.nasa.gov>, ", "pspod@bigbird.lerc.nasa.gov ", " >arc@cco.ca
    "long_string": { "0": [] },
    "tag_reply": {"0": "veto proof majority house story bill power addition body hand ban cent house bill order Science class
    "tag_reference_one": { "0": "people Texans congressmen Republicans" },
    "tag_reference_two": { "0": "comment foot mouth damn politician days politicians stand majority opposition concern image"
}
```


**Fig 2: sample document after parsing**

The reply contains all the reply body information of this email. The reference_one contains the previously received information. The reference_two contains all the contents before the previous email was sent to this sender. The long_string is used for binary data detection.

The reason why this project separates the reply and reference is that some models there will need to encode the sentence information. With order information, the language model and BERT-based model can recognize more patterns from the corpus in a correct way.

### 3.2.2 Bag of Words features

Excepts for considering the sequence information, we can use only the words frequency information. With the well-built NLP techniques, we can directly tokenize all the sentences in emails with regular expressions or well-implemented Tokenizer class from Sklearn. By treating each email as a sample, we can build the term of frequency matrix (TF matrix) or term frequency-inverse document frequency (TF-IDF matrix). And further preprocessing option describes as follows:

- Lemmatization and Stemming: without any filter, the number of unique tokens will be 127,414, which is not acceptable since the curse of dimensionality. It will consume too many computational resources, which probably lead to OOM. Therefore, before tokenization, the lemmatization and stemming for each vocabulary is included, which is also implemented as an option in the program. And only 10,593 vocabularies will be considered.
- The Part of Speech tag parser also implemented in case that the NOUN already covers lots of information in the documents. They are treated as optional extra features in this project.
- For stop words, we need to remove it in this direction since it is the noise and will not add any information for helping prediction task. The later grid search experiment result also proved this.
- The high frequency words will be multiplied by inverse-document frequency (IDF) weight to lower down the importance of the columns, which is quite useful for reducing the noise signal underlying features.

Before the preprocessing, the highest frequent word in this dataset shows as the left word clouds. And the right one is after filtering symbols, lemmatization, stemming and removing stop words.


Fig 3: wordcloud before cleaning

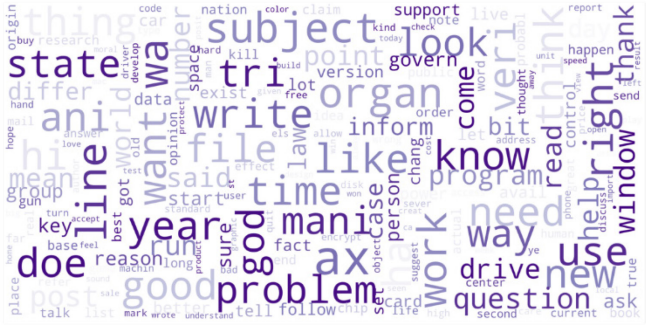



Fig 4: wordcloud before cleaning

### 3.3 Document Length and Word Frequency

After previous preprocessing, the following graph shows the frequency distribution of the words across all documents. The x-axis is the word index generated by Keras Tokenizer class, which will treat the higher frequency word with a lower index value. The y-axis is the cumulative frequency ratio of the words in all corpus. When setting the threshold equal to 98% of the frequent words, we need to consider 4587 words in the vocabulary. With 95% threshold, we only need to consider 2899 words.

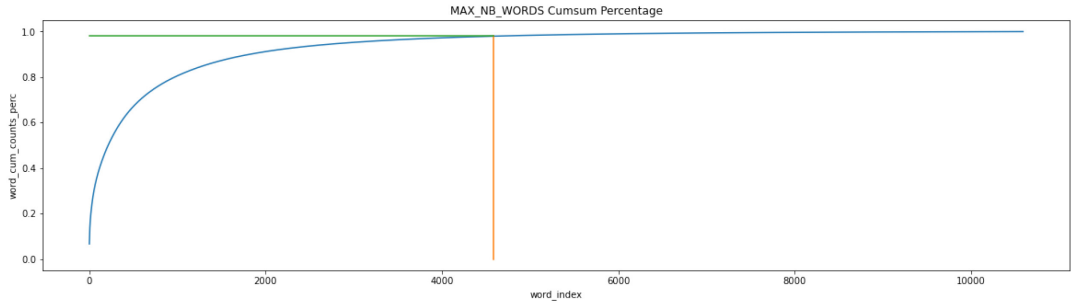



Fig 5: word frequency cumsum distribution

For the document length, the following graph shows the document length distribution across all documents. When setting the threshold equal to 95% of the frequent length of the document, we need to consider 210 as the max length of all documents. In other words, it means 95% of the document has a length of less than 210 after being preprocessed. The x-axis is the length of the document, the y-axis is the frequency ratio of the corresponding length. Some of the extreme long documents are the email attached the binary image data, for example, the file comp.os.ms-windows.misc named as 9986 only contains roman.bmp binary data, which has 956 lines and 59,105 characters.

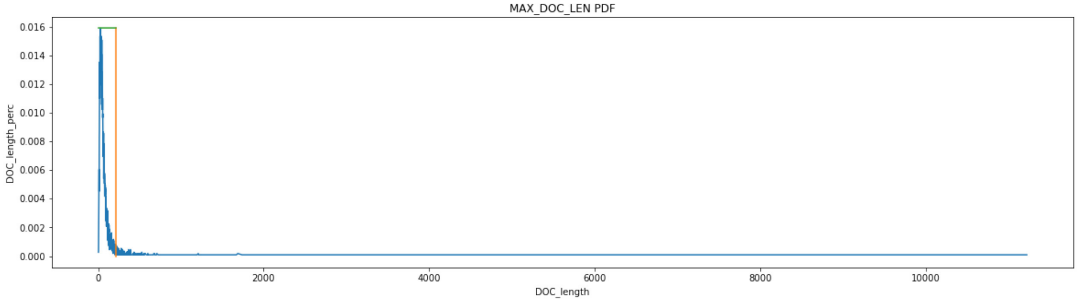



Fig 6: document length frequency distribution

## 4. Best Performance Summarization

All the models are trained only with the train data. But with different preprocessing methods, the training input will be slightly different. The Jupyter notebook files keep the evaluation record inside of them. The models are reproducible in a short time, so the models' parameters did not save locally in this period. The augmentation means doubling the training set by extracting reply and reference_one columns separately to double the training set.

| Model | Preprocessing | Input | Hyper-params | Best F1-macro Avg till Dec 13th |
|---|---|---|---|---|
| SVM | Augmentation[1] | TFIDF matrix | C=3, penalty='l2' | **0.84±0.01** |
| Multinomial Naïve bayes | Augmentation | TFIDF matrix | - | 0.787±0.01 |
| Logistic Regression | Augmentation | TFIDF matrix + Dimension reduction | - | 0.807 |
| Xgboost | Augmentation | TFIDF matrix | - | 0.835 |
| Deep Neural Networks | Up-sampling, Lemmatizing, Stemming, one-hot for Subject Organization | TFIDF matrix + extra one-hot encoding | Input dim 3236+5691<br>Batch size 256<br>Optimizer Adam lr 0.005 | 0.73±0.01 |
| Multi-channel Text CNN + Dense Neural Networks | Up-sampling | document -> embedding | Max Doc length 560<br>Max Number word 15235<br>Filter Size [1,3,5]<br>Number filters 64<br>Optimizer RMSprop 0.0005<br>Batch size 32 | 0.746 |
| Finetune BERT + Dense Neural Networks | Up-sampling, Feature selection [2] | document -> embedding | Max Doc length 300<br>Embed dim 200<br>Filter Size [1,3,5]<br>Linear Hidden units 64<br>Optimizer AdamW 0.00005<br>Batch size 32 | **0.84±0.01** |
| Pretrain BERT embedding + LSTM-CNN | - | pretrain embedding | - | less than 0.6 |
| Kmeans + Majority vote | - | TFIDF matrix + Dimension reduction | - | less than 0.5 |
| Latent Dirichlet allocation + Majority vote mapping | - | TFIDF matrix + Dimension reduction | - | less than 0.5 |
| Multi-layer Bidirectional LSTM | - | document -> embedding | - | Not implemented |

**Table Table 2: Summary of model performance**

[1] Treat combination [['text'], ['reply', 'reference_one']] separately to double the training set
[2] Select columns: ['Subject','Organization', 'reply', 'reference_one']

# 5. Experimental Evaluation

## 4.1 Preprocessing

The model input is the TF-IDF matrix, and the output is the prediction labels for each test sample. To achieve better result, the first step in this project is defined preprocessing procedure, such as up-sampling for small class, data augmentation, string normalization. Select proper preprocessing methods will increase the final performance at least 5%.

- Up-sampling is a bootstrap technique that sampling with replacement from original train set. In our case, this is used especially for handling the imbalance problem in the small group class like rec.sport.hockey, talk.religion.misc. Model may treat the features underlying classes differently because the sample size are different. Another method is apply the class weight in the training process, for example increase the weight of rec.sport.hockey as 2, and the others are 1.

- Data augmentation in there is based on the preprocessing that this project already done before. The original email is spitted into subject, reply, reference one and reference two etc. This project will treat them as different samples for different combinations of them. For example, with the text and the label pair, the reply and the label pair, and the reply and all other reference pair, the model's input will be triple for training.

- The string normalization is for removing stop words and parsing special symbols.

## 4.2 Machine Learning Models

### 4.2.1 Comparison between SVM, Naïve Bayes and Logistic Regression

The following table summary the best model performance on different preprocessing methods.

| model_preprocessing | mean_fit_time | mean_test_score | std_test_score |
|---|---|---|---|
| SVC-augmentation[3] | 9.607 | 0.992 | 0.005 |
| NB-augmentation | 3.437 | 0.939 | 0.008 |
| SVC-upsampling+normalstring_stage2[4] | 4.301 | 0.924 | 0.012 |
| SVC-upsampling+normalstring | 3.716 | 0.924 | 0.012 |
| SVC-upsampling | 3.933 | 0.923 | 0.012 |
| LR_1-upsampling+normalstring_stage2 | 56.258 | 0.893 | 0.003 |
| SVC-upsampling+normalstring+augment_stage2 | 12.126 | 0.893 | 0.124 |
| NB-upsampling+normalstring | 2.007 | 0.892 | 0.01 |
| NB-upsampling+normalstring_stage2 | 1.953 | 0.892 | 0.01 |
| NB-upsampling | 2.289 | 0.889 | 0.01 |
| NB-upsampling+normalstring+augment_stage2 | 3.508 | 0.861 | 0.125 |
| LR_1-upsampling+normalstring+augment_stage2 | 41.108 | 0.847 | 0.085 |
| SVC-upsampling+stem_voc_stage2 | 1.651 | 0.839 | 0.024 |
| NB-upsampling+stem_voc_stage2 | 1.025 | 0.813 | 0.014 |
| LR_1-upsampling+stem_voc_stage2 | 1.489 | 0.806 | 0.002 |
| LR_2-upsampling+stem_voc_stage2 | 162.465 | 0.802 | 0.001 |

**Table 3: Best model average score with different preprocessing methods**

[3] Treat combination [['text'], ['reply', 'reference_one']] separately to double the training set
[4] Stage 2 meaning the additional grid search setting for the models

This table show the data augmentation is quite useful in Support Vector Classifier (SVC). Since the training set is also enlarged, which mean the model will be evaluated in larger validation set. However, the model average performance still increases with such techniques.

The second step is for finding the best hyper-parameters setting. In each preprocessing setting with grid search and cross-validation. This project applies the grid search to find the best hyper-parameters settings to obtain the TF-IDF matrix and the best model settings. Based on the F1-macro score with 3-fold cross-validation, the following table briefly summarizes the performance with different hyper-parameters setting for SVC. The grid search is performed on the TF-IDF hyper-parameters, including binary, minimum document frequency, stop words, inverse document frequency. It also combined with the hyper-parameters on SVC, including regularization weight C and the coefficient penalty norm.

| param_clf__C | param_clf__penalty | param_tfidf__binary | param_tfidf__min_df | param_tfidf__stop_words | param_tfidf__use_idf | mean_test_score |
|---|---|---|---|---|---|---|
| 3 | l2 | TRUE | 1 | | TRUE | 0.9919 |
| 3 | l2 | TRUE | 1 | english | TRUE | 0.9913 |
| 2 | l2 | TRUE | 1 | | TRUE | 0.991 |
| 2 | l2 | TRUE | 1 | english | TRUE | 0.9905 |
| 3 | l2 | TRUE | 3 | | TRUE | 0.9905 |
| 2 | l2 | TRUE | 3 | | TRUE | 0.9901 |
| 3 | l2 | TRUE | 3 | english | TRUE | 0.99 |
| 3 | l2 | TRUE | 5 | | TRUE | 0.9898 |
| 2 | l2 | TRUE | 3 | english | TRUE | 0.9897 |
| 3 | l2 | FALSE | 1 | english | TRUE | 0.9894 |
| 2 | l2 | TRUE | 5 | | TRUE | 0.9893 |
| 3 | l2 | FALSE | 1 | | TRUE | 0.9893 |
| 1 | l2 | TRUE | 1 | | TRUE | 0.9889 |

**Table 4: Grid Search setting for SVC**

The table shows the binarize the term of frequency is useful in this case. It will treat the words equally as the word appears in one document, even maybe some of the words appear several times. The IDF is needed for the lower weight of some trivial words like the conjunction, article, etc. The stop words are not that influential is because the IDF and binarize setting already flatten the signal that stopwords have. For the penalty term and coefficient C in the SVC, the higher C will add more penalty on the coefficient norm, which will improve the generalization capability of the model. The SVD dimension reduction transformation is also tested in this experiment. After shrinking the dimension to 1000, the performance will only reduce at most 5%. The option is adjustable, and it is dependent on the deployment environment.

The related tools are wrapped as classification_utils.py and models are implemented in Jupyter notebook files in the repository. And in this direction, the best SVC model has F1 macro average score is 0.835, F1 micro average score is 0.847 on the test set. The hyper-parameters C is 3 and penalty norm is L2. The best Multinomial Naïve Bayes (NB) has F1-macro with 0.815 and F1 micro average score is 0.830 on the test set. The hyper-parameters alpha is 0.6 for NB.

### 4.3 Topic modeling and K-means Clustering

This project also made exploration on K-means clustering and the topic modeling with Latent Dirichlet allocation model. With the labeled train dataset in each group, the majority rule will map the highest frequent labels in each cluster or each topic into the ground truth label. In other words, all the samples in the group will be treated as the label with the largest size in the group. However, both are performed not well in such a dataset. Even considering the cosine similarity between each sample, the models still performed badly. The highest accuracy can only achieve 45% in experiments. In addition, the feature space is large, and such clustering methods are computationally expensive. Even after the truncated singular value decomposition (SVD), the model cannot perform well after transformation in the 500 largest eigenvector space. At the last stage, this direction is disposed of, but it might perform well in the small size dataset and a small number of classes. The toolkit is prepared and wrapped as clustering_utils.py for future reference.

### 4.4 Neural Network Based Models

In this part, the project explores three types of Neural Networks, including the Deep Neural Network with only dense layers (Dense NN), Multi-Channel Text Convolution Neural Network (TextCNN), and the BERT based models. The RNN and its variants are not explored since the training processes cannot be computed by GPU, which means the model is slow to converge to get the evaluation result. All the training process applied the early stopping techniques based on the categorical accuracy on the validation set, which is stratified samples from 20% of the training data.

#### 4.4.1 Dense Neural Network

For the Dense NN, it was constructed by several fully connected dense layer. Rather than use the embedding layer to extract information from text, this model use TF-IDF matrix as it's input. It has the horizontal structure shows as the following simple graph.

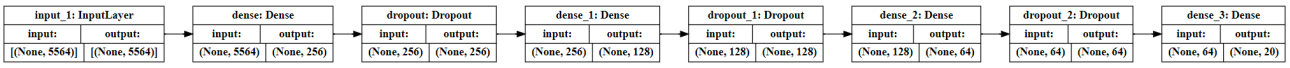



**Fig 7 Deep NN structure**

In this model, this project also tried to append extra keywords features as one-hot encoding along with the TF-IDF after dimension reduction, but the performance even worst due to the information lost in this case. Since it is kind of model based on Bag of Word, with enough computational capabilities, more information should be included in the input.

The code is implemented with Keras and wrapped as nn_utils.py in the repository. After tuning the hyper-parameters, the best F1 macro average score is 0.702, F1 micro average score is 0.712.

#### 4.4.2 Multi-channel TextCNN

For the TextCNN, this project sets the embedding dimension with 200. It applies the several 1-dimension Convolution kernel to filter features from the embedding matrix. The kernel size will determine the observed window in the document, which acting like n-gram in language model. But the

TextCNN will not consider the order information. For example, “cat love dog” is the same as “dog love cat” in this model. As the following graph shows, several channels are used to extract n-gram features from the document input. Finally, the feature maps will be flattened and concatenated together for the next fully connected dense layers. Basically, the multi-channel CNN acted like a feature extractor. Like pre-train BERT did. But the BERT will consider more detailed sequential information rather than only bag of words and n-gram combinations in TextCNN. The CNN extractor has the structure shown as the following simple graph. And the classifier on the top of this extractor is similar to the Dense NN. The hyper parameters in the final version make a trivial adjustment.

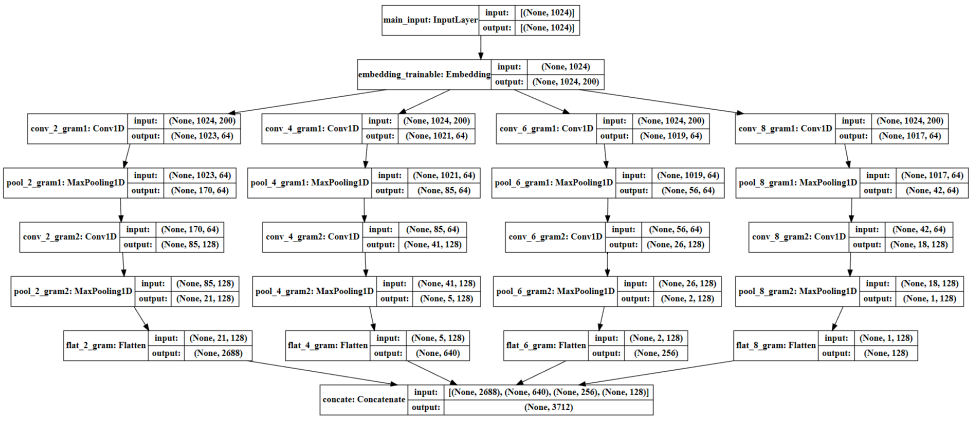



**Fig 8 Multi-channel CNN feature extractor structure**

In this model, with enough regularization tricks like dropout to prevent overfitting. The model seems cannot extract more information from the train dataset after 10 epochs. In other words, the model achieves its structure limit to exploit more information from the original dataset.

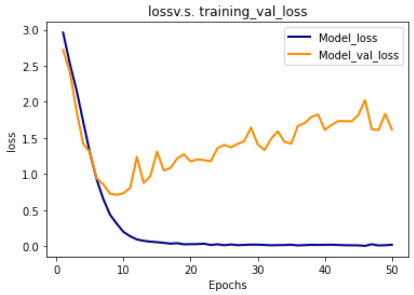



**Fig 9 TextCNN training loss history**

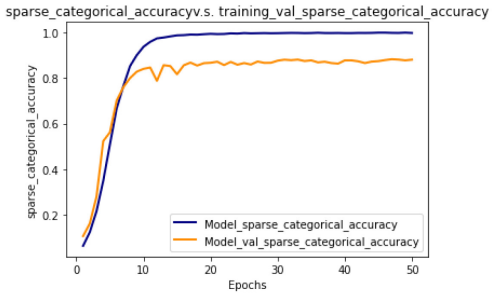



**Fig 10 TextCNN training accuracy history**

Although the SVC has the same input, TextCNN may be easier influenced by the noise in the dataset. To further improve the performance in this classification task. This project further explores the BERT model structure with the previous split reply, reference in the document since those kinds of preprocessing keeps the sequential information on the document.

The code is implemented with Keras and wrapped as nn_utils.py in the repository. The model is training on the Google colab. After tuning the hyper-parameters, the best F1 macro average score is 0.75, F1 micro average score is 0.76.

### 4.4.3 Pretrain-BERT

In this direction, this project explores the pretrain BERT contextual embedding. With treated BERT as a document encoder, it will generate hidden state on the last layer for every word, which is also including the special tokens [CLS]. For obtaining better performance, this project explores four different ways to use the BERT output.

A. Use the [CLS] token embedding, which compressed all the documents information into it.

B. Use all contextual embedding output for every word in the document, which will consider all the tokens embedding as the input of the next stage. This way is computational expensive. In this case, the classifier on the top of this output is LSTM and CNN, with treated the BERT output only as a special embedding which probably encode the document in a proper way.

C. Like the previous one, the hidden states from last four layers can be averaged to represent the whole document.

D. Use the global pooler output. But this output is not a good summary of the semantic content of the input from the experiment outcome.

However, the performance of with pretrain BERT and LSTM-CNN is not acceptable. It cannot even beat the baseline from the SVC. That's why this project further explores the finetune version of BERT, which is far better than pretrain one.

### 4.4.4 Finetune-BERT

Similar to the pretrain BERT, this project explores different usage of the embedding output from BERT. However, the parameters in there will be adjusted and finetune by the training dataset. This model finally chooses type A embedding, the [CLS] token embedding, for the downstream tasks. On the top of BERT, the whole model structure further stacks two dense layers to handle the final classification task. The following graphs show the training accuracy and loss along with the epochs. The same, early stopping technique applied there, which is stratified samples from 20% of the training data.

During the training process, the norm clipping is added to make sure the gradient will not explode. The maximum norm of the gradient is limited to 1. The other hyper-parameters of this model are: learning_rate = 0.00005, epochs = 20, batch_size = 32, hidden_units = 64, MAX_DOC_LEN = 300.

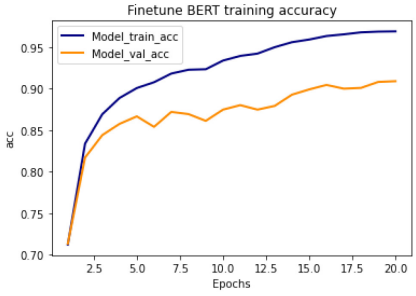



**Fig 11 Finetune BERT training loss history**

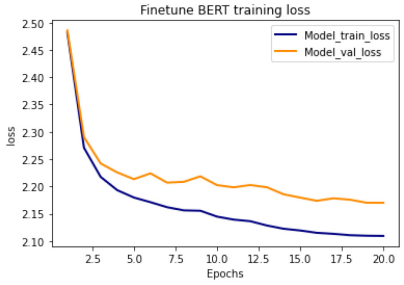



**Fig 12 Finetune BERT training accuracy history**

The code is implemented with Pytorch and Transformer from hugging face. The related functions are wrapped into bert_utils folder in the repository. The model is training on the Google colab. After tuning the hyper-parameters, the best F1 macro average score is 0.83, F1 micro average score is 0.85.

## 6. Alternative Methods & Future Work

- For this classification task, some well-implemented toolkit like Vowpal Wabbit, an interactive machine learning library, could be explored.
- With the larger dataset, for a faster training process on machine learning solutions, the model could be deployed with AWS EMR and finished by the training process by distributed clusters.
- After further organized and storing the model's parameters, they can be loaded together and ensembled with a majority vote for label prediction.
- Implemented Graph-based BERT to further exploit language information on the document.
- More detailed parameters tuning for a large models such as BERT and TextCNN.

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