TEXT CLASSIFICATION ON NEWS ARTICLES

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TEXT CLASSIFICATION ON NEWS ARTICLES

ABSTRACT

An abstract must not exceed 500 words, typed in a single paragraph with double- spacing, and written in Bahasa Malaysia and English language. A maximum of five (5) keywords should also be listed below the abstract.

Keywords: Keyword, keyword, keyword, keyword.

ABSTRAK

Ini merupakan abstrak dalam Bahasa Melayu (satu perenggan).

ACKNOWLEDGEMENTS

Thanks guys. I owe you many.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

As optical character recognition technology advances, large number of physical documents are made electronically available and many more articles are created and available online. The information contain within these documents would need to be extracted, analyzed, stored and made searchable so that others can make use of it. Natural language processing (NLP) methods are needed to analyze the content or the sentiment in the text.

Document classification is one of the NLP method that categorize the text into different topics or categories. This classification would be helpful to future researchers who want to find some topic from the text. The researchers could just focus on the category they are interested in rather than skimming through all the documents to obtain the intended information.

The technology breakthrough in recent years, machine learning algorithms, processing power of processors have been a boost in NLP field. With the breakthroughs, there has been an advancement of the methods used in NLP with artificial intelligence without the need of intervention of domain experts.

There are several approaches to the document classification problem, multilabel where each document can belong to several categories or classification, where each document can only belong to one category. Within machine learning methods, there is clustering which is an unsupervised learning method or the supervised learning approach. This shall focus in the the direction of classification rather than multilabel and clustering.

In document classification most of the algorithms used vector space model to represent the unstrucutured textual data. (Ababneh, Almanmomani, Hadi, El-Omari, & Alibrahim, 2014). This vector space model represent the sequence of the textual features and their

weight, it is easy to implement and provide uniform representation for documents. However, it has a drawback, it represent all the words in the documents, the dimension of the vector would be huge. This huge vector space model would impact the performance of the machine learning tasks. (Moldagulova & Sulaiman, 2018). Therefore, this study would focus on the dimension reduction on vector space model on document classification.

1.1.1 Problem Statement

Term vectors is one of the most commonly used document representation algorithms, but dimension of the feature space can too large and the vectors can be too sparse. (Moldagulova & Sulaiman, 2018)

1.1.2 Research Objectives

1. To identify a document representation algorithm that is optimized to extract the features from news articles
2. To investigate the machine learning (ML) algorithm used in document classification and apply the most suitable algorithm.
3. To evaluate the performance of the document represenation and document classification algorithm.

1.1.3 Research Questions

1. Which dimension reduction algorithm is optimized for news article?
2. How complexities of the features influence the accuracy?
3. Which is the best machine learning algorithms in document classification?

1.1.4 Research Motivation

In the age of big data, the amount of data generated and collected is growing at an explosive rate. Much of the data generated and collected is in the form of unstructured

text. The value contained within the text cannot be extracted and be useful to us without natural language processing (NLP). Document classification is one of the pillars in natural language processing.

In document classification, the unstructured text would be given a label or multiple label dependent on the method used. These labels would make the data more meaningful and searchable. Users can search for a topic just by selecting text with the particular label rather than performing a manual word search on all the text document.

Bag of words is the most commonly used document representation method in document classification. Bag of words would produce a vector space model of the textual data representation. The dimension of this vector space model would be big because of the amount of words in the documents. This huge dimension of vector space model would decrease the performance of the document classification algorithms.

With dimension reduction algorithms, the dimension of the vector space would be decreased and the performance of the machine learning algorithms would be increased. However, the effect of the different dimension reduction algorithms might have a different effect on the performance of the machine learning algorithms.

This study would investigate the effect of the dimension reduction algorithms on the performance of the machine learning algorithms.

1.1.5 Research Significance

This ressearch would classify news articles into different categories. In order to do that, first the features have to be extracted from the documents. The features might need to be compressed. Then the features are used to train machine learning models. After that, the trained machine learning models are validated and tested to evaluate its performance.

The document representation method is the most commonly used bag of words approach, Term Frequency - Inverse Document Frequency (TF-IDF). In this approach, the documents

are converted into vector space models. Due to the large amount of words in the documents, the vector space would be large and sparse, this is known as the curse of dimensionality problem. This large and sparse vector space would be an obstacle to document classification, machine learning models accuracy would be impacted due to the large vector space.

By applying dimension reduction algorithms to the vector space model, the vector space and sparsity of the vector could be reduced. With the reduced vector, the accuracy of the machine learning models would be increased. However, which of the dimension reduction algorithms would perform best for document classification on news articles? This study would try to answer this question by studying which of the dimension reduction algorithm is most suitabled and applying it on a dataset.

1.1.6 Expected Outcome

1. A prototype document classification application with 80
2. A dimension reduction algorithm is applied on the extracted features of the documents
3. A best suited machine learning algorithm is applied on the document classification application
4. Evaluate the accuracy of the document classification application

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In text classification proposed in this study, there are 3 stages namely document representation, dimension reduction and classification. For document representation the chosen method is Term Frequency-Inverse Document Frequency (TF-IDF) which is based on the bag of words method. TF-IDF provide a measure of weight or importance to the words. The value of TF-IDF estimate the amount of information provided by each word in its document. (Arroyo-Fernández, Méndez-Cruz, Sierra, Torres-Moreno, & Sidorov, 2019) The value of TF-IDF increases proportionally to the number of times a word appears in a document but is offset by the frequency of the word in the corpus. This means that if a word appears for many times in a document but it also appears for many times in many other documents in the corpus, then it is not an important word. TF-IDFThe formula for TF-IDF is shown below:

$$TFIDF = tf \times \log_e \frac{N}{df} \tag{2.1}$$

where:

tf = the number of times a word appears in a document

N = the total number of documents in the corpus

df = the number of documents that contain the word

The remaining parts are dimension reduction and classification, the methods in these 2 parts would be evaluated and chosen.

2.2 Dimension Reduction

2.2.1 Single Value Decomposition (SVD)

Single value decomposition is one of the most commonly used dimension reduction algorithms. It generalizes a complex matrix with many dimensions into a matrix of lower dimension via an extension of the polar decomposition. SVD detects the part of the data that contains the maximum variance in a set of orthogonal basis vectors. The data with the maximum variance would be the most prominent features of the data. (Sweeney et al., 2014)

Latent Semantic Analysis (LSA) a technique applied in natural language processing that apply SVD in its process. SVD is applied in LSA to transform the features by dropping the least significant values in the matrix thus reducing the dimensions of the matrix. (Karami, 2017)

Even though SVD has been applied in LSA and in other fields, it has been found that SVD is not as efficient as principal component analysis (PCA) and has a few drawbacks. SVD can extract the prominent features of the matrix but it does not help in reducing the sparsity of the matrix. In some of text clustering algorithms that used SVD for dimension reduction only find SVD useful when the features are redundant. (Narhari & Shedge, 2017)

2.2.2 Nonnegative Matrix Factorization (NMF)

Nonnegative matrix factorization (NMF) is a multiplicative updating solution to decompose a nonnegative temporal-frequency data matrix into the sum of individual components. The sum of individual components are calculated from a nonnegative basis matrix. (Chien, 2019)

NMF and its variant have found to be applied in many fields such as feature extractions, segmentation and clustering, dimension reduction and others. However, the nonnegativity constraints of NMF proved to be problematic when the data matrix is not strictly non-

negative. The semi-NMF relaxes the non-negativity constraint of NMF so that the resulting matrix has mixed signs. (Allab, Labiod, & Nadif, 2017)

Researchers who performed experiments to compare the performance of SVD, NMF and PCA have found that NMF do not perform as well as PCA. SVD and NMF achieved a similar accuracy in the experiment. This might due to both SVD and NMF are dependent on matrix decomposition technique while PCA is dependent on eigenvalue decomposition. (Mohamed, 2019)

NMF might be more suitabled for clustering as it took the least amount of time in clustering the data compared with SVD and PCA. (Mohamed, 2019). This advantage of NMF over SVD and PCA is negligible in this study since this study would focus on classification rather than clustering.

2.2.3 Principal Component Analysis (PCA)

Principal component analysis is one the state of the art dimension reduction algorithm. The main purpose of PCA is to project data samples from high dimensional space into low dimensional space by linear transformation while preserving the original data features as much as possible. (Ma & Yuan, 2019) In other words, PCA is used to emphasize the variations in the data, bring out the important features in the data.

PCA is no stranger to the text classification field. It has been applied to different languages of text classification other than English. Label Induction Grouping (LINGO) a technique used in categorizing Indian Marathi language text document. PCA is applied in LINGO performed better than SVD as PCA extract the features better and has less loss of information. (Narhari & Shedge, 2017)

In another research on text classification on Arabic text and English text, it is also found that PCA outperformed SVD and NMF. The researchers found that PCA yields better result in terms of accuracy and normalized mutual information. The advantage of PCA is

that after transforming the matrix, the important features vector are orthogonal to each other. PCA also has a whiting transform that reduce noises in the data which in turn boost the performance and the accuracy of the machine learning algorithm.(Mohamed, 2019)

A variant of PCA which is in the form of a tree structure has been applied on the dimension reduction on sentiment analysis. The technique is called tree-structured multi-linear principal component analysis (TMPCA). TMPCA can retain the sentence structure and word correlations. (Su, Huang, & Kuo, 2018). However, this is a novel technique and PCA has been proven to be effective enough to handle the amount of data in this study.

2.2.4 Summary

The 3 dimension reduction or matrix decomposition algorithms above are considered blind source separation (BSS) methods, unsupervised learning algorithms. Its performance might not be as good as a deep learning algorithm such as Word2vec but deep learning algorithm's performance is dependent on the the scale of the data. Deep learning algorithm can only perform well when there is a lot of data. In our study, the data might not be sufficient to use a deep learning algorithm, thus the above methods are reviewed. Out of the 3 dimension reduction algorithms reviewed above, PCA seems to be the most promising in the field of text classification. Therefore, PCA would be chosen as the dimension reduction algorithm in this study.

2.3 Document Classification

2.3.1 Support Vector Machine

Support vector machine is a machine learning algorithm that construct a hyper plane to separate the examples into different classes. It has been proven to be very effective in dealing with high dimensional data. (Shinde, Joeg, & Vanjale, 2017). It is also proven to produce dramatically best results for topic modelling in experiments with the Reuters dataset.

(Dumais, Platt, Heckerman, & Sahami, 1998). Various issues need to be considered when applying SVM in document classification, the processing of the data, which kernel to use, and the parameters of SVM. A variant of SVM, called one-class SVM which is trained only with positive information has been used in document classification. (L. M. Manevitz & Yousef, 2002). The authors experimented with different kernels of SVM (linear, sigmoid, polynomial, and radial basis) with different type of document representation method (binary representation, frequency representation, TF-IDF representation, and Hadamard representation). The best result (F1 score of 0.507) is achieved with binary representation, feature length 10 and with linear kernel function.

In another research, the researchers apply SVM in the classification on web document instead of news or ordinary text document. The document representation method used in this research is vector space model, just the nouns term in the web pages. The researchers experimented with different SVM kernels and varying the size of the training sets. Expectedly, the precision, recall and accuracy increased as the size of the training set increase. Linear kernel achieved the best result out of the various SVM kernels, a classification accuracy of 80% is achieved. (Shinde et al., 2017).

SVM is relatively new compare to others algorithm in the field of document representation. It is not very efficient with large number of observations and it can be tricky to find an appropriate kernel for the problem.

2.3.2 k-Nearest Neighbours (kNN)

kNN is a classification machine learning algorithm that classify objects based on the closest training examples in the feature space based on a similarity measure. It is a simple and effective classification, as it only need 3 prerequisites. The 3 prerequisites are training dataset, similarity measure and the value of k which is the number of closest neighbours to be considered.

kNN needs minimal training, it only needs to plot the training examples into a feature space. kNN has been applied in document classification before, it is found that kNN take significant longer time to classify a document into a topic. This is because kNN uses all the features of the data to compute the distance. Since the authors are using term vector space document representation method, the dimension of the feature space is high, thus the more time is needed for kNN to compute all the distance between the test object with the training objects. Other than the time taken to compute the distance, the k value is another obstacle in kNN algorithm. In a high dimensionality feature space and the points are not evenly distributed, the k value is hard to be determined.

To overcome the problems mentioned above, the authors applied term vector space reduction method, divide the document feature matrix into parts. Term vector space reduction reduces the sparsity of the document term matrix by removing the features less appeared in the corpus. By reducing the term vector space, a slight deterioration in the classification accuracy but the time cost is dramatically reduced. kNN still achieved an accuracy of 92.7% but the time taken reduced from 53 minutes to 11 minutes. (Moldagulova & Sulaiman, 2018)

2.3.3 Neural Network

Neural network has a resurgence in recent years as there is a breakthrough in the neural network as Geofrey Hinton (et al.) discovered a technique called Contrastive Divergence that could quickly model inputs in a Restricted Boltzmann Machine (RBM). RBM is a 2-layer neural network that model the input by bouncing it through the network. This process is less computationally complex than backpropagation. (Hinton, 2002).

Currently, neural network is applied in deep learning to solve various problems, document representation is one of them. Ranjan (et al.) applied Lion Fuzzy Neural Network on document classification. The researchers used WordNet ontology to retrieve

the semantic of the words, and then added the context information onto it, thus the features obtained are semantic-context features. The classification part is performed by Lion Fuzzy Neural Network, which is a variant of Back Propagation Lion (BPLion) Neural Network that includes fuzzy bounding and Lion Algorithm. The neural network model used is trained incrementally. It achieves a higher accuracy than Naïve Bayes and some variant of the Lion Neural Network. (Ranjan & Prasad, 2018)

Other than the modified neural network shown above, a simple feed-forward neural network is also efficient in document classification. By using the Hadamard product as document representation method, a simple neural network also can achieve a good classification accuracy in document classification compare to Naïve Bayes, kNN, and SVM. (L. Manevitz & Yousef, 2007)

2.4 Conclusion

From the review of dimension reduction algorithms, PCA performed best compared to SVD and NMF. In addition, PCA performed well in text classification field.

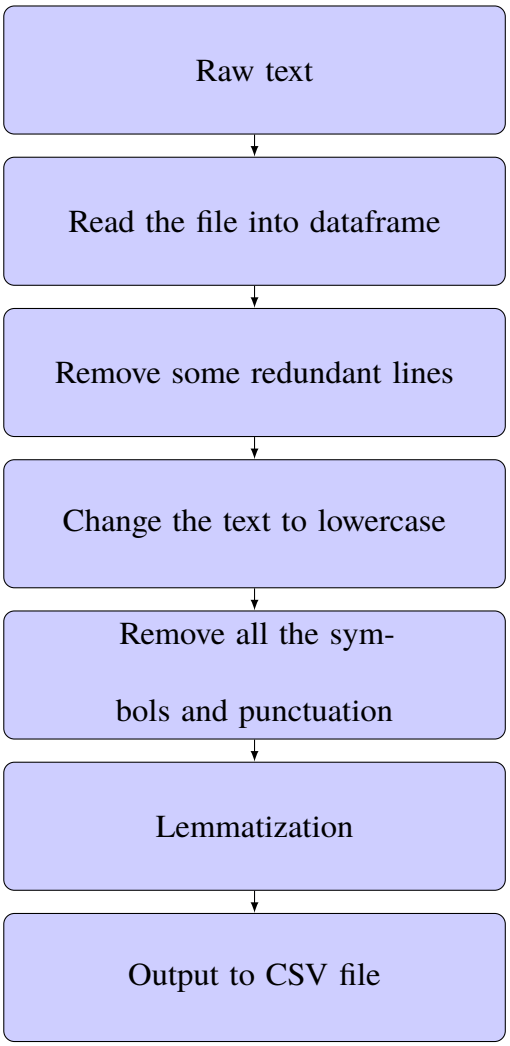
In machine learning algorithms for text classification, all 3 machine learning algorithms reviewed above would be applied. One of the objectives of this study is to investigate the performance of different machine learning algorithms in text classification. The same dataset would be used to train 3 models and the performance would be evaluated.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This section would illustrate process flow to carry out the experiments to fulfill the aforementioned objectives of this research. The following flow charts would illustrates the steps taken in the several experiments.

3.2 Text preprocessing process flow

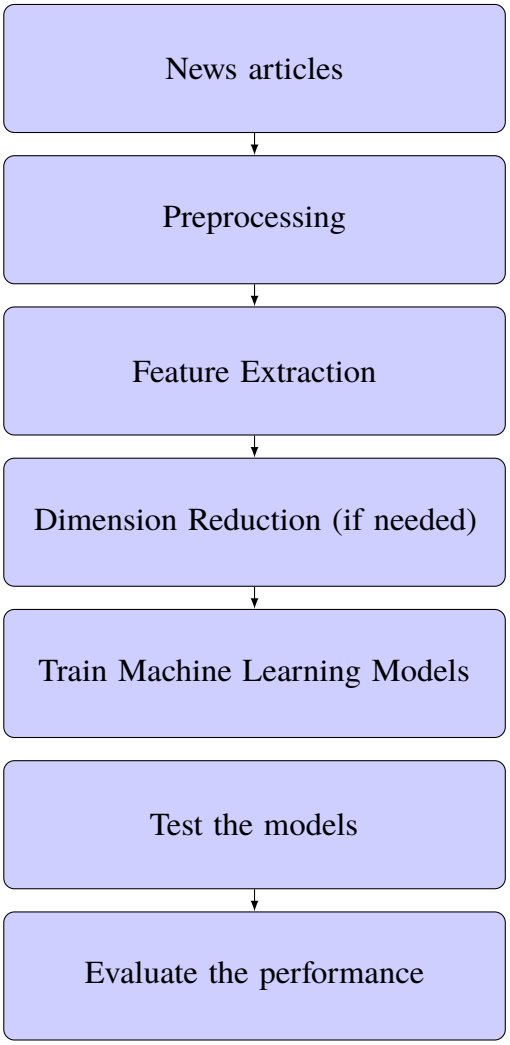


This flow chart above illustrates the preprocessing process. The news articles articles dataset would be in the form of raw text. There are some preprocessing to be done before feature can be extracted from the text to build the text classification models. First, the raw text would be read into a dataframe or a data structure for ease of access and processing.

In the raw text files, there are some lines that are not relevant for text classification purpose, these lines would remove to reduce the noise in the dataset. All the text in the dataset would be converted to lowercase and all the symbols and punctuation in the text would be removed.

After that, there is an important step, lemmatization. Lemmatization would convert most of the words in the text to their root form which is known as a lemma. This would reduce the noise in the data by transforming similar words into a single word. The alternative to lemmatization would be stemming. Stemming would be faster than and need less processing power than lemmatization but stemming has a drawback against lemmatization. The result of stemming may not be a real word because stemming just chop off the ends of the words thus the resulting words may not be a real words. On the other hand, lemmatization uses vocabulary and morphological analysis of words to remove the inflectional endings only and resulting the root form of words. (reference needed)

3.3 Overall Process Flow



The process flow chart above is the overall process for the few experiments. As mentioned above, the news articles dataset has to be preprocessed before it can undergo feature extraction and train machine learning models.

After preprocessing, the resulting data would be used in several experiments with a few subtle differences. The differences in the experiments would be in the feature extraction stage and the dimension reduction stage.

3.4 The experiments

The experiments that has been conducted in this research is as follows:

1. Term frequency
2. Term frequency with naive dimension reduction

3. Term frequency with SVD
4. TF-IDF
5. TF-IDF with naive dimension reduction
6. TF-IDF with SVD

Basically, there are 2 feature extraction method used in the experiments, namely term frequency and term frequency - inverse document frequency (TF-IDF). Each of the feature extraction method would be tested with and without dimension reduction algorithm.

There are 2 dimension algorithms involved, one is a naive method, which means that the features or columns lesser than a certain value would be removed. In other words, words or terms that do not appear much in the dataset would be removed. Another dimension reduction algorithm is single value decomposition (SVD). This method would retain the essence of the data, the part of the data with maximum variance.

After feature extraction and dimension reduction (if needed) are applied, the resulting features would be used to train machine learning models. There are 3 machine learning algorithms chosen in these experiments namely k-nearest neighbour (kNN), support vector machine (SVM), and neural network (NN). All 3 of the machine algorithms would be applied to all the different resulting features and the accuracy scores would be evaluated.

3.5 Conclusion

With the method mentioned above, the experiments would be carry out and the results would be recorded. The results would be compared and the differences would be analysed.

CHAPTER 4: RESULTS

4.1 Term frequency

ML	no of features	accuracy	time taken (s)
kNN	8000	0.28	3.65
SVM	8000	0.81	5.27
NN	8000	0.84	91.82

4.2 Term frequency with naive dimension reduction

ML	parameter value	no of features	accuracy	time taken (s)
kNN	100	2530	0.27	4.16
kNN	500	478	0.32	4.88
kNN	1000	173	0.34	5.24
SVM	7	15854	0.83	6.5
SVM	10	12705	0.83	6.58
SVM	100	2530	0.76	6.16
NN	10	12705	0.87	116.78
NN	100	2530	0.80	48.08
NN	500	478	0.65	61.87

The parameter value is just a integer value in the function implemented. It has an inversely proportional relationship with the number of features. The larger the parameter value, the more columns would be removed and the number of features would decrease.

4.3 Term frequency with SVD

ML	no of features	accuracy	time taken (s)
kNN	2000	0.38	216.59
kNN	4000	0.31	482.66
SVM	2000	0.78	172.58
SVM	4000	0.80	370.43
NN	2000	0.79	91.13
NN	4000	0.8	220.76

4.4 TF-IDF

ML	no of features	accuracy	time taken (s)
kNN	8000	0.76	3.71
SVM	8000	0.87	2.39
NN	8000	0.88	55.82

4.5 TF-IDF with naive dimension reduction

ML	parameter value	no of features	accuracy	time taken (s)
kNN	50	4221	0.74	4.00
kNN	100	2530	0.71	4.11
kNN	500	478	0.49	5.15
SVM	50	4221	0.86	2.58
SVM	100	2503	0.83	2.63
SVM	500	478	0.66	2.94
NN	50	4221	0.85	38.80
NN	100	2530	0.83	34.28
NN	500	478	0.64	77.12

4.6 TF-IDF with SVD

ML	no of features	accuracy	time taken (s)
kNN	2000	0.58	208.64
kNN	4000	0.77	457.16
SVM	2000	0.86	69.63
SVM	4000	0.87	189.32
NN	2000	0.84	87.12
NN	4000	0.85	215.73

CHAPTER 5: DISCUSSION

5.1 Introduction

The results from the experiments are displayed above. It show the performance of the 3 machine learning algorithms with different feature extraction and dimension reduction method or lack thereof.

5.2 Overall

CHAPTER 6: CONCLUSION

I guess here we should conclude the research. Off the top of my head I would said TF-IDF would be the best, dimension reduction shouldn't be apply to TF-IDF

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APPENDIX A: MANUALS, TECHNICAL SPECIFICATIONS, DOCUMENTATIONS, EXAMPLE SCENARIOS

APPENDIX B: TRY

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