A MINI PROJECT REPORT OF NATUARL LANGUAGE PROCESSING

ON

“Text Classification”

Submitted in partial fulfillment of the

BE in Computer Engineering

(Semester-VII)

By

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CERTIFICATE

This is to certify that the Machine Learning Mini Project Report Entitled

"Text Classification"

Submitted by

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is a record of bonafide work carried out by them, under our guidance, in partial fulfillment of the requirement for Bachelors of Engineering (Computer Engineering) Sem-VII at GIT, Lavel under the University of Mumbai. This work is done during July 2022- October 2022 of the Academic year 2022-23.

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INTRODUCTION

Text classification has been an important application and research subject since the origin of digital documents. Today, as more and more data are stored in the form of electronic documents, the text classification approach is even more vital. There exist various studies that apply machine learning methods such as Naive Bayes and Convolutional Neural Networks (CNN) to text classification and sentiment analysis. However, most of these studies do not focus on cross-domain classification i.e., machine learning models that have been trained on a dataset from one context are tested on another dataset from another context. This is useful when there is not enough training data for the specific domain where text data is to be classified. This thesis investigates how the machine learning methods Naive Bayes and CNN perform when they are trained in one context and then tested in another slightly different context. The study uses data from employee reviews in order to train the models, and the models are then tested on both the employee-review data but also on human resources-related data. Thus, the aim with the thesis is to gain insights on how to develop a system with the capability to perform an accurate cross-domain classification and to provide more insights to the text classification research area in general.A comparative analysis of the models Naive Bayes and CNN was done, and the results showed that both of the models performed quite similarly when classifying sentences by only using the employee-review data to train and test the models. However, CNN performed slightly better when it comes to multiclass classification for the employee data, which indicates that CNN might be a better model in that context. From a cross-domain perspective, Naive Bayes turned out to be the better model since it performed better in all of the metrics evaluated. However, both of the models can be used as guidance tools in order to classify human-resources-related data quickly, even if Naive Bayes is the model that performs the best in the cross-domain context. The results can possibly be improved with more research and need to be verified with more data. Suggestions on how to improve the results are among others to enhance the hyperparameter optimization, use another approach to handle the data imbalance, and adjust the preprocessing methods used. It is also worth noting that the statistical significance could not be confirmed in all of the different test cases, meaning that no absolute conclusions can be drawn, but the results from this thesis work still provide an indication of how well the models perform.

LITERATURE SURVEY

Text classification is an essential part of the NLP, which aims to predict the categories for given texts in a particular classification system. There are many ways of feature selection and classification models. However, most researchers would like to use the encapsulated methods of third-party libraries to achieve their goals. Therefore, in this paper, we propose to implement code to achieve functions, instead of using third-party libraries. We evaluate our code in different classification models, and the result of our experiment shows that our code is feasible.[1]

Text classification is an essential advance in characteristic dialect processing. It very well may be performed utilizing different classification algorithms. Hadoop Map Reduce is widely utilized in text classification to perform classification on colossal measures of text data. However, Map Reduce required a ton of time to perform the tasks thereby increasing latency and since the data is distributed over the cluster it builds time and thus reduces processing speed. Also, Hadoop utilizes a long queue of code. Motivated by this, we propose a basic yet compelling machine learning method that uses a Naïve Bayes classifier for text data. In the Machine Learning approach, the classifier is built automatically by learning the properties of categories from a set of pre-defined training data. Hence, it can process a complex furthermore, the multi assortment of information in dynamic situations. Here we propose a naïve Bayes classifier that scales directly with the number of indicators and data points that can be used for both binary and multiclass classification problems. We implemented the presented schemes using a Machine Learning tool. The experimental results demonstrate the performance improvement in the classification technique.[2]

Classification of text is the major challenge faced by the industries so that they can extract the required information from that data. With the advent of machine learning, it becomes a lot easier for the engineers to classify the data as per requirement. Writing an effective code and algorithm is required to classify the data accurately. In this paper, we have tried to solve a problem where we have taken a raw dataset which contains tweets by users where the name of the disease in every tweet begins with a hashtag (‘#’) symbol. These disease names are extracted and stored it in a new column preceding to every tweet with the help of python.[3]

PROBLEM STATEMENT AND OBJECTIVE

- **Problem Statement:**

  To identify the spam and non-spam(Ham) words from the given dataset.

- **Objective:**

  We tried different ways to improve our text classification results. We have used:

- Regular Expressions
- Feature Engineering
- Multiple sci-kit-learn Classifiers
- Ensemble Methods

DATA SET DETAILS

This corpus has been collected from free or free research sources on the Internet:

A collection of 425 SMS spam messages was manually extracted from the Grumbletext Web site. This is a UK forum in which cell phone users make public claims about SMS spam messages, most of them without reporting the very spam message received. The identification of the text of spam messages in the claims is a very hard and time-consuming task, and it involved carefully scanning hundreds of web pages.
A subset of 3,375 SMS randomly chosen ham messages of the NUS SMS Corpus (NSC), which is a dataset of about 10,000 legitimate messages collected for research at the Department of Computer Science at the National University of Singapore. The messages largely originate from Singaporeans and mostly from students attending the University. These messages were collected from volunteers who were made aware that their contributions were going to be made publicly available
A list of 450 SMS ham messages was collected from Caroline Tag's Ph.D.
Finally, we have incorporated the SMS Spam Corpus v.0.1 Big. It has 1,002 SMS ham messages and 322 spam messages. This corpus has been used in the following academic research:

[1] GÃ³mez Hidalgo, J.M., Cajigas Bringas, G., Puertas Sanz, E., Carrero GarcÃa, F. Content Based SMS Spam Filtering. Proceedings of the 2006 ACM Symposium on Document Engineering (ACM DOCENG'06), Amsterdam, The Netherlands, 10-13, 2006.
[2] Cormack, G. V., GÃ³mez Hidalgo, J. M., and Puertas SÃ¡nz, E. Feature engineering for mobile (SMS) spam filtering. Proceedings of the 30th Annual International ACM Conference on Research and Development in Information Retrieval (ACM SIGIR'07), New York, NY, 871-872, 2007.
[3] Cormack, G. V., GÃ³mez Hidalgo, J. M., and Puertas SÃ¡nz, E. Spam filtering for short messages. Proceedings of the 16th ACM Conference on Information and Knowledge Management (ACM CIKM'07). Lisbon, Portugal, 313-320, 2007.

Dataset Links:

- http://etheses.bham.ac.uk/253/1/Tagg09PhD.pdf
- http://www.grumbletext.co.uk/

ALGORITHMS AND LIBRARIES USED

- **Sys:**
  The python sys module provides functions and variables which are used to manipulate different parts of the Python Runtime Environment. It lets us access system-specific parameters and functions.

- **nltk:**
  NLTK is a toolkit build for working with NLP in Python. It provides us various text processing libraries with a lot of test datasets. A variety of tasks can be performed using NLTK such as tokenizing, parse tree visualization, etc.

- **sklearn**
  Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python.

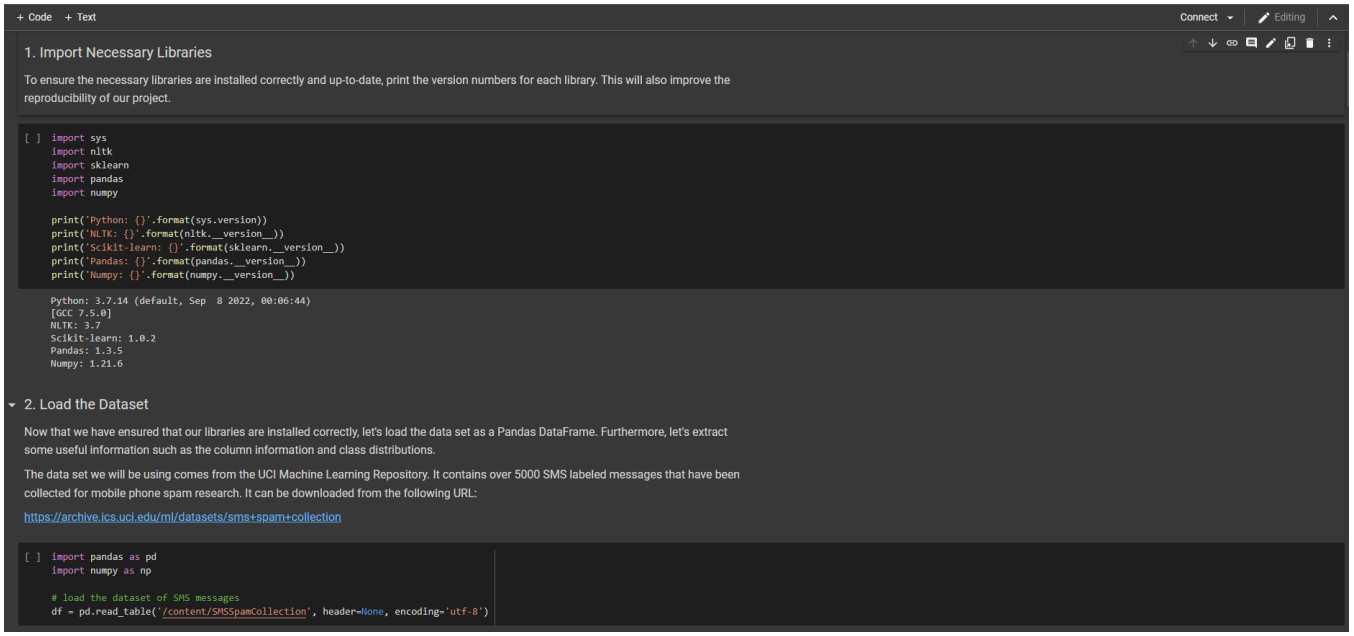
- **Pandas**

  Pandas is defined as an open-source library that provides high-performance data manipulation in Python. The name of Pandas is derived from the word Panel Data, which means an Econometrics from Multidimensional data. It is used for data analysis in Python.

  Data analysis requires lots of processing, such as restructuring, cleaning or merging, etc. There are different tools are available for fast data processing, such as Numpy, Scipy, Cython, and Panda. But we prefer Pandas because working with Pandas is fast, simple and more expressive than other tools.

- **numpy**
  NumPy can be used to perform a wide variety of mathematical operations on arrays. It adds powerful data structures to Python that guarantee efficient calculations with arrays and matrices and it supplies an enormous library of high-level mathematical functions that operate on these arrays and matrices.

CODE, RESULTS, OUTPUTS



+ Code + Text

Connect Editing

1. Import Necessary Libraries

To ensure the necessary libraries are installed correctly and up-to-date, print the version numbers for each library. This will also improve the reproducibility of our project.

```
[ ] import sys
    import nltk
    import sklearn
    import pandas
    import numpy

    print('Python: {}'.format(sys.version))
    print('NLTK: {}'.format(nltk.__version__))
    print('Scikit-learn: {}'.format(sklearn.__version__))
    print('Pandas: {}'.format(pandas.__version__))
    print('Numpy: {}'.format(numpy.__version__))
```

```
Python: 3.7.14 (default, Sep  8 2022, 00:06:44)
[GCC 7.5.0]
NLTK: 3.7
Scikit-learn: 1.0.2
Pandas: 1.3.5
Numpy: 1.21.6
```

2. Load the Dataset

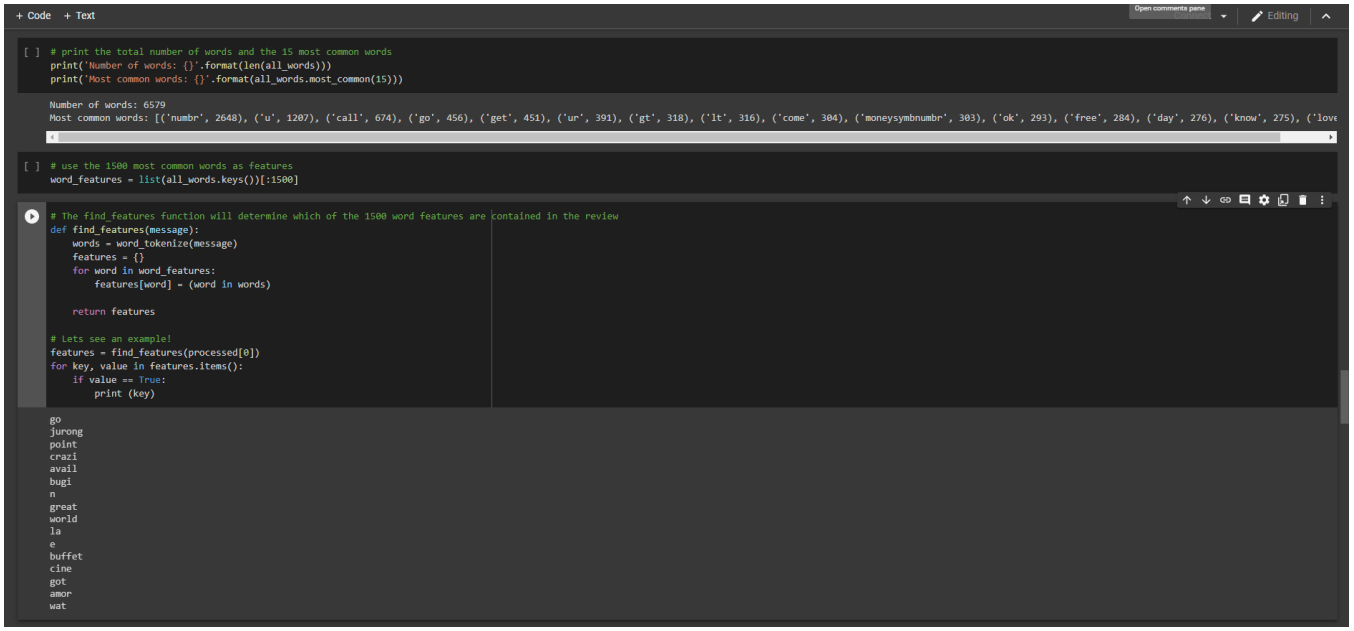
Now that we have ensured that our libraries are installed correctly, let's load the data set as a Pandas DataFrame. Furthermore, let's extract some useful information such as the column information and class distributions.

The data set we will be using comes from the UCI Machine Learning Repository. It contains over 5000 SMS labeled messages that have been collected for mobile phone spam research. It can be downloaded from the following URL:

https://archive.ics.uci.edu/ml/datasets/sms+spam+collection

```
[ ] import pandas as pd
    import numpy as np

    # load the dataset of SMS messages
    df = pd.read_table('/content/SMSSpamCollection', header=None, encoding='utf-8')
```



+ Code + Text

Open comments pane Editing

```
[ ] # print the total number of words and the 15 most common words
    print('Number of words: {}'.format(len(all_words)))
    print('Most common words: {}'.format(all_words.most_common(15)))
```

```
Number of words: 6579
Most common words: [('numbr', 2648), ('u', 1207), ('call', 674), ('go', 456), ('get', 451), ('ur', 391), ('gt', 318), ('lt', 316), ('come', 304), ('moneysymbnumbr', 303), ('ok', 293), ('free', 284), ('day', 276), ('know', 275), ('love
```

```
[ ] # use the 1500 most common words as features
    word_features = list(all_words.keys())[:1500]
```

```
# The find_features function will determine which of the 1500 word features are contained in the review
def find_features(message):
    words = word_tokenize(message)
    features = {}
    for word in word_features:
        features[word] = (word in words)

    return features

# Lets see an example!
features = find_features(processed[0])
for key, value in features.items():
    if value == True:
        print (key)
```

```
go
jurong
point
crazi
avail
bugi
n
great
world
la
e
buffet
cine
got
amor
wat
```

accuracy_score and classification_report.

```
[ ] # We can use sklearn algorithms in NLTK
    from nltk.classify.scikitlearn import SklearnClassifier
    from sklearn.svm import SVC

    model = SklearnClassifier(SVC(kernel = 'linear'))

    # train the model on the training data
    model.train(training)

    # and test on the testing dataset!
    accuracy = nltk.classify.accuracy(model, testing)*100
    print("SVC Accuracy: {}".format(accuracy))
```

```
SVC Accuracy: 98.77961234745155
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix

# Define models to train
names = ["K Nearest Neighbors", "Decision Tree", "Random Forest", "Logistic Regression", "SGD Classifier",
         "Naive Bayes", "SVM Linear"]

classifiers = [
    KNeighborsClassifier(),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    LogisticRegression(),
    SGDClassifier(max_iter = 100),
    MultinomialNB(),
    SVC(kernel = 'linear')
]

models = zip(names, classifiers)

for name, model in models:
```

+ Code + Text Connect Editing

```
[ ]     SGDClassifier(max_iter = 100),
        MultinomialNB(),
        SVC(kernel = 'linear')
    ]

    models = list(zip(names, classifiers))

    nltk_ensemble = SklearnClassifier(VotingClassifier(estimators = models, voting = 'hard', n_jobs = -1))
    nltk_ensemble.train(training)
    accuracy = nltk.classify.accuracy(nltk_model, testing)*100
    print("Voting Classifier: Accuracy: {}".format(accuracy))
```

```
Voting Classifier: Accuracy: 98.77961234745155
```

```
[ ] # make class label prediction for testing set
    txt_features, labels = zip(*testing)

    prediction = nltk_ensemble.classify_many(txt_features)
```

```
# print a confusion matrix and a classification report
print(classification_report(labels, prediction))

pd.DataFrame(
    confusion_matrix(labels, prediction),
    index = [['actual', 'actual'], ['ham', 'spam']],
    columns = [['predicted', 'predicted'], ['ham', 'spam']])
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1211
           1       1.00      0.92      0.96       182

    accuracy                           0.99      1393
   macro avg       0.99      0.96      0.98      1393
weighted avg       0.99      0.99      0.99      1393
```

		predicted	
		ham	spam
actual	ham	1211	0
	spam	14	168

CONCLUSION

In the project, we learned the basics of tokenizing, part-of-speech tagging, stemming, chunking, and named entity recognition; furthermore, we dove into machine learning and text classification using a simple support vector classifier and a dataset which contains the large amount of words. We characterised the word as per their category as spam and not spam that is ham words.

REFERENCES

[1] Y. Zheng, "An Exploration on Text Classification with Classical Machine Learning Algorithm," 2019 International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI), 2019, pp. 81-85, doi: 10.1109/MLBDBI48998.2019.00023.

[2] Venkatesh and K. V. Ranjitha, "Classification and Optimization Scheme for Text Data using Machine Learning Naïve Bayes Classifier," 2018 IEEE World Symposium on Communication Engineering (WSCE), 2018, pp. 33-36, doi: 10.1109/WSCE.2018.8690536.

[3] Ruchika, M. Sharma, and S. A. Hossain, "Text Classification on Twitter Data Using Machine Learning Algorithm," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 2021, pp. 1-3, DOI: 10.1109/ICRITO51393.2021.9596132.