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Fake News Detection Using NLP Machine Learning Algorithm

Exploring the fake news dataset, performing data analysis such as word clouds and ngrams, and fine-tuning BERT transformer to build a fake news detector in Python using transformers library.

Fake news is the intentional broadcasting of false or misleading claims as news, where the statements are purposely deceitful.

Newspapers, tabloids, and magazines have been supplanted by digital news platforms, blogs, social media feeds, and a plethora of mobile news applications. News organizations benefitted from the increased use of social media and mobile platforms by providing subscribers with up-to-the-minute information.

Consumers now have instant access to the latest news. These digital media platforms have increased in prominence due to their easy connectedness to the rest of the world and allow users to discuss and share ideas and debate topics such as democracy, education, health, research, and history. Fake news items on digital

platforms are getting more popular and are used for profit, such as political and financial gain.

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- The Solution
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Distribution of Classes

- Data Cleaning for Analysis
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Single-word Cloud

Most Frequent Bigram (Two-word Combination)

Most Frequent Trigram (Three-word Combination)

- Building a Classifier by Fine-tuning BERT

Data Preparation

Tokenizing the Dataset

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- Appendix: Creating a Submission File for Kaggle
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Data Exploration:

we utilized the fake news dataset from Kaggle to classify untrustworthy news articles as fake news. We have a complete training dataset containing the following characteristics:

- id: unique id for a news article
- title: title of a news article
- author: author of the news article
- text: text of the article; could be incomplete
- label: a label that marks the article as potentially unreliable denoted by 1 (unreliable or fake) or 0 (reliable).

It is a binary classification problem in which we must predict if a particular news story is reliable or not.

If you have a Kaggle account, you can simply download the dataset from the website there and extract the ZIP file.

I also uploaded the dataset into Google Drive, and you can get it here or use the gdown library to download it in Google Colab or Jupyter notebooks automatically:

```
$ pip install gdown
```

```
# download from Google Drive
```

```
$ gdown
```

```
"https://drive.google.com/uc?id=178f_VkNxcccNidap-5-uffXUW475pAuPy&confirm=t"
```

Downloading...

From:

https://drive.google.com/uc?id=178f_VkNxcccNidap-5-uffXUW475pAuPy&confirm=t

To: /content/fake-news.zip

100% 48.7M/48.7M [00:00<00:00, 74.6MB/s]

Unzipping the files:

```
$ unzip fake-news.zip
```

Installing the required dependencies:

```
$ pip install transformers nltk pandas numpy matplotlib seaborn  
wordcloud
```

Let's import the essential libraries for analysis:

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

The NLTK corpora and modules must be installed using the standard NLTK downloader:

```
import nltk
```

```
nltk.download('stopwords')
```

```
nltk.download('wordnet')
```

The fake news dataset comprises various authors' original and fictitious article titles and text. Let's import our dataset:

```
# load the dataset
```

```
news_d = pd.read_csv("train.csv")
```

```
print("Shape of News data:", news_d.shape)
```

```
print("News data columns", news_d.columns)
```

Output:

```
Shape of News data: (20800, 5)
```

```
News data columns Index(['id', 'title', 'author', 'text', 'label'], dtype='object')
```

Here's how the dataset looks:

by using `df.head()`, we can immediately familiarize ourselves with the dataset.

```
news_d.head()
```

Output:

id	title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let... 1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou... 0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ... 1
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Aistr... 1
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to... 1

We have 20,800 rows, which have five columns. Let's see some statistics of the text column:

#Text Word startistics: min.mean, max and interquartile range

```
txt_length = news_d.text.str.split().str.len()
```

```
txt_length.describe()
```

Output:

count 20761.000000

mean 760.308126

std 869.525988

min 0.000000

25% 269.000000

50% 556.000000

75% 1052.000000

max 24234.000000

Name: text, dtype: float64

Stats for the title column:

#Title statistics

```
title_length = news_d.title.str.split().str.len()
```

```
title_length.describe()
```

Output:

count 20242.000000

mean 12.420709

std 4.098735

min 1.000000

25% 10.000000

50% 13.000000

75% 15.000000

max 72.000000

Name: title, dtype: float64

The statistics for the training and testing sets are as follows:

- The text attribute has a higher word count with an average of 760 words and 75% having more than 1000 words.
- The title attribute is a short statement with an average of 12 words, and 75% of them are around 15 words.

Distribution of Classes:

Counting plots for both labels:

```
sns.countplot(x="label", data=news_d);
```

```
print("1: Unreliable")
```

```
print("0: Reliable")
```

```
print("Distribution of labels:")
```

```
print(news_d.label.value_counts());
```

Output:

1: Unreliable

0: Reliable

Distribution of labels:

1 10413

0 10387

Name: label, dtype: int64

```
print(round(news_d.label.value_counts(normalize=True),2)*100);
```

Output:

1 50.0

0 50.0

Name: label, dtype: float64

Data Cleaning for Analysis :

- Drop unused rows and columns.
- Perform null value imputation.
- Remove special characters.
- Remove stop words.

Constants that are used to sanitize the datasets

```
column_n = ['id', 'title', 'author', 'text', 'label']
```

```
remove_c = ['id','author']
```

```
categorical_features = []
```

```
target_col = ['label']
```

```
text_f = ['title', 'text']
```

```
# Clean Datasets
```

```
import nltk
```

```
from nltk.corpus import stopwords
```

```
import re
```

```
from nltk.stem.porter import PorterStemmer
```

```
from collections import Counter
```

```
ps = PorterStemmer()
```

```
wnl = nltk.stem.WordNetLemmatizer()
```

```
stop_words = stopwords.words('english')
```

```
stopwords_dict = Counter(stop_words)
```

```
# Removed unused clumns
```

```
def remove_unused_c(df,column_n=remove_c):
```

```
df = df.drop(column_n,axis=1)
```

```
return df
```

```
# Impute null values with None
```

```
def null_process(feature_df):
```

```
    for col in text_f:
```

```
        feature_df.loc[feature_df[col].isnull(), col] = "None"
```

```
    return feature_df
```

```
def clean_dataset(df):
```

```
    # remove unused column
```

```
    df = remove_unused_c(df)
```

```
    #impute null values
```

```
    df = null_process(df)
```

```
    return df
```

```
# Cleaning text from unused characters
```

```
def clean_text(text):
```

```
    text = str(text).replace(r'http[¥w:/¥.]+', ' ') # removing urls
```

```
text = str(text).replace(r'[^\w\s]', ' ') # remove everything but
characters and punctuation
```

```
text = str(text).replace('[^a-zA-Z]', ' ')
```

```
text = str(text).replace(r'\s\s+', ' ')
```

```
text = text.lower().strip()
```

```
#text = ' '.join(text)
```

```
return text
```

```
## Nltk Preprocessing include:
```

```
# Stop words, Stemming and Lemmetization
```

```
# For our project we use only Stop word removal
```

```
def nltk_preprocess(text):
```

```
text = clean_text(text)
```

```
wordlist = re.sub(r'[^\w\s]', '', text).split()
```

```
#text = ' '.join([word for word in wordlist if word not in
stopwords_dict])
```

```
#text = [ps.stem(word) for word in wordlist if not word in
stopwords_dict]
```

```
text = ' '.join([wnl.lemmatize(word) for word in wordlist if word not in
stopwords_dict])
```

```
return text
```

In the code block above:

- We have imported NLTK, which is a famous platform for developing Python applications that interact with human language. Next, we import re for regex.
- We import stopwords from nltk.corpus. When working with words, particularly when considering semantics, we sometimes need to eliminate common words that do not add any significant meaning to a statement, such as "but", "can", "we", etc.
- PorterStemmer is used to perform stemming words with NLTK. Stemmers strip words of their morphological affixes, leaving the word stem solely.
- We import WordNetLemmatizer() from NLTK library for lemmatization. Lemmatization is much more effective than stemming. It goes beyond word reduction and evaluates a language's whole lexicon to apply morphological analysis to words, with the goal of just removing inflectional ends and returning the base or dictionary form of a word, known as the lemma.
- stopwords.words('english') allow us to look at the list of all the English stop words supported by NLTK.
- remove_unused_c() function is used to remove the unused columns.
- We impute null values with None using the null_process() function.
- Inside the function clean_dataset(), we call remove_unused_c() and null_process() functions. This function is responsible for data cleaning.

- To clean text from unused characters, we have created the `clean_text()` function.
- For preprocessing, we will use only stop word removal. We created the `nlTK_preprocess()` function for that purpose.