

Fake News Project

The goal of this project is to create a fake news prediction system. Fake news is a major problem that can have serious negative effects on how people understand the world around them. You will work with a dataset containing real and fake news in order to train a simple and a more advanced classifier to solve this problem. This project covers the full Data Science pipeline, from data processing, to modelling, to visualization and interpretation.

We ran the notebook with the following specs:

- CPU: Intel(R) Xeon(R) CPU E5-2687W v3 @ 3.10GHz
- Cores: 10
- Threads: 20
- Memory: 64GB Ram

Part 1 Data Processing

Task 1

Pandas is used to process The fake news corpus. Since content will be used for our models we drop any rows that don't have any content.

```
In [ ]: import pandas as pd

df = pd.read_csv("news_sample.csv")
dfcpy = df.copy()
dfcpy = dfcpy.dropna(subset=['content'])
```

```
In [ ]: import nltk
nltk.download('punkt')
nltk.download('stopwords')
```

We've implemented data processing functions to do the following:

- Clean the text
- Tokenize the text
- Remove stopwords
- Remove word variations with stemming

We use nltk because it has built-in support for many of these operations.

```
In [ ]: import re
import nltk
from nltk.tokenize.regexp import RegexpTokenizer
from nltk.stem import PorterStemmer
from collections import Counter
from cleantext import clean

def clean_text(text):
    clean_text = re.sub(r'([A-Z][A-z]+.?) ([0-9]{1,2}?), ([0-9]{4})', '<DATE>', text)
    clean_text = clean(clean_text,
        lower=True,
        no_urls=True, replace_with_url="<URL>",
        no_emails=True, replace_with_email="<EMAIL>",
        no_numbers=True, replace_with_number="<NUM>",
        no_currency_symbols=True, replace_with_currency_symbol="<CUR>",
        no_punct=True, replace_with_punct="",
        no_line_breaks=True
    )
    return clean_text

def rmv_stopwords(tokens):
    stop_words = set(nltk.corpus.stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]
    return tokens

def stem_tokens(tokens):
    stemmer=PorterStemmer()
    Output=[stemmer.stem(word) for word in tokens]
    return Output

def build_vocabulary(df_tokens):
```

```
tokens = []
for lst in df_tokens:
    tokens += lst
token_counter = Counter(tokens)
return token_counter
```

```
In [ ]: dfcpy = df.copy()

dfcpy.content = dfcpy.content.apply(clean_text)

tokenizer = RegexpTokenizer(r'<[\w]+>|[\w]+' )
dfcpy["tokenized"] = dfcpy.content.apply(tokenizer.tokenize)

vocab = build_vocabulary(dfcpy.tokenized)
vocab_size = len(vocab)
print("After cleaning:")
print(f"vocabulary size: {vocab_size}\n")

dfcpy.tokenized = dfcpy.tokenized.apply(rmv_stopwords)
vocab = build_vocabulary(dfcpy.tokenized)
# reduction rate of the vocabulary size
reduction = ((vocab_size - len(vocab))/vocab_size)*100
vocab_size = len(vocab)
print("After removing stopwords:")
print(f"vocabulary size: {vocab_size}")
print(f"reduction rate of the vocabulary size: {reduction:.2f}%\n")

dfcpy.tokenized = dfcpy.tokenized.apply(stem_tokens)
vocab = build_vocabulary(dfcpy.tokenized)
reduction = ((vocab_size - len(vocab))/vocab_size)*100
vocab_size = len(vocab)
print("After stemming:")
print(f"vocabulary size: {vocab_size}")
print(f"reduction rate of the vocabulary size: {reduction:.2f}%\n")
```

After cleaning:
vocabulary size: 16577

After removing stopwords:
vocabulary size: 16445
reduction rate of the vocabulary size: 0.80%

After stemming:
vocabulary size: 11031
reduction rate of the vocabulary size: 32.92%

Task 2

We apply our data processing pipeline from task 1 on the *995k FakeNewsCorpus*.

Pandas is slow when used on bigger amounts of data, this is because it doesn't allow for multithreading. Modin and ray are libraries that optimize pandas by allowing pandas to run on all cores, thereby giving a speed up for the data processing. By using modin with ray as an engine you can use pandas as usual, but have it use all threads in the CPU. We used a Intel Xeon cpu with 20 threads and therefore saw huge performance gain by using modin.

Modin and ray can be installed by running the following command: `pip install "modin[ray]"`

```
In [ ]: import modin.config as modin_cfg
modin_cfg.Engine.put("ray") # make sure to use Ray engine and other than could be installed
import modin.pandas as pd
```

```
In [ ]: # only read the columns we need
df = pd.read_csv("995,000_rows.csv",
                usecols=['content', 'type', 'title', 'domain'],
                engine='c',
                dtype = str)
dfcpy = df.copy()
dfcpy = dfcpy.dropna(subset=['content'])
dfcpy = dfcpy.dropna(subset=['type'])
dfcpy = dfcpy.dropna(subset=['title'])
```

2024-04-02 19:53:36,957 INFO worker.py:1752 -- Started a local Ray instance.

```
In [ ]: from time import time
start = time()
dfcpy.title = dfcpy.title.apply(clean_text)
dfcpy.content = dfcpy.content.apply(clean_text)
print(f"time to clean the data: {time() - start:.2f} sec")

t = time()
tokenizer = RegexpTokenizer(r'<[\w]+>|[\w]+')
dfcpy.title = dfcpy.title.apply(tokenizer.tokenize)
dfcpy.content = dfcpy.content.apply(tokenizer.tokenize)
print(f"time to tokenize the data: {(time() - t)/60:.2f} min" )

t = time()
dfcpy.title = dfcpy.title.apply(rmv_stopwords)
dfcpy.content = dfcpy.content.apply(rmv_stopwords)
print(f"time to remove stopwords: {(time() - t)/60:.2f} min")

t = time()
dfcpy.title = dfcpy.title.apply(stem_tokens)
dfcpy.content = dfcpy.content.apply(stem_tokens)
print(f"time to stem the data: {(time() - t)/60:.2f} sec")

print(f"total time: {(time() - start)/60:.2f} min")
```

```
time to clean the data: 21.82 sec
time to tokenize the data: 9.27 min
time to remove stopwords: 1.67 min
time to stem the data: 1.65 sec
total time: 12.96 min
```

(raylet) [2024-04-02 20:04:36,876 E 14353 14353] (raylet) node_manager.cc:2967: 3 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

(raylet) [2024-04-02 20:05:36,878 E 14353 14353] (raylet) node_manager.cc:2967: 3 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

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(raylet) A worker died or was killed while executing a task by an unexpected system error. To troubleshoot the problem, check the logs for the dead worker. RayTask ID: db940c539036c98e50d4183304635b2164d14ac601000000 Worker ID: 7e12927b58548ea6150e35d5407c0343e5051661126b8e38b20327e1 Node ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061 Worker IP address: 10.3.32.4 Worker port: 32885 Worker PID: 14446 Worker exit type: SYSTEM_ERROR Worker exit detail: Worker unexpectedly exits with a connection error code 2. End of file. There are some potential root causes. (1) The process is killed by SIGKILL by OOM killer due to high memory usage. (2) ray stop --force is called. (3) The worker is crashed unexpectedly due to SIGSEGV or other unexpected errors.

(raylet) [2024-04-02 20:06:36,880 E 14353 14353] (raylet) node_manager.cc:2967: 3 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

(raylet) [2024-04-02 20:16:37,634 E 14353 14353] (raylet) node_manager.cc:2967: 2 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

(raylet) [2024-04-02 20:17:37,636 E 14353 14353] (raylet) node_manager.cc:2967: 5 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

(raylet) [2024-04-02 20:18:37,638 E 14353 14353] (raylet) node_manager.cc:2967: 7 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

(raylet) [2024-04-02 20:19:37,639 E 14353 14353] (raylet) node_manager.cc:2967: 2 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

3e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`

(raylet)

(raylet) Refer to the documentation on how to address the out of memory issue: <https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html>. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.

Data exploration

We've explored the dataset and made some observations which are used to determine importance of certain metadata in the fake news corpus, such observations are:

- The amount of numerics in the dataset
- The 100 most frequent words
- The 20 most frequent domains and how their articles are classified in terms of type
- The distribution of types in the dataset
- The amount of rows missing content, title or type (amount of rows that will be dropped from the dataset).

```
In [ ]: start = time()
vocab_content = build_vocabulary(dfcpy.content)
print(f"time to build vocabulary for content: {(time() - start)/60:.2f} min")

start = time()
vocab_title = build_vocabulary(dfcpy.title)
print(f"time to build vocabulary for title: {(time() - start)/60:.2f} min")
```

```
time to build vocabulary for content: 18.94 min
time to build vocabulary for title: 0.08 min
```

```
In [ ]: import matplotlib.pyplot as plt
import seaborn as sns
# plot the frequency of the top n words
def plot_freq(counter, top_n):
    common_words = counter.most_common(top_n)

    all_freq = {}
    for word, freq in common_words:
```



```

    all_freq[word] = freq

plt.figure(figsize = (top_n*0.1, 5))
plt.xticks(rotation = 90, fontsize = 5)
sns.lineplot(x = list(all_freq.keys()), y = list(all_freq.values()), color = 'red')
sns.barplot(x = list(all_freq.keys()), y = list(all_freq.values()))
plt.title(f'Top {top_n} most common words')
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.grid(axis = 'y')
plt.show()
return

def plot_domain_with_type(df):
    top_domains = df.domain.value_counts().head(20).index
    df = df[df.domain.isin(top_domains)]
    df = df.groupby(['domain', 'type']).size().unstack().fillna(0)

    df.plot(kind='bar', stacked=True, figsize=(10,5), title='Domain distribution with types')
    plt.show()
    return

```

```

In [ ]: # top 100 most frequent words
print("numerics in content: ", vocab_content["<num>"])
plot_freq(vocab_content, 100)
print("numerics in titles: ", vocab_title["<num>"])
plot_freq(vocab_title, 100)

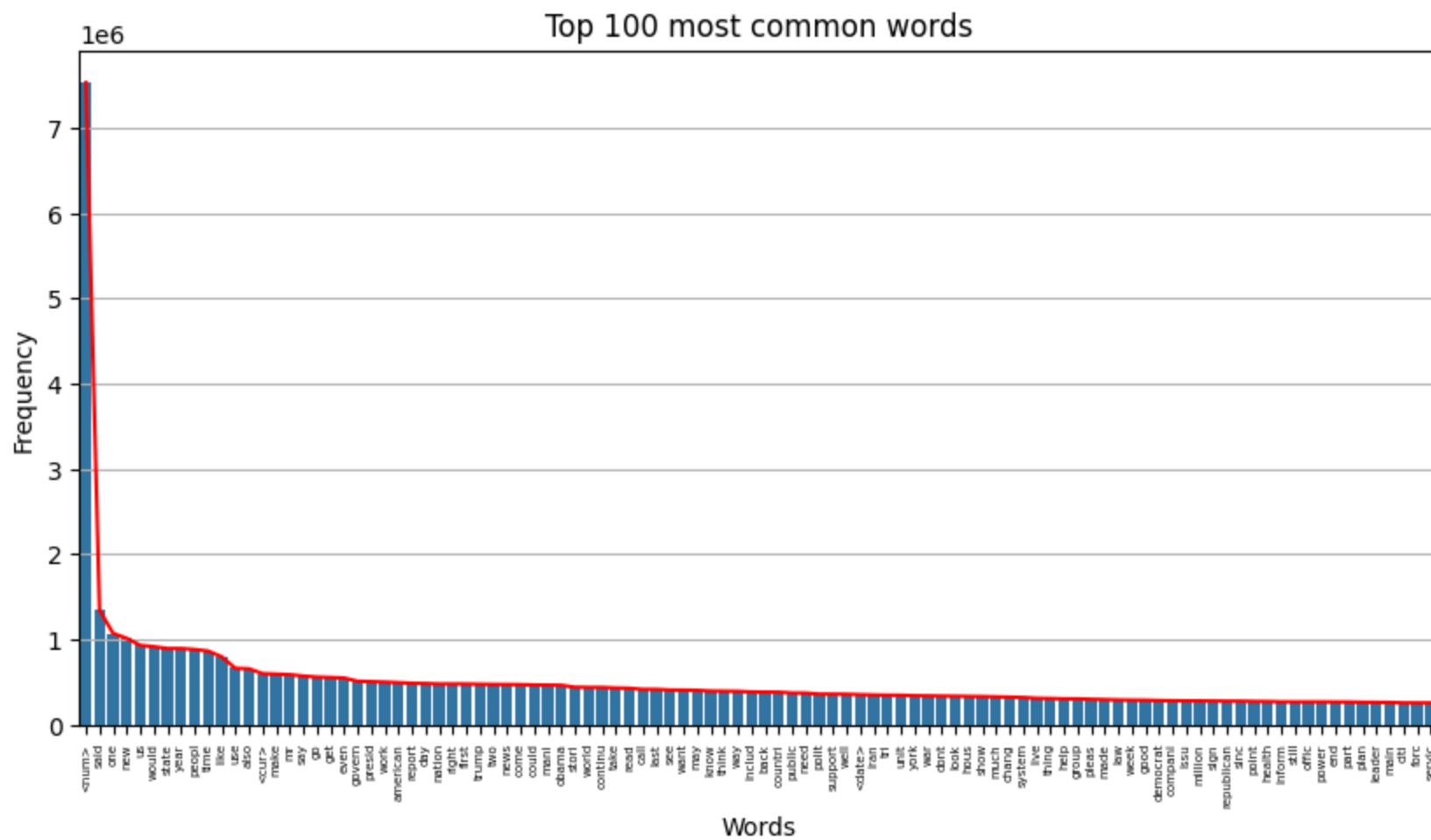
# top 20 domains with their types
plot_domain_with_type(dfcpy)

# pie chart for the distribution of the types
dfcpy.type.value_counts().plot.pie(autopct='%1.1f%%', figsize=(10,5), title='Types distribution')
plt.show()

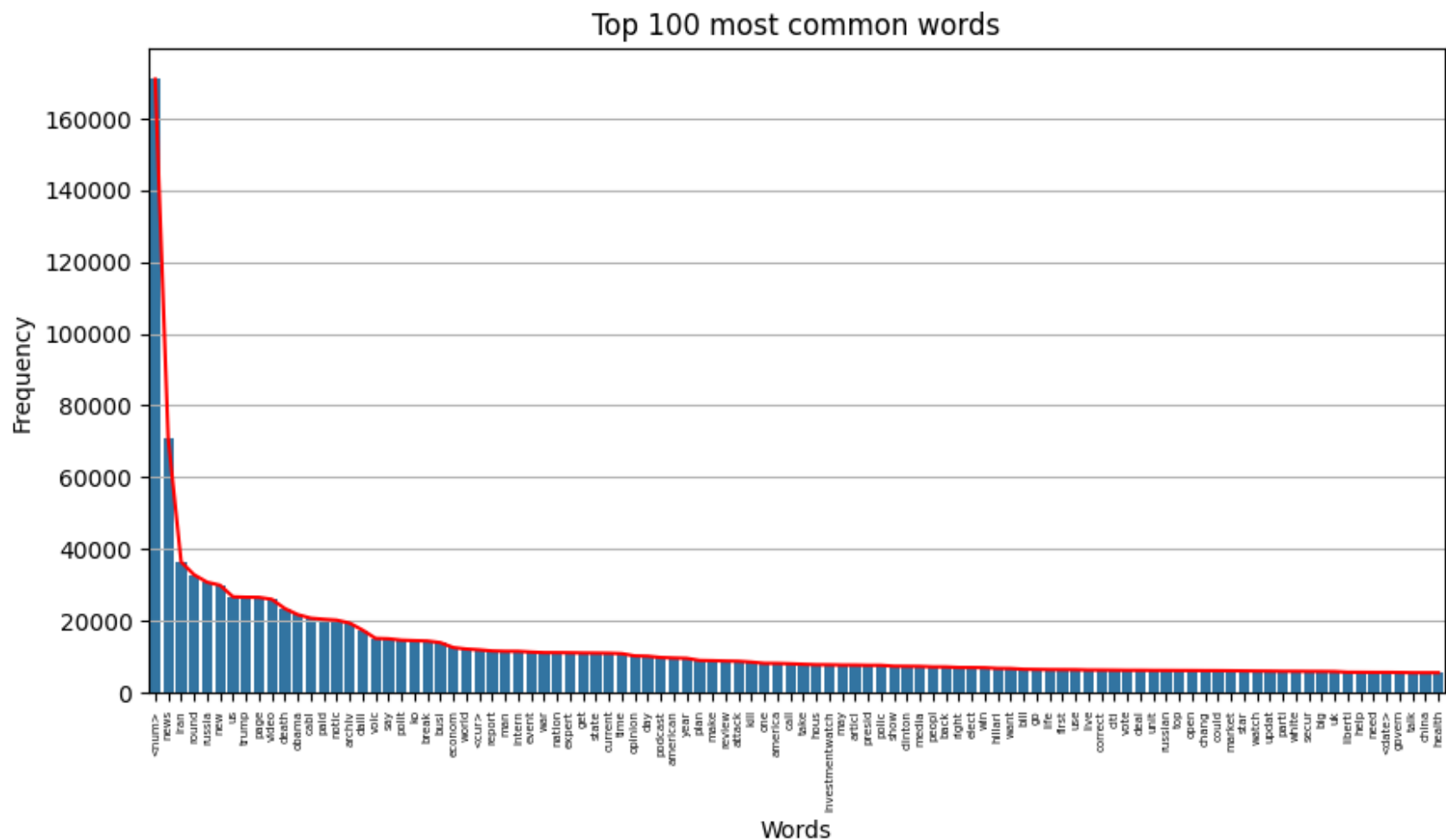
# ammount of dropped rows
print(f"Number of dropped rows: {df.shape[0] - dfcpy.shape[0]}")

```

numerics in content: 7530933



numerics in titles: 170894



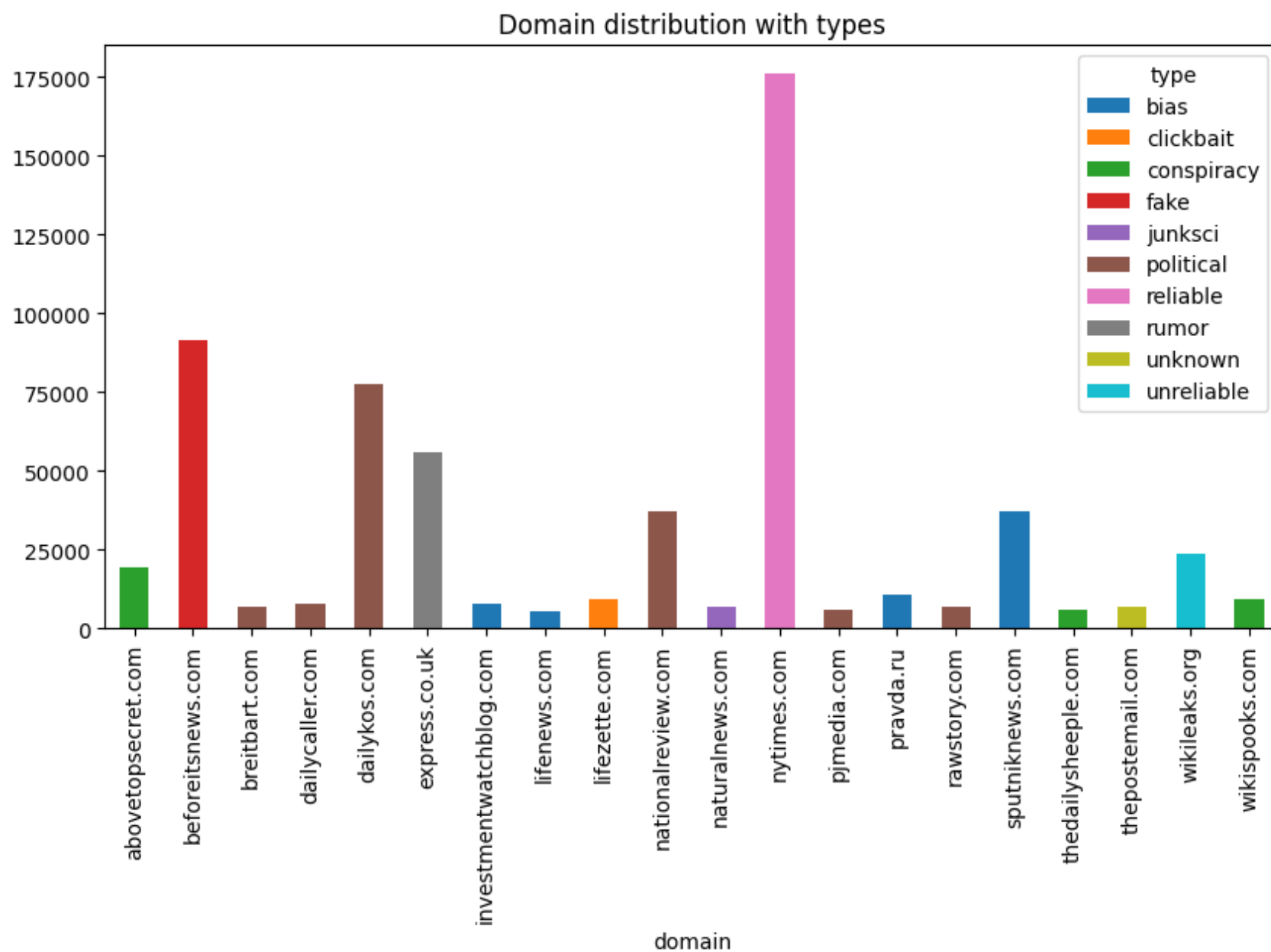
UserWarning: `df.groupby(categorical_by, sort=False)` implementation has mismatches with pandas: the groupby keys will be sorted anyway, although the 'sort=False' was passed. See the following issue for more details: <https://github.com/modin-project/modin/issues/3571>.

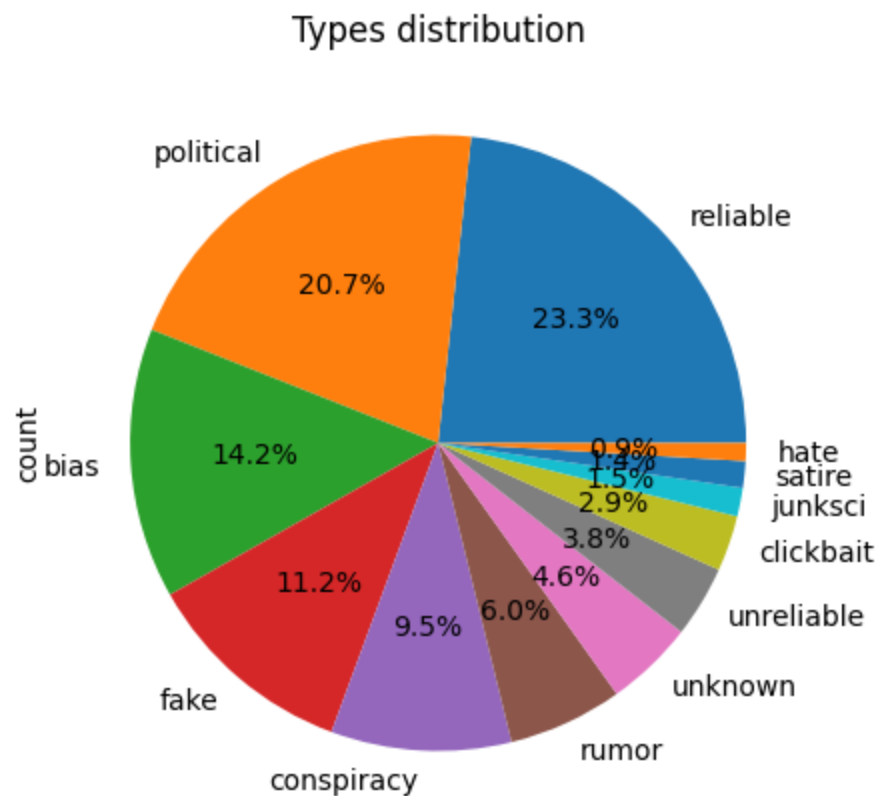
(raylet) A worker died or was killed while executing a task by an unexpected system error. To troubleshoot the problem, check the logs for the dead worker. RayTask ID: 862a43f6ea08922a18a9cf3d5f68dff17e5fd863010000 Worker ID: 27977a9715984320a34780ae66061076bc125119d0cd8a1e97fa5139 Node ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061 Worker IP address: 10.3.32.4 Worker port: 43795 Worker PID: 14450 Worker exit type: SYSTEM_ERROR Worker exit detail: The leased worker has unrecoverable failure. Worker is requested to be destroyed when it is returned. RPC Error message: Socket closed; RPC Error details:

```
(raylet) [2024-04-02 20:26:45,994 E 14353 14353] (raylet) node_manager.cc:2967: 1 Workers (tasks / actors) killed due to memory pressure (OOM), 0 Workers crashed due to other reasons at node (ID: e08b31605fb17e00a93e5c9c60a20ccc71f93e8c8c669311043b7061, IP: 10.3.32.4) over the last time period. To see more information about the Workers killed on this node, use `ray logs raylet.out -ip 10.3.32.4`
```

```
(raylet)
```

```
(raylet) Refer to the documentation on how to address the out of memory issue: https://docs.ray.io/en/latest/ray-core/scheduling/ray-oom-prevention.html. Consider provisioning more memory on this node or reducing task parallelism by requesting more CPUs per task. To adjust the kill threshold, set the environment variable `RAY_memory_usage_threshold` when starting Ray. To disable worker killing, set the environment variable `RAY_memory_monitor_refresh_ms` to zero.
```





Number of dropped rows: 56368

When exporting the cleaned dataset we have to make sure the tokens are stored correctly in the csv. A csv can correctly store a python list, therefore we store the tokens as a string using space as a separator for each token.

```
In [ ]: dfcpy.content = dfcpy.content.apply(lambda x: ' '.join(x))
dfcpy.title = dfcpy.title.apply(lambda x: ' '.join(x))
dfcpy.to_csv('995k_rows_cleaned.csv', index=False)
print("done cleaning the data")

# shutdown the ray engine to free up the memory
import ray
ray.shutdown()
```

Task 4

Using the types we label articles as either fake or reliable. Some article types are omitted since it's ambiguous whether they are fake news or not.

```
In [ ]: import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('995k_rows_cleaned.csv', usecols=['content', 'type', 'title'], engine='c', dtype = str)
dfcpy = df.copy()

# label is 1 if the article is fake, 0 if the article is reliable
dfcpy['label'] = dfcpy['type'].map({'fake': 1,
                                   'conspiracy': 1,
                                   'junksci': 1,
                                   'bias': 1,
                                   'clickbait': 0,
                                   'political': 0,
                                   'reliable': 0})

dfcpy = dfcpy.dropna(subset=['label'])
dfcpy['label'] = dfcpy['label'].astype(int)

dfcpy = dfcpy.dropna(subset=['content'])
dfcpy = dfcpy.dropna(subset=['title'])
```

We split the dataset into a random 80/10/10 split where 80% is used for training. 10% is used for validation and 10% is used for testing.

```
In [ ]: from sklearn.model_selection import train_test_split
# Splitting the data into training (80%) and the rest (20%)
train_df, rest_df = train_test_split(dfcpy, test_size=0.2, random_state=42, stratify=dfcpy['label'])
# Splitting the rest into validation (50%) and test (50%)
validation_df, test_df = train_test_split(rest_df,
                                          test_size=0.5,
                                          random_state=42,
                                          stratify=rest_df['label'])

content_train, title_train, y_train = train_df['content'], train_df['title'], train_df['label']
```

```

content_val, title_val, y_val = validation_df['content'], validation_df['title'], validation_df['label']
content_test, title_test, y_test = test_df['content'], test_df['title'], test_df['label']

print("Training Set:")
print(train_df.content.head())
print(train_df.title.head())

```

Training Set:

```

779426    <num> year old iranian man share life iran wor...
51493     love love harlem said could walk favorit resta...
325203    plu one articl googl plu thank ali alfoneh ass...
272377    larri silverstein caught admit camera plan bui...
38281     artifici intellig complex creator cant trust m...
Name: content, dtype: object
779426                                     tale iranian blogger
51493                                     home daniel brook orang new black
325203                                     iran news round
272377                                     news wire mintpress news
38281     artifici intellig complex creator cant trust m...
Name: title, dtype: object

```

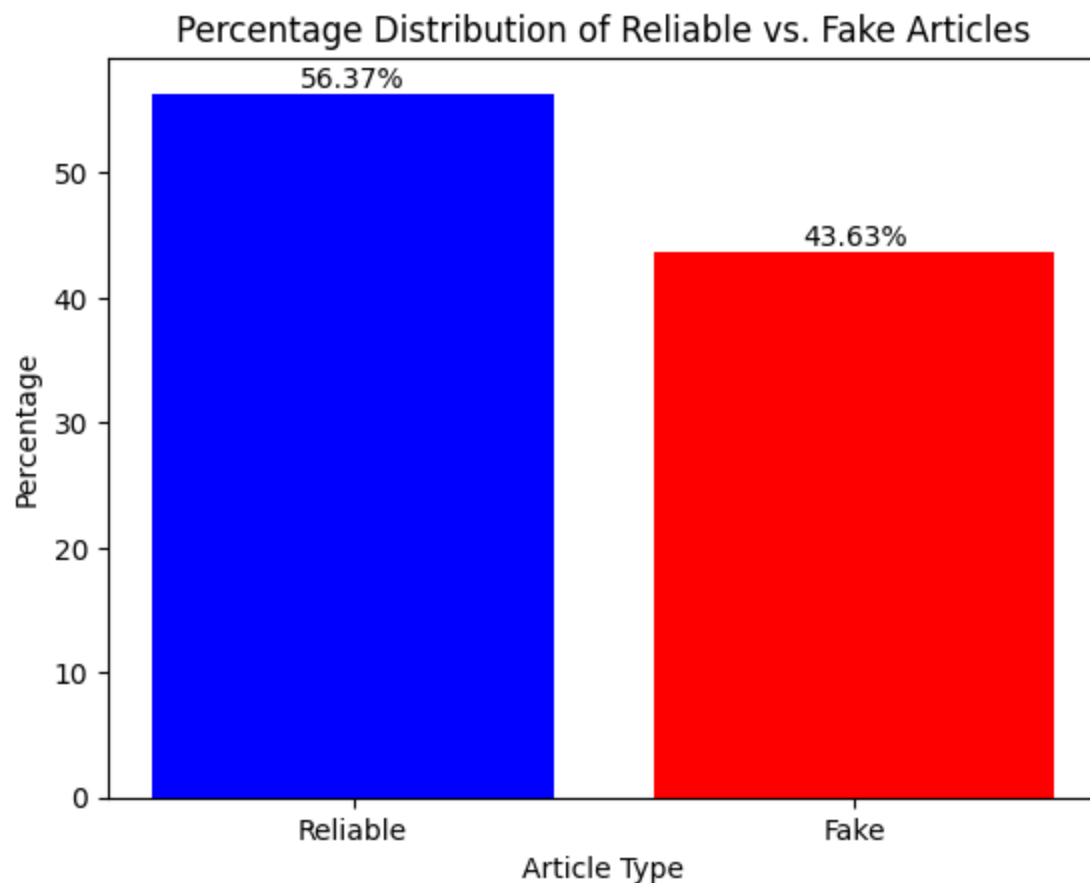
We plot the Distrubution of Fake and reliable articles to get and idea on wheter our data is balanced or not

```

In [ ]: # Examine the percentage distribution of 'reliable' vs. 'fake' articles
grouped_type = dfcpy['label'].value_counts()
grouped_type = grouped_type / grouped_type.sum() * 100

# make a bar plot with percentages on bars
plt.bar([0, 1], grouped_type, tick_label=['Reliable', 'Fake'], color=['blue', 'red'])
plt.text(0, grouped_type[0], f'{grouped_type[0]:.2f}%', ha='center', va='bottom')
plt.text(1, grouped_type[1], f'{grouped_type[1]:.2f}%', ha='center', va='bottom')
plt.xlabel('Article Type')
plt.ylabel('Percentage')
plt.title('Percentage Distribution of Reliable vs. Fake Articles')
plt.show()

```

Importing and cleaning extra reliable articles scraped from BBC news.

```
In [ ]: df_extra = pd.read_csv("scraped_articles.csv", usecols=['content'])
df_extra_cpy = df_extra.copy()
df_extra_cpy = df_extra_cpy.dropna(subset=['content'])
df_extra_cpy.content = df_extra_cpy.content.apply(clean_text)
tokenizer = RegexpTokenizer(r'<[\w]+>|[\w]+')
df_extra_cpy.content = df_extra_cpy.content.apply(tokenizer.tokenize)
df_extra_cpy.content = df_extra_cpy.content.apply(rmv_stopwords)
df_extra_cpy.content = df_extra_cpy.content.apply(stem_tokens)
df_extra_cpy['label'] = 0

df_extra_cpy.content = df_extra_cpy.content.apply(lambda x: ' '.join(x))
```

```
x_train_extra = pd.concat([content_train, df_extra_cpy.content], ignore_index=True)
y_train_extra = pd.concat([y_train, df_extra_cpy.label], ignore_index=True)
```

```
In [ ]: import seaborn as sns
        from sklearn import metrics
        def make_confusion_matrix(y_val, y_pred, model_name):
            confusion_matrix = metrics.confusion_matrix(y_val, y_pred, labels=[1, 0])
            sns.heatmap(confusion_matrix,
                        annot=True,
                        fmt='g',
                        cmap='Blues',
                        xticklabels=['real', 'fake'],
                        yticklabels=['real', 'fake'])
            plt.xlabel('Predicted')
            plt.ylabel('Actual')
            plt.title(f'{model_name}')
            plt.show()
```

Part 2: A simple model

We use logistic regression for our simple model. The model is simple in terms of vector representation (bag of words) and lack of hyperparameter tuning.

```
In [ ]: from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.linear_model import LogisticRegression
        from sklearn.preprocessing import StandardScaler
        from sklearn.pipeline import Pipeline
        import sklearn.metrics as metrics
        from scipy.sparse import hstack
        from joblib import dump

        vectorizer = CountVectorizer(lowercase = False, max_features = 5000, token_pattern=r'<[\w]+>|[\w]+')
        pipeline = Pipeline([
            ('vectorizer', vectorizer),
            ('scaler', StandardScaler(with_mean=False))
        ])

        model = LogisticRegression(max_iter=10000, random_state=42)
```

```
# making bag of words for the content and extra data
BoW_extra = pipeline.fit_transform(x_train_extra)
BoW_content_val = pipeline.transform(content_val)

# Model with only content, but with extra data
model.fit(BoW_extra, y_train_extra)
y_pred = model.predict(BoW_content_val)
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Only content, but with extra data:")
print("f1 score:", f1)
print("accuracy:", accuracy)

# mkain bag of words for the content
BoW_content_train = pipeline.fit_transform(content_train)
BoW_content_val = pipeline.transform(content_val)
content_test_bow = pipeline.transform(content_test)

# Model with only content
model.fit(BoW_content_train, y_train)
y_pred = model.predict(BoW_content_val)
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Only content:")
print("f1 score:", f1)
print("accuracy:", accuracy)
# saving the model
dump(model, 'models/simple_model_content.joblib')

# making bag of words for the title and content
BoW_title_train = pipeline.fit_transform(title_train)
BoW_title_val = pipeline.transform(title_val)
BoW_combined_train = hstack((BoW_content_train, BoW_title_train))
BoW_combined_val = hstack((BoW_content_val, BoW_title_val))

# Model with content and title
model.fit(BoW_combined_train, y_train)
y_pred = model.predict(BoW_combined_val)
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("\nContent and title:")
```

```
print("f1 score:", f1)
print("accuracy:", accuracy)
# saving the model
dump(model, 'models/simple_model_combined.joblib')
```

Only content, but with extra data:

f1 score: 0.8240011926058439

accuracy: 0.8488928708562652

Only content:

f1 score: 0.8239501683903079

accuracy: 0.8487904774094458

Content and title:

f1 score: 0.860425111812484

accuracy: 0.8805708434660182

Out[]: ['models/simple_model_combined.joblib']

Part 3: Advanced model

We have tried 3 models:

- LinearSVM
- Naive bayes
- Logistic regression (using TF-IDF and cross validation)

We tried 2 vector representations:

- TF-IDF (1, 2 and 3 grams)
- Sentence embedding (Doc2Vec)

We perform cross validation (gridsearch) on hyper parameters to find the best hyperparameters for each model

We started with limiting the amount of features to 3500. the LIAR data set only has 7000 features, since we train our models using 3500 features from content and 3500 features content we get a model trained on 7000 features and won't have to retrain them for the LIAR dataset

Model 1: Linear SVC

```
In [ ]: from sklearn.svm import LinearSVC
        from sklearn.model_selection import GridSearchCV
        import sklearn.metrics as metrics
        from joblib import dump
        from time import time

        def svm(x_train, y_train, x_val, model_name):
            time_start = time()
            svc = LinearSVC(max_iter=10000, dual=False, random_state=42)
            parameters = dict(C=[0.1, 1, 10, 20, 50, 100])
            # Cross-validation
            grid_search = GridSearchCV(svc, parameters, cv=3, n_jobs=-1, scoring = 'f1', pre_dispatch=3)
            grid_search.fit(x_train, y_train)
            print(f"Time to train the model: {(time() - time_start)/60:.2f} min")

            best_params = grid_search.best_params_
            print("Best Parameters for svm:", best_params)

            dump(grid_search, f'models/{model_name}.joblib')

            return grid_search.predict(x_val)
```

Model 2: Naive Bayes

```
In [ ]: from sklearn.naive_bayes import MultinomialNB
        from sklearn.model_selection import GridSearchCV
        import sklearn.metrics as metrics
        from joblib import dump
        from time import time

        def naive_bayes(x_train, y_train, x_val, model_name):
            time_start = time()
            nb = MultinomialNB()
            parameters = dict(alpha=[0.01, 0.1, 1, 10])
            # Cross-validation
            grid_search = GridSearchCV(nb, parameters, cv=3, n_jobs=-1, scoring = 'f1')
            grid_search.fit(x_train, y_train)
```

```
print(f"Time to train the model: {(time() - time_start)/60:.2f} min")
best_params = grid_search.best_params_
print("Best parameters for Naive Bayes model:", best_params)

dump(grid_search, f'models/{model_name}.joblib')

return grid_search.predict(x_val)
```

Model 3: Logistic regression

We noticed our simple model performed quite well, therefore we tried to optimize hyperparameters and use n-grams to see if this would improve the simple model further

```
In [ ]: from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import GridSearchCV
        import sklearn.metrics as metrics
        from joblib import dump
        from time import time

        def logistic_advanced(x_train, y_train, x_val, model_name):
            time_start = time()
            logistic = LogisticRegression(max_iter = 10000, random_state=42)
            parameters = dict(C=[0.1, 1, 10], solver=['sag', 'saga'])
            # Cross-validation
            grid_search = GridSearchCV(logistic, parameters, cv=3, n_jobs=-1, scoring = 'f1', pre_dispatch=3)
            grid_search.fit(x_train, y_train)

            print(f"time to train the model: {(time() - time_start)/3600:.2f} hours")

            best_params = grid_search.best_params_
            print("Best parameters for logistic regression model:", best_params)
            # saving the model
            dump(grid_search, f'models/{model_name}.joblib')

            return grid_search.predict(x_val)
```

TF-IDF

```
In [ ]: from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from scipy.sparse import hstack
from time import time

def make_TFIDF(features, ngrams):
    time_start = time()
    global content_test, content_train, content_val, title_test, title_train, title_val
    global y_test, y_train, y_val
    pipeline = Pipeline([
        ('vectorizer', TfidfVectorizer(lowercase = False,
                                      max_features=features,
                                      min_df = 1,
                                      max_df= 0.9,
                                      token_pattern=r'<[\w]+>|[\w]+',
                                      ngram_range = ngrams)),
        ('scaler', StandardScaler(with_mean=False)),
    ])

    content_train_TFIDF = pipeline.fit_transform(content_train, y_train)
    content_val_TFIDF = pipeline.transform(content_val)
    content_test_TFIDF = pipeline.transform(content_test)

    title_train_TFIDF = pipeline.fit_transform(title_train, y_train)
    title_val_TFIDF = pipeline.transform(title_val)
    title_test_TFIDF = pipeline.transform(title_test)

    X_train_TFIDF = hstack((content_train_TFIDF, title_train_TFIDF))
    X_val_TFIDF = hstack((content_val_TFIDF, title_val_TFIDF))
    X_test_TFIDF = hstack((content_test_TFIDF, title_test_TFIDF))
    return X_train_TFIDF, X_val_TFIDF, X_test_TFIDF
```

Validating the model

1 gram:

```
In [ ]: X_train_TFIDF, X_val_TFIDF, X_test_TFIDF = make_TFIDF(3500, (1, 1))
```

SVM:

```
In [ ]: y_pred = svm(X_train_TFIDF, y_train, X_val_TFIDF, 'svm_1gram')

accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Time to train the model: 16.72 min
Best Parameters for svm: {'C': 20}
Support vector machine:
f1 score: 0.8662668131476589
accuracy score: 0.8847049788813516

Logistic regression

```
In [ ]: print("Logistic regression:")
y_pred = logistic_advanced(X_train_TFIDF, y_train, X_val_TFIDF, 'logistic_1gram')

accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Logistic regression:
time to train the model: 2.37 hours
Best parameters for logistic regression model: {'C': 0.1, 'solver': 'saga'}
f1 score: 0.867032690571678
accuracy score: 0.8849993600409574

Naive Bayes

```
In [ ]: print("Naive Bayes:")
y_pred = naive_bayes(X_train_TFIDF, y_train, X_val_TFIDF, 'naive_bayes_1gram')

accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("f1 score:", f1)
print("accuracy score:", accuracy)
```


Naive Bayes:

Time to train the model: 0.08 min

Best parameters for Naive Bayes model: {'alpha': 0.01}

f1 score: 0.8026344676180022

accuracy score: 0.8158965826187125

2 grams:

```
In [ ]: X_train_TFIDF, X_val_TFIDF, X_test_TFIDF = make_TFIDF(3500, (2, 2))
```

SVM

```
In [ ]: y_pred = svm(X_train_TFIDF, y_train, X_val_TFIDF, 'svm_2gram')
```

```
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Time to train the model: 9.60 min

Best Parameters for svm: {'C': 50}

Support vector machine:

f1 score: 0.8299009565471881

accuracy score: 0.8586586458466658

Logistic regression

```
In [ ]: print("Logistic regression:")
y_pred = logistic_advanced(X_train_TFIDF, y_train, X_val_TFIDF, 'logistic_2gram')

accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Logistic regression:

time to train the model: 2.17 hours

Best parameters for logistic regression model: {'C': 10, 'solver': 'sag'}

f1 score: 0.8448520515616366

accuracy score: 0.8670549084858569

Naive Bayes

```
In [ ]: print("Naive Bayes:")
y_pred = naive_bayes(X_train_TFIDF, y_train, X_val_TFIDF, 'naive_bayes_2gram')

accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Naive Bayes:

Time to train the model: 0.04 min

Best parameters for Naive Bayes model: {'alpha': 0.01}

f1 score: 0.7947007497932065

accuracy score: 0.8030462050428773

Testing with different ammount of features

It seems that the linearSVC model and logistic regression model both have good performance, but it's much faster to train the linearSVC model. We therefore keep testing on the LinearSVC model with different values of max_feature in the TFIDF vector.

```
In [ ]: X_train_TFIDF, X_val_TFIDF, X_test_TFIDF = make_TFIDF(5000, (1, 1))
y_pred = svm(X_train_TFIDF, y_train, X_val_TFIDF, 'svm_5000')
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Time to train the model: 20.50 min

Best Parameters for svm: {'C': 10}

Support vector machine:

f1 score: 0.8730297853375918

accuracy score: 0.8906054012543198

```
In [ ]: X_train_TFIDF, X_val_TFIDF, X_test_TFIDF = make_TFIDF(10000, (1, 1))
y_pred = svm(X_train_TFIDF, y_train, X_val_TFIDF, 'svm_10000')
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
```

```
print("accuracy score:", accuracy)
```

Time to train the model: 34.49 min

Best Parameters for svm: {'C': 50}

Support vector machine:

f1 score: 0.8799549849703109

accuracy score: 0.8962370408293869

```
In [ ]: X_train_TFIDF, X_val_TFIDF, X_test_TFIDF = make_TFIDF(20000, (1, 1))
y_pred = svm(X_train_TFIDF, y_train, X_val_TFIDF, 'svm_20000')
accuracy = metrics.accuracy_score(y_val, y_pred)
f1 = metrics.f1_score(y_val, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

Time to train the model: 85.78 min

Best Parameters for svm: {'C': 0.1}

Support vector machine:

f1 score: 0.8823268468681612

accuracy score: 0.8981441187763983

We opted to not test different amount of features on logistic regression since. After training the model for 8 hours we gave up, since we it did not converge.

Doc2Vec

Training a Doc2Vec model on the full dataset takes a long time and is actually not needed, it's sufficient to train the model on a subset where we take 1000 articles from each type and train a sentence embedding model using Doc2Vec.

```
In [ ]: ## Create a new split using x amount of each type of article
type_amount = 1000

dfcpy_subset = dfcpy.groupby('type').head(type_amount)
print("Number of articles of each type in the new dataset:",
      dfcpy['type'].value_counts())

dfcpy_subset = dfcpy_subset.dropna(subset=['content'])
dfcpy_subset = dfcpy_subset.dropna(subset=['title'])

X = dfcpy_subset.content
```

```

y = dfcpy_subset.label

print("Training Set:")
print(train_df.content.head())

```

Number of articles of each type in the new dataset: type

```

reliable      218527
political     194445
bias          133179
fake          104850
conspiracy    88847
clickbait     27412
junksci       14039

```

Name: count, dtype: int64

Training Set:

```

779426    <num> year old iranian man share life iran wor...
51493     love love harlem said could walk favorit resta...
325203    plu one articl googl plu thank ali alfoneh ass...
272377    larri silverstein caught admit camera plan bui...
38281     artifici intellig complex creator cant trust m...

```

Name: content, dtype: object

```

In [ ]: from sklearn.model_selection import train_test_split
        from gensim.models.doc2vec import Doc2Vec, TaggedDocument
        from nltk.tokenize import word_tokenize
        from sklearn.preprocessing import StandardScaler
        from time import time
        def doc2vec(X, y, size, win, epo):
            time_start = time()
            doc2vec_model = Doc2Vec(vector_size=size, window=win, min_count=1, epochs = epo, workers = 19)
            tagged_data = [TaggedDocument(words = word_tokenize(doc), tags=[i]) for i, doc in enumerate(X)]

            doc2vec_model.build_vocab(tagged_data)
            doc2vec_model.train(tagged_data,
                               total_examples = doc2vec_model.corpus_count,
                               epochs = doc2vec_model.epochs)
            doc_vectors = [doc2vec_model.infer_vector(word_tokenize(doc)) for doc in X]

            # scale the data
            scaler = StandardScaler()
            doc_vectors = scaler.fit_transform(doc_vectors)
            X_train_D2V, X_rest_D2V, y_train_D2V, y_res_D2V = train_test_split(doc_vectors,y,

```

```
test_size=0.2,  
random_state=42)  
  
X_val_D2V, X_test_D2V, y_val_D2V, y_test_D2V = train_test_split(X_rest_D2V,  
                                                                y_res_D2V,  
                                                                test_size=0.5,  
                                                                random_state=42)  
  
print(f"time to train the model: {(time() - time_start)/60:.2f} min")  
return X_train_D2V, X_val_D2V, X_test_D2V, y_train_D2V, y_val_D2V, y_test_D2V
```

Making the document vectors

```
In [ ]: X_train_D2V, X_val_D2V, X_test_D2V, y_train_D2V, y_val_D2V, y_test_D2V = doc2vec(X, y, 100, 5, 20)
```

time to train the model: 2.54 min

```
In [ ]: y_pred = svm(X_train_D2V, y_train_D2V, X_val_D2V, 'svm_D2V')  
accuracy = metrics.accuracy_score(y_val_D2V, y_pred)  
f1 = metrics.f1_score(y_val_D2V, y_pred)  
print("Support vector machine:")  
print("f1 score:", f1)  
print("accuracy score:", accuracy)
```

Time to train the model: 0.09 min
Best Parameters for svm: {'C': 0.1}
Support vector machine:
f1 score: 0.7747318235995232
accuracy score: 0.73

```
In [ ]: y_pred = logistic_advanced(X_train_D2V, y_train_D2V, X_val_D2V, 'logistic_D2V')  
f1 = metrics.f1_score(y_val_D2V, y_pred)  
accuracy = metrics.accuracy_score(y_val_D2V, y_pred)  
print("Logistic regression:")  
print("f1 score:", f1)  
print("accuracy score:", accuracy)
```

time to train the model: 0.00 hours
Best parameters for logistic regression model: {'C': 1, 'solver': 'sag'}
Logistic regression:
f1 score: 0.7805456702253855
accuracy score: 0.7357142857142858

```
In [ ]: X_train_D2V, X_val_D2V, X_test_D2V, y_train_D2V, y_val_D2V, y_test_D2V = doc2vec(X, y, 3500, 5, 20)
```

time to train the model: 728.45 sec

SVM

```
In [ ]: y_pred = svm(X_train_D2V, y_train_D2V, X_val_D2V, 'svm_D2V')
accuracy = metrics.accuracy_score(y_val_D2V, y_pred)
f1 = metrics.f1_score(y_val_D2V, y_pred)
print("Support vector machine:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

/home/katikistan/miniconda3/envs/fake2/lib/python3.10/site-packages/sklearn/svm/_base.py:1242: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

Time to train the model: 313.88 min

Best Parameters for svm: {'C': 0.1}

Support vector machine:

f1 score: 0.7769607843137255

accuracy score: 0.74

Logistic regression

```
In [ ]: y_pred = logistic_advanced(X_train_D2V, y_train_D2V, X_val_D2V, 'logistic_D2V')
f1 = metrics.f1_score(y_val_D2V, y_pred)
```

```
accuracy = metrics.accuracy_score(y_val_D2V, y_pred)
print("Logistic regression:")
print("f1 score:", f1)
print("accuracy score:", accuracy)
```

time to train the model: 1.63 hours

Best parameters for logistic regression model: {'C': 0.1, 'solver': 'saga'}

Logistic regression:

f1 score: 0.7822966507177034

accuracy score: 0.74

The performance from our Doc2Vec models was worse than our TF-IDF models. We expected to see an increase in performance, but we didn't. This could be because this particular dataset isn't suited for sentence embedding as a vector representation or it could be because we didn't implement sentence embedding correctly. Either way our TF-IDF models did perform quite well and therefore we use a SVM with TF-IDF instead.

We didn't test naive bayes since with Doc2Vec since naive bayes doesn't work with negative values and therefore don't work with Doc2Vec

Part 4: Evaluation

Logistic regression is with tuned hyperparameters is slightly better (0.001 higher f1 score) than linearsvc however it much longer to train the logistic regression model (svm takes 16 minutes and logistic regression takes 2.5 hours), therefore we have chosen the Support vector machine instead as our model to test and evaluate, since it's better in terms of time to train and almost just as good in terms of f1 score and accuracy. Logistic regression is with tuned hyperparameters is slightly better than linearsvc however it takes double the amount of time to train the logistic regression model, therefore we have chosen the Support vector machine instead as our model to test and evaluate

Testing models with FakeNewsCorpus test set

```
In [ ]: from joblib import load
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.preprocessing import StandardScaler
        from sklearn.pipeline import Pipeline
        from scipy.sparse import hstack
```

```
import sklearn.metrics as metrics

simple_model = load('models/simple_model_combined.joblib')
advanced_model = load('models/svm_20000.joblib')

pipeline_bow = Pipeline([
    ('vectorizer', CountVectorizer(max_features=5000, token_pattern=r'<[\w]+>|[\w]+')),
    ('scaler', StandardScaler(with_mean=False)),
])
# 3500 hvis titler er med
pipeline_tfidf = Pipeline([
    ('vectorizer', TfidfVectorizer(lowercase = False,
                                   max_features=20000,
                                   min_df = 1,
                                   max_df= 0.9,
                                   token_pattern=r'<[\w]+>|[\w]+',
                                   ngram_range = (1, 1))),
    ('scaler', StandardScaler(with_mean=False)),
])

BoW_content_train = pipeline_bow.fit_transform(content_train)
BoW_content_test = pipeline_bow.transform(content_test)

BoW_title_train = pipeline_bow.fit_transform(title_train)
BoW_title_test = pipeline_bow.transform(title_test)

combined_test_bow = hstack((BoW_content_test, BoW_title_test))
simple_pred_test = simple_model.predict(combined_test_bow)

accuracy_simple = metrics.accuracy_score(y_test, simple_pred_test)
f1_simple = metrics.f1_score(y_test, simple_pred_test)

print("\nSimple model:")
print("Test set:")
print("f1 score:", f1_simple)
print("accuracy score:", accuracy_simple)
make_confusion_matrix(y_test, simple_pred_test, "Simple model")

content_train_tfidf = pipeline_tfidf.fit_transform(content_train)
content_test_tfidf = pipeline_tfidf.transform(content_test)

title_train_tfidf = pipeline_tfidf.fit_transform(title_train)
```



```
title_test_tfidf = pipeline_tfidf.transform(title_test)

combined_test_tfidf = hstack((content_test_tfidf, title_test_tfidf))
advanced_pred_test = advanced_model.predict(combined_test_tfidf)

accuracy_advanced = metrics.accuracy_score(y_test, advanced_pred_test)
f1_advanced = metrics.f1_score(y_test, advanced_pred_test)

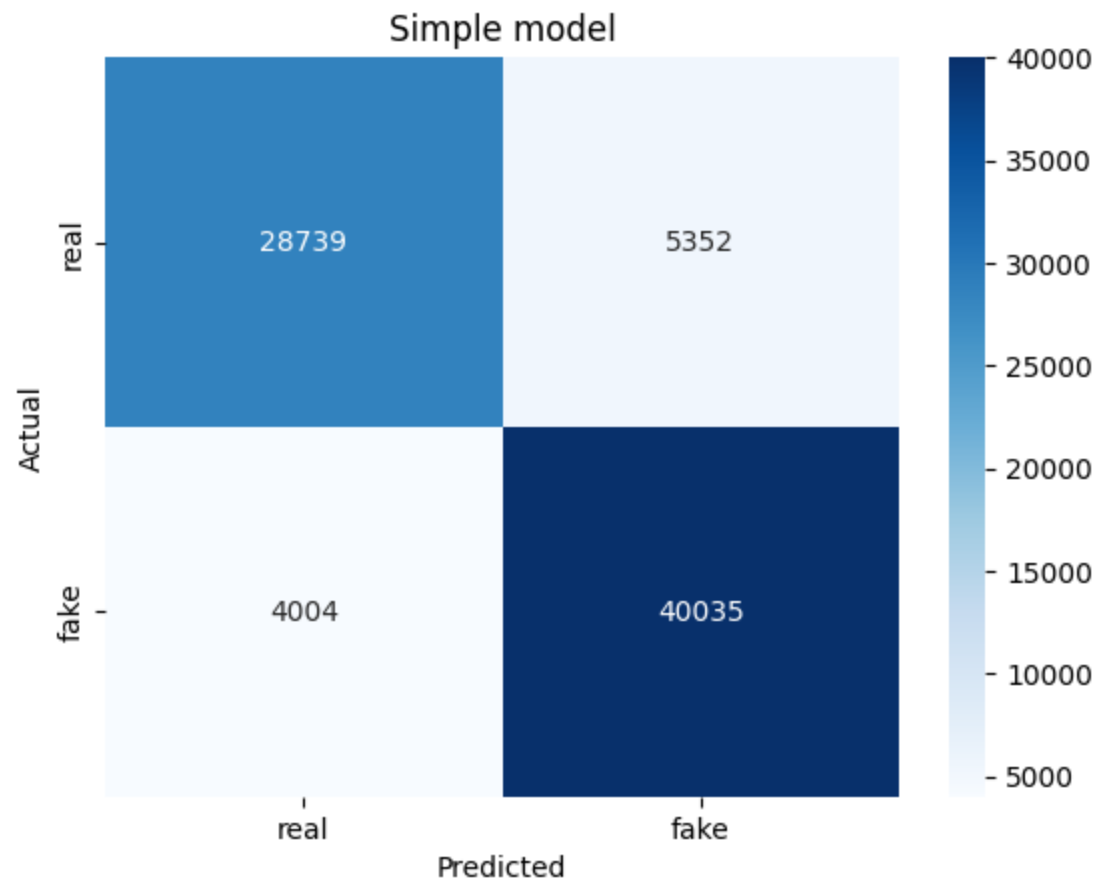
print("\nAdvanced model:")
print("Test set:")
print("f1 score:", f1_advanced)
print("accuracy score:", accuracy_advanced)
make_confusion_matrix(y_test, advanced_pred_test, "Advanced model")
```

Simple model:

Test set:

f1 score: 0.8600113714576413

accuracy score: 0.8802508639447075

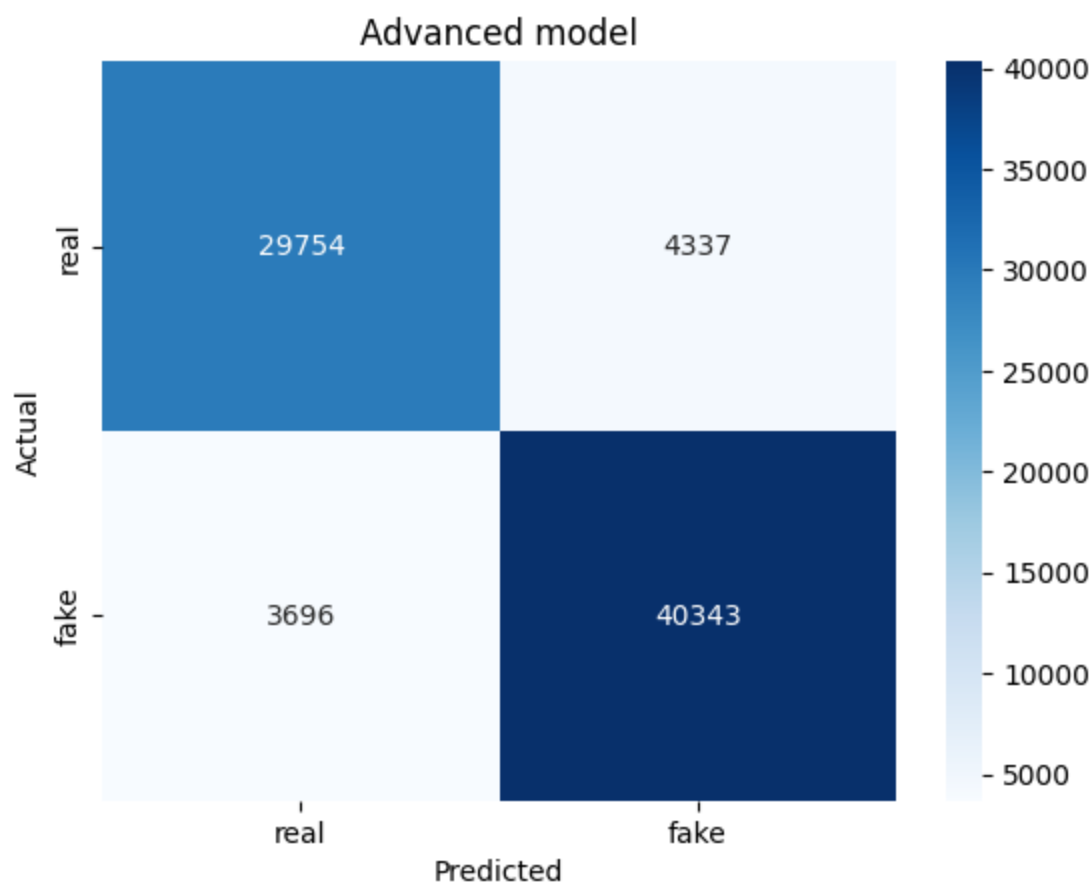


Advanced model:

Test set:

f1 score: 0.8810648346930012

accuracy score: 0.8971841802124664



Testing Models on LIAR dataset

The LIAR dataset only has around 7000 features when combining the whole dataset. Our models are trained on higher amounts of features. Therefore we need to retrain our models on the FakeNewsCorpus with lower amounts of features. Since we combine a content vector and a title vector, they can in total only have 7000 features or 3500 features each. By doing this we have two models trained on 7000 features which can be used to make predictions on the LIAR dataset.

```
In [ ]: import pandas as pd
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.preprocessing import StandardScaler
        import sklearn.metrics as metrics
```

```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from joblib import load
from scipy.sparse import hstack

liar_train = pd.read_csv('train.tsv', sep='\t', header=None)
liar_val = pd.read_csv('valid.tsv', sep='\t', header=None)
liar_test = pd.read_csv('test.tsv', sep='\t', header=None)
liar = pd.concat([liar_train, liar_val, liar_test], ignore_index=True)
liar_cpy = liar.copy()

liar_cpy[2] = liar_cpy[2].apply(clean_text)
tokenizer = RegexpTokenizer(r'<[\w]+>|[\w]+')
liar_cpy[2] = liar_cpy[2].apply(tokenizer.tokenize)
liar_cpy[2] = liar_cpy[2].apply(rmv_stopwords)
liar_cpy[2] = liar_cpy[2].apply(stem_tokens)
liar_cpy[2] = liar_cpy[2].apply(lambda x: ' '.join(x))

labels_used = ['pants-fire', 'false', 'mostly-true', 'true']
liar_cpy = liar_cpy.dropna(subset=[1])
liar_cpy = liar_cpy[liar_cpy[1].isin(labels_used)]
liar_cpy[1] = liar_cpy[1].map({'pants-fire': 1,
                              'false': 1,
                              'mostly-true': 0,
                              'true': 0})

liar_cpy = liar_cpy.dropna(subset=[2])

pipeline_bow = Pipeline([
    ('vectorizer', CountVectorizer(max_features=3500, token_pattern=r'<[\w]+>|[\w]+')),
    ('scaler', StandardScaler(with_mean=False)),
])

BoW_content_train = pipeline_bow.fit_transform(content_train)
BoW_title_train = pipeline_bow.fit_transform(title_train)
combined_train_bow = hstack((BoW_content_train, BoW_title_train))
simple_model = LogisticRegression(max_iter=10000, random_state=42)
simple_model.fit(combined_train_bow, y_train)

advanced_model = load('models/svm_lgram.joblib')
```

```
In [ ]: simple_model.fit(combined_train_bow, y_train)
pipeline_bow = Pipeline([
    ('vectorizer', CountVectorizer(max_features=7000, token_pattern=r'<[\w]+>|[\w]+')),
    ('scaler', StandardScaler(with_mean=False)),
])

pipeline_tfidf = Pipeline([
    ('vectorizer', TfidfVectorizer(lowercase = False,
                                   max_features=7000,
                                   min_df = 1,
                                   max_df= 0.9,
                                   token_pattern=r'<[\w]+>|[\w]+',
                                   ngram_range = (1, 1))),
    ('scaler', StandardScaler(with_mean=False)),
])

x_liar = liar_cpy[2]
y_liar = liar_cpy[1]

liar_bow = pipeline_bow.fit_transform(x_liar, y_liar)

simple_pred_liar = simple_model.predict(liar_bow)

accuracy_simple_liar = metrics.accuracy_score(y_liar, simple_pred_liar)
f1_simple_liar = metrics.f1_score(y_liar, simple_pred_liar)
print("\nSimple model:")
print("Liar dataset:")
print("f1 score:", f1_simple_liar)
print("accuracy score:", accuracy_simple_liar)
make_confusion_matrix(y_liar, simple_pred_liar, "Simple model on LIAR dataset")

liar_tfidf = pipeline_tfidf.fit_transform(x_liar, y_liar)
advanced_pred_liar = advanced_model.predict(liar_tfidf)

accuracy_advanced_liar = metrics.accuracy_score(y_liar, advanced_pred_liar)
f1_advanced_liar = metrics.f1_score(y_liar, advanced_pred_liar)

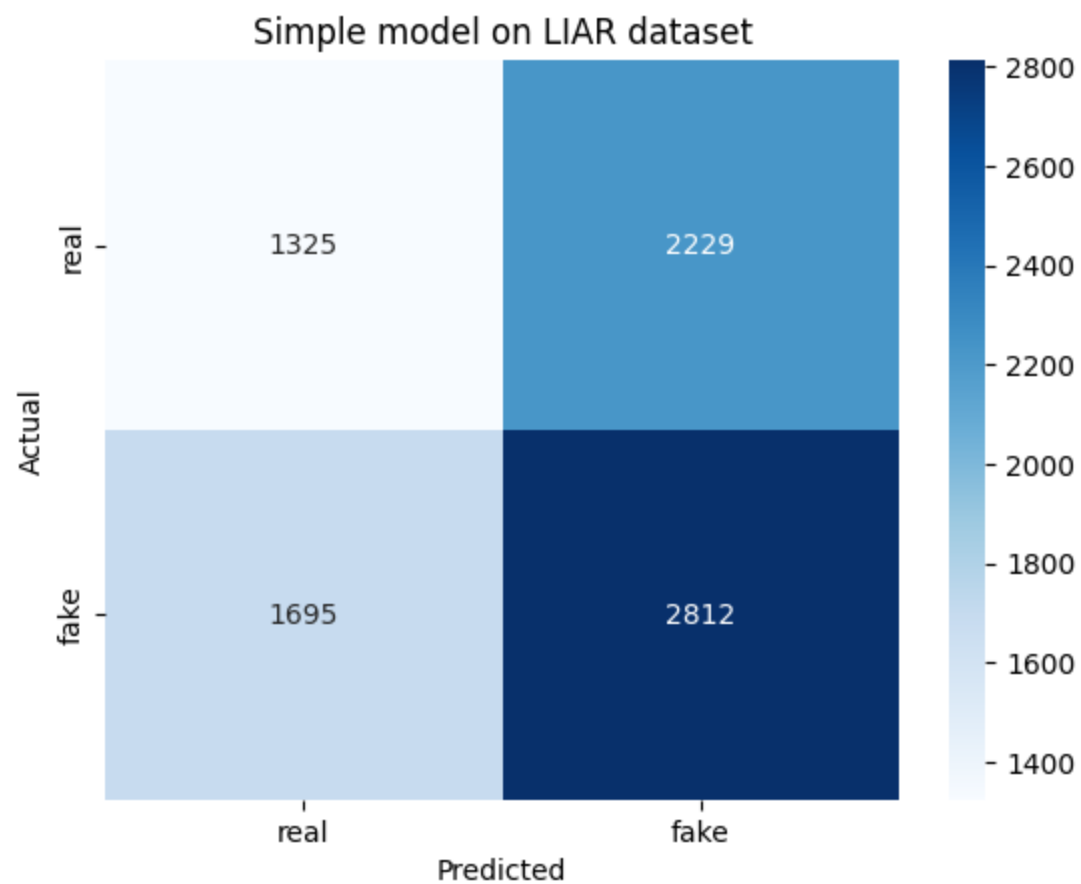
print("\nAdvanced model:")
print("Liar dataset:")
print("f1 score:", f1_advanced_liar)
print("accuracy score:", accuracy_advanced_liar)
make_confusion_matrix(y_liar, advanced_pred_liar, "Advanced model on LIAR dataset")
```

Simple model:

Liar dataset:

f1 score: 0.40310313355643446

accuracy score: 0.5132117603275028



Advanced model:

Liar dataset:

f1 score: 0.4188172835864917

accuracy score: 0.5111028408386056

