In [1]:

```
#import important libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# import libraries for EDA and preprocessing
from datetime import datetime
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
nltk.download('wordnet')
from nltk.stem import WordNetLemmatizer

# import libraries for modeling
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF
from sklearn.cluster import KMeans
import sklearn.metrics as metrics
import itertools
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# import libraries for evaluating
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score, recall_score,precision_score, f1_sco
import time
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/linhtran/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     /Users/linhtran/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Step 1: Gather data, determine the method of data collection and provenance of the data

Fake news is the deliberate spread of misinformation via traditional news media or via social media. False information spreads extraordinarily fast. This is demonstrated by the fact that, when one fake news site is taken down, another will promptly take its place. In addition, fake news can become indistinguishable from accurate reporting since it spreads so fast. People can download articles from sites, share the information, re-share from others and by the end of the day the false information has gone so far from its original site that it becomes indistinguishable from real news (Rubin, Chen, & Conroy, 2016).

Thus, detecting false information or fake news can help people get the true stories, good information. In this project, I use data from Kaggle, were downloaded from the link: https://www.kaggle.com/datasets/clmentbisaillon/fake-and-real-news-dataset

There are two data from this resource, included true and fake data. There are 23481 entries in fake and 21417 entries in true data. There are 4 columns in each data, included: title, text, subject and date. After reading these two data, I will create a new data by concatenating them together for training model later.

In [2]:

```
# read fake data
fake = pd.read_csv('Fake.csv')

# take a look at some rows of fake data
fake.head()
```

Out[2]:

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017

In [3]:

```
# read true data
true = pd.read_csv('True.csv')

# take a look at some rows of fake data
true.head()
```

Out[3]:

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017

In [4]:

```
# the shape of fake data
fake.shape
```

Out[4]: (23481, 4)

In [5]:
```
# the shape of true data
true.shape
```

Out[5]: (21417, 4)

In [6]:
```
# create label for concatenating data
fake["label"] = "fake"
true["label"] = "true"
```

In [7]:
```
# Concatenate fake and true news
df = pd.concat([fake, true]).reset_index(drop = True)

# take a look at some sample rows of new data
df.sample(10)
```

Out[7]:

	title	text	subject	date	label
22467	Syria: US Peace Council Addresses United Natio...	Photo: Henry Lowendorf21st Century Wire says ...	US_News	September 27, 2016	fake
3482	House Republicans Just Introduced Bill To Sla...	The Republican effort to let Social Security ...	News	December 9, 2016	fake
38792	Cambodia marks independence from France with d...	PHNOM PENH (Reuters) - Cambodians on Thursday ...	worldnews	November 9, 2017	true
40833	Czech ANO party dips but keeps commanding lead...	PRAGUE (Reuters) - Support for billionaire And...	worldnews	October 16, 2017	true
3274	The Internet Loses It Over RNC's Bizarre Stat...	The Republican National Committee released a b...	News	December 25, 2016	fake
13979	HOUSE SPEAKER PAUL RYAN Puts The Party Before ...	HOUSE SPEAKER PAUL RYAN HAS SOUR GRAPES ABOUT ...	politics	May 5, 2016	fake
15392	[VIDEO] HERO WHO EXPOSED PLANNED PARENTHOOD SA...	David Daleiden: We probably have hundreds to ...	politics	Jul 30, 2015	fake
21609	HIGH SCHOOL TEACHER SEEKS HELP FROM UNION AFTE...	This is just another example of the rampant in...	left-news	Jun 30, 2015	fake
19321	NICOLE KIDMAN BREAKS RANKS With Hollywood Left...	She s travelling the world to promote her new ...	left-news	Jan 12, 2017	fake
27941	Trump to speak with Germany's Merkel, Japan's ...	WASHINGTON (Reuters) - U.S. President Donald T...	politicsNews	April 5, 2017	true

Step 2: Identify an Unsupervised Learning Problem

After concatenating fake and true data, the new data has two labels. And the goal is to assign one label to a news article in test data. The two labels we want to identify are fake and true.

To do this, we will train two kind of models:
(1) two unsupervised models: included NMF using matrix factorization and clustering Kmeans.
(2) multiple supervised models such as Random Forest, Logistic Regression and Decision Tree Classifier.

These models are built to have their testing accuracy, RMSE score and confusion matrix, then I will compare these models for their performance.

Step 3: Exploratory Data Analysis (EDA) - Inspect, Visualize, and Clean the Data

3.1 Inspect the data

In [8]:
```
# get a quick description of the data
df.describe()
```

Out[8]:

	title	text	subject	date	label
count	44898	44898	44898	44898	44898
unique	38729	38646	8	2397	2
top	Factbox: Trump fills top jobs for his administ...		politicsNews	December 20, 2017	fake
freq	14	627	11272	182	23481

In [9]:
```
# check null values in data
df.isnull().sum()
```

Out[9]:
```
title      0
text       0
subject    0
date       0
label      0
dtype: int64
```

In [10]:
```
# check for duplicate articles
df.duplicated(keep=False).sum()
```

Out[10]:
```
405
```

In [11]:
```
# remove duplicates articles
df = df.drop_duplicates(keep=False)

# check shape of new data
df.shape
```

Out[11]:
```
(44493, 5)
```

In [12]:
```
# the structure of data also tells us the number of rows (observations) and colu
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44493 entries, 0 to 44897
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   title    44493 non-null  object
 1   text     44493 non-null  object
 2   subject  44493 non-null  object
 3   date     44493 non-null  object
 4   label    44493 non-null  object
dtypes: object(5)
memory usage: 2.0+ MB
```

In [13]:

```
# convert date column from object to datetime format
df['date'] = pd.to_datetime(df['date'], errors='coerce')

# view some first rows of the data
df.head()
```

Out[13]:

	title	text	subject	date	label
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	2017-12-31	fake
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	2017-12-31	fake
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	2017-12-30	fake
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	2017-12-29	fake
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	2017-12-25	fake

In [14]:

```
# get the label of data
df['label'].unique()
```

Out[14]:

```
array(['fake', 'true'], dtype=object)
```

In [15]:

```
# get the label of data
df['subject'].unique()
```

Out[15]:

```
array(['News', 'politics', 'Government News', 'left-news', 'US_News',
       'Middle-east', 'politicsNews', 'worldnews'], dtype=object)
```

From the output above, after concatenating fake and true news data, we can summarize that:

- There are 44898 entries and 5 columns in new data.
- There is no missing values.
- There are 405 duplicated articles.
- After removing duplicated rows, our data has 44493 entries and 5 columns.
- All columns are object. Therefore, date column was converted to date time.

- There are 2 labels: fake and true.
- There are 8 subjects: 'News', 'politics', 'Government News', 'left-news', 'US_News', 'Middle-east', 'politicsNews' and 'worldnews'.

3.2 Visualize the data

Next, I will do some works for visualizing the data:

- calculate and visualize the count and the proportion of each label.
- calculate and visualize the count and the proportion of each subject.
- explore the label by year.
- explore the label by month.

In [16]:

```
# calculate the count of each label
df['label'].value_counts()
```

Out[16]:

```
fake    23475
true    21018
Name: label, dtype: int64
```

In [17]:

```
# calculate the proportion of each label
df['label'].value_counts()/len(df)*100
```

Out[17]:

```
fake    52.761108
true    47.238892
Name: label, dtype: float64
```

In [18]:

```
# plot the count of each label
fig, ax = plt.subplots(figsize=(6,6))
sns.countplot(data=df, y='label', ax=ax).set(title='\nFigure 1. The Count of Eac

# plot the proportion of each category
labels = df['label'].unique().tolist()
counts = df['label'].value_counts()
sizes = [counts[v] for v in labels]
fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%0.2f%%')
ax1.axis('equal')
plt.title("\nFigure 2. The Proportion of Each Label\n")
plt.tight_layout()
plt.show()
```

Figure 1. The Count of Each Label

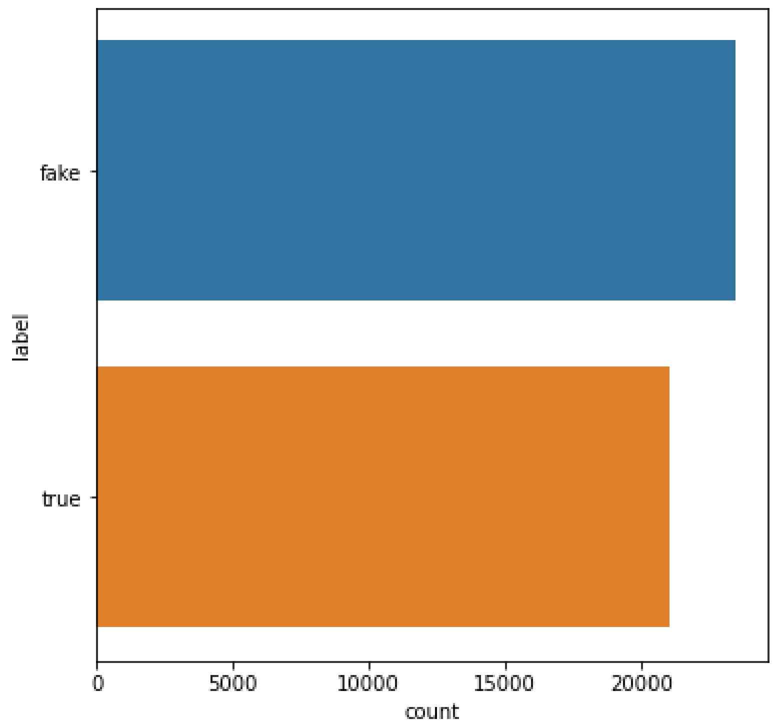


Figure 2. The Proportion of Each Label

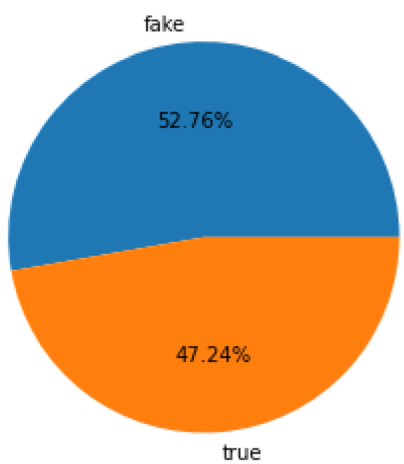


Figure 1 shows the count of each label and figure 2 shows the proportions of each label. Looking at these two figures, we can see that in overall, the number of article for each category is not different too much. I think this is good since if one or two categories was severely underrepresentated or, in contrast, overrepresentative in the train data, then it may cause our model to be biased and/or perform poorly on some or all of the test data.

In [19]:

```
# calculate the count of each subject
subjects = df['subject'].value_counts()
subjects
```

Out[19]:

```
politicsNews       11181
worldnews           9837
News                9050
politics            6835
```

```
left-news            4459
Government News      1570
US_News               783
Middle-east           778
Name: subject, dtype: int64
```

In [20]:

```
# calculate the proportion of each subject
proportions = subjects/len(df)*100
print(proportions)
```

```
politicsNews       25.129796
worldnews          22.109096
News               20.340278
politics           15.361967
left-news          10.021801
Government News     3.528645
US_News             1.759827
Middle-east         1.748590
Name: subject, dtype: float64
```

In [21]:

```
# plot the count of each subject
fig, ax = plt.subplots(figsize=(10,6))
sns.countplot(data=df, y='subject', ax=ax).set(title='\nFigure 3. The Count of E

# plot the proportion of each category
sub_labels = df['subject'].unique().tolist()
counts = df['subject'].value_counts()
sizes = [counts[v] for v in sub_labels]
fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=sub_labels, autopct='%0.2f%%')
ax1.axis('equal')
plt.title("\nFigure 4. The Proportion of Each Subject\n")

plt.tight_layout()
plt.show()
```

Figure 3. The Count of Each Subject

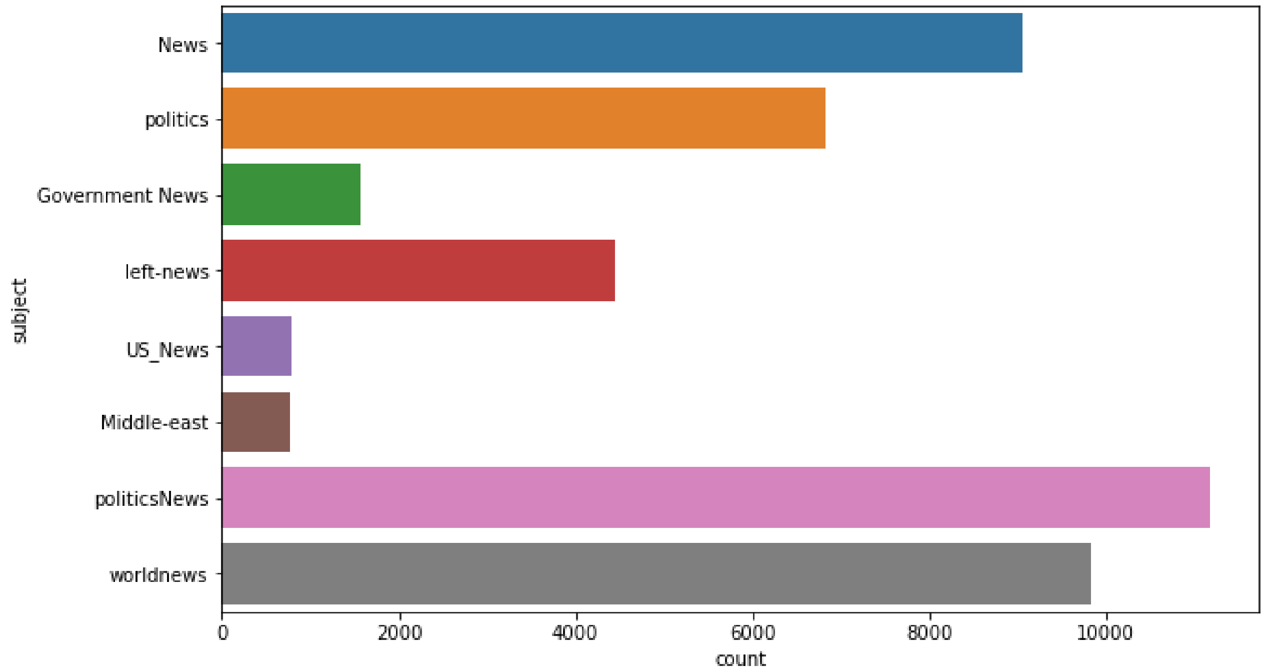


Figure 4. The Proportion of Each Subject

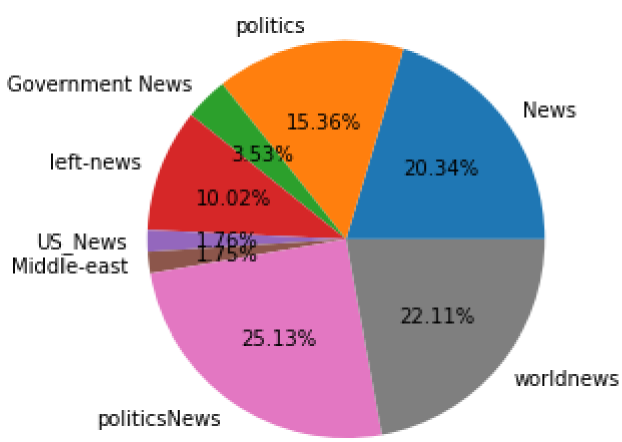


Figure 3 shows the count of each subject, figure 4 shows the proportion of each subject. There are 8 subjects in the data, included News, Polictics, Government News, Left-news, US_News, Middle-east, Polictic News and World News. Among these subjects, the number of Polictic News articles is the most (25.13%), next are World News (22.11%) and News (20.34%). The least number of articles belongs to US News (1.76%) and Middle-east (1.75%).

In [22]:

```
# extract month and year from date column
df["year"] = pd.DatetimeIndex(df['date']).year
df["month"] = pd.DatetimeIndex(df['date']).month
df.head()
```

Out[22]:

	title	text	subject	date	label	year	month
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	2017-12-31	fake	2017.0	12.0

	title	text	subject	date	label	year	month
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	2017-12-31	fake	2017.0	12.0
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	2017-12-30	fake	2017.0	12.0
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	2017-12-29	fake	2017.0	12.0
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	2017-12-25	fake	2017.0	12.0

In [23]:

```
# explore each label by year
fig, ax = plt.subplots(figsize=(12,6))
sns.countplot(x="year", data=df, hue="label", ax=ax).set(title='\nFigure 5. The
plt.show()
```

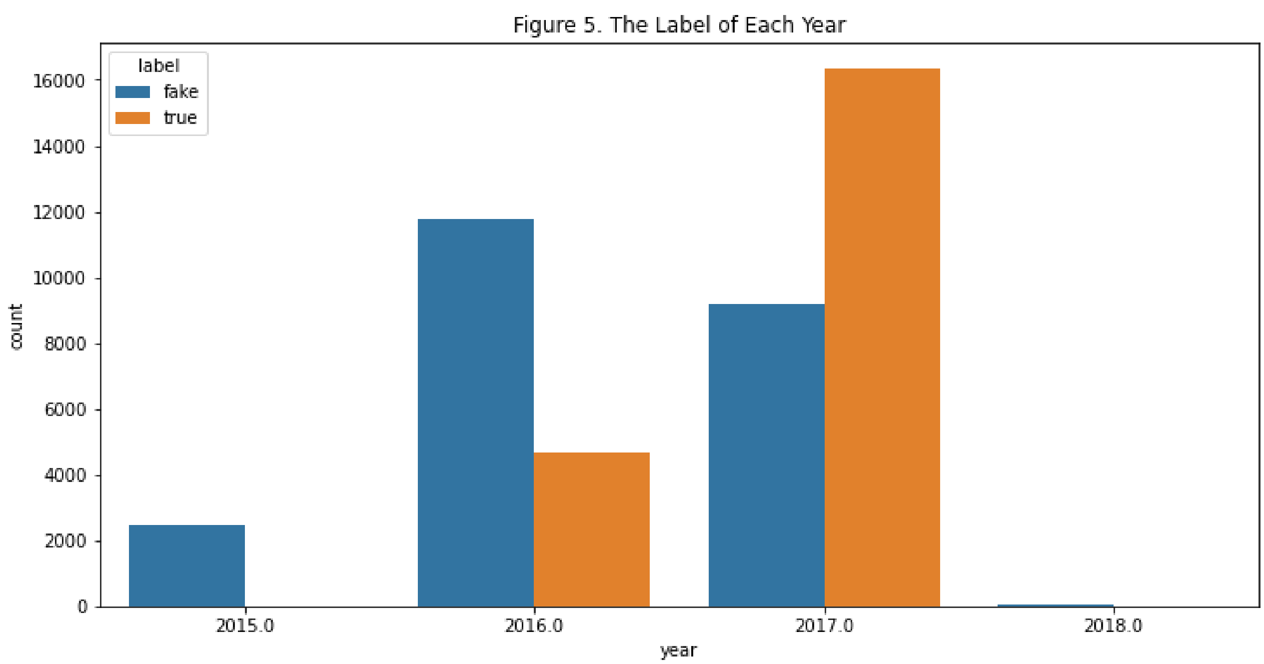
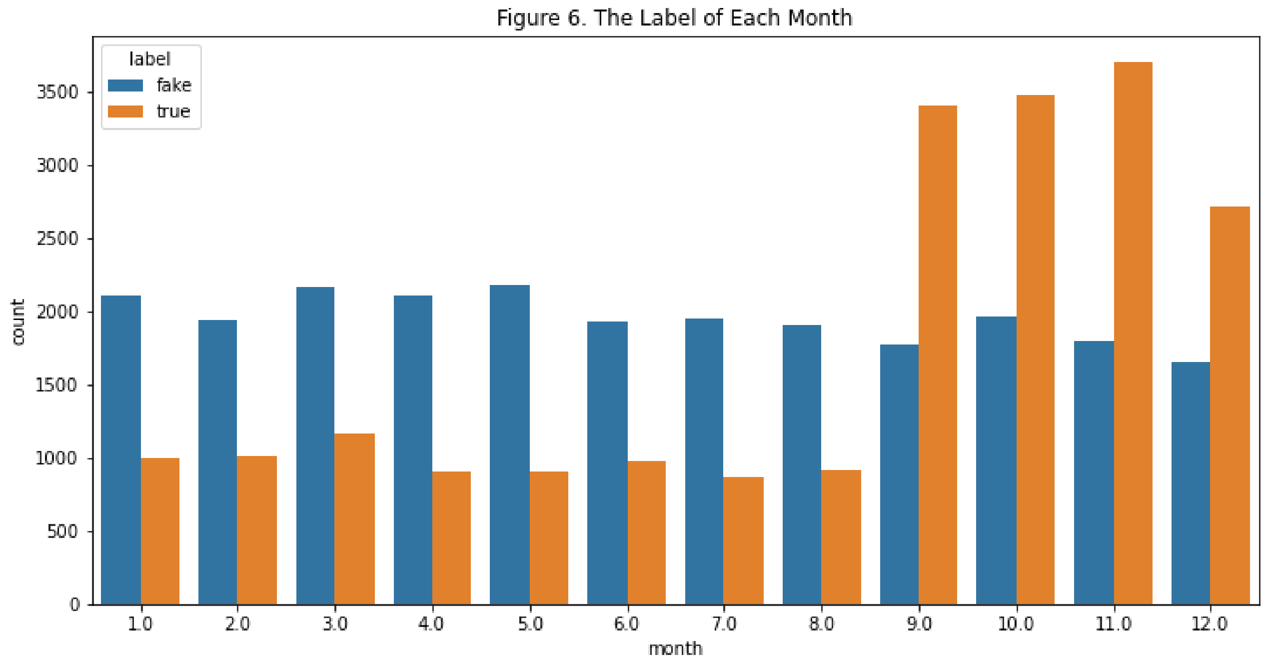


Figure 5 shows that in 2015, there is no true news, but fake news and misinformation had become prevalent during 2016. However, on the contrary, the number of true news was much more than the number of fake news in 2017. We do not have much data in 2018.

In [24]:

```
# explore each label by month
fig, ax = plt.subplots(figsize=(12,6))
sns.countplot(x="month", data=df, hue="label", ax=ax).set(title='\nFigure 6. The
plt.show()
```



Looking at figure 6, we can see that in overall, the number of fake news is larger than the number of true news from January to August and then on the contrary, the number of true news is larger than the number of fake news from September to December.

3.3 Clean the data

To prepare the data for training models, some works have to be done such as:

- create new feature by combining title and text column.
- drop unused columns such as: date, year, month, title.

To preprocess our text simply means to bring our text into a form that is predictable and analyzable for our task. So, what I am going to do is:

(1) lowercasing all our text data
(2) remove punctuation
(3) remove stop words: stop words are a set of commonly used words in a language. Examples of stop words in English are “a”, “the”, “is”, “are” and etc. The intuition behind using stop words is that, by removing low information words from text, we can focus on the important words instead.
(4) lemmatization: lemmatization usually refers to doing things properly with the use of a vocabulary and morphological analysis of words, normally aiming to remove inflectional endings only and to return the base or dictionary form of a word, which is known as the lemma. For example, runs, running, ran are all forms of the word run, therefore run is the lemma of all these words.

Since I'm planning to redo these cleaning steps for a test data without label as well, thus for convenience, I will create a clean_text function for this data and reuse it for cleaning unlabeled test data later.

In [25]:
```python
# create new feature by combining the title and text column
df['text'] = df['title'] + ' ' + df['text']

# drop date, year, month, title columns and reorder the columns
df_news = df.drop(columns=["date", "year", "month", "title"])
df_news = df_news.loc[:,['text','subject','label']]

# view some sample rows of df_news
df_news.sample(10)
```

Out[25]:

	text	subject	label
9637	BOOM! WATCH VIDEO FOUND Proving Gen. Kelly Rig...	politics	fake
38724	War crimes court backs Burundi investigation A...	worldnews	true
7667	SNL Perfectly SLAMS Trump Supporters With 'Ra...	News	fake
29380	Syrian Christians denied entry to U.S. in Phil...	politicsNews	true
42018	Two-thirds of Germans see persistent east-west...	worldnews	true
11763	BOOM! Companies That Openly Criticized Trump F...	politics	fake
43041	Kyrgyzstan accuses Kazakhstan of backing oppos...	worldnews	true
19717	ANTI-HILLARY HALLOWEEN HOUSE Gets Violent Thre...	left-news	fake
14610	GERMANY CRISIS ESCALATES: Muslim Migrants Mast...	politics	fake
4863	Comedy Central's Roast Of Rob Lowe HIJACKED A...	News	fake

In [26]:
```python
def clean_text(data, text):
    # lowercasing all text data
    data[text] = data[text].str.lower()
    # remove punctuation
    data[text] = data[text].str.replace('[^\w\s]', '', regex=True)
    # remove stop words
    stop_words = stopwords.words('english')
    data[text] = data[text].apply(lambda x: ' '.join([word for word in x.split()
    # lemmatization
    lemmatizer = WordNetLemmatizer()
    data[text] = data[text].apply(lambda x: ' '.join([lemmatizer.lemmatize(word)
    return
```

In [27]:
```python
# clean news data
clean_text(df_news, "text")

# view text in the first row after cleaning all text data
df_news["text"][0]
```

Out[27]:
```
'donald trump sends embarrassing new year eve message disturbing donald trump wi
sh american happy new year leave instead give shout enemy hater dishonest fake n
ews medium former reality show star one job country rapidly grows stronger smart
er want wish friend supporter enemy hater even dishonest fake news medium happy
healthy new year president angry pant tweeted 2018 great year america country ra
pidly grows stronger smarter want wish friend supporter enemy hater even dishone
st fake news medium happy healthy new year 2018 great year america donald j trum
p realdonaldtrump december 31 2017trump tweet went welll expectwhat kind preside
nt sends new year greeting like despicable petty infantile gibberish trump lack
```

```
decency even allow rise gutter long enough wish american citizen happy new year
bishop talbert swan talbertswan december 31 2017no one like calvin calvinstowell
december 31 2017your impeachment would make 2018 great year america also accept
regaining control congress miranda yaver mirandayaver december 31 2017do hear ta
lk include many people hate wonder hate alan sandoval alansandoval13 december 31
2017who us word hater new year wish marlene marlene399 december 31 2017you say h
appy new year koren pollitt korencarpenter december 31 2017here trump new year e
ve tweet 2016happy new year including many enemy fought lost badly know love don
ald j trump realdonaldtrump december 31 2016this nothing new trump yearstrump di
rected message enemy hater new year easter thanksgiving anniversary 911 pictwitt
ercom4fpae2kypa daniel dale ddale8 december 31 2017trump holiday tweet clearly p
residentialhow long work hallmark becoming president steven goodine sgoodine dec
ember 31 2017he always like difference last year filter breaking roy schulze thb
thttt december 31 2017who apart teenager us term hater wendy wendywhistles decem
ber 31 2017he fucking 5 year old know rainyday80 december 31 2017so people voted
hole thinking would change got power wrong 70yearold men change year olderphoto
andrew burtongetty image'
```

In [28]:

```
# calculate the count of word per article
df_news["Word_Count"] = df_news['text'].apply(lambda x: len(x.split()))
```

In [29]:

```
# view some first rows of news data
df_news.head()
```

Out[29]:

	text	subject	label	Word_Count
0	donald trump sends embarrassing new year eve m...	News	fake	296
1	drunk bragging trump staffer started russian c...	News	fake	187
2	sheriff david clarke becomes internet joke thr...	News	fake	349
3	trump obsessed even obamas name coded website ...	News	fake	273
4	pope francis called donald trump christmas spe...	News	fake	218

In [30]:

```
# The average count of word per article
print("\nThe mean count of word per article is ", round(np.mean(df_news.Word_Cou

# The maximum count of word per article
print("\nThe maximum count of word per article is ", round(np.max(df_news.Word_C

# The minimum count of word per article
print("\nThe minimum count of word per article is ", round(np.min(df_news.Word_C
```

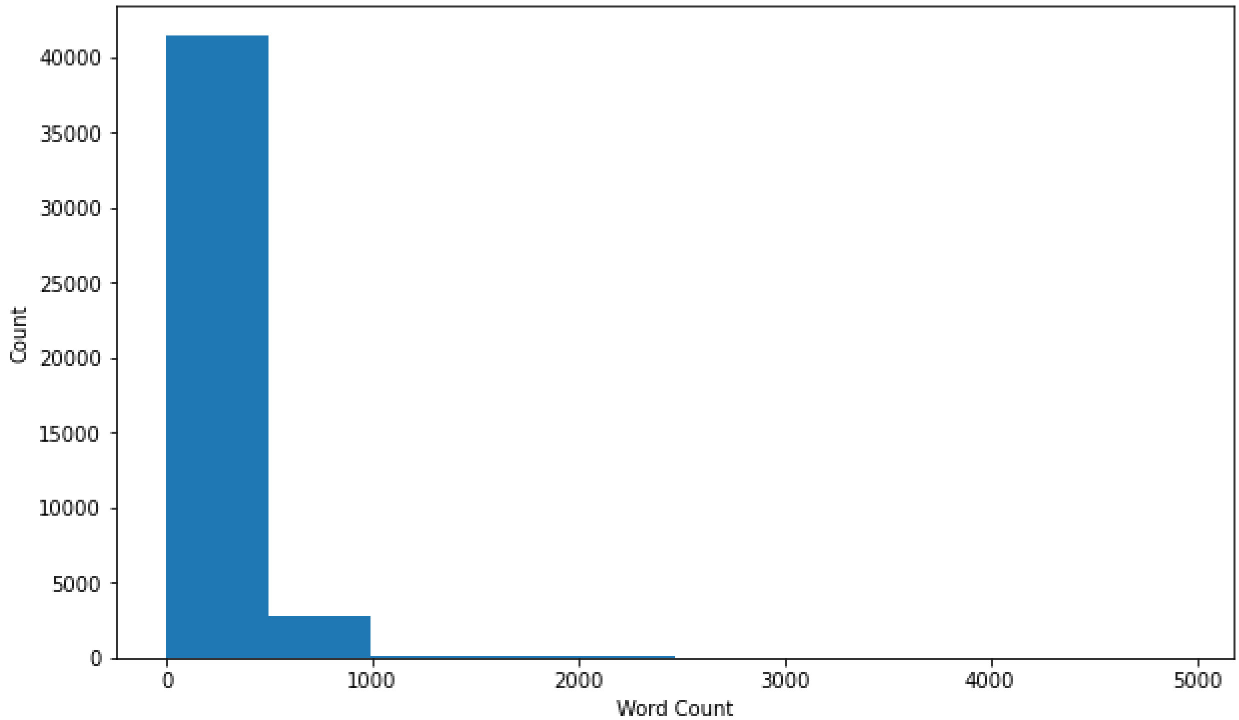
```
The mean count of word per article is  242

The maximum count of word per article is  4933

The minimum count of word per article is  2
```

In [31]:

```
# plot the count of word per article
fig, ax = plt.subplots(figsize=(10,6))
df_news['Word_Count'].plot(kind='hist')
plt.xlabel("Word Count")
plt.xticks(rotation=360)
plt.ylabel("Count")
```

```
plt.title("Figure 7. The count of words per Article\n")
plt.show()
```

Figure 7. The count of words per Article



We see that the average count of words per article is about 252 and looking at Figure 7, there are some outliers that have over 1000 word count per article. Thus, I would like to remove articles that have more than 1000 words. And then I will plot the count of words per subject.

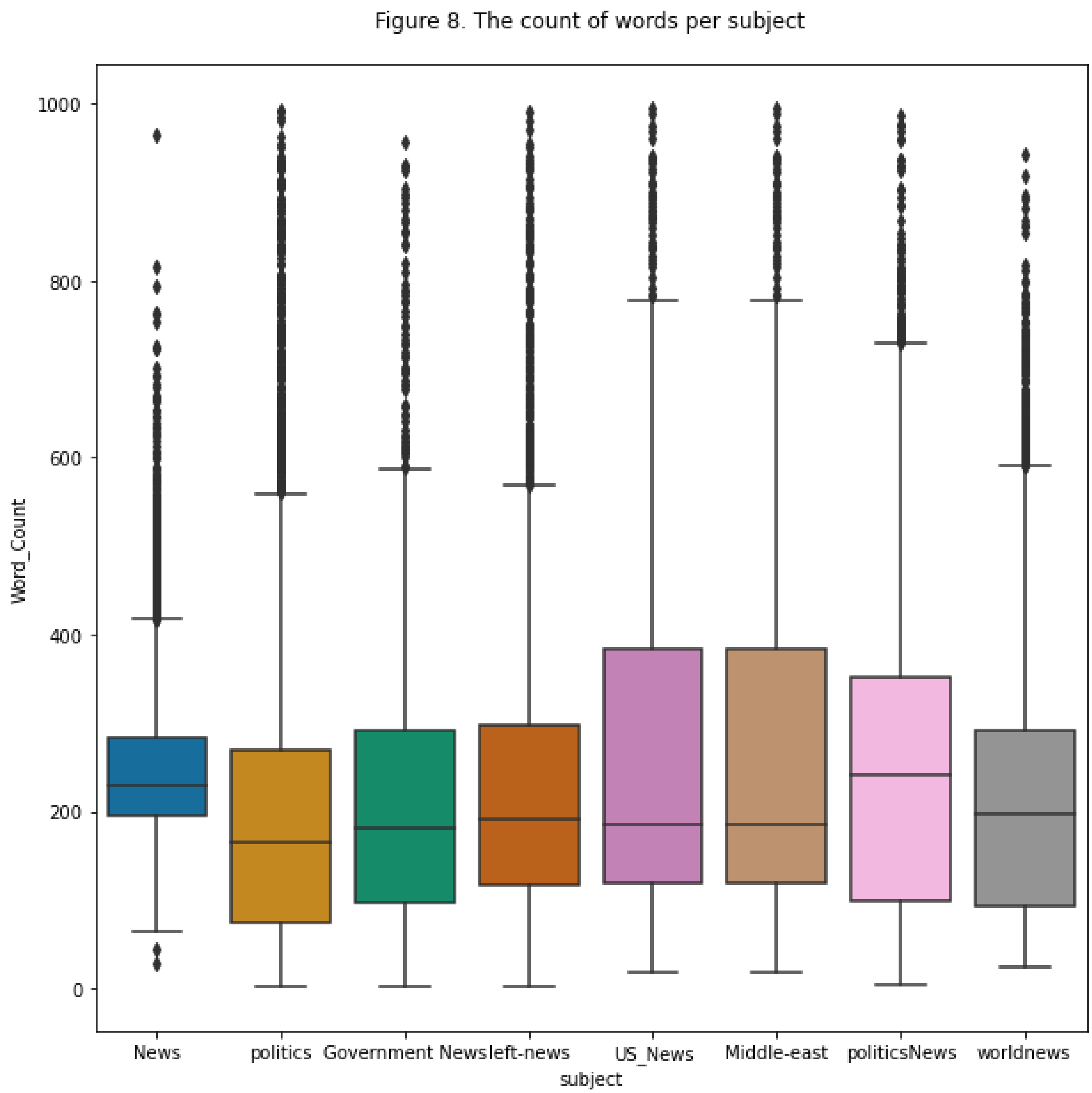
In [32]:

```
# remove outliers have more than 1000 words
df_news = df_news[df_news.Word_Count <= 1000]
len(df_news)
```

Out[32]: 44189

In [33]:

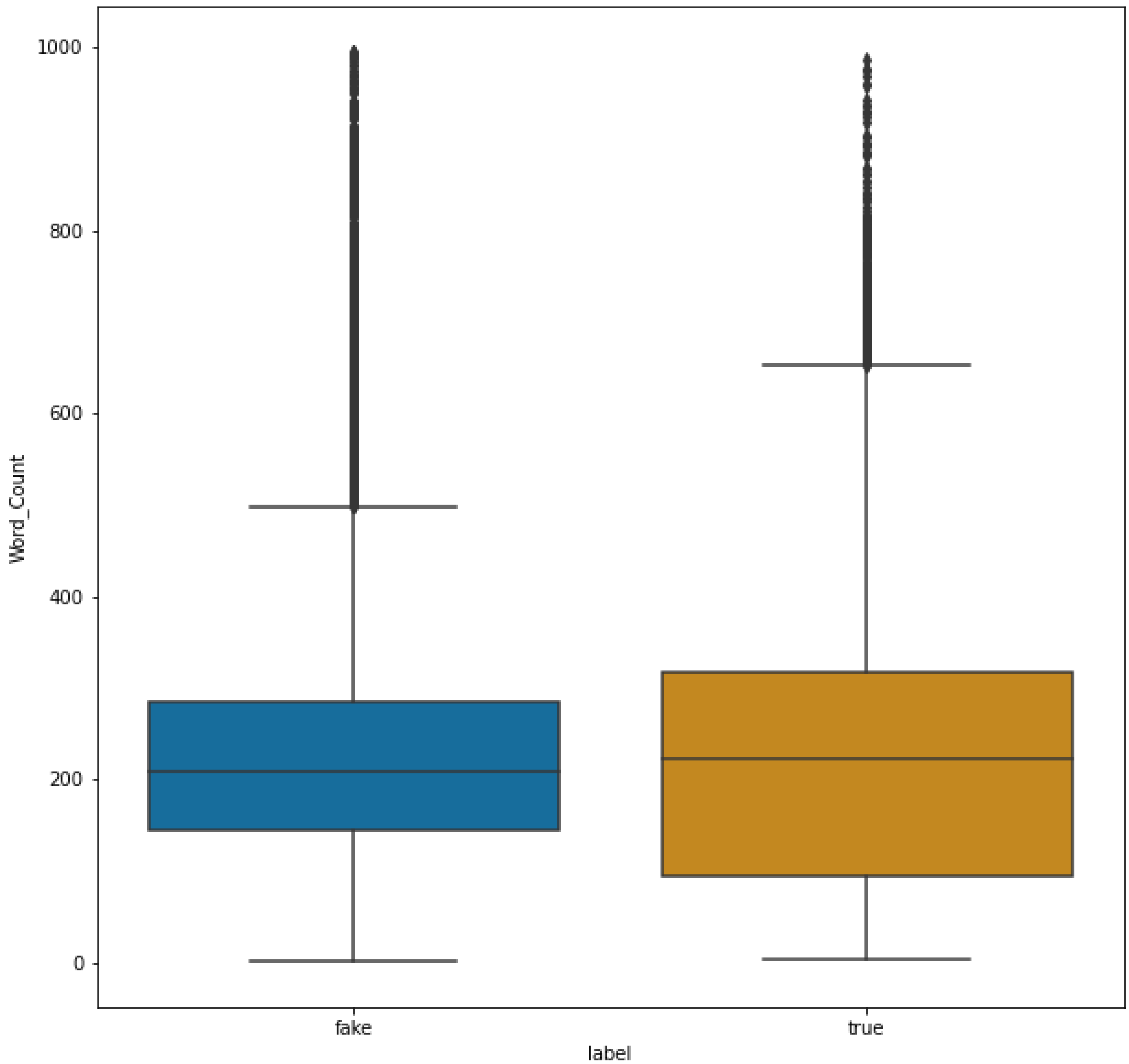
```
# visualize the count of words per subject
fig, ax = plt.subplots(figsize=(10, 10))
sns.boxplot(data = df_news, x = 'subject', y = 'Word_Count', palette = 'colorbli
            ).set(title = 'Figure 8. The count of words per subject\n')
plt.show()
```



Looking at Figure 8, we observe that the mean of word count of each subject is not different much, News and politics News have more words than other subjects. There is a greater variability for US News and Middle-east compare with others.

In [34]:
```
# visualize the count of words per label
fig, ax = plt.subplots(figsize=(10, 10))
sns.boxplot(data = df_news, x = 'label', y = 'Word_Count', palette = 'colorblind
            ).set(title = 'Figure 9. The count of words per label\n')
plt.show()
```

Figure 9. The count of words per label



Looking at figure 9, we observe that the mean of word count of fake and true news is approximately the same, the variability for true news is a little bit greater than fake news.

Split data

After cleaning, to prepare for building and training models, I'll:

- first, drop word_count column.
- split 20% of the data into test set. Noted that, I'll use sklearn train_test_split to split the data, with default shuffle = True, means this method will split our data into random train and test subsets.

In [35]:

```
# drop word_count column
df_news = df_news.drop(columns='Word_Count')

# shuffle and split the data into train and test set
train, test = train_test_split(df_news, test_size=0.2, random_state = 42)

# view some first rows of train data
```

```python
print('Training set:')
train. head()
```

Training set:

Out[35]:

	text	subject	label
41208	mattis say u work stay aligned turkey despite ...	worldnews	true
26913	trump dismay anger ally abandoning global clim...	politicsNews	true
16381	obama made christian pastor pay ticket home ir...	Government News	fake
35960	bulgaria freeze asset independent medium publi...	worldnews	true
41134	zimbabwe ruling party plan vote strengthen mug...	worldnews	true

In [36]:

```python
# get shape of train dataset after splitting
train.shape
```

Out[36]: (35351, 3)

In [37]:

```python
# view some first rows of test data
print('Test set:')
test.head()
```

Test set:

Out[37]:

	text	subject	label
6430	happening trump say rudy giuliani head commiss...	News	fake
33613	u top court hand win union split 44 without sc...	politicsNews	true
34502	trump cruz tamp expectation uncertain iowa vot...	politicsNews	true
9772	college conservative stalked antifa campus sto...	politics	fake
20824	latina restaurant owner threatened called stag...	left-news	fake

In [38]:

```python
# get shape of test set after splitting
test.shape
```

Out[38]: (8838, 3)

Step 4: Building and training models

4.1 Vectorizing Text by TfidfVectorizer

Text data requires a special approach to machine learning. This is because text data can have hundreds of thousands of dimensions (words and phrases) but tends to be very sparse. For example, the English language has around 100,000 words in common use. But in this data, average word count of an article only contains about 240 words.

Machines, unlike humans, cannot understand the raw text. Machines can only see numbers. Particularly, statistical techniques such as machine learning can only deal with numbers.

Therefore, we need to convert our text into numbers (vectors) so as the algorithms will be able make predictions.

Different approaches exist to convert text into the corresponding numerical form. In this case I will use the Term Frequency — Inverse Document Frequency (TFIDF) weight to evaluate how important a word is to a document in a collection of documents. Note that we are passing a number of parameters to this work:

- min_df is used for removing terms that appear too infrequently, set to 2 means "ignore word that appear in less than 2 articles". This is to avoid rare words, which drastically increase the size of our features and might cause overfitting.
- max_df is used for removing terms that appear too frequently, set to 0.95 means "ignore terms that appear in more than 95% of the documents".
- norm is set to l2, to ensure all our feature vectors have a euclidian norm of 1. This is helpful for visualizing these vectors, and can also improve (or deteriorate) the performance of some models.
- ngram_range is set to (1, 2) to indicate that we want to consider both unigrams and bigrams, or in other terms: we want to consider single words ("prices", "player") and pairs of words ("stock prices", "football player").
- stop_words is set to "english" to remove all common pronouns ("a", "the", ...) and further reduce the number of noisy features.
- sublinear_df is set to True to use a logarithmic form for frequency, to give diminishing returns as the frequency of a word increases.

In [39]:

```
# use TFIDF to convert words into numerical features
vectorizer = TfidfVectorizer(min_df=2, max_df=0.95, norm='l2', ngram_range=(1, 2

# fit and transform on train data
X = vectorizer.fit_transform(train.text)
```

In [40]:

```
# Get a feel of the features identified by tfidf
X.toarray()
```

Out[40]:

```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [41]:

```
# get the shape of the features
X.shape
```

Out[41]:

```
(35351, 1124227)
```

4.2 Unsupervised Machine Learning for Natural Language Processing and Text Analytics

Unsupervised machine learning involves training a model without pre-tagging or annotating.

4.2.1 NMF

Matrix Factorization is another technique for unsupervised NLP machine learning. This uses "latent factors" to break a large matrix down into the combination of two smaller matrices. Latent factors are similarities between the items.

In this project, I would like to build a Non-Negative Matrix Factorization (NMF) model. I will pass n_components=2 into the model because we have 2 labels, with other parameters, in order to find best ones for this model, I will:

- create predict function: this function predict label of an article based on the largest value of each row in features matrix.
- create label_permute_compare function: this function will return permuted label order, accuracy and RMSE score.

Then, I will apply these two functions into the next step that programmatically evaluate which init, solver and beta_loss metric lead to the best performance.

In [42]:

```
# create predict function
def predict(W_matrix):
    sortedW = np.argsort(W_matrix)
    n_prediction, maxValue = sortedW.shape
    prediction = [[sortedW[i][maxValue - 1]] for i in range(n_prediction)]
    topic = np.empty(n_prediction, dtype = np.int64)
    for i in range(n_prediction):
        topic[i] = prediction[i][0]
    return topic
```

In [43]:

```
# create label permuation compare
def label_permute_compare(ytdf, yp, n=2):
    """
    ytdf: labels dataframe object
    yp: clustering label prediction output
    Returns permuted label order and accuracy.
    Example output: (3, 4, 1, 2, 0), 0.74
    """
    p = list(itertools.permutations(list(range(n))))
    label_ls = list(ytdf['label'].unique())
    acc_score = []
    rmse_score = []
    #recall_score = []
    #pre_score = []
    #f1_score = []
    for i in range(len(p)):
        map_dict = dict(zip(label_ls, list(p[i])))
        yt = ytdf['label'].apply(lambda x:map_dict[x])
        acc_score.append(accuracy_score(yt, yp))
        #recall_score.append(recall_score(yt, yp))
        #pre_score.append(precision_score(yt, yp))
        #f1_score.append(f1_score(yt, yp))
        rmse_score.append(np.sqrt(mean_squared_error(yt, yp)))
    index = np.argmax(acc_score)
```

```
    #return p[index], acc_score[index], recall_score[index], pre_score[index], f
    return p[index], acc_score[index], rmse_score[index]
```

In [46]:

```
# programmatically evaluate which init, solver and beta_loss metric lead to the

#dic = {"time":0, "init":"", "solver": "", "beta_loss":"", "labelorder":[], "acc
dic = {"time":0, "init":"", "solver": "", "beta_loss":"", "labelorder":[], "acc"
df_nmf = pd.DataFrame(dic)
for init in ["random", "nndsvda", "nndsvdar", "custom"]:
    for beta_loss in ["frobenius", "kullback-leibler", "itakura-saito"]:
        for solver in ["cd", "mu"]:
            acc = 0
            t0 = time.time()
            try:
                model = NMF(n_components=2, init=init, solver = solver, beta_los
                yhat_train = predict(model.fit_transform(X))
                label_order, acc, rmse = label_permute_compare(train, yhat_train
                t1 = time.time()
                df_nmf.loc[len(df_nmf.index)] = [t1-t0, init, solver, beta_loss,

            except:
                print(init, "with", beta_loss, "with", solver, "not allowed.")
df_nmf = df_nmf.sort_values(by='acc', ascending = False)
display(df_nmf)
```

```
random with kullback-leibler with cd not allowed.
random with itakura-saito with cd not allowed.
random with itakura-saito with mu not allowed.
nndsvda with kullback-leibler with cd not allowed.
nndsvda with itakura-saito with cd not allowed.
nndsvda with itakura-saito with mu not allowed.
nndsvdar with kullback-leibler with cd not allowed.
nndsvdar with itakura-saito with cd not allowed.
nndsvdar with itakura-saito with mu not allowed.
custom with frobenius with cd not allowed.
custom with frobenius with mu not allowed.
custom with kullback-leibler with cd not allowed.
custom with kullback-leibler with mu not allowed.
custom with itakura-saito with cd not allowed.
custom with itakura-saito with mu not allowed.
```

	time	init	solver	beta_loss	labelorder	acc	rmse
3	32.389216	nndsvda	cd	frobenius	(1, 0)	0.819864	0.424425
6	28.144366	nndsvdar	cd	frobenius	(1, 0)	0.819864	0.424425
1	9.588517	random	mu	frobenius	(0, 1)	0.814065	0.431202
8	126.670549	nndsvdar	mu	kullback-leibler	(1, 0)	0.806455	0.439937
5	104.159139	nndsvda	mu	kullback-leibler	(1, 0)	0.804843	0.441766
4	13.074447	nndsvda	mu	frobenius	(1, 0)	0.744477	0.505493
7	12.844088	nndsvdar	mu	frobenius	(1, 0)	0.740149	0.509756
2	274.391801	random	mu	kullback-leibler	(0, 1)	0.679189	0.566402
0	6.443513	random	cd	frobenius	(1, 0)	0.514865	0.696516

In [47]:

```python
# show the best model
best_nmf_model = NMF(n_components=2, init="nndsvda", solver = "cd", beta_loss="f

# fit and transform the model to TF-IDF:
W = best_nmf_model.fit_transform(X)
H = best_nmf_model.components_
```

In [48]:

```python
# features dimension
W.shape
```

Out[48]:

```
(35351, 2)
```

In [49]:

```python
# components dimension
H.shape
```

Out[49]:

```
(2, 1124227)
```

In [50]:

```python
# Create a DataFrame: components_df
components_df = pd.DataFrame(H, columns=vectorizer.get_feature_names())
components_df
```

Out[50]:

	00	000	000 child	000 hospital	000 today	000 year	0000	0000 gmt	0005
0	0.000351	0.000861	0.000122	0.000087	0.000087	0.000087	0.000069	0.000069	0.000000
1	0.000102	0.000000	0.000000	0.000015	0.000015	0.000015	0.000177	0.000177	0.000294

2 rows × 1124227 columns

We have created the 2 labels using NMF. Let's have a look at the 10 more important words for each label.

In [51]:

```python
# get 10 more important words for each label
mapdict_df = dict(zip(label_order, list(train["label"].unique())))
for label in range(components_df.shape[0]):
    tmp = components_df.iloc[label]
    print(f'For label {mapdict_df[label]}, the words with the highest value are:
    print(tmp.nlargest(10))
    print('\n')
```

```
For label fake, the words with the highest value are:
trump           0.928233
republican      0.570412
clinton         0.456049
donald          0.445448
donald trump    0.426279
people          0.413081
president       0.402421
image           0.383837
like            0.382337
said            0.381882
```

```
Name: 0, dtype: float64


For label true, the words with the highest value are:
said               0.590084
reuters            0.456924
state              0.418777
united             0.359840
minister           0.355655
government         0.354960
north              0.317334
korea              0.314728
official           0.306373
united state       0.301514
Name: 1, dtype: float64
```

Use best NMF model to predict test data

In [57]:

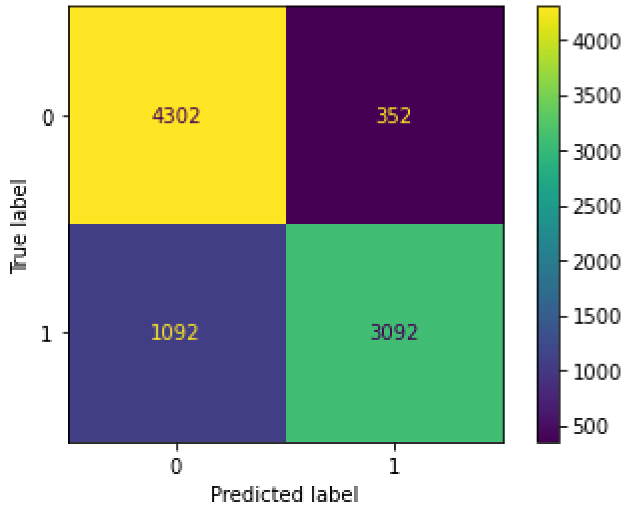
```python
# use best model for predicting test set and calculate accuracy
X_test = vectorizer.fit_transform(test.text)
W_test = best_nmf_model.fit_transform(X_test)

# predict label for test data
yhat_test = predict(W_test)
#label_order_test, accuracy_test, recall_test, pre_test, f1_test = label_permute
label_order_test, accuracy_test, rmse_test = label_permute_compare(test, yhat_te
mapdict_test = dict(zip(list(test["label"].unique()), label_order_test))
print('\nLabel order for test set based on best NMF model: ', mapdict_test)
print('\nAccuracy for test set based on best NMF model: {:.3f}%'.format(accuracy
print('\nRMSE for test set based on best NMF model: {:.3f}'.format(rmse_test))
#print('\nRecall score for test set based on best NMF model: {:.3f}%'.format(rec
#print('\nPrecision score for test set based on best NMF model: {:.3f}%'.format(
#print('\nF1 score for test set based on best NMF model: {:.3f}%'.format(f1_test
```

```
Label order for test set based on best NMF model:  {'fake': 0, 'true': 1}

Accuracy for test set based on best NMF model: 83.661%

RMSE for test set based on best NMF model: 0.404
```

In [53]:

```python
# Check confusion matrix
yt_test = test["label"].apply(lambda x: mapdict_test[x])
print('\nFigure 10. Best NMF - Confusion matrix for test set: ')
cm = confusion_matrix(yt_test, yhat_test)

# display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.show()
```

```
Figure 10. Best NMF - Confusion matrix for test set:
```



From Figure 10, the confusion matrix for test set based on best NMF model, we can summarize that:

- Our model predicted that 5394/8838 articles are fake news when there were actually 4654/8838 articles with fake news.
- Our model has an accuracy of 7394/8838 or 83.661%

4.2.2 Kmeans

Clustering means grouping similar documents together into groups or sets. These clusters are then sorted based on importance and relevancy (hierarchical clustering).

K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. The K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. The 'means' in the K-means refers to averaging of the data, finding the centroid.

In [54]:

```
# build kmeans model
kmeans = KMeans(n_clusters=2, init = 'k-means++' , max_iter = 100, random_state=

# fit and transform kmeans model to TF-IDF:
W_kmeans = kmeans.fit_transform(X)
```

In [55]:

```
# use kmeans model for predicting test set and calculate accuracy
X_test = vectorizer.fit_transform(test.text)
W_test_kmeans = kmeans.fit_transform(X_test)

# predict label for test data
yhat_test_kmeans = predict(W_test_kmeans)
label_order_test_kmeans, accuracy_test_kmeans, rmse_test_kmeans = label_permute_
mapdict_test_kmeans = dict(zip(list(test["label"].unique()), label_order_test_km
print('\nLabel order for test set based on Kmeans model: ', mapdict_test_kmeans)
print('\nAccuracy for test set based on Kmeans model: {:.3f}%'.format(accuracy_t
print('\nRMSE for test set based on best Kmeans model: {:.3f}'.format(rmse_test_
```

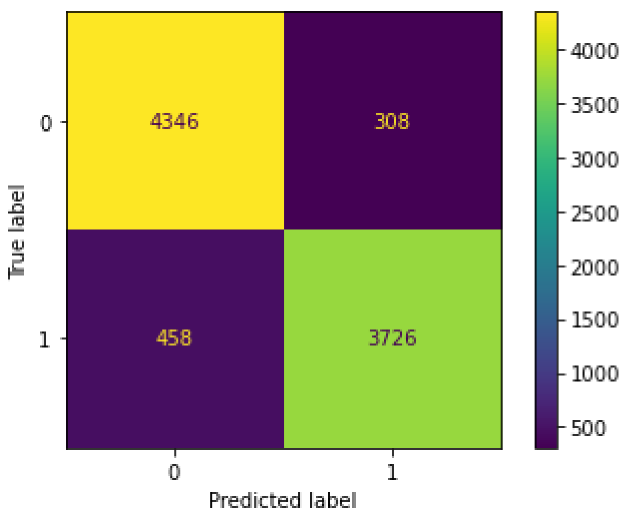
```
Label order for test set based on Kmeans model:  {'fake': 0, 'true': 1}
```

```
Accuracy for test set based on Kmeans model: 91.333%

RMSE for test set based on best Kmeans model: 0.294
```

In [56]:

```python
# Check confusion matrix
yt_test_kmeans = test["label"].apply(lambda x: mapdict_test_kmeans[x])
print('\nFigure 11. Kmeans - Confusion matrix for test set: ')
cm_kmeans = confusion_matrix(yt_test_kmeans, yhat_test_kmeans)

# display confusion matrix
disp_kmeans = ConfusionMatrixDisplay(confusion_matrix=cm_kmeans)
disp_kmeans.plot()
plt.show()
```

```
Figure 11. Kmeans - Confusion matrix for test set:
```



From Figure 11, the confusion matrix for test set based on Kmeans model, we can summarize that:

- Our model predicted that 4804/8838 articles are fake news when there were actually 4654/8838 articles with fake news.
- Our model has an accuracy of 8072/8838 or 91.333%

4.2.3 Compare unsupervised learning models

In [58]:

```python
# create unsupervised dataframe to compare NMF and Kmeans model on test data
unsuper_models = {'Model': ["NMF", "Kmeans"],
         'Accuracy': [accuracy_test, accuracy_test_kmeans],
         'RMSE': [rmse_test, rmse_test_kmeans]}
unsuper_data = pd.DataFrame(unsuper_models)
unsuper_data = unsuper_data.sort_values(by='Accuracy', ascending = False, ignore
print("Compare unsupervised machine learning models on test data: ")
display(unsuper_data)
```

```
Compare unsupervised machine learning models on test data:
```

	Model	Accuracy	RMSE
0	Kmeans	0.913329	0.29440

	Model	Accuracy	RMSE
1	NMF	0.836615	0.40421

With the result above, we observe that Kmeans has better performance with higher Accuracy and lower RMSE.

4.3 Supervised Machine Learning for Natural Language Processing and Text Analytics

In supervised machine learning, a batch of text documents are tagged or annotated with examples of what the machine should look for and how it should interpret that aspect. These documents are used to “train” a statistical model, which is then given un-tagged text to analyze.

In this project, since our train data has the labels, we can use supervised models to solve the label of each news article. That is, we look for a classifier that can take a word embedding as an input and predict a text class. To keep things simple, we will use the same preprocessing and word embedding produced by TfidfVectorizer with the same hyperparameters.

I would like to choose building a Random Forest model, because it can perform classification tasks and produces good predictions that can be understood easily. Moreover, it can handle large datasets efficiently. The random forest algorithm provides a higher level of accuracy in predicting outcomes over the decision tree algorithm. To build Random Forest, I will do hyperparameter tuning for Random Forest using GridSearchCV to find the best one. Then fit the data and use it for predicting test data.

Next, I would like to use some supervised NLP machine learning algorithms such as:

```
+ Logistic Regression
+ Decision Tree
```

I choose to build Logistic Regression because it is a calculation used to predict a binary outcome: either something happens, or does not. And in this case, since we want to predict a news is fake news or not, thus Logistic Regression is suitable for this project.

Besides that, a decision tree is also good for this project because it is a supervised learning algorithm that is perfect for classification problems, as it’s able to order classes on a precise level. It works like a flow chart, separating data points into two similar categories at a time from the “tree trunk” to “branches,” to “leaves,” where the categories become more finitely similar. This creates categories within categories, allowing for organic classification with limited human supervision.

To do this work, first, I will a Random Forest model by using GridSearchCV to find the best one with best parameters and best score. Then I will use it to predict for test data, calculate accuracy score and confusion matrix as well. Since I prepare for building other supervised models as well, so I will create a pipeline function, it helps to enforce desired order of application steps, creating a convenient work-flow, which makes sure of the reproducibility of the work.

After finding the best Random Forest model, I will use pipeline above to train Logistic Regression and Decision Tree to predict for test data, calculate accuracy, recall, precision, f1 score and confusion matrix.

4.3.1 Random Forest

In [59]:
```
# Let’s do hyperparameter tuning for Random Forest using GridSearchCV and fit th
rf = RandomForestClassifier(random_state=42, n_jobs=-1)
params = {
    'max_depth': [5,10,20],
    'min_samples_leaf': [5,10,20,50],
    'n_estimators': [30,50,100,200]
}

# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv = 4,
                           n_jobs=-1, verbose=1, scoring="accuracy")
grid_search.fit(X, train.label)
```

```
Fitting 4 folds for each of 48 candidates, totalling 192 fits
```

Out[59]:
```
GridSearchCV(cv=4, estimator=RandomForestClassifier(n_jobs=-1, random_state=42),
             n_jobs=-1,
             param_grid={'max_depth': [5, 10, 20],
                         'min_samples_leaf': [5, 10, 20, 50],
                         'n_estimators': [30, 50, 100, 200]},
             scoring='accuracy', verbose=1)
```

In [60]:
```
# get the best score
rf_best_score = grid_search.best_score_
print("\nRandom Forest best score: {:.3f}%".format(rf_best_score*100))

# best model
rf_best = grid_search.best_estimator_
print("\nRandom Forest best model:", rf_best)
```

```
Random Forest best score: 96.716%

Random Forest best model: RandomForestClassifier(max_depth=20, min_samples_leaf=
5, n_estimators=200,
                       n_jobs=-1, random_state=42)
```

After getting the best Random Forest model, now I will use it to predict test data.

In [61]:
```
# set up the model pipeline
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_sc
def pipeline_func(vectorizer, clf):
    pipeline = Pipeline(
        [
            ('vect', vectorizer),
            ('clf', clf)
```

```
        ]
    )

    # fit and predict for test set
    pipeline.fit(train.text, train.label)
    y_pred = pipeline.predict(test.text)

    # calculate accuracy
    accuracy_test = accuracy_score(test.label, y_pred)
    #rmse_test = np.sqrt(mean_squared_error(test.label, y_pred))
    recall_test = recall_score(test.label, y_pred, pos_label="true")
    pre_test = precision_score(test.label, y_pred, pos_label="true")
    f1_test = f1_score(test.label, y_pred, pos_label="true")
    cm = confusion_matrix(test.label, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    return accuracy_test, recall_test, pre_test, f1_test, disp
```

Recall score is used to measure the model performance in terms of measuring the count of true positives in a correct manner out of all the actual positive values

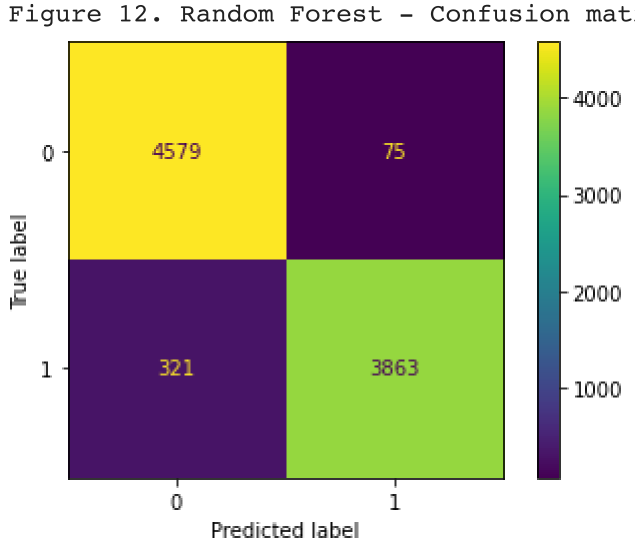
In [67]:

```
# fit model and predict test data
rf_acc, rf_recall, rf_pre, rf_f1, rf_disp = pipeline_func(vectorizer, rf_best)
```

In [68]:

```
print('\nAccuracy for test set based on best Random Forest model: {:.3f}'.format
print('\nRecall score for test set based on best Random Forest model: {:.3f}'.fo
print('\nPrecision score for test set based on best Random Forest model: {:.3f}'
print('\nF1 score for test set based on best Random Forest model: {:.3f}'.format
print('\nFigure 12. Random Forest - Confusion matrix for test set')
rf_disp.plot()
plt.show()
```

```
Accuracy for test set based on best Random Forest model: 0.955

Recall score for test set based on best Random Forest model: 0.923

Precision score for test set based on best Random Forest model: 0.981

F1 score for test set based on best Random Forest model: 0.923

Figure 12. Random Forest - Confusion matrix for test set
```



From the confusion matrix for test set based on best Random Forest model, we can summarize that:

- Our model predicted that 4900/8838 articles are fake news when there were actually 4654/8838 articles with fake news.
- Our model has an accuracy of 8442/8838 or 95.519%

4.3.2 Other supervised machine learning

After finding the best Random Forest model, now I would like to run some other models such as: Logistic Regression and Decision Tree as well.

Logistic Regression

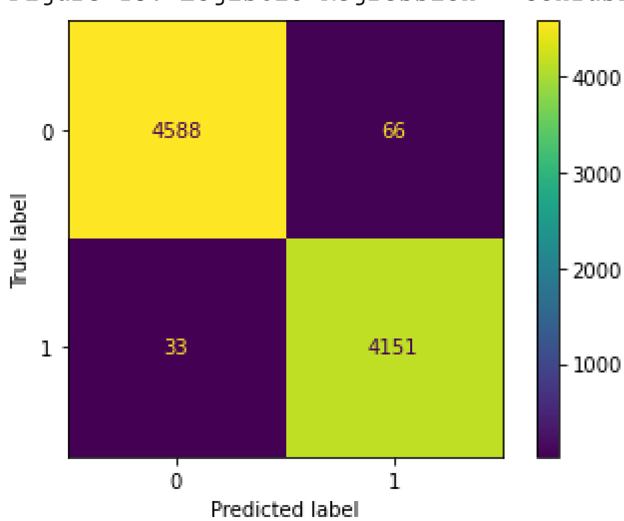
In [63]:

```
# fit model and predict test data
log_acc, log_recall, log_pre, log_f1, log_disp = pipeline_func(vectorizer, Logis
```

In [70]:

```
print('\nAccuracy for test set based on Logistic Regression model: {:.3f}'.forma
print('\nRecall score for test set based on Logistic Regression model: {:.3f}'.f
print('\nPrecision score for test set based on Logistic Regression model: {:.3f}
print('\nF1 score for test set based on Logistic Regression model: {:.3f}'.forma
print('\nFigure 13. Logistic Regression - Confusion matrix for test set')
log_disp.plot()
plt.show()
```

```
Accuracy for test set based on Logistic Regression model: 0.989

Recall score for test set based on Logistic Regression model: 0.992

Precision score for test set based on Logistic Regression model: 0.984

F1 score for test set based on Logistic Regression model: 0.988

Figure 13. Logistic Regression - Confusion matrix for test set
```



Looking at Figure 13, we can summarize:

- Our model predicted that 4621/8838 articles are fake news when there were actually 4654/8838 articles with fake news.

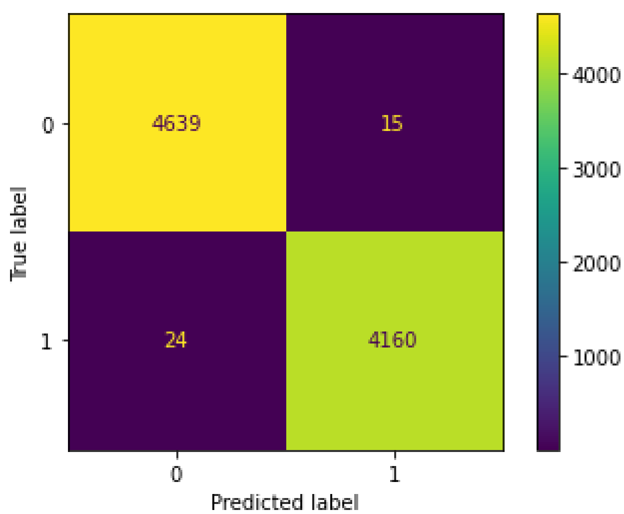
- Our model has an accuracy of 8739/8838 or 98.880%

Decision Tree Classifier

In [65]:
```
# fit model and predict test data
dt_acc, dt_recall, dt_pre, dt_f1, dt_disp = pipeline_func(vectorizer, DecisionTr
```

In [71]:
```
print('\nAccuracy for test set based on Decision Tree Classifier model: {:.3f}'.
print('\nRecall score for test set based on Decision Tree Classifier model: {:.3
print('\nPrecision score for test set based on Decision Tree Classifier model: {
print('\nF1 score for test set based on Decision Tree Classifier model: {:.3f}'.
print('\nFigure 14. Decision Tree Classifier - Confusion matrix for test set')
dt_disp.plot()
plt.show()
```

```
Accuracy for test set based on Decision Tree Classifier model: 0.996

Recall score for test set based on Decision Tree Classifier model: 0.994

Precision score for test set based on Decision Tree Classifier model: 0.996

F1 score for test set based on Decision Tree Classifier model: 0.995

Figure 14. Decision Tree Classifier - Confusion matrix for test set
```



Looking at Figure 14, we can summarize:

- Our model predicted that 4661/8838 articles are fake news when there were actually 4654/8838 articles with fake news.

- Our model has an accuracy of 8797/8838 or 99.536%

4.3.3 Compare supervised machine learning models

In [72]:
```
# create unsupervised dataframe to compare NMF and Kmeans model on test data
```

```
super_models = {'Model': ["Random Forest", "Logistic Regression", "Decision Tree
        'Accuracy': [rf_acc, log_acc, dt_acc],
        'Recall': [rf_recall, log_recall, dt_recall],
        'Precision': [rf_pre, log_pre, dt_pre],
        'F1': [rf_f1, log_f1, dt_f1],}
super_data = pd.DataFrame(super_models)
super_data = super_data.sort_values(by='Accuracy', ascending = False, ignore_ind
print("Compare supervised machine learning models on test data: ")
display(super_data)
```

```
Compare supervised machine learning models on test data:
```

	Model	Accuracy	Recall	Precision	F1
0	Decision Tree	0.995587	0.994264	0.996407	0.995334
1	Logistic Regression	0.988798	0.992113	0.984349	0.988216
2	Random Forest	0.955193	0.923279	0.980955	0.951244

We observe that Decision Tree Classifier is the best supervised model with highest accuracy, recall, precison and f1 score.

4.4 Compare Unsupervised and Supervised Machine Learning models

In [74]:

```
# create unsupervised dataframe to compare NMF and Kmeans model on test data
models = {'Model': ["NMF", "Kmeans", "Random Forest", "Logistic Regression", "De
        'Accuracy': [accuracy_test, accuracy_test_kmeans, rf_acc, log_acc, dt_ac

data = pd.DataFrame(models)
data = data.sort_values(by='Accuracy', ascending = False, ignore_index=True)
print("Compare unsupervised and supervised machine learning models on test data:
display(data)
```

```
Compare unsupervised and supervised machine learning models on test data:
```

	Model	Accuracy
0	Decision Tree	0.995587
1	Logistic Regression	0.988798
2	Random Forest	0.955193
3	Kmeans	0.913329
4	NMF	0.836615

Looking at table above, we can see that, in overall, supervised machine learning algorithms show a better performance compare with unsupervised machine learning algorithms and in this project, Decision Tree is the best model.

4.5 Use supervised models to predict new text data without label

In [76]:

```
news = str(input())
```

```
"Daniel Greenfield, a Shillman Journalism Fellow at the Freedom Center, is a New
```

York writer focusing on radical Islam. In the final stretch of the election, Hillary Rodham Clinton has gone to war with the FBI. The word “unprecedented” has been thrown around so often this election that it ought to be retired. But it’s still unprecedented for the nominee of a major political party to go war with the FBI. But that’s exactly what Hillary and her people have done. Coma patients just waking up now and watching an hour of CNN from their hospital beds would assume that FBI Director James Comey is Hillary’s opponent in this election. The FBI is under attack by everyone from Obama to CNN. Hillary’s people have circulated a letter attacking Comey. There are currently more media hit pieces lambasting him than targeting Trump. It wouldn’t be too surprising if the Clintons or their allies were to start running attack ads against the FBI. The FBI’s leadership is being warned that the entire left-wing establishment will form a lynch mob if they continue going after Hillary. And the FBI’s credibility is being attacked by the media and the Democrats to preemptively head off the results of the investigation of the Clinton Foundation and Hillary Clinton. The covert struggle between FBI agents and Obama’s DOJ people has gone explosively public. The New York Times has compared Comey to J. Edgar Hoover. Its bizarre headline, “James Comey Role Recalls Hoover’s FBI, Fairly or Not” practically admits up front that it’s spouting nonsense. The Boston Globe has published a column calling for Comey’s resignation. Not to be outdone, Time has an editorial claiming that the scandal is really an attack on all women. James Carville appeared on MSNBC to remind everyone that he was still alive and insane. He accused Comey of coordinating with House Republicans and the KGB. And you thought the “vast right wing conspiracy” was a stretch. Countless media stories charge Comey with violating procedure. Do you know what’s a procedural violation? Emailing classified information stored on your bathroom server. Senator Harry Reid has sent Comey a letter accusing him of violating the Hatch Act. The Hatch Act is a nice idea that has as much relevance in the age of Obama as the Tenth Amendment. But the cable news spectrum quickly filled with media hacks glancing at the Wikipedia article on the Hatch Act under the table while accusing the FBI director of one of the most awkward conspiracies against Hillary ever. If James Comey is really out to hurt Hillary, he picked one hell of a strange way to do it. Not too long ago Democrats were breathing a sigh of relief when he gave Hillary Clinton a pass in a prominent public statement. If he really were out to elect Trump by keeping the email scandal going, why did he trash the investigation? Was he on the payroll of House Republicans and the KGB back then and playing it coy or was it a sudden development where Vladimir Putin and Paul Ryan talked him into taking a look at Anthony Weiner’s computer? Either Comey is the most cunning FBI director that ever lived or he’s just awkwardly trying to navigate a political mess that has trapped him between a DOJ leadership whose political futures are tied to Hillary’s victory and his own bureau whose apolitical agents just want to be allowed to do their jobs. The only truly mysterious thing is why Hillary and her associates decided to go to war with a respected Federal agency. Most Americans like the FBI while Hillary Clinton enjoys a 60% unfavorable rating. And it’s an interesting question. Hillary’s old strategy was to lie and deny that the FBI even had a criminal investigation underway. Instead her associates insisted that it was a security review. The FBI corrected her and she shrugged it off. But the old breezy denial approach has given way to a savage assault on the FBI. Pretending that nothing was wrong was a bad strategy, but it was a better one that picking a fight with the FBI while lunatic Clinton associates try to claim that the FBI is really the KGB. There are two possible explanations. Hillary Clinton might be arrogant enough to lash out at the FBI now that she believes that victory is near. The same kind of hubris that led her to plan her victory fireworks display could lead her to declare a war on the FBI for irritating her during the final miles of her campaign. But the other explanation is that her people panicked. Going to war with the FBI is not the behavior of a smart and focused presidential campaign. It’s an act of desperation. When a presidential candidate decides that her only option is to try and destroy the credibility of the FBI, that’s not hubris, it’s fear of what the FBI might be about to reveal about her. During the original FBI investigation, Hillary Clinton was confident that she could ride it out. And she ha

```
d good reason for believing that. But that Hillary Clinton is gone. In her place
is a paranoid wreck. Within a short space of time the “positive” Clinton campaig
n promising to unite the country has been replaced by a desperate and flailing o
peration that has focused all its energy on fighting the FBI.  There’s only one
reason for such bizarre behavior.  The Clinton campaign has decided that an FBI
investigation of the latest batch of emails poses a threat to its survival. And
so it’s gone all in on fighting the FBI. It’s an unprecedented step born of fea
r. It’s hard to know whether that fear is justified. But the existence of that f
ear already tells us a whole lot.  Clinton loyalists rigged the old investigatio
n. They knew the outcome ahead of time as well as they knew the debate question
s. Now suddenly they are no longer in control. And they are afraid.  You can sme
ll the fear.  The FBI has wiretaps from the investigation of the Clinton Foundat
ion. It’s finding new emails all the time. And Clintonworld panicked. The spinme
isters of Clintonworld have claimed that the email scandal is just so much smoke
without fire. All that’s here is the appearance of impropriety without any of th
e substance. But this isn’t how you react to smoke. It’s how you respond to a fi
re.  The misguided assault on the FBI tells us that Hillary Clinton and her alli
es are afraid of a revelation bigger than the fundamental illegality of her emai
l setup. The email setup was a preemptive cover up. The Clinton campaign has pan
icked badly out of the belief, right or wrong, that whatever crime the illegal s
etup was meant to cover up is at risk of being exposed.  The Clintons have weath
ered countless scandals over the years. Whatever they are protecting this time a
round is bigger than the usual corruption, bribery, sexual assaults and abuses o
f power that have followed them around throughout the years. This is bigger and
more damaging than any of the allegations that have already come out. And they d
on’t want FBI investigators anywhere near it.  The campaign against Comey is pur
e intimidation. It’s also a warning. Any senior FBI people who value their caree
rs are being warned to stay away. The Democrats are closing ranks around their n
ominee against the FBI. It’s an ugly and unprecedented scene. It may also be the
ir last stand.  Hillary Clinton has awkwardly wound her way through numerous sca
ndals in just this election cycle. But she’s never shown fear or desperation bef
ore. Now that has changed. Whatever she is afraid of, it lies buried in her emai
ls with Huma Abedin. And it can bring her down like nothing else has."
```

In [77]:
```python
# create dataframe of new data
news_dic = {"text": news}
new_data = pd.DataFrame([news_dic])
```

In [78]:
```python
# clean news data
clean_text(new_data, "text")

# view new data after cleaning
new_data["text"][0]
```

Out[78]:
```
'daniel greenfield shillman journalism fellow freedom center new york writer foc
using radical islam final stretch election hillary rodham clinton gone war fbi w
ord unprecedented thrown around often election ought retired still unprecedented
nominee major political party go war fbi thats exactly hillary people done coma
patient waking watching hour cnn hospital bed would assume fbi director james co
mey hillary opponent election fbi attack everyone obama cnn hillary people circu
lated letter attacking comey currently medium hit piece lambasting targeting tru
mp wouldnt surprising clinton ally start running attack ad fbi fbi leadership wa
rned entire leftwing establishment form lynch mob continue going hillary fbi cre
dibility attacked medium democrat preemptively head result investigation clinton
foundation hillary clinton covert struggle fbi agent obamas doj people gone expl
osively public new york time compared comey j edgar hoover bizarre headline jame
s comey role recall hoover fbi fairly practically admits front spouting nonsense
boston globe published column calling comeys resignation outdone time editorial
```

```
claiming scandal really attack woman james carville appeared msnbc remind everyo
ne still alive insane accused comey coordinating house republican kgb thought va
st right wing conspiracy stretch countless medium story charge comey violating p
rocedure know whats procedural violation emailing classified information stored 
bathroom server senator harry reid sent comey letter accusing violating hatch ac
t hatch act nice idea much relevance age obama tenth amendment cable news spectr
um quickly filled medium hack glancing wikipedia article hatch act table accusin
g fbi director one awkward conspiracy hillary ever james comey really hurt hilla
ry picked one hell strange way long ago democrat breathing sigh relief gave hill
ary clinton pas prominent public statement really elect trump keeping email scan
dal going trash investigation payroll house republican kgb back playing coy sudd
en development vladimir putin paul ryan talked taking look anthony weiners compu
ter either comey cunning fbi director ever lived he awkwardly trying navigate po
litical mess trapped doj leadership whose political future tied hillary victory 
bureau whose apolitical agent want allowed job truly mysterious thing hillary as
sociate decided go war respected federal agency american like fbi hillary clinto
n enjoys 60 unfavorable rating interesting question hillary old strategy lie den
y fbi even criminal investigation underway instead associate insisted security r
eview fbi corrected shrugged old breezy denial approach given way savage assault 
fbi pretending nothing wrong bad strategy better one picking fight fbi lunatic c
linton associate try claim fbi really kgb two possible explanation hillary clint
on might arrogant enough lash fbi belief victory near kind hubris led plan victo
ry firework display could lead declare war fbi irritating final mile campaign ex
planation people panicked going war fbi behavior smart focused presidential camp
aign act desperation presidential candidate decides option try destroy credibili
ty fbi thats hubris fear fbi might reveal original fbi investigation hillary cli
nton confident could ride good reason believing hillary clinton gone place paran
oid wreck within short space time positive clinton campaign promising unite coun
try replaced desperate flailing operation focused energy fighting fbi there one 
reason bizarre behavior clinton campaign decided fbi investigation latest batch 
email pose threat survival gone fighting fbi unprecedented step born fear hard k
now whether fear justified existence fear already tell u whole lot clinton loyal
ist rigged old investigation knew outcome ahead time well knew debate question s
uddenly longer control afraid smell fear fbi wiretap investigation clinton found
ation finding new email time clintonworld panicked spinmeister clintonworld clai
med email scandal much smoke without fire thats appearance impropriety without s
ubstance isnt react smoke respond fire misguided assault fbi tell u hillary clin
ton ally afraid revelation bigger fundamental illegality email setup email setup
preemptive cover clinton campaign panicked badly belief right wrong whatever cri
me illegal setup meant cover risk exposed clinton weathered countless scandal ye
ar whatever protecting time around bigger usual corruption bribery sexual assaul
t abuse power followed around throughout year bigger damaging allegation already
come dont want fbi investigator anywhere near campaign comey pure intimidation a
lso warning senior fbi people value career warned stay away democrat closing ran
k around nominee fbi ugly unprecedented scene may also last stand hillary clinto
n awkwardly wound way numerous scandal election cycle shes never shown fear desp
eration changed whatever afraid lie buried email huma abedin bring like nothing 
else'
```

Use supervised machine learning to predict new unlabeled data

In [79]:

```python
def new_pipeline_func(vectorizer, clf):
    pipeline = Pipeline(
        [
            ('vect', vectorizer),
            ('clf', clf)
        ]
    )
```

```
    # fit and predict test set
    pipeline.fit(train.text, train.label)
    y_pred = pipeline.predict(new_data.text)
    return y_pred
```

In [80]:
```
# random forest
rf_pred = new_pipeline_func(vectorizer, rf_best)

# logistic regression
log_pred = new_pipeline_func(vectorizer, LogisticRegression())

# decison tree
dt_pred = new_pipeline_func(vectorizer, DecisionTreeClassifier())
```

In [81]:
```
print("Random Forest Prediction: ", rf_pred[0])
print("Logistic Regression Prediction: ", log_pred[0])
print("Decision Tree Prediction: ", dt_pred[0])
```

```
Random Forest Prediction:  fake
Logistic Regression Prediction:  fake
Decision Tree Prediction:  fake
```

Step 5: Summary

In this project, there are 5 parts:

(1) Gather data, determine the method of data collection and provenance of the data.

(2) Identify Unsupervised Learning Problem.

(3) EDA - Inspect, Visualize, and Clean the data.

(4) Building and training models:

- NMF
- Kmeans
- Random Forest
- Logistic Regression
- Decision Tree

(5) Summary

The goal of this project is to detect fake news, to help news readers to identify bias and misinformation in news articles in a quick and reliable fashion. By comparing two unsupervised and three supervised learning algorithms, we can conclude that, in this project:

- in overall, supervised learning algorithms have better performance compare with unsupervised learning algorithms.
- Decision Tree Classifier is the best model with the highest accuracy score on the test set 99.5%.
- Logistic Regression model is the second best model with the accuracy score on the test set 98.9%.

- Compare between two unsupervised learning models, Kmeans performance is better than NMF with the accuracy score on the test set 91.3% and 83.7% for NMF.

Finally, I used supervised learning models, included Random Forest, Logistic Regression and Decision Tree to predict new unlabeled data and all three models predict new data is fake.

Because of the limitation of data and the running time was too costly, the models just were trained on limited data and limited approach. I think there are many other ways can improve this kind of project such as: building more unsupervised models by tuning hyperparameters to get optimal results, or use other type of Word Embeddings such as: Tokenization, Bag-of-Words or Count Vectorizer. Besides that, I could not test models on more new data because of the costly running time.

In [ ]:

```
```