Fake News Detection Project

- Pranav Desai

In [182]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import spacy
import spacy as displacy
import spacy as tokenizer
import re
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')
import gensim
import gensim.corpora as corpora
from gensim.models.coherencemodel import CoherenceModel
from gensim.models import LsiModel, TfidfModel
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.metrics import accuracy_score, classification_report
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\INDIA\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

In [183]:

```
#set plot options
plt.rcParams['figure.figsize']=(12,8)
default_plot_colour= "#00bfbf"
```

In [184]:

```
data=pd.read_csv("C:\\Users\\INDIA\\Downloads\\fake_news_data.csv")
```

In [185]:

```
data.head()
```

Out[185]:

	title	text	date	fake_or_factual
0	HOLLYWEIRD LIB SUSAN SARANDON Compares Muslim ...	There are two small problems with your analogy...	Dec 30, 2015	Fake News
1	Elijah Cummings Called Trump Out To His Face ...	Buried in Trump s bonkers interview with New Y...	April 6, 2017	Fake News
2	Hillary Clinton Says Half Her Cabinet Will Be...	Women make up over 50 percent of this country,...	April 26, 2016	Fake News
3	Russian bombing of U.S.-backed forces being di...	WASHINGTON (Reuters) - U.S. Defense Secretary ...	September 18, 2017	Factual News
4	Britain says window to restore Northern Irelan...	BELFAST (Reuters) - Northern Ireland s politic...	September 4, 2017	Factual News

In [186]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 198 entries, 0 to 197
Data columns (total 4 columns):
 #   Column           Non-Null Count   Dtype
```

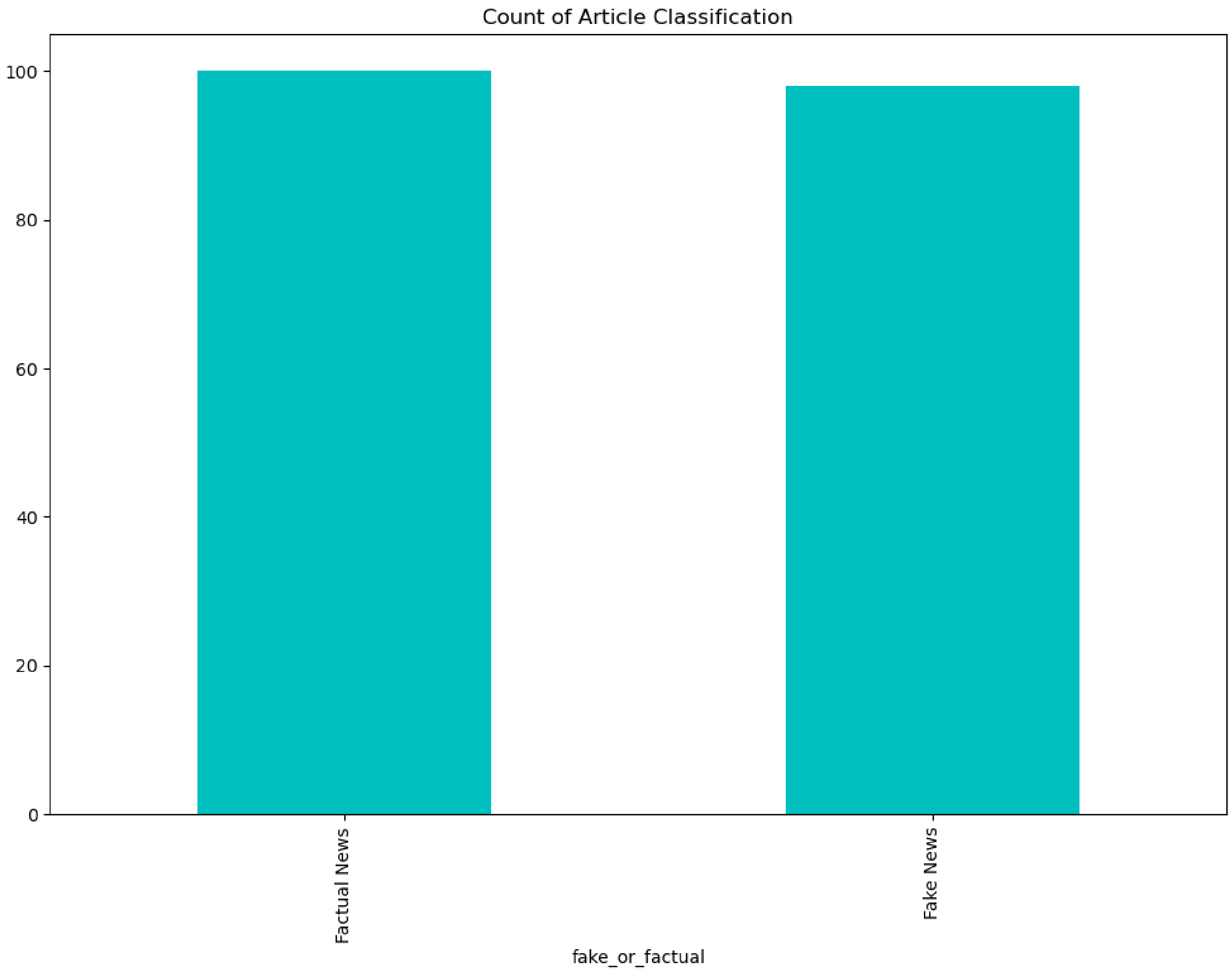
```
---  ------           --------------  -----
 0   title            198 non-null    object
 1   text             198 non-null    object
 2   date             198 non-null    object
 3   fake_or_factual  198 non-null    object
dtypes: object(4)
memory usage: 6.3+ KB
```

In [187]:

```
data['fake_or_factual'].value_counts().plot(kind='bar',color=default_plot_colour)
plt.title("Count of Article Classification")
```

Out[187]:

```
Text(0.5, 1.0, 'Count of Article Classification')
```



In [194]:

```
nlp=spacy.load('en_core_web_sm')
```

In [195]:

```
fake_news=data[data['fake_or_factual'] == "Fake News"]
fact_news=data[data['fake_or_factual'] == "Factual News"]
```

In [196]:

```
fake_spacydocs=list(nlp.pipe(fake_news['text']))
fact_spacydoc=list(nlp.pipe(fact_news['text']))
```

In [197]:

```
def extract_token_tags(doc:spacy.tokens.doc.Doc):
```

```
    return[(i.text,i.ent_type_,i.pos_) for i in doc]
```

In [198]:

```
fake_tagsdf=[]
columns=["token","ner_tag","pos_tag"]
```

In [199]:

```
for ix,doc in enumerate(fake_spacydocs):
    tags=extract_token_tags(doc)
    tags=pd.DataFrame(tags)
    tags.columns=columns
    fake_tagsdf.append(tags)
```

In [200]:

```
fake_tagsdf=pd.concat(fake_tagsdf)
```

In [201]:

```
fact_tagsdf=[]

for ix,doc in enumerate(fact_spacydoc):
    tags=extract_token_tags(doc)
    tags=pd.DataFrame(tags)
    tags.columns=columns
    fact_tagsdf.append(tags)
```

In [202]:

```
fact_tagsdf=pd.concat(fact_tagsdf)
```

In [203]:

```
fake_tagsdf.head()
```

Out[203]:

	token	ner_tag	pos_tag
0	There		PRON
1	are		VERB
2	two	CARDINAL	NUM
3	small		ADJ
4	problems		NOUN

In [204]:

```
pos_counts_fake=fake_tagsdf.groupby(["token","pos_tag"]).size().reset_index(name="counts
").sort_values(by="counts",ascending=False)
pos_counts_fake.head(10)
```

Out[204]:

	token	pos_tag	counts
28	,	PUNCT	1908
7446	the	DET	1834
39	.	PUNCT	1531
5759	of	ADP	922
2661	and	CCONJ	875
2446	a	DET	804
0		SPACE	795

	token	pos_tag	counts
7523	to	PART	[illegible]
4915	in	ADP	667
5094	is	AUX	419

In [205]:

```python
pos_counts_fact=fact_tagsdf.groupby(["token","pos_tag"]).size().reset_index(name="counts
").sort_values(by="counts",ascending=False)
pos_counts_fact.head(10)
```

Out[205]:

	token	pos_tag	counts
6169	the	DET	1903
15	,	PUNCT	1698
22	.	PUNCT	1381
4733	of	ADP	884
1905	a	DET	789
2100	and	CCONJ	757
4015	in	ADP	672
6230	to	PART	660
4761	on	ADP	482
5586	said	VERB	452

In [206]:

```python
pos_counts_fake.groupby("pos_tag")["token"].count().sort_values(ascending=False).head(10
)
```

Out[206]:

```
pos_tag
NOUN     2597
VERB     1814
PROPN    1657
ADJ       876
ADV       412
NUM       221
PRON       99
ADP        88
AUX        58
SCONJ      54
Name: token, dtype: int64
```

In [207]:

```python
pos_counts_fact.groupby("pos_tag")["token"].count().sort_values(ascending=False).head(10
)
```

Out[207]:

```
pos_tag
NOUN     2182
VERB     1535
PROPN    1387
ADJ       753
ADV       271
NUM       203
PRON       81
ADP        70
AUX        44
SCONJ      39
Name: token, dtype: int64
```

In [208]:

```
pos_counts_fake[pos_counts_fake.pos_tag=="NOUN"][:15]
```

Out[208]:

	token	pos_tag	counts
5969	people	NOUN	77
7959	women	NOUN	55
6204	president	NOUN	53
7511	time	NOUN	52
8011	year	NOUN	44
3134	campaign	NOUN	44
4577	government	NOUN	41
5208	law	NOUN	40
7344	t	NOUN	40
8013	years	NOUN	40
7157	state	NOUN	39
4010	election	NOUN	37
5474	media	NOUN	36
3639	day	NOUN	35
3534	country	NOUN	33

In [209]:

```
pos_counts_fact[pos_counts_fact.pos_tag=="NOUN"][:15]
```

Out[209]:

	token	pos_tag	counts
3748	government	NOUN	71
6639	year	NOUN	64
5927	state	NOUN	58
2373	bill	NOUN	55
1982	administration	NOUN	51
3289	election	NOUN	48
5084	president	NOUN	47
4804	order	NOUN	45
4937	people	NOUN	45
2509	campaign	NOUN	42
4271	law	NOUN	42
6118	tax	NOUN	39
5415	reporters	NOUN	38
5930	statement	NOUN	37
4941	percent	NOUN	36

In [210]:

```
top_entities_fake=fake_tagsdf[fake_tagsdf["ner_tag"] !=""].groupby(["token","ner_tag"]).
size().reset_index(name="counts").sort_values(by="counts",ascending=False)
```

In [211]:

```
top_entities_fact=fact_tagsdf[fact_tagsdf["ner_tag"] !=""].groupby(["token","ner_tag"]).
size().reset_index(name="counts").sort_values(by="counts",ascending=False)
```

In [212]:

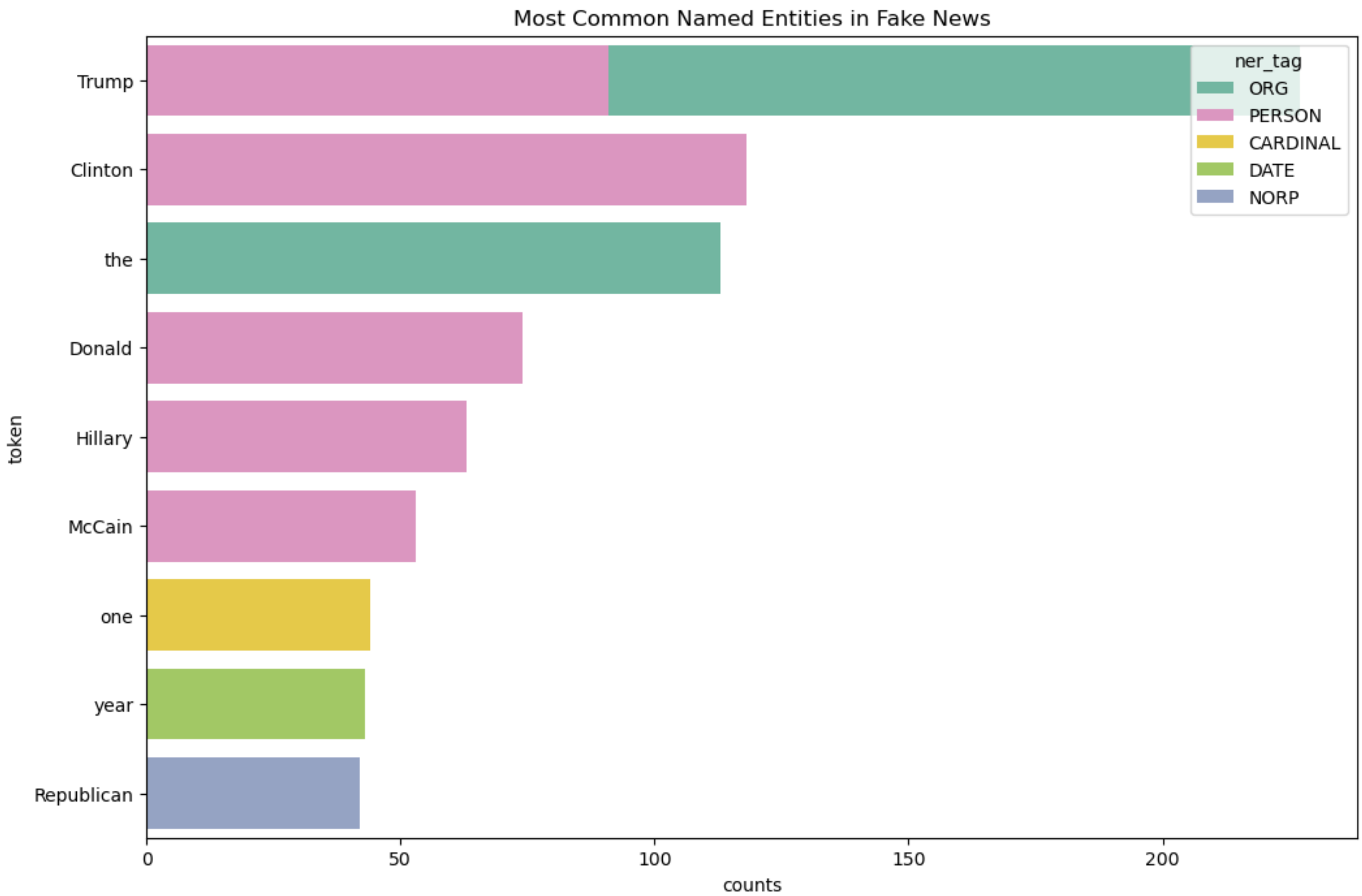
```
ner_palette={
    'ORG':sns.color_palette("Set2").as_hex()[0],
    'GPE':sns.color_palette("Set2").as_hex()[1],
    'NORP':sns.color_palette("Set2").as_hex()[2],
    'PERSON':sns.color_palette("Set2").as_hex()[3],
    'DATE':sns.color_palette("Set2").as_hex()[4],
    'CARDINAL':sns.color_palette("Set2").as_hex()[5],
    'PERCENT':sns.color_palette("Set2").as_hex()[6],

}
```

In [213]:

```
sns.barplot(
    x='counts',
    y='token',
    hue='ner_tag',
    palette=ner_palette,
    data=top_entities_fake[:10],
    orient='h',
    dodge=False
).set(title="Most Common Named Entities in Fake News")
```

Out[213]:

```
[Text(0.5, 1.0, 'Most Common Named Entities in Fake News')]
```



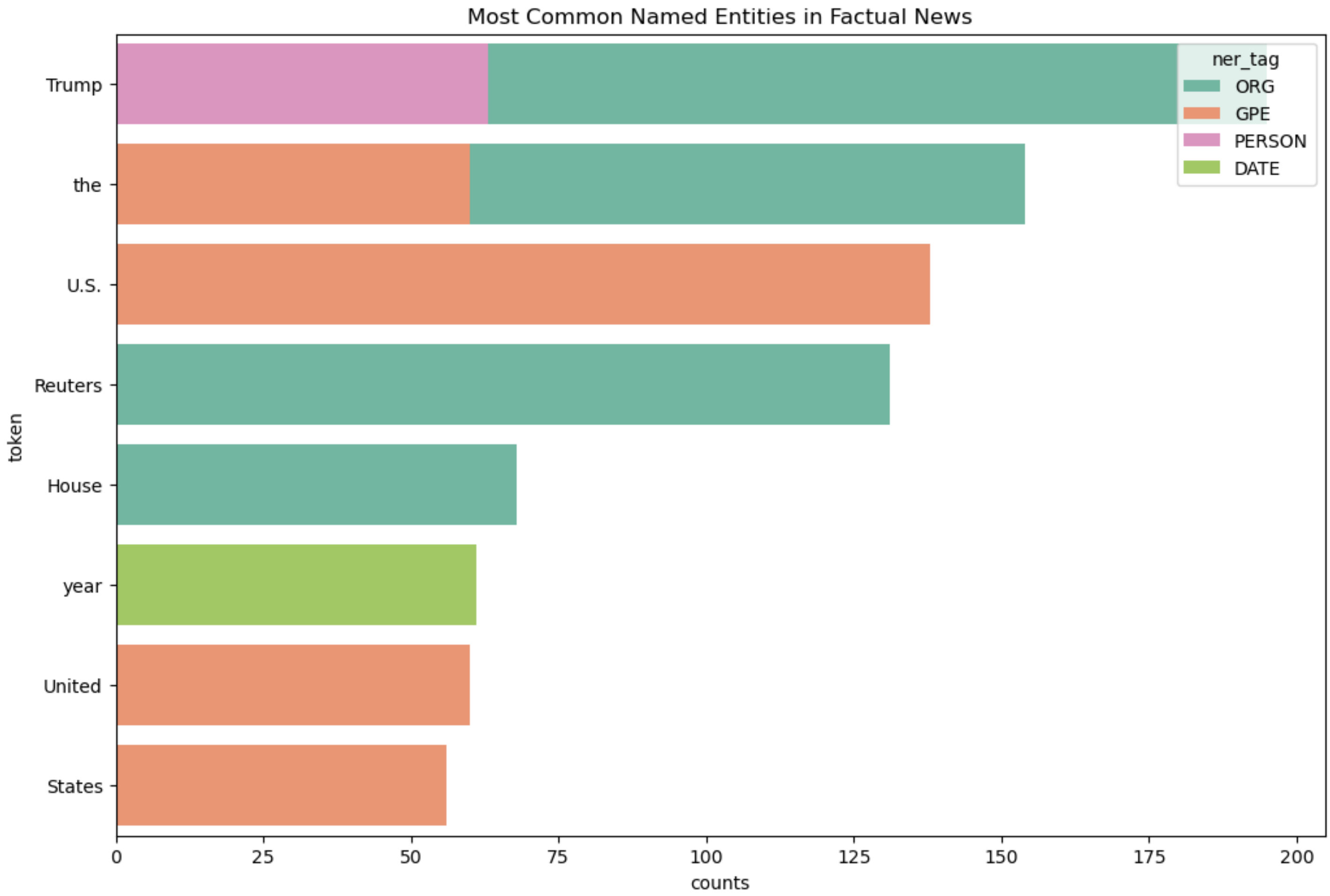
In [214]:

```
sns.barplot(
    x='counts',
    y='token',
    hue='ner_tag',
    palette=ner_palette,
```

```
    data=top_entities_fact[:10],
    orient='h',
    dodge=False
).set(title="Most Common Named Entities in Factual News")
```

Out[214]:

```
[Text(0.5, 1.0, 'Most Common Named Entities in Factual News')]
```



In [215]:

```
data.head()
```

Out[215]:

	title	text	date	fake_or_factual
0	HOLLYWEIRD LIB SUSAN SARANDON Compares Muslim ...	There are two small problems with your analogy...	Dec 30, 2015	Fake News
1	Elijah Cummings Called Trump Out To His Face ...	Buried in Trump s bonkers interview with New Y...	April 6, 2017	Fake News
2	Hillary Clinton Says Half Her Cabinet Will Be...	Women make up over 50 percent of this country,...	April 26, 2016	Fake News
3	Russian bombing of U.S.-backed forces being di...	WASHINGTON (Reuters) - U.S. Defense Secretary ...	September 18, 2017	Factual News
4	Britain says window to restore Northern Irelan...	BELFAST (Reuters) - Northern Ireland s politic...	September 4, 2017	Factual News

In [216]:

```
data['text_clean']=data.apply(lambda x: re.sub(r"^[^-]*-\s", "", x['text']), axis=1)
```

In [217]:

```
data['text_clean']=data['text_clean'].str.lower()
```

In [218]:

```
data['text_clean']=data.apply(lambda x: re.sub(r"([^\w\s])", "", x['text_clean']), axis=
1)
```

In [219]:

```
en_stopwords=stopwords.words('english')
print(en_stopwords)
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
"you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himsel
f', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'the
m', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "tha
t'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',
'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if
', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'ag
ainst', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to'
, 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 't
hen', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each
', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'sa
me', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'shoul
d', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'c
ouldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn
't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't",
'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren',
"weren't", 'won', "won't", 'wouldn', "wouldn't"]
```

In [220]:

```
data['text_clean']=data['text_clean'].apply(lambda x: ' '.join([word for word in x.split
() if word not in(en_stopwords)]))
```

In [221]:

```
data['text_clean']=data.apply(lambda x: word_tokenize(x['text_clean']),axis=1)
```

In [222]:

```
lemmatizer=WordNetLemmatizer()
data['text_clean']=data['text_clean'].apply(lambda tokens: [lemmatizer.lemmatize(token)
for token in tokens])
```

In [223]:

```
tokens_clean=sum(data['text_clean'], [])
```

In [224]:

```
unigrams=(pd.Series(nltk.ngrams(tokens_clean, 1)).value_counts())
print(unigrams[:10])
```

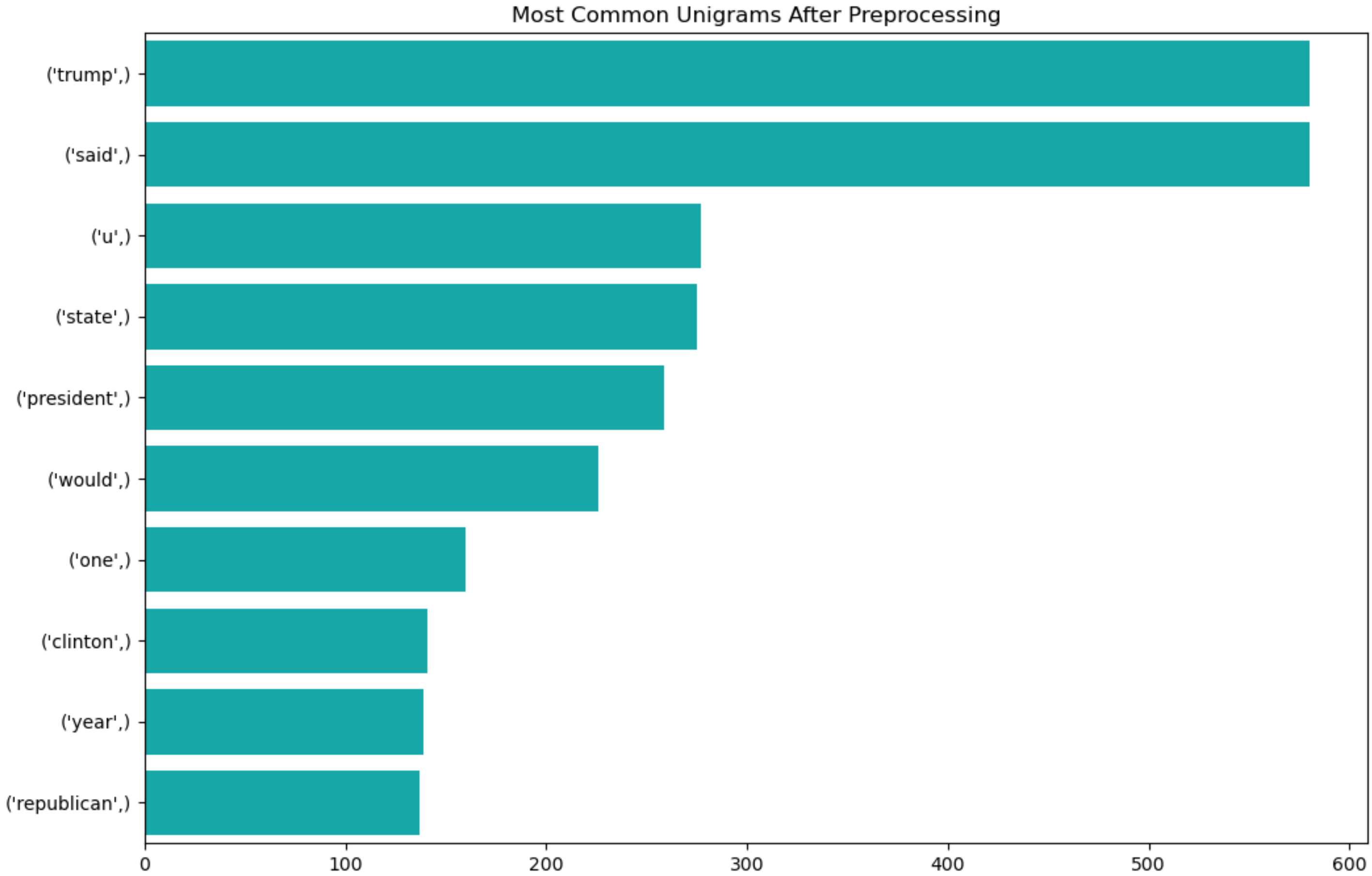
```
(trump,)          580
(said,)           580
(u,)              277
(state,)          275
(president,)      259
(would,)          226
(one,)            160
(clinton,)        141
(year,)           139
(republican,)     137
Name: count, dtype: int64
```

In [225]:

```
sns.barplot(x=unigrams.values[:10],
            y=unigrams.index[:10],
            orient='h',
            palette=[default_plot_colour]
).set(title="Most Common Unigrams After Preprocessing")
```

Out[225]:

```
[Text(0.5, 1.0, 'Most Common Unigrams After Preprocessing')]
```



In [226]:

```
bigrams=(pd.Series(nltk.ngrams(tokens_clean, 2)).value_counts())
print(bigrams[:10])
```

```
(donald, trump)           113
(united, state)            84
(white, house)             74
(president, donald)        47
(hillary, clinton)         39
(new, york)                33
(supreme, court)           30
(image, via)               29
(official, said)           26
(trump, administration)    26
Name: count, dtype: int64
```

In [227]:

```
vader_sentiment=SentimentIntensityAnalyzer()
```

In [228]:

```
data['vader_sentiment_score']=data['text'].apply(lambda x: vader_sentiment.polarity_score
s(x)['compound'])
```

In [229]:

```
data.head()
```

Out[229]:

	title	text	date	fake_or_factual	text_clean	vader_sentiment_score
0	HOLLYWEIRD LIB SUSAN SARANDON Compares Muslim ...	There are two small problems with your analogy...	Dec 30, 2015	Fake News	[two, small, problem, analogy, susan, jesus, m...	-0.3660

	title	text	date	fake_or_factual	text_clean	vader_sentiment_score
1	Elijah Cummings Called Trump Out To His Face ...	Buried in Trump s bonkers interview with New Y...	April 6, 2017	Fake News	[buried, trump, bonkers, interview, new, york,...	-0.7973
2	Hillary Clinton Says Half Her Cabinet Will Be...	Women make up over 50 percent of this country,...	April 26, 2016	Fake News	[woman, make, 50, percent, country, grossly, u...	0.9886
3	Russian bombing of U.S.-backed forces being di...	WASHINGTON (Reuters) - U.S. Defense Secretary ...	September 18, 2017	Factual News	[u, defense, secretary, jim, mattis, said, mon...	-0.3400
4	Britain says window to restore Northern Irelan...	BELFAST (Reuters) - Northern Ireland s politic...	September 4, 2017	Factual News	[northern, ireland, political, party, rapidly,...	0.8590

In [230]:

```
bins=[-1,-0.1,0.1,1]
names=['negative','neutral','positive']
```

In [231]:

```
data['vader_sentiment_label']=pd.cut(data['vader_sentiment_score'],bins,labels=names)
```

In [232]:

```
data.head()
```

Out[232]:

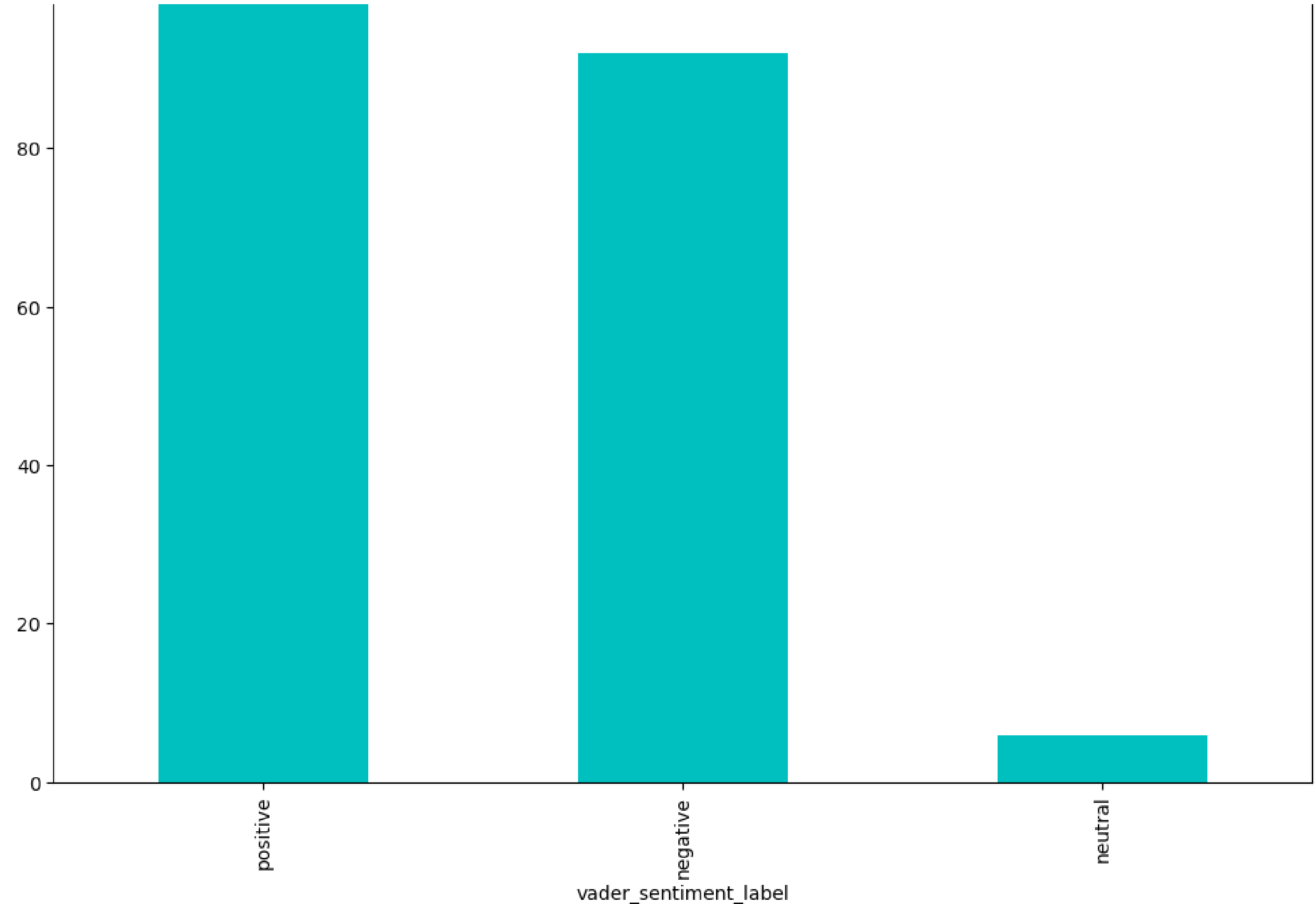
	title	text	date	fake_or_factual	text_clean	vader_sentiment_score	vader_sentiment_label
0	HOLLYWEIRD LIB SUSAN SARANDON Compares Muslim ...	There are two small problems with your analogy...	Dec 30, 2015	Fake News	[two, small, problem, analogy, susan, jesus, m...	-0.3660	negative
1	Elijah Cummings Called Trump Out To His Face ...	Buried in Trump s bonkers interview with New Y...	April 6, 2017	Fake News	[buried, trump, bonkers, interview, new, york,...	-0.7973	negative
2	Hillary Clinton Says Half Her Cabinet Will Be...	Women make up over 50 percent of this country,...	April 26, 2016	Fake News	[woman, make, 50, percent, country, grossly, u...	0.9886	positive
3	Russian bombing of U.S.-backed forces being di...	WASHINGTON (Reuters) - U.S. Defense Secretary ...	September 18, 2017	Factual News	[u, defense, secretary, jim, mattis, said, mon...	-0.3400	negative
4	Britain says window to restore Northern Irelan...	BELFAST (Reuters) - Northern Ireland s politic...	September 4, 2017	Factual News	[northern, ireland, political, party, rapidly,...	0.8590	positive

In [233]:

```
data['vader_sentiment_label'].value_counts().plot.bar(color=default_plot_colour)
```

Out[233]:

```
&lt;Axes: xlabel='vader_sentiment_label'&gt;
```

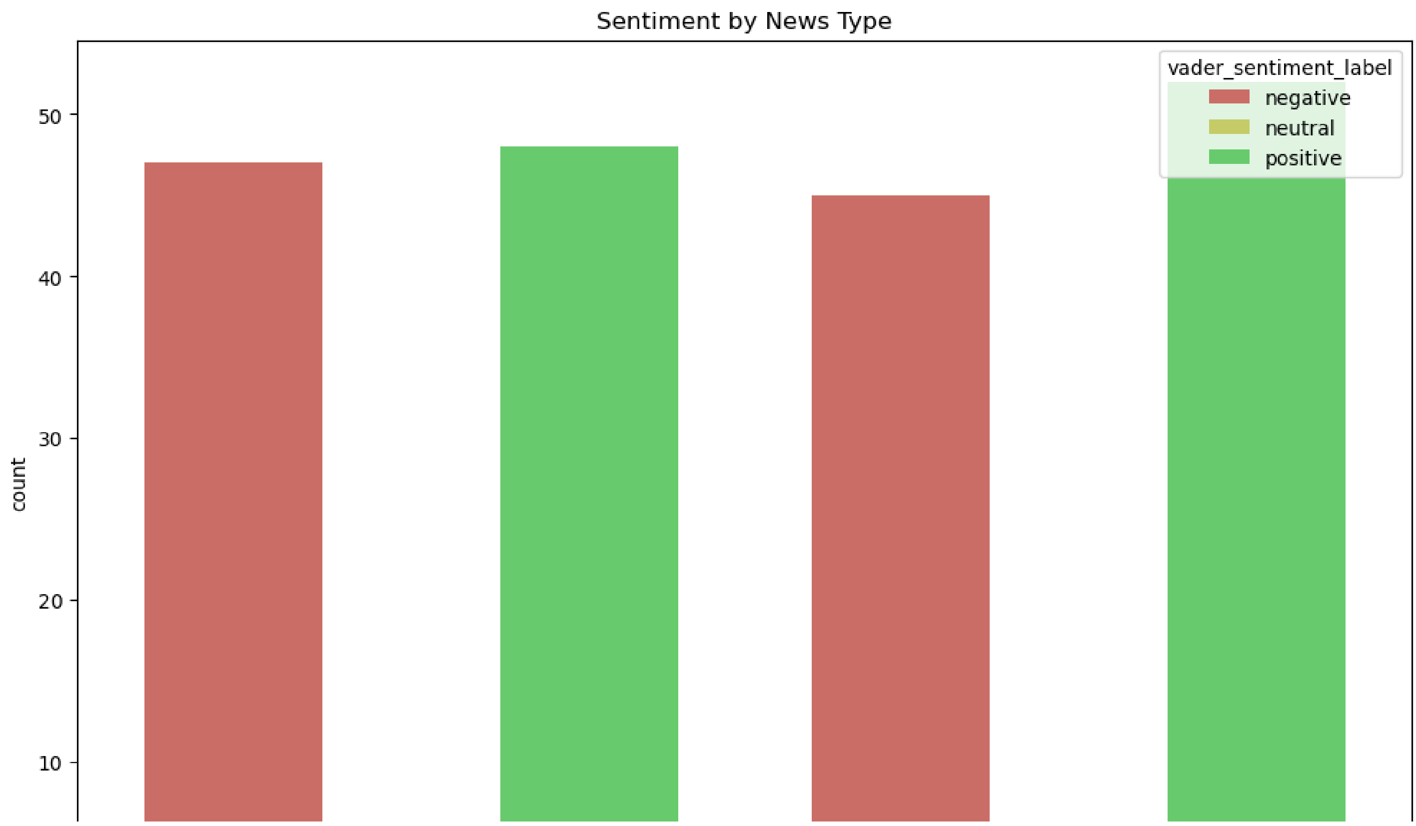


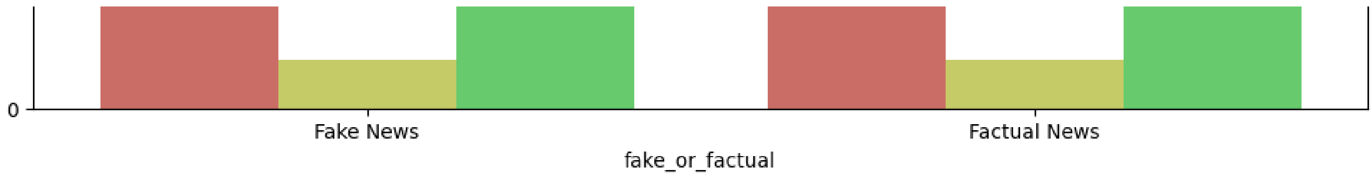
In [234]:

```
sns.countplot(
    x='fake_or_factual',
    hue='vader_sentiment_label',
    palette=sns.color_palette("hls"),
    data=data
).set(title="Sentiment by News Type")
```

Out[234]:

```
[Text(0.5, 1.0, 'Sentiment by News Type')]
```





In [235]:

```
fake_news_text=data[data['fake_or_factual']=="Fake News"] ['text_clean'].reset_index(dro
p=True)
```

In [236]:

```
dictionary_fake=corpora.Dictionary(fake_news_text)
```

In [242]:

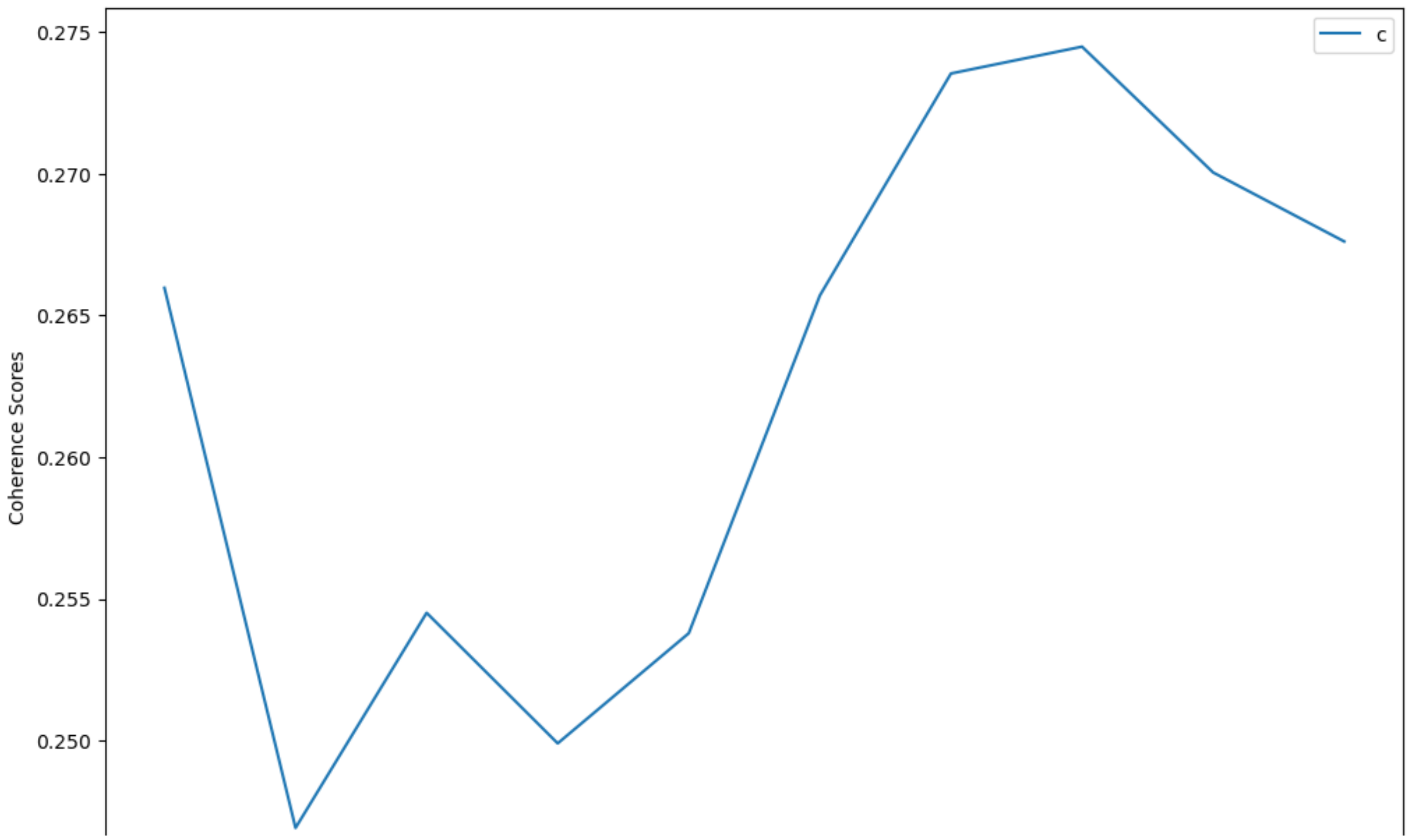
```
doc_term_fake=[dictionary_fake.doc2bow(text) for text in fake_news_text]
```

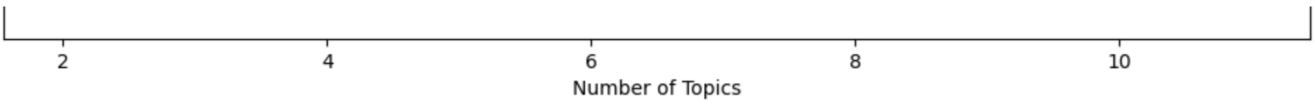
In [243]:

```
coherence_values=[]
model_list=[]

min_topics=2
max_topics=11

for num_topics_i in range(min_topics,max_topics+1):
    model=gensim.models.LdaModel(doc_term_fake, num_topics=num_topics_i, id2word=diction
ary_fake)
    model_list.append(model)
    coherence_model=CoherenceModel(model=model, texts=fake_news_text, dictionary=dictiona
ry_fake, coherence='c_v')
    coherence_values.append(coherence_model.get_coherence())
```

In [244]:

```
plt.plot(range(min_topics, max_topics+1), coherence_values)
plt.xlabel("Number of Topics")
plt.ylabel("Coherence Scores")
plt.legend(("coherence_values"), loc='best')
plt.show()
```





In [245]:

```
num_topics_lda=7
lda_model=gensim.models.LdaModel(corpus=doc_term_fake, id2word=dictionary_fake, num_topic
s=num_topics_lda)
```

In [246]:

```
lda_model.print_topics(num_topics_lda, num_words=10)
```

Out[246]:

```
[(0,
  '0.006*"clinton" + 0.005*"said" + 0.005*"state" + 0.005*"trump" + 0.004*"u" + 0.004*"ob
ama" + 0.004*"stamp" + 0.004*"president" + 0.003*"food" + 0.003*"go"'),
 (1,
  '0.007*"trump" + 0.005*"would" + 0.005*"president" + 0.004*"clinton" + 0.004*"one" + 0.
004*"said" + 0.004*"state" + 0.003*"republican" + 0.003*"year" + 0.003*"people"'),
 (2,
  '0.011*"trump" + 0.006*"president" + 0.006*"said" + 0.005*"donald" + 0.005*"u" + 0.003*
"state" + 0.003*"time" + 0.003*"one" + 0.003*"would" + 0.003*"know"'),
 (3,
  '0.011*"trump" + 0.005*"u" + 0.005*"clinton" + 0.004*"president" + 0.003*"state" + 0.00
3*"woman" + 0.003*"said" + 0.003*"would" + 0.003*"year" + 0.003*"donald"'),
 (4,
  '0.024*"trump" + 0.005*"said" + 0.004*"time" + 0.004*"republican" + 0.004*"state" + 0.0
03*"president" + 0.003*"one" + 0.003*"would" + 0.003*"even" + 0.003*"donald"'),
 (5,
  '0.009*"trump" + 0.005*"president" + 0.005*"state" + 0.004*"mccain" + 0.004*"one" + 0.0
04*"would" + 0.004*"time" + 0.004*"clinton" + 0.003*"said" + 0.003*"u"'),
 (6,
  '0.009*"trump" + 0.006*"said" + 0.005*"clinton" + 0.004*"people" + 0.004*"one" + 0.004*
"would" + 0.003*"state" + 0.003*"u" + 0.003*"time" + 0.003*"two"')]
```

In [247]:

```
def tfidf_corpus(doc_term_matrix):
    tfidf= TfidfModel(corpus=doc_term_matrix, normalize=True)
    corpus_tfidf=tfidf[doc_term_matrix]
    return corpus_tfidf
```

In [248]:

```
def get_coherence_scores(corpus, dictionary, text, min_topics, max_topics):
    coherence_values=[]
    model_list=[]
    for num_topics_i in range(min_topics,max_topics+1):
        model=LsiModel(corpus, num_topics=num_topics_i, id2word=dictionary)
        model_list.append(model)
        coherence_model=CoherenceModel(model=model, texts=text, dictionary=dictionary, c
oherence='c_v')
        coherence_values.append(coherence_model.get_coherence())

    plt.plot(range(min_topics, max_topics+1), coherence_values)
    plt.xlabel("Number of Topics")
    plt.ylabel("Coherence Scores")
    plt.legend(("coherence_values"), loc='best')
    plt.show()
```

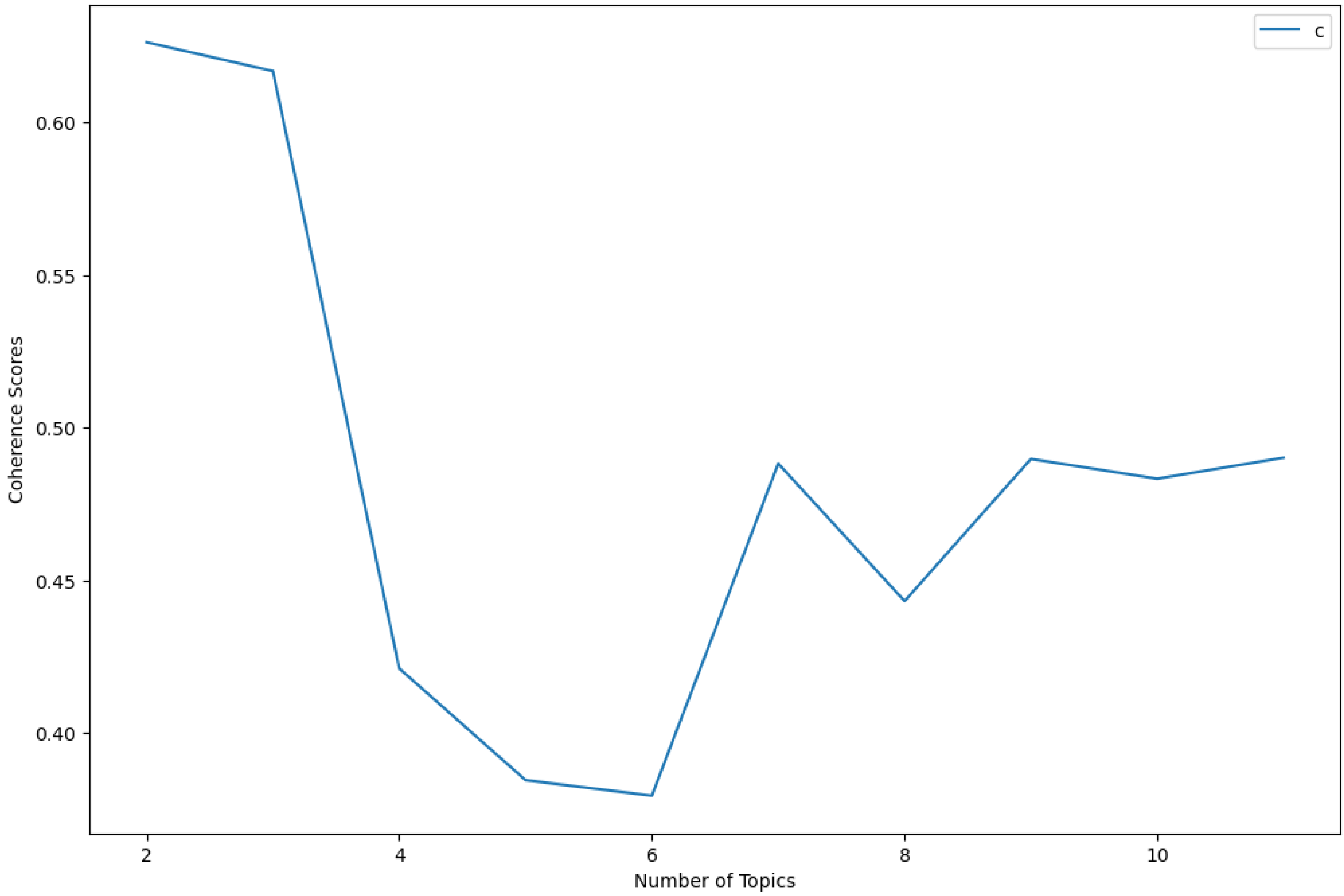
In [249]:

```
corpus_tfidf_fake= tfidf_corpus(doc_term_fake)
```

In [250]:

```
get_coherence_scores(corpus_tfidf_fake, dictionary_fake, fake_news_text, min_topics=2, m
```

```
ax_topics=11)
```



In [251]:

```
lsa_model= LsiModel(corpus_tfidf_fake, id2word=dictionary_fake, num_topics=7)
```

In [252]:

```
lsa_model.print_topics()
```

Out[252]:

```
[(0,
  '-0.190*"trump" + -0.136*"clinton" + -0.095*"hillary" + -0.094*"obama" + -0.089*"presid
ent" + -0.087*"woman" + -0.078*"republican" + -0.077*"party" + -0.077*"flynn" + -0.074*"c
andidate"'),
 (1,
  '-0.325*"boiler" + -0.284*"acr" + -0.244*"room" + -0.240*"pm" + -0.186*"broadcast" + -
0.180*"radio" + -0.142*"animal" + -0.142*"tune" + -0.134*"jay" + -0.132*"episode"'),
 (2,
  '-0.622*"flynn" + -0.182*"immunity" + -0.122*"nana" + -0.116*"mr" + -0.110*"30" + -0.10
8*"march" + -0.102*"russian" + -0.100*"source" + 0.095*"school" + -0.092*"adviser"'),
 (3,
  '0.217*"clinton" + -0.185*"school" + -0.175*"student" + 0.141*"hillary" + -0.122*"flynn
" + -0.121*"county" + 0.110*"sander" + 0.097*"debate" + 0.097*"woman" + 0.091*"nominee"')
,
 (4,
  '0.200*"email" + -0.194*"trump" + 0.168*"dnc" + -0.143*"flynn" + 0.126*"clinton" + -0.1
12*"cruz" + 0.111*"department" + 0.110*"rich" + 0.102*"wikileaks" + 0.099*"sander"'),
 (5,
  '-0.276*"student" + -0.162*"conference" + -0.160*"school" + -0.138*"trump" + 0.124*"oba
ma" + 0.124*"mccain" + -0.103*"flynn" + -0.102*"campus" + -0.101*"yearbook" + 0.101*"puti
n"'),
 (6,
  '0.348*"conference" + -0.194*"flynn" + 0.186*"press" + 0.171*"mark" + 0.165*"levin" + 0
.165*"hannity" + 0.165*"sean" + 0.141*"discussing" + 0.134*"iowa" + 0.112*"immigration"')
]
```

In [253]:

```
data.head()
```

Out[253]:

	title	text	date	fake_or_factual	text_clean	vader_sentiment_score	vader_sentiment_label
0	HOLLYWEIRD LIB SUSAN SARANDON Compares Muslim ...	There are two small problems with your analogy...	Dec 30, 2015	Fake News	[two, small, problem, analogy, susan, jesus, m...	-0.3660	negative
1	Elijah Cummings Called Trump Out To His Face ...	Buried in Trump s bonkers interview with New Y...	April 6, 2017	Fake News	[buried, trump, bonkers, interview, new, york,...	-0.7973	negative
2	Hillary Clinton Says Half Her Cabinet Will Be...	Women make up over 50 percent of this country,...	April 26, 2016	Fake News	[woman, make, 50, percent, country, grossly, u...	0.9886	positive
3	Russian bombing of U.S.-backed forces being di...	WASHINGTON (Reuters) - U.S. Defense Secretary ...	September 18, 2017	Factual News	[u, defense, secretary, jim, mattis, said, mon...	-0.3400	negative
4	Britain says window to restore Northern Irelan...	BELFAST (Reuters) - Northern Ireland s politic...	September 4, 2017	Factual News	[northern, ireland, political, party, rapidly,...	0.8590	positive

In [254]:

```
X= [','.join(map(str,l)) for l in data['text_clean']]
```

In [255]:

```
Y=data['fake_or_factual']
```

In [256]:

```
countvec= CountVectorizer()
```

In [257]:

```
countvec_fit= countvec.fit_transform(X)
```

In [258]:

```
bag_of_words=pd.DataFrame(countvec_fit.toarray(), columns=countvec.get_feature_names_out
())
```

In [259]:

```
X_train, X_test, y_train, y_test= train_test_split(bag_of_words, Y, test_size=0.3)
```

In [260]:

```
lr= LogisticRegression(random_state=0).fit(X_train, y_train)
```

In [261]:

```
y_pred_lr= lr.predict(X_test)
```

In [262]:

```
accuracy_score(y_pred_lr, y_test)
```

Out[262]:

```
0.95
```

In [263]:

```
print(classification_report(y_test, y_pred_lr))
```

```
              precision    recall  f1-score   support

Factual News       0.96      0.93      0.95        29
   Fake News       0.94      0.97      0.95        31

    accuracy                           0.95        60
   macro avg       0.95      0.95      0.95        60
weighted avg       0.95      0.95      0.95        60
```

In [264]:

```
svm= SGDClassifier().fit(X_train, y_train)
```

In [265]:

```
y_pred_svm= svm.predict(X_test)
```

In [266]:

```
accuracy_score(y_pred_svm, y_test)
```

Out[266]:

```
0.9333333333333333
```

In [267]:

```
print(classification_report(y_test, y_pred_svm))
```

```
              precision    recall  f1-score   support

Factual News       1.00      0.86      0.93        29
   Fake News       0.89      1.00      0.94        31

    accuracy                           0.93        60
   macro avg       0.94      0.93      0.93        60
weighted avg       0.94      0.93      0.93        60
```

In [ ]:

In [ ]:

In [ ]: