```python
from transformers import AutoModelForTokenClassification,
AutoTokenizer
from torch.nn.functional import softmax
import torch
import os
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
device = "cuda" if torch.cuda.is_available() else "cpu"
print("Device: ", device)
```

```
Device:  cpu
```

```python
import pandas as pd
df =
pd.read_csv('/content/drive/MyDrive/94812/hw1/bbc_sentiment_ner.csv')
df
```

```
      Unnamed: 0.1  Unnamed: 0     topic  \
0                0           0  business
1                1           1  business
2                2           2  business
3                3           3  business
4                4           4  business
...            ...         ...       ...
2220          2220        2220      tech
2221          2221        2221      tech
2222          2222        2222      tech
2223          2223        2223      tech
2224          2224        2224      tech

                                                content sentiment
score  \
0     Golden rule 'intact' says ex-aide\n\nChancello...  Negative
0.003080
1     Beer giant swallows Russian firm\n\nBrewing gi...   Neutral
0.687573
2     Deutsche Boerse set to 'woo' LSE\n\nBosses of ...  Negative
0.000259
3     GM in crunch talks on Fiat future\n\nFiat will...  Negative
0.001180
4     Sluggish economy hits German jobs\n\nThe numbe...  Negative
0.000155
...                                                 ...       ...
...
2220  Fast moving phone viruses appear\n\nSecurity f...  Negative
0.000176
```

```
2221  Musical future for phones\n\nAnalyst Bill Thom...  Positive
0.961024
2222  'No re-draft' for EU patent law\n\nA proposed ...  Negative
0.000900
2223  Apple sues 'Tiger' file sharers\n\nApple has t...  Negative
0.000158
2224  Can Yahoo dominate next decade?\n\nYahoo has r...  Negative
0.005561

                                                    ner  CARDINAL
DATE  \
0     [('Gordon Brown', 'PERSON'), ("Mr Brown's", 'O...         1
5
1     [('Russian', 'NORP'), ('Inbev', 'ORG'), ("Alfa...         7
3
2     [('Deutsche Boerse', 'ORG'), ('Deutsche Boerse...         1
8
3     [('GM', 'ORG'), ('Fiat', 'ORG'), ('Fiat', 'ORG...         1
6
4     [('German', 'NORP'), ('Europe', 'LOC'), ('the ...         3
5
...                                                 ...       ...   ..
.
2220  [('Cabir', 'ORG'), ('Cabir', 'GPE'), ('the Sym...         5
2
2221  [('Bill Thompson', 'PERSON'), ('Max', 'PERSON'...        11
2
2222  [('EU', 'ORG'), ('European', 'NORP'), ('the Eu...         1
4
2223  [('Apple', 'ORG'), ('Apple', 'ORG'), ('three',...         2
9
2224  [('next decade', 'DATE'), ('Yahoo', 'ORG'), ('...         3
9

      EVENT  ...  MONEY  NORP  ORDINAL  ORG  PERCENT  PERSON  PRODUCT
\
0         0  ...      0     0        0   15        0       6        0

1         0  ...      2     6        1   12        2       6        2

2         0  ...      3     3        2   13        0       9        0

3         0  ...      0     2        0   29        4       4        0

4         0  ...      0     3        0    2        3       3        0

...     ...  ...    ...   ...      ...  ...      ...     ...      ...

2220      1  ...      0     4        0   11        0       0        1
```

```
2221       0  ...       0      1         0   11          0       7         2

2222       0  ...       0      2         1   17          0       3         0

2223       0  ...       0      0         1   15          0       2         0

2224       0  ...       2      0         2   34          0      12         0


      QUANTITY  TIME  WORK_OF_ART
0            0     0            1
1            0     0            0
2            0     0            0
3            0     0            0
4            0     0            0
...        ...   ...          ...
2220         0     0            0
2221         0     0            1
2222         0     0            0
2223         0     0            0
2224         0     0            0

[2225 rows x 25 columns]
```

```
from gensim import corpora
from nltk.corpus import stopwords
import nltk
nltk.download('stopwords')

# %%
def preprocess_text(doc):
    # Tokenize, remove stopwords, and lowercase
    stop_words = set(stopwords.words('english'))
    return [word for word in gensim.utils.simple_preprocess(doc) if
word not in stop_words]
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
import gensim
df['processed_docs'] = df['content'].map(preprocess_text)
dictionary = corpora.Dictionary(df['processed_docs'])
dictionary.filter_extremes(no_below=20, no_above=0.5)
corpus = [dictionary.doc2bow(doc) for doc in df['processed_docs']]

# Set up the LDA model
lda_model = gensim.models.LdaMulticore(corpus, num_topics=20,
id2word=dictionary, passes=10, workers=2)

# Print the topics
```

```python
for idx, topic in lda_model.print_topics(-1):
    print('Topic: {} \nWords: {}'.format(idx, topic))
```

```
Topic: 0
Words: 0.016*"india" + 0.014*"oil" + 0.010*"bn" + 0.009*"prices" +
0.008*"indian" + 0.008*"government" + 0.007*"market" + 0.007*"company"
+ 0.007*"energy" + 0.007*"us"
Topic: 1
Words: 0.020*"ferguson" + 0.019*"arsenal" + 0.010*"henry" + 0.010*"mr"
+ 0.010*"scottish" + 0.009*"world" + 0.007*"united" + 0.007*"shot" +
0.007*"meeting" + 0.007*"france"
Topic: 2
Words: 0.049*"film" + 0.022*"best" + 0.014*"films" + 0.012*"director"
+ 0.012*"actor" + 0.010*"awards" + 0.010*"oscar" + 0.009*"actress" +
0.008*"award" + 0.008*"dvd"
Topic: 3
Words: 0.015*"government" + 0.010*"world" + 0.008*"aid" +
0.008*"countries" + 0.007*"people" + 0.007*"mr" + 0.006*"lord" +
0.006*"could" + 0.006*"international" + 0.005*"debt"
Topic: 4
Words: 0.015*"us" + 0.014*"economy" + 0.013*"growth" +
0.011*"economic" + 0.010*"bn" + 0.007*"market" + 0.007*"dollar" +
0.007*"bank" + 0.006*"rate" + 0.006*"rise"
Topic: 5
Words: 0.011*"people" + 0.011*"world" + 0.010*"olympic" +
0.010*"education" + 0.009*"indoor" + 0.008*"european" +
0.008*"schools" + 0.008*"students" + 0.007*"race" + 0.007*"british"
Topic: 6
Words: 0.019*"us" + 0.017*"mr" + 0.016*"yukos" + 0.011*"court" +
0.010*"bn" + 0.010*"company" + 0.009*"russian" + 0.008*"fraud" +
0.008*"firm" + 0.007*"legal"
Topic: 7
Words: 0.021*"games" + 0.016*"game" + 0.016*"gaming" + 0.012*"mr" +
0.010*"gamers" + 0.008*"xbox" + 0.007*"people" + 0.007*"software" +
0.007*"time" + 0.007*"titles"
Topic: 8
Words: 0.022*"film" + 0.019*"festival" + 0.010*"public" +
0.008*"workers" + 0.008*"dutch" + 0.008*"government" + 0.007*"choice"
+ 0.007*"day" + 0.006*"life" + 0.006*"february"
Topic: 9
Words: 0.020*"mr" + 0.013*"home" + 0.011*"rights" + 0.010*"government"
+ 0.010*"law" + 0.009*"human" + 0.009*"trial" + 0.008*"told" +
0.008*"secretary" + 0.008*"without"
Topic: 10
Words: 0.015*"bn" + 0.014*"sales" + 0.010*"firm" + 0.009*"company" +
0.008*"uk" + 0.008*"companies" + 0.007*"business" + 0.007*"profits" +
0.007*"new" + 0.007*"people"
Topic: 11
Words: 0.014*"users" + 0.012*"software" + 0.012*"people" + 0.011*"net"
+ 0.011*"security" + 0.010*"microsoft" + 0.009*"use" + 0.009*"mail" +
```

```
0.009*"virus" + 0.008*"many"
Topic: 12
Words: 0.012*"government" + 0.011*"new" + 0.009*"council" +
0.008*"could" + 0.007*"law" + 0.007*"legal" + 0.007*"lord" +
0.006*"airline" + 0.005*"may" + 0.005*"airlines"
Topic: 13
Words: 0.015*"police" + 0.010*"women" + 0.010*"people" + 0.007*"new" +
0.006*"wales" + 0.006*"mr" + 0.006*"health" + 0.006*"plans" +
0.006*"public" + 0.005*"one"
Topic: 14
Words: 0.017*"us" + 0.017*"china" + 0.009*"company" + 0.009*"bank" +
0.009*"deal" + 0.009*"mr" + 0.009*"bn" + 0.008*"new" + 0.008*"foreign"
+ 0.007*"eu"
Topic: 15
Words: 0.017*"music" + 0.010*"best" + 0.010*"show" + 0.010*"one" +
0.009*"new" + 0.008*"us" + 0.007*"band" + 0.006*"number" +
0.006*"first" + 0.006*"uk"
Topic: 16
Words: 0.020*"club" + 0.012*"united" + 0.011*"bid" + 0.009*"offer" +
0.008*"mr" + 0.008*"board" + 0.007*"football" + 0.007*"decision" +
0.006*"deutsche" + 0.006*"manchester"
Topic: 17
Words: 0.009*"game" + 0.009*"first" + 0.008*"england" + 0.008*"win" +
0.007*"time" + 0.007*"one" + 0.007*"two" + 0.007*"back" + 0.006*"last"
+ 0.006*"play"
Topic: 18
Words: 0.035*"mr" + 0.018*"labour" + 0.015*"election" + 0.014*"party"
+ 0.014*"blair" + 0.010*"brown" + 0.009*"minister" +
0.008*"government" + 0.008*"people" + 0.008*"howard"
Topic: 19
Words: 0.014*"people" + 0.010*"technology" + 0.008*"digital" +
0.008*"mobile" + 0.007*"tv" + 0.007*"could" + 0.007*"music" +
0.007*"one" + 0.006*"new" + 0.006*"like"

import warnings
warnings.filterwarnings('ignore')
from tqdm.auto import tqdm
def format_topics_sentences(ldamodel, corpus):
    topics_df = pd.DataFrame()

    # Get main topic in each document
    for i, row in tqdm(enumerate(ldamodel[corpus])):
        row = sorted(row, key=lambda x: (x[1]), reverse=True)
        # Get the Dominant topic, Perc Contribution and Keywords for
each document
        for j, (topic_num, prop_topic) in enumerate(row):
            if j == 0:  # => dominant topic
                wp = ldamodel.show_topic(topic_num)
                topic_keywords = ", ".join([word for word, prop in
wp])
```

```
                topics_df =
topics_df.append(pd.Series([int(topic_num), round(prop_topic,4),
topic_keywords]), ignore_index=True)
            else:
                break
    topics_df.columns = ['Dominant_Topic', 'Perc_Contribution',
'Topic_Keywords']

    return topics_df

df_topic_sents_keywords = format_topics_sentences(ldamodel=lda_model,
corpus=corpus)
df = pd.concat([df.reset_index(drop=True),
df_topic_sents_keywords.reset_index(drop=True)], axis=1)
df
```

{"model_id":"25be37a2c6c3422fb38996d8bc6ea81a","version_major":2,"vers
ion_minor":0}

```
      Unnamed: 0.1  Unnamed: 0     topic  \
0                0           0  business
1                1           1  business
2                2           2  business
3                3           3  business
4                4           4  business
...            ...         ...       ...
2220          2220        2220      tech
2221          2221        2221      tech
2222          2222        2222      tech
2223          2223        2223      tech
2224          2224        2224      tech

                                                content sentiment
score  \
0     Golden rule 'intact' says ex-aide\n\nChancello...  Negative
0.003080
1     Beer giant swallows Russian firm\n\nBrewing gi...   Neutral
0.687573
2     Deutsche Boerse set to 'woo' LSE\n\nBosses of ...  Negative
0.000259
3     GM in crunch talks on Fiat future\n\nFiat will...  Negative
0.001180
4     Sluggish economy hits German jobs\n\nThe numbe...  Negative
0.000155
...                                                 ...       ...
...
2220  Fast moving phone viruses appear\n\nSecurity f...  Negative
0.000176
2221  Musical future for phones\n\nAnalyst Bill Thom...  Positive
0.961024
```

```
2222  'No re-draft' for EU patent law\n\nA proposed ...  Negative
0.000900
2223  Apple sues 'Tiger' file sharers\n\nApple has t...  Negative
0.000158
2224  Can Yahoo dominate next decade?\n\nYahoo has r...  Negative
0.005561

                                                    ner  CARDINAL
DATE  \
0     [('Gordon Brown', 'PERSON'), ("Mr Brown's", 'O...         1
5
1     [('Russian', 'NORP'), ('Inbev', 'ORG'), ("Alfa...         7
3
2     [('Deutsche Boerse', 'ORG'), ('Deutsche Boerse...         1
8
3     [('GM', 'ORG'), ('Fiat', 'ORG'), ('Fiat', 'ORG...         1
6
4     [('German', 'NORP'), ('Europe', 'LOC'), ('the ...         3
5
...                                                  ...       ...   ..
.
2220  [('Cabir', 'ORG'), ('Cabir', 'GPE'), ('the Sym...         5
2
2221  [('Bill Thompson', 'PERSON'), ('Max', 'PERSON'...        11
2
2222  [('EU', 'ORG'), ('European', 'NORP'), ('the Eu...         1
4
2223  [('Apple', 'ORG'), ('Apple', 'ORG'), ('three',...         2
9
2224  [('next decade', 'DATE'), ('Yahoo', 'ORG'), ('...         3
9

      EVENT  ...  PERCENT  PERSON  PRODUCT  QUANTITY  TIME
WORK_OF_ART  \
0         0  ...        0       6        0         0     0
1
1         0  ...        2       6        2         0     0
0
2         0  ...        0       9        0         0     0
0
3         0  ...        4       4        0         0     0
0
4         0  ...        3       3        0         0     0
0
...     ...  ...      ...     ...      ...       ...   ...           ..
.
2220      1  ...        0       0        1         0     0
0
2221      0  ...        0       7        2         0     0
```

```
1
2222      0  ...        0       3        0         0     0
0
2223      0  ...        0       2        0         0     0
0
2224      0  ...        0      12        0         0     0
0

                                          processed_docs
Dominant_Topic  \
0     [golden, rule, intact, says, ex, aide, chancel...
18
1     [beer, giant, swallows, russian, firm, brewing...
10
2     [deutsche, boerse, set, woo, lse, bosses, deut...
16
3     [gm, crunch, talks, fiat, future, fiat, meet, ...
10
4     [sluggish, economy, hits, german, jobs, number...
4
...                                                 ...               ..
.
2220  [fast, moving, phone, viruses, appear, securit...
11
2221  [musical, future, phones, analyst, bill, thomp...
19
2222  [draft, eu, patent, law, proposed, european, l...
12
2223  [apple, sues, tiger, file, sharers, apple, tak...
11
2224  [yahoo, dominate, next, decade, yahoo, reached...
19

      Perc_Contribution
Topic_Keywords
0                0.6512  mr, labour, election, party, blair, brown,
min...
1                0.4596  bn, sales, firm, company, uk, companies,
busin...
2                0.6447  club, united, bid, offer, mr, board,
football,...
3                0.4493  bn, sales, firm, company, uk, companies,
busin...
4                0.9081  us, economy, growth, economic, bn, market,
dol...
...                 ...
...
2220             0.9525  users, software, people, net, security,
micros...
```

```
2221             0.9974  people, technology, digital, mobile, tv,
could...
2222             0.9939  government, new, council, could, law, legal,
l...
2223             0.6783  users, software, people, net, security,
micros...
2224             0.5620  people, technology, digital, mobile, tv,
could...

[2225 rows x 29 columns]
```

```
topic_list =
list(df[['Dominant_Topic','Topic_Keywords']].value_counts().index.valu
es)
topic_list = sorted(topic_list, key=lambda x:x[0])
topic_list = [i[1] for i in topic_list]
topic_list
```

```
['india, oil, bn, prices, indian, government, market, company, energy,
us',
 'ferguson, arsenal, henry, mr, scottish, world, united, shot,
meeting, france',
 'film, best, films, director, actor, awards, oscar, actress, award,
dvd',
 'government, world, aid, countries, people, mr, lord, could,
international, debt',
 'us, economy, growth, economic, bn, market, dollar, bank, rate,
rise',
 'people, world, olympic, education, indoor, european, schools,
students, race, british',
 'us, mr, yukos, court, bn, company, russian, fraud, firm, legal',
 'games, game, gaming, mr, gamers, xbox, people, software, time,
titles',
 'film, festival, public, workers, dutch, government, choice, day,
life, february',
 'mr, home, rights, government, law, human, trial, told, secretary,
without',
 'bn, sales, firm, company, uk, companies, business, profits, new,
people',
 'users, software, people, net, security, microsoft, use, mail, virus,
many',
 'government, new, council, could, law, legal, lord, airline, may,
airlines',
 'police, women, people, new, wales, mr, health, plans, public, one',
 'us, china, company, bank, deal, mr, bn, new, foreign, eu',
 'music, best, show, one, new, us, band, number, first, uk',
 'club, united, bid, offer, mr, board, football, decision, deutsche,
manchester',
 'game, first, england, win, time, one, two, back, last, play',
 'mr, labour, election, party, blair, brown, minister, government,
```

```
people, howard',
 'people, technology, digital, mobile, tv, could, music, one, new,
like']
```

```
df_topic_sentiment=df[['score',
'Dominant_Topic']].groupby('Dominant_Topic').mean().reset_index()
df_topic_sentiment['Topic'] = topic_list
df_topic_sentiment
```

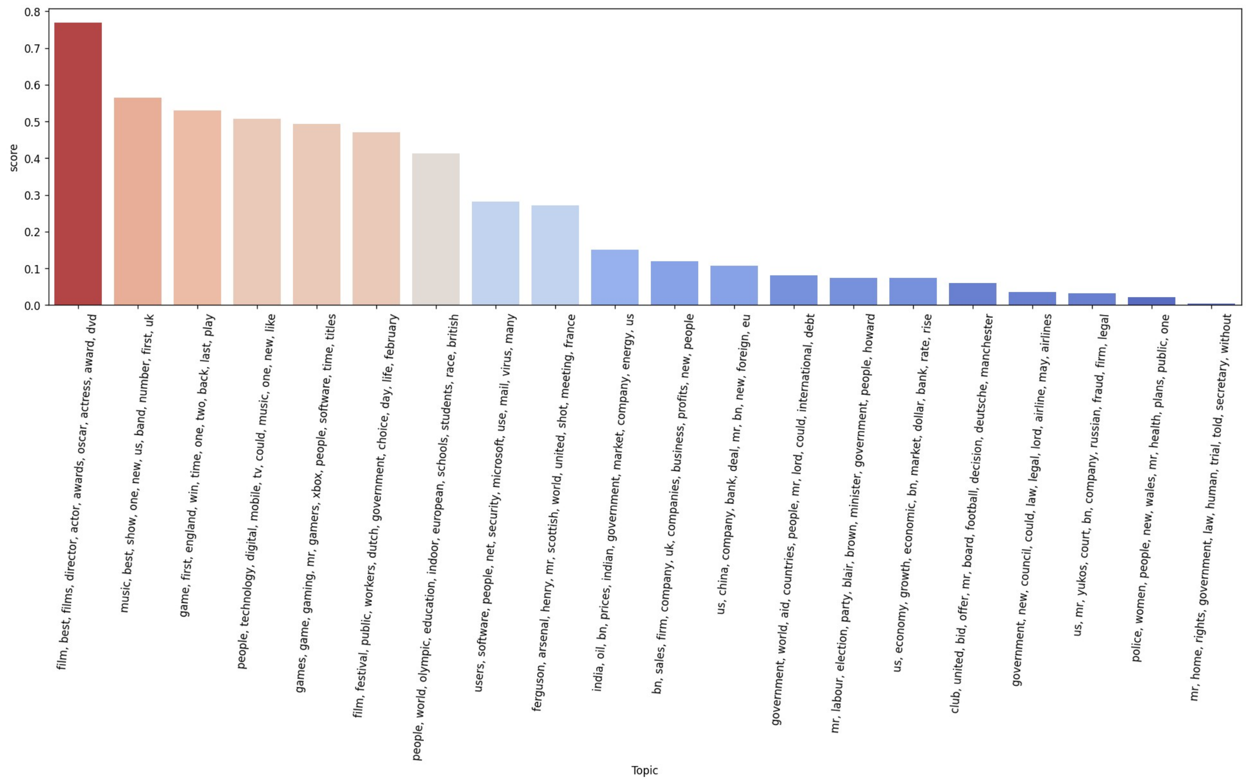
```
    Dominant_Topic     score  \
0                0  0.150292
1                1  0.271478
2                2  0.768828
3                3  0.079970
4                4  0.074410
5                5  0.413270
6                6  0.031563
7                7  0.492354
8                8  0.471171
9                9  0.004017
10              10  0.119677
11              11  0.280960
12              12  0.035178
13              13  0.021554
14              14  0.106886
15              15  0.564531
16              16  0.060588
17              17  0.530428
18              18  0.074526
19              19  0.506668

                                                Topic
0   india, oil, bn, prices, indian, government, ma...
1   ferguson, arsenal, henry, mr, scottish, world,...
2   film, best, films, director, actor, awards, os...
3   government, world, aid, countries, people, mr,...
4   us, economy, growth, economic, bn, market, dol...
5   people, world, olympic, education, indoor, eur...
6   us, mr, yukos, court, bn, company, russian, fr...
7   games, game, gaming, mr, gamers, xbox, people,...
8   film, festival, public, workers, dutch, govern...
9   mr, home, rights, government, law, human, tria...
10  bn, sales, firm, company, uk, companies, busin...
11  users, software, people, net, security, micros...
12  government, new, council, could, law, legal, l...
13  police, women, people, new, wales, mr, health,...
14  us, china, company, bank, deal, mr, bn, new, f...
15  music, best, show, one, new, us, band, number,...
16  club, united, bid, offer, mr, board, football,...
17  game, first, england, win, time, one, two, bac...
```

```
18  mr, labour, election, party, blair, brown, min...
19  people, technology, digital, mobile, tv, could...
```

```
def colors_from_values(values, palette_name):
    normalized = (values - min(values)) / (max(values) - min(values))
    indices = np.round(normalized * (len(values) -
1)).astype(np.int32)
    palette = sns.color_palette(palette_name, len(values))
    return np.array(palette).take(indices, axis=0)

plt.figure(figsize=(20,5), dpi=120)
dff=df_topic_sentiment.sort_values('score', ascending=False)
sns.barplot(dff, x='Topic',y='score',
palette=colors_from_values(dff['score'].values, "coolwarm"))
plt.xticks(rotation=85)
```

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18,
19],
 [Text(0, 0, 'film, best, films, director, actor, awards, oscar,
actress, award, dvd'),
  Text(1, 0, 'music, best, show, one, new, us, band, number, first,
uk'),
  Text(2, 0, 'game, first, england, win, time, one, two, back, last,
play'),
  Text(3, 0, 'people, technology, digital, mobile, tv, could, music,
one, new, like'),
  Text(4, 0, 'games, game, gaming, mr, gamers, xbox, people, software,
time, titles'),
  Text(5, 0, 'film, festival, public, workers, dutch, government,
choice, day, life, february'),
  Text(6, 0, 'people, world, olympic, education, indoor, european,
schools, students, race, british'),
  Text(7, 0, 'users, software, people, net, security, microsoft, use,
mail, virus, many'),
  Text(8, 0, 'ferguson, arsenal, henry, mr, scottish, world, united,
shot, meeting, france'),
  Text(9, 0, 'india, oil, bn, prices, indian, government, market,
company, energy, us'),
  Text(10, 0, 'bn, sales, firm, company, uk, companies, business,
profits, new, people'),
  Text(11, 0, 'us, china, company, bank, deal, mr, bn, new, foreign,
eu'),
  Text(12, 0, 'government, world, aid, countries, people, mr, lord,
could, international, debt'),
  Text(13, 0, 'mr, labour, election, party, blair, brown, minister,
government, people, howard'),
  Text(14, 0, 'us, economy, growth, economic, bn, market, dollar,
bank, rate, rise'),
  Text(15, 0, 'club, united, bid, offer, mr, board, football,
```

```
decision, deutsche, manchester'),
  Text(16, 0, 'government, new, council, could, law, legal, lord,
airline, may, airlines'),
  Text(17, 0, 'us, mr, yukos, court, bn, company, russian, fraud,
firm, legal'),
  Text(18, 0, 'police, women, people, new, wales, mr, health, plans,
public, one'),
  Text(19, 0, 'mr, home, rights, government, law, human, trial, told,
secretary, without')])
```



We can see from the plot that the topic (2, 0, 'film, best, films, director, actor, awards, oscar, actress, award, dvd') has the highest sentiment score, and the topic (15, 0, 'music, best, show, one, new, us, band, number, first, uk'), (17, 0, 'game, first, england, win, time, one, two, back, last, play'), (19, 0, 'people, technology, digital, mobile, tv, could, music, one, new, like') also have very high sentiment score. The topic (9, 0, 'mr, home, rights, government, law, human, trial, told, secretary, without') has the most negative sentiment. And the topics (6, 0, 'us, mr, yukos, court, bn, company, russian, fraud, firm, legal'), (13, 0, 'police, women, people, new, wales, mr, health, plans, public, one') (12, 0, 'government, new, council, could, law, legal, lord, airline, may, airlines') also have very low sentiment score.

```
df.columns

Index(['Unnamed: 0.1', 'Unnamed: 0', 'topic', 'content', 'sentiment',
'score',
       'ner', 'CARDINAL', 'DATE', 'EVENT', 'FAC', 'GPE', 'LANGUAGE',
```

```
'LAW',
       'LOC', 'MONEY', 'NORP', 'ORDINAL', 'ORG', 'PERCENT', 'PERSON',
       'PRODUCT', 'QUANTITY', 'TIME', 'WORK_OF_ART', 'processed_docs',
       'Dominant_Topic', 'Perc_Contribution', 'Topic_Keywords'],
      dtype='object')
```

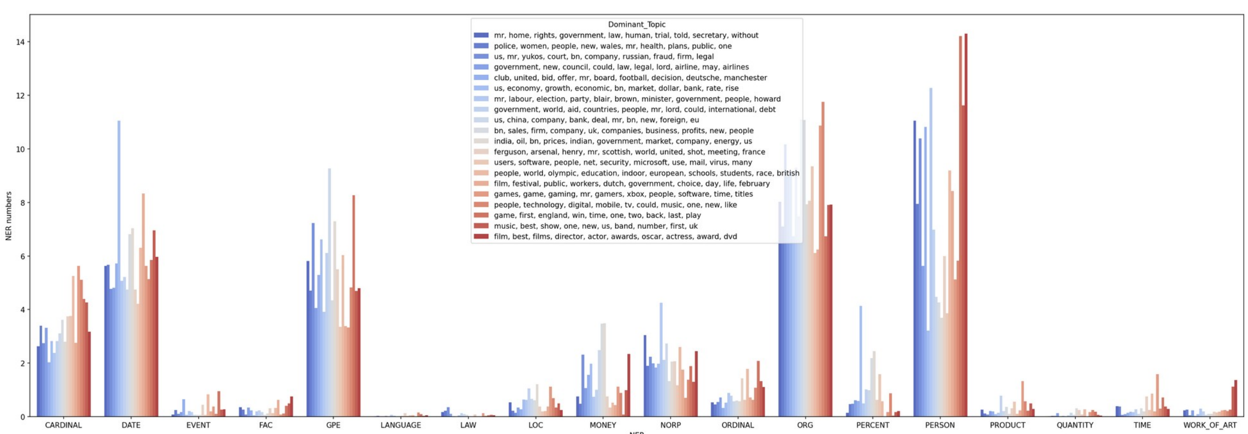
```
df_topic_ner_sentiment = df[['CARDINAL', 'score','DATE', 'EVENT',
'FAC', 'GPE', 'LANGUAGE', 'LAW',
       'LOC', 'MONEY', 'NORP', 'ORDINAL', 'ORG', 'PERCENT', 'PERSON',
       'PRODUCT', 'QUANTITY', 'TIME', 'WORK_OF_ART',
'Dominant_Topic']].groupby('Dominant_Topic').mean().reset_index()
df_topic_ner_sentiment = df_topic_ner_sentiment.sort_values('score')
df_topic_ner_sentiment
```

	Dominant_Topic	CARDINAL	score	DATE	EVENT	FAC \
9	9	2.629630	0.004017	5.629630	0.074074	0.351852
13	13	3.389610	0.021554	5.675325	0.246753	0.259740
6	6	2.750000	0.031563	4.766667	0.100000	0.083333
12	12	3.312500	0.035178	4.812500	0.171875	0.343750
16	16	2.029851	0.060588	5.716418	0.656716	0.238806
4	4	2.826667	0.074410	11.053333	0.066667	0.053333
18	18	2.377990	0.074526	5.076555	0.215311	0.191388
3	3	2.823529	0.079970	5.215686	0.176471	0.235294
14	14	3.103093	0.106886	4.742268	0.072165	0.164948
10	10	3.621622	0.119677	6.810811	0.072072	0.072072
0	0	2.795181	0.150292	7.036145	0.060241	0.120482
1	1	3.750000	0.271478	4.750000	0.437500	0.312500
11	11	3.759259	0.280960	4.212963	0.064815	0.129630
5	5	5.250000	0.413270	6.303571	0.839286	0.321429
8	8	2.761905	0.471171	8.333333	0.190476	0.619048
7	7	5.625000	0.492354	5.625000	0.375000	0.083333
19	19	5.115385	0.506668	5.134615	0.100962	0.120192
17	17	4.400966	0.530428	5.847826	0.954106	0.398551

```
15                15  4.271967  0.564531   6.962343  0.263598  0.489540

2                  2  3.172414  0.768828   5.974138  0.275862  0.758621


         GPE  LANGUAGE       LAW       LOC     MONEY      NORP
ORDINAL  \
9   5.814815  0.018519  0.166667  0.537037  0.759259  3.037037
0.537037
13  4.701299  0.025974  0.220779  0.220779  0.480519  1.896104
0.454545
6   7.233333  0.016667  0.350000  0.150000  2.316667  2.233333
0.550000
12  4.062500  0.015625  0.109375  0.343750  1.062500  1.984375
0.718750
16  5.298507  0.029851  0.014925  0.268657  1.567164  1.835821
0.328358
4   6.620000  0.013333  0.000000  0.640000  1.973333  1.980000
0.526667
18  3.909091  0.062201  0.047847  0.622010  0.741627  4.258373
0.889952
3   6.117647  0.039216  0.137255  1.058824  1.000000  2.117647
0.784314
14  9.268041  0.000000  0.092784  0.659794  2.484536  2.731959
0.577320
10  4.342342  0.009009  0.072072  0.612613  3.477477  1.324324
0.603604
0   7.289157  0.024096  0.000000  1.204819  3.481928  2.060241
0.578313
1   5.500000  0.125000  0.000000  0.375000  0.750000  2.062500
1.437500
11  3.351852  0.027778  0.074074  0.194444  0.333333  1.175926
0.620370
5   6.035714  0.053571  0.000000  0.214286  0.517857  2.607143
1.785714
8   3.380952  0.047619  0.000000  0.380952  0.428571  1.761905
0.714286
7   3.333333  0.000000  0.125000  1.125000  1.125000  0.708333
0.625000
19  4.822115  0.163462  0.024038  0.692308  0.879808  1.379808
1.081731
17  8.268116  0.086957  0.055556  0.345411  0.082126  1.891304
2.086957
15  4.694561  0.033473  0.066946  0.493724  0.991632  1.297071
1.330544
2   4.793103  0.051724  0.051724  0.250000  2.344828  2.448276
1.112069

          ORG   PERCENT     PERSON   PRODUCT  QUANTITY      TIME
```

```
WORK_OF_ART
9    8.018519  0.148148  11.055556  0.259259  0.018519  0.388889
0.240741
13   7.103896  0.467532   7.948052  0.116883  0.025974  0.376623
0.259740
6   10.166667  0.483333  10.383333  0.083333  0.033333  0.066667
0.050000
12   8.968750  0.609375   5.625000  0.203125  0.125000  0.093750
0.234375
16   9.179104  0.582090  10.820896  0.194030  0.014925  0.149254
0.029851
4    6.733333  4.140000   3.213333  0.086667  0.026667  0.186667
0.093333
18   9.296651  0.497608  12.277512  0.143541  0.014354  0.172249
0.306220
3    7.470588  1.019608   6.980392  0.784314  0.058824  0.274510
0.196078
14  11.092784  0.989691   4.474227  0.206186  0.144330  0.103093
0.072165
10  11.072072  2.180180   4.270270  0.369369  0.063063  0.315315
0.108108
0    7.927711  2.445783   3.698795  0.108434  0.313253  0.192771
0.108434
1    8.062500  0.625000   6.000000  0.312500  0.250000  0.750000
0.187500
11   9.351852  1.583333   3.861111  0.555556  0.083333  0.250000
0.157407
5    6.107143  0.571429   9.196429  0.107143  0.267857  0.857143
0.178571
8    6.238095  0.000000   8.428571  0.238095  0.000000  0.190476
0.238095
7   10.875000  0.166667   5.125000  1.333333  0.166667  1.583333
0.250000
19  11.750000  0.870192   5.826923  0.567308  0.245192  0.298077
0.206731
17   6.736715  0.041063  14.214976  0.227053  0.181159  0.714976
0.260870
15   7.899582  0.167364  11.627615  0.497908  0.071130  0.372385
1.117155
2    7.922414  0.215517  14.301724  0.293103  0.034483  0.284483
1.362069

plt.figure(figsize=(30,10), dpi=150)
df_result =
df_topic_ner_sentiment.drop(columns=['score']).melt(id_vars='Dominant_
Topic', var_name='Name', value_name='Value')
df_result['Dominant_Topic'] = df_result['Dominant_Topic'].apply(lambda
x:topic_list[x])
display(df_result)
sns.barplot(df_result, x='Name', y='Value', hue="Dominant_Topic",
```

```
palette='coolwarm')
plt.xlabel('NER')
plt.ylabel('NER numbers')

                                                Dominant_Topic          Name
Value
0    mr, home, rights, government, law, human, tria...      CARDINAL
2.629630
1    police, women, people, new, wales, mr, health,...      CARDINAL
3.389610
2    us, mr, yukos, court, bn, company, russian, fr...      CARDINAL
2.750000
3    government, new, council, could, law, legal, l...      CARDINAL
3.312500
4    club, united, bid, offer, mr, board, football,...      CARDINAL
2.029851
..                                                 ...           ...
...
355  games, game, gaming, mr, gamers, xbox, people,...   WORK_OF_ART
0.250000
356  people, technology, digital, mobile, tv, could...   WORK_OF_ART
0.206731
357  game, first, england, win, time, one, two, bac...   WORK_OF_ART
0.260870
358  music, best, show, one, new, us, band, number,...   WORK_OF_ART
1.117155
359  film, best, films, director, actor, awards, os...   WORK_OF_ART
1.362069

[360 rows x 3 columns]

Text(0, 0.5, 'NER numbers')
```



In the graph:\ Bars are of 20 topics shown in legend, bar height shows average numbers in 18 NER. Red color means positive sentiment, while blue means negative sentiment. Negative sentiment are often associated with topics including government, policy, police, fraud, economy... and NER has more number of Date, Law, NORP... Positive sentiment are often associated iwth topics including film, music, game technology... and NER has more work_of_art, product, time, person...