Predicting Outcomes of US Supreme Court Oral Arguments

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Description

The Supreme Court of the US (SCOTUS) is the highest court in the United States. It holds the power of judicial review – determining whether a statute violates the Constitution. The court consists of nine Justices (a chief justice and eight associate justices). Justices can serve for life (i.e., until they die, retire, resign, get impeached, etc.), so one Justice can influence decisions for many decades. Clearly, the decisions made by the SCOTUS have great public policy impact in the US.

In general, the cases that the SCOTUS review have been given a decision by a lower court, and are brought to the Court for appeal of said decision. For these cases, the Court will take briefs and conduct an oral argument with the attorneys representing the (usually 2) parties in this case. Following the oral argument, each Justice gets one vote, and the majority vote determines the case outcome. Example SCOTUS case: https://www.oyez.org/cases/2018/17-204

For this project, we are interested in predicting the outcome of the case (i.e., which party gets the majority vote) from the oral argument transcripts. These transcripts (see Dataset) are dialogs of English natural language text. This can be thought of as a text classification task, where the transcripts are the input documents. The labels we want to predict are the outcomes (e.g., Y/N the petitioner "wins").

Dataset

Supreme Court Oral Arguments Corpus from Convokit. We analyzed data across eight years of the George W. Bush and two terms (8 years) of the Barack Obama administration (2001 - 2018).

Why did we select this subset of data?

As justices in the US Supreme Court are political appointees -- confirmed to their positions via Senate -- we wanted to evaluate outcomes across two different political periods. We settled on choosing an administration under a Democratic President and another under a Republican President.

Our initial idea was to evaluate courts across the Obama and the Trump administrations; however, the dataset does not cover the entire Trump administration. We, thus, decided to select the Bush and Obama administrations. Both these administrations had fairly balanced courts in terms of political / legal leanings. Additionally, both Presidents Bush and Obama appointed two justices each to the Supreme Court during their tenures - implying that the constitution of our courts remained fairly consistent with the same "number of changes." The choice of successive administrations was also important to reflect the fairly contiguous nature of the Supreme Court where Justices serve until retirement or passing.

We decided to choose Presidents with two terms to see if there was a difference at play between how a court would vote between the first and second terms of a President - and more broadly speaking - whether the term had an impact at all.The long time span allowed for us to also compare - for some justices - whether their votes differed between their times under the Bush and subsequently the Obama administration.

Data downloaded and saved as csv using this script: download_data.py

Data Exploration

Load Data

In [ ]:
```
import pandas as pd
import statsmodels.formula.api as sm
from ast import literal_eval
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [ ]:
```
path = 'http://rezarzky.my.id/dataset/' #change to your data location
```

In [ ]:
```
# Load downloaded data
df_convos = pd.read_csv(path+'/conversations.csv')
df_speakers = pd.read_csv(path+'/speakers.csv')
df_utts = pd.read_csv(path+'/utterances.csv')
df_cases = pd.read_json(path_or_buf='https://zissou.infosci.cornell.edu/convokit/datasets/supreme-corpus/cases.jsonl', lines=True)
```

Cases

In [ ]:
```
# filter out cases that 2011-2018 AND win_side [0,1]
df_cases = df_cases[(df_cases['year'] >= 2011) & (df_cases['year'] <= 2018) & (df_cases['win_side'].isin([0,1]))]
df_cases.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 601 entries, 7065 to 7686
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    601 non-null    object 
 1   year                  601 non-null    int64  
 2   citation              599 non-null    object 
 3   title                 601 non-null    object 
 4   petitioner            601 non-null    object 
 5   respondent            601 non-null    object 
 6   docket_no             601 non-null    object 
 7   court                 601 non-null    object 
 8   decided_date          601 non-null    object 
 9   url                   601 non-null    object 
 10  transcripts           601 non-null    object 
 11  adv_sides_inferred    601 non-null    bool   
 12  known_respondent_adv  601 non-null    bool   
 13  advocates             601 non-null    object 
 14  win_side              601 non-null    float64
 15  win_side_detail       601 non-null    float64
 16  scdb_docket_id        601 non-null    object 
 17  votes                 601 non-null    object 
 18  votes_detail          601 non-null    object 
 19  is_eq_divided         601 non-null    float64
 20  votes_side            601 non-null    object 
dtypes: bool(2), float64(3), int64(1), object(15)
memory usage: 95.1+ KB
```

In [ ]:

```
# Count number of cases per year
df_cases.groupby(['year']).size()
```

Out[ ]:

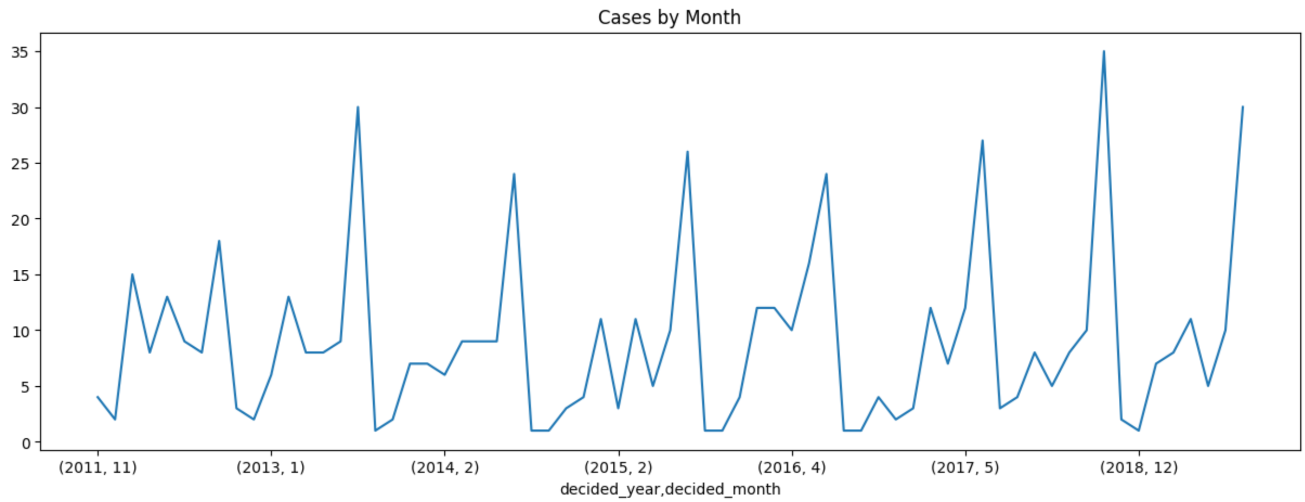
```
year
2011    78
2012    78
2013    75
2014    74
2015    80
2016    69
2017    73
2018    74
dtype: int64
```

In [ ]:

```
# Check in what month the case usually decided
df_cases['decided_date'] = pd.to_datetime(df_cases['decided_date'])
df_cases['decided_month'] = df_cases['decided_date'].dt.month
df_cases['decided_year'] = df_cases['decided_date'].dt.year
```

In [ ]:

```
# Create Line Graph of Cases by Per Month
df_cases.groupby(['decided_year', 'decided_month']).size().plot(kind='line', figsize=(15, 5), title='Cases by Month')
plt.show()
```



Conversation

In [ ]:

```
# Check head
df_convos.head()
```

Out[ ]:

	id	vectors	meta.case_id	meta.advocates	meta.win_side	meta.votes_side	year
0	22149	[]	2001_01-584	{'john_crabtree': {'side': 1, 'role': 'on beha...	0.0	{'j__william_h_rehnquist': 0, 'j__john_paul_st...	2001
1	22721	[]	2001_00-730	{'william_perry_pendley': {'side': 1, 'role': ...	0.0	{'j__william_h_rehnquist': 0, 'j__john_paul_st...	2001
2	21448	[]	2001_00-1214	{'william_h_mills': {'side': 0, 'role': 'Argue...	0.0	{'j__william_h_rehnquist': 1, 'j__john_paul_st...	2001
3	22788	[]	2001_00-1293	{'ann_e_beeson': {'side': 0, 'role': 'Argued t...	1.0	{'j__william_h_rehnquist': 1, 'j__john_paul_st...	2001
4	21372	[]	2001_00-795	{'paul_d_clement': {'side': 1, 'role': 'Depart...	0.0	{'j__william_h_rehnquist': 1, 'j__john_paul_st...	2001

In [ ]:

```
# Check datatype
df_convos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1292 entries, 0 to 1291
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   id               1292 non-null   int64  
 1   vectors          1292 non-null   object 
 2   meta.case_id     1292 non-null   object 
 3   meta.advocates   1292 non-null   object 
 4   meta.win_side    1290 non-null   float64
 5   meta.votes_side  1290 non-null   object 
 6   year             1292 non-null   int64  
dtypes: float64(1), int64(2), object(4)
memory usage: 70.8+ KB
```

In [ ]:

```
# Check for number of unique meta.win_side
df_convos['meta.win_side'].value_counts()
```

Out[ ]:

```
1.0    853
0.0    435
2.0      2
Name: meta.win_side, dtype: int64
```

In [ ]:

```
# Filtering the non binary values in meta.win_side (only do binary variable)
df_convos = df_convos.loc[df_convos['meta.win_side'].isin([0,1])]
df_convos['meta.win_side'].value_counts()
```

Out[ ]:

```
1.0    853
0.0    435
Name: meta.win_side, dtype: int64
```

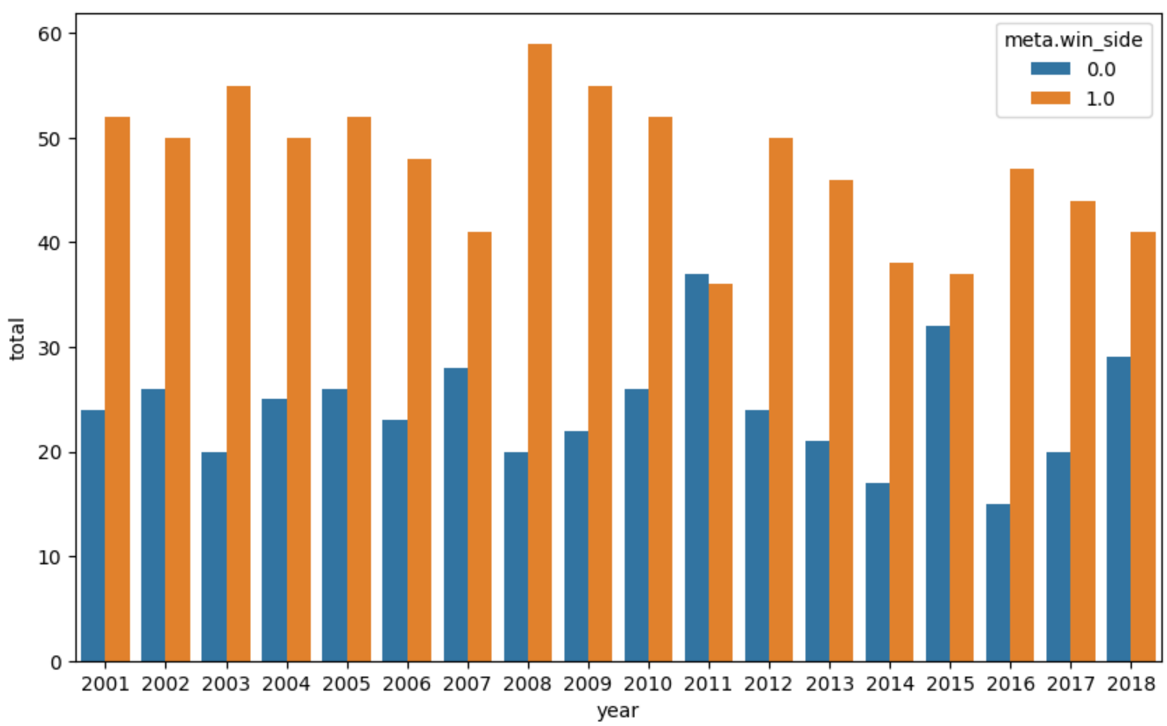
In [ ]:

```
# how many convos and winner per year
aggregate_df = df_convos.groupby(['year', 'meta.win_side']).size().reset_index(name='total')

plt.figure(figsize=(10, 6))
sns.barplot(x='year', y='total', hue='meta.win_side', data=aggregate_df)
```

Out[ ]:

```
<Axes: xlabel='year', ylabel='total'>
```



In [ ]:

```
# Extract Advocate based on Role
import ast
def extract_advocate_names(row, side):
    advocates_dict = ast.literal_eval(row['meta.advocates'])
    names = []
    for advocate, info in advocates_dict.items():
        if info['side'] == side:
            names.append(advocate)
    return ', '.join(names)

df_convos['respondents'] = df_convos.apply(lambda row: extract_advocate_names(row, 0), axis=1)
df_convos['petitioner'] = df_convos.apply(lambda row: extract_advocate_names(row, 1), axis=1)
df_convos['amicus_curiae'] = df_convos.apply(lambda row: extract_advocate_names(row, 2), axis=1)
```

In [ ]:

```
# Top 10
advocate_wins = df_convos[df_convos['meta.win_side'] == 1].groupby('petitioner')['petitioner'].count().reset_index(name='win_count
advocate_total_cases = df_convos.groupby('petitioner')['petitioner'].count().reset_index(name='total_cases')
advocate_stats = pd.merge(advocate_wins, advocate_total_cases, on='petitioner', how='outer')
advocate_stats['win_count'] = advocate_stats['win_count'].fillna(0)
advocate_stats['win_pct'] = advocate_stats['win_count'] / advocate_stats['total_cases'] * 100
advocate_stats.columns = ['advocate_name', 'win_count', 'total_cases', 'win_pct']
advocate_stats.nlargest(10, 'total_cases')
```

Out[ ]:

	advocate_name	win_count	total_cases	win_pct
374	paul_d_clement	22.0	32	68.750000
49	carter_g_phillips	15.0	27	55.555556
209	jeffrey_l_fisher	13.0	26	50.000000
455	seth_p_waxman	18.0	22	81.818182
490	theodore_b_olson	16.0	19	84.210526
126	edwin_s_kneedler	11.0	15	73.333333
492	thomas_c_goldstein	7.0	15	46.666667
164	gregory_g_garre	8.0	14	57.142857
255	kannon_k_shanmugam	7.0	13	53.846154
93	david_c_frederick	10.0	12	83.333333

Initial questions about judge:

- does any judge prefers to vote 1 or 0
- does any judge who votes 1 has high percentage leads to win side
- does judges have same perefernce (like if he/she votes one, there is a high percentage that the other one would vote 1 too) or speakers

(trying to transfer them into apply + function, but haven't success)

In [ ]:

```
import json

dfconc = df_convos.copy()
dfconc = dfconc.loc[~(dfconc.loc[:,'meta.win_side'].isna()) &
                    ~(dfconc.loc[:,'meta.votes_side'].isna()), ]
dfconc.reset_index(inplace=True)
dfconc.loc[:, 'meta.votes_side'] = dfconc.loc[:, 'meta.votes_side'].apply(lambda x: json.loads(x.replace("'", "\"")))
```

How many yes(1) votes and percentage for each judge

In [ ]:

```
judges_dic1 = {}

for judges in dfconc.loc[:, 'meta.votes_side']:

    for judge, vote in judges.items():
        if judge not in judges_dic1:
            judges_dic1[judge] = 0
        judges_dic1[judge] += vote
```

In [ ]:

```
judges_dic2 = {}
for judges in dfconc.loc[:, 'meta.votes_side']:

    for judge, vote in judges.items():
        if judge not in judges_dic2:
            judges_dic2[judge] = 0
        judges_dic2[judge] += 1
```

In [ ]:
```
dfj_info = pd.DataFrame({'judges': judges_dic1.keys(),
                         'yes_ct': judges_dic1.values(),
                         'total_ct':judges_dic2.values()})
dfj_info.loc[:, 'yes_rate'] = dfj_info.loc[:, 'yes_ct'] / dfj_info.loc[:, 'total_ct']
```

Does any judge who votes 1 has high percentage leads to win side

In [ ]:
```
judges_dic3 = {}
for i in range(len(dfconc)):

    for judge, vote in dfconc.loc[:, 'meta.votes_side'][i].items():

        if judge not in judges_dic3:
            judges_dic3[judge] = 0
        if (vote == 1) and (dfconc.loc[:, 'meta.win_side'][i] == 1.0):
            judges_dic3[judge] += 1
```

In [ ]:
```
dfj_info.loc[:, 'win_ct'] = judges_dic3.values()
dfj_info.loc[:, 'yes_win_rate'] = dfj_info.loc[:, 'win_ct'] / dfj_info.loc[:, 'yes_ct']
dfj_info.loc[:, 'total_win_rate'] = dfj_info.loc[:, 'win_ct'] / dfj_info.loc[:, 'total_ct']
```

Who has the same agreement

In [ ]:
```
judge_dic4 = {}

for judge in dfj_info['judges']:
    judge_dic4[judge] = {}
    for i in range(len(dfconc)):
        for judge2, vote in dfconc.loc[:, 'meta.votes_side'][i].items():
            if judge2 != judge and judge in dfconc.loc[:, 'meta.votes_side'][i]:
                if judge2 not in judge_dic4[judge]:
                    judge_dic4[judge][judge2] = {}
                    judge_dic4[judge][judge2]['1_1'] = 0
                    judge_dic4[judge][judge2]['1_0'] = 0
                    judge_dic4[judge][judge2]['0_1'] = 0
                    judge_dic4[judge][judge2]['0_0'] = 0
                    judge_dic4[judge][judge2]['total'] = 0

                judge_dic4[judge][judge2]['total'] += 1

                if dfconc.loc[:, 'meta.votes_side'][i][judge] == 1:
                    if vote == 1:
                        judge_dic4[judge][judge2]['1_1'] += 1
                    else:
                        judge_dic4[judge][judge2]['1_0'] += 1
                else:
                    if vote == 1:
                        judge_dic4[judge][judge2]['0_1'] += 1
                    else:
                        judge_dic4[judge][judge2]['0_0'] += 1
```

In [ ]:
```
judge_dic5 = {}
for judge, peers in judge_dic4.items():
    judge_dic5[judge] = []
    for peer, vote in peers.items():

        if vote['1_1'] / vote['total'] > 0.55: # set a threshold
            judge_dic5[judge].append(peer)
```

In [ ]:
```
dfj_info.loc[:, 'friends'] = judge_dic5.values()
dfj_info.loc[:, 'j_short'] = dfj_info.loc[:, 'judges'].str[3:7]
```

In [ ]:
```
dfj_info
```

Out[ ]:

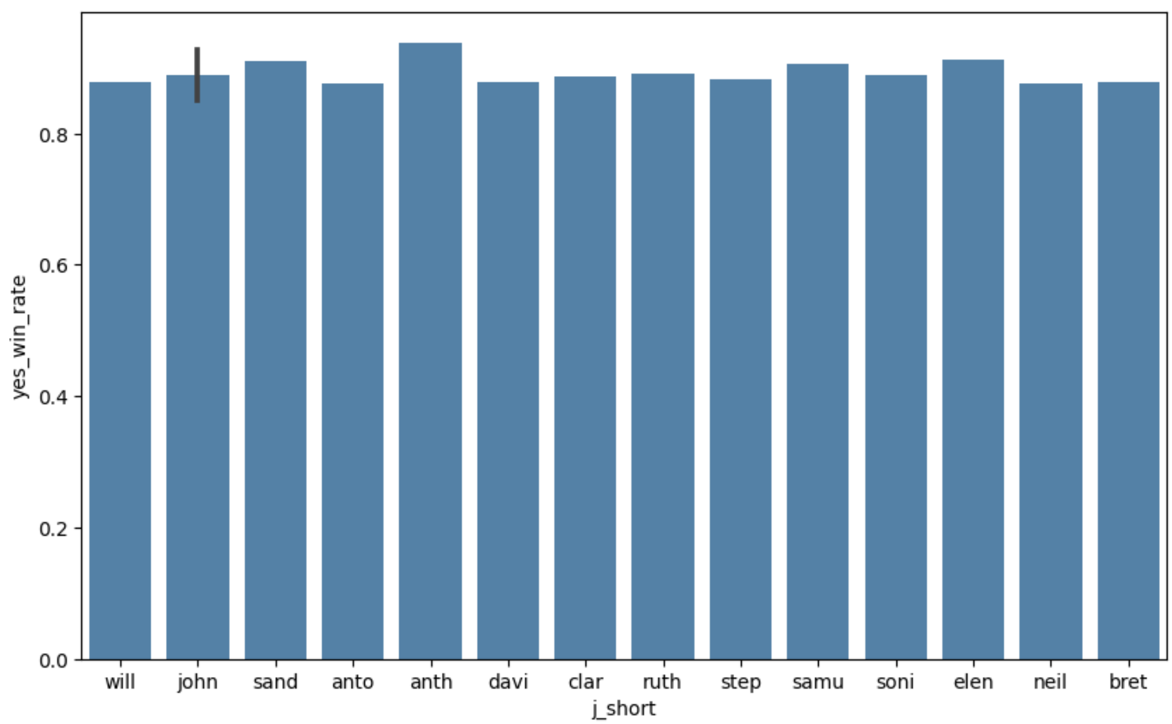
	judges	yes_ct	total_ct	yes_rate	win_ct	yes_win_rate	total_win_rate	friends	j_short
0	j__william_h_rehnquist	198	291	0.680412	174	0.878788	0.597938	[j__sandra_day_oconnor, j__antonin_scalia, j__...	will
1	j__john_paul_stevens	384	674	0.569733	327	0.851562	0.485163	[]	john
2	j__sandra_day_oconnor	225	316	0.712025	205	0.911111	0.648734	[j__william_h_rehnquist, j__anthony_m_kennedy,...	sand
3	j__antonin_scalia	648	1035	0.626087	568	0.876543	0.548792	[j__william_h_rehnquist, j__clarence_thomas, j...	anto
4	j__anthony_m_kennedy	802	1216	0.659539	753	0.938903	0.619243	[j__william_h_rehnquist, j__sandra_day_oconnor...	anth
5	j__david_h_souter	359	596	0.602349	315	0.877437	0.528523	[j__stephen_g_breyer]	davi
6	j__clarence_thomas	746	1285	0.580545	661	0.886059	0.514397	[j__william_h_rehnquist, j__antonin_scalia]	clar
7	j__ruth_bader_ginsburg	732	1288	0.568323	653	0.892077	0.506988	[]	ruth
8	j__stephen_g_breyer	779	1275	0.610980	688	0.883184	0.539608	[j__sandra_day_oconnor, j__david_h_souter]	step
9	j__john_g_roberts_jr	625	975	0.641026	580	0.928000	0.594872	[j__antonin_scalia, j__anthony_m_kennedy, j__s...	john
10	j__samuel_a_alito_jr	558	941	0.592986	506	0.906810	0.537726	[j__john_g_roberts_jr, j__brett_m_kavanaugh]	samu
11	j__sonia_sotomayor	390	678	0.575221	347	0.889744	0.511799	[]	soni
12	j__elena_kagan	335	571	0.586690	306	0.913433	0.535902	[]	elen
13	j__neil_gorsuch	89	144	0.618056	78	0.876404	0.541667	[j__anthony_m_kennedy]	neil
14	j__brett_m_kavanaugh	41	62	0.661290	36	0.878049	0.580645	[j__john_g_roberts_jr, j__samuel_a_alito_jr]	bret

In [ ]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='j_short', y='yes_win_rate',color = 'steelblue', data = dfj_info)
```

Out[ ]:

```
<Axes: xlabel='j_short', ylabel='yes_win_rate'>
```

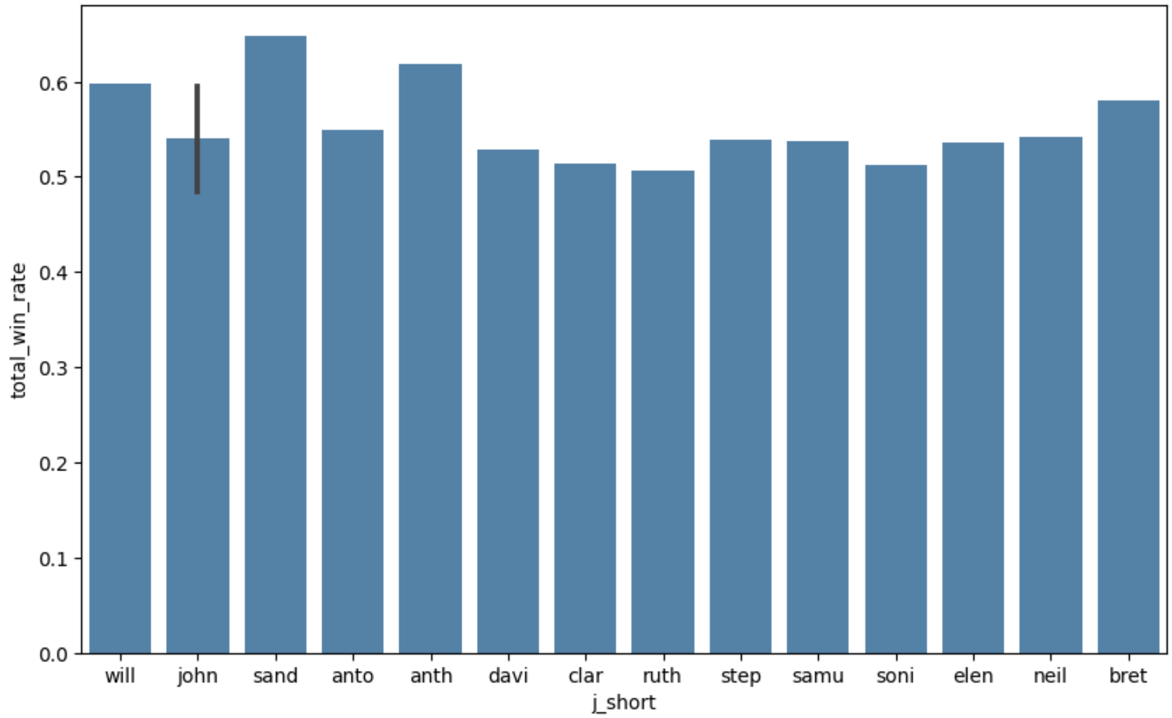


In [ ]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='j_short', y='total_win_rate',color = 'steelblue', data = dfj_info)
```

Out[ ]:

```
<Axes: xlabel='j_short', ylabel='total_win_rate'>
```



Test Prediction without Further Preprocess and not setting hyperparameter

In [ ]:
```
import nltk
import re
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
```

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

In [ ]:
```
# combine text from all utterances in a conversation back into one string based on the conversation_id
utt_per_conv = df_utts.groupby('conversation_id')['text'].apply(lambda x: ' '.join(x)).reset_index()

# add the combined text to the conversations dataframe, merge on conversation_id in utt_per_conv and id in df_convo
df_convos_merge = df_convos.merge(utt_per_conv, left_on='id', right_on='conversation_id', how='left')

df_convos_merge.head(1)
```

Out[ ]:

	id	vectors	meta.case_id	meta.advocates	meta.win_side	meta.votes_side	year	respondents	petitioner	amicus_curiae	conversation_
0	22149	[]	2001_01-584	{'john_crabtree': {'side': 1, 'role': 'on beha...	0.0	{'j__william_h_rehnquist': 0, 'j__john_paul_st...	2001	glen_d_nager	john_crabtree	alfred_w_blumrosen, ruth_g_blumrosen, archibal...	221

In [ ]:
```
# Cleaning the text
def preprocess_text(text):
    text = text.lower() # Lowercase the text
    text = re.sub('[^a-z]+', ' ', text)  # Remove special characters and numbers
    words = nltk.word_tokenize(text) # Tokenize the text
    stop_words = set(stopwords.words('english')) # Remove stopwords
    words = [word for word in words if word not in stop_words]
    #lemmatizer = WordNetLemmatizer() # Lemmatize the words comment because slow
    #words = [lemmatizer.lemmatize(word) for word in words]
    text = ' '.join(words) # Reconstruct the text
```

```
    return text
```

In [ ]:
```
text = df_convos_merge.loc[:,['text','meta.win_side']]
text['text'] = text['text'].apply(preprocess_text) #apply preprocess
text.head(1)
```

Out[ ]:

	text	meta.win_side
0	hear argument number wanda adams vs florida po...	0.0

In [ ]:
```
# Vectorize the text using TF-IDF
vectorizer = TfidfVectorizer(ngram_range=(2, 2)) # check bigram
X = vectorizer.fit_transform(text['text'])

y = text['meta.win_side']
```

In [ ]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, f1_score, precision_score, recall_score

logistic_regression = LogisticRegression()
naive_bayes = MultinomialNB()
linear_svc = LinearSVC()


# Train and evaluate the classifiers
classifiers = {
    "Logistic Regression": logistic_regression,
    "Naive Bayes": naive_bayes,
    "Linear SVC": linear_svc
}

results = []

for classifier_name, classifier in classifiers.items():

    # Train the classifier
    classifier.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = classifier.predict(X_test)

    # Add the scores to the results dictionary
    results.append({
        'classifier': classifier,
        'accuracy': accuracy_score(y_test, y_pred),
        'f1': f1_score(y_test, y_pred),
        'precision': precision_score(y_test, y_pred),
        'recall': recall_score(y_test, y_pred)
    })
```

In [ ]:
```
# Create a DataFrame from the results list
results_df = pd.DataFrame(results)
results_df
```

Out[ ]:

	classifier	accuracy	f1	precision	recall
0	LogisticRegression()	0.651163	0.788732	0.651163	1.000000
1	MultinomialNB()	0.651163	0.788732	0.651163	1.000000
2	LinearSVC()	0.635659	0.775120	0.648000	0.964286

In [ ]:

Questions about gender?

- What was the gender breakdown of the advocates?
- What was the most common first name of the speakers?
- Does the gender of the advocates influence whether they win or not?

So I downloaded a dataset from the Uni of Cali, Irvine that predicts the gender of the speaker based off their first name. Link: https://archive.ics.uci.edu/ml/datasets/Gender+by+Name

In [ ]:
```
df_gender = pd.read_csv(r'https://raw.githubusercontent.com/rezarzky/supreme-prediction/main/dataset/name_gender_dataset.csv')
idx = df_gender.groupby(['Name'])['Probability'].idxmax()
df_gender = df_gender.loc[idx]
```

In [ ]:
```
speaker_gender_df = df_speakers.copy()
speaker_gender_df.loc[:, ['first_name']] = speaker_gender_df.loc[:, 'meta.name'].str.split(' ').str[0]
speaker_gender_df = pd.merge(speaker_gender_df, df_gender, how='inner', left_on = 'first_name', right_on = 'Name')
speaker_gender_df["Gender"].value_counts()
```

Out[ ]:
```
M    1921
F     452
Name: Gender, dtype: int64
```

In [ ]:
```
speaker_gender_df["Gender"].value_counts(normalize=True)
```

Out[ ]:
```
M    0.809524
F    0.190476
Name: Gender, dtype: float64
```

In [ ]:
```
speaker_gender_df.groupby(['meta.type'])['Gender'].value_counts()
```

Out[ ]:
```
meta.type  Gender
A          M         1808
           F          407
J          M          113
           F           45
Name: Gender, dtype: int64
```

In [ ]:
```
speaker_gender_df["first_name"].value_counts(normalize=True).loc[lambda x : x>.02]
```

Out[ ]:
```
David      0.039612
John       0.038769
Michael    0.031606
Paul       0.028234
Thomas     0.026970
Jeffrey    0.023599
Stephen    0.023177
Robert     0.022335
James      0.021492
Name: first_name, dtype: float64
```

In [ ]:
```
df_convos_gender = df_convos.copy()
test_tup = [tuple(r) for r in df_convos_gender.loc[:, ['meta.case_id', \
                               'meta.advocates', 'meta.win_side']].to_numpy()]
lst_case_person = []

for case_id, person_deets, win_side in test_tup:
    person_deets = eval(person_deets)
    for person, details in person_deets.items():
        lst_case_person.append((case_id, person, win_side))


person_case_df = pd.DataFrame(lst_case_person, columns=['meta.case_id', 'id', 'win_side'])
```

In [ ]:
```
#cleaning
#going to remove 27 rows w/empty value in id column
person_case_df = person_case_df.loc[(person_case_df.loc[:,'id'] != ''), :]
```

In [ ]:
```
small_speakergenderdf = speaker_gender_df.loc[:, ['id', 'meta.name',\
                                              'meta.type', 'Gender']]


person_case_gender_df = pd.merge(person_case_df, small_speakergenderdf, how='inner', left_on = 'id', right_on = 'id')
person_case_gender_df = person_case_gender_df.drop_duplicates()
person_case_gender_df.head(5)
```

Out[ ]:

	meta.case_id	id	win_side	meta.name	meta.type	Gender
0	2001_01-584	john_crabtree	0.0	John Crabtree	A	M
1	2001_01-584	glen_d_nager	0.0	Glen D. Nager	A	M
7	2001_00-1045	glen_d_nager	1.0	Glen D. Nager	A	M
13	2002_01-1269	glen_d_nager	1.0	Glen D. Nager	A	M
19	2004_03-1160	glen_d_nager	0.0	Glen D. Nager	A	M

In [ ]:
```
result = sm.ols(formula = "win_side ~ Gender", data = person_case_gender_df).fit()
print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               win_side   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.9162
Date:                Sat, 22 Apr 2023   Prob (F-statistic):              0.339
Time:                        03:33:01   Log-Likelihood:                -2192.5
No. Observations:                3256   AIC:                             4389.
Df Residuals:                    3254   BIC:                             4401.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept       0.6749      0.020     33.832      0.000       0.636       0.714
Gender[T.M]    -0.0210      0.022     -0.957      0.339      -0.064       0.022
==============================================================================
Omnibus:                    18142.750   Durbin-Watson:                   1.771
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              568.476
Skew:                          -0.664   Prob(JB):                    3.61e-124
Kurtosis:                       1.442   Cond. No.                         4.60
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Gender is not expected to affect the outcome of case (1,0 ~ winning or not winning side).

Who are our Justices?

- Who are our justices?
- What percentage of the justices were installed during Republican v Democratic administrations?
- How do justices' votes correlate with each other's and with the average votes of their fellow political party's appointees? -What are our bigrams for the first year of each administration versus the last year?

In [ ]:
```
df_speakers.loc[(df_speakers.loc[:, 'meta.role'] == 'justice') & (df_speakers['year'].isin(range(2001,2019))), ['meta.name']].drop
```

Out[ ]:

	meta.name
0	William H. Rehnquist
2	Antonin Scalia
3	Anthony M. Kennedy
4	John Paul Stevens
5	Ruth Bader Ginsburg
6	Stephen G. Breyer
7	Sandra Day O'Connor
8	David H. Souter
55	Clarence Thomas
71	John G. Roberts, Jr.
373	John M. Harlan II
465	Harry A. Blackmun
633	Samuel A. Alito, Jr.
1094	Sonia Sotomayor
1096	Elena Kagan
2102	Neil Gorsuch
2321	Brett M. Kavanaugh

In [ ]:
```
df_polj = pd.read_csv(r'https://raw.githubusercontent.com/rezarzky/supreme-prediction/main/dataset/Justices_Political.csv')
```

In [ ]:
```
composition = df_polj['Administration Appointed'].value_counts(normalize=True) * 100
print(f"Percentage of Justices based on Administrations they were appointed under {composition}")
```

```
Percentage of Justices based on Administrations they were appointed under R    76.470588
D    23.529412
Name: Administration Appointed, dtype: float64
```

Which justices served on the most cases in our dataset (i.e how many times did they vote?)

In [ ]:
```
import ast

df_convos['meta.votes_side'] = df_convos['meta.votes_side'].apply(lambda x: ast.literal_eval(x) if isinstance(x, str) else x)
df_convos['justice_names'] = df_convos['meta.votes_side'].apply(lambda x: list(x.keys()) if isinstance(x, dict) else [])
df_exploded = df_convos.explode('justice_names')
name_counts = df_exploded['justice_names'].value_counts()
```

In [ ]:
```
print(f"How many times each Justice appears in our subset {name_counts}")
```

```
How many times each Justice appears in our subset j__ruth_bader_ginsburg    1288
j__clarence_thomas        1285
j__stephen_g_breyer       1275
j__anthony_m_kennedy      1216
j__antonin_scalia         1035
j__john_g_roberts_jr       975
j__samuel_a_alito_jr       941
j__sonia_sotomayor         678
j__john_paul_stevens       674
j__david_h_souter          596
j__elena_kagan             571
j__sandra_day_oconnor      316
j__william_h_rehnquist     291
j__neil_gorsuch            144
j__brett_m_kavanaugh        62
Name: justice_names, dtype: int64
```

Understanding Correlations

We are trying to understand correlations between how justices appointed during Republican administrations and those appointed during Democratic administrations vote. Additionally, we are analyzing correlations in voting patterns between each individual justice versus others.

In [ ]:
```
import ast

rep_judge = ['j__clarence_thomas', 'j__anthony_m_kennedy', 'j__antonin_scalia', 'j__john_g_roberts_jr', 'j__samuel_a_alito_jr',\
             'j__john_paul_stevens', 'j__david_h_souter', 'j__william_h_rehnquist', 'j__neil_gorsuch', 'j__brett_m_kavanaugh']
dem_judge = ['j__ruth_bader_ginsburg', 'j__stephen_g_breyer','j__sonia_sotomayor','j__elena_kagan']

df_convos['meta.votes_side'] = df_convos['meta.votes_side'].apply(lambda x: ast.literal_eval(x) if isinstance(x, str) else x)
df_convos['party'] = df_convos['meta.votes_side'].apply(lambda x: 'Republican' if isinstance(x, dict) and any(name in x for name i
for name in rep_judge + dem_judge:
    df_convos[name] = df_convos['meta.votes_side'].apply(lambda x: x.get(name) if isinstance(x, dict) else None)

df_convos['avg_rep_vote'] = df_convos[rep_judge].mean(axis=1)
df_convos['avg_dem_vote'] = df_convos[dem_judge].mean(axis=1)

corr = df_convos[['party'] + rep_judge + dem_judge + ['avg_rep_vote', 'avg_dem_vote']].corr(numeric_only=True)
```

In [ ]:
```
print(f"Here is our correlation matrix {corr}")
#Note: the NaN represents Justices who were not likely to have served at the Court during the same time periods. E.g David H Soute
```

```
Here is our correlation matrix                          j__clarence_thomas  j__anthony_m_kennedy  \
j__clarence_thomas               1.000000              0.553479
j__anthony_m_kennedy             0.553479              1.000000
j__antonin_scalia                0.784898              0.564426
j__john_g_roberts_jr             0.668051              0.697952
j__samuel_a_alito_jr             0.727476              0.669186
j__john_paul_stevens             0.063300              0.290381
j__david_h_souter                0.141161              0.355850
j__william_h_rehnquist           0.652448              0.722813
j__neil_gorsuch                  0.663678              0.722555
j__brett_m_kavanaugh             0.592766                   NaN
j__ruth_bader_ginsburg           0.183185              0.432897
j__stephen_g_breyer              0.199934              0.488800
j__sonia_sotomayor               0.236567              0.509679
j__elena_kagan                   0.305065              0.592255
avg_rep_vote                     0.814503              0.810024
avg_dem_vote                     0.212719              0.504552

                        j__antonin_scalia  j__john_g_roberts_jr  \
j__clarence_thomas               0.784898              0.668051
j__anthony_m_kennedy             0.564426              0.697952
j__antonin_scalia                1.000000              0.749481
j__john_g_roberts_jr             0.749481              1.000000
j__samuel_a_alito_jr             0.682389              0.760016
j__john_paul_stevens             0.093895              0.207806
j__david_h_souter                0.169331              0.290053
j__william_h_rehnquist           0.642813                   NaN
j__neil_gorsuch                       NaN              0.516612
j__brett_m_kavanaugh                  NaN              0.818620
j__ruth_bader_ginsburg           0.216908              0.359199
j__stephen_g_breyer              0.191894              0.432870
j__sonia_sotomayor               0.281112              0.426128
j__elena_kagan                   0.365087              0.467979
avg_rep_vote                     0.817881              0.875394
avg_dem_vote                     0.235711              0.432580

                        j__samuel_a_alito_jr  j__john_paul_stevens  \
j__clarence_thomas                  0.727476              0.063300
j__anthony_m_kennedy                0.669186              0.290381
j__antonin_scalia                   0.682389              0.093895
j__john_g_roberts_jr                0.760016              0.207806
j__samuel_a_alito_jr                1.000000              0.121698
j__john_paul_stevens                0.121698              1.000000
j__david_h_souter                   0.188967              0.714818
j__william_h_rehnquist                   NaN              0.143537
j__neil_gorsuch                     0.562120                   NaN
j__brett_m_kavanaugh                0.818405                   NaN
j__ruth_bader_ginsburg              0.259121              0.690461
j__stephen_g_breyer                 0.330167              0.639790
j__sonia_sotomayor                  0.268537              0.609649
j__elena_kagan                      0.339784                   NaN
avg_rep_vote                        0.869463              0.512504
avg_dem_vote                        0.314442              0.721229

                        j__david_h_souter  j__william_h_rehnquist  \
j__clarence_thomas               0.141161                0.652448
j__anthony_m_kennedy             0.355850                0.722813
j__antonin_scalia                0.169331                0.642813
j__john_g_roberts_jr             0.290053                     NaN
j__samuel_a_alito_jr             0.188967                     NaN
j__john_paul_stevens             0.714818                0.143537
j__david_h_souter                1.000000                0.232338
j__william_h_rehnquist           0.232338                1.000000
j__neil_gorsuch                       NaN                     NaN
j__brett_m_kavanaugh                  NaN                     NaN
j__ruth_bader_ginsburg           0.764784                0.276552
j__stephen_g_breyer              0.672631                0.314145
j__sonia_sotomayor                    NaN                     NaN
j__elena_kagan                        NaN                     NaN
avg_rep_vote                     0.596194                0.794187
avg_dem_vote                     0.775341                0.317181

                        j__neil_gorsuch  j__brett_m_kavanaugh  \
j__clarence_thomas             0.663678              0.592766
j__anthony_m_kennedy           0.722555                   NaN
j__antonin_scalia                   NaN                   NaN
j__john_g_roberts_jr           0.516612              0.818620
j__samuel_a_alito_jr           0.562120              0.818405
j__john_paul_stevens                NaN                   NaN
j__david_h_souter                   NaN                   NaN
j__william_h_rehnquist              NaN                   NaN
j__neil_gorsuch                1.000000              0.395199
j__brett_m_kavanaugh           0.395199              1.000000
j__ruth_bader_ginsburg         0.206910              0.261090
j__stephen_g_breyer            0.151106              0.329977
j__sonia_sotomayor             0.148717              0.215585
```

```
j__elena_kagan                 0.284701             0.351976
avg_rep_vote                   0.780359             0.884933
avg_dem_vote                   0.211930             0.319991

                         j__ruth_bader_ginsburg  j__stephen_g_breyer  \
j__clarence_thomas                     0.183185             0.199934
j__anthony_m_kennedy                   0.432897             0.488800
j__antonin_scalia                      0.216908             0.191894
j__john_g_roberts_jr                   0.359199             0.432870
j__samuel_a_alito_jr                   0.259121             0.330167
j__john_paul_stevens                   0.690461             0.639790
j__david_h_souter                      0.764784             0.672631
j__william_h_rehnquist                 0.276552             0.314145
j__neil_gorsuch                        0.206910             0.151106
j__brett_m_kavanaugh                   0.261090             0.329977
j__ruth_bader_ginsburg                 1.000000             0.729469
j__stephen_g_breyer                    0.729469             1.000000
j__sonia_sotomayor                     0.797874             0.739943
j__elena_kagan                         0.820931             0.796208
avg_rep_vote                           0.458494             0.484804
avg_dem_vote                           0.923466             0.908829

                         j__sonia_sotomayor  j__elena_kagan  avg_rep_vote  \
j__clarence_thomas                 0.236567        0.305065      0.814503
j__anthony_m_kennedy               0.509679        0.592255      0.810024
j__antonin_scalia                  0.281112        0.365087      0.817881
j__john_g_roberts_jr               0.426128        0.467979      0.875394
j__samuel_a_alito_jr               0.268537        0.339784      0.869463
j__john_paul_stevens               0.609649             NaN      0.512504
j__david_h_souter                       NaN             NaN      0.596194
j__william_h_rehnquist                  NaN             NaN      0.794187
j__neil_gorsuch                    0.148717        0.284701      0.780359
j__brett_m_kavanaugh               0.215585        0.351976      0.884933
j__ruth_bader_ginsburg             0.797874        0.820931      0.458494
j__stephen_g_breyer                0.739943        0.796208      0.484804
j__sonia_sotomayor                 1.000000        0.798378      0.409107
j__elena_kagan                     0.798378        1.000000      0.486256
avg_rep_vote                       0.409107        0.486256      1.000000
avg_dem_vote                       0.913737        0.932110      0.516898

                         avg_dem_vote
j__clarence_thomas           0.212719
j__anthony_m_kennedy         0.504552
j__antonin_scalia            0.235711
j__john_g_roberts_jr         0.432580
j__samuel_a_alito_jr         0.314442
j__john_paul_stevens         0.721229
j__david_h_souter            0.775341
j__william_h_rehnquist       0.317181
j__neil_gorsuch              0.211930
j__brett_m_kavanaugh         0.319991
j__ruth_bader_ginsburg       0.923466
j__stephen_g_breyer          0.908829
j__sonia_sotomayor           0.913737
j__elena_kagan               0.932110
avg_rep_vote                 0.516898
avg_dem_vote                 1.000000
```

In [ ]:

```
print(df_utts.head())
```

```
              id  timestamp                                               text  \
0  22149__0_000        NaN  We'll hear argument now on number 01-584, Wand...
1  22149__0_001        NaN  Mr. Chief Justice, may it please the Court: Th...
2  22149__0_002        NaN  Mr. Crabtree, we are not talking about a situa...
3  22149__0_003        NaN  No, Your Honor.\nWe believe that disparate imp...
4  22149__0_004        NaN  Well, now in Washington against Davis, we held...

                  speaker      reply_to  conversation_id meta.case_id  \
0  j__william_h_rehnquist           NaN            22149   2001_01-584
1           john_crabtree  22149__0_000            22149   2001_01-584
2  j__william_h_rehnquist  22149__0_001            22149   2001_01-584
3           john_crabtree  22149__0_002            22149   2001_01-584
4  j__william_h_rehnquist  22149__0_003            22149   2001_01-584

   meta.start_times   meta.stop_times meta.speaker_type  meta.side  \
0     [0.0, 10.031]  [10.031, 11.972]                 J        NaN
1  [11.972, 22.663]  [22.663, 34.513]                 A        1.0
2  [34.513, 47.061]  [47.061, 51.064]                 J        NaN
3  [51.064, 51.641]   [51.641, 63.53]                 A        1.0
4   [63.53, 80.786]  [80.786, 92.137]                 J        NaN

   meta.timestamp vectors  year
0           0.000      []  2001
1          11.972      []  2001
2          34.513      []  2001
3          51.064      []  2001
4          63.530      []  2001
```

For the first year of the Bush administration (2001) and the first year of the Obama administration (2008), what are our bigrams?

In [ ]:

```python
from sklearn.feature_extraction.text import CountVectorizer
import nltk

mask = (df_utts['year'] == 2001) | (df_utts['year'] == 2009)
df_filtered = df_utts[mask]
vectorizer = CountVectorizer(ngram_range=(2, 2), stop_words = 'english')
X = vectorizer.fit_transform(df_filtered['text'])
bigrams = pd.DataFrame(X.toarray(), columns=vectorizer.get_feature_names_out())
bigram_counts = bigrams.sum()
most_common_bigrams = bigram_counts.nlargest(n=3)

print(most_common_bigrams)
```

```
chief justice     845
don think         773
district court    755
dtype: int64
```

In [ ]:

```python
from sklearn.feature_extraction.text import CountVectorizer
import nltk

mask = (df_utts['year'] == 2008) | (df_utts['year'] == 2016)
df_filtered = df_utts[mask]
vectorizer = CountVectorizer(ngram_range=(2, 2), stop_words = 'english')
X = vectorizer.fit_transform(df_filtered['text'])
bigrams = pd.DataFrame(X.toarray(), columns=vectorizer.get_feature_names_out())
bigram_counts = bigrams.sum()
most_common_bigrams_2 = bigram_counts.nlargest(n=3)

print(most_common_bigrams_2)
```

```
don think         1033
district court     922
chief justice      906
dtype: int64
```