Python Code for QSS Chapter 5: Discovery

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First Printing

Section 5.1: Textual Data

Section 5.1.1: The Disputed Authorship of 'The Federalist Papers'

Importing textual data into a DataFrame

[ ]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import glob
```

[ ]:
```python
# Get a list of all txt files in the federalist directory
file_paths = glob.glob('federalist/*.txt')

# Create an empty list
file_contents = []

# Read txt files into the empty list
for file in file_paths:
    # with: open and close file automatically
    # open(file, 'r'): open file in read mode
    # assign opened file to f
    with open(file, 'r') as f:
        file_contents.append(f.read())

# Take a look at the first 100 characters of essay number 10
file_contents[9][:100]
```

[ ]:
```
'AMONG the numerous advantages promised by a well-constructed Union, none \n
deserves to be mor'
```

[ ]:
```python
# Create a data frame with essay number, a placeholder for author, and the text
federalist = pd.DataFrame({'fed_num': np.arange(1,86), 'author': None,
                           'text': file_contents})

# store authorship information
hamilton = ([1] + list(range(6,10)) + list(range(11, 14)) +
            list(range(15, 18)) + list(range(21, 37)) + list(range(59, 62)) +
            list(range(65, 86)))
```

```
madison = [10] + [14] + list(range(37, 49)) + [58]

jay = list(range(2,6)) + [64]

joint = [18, 19, 20] # Madison and Hamilton

# store conditions for authorship
conditions = [
      federalist['fed_num'].isin(hamilton),
      federalist['fed_num'].isin(madison),
      federalist['fed_num'].isin(jay),
      federalist['fed_num'].isin(joint)
]

choices  = ['Hamilton', 'Madison', 'Jay', 'Joint']

# populate the author column; assign 'Disputed' to unassigned essays
federalist['author'] = np.select(conditions, choices, 'Disputed')

federalist
```

[ ]:

```
    fed_num    author                                               text
0         1  Hamilton  AFTER an unequivocal experience of the ineffic…
1         2       Jay  WHEN the people of America reflect that they a…
2         3       Jay  IT IS not a new observation that the people of…
3         4       Jay  MY LAST paper assigned several reasons why the…
4         5       Jay  QUEEN ANNE, in her letter of the 1st July, 170…
..      …       …                                                  …
80       81  Hamilton  LET US now return to the partition of the judi…
81       82  Hamilton  THE erection of a new government, whatever car…
82       83  Hamilton  THE objection to the plan of the convention, w…
83       84  Hamilton  IN THE course of the foregoing review of the C…
84       85  Hamilton  ACCORDING to the formal division of the subjec…

[85 rows x 3 columns]
```

[ ]:

```
federalist['author'].value_counts()
```

[ ]:

```
author
Hamilton    51
Madison     15
Disputed    11
Jay          5
Joint        3
Name: count, dtype: int64
```

Pre-processing textual data

[ ]:
```python
import re # regular expressions
import string # string manipulation
import nltk # natural language toolkit

# Pre-process the text using regular expressions, list comprehensions, apply()

# make lower case and remove punctuation
federalist['text_processed'] = (
    federalist['text'].apply(lambda x: "".join(
        [word.lower() for word in x if word not in string.punctuation])
    )
)

federalist[['text', 'text_processed']].head()
```

[ ]:
```
                                                text  \
0  AFTER an unequivocal experience of the ineffic…
1  WHEN the people of America reflect that they a…
2  IT IS not a new observation that the people of…
3  MY LAST paper assigned several reasons why the…
4  QUEEN ANNE, in her letter of the 1st July, 170…

                                      text_processed
0  after an unequivocal experience of the ineffic…
1  when the people of america reflect that they a…
2  it is not a new observation that the people of…
3  my last paper assigned several reasons why the…
4  queen anne in her letter of the 1st july 1706 …
```

[ ]:
```python
# download stopwords: only need to run once
# nltk.download('stopwords')

# save and inspect stopwords
stopwords = nltk.corpus.stopwords.words('english')
stopwords[:10]
```

[ ]:
```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're"]
```

[ ]:
```python
stopwords[-10:] # interestingly, includes wouldn't but not would
```

[ ]:
```
['shouldn',
 "shouldn't",
 'wasn',
 "wasn't",
 'weren',
 "weren't",
 'won',
```

```
 "won't",
 'wouldn',
 "wouldn't"]
```

[ ]:
```
type(stopwords)
```

[ ]:
```
list
```

We can add to the list as appropriate. For example, 'would' is included in many stopword dictionaries.

[ ]:
```
stopwords.append('would')
```

[ ]:
```
# instantiate the Porter stemmer to stem the words
ps = nltk.PorterStemmer()

'''
It is more efficient to define a function to apply to the text column than to
use a lambda function for every step.
'''
def preprocess_text(text):
    # make lower case
    text = text.lower()
    # remove punctuation
    text = "".join([word for word in text if word not in string.punctuation])
    # remove numbers
    text = re.sub('[0-9]+', '', text)
    # create a list of individual tokens, removing whitespace
    tokens = re.split('\W+', text)
    # remove stopwords
    tokens = [word for word in tokens if word not in stopwords]
    # remove any empty strings associated with trailing spaces
    tokens = [word for word in tokens if word !='']
    # finally, stem each word
    tokens = [ps.stem(word) for word in tokens]
    return tokens

# apply function to the text column; no need for lambda with a named function
federalist['text_processed'] = federalist['text'].apply(preprocess_text)

federalist[['text', 'text_processed']].head()
```

[ ]:
```
                                               text  \
0  AFTER an unequivocal experience of the ineffic…
1  WHEN the people of America reflect that they a…
2  IT IS not a new observation that the people of…
3  MY LAST paper assigned several reasons why the…
4  QUEEN ANNE, in her letter of the 1st July, 170…
```

```
                                   text_processed
0  [unequivoc, experi, ineffici, subsist, feder, …
1  [peopl, america, reflect, call, upon, decid, q…
2  [new, observ, peopl, countri, like, american, …
3  [last, paper, assign, sever, reason, safeti, p…
4  [queen, ann, letter, st, juli, scotch, parliam…
```

[ ]:
```
# each element of the text_processed column is a list of tokens
type(federalist['text_processed'][0])
```

[ ]:
```
list
```

[ ]:
```
# compare the pre-processed text to the original text for essay number 10
federalist['text_processed'][9][:15]
```

[ ]:
```
['among',
 'numer',
 'advantag',
 'promis',
 'wellconstruct',
 'union',
 'none',
 'deserv',
 'accur',
 'develop',
 'tendenc',
 'break',
 'control',
 'violenc',
 'faction']
```

[ ]:
```
federalist['text'][9][:100]
```

[ ]:
```
'AMONG the numerous advantages promised by a well-constructed Union, none \n
deserves to be mor'
```

Section 5.1.2: Document-Term Matrix

[ ]:
```
from sklearn.feature_extraction.text import CountVectorizer

'''
Instantiate the CountVectorizer and pass the preprocess_text function to the
analyzer argument.
'''
count_vect = CountVectorizer(analyzer=preprocess_text)

# transform the text_processed column into a document-term matrix
```

```
dtm = count_vect.fit_transform(federalist['text'])

# the dtm is a sparse matrix
type(dtm)
```

[ ]: scipy.sparse._csr.csr_matrix

[ ]:
```
# convert the sparse matrix to a dense matrix and store in a DataFrame
dtm_mat = pd.DataFrame(dtm.toarray(),
                       columns=count_vect.get_feature_names_out())

dtm_mat.iloc[:,:10].head()
```

[ ]:

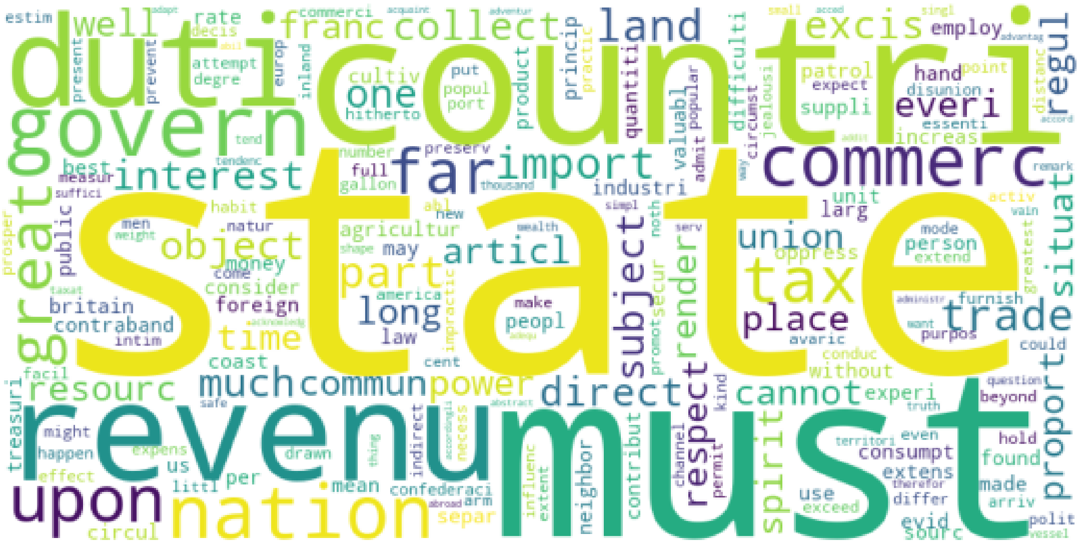
	abandon	abat	abb	abet	abhorr	abil	abject	abl	ablest	abolish
0	0	0	0	0	0	0	0	1	0	0
1	0	0	0	0	0	1	0	0	0	0
2	0	0	0	0	0	0	0	2	0	0
3	0	0	0	0	0	0	0	1	1	0
4	0	0	0	0	0	0	0	0	0	0

Section 5.1.3: Topic Discovery

[ ]:
```
from wordcloud import WordCloud

essay_12 = dtm_mat.iloc[11,:]
essay_24 = dtm_mat.iloc[23,:]

# Essay 12 word cloud
wordcloud_12 = WordCloud(
    width=800, height=400, background_color ='white'
).generate_from_frequencies(essay_12)

# Essay 24 word cloud
wordcloud_24 = WordCloud(
    width=800, height=400, background_color ='white'
).generate_from_frequencies(essay_24)

# plot word clouds vertically
fig, axs = plt.subplots(2, 1, figsize=(8,8))

axs[0].imshow(wordcloud_12)
axs[0].axis('off')
axs[0].set_title('Essay 12')

axs[1].imshow(wordcloud_24)
axs[1].axis('off')
axs[1].set_title('Essay 24')
```

[ ]: Text(0.5, 1.0, 'Essay 24')

Essay 12



Essay 24

[ ]:
```
# Import the tf-idf vectorizer
from sklearn.feature_extraction.text import TfidfVectorizer

# Create a tf-idf dtm following the same steps as before
tfidf_vect = TfidfVectorizer(analyzer=preprocess_text)

dtm_tfidf = tfidf_vect.fit_transform(federalist['text'])
```

```
dtm_tfidf_mat = pd.DataFrame(dtm_tfidf.toarray(),
                             columns=tfidf_vect.get_feature_names_out())

# 10 most important words for Paper No. 12
dtm_tfidf_mat.iloc[11,:].sort_values(ascending=False).head(10)
```

[ ]:
```
revenu        0.214827
state         0.186738
excis         0.155990
must          0.149053
commerc       0.148469
trade         0.143082
tax           0.141690
countri       0.134673
contraband    0.127014
patrol        0.127014
Name: 11, dtype: float64
```

[ ]:
```
# 10 most important words for Paper No. 24
dtm_tfidf_mat.iloc[23,:].sort_values(ascending=False).head(10)
```

[ ]:
```
garrison      0.238167
armi          0.169594
peac          0.155266
dockyard      0.141620
settlement    0.141620
spain         0.141201
frontier      0.119084
establish     0.113686
western       0.109730
post          0.105901
Name: 23, dtype: float64
```

[ ]:
```
from sklearn.cluster import KMeans

'''
subset The Federalist papers written by Hamilton using the author column of
the federalist DataFrame
'''
dtm_tfidf_hamilton = dtm_tfidf_mat[federalist['author']=='Hamilton']

k = 4 # number of clusters
# instantiate the KMeans object; set random_state for reproducibility
km_out = KMeans(n_clusters=k, n_init=1, random_state=42)
# fit the model
km_out.fit(dtm_tfidf_hamilton)
```

```
# check convergence; number of iterations may vary
km_out.n_iter_
```

[ ]: 3

[ ]:
```
# create data frame from the cluster centers
centers = pd.DataFrame(km_out.cluster_centers_,
                       columns=dtm_tfidf_hamilton.columns)

# extract Hamilton's papers from the federalist DataFrame
hamilton_df = (federalist.loc[federalist['author']=='Hamilton']
               .copy().reset_index(drop=True))

km_out.labels_ # cluster labels
```

[ ]:
```
array([2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 1, 0, 0, 2, 2,
       2, 1, 2, 2, 2, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1, 1, 1, 3,
       3, 2, 3, 3, 3, 1, 2])
```

[ ]:
```
# add the cluster labels + 1 to the Hamilton DataFrame
hamilton_df['cluster'] = km_out.labels_ + 1

hamilton_df.head()
```

[ ]:
```
   fed_num    author                                               text  \
0        1  Hamilton  AFTER an unequivocal experience of the ineffic…
1        6  Hamilton  THE three last numbers of this paper have been…
2        7  Hamilton  IT IS sometimes asked, with an air of seeming …
3        8  Hamilton  ASSUMING it therefore as an established truth …
4        9  Hamilton  A FIRM Union will be of the utmost moment to t…

                                      text_processed  cluster
0  [unequivoc, experi, ineffici, subsist, feder, …        3
1  [three, last, number, paper, dedic, enumer, da…        3
2  [sometim, ask, air, seem, triumph, induc, coul…        3
3  [assum, therefor, establish, truth, sever, sta…        1
4  [firm, union, utmost, moment, peac, liberti, s…        3
```

[ ]:
```
# store cluster numbers
clusters = np.arange(1, k+1)
```

[ ]:
```
# loop through the clusters and print the 10 most important words
for i in range(len(clusters)):
    print(f'CLUSTER {clusters[i]}')
    print('Top 10 words:')
    print(centers.iloc[i].sort_values(ascending=False).head(10))
```

```python
    # store the essay numbers associated with each cluster
    essays = hamilton_df.loc[hamilton_df['cluster']==clusters[i], 'fed_num']
    print(f'Federalist Papers: {list(essays)}')
    print('\n')
```

```
CLUSTER 1
Top 10 words:
armi        0.183142
militia     0.130365
state       0.127613
govern      0.123254
militari    0.119783
nation      0.104917
power       0.102766
peac        0.085124
time        0.078243
upon        0.074360
Name: 0, dtype: float64
Federalist Papers: [8, 23, 24, 25, 26, 28, 29]


CLUSTER 2
Top 10 words:
senat        0.132368
state        0.127933
power        0.118810
execut       0.098908
presid       0.095185
may          0.091496
upon         0.088398
govern       0.086577
appoint      0.079907
constitut    0.076724
Name: 1, dtype: float64
Federalist Papers: [27, 33, 59, 60, 61, 66, 67, 68, 69, 70, 71, 73, 74, 75, 76,
77, 84]


CLUSTER 3
Top 10 words:
state        0.200525
govern       0.111188
nation       0.099455
upon         0.098069
power        0.084704
union        0.080497
may          0.079779
interest     0.056737
```

```
must          0.056169
constitut     0.052729
Name: 2, dtype: float64
Federalist Papers: [1, 6, 7, 9, 11, 12, 13, 15, 16, 17, 21, 22, 30, 31, 32, 34,
35, 36, 80, 85]


CLUSTER 4
Top 10 words:
court         0.284571
juri          0.137047
state         0.105975
judg          0.099175
may           0.095400
constitut     0.092347
trial         0.079088
upon          0.078822
jurisdict     0.078224
offic         0.077051
Name: 3, dtype: float64
Federalist Papers: [65, 72, 78, 79, 81, 82, 83]
```

A few themes that emerge:

- Cluster 1: armed forces
- Cluster 2: institutional design, executive, legislature
- Cluster 3: state power, national government
- Cluster 4: courts, law, jurisprudence

Section 5.1.4: Authorship Prediction

[ ]:
```python
import statsmodels.formula.api as smf

'''
Customize the preprocessing function to make stemming and stopword removal
optional and to optionally return strings instead of lists of tokens.
'''
def preprocess_text(text, remove_stopwords=True, stem=True,
                    return_string=False):
    # make lower case
    text = text.lower()
    # remove punctuation
    text = "".join([word for word in text if word not in string.punctuation])
    # remove numbers
    text = re.sub('[0-9]+', '', text)
    # create a list of individual tokens, removing whitespace
```

```
    tokens = re.split('\W+', text)
    # remove stopwords if remove_stopwords=True
    if remove_stopwords:
        tokens = [word for word in tokens if word not in stopwords]
    # remove any empty strings associated with trailing spaces
    tokens = [word for word in tokens if word !='']
    # stem each word if stem=True
    if stem:
        tokens = [ps.stem(word) for word in tokens]
    if return_string:
        return ' '.join(tokens)
    else:
        return tokens

# If we preprocess before using the CountVectorizer, it expects strings
federalist['text_processed_v2'] = (
    federalist['text'].apply(lambda x: preprocess_text(
        x, stem=False, remove_stopwords=False, return_string=True))
)

federalist['text_processed_v2'].head()
```

[ ]:
```
0    after an unequivocal experience of the ineffic…
1    when the people of america reflect that they a…
2    it is not a new observation that the people of…
3    my last paper assigned several reasons why the…
4    queen anne in her letter of the st july to the…
Name: text_processed_v2, dtype: object
```

[ ]:
```
# this time, do not pass the preprocess_text function to the analyzer argument
count_vect1 = CountVectorizer()

dtm1 = count_vect1.fit_transform(federalist['text_processed_v2'])

dtm1_mat = pd.DataFrame(dtm1.toarray(),
                        columns=count_vect1.get_feature_names_out())

# term frequency per 1000 words
row_sums = dtm1_mat.sum(axis='columns')
tfm = dtm1_mat.div(row_sums, axis='rows')*1000

# words of interest
words = ['although', 'always', 'commonly', 'consequently', 'considerable',
         'enough', 'there', 'upon', 'while', 'whilst']

# select only these words
tfm = tfm.loc[:, words]
```

```python
# average among Hamilton/Madison essays
tfm_ave = (pd.concat(
    [tfm.loc[federalist['author']=='Hamilton'].sum(axis='rows') / len(hamilton),
     tfm.loc[federalist['author']=='Madison'].sum(axis='rows') / len(madison)],
     axis=1
)).T # transpose

tfm_ave
```

[ ]:

```
   although    always  commonly  consequently  considerable    enough  \
0  0.013654  0.577750  0.203337      0.019854      0.417913  0.303319
1  0.212740  0.158571  0.000000      0.353982      0.126829  0.000000

      there     upon     while    whilst
0  3.395702  3.380919  0.282721  0.005320
1  0.876109  0.156989  0.000000  0.300338
```

[ ]:

```python
# add tfm to the federalist data frame
federalist = pd.concat([federalist, tfm], axis=1)

model_words = ['upon', 'there', 'consequently', 'whilst']

select_vars = ['fed_num', 'author'] + model_words

hm_data = (
    federalist.loc[federalist['author'].isin(['Hamilton', 'Madison']),
                   select_vars]
).copy().reset_index(drop=True)

hm_data['author_y'] = np.where(hm_data['author'] == "Hamilton", 1, -1)

hm_data.head()
```

[ ]:

	fed_num	author	upon	there	consequently	whilst	author_y
0	1	Hamilton	3.886010	1.295337	0.0	0.0	1
1	6	Hamilton	2.119767	4.239534	0.0	0.0	1
2	7	Hamilton	4.993191	4.085338	0.0	0.0	1
3	8	Hamilton	1.547189	1.031460	0.0	0.0	1
4	9	Hamilton	2.082249	1.561687	0.0	0.0	1

[ ]:

```python
hm_model = 'author_y ~ upon + there + consequently + whilst'

hm_fit = smf.ols(hm_model, data=hm_data).fit()

hm_fit.params
```

```
[ ]: Intercept      -0.271853
     upon            0.218922
     there           0.124089
     consequently   -0.556267
     whilst         -0.821720
     dtype: float64
```

```
[ ]: hm_fitted = hm_fit.fittedvalues

     np.std(hm_fitted)
```

```
[ ]: 0.7128452675676532
```

Section 5.1.5: Cross-Validation

```
[ ]: # proportion of correctly classified essays for Hamilton
     (hm_fitted[hm_data['author_y']==1] > 0).mean()
```

```
[ ]: 1.0
```

```
[ ]: # proportion of correctly classified essays for Madison
     (hm_fitted[hm_data['author_y']==-1] < 0).mean()
```

```
[ ]: 1.0
```

```
[ ]: n = len(hm_data)

     # a container vector
     hm_classify = np.zeros(n)

     for i in range(n):
         # fit the model to the data after removing the ith observation
         sub_fit = smf.ols(hm_model, data=hm_data.drop(i)).fit()
         # predict the authorship for the ith observation
         # [[]] ensures the row remains a data frame
         # finally, extract value from prediction Series without index
         hm_classify[i] = sub_fit.predict(hm_data.iloc[[i]]).iloc[0]

     # proportion of correctly classified essays for Hamilton
     (hm_classify[hm_data['author_y']==1] > 0).mean()
```

```
[ ]: 1.0
```

```
[ ]: # proportion of correctly classified essays for Madison
     (hm_classify[hm_data['author_y']==-1] < 0).mean()
```

```
[ ]: 1.0
```

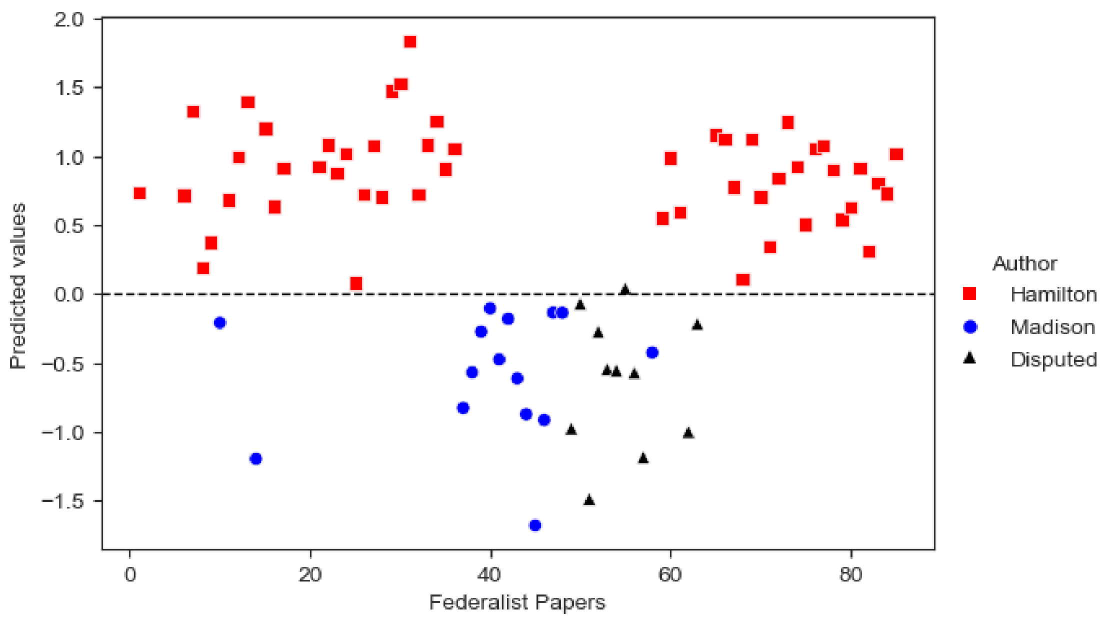
[ ]:
```
# subset essays with disputed authorship
disputed = federalist.loc[federalist['author']=='Disputed', select_vars]

# predict the authorship of the disputed essays
pred = hm_fit.predict(disputed)
pred
```

[ ]:
```
48   -0.974471
49   -0.069148
50   -1.484745
51   -0.271853
52   -0.543932
53   -0.553347
54    0.041819
55   -0.569111
56   -1.182493
61   -0.997734
62   -0.214164
dtype: float64
```

[ ]:
```
# prepare the data for plotting
hm_data['pred'] = hm_fitted
disputed['pred'] = pred

plot_vars = ['fed_num', 'author', 'pred']

plot_data = pd.concat([hm_data[plot_vars], disputed[plot_vars]],
                      axis=0, ignore_index=True)
```

[ ]:
```
sns.set_style('ticks')

(sns.relplot(
    data=plot_data, x='fed_num', y='pred', hue='author', style='author',
    palette=['red', 'blue', 'black'], markers = ['s', 'o', '^'],
    height=4, aspect=1.5
).set(xlabel='Federalist Papers', ylabel='Predicted values')
.despine(right=False, top=False)._legend.set_title('Author'))

plt.axhline(y=0, color='black', linestyle='--', linewidth=1)
```

[ ]:
```
<matplotlib.lines.Line2D at 0x1c811e87880>
```



Section 5.2: Network Data

Section 5.2.1: Marriage Network in Renaissance Florence

[ ]:
```
florence = pd.read_csv('florentine.csv', index_col='FAMILY')

florence.iloc[:5,:5]
```

[ ]:

FAMILY	ACCIAIUOL	ALBIZZI	BARBADORI	BISCHERI	CASTELLAN
ACCIAIUOL	0	0	0	0	0
ALBIZZI	0	0	0	0	0
BARBADORI	0	0	0	0	1
BISCHERI	0	0	0	0	0
CASTELLAN	0	0	1	0	0

[ ]:
```
florence.sum(axis='columns')
```

[ ]:
```
FAMILY
ACCIAIUOL    1
ALBIZZI      3
BARBADORI    2
BISCHERI     3
CASTELLAN    3
GINORI       1
GUADAGNI     4
LAMBERTES    1
```

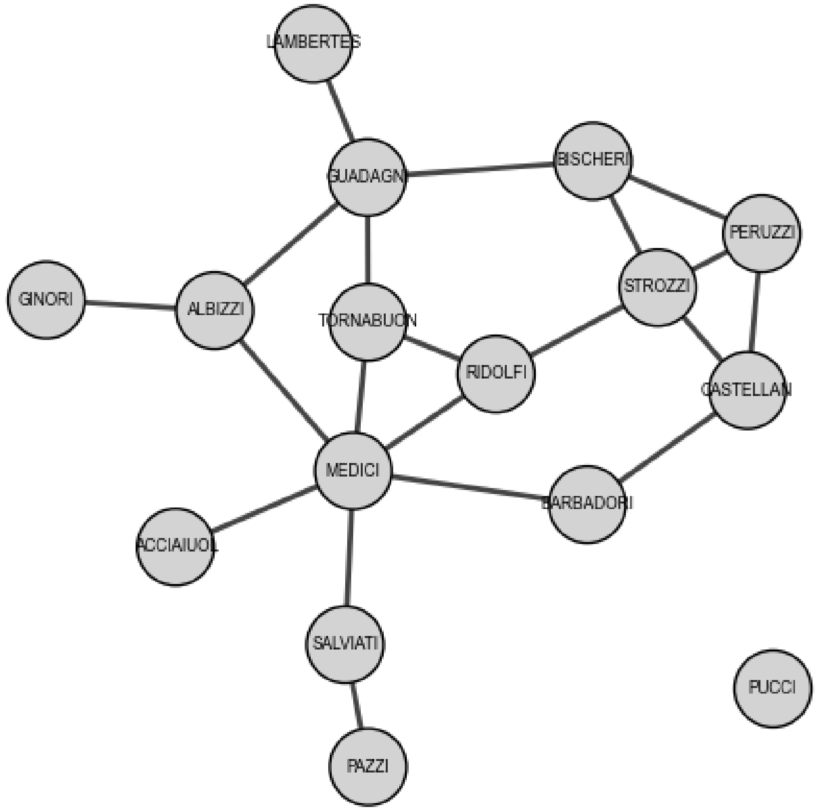
```
MEDICI        6
PAZZI         1
PERUZZI       3
PUCCI         0
RIDOLFI       3
SALVIATI      2
STROZZI       4
TORNABUON     3
dtype: int64
```

Section 5.2.2: Undirected Graph and Centrality Measures

[ ]:
```python
# Note: if installing from conda forge, install 'python-igraph'
import igraph as ig

florence_g = ig.Graph.Adjacency(florence, mode='undirected')
```

[ ]:
```python
# plot the graph
fig, ax = plt.subplots(figsize=(6,6))

ig.plot(
    florence_g,
    target=ax,
    vertex_size=40,
    vertex_label=florence_g.vs["name"],
    vertex_label_size=6.0,
    vertex_color='lightgray'
)
```

[ ]:
```
<igraph.drawing.matplotlib.graph.GraphArtist at 0x1c811526500>
```



[ ]:
```
florence_g.degree() # list
```

[ ]:
```
[1, 3, 2, 3, 3, 1, 4, 1, 6, 1, 3, 0, 3, 2, 4, 3]
```

[ ]:
```
florence_g.vs['name']
```

[ ]:
```
['ACCIAIUOL',
 'ALBIZZI',
 'BARBADORI',
 'BISCHERI',
 'CASTELLAN',
 'GINORI',
 'GUADAGNI',
 'LAMBERTES',
 'MEDICI',
 'PAZZI',
 'PERUZZI',
 'PUCCI',
```

```
 'RIDOLFI',
 'SALVIATI',
 'STROZZI',
 'TORNABUON']
```

[ ]:
```python
pd.Series(florence_g.degree(), index=florence_g.vs['name'])
```

[ ]:
```
ACCIAIUOL    1
ALBIZZI      3
BARBADORI    2
BISCHERI     3
CASTELLAN    3
GINORI       1
GUADAGNI     4
LAMBERTES    1
MEDICI       6
PAZZI        1
PERUZZI      3
PUCCI        0
RIDOLFI      3
SALVIATI     2
STROZZI      4
TORNABUON    3
dtype: int64
```

[ ]:
```python
pd.Series(florence_g.closeness(normalized=False), index=florence_g.vs['name'])
```

[ ]:
```
ACCIAIUOL    0.026316
ALBIZZI      0.034483
BARBADORI    0.031250
BISCHERI     0.028571
CASTELLAN    0.027778
GINORI       0.023810
GUADAGNI     0.033333
LAMBERTES    0.023256
MEDICI       0.040000
PAZZI        0.020408
PERUZZI      0.026316
PUCCI             NaN
RIDOLFI      0.035714
SALVIATI     0.027778
STROZZI      0.031250
TORNABUON    0.034483
dtype: float64
```

[ ]:
```python
1 / (pd.Series(florence_g.closeness(normalized=False),
               index=florence_g.vs['name']) * 15)
```

```
[ ]: ACCIAIUOL    2.533333
     ALBIZZI      1.933333
     BARBADORI    2.133333
     BISCHERI     2.333333
     CASTELLAN    2.400000
     GINORI       2.800000
     GUADAGNI     2.000000
     LAMBERTES    2.866667
     MEDICI       1.666667
     PAZZI        3.266667
     PERUZZI      2.533333
     PUCCI             NaN
     RIDOLFI      1.866667
     SALVIATI     2.400000
     STROZZI      2.133333
     TORNABUON    1.933333
     dtype: float64
```

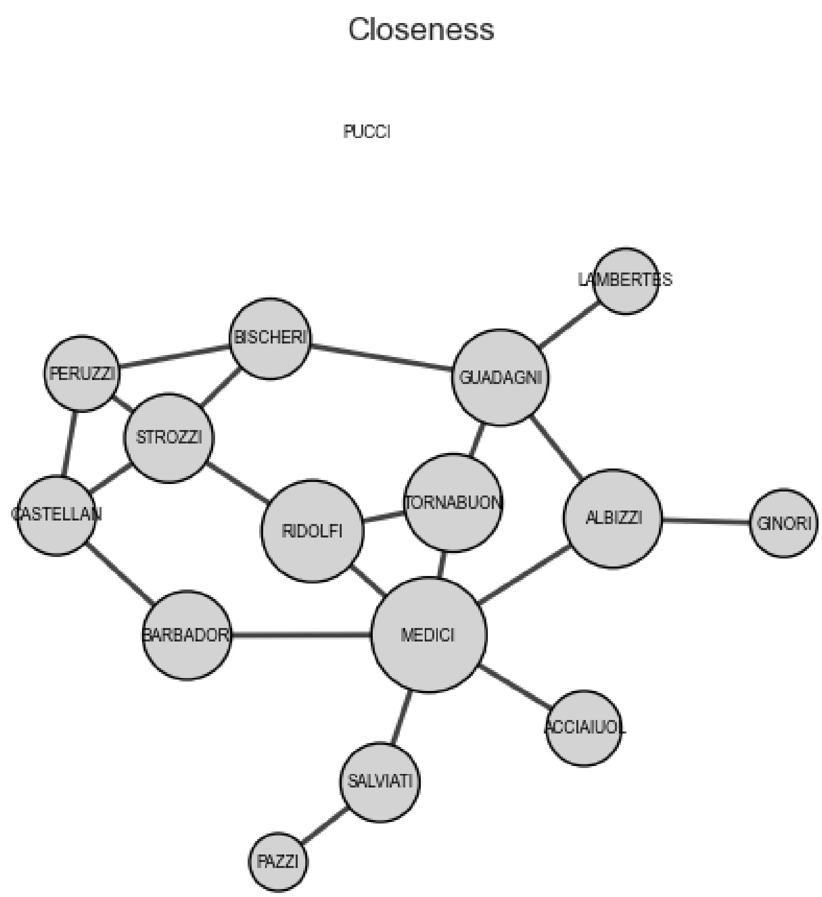
```
[ ]: pd.Series(florence_g.betweenness(directed=False), index=florence_g.vs['name'])
```

```
[ ]: ACCIAIUOL     0.000000
     ALBIZZI      19.333333
     BARBADORI     8.500000
     BISCHERI      9.500000
     CASTELLAN     5.000000
     GINORI        0.000000
     GUADAGNI     23.166667
     LAMBERTES     0.000000
     MEDICI       47.500000
     PAZZI         0.000000
     PERUZZI       2.000000
     PUCCI         0.000000
     RIDOLFI      10.333333
     SALVIATI     13.000000
     STROZZI       9.333333
     TORNABUON     8.333333
     dtype: float64
```

```
[ ]: close = pd.Series(florence_g.closeness(normalized=False),
                       index=florence_g.vs['name'])

     close['PUCCI'] = 0

     fig, ax = plt.subplots(figsize=(6,6))

     ig.plot(
         florence_g,
```

```
    target=ax,
    vertex_size=close * 1500,
    vertex_label=florence_g.vs["name"],
    vertex_label_size=6.0,
    vertex_color='lightgray'
)

ax.set(title='Closeness')
```

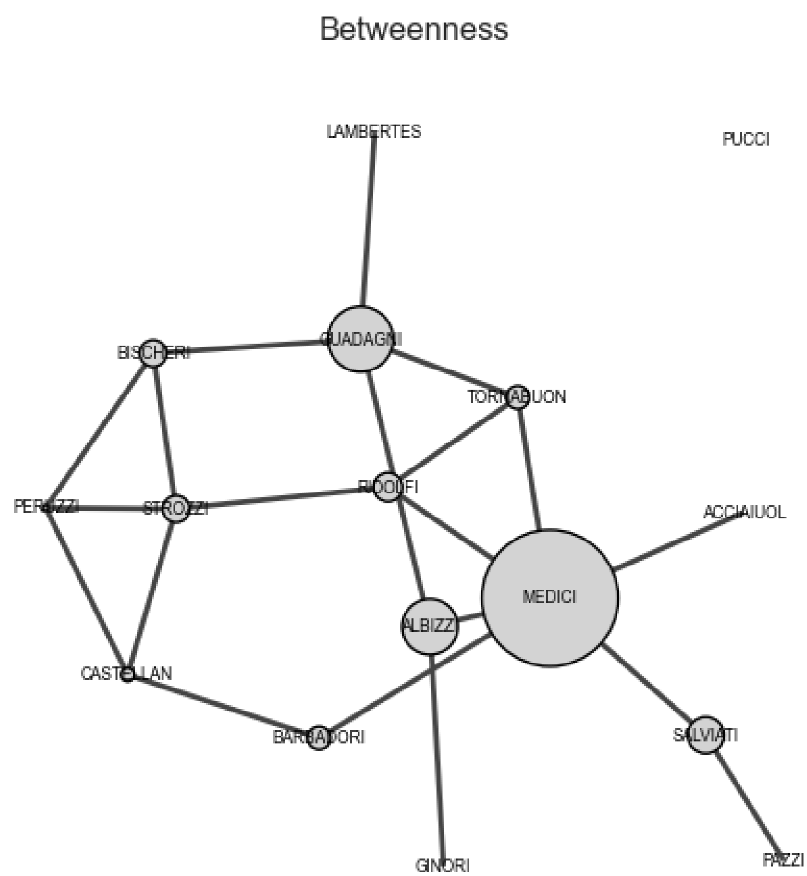
[ ]: [Text(0.5, 1.0, 'Closeness')]



[ ]:
```
fig, ax = plt.subplots(figsize=(6,6))

ig.plot(
    florence_g,
    target=ax,
    vertex_size=pd.Series(florence_g.betweenness(directed=False)) * 1.5,
```

```
    vertex_label=florence_g.vs["name"],
    vertex_label_size=6.0,
    vertex_color='lightgray'
)

ax.set(title='Betweenness')
```

[ ]: [Text(0.5, 1.0, 'Betweenness')]



Section 5.2.3: Twitter-Following Network

```
[ ]: twitter = pd.read_csv('twitter-following.csv')
senator = pd.read_csv('twitter-senator.csv')

n = senator.shape[0] # number of senators

# initialize adjacency matrix
```

```
twitter_adj = pd.DataFrame(np.zeros((n, n)),
                           columns=senator['screen_name'],
                           index=senator['screen_name'])

# change 0 to 1 when edge goes from node i to node j
for i in range(len(twitter)):
    twitter_adj.loc[twitter.loc[i,'following'], twitter.loc[i,'followed']] = 1

twitter_g = ig.Graph.Adjacency(twitter_adj, mode='directed')
```

Section 5.2.4: Directed Graph and Centrality

[ ]:
```
senator['indegree'] = twitter_g.indegree()
senator['outdegree'] = twitter_g.outdegree()

# 5 greatest indegree
senator.sort_values(by='indegree', ascending=False).head(5)
```

[ ]:

	screen_name	name	party	state	indegree	outdegree
50	SenJohnMcCain	John McCain	R	AZ	64	15
56	lisamurkowski	Lisa Murkowski	R	AK	60	87
62	senrobportman	Rob Portman	R	OH	58	9
82	SenToomey	Patrick J. Toomey	R	PA	58	50
17	SenatorCollins	Susan M. Collins	R	ME	58	79

[ ]:
```
# 5 greatest outdegree
senator.sort_values(by='outdegree', ascending=False).head(5)
```

[ ]:

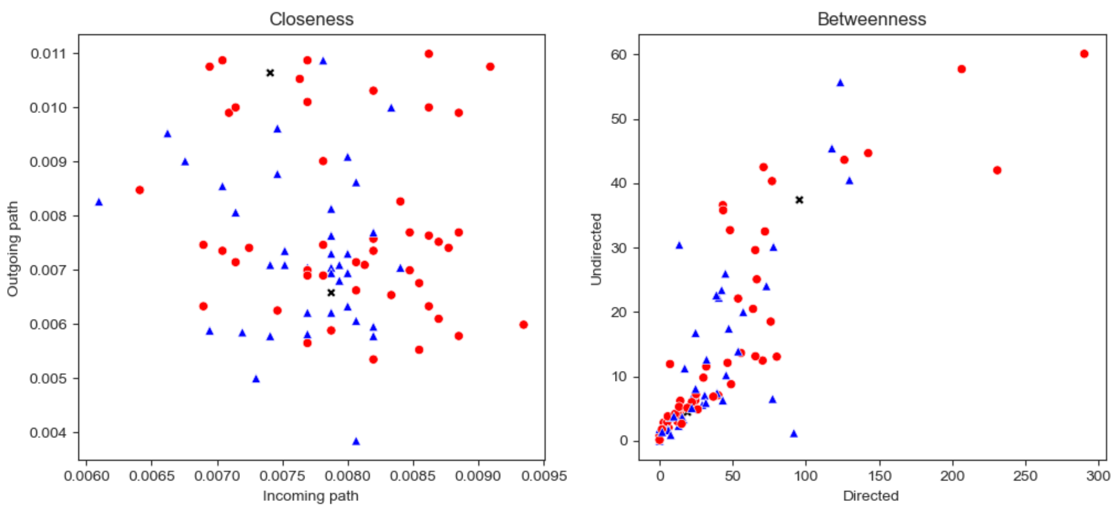
	screen_name	name	party	state	indegree	outdegree
36	SenDeanHeller	Dean Heller	R	NV	55	89
64	sendavidperdue	David Perdue	R	GA	30	88
77	SenatorTimScott	Tim Scott	R	SC	41	88
20	SenBobCasey	Robert P. Casey, Jr.	D	PA	43	88
56	lisamurkowski	Lisa Murkowski	R	AK	60	87

[ ]:
```
# closeness for incoming and outgoing paths
senator['close_in'] = twitter_g.closeness(mode='in', normalized=False)
senator['close_out'] = twitter_g.closeness(mode='out', normalized=False)

# directed and undirected betweenness
senator['betweenness_d'] = twitter_g.betweenness(directed=True)
senator['betweenness_u'] = twitter_g.betweenness(directed=False)
```

[ ]:
```
fig, axs = plt.subplots(1, 2, figsize=(12,5))

sns.scatterplot(
    data=senator, x='close_in', y='close_out', ax=axs[0],
```

```
    hue='party', palette=['r', 'b', 'k'], legend=False,
    style='party', markers=['o', '^', 'X']
).set(title='Closeness', xlabel='Incoming path', ylabel='Outgoing path')

sns.scatterplot(
    data=senator, x='betweenness_d', y='betweenness_u', ax=axs[1],
    hue='party', palette=['r', 'b', 'k'], legend=False,
    style='party', markers=['o', '^', 'X']
).set(title='Betweenness', xlabel='Directed', ylabel='Undirected')
```

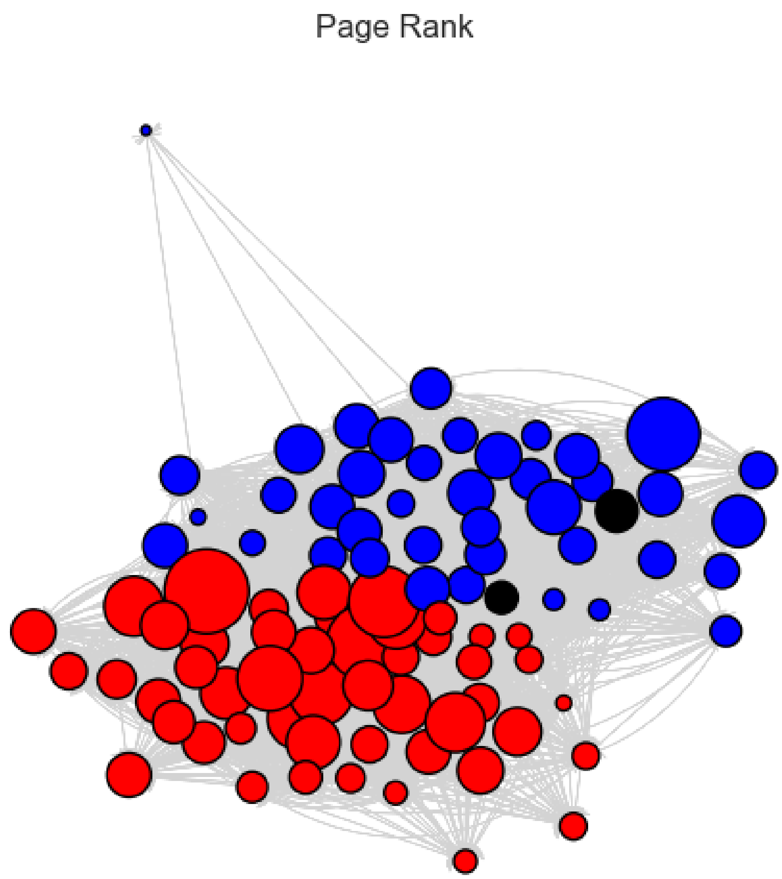
[ ]:
```
[Text(0.5, 1.0, 'Betweenness'),
 Text(0.5, 0, 'Directed'),
 Text(0, 0.5, 'Undirected')]
```



[ ]:
```
# senator PageRank
senator['pagerank'] = twitter_g.pagerank()

# save colors for plotting
v_color = np.where(senator.party=='R', 'red',
                   np.where(senator.party=='D', 'blue', 'black'))

fig, ax = plt.subplots(figsize=(6,6))

ig.plot(
    twitter_g,
    target=ax,
    vertex_size=senator['pagerank'] * 2000,
    vertex_color=v_color,
    edge_color='lightgray',
```

```
    edge_width=0.5,
    edge_arrow_size=0.75,
)

ax.set(title='Page Rank')
```

[ ]: [Text(0.5, 1.0, 'Page Rank')]



[ ]:
```
def PageRank(n, A, d, pr):
    g = ig.Graph.Adjacency(A)
    deg = g.outdegree()
    for j in range(n):
        pr[j] = (1 - d) / n + d * sum(adj[:,j] * pr / deg)
    return pr

nodes = 4
```

```
# adjacency matrix with arbitrary values
adj = (np.array([0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0]).
       reshape(nodes, nodes))

# typical choice of constant
d = 0.85

# starting values
pr = np.array([1/nodes] * nodes)

# maximum absolute difference; use value greater than threshold
diff = 100

# while loop with 0.001 as the threshold
while diff > 0.001:
    # save the previous iteration
    pr_pre = pr.copy()
    pr = PageRank(n=nodes, A=adj, d=d, pr=pr)
    diff = max(abs(pr - pr_pre))

pr
```

[ ]:
```
array([0.22130901, 0.43166231, 0.22095648, 0.13155633])
```

Section 5.3: Spatial Data

Section 5.3.1: The 1854 Cholera Outbreak in Action

Section 5.3.2: Spatial Data with GeoPandas

This section utilizes the U.S. Census Bureau's Cartographic Boundary Shapefiles.

[ ]:
```
import geopandas as gpd

# read in the shapefile (.shp) of the U.S. states
usa = gpd.read_file('cb_2022_us_state_500k/cb_2022_us_state_500k.shp')

type(usa) # a GeoDataFrame
```

[ ]:
```
geopandas.geodataframe.GeoDataFrame
```

[ ]:
```
# a GeoDataFrame is a pandas DataFrame with 'GeoSeries.'
usa.head()
```

[ ]:
```
  STATEFP   STATENS     AFFGEOID GEOID STUSPS          NAME LSAD  \
0      35  00897535  0400000US35    35     NM    New Mexico   00
1      46  01785534  0400000US46    46     SD  South Dakota   00
2      06  01779778  0400000US06    06     CA    California   00
3      21  01779786  0400000US21    21     KY      Kentucky   00
```

```
4      01  01779775  0400000US01    01     AL       Alabama   00

          ALAND       AWATER  \
0  314198573403    726463825
1  196341552329   3387681983
2  403673617862  20291712025
3  102266581101   2384240769
4  131185042550   4582333181

                                            geometry
0  POLYGON ((-109.05017 31.48000, -109.04984 31.4…
1  POLYGON ((-104.05788 44.99761, -104.05078 44.9…
2  MULTIPOLYGON (((-118.60442 33.47855, -118.5987…
3  MULTIPOLYGON (((-89.40565 36.52817, -89.39869 …
4  MULTIPOLYGON (((-88.05338 30.50699, -88.05109 …
```

[ ]:
```
usa.shape
```

[ ]:
```
(56, 10)
```

The Census Bureau uses the North American Datum 1983 (NAD83) Coordinate Reference System (CRS).

[ ]:
```
usa.crs
```

[ ]:
```
<Geographic 2D CRS: EPSG:4269>
Name: NAD83
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: North America - onshore and offshore: Canada - Alberta; British
Columbia; Manitoba; New Brunswick; Newfoundland and Labrador; Northwest
Territories; Nova Scotia; Nunavut; Ontario; Prince Edward Island; Quebec;
Saskatchewan; Yukon. Puerto Rico. United States (USA) - Alabama; Alaska;
Arizona; Arkansas; California; Colorado; Connecticut; Delaware; Florida;
Georgia; Hawaii; Idaho; Illinois; Indiana; Iowa; Kansas; Kentucky; Louisiana;
Maine; Maryland; Massachusetts; Michigan; Minnesota; Mississippi; Missouri;
Montana; Nebraska; Nevada; New Hampshire; New Jersey; New Mexico; New York;
North Carolina; North Dakota; Ohio; Oklahoma; Oregon; Pennsylvania; Rhode
Island; South Carolina; South Dakota; Tennessee; Texas; Utah; Vermont; Virginia;
Washington; West Virginia; Wisconsin; Wyoming. US Virgin Islands. British Virgin
Islands.
- bounds: (167.65, 14.92, -40.73, 86.45)
Datum: North American Datum 1983
- Ellipsoid: GRS 1980
- Prime Meridian: Greenwich
```

[ ]:
```python
# focus on the continental U.S.
non_cont = ['Alaska', 'Hawaii', 'Puerto Rico', 'United States Virgin Islands',
            'Commonwealth of the Northern Mariana Islands', 'Guam',
            'American Samoa']

usa_cont = usa.loc[~usa['NAME'].isin(non_cont)].copy().reset_index(drop=True)

usa_cont.boundary.plot(edgecolor='black', linewidth=0.5).axis('off')
```

[ ]:
```
(-127.65372665000001, -64.05923634999999, 23.2781513, 50.6275107)
```

[ ]:
```python
# import cities data; source: Becker and others (2021)
us_cities = pd.read_csv('us_cities.csv')

# convert to GeoDataFrame
us_cities = gpd.GeoDataFrame(
    us_cities,
    geometry=gpd.points_from_xy(us_cities['long'], us_cities['lat']),
    # specify the CRS associated with lat and long measurements
    crs='EPSG:4326'
)

us_cities.crs
```

[ ]:
```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
```

```
Area of Use:
- name: World.
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

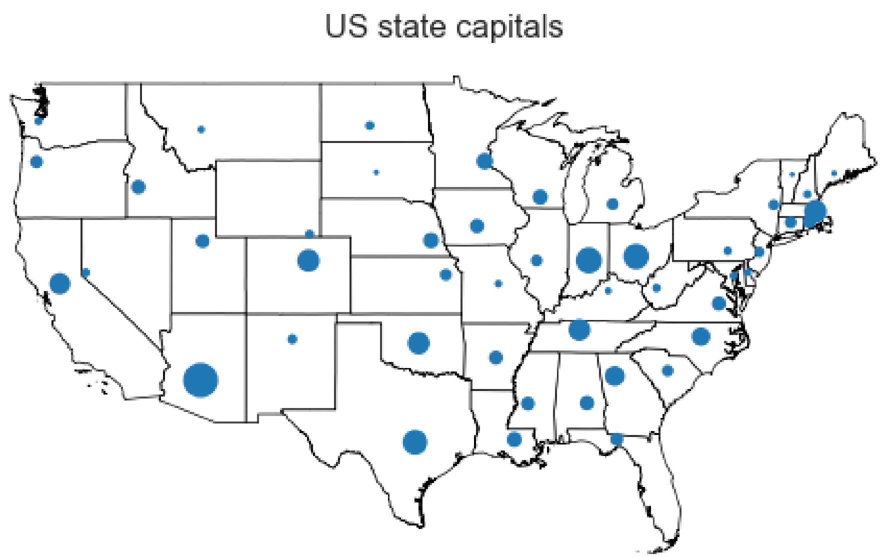
[ ]:
```
# subset capitals of continental U.S. states
usa_cont_capitals = (
    us_cities.loc[(us_cities['capital']==2) &
                  ~us_cities['country_etc'].isin(['AK', 'HI'])]
                  .copy().reset_index(drop=True)
)
```

[ ]:
```
# Re-project the usa_cont GeoDataFrame to match the CRS of the us_cities
usa_cont = usa_cont.to_crs(us_cities.crs)

usa_cont.crs
```

[ ]:
```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World.
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

[ ]:
```
# plot capitals on top of state map
base_map = usa_cont.plot(color='white', edgecolor='black', linewidth=0.5)

usa_cont_capitals.plot(ax=base_map, markersize=usa_cont_capitals['pop']/10000)

base_map.set_axis_off()

base_map.set_title('US state capitals')
```

[ ]:
```
Text(0.5, 1.0, 'US state capitals')
```




```
[ ]: california = usa_cont.loc[usa_cont['NAME']=='California']

     cal_cities = us_cities.loc[us_cities['country_etc']=='CA']

     top7 = cal_cities.sort_values(by='pop', ascending=False).head(7)

     # Extract the city name from the name column (i.e., remove 'CA')
     top7['city_name'] = top7['name'].str[:-3]
```

```
[ ]: # plot top 7 cities on top of California
     cal_map = california.boundary.plot(edgecolor='black', linewidth=0.75)

     top7.plot(ax=cal_map, color='black')

     for i in range(len(top7)):
         plt.annotate(top7.iloc[i]['city_name'],
                      (top7.iloc[i]['long'] + 0.25, top7.iloc[i]['lat']),
                      fontsize=8)

     cal_map.set_axis_off()

     cal_map.set_title('Largest cities in California')
```

```
[ ]: Text(0.5, 1.0, 'Largest cities in California')
```

[ ]:
```
# review geometric attributes of states

# geometry type
usa_cont.geom_type.head(5)
```

[ ]:
```
0         Polygon
1         Polygon
2    MultiPolygon
3    MultiPolygon
4    MultiPolygon
dtype: object
```

[ ]:
```
# geometries
usa_cont.geometry.head(5)
```

[ ]:
```
0    POLYGON ((-109.05018 31.48000, -109.04985 31.4…
1    POLYGON ((-104.05788 44.99761, -104.05078 44.9…
2    MULTIPOLYGON (((-118.60442 33.47855, -118.5987…
3    MULTIPOLYGON (((-89.40565 36.52816, -89.39868 …
4    MULTIPOLYGON (((-88.05337 30.50698, -88.05109 …
Name: geometry, dtype: geometry
```

[ ]:
```
# bounds of each state
usa_cont.bounds.head(5)
```

[ ]:
```
         minx       miny        maxx       maxy
0 -109.050177  31.332300 -103.001967  37.000232
1 -104.057881  42.479634  -96.436592  45.945453
2 -124.409588  32.534436 -114.131209  42.009487
3  -89.571509  36.497128  -81.964970  39.147457
4  -88.473226  30.223327  -84.889080  35.008028
```

Section 5.3.3: Colors in Matplotlib

[ ]:
```
import matplotlib.colors as mcolors

# base colors with intensities on rgb scale
mcolors.BASE_COLORS
```

[ ]:
```
{'b': (0, 0, 1),
 'g': (0, 0.5, 0),
 'r': (1, 0, 0),
 'c': (0, 0.75, 0.75),
 'm': (0.75, 0, 0.75),
 'y': (0.75, 0.75, 0),
 'k': (0, 0, 0),
 'w': (1, 1, 1)}
```

[ ]:
```
# Number of supported colors from different color palettes
print(len(mcolors.TABLEAU_COLORS))
print(len(mcolors.CSS4_COLORS))
print(len(mcolors.XKCD_COLORS))
```

```
10
148
949
```

[ ]:
```
# Colors in the CSS4 palette with Hex codes
pd.Series(mcolors.CSS4_COLORS)
```

[ ]:
```
aliceblue        #F0F8FF
antiquewhite     #FAEBD7
aqua             #00FFFF
aquamarine       #7FFFD4
azure            #F0FFFF
                   …
wheat            #F5DEB3
white            #FFFFFF
whitesmoke       #F5F5F5
yellow           #FFFF00
```

```
yellowgreen     #9ACD32
Length: 148, dtype: object
```

[ ]:
```python
red = (1, 0, 0)
green = (0, 1, 0)
blue = (0, 0, 1)

# case-insensitive hex codes
print(f'''
Red: {mcolors.to_hex(red)}
Green: {mcolors.to_hex(green)}
Blue: {mcolors.to_hex(blue)}''')
```

```
Red: #ff0000
Green: #00ff00
Blue: #0000ff
```

[ ]:
```python
black = (0, 0, 0)
white = (1, 1, 1)

print(f'''
Black: {mcolors.to_hex(black)}
White: {mcolors.to_hex(white)}''')
```

```
Black: #000000
White: #ffffff
```

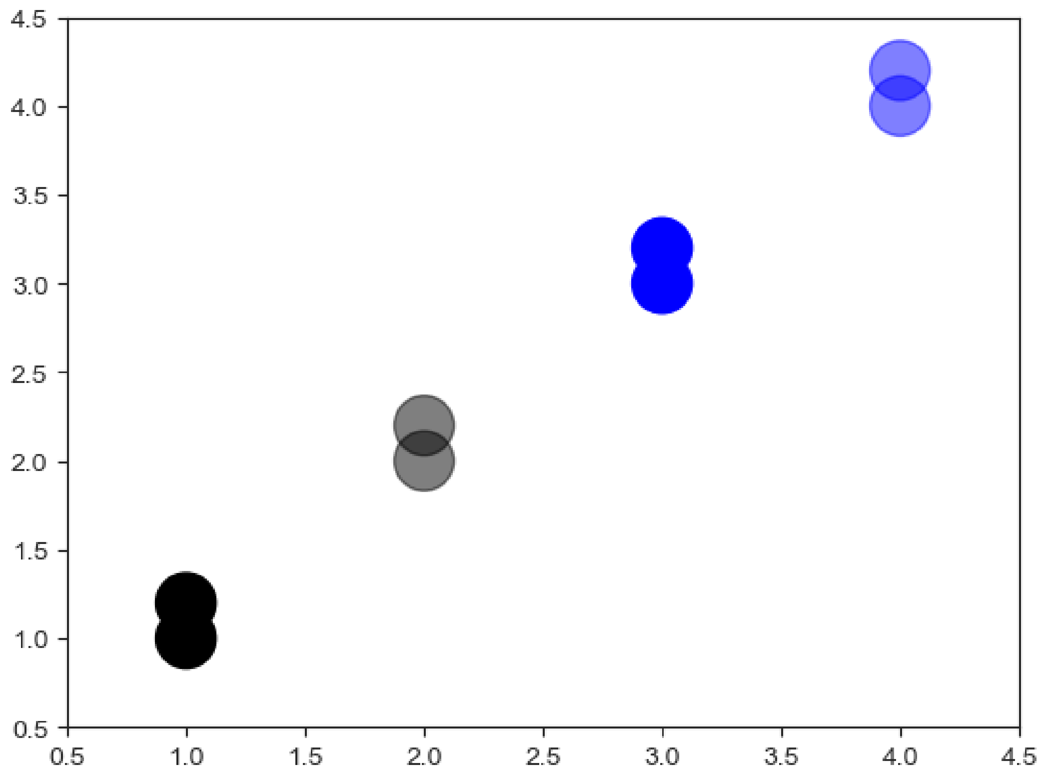
[ ]:
```python
purple = (0.5, 0, 0.5)
yellow = (1, 1, 0)

print(f'''
Purple: {mcolors.to_hex(purple)}
Yellow: {mcolors.to_hex(yellow)}''')
```

```
Purple: #800080
Yellow: #ffff00
```

[ ]:
```python
# semi-transparent blue; specify alpha (r, g, b, alpha)
blue_trans = (0, 0, 1, 0.5)
# semi-transparent black
black_trans = (0, 0, 0, 0.5)

x = [1, 1, 2, 2, 3, 3, 4, 4]
y = [1, 1.2, 2, 2.2, 3, 3.2, 4, 4.2]

colors = [black]*2 + [black_trans]*2 + [blue]*2 + [blue_trans]*2
```

```
# completely colored dots difficult to distinguish
# semi-transparent dots easier to distinguish
plt.figure() # open a new figure
plt.scatter(x, y, s=500, color=colors)
plt.xlim(0.5, 4.5)
plt.ylim(0.5, 4.5)
```

[ ]: (0.5, 4.5)



Section 5.3.4: US Presidential Elections

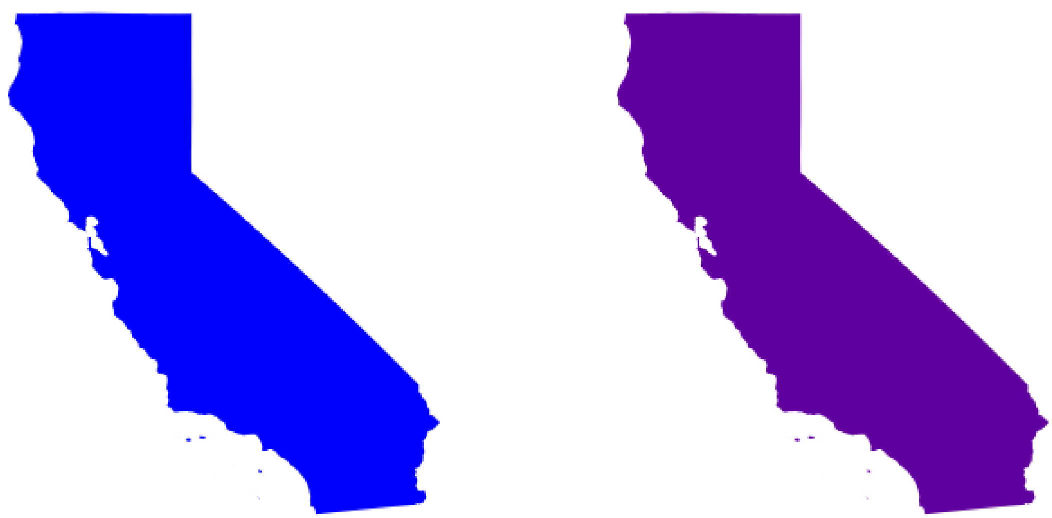
[ ]:
```
pres08 = pd.read_csv('pres08.csv')

# two-party vote share
pres08['Dem'] = pres08['Obama'] / (pres08['Obama'] + pres08['McCain'])
pres08['Rep'] = pres08['McCain'] / (pres08['Obama'] + pres08['McCain'])

# assign red and blue colors based on two-party vote share
pres08['color'] = np.where(pres08['Rep'] > pres08['Dem'], 'r', 'b')

# add tuples of rgb values based on two-party vote share
```

```
pres08['color_p'] = pres08.apply(lambda x: (x['Rep'], 0, x['Dem']), axis=1)

pres08['color_p'].head(5)
```

[ ]:
```
0     (0.6060606060606061, 0, 0.3939393939393939)
1     (0.6082474226804123, 0, 0.3917525773195876)
2    (0.5454545454545454, 0, 0.45454545454545453)
3     (0.6020408163265306, 0, 0.3979591836734694)
4    (0.37755102040816324, 0, 0.6224489795918368)
Name: color_p, dtype: object
```

[ ]:
```
fig, axs = plt.subplots(1, 2, figsize=(8,4))

# California as a blue state
california.plot(ax=axs[0],
                color=pres08['color'].loc[pres08.state=='CA'].iloc[0])

axs[0].axis('off')

# California as a purple state
california.plot(ax=axs[1],
                color=pres08['color_p'].loc[pres08.state=='CA'].iloc[0])

axs[1].axis('off')
```

[ ]:
```
(-124.92350729681908,
 -113.61729012187558,
 32.06068360992628,
 42.483239898889416)
```

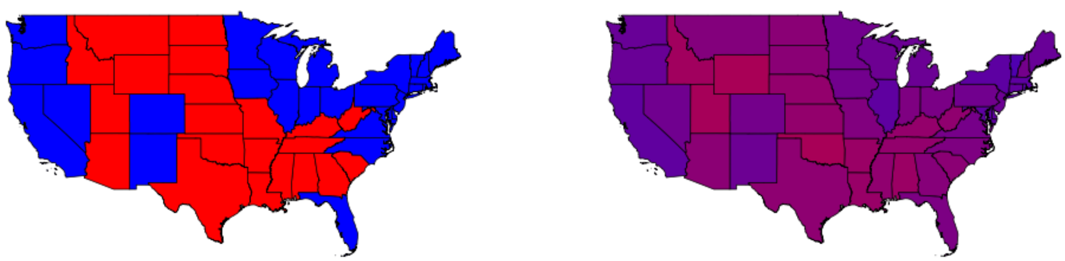


[ ]:
```
# merge the GeoDataFrame and the colors from pres08 on state abbreviations
usa_cont = pd.merge(
    usa_cont, pres08[['state', 'color', 'color_p']],
    left_on='STUSPS', right_on='state', how='left'
).drop('state', axis='columns')

usa_cont.columns
```

[ ]:
```
Index(['STATEFP', 'STATENS', 'AFFGEOID', 'GEOID', 'STUSPS', 'NAME', 'LSAD',
       'ALAND', 'AWATER', 'geometry', 'color', 'color_p'],
      dtype='object')
```

[ ]:
```
fig, axs = plt.subplots(1, 2, figsize=(12,6))

usa_cont.plot(ax=axs[0], color=usa_cont['color'], edgecolor='black',
              linewidth=0.5).axis('off')

usa_cont.plot(ax=axs[1], color=usa_cont['color_p'], edgecolor='black',
              linewidth=0.5).axis('off')
```

[ ]:
```
(-127.65372492089249,
 -64.05923571655354,
 23.278148779981684,
 50.62751082000087)
```



Section 5.3.5: Expansion of Walmart

[ ]:
```
walmart = pd.read_csv('walmart.csv')

walmart.head()
```

[ ]:
```
     opendate                   st.address         city state  \
0  1962-03-01  5801 SW Regional Airport Blvd  Bentonville    AR
1  1962-07-01              2110 WEST WALNUT       Rogers    AR
```

```
2  1964-08-01              1417 HWY 62/65 N          Harrison    AR
3  1965-08-01             2901 HWY 412 EAST     Siloam Springs    AR
4  1967-10-01         3801 CAMP ROBINSON RD.  North Little Rock    AR

        long        lat                type
0 -94.239816  36.350885  DistributionCenter
1 -94.071410  36.342235         SuperCenter
2 -93.093450  36.236984         SuperCenter
3 -94.502080  36.179905         SuperCenter
4 -92.302290  34.813269       Wal-MartStore
```

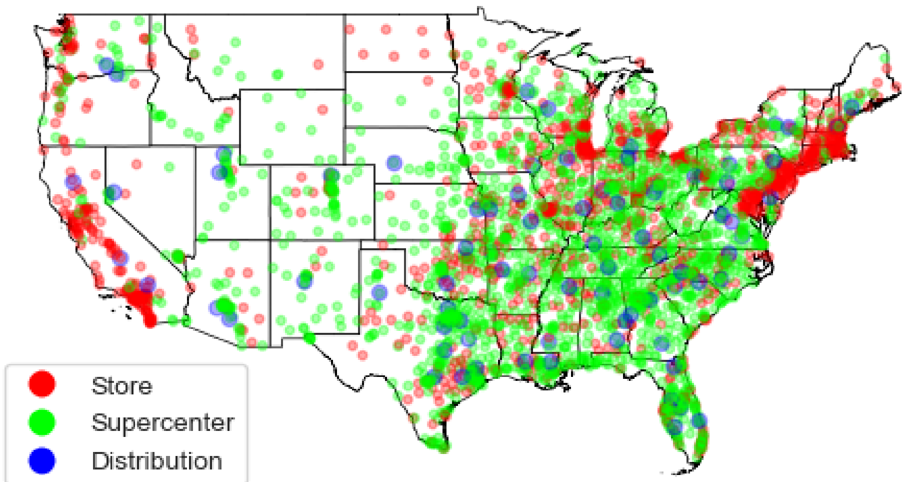
[ ]:
```
walmart['type'].value_counts()
```

[ ]:
```
type
SuperCenter           1977
Wal-MartStore         1196
DistributionCenter      78
Name: count, dtype: int64
```

[ ]:
```
# create store_type column for easier plotting
walmart['store_type'] = np.where(
    walmart['type']=='Wal-MartStore', 'Store',
    np.where(walmart['type']=='SuperCenter', 'Supercenter', 'Distribution')
)

# convert to categorical and reorder categories
walmart['store_type'] = (
    walmart['store_type'].astype('category').cat.reorder_categories(
        ['Store', 'Supercenter', 'Distribution'])
)

# add marker size column
walmart['msize'] = np.where(walmart['store_type']=='Distribution', 30, 10)

# convert to GeoDataFrame
walmart = gpd.GeoDataFrame(
    walmart,
    geometry=gpd.points_from_xy(walmart['long'], walmart['lat']),
    crs='EPSG:4326'
)
```

[ ]:
```
# define colors and transparency
store = (1, 0, 0, 1/3)
supercenter = (0, 1, 0, 1/3)
distribution = (0, 0, 1, 1/3)

# plot Walmart locations on top of state map
```

```
usa_map = usa_cont.plot(color='white', edgecolor='black', linewidth=0.5)

walmart.plot(ax=usa_map, column='store_type', categorical=True, legend=True,
             markersize=walmart['msize'],
             # define custom colormap
             cmap=mcolors.ListedColormap([store, supercenter, distribution]))

usa_map.set_axis_off()
```

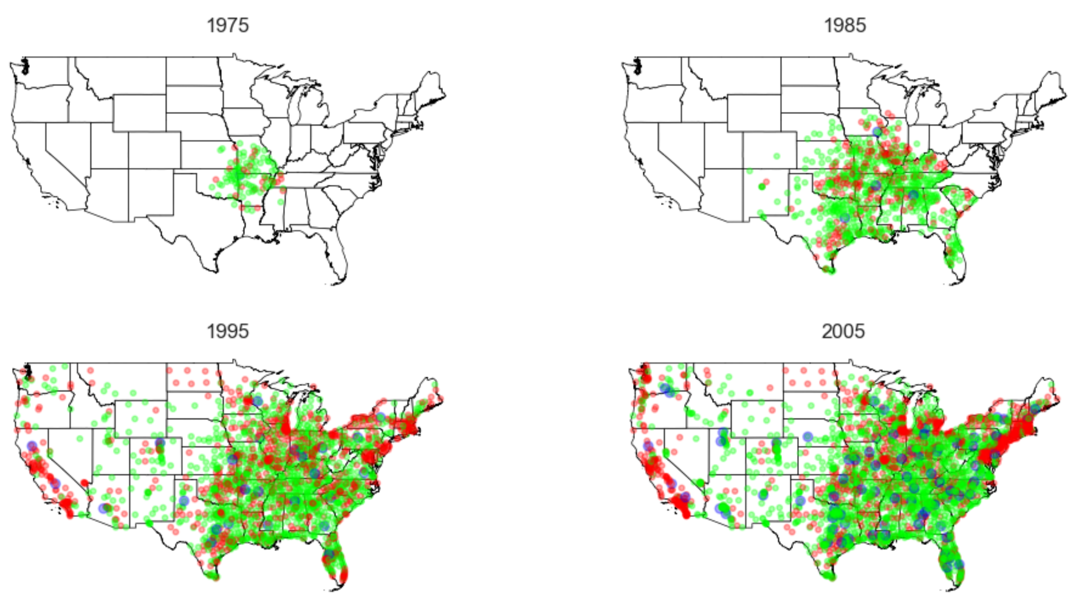


Section 5.3.6: Animation in Matplotlib

[ ]:
```
# convert 'opendate' to datetime
walmart['opendate'] = pd.to_datetime(walmart['opendate'])

# extract year
walmart['year'] = walmart['opendate'].dt.year

# define a function to plot Walmart locations as of year-end for a given year
def walmart_map(base_map, data, year, ax=None):

    # if ax is not specified, use the current axis or create a new one
    if ax is None:
        ax = plt.gca()

    # define colors and transparency
    store = (1, 0, 0, 1/3)
    supercenter = (0, 1, 0, 1/3)
    distribution = (0, 0, 1, 1/3)
```

```python
    walmart_sub = data.loc[data['year'] <= year]

    base_map.plot(ax=ax, color='white', edgecolor='black', linewidth=0.5)

    walmart_sub.plot(
        ax=ax, column='store_type', categorical=True, legend=False,
        markersize=walmart['msize'],
        cmap=mcolors.ListedColormap([store, supercenter, distribution]))

    ax.set_axis_off()

    ax.set_title(f'{year}')
```

[ ]:
```python
fig, axs = plt.subplots(2, 2, figsize=(12,6))

walmart_map(usa_cont, walmart, 1975, ax=axs[0,0])

walmart_map(usa_cont, walmart, 1985, ax=axs[0,1])

walmart_map(usa_cont, walmart, 1995, ax=axs[1,0])

walmart_map(usa_cont, walmart, 2005, ax=axs[1,1])
```



[ ]:
```python
## Animation using FuncAnimation
# from matplotlib.animation import FuncAnimation
```

```
# years = range(walmart['year'].min(), walmart['year'].max() + 1)

# fig, ax = plt.subplots()

# ani = FuncAnimation(
#     fig, lambda year: walmart_map(usa_cont, walmart, year, ax),
#     frames=years, repeat=False
# )

# ani.save('walmart.html', writer='html', fps=2)
```

References

Becker, Richard A., Allan R. Wilks, Ray Brownrigg, Thomas P. Minka, and Alex Deckmyn. 2021. maps: Draw Geographical Maps. R package version 3.4.0. Original S code by Richard A. Becker and Allan R. Wilks. R version by Ray Brownrigg. Enhancements by Thomas P Minka and Alex Deckmyn. https://CRAN.R-project.org/package=maps.