Python Code for QSS Chapter 4: Prediction

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First Printing

[ ]:
```
# import libraries with conventional aliases
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Section 4.1: Predicting Election Outcomes

Section 4.1.1: Loops in Python

[ ]:
```
values = np.array([2, 4, 6])
n = len(values) # number of elements in values
results = np.zeros(n) # empty container vector for storing the results

# loop counter `i` will take on values 0, 1, ..., n in that order
for i in range(n):
    # store multiplication results as the ith element of `results` vector
    results[i] = values[i] * 2
    print(f"{values[i]} times 2 is equal to {results[i]}")

results
```

```
2 times 2 is equal to 4.0
4 times 2 is equal to 8.0
6 times 2 is equal to 12.0
```

[ ]:
```
array([ 4.,  8., 12.])
```

[ ]:
```
# check if the code runs when i = 0
# i = 0 represents the first element in 'values'
i = 0
x = values[i] * 2
print(f"{values[i]} times 2 is equal to {x}")
```

```
2 times 2 is equal to 4
```

Section 4.1.2: General Conditional Statements in Python

[ ]:
```
# define the operation to be executed
operation = 'add'

if operation=='add':
    print('I will perform addition 4 + 4')
    print(4 + 4)

if operation=='multiply':
    print('I will perform multiplication 4 * 4')
    print(4 * 4)
```

```
I will perform addition 4 + 4
8
```

[ ]:
```
# Note that 'operation' is redefined
operation = 'multiply'

if operation=='add':
    print('I will perform addition 4 + 4')
    print(4 + 4)
else:
    print('I will perform multiplication 4 * 4')
    print(4 * 4)
```

```
I will perform multiplication 4 * 4
16
```

[ ]:
```
# Note that 'operation' is redefined
operation = 'subtract'

if operation=='add':
    print('I will perform addition 4 + 4')
    print(4 + 4)
elif operation=='multiply':
    print('I will perform multiplication 4 * 4')
    print(4 * 4)
else:
    print(f"'{operation}' is invalid. Use either 'add' or 'multiply'.")
```

```
'subtract' is invalid. Use either 'add' or 'multiply'.
```

[ ]:
```
values = np.arange(1,6)
n = len(values)
results = np.zeros(n)

for i in range(n):
    # x and r get overwritten in each iteration
```

```
    x = values[i]
    r = x % 2 # remainder of x divided by 2 to check if x is even or odd
    if r==0: # remainder is 0
        print(f"{x} is even and I will perform addition {x} + {x}")
        results[i] = x + x
    else: # remainder is not 0
        print(f"{x} is odd and I will perform multiplication {x} * {x}")
        results[i] = x * x

results
```

```
1 is odd and I will perform multiplication 1 * 1
2 is even and I will perform addition 2 + 2
3 is odd and I will perform multiplication 3 * 3
4 is even and I will perform addition 4 + 4
5 is odd and I will perform multiplication 5 * 5
```

[ ]:

```
array([ 1.,  4.,  9.,  8., 25.])
```

Section 4.1.3: Poll Predictions

[ ]:

```
# import the datetime module
from datetime import datetime

# load election results, by state
pres08 = pd.read_csv('pres08.csv')

# load polling data
polls08 = pd.read_csv('polls08.csv')

# compute Obama's margin
polls08['margin'] = polls08['Obama'] - polls08['McCain']
pres08['margin'] = pres08['Obama'] - pres08['McCain']

x = datetime.strptime('2008-11-04', '%Y-%m-%d')
y = datetime.strptime('2008/9/1', '%Y/%m/%d')

# number of days between 9/1/2008 and 11/4/2008
x-y # a timedelta object
```

[ ]:

```
datetime.timedelta(days=64)
```

[ ]:

```
# number of days as an integer
(x-y).days
```

[ ]:

```
64
```

```
[ ]: # convert middate to datetime object using pandas convenience function
polls08['middate'] = pd.to_datetime(polls08['middate'])

# compute the number of days to the election; use x defined above
# extract days using the .dt accessor
polls08['days_to_election'] = (x - polls08['middate']).dt.days

# extract unique state names which the loop will iterate through
st_names = polls08['state'].unique()

# initialize a container vector for storing the results as a series
poll_pred = pd.Series(index=st_names)

poll_pred.head()
```

```
[ ]: AL   NaN
AK   NaN
AZ   NaN
AR   NaN
CA   NaN
dtype: float64
```

```
[ ]: # loop across the 50 states plus DC
for i in range(len(st_names)):
    # subset the ith state
    state_data = polls08[polls08['state']==st_names[i]]
    # further subset the latest polls within the state
    latest = (state_data[state_data['days_to_election']==
                         state_data['days_to_election'].min()])
    # compute the mean of the latest polls and store it
    poll_pred[i] = latest['margin'].mean()

poll_pred.head(10)
```

```
[ ]: AL   -25.0
AK   -19.0
AZ    -2.5
AR    -7.0
CA    24.0
CO     7.0
CT    25.0
DC    69.0
DE    30.0
FL     2.0
dtype: float64
```

Because we stored the state identifier as the index, we could use states as the loop counter. In complex numeric indexing cases, looping through names can be a good alternative.

[ ]:
```
poll_pred_alt = pd.Series(index=st_names)

# loop across the 50 states plus DC
for state in st_names:
    # subset the polls data for the current state
    state_data = polls08[polls08['state']==state]
    # subset the latest poll for the current state
    latest = (state_data[state_data['days_to_election']==
                         state_data['days_to_election'].min()])
    # compute the mean of the latest poll and store it in the results vector
    poll_pred_alt[state] = latest['margin'].mean()

# check that results are the same
poll_pred.equals(poll_pred_alt)
```

[ ]:
```
True
```

Recall from chapter 3 that if we want to perform element-wise arithmetic on two equal length vectors whose elements are sorted correctly, the indexes should be identical. Since the `poll_pred` index is state abbreviations, we can reset the `pres08` index to state abbreviations and then extract the margin column without modifying the data frame in place. Of course, we could also add `poll_pred` to the data frame, which we will illustrate later.

[ ]:
```
# errors of latest polls
errors = pres08.set_index('state')['margin'] - poll_pred

errors.head()
```

[ ]:
```
state
AL     4.0
AK    -2.0
AZ    -6.5
AR   -13.0
CA     0.0
dtype: float64
```

[ ]:
```
# mean prediction error
errors.mean()
```

[ ]:
```
1.0620915032679739
```

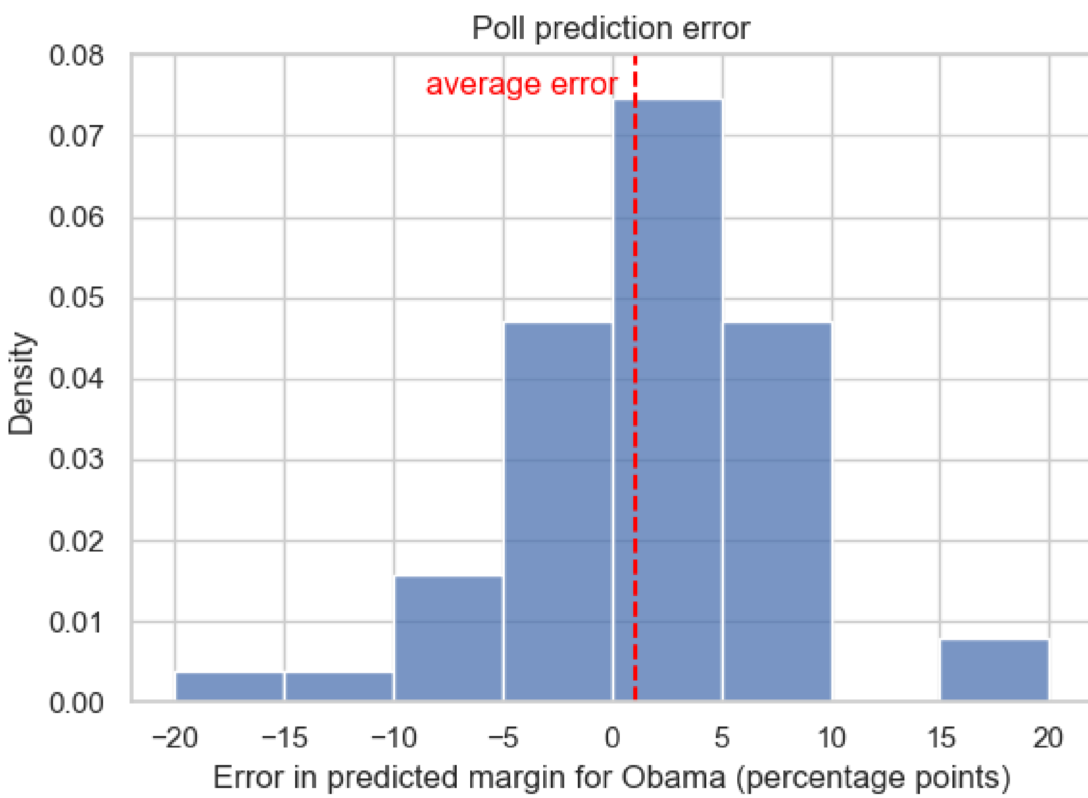
[ ]:
```
# root mean squared prediction error
np.sqrt((errors**2).mean())
```

[ ]:
```
5.908940458495747
```

[ ]:
```
# histogram of errors
sns.set_theme(style="whitegrid")
```

```python
sns.displot(
    x=errors, stat='density', binrange=(-20, 20), binwidth=5,
    height=4, aspect=1.5,
).set(xlabel='Error in predicted margin for Obama (percentage points)',
      title='Poll prediction error',
      ylim=(0, 0.08)).despine(right=False, top=False)

# add a vertical line representing the mean
plt.axvline(x=errors.mean(), color='red', linestyle='--')

# add a text label for the median
plt.text(x=-8.5, y=0.075, s='average error', color='red')
```

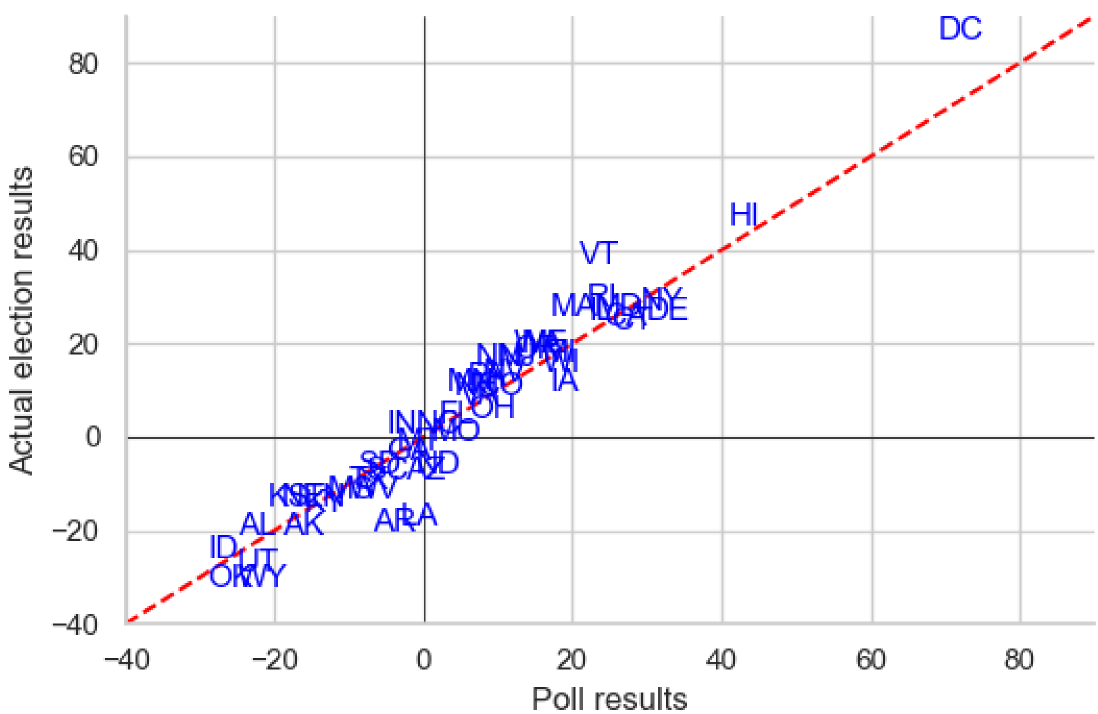
[ ]: Text(-8.5, 0.075, 'average error')



[ ]:
```python
# add poll_pred to pres08 for easier plotting and analysis
# reset the index to match the index of pres08 and drop the old index
pres08['poll_pred'] = poll_pred.reset_index(drop=True)

# marker='' generates an "empty" plot
```

```python
sns.relplot(
    data=pres08, x='poll_pred', y='margin', marker='',
    height=4, aspect=1.5,
).set(xlabel='Poll results', ylabel='Actual election results',
      ylim=(-40, 90), xlim=(-40, 90))

# add state abbreviations
for i in range(len(pres08['state'])):
    plt.text(x=pres08['poll_pred'][i], y=pres08['margin'][i],
             s=pres08['state'][i], color='blue')

# add 45 degree line
plt.gca().axline((0, 0), slope=1, color='red', linestyle='--')

# add vertical and horizontal lines at 0
plt.axvline(x=0, color='black', linewidth=0.5)
plt.axhline(y=0, color='black', linewidth=0.5)
```

[ ]: <matplotlib.lines.Line2D at 0x27b86e79360>




```python
[ ]: # which state polls called the election wrong?
pres08['state'][np.sign(pres08['poll_pred']) != np.sign(pres08['margin'])]
```

[ ]:
```
14    IN
25    MO
33    NC
Name: state, dtype: object
```

[ ]:
```python
# what was the actual margin for these states?
pres08['margin'][np.sign(pres08['poll_pred']) != np.sign(pres08['margin'])]
```

[ ]:
```
14    1
25   -1
33    1
Name: margin, dtype: int64
```

[ ]:
```python
# actual results: total number of electoral votes won by Obama
pres08['EV'][pres08['margin']>0].sum()
```

[ ]:
```
364
```

[ ]:
```python
# poll prediction
pres08['EV'][pres08['poll_pred']>0].sum()
```

[ ]:
```
349
```

[ ]:
```python
# load the data
pollsUS08 = pd.read_csv('pollsUS08.csv')

# compute number of days to the election as before
pollsUS08['middate'] = pd.to_datetime(pollsUS08['middate'])

pollsUS08['days_to_election'] = (x - pollsUS08['middate']).dt.days

# empty numpy vectors to store predictions for Obama and McCain
Obama_pred = np.zeros(90)
McCain_pred = np.zeros(90)
```

With zero-based indexing, the days sequence 1-90 does not match the vector index 0-89. We need to account for this somewhere. One option, among many, is to add 1 to the loop counter when working with the days sequence.

[ ]:
```python
for i in range(len(Obama_pred)):
    # take all polls conducted within the past 7 days
    week_data = (pollsUS08[(pollsUS08['days_to_election'] <= (90 - (i + 1) + 7))
                           & (pollsUS08['days_to_election'] > (90 - (i + 1)))])
    # compute the mean of the polls for Obama and McCain
    Obama_pred[i] = week_data['Obama'].mean()
    McCain_pred[i] = week_data['McCain'].mean()

# put together a data frame for plotting
```

```
pollsUS08_avg = pd.DataFrame({'Obama': Obama_pred,
                              'McCain': McCain_pred,
                              'days_to_election': np.arange(90, 0, -1)})

pollsUS08_avg.head()
```

[ ]:

```
       Obama     McCain  days_to_election
0  44.538462  40.692308                90
1  45.000000  40.692308                89
2  45.230769  40.846154                88
3  45.750000  42.000000                87
4  45.888889  42.000000                86
```

Recall from chapter 3 that plotting groups in seaborn works best when the grouping variable is stored in its own column. In this case, the grouping variable is the candidate. To pivot the candidates into a single column, we need to reshape the data into a longer format, which can be accomplished with the `melt()` method in pandas.

[ ]:

```
# reshape the data: pivot longer using melt
pollsUS08_avg_long = pollsUS08_avg.melt(id_vars='days_to_election',
                                        var_name='Candidate',
                                        value_name='poll_avg')

pollsUS08_avg_long.head()
```

[ ]:

```
   days_to_election Candidate   poll_avg
0                90     Obama  44.538462
1                89     Obama  45.000000
2                88     Obama  45.230769
3                87     Obama  45.750000
4                86     Obama  45.888889
```

[ ]:

```
pollsUS08_avg_long.tail()
```

[ ]:

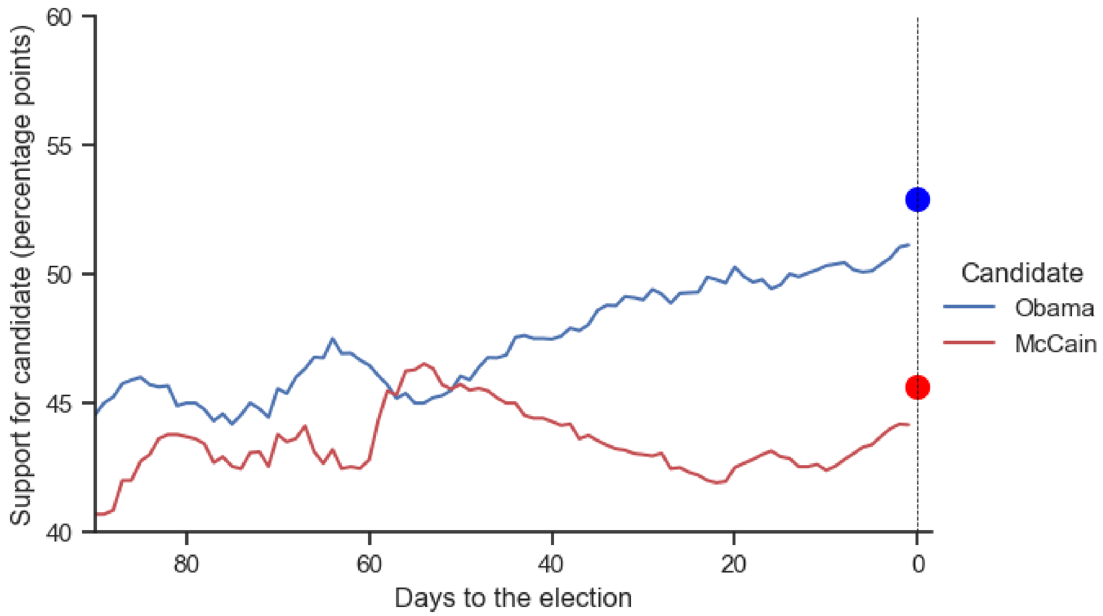
```
     days_to_election Candidate   poll_avg
175                 5    McCain  43.384615
176                 4    McCain  43.708333
177                 3    McCain  44.000000
178                 2    McCain  44.185185
179                 1    McCain  44.160000
```

[ ]:

```
sns.set_theme(style="ticks")

# plot going from 90 days to 1 day before the election
sns.relplot(
    data=pollsUS08_avg_long, x='days_to_election', y='poll_avg',
    hue='Candidate', kind='line',
    palette=['b', 'r'], height=4, aspect=1.5
```

```
).set(ylim=(40, 60), yticks=range(40, 61, 5),
      xlim=(90, -1.5), # small buffer in right limit for aesthetics
      xlabel='Days to the election',
      ylabel='Support for candidate (percentage points)')

# line indicating election day
plt.axvline(x=0, color='black', linestyle='--', linewidth=0.5)

# actual election results
plt.scatter(0, 52.93, color='blue', s=100)
plt.scatter(0, 45.65, color='red', s=100)
```

[ ]: <matplotlib.collections.PathCollection at 0x27b8647b6a0>



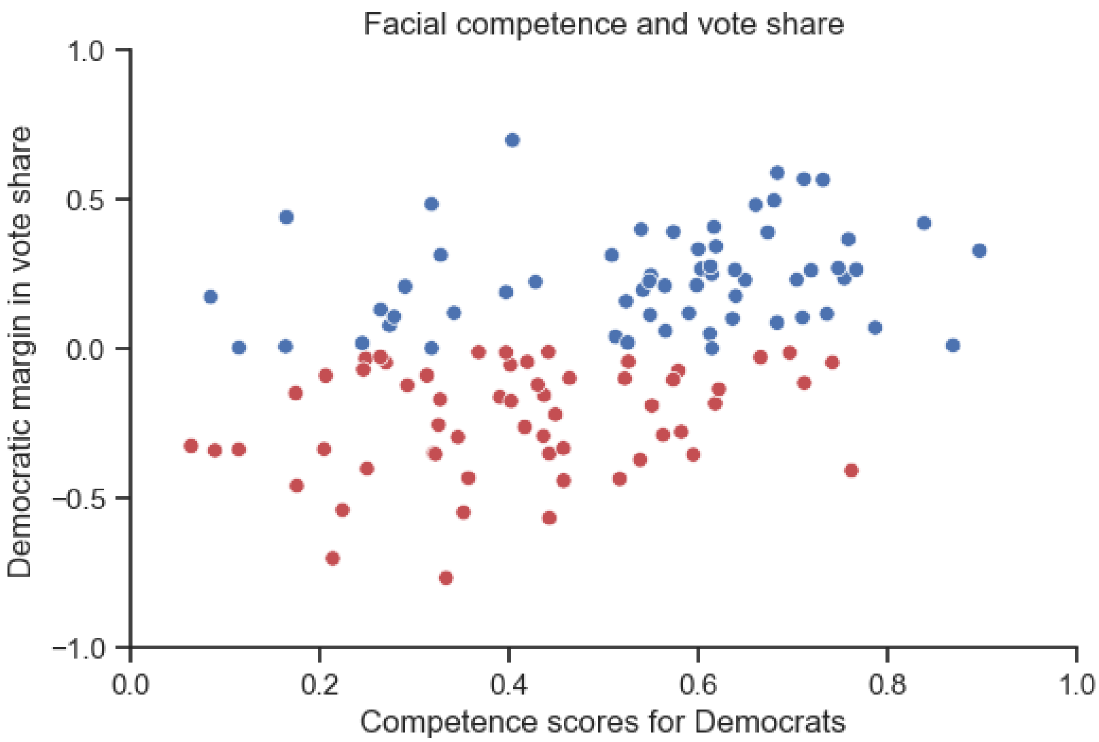
Section 4.2: Linear Regression

Section 4.2.1: Facial Appearance and Election Outcomes

[ ]:
```
# load the data
face = pd.read_csv('face.csv')

# two-party vote share for Democrats and Republicans
face['d_share'] = face['d.votes'] / (face['d.votes'] + face['r.votes'])
face['r_share'] = face['r.votes'] / (face['d.votes'] + face['r.votes'])
face['diff_share'] = face['d_share'] - face['r_share']

sns.relplot(
```

```
    data=face, x='d.comp', y='diff_share',
    hue='w.party', palette=['b','r'], legend=False, height=4, aspect=1.5
).set(xlim=(0, 1), ylim=(-1, 1), yticks=np.arange(-1.0, 1.5, 0.5),
      title='Facial competence and vote share',
      xlabel='Competence scores for Democrats',
      ylabel='Democratic margin in vote share')
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x27b86ec7d00>



Section 4.2.2: Correlation and Scatter Plots

[ ]:
```
face['d.comp'].corr(face['diff_share'])
```

[ ]: 0.43277434572761064

Section 4.2.3: Least Squares

[ ]:
```
# import the statsmodels formula API
import statsmodels.formula.api as smf

# replace dots in column names with underscores
face.columns = face.columns.str.replace('.', '_')
```

```
face.columns
```

```
[ ]: Index(['year', 'state', 'winner', 'loser', 'w_party', 'l_party', 'd_comp',
       'r_comp', 'd_votes', 'r_votes', 'd_share', 'r_share', 'diff_share'],
      dtype='object')
```

*Note: **statsmodels** works best when column names do not contain spaces or special characters, such as dots. The formula interface, which is powered by the **patsy** package, enables the use of Python code in formula strings. For example, we may wish to perform a log transformation on a variable using **np.log()** directly in the formula. This capability requires that the formula contain valid Python object names. Spaces and dots are generally not valid in Python object names, though pandas allows them in column names. One can circumvent this issue by wrapping column names in **Q()**. Often, though, it is easier to simply replace spaces and dots with underscores, as above.*

```
[ ]: # fit the model; the statsmodels formula API uses R-style formulas
fit = smf.ols('diff_share ~ d_comp', data=face).fit()

fit.model.formula
```

```
[ ]: 'diff_share ~ d_comp'
```

```
[ ]: # get the estimated coefficients
fit.params
```

```
[ ]: Intercept   -0.312226
d_comp       0.660381
dtype: float64
```

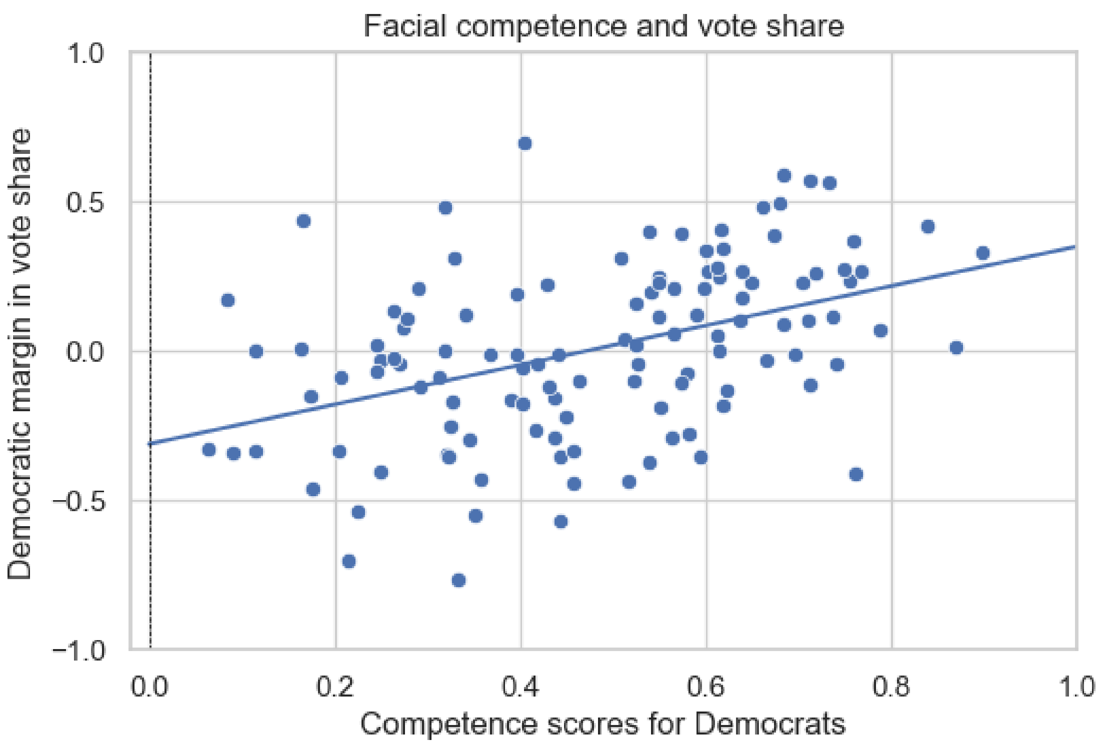
```
[ ]: # get fitted or predicted values
fit.fittedvalues.head(n=10)
```

```
[ ]: 0    0.060604
1   -0.086433
2    0.092171
3    0.045392
4    0.136987
5   -0.100572
6   -0.045593
7    0.085994
8    0.043438
9    0.261788
dtype: float64
```

```
[ ]: # store the intercept and slope for plotting a regression line
intercept, slope = fit.params

# create a vector for the x-axis limits
x_values = np.array([0,1])
```

```python
# using the slope and intercept, predict y values for the x axis limits
y_values = intercept + slope * x_values

sns.set_theme(style="whitegrid")

# plot a scatterplot and overlay a regression line
sns.relplot(
    data=face, x='d_comp', y='diff_share', height=4, aspect=1.5
).set(ylim=(-1, 1), yticks=np.arange(-1.0, 1.5, 0.5),
      xlim=(-0.02, 1), # small buffer in left limit for aesthetics
      title='Facial competence and vote share',
      xlabel='Competence scores for Democrats',
      ylabel='Democratic margin in vote share').despine(right=False, top=False)

plt.plot(x_values, y_values) # regression line

plt.axvline(x=0, color='black', linewidth=0.5, linestyle='--')
```

[ ]: <matplotlib.lines.Line2D at 0x27b86ec7940>



Note that seaborn has a built-in function for plotting regression lines, which we will use later, but it is not as easy to show the regression line's intercept.

```
[ ]: epsilon_hat = fit.resid # residuals
     np.sqrt((epsilon_hat**2).mean()) # RMSE
```

```
[ ]: 0.2642360764039512
```

Section 4.2.4: Regression Towards the Mean

Section 4.2.5: Merging Datasets in Pandas

```
[ ]: # load the 2012 data
     pres12 = pd.read_csv('pres12.csv')

     # remove poll_pred from pres08
     pres08.drop('poll_pred', axis=1, inplace=True)

     # quick look at the two data sets
     pres08.head()
```

```
[ ]:   state.name state  Obama  McCain  EV  margin
     0    Alabama    AL     39      60   9     -21
     1     Alaska    AK     38      59   3     -21
     2    Arizona    AZ     45      54  10      -9
     3   Arkansas    AR     39      59   6     -20
     4 California    CA     61      37  55      24
```

```
[ ]: pres12.head()
```

```
[ ]:   state  Obama  Romney  EV
     0    AL     38      61   9
     1    AK     41      55   3
     2    AZ     45      54  11
     3    AR     37      61   6
     4    CA     60      37  55
```

```
[ ]: # merge two data frames
     pres = pd.merge(pres08, pres12, on='state')

     pres.head()
```

```
[ ]:   state.name state  Obama_x  McCain  EV_x  margin  Obama_y  Romney  EV_y
     0    Alabama    AL       39      60     9     -21       38      61     9
     1     Alaska    AK       38      59     3     -21       41      55     3
     2    Arizona    AZ       45      54    10      -9       45      54    11
     3   Arkansas    AR       39      59     6     -20       37      61     6
     4 California    CA       61      37    55      24       60      37    55
```

```
[ ]: pres.describe().round(2)
```

[ ]:

	Obama_x	McCain	EV_x	margin	Obama_y	Romney	EV_y
count	51.00	51.00	51.00	51.00	51.00	51.00	51.00
mean	51.37	47.06	10.55	4.31	49.06	49.04	10.55
std	11.04	11.04	9.58	22.07	11.80	11.79	9.69
min	33.00	7.00	3.00	-32.00	25.00	7.00	3.00
25%	43.00	40.00	4.50	-13.00	40.50	41.00	4.50
50%	51.00	47.00	8.00	4.00	51.00	48.00	8.00
75%	57.50	56.00	11.50	17.50	56.00	58.00	11.50
max	92.00	66.00	55.00	85.00	91.00	73.00	55.00

[ ]:

```python
# change the variable name for illustration
pres12.rename(columns={'state': 'state_abb'}, inplace=True)

pres12.head()
```

[ ]:

	state_abb	Obama	Romney	EV
0	AL	38	61	9
1	AK	41	55	3
2	AZ	45	54	11
3	AR	37	61	6
4	CA	60	37	55

[ ]:

```python
# merging data sets using variable keys with different names
pres = (pd.merge(pres08, pres12, left_on='state', right_on='state_abb').
        drop('state_abb', axis=1))

pres.head()
```

[ ]:

	state.name	state	Obama_x	McCain	EV_x	margin	Obama_y	Romney	EV_y
0	Alabama	AL	39	60	9	-21	38	61	9
1	Alaska	AK	38	59	3	-21	41	55	3
2	Arizona	AZ	45	54	10	-9	45	54	11
3	Arkansas	AR	39	59	6	-20	37	61	6
4	California	CA	61	37	55	24	60	37	55

[ ]:

```python
pres.describe().round(2)
```

[ ]:

	Obama_x	McCain	EV_x	margin	Obama_y	Romney	EV_y
count	51.00	51.00	51.00	51.00	51.00	51.00	51.00
mean	51.37	47.06	10.55	4.31	49.06	49.04	10.55
std	11.04	11.04	9.58	22.07	11.80	11.79	9.69
min	33.00	7.00	3.00	-32.00	25.00	7.00	3.00
25%	43.00	40.00	4.50	-13.00	40.50	41.00	4.50
50%	51.00	47.00	8.00	4.00	51.00	48.00	8.00
75%	57.50	56.00	11.50	17.50	56.00	58.00	11.50
max	92.00	66.00	55.00	85.00	91.00	73.00	55.00

[ ]:
```python
# concatenate two data frames
pres1 = pd.concat([pres08, pres12], axis='columns')

pres1.head()
```

[ ]:

	state.name	state	Obama	McCain	EV	margin	state_abb	Obama	Romney	EV
0	Alabama	AL	39	60	9	-21	AL	38	61	9
1	Alaska	AK	38	59	3	-21	AK	41	55	3
2	Arizona	AZ	45	54	10	-9	AZ	45	54	11
3	Arkansas	AR	39	59	6	-20	AR	37	61	6
4	California	CA	61	37	55	24	CA	60	37	55

[ ]:
```python
'''
DC and DE are flipped in this alternative approach, and we have overlapping
column names.
'''
pres1.iloc[7:9]
```

[ ]:

	state.name	state	Obama	McCain	EV	margin	state_abb	Obama	Romney	EV
7	D.C.	DC	92	7	3	85	DE	59	40	3
8	Delaware	DE	62	37	3	25	DC	91	7	3

[ ]:
```python
# merge() does not have this problem
pres.iloc[7:9]
```

[ ]:

	state.name	state	Obama_x	McCain	EV_x	margin	Obama_y	Romney	EV_y
7	D.C.	DC	92	7	3	85	91	7	3
8	Delaware	DE	62	37	3	25	59	40	3

If we move the state identifier to the index, then `concat()` will align the indexes correctly. We still have overlapping column names, though.

[ ]:
```python
pres2 = pd.concat([pres08.set_index('state'),
                   pres12.set_index('state_abb')], axis='columns')

pres2.iloc[7:9]
```

[ ]:

	state.name	Obama	McCain	EV	margin	Obama	Romney	EV
DC	D.C.	92	7	3	85	91	7	3
DE	Delaware	62	37	3	25	59	40	3

Pandas and numpy do not have built-in z-score functions. We can either calculate the z-scores manually, use the zscore function from the scipy module, or build a simple function of our own. In this case, the final option is straightforward.

[ ]:
```python
# define a function to standardize a vector (calculate z-scores)
def standardize(x):
    return (x - x.mean()) / x.std()
```

```
pres['Obama2008_z'] = standardize(pres['Obama_x'])
pres['Obama2012_z'] = standardize(pres['Obama_y'])

# estimated intercept is essentially zero
fit1 = smf.ols('Obama2012_z ~ Obama2008_z', data=pres).fit()
fit1.params
```

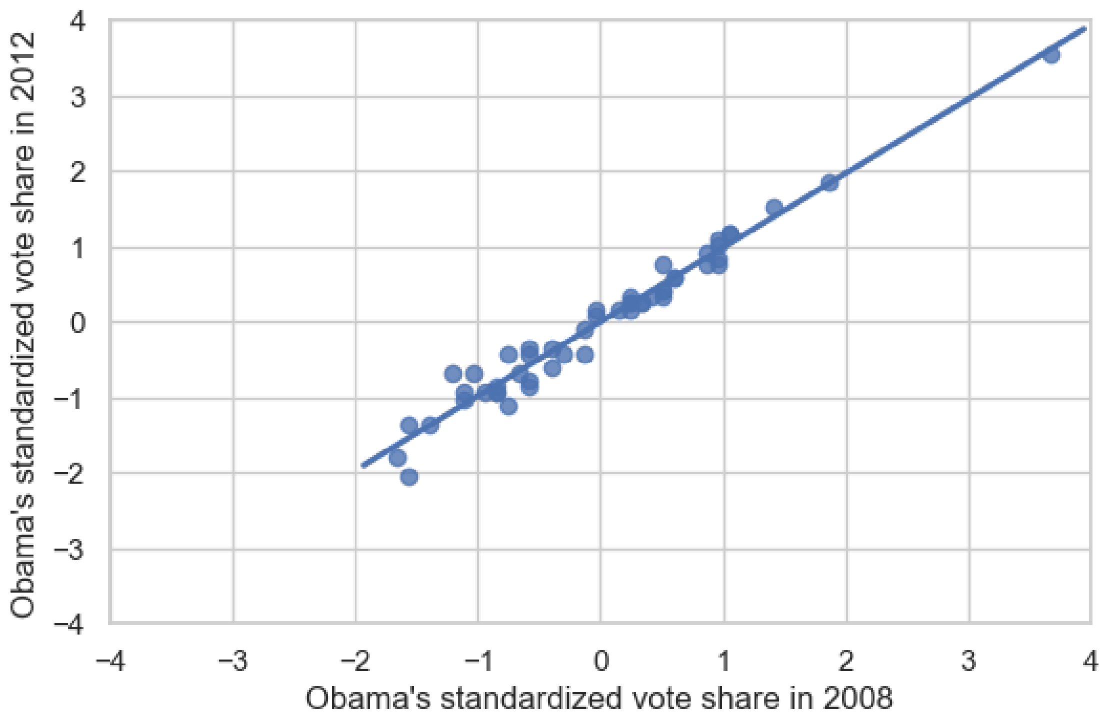
```
[ ]: Intercept     -2.914335e-16
     Obama2008_z    9.834419e-01
     dtype: float64
```

```
[ ]: # regression without an intercept
fit1 = smf.ols('Obama2012_z ~ -1 + Obama2008_z', data=pres).fit()

# estimated slope is identical
fit1.params
```

```
[ ]: Obama2008_z    0.983442
     dtype: float64
```

```
[ ]: # plot using seaborn's built-in lmplot function
sns.lmplot(
    data=pres, x='Obama2008_z', y='Obama2012_z', ci=None, truncate=False,
    height=4, aspect=1.5,
).set(xlim=(-4, 4), ylim=(-4, 4),
      xlabel="Obama's standardized vote share in 2008",
      ylabel="Obama's standardized vote share in 2012").despine(
          right=False, top=False)
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x27b88971600>
```



Setting `truncate=False` *extends the regression line a bit past the data range, but only up to the axis limits that* `lmplot()` *sets internally, not to the axis limits we set manually in* `.set()`.

[ ]:
```
# bottom quartile
((pres['Obama2012_z'] > pres['Obama2008_z'])[
    (pres['Obama2008_z'] <= pres['Obama2008_z'].quantile(0.25))].mean())
```

[ ]: 0.5714285714285714

[ ]:
```
# top quartile
((pres['Obama2012_z'] > pres['Obama2008_z'])[
    (pres['Obama2008_z'] >= pres['Obama2008_z'].quantile(0.75))].mean())
```

[ ]: 0.46153846153846156

Section 4.2.6: Model Fit

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

# regress Buchanan's 2000 votes on Perot's 1996 votes
fit2 = smf.ols('Buchanan00 ~ Perot96', data=florida).fit()

fit2.params
```

```
[ ]: Intercept    1.345752
     Perot96      0.035915
     dtype: float64
```

```
[ ]: # compute TSS (total sum of squares)
     TSS2 = ((florida['Buchanan00'] - florida['Buchanan00'].mean())**2).sum()

     # compute SSR (sum of squared residuals)
     SSR2 = (fit2.resid**2).sum()

     # Coefficient of determination (R-squared)
     (TSS2 - SSR2) / TSS2
```

```
[ ]: 0.513033325505709
```

```
[ ]: def R2(fit):
         resid = fit.resid # residuals
         y = fit.fittedvalues + resid # outcome variable
         TSS = ((y - y.mean())**2).sum()
         SSR = (resid**2).sum()
         R2 = (TSS - SSR) / TSS
         return R2

     R2(fit2)
```

```
[ ]: 0.513033325505709
```

```
[ ]: # built-in statsmodels R2 attribute
     fit2.rsquared
```

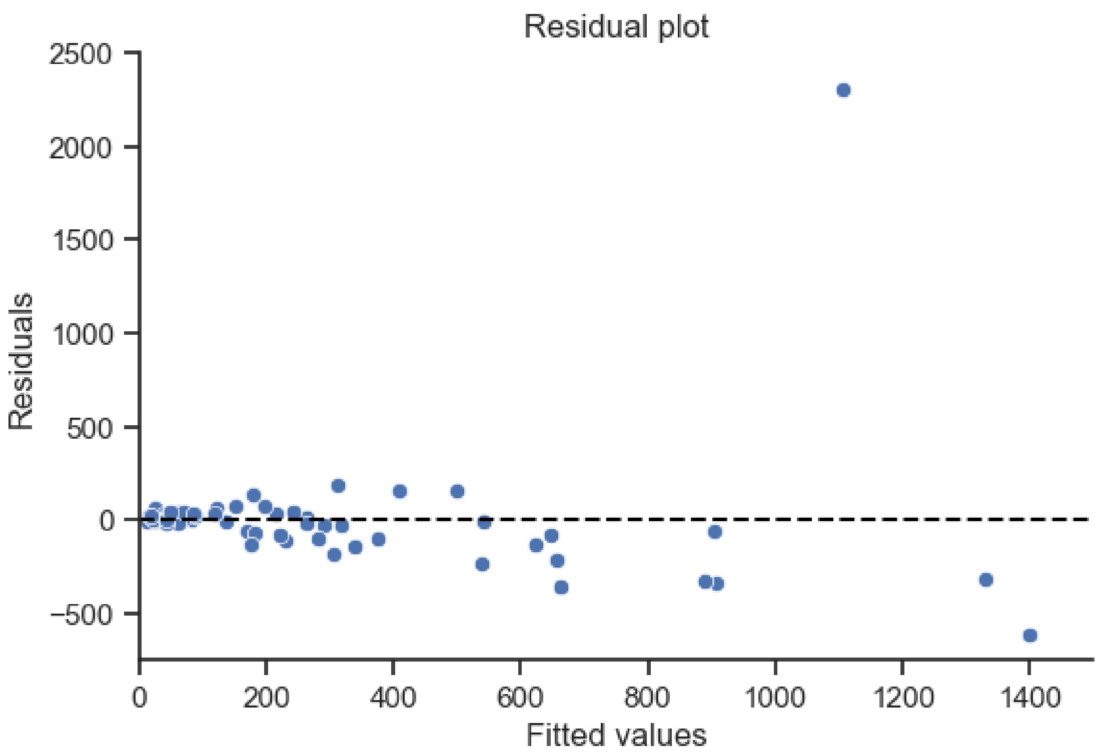
```
[ ]: 0.5130333255057089
```

```
[ ]: fit1.rsquared
```

```
[ ]: 0.9671579118703088
```

```
[ ]: sns.set_theme(style="ticks")

     sns.relplot(
         x=fit2.fittedvalues, y=fit2.resid, height=4, aspect=1.5
     ).set(xlabel='Fitted values', ylabel='Residuals', title='Residual plot',
           xlim=(0,1500), ylim=(-750, 2500))

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

```
[ ]: <matplotlib.lines.Line2D at 0x27b889ef430>
```



[ ]:
```
florida['county'][fit2.resid == fit2.resid.max()]
```

[ ]:
```
49    PalmBeach
Name: county, dtype: object
```

[ ]:
```
# data without palm beach
florida_pb = florida.loc[florida.county != 'PalmBeach'].copy()

fit3 = smf.ols('Buchanan00 ~ Perot96', data=florida_pb).fit()

fit3.params
```

[ ]:
```
Intercept    45.841933
Perot96       0.024352
dtype: float64
```

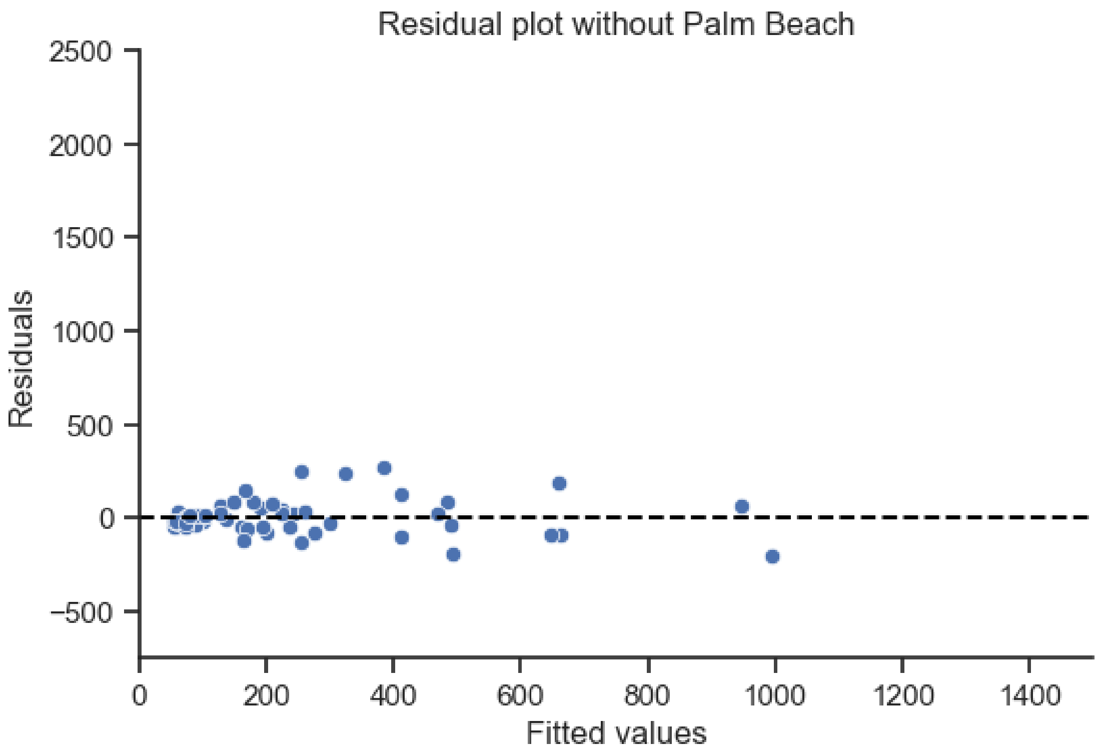
[ ]:
```
R2(fit3)
```

[ ]:
```
0.8511674585300796
```

[ ]:
```
sns.relplot(
    x=fit3.fittedvalues, y=fit3.resid, height=4, aspect=1.5
).set(xlabel='Fitted values', ylabel='Residuals',
```

```
      title='Residual plot without Palm Beach',
      xlim=(0,1500), ylim=(-750, 2500))

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

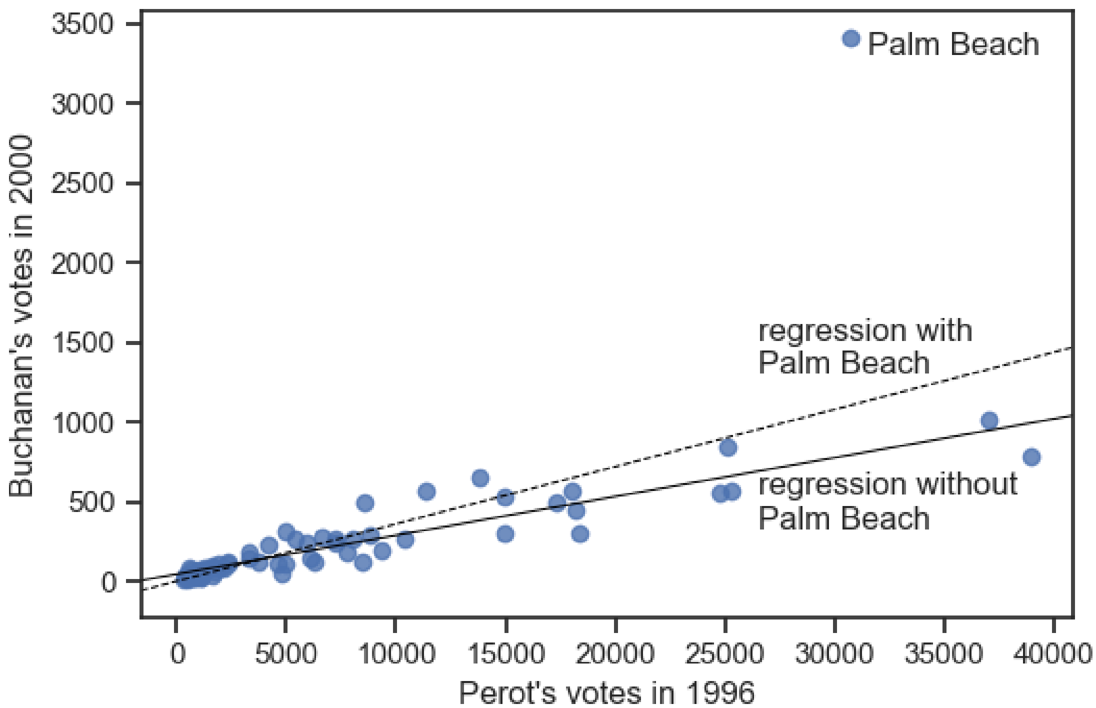
[ ]: <matplotlib.lines.Line2D at 0x27b88a13d30>



[ ]:
```
# plot both regression lines on the same scatterplot

# use seaborn's lmplot() to plot the regression line associated with fit2
sns.lmplot(
    data=florida, x='Perot96', y='Buchanan00', ci=None, truncate=False,
    height=4, aspect=1.5,
    line_kws={'color': 'black', 'linestyle': '--', 'linewidth': 0.75},
).set(xlabel="Perot's votes in 1996",
      ylabel="Buchanan's votes in 2000").despine(right=False, top=False)

# store the x-axis limits from the plot
x_lim = plt.gca().get_xlim()

# store the limits as a data frame with the same column name as the predictor
# note: we only need two points to plot a linear regression line
```

```python
x_values = pd.DataFrame({'Perot96': x_lim})

# use the fit3 model and the predict method to generate y values
y_values = fit3.predict(x_values)

# plot the regression line associated with fit3
plt.plot(x_values, y_values, color='black', linewidth=0.75)

plt.text(x=31500, y=3300, s='Palm Beach')
plt.text(x=26500, y=1300, s='regression with\nPalm Beach')
plt.text(x=26500, y=330, s='regression without\nPalm Beach')
```

[ ]: Text(26500, 330, 'regression without\nPalm Beach')



Section 4.3: Regression and Causation

Section 4.3.1: Randomized Experiments

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

# proportion of female politicians in reserved GP vs. unreserved GP
women['female'][women.reserved==1].mean()
```

[ ]: 1.0

[ ]:
```python
women['female'][women.reserved==0].mean()
```

[ ]: 0.07476635514018691

[ ]:
```python
# drinking water facilities
(women['water'][women.reserved==1].mean() -
 women['water'][women.reserved==0].mean())
```

[ ]: 9.252422983731394

[ ]:
```python
# irrigation facilities
(women['irrigation'][women.reserved==1].mean() -
 women['irrigation'][women.reserved==0].mean())
```

[ ]: -0.369331948771201

[ ]:
```python
smf.ols('water ~ reserved', data=women).fit().params
```

[ ]:
```
Intercept    14.738318
reserved      9.252423
dtype: float64
```

[ ]:
```python
smf.ols('irrigation ~ reserved', data=women).fit().params
```

[ ]:
```
Intercept    3.387850
reserved    -0.369332
dtype: float64
```

Section 4.3.2: Regression with Multiple Predictors

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

# convert messages to categorical with Control as the reference category
cats = ['Control', 'Civic Duty', 'Hawthorne', 'Neighbors']

social['messages'] = (social['messages'].astype('category').
                      cat.reorder_categories(cats))

social['messages'].cat.categories
```

[ ]: Index(['Control', 'Civic Duty', 'Hawthorne', 'Neighbors'], dtype='object')

[ ]:
```python
social['messages'].value_counts()
```

[ ]:
```
messages
Control       191243
Civic Duty     38218
Hawthorne      38204
```

```
Neighbors      38201
Name: count, dtype: int64
```

[ ]:
```python
fit = smf.ols('primary2006 ~ messages', data=social).fit()

fit.params
```

[ ]:
```
Intercept                  0.296638
messages[T.Civic Duty]     0.017899
messages[T.Hawthorne]      0.025736
messages[T.Neighbors]      0.081310
dtype: float64
```

[ ]:
```python
# create indicator variables
social['Civic_Duty'] = np.where(social['messages']=='Civic Duty', 1, 0)
social['Hawthorne'] = np.where(social['messages']=='Hawthorne', 1, 0)
social['Neighbors'] = np.where(social['messages']=='Neighbors', 1, 0)

# an alternative using pandas get_dummies method
dummies = (pd.get_dummies(social['messages'], drop_first=True, dtype='int').
           rename(columns={'Civic Duty': 'Civic_Duty'}))

social[['Civic_Duty', 'Hawthorne', 'Neighbors']].equals(dummies)
```

[ ]:
```
True
```

[ ]:
```python
# fit the same regression as above using the indicator variables
smf.ols('primary2006 ~ Civic_Duty + Hawthorne + Neighbors',
        data=social).fit().params
```

[ ]:
```
Intercept     0.296638
Civic_Duty    0.017899
Hawthorne     0.025736
Neighbors     0.081310
dtype: float64
```

[ ]:
```python
# create a data frame with unique values of messages
unique_messages = pd.DataFrame({'messages': social['messages'].cat.categories})

unique_messages
```

[ ]:
```
     messages
0     Control
1  Civic Duty
2   Hawthorne
3   Neighbors
```

[ ]:
```
# make prediction for each observation from the new data frame
fit.predict(unique_messages)
```

[ ]:
```
0    0.296638
1    0.314538
2    0.322375
3    0.377948
dtype: float64
```

[ ]:
```
# sample average
social.groupby('messages')['primary2006'].mean()
```

[ ]:
```
messages
Control        0.296638
Civic Duty     0.314538
Hawthorne      0.322375
Neighbors      0.377948
Name: primary2006, dtype: float64
```

[ ]:
```
# linear regression without intercept
fit_noint = smf.ols('primary2006 ~ -1 + messages', data=social).fit()

fit_noint.params
```

[ ]:
```
messages[Control]       0.296638
messages[Civic Duty]    0.314538
messages[Hawthorne]     0.322375
messages[Neighbors]     0.377948
dtype: float64
```

[ ]:
```
# estimated average effect of Neighbors condition
fit.params['messages[T.Neighbors]'].round(7)
```

[ ]:
```
0.0813099
```

[ ]:
```
# difference in means
(social['primary2006'][social['messages']=='Neighbors'].mean() -
 social['primary2006'][social['messages']=='Control'].mean()).round(7)
```

[ ]:
```
0.0813099
```

[ ]:
```
# adjusted Rsqure
def adjR2(fit):
    resid = fit.resid # residuals
    y = fit.fittedvalues + resid # outcome variable
    n = len(y)
    p = len(fit.params)
    TSS_adj = ((y - y.mean())**2).sum() / (n - 1)
```

```
    SSR_adj = (resid**2).sum() / (n - p)
    R2_adj = 1 - SSR_adj / TSS_adj
    return R2_adj

adjR2(fit).round(7)
```

[ ]: 0.0032728

[ ]:
```
R2(fit).round(7) # unadjusted Rsquare calculation
```

[ ]: 0.0032826

[ ]:
```
fit.rsquared_adj.round(7)
```

[ ]: 0.0032728

Section 4.3.3: Heterogeneous Treatment Effects

[ ]:
```
# average treatment effect (ATE) among those who voted in 2004 primary
social_voter = social.loc[social['primary2004']==1].copy()

ate_voter = (
    social_voter['primary2006'][social_voter['messages']=='Neighbors'].mean()
    - social_voter['primary2006'][social_voter['messages']=='Control'].mean()
)

ate_voter
```

[ ]: 0.09652525355693264

[ ]:
```
# ATE among those who did not vote in 2004 primary
social_nonvoter = social.loc[social['primary2004']==0].copy()

ate_nonvoter = (
    social_nonvoter['primary2006'][social_nonvoter['messages']=='Neighbors'].
    mean() -
    social_nonvoter['primary2006'][social_nonvoter['messages']=='Control'].
    mean()
)

ate_nonvoter
```

[ ]: 0.0692961746200847

[ ]:
```
# difference
ate_voter - ate_nonvoter
```

[ ]: 0.02722907893684795

```
[ ]: # subset neighbors and control groups
social_neighbor = (
    social.loc[social['messages'].isin(['Control', 'Neighbors'])].copy()
)

# re-encode the categorical variable to remove original levels
social_neighbor['messages'] = (
    social_neighbor['messages'].astype('object').astype('category')
)

# standard way to generate main and interaction effects
fit_int = smf.ols(
    'primary2006 ~ primary2004 + messages + primary2004:messages',
    data=social_neighbor).fit()

fit_int.params
```

```
[ ]: Intercept                              0.237110
     messages[T.Neighbors]                  0.069296
     primary2004                            0.148695
     primary2004:messages[T.Neighbors]      0.027229
     dtype: float64
```

```
[ ]: social_neighbor['age'] = 2006 - social_neighbor['yearofbirth']

social_neighbor['age'].describe().round(2)
```

```
[ ]: count    229444.00
     mean         49.82
     std          14.46
     min          20.00
     25%          41.00
     50%          50.00
     75%          59.00
     max         106.00
     Name: age, dtype: float64
```

```
[ ]: fit_age = smf.ols('primary2006 ~ age * messages', data=social_neighbor).fit()

fit_age.params
```

```
[ ]: Intercept                      0.097473
     messages[T.Neighbors]          0.049829
     age                            0.003998
     age:messages[T.Neighbors]      0.000628
     dtype: float64
```

[ ]:
```python
# age = 25, 45, 65, 85 in Neighbors group
age_neighbor = pd.DataFrame({'age': np.arange(25, 86, 20),
                             'messages': 'Neighbors'})

# age = 25, 45, 65, 85 in Control group
age_control = pd.DataFrame({'age': np.arange(25, 86, 20),
                            'messages': 'Control'})

# average treatment effect for age = 25, 45, 65, 85
ate_age = fit_age.predict(age_neighbor) - fit_age.predict(age_control)

ate_age
```

[ ]:
```
0    0.065537
1    0.078103
2    0.090669
3    0.103236
dtype: float64
```

[ ]:
```python
fit_age2 = smf.ols(
    # note: concatenate two strings with '+'
    'primary2006 ~ age + I(age**2) + messages + age:messages + ' +
    'I(age**2):messages', data=social_neighbor).fit()

fit_age2.params
```

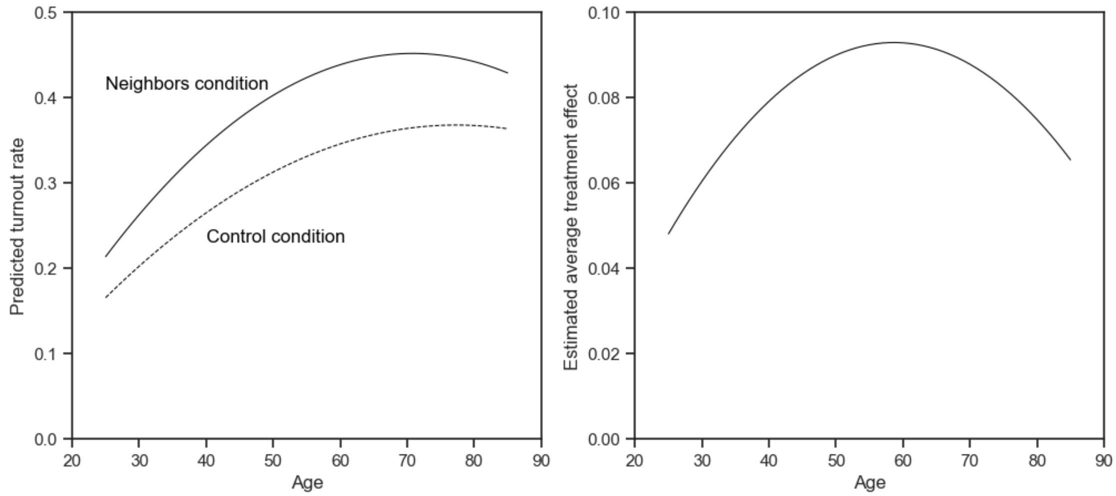
[ ]:
```
Intercept                          -0.073846
messages[T.Neighbors]              -0.043302
age                                 0.011427
age:messages[T.Neighbors]           0.004646
I(age ** 2)                        -0.000074
I(age ** 2):messages[T.Neighbors]  -0.000040
dtype: float64
```

[ ]:
```python
# predict turnout rate under the Neighbors treatment condition
yT_hat = fit_age2.predict(pd.DataFrame({'age': np.arange(25, 86),
                                        'messages': 'Neighbors'}))

# predict turnout rate under the Control condition
yC_hat = fit_age2.predict(pd.DataFrame({'age': np.arange(25, 86),
                                        'messages': 'Control'}))

# save ATE
ate_age2 = yT_hat - yC_hat

ate_age2.head()
```

[ ]:
```
0    0.048091
1    0.050717
2    0.053264
3    0.055731
4    0.058120
dtype: float64
```

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

# plotting the predicted turnout rate under each condition
sns.lineplot(
    x=np.arange(25, 86), y=yT_hat, color='black', linewidth=0.75, ax=axs[0]
).set(xlabel='Age', ylabel='Predicted turnout rate',
      xlim=(20, 90), ylim=(0, 0.5))

sns.lineplot(
    x=np.arange(25, 86), y=yC_hat, color='black', linewidth=0.75,
    linestyle='--', ax=axs[0]
)

# add text labels
axs[0].text(x=25, y=0.41, s='Neighbors condition', color='black')
axs[0].text(x=40, y=0.23, s='Control condition', color='black')

# plotting the average treatment effect as a function of age
sns.lineplot(
    x=np.arange(25, 86), y=ate_age2, color='black', linewidth=0.75, ax=axs[1]
).set(xlabel='Age', ylabel='Estimated average treatment effect',
      xlim=(20, 90), ylim=(0, 0.1))
```

[ ]:
```
[Text(0.5, 0, 'Age'),
 Text(0, 0.5, 'Estimated average treatment effect'),
 (20.0, 90.0),
 (0.0, 0.1)]
```



Section 4.3.4: Regression Discontinuity Design

```
[ ]: # load the data
MPs = pd.read_csv('MPs.csv')

MPs.columns
```

```
[ ]: Index(['surname', 'firstname', 'party', 'ln.gross', 'ln.net', 'yob', 'yod',
        'margin.pre', 'region', 'margin'],
       dtype='object')
```

```
[ ]: # replace dots in column names with underscores
MPs.columns = MPs.columns.str.replace('.', '_')

MPs.columns
```

```
[ ]: Index(['surname', 'firstname', 'party', 'ln_gross', 'ln_net', 'yob', 'yod',
        'margin_pre', 'region', 'margin'],
       dtype='object')
```

```
[ ]: # subset the data into two parties
MPs_labour = MPs.loc[MPs['party']=='labour'].copy()

MPs_tory = MPs.loc[MPs['party']=='tory'].copy()

# two regressions for Labour: negative and positive margin
labour_fit1 = smf.ols('ln_net ~ margin',
                      data=MPs_labour[MPs_labour.margin < 0]).fit()

labour_fit2 = smf.ols('ln_net ~ margin',
```

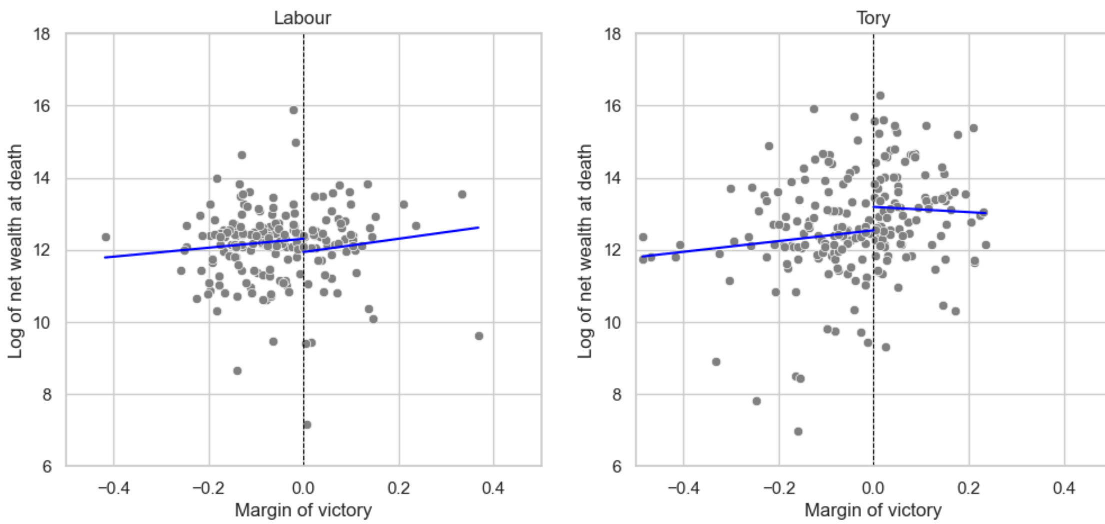
```
                      data=MPs_labour[MPs_labour.margin > 0]).fit()

# two regressions for Tory: negative and positive margin
tory_fit1 = smf.ols('ln_net ~ margin',
                    data=MPs_tory[MPs_tory.margin < 0]).fit()

tory_fit2 = smf.ols('ln_net ~ margin',
                    data=MPs_tory[MPs_tory.margin > 0]).fit()
```

[ ]:
```
# Labour: range of predictions
y1l_range = np.array([MPs_labour['margin'].min(), 0])
y2l_range = np.array([0, MPs_labour['margin'].max()])

# prediction: Labor
y1_labour = labour_fit1.predict(pd.DataFrame({'margin': y1l_range}))
y2_labour = labour_fit2.predict(pd.DataFrame({'margin': y2l_range}))

# Tory: range of predictions
y1t_range = np.array([MPs_tory['margin'].min(), 0])
y2t_range = np.array([0, MPs_tory['margin'].max()])

# prediction: Tory
y1_tory = tory_fit1.predict(pd.DataFrame({'margin': y1t_range}))
y2_tory = tory_fit2.predict(pd.DataFrame({'margin': y2t_range}))
```

[ ]:
```
# Plot comparison
sns.set_theme(style="whitegrid")

fig, axs = plt.subplots(1, 2, figsize=(12, 5))

# scatterplot with regression lines for labour
sns.scatterplot(
    data=MPs_labour, x='margin', y='ln_net', color='gray', ax=axs[0]
).set(xlim=(-0.5, 0.5), ylim=(6, 18), xlabel='Margin of victory',
      ylabel='Log of net wealth at death', title='Labour')

axs[0].axvline(x=0, color='black', linestyle='--', linewidth=0.75)

# add regression lines
axs[0].plot(y1l_range, y1_labour, color='blue')
axs[0].plot(y2l_range, y2_labour, color='blue')

# scatterplot with regression lines for tory
sns.scatterplot(
    data=MPs_tory, x='margin', y='ln_net', color='gray', ax=axs[1]
).set(xlim=(-0.5, 0.5), ylim=(6, 18), xlabel='Margin of victory',
      ylabel='Log of net wealth at death', title='Tory')
```

```
axs[1].axvline(x=0, color='black', linestyle='--', linewidth=0.75)

# add regression lines
axs[1].plot(y1t_range, y1_tory, color='blue')
axs[1].plot(y2t_range, y2_tory, color='blue')
```

[ ]: [<matplotlib.lines.Line2D at 0x27b8de1c4f0>]



[ ]:
```
# average net wealth for Tory MP
tory_MP = np.exp(y2_tory[0])
tory_MP.round(2)
```

[ ]: 533813.47

[ ]:
```
# average net wealth for Tory non-MP
tory_nonMP = np.exp(y1_tory[1])
tory_nonMP.round(2)
```

[ ]: 278762.55

[ ]:
```
# causal effects in pounds
(tory_MP - tory_nonMP).round(2)
```

[ ]: 255050.92

[ ]:
```
# two regressions for Tory: negative and positive margin
tory_fit3 = smf.ols('margin_pre ~ margin',
                    data=MPs_tory[MPs_tory.margin < 0]).fit()
```

```python
tory_fit4 = smf.ols('margin_pre ~ margin',
                    data=MPs_tory[MPs_tory.margin > 0]).fit()

# the difference between the two incercepts is the estimated effect
tory_fit4.params['Intercept'] - tory_fit3.params['Intercept']
```

[ ]: -0.017255775697591326