

Python Code for QSS Chapter 6: Probability

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First Printing

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from math import comb, exp, factorial, log
```

Section 6.1: Probability

Section 6.1.1: Frequentist versus Bayesian

Section 6.1.2: Definition and Axioms

Section 6.1.3: Permutations

```
[ ]: def birthday(k):
    logdenom = k * log(365) + log(factorial(365 - k)) # log denominator
    lognumer = log(factorial(365)) # log numerator
    # P(at least two have the same bday) = 1 - P(nobody has the same bday)
    pr = 1 - exp(lognumer - logdenom) # transform back
    return pr

k = pd.Series(np.arange(1, 51))

bday = k.apply(birthday) # apply the function to each element of k

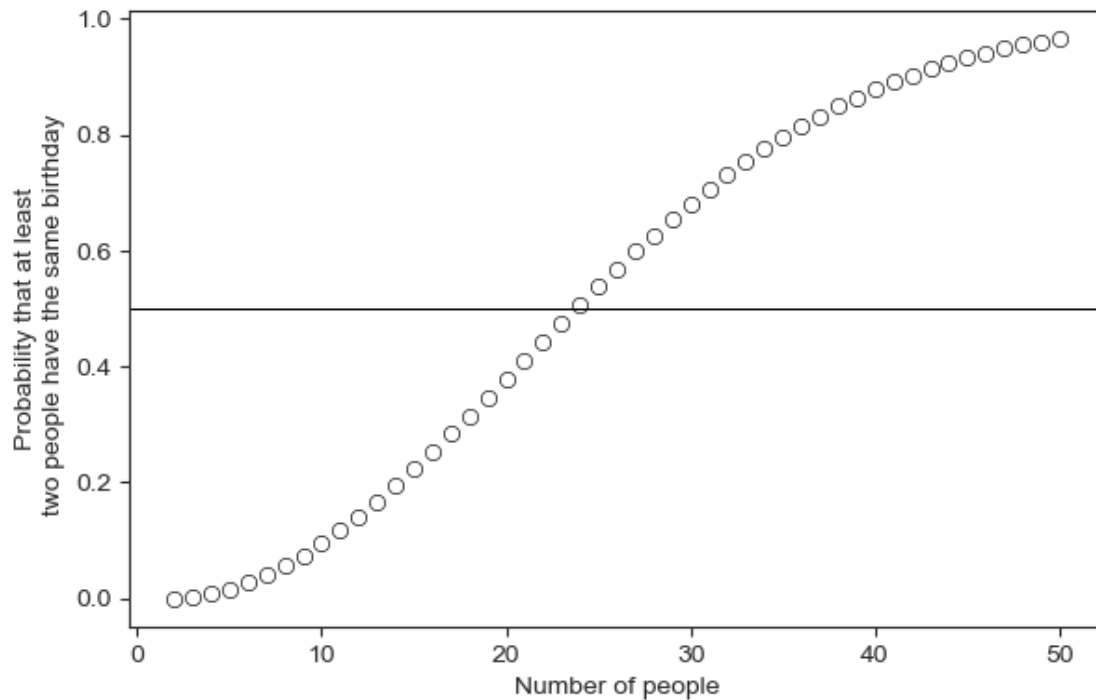
bday.index = k # add labels

sns.set_style('ticks')

sns.relplot(
    x=k, y=bday, color='white', edgecolor='black', height=4, aspect=1.5
).set(ylabel='Probability that at least\n two people have the same birthday',
      xlabel='Number of people').despine(right=False, top=False)

# horizontal line at 0.5
plt.axhline(0.5, color='black', linewidth=0.75)
```

```
[ ]: <matplotlib.lines.Line2D at 0x25f6a1deec0>
```



```
[ ]: bday.loc[20:25]
```

```
[ ]: 20    0.411438
      21    0.443688
      22    0.475695
      23    0.507297
      24    0.538344
      25    0.568700
      dtype: float64
```

Section 6.1.4: Sampling With and Without Replacement

```
[ ]: k = 23 # number of people
      sims = 10000 # number of simulations
      event = 0 # initialize counter

      for i in range(sims):
          days = np.random.choice(np.arange(1,366), size=k, replace=True)
          days_unique = np.unique(days) # number of unique days
          '''
          if there are duplicates, the number of unique birthdays will be less than
          the number of birthdays, which is 'k'
          '''
          if len(days_unique) < len(days):
```

```

        event += 1

answer = event / sims
answer

```

```
[ ]: 0.5079
```

Section 6.1.5: Combinations

```
[ ]: comb(84, 6)
```

```
[ ]: 406481544
```

Section 6.2: Conditional Probability

Section 6.2.1: Conditional, Marginal, and Joint Probabilities

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

FLVoters.shape # before removal of missing data

```

```
[ ]: (10000, 6)
```

```
[ ]: FLVoters.info() # there is one missing surname
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 6 columns):
#   Column      Non-Null Count  Dtype
---  -
0   surname     9999 non-null   object
1   county      10000 non-null  int64
2   VTD         10000 non-null  int64
3   age         9992 non-null   float64
4   gender      9992 non-null   object
5   race        9126 non-null   object
dtypes: float64(1), int64(2), object(3)
memory usage: 468.9+ KB

```

```
[ ]: # print the record with the missing surname
FLVoters[FLVoters['surname'].isnull()]

```

```
[ ]:
   surname  county  VTD  age  gender  race
349    NaN       5   14  70.0      f  white

```

Looking at the raw data, it turns out that one voter's surname is Null. Pandas treated the name as missing. We need to override this behavior and treat Ms. Null's name as a string.

```
[ ]: FLVoters.head() # the surnames are in all caps
```

```
[ ]: surname county VTD age gender race
0   PIEDRA      115   66  58.0      f  white
1   LYNCH       115   13  51.0      m  white
2   CHESTER     115  103  63.0      m   NaN
3   LATHROP     115   80  54.0      m  white
4   HUMMEL      115    8  77.0      f  white
```

```
[ ]: FLVoters['surname'] = np.where(
    FLVoters['surname'].isnull(), 'NULL', FLVoters['surname'])

FLVoters = FLVoters.dropna()

FLVoters.shape # after removal of missing data
```

```
[ ]: (9113, 6)
```

```
[ ]: margin_race = FLVoters['race'].value_counts(normalize=True).sort_index()

margin_race
```

```
[ ]: race
asian      0.019203
black      0.131022
hispanic   0.130802
native     0.003182
other      0.034017
white     0.681773
Name: proportion, dtype: float64
```

```
[ ]: margin_gender = FLVoters['gender'].value_counts(normalize=True)

margin_gender
```

```
[ ]: gender
f      0.535828
m      0.464172
Name: proportion, dtype: float64
```

```
[ ]: FLVoters['race'][FLVoters.gender == 'f'].value_counts(
    normalize=True).sort_index()
```

```
[ ]: race
asian      0.016998
black      0.138849
hispanic   0.136392
native     0.003481
other      0.032357
white     0.671923
```

Name: proportion, dtype: float64

```
[ ]: joint_p = pd.crosstab(FLVoters.race, FLVoters.gender, normalize=True)
```

```
joint_p
```

```
[ ]: gender      f      m
race
asian    0.009108  0.010095
black    0.074399  0.056622
hispanic 0.073082  0.057720
native   0.001865  0.001317
other    0.017338  0.016679
white    0.360035  0.321738
```

To obtain the row sums in pandas, we specify `axis='columns'` in the `.sum()` method. This may seem counterintuitive, but the logic is that we need to collapse the columns to calculate the sum of each row.

```
[ ]: # row sums
joint_p.sum(axis='columns')
```

```
[ ]: race
asian    0.019203
black    0.131022
hispanic 0.130802
native   0.003182
other    0.034017
white    0.681773
dtype: float64
```

```
[ ]: # column sums
joint_p.sum(axis='rows')
```

```
[ ]: gender
f    0.535828
m    0.464172
dtype: float64
```

```
[ ]: # Develop age group categories; start with a list of n-1 conditions
conditions = [
    (FLVoters.age <= 20)
    , (FLVoters.age > 20) & (FLVoters.age <= 40)
    , (FLVoters.age > 40) & (FLVoters.age <= 60)
]

choices = [1, 2, 3]
```

```

# Assign 4 to voters older than 60
FLVoters["age_group"] = np.select(conditions, choices, 4)

joint3 = pd.crosstab([FLVoters.race, FLVoters.age_group], FLVoters.gender,
                     normalize=True)

# print the first 8 rows
joint3.head(8)

```

```

[ ]: gender          f          m
     race age_group
asian 1          0.000110  0.000219
      2          0.002634  0.002853
      3          0.004170  0.005157
      4          0.002195  0.001865
black 1          0.001646  0.001646
      2          0.028092  0.022825
      3          0.025787  0.018984
      4          0.018874  0.013168

```

```

[ ]: # marginal probabilities for age groups
margin_age = FLVoters['age_group'].value_counts(normalize=True).sort_index()

margin_age

```

```

[ ]: age_group
1    0.017667
2    0.270932
3    0.360474
4    0.350927
Name: proportion, dtype: float64

```

```

[ ]: # take a look at the joint3 index for a few observations
joint3.index[:3]

```

```

[ ]: MultiIndex([('asian', 1),
                ('asian', 2),
                ('asian', 3)],
                names=['race', 'age_group'])

```

```

[ ]: # select elements from a multi-index using .loc and tuples
joint3.loc[('asian', 3), 'f']

```

```

[ ]: 0.004169867222648963

```

```

[ ]: # P(black and female / above 60)
joint3.loc[('black', 4), 'f'] / margin_age[4]

```

```
[ ]: 0.05378361475922452
```

```
[ ]: # two-way joint probability table for age group and gender
joint2 = pd.crosstab(FLVoters['age_group'], FLVoters['gender'],
                    normalize=True)

joint2
```

```
[ ]: gender          f          m
age_group
1      0.009657  0.008011
2      0.143092  0.127839
3      0.189839  0.170635
4      0.193240  0.157687
```

```
[ ]: # P(above 60 and female)
joint2.loc[4, 'f']
```

```
[ ]: 0.1932404257653901
```

```
[ ]: # P(black / female and above 60)
joint3.loc(['black', 4), 'f'] / joint2.loc[4, 'f']
```

```
[ ]: 0.097671777399205
```

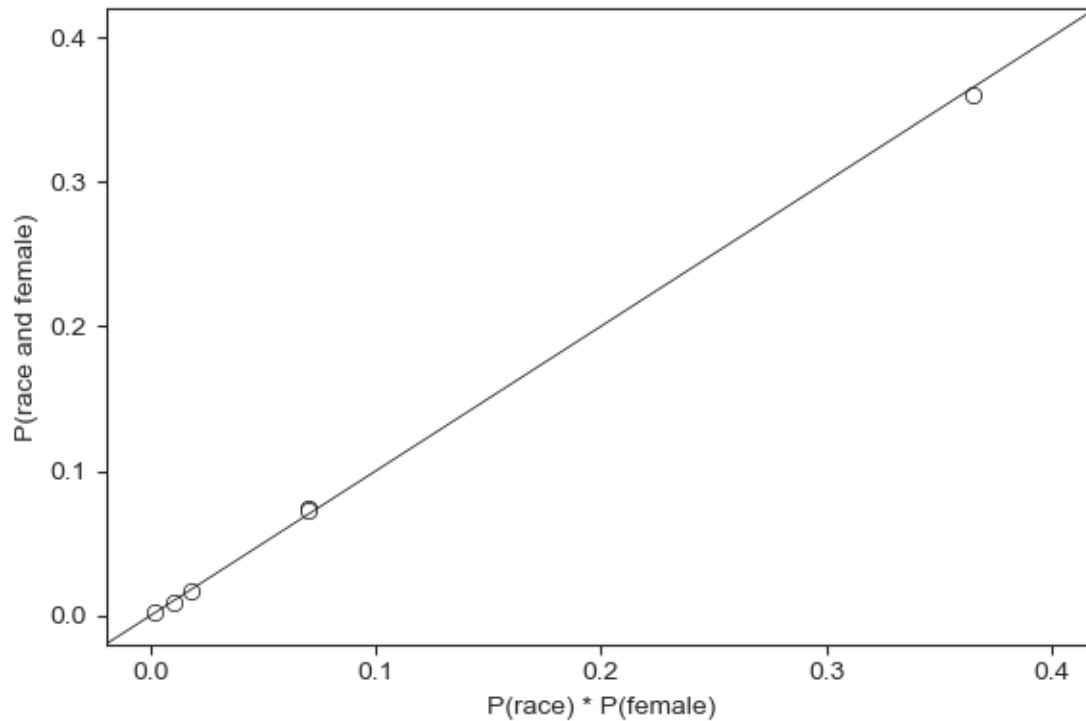
Section 6.2.2: Independence

```
[ ]: # store plotting parameters
lims = (-0.02, 0.42)
ticks = [0, .1, .2, .3, .4]

sns.relplot(
    x=margin_race * margin_gender['f'], y=joint_p['f'],
    color='white', edgecolor='black', height=4, aspect=1.5
).set(xlabel='P(race) * P(female)', ylabel='P(race and female)',
     xlim=lims, ylim=lims, xticks=ticks, yticks=ticks).despine(
    right=False, top=False)

plt.gca().axline((0, 0), slope=1, color='black', linewidth=0.5)
```

```
[ ]: <matplotlib.lines._AxLine at 0x25f6cdfdc0>
```



```
[ ]: # subplots for joint and conditional independence
fig, axs = plt.subplots(1, 2, figsize=(12, 5))

lims = (-0.02, 0.32)

# joint independence
sns.scatterplot(
    x=joint3.loc[(slice(None), 4), 'f'].droplevel('age_group'),
    y=margin_race * margin_age[4] * margin_gender['f'],
    color='white', edgecolor='black', ax=axs[0]
).set(xlabel='P(race and above 60 and female)',
      ylabel='P(race) * P(above 60) * P(female)',
      title='Joint Independence', xlim=lims, ylim=lims)

axs[0].axline((0, 0), slope=1, color='black', linewidth=0.5)

# conditional independence given female
sns.scatterplot(
    x=(joint3.loc[(slice(None), 4), 'f'] /
      margin_gender['f']).droplevel('age_group'),
    y=((joint_p['f'] / margin_gender['f']) *
      (joint2.loc[4, 'f'] / margin_gender['f'])),
    color='white', edgecolor='black', ax=axs[1])
```



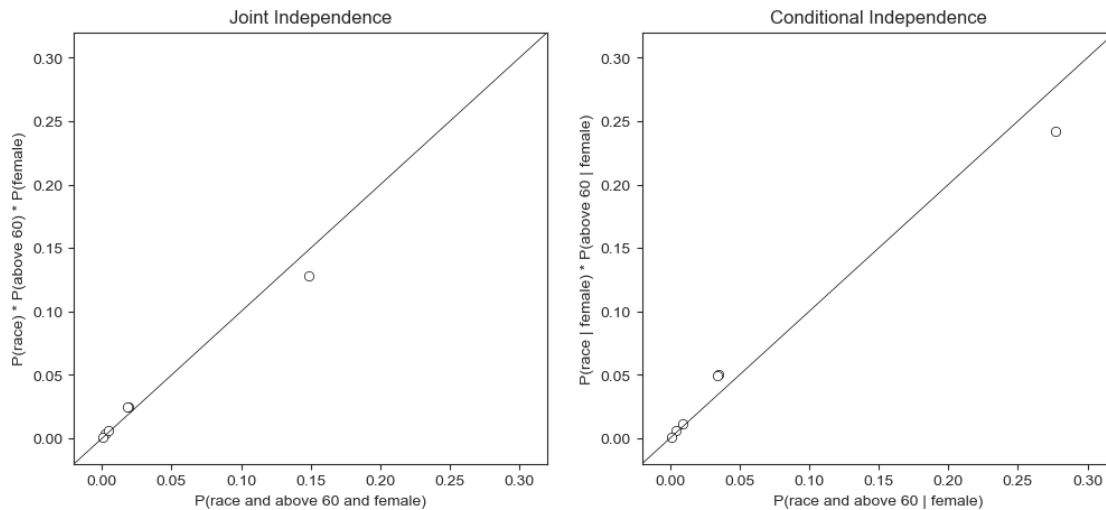
```

).set(xlabel='P(race and above 60 | female)',
      ylabel='P(race | female) * P(above 60 | female)',
      title='Conditional Independence', xlim=lims, ylim=lims)

axs[1].axline((0, 0), slope=1, color='black', linewidth=0.5)

```

```
[ ]: <matplotlib.lines._AxLine at 0x25f6ce9fac0>
```



```

[ ]: # Monty Hall problem
sims = 1000
doors = np.array(['goat', 'goat', 'car'])
# Store empty vector of strings with same dtype as doors
result_switch = np.empty(sims, dtype=doors.dtype)
result_noswitch = np.empty(sims, dtype=doors.dtype)

for i in range(sims):
    # randomly choose the initial door
    first = np.random.choice(np.arange(0,3))
    result_noswitch[i] = doors[first]
    remain = np.delete(doors, first) # remaining two doors
    if doors[first] == 'car': # two goats left
        monty = np.random.choice(np.arange(0,2))
    else: # one goat and one car left
        monty = np.arange(0,2)[remain=='goat']
    result_switch[i] = np.delete(remain, monty)[0]

(result_noswitch == 'car').mean()

```

```
[ ]: 0.311
```

```
[ ]: (result_switch == 'car').mean()
```

```
[ ]: 0.689
```

Section 6.2.3: Bayes' Rule

Section 6.2.4: Predicting Race Using Surname and Residence Location

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

```
cnames.info() # one surname is missing
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151671 entries, 0 to 151670
Data columns (total 7 columns):
#   Column          Non-Null Count  Dtype
---  ---
0   surname         151670 non-null  object
1   count           151671 non-null  int64
2   pctwhite        151671 non-null  float64
3   pctblack        151671 non-null  float64
4   pctapi          151671 non-null  float64
5   pcthispanic     151671 non-null  float64
6   pctothers       151671 non-null  float64
dtypes: float64(5), int64(1), object(1)
memory usage: 8.1+ MB
```

```
[ ]: # As with FLVoters, ensure the surname "NULL" is treated as a string
cnames['surname'] = np.where(
    cnames['surname'].isnull(), 'NULL', cnames['surname'])

cnames.shape
```

```
[ ]: (151671, 7)
```

```
[ ]: # merge the two data frames (inner join)
FLVoters = pd.merge(FLVoters, cnames, on='surname')

FLVoters.shape
```

```
[ ]: (8022, 13)
```

```
[ ]: # store relevant variables
vars = ["pctwhite", "pctblack", "pctapi", "pcthispanic", "pctothers"]

# Whites
whites = FLVoters.loc[FLVoters.race == 'white'].copy()
(whites[vars].max(axis='columns') == whites['pctwhite']).mean()
```

```
[ ]: 0.950218023255814
```

```
[ ]: # Blacks  
blacks = FLVoters.loc[FLVoters.race == 'black'].copy()  
(blacks[vars].max(axis='columns') == blacks['pctblack']).mean()
```

```
[ ]: 0.16048237476808905
```

```
[ ]: # Hispanics  
hispanics = FLVoters.loc[FLVoters.race == 'hispanic'].copy()  
(hispanics[vars].max(axis='columns') == hispanics['pcthispanic']).mean()
```

```
[ ]: 0.8465298142717498
```

```
[ ]: # Asian  
asians = FLVoters.loc[FLVoters.race == 'asian'].copy()  
(asians[vars].max(axis='columns') == asians['pctapi']).mean()
```

```
[ ]: 0.5642857142857143
```

```
[ ]: # White false discovery rate  
1 - (FLVoters['race'][FLVoters[vars].max(axis='columns') ==  
      FLVoters['pctwhite']] == "white").mean()
```

```
[ ]: 0.19736034376918354
```

```
[ ]: # Black false discovery rate  
1 - (FLVoters['race'][FLVoters[vars].max(axis='columns') ==  
      FLVoters['pctblack']] == "black").mean()
```

```
[ ]: 0.3294573643410853
```

```
[ ]: # Hispanic false discovery rate  
1 - (FLVoters['race'][FLVoters[vars].max(axis='columns') ==  
      FLVoters['pcthispanic']] == "hispanic").mean()
```

```
[ ]: 0.22747546833184662
```

```
[ ]: # Asian false discovery rate  
1 - (FLVoters['race'][FLVoters[vars].max(axis='columns') ==  
      FLVoters['pctapi']] == "asian").mean()
```

```
[ ]: 0.3416666666666667
```

```
[ ]: FLCensus = pd.read_csv('FLCensusVTD.csv')  
  
# compute proportions by applying np.average to each column with pop weight  
census_race = ['white', 'black', 'api', 'hispanic', 'others']
```

```

race_prop = FLCensus[census_race].apply(
    lambda x: np.average(x, weights=FLCensus['total.pop']))

```

```

race_prop # race proportions in Florida

```

```

[ ]: white      0.578934
     black      0.151644
     api         0.024197
     hispanic    0.224655
     others      0.020570
     dtype: float64

```

```

[ ]: # store total count from original cnames data
total_count = cnames['count'].sum()

# P(surname | race) = P(race | surname) * P(surname) / P(race) in Florida
FLVoters['name_white'] = (
    (FLVoters['pctwhite'] / 100) * (FLVoters['count'] / total_count) /
    race_prop['white'])

FLVoters['name_black'] = (
    (FLVoters['pctblack'] / 100) * (FLVoters['count'] / total_count) /
    race_prop['black'])

FLVoters['name_hispanic'] = (
    (FLVoters['pcthispanic'] / 100) * (FLVoters['count'] / total_count) /
    race_prop['hispanic'])

FLVoters['name_asian'] = (
    (FLVoters['pctapi'] / 100) * (FLVoters['count'] / total_count) /
    race_prop['api'])

FLVoters['name_others'] = (
    (FLVoters['pctothers'] / 100) * (FLVoters['count'] / total_count) /
    race_prop['others'])

```

```

[ ]: # merge FLVoters with FLCensus by county and VTD using left join
FLVoters = pd.merge(FLVoters, FLCensus, on=['county', 'VTD'], how='left')

# P(surname | residence) = sum_race P(surname | race) P(race | residence)
FLVoters['name_residence'] = (
    FLVoters['name_white'] * FLVoters['white'] +
    FLVoters['name_black'] * FLVoters['black'] +
    FLVoters['name_hispanic'] * FLVoters['hispanic'] +
    FLVoters['name_asian'] * FLVoters['api'] +
    FLVoters['name_others'] * FLVoters['others'])

```

```
[ ]: '''
P(race | surname, residence) = P(surname | race) * P(race | residence) /
P(surname | residence)
'''

FLVoters['pre_white'] = (FLVoters.name_white * FLVoters.white /
                        FLVoters.name_residence)

FLVoters['pre_black'] = (FLVoters.name_black * FLVoters.black /
                        FLVoters.name_residence)

FLVoters['pre_hispanic'] = (FLVoters.name_hispanic * FLVoters.hispanic /
                           FLVoters.name_residence)

FLVoters['pre_asian'] = (FLVoters.name_asian * FLVoters.api /
                        FLVoters.name_residence)

FLVoters['pre_others'] = (1 - FLVoters.pre_white - FLVoters.pre_black -
                        FLVoters.pre_hispanic - FLVoters.pre_asian)

[ ]: # relevant variables
vars1 = ['pre_white', 'pre_black', 'pre_hispanic', 'pre_asian', 'pre_others']

# Whites
whites = FLVoters.loc[FLVoters.race == 'white'].copy()
(whites[vars1].max(axis='columns') == whites['pre_white']).mean()

[ ]: 0.9418604651162791

[ ]: # Blacks
blacks = FLVoters.loc[FLVoters.race == 'black'].copy()
(blacks[vars1].max(axis='columns') == blacks['pre_black']).mean()

[ ]: 0.62708719851577

[ ]: # Hispanics
hispanics = FLVoters.loc[FLVoters.race == 'hispanic'].copy()
(hispanics[vars1].max(axis='columns') == hispanics['pre_hispanic']).mean()

[ ]: 0.8572825024437928

[ ]: # Asians
asians = FLVoters.loc[FLVoters.race == 'asian'].copy()
(asians[vars1].max(axis='columns') == asians['pre_asian']).mean()

[ ]: 0.6071428571428571
```

```
[ ]: # proportion of blacks among those with surname "White"
cnames['pctblack'][cnames.surname == "WHITE"]
```

```
[ ]: 19      27.38
      Name: pctblack, dtype: float64
```

```
[ ]: # predicted probability of being black given residence location
FLVoters['pre_black'][FLVoters.surname == "WHITE"].describe()
```

```
[ ]: count      24.000000
      mean       0.250711
      std       0.293894
      min       0.004588
      25%       0.072232
      50%       0.159496
      75%       0.293640
      max       0.981864
      Name: pre_black, dtype: float64
```

```
[ ]: # Whites
1 - (FLVoters['race'][FLVoters[vars1].max(axis='columns') ==
      FLVoters['pre_white']] == "white").mean()
```

```
[ ]: 0.12239715591670897
```

```
[ ]: # Blacks
1 - (FLVoters['race'][FLVoters[vars1].max(axis='columns') ==
      FLVoters['pre_black']] == "black").mean()
```

```
[ ]: 0.22029988465974626
```

```
[ ]: # Hispanics
1 - (FLVoters['race'][FLVoters[vars1].max(axis='columns') ==
      FLVoters['pre_hispanic']] == "hispanic").mean()
```

```
[ ]: 0.21133093525179858
```

```
[ ]: # Asians
1 - (FLVoters['race'][FLVoters[vars1].max(axis='columns') ==
      FLVoters['pre_asian']] == "asian").mean()
```

```
[ ]: 0.3307086614173228
```

Section 6.3: Random Variables and Probability Distributions

Section 6.3.1: Random Variables

Section 6.3.2: Bernoulli and Uniform Distributions

```
[ ]: from scipy import stats

# uniform PDF: x = 0.5, interval = [0,1]
stats.uniform.pdf(x=0.5, loc=0, scale=1) # loc = a, scale = b-a
```

```
[ ]: 1.0
```

```
[ ]: # uniform CDF: x = 1, interval = [-2, 2]
a = -2
b = 2
stats.uniform.cdf(x=1, loc=a, scale=b-a)
```

```
[ ]: 0.75
```

```
[ ]: sims = 1000
p = 0.5 # success probabilities
x = stats.uniform.rvs(size=sims, loc=0, scale=1)

type(x) # a numpy array
```

```
[ ]: numpy.ndarray
```

```
[ ]: x[:6]
```

```
[ ]: array([0.14432593, 0.24617993, 0.33183618, 0.38388235, 0.26991479,
        0.93488133])
```

```
[ ]: y = (x <= p).astype(int)
y[:6]
```

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

```
[ ]: y.mean() # close to success probability p, proportion of 1's vs. 0's
```

```
[ ]: 0.506
```

Section 6.3.3: Binomial Distribution

```
[ ]: # PMF: k = 2, n = 3, p = 0.5
stats.binom.pmf(k=2, n=3, p=0.5)
```

```
[ ]: 0.37500000000000001
```

```
[ ]: # CDF: k = 1, n = 3, p = 0.5  
stats.binom.cdf(k=1, n=3, p=0.5)
```

```
[ ]: 0.5
```

```
[ ]: # number of voters who turn out  
voters = np.array([1000, 10000, 100000])  
  
stats.binom.pmf(voters/2, n=voters, p=0.5)
```

```
[ ]: array([0.02522502, 0.00797865, 0.00252313])
```

Section 6.3.4: Normal Distribution

```
[ ]: # plus minus 1 standard deviation from the mean  
stats.norm.cdf(1) - stats.norm.cdf(-1)
```

```
[ ]: 0.6826894921370859
```

```
[ ]: # plus minus 2 standard deviations from the mean  
stats.norm.cdf(2) - stats.norm.cdf(-2)
```

```
[ ]: 0.9544997361036416
```

```
[ ]: mu = 5  
sigma = 2  
  
# plus minus 1 standard deviation from the mean  
(stats.norm.cdf(mu + sigma, loc=mu, scale=sigma) -  
 stats.norm.cdf(mu - sigma, loc=mu, scale=sigma))
```

```
[ ]: 0.6826894921370859
```

```
[ ]: # plus minus 2 standard deviations from the mean  
(stats.norm.cdf(mu + 2*sigma, loc=mu, scale=sigma) -  
 stats.norm.cdf(mu - 2*sigma, loc=mu, scale=sigma))
```

```
[ ]: 0.9544997361036416
```

```
[ ]: # Replicate model from 4.2.5  
pres08 = pd.read_csv('pres08.csv')  
  
# import pres12 from the PREDICTION folder  
pres12 = pd.read_csv('../PREDICTION/pres12.csv')  
  
# merge the two elections by state  
pres = pd.merge(pres08, pres12, on='state')
```



```
# Use the scipy zscore function to standardize Obama's vote share
# Set ddof=1 to ensure the standard deviation denominator is n-1
pres['Obama2008_z'] = stats.zscore(pres['Obama_x'], ddof=1)
pres['Obama2012_z'] = stats.zscore(pres['Obama_y'], ddof=1)
```

Note that in chapter 4, we built a function to calculate the z-score using the pandas `.std()` method. The default `ddof=1` for the pandas method. By contrast, the default `ddof=0` for the numpy `std` function and the scipy `zscore` function.

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

fit1 = smf.ols('Obama2012_z ~ -1 + Obama2008_z', data=pres).fit()

e = fit1.resid

# z-score of residuals
e_zscore = stats.zscore(e, ddof=1)

# alternatively, we can divide the residuals by the standard deviation
e_zscore = e / np.std(e, ddof=1)

[ ]: # Plot a histogram and Q-Q plot of the standardized residuals

## First, calculate some inputs for the plots
x = np.arange(-3, 3, 0.01)
y = stats.norm.pdf(x) # PDF of x

## Find quantiles for Q-Q plot using scipy.stats.probplot
quantiles = stats.probplot(e_zscore)
osm = quantiles[0][0] # ordered statistic medians (theoretical quantiles)
osr = quantiles[0][1] # ordered statistic ranks (sample quantiles)

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

# Histogram of residuals
sns.histplot(e_zscore, stat='density', color='gray', ax=axs[0]).set(
    xlabel='Standardized residuals',
    title='Distribution of Standardized Residuals')

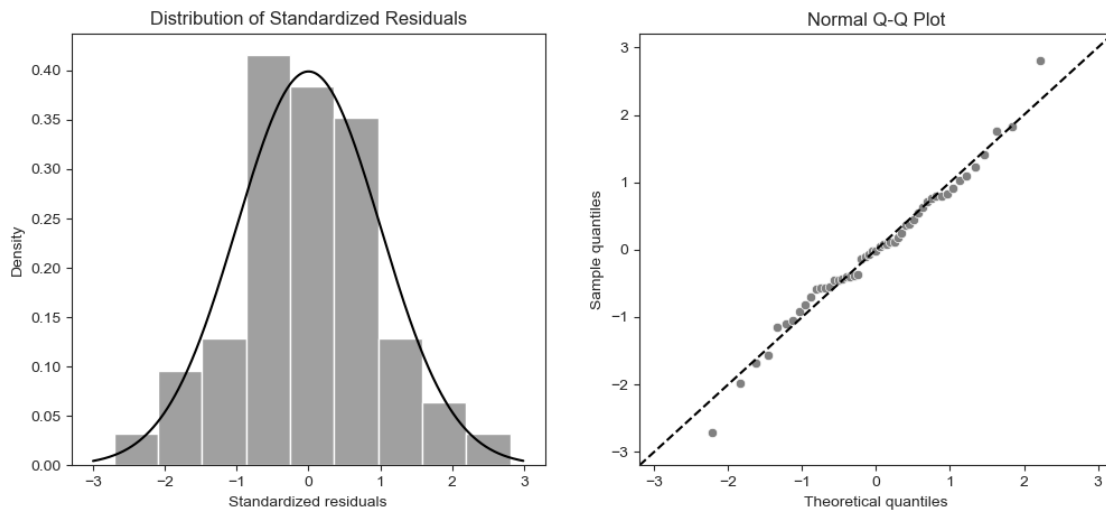
# Overlay the normal density
sns.lineplot(x=x, y=y, color='black', ax=axs[0])

# Q-Q plot
sns.scatterplot(x=osm, y=osr, color='gray', ax=axs[1]).set(
    xlabel='Theoretical quantiles', ylabel='Sample quantiles',
    title='Normal Q-Q Plot', xlim=(-3.2, 3.2), ylim=(-3.2, 3.2))

# 45-degree line
```

```
axs[1].axline((0, 0), slope=1, color='black', linestyle='--')
```

```
[ ]: <matplotlib.lines._AxLine at 0x25f6e07f580>
```



Note that we could have used `probplot` to create a Q-Q plot directly by passing a plot or an axis to the `plot` argument. However, obtaining the quantiles enables us to customize the plot a bit more.

```
[ ]: # e is a pandas series; we can use the pandas .std() method
e_sd = e.std()
e_sd
```

```
[ ]: 0.1812238619213575
```

```
[ ]: CA_2008 = pres['Obama2008_z'][pres['state'] == 'CA']
CA_2008
```

```
[ ]: 4      0.872063
      Name: Obama2008_z, dtype: float64
```

```
[ ]: # CA_2008 is a series with index 4; extract the value using .iloc
CA_mean2012 = fit1.params * CA_2008.iloc[0]
CA_mean2012
```

```
[ ]: Obama2008_z      0.857623
      dtype: float64
```

```
[ ]: # area to the right; greater than CA_2008
1 - stats.norm.cdf(CA_2008, loc=CA_mean2012, scale=e_sd)
```

```
[ ]: array([0.46824629])
```

```
[ ]: TX_2008 = pres['Obama2008_z'][pres['state'] == 'TX']
TX_mean2012 = fit1.params * TX_2008.iloc[0]
TX_mean2012
```

```
[ ]: Obama2008_z    -0.656754
dtype: float64
```

```
[ ]: 1 - stats.norm.cdf(TX_2008, loc=TX_mean2012, scale=e_sd)
```

```
[ ]: array([0.52432713])
```

Section 6.3.5: Expectation and Variance

In Progress