Project

February 11, 2022

[1]:
```
import pandas as pd                      # for data handling
import numpy as np                       # for numerical methods and data␣
 ↪structures
import matplotlib.pyplot as plt          # for plotting
import seaborn as sns                    # advanced plotting
import geopandas
from matplotlib.legend_handler import HandlerLine2D
import patsy                             # provides a syntax for specifying␣
 ↪models
import statsmodels.api as sm             # provides statistical models like ols,␣
 ↪gmm, anova, etc...
import statsmodels.formula.api as smf  # provides a way to directly spec models␣
 ↪from formulas
```

[2]:
```
# load in data

df = pd.read_csv('MERGED2016_17_PP.csv')
print(df.info())       #check the basic information of the dataframe that I␣
 ↪just loaded in.
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:2785: DtypeWarning: Columns (6,9,1379,
1380,1381,1382,1383,1384,1385,1386,1387,1388,1389,1390,1391,1392,1393,1394,1395,
1396,1397,1398,1399,1400,1401,1402,1403,1404,1405,1406,1407,1408,1431,1432,1503,
1504,1517,1518,1519,1529,1530,1531,1532,1534,1535,1537,1538,1539,1540,1542,1575,
1576,1577,1578,1579,1580,1581,1582,1583,1584,1585,1586,1587,1588,1589,1590,1591,
1592,1593,1594,1595,1596,1597,1598,1599,1600,1601,1602,1606,1610,1611,1614,1615,
1616,1708,1725,1726,1727,1728,1729,1743,1815,1816,1817,1818,1823,1824,1830,1831,
1879,1880,1881,1882,1883,1884,1885,1886,1887,1888,1889,1890,1891,1892,1893,1894,
1895,1896,1897,1898) have mixed types. Specify dtype option on import or set
low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7175 entries, 0 to 7174
Columns: 1899 entries, UNITID to OMENRUP8_PTNFT_POOLED_SUPP
dtypes: float64(1662), int64(17), object(220)
```

```
memory usage: 104.0+ MB
None
```

[3]:
```python
#examine and clean up

df.head(2)
cols_to_get = ['INSTNM', 'STABBR',␣
↪'NUMBRANCH','PREDDEG','HIGHDEG','MENONLY','WOMENONLY','SAT_AVG','ACTCMMID','UGDS','UGDS_WHI
␣
↪'UGDS_BLACK','UGDS_HISP','UGDS_ASIAN','UGDS_AIAN','UGDS_NHPI','UGDS_NRA','UGDS_UNKN','NPT4_
             ␣
↪'C150_L4','C150_4_NRA','C150_4_UNKN','C150_4_WHITENH','C150_4_BLACKNH','C150_4_API','C150_4
             ␣
↪'LO_INC_WDRAW_ORIG_YR4_RT','MD_INC_WDRAW_ORIG_YR4_RT','HI_INC_WDRAW_ORIG_YR4_RT','NUM41_PUB
             ␣
↪,'NUM45_PUB','NUM41_PRIV','NUM42_PRIV','NUM43_PRIV','NUM44_PRIV','NUM45_PRIV','LO_INC_COMP_
              ,'FEMALE']
df_og = df[cols_to_get]          # get all the columns that I potentially␣
↪need in the following anaylysis
df_og.head(10)                   # check if all the columns that I might need␣
↪is loaded in correctly and also check if there are any missing values.
```

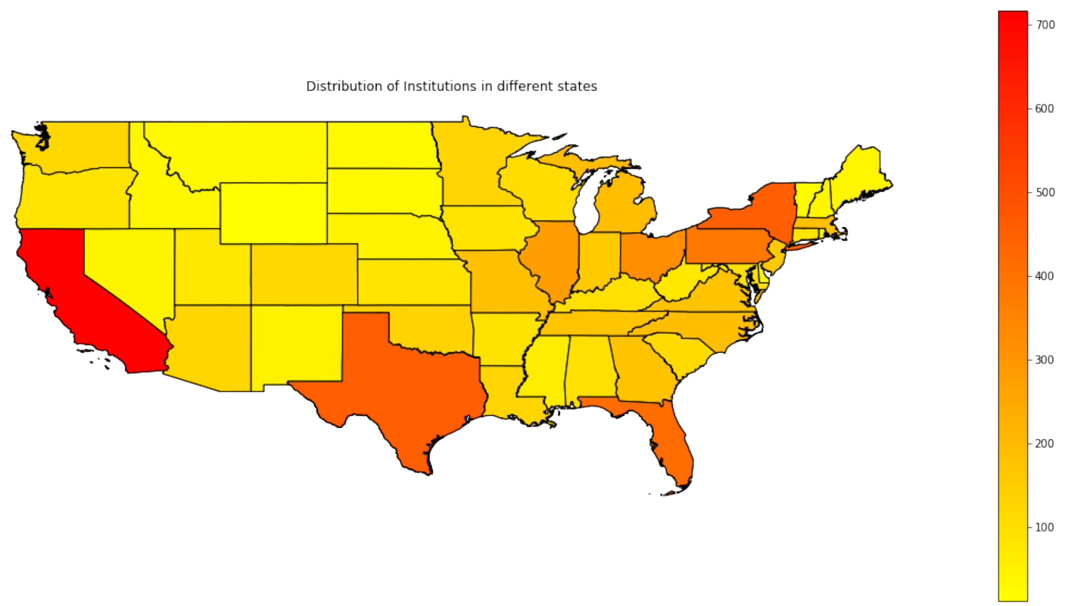
[3]:
```
                              INSTNM STABBR  NUMBRANCH  PREDDEG  HIGHDEG  \
0            Alabama A & M University     AL          1        3        4
1  University of Alabama at Birmingham     AL          1        3        4
2                  Amridge University     AL          1        3        4
3  University of Alabama in Huntsville     AL          1        3        4
4            Alabama State University     AL          1        3        4
5           The University of Alabama     AL          1        3        4
6   Central Alabama Community College     AL          1        2        2
7             Athens State University     AL          1        3        3
8     Auburn University at Montgomery     AL          1        3        4
9                   Auburn University     AL          1        3        4

   MENONLY  WOMENONLY  SAT_AVG  ACTCMMID     UGDS      ...       NUM43_PRIV  \
0      0.0        0.0    849.0      18.0   4616.0      ...              NaN
1      0.0        0.0   1125.0      25.0  12047.0      ...              NaN
2      0.0        0.0      NaN       NaN    293.0      ...              0.0
3      0.0        0.0   1257.0      28.0   6346.0      ...              NaN
4      0.0        0.0    825.0      17.0   4704.0      ...              NaN
5      0.0        0.0   1202.0      27.0  31663.0      ...              NaN
6      0.0        0.0      NaN       NaN   1492.0      ...              NaN
7      0.0        0.0      NaN       NaN   2888.0      ...              NaN
8      0.0        0.0   1009.0      22.0   4171.0      ...              NaN
9      0.0        0.0   1217.0      27.0  22095.0      ...              NaN

   NUM44_PRIV  NUM45_PRIV  LO_INC_COMP_ORIG_YR4_RT  MD_INC_COMP_ORIG_YR4_RT  \
```

```
0          NaN          NaN                        NaN                        NaN
1          NaN          NaN                        NaN                        NaN
2          0.0          0.0                        NaN                        NaN
3          NaN          NaN                        NaN                        NaN
4          NaN          NaN                        NaN                        NaN
5          NaN          NaN                        NaN                        NaN
6          NaN          NaN                        NaN                        NaN
7          NaN          NaN                        NaN                        NaN
8          NaN          NaN                        NaN                        NaN
9          NaN          NaN                        NaN                        NaN

   HI_INC_COMP_ORIG_YR4_RT  FEMALE_COMP_ORIG_YR8_RT  MALE_COMP_ORIG_YR8_RT  \
0                      NaN                      NaN                    NaN
1                      NaN                      NaN                    NaN
2                      NaN                      NaN                    NaN
3                      NaN                      NaN                    NaN
4                      NaN                      NaN                    NaN
5                      NaN                      NaN                    NaN
6                      NaN                      NaN                    NaN
7                      NaN                      NaN                    NaN
8                      NaN                      NaN                    NaN
9                      NaN                      NaN                    NaN

   COSTT4_A        FEMALE
0   22667.0  0.5640301318
1   22684.0  0.6390907397
2   13380.0  0.6486486486
3   22059.0  0.4763499372
4   19242.0  0.6134185304
5   28422.0  0.6152524168
6   13868.0  0.6037383178
7       NaN   0.705078125
8   19255.0  0.6929480901
9   29794.0   0.531504671

[10 rows x 51 columns]
```

[4]:

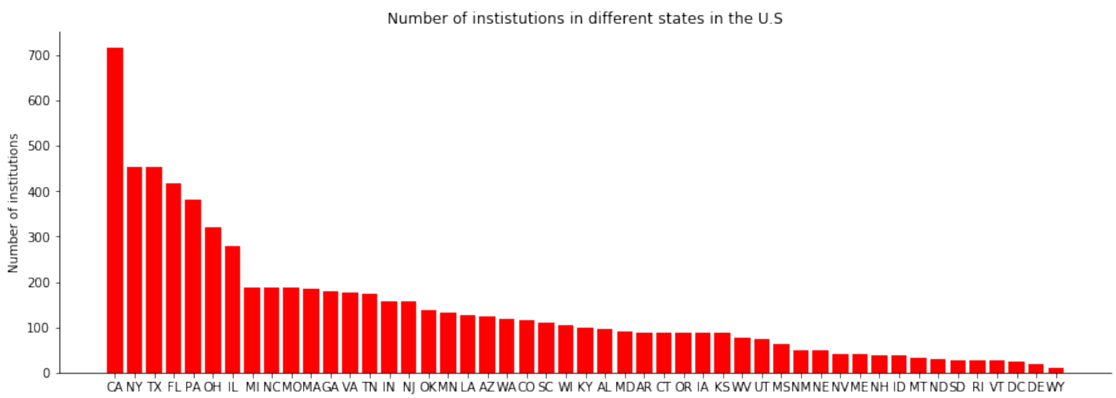
```python
# map for number of institutions in different states
states = geopandas.read_file('cb_2017_us_state_500k/cb_2017_us_state_500k.shp')␣
 ↪       #load and graph the map of the u.s.
states.columns = [col_name.lower() for col_name in states.columns]
stusps = [ 'GU', 'MP', 'AS', 'PR', 'VI', 'AK', 'HI','FM', 'MH','PW']              ␣
 ↪       # in the dataset, there are some states that are missing all the␣
 ↪necessary values
states = states[ ~states['stusps'].isin(stusps) ]                                 ␣
 ↪       # exclude all the states that does not have valid value
states = states.rename(columns={'stusps':'state'})
```

```
map_st = df[['INSTNM', 'STABBR']]                                                    ␣
 ↪          #make the dataframe that contains only number of states and name of␣
 ↪states
map_st = map_st.rename(columns={'STABBR':'state','INSTNM':'num'})
map_st = map_st.groupby('state').count()
map_st = map_st[ ~map_st.index.isin(stusps) ]
map_st = map_st.reset_index()
map_st = map_st.sort_values('num',ascending = False)


mp = pd.merge(left=states, right=map_st, on=['state'], how='outer')


fig, gax = plt.subplots(figsize=(20,10))                                             ␣
 ↪        # plot the map based on the table
states.plot(ax = gax,edgecolor='black', color = 'white')
mp.plot(ax = gax, edgecolor='black', column='num',  legend = True,␣
 ↪cmap='autumn_r')
plt.axis('off')
gax.set_title('Distribution of Institutions in different states')
plt.savefig('map.pdf')
```

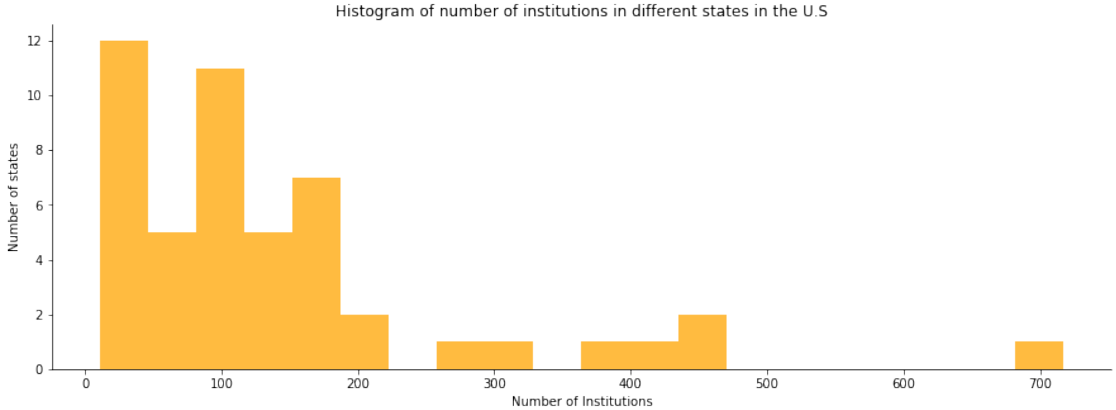


[5]:
```
#bar chart for better illustration of number of institutions in different␣
 ↪states

fig, ax = plt.subplots(figsize=(15,5))
```

```
ax.bar(map_st.state, map_st['num'], color='red', alpha=1)

ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

ax.set_ylabel('Number of institutions')
ax.set_title('Number of inststitutions in different states in the U.S')
plt.savefig('bar_1.pdf')
plt.show()
```



[6]:
```
#histogram to see the distribution of number of institutions in different␣
↪states in the U.S
fig, ax = plt.subplots(figsize=(15,5))
ax.hist(map_st['num'], bins=20, color='orange', alpha=0.75)
ax.set_xlabel('Number of Institutions')
ax.set_ylabel('Number of states')
ax.set_title('Histogram of number of institutions in different states in the U.
↪S')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.savefig('his_1.pdf')
```

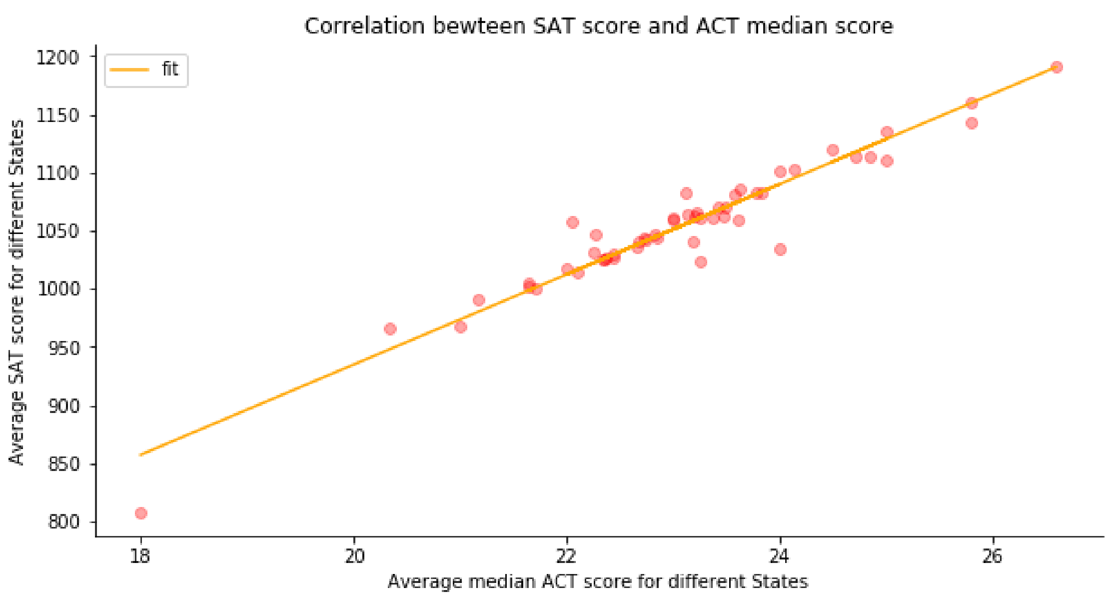


[7]:
```python
#SAT _ avg, act_median vs state
score = df[['INSTNM', 'STABBR','SAT_AVG','ACTCMMID','C150_4']]                # create a tabe that only contains average SAT score,
score = score.rename(columns={'STABBR':'state','SAT_AVG':'sat', 'ACTCMMID':'act', 'C150_4':'complete_r'})      #median act score and average completion rate
score = score.groupby('state').mean()
score = score.dropna()
score = score.sort_values('sat',ascending = False)
score.to_excel('score.xlsx')
score.head(10)
```

[7]:
```
               sat        act  complete_r
state
DC     1190.800000  26.600000    0.464325
RI     1160.400000  25.800000    0.703270
MA     1142.800000  25.800000    0.623126
UT     1136.000000  25.000000    0.418642
NH     1119.833333  24.500000    0.580727
WA     1113.888889  24.722222    0.464052
CA     1113.859155  24.859155    0.555366
NY     1110.494505  25.012195    0.528128
MN     1102.066667  24.133333    0.512270
WY     1102.000000  24.000000    0.353150
```

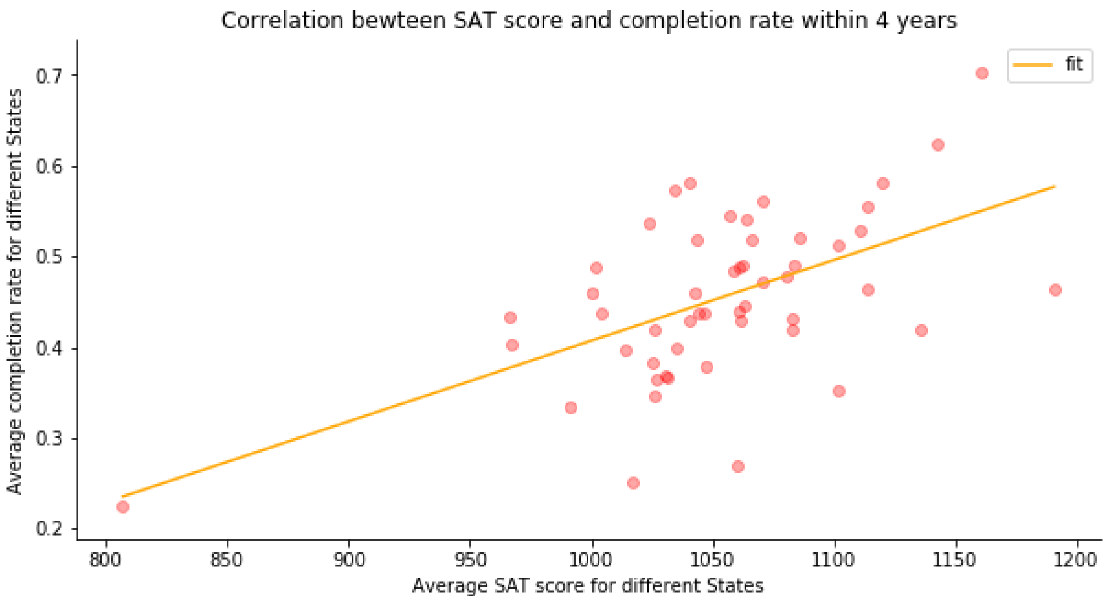
[8]:
```python
# graph the correlation bewteen average SAT score and average ACT median  in different states
fig, ax = plt.subplots(figsize = (10, 5))
ax.scatter(score["act"], score["sat"], color = 'red' , alpha = 0.35)

score['1'] = 1                                                              # creates a fitted line function that takes x as ACT median
```

```
res = np.linalg.lstsq(score[['act','1']] , score['sat'], rcond=None)      # y␣
↪as fitted value


coefficients = res[0]
m = coefficients[0]
n = coefficients[1]
score["fit"] = score["act"] * m + n
score.plot.line(x='act', y='fit', c='orange', ax=ax,alpha = 5)


ax.set_ylabel('Average SAT score for different States')
ax.set_xlabel('Average median ACT score for different States')
ax.set_title('Correlation bewteen SAT score and ACT median score')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.savefig('line_1.pdf')
```



[9]:
```
# graph the correlation bewteen average SAT score and completion rate in␣
↪different state
fig, ax = plt.subplots(figsize = (10, 5))
ax.scatter(score["sat"], score["complete_r"], color = 'red' , alpha = 0.35)

score['1'] = 1
res = np.linalg.lstsq(score[['sat','1']] , score['complete_r'], rcond=None)     ␣
↪     # create a fitted line function that takes x as
                                                                               ␣
↪     # fitted value as y
```

```
coefficients = res[0]
m = coefficients[0]
n = coefficients[1]
score["fit"] = score["sat"] * m + n
score.plot.line(x='sat', y='fit', c='orange', ax=ax,alpha = 5)


ax.set_ylabel('Average completion rate for different States')
ax.set_xlabel('Average SAT score for different States')
ax.set_title('Correlation bewteen SAT score and completion rate within 4 years')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.savefig('line_2.pdf')
```



[10]:
```
# table between different race and completion rate

race =␣
↪df[['STABBR','C150_4_WHITE','C150_4_BLACK','C150_4','C150_4_NRA','C150_4_UNKN','C150_4_WHIT
    'C150_4_HISPOLD']]
race =  df[['STABBR','C150_4_WHITE','C150_4_BLACK','C150_4_NRA','C150_4_UNKN']]␣
↪                                                                               ␣
↪# load in value that contains different race cohort
race = race.groupby('STABBR').mean()
race = race.rename(columns={'STABBR':'state','SAT_AVG':'sat', 'ACTCMMID':'act',␣
↪'C150_4_WHITE':'white','C150_4_BLACK':'black','C150_4_NRA':'alien',         ␣
↪# label them  white race cohort as white, black race cohort
```

```python
                        'C150_4_UNKN':'unknow' })
↪
↪# non resident of alien as alien, unknow as unknow
race = race.dropna()

race_sample1 = race.
↪loc[['AK','AL','AR','AZ','CA','CO','CT','DC','DE','FL','GA','GU','HI','IA','ID','IL','IN',
↪                                            # seperate them into two
↪groups since one graph will not fit all
'KS','KY','LA','MA','MD','ME','MI','MN','MO']]

race_sample2 = race.
↪loc[['MS','MT','NC','ND','NE','NH','NJ','NM','NV','NY','OH','OH','OK','OR','PA','PR','RI',
'SC','SD','TN','TX','UT','VA','VI','VT','WA','WI','WV','WY']]


race = race.reset_index()
race_sample1 =  race_sample1.reset_index()
race_sample2 = race_sample2.reset_index()
race = race.melt(id_vars=['STABBR'])
race_sample1 = race_sample1.melt(id_vars=['STABBR'])
race_sample2 = race_sample2.melt(id_vars=['STABBR'])
race = race.rename(columns={'STABBR':'state','variable':'race','value':
↪'completion_r'})
race_sample1 = race_sample1.rename(columns={'STABBR':'state','variable':
↪'race','value':'completion_r'})
race_sample2 = race_sample2.rename(columns={'STABBR':'state','variable':
↪'race','value':'completion_r'})
race.to_excel('race.xlsx')
race.head()
# setup the table so that 'race' is the new column name and different cohorts
↪can be turned into dummy varaibles
# it will be easier for the linear regression
```

[10]:

	state	race	completion_r
0	AK	white	0.293780
1	AL	white	0.438915
2	AR	white	0.442991
3	AZ	white	0.458039
4	CA	white	0.574838

[11]:

```python
# turn four cohorts into four dummy variables. For instance white cohort will
↪have white:1 black:0 alien: 0 unknow :0
race.loc[race['race']=='white', 'white'] = 1
race.loc[race['race']=='black', 'black'] = 1
race.loc[race['race']=='alien', 'alien'] = 1
race.loc[race['race']=='unknow', 'unknow'] = 1
```

```
race['white'] = race['white'].fillna(0)
race['black'] = race['black'].fillna(0)
race['alien'] = race['alien'].fillna(0)
race['unknow'] = race['unknow'].fillna(0)
race.head(10)
```

[11]:

	state	race	completion_r	white	black	alien	unknow
0	AK	white	0.293780	1.0	0.0	0.0	0.0
1	AL	white	0.438915	1.0	0.0	0.0	0.0
2	AR	white	0.442991	1.0	0.0	0.0	0.0
3	AZ	white	0.458039	1.0	0.0	0.0	0.0
4	CA	white	0.574838	1.0	0.0	0.0	0.0
5	CO	white	0.504049	1.0	0.0	0.0	0.0
6	CT	white	0.651404	1.0	0.0	0.0	0.0
7	DC	white	0.525022	1.0	0.0	0.0	0.0
8	DE	white	0.477750	1.0	0.0	0.0	0.0
9	FL	white	0.482558	1.0	0.0	0.0	0.0

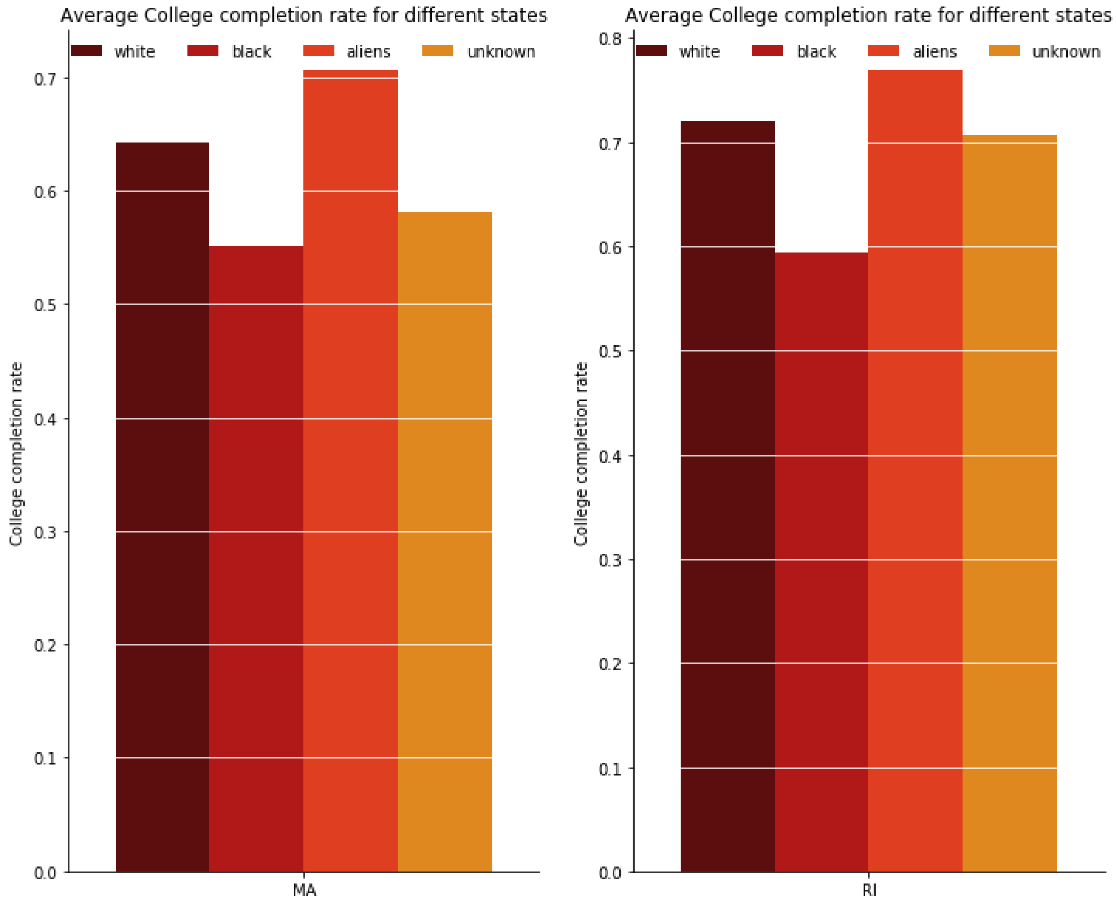
[12]:

```
# make the table for a individaul state plot so that the comparison between␣
 ↪different cohorts is more clear
race_plot_1 = race.set_index('state')
race_plot_1 = race_plot_1.loc[['MA' ]]                  # MA and RI are picked␣
 ↪because they are realtively the highest for all four cohorts
race_plot_2 = race.set_index('state')
race_plot_2 = race_plot_2.loc[['RI']]
race_plot_1 = race_plot_1.reset_index()

race_plot_2 = race_plot_2.reset_index()
```

[13]:

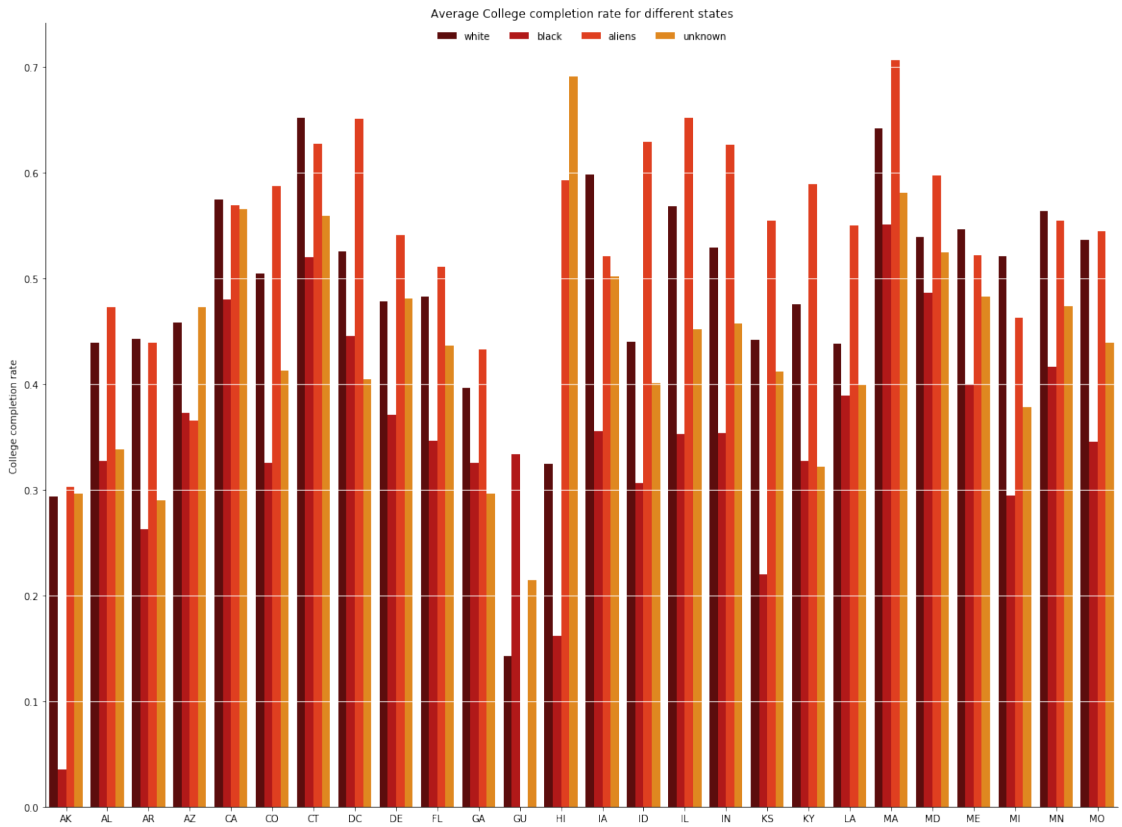
```
#plot the graph for two individaul states so that the comparison between␣
 ↪different cohorts is more clear
fig, ax = plt.subplots(1,2 ,figsize=(12,10))


sns.barplot(x='state', y = 'completion_r', hue='race', data=race_plot_1,
           ax = ax[0], palette = sns.color_palette('hot'),
           )

sns.despine()
# first graph on the left
ax[0].set_xlabel('')
ax[0].set_ylabel('College completion rate')
ax[0].set_title('Average College completion rate for different states')

# Clean up the legend.
ax[0].legend().set_title('')
handles, labels = ax[0].get_legend_handles_labels()
```

```
ax[0].legend(handles, ['white', 'black', 'aliens', 'unknown'], frameon=False,␣
↪ncol=10, loc='upper center')

ax[0].grid(axis='y', color='white')

sns.barplot(x='state', y = 'completion_r', hue='race', data=race_plot_2,
            ax = ax[1], palette = sns.color_palette('hot'),
            )

sns.despine()
# second graph on the right
ax[1].set_xlabel('')
ax[1].set_ylabel('College completion rate')
ax[1].set_title('Average College completion rate for different states')

# Clean up the legend.
ax[1].legend().set_title('')
handles, labels = ax[1].get_legend_handles_labels()
ax[1].legend(handles, ['white', 'black', 'aliens', 'unknown'], frameon=False,␣
↪ncol=10, loc='upper center')

ax[1].grid(axis='y', color='white')
plt.savefig('his2.pdf')
plt.show()
```



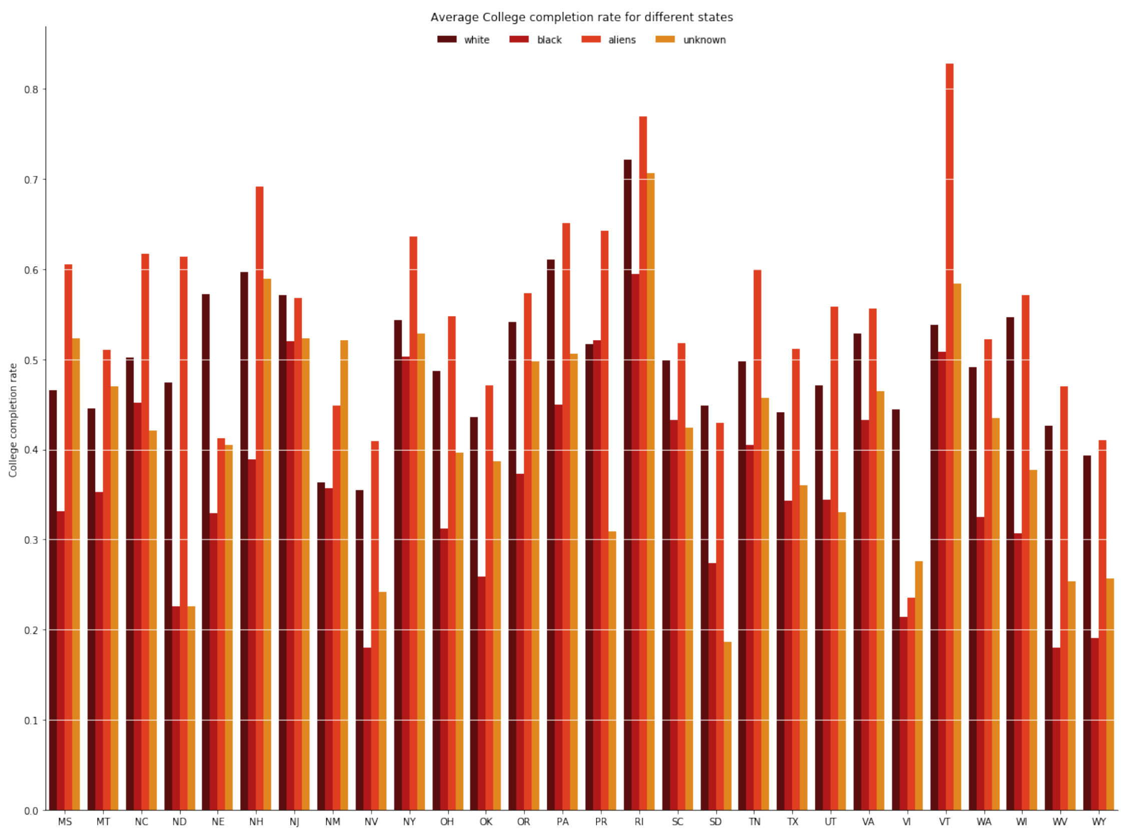
[14]:
```python
#graph different cohorts' completion rate.
fig, ax = plt.subplots(figsize=(20,15))


sns.barplot(x='state', y = 'completion_r', hue='race', data=race_sample1,
            ax = ax, palette = sns.color_palette('hot'),
            )

sns.despine()

ax.set_xlabel('')
ax.set_ylabel('College completion rate')
ax.set_title('Average College completion rate for different states')

# Clean up the legend.
ax.legend().set_title('')
handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, ['white', 'black', 'aliens', 'unknown'], frameon=False,␣
 ↪ncol=10, loc='upper center')
```

```
ax.grid(axis='y', color='white')
plt.savefig('his3.pdf')
plt.show()
```



[15]:
```
#GRAPH the rest of states for different cohorts' completion rate
fig, ax = plt.subplots(figsize=(20,15))


sns.barplot(x='state', y = 'completion_r', hue='race', data=race_sample2,
            ax = ax, palette = sns.color_palette('hot'),
            )

sns.despine()

ax.set_xlabel('')
ax.set_ylabel('College completion rate')
ax.set_title('Average College completion rate for different states')

# Clean up the legend.
ax.legend().set_title('')
handles, labels = ax.get_legend_handles_labels()
```

```
ax.legend(handles, ['white', 'black', 'aliens', 'unknown'], frameon=False,
    ncol=10, loc='upper center')

ax.grid(axis='y', color='white')
plt.savefig('his4.pdf')

plt.show()
```



[16]:

```
#table of net price for different income gorup for public school
# income gorup are seperated in $0-$30,000, $30,001-$48,000, $48,001-$75,000,
    $75,001-$110,000 and $110,000 over
# they will be labeled from low to high in 0 -4

income_pub = df[['STABBR','NUM41_PUB','NUM42_PUB','NUM43_PUB','NUM44_PUB'
               ,'NUM45_PUB']]
income_pub = income_pub.dropna()
income_pub = income_pub.rename(columns={'STABBR':'state','NUM41_PUB':'0',
    'NUM42_PUB':'1', 'NUM43_PUB':'2','NUM44_PUB':'3','NUM45_PUB':'4'})
income_pub = income_pub.groupby('state').mean()
income_pub = income_pub.reset_index()
income_pub.to_excel('income_1.xlsx')
```

```
income_pub.head(10)
```

[16]:

	state	0	1	2	3	4
0	AK	69.000000	28.200000	34.400000	23.200000	21.400000
1	AL	297.842105	76.421053	55.894737	44.078947	43.921053
2	AR	179.000000	70.764706	57.117647	32.823529	28.588235
3	AS	199.000000	27.000000	15.000000	1.000000	0.000000
4	AZ	228.300000	105.933333	81.066667	52.800000	51.633333
5	CA	372.531646	143.265823	103.303797	44.000000	48.645570
6	CO	131.100000	75.566667	78.400000	78.300000	79.566667
7	CT	153.869565	52.304348	52.565217	43.565217	71.217391
8	DC	76.000000	29.000000	13.000000	4.000000	2.000000
9	DE	257.666667	137.333333	143.333333	97.000000	123.333333

[17]:

```
#table of net price for different income gorup for private school
# income gorup are seperated in $0-$30,000, $30,001-$48,000, $48,001-$75,000,␣
↪$75,001-$110,000 and $110,000 over
# they will be labeled from low to high in 0 -4
income_pri =␣
↪df[['STABBR','NUM41_PRIV','NUM42_PRIV','NUM43_PRIV','NUM44_PRIV','NUM45_PRIV']]
income_pri = income_pri.dropna()
income_pri = income_pri.rename(columns={'STABBR':'state','NUM41_PRIV':'0',␣
↪'NUM42_PRIV':'1', 'NUM43_PRIV':'2','NUM44_PRIV':'3','NUM45_PRIV':'4'})
income_pri = income_pri.groupby('state').mean()
income_pri = income_pri.reset_index()
income_pri.to_excel('income_2.xlsx')
income_pri.head(10)
```

[17]:

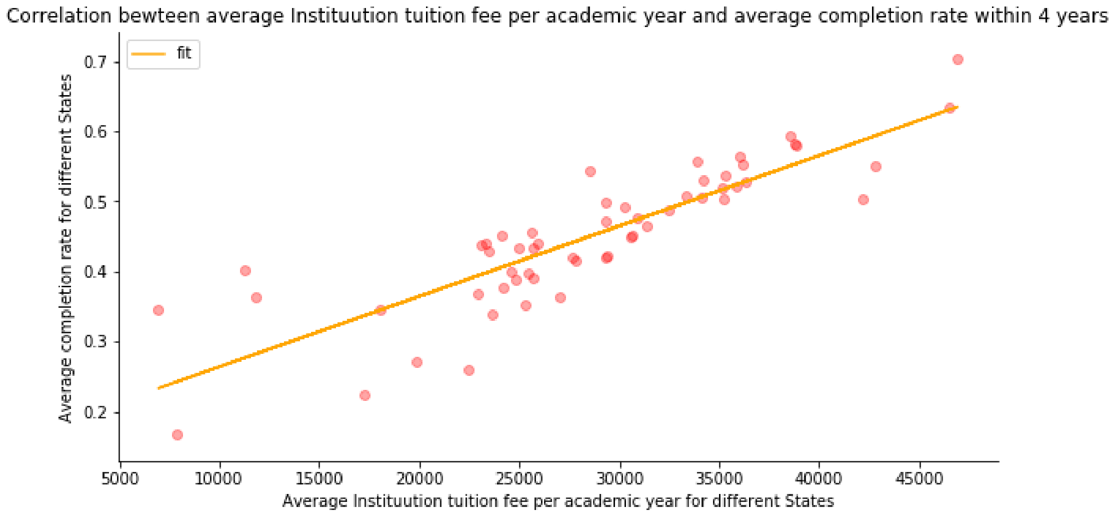
	state	0	1	2	3	4
0	AK	34.500000	8.500000	2.000000	1.500000	1.750000
1	AL	59.714286	16.119048	16.214286	10.333333	10.666667
2	AR	45.071429	10.404762	11.833333	10.190476	13.380952
3	AZ	134.576923	25.679487	14.282051	9.961538	10.692308
4	CA	52.384615	13.781638	10.846154	8.414392	13.560794
5	CO	45.809524	11.460317	9.253968	8.269841	13.380952
6	CT	68.346154	25.596154	23.788462	25.596154	59.019231
7	DC	121.357143	49.714286	50.000000	55.000000	133.357143
8	DE	64.750000	17.583333	12.583333	8.666667	7.666667
9	FL	104.820833	19.475000	13.716667	10.262500	14.704167

[18]:

```
# the table for average tuition fee with average college completion rate
# tuition fee will be labeled as cost
cost= df[['STABBR','COSTT4_A','C150_4']]
cost = cost.dropna()
cost = cost.rename(columns={'STABBR':'state','COSTT4_A':'fee',  'C150_4':
↪'complete_r'})
cost = cost.groupby('state').mean()
cost.to_excel('cost.xlsx')
cost.head(10)
```

[18]:
```
                 fee  complete_r
state
AK      19881.200000    0.270360
AL      25449.257143    0.396829
AR      25688.318182    0.391655
AS       6940.000000    0.346000
AZ      27848.038462    0.414596
CA      36171.382166    0.551950
CO      29364.931034    0.421907
CT      38527.814815    0.594556
DC      42153.090909    0.504009
DE      25008.333333    0.433433
```

[19]:
```
# the graph for average tuition fee with average college completion rate
fig, ax = plt.subplots(figsize = (10, 5))
ax.scatter(cost["fee"], cost["complete_r"], color = 'red' , alpha = 0.35)

cost['1'] = 1
res = np.linalg.lstsq(cost[['fee','1']] , cost['complete_r'], rcond=None)
 ↪             # fitted line function for the scatter plot

 ↪             # x value will be tuition fee: cost

 ↪             # y value will be the fitted value
coefficients = res[0]
m = coefficients[0]
n = coefficients[1]
cost["fit"] = cost["fee"] * m + n
cost.plot.line(x='fee', y='fit', c='orange', ax=ax,alpha = 5)


ax.set_ylabel('Average completion rate for different States')
ax.set_xlabel('Average Instituution tuition fee per academic year for different
 ↪States')
ax.set_title('Correlation bewteen average Instituution tuition fee per academic
 ↪year and average completion rate within 4 years')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.savefig('hist5.pdf')
```



[20]:
```
#linear regression table setup
score = score.reset_index()

cost = cost.reset_index()

tem = pd.merge(left=score, right=race, on=['state'], how='inner')

ols = pd.merge(left=tem, right=cost, on=['state'], how='inner')


ols = ols[['state','sat','white','completion_r','fee','black','alien','unknow']]
ols.to_excel('ols.xlsx')
ols.head(10)
```

[20]:

	state	sat	white	completion_r	fee	black	alien	unknow
0	DC	1190.8	1.0	0.525022	42153.090909	0.0	0.0	0.0
1	DC	1190.8	0.0	0.444992	42153.090909	1.0	0.0	0.0
2	DC	1190.8	0.0	0.650700	42153.090909	0.0	1.0	0.0
3	DC	1190.8	0.0	0.404644	42153.090909	0.0	0.0	1.0
4	RI	1160.4	1.0	0.721040	46945.300000	0.0	0.0	0.0
5	RI	1160.4	0.0	0.594310	46945.300000	1.0	0.0	0.0
6	RI	1160.4	0.0	0.769370	46945.300000	0.0	1.0	0.0
7	RI	1160.4	0.0	0.706840	46945.300000	0.0	0.0	1.0
8	MA	1142.8	1.0	0.641865	46497.233766	0.0	0.0	0.0
9	MA	1142.8	0.0	0.550404	46497.233766	1.0	0.0	0.0

[21]:
```
ols.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 208 entries, 0 to 207
Data columns (total 8 columns):
```

```
state            208 non-null object
sat              208 non-null float64
white            208 non-null float64
completion_r     208 non-null float64
fee              208 non-null float64
black            208 non-null float64
alien            208 non-null float64
unknow           208 non-null float64
dtypes: float64(7), object(1)
memory usage: 14.6+ KB
```

[22]:
```
#linear regression model where average completion rate is dependent variable.
# average SAT score , tuition fee, white race  , black race, non_resident of␣
↪aliens and unknow as independent variables.
#white balck alien and unknow are dummy variables. white as baseline
res_ols = smf.ols('completion_r ~ sat + fee + C(black) + C(unknow) + C(alien)',␣
↪data=ols).fit()
with open('summary.csv', 'w') as fh:
    fh.write(res_ols.summary().as_csv())
print(res_ols.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           completion_r   R-squared:                       0.693
Model:                            OLS   Adj. R-squared:                  0.685
Method:                 Least Squares   F-statistic:                     91.00
Date:                Fri, 14 Dec 2018   Prob (F-statistic):           8.36e-50
Time:                        11:53:22   Log-Likelihood:                 259.71
No. Observations:                 208   AIC:                            -507.4
Df Residuals:                     202   BIC:                            -487.4
Df Model:                           5
Covariance Type:            nonrobust
================================================================================
====
                       coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----
Intercept            0.1920      0.098      1.962      0.051      -0.001
0.385
C(black)[T.1.0]     -0.1436      0.014    -10.396      0.000      -0.171
-0.116
C(unknow)[T.1.0]    -0.0655      0.014     -4.738      0.000      -0.093
-0.038
C(alien)[T.1.0]      0.0483      0.014      3.499      0.001       0.021
0.076
sat              -3.311e-05      0.000     -0.318      0.751      -0.000
```

```
0.000
fee              1.127e-05   8.73e-07     12.912      0.000    9.55e-06
1.3e-05
==============================================================================
Omnibus:                       24.032   Durbin-Watson:                   1.577
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               67.475
Skew:                           0.435   Prob(JB):                     2.23e-15
Kurtosis:                       5.651   Cond. No.                     6.19e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.19e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```