

Project 2 by Weitng Lin & Linlin Zhu

```
In [2]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [3]: df=pd.read_csv('Most_recent.csv')
```

```
/Users/xiuronglin/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3020: DtypeWarning: Columns (6,9,31,1608,1619,1620,1621,1622,1623,1624,1625,1626,1627,1628,1629,1688,1689,1690,1691,1692,1703,1704,1725,1726,1727,1728,1729,1743,1815,1816,1817,1818,1823,1824,1830,1831,1879,1880,1881,1882,1883,1884,1885,1886,1887,1888,1889,1890,1891,1892,1893,1894,1895,1896,1897,1898,1909,1910,1911,1912,1913,1957,1958,1959,1960,1961,1962,1963,1964,1965,1966,1967,1968,1969,1970,1971,1972,1973,1974,1975,1976) have mixed types. Specify dtype option on import or set low_memory=False.
interactivity=interactivity, compiler=compiler, result=result)
```

```
In [4]: df.shape
```

```
Out[4]: (7058, 1977)
```

```
In [5]: df.columns
```

```
Out[5]: Index(['UNITID', 'OPEID', 'OPEID6', 'INSTNM', 'CITY', 'STABBR', 'ZIP',
'ACCREDITAGENCY', 'INSTURL', 'NPCURL',
...,
'OMAWDP8_NOTFIRSTTIME_POOLED_SUPP', 'OMENRUP_NOTFIRSTTIME_POOLED_SUPP',
'OMENRYP_FULLTIME_POOLED_SUPP', 'OMENRAP_FULLTIME_POOLED_SUPP',
'OMAWDP8_FULLTIME_POOLED_SUPP', 'OMENRUP_FULLTIME_POOLED_SUPP',
'OMENRYP_PARTTIME_POOLED_SUPP', 'OMENRAP_PARTTIME_POOLED_SUPP',
'OMAWDP8_PARTTIME_POOLED_SUPP', 'OMENRUP_PARTTIME_POOLED_SUPP'],
dtype='object', length=1977)
```

In [6]: `df.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7058 entries, 0 to 7057
Columns: 1977 entries, UNITID to OMENRUP_PARTTIME_POOLED_SUPP
dtypes: float64(617), int64(14), object(1346)
memory usage: 106.5+ MB
```

In [7]: `df.head()`

Out[7]:

	UNITID	OPEID	OPEID6	INSTNM	CITY	STABBR	ZIP	ACCREDITAGENCY	INSTURL
0	100654	100200	1002	Alabama A & M University	Normal	AL	35762	Southern Association of Colleges and Schools C...	www.aamu.edu/ https://galileo.aamu.ed
1	100663	105200	1052	University of Alabama at Birmingham	Birmingham	AL	35294-0110	Southern Association of Colleges and Schools C...	www.uab.edu uab.studentaidc
2	100690	2503400	25034	Amridge University	Montgomery	AL	36117-3553	Southern Association of Colleges and Schools C...	www.amridgeuniversity.edu www2.an
3	100706	105500	1055	University of Alabama in Huntsville	Huntsville	AL	35899	Southern Association of Colleges and Schools C...	www.uah.edu
4	100724	100500	1005	Alabama State University	Montgomery	AL	36104-0271	Southern Association of Colleges and Schools C...	www.alasu.edu aic

5 rows × 1977 columns

In [8]: `print('The data has {0} rows and {1} columns'.format(df.shape[0],df.shape[1]))`

The data has 7058 rows and 1977 columns

1.What is the most costly college? What is the cheapest?

```
In [9]: df['total_tution'] = df['COSTT4_A'].fillna(0) + df['COSTT4_P'].fillna(0)
df = df[df['total_tution'] != 0]
```

```
In [10]: df.groupby('INSTNM')['total_tuition'].mean().sort_values(ascending=False)
```

```
Out[10]: INSTNM
L3 Commercial Training Solutions Airline Academy      105745.0
Aviator College of Aeronautical Science and Technology  93704.0
University of Chicago                                72717.0
Jewish Theological Seminary of America                 72120.0
Columbia University in the City of New York            71972.0
Harvey Mudd College                                   71917.0
Northwestern University                               70317.0
Washington University in St Louis                     69754.0
University of Southern California                     69547.0
Dartmouth College                                     69474.0
Drexel University                                     69462.0
Occidental College                                    69442.0
Haverford College                                    69387.0
Claremont McKenna College                             69385.0
Southern Methodist University                         69358.0
University of Pennsylvania                           69340.0
Georgetown University                               69313.0
Duke University                                       69169.0
Landmark College                                     69020.0
Amherst College                                      68986.0
Yale University                                      68950.0
Trinity College                                      68940.0
Oberlin College                                      68670.0
Bard College                                          68528.0
Barnard College                                      68512.0
Scripps College                                      68464.0
Williams College                                     68430.0
Bennington College                                   68420.0
Bard College at Simon's Rock                         68409.0
Pepperdine University                               68352.0
...
Wytheville Community College                          7084.0
Instituto Tecnologico de Puerto Rico-Recinto de Guayama 7061.0
Lake Career and Technical Center                     7050.0
Gordon Cooper Technology Center                      7044.0
Baldwin Park Adult & Community Education             7040.0
Southeastern Baptist College                         6950.0
Chattahoochee Valley Community College               6854.0
South Texas College                                 6787.0
American Technical Institute                         6782.0
```

Carver Career Center	6562.0
Lincoln Trail College	6551.0
Hacienda La Puente Adult Education	6509.0
Virginia Beach City Public Schools School of Practical Nursing	6407.0
Indian River State College	6276.0
Cloyd's Barber School 2 Inc	6255.0
Palau Community College	6085.0
Mineral County Vocational Technical Center	5957.0
Colegio Universitario de San Juan	5950.0
Putnam Career and Technical Center	5925.0
Kiamichi Technology Center-Durant	5894.0
D A Dorsey Technical College	5854.0
Aparicio-Levy Technical College	5705.0
J F Ingram State Technical College	5496.0
Escuela De Troqueleria Y Herramientaje	5481.0
Cleveland Community College	5185.0
Wes Watkins Technology Center	5180.0
Instituto Tecnologico de Puerto Rico-Recinto de Manati	5025.0
Instituto Tecnologico de Puerto Rico-Recinto de San Juan	4007.0
Instituto Tecnologico de Puerto Rico-Recinto de Ponce	3930.0
C. Alexander School of Cosmetology	3522.0

Name: total_tution, Length: 5751, dtype: float64

```
In [11]: df.groupby('INSTNM')['total_tuition'].mean().sort_values(ascending =True)
```

```
Out[11]: INSTNM
C. Alexander School of Cosmetology      3522.0
Instituto Tecnologico de Puerto Rico-Recinto de Ponce 3930.0
Instituto Tecnologico de Puerto Rico-Recinto de San Juan 4007.0
Instituto Tecnologico de Puerto Rico-Recinto de Manati 5025.0
Wes Watkins Technology Center           5180.0
Cleveland Community College            5185.0
Escuela De Troquelaria Y Herramientaje  5481.0
J F Ingram State Technical College      5496.0
Aparicio-Levy Technical College         5705.0
D A Dorsey Technical College            5854.0
Kiamichi Technology Center-Durant      5894.0
Putnam Career and Technical Center      5925.0
Colegio Universitario de San Juan       5950.0
Mineral County Vocational Technical Center 5957.0
Palau Community College                6085.0
Cloyd's Barber School 2 Inc            6255.0
Indian River State College              6276.0
Virginia Beach City Public Schools School of Practical Nursing 6407.0
Hacienda La Puente Adult Education     6509.0
Lincoln Trail College                  6551.0
Carver Career Center                   6562.0
American Technical Institute           6782.0
South Texas College                    6787.0
Chattahoochee Valley Community College 6854.0
Southeastern Baptist College           6950.0
Baldwin Park Adult & Community Education 7040.0
Gordon Cooper Technology Center         7044.0
Lake Career and Technical Center        7050.0
Instituto Tecnologico de Puerto Rico-Recinto de Guayama 7061.0
Wytheville Community College            7084.0
...
Pepperdine University                  68352.0
Bard College at Simon's Rock           68409.0
Bennington College                     68420.0
Williams College                       68430.0
Scripps College                        68464.0
Barnard College                        68512.0
Bard College                           68528.0
Oberlin College                        68670.0
Trinity College                        68940.0
```

Yale University	68950.0
Amherst College	68986.0
Landmark College	69020.0
Duke University	69169.0
Georgetown University	69313.0
University of Pennsylvania	69340.0
Southern Methodist University	69358.0
Claremont McKenna College	69385.0
Haverford College	69387.0
Occidental College	69442.0
Drexel University	69462.0
Dartmouth College	69474.0
University of Southern California	69547.0
Washington University in St Louis	69754.0
Northwestern University	70317.0
Harvey Mudd College	71917.0
Columbia University in the City of New York	71972.0
Jewish Theological Seminary of America	72120.0
University of Chicago	72717.0
Aviator College of Aeronautical Science and Technology	93704.0
L3 Commercial Training Solutions Airline Academy	105745.0

Name: total_tution, Length: 5751, dtype: float64

```
In [12]: #the most costly college is L3 Commercial Training Solutions Airline Academy
         #the cheapest college is C. Alexander School of Cosmetology
```

2.What is the average cost for college for colleges in different parts of the US

```
In [13]: df.groupby('STABBR')['total_tution'].mean()
```

```
Out[13]: STABBR
AK      20202.666667
AL      20661.987179
AR      18277.480000
AS       7400.000000
AZ      21326.971429
CA      25254.285971
CO      23154.380435
CT      26631.231884
DC      36920.666667
DE      24394.266667
FL      23675.617089
FM       9554.000000
GA      23428.047297
GU      12339.000000
HI      20745.285714
IA      25967.620253
ID      19609.424242
IL      23245.472477
IN      27260.939394
KS      21792.555556
KY      22480.465909
LA      20873.833333
MA      35062.945946
MD      25328.820513
ME      28090.529412
MH       8750.000000
MI      22736.019737
MN      24886.870968
MO      22620.850340
MP       8734.000000
MS      19143.018868
MT      17119.900000
NC      22907.287425
ND      17174.206897
NE      24390.181818
NH      28653.166667
NJ      25148.864286
NM      18100.279070
NV      22693.571429
NY      27910.160000
```



```
OH      23277.090909
OK      17511.097345
OR      23797.000000
PA      29006.827044
PR      11653.033058
PW       6085.000000
RI      34898.300000
SC      24322.868687
SD      21214.333333
TN      22750.207792
TX      21572.531335
UT      20058.442623
VA      25169.522388
VI      16786.000000
VT      39868.857143
WA      22176.948454
WI      24552.855422
WV      18101.865672
WY      14714.200000
Name: total_tution, dtype: float64
```

```
In [14]: #What is the average cost for college for colleges in different parts of the US  
df.groupby('STABBR')['total_tution'].mean()
```

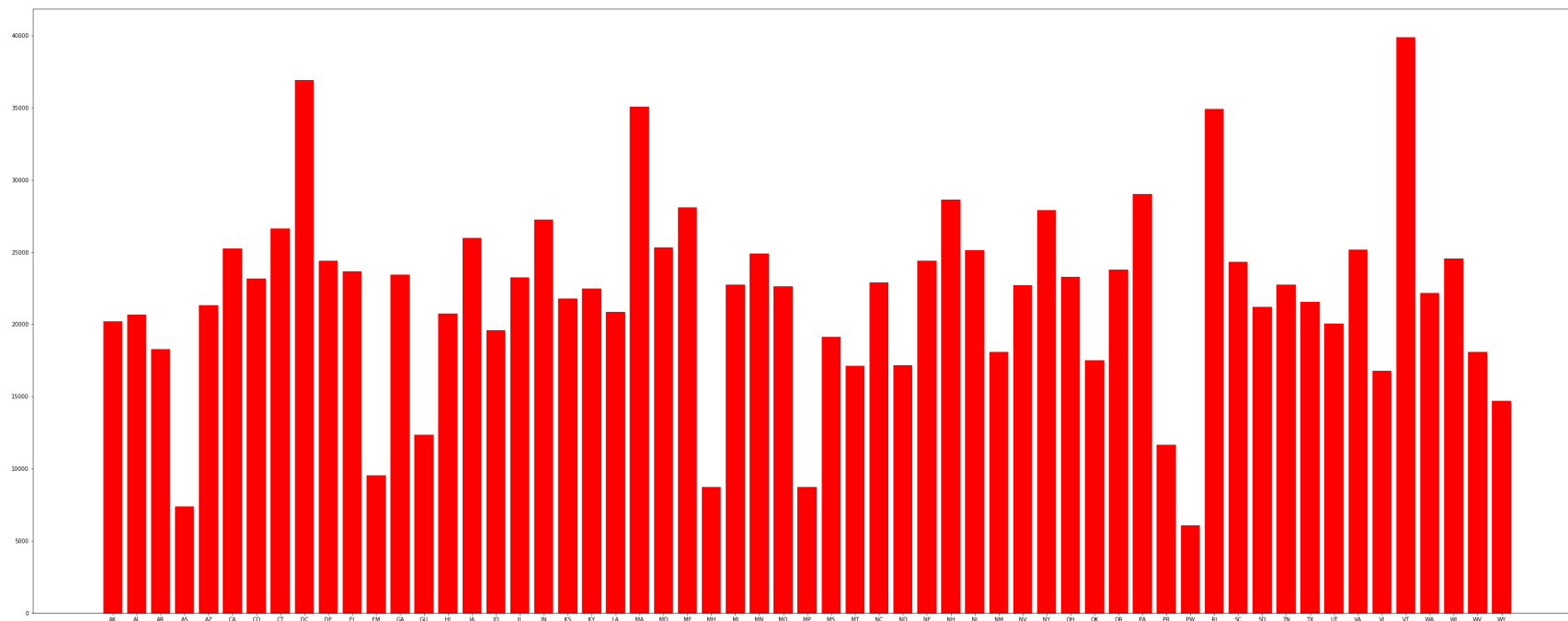
```
Out[14]: STABBR  
AK      20202.666667  
AL      20661.987179  
AR      18277.480000  
AS       7400.000000  
AZ      21326.971429  
CA      25254.285971  
CO      23154.380435  
CT      26631.231884  
DC      36920.666667  
DE      24394.266667  
FL      23675.617089  
FM       9554.000000  
GA      23428.047297  
GU      12339.000000  
HI      20745.285714  
IA      25967.620253  
ID      19609.424242  
IL      23245.472477  
IN      27260.939394  
KS      21792.555556  
KY      22480.465909  
LA      20873.833333  
MA      35062.945946  
MD      25328.820513  
ME      28090.529412  
MH       8750.000000  
MI      22736.019737  
MN      24886.870968  
MO      22620.850340  
MP       8734.000000  
MS      19143.018868  
MT      17119.900000  
NC      22907.287425  
ND      17174.206897  
NE      24390.181818  
NH      28653.166667  
NJ      25148.864286  
NM      18100.279070  
NV      22693.571429
```

NY	27910.160000
OH	23277.090909
OK	17511.097345
OR	23797.000000
PA	29006.827044
PR	11653.033058
PW	6085.000000
RI	34898.300000
SC	24322.868687
SD	21214.333333
TN	22750.207792
TX	21572.531335
UT	20058.442623
VA	25169.522388
VI	16786.000000
VT	39868.857143
WA	22176.948454
WI	24552.855422
WV	18101.865672
WY	14714.200000

Name: total_tution, dtype: float64

```
In [15]: state = df.groupby(['STABBR']).mean()  
plt.figure(figsize=(50,20))  
plt.bar(state.index,state['total_tution'],color='red')
```

Out[15]: <BarContainer object of 59 artists>



3.What is the average cost of religious vs. secular institutions?

```
In [16]: # Create a new dataset indecate the different religions
religiou= df.groupby('RELAFFIL').mean()
# Create a new dataset indecate the doesn't have religions
secular = df[df['RELAFFIL'].isnull()]

rel = religiou['total_tution'].mean()
sec = secular['total_tution'].mean()
```

```
In [17]: rel
```

```
Out[17]: 35304.21875642725
```

```
In [18]: sec
```

```
Out[18]: 21895.61946729338
```

```
In [19]: #The average cost of all religious institutions is $35304.21875642725
#The average cost of all secular institutions is $21895.61946729338
```

4.What percent of colleges have an open admission policy?

```
In [20]: # Open admission is represented by the column OPENADMP
# Colleges with an open admission policy are represented by 1.0
adm = df[df['OPENADMP'].notnull()]
openadm = adm.groupby('OPENADMP').size()
openrate = float(openadm[1.0]) / len(df['OPENADMP']) * 100
openrate = round(openrate,2)
```

```
In [21]: print(openrate)
```

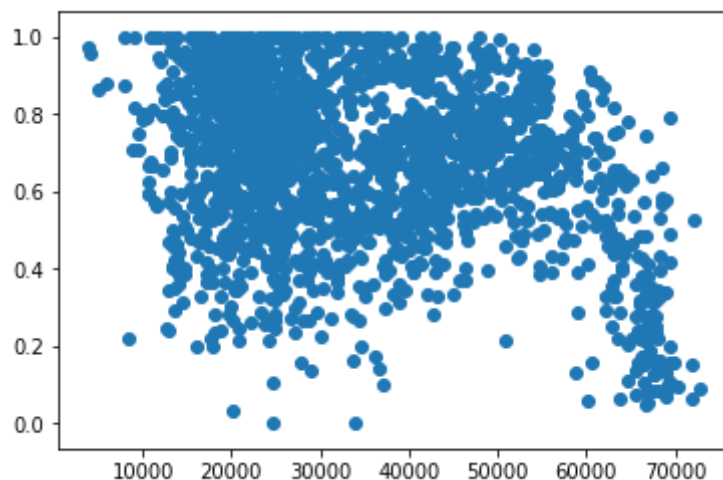
```
65.76
```

```
In [22]: #65.76 percent of colleges have an open admission policy
```

5. What is the correlation (scatterplot) between admission rates and college cost?

```
In [23]: plt.scatter(df['total_tuition'], df['ADM_RATE'])
```

```
Out[23]: <matplotlib.collections.PathCollection at 0x1a3033f5f8>
```



6. What is the correlation between SAT scores and admission rates? Are there any outliers?

```
In [24]: corr=df.corr()
```

In [25]: corr

Out[25]:

	UNITID	OPEID	OPEID6	SCH_DEG	HCM2	MAIN	NUMBRANCH	PREDDEG	HIGHDEG	CONT
UNITID	1.000000	0.404391	0.703476	-0.403578	0.060837	-0.399365	0.218942	-0.416574	-0.411594	0.48
OPEID	0.404391	1.000000	0.506002	-0.222312	0.032336	-0.122262	0.208191	-0.226693	-0.225232	0.31
OPEID6	0.703476	0.506002	1.000000	-0.564070	0.075663	-0.067748	-0.009493	-0.565021	-0.565996	0.55
SCH_DEG	-0.403578	-0.222312	-0.564070	1.000000	-0.005817	0.147829	0.035107	0.946966	0.899707	-0.40
HCM2	0.060837	0.032336	0.075663	-0.005817	1.000000	-0.083521	0.117531	0.000228	-0.009318	0.09
MAIN	-0.399365	-0.122262	-0.067748	0.147829	-0.083521	1.000000	-0.541109	0.167519	0.137340	-0.31
NUMBRANCH	0.218942	0.208191	-0.009493	0.035107	0.117531	-0.541109	1.000000	0.014370	0.051479	0.22
PREDDEG	-0.416574	-0.226693	-0.565021	0.946966	0.000228	0.167519	0.014370	1.000000	0.902380	-0.40
HIGHDEG	-0.411594	-0.225232	-0.565996	0.899707	-0.009318	0.137340	0.051479	0.902380	1.000000	-0.38
CONTROL	0.482515	0.315501	0.555806	-0.401863	0.093042	-0.311192	0.221663	-0.401687	-0.382893	1.00
ST_FIPS	0.141743	-0.012795	-0.039005	0.030508	-0.045248	-0.014274	-0.014349	0.032446	0.025705	-0.03
REGION	0.097989	0.102737	0.163336	-0.117991	0.058573	-0.051692	0.010553	-0.114964	-0.072736	0.05
LOCALE	-0.141363	-0.089669	-0.151339	0.040276	-0.058035	0.113280	-0.098476	0.024273	-0.009425	-0.33
LOCALE2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
LATITUDE	-0.145927	-0.096769	-0.183972	0.108464	-0.030577	0.094079	-0.049475	0.107136	0.074661	-0.10
LONGITUDE	0.005157	-0.057375	-0.072721	0.075764	-0.055800	0.016974	-0.000509	0.073179	0.051464	-0.02
CCBASIC	-0.307206	-0.162033	-0.431689	0.799136	0.016306	0.055523	0.107842	0.800780	0.883162	-0.25
CCUGPROF	-0.396347	-0.220180	-0.528604	0.858298	-0.033482	0.143404	-0.011756	0.863897	0.914610	-0.33
CCSIZSET	-0.458946	-0.274698	-0.601761	0.865236	-0.037810	0.199471	-0.024481	0.870958	0.924810	-0.46
HBCU	-0.097495	-0.063716	-0.118361	0.135732	0.026512	0.059568	-0.039517	0.132983	0.123301	-0.09
PBI	-0.038697	-0.024972	-0.039826	0.007795	0.015751	-0.007941	0.004172	0.006734	0.041477	-0.09
ANNHI	-0.037743	-0.015005	-0.024652	0.034803	0.011080	0.025239	-0.014402	0.034233	0.033730	-0.06
TRIBAL	0.000620	0.023418	0.053823	0.002351	0.008343	0.035074	-0.023150	0.002701	0.014235	-0.07
AANAPII	-0.089836	-0.045586	-0.079923	0.084640	-0.019117	0.044170	-0.031741	0.086222	0.096905	-0.14

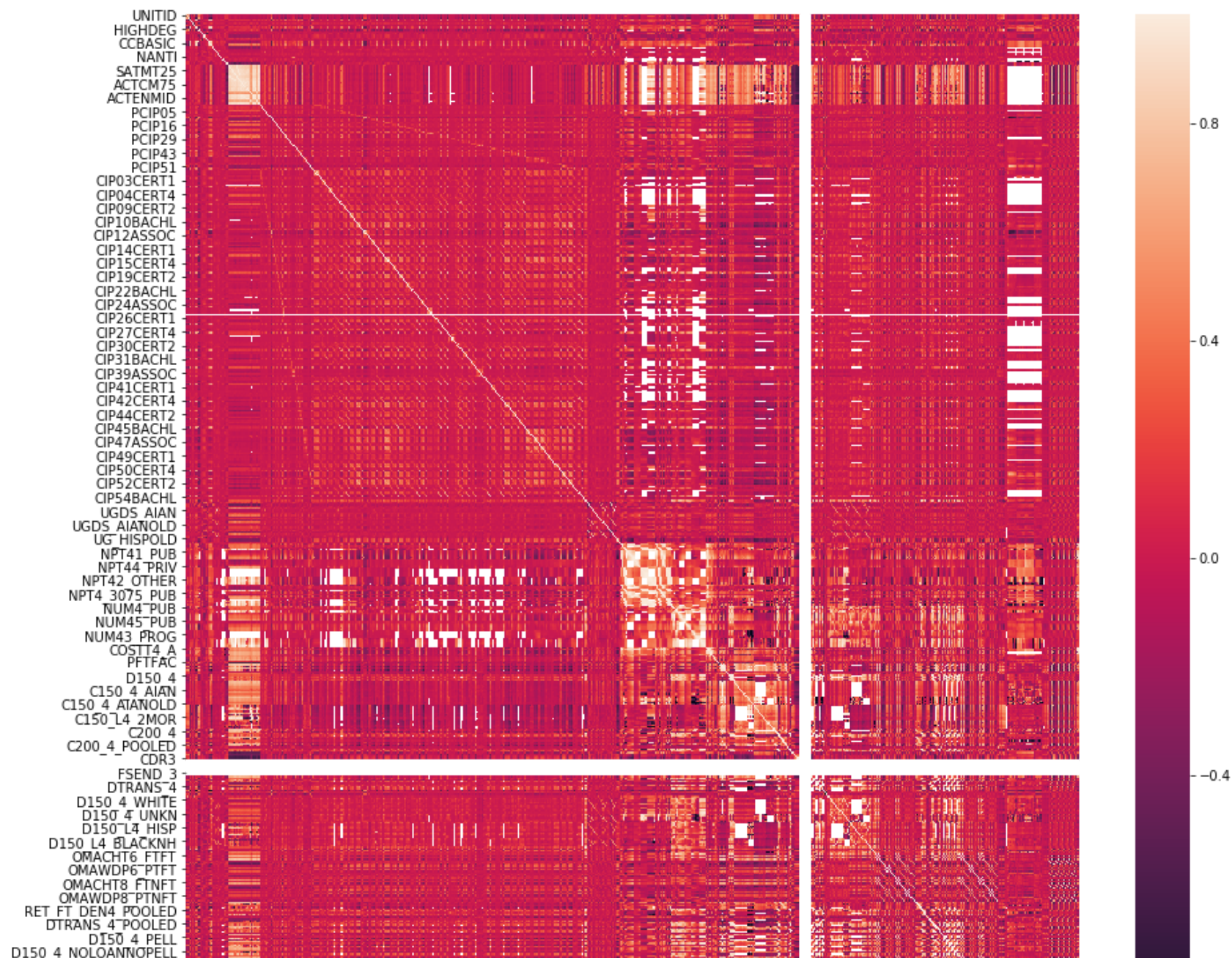
	UNITID	OPEID	OPEID6	SCH_DEG	HCM2	MAIN	NUMBRANCH	PREDDEG	HIGHDEG	CONT
NANTI	-0.033184	-0.023565	-0.042107	0.035105	0.011604	0.017849	-0.016543	0.028701	0.024563	-0.07
MENONLY	-0.037816	-0.009893	-0.012054	0.123918	-0.012195	0.044226	-0.029641	0.103872	0.082402	-0.01
WOMENONLY	-0.061770	-0.042622	-0.079336	0.102761	-0.010350	0.037536	-0.024790	0.104683	0.101058	-0.01
RELAFFIL	0.075427	0.142742	0.143405	-0.008700	0.013851	-0.009468	0.000099	0.030766	-0.121881	0.08
ADM_RATE	0.114609	0.130341	0.130341	-0.080637	0.005388	-0.084669	0.108254	-0.117781	-0.071292	-0.01
ADM_RATE_ALL	0.119586	0.119228	0.138030	-0.083913	0.005739	-0.042408	0.054345	-0.121068	-0.076443	-0.00
...
MTHCMP3	-0.014976	-0.122831	-0.122832	0.229917	-0.020988	-0.064633	0.145573	0.276222	0.462006	-0.15
MTHCMP4	-0.045400	-0.183845	-0.183846	0.251932	0.012391	-0.065158	0.161554	0.330341	0.462249	-0.15
MTHCMP5	-0.102229	-0.219415	-0.219415	0.193211	-0.043913	-0.121937	0.135052	0.196352	0.412997	-0.12
MTHCMP6	-0.059024	-0.207428	-0.207429	0.247293	-0.030993	-0.136376	0.203557	0.211246	0.398564	-0.03
POOLYRSOM_ALL	0.174177	0.055468	0.181240	-0.001949	-0.012183	-0.021549	0.053552	-0.010157	-0.017620	0.09
POOLYRSOM_FIRSTTIME	0.206620	0.070644	0.238201	0.051038	0.007070	-0.027526	0.021351	0.010869	0.027892	0.11
POOLYRSOM_NOTFIRSTTIME	0.269315	0.093720	0.326309	-0.138725	-0.007928	-0.086831	-0.001980	-0.140837	-0.144221	0.25
POOLYRSOM_FULLTIME	0.243266	0.081396	0.264131	-0.011362	0.033879	-0.042287	0.075467	-0.021640	-0.010135	0.11
POOLYRSOM_PARTTIME	0.243661	0.178441	0.294154	-0.002022	-0.039130	-0.098215	-0.003833	0.006762	0.008099	0.46
OMENRYP_ALL	-0.043783	-0.006866	-0.007344	-0.043389	-0.006825	-0.001302	-0.014770	-0.064118	-0.068836	-0.14
OMENRAP_ALL	-0.297737	-0.179910	-0.331517	0.222794	-0.070372	0.225292	-0.121971	0.205087	0.078577	-0.45
OMAWDP8_ALL	0.066657	-0.011503	0.057823	0.138330	-0.086340	0.016372	-0.111412	0.161615	0.277867	0.33
OMENRUP_ALL	0.156753	0.145911	0.184810	-0.301127	0.143901	-0.183121	0.209670	-0.310492	-0.338762	0.00
OMENRYP_FIRSTTIME	-0.044914	-0.008823	-0.003797	-0.046365	-0.005683	0.002046	-0.024727	-0.067568	-0.073269	-0.16
OMENRAP_FIRSTTIME	-0.281993	-0.179957	-0.339375	0.315836	-0.062710	0.218100	-0.130393	0.302094	0.200274	-0.39
OMAWDP8_FIRSTTIME	0.041181	-0.048217	0.046538	0.100998	-0.101397	0.039903	-0.146648	0.118887	0.228282	0.30
OMENRUP_FIRSTTIME	0.162912	0.175201	0.191207	-0.312919	0.145876	-0.192484	0.241291	-0.319065	-0.356216	-0.00
OMENRYP_NOTFIRSTTIME	-0.042107	-0.006955	-0.020443	-0.021044	-0.022192	-0.018316	-0.005107	-0.043984	-0.035645	-0.12
OMENRAP_NOTFIRSTTIME	-0.279043	-0.157296	-0.287827	0.038551	-0.082179	0.194366	-0.102678	0.016648	-0.115459	-0.47

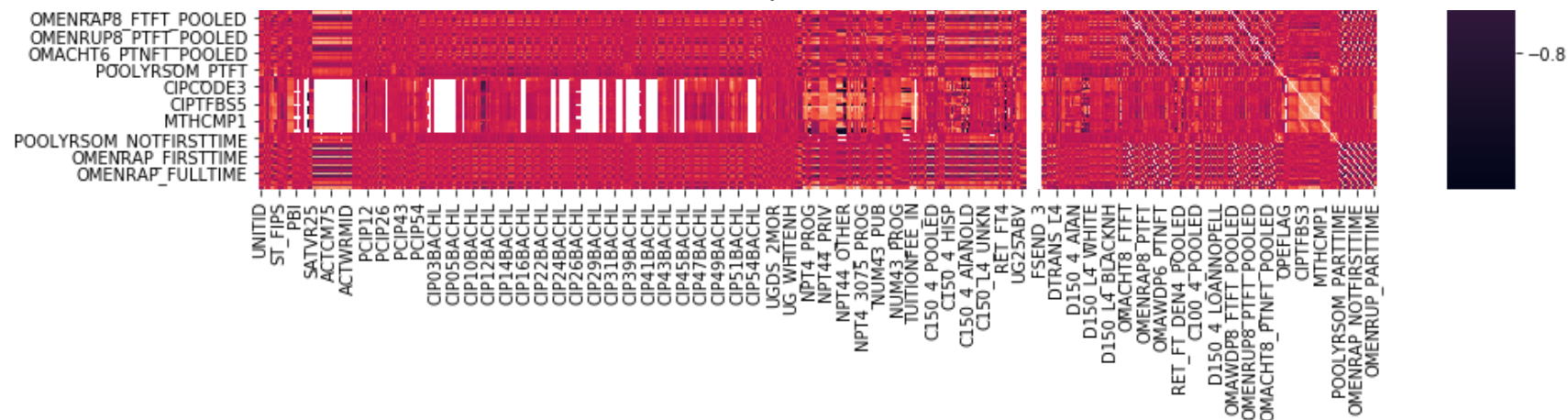
	UNITID	OPEID	OPEID6	SCH_DEG	HCM2	MAIN	NUMBRANCH	PREDDEG	HIGHDEG	CONT
OMAWDP8_NOTFIRSTTIME	0.075317	0.004635	0.049882	0.173103	-0.059508	0.013698	-0.090166	0.200870	0.304076	0.30
OMENRUP_NOTFIRSTTIME	0.145377	0.120772	0.176782	-0.217223	0.134129	-0.166226	0.181294	-0.226727	-0.236672	0.06
OMENRYP_FULLTIME	-0.042959	-0.008380	-0.017061	-0.019971	-0.000542	-0.002759	-0.007416	-0.042180	-0.059235	-0.17
OMENRAP_FULLTIME	-0.289722	-0.179799	-0.332451	0.239914	-0.064084	0.218658	-0.109640	0.223789	0.099332	-0.43
OMAWDP8_FULLTIME	0.063716	-0.024328	0.051463	0.106959	-0.063627	0.001227	-0.071317	0.129895	0.250215	0.32
OMENRUP_FULLTIME	0.165000	0.166552	0.206570	-0.293151	0.116856	-0.170410	0.161486	-0.303184	-0.330512	0.02
OMENRYP_PARTTIME	-0.027792	0.022581	0.028471	-0.098456	-0.017747	-0.013196	-0.024178	-0.106725	-0.062875	0.00
OMENRAP_PARTTIME	-0.235909	-0.251556	-0.287530	0.073843	-0.091773	0.159551	-0.080814	0.076461	-0.005540	-0.35
OMAWDP8_PARTTIME	0.035847	0.028747	0.027627	0.178739	-0.075054	0.027880	-0.046486	0.196673	0.286352	0.18
OMENRUP_PARTTIME	0.149171	0.154013	0.180179	-0.194677	0.142310	-0.140696	0.109423	-0.210647	-0.244499	0.09
total_tution	-0.135507	-0.123956	-0.231899	0.472730	-0.006195	0.014980	0.026661	0.476438	0.483530	0.16

632 rows × 632 columns

```
In [26]: plt.figure(figsize=(15,15))
sns.heatmap(corr)
```

```
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2f51bf98>
```





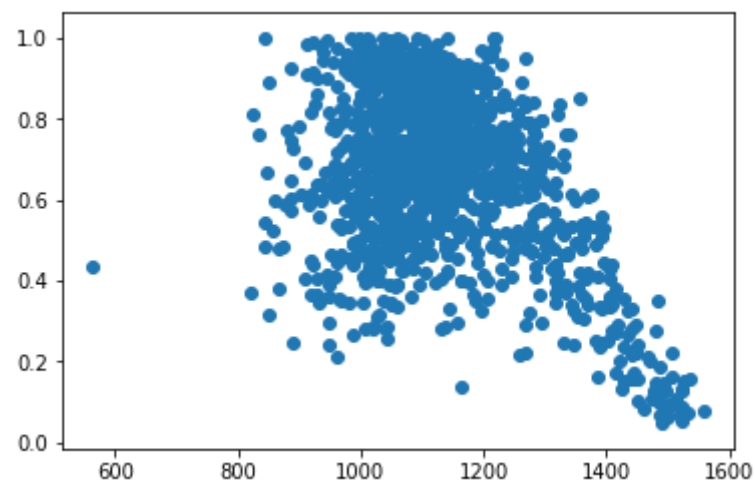
```
In [27]: df['SAT_AVG'].corr(df['ADM_RATE'])
```

Out[27]: -0.4106203354294415

```
In [28]: #the correlation between SAT scores
#         and admission rates is -0.4106203354294415 which means it's weak correlation
```

```
In [29]: plt.scatter(df['SAT_AVG'], df['ADM_RATE'])
```

```
Out[29]: <matplotlib.collections.PathCollection at 0x1a28ea7b70>
```



```
In [30]: #yes there is a outliar
```

```
In [ ]:
```

```
In [ ]:
```