ChandonnetPythonProject

December 16, 2022

1 Final Python Project

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1.0.2 12/16/2022

Key Assumptions and modeling approaches:

Assumptions: - All salaries in the Salary file are already in USD and so no FX conversion was done (this wasn't totally clear but seemed the case) - Only used salary for jobs titled as Data Scientist - Assigned experience levels as follows: ~ 0-5 years experience = "Junior" ~ >5 years experience = ""Senior" - Used all salaries for all dates, meaning I assume the data is pretty evenly distributed across years for all cities (Otherwise data is actually not granular enough to be meaningful) - I only use CASH compensation to calculate affordability, since you can't pay bills with stock grants, which are intended to build wealth and usually are on a vesting schedule

Modeling approaches:

- I consider the most important index to be "Cost of Living Plus Rent" which factors in housing costs which are a critical component of cost of living
- The cost of living indexes provided use NYC as the baseline index of 100, so all other indexes are expressed relative to NYC
- Given that, I construct a comparable "salary index" for all cities in the salary file, also relative to NYC. So NYC is 100; if a job pays only 75% less than the average comparable job in NYC it gets a salary index of 75; If it pays 1.2x a comparable job in NYC it gets a salary index of 120
- These indexes are done using separate average salaries for the two experience levels I created, to avoid skewing results where more junior or senior people exist in a given city, making salaries seem higher or lower than they really area
- I then create an "affordability index" which is salary index divided by cost of living index. Since both indices are relative to NYC, NYC is deemed to have an affordability index of 100, with more affordable cities than NYC having an index higher than 100 and less affordable cities than NYC having an index the result
- The idea is that how affordable a city is a function of how much you earn relative to the cost of living there. If an area costs a lot less to live than NYC, but pays almost as much, it's more affordable. The converse is also true.

- I then rank order the cities by affordability, for both junior and senior people.
- I also ran a few plots to see if there was a difference (skew) in overall affordability for junior vs senior people, and also ran

[27]:
```
# import needed libraries and set file path prefix
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
path = "/users/raychandonnet/Dropbox (Personal)/Merrimack College - \
MS in Data Science/DSE5002/Python Project/"
```

2 Part 1: Data Wrangling the Cost of Living Index File

[28]:
```
cost_of_living=pd.read_csv(path + "cost_of_living.csv")
cost_of_living=cost_of_living.rename(columns=\
  {"Cost of Living Plus Rent Index":"RealCOL_Index"})
# Step 1 - Break the City up - requires a lot of cleaning because city and
# country are in the same field separated by
# a comma, and US cities also have the state in form city, st, country.
# I want to break these up into separate columns to link to the country
# code data, then pull in job info for those city / country combos
# First, split the city into three separate fields
cost_of_living[['City','State','Country']]=cost_of_living['City'].str.\
    split(pat=",",n=2,expand=True)
# This leaves the city state and country correct for US cities, but has the
# country in the city column for non-US cities and "None" for country, so we
# have to fix that  It's two steps:
# First, repalce all the "None" in Country column with the State value which
# is where the Country is. Then eliminate the dups by putting "-" in the State
# field for all those.  So we basically just swapped values to get the country
# in the right place
cost_of_living['Country']=cost_of_living['Country'].\
    fillna(cost_of_living['State']) # Puts the state value in country where NA
cost_of_living['State']=np.where(cost_of_living['State']\
                                ==cost_of_living['Country'],
                                "-",cost_of_living['State'])
# It took me more time than I care to admit to realize that my states and
# countries had padded whitespace and so weren't matching when I tried to
# merge in the country code data!!! Sigh....using the strip method fixes that
cost_of_living['Country']=cost_of_living['Country'].str.strip()
cost_of_living['State']=cost_of_living['State'].str.strip()
# This leaves us with City, State and Country, with country spelled out
# Now I can merge in the country codes from that file into my table.  This
# will let me connect to data in the salary and jobs files once I do some
# stuff with that data, if I need to use a code instead of the country
# spelled out
countrycodes=pd.read_excel(path+"country_codes.xlsx")
cost_of_living=pd.merge(left=cost_of_living,right=countrycodes,
                        how='left',on='Country')
```

```python
print(cost_of_living.head(10))
```

```
   Rank       City  Cost of Living Index  Rent Index  RealCOL_Index  \
0   NaN   Hamilton                149.02       96.10         124.22
1   NaN     Zurich                131.24       69.26         102.19
2   NaN      Basel                130.93       49.38          92.70
3   NaN        Zug                128.13       72.12         101.87
4   NaN     Lugano                123.99       44.99          86.96
5   NaN   Lausanne                122.03       59.55          92.74
6   NaN     Beirut                120.47       27.76          77.01
7   NaN       Bern                118.16       46.12          84.39
8   NaN     Geneva                114.05       75.05          95.77
9   NaN  Stavanger                104.61       35.38          72.16

   Groceries Index  Restaurant Price Index  Local Purchasing Power Index  \
0           157.89                  155.22                         79.43
1           136.14                  132.52                        129.79
2           137.07                  130.95                        111.53
3           132.61                  130.93                        143.40
4           129.17                  119.80                        111.96
5           122.56                  127.01                        127.01
6           141.33                  116.95                         15.40
7           118.37                  120.88                        112.46
8           112.70                  126.31                        120.60
9           102.46                  107.51                         85.90

  State      Country Alpha-2 code Alpha-3 code  Numeric
0     -      Bermuda           BM          BMU     60.0
1     -  Switzerland           CH          CHE    756.0
2     -  Switzerland           CH          CHE    756.0
3     -  Switzerland           CH          CHE    756.0
4     -  Switzerland           CH          CHE    756.0
5     -  Switzerland           CH          CHE    756.0
6     -      Lebanon           LB          LBN    422.0
7     -  Switzerland           CH          CHE    756.0
8     -  Switzerland           CH          CHE    756.0
9     -       Norway           NO          NOR    578.0
```

3 Part 2 - Data wrangling the salary data

I chose to use this data as the source for my income in calculating salary indexes relative to NY, a necessary pre-requisite to calculating an affordability index. There so many different ways we could slice and dice the data - I will be focusing on cash compensation and seniority, specifically for the salaries listed there as Data Scientist

[29]:
```python
# Read in the salaries file and do some data wrangling here as well to
# convert the time stamp to a date, and put the cities and countries in the
```

```
# right columns
#
# I did not end up using the date column in any way - ran out of time
# But wanted to show I knew how to convert it
salaries=pd.read_csv(path+"Levels_Fyi_Salary_Data.csv") # read data
salaries=salaries[salaries['title']=="Data Scientist"] # Slice the DS jobs
salaries['timestamp'] = pd.to_datetime(salaries['timestamp']) # convert date
salaries=salaries.rename({"timestamp":"date"},axis=1) #rename date column
salaries[['City','State','Country']]=salaries['location'].\
    str.split(pat=",",n=2,expand=True)
# Now fill in "United States" where country is blank, delete the state for
# non-US locations, and remove whitespace
salaries['Country']=salaries['Country'].fillna("United States")
salaries['State']=np.where(salaries['Country']!='United States',
                           "-",salaries['State']) # delete states for non-US
salaries['Country']=salaries['Country'].str.strip()
salaries['State']=salaries['State'].str.strip()
print(salaries.head(10))
```

```
                   date    company            level           title  \
419 2018-06-05 14:06:30   LinkedIn           Senior  Data Scientist
440 2018-06-08 09:49:25  Microsoft               64  Data Scientist
444 2018-06-08 17:55:09       ebay               26  Data Scientist
454 2018-06-10 19:39:35    Twitter            Staff  Data Scientist
495 2018-06-17 11:39:38   Facebook                5  Data Scientist
499 2018-06-17 19:02:50     Amazon               L5  Data Scientist
509 2018-06-20 00:47:43  Microsoft               65  Data Scientist
510 2018-06-20 00:49:11     Google               L6  Data Scientist
513 2018-06-21 10:54:35    Netflix           Senior  Data Scientist
523 2018-06-25 08:45:29      Tesla  Senior Engineer  Data Scientist

     totalyearlycompensation           location  yearsofexperience  \
419                   233000  San Francisco, CA                4.0
440                   218000        Seattle, WA               11.0
444                   180000       San Jose, CA               10.0
454                   500000  San Francisco, CA                4.0
495                   370000        Seattle, WA                8.0
499                   200000        Seattle, WA                3.0
509                   340000       Bellevue, WA               11.0
510                   690000       Kirkland, WA               10.0
513                   600000      Los Gatos, CA                3.0
523                   168000      Palo Alto, CA                8.0

     yearsatcompany                tag  basesalary  ...  Race_Asian  \
419             0.0      Data Analysis    162000.0  ...           0
440            11.0            ML / AI    165000.0  ...           0
444             5.0                NaN         0.0  ...           0
454             4.0            ML / AI    200000.0  ...           0
```

```
495           3.0                     NaN    190000.0  ...           0
499           0.0                 ML / AI    150000.0  ...           0
509          11.0                 ML / AI    200000.0  ...           0
510           0.0                 ML / AI    240000.0  ...           0
513           1.0                 ML / AI    600000.0  ...           0
523           3.0  Mechanical Engineering    118000.0  ...           0

     Race_White Race_Two_Or_More Race_Black  Race_Hispanic  Race  Education  \
419           0                0          0              0   NaN        NaN
440           0                0          0              0   NaN        NaN
444           0                0          0              0   NaN        NaN
454           0                0          0              0   NaN        NaN
495           0                0          0              0   NaN        NaN
499           0                0          0              0   NaN        NaN
509           0                0          0              0   NaN        NaN
510           0                0          0              0   NaN        NaN
513           0                0          0              0   NaN        NaN
523           0                0          0              0   NaN        NaN

              City  State        Country
419  San Francisco     CA  United States
440        Seattle     WA  United States
444       San Jose     CA  United States
454  San Francisco     CA  United States
495        Seattle     WA  United States
499        Seattle     WA  United States
509       Bellevue     WA  United States
510       Kirkland     WA  United States
513      Los Gatos     CA  United States
523      Palo Alto     CA  United States

[10 rows x 32 columns]
```

4 Part 3: Enriching the salary data

Now I'm going to enrich the data a bit to make it more granular and make more sense: First, I calculate "cashcomp" as cash compensation = base + bonus.Then I tag each salary with a "Junior" or "Senior" experience level as noted above

[30]:
```
salaries['cashcomp']=salaries['basesalary']+salaries['bonus']
salaries=salaries[salaries['cashcomp']!=0]  # eliminate zeros
salaries['explevel']=np.where(salaries['yearsofexperience']<=5,
                              "Junior","Senior")
print(salaries.head(10))
```

```
                    date    company           level           title  \
419 2018-06-05 14:06:30   LinkedIn          Senior  Data Scientist
440 2018-06-08 09:49:25  Microsoft              64  Data Scientist
```

```
454 2018-06-10 19:39:35    Twitter           Staff  Data Scientist
495 2018-06-17 11:39:38   Facebook               5  Data Scientist
499 2018-06-17 19:02:50     Amazon              L5  Data Scientist
509 2018-06-20 00:47:43  Microsoft              65  Data Scientist
510 2018-06-20 00:49:11     Google              L6  Data Scientist
513 2018-06-21 10:54:35    Netflix          Senior  Data Scientist
523 2018-06-25 08:45:29      Tesla  Senior Engineer  Data Scientist
535 2018-06-26 21:37:46    GrubHub              II  Data Scientist

     totalyearlycompensation          location  yearsofexperience  \
419                   233000  San Francisco, CA                4.0
440                   218000        Seattle, WA               11.0
454                   500000  San Francisco, CA                4.0
495                   370000        Seattle, WA                8.0
499                   200000        Seattle, WA                3.0
509                   340000       Bellevue, WA               11.0
510                   690000       Kirkland, WA               10.0
513                   600000      Los Gatos, CA                3.0
523                   168000      Palo Alto, CA                8.0
535                   187000       New York, NY                4.0

     yearsatcompany                     tag  basesalary  ...  \
419             0.0           Data Analysis    162000.0  ...
440            11.0                 ML / AI    165000.0  ...
454             4.0                 ML / AI    200000.0  ...
495             3.0                     NaN    190000.0  ...
499             0.0                 ML / AI    150000.0  ...
509            11.0                 ML / AI    200000.0  ...
510             0.0                 ML / AI    240000.0  ...
513             1.0                 ML / AI    600000.0  ...
523             3.0  Mechanical Engineering    118000.0  ...
535             1.0                 ML / AI    150000.0  ...

     Race_Two_Or_More  Race_Black Race_Hispanic Race  Education  \
419                 0           0             0  NaN        NaN
440                 0           0             0  NaN        NaN
454                 0           0             0  NaN        NaN
495                 0           0             0  NaN        NaN
499                 0           0             0  NaN        NaN
509                 0           0             0  NaN        NaN
510                 0           0             0  NaN        NaN
513                 0           0             0  NaN        NaN
523                 0           0             0  NaN        NaN
535                 0           0             0  NaN        NaN

              City  State        Country  cashcomp  explevel
419  San Francisco     CA  United States  172000.0    Junior
440        Seattle     WA  United States  188000.0    Senior
```

```
454  San Francisco     CA  United States  220000.0    Junior
495        Seattle     WA  United States  230000.0    Senior
499        Seattle     WA  United States  231000.0    Junior
509       Bellevue     WA  United States  260000.0    Senior
510       Kirkland     WA  United States  312000.0    Senior
513      Los Gatos     CA  United States  600000.0    Junior
523      Palo Alto     CA  United States  118000.0    Senior
535       New York     NY  United States  160000.0    Junior

[10 rows x 34 columns]
```

5 Part 4 - Aggregating by city/level, isolating NYC

Now I aggregate by city, state, country and experience level, calculating mean salary for each subset. Then, since in the cost of living data, the indexes re calculated using NYC as baseline (100 index), I calculate a "salary index" for each city and experience combination, relative to that same experience level in NYC so everything is on a common denominator

[31]:
```
sal_by_city=salaries.groupby(['Country','City','State','explevel'],
                             as_index=False).agg(avg_salary=('cashcomp',
                                                              np.mean))
NYCsal=salaries[salaries['City']=="New York"] # Extract all the NYC jobs
NYC_by_level=NYCsal.groupby('explevel').agg(
    NYC_avg_salary=('cashcomp', np.mean))  # Calc NYC mean salaries by level
print(sal_by_ctry.head(5))
print(sal_by_city.head(5))
print(NYC_by_level.head())
```

```
     Country explevel     avg_salary
0  Australia   Junior   89333.333333
1  Australia   Senior  213500.000000
2    Austria   Junior   17000.000000
3     Brazil   Senior   28000.000000
4     Canada   Junior   95297.297297
     Country       City State explevel  avg_salary
0  Australia   Canberra     -   Junior     93000.0
1  Australia  Melbourne     -   Junior     67000.0
2  Australia  Melbourne     -   Senior    142000.0
3  Australia     Sydney     -   Junior    108000.0
4  Australia     Sydney     -   Senior    285000.0
          NYC_avg_salary
explevel
Junior     156672.131148
Senior     230960.784314
```

6 Part 5 - Calculate salary and affordability indexes

Here comes the magic! Now that I have average salaries for NYC by level, I can use those to create a salary index, with NYC as the baseline at 100, for each city/level combo I found. Once that cost of living index is calculated, I can derive an "affordability" index dividing the salary index for that city/country/level into the cost of living index for that city/country. So for example if the salary index is 80 (80% of NYC) but the cost of living index is 40 (50% of NYC), then that location for that experience level is twice as affordable as NYC (80/40=2x) or affordability = 200 meaning your money goes twice as far

[32]:

```python
afford_city_level=pd.merge(left=sal_by_city,right=NYC_by_level,
                           how='left',on='explevel') #Pull in NYC salary/level
afford_city_level['sal_index']=afford_city_level['avg_salary']\
    /afford_city_level['NYC_avg_salary']*100 # Calculate salary index
afford_city_level=pd.merge(left=afford_city_level,
                           right=cost_of_living,
                           how='left',
                           on=['City','State','Country'])
afford_city_level['affordability']=afford_city_level['sal_index']\
    /afford_city_level['RealCOL_Index']*100
print(afford_city_level.head())
```

```
     Country       City State explevel  avg_salary  NYC_avg_salary  \
0  Australia   Canberra     -   Junior     93000.0   156672.131148
1  Australia  Melbourne     -   Junior     67000.0   156672.131148
2  Australia  Melbourne     -   Senior    142000.0   230960.784314
3  Australia     Sydney     -   Junior    108000.0   156672.131148
4  Australia     Sydney     -   Senior    285000.0   230960.784314

    sal_index  Rank  Cost of Living Index  Rent Index  RealCOL_Index  \
0   59.359632   NaN                 75.94       42.50          60.26
1   42.764466   NaN                 76.76       38.65          58.90
2   61.482299   NaN                 76.76       38.65          58.90
3   68.933766   NaN                 83.21       58.03          71.41
4  123.397572   NaN                 83.21       58.03          71.41

   Groceries Index  Restaurant Price Index  Local Purchasing Power Index  \
0            76.81                   79.07                        105.11
1            77.78                   74.68                        102.16
2            77.78                   74.68                        102.16
3            79.65                   73.06                        104.52
4            79.65                   73.06                        104.52

  Alpha-2 code Alpha-3 code  Numeric  affordability
0           AU          AUS     36.0      98.505861
1           AU          AUS     36.0      72.605205
2           AU          AUS     36.0     104.384209
3           AU          AUS     36.0      96.532371
```

```
4           AU           AUS      36.0      172.801529
```

7 Part 6 - Slice and analyze the results

I want to rank order affordability individually for junior and senior people, as well as overall. For overall, I will average the affordability index for junior and senior people. But I think it's more interesting to look at junior and senior people separately to see if there are big differences

[33]:
```
# First delete all the NaN's, which represent cities for which we have no
# cost of living index and thus no affordability calculation
afford_city_level=afford_city_level[afford_city_level['affordability'].notna()]
# Now slice the data into Junior vs Senior people, and also average the
# affordability for each city/state/country
afford_city_junior=afford_city_level[afford_city_level['explevel']=="Junior"]
afford_city_junior=afford_city_junior[['Country','City','State',
                                       'RealCOL_Index','sal_index',
                                       'affordability']] # slice columns needed
afford_city_senior=afford_city_level[afford_city_level['explevel']=="Senior"]
afford_city_senior=afford_city_senior[['Country','City','State',
                                       'RealCOL_Index','sal_index',
                                       'affordability']] # slice columns needed
# Now group everything, averaging out the indexes for junior and senior people
afford_city_both=afford_city_level.groupby(['Country','City','State'],\
    as_index=False).agg(
                        RealCOL_Index=('RealCOL_Index',np.mean),
                        sal_index=('sal_index',np.mean),
                        affordability=('affordability',np.mean))
# Sort all 3 tables descending by affordability
afford_city_junior=afford_city_junior.sort_values(by=['affordability'],
                                                  ascending=False)
afford_city_junior=afford_city_junior.sort_values(by=['affordability'],
                                                  ascending=False)
afford_city_senior=afford_city_senior.sort_values(by=['affordability'],
                                                  ascending=False)
afford_city_both=afford_city_both.sort_values(by=['affordability'],
                                                  ascending=False)
print("Top five most affordable cities for JUNIOR data scientists:")
print(afford_city_junior.head(5))
print("Top five most affordable cities for SENIOR data scientists:")
print(afford_city_senior.head(5))
print("Top five most affordable cities for data scientists regardless of \
level:")
print(afford_city_both.head(5))
```

```
Top five most affordable cities for JUNIOR data scientists:
                 Country        City State  RealCOL_Index   sal_index  \
79   United Arab Emirates       Dubai     -          54.83   93.826515
109         United States    Berkeley    CA          91.48  155.100973
```

```
233         United States     Oakland    CA          90.52  151.909595
244         United States  Pittsburgh    PA          62.10  104.038924
87          United States   Ann Arbor    MI          59.82  100.209271

     affordability
79      171.122587
109     169.546320
233     167.818819
244     167.534500
87      167.518005
Top five most affordable cities for SENIOR data scientists:
           Country         City State  RealCOL_Index   sal_index  \
271  United States  San Antonio    TX          51.19  173.189575
43           India       Mumbai     -          24.82   57.152560
198  United States  Los Angeles    CA          76.98  170.358591
33           India    Bangalore     -          19.01   34.767807
302  United States        Tulsa    OK          46.68   82.265048

     affordability
271     338.326968
43      230.268169
198     221.302405
33      182.892199
302     176.231894
Top five most affordable cities for data scientists regardless of level:
                 Country         City State  RealCOL_Index   sal_index  \
92         United States  San Antonio    TX          51.19  123.295635
73         United States  Los Angeles    CA          76.98  144.919438
25                 India       Mumbai     -          24.82   44.533170
99         United States        Tulsa    OK          46.68   82.265048
42  United Arab Emirates        Dubai     -          54.83   93.826515

    affordability
92     240.858830
73     188.255960
25     179.424537
99     176.231894
42     171.122587
```

8 Part 7 - Comparing junior to senior affordability

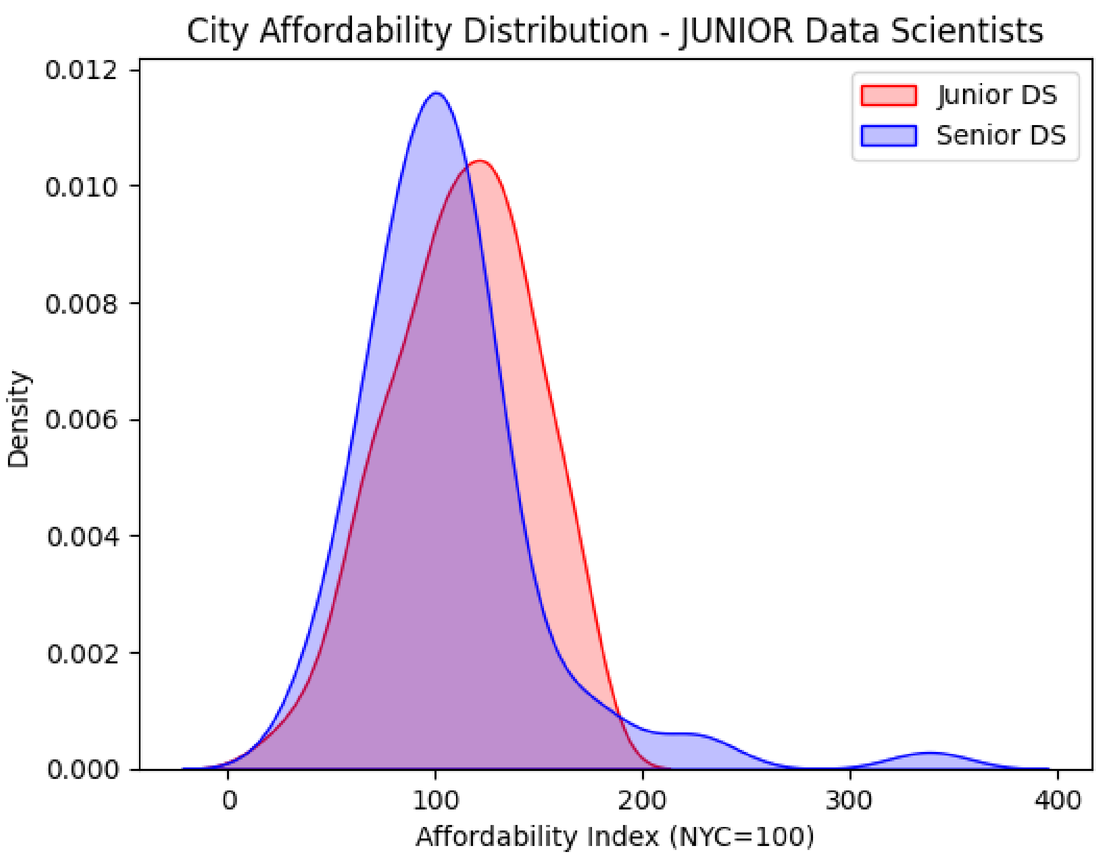
If we plot the kernel density of affordability indexes to see if there are insights, an interesting insight comes out of it: Both affordability plots seem pretty normally distributed. But given that 100 is the index base for NYC, we see the following:

- For Senior people, New York is right in the middle of the distribution meaning there are as many cities less affordable than NYC than more
- However, for Junior people, the median of the distribution is shifted to the left meaning there

are more cities that are more affordable than NYC than there are those less affordable. Seems NYC hero worship of experience, and making lower level people suffer, are alive and well!

One other thing of note is that the distribution of affordability for Senior people has a long "tail" to the right, suggesting that there are outliers in the data where Senior people were well overpaid to be lured to a low cost of living city. Digging into the data, this seems to be why San Antonio found its way into the top 5 for Senior people

[34]:
```
junior_scores=afford_city_junior['affordability']
junior_scores=junior_scores.rename("Junior") # rename
senior_scores=afford_city_senior['affordability']
junior_scores=junior_scores.rename("Senior") # rename
fig = sns.kdeplot(junior_scores, fill=True, color="r") # plot junior scores
fig = sns.kdeplot(senior_scores, fill=True, color="b") # plot senior scores
plt.title('City Affordability Distribution - JUNIOR Data Scientists')
plt.ylabel('Density')
plt.xlabel('Affordability Index (NYC=100)')
plt.legend(labels=["Junior DS","Senior DS"],loc='upper right')
plt.show()
```



9 Part 8 - Identifying factors driving affordability

One other useful graphing analysis looks at what drives affordability in a given city for data scientists, and if it's different for Junior versus Senior people. If cost of living and salaries are in synch, there shouldn't be much to infer. But what if they are not? I looked at two possible factors:

1) Affordability is driven by cost-of-living - meaning, cities with lower cost of living (including housing) are more affordable even despite paying lower salaries.

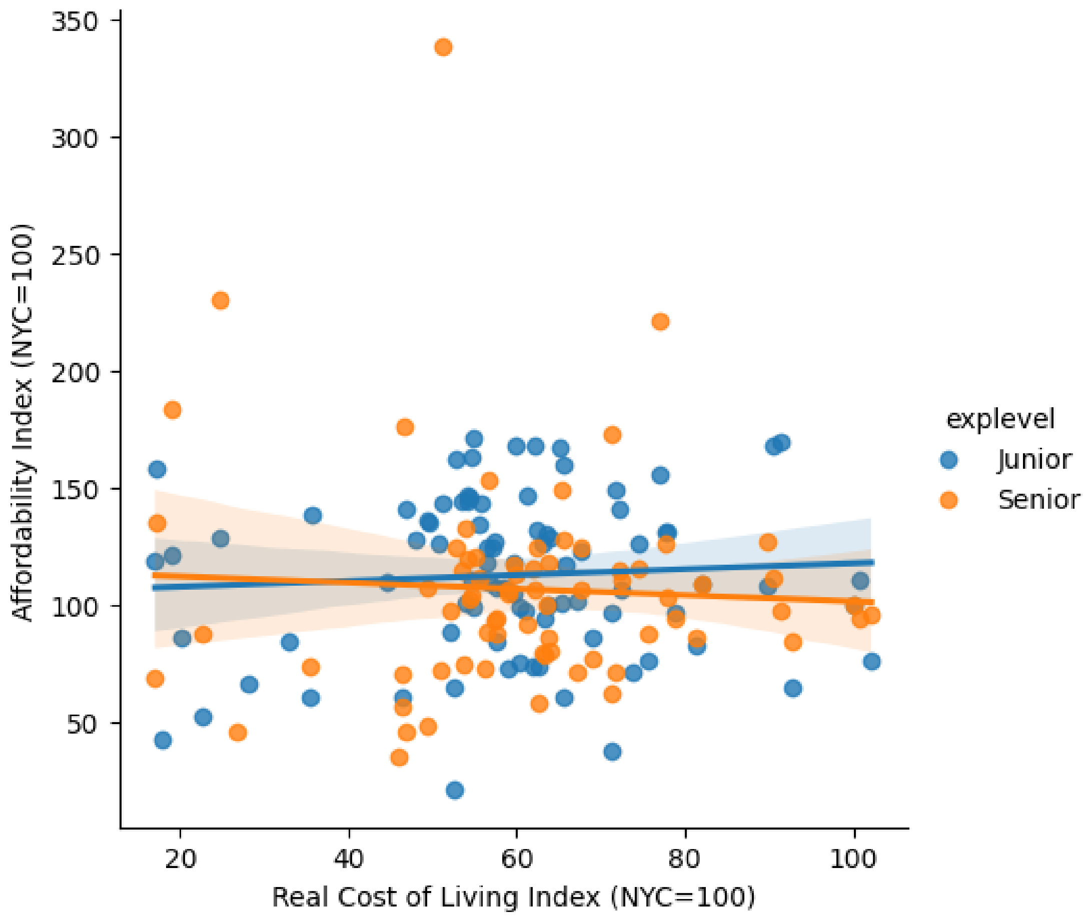
2) Affordability is driven by salaries - meaning, cities with higher salaries are more affordable even when real cost of living is high

What the below plots seem to show is :

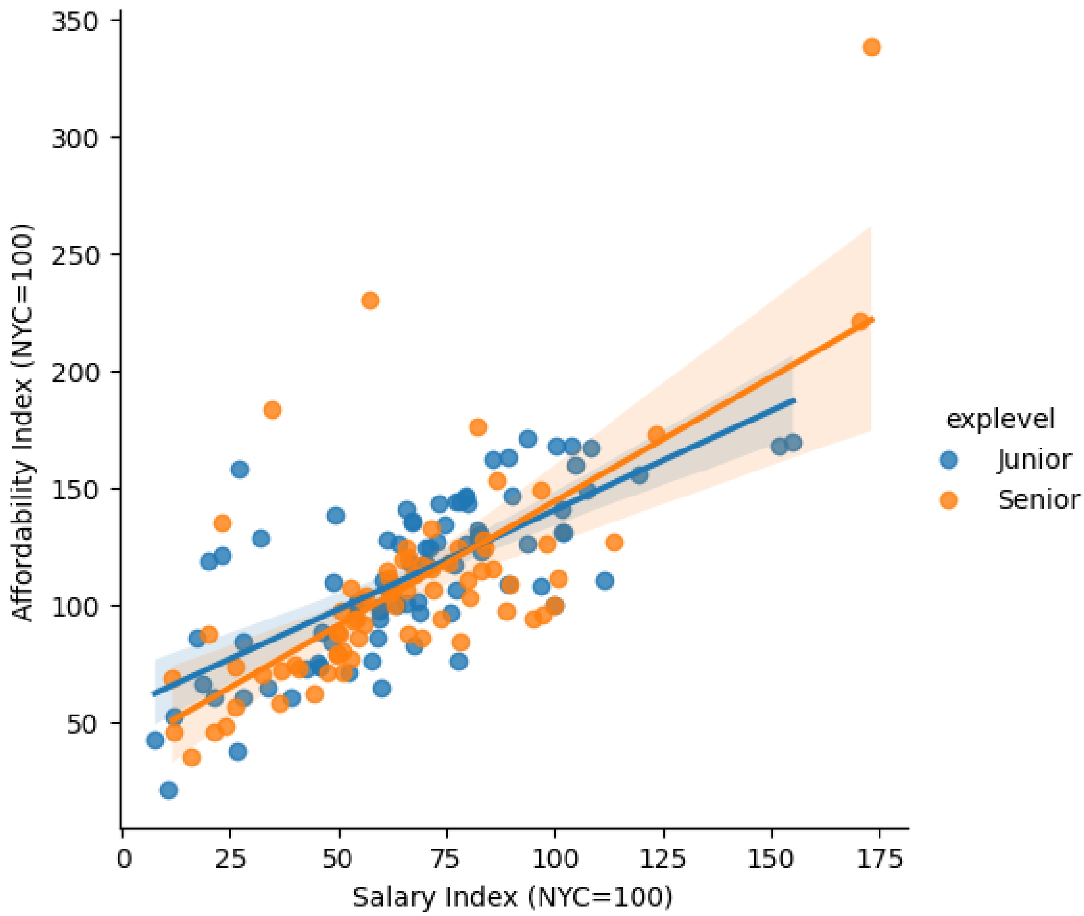
1) Cost of living isn't a very big driver of affordability of a place.
   The vast majority of cities are cheaper than NYC, but as many of them are less affordable (affordability index <100) as more affordable, and it doesn't seem to matter how cheap a place is to live.
   The flat trendline on the first graph shows this
2) On the other hand, the second plot seems to suggest that local salaries are a significant driver of affordability. The more money you make, both at a junior and senior level, the more a specific city is affordable no mater what the local cost of living is

It could be that some of my assumptions (especially assuming offshore salaries are in USD in that file) are faulty. It could also be that the data sample size is too small. But hopefully I've demonstrated the power of data analytics!

[35]:
```
# Now show regression of affordability vs cost of living to see if strong
# relationshp
data_to_plot=afford_city_level[['explevel','RealCOL_Index','affordability']]
sns.lmplot(x = 'RealCOL_Index',
           y = 'affordability',
           hue = 'explevel',
           data=data_to_plot)
plt.ylabel('Affordability Index (NYC=100)')
plt.xlabel('Real Cost of Living Index (NYC=100)')
plt.show()
# Finally, show regression of affordability vs salaries to see if strong
# relationshp
data_to_plot=afford_city_level[['explevel','sal_index','affordability']]
sns.lmplot(x = 'sal_index',
           y = 'affordability',
           hue = 'explevel',
           data=data_to_plot)
plt.ylabel('Affordability Index (NYC=100)')
plt.xlabel('Salary Index (NYC=100)')
plt.show()
```



350
300
250
200
150
100
50
20
40
60
80
100
Affordability Index (NYC=100)
Real Cost of Living Index (NYC=100)
explevel
Junior
Senior



10 Thank you for listening to my TED Talk

I enjoyed this class a ton! I can't believe how much I learned in two languages I had never seen (and one, "R", that I'd never even heard of.