pythonproject.melissanooney

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0.0.1 Python Project

0.0.2 Melissa Nooney

0.0.3 8/22/2024

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
#import my files to work with
COL=pd.read_csv('C:/Users/mnoon/OneDrive/Desktop/R and Python Programming/Python␣
↪Project/cost_of_living.csv')

salaries=pd.read_csv('C:/Users/mnoon/OneDrive/Desktop/R and Python Programming/
↪Python Project/ds_salaries.csv')

FYI=pd.read_csv('C:/Users/mnoon/OneDrive/Desktop/R and Python Programming/Python␣
↪Project/Levels_Fyi_Salary_Data.csv')

country_codes=pd.read_csv('C:/Users/mnoon/OneDrive/Desktop/R and Python␣
↪Programming/Python Project/country_codes.csv')
```

One of the first things I want to do is figure out what a good cost of living ratio is, so that I may understand what the indexes mean in relation to each other. A brief glance at the cost of living file, I can see New York is 100 across the board. NY is used as a base value.

[5]:
```
COL.iloc[13]
```

[5]:
```
Rank                                                     NaN
City                               New York, NY, United States
Cost of Living Index                                   100.0
Rent Index                                             100.0
Cost of Living Plus Rent Index                         100.0
Groceries Index                                        100.0
Restaurant Price Index                                 100.0
Local Purchasing Power Index                           100.0
Name: 13, dtype: object
```

What I want to try to figure out is where is there is indexes under 100, but the salaries are higher, to create a disposible income situation. I also am interested in the Local Purchasing Power Index. High LPPI and low COL is probably an ideal scenario. I think some other factors to consider would be quality of life and safety. We can have a very low index, but does location provide a proper quality of life. Not sure if that's something out of the scope of this project, but definitely a real-world scenario. Another scenario is, if I can work remotely, where is the ideal place to make the most money. Another scenario, if I can't work remote, where is the ideal place to live/relocate for purchasing power and salary "ideal disposable income" situation....the unicorn.

0.0.4 Breakdown of remote and on-site salaries of Data Scientists

[6]:
```
data_science= salaries.loc[salaries['job_title'] == 'Data Scientist'] #create my␣
↪data science dataframe to work with
data_science.head
```

[6]:
```
<bound method NDFrame.head of      Unnamed: 0  work_year experience_level
employment_type       job_title  \
0             0       2020               MI              FT  Data Scientist
7             7       2020               MI              FT  Data Scientist
10           10       2020               EN              FT  Data Scientist
11           11       2020               MI              FT  Data Scientist
12           12       2020               EN              FT  Data Scientist
..          ...        ...              ...             ...             ...
592         592       2022               SE              FT  Data Scientist
593         593       2022               SE              FT  Data Scientist
596         596       2022               SE              FT  Data Scientist
598         598       2022               MI              FT  Data Scientist
599         599       2022               MI              FT  Data Scientist

       salary salary_currency  salary_in_usd employee_residence  remote_ratio  \
0       70000             EUR          79833                 DE             0
7    11000000             HUF          35735                 HU            50
10      45000             EUR          51321                 FR             0
11    3000000             INR          40481                 IN             0
12      35000             EUR          39916                 FR             0
..        ...             ...            ...                ...           ...
592    230000             USD         230000                 US           100
593    150000             USD         150000                 US           100
596    210000             USD         210000                 US           100
598    160000             USD         160000                 US           100
599    130000             USD         130000                 US           100

    company_location company_size
0                 DE            L
7                 HU            L
10                FR            S
11                IN            L
```

```
12                FR           M
..               ...          ...
592               US           M
593               US           M
596               US           M
598               US           M
599               US           M

[143 rows x 12 columns]>
```

[8]:
```
#not sure I want all these dataframes, but starting here for  now, just to have␣
 ↪a bunch of subsetted information
#without having to aggregate and then convert back to a dataframe. I will if/
 ↪when I need to, but I want to start here.
data_remote= data_science.loc[data_science['remote_ratio'] == 0]
data_hybrid= data_science.loc[data_science['remote_ratio'] == 50]
data_onsite= data_science.loc[data_science['remote_ratio'] == 100]
```

I think now I want to start working on some cost of living information. I think I want to figure out the locations that have low COL, and high purchasing power. I might add quality of life later for "fun". If 100 is my base number, I can use that to subset my COL dataframe.

[9]:
```
unicorn = COL.loc[(COL["Cost of Living Index"] < 100) & (COL["Local Purchasing␣
 ↪Power Index"] > 100)]
unicorn.head
```

[9]:
```
<bound method NDFrame.head of      Rank                             City  Cost
of Living Index  Rent Index  \
21    NaN  San Francisco, CA, United States                 93.91      108.42
22    NaN        Oakland, CA, United States                 92.93       87.79
23    NaN      Anchorage, AK, United States                 91.23       39.29
24    NaN    Santa Clara, CA, United States                 89.41       90.39
27    NaN        Seattle, WA, United States                 88.52       65.84
..    ...                              ...                   ...         ...
299   NaN    Little Rock, AR, United States                 59.26       25.60
304   NaN        Wichita, KS, United States                 58.92       24.26
314   NaN        El Paso, TX, United States                 55.92       23.17
524   NaN                  Bangalore, India                 28.20        8.59
547   NaN     Cyberjaya, Selangor, Malaysia                 24.85        6.93

     Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
21                           100.72            97.05                   93.40
22                            90.52            98.46                   78.71
23                            66.88            97.95                   78.76
24                            89.87           100.63                   73.46
27                            77.89            87.34                   93.09
..                              ...              ...                     ...
```

```
299                          43.48            57.28                   64.63
304                          42.67            53.08                   57.42
314                          40.56            54.45                   48.18
524                          19.01            31.14                   20.04
547                          16.45            26.29                   14.60

     Local Purchasing Power Index
21                         133.16
22                         111.73
23                         118.63
24                         155.41
27                         145.39
..                            ...
299                        131.07
304                        119.24
314                        118.77
524                        102.64
547                        128.47

[125 rows x 8 columns]>
```

I need to figure out what a good ratio is. For instance San Fran, COL and purchasing power are very close, I don't feel this trasnlates well to money going far, but does go further than the base of NY. I think I would want a bigger difference between the two. But what is a good difference? The bigger the better? Then let's consider what the pay in those low COL locations could be. In general low COL usually means lower pay.

[15]:
```python
unicorn['differences'] = unicorn["Local Purchasing Power Index"] - unicorn["Cost␣
↪of Living Index"]
unicorn.head(3)

#add column so I can see the diffrences between the two columns
#I looked up this error below, and doesn't make too much sense too me. I was␣
↪able to do my calculation, but I didn't want to make a copy
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\3015041207.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  unicorn['differences'] = unicorn["Local Purchasing Power Index"] -
unicorn["Cost of Living Index"]
```

[15]:
```
    Rank                            City  Cost of Living Index  Rent Index  \
21   NaN  San Francisco, CA, United States                 93.91      108.42
22   NaN        Oakland, CA, United States                 92.93       87.79
```

```
23   NaN      Anchorage, AK, United States                  91.23       39.29

    Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
21                          100.72            97.05                  93.40
22                           90.52            98.46                  78.71
23                           66.88            97.95                  78.76

    Local Purchasing Power Index  differences
21                        133.16        39.25
22                        111.73        18.80
23                        118.63        27.40
```

Now that I have the cost ofliving somewhat to my liking for now, I want to start breaking down some data science salaries further.

[16]:
```
remote_agg = data_remote.groupby('company_location')['salary_in_usd'].agg([np.
 ↪mean, np.median])
remote_agg.idxmax()
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1677310710.py:1: FutureWarning:
The provided callable <function mean at 0x0000016A0CEF0A40> is currently using
SeriesGroupBy.mean. In a future version of pandas, the provided callable will be
used directly. To keep current behavior pass the string "mean" instead.
  remote_agg =
data_remote.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1677310710.py:1: FutureWarning:
The provided callable <function median at 0x0000016A0D02E480> is currently using
SeriesGroupBy.median. In a future version of pandas, the provided callable will
be used directly. To keep current behavior pass the string "median" instead.
  remote_agg =
data_remote.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
```

[16]:
```
mean      US
median    US
dtype: object
```

[19]:
```
hybrid_agg = data_hybrid.groupby('company_location')['salary_in_usd'].agg([np.
 ↪mean, np.median])
hybrid_agg.idxmax()
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1408682972.py:1: FutureWarning:
The provided callable <function mean at 0x0000016A0CEF0A40> is currently using
SeriesGroupBy.mean. In a future version of pandas, the provided callable will be
used directly. To keep current behavior pass the string "mean" instead.
  hybrid_agg =
data_hybrid.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1408682972.py:1: FutureWarning:
The provided callable <function median at 0x0000016A0D02E480> is currently using
SeriesGroupBy.median. In a future version of pandas, the provided callable will
be used directly. To keep current behavior pass the string "median" instead.
  hybrid_agg =
data_hybrid.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
```

[19]:
```
mean      US
median    US
dtype: object
```

[20]:
```
onsite_agg = data_onsite.groupby('company_location')['salary_in_usd'].agg([np.
 ↪mean, np.median])
onsite_agg.idxmax()
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1392500125.py:1: FutureWarning:
The provided callable <function mean at 0x0000016A0CEF0A40> is currently using
SeriesGroupBy.mean. In a future version of pandas, the provided callable will be
used directly. To keep current behavior pass the string "mean" instead.
  onsite_agg =
data_onsite.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\1392500125.py:1: FutureWarning:
The provided callable <function median at 0x0000016A0D02E480> is currently using
SeriesGroupBy.median. In a future version of pandas, the provided callable will
be used directly. To keep current behavior pass the string "median" instead.
  onsite_agg =
data_onsite.groupby('company_location')['salary_in_usd'].agg([np.mean,
np.median])
```

[20]:
```
mean      US
median    US
dtype: object
```

all 3 scenarios have US as the highest paying company location, not too surprising there honestly. My theory at the moment is that if you are to work on site, being located in US is best option. Hybrid work I would say is probably one in the same. For remote work though, potentially being located elsewhere in the world could provide more financial benefits.

0.0.5 Onsite

[36]:
```
unicorn.nlargest(n=10, columns=['differences'])
#top 10 largest COL and purchasing power differences. This shows me where the␣
 ↪COl is relatively low and my dollar will go the furthest
```

[36]:
```
     Rank                             City  Cost of Living Index  \
276   NaN          Houston, TX, United States                 63.94
547   NaN      Cyberjaya, Selangor, Malaysia                 24.85
```

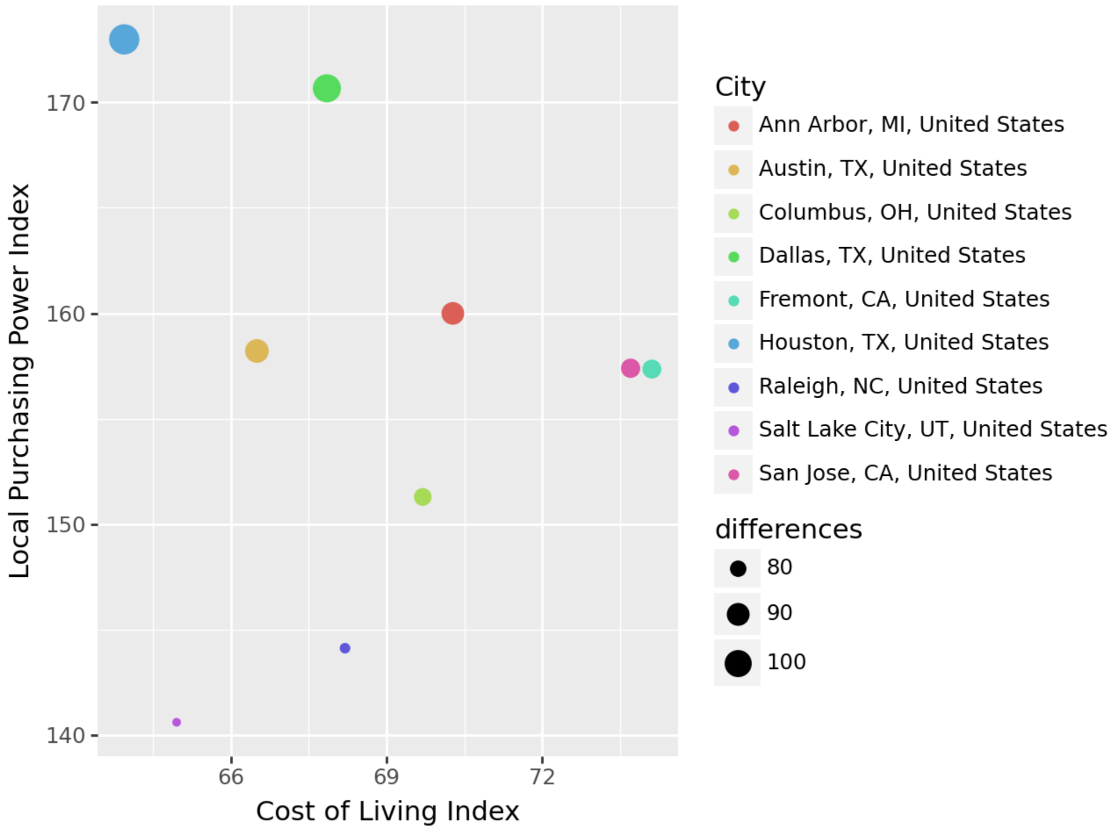
```
233   NaN         Dallas, TX, United States                 67.85
250   NaN         Austin, TX, United States                 66.50
190   NaN      Ann Arbor, MI, United States                 70.28
130   NaN       San Jose, CA, United States                 73.71
123   NaN        Fremont, CA, United States                 74.12
202   NaN       Columbus, OH, United States                 69.70
227   NaN        Raleigh, NC, United States                 68.20
266   NaN  Salt Lake City, UT, United States                 64.95

     Rent Index  Cost of Living Plus Rent Index  Groceries Index  \
276       43.38                           54.30            61.26
547        6.93                           16.45            26.29
233       50.17                           59.56            63.61
250       57.68                           62.36            67.33
190       47.97                           59.82            74.16
130       82.30                           77.74            70.53
123       74.93                           74.50            75.40
202       37.02                           54.38            67.90
227       41.39                           55.63            70.36
266       42.34                           54.35            61.40

     Restaurant Price Index  Local Purchasing Power Index  differences
276                   67.45                        172.98       109.04
547                   14.60                        128.47       103.62
233                   71.74                        170.66       102.81
250                   73.74                        158.21        91.71
190                   63.62                        159.99        89.71
130                   74.25                        157.39        83.68
123                   71.00                        157.35        83.23
202                   68.94                        151.29        81.59
227                   69.44                        144.12        75.92
266                   65.68                        140.61        75.66
```

[40]:
```
top_10 = unicorn.nlargest(n=10, columns=['differences']) #want to create a␣
↪datframe, so that I can graph this
top_10 = top_10.drop(547) #removing the non-US value because I don't need it for␣
↪this right now, I also don't want my graph
#to have this value, so really it's now top 9
```

[41]:
```
from plotnine import ggplot, aes, labs, geom_point
```

[42]:
```
(
    ggplot(top_10)
    + aes(x="Cost of Living Index", y="Local Purchasing Power Index", size =␣
↪"differences")
    + geom_point(aes(color= "City"))
```

```
) #Houston Texas is a clear winner here
```



Texas holds the majority of cities that have the biggest differences between the COL and purchasing power, in a positive way. This may be valuable information when looking for work, as well as what companies are in those areas, and what they are paying. Another avenue to potentially look at could be living in those areas but working remotely in an area that pays even more? Saving the remote breakdown for later.

[45]:
```
print(onsite_agg) #median salary for all US based companies is $140k, now I want␣
↪to know if our Top 5 locations
#pay at or above our median salary.
```

```
                            mean    median
company_location
CA                  77787.000000   75774.0
CL                  40038.000000   40038.0
DE                  25532.000000   25532.0
ES                  41136.666667   38776.0
GB                  76958.000000   76958.0
IL                 119059.000000  119059.0
IN                  23840.000000   23420.5
```

```
MY                  40000.000000   40000.0
NG                  50000.000000   50000.0
PL                  35590.000000   35590.0
UA                  13400.000000   13400.0
US                 147774.016949  140000.0
```

[46]:
```python
FYI_onsite= FYI.loc[FYI['title'] == 'Data Scientist']
```

[48]:
```python
agg_FYI = FYI_onsite.groupby(['location']).agg(
    median_salary=('totalyearlycompensation', np.median),

)
agg_FYI.reset_index(inplace=True)
```

```
C:\Users\mnoon\AppData\Local\Temp\ipykernel_6992\3053298991.py:1: FutureWarning:
The provided callable <function median at 0x0000016A0D02E480> is currently using
SeriesGroupBy.median. In a future version of pandas, the provided callable will
be used directly. To keep current behavior pass the string "median" instead.
```

[50]:
```python
agg_FYI[agg_FYI.location.isin(["Houston, TX","Dallas, TX", "Austin, TX", "Ann␣
↪Arbor, MI", "San Jose, CA"])]
#looking at this we can see only 3 of the TOP 5 are at or above or national␣
↪median of $140k
```

[50]:

	location	median_salary
4	Ann Arbor, MI	164000.0
11	Austin, TX	146000.0
57	Dallas, TX	115000.0
85	Houston, TX	120000.0
176	San Jose, CA	205000.0

What I can gather from this information is that while Houston, and Dallas have a great COL and Purchase Power relationship, the median salaries are below the national average. So I wouldn't count those towards the Top 5 on-site locations. Something to look into could be WHY they are lower than average…could be alot of factors…COL is lower which generally means pay is lower, those locations may have smaller companies with less of a budget, there could also be some outliers pulling the median down. I used median though to adjust for outliers as opposed to using mean. Do I want to explore those? Let's find the Top 5 for onsite, hybrid(which will probably be the same honestly bc you still have to go on-site, and remote, and then see if we want to go deeper here. But the questions are being asked.

[51]:
```python
agg_FYI[agg_FYI.location.isin(["Fremont, CA","Columbus, OH", "Raleigh, NC",␣
↪"Salt Lake City, UT"])] #adding Fremont, but SLC has no on-site data science␣
↪companies
```

[51]:

	location	median_salary
55	Columbus, OH	124000.0
72	Fremont, CA	210000.0
159	Raleigh, NC	120000.0

[52]:
```
agg_FYI[agg_FYI.location.isin(["Jersey City, NJ","San Antonio, TX", "Charlotte,␣
↪NC", "Jacksonville, FL"])]
#referenced my unicorn dataframe and just went down the list for the next␣
↪contenders in descending order in the diffrences column.
#Jersey City wins it.
```

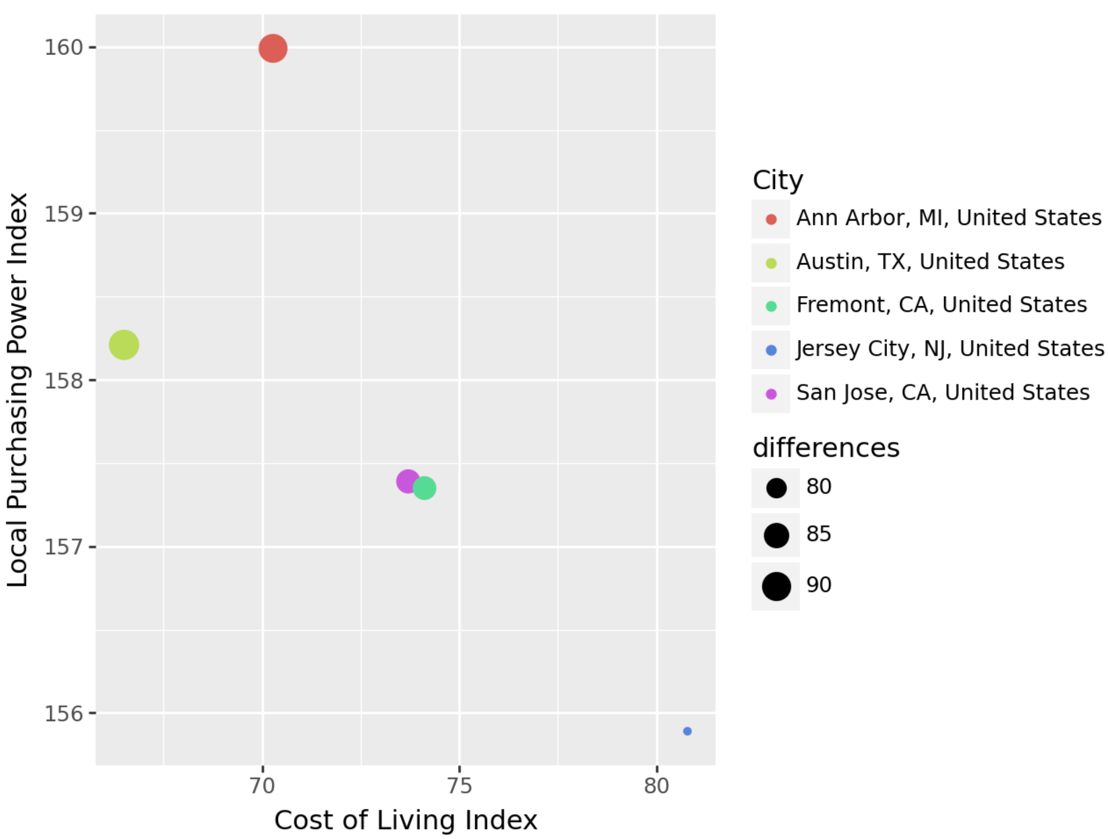
[52]:

	location	median_salary
46	Charlotte, NC	155000.0
96	Jersey City, NJ	189000.0
172	San Antonio, TX	257500.0

[55]:
```
top_15 = unicorn.nlargest(n=15, columns=['differences'])
top_15.reset_index(inplace=True)
```

[58]:
```
top_onsite_drop = top_15.drop(index=[0, 1, 2, 7, 8, 9, 11, 12, 13, 14])
```

[59]:
```
(
    ggplot(top_onsite_drop)
    + aes(x="Cost of Living Index", y="Local Purchasing Power Index", size =␣
↪"differences")
    + geom_point(aes(color= "City"))

)
```



[69]:
```
FYI_onsite.loc[FYI_onsite["location"]== "Austin, TX"].head() #just to show␣
↪whatthis looks like. did a full view in Spyder to get companies
```

[69]:
```
                  timestamp              company   level           title  \
1996   10/16/2018 14:21:06               Indeed       1  Data Scientist
3296    12/21/2018 6:47:06       Electronic Arts  Senior  Data Scientist
3297    12/21/2018 6:47:06       Electronic Arts  Senior  Data Scientist
15002   1/15/2020 10:28:44     Dell Technologies      i7  Data Scientist
20063   4/26/2020 12:23:27     Dell Technologies      I8  Data Scientist

       totalyearlycompensation    location  yearsofexperience  yearsatcompany  \
1996                    100000  Austin, TX                1.0             1.0
3296                    100000  Austin, TX                2.0             2.0
3297                    100000  Austin, TX                2.0             2.0
15002                   113000  Austin, TX                1.0             0.0
20063                   134000  Austin, TX                2.0             2.0

                         tag  basesalary  ...  Doctorate_Degree  Highschool  \
1996   business intelligence     85000.0  ...                 0           0
3296                 ML / AI     88000.0  ...                 0           0
3297                 ML / AI     88000.0  ...                 0           0
15002                ML / AI    105000.0  ...                 0           0
20063                ML / AI    111000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
1996             0          0           0                 0           0
3296             0          0           0                 0           0
3297             0          0           0                 0           0
15002            0          0           0                 0           0
20063            0          0           0                 0           0

       Race_Hispanic  Race        Education
1996               0   NaN              NaN
3296               0   NaN              NaN
3297               0   NaN              NaN
15002              0   NaN  Master's Degree
20063              0   NaN  Master's Degree

[5 rows x 29 columns]
```

[71]:
```
FYI_onsite.loc[FYI_onsite["location"]== "Ann Arbor, MI"].head()
```

[71]:
```
                  timestamp        company     level           title  \
12274  10/21/2019 17:12:54          Cisco   Grade 8  Data Scientist
22406   6/11/2020 17:21:26          MITRE         5  Data Scientist
```

```
60419    8/5/2021 19:47:53  XPO Logistics       L4  Data Scientist

       totalyearlycompensation       location  yearsofexperience  \
12274                   164000  Ann Arbor, MI                3.0
22406                   170000  Ann Arbor, MI               23.0
60419                   142000  Ann Arbor, MI               12.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
12274             3.0  ML / AI    140000.0  ...                 0           0
22406            14.0  ML / AI    170000.0  ...                 0           0
60419             4.0  General    123000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
12274            0          0           0                 0           0
22406            0          0           0                 0           0
60419            0          0           0                 0           0

       Race_Hispanic  Race         Education
12274              0   NaN               NaN
22406              0   NaN  Master's Degree
60419              0   NaN               NaN

[3 rows x 29 columns]
```

[72]:
```python
FYI_onsite.loc[FYI_onsite["location"]== "San Jose, CA"].head()
```

[72]:
```
                timestamp company level           title  \
444     6/8/2018 17:55:09    ebay    26  Data Scientist
1398   9/23/2018 13:26:28  PayPal     5  Data Scientist
2162  10/27/2018 12:49:19     IBM     7  Data Scientist
3173  12/13/2018 20:37:34  PayPal   T24  Data Scientist
4110     2/5/2019 8:46:34    eBay    25  Data Scientist

      totalyearlycompensation      location  yearsofexperience  \
444                    180000  San Jose, CA               10.0
1398                   220000  San Jose, CA                7.0
2162                   137000  San Jose, CA                2.0
3173                   182000  San Jose, CA                5.0
4110                   176000  San Jose, CA                2.0

      yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
444              5.0      NaN         0.0  ...                 0           0
1398             2.5     data    150000.0  ...                 0           0
2162             1.0  ML / AI    135000.0  ...                 0           0
3173             2.0  ML / AI    140000.0  ...                 0           0
4110             2.0  ML / AI    140000.0  ...                 0           0
```

```
     Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
444             0          0           0                 0           0
1398            0          0           0                 0           0
2162            0          0           0                 0           0
3173            0          0           0                 0           0
4110            0          0           0                 0           0

      Race_Hispanic  Race  Education
444               0   NaN        NaN
1398              0   NaN        NaN
2162              0   NaN        NaN
3173              0   NaN        NaN
4110              0   NaN        NaN

[5 rows x 29 columns]
```

[73]:

```
FYI_onsite.loc[FYI_onsite["location"]== "Fremont, CA"].head()
```

[73]:

```
                  timestamp   company            level           title  \
7773    6/17/2019 22:22:26     Tesla  Senior Engineer  Data Scientist
22918   6/22/2020 11:33:19  Facebook              IC5  Data Scientist
33605  10/23/2020 23:54:54     Tesla               P1  Data Scientist
33845  10/26/2020 22:52:19     Tesla               P2  Data Scientist
55822   6/27/2021 23:05:46  Facebook              IC4  Data Scientist

       totalyearlycompensation     location  yearsofexperience  \
7773                    185000  Fremont, CA                1.0
22918                   300000  Fremont, CA               11.0
33605                   175000  Fremont, CA                0.0
33845                   210000  Fremont, CA                2.0
55822                   226000  Fremont, CA               10.0

       yearsatcompany         tag  basesalary  ...  Doctorate_Degree  \
7773              1.0     ML / AI    135000.0  ...                 0
22918             2.0        Data    190000.0  ...                 0
33605             0.0        Data    140000.0  ...                 0
33845             2.0  Production    160000.0  ...                 0
55822             2.0       Infra    160000.0  ...                 0

       Highschool Some_College Race_Asian  Race_White  Race_Two_Or_More  \
7773            0            0          0           0                 0
22918           0            0          0           0                 0
33605           0            0          1           0                 0
33845           0            0          1           0                 0
55822           0            0          0           1                 0

       Race_Black  Race_Hispanic   Race        Education
```

```
7773           0              0    NaN              NaN
22918          0              0    NaN  Master's Degree
33605          0              0  Asian  Master's Degree
33845          0              0  Asian  Master's Degree
55822          0              0  White  Master's Degree

[5 rows x 29 columns]
```

[74]:
```
FYI_onsite.loc[FYI_onsite["location"]== "Jersey City, NJ"].head()
```

[74]:
```
                timestamp              company  \
9691    8/15/2019 0:05:18        Goldman Sachs
17233  2/21/2020 14:58:03       JPMorgan Chase
42678  2/21/2021 15:26:25       Jp morgan chase
43867    3/4/2021 4:44:27  Fidelity Investments
60927  8/10/2021 11:27:21       JPMorgan Chase

                                   level           title  \
9691   Executive Director / Vice-President  Data Scientist
17233                                   VP  Data Scientist
42678                       Vice President  Data Scientist
43867                                    6  Data Scientist
60927                                  601  Data Scientist

       totalyearlycompensation         location  yearsofexperience  \
9691                    210000  Jersey City, NJ               12.0
17233                   160000  Jersey City, NJ               20.0
42678                   210000  Jersey City, NJ                6.0
43867                   189000  Jersey City, NJ                8.0
60927                   121000  Jersey City, NJ                1.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
9691              3.0  ML / AI    170000.0  ...                 0           0
17233             5.0     Data    145000.0  ...                 0           0
42678             2.0  General    160000.0  ...                 0           0
43867             8.0  General    135000.0  ...                 0           0
60927             1.0  ML, NLP    115000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
9691             0          0           0                 0           0
17233            0          0           0                 0           0
42678            0          0           0                 0           0
43867            0          0           1                 0           0
60927            0          1           0                 0           0

       Race_Hispanic   Race        Education
9691               0    NaN              NaN
```

```
17233                 0    NaN               NaN
42678                 0    NaN               NaN
43867                 0  White  Master's Degree
60927                 0  Asian  Master's Degree

[5 rows x 29 columns]
```

0.0.6 Hybrid

Again, I feel that as far as locations, these will be the same, as hybrid requires being in office a few days per week. What I can look at here, is at least the median ranges of pay for hybrid work.

[78]:
```
hybrid_agg.loc["US"]
```

[78]:
```
mean      113166.666667
median    117500.000000
Name: US, dtype: float64
```

Our median salary is actually much less than onsite, so our TOP 5 hybrid locations can actually change. Looks like our original TOP 5 will work in this scenario.

[79]:
```
#referring back to this
agg_FYI[agg_FYI.location.isin(["Houston, TX","Dallas, TX", "Austin, TX", "Ann␣
↪Arbor, MI", "San Jose, CA"])]
```

[79]:
```
          location  median_salary
4    Ann Arbor, MI       164000.0
11      Austin, TX       146000.0
57      Dallas, TX       115000.0
85     Houston, TX       120000.0
176   San Jose, CA       205000.0
```

While Dallas is just shy of the $117.5k national median, I think the COL and Purchase Power difference is enough to offset the slightly less median pay.

0.0.7 Remote

This is where we will see some differences. Working remotely, the best scenario would be living in a low COL and high purchase power location, while working remotely at a higher paying company. Initial review, I do have to weed out some outliers, for instance Illinois City, IL, looks like they have a median salary of $510k, but there is only one company reported, not a true median value.

[106]:
```
agg_FYI.nlargest(n=12, columns=['median_salary']) #I want too see now if any of␣
↪these top values are a similar situation and not count them,
#and/or get an overall median salary of all locations nationwide based on my FYI␣
↪dataframe.
```

[106]:
```
              location  median_salary
90   Illinois City, IL       510000.0
```

```
102       Kirkland, WA      505500.0
108      Los Gatos, CA      420000.0
222      Worcester, MA      375000.0
144        Oakland, CA      350000.0
103       La Jolla, CA      300000.0
160        Raritan, NJ      300000.0
41        Campbell, CA      290000.0
131  Mountain View, MO      283000.0
22        Berkeley, CA      277000.0
31         Boulder, CO      265500.0
178      San Mateo, CA      260000.0
```

[93]:
```
agg_FYI['median_salary'].median() #median salary of all locations is below the␣
↪national average of 140.4k for remote work. But we want
#the big bucks, so going for the gusto here.
```

[93]:
```
129500.0
```

[81]:
```
FYI_onsite.loc[FYI_onsite['location']=='Illinois City, IL'] #using the onsite␣
↪because there is no remote/onsite breakdown
#in this dataframe, so no need to make multiples with same information
```

[81]:
```
               timestamp       company level          title  \
12704  11/4/2019 5:30:38  Goldman Sachs     5  Data Scientist

       totalyearlycompensation          location  yearsofexperience  \
12704                   510000  Illinois City, IL                8.0

       yearsatcompany                         tag  basesalary  ...  \
12704             2.0  Web Development (Front-End)    450000.0  ...

       Doctorate_Degree  Highschool Some_College Race_Asian  Race_White  \
12704                 1           0            0          0           0

       Race_Two_Or_More  Race_Black  Race_Hispanic  Race  Education
12704                 0           0              0   NaN        PhD

[1 rows x 29 columns]
```

[82]:
```
FYI_onsite.loc[FYI_onsite['location']=='Kirkland, WA'] #more data here
```

[82]:
```
                 timestamp     company level          title  \
510      6/20/2018 0:49:11      Google    L6  Data Scientist
32297   10/9/2020 12:00:22  ServiceNow   IC4  Data Scientist
35478  11/17/2020 22:09:19      Google    L4  Data Scientist
62529   6/12/2018 20:54:06      Google    T6  Data Scientist
```

```
       totalyearlycompensation      location  yearsofexperience  \
510                     690000  Kirkland, WA               10.0
32297                   326000  Kirkland, WA                7.0
35478                   203000  Kirkland, WA                5.0
62529                   685000  Kirkland, WA               22.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
510               0.0  ML / AI    240000.0  ...                 0           0
32297             0.0  ML / AI    205000.0  ...                 1           0
35478             5.0   DevOps    189000.0  ...                 0           0
62529             2.0  ML / AI    221000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
510              0          0           0                 0           0
32297            0          0           1                 0           0
35478            0          0           0                 0           0
62529            0          0           0                 0           0

       Race_Hispanic   Race  Education
510                0    NaN        NaN
32297              0  White        PhD
35478              0    NaN        NaN
62529              0    NaN        NaN

[4 rows x 29 columns]
```

[84]:
```
FYI_onsite.loc[FYI_onsite['location']=='Los Gatos, CA'].head() #plenty more data␣
↪here, so cane rule out outlier for purposes of median values
```

[84]:
```
               timestamp  company                 level           title  \
513   6/21/2018 10:54:35  Netflix                Senior  Data Scientist
1934  10/13/2018 6:05:30  Netflix                Senior  Data Scientist
2604  11/6/2018 14:08:01  Netflix         Data Engineer  Data Scientist
4347  2/15/2019 20:38:59  Netflix               Manager  Data Scientist
6625  5/20/2019 22:31:17  Netflix  Senior Data Scientist  Data Scientist

      totalyearlycompensation       location  yearsofexperience  \
513                    600000  Los Gatos, CA                3.0
1934                   400000  Los Gatos, CA                2.0
2604                   425000  Los Gatos, CA               10.0
4347                   655000  Los Gatos, CA                5.0
6625                   368000  Los Gatos, CA                0.0

      yearsatcompany               tag  basesalary  ...  Doctorate_Degree  \
513              1.0           ML / AI    600000.0  ...                 0
1934             2.0               Exp         0.0  ...                 0
2604             7.0  Data Engineering         0.0  ...                 0
```

```
4347            2.0      Data Science    655000.0  ...                 0
6625            0.0           ML / AI    350000.0  ...                 0

      Highschool Some_College Race_Asian  Race_White  Race_Two_Or_More  \
513            0            0          0           0                 0
1934           0            0          0           0                 0
2604           0            0          0           0                 0
4347           0            0          0           0                 0
6625           0            0          0           0                 0

      Race_Black  Race_Hispanic  Race  Education
513            0              0   NaN        NaN
1934           0              0   NaN        NaN
2604           0              0   NaN        NaN
4347           0              0   NaN        NaN
6625           0              0   NaN        NaN

[5 rows x 29 columns]
```

[85]:
```
FYI_onsite.loc[FYI_onsite['location']=='Worcester, MA'] #only one here, will␣
↪remove as Top 5 work location bc can not count on this median to be accurate
```

[85]:
```
                timestamp company level           title  \
47805  4/10/2021 14:55:38    Lyft    T5  Data Scientist

       totalyearlycompensation       location  yearsofexperience  \
47805                   375000  Worcester, MA                5.0

       yearsatcompany          tag  basesalary  ...  Doctorate_Degree  \
47805             0.0   Algorithms    190000.0  ...                 1

       Highschool Some_College Race_Asian  Race_White  Race_Two_Or_More  \
47805           0            0          1           0                 0

       Race_Black  Race_Hispanic   Race  Education
47805           0              0  Asian        PhD

[1 rows x 29 columns]
```

[86]:
```
FYI_onsite.loc[FYI_onsite['location']=='Oakland, CA']
```

[86]:
```
                 timestamp       company  level           title  \
35300  11/15/2020 14:47:09     Microsoft     64  Data Scientist
37855  12/21/2020 13:00:12       Pandora  Staff  Data Scientist
48110   4/13/2021 11:00:09  Credit Karma     L5  Data Scientist

       totalyearlycompensation     location  yearsofexperience  \
```

```
35300                   350000  Oakland, CA               4.0
37855                   310000  Oakland, CA              11.0
48110                   520000  Oakland, CA               9.0

       yearsatcompany               tag  basesalary  ...  Doctorate_Degree  \
35300             2.0           ML / AI    204000.0  ...                 0
37855             6.0           ML / AI    200000.0  ...                 0
48110             3.0  Machine Learning    236000.0  ...                 0

       Highschool Some_College Race_Asian  Race_White  Race_Two_Or_More  \
35300           0            0          0           1                 0
37855           0            0          0           0                 0
48110           0            0          0           1                 0

       Race_Black  Race_Hispanic   Race        Education
35300           0              0  White  Master's Degree
37855           0              0    NaN              NaN
48110           0              0  White  Master's Degree

[3 rows x 29 columns]
```

[87]:
```python
FYI_onsite.loc[FYI_onsite['location']=='La Jolla, CA'] #also only one, so do not␣
↪want to use this location
```

[87]:
```
                timestamp            company     level           title  \
45557  3/20/2021 5:18:06  Johnson & Johnson  Director  Data Scientist

       totalyearlycompensation      location  yearsofexperience  \
45557                   300000  La Jolla, CA               20.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
45557            15.0  General    210000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
45557            0          0           0                 0           0

       Race_Hispanic  Race  Education
45557              0   NaN        NaN

[1 rows x 29 columns]
```

[94]:
```python
FYI_onsite.loc[FYI_onsite['location']=='Raritan, NJ']
```

[94]:
```
                  timestamp               company level           title  \
12584  10/31/2019 19:15:53  Johnson and Johnson    D1  Data Scientist

       totalyearlycompensation     location  yearsofexperience  \
```

```
12584                   300000  Raritan, NJ              19.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
12584            13.0  ML / AI    200000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
12584            0          0           0                 0           0

       Race_Hispanic  Race        Education
12584              0   NaN  Master's Degree

[1 rows x 29 columns]
```

[95]:
```python
FYI_onsite.loc[FYI_onsite['location']=='Campbell, CA']
```

[95]:
```
                timestamp company level           title  \
25268  7/29/2020 21:42:13    Ebay  MTS2  Data Scientist

       totalyearlycompensation      location  yearsofexperience  \
25268                   290000  Campbell, CA               15.0

       yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
25268             5.0  ML / AI    200000.0  ...                 0           0

      Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
25268            0          0           0                 0           0

       Race_Hispanic  Race  Education
25268              0   NaN        NaN

[1 rows x 29 columns]
```

[96]:
```python
FYI_onsite.loc[FYI_onsite['location']=='Mountainview, MO']
```

[96]:
```
Empty DataFrame
Columns: [timestamp, company, level, title, totalyearlycompensation, location,
yearsofexperience, yearsatcompany, tag, basesalary, stockgrantvalue, bonus,
gender, otherdetails, cityid, dmaid, rowNumber, Masters_Degree,
Bachelors_Degree, Doctorate_Degree, Highschool, Some_College, Race_Asian,
Race_White, Race_Two_Or_More, Race_Black, Race_Hispanic, Race, Education]
Index: []

[0 rows x 29 columns]
```

[97]:
```python
FYI_onsite.loc[FYI_onsite['location']=='Berkeley, CA']
```

```
[97]:                 timestamp    company   level           title  \
      4930   3/13/2019 14:36:37  Microsoft      62  Data Scientist
      11040  9/17/2019 20:49:29  Microsoft      63  Data Scientist
      23324  6/30/2020 22:17:28  Microsoft      66  Data Scientist
      50927   5/9/2021 19:59:24      Bayer  VS 1.3  Data Scientist

             totalyearlycompensation      location  yearsofexperience  \
      4930                    245000  Berkeley, CA                3.0
      11040                   309000  Berkeley, CA                3.0
      23324                   390000  Berkeley, CA                5.0
      50927                   205000  Berkeley, CA                6.0

             yearsatcompany      tag  basesalary  ...  Doctorate_Degree  Highschool  \
      4930              1.0  ML / AI    160000.0  ...                 0           0
      11040             3.0  ML / AI    186000.0  ...                 0           0
      23324             2.0  ML / AI    285000.0  ...                 1           0
      50927             0.0  General    165000.0  ...                 1           0

            Some_College Race_Asian  Race_White  Race_Two_Or_More  Race_Black  \
      4930             0          0           0                 0           0
      11040            0          0           0                 0           0
      23324            0          0           0                 0           0
      50927            0          0           1                 0           0

             Race_Hispanic   Race        Education
      4930               0    NaN              NaN
      11040              0    NaN              NaN
      23324              0    NaN  Master's Degree
      50927              0  White              PhD

      [4 rows x 29 columns]
```

```
[99]: FYI_onsite.loc[FYI_onsite['location']=='Boulder, CO'] #Finally have our number 5␣
       ↪company location winner
```

```
[99]:                 timestamp  company       level           title  \
      5039   3/18/2019 14:19:21  Twitter          II  Data Scientist
      19160   4/6/2020 13:45:37  Twitter          L6  Data Scientist
      21375  5/22/2020 12:37:17  Workday          P3  Data Scientist
      37401  12/16/2020 2:32:33  Twitter  Senior SWE  Data Scientist
      52197  5/23/2021 16:25:45  Workday          P4  Data Scientist
      58769  7/23/2021 12:55:03  Workday          P4  Data Scientist

             totalyearlycompensation     location  yearsofexperience  \
      5039                    211000  Boulder, CO                3.0
      19160                   266000  Boulder, CO                4.0
      21375                   244000  Boulder, CO                5.0
```

```
37401                  290000  Boulder, CO              17.0
52197                  265000  Boulder, CO               5.0
58769                  311000  Boulder, CO               6.0

       yearsatcompany           tag  basesalary  ...  Doctorate_Degree  \
5039              2.0       ML / AI    136000.0  ...                 0
19160             3.0  data science    151000.0  ...                 0
21375             1.0       ML / AI    154000.0  ...                 0
37401             6.0       ML / AI    170000.0  ...                 0
52197             2.0       General    165000.0  ...                 0
58769             2.0      Research    175000.0  ...                 0

       Highschool Some_College Race_Asian  Race_White  Race_Two_Or_More  \
5039            0            0          0           0                 0
19160           0            0          0           0                 0
21375           0            0          0           0                 0
37401           0            0          0           0                 1
52197           0            0          0           1                 0
58769           0            0          0           1                 0

       Race_Black  Race_Hispanic         Race        Education
5039            0              0          NaN              NaN
19160           0              0          NaN  Master's Degree
21375           0              0          NaN  Master's Degree
37401           0              0  Two Or More  Master's Degree
52197           0              0        White  Master's Degree
58769           0              0        White  Master's Degree

[6 rows x 29 columns]
```

[109]:
```
international = unicorn[~unicorn.City.str.contains("States")] #wanted to know␣
↪Top 5 international locations for living
```

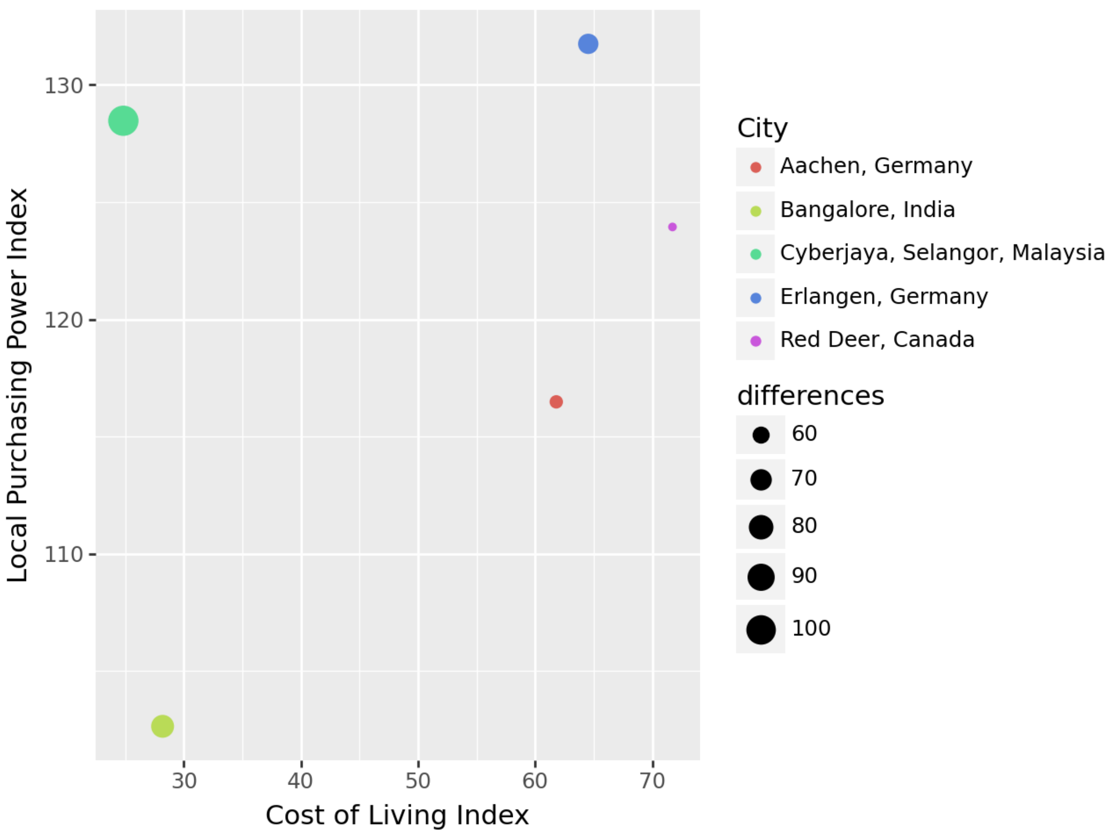
[110]:
```
international.nlargest(n=5, columns=['differences'])
```

[110]:
```
     Rank                           City  Cost of Living Index  Rent Index  \
547   NaN  Cyberjaya, Selangor, Malaysia                 24.85        6.93
524   NaN               Bangalore, India                 28.20        8.59
271   NaN              Erlangen, Germany                 64.54       24.83
295   NaN                Aachen, Germany                 61.81       21.74
162   NaN               Red Deer, Canada                 71.73       22.46

     Cost of Living Plus Rent Index  Groceries Index  Restaurant Price Index  \
547                           16.45            26.29                   14.60
524                           19.01            31.14                   20.04
271                           45.93            49.25                   67.89
295                           43.03            49.49                   57.99
```

```
162                           48.64             70.32                      65.19

     Local Purchasing Power Index  differences
547                        128.47       103.62
524                        102.64        74.44
271                        131.75        67.21
295                        116.48        54.67
162                        123.94        52.21
```

[112]:
```
int_top5 = international.nlargest(n=5, columns=['differences'])
```

[113]:
```
(
    ggplot(int_top5)
    + aes(x="Cost of Living Index", y="Local Purchasing Power Index", size =␣
 ↪"differences")
    + geom_point(aes(color= "City"))

)
```



In summary, remote, hybrid, and onsite, have some differences in locations as well as pay. Hybrid seems to pay the lowest median, as compared to remote and onsite, which are nearly identical. The

United States paid the most across all types of work. I used totaly yearly compensation from the FYI datasets, which included bonuses. I think another way to go would have been base salary, as not all companies or locations will pay bonuses, base salary probably would have been a more accurate measure. This could have led to which companies are paying bonuses, and in which type of work role (remote vs. hybrid. vs. onsite) Another avenue to pursue, would have been quality of life(safety, health, etc) however, I could not find a proper dataset without having to pay for it. As far as COL and Local Purchase Power, I feel ideally you want a location with COL under 100 (as compared to the base of NYC) and a purchase power of over 100. I feel like you get the most bang for your buck that way. Also I think you would want a bigger difference between the two. A COL of 90 and purchase power of 110, would be better than a COL of 90 and purchase power of 105, just as a small example.

[ ]:

```

```