Project_Code_Team12

December 7, 2022

0.1 IST652_Analysis of Citywide Payroll Data in NYC

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0.1.2 Data Set

[1]:
```
# EXECUTE THIS CELL to setup the modules
%matplotlib inline

import pandas as pd
import numpy as np
```

[2]:
```
# Defining location of dataset
filepath = "~/datasets/ist652/Fall2022/Team12/
↪Citywide_Payroll_Data__Fiscal_Year_.zip"
```

[3]:
```
# EXECUTE THIS CELL to load the dataset into your environment - THIS WILL TAKE␣
↪ABOUT A MINUTE - be patient
# a security warning will appear. You can ignore it.
payroll_data = pd.read_csv(filepath)
```

```
/opt/conda/lib/python3.9/site-packages/IPython/core/interactiveshell.py:3441:
DtypeWarning: Columns (7) have mixed types.Specify dtype option on import or set
low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[4]:
```
payroll_data.head()
```

[4]:
```
   Fiscal Year  Payroll Number                     Agency Name  Last Name  \
0         2020            17.0  OFFICE OF EMERGENCY MANAGEMENT    BEREZIN
1         2020            17.0  OFFICE OF EMERGENCY MANAGEMENT     GEAGER
2         2020            17.0  OFFICE OF EMERGENCY MANAGEMENT     RAMANI
3         2020            17.0  OFFICE OF EMERGENCY MANAGEMENT      ROTTA
4         2020            17.0  OFFICE OF EMERGENCY MANAGEMENT  WILSON II

  First Name Mid Init Agency Start Date Work Location Borough  \
0    MIKHAIL      NaN        08/10/2015              BROOKLYN
```

```
1   VERONICA        M       09/12/2016              BROOKLYN
2   SHRADDHA      NaN       02/22/2016              BROOKLYN
3   JONATHAN        D       09/16/2013              BROOKLYN
4     ROBERT        P       04/30/2018              BROOKLYN

                Title Description Leave Status as of June 30  Base Salary  \
0  EMERGENCY PREPAREDNESS MANAGER                     ACTIVE      86005.0
1  EMERGENCY PREPAREDNESS MANAGER                     ACTIVE      86005.0
2  EMERGENCY PREPAREDNESS MANAGER                     ACTIVE      86005.0
3  EMERGENCY PREPAREDNESS MANAGER                     ACTIVE      86005.0
4  EMERGENCY PREPAREDNESS MANAGER                     ACTIVE      86005.0

   Pay Basis  Regular Hours  Regular Gross Paid  OT Hours  Total OT Paid  \
0  per Annum         1820.0            84698.21       0.0            0.0
1  per Annum         1820.0            84698.21       0.0            0.0
2  per Annum         1820.0            84698.21       0.0            0.0
3  per Annum         1820.0            84698.21       0.0            0.0
4  per Annum         1820.0            84698.21       0.0            0.0

   Total Other Pay
0              0.0
1              0.0
2              0.0
3              0.0
4              0.0
```

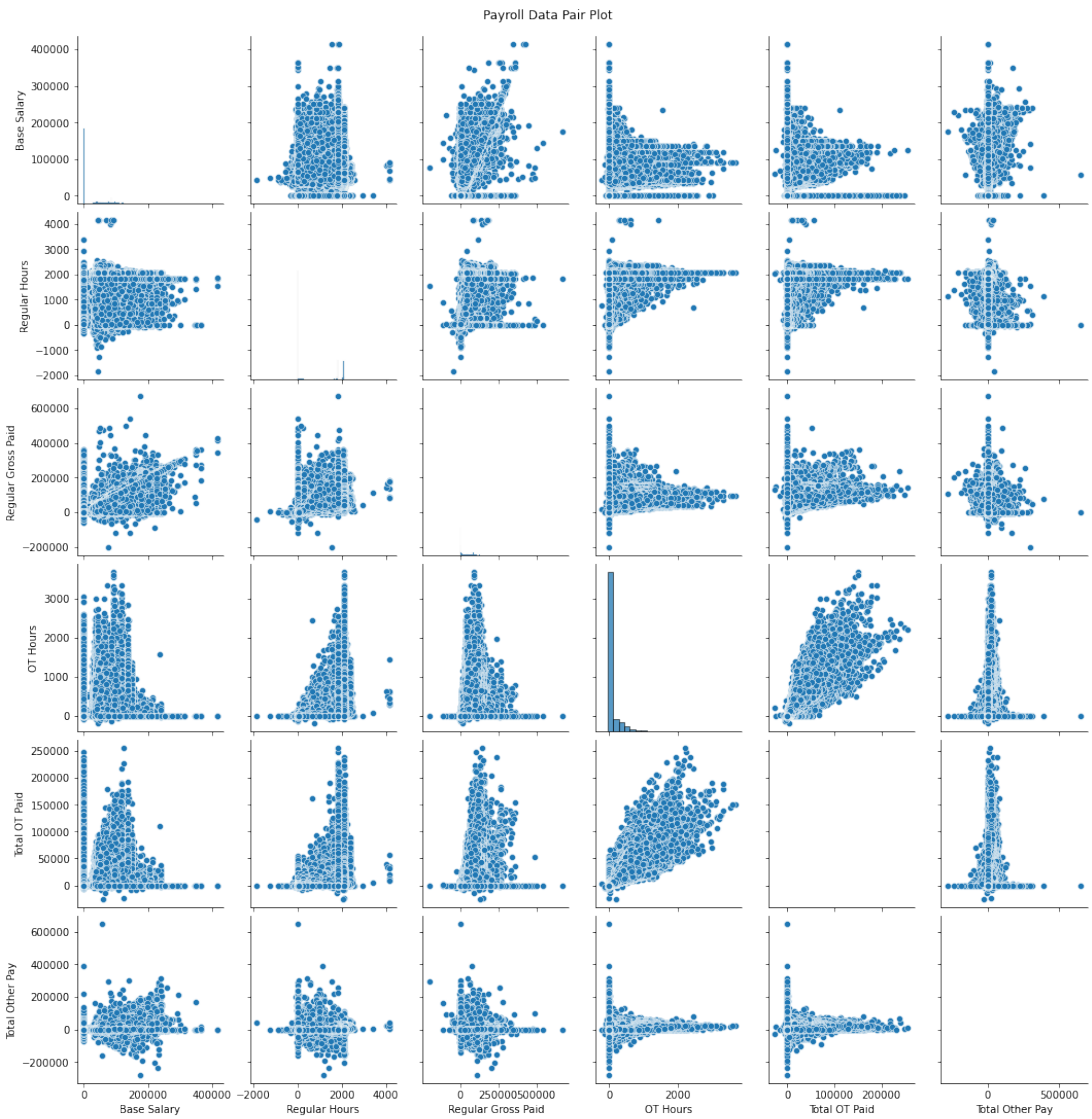
[5]:
```python
payroll_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5109775 entries, 0 to 5109774
Data columns (total 17 columns):
 #   Column                      Dtype
---  ------                      -----
 0   Fiscal Year                 int64
 1   Payroll Number              float64
 2   Agency Name                 object
 3   Last Name                   object
 4   First Name                  object
 5   Mid Init                    object
 6   Agency Start Date           object
 7   Work Location Borough       object
 8   Title Description           object
 9   Leave Status as of June 30  object
 10  Base Salary                 float64
 11  Pay Basis                   object
 12  Regular Hours               float64
 13  Regular Gross Paid          float64
```

```
 14  OT Hours                  float64
 15  Total OT Paid             float64
 16  Total Other Pay           float64
dtypes: float64(7), int64(1), object(9)
memory usage: 662.7+ MB
```

[6]:
```python
import seaborn as sns
ax = sns.pairplot(payroll_data.drop(['Fiscal Year', 'Payroll Number'], axis =␣
 ↪1))
ax.fig.suptitle("Payroll Data Pair Plot", y=1.01)
```

[6]:
```
Text(0.5, 1.01, 'Payroll Data Pair Plot')
```



0.1.3 Data Cleaning

[7]:
```
# Counting missing values across entire dataframe
payroll_data.isna().sum()
```

[7]:
```
Fiscal Year                         0
Payroll Number                1745440
Agency Name                         0
Last Name                       12830
First Name                      12871
Mid Init                      2093578
Agency Start Date                  63
Work Location Borough          506232
Title Description                  93
Leave Status as of June 30          0
Base Salary                         0
Pay Basis                           0
Regular Hours                       0
Regular Gross Paid                  0
OT Hours                            0
Total OT Paid                       0
Total Other Pay                     0
dtype: int64
```

[8]:
```
# Changing missing values in Work Location Borough and Title Description into␣
↪"Unknown".
payroll_data['Work Location Borough'] = payroll_data['Work Location Borough'].
↪fillna('Unknown')
payroll_data['Title Description'] = payroll_data['Title Description'].
↪fillna('Unknown')
```

[9]:
```
# Transforming columns of Agency Name, Work Location Borough, and Title␣
↪Description into types of string.
payroll_data['Agency Name'] = payroll_data['Agency Name'].astype(str)
payroll_data['Work Location Borough'] = payroll_data['Work Location Borough'].
↪astype(str)
payroll_data['Title Description'] = payroll_data['Title Description'].
↪astype(str)
```

[10]:
```
# Transforming column of Agency Name, Work Location Borough, and Title␣
↪Description into lower case.
payroll_data['Agency Name'] = payroll_data['Agency Name'].str.lower()
payroll_data['Work Location Borough'] = payroll_data['Work Location Borough'].
↪str.lower()
```

```
payroll_data['Title Description'] = payroll_data['Title Description'].str.
↪lower()
```

0.1.4 Analyzing Data

1. Trend change in base salary over years

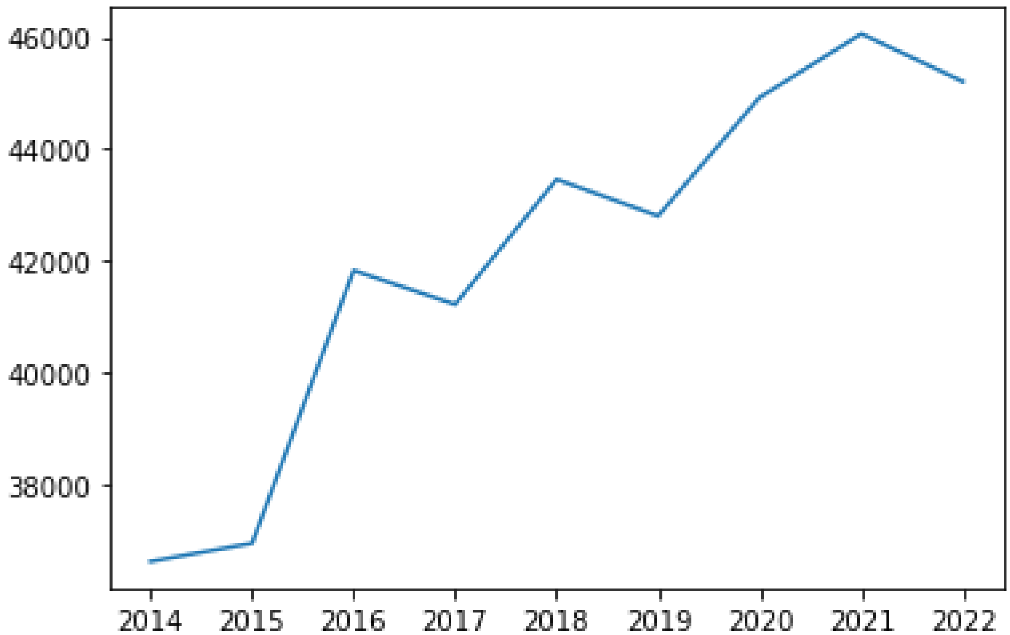
[11]:
```
payroll_data_y_base = payroll_data.groupby('Fiscal Year')['Base Salary'].
↪median()
payroll_data_y_base
```

[11]:
```
Fiscal Year
2014    36602.0
2015    36928.0
2016    41824.0
2017    41214.0
2018    43457.0
2019    42799.0
2020    44930.0
2021    46066.0
2022    45212.0
Name: Base Salary, dtype: float64
```

[12]:
```
# Visualization the results
import matplotlib.pyplot as plt

x = payroll_data_y_base.index
y = list(payroll_data_y_base)
plt.plot(x,y)
```

[12]:
```
[<matplotlib.lines.Line2D at 0x7fa654fc2520>]
```



Insights: This plot shows that the base salary overall goes up since 2014. However, as we pay attention to recent years (2021-2022), it has a trend of going down. After we reviewed some news and reports in the past few years, we found that the COVID-19 pandemic did not affect people's base salary that much. This might be related to the relevant decrees issued by the government during the COVID-19 pandemic.

2. Trend change in average overtime pay over years

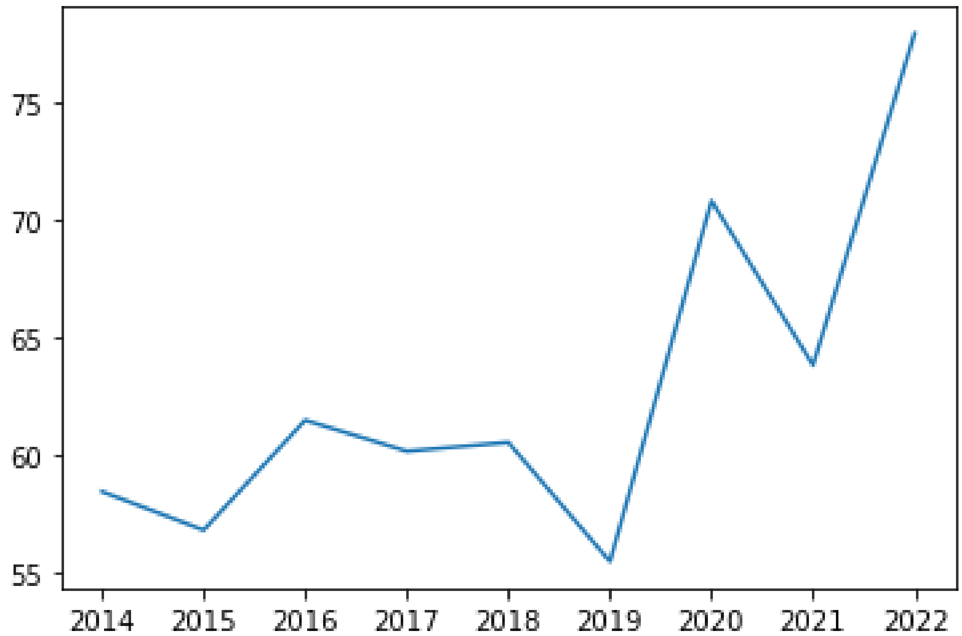
[13]:
```
payroll_data_y_oth = payroll_data.groupby('Fiscal Year')['OT Hours'].mean()
payroll_data_y_oth
```

[13]:
```
Fiscal Year
2014    58.408411
2015    56.768090
2016    61.450874
2017    60.129853
2018    60.506053
2019    55.435181
2020    70.784212
2021    63.790763
2022    77.912620
Name: OT Hours, dtype: float64
```

[14]:
```
# Visualization the results
x = payroll_data_y_oth.index
y = list(payroll_data_y_oth)
```

```
plt.plot(x,y)
```

[14]: [<matplotlib.lines.Line2D at 0x7fa654fb4be0>]



Insights: This plot shows that the total overtime was stable before COVID-19 pandemic (2014-2018). And the total overtime surge to a high level after COVID-19 pandemic (2019-2020). It went down a little from 2020 to 2021 and went up to high again from 2021 to 2022. Our guess is the agencies in this dataset may require over time during the COVID-19 pandemic.

3. Jobs that have the most base salary from 2014 to 2018

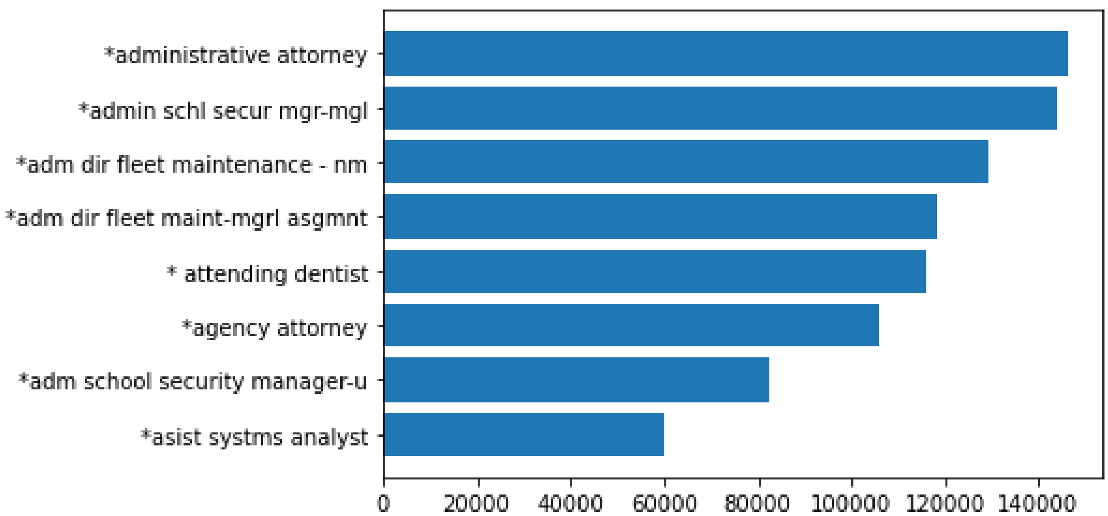
[15]:
```
payroll_data_job_titles_14_18 = payroll_data[payroll_data['Fiscal Year'].
 ↪between(2014,2018)]
payroll_data_14_18 = payroll_data_job_titles_14_18.
 ↪loc[payroll_data_job_titles_14_18['Title Description']!= 'Unknown']
payroll_data_14_18 = payroll_data_14_18.groupby('Title Description')['Base␣
 ↪Salary'].median()
payroll_data_14_18_top8 = payroll_data_14_18[0:8]
payroll_data_14_18_top8
```

[15]:
```
Title Description
* attending dentist                 115771.0
*adm dir fleet maint-mgrl asgmnt    118034.0
*adm dir fleet maintenance - nm     129158.0
*adm school security manager-u       82309.5
*admin schl secur mgr-mgl           143850.0
```

```
*administrative attorney            146111.0
*agency attorney                    106003.0
*asist systms analyst                60163.0
Name: Base Salary, dtype: float64
```

[16]:
```
# Visualization the results
payroll_data_14_18_top8_ascend = payroll_data_14_18_top8.
↪sort_values(ascending=True)
```

[17]:
```
x = payroll_data_14_18_top8_ascend.index
y = list(payroll_data_14_18_top8_ascend)
fig, ax = plt.subplots()
ax.barh(x, y)
plt.show()
```



4. Jobs that have the most base salary from 2019 to 2021

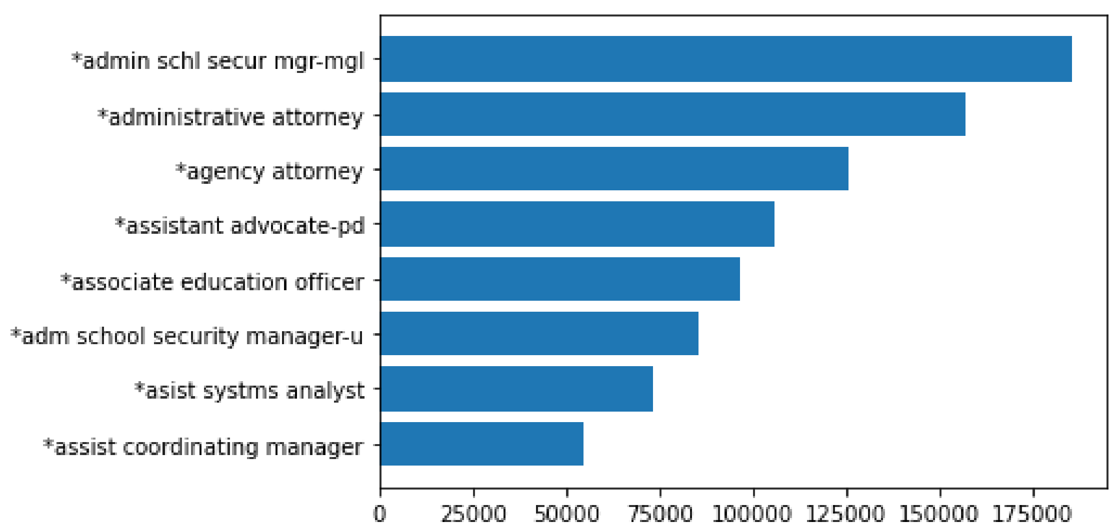
[18]:
```
payroll_data_job_titles_19_21 = payroll_data[payroll_data['Fiscal Year'].
↪between(2019,2022)]
payroll_data_19_21 = payroll_data_job_titles_19_21.
↪loc[payroll_data_job_titles_19_21['Title Description']!= 'Unknown']
payroll_data_19_21 = payroll_data_19_21.groupby('Title Description')['Base␣
↪Salary'].median()
payroll_data_19_21_top8 = payroll_data_19_21[0:8]
payroll_data_19_21_top8
```

[18]:
```
Title Description
*adm school security manager-u      85725.0
*admin schl secur mgr-mgl          185587.0
```

```
*administrative attorney          156958.0
*agency attorney                  125681.0
*asist systms analyst              73482.0
*assist coordinating manager       54673.0
*assistant advocate-pd            105694.0
*associate education officer       96672.0
Name: Base Salary, dtype: float64
```

[19]:
```python
# Visualization the results
payroll_data_19_21_top8_ascend = payroll_data_19_21_top8.
 ↪sort_values(ascending=True)
```

[20]:
```python
x = payroll_data_19_21_top8_ascend.index
y = list(payroll_data_19_21_top8_ascend)
fig, ax = plt.subplots()
ax.barh(x, y)
plt.show()
```



Insights: By camparing both bar plots, we can see how top8 job titles with highest base salary shiftted before (2014-2018) and after (2019-2022) the COVID-19 pandemic. Jobs like School Safety Admin has gone up by a lot; Hardcore jobs like attorney still hold up their places in the top3.

5. Base Salary in different borough

[21]:
```python
payroll_data_boro = payroll_data.groupby('Work Location Borough')['Base␣
 ↪Salary'].median()
payroll_data_boro
```

[21]:
```
Work Location Borough
albany            74247.50
```

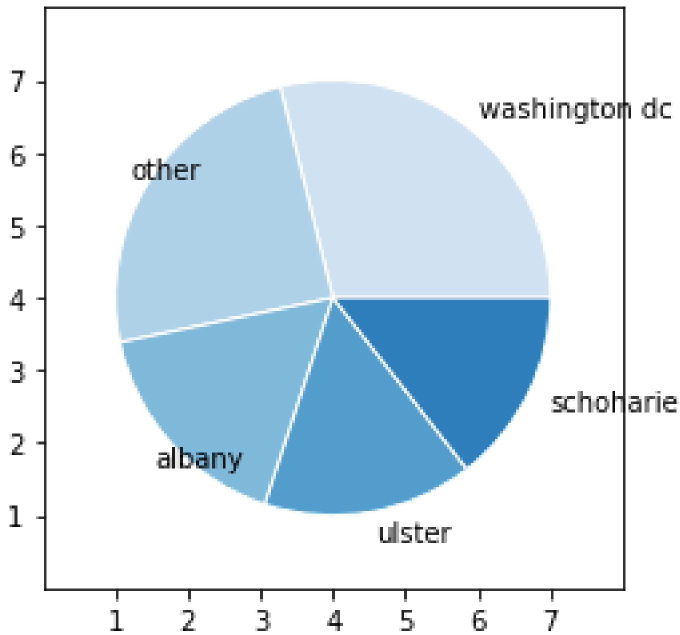
```
bronx              48712.00
brooklyn           50957.00
delaware           60156.00
dutchess           60017.00
greene             60138.00
manhattan          32426.00
nassau                66.93
orange             54569.50
other             108811.00
putnam             60076.00
queens             52649.00
richmond           57206.00
schoharie          64397.00
sullivan           62776.00
ulster             69740.00
unknown            36423.00
washington dc     128909.00
westchester        64397.00
Name: Base Salary, dtype: float64
```

[22]:

```
# Visualization the results
payroll_data_boro_ascend = payroll_data_boro.sort_values(ascending=False)
payroll_data_boro_top5 = payroll_data_boro_ascend[0:5]
payroll_data_boro_top5 = pd.DataFrame(payroll_data_boro_top5)
```

[23]:

```
x = list(payroll_data_boro_top5['Base Salary'])
labels = payroll_data_boro_top5.index
colors = plt.get_cmap('Blues')(np.linspace(0.2, 0.7, len(x)))
fig, ax = plt.subplots()
ax.pie(x, labels=labels, colors=colors, radius=3, center=(4,␣
 ↪4),wedgeprops={"linewidth": 1, "edgecolor": "white"}, frame=True)
ax.set(xlim=(0, 8), xticks=np.arange(1, 8), ylim=(0, 8), yticks=np.arange(1, 8))
plt.show()
```



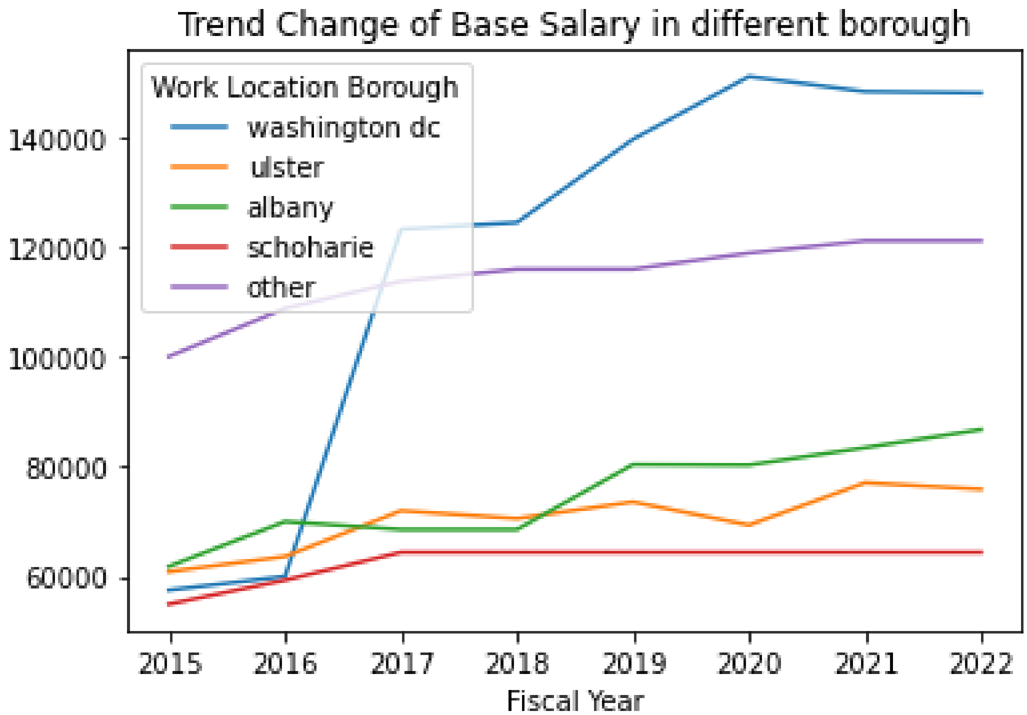
6. Trend of Base Salary in different borough

[24]:
```
payroll_data_boro_year = payroll_data.groupby(['Work Location Borough','Fiscal␣
↪Year'])['Base Salary'].median()
payroll_data_boro_year_count = payroll_data_boro_year.unstack('Work Location␣
↪Borough')
payroll_data_boro_year_count = pd.DataFrame(payroll_data_boro_year_count)
```

[25]:
```
payroll_data_boro_year_count_top5 = payroll_data_boro_year_count[['washington␣
↪dc', 'ulster','albany','schoharie','other']]
```

[26]:
```
# Visualization of the result:
payroll_data_boro_year_count_top5.plot(title="Trend Change of Base Salary in␣
↪different borough")
```

[26]:
```
<AxesSubplot:title={'center':'Trend Change of Base Salary in different
borough'}, xlabel='Fiscal Year'>
```



Insights: From the pie chart, we noticed that Washington DC is the borough which has the highest base salary in New York City. And from the line chart below, we found that Washinton DC has a very high jump since year 2016. And always leads the place than other boroughs. Regards to the other 4 boroughs, seems like there were no major upwards and downwards from 2015 to 2022.

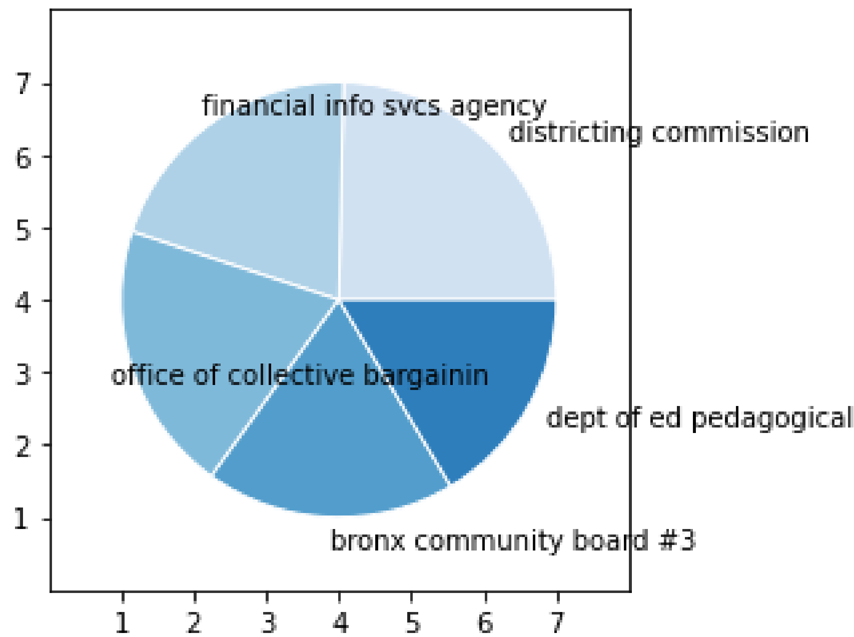
7. Base Salary in different Agencies

[27]:
```
payroll_data_agency = payroll_data.groupby('Agency Name')['Base Salary'].
 ↪median()
payroll_data_agency
```

[27]:
```
Agency Name
admin for children's svcs        59480.00
admin trials and hearings           57.99
board of correction              70497.00
board of corrections             59441.00
board of election                33220.00
                                   …
staten island community bd #2       30.22
staten island community bd #3    64718.50
tax commission                   80319.00
taxi & limousine commission      46119.00
teachers retirement system       64963.00
Name: Base Salary, Length: 165, dtype: float64
```

```
[28]: # Visualization the results
payroll_data_agency_ascend = payroll_data_agency.sort_values(ascending=False)
payroll_data_agency_top5 = payroll_data_agency_ascend[0:5]
payroll_data_agency_top5 = pd.DataFrame(payroll_data_agency_top5)
```

```
[29]: x = list(payroll_data_agency_top5['Base Salary'])
labels = payroll_data_agency_top5.index
colors = plt.get_cmap('Blues')(np.linspace(0.2, 0.7, len(x)))
fig, ax = plt.subplots()
ax.pie(x, labels=labels, colors=colors, radius=3, center=(4,␣
↪4),wedgeprops={"linewidth": 1, "edgecolor": "white"}, frame=True)
ax.set(xlim=(0, 8), xticks=np.arange(1, 8), ylim=(0, 8), yticks=np.arange(1, 8))
plt.show()
```



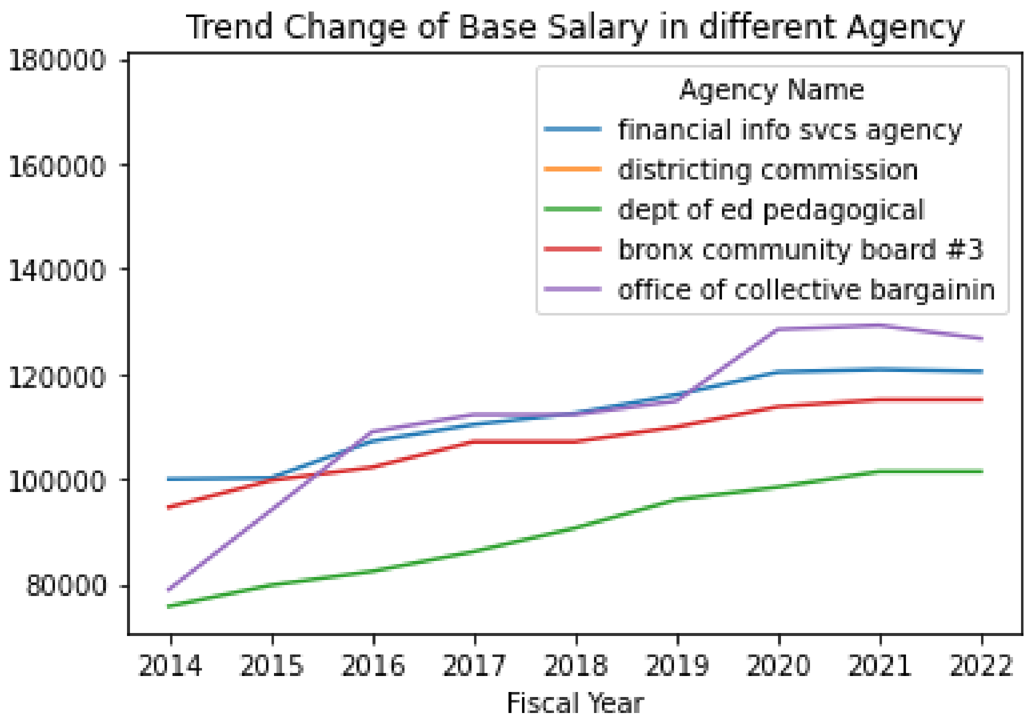
8. Trend of Base Salary in different Agencies

```
[30]: payroll_data_agency_year = payroll_data.groupby(['Agency Name','Fiscal␣
↪Year'])['Base Salary'].median()
payroll_data_agency_year_count = payroll_data_agency_year.unstack('Agency Name')
payroll_data_agency_year_count = pd.DataFrame(payroll_data_agency_year_count)
```

```
[31]: payroll_data_agency_year_count_top5 =␣
↪payroll_data_agency_year_count[['financial info svcs agency', 'districting␣
↪commission','dept of ed pedagogical','bronx community board #3','office of␣
↪collective bargainin']]
```

[32]:
```
# Visualization of the result:
payroll_data_agency_year_count_top5.plot(title="Trend Change of Base Salary in␣
↪different Agency")
```

[32]:
```
<AxesSubplot:title={'center':'Trend Change of Base Salary in different Agency'},
xlabel='Fiscal Year'>
```



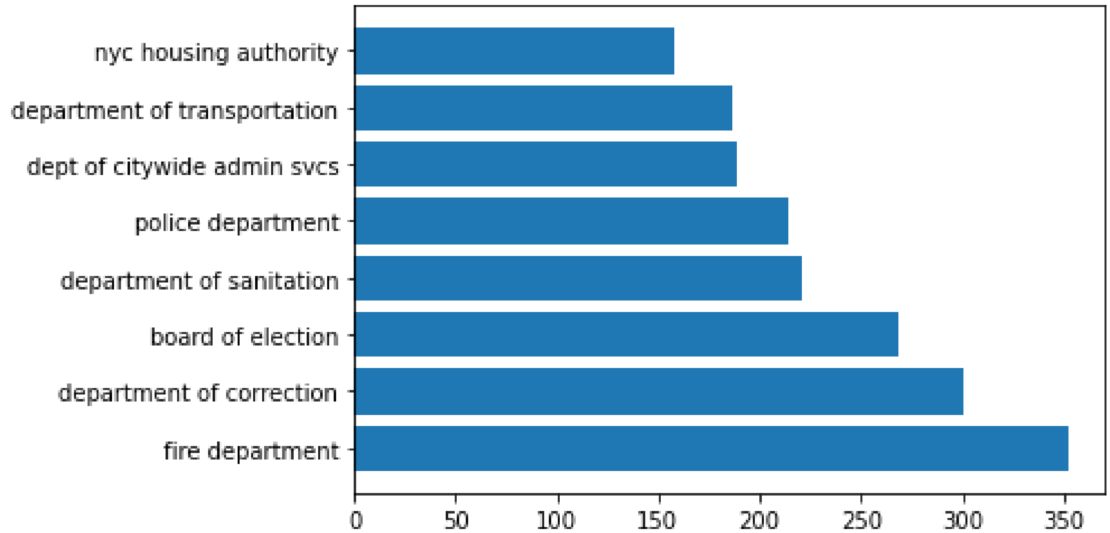
Insights: From the pie chart, we can see that top5 agencies which have the most base salary have almost the same amount of base salary from 2014 to 2022. However Districting Commission is the highest. And from the line chart, we found that the overall trend keeps going up from 2014 to 2022; however no major bump among top5 agencies. Good thing is the COVID-19 pandemic didn't affact these agencies by a lot in regards of base salary they assigned to employees.

9. OverTime Hours among different Agencies

[33]:
```
payroll_data_agency_ot = payroll_data.groupby('Agency Name')['OT Hours'].mean()
payroll_data_agency_ot_ascend = payroll_data_agency_ot.
↪sort_values(ascending=False)
payroll_data_agency_ot_ascend_top8 = payroll_data_agency_ot_ascend[0:8]
```

[34]:
```
# Visualization the results
x = payroll_data_agency_ot_ascend_top8.index
y = list(payroll_data_agency_ot_ascend_top8)
fig, ax = plt.subplots()
```

```
ax.barh(x, y)
plt.show()
```



10. Trend of OverTime Hours among different Agency

[35]:
```
payroll_data_ot_year = payroll_data.groupby(['Agency Name','Fiscal Year'])['OT␣
↪Hours'].mean()
payroll_data_ot_year_count = payroll_data_ot_year.unstack('Agency Name')
payroll_data_ot_year_count = pd.DataFrame(payroll_data_ot_year_count)
payroll_data_ot_year_count.head()
```

[35]:
```
Agency Name  admin for children's svcs  admin trials and hearings  \
Fiscal Year
2014                        102.384335                   5.904668
2015                         95.038892                   1.712759
2016                        119.329520                   1.959564
2017                        152.831746                   1.943713
2018                        175.238263                   2.830070

Agency Name  board of correction  board of corrections  board of election  \
Fiscal Year
2014                         NaN              0.235294         248.010545
2015                    0.000000                   NaN         106.946519
2016                    0.195652                   NaN         249.786088
2017                    0.000000                   NaN         307.164253
2018                    0.227941                   NaN         229.639587

Agency Name  board of election poll workers  borough president-bronx  \
Fiscal Year
```

```
2014                                  0.0                 7.941667
2015                                  0.0                13.393939
2016                                  0.0                13.570312
2017                                  0.0                10.560345
2018                                  0.0                13.173276

Agency Name  borough president-brooklyn  borough president-queens  \
Fiscal Year
2014                           7.356322                  0.876712
2015                           9.280952                  0.000000
2016                           5.289474                  0.000000
2017                           5.750000                  0.552239
2018                           4.631757                  0.000000

Agency Name  borough president-staten is  …  queens community board #9  \
Fiscal Year                                …
2014                                 0.0  …                        0.0
2015                                 0.0  …                        0.0
2016                                 0.0  …                        0.0
2017                                 0.0  …                        0.0
2018                                 0.0  …                        0.0

Agency Name  queens da  richmond da  spec narcs-da  \
Fiscal Year
2014         35.418561    24.283482       6.157371
2015               NaN          NaN            NaN
2016               NaN          NaN            NaN
2017               NaN          NaN            NaN
2018               NaN          NaN            NaN

Agency Name  staten island community bd #1  staten island community bd #2  \
Fiscal Year
2014                                   0.0                            0.0
2015                                   0.0                            0.0
2016                                   0.0                            0.0
2017                                   0.0                            0.0
2018                                   0.0                            0.0

Agency Name  staten island community bd #3  tax commission  \
Fiscal Year
2014                                   0.0       48.596939
2015                                   0.0       60.012500
2016                                   0.0       47.815574
2017                                   0.0       47.415254
2018                                   0.0       35.445312

Agency Name  taxi & limousine commission  teachers retirement system
```

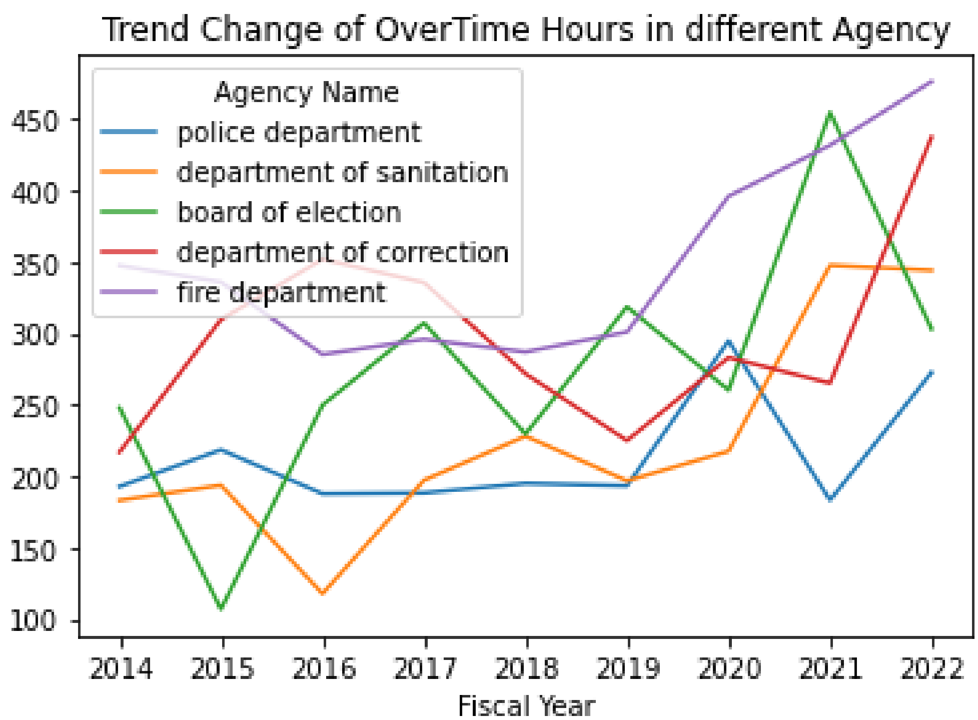
```
Fiscal Year
2014                          71.846512                  15.989684
2015                          57.976343                   8.309890
2016                          38.299362                   8.988527
2017                          44.863791                  11.870732
2018                          45.795267                  13.742299

[5 rows x 165 columns]
```

[36]:
```
payroll_data_ot_year_count_top5 = payroll_data_ot_year_count[['police␣
 ↪department','department of sanitation','board of election','department of␣
 ↪correction','fire department']]
```

[37]:
```
# Visualization of the result:
payroll_data_ot_year_count_top5.plot(title="Trend Change of OverTime Hours in␣
 ↪different Agency")
```

[37]:
```
<AxesSubplot:title={'center':'Trend Change of OverTime Hours in different
Agency'}, xlabel='Fiscal Year'>
```



Insights: From the pie chart above, we noticed that the Fire Department has the highest amount of overtime hours which does not surprise us. However, when by looking at the line chart above, we noticed that most of these agencies' overtime hours went up after the outbreak of COVID-19 in 2019. Especially for the Police Department, the overtime hours went up by lot in 2019. On the other hand, we notice that the Board of Election also had higher overtime hours over years. The reason behind this may because the election of President of United States.