Analysis of San Francisco Employee Salary Compensation

- K Venkata Bharadwaj

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[306]:
```
import pandas as pd
df = pd.read_csv('/kaggle/input/san-francisco-employee-salary-compensation/
↪Employee_Salary_Compensation.csv')
df.head()
```

[306]:

	Organization Group Code	Job Family Code	Job Code	Year Type	Year
0	1	1000	1021	Calendar	2013
1	1	1000	1023	Calendar	2013
2	1	1000	1031	Calendar	2013
3	1	1000	1054	Calendar	2013
4	1	1000	1062	Calendar	2013

	Organization Group	Department Code	Department	Union Code
0	Public Protection	ADP	ADP Adult Probation	21.0
1	Public Protection	ADP	ADP Adult Probation	21.0
2	Public Protection	ADP	ADP Adult Probation	21.0
3	Public Protection	ADP	ADP Adult Probation	21.0
4	Public Protection	ADP	ADP Adult Probation	21.0

	Union	...	Employee Identifier
0	Prof & Tech Engineers - Miscellaneous, Local 21	...	37730
1	Prof & Tech Engineers - Miscellaneous, Local 21	...	26574
2	Prof & Tech Engineers - Miscellaneous, Local 21	...	8148
3	Prof & Tech Engineers - Miscellaneous, Local 21	...	27436
4	Prof & Tech Engineers - Miscellaneous, Local 21	...	37730

	Salaries	Overtime	Other Salaries	Total Salary	Retirement
0	57534.65	0.0	0.00	57534.65	11253.16
1	57678.50	0.0	0.00	57678.50	10284.88
2	63532.93	0.0	0.00	63532.93	12495.83
3	101274.51	0.0	-7058.59	94215.92	19644.45
4	5084.00	0.0	0.00	5084.00	1083.90

	Health and Dental	Other Benefits	Total Benefits	Total Compensation
0	11961.34	4532.63	27747.13	85281.78
1	7176.80	4755.14	22216.82	79895.32
2	12918.24	4702.71	30116.78	93649.71

3	12918.24	7458.76	40021.45	134237.37
4	956.91	387.50	2428.31	7512.31

[5 rows x 22 columns]

[307]:
```
df.shape
```

[307]: (678524, 22)

[308]:
```
df.dtypes
```

[308] :
Organization Group Code	int64
Job Family Code	object
Job Code	object
Year Type	object
Year	int64
Organization Group	object
Department Code	object
Department	object
Union Code	float64
Union	object
Job Family	object
Job	object
Employee Identifier	int64
Salaries	float64
Overtime	float64
Other Salaries	float64
Total Salary	float64
Retirement	float64
Health and Dental	float64
Other Benefits	float64
Total Benefits	float64
Total Compensation	float64

dtype: object

Not many null values . So left them

[309]:
```
df.isnull().sum()
```

[309] :
Organization Group Code	0
Job Family Code	0
Job Code	0
Year Type	0
Year	0
Organization Group	0
Department Code	2
Department	2

```
Union Code                179
Union                     179
Job Family                  0
Job                         5
Employee Identifier         0
Salaries                    0
Overtime                    0
Other Salaries              0
Total Salary                0
Retirement                  0
Health and Dental           0
Other Benefits              0
Total Benefits              0
Total Compensation          0
dtype: int64
```

[310]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 678524 entries, 0 to 678523
Data columns (total 22 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   Organization Group Code   678524 non-null  int64  
 1   Job Family Code           678524 non-null  object 
 2   Job Code                  678524 non-null  object 
 3   Year Type                 678524 non-null  object 
 4   Year                      678524 non-null  int64  
 5   Organization Group        678524 non-null  object 
 6   Department Code           678522 non-null  object 
 7   Department                678522 non-null  object 
 8   Union Code                678345 non-null  float64
 9   Union                     678345 non-null  object 
 10  Job Family                678524 non-null  object 
 11  Job                       678519 non-null  object 
 12  Employee Identifier       678524 non-null  int64  
 13  Salaries                  678524 non-null  float64
 14  Overtime                  678524 non-null  float64
 15  Other Salaries            678524 non-null  float64
 16  Total Salary              678524 non-null  float64
 17  Retirement                678524 non-null  float64
 18  Health and Dental         678524 non-null  float64
 19  Other Benefits            678524 non-null  float64
 20  Total Benefits            678524 non-null  float64
 21  Total Compensation        678524 non-null  float64
dtypes: float64(10), int64(3), object(9)
memory usage: 113.9+ MB
```

[311]:
```
def convert(x):
    x = x.lower()
    x = x.strip()
    return x
```

[312]:
```
df["Job Family Code"] = df["Job Family Code"].apply(convert)
df["Job Code"] = df["Job Code"].apply(convert)
df["Year Type"] = df["Year Type"].apply(convert)
df["Job Family"] = df["Job Family"].apply(convert)
```

[313]:
```
df["Union Code"] = df["Union Code"].fillna(df["Union Code"].mode()[0])
df["Job"] = df["Job"].fillna(df["Job"].mode()[0])
df["Department"] = df["Department"].fillna(df["Department"].mode()[0])
df["Department Code"] = df["Department Code"].fillna(df["Department Code"].
↪mode()[0])
```

All the null values are replaced for object types with their mode value for best predecition

[314]:
```
df.isnull().sum()
```

[314]:
```
Organization Group Code      0
Job Family Code              0
Job Code                     0
Year Type                    0
Year                         0
Organization Group           0
Department Code              0
Department                   0
Union Code                   0
Union                      179
Job Family                   0
Job                          0
Employee Identifier          0
Salaries                     0
Overtime                     0
Other Salaries               0
Total Salary                 0
Retirement                   0
Health and Dental            0
Other Benefits               0
Total Benefits               0
Total Compensation           0
dtype: int64
```

[315]:
```
df.head()
```

[315]:
	Organization Group Code	Job Family Code	Job Code	Year Type	Year
0	1	1000	1021	calendar	2013
1	1	1000	1023	calendar	2013
2	1	1000	1031	calendar	2013
3	1	1000	1054	calendar	2013
4	1	1000	1062	calendar	2013

	Organization Group	Department Code	Department	Union Code
0	Public Protection	ADP	ADP Adult Probation	21.0
1	Public Protection	ADP	ADP Adult Probation	21.0
2	Public Protection	ADP	ADP Adult Probation	21.0
3	Public Protection	ADP	ADP Adult Probation	21.0
4	Public Protection	ADP	ADP Adult Probation	21.0

	Union	...	Employee Identifier
0	Prof & Tech Engineers - Miscellaneous, Local 21	...	37730
1	Prof & Tech Engineers - Miscellaneous, Local 21	...	26574
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	Salaries	Overtime	Other Salaries	Total Salary	Retirement
0	57534.65	0.0	0.00	57534.65	11253.16
1	57678.50	0.0	0.00	57678.50	10284.88
2	63532.93	0.0	0.00	63532.93	12495.83
3	101274.51	0.0	-7058.59	94215.92	19644.45
4	5084.00	0.0	0.00	5084.00	1083.90

	Health and Dental	Other Benefits	Total Benefits	Total Compensation
0	11961.34	4532.63	27747.13	85281.78
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3	12918.24	7458.76	40021.45	134237.37
4	956.91	387.50	2428.31	7512.31

[5 rows x 22 columns]

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1. Salary analysis by department,job family, year

Analysis of Total Salary by Department

[316]:
```
df['Department'] = df['Department'].str.lower()
df['Department'] = df['Department'].str.strip()
df['Department Code'] = df['Department Code'].str.lower()
df['Department Code'] = df['Department Code'].str.strip()
```

[317]:
```
print(len(df['Department Code'].unique()) , len(df['Department'].unique()))
```

```
60 108
```

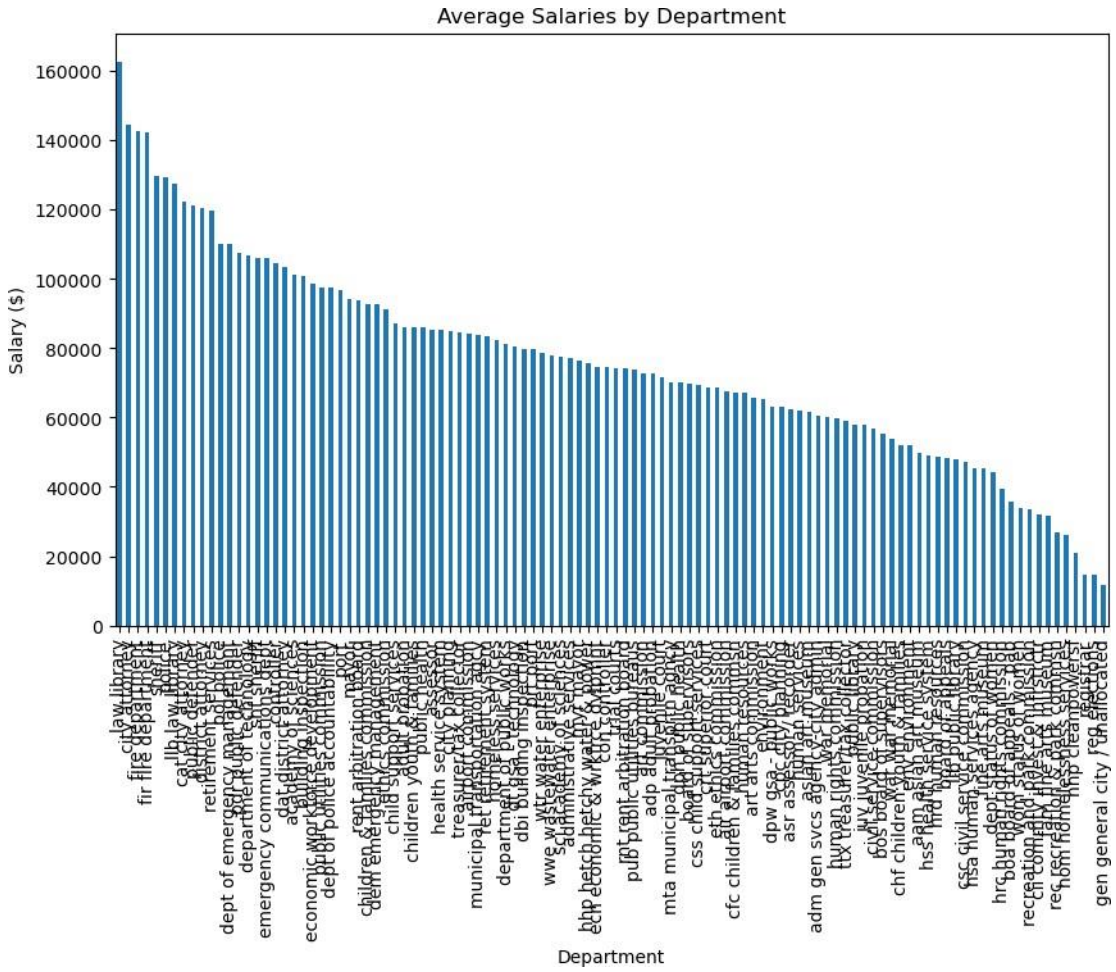
[318]:
```
salary_by_department = df.groupby('Department')['Total Salary'].mean().
↪sort_values(ascending=False)
pd.DataFrame(salary_by_department.head())
```

[318]:

Department	Total Salary
law library	162770.802500
city attorney	144588.487050
fire department	142826.919294
fir fire department	142240.134871
sheriff	129562.048436

[319]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
salary_by_department.plot(kind='bar')
plt.title('Average Salaries by Department')
plt.xlabel('Department')
plt.ylabel('Salary ($)')
```

[319]:
```
Text(0, 0.5, 'Salary ($)')
```



Analysis by Department Code

[320]:
```
salary_by_department_code = df.groupby('Department Code')['Total Salary'].
↪mean().sort_values(ascending = False)
pd.DataFrame(salary_by_department_code).head()
```

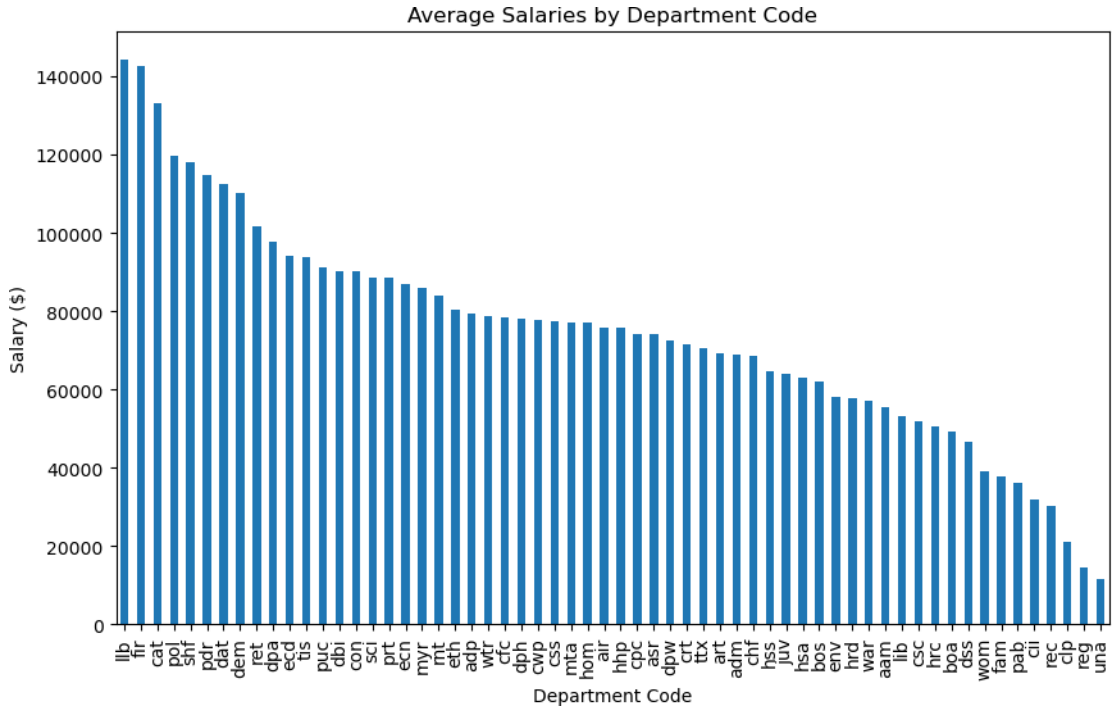
[320]:

Department Code	Total Salary
llb	144122.217353
fir	142552.876339
cat	133241.515633
pol	119582.211678
shf	117998.065680

[321]:
```
plt.figure(figsize=(10, 6))
salary_by_department_code.plot(kind='bar')
plt.title('Average Salaries by Department Code')
```

```
plt.xlabel("Department Code")
plt.ylabel("Salary ($)")
```

[321]: Text(0, 0.5, 'Salary ($)')



Analysis by Job Family

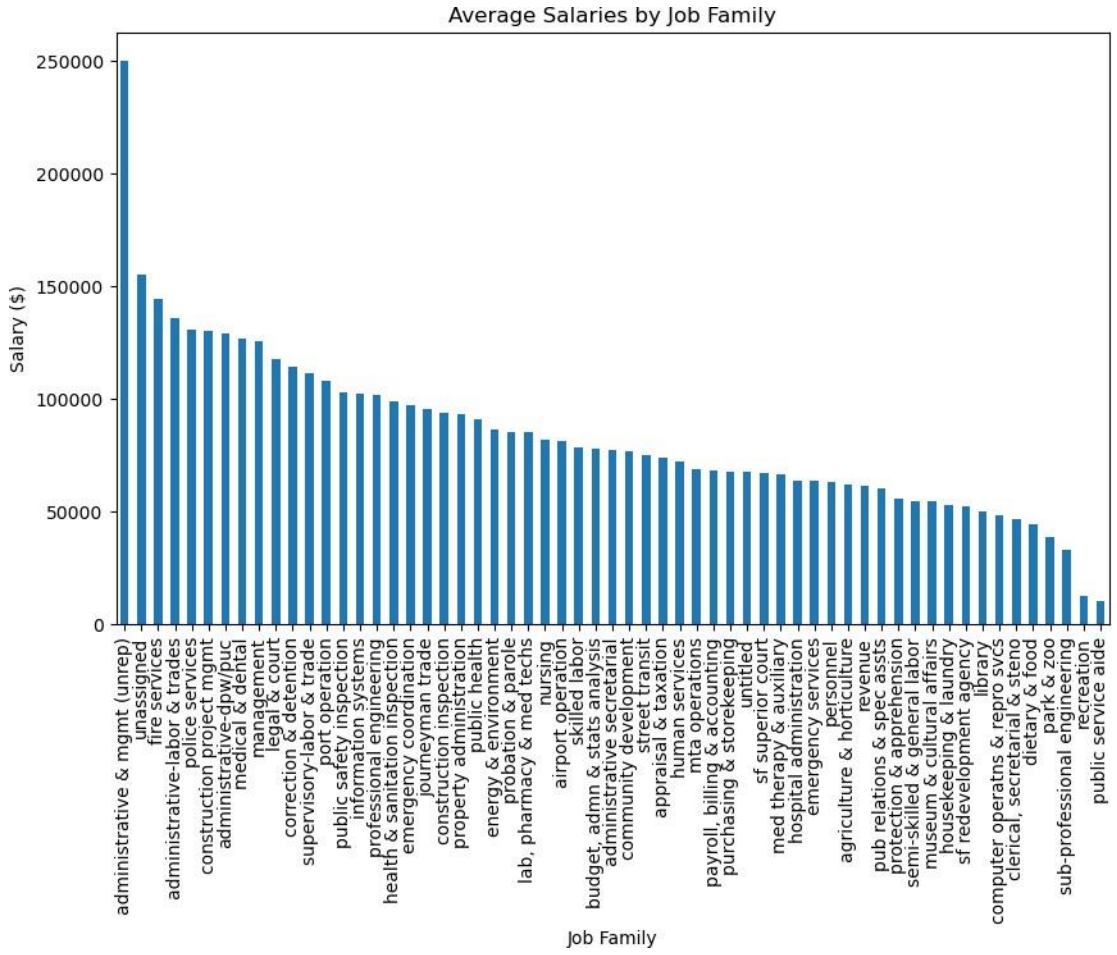
[322]:
```
salary_by_job_family = df.groupby("Job Family")["Total Salary"].mean().
↪sort_values(ascending=False)
pd.DataFrame(salary_by_job_family).head()
```

[322]:

Job Family	Total Salary
administrative & mgmt (unrep)	250272.775269
unassigned	154961.578571
fire services	144436.584976
administrative-labor & trades	135589.014858
police services	130925.354525

[323]:
```
plt.figure(figsize=(10, 6))
salary_by_job_family.plot(kind="bar")
plt.title("Average Salaries by Job Family")
plt.xlabel("Job Family")
plt.ylabel("Salary ($)")
```

[323]: Text(0, 0.5, 'Salary ($)')



Analysis by Year

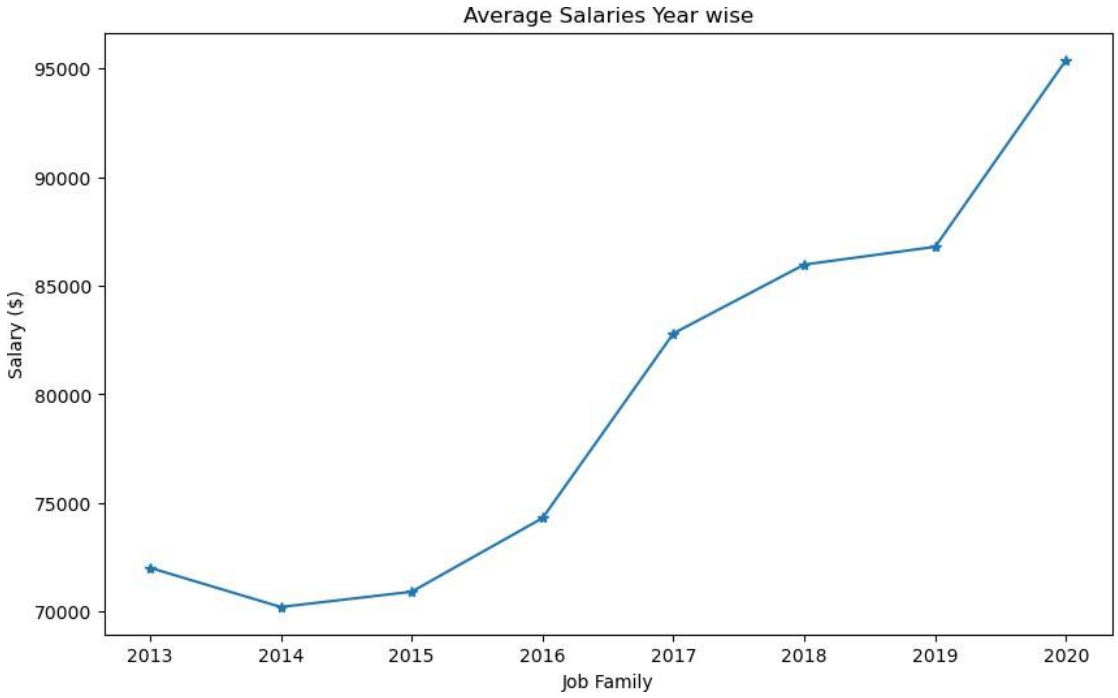
[324]:
```
salary_by_year = df.groupby('Year')['Total Salary'].mean()
pd.DataFrame(salary_by_year)
```

[324]:

Year	Total Salary
2013	72023.350326
2014	70218.111979
2015	70920.055925
2016	74309.361928
2017	82805.335110
2018	85970.822735
2019	86788.806866
2020	95380.094185

[325]:
```
plt.figure(figsize=(10, 6))
salary_by_year.plot(kind='line',marker = '*')
plt.title('Average Salaries Year wise')
plt.xlabel('Job Family')
plt.ylabel('Salary ($)')
```

[325]: Text(0, 0.5, 'Salary ($)')



Conclusion: 1. Law Library, City attorney and Fire Department has highest average salary in order according to the department wise analysis 2. Administrative & mgmt (unrep), unassigned ,fire services are having high average salary by job_family wise analysis 3. Slight decrement in average salaries from 2013 to 2014 but after that they increased continously

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2. Benefits Analysis for Overall Compensation

[326]:
```
df_b = pd.concat([df['Retirement'],df['Health and Dental'],df['Other␣
↪Benefits'],df['Total Compensation']], axis = 1)
df_b.head()
```

[326] :

	Retirement	Health and Dental	Other Benefits	Total Compensation
0	11253.16	11961.34	4532.63	85281.78
1	10284.88	7176.80	4755.14	79895.32
2	12495.83	12918.24	4702.71	93649.71
3	19644.45	12918.24	7458.76	134237.37

```
4      1083.90              956.91          387.50              7512.31
```

Finding the correlation to understand contibution of benefits

[327]:
```
df_b.corr()
```

[327] :
```
                    Retirement  Health and Dental  Other Benefits  \
Retirement            1.000000           0.779367        0.675334
Health and Dental     0.779367           1.000000        0.630131
Other Benefits        0.675334           0.630131        1.000000
Total Compensation    0.951269           0.793772        0.701674

                    Total Compensation
Retirement                    0.951269
Health and Dental             0.793772
Other Benefits                0.701674
Total Compensation            1.000000
```

Conclusion:

1. We can clearly observe that Retirement have high correlation with Total Compensation(0.951)

2. So we can say Retirement benefits contribution is more followed by (Health and Dental) and Other Benefits

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3. Total Compensation Analysis

Exploring the factors that contribute to the total compensation of employees, including salaries, overtime, other salaries, and benefits.

[328]:
```
df.head()
```

[328] :
```
   Organization Group Code Job Family Code Job Code Year Type  Year  \
0                        1            1000     1021  calendar  2013
1                        1            1000     1023  calendar  2013
2                        1            1000     1031  calendar  2013
3                        1            1000     1054  calendar  2013
4                        1            1000     1062  calendar  2013

  Organization Group Department Code          Department  Union Code  \
0  Public Protection             adp  adp adult probation        21.0
1  Public Protection             adp  adp adult probation        21.0
2  Public Protection             adp  adp adult probation        21.0
3  Public Protection             adp  adp adult probation        21.0
4  Public Protection             adp  adp adult probation        21.0

                                          Union  ... Employee Identifier  \
0  Prof & Tech Engineers - Miscellaneous, Local 21  ...              37730
```

```
1  Prof & Tech Engineers - Miscellaneous, Local 21  ...          26574
2  Prof & Tech Engineers - Miscellaneous, Local 21  ...           8148
3  Prof & Tech Engineers - Miscellaneous, Local 21  ...          27436
4  Prof & Tech Engineers - Miscellaneous, Local 21  ...          37730

    Salaries  Overtime  Other Salaries  Total Salary  Retirement  \
0   57534.65       0.0            0.00      57534.65    11253.16
1   57678.50       0.0            0.00      57678.50    10284.88
2   63532.93       0.0            0.00      63532.93    12495.83
3  101274.51       0.0        -7058.59      94215.92    19644.45
4    5084.00       0.0            0.00       5084.00     1083.90

    Health and Dental  Other Benefits  Total Benefits  Total Compensation
0            11961.34         4532.63        27747.13            85281.78
1             7176.80         4755.14        22216.82            79895.32
2            12918.24         4702.71        30116.78            93649.71
3            12918.24         7458.76        40021.45           134237.37
4              956.91          387.50         2428.31             7512.31

[5 rows x 22 columns]
```

[329]:
```
df_c = pd.concat([df['Salaries'],df['Overtime'],df['Other Salaries'],df['Total␣
↪Benefits'],df['Total Compensation']], axis = 1)
df_c.head()
```

[329] :
```
    Salaries  Overtime  Other Salaries  Total Benefits  Total Compensation
0   57534.65       0.0            0.00        27747.13            85281.78
1   57678.50       0.0            0.00        22216.82            79895.32
2   63532.93       0.0            0.00        30116.78            93649.71
3  101274.51       0.0        -7058.59        40021.45           134237.37
4    5084.00       0.0            0.00         2428.31             7512.31
```

[330]:
```
df_c.describe()
```

[330]:
```
              Salaries       Overtime  Other Salaries  Total Benefits  \
count   678524.000000  678524.000000   678524.000000   678524.000000
mean     70626.560805    5592.672838     3869.976380    29290.924481
std      48190.977875   13324.789874     8631.413917    18202.223207
min     -68771.780000  -12308.660000   -19131.100000   -21295.150000
25%      30502.342500       0.000000        0.000000    12486.985000
50%      68942.825000       0.000000      720.000000    33102.795000
75%     101887.527500    4429.512500     4399.657500    41566.422500
max     651936.710000  321523.310000   568163.120000   166068.180000

        Total Compensation
count        678524.000000
mean         109159.269539
```

```
std          73062.782901
min         -74082.610000
25%          46834.075000
50%         109394.735000
75%         156607.520000
max         807625.250000
```

1. We can observe that Salaries + Overtime + Other Salaries + Total Benefits = Total Compensation

2. We are having negative values and zero values for Salaries, Overtime , Other Salaries, Total Benefits

[331]:
```
print('Negative Salaries Count = ',len(df[df['Salaries']<0]))
print('Negative Overtime Count = ',len(df[df['Overtime']<0]))
print('Negative Other Salaries Count = ',len(df[df['Other Salaries']<0]))
print('Negative Total Benefits Count = ',len(df[df['Total Benefits']<0]))
```

```
Negative Salaries Count =  130
Negative Overtime Count =  49
Negative Other Salaries Count =  108
Negative Total Benefits Count =  499
```

[332]:
```
print('Zero Salaries Count = ',len(df[df['Salaries']==0]))
print('Zero Overtime Count = ',len(df[df['Overtime']==0]))
print('Zero Other Salaries Count = ',len(df[df['Other Salaries']==0]))
print('Zero Total Benefits Count = ',len(df[df['Total Benefits']==0]))
```

```
Zero Salaries Count =  11278
Zero Overtime Count =  358547
Zero Other Salaries Count =  219088
Zero Total Benefits Count =  623
```

Conclusion:

Thus the Total Compensation Values are positive , negative as well as zero due to values of factors **Salaries, Overtime, Other Salaries, Benefits**

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4. Organisational Group Analysis

Investigating the variations in compensation across different organizational groups to understand how compensation differs based on the nature of work.

[333]:
```
df.columns
```

[333]:
```
Index(['Organization Group Code', 'Job Family Code', 'Job Code', 'Year Type',
       'Year', 'Organization Group', 'Department Code', 'Department',
       'Union Code', 'Union', 'Job Family', 'Job', 'Employee Identifier',
       'Salaries', 'Overtime', 'Other Salaries', 'Total Salary', 'Retirement',
```

```
       'Health and Dental', 'Other Benefits', 'Total Benefits',
       'Total Compensation'],
      dtype='object')
```

[334]:
```
len(df['Organization Group'].unique())
```

[334]: 7

[335]:
```
df['Organization Group'].value_counts()
```

[335]:
```
Public Works, Transportation & Commerce     214276
Community Health                            149768
Public Protection                           130170
General Administration & Finance             61992
Culture & Recreation                         61240
Human Welfare & Neighborhood Development     60685
General City Responsibilities                  393
Name: Organization Group, dtype: int64
```

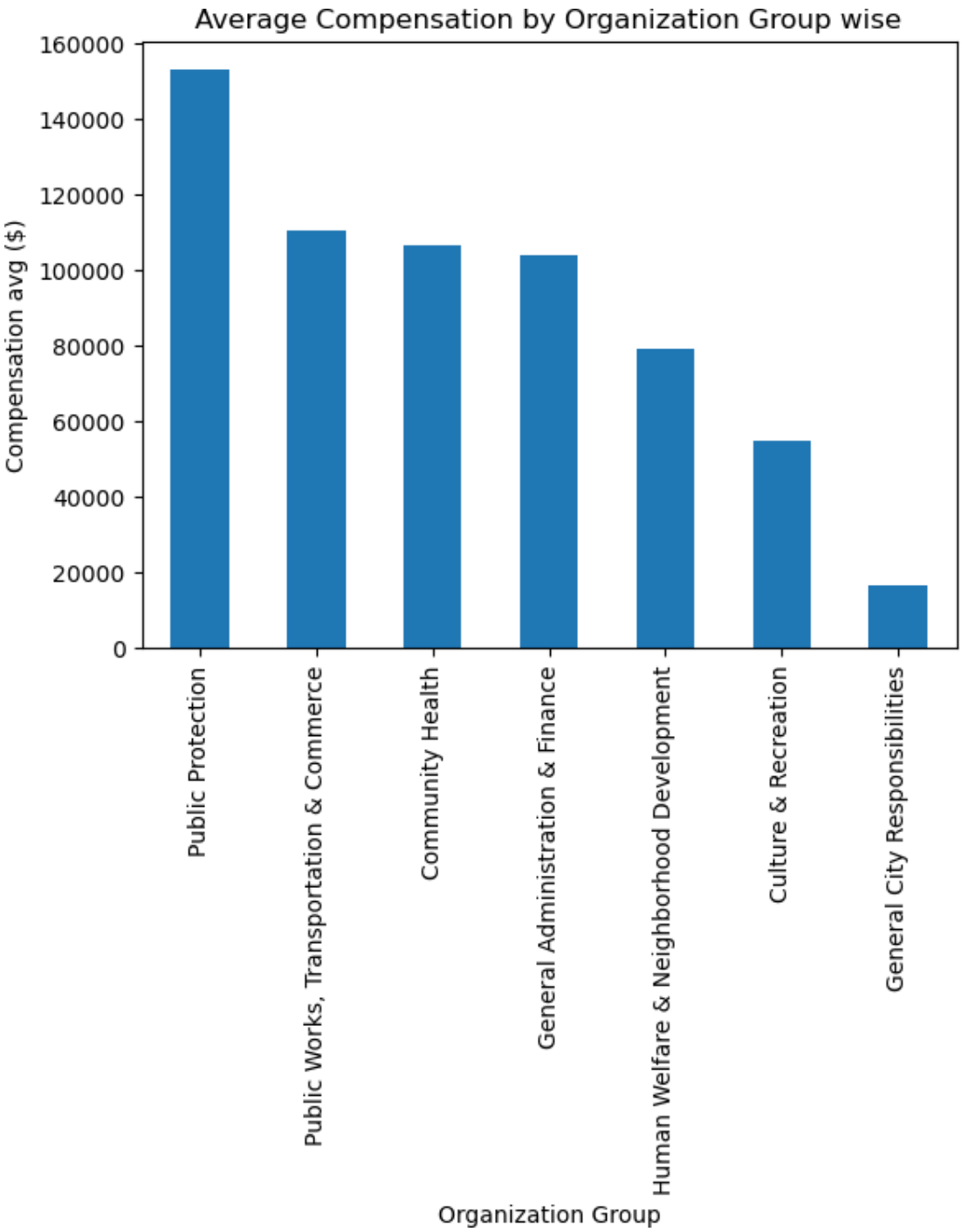
[336]:
```
compensation_by_organisation = df.groupby('Organization Group')['Total
↪Compensation'].mean().sort_values(ascending=False)
pd.DataFrame(compensation_by_organisation)
```

[336]:

Organization Group	Total Compensation
Public Protection	152847.613476
Public Works, Transportation & Commerce	110335.157055
Community Health	106296.832312
General Administration & Finance	103844.990275
Human Welfare & Neighborhood Development	79091.183202
Culture & Recreation	54952.370482
General City Responsibilities	16488.564631

[337]:
```
compensation_by_organisation.plot(kind='bar')
plt.title('Average Compensation by Organization Group wise')
plt.xlabel('Organization Group')
plt.ylabel('Compensation avg ($)')
```

[337]: Text(0, 0.5, 'Compensation avg ($)')



Conclusion:

The Public Protection organization employees recieved high compensation followed by Public Works,Transporattion, Commerce

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5. Yearly Trends:

Observing the changes in salary and compensation patterns over the years to identify any significant shifts or anomalies.

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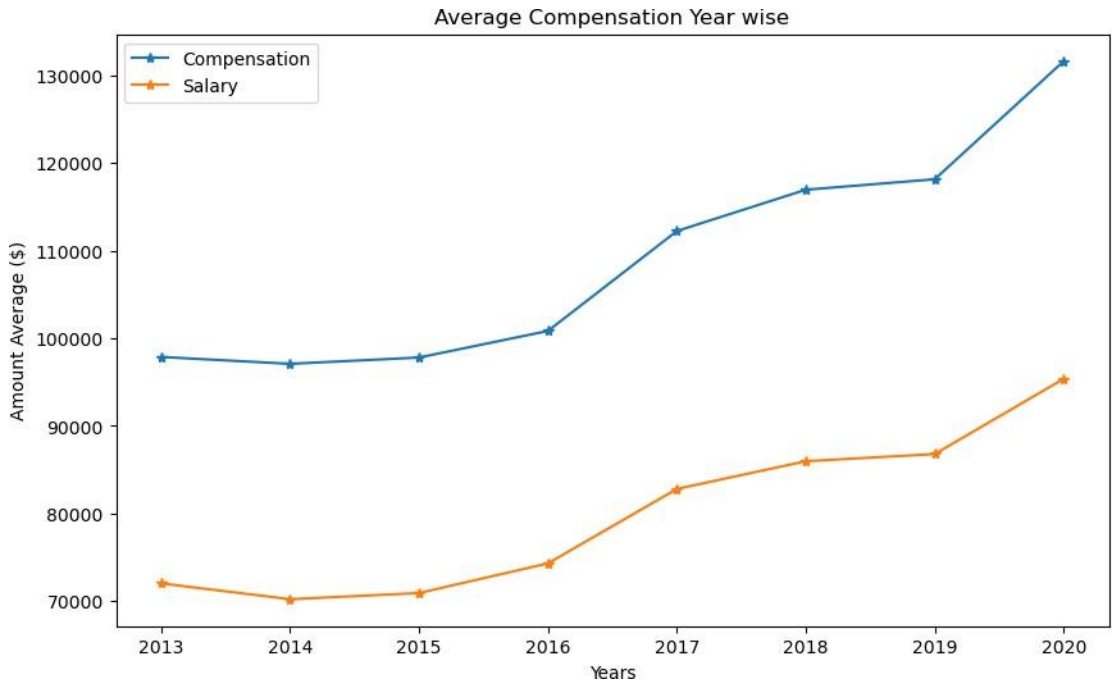
[339]:
```
salary_by_year = df.groupby("Year")["Total Salary"].mean()
comp_by_year = df.groupby("Year")["Total Compensation"].mean()
```

[340]:
```
plt.figure(figsize = (10,6))
comp_by_year.plot(kind='line',marker = '*', label = 'Compensation')
salary_by_year.plot(kind='line',marker = '*', label = 'Salary')
plt.title('Average Compensation Year wise')
plt.xlabel('Years')
plt.ylabel('Amount Average ($)')
plt.legend()
plt.show()
```



Conclusion:

Both the salary and compensation were increeased as the year proceeds

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6. Union Analysis:

Assessing the impact of union representation on salary and benefits, comparing unionized and non-unionized positions.

[341]:
```
len(df['Union'].unique())
```

[341]: 129

[342]:
```
df['Union'] = df['Union'].str.lower()
df['Union'] = df['Union'].str.strip()
```

[343]:
```
len(df['Union'].unique())
```

[343]: 128

[344]:
```
df['Union'].unique()
```

[344] : array(['prof & tech engineers - miscellaneous, local 21',
'prof & tech engineers - personnel, local 21',
'municipal executive association - miscellaneous',
"deputy probation officers' association",
'seiu - miscellaneous, local 1021',
'operating engineers - sup probation ofcrs, local 3',
'prof & tech engineers - court employees, local 21',
'prof & tech engineers - court attorneys, local 21',
'court interpreters, local 39521',
'court unrepresented professionals',
'court unrepresented managers',
'prof & tech engineers - court reporters, local 21',
'municipal executive association - court',
'seiu - court employees, local 1021',
'court unrepresented bench officers',
'management unrepresented employees',
"municipal attorneys' association",
"district attorney investigators' association",
'elected officials', 'miscellaneous unrepresented employees',
'physicians and dentists - spv physician specialist',
'physicians and dentists - miscellaneous',
'members of boards and commissions',
'municipal executive association - fire',
'seiu - staff and per diem nurses, local 1021',
'seiu - firefighter paramedics, local 1021',
'firefighters - miscellaneous, local 798',
'firefighters - chiefs/fire boat workers, local 798',
"police officers' association", 'stationary engineers, local 39',
'seiu - health workers, local 1021',
'seiu - human services, local 1021',
'teamsters - miscellaneous, local 856',
'transportation workers, local 200',
'transport workers - auto svc workers, local 250-a',
'municipal executive association - police',

'electrical workers, local 6',
'plumbers and pipefitters, local 38', 'laborers, local 261',
"deputy sheriffs' association",
"sheriff's managers and supervisors association",
"institutional police officers' association",
'operating engineers - miscellaneous, local 3',
'painters, local 1176', 'bricklayers, local 3',
'sheet metal workers, local 104',
'automotive machinists, local 1414', 'teamsters, local 853',
'carpenters, local 22',
'transport workers - miscellaneous, local 250-a',
"building inspectors' association - inspectors",
"building inspectors' association - chiefs",
'carpet, linoleum and soft tile workers, local 12',
'hod carriers, local 166',
'transport workers - transit operators, local 250-a',
'cement masons, local 300',
'glaziers, metal, and glass workers, local 718',
'transport workers - fare inspectors, local 250-a',
'management unrepresented employees - mta',
'pile drivers, local 34', 'roofers and waterproofers, local 40',
'iron workers, local 377', 'port director',
'members of boards and commissions - no benefits',
'executive contract employees',
'teamsters - supervising nurses, local 856',
'theatrical and stage employees, local 16',
'law librarian and assistant',
'members of the board of supervisors',
'firefighters unit 1, local 798', 'poa', 'laborers int, local 261',
'municipal exec assoc-misc', nan, 'prof & tech eng, local 21',
'municipal exec assoc, misc', 'seiu, local 1021, misc',
'probation off assoc (dpoa)', 'sup probation ofcr, op eng 3',
'court-local 21 professional', 'court local 21 staff attorneys',
'court-supr court interpreters', 'court-unrep professional', 'court-
unrep management', 'court-court reporters', 'court-mea','sf
courts commissioner assoc', 'utd pub empl790 seiu-crt clrks',
'court-judge', 'municipal attorneys assoc',
'sfda investigators assn', 'twu, local 200',
'physician/dentists 11-aa, uapd', 'physician/dentists 8-cc, uapd',
'member, board or commission', 'municipal exec assoc, fire',
'seiu, local 1021, rn', 'seiu, local 1021, h-1',
'firefighters,local 798, unit 1', 'firefighters,local 798, unit 2',
'teamsters, local 856, multi', 'theatrical stage emp, local 16',
'twu, local 250-a, autoserv', 'municipal exec assoc, police',
'plumbers, local 38', "deputy sheriffs' assoc (dsa)",
"sheriffs' mgrs and supv (msa)", 'sfipoa, op eng, local 3',
'operating engineers, local 3', 'sf city workers united',

```
       'auto machinist, local 1414', 'twu, local 250-a, misc',
       'building inspects - 6331/33', 'building inspects - 6332',
       'carpet, linoleum & soft tile', 'hod carriers, local 36',
       'cement masons, local 300 (580)', 'glaziers, local 718',
       'misc. unrepresented employees', 'twu, local 250-a, transitopr',
       'twu, local 250-a, tranfare', 'indv. employment contract-mta',
       'roofers, local 40', 'commissioner no benefits',
       'unrepresented contract rte fbp', 'teamsters, local 856, spv rn',
      'member, board of sups', 'mgt. unrepresented employees'],
      dtype=object)
```

[345]:
```
salary_by_union = df.groupby("Union")["Total Salary"].mean().
  ↪sort_values(ascending = False)
pd.DataFrame(salary_by_union).head()
```

[345] :

Union	Total Salary
unrepresented contract rte fbp	332080.805000
management unrepresented employees - mta	302650.025000
municipal executive association - police	302541.463333
indv. employment contract-mta	285532.422222
municipal exec assoc, police	280622.170965

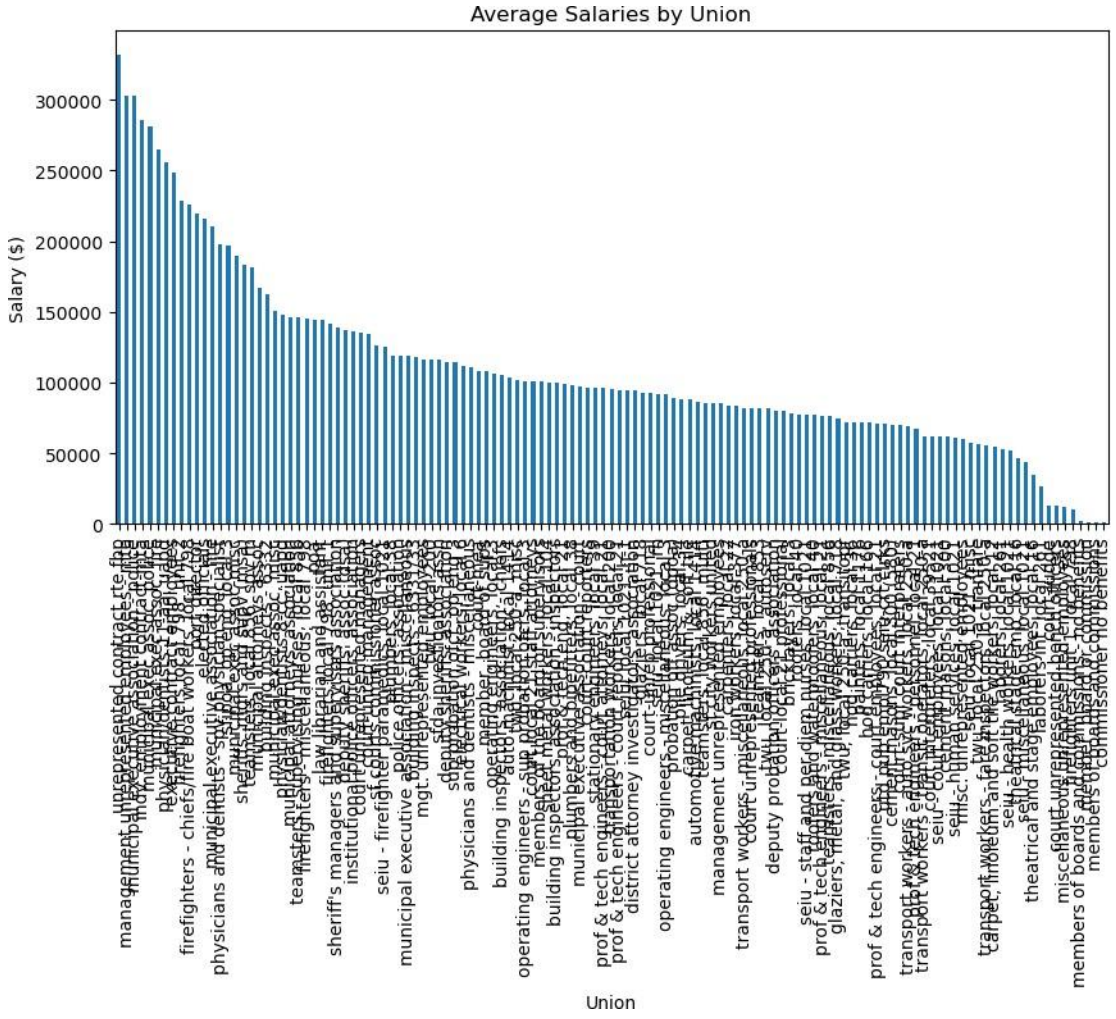
[346]:
```
benefit_by_union = df.groupby("Union")["Total Benefits"].mean().
  ↪sort_values(ascending = False)
pd.DataFrame(benefit_by_union).head()
```

[346] :

Union	Total Benefits
unrepresented contract rte fbp	96188.791250
management unrepresented employees - mta	93455.238750
indv. employment contract-mta	79066.208889
municipal exec assoc, police	75830.340000
physician/dentists 11-aa, uapd	74236.745562

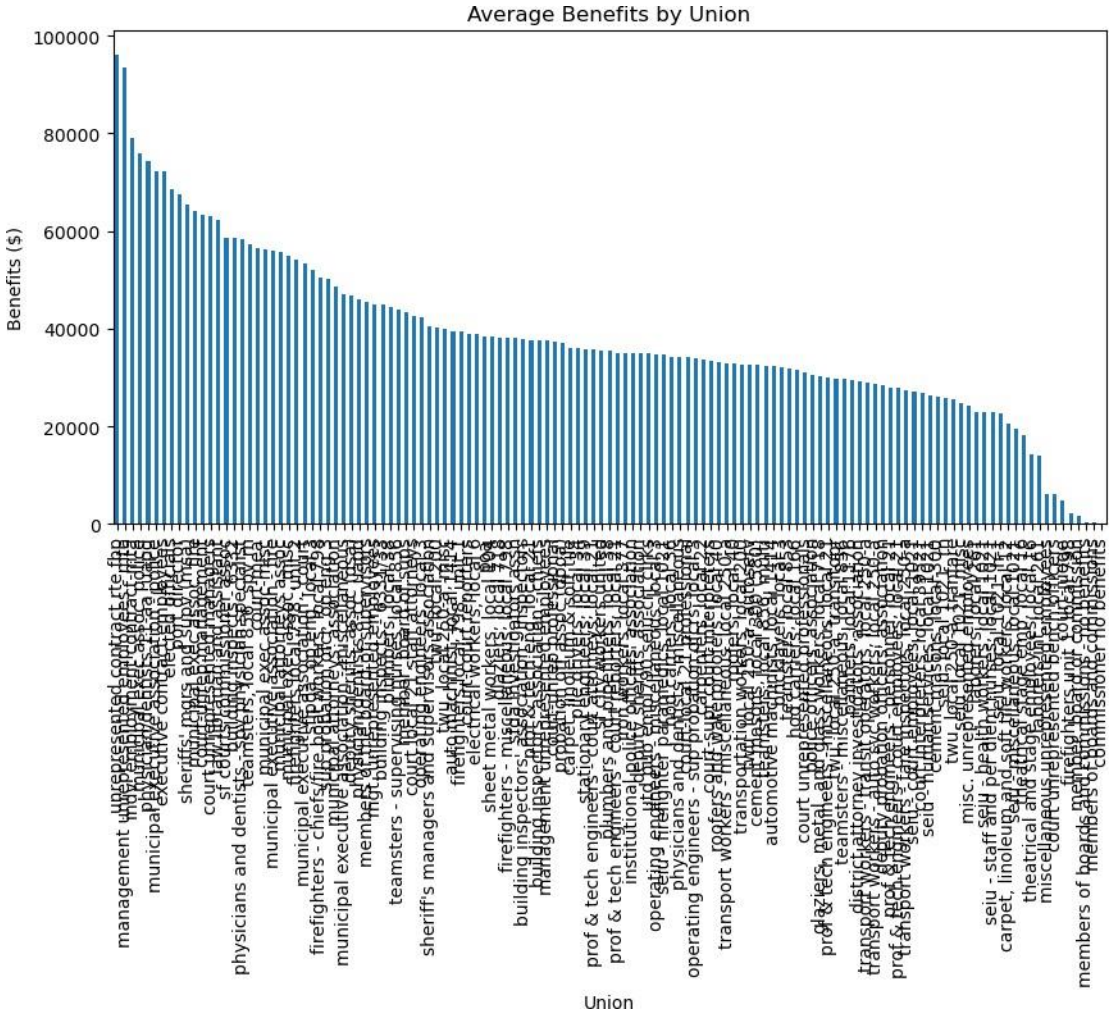
[347]:
```
plt.figure(figsize=(10, 5))
salary_by_union.plot(kind="bar")
plt.title("Average Salaries by Union")
plt.xlabel("Union")
plt.ylabel("Salary ($)")
```

[347]: Text(0, 0.5, 'Salary ($)')



[348]:
```
plt.figure(figsize=(10, 5))
benefit_by_union.plot(kind="bar")
plt.title("Average Benefits by Union")
plt.xlabel("Union")
plt.ylabel("Benefits ($)")
```

[348]: Text(0, 0.5, 'Benefits ($)')



Unionized and NON- Unionized Analysis

Union as NULL Values are considered as non-unionised category

[349]:
```
non_unionised = df[df["Union"].isnull()]
unionised = df[df["Union"].notnull()]
```

[350]:
```
print("Non - Unionised avg Salary = ",non_unionised["Total Salary"].
↪mean(),"\n","Non - Unionised avg Benefits = ",non_unionised["Total␣
↪Benefits"].mean())
```

```
Non - Unionised avg Salary =  14408.221675977655
 Non - Unionised avg Benefits =  6219.160502793296
```

[351]:
```
print("Unionised avg Salary = ",unionised["Total Salary"].
↪mean(),"\n","Unionised avg Benefits = ",unionised["Total Benefits"].mean())
```

Unionised avg Salary = 79885.6185140157
Unionised avg Benefits = 29297.01260065306

Conclusion:

We can clearly check the huge difference between Benefits and Salaries of non-unionised and unionised employees

1. Non Unionised employees are getting lesser salaries and benefits compared to unionised employees

———————————————————-

7. Total Compensation Prediction

[352]:
```
df1 = df
df1.head()
```

[352]:

	Organization Group Code	Job Family Code	Job Code	Year Type	Year	\
0	1	1000	1021	calendar	2013	
1	1	1000	1023	calendar	2013	
2	1	1000	1031	calendar	2013	
3	1	1000	1054	calendar	2013	
4	1	1000	1062	calendar	2013	

	Organization Group	Department Code	Department	Union Code	\
0	Public Protection	adp	adp adult probation	21.0	
1	Public Protection	adp	adp adult probation	21.0	
2	Public Protection	adp	adp adult probation	21.0	
3	Public Protection	adp	adp adult probation	21.0	
4	Public Protection	adp	adp adult probation	21.0	

	Union	...	Employee Identifier	\
0	prof & tech engineers - miscellaneous, local 21	...	37730	
1	prof & tech engineers - miscellaneous, local 21	...	26574	
2	prof & tech engineers - miscellaneous, local 21	...	8148	
3	prof & tech engineers - miscellaneous, local 21	...	27436	
4	prof & tech engineers - miscellaneous, local 21	...	37730	

	Salaries	Overtime	Other Salaries	Total Salary	Retirement	\
0	57534.65	0.0	0.00	57534.65	11253.16	
1	57678.50	0.0	0.00	57678.50	10284.88	
2	63532.93	0.0	0.00	63532.93	12495.83	
3	101274.51	0.0	-7058.59	94215.92	19644.45	
4	5084.00	0.0	0.00	5084.00	1083.90	

	Health and Dental	Other Benefits	Total Benefits	Total Compensation
0	11961.34	4532.63	27747.13	85281.78
1	7176.80	4755.14	22216.82	79895.32
2	12918.24	4702.71	30116.78	93649.71

```
3          12918.24          7458.76          40021.45          134237.37
4            956.91           387.50           2428.31            7512.31

[5 rows x 22 columns]
```

[353]:
```
df1["Union"] = df1["Union"].fillna(df1["Union"].mode()[0])
```

[354]:
```
df1.isnull().sum()
```

[354]:
```
Organization Group Code    0
Job Family Code            0
Job Code                   0
Year Type                  0
Year                       0
Organization Group         0
Department Code            0
Department                 0
Union Code                 0
Union                      0
Job Family                 0
Job                        0
Employee Identifier        0
Salaries                   0
Overtime                   0
Other Salaries             0
Total Salary               0
Retirement                 0
Health and Dental          0
Other Benefits             0
Total Benefits             0
Total Compensation         0
dtype: int64
```

[355]:
```
#Dropping because they have similar features in column.
df1.drop(["Organization Group Code","Job Family Code","Job Code","Department
 ↪Code","Union Code","Total Salary","Total Benefits"],inplace=True,axis=1)
```

[356]:
```
index_names = df1[(df1["Salaries"]<0) | (df1["Overtime"]<0) | (df1["Other
 ↪Salaries"]<0) | (df1["Retirement"]<0) | (df1["Health and Dental"]<0) |
 ↪(df1["Other Benefits"]<0) | (df1["Total Compensation"]<0)].index
```

[357]:
```
df1.drop(index=index_names,inplace=True)
```

[358]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in df1:
    if df1[i].dtype=="object":
```

```
        df1[i] = le.fit_transform(df1[i])
    else:
        continue
```

[359]:
```
X = df1.drop("Total Compensation",axis=1)
y = df1["Total Compensation"]
```

[360]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
↪2,random_state=100)
```

[361]:
```
model.fit(X_train,y_train)
```

[361]: LinearRegression()

[362]:
```
prediction = model.predict(X_test)
```

[363]:
```
from sklearn.metrics import r2_score
r2Score = r2_score(y_test,prediction)
r2Score
```

[363]: 0.9994393815811299

Conclusion

Predictions are made with r2_score = 0.9994 using Linear Regression

Link for Code: https://www.kaggle.com/code/kvenkatabharadwaj/project