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Setup the Spark VM and complete the below assignment

Objective:- Build a ML model to predict the employee compensation. The application should be modelled using Spark.

You can refer to the below links for spark commands:-

- https://spark.apache.org/docs/latest/ml-pipeline.html
- https://github.com/spark-in-action/first-edition
- https://github.com/FavioVazquez/first_spark_model

Predicting Employee Compensation

Data Dictionary

Year Type - Fiscal (July through June) or Calendar (January through December)
Year - An accounting period of 12 months. The City and County of San Francisco operates on a fiscal year that begins on July 1 and ends on June 30 the following year. The Fiscal Year ending June 30, 2012 is represented as FY2011-2012.
Organization Group Code - Org Group is a group of Departments. For example, the Public Protection Org Group includes departments such as the Police,Fire, Adult Probation, District Attorney, and Sheriff.
Organization Group - Org Group is a group of Departments. For example, the Public Protection Org Group includes departments such as the Police, Fire, Adult Probation, District Attorney, and Sheriff.
Department Code - Departments are the primary organizational unit used by the Cityand County of San Francisco. Examples include Recreation and Parks, Public Works, and the Police Department.
Department Code - Departments are the primary organizational unit used by the City and County of San Francisco. Examples include Recreation and Parks, Public Works, and the Police Department.
Union Code - Unions represent employees in collective bargaining agreements. A job belongs to one union, although some jobs are unrepresented (usually temporarily).
Union - Unions represent employees in collective bargaining agreements. A job belongs to one union, although some jobs are unrepresented (usually temporarily).
Job Family Code Job Family combines similar Jobs into meaningful groups.
Job Family Job Family combines similar Jobs into meaningful groups.

Employee Identifier Each distinct number in the “Employee Identifier” column represents one employee. These identifying numbers are not meaningful but rather are randomly assigned for the purpose of building this dataset. The column does not appear on the Employee Compensation report hosted on openbook.sfgov.org, but that report does show one row for each employee. Employee ID has been included here to allow users to reconstruct the original report. Note that each employee’s identifier will change each time this dataset is updated, so comparisons by employee across multiple versions of the dataset are not possible.
Salaries - Normal salaries paid to permanent or temporary City employees.
Overtime - Amounts paid to City employees working in excess of 40 hours per week.
Other Salaries - Various irregular payments made to City employees including premium pay, incentive pay, or other one-time payments. Total Salary Number The sum of all salaries paid to City employees.
Retirement City contributions to employee retirement plans.
Health/Dental City-paid premiums to health and dental insurance plans covering City employees. To protect confidentiality as legally required, pro-rated citywide averages are presented in lieu of employee-specific health and dental benefits.
Other Benefits Mandatory benefits paid on behalf of employees, such as Social Security (FICA and Medicare) contributions, unemployment insurance premiums, and minor discretionary benefits not included in the above categories.
Total Benefits The sum of all benefits paid to City employees.
Total Compensation The sum of all salaries and benefits paid to City employees.

Read the data and answer the following questions to predict employee compensation

1. Read the Data

In [1]:
```
# Basic libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import pyspark

# Libraries for pyspark session
from pyspark.sql import SparkSession
from pyspark import SparkConf
from pyspark import SparkContext

# PySpark related libraries
from pyspark.sql.functions import isnull, when, count, col
from pyspark.ml.feature import StringIndexer
from pyspark.ml.feature import OneHotEncoder
from pyspark.ml.feature import VectorAssembler

# Importing PySpark libraries for co-relation matrix
from pyspark.ml.stat import Correlation

# Importing LinearRegression library
from pyspark.ml.regression import LinearRegression
```

```
# Importing Decision Tree regressor libraries
from pyspark.ml.regression import DecisionTreeRegressor
from pyspark.ml.evaluation import RegressionEvaluator
```

In [2]:
```
# Setting up the spark session
conf=pyspark.SparkConf().setAppName('Part2').setMaster('local')
sc=pyspark.SparkContext(conf=conf)
spark=SparkSession(sc)
```

```
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setL
ogLevel(newLevel).
23/07/16 21:13:45 WARN NativeCodeLoader: Unable to load native-hadoop libr
ary for your platform... using builtin-java classes where applicable
```

In [3]:
```
# Let's read the iot_devices.json into a dataframe
df = spark.read.csv("Employee_Compensation.csv", inferSchema=True, header
```

1.1 Display the number of rows and columns in the dataset

In [4]:
```
row_count = df.count()
column_count = len(df.columns)

print("Number of rows: ", row_count)
print("Number of columns: ", column_count)
```

```
Number of rows:  291825
Number of columns:  22
```

1.2 Check the datatype of the variables

In [5]:
```
df.printSchema()
```

```
root
 |-- Year Type: string (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Organization Group Code: integer (nullable = true)
 |-- Organization Group: string (nullable = true)
 |-- Department Code: string (nullable = true)
 |-- Department: string (nullable = true)
 |-- Union Code: integer (nullable = true)
 |-- Union: string (nullable = true)
 |-- Job Family Code: string (nullable = true)
 |-- Job Family: string (nullable = true)
 |-- Job Code: string (nullable = true)
 |-- Job: string (nullable = true)
 |-- Employee Identifier: integer (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Other Salaries: double (nullable = true)
 |-- Total Salary: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Health/Dental: double (nullable = true)
 |-- Other Benefits: double (nullable = true)
 |-- Total Benefits: double (nullable = true)
 |-- Total Compensation: double (nullable = true)
```

2. Convert the incorrect column type into its suitable column type. And drop the redundant features

In [6]:
```
# Let's run a SQL query to understand the Organization Group and Organiza
temp_df = df.select("Organization Group Code","Organization Group")
temp_df = temp_df.withColumn("Organization_Group_Code", df["Organization
temp_df = temp_df.withColumn("Organization_Group", df["Organization Group
temp_df = temp_df.drop("Organization Group", "Organization Group Code")
temp_df.createOrReplaceTempView("temp_compensation")
result = spark.sql("SELECT Organization_Group_Code, Organization_Group FR
result.show(vertical=True)
```

```
-RECORD 0----------------------------------
 Organization_Group_Code | 4
 Organization_Group      | Community Health
-RECORD 1----------------------------------
 Organization_Group_Code | 6
 Organization_Group      | General Administr...
-RECORD 2----------------------------------
 Organization_Group_Code | 1
 Organization_Group      | Public Protection
-RECORD 3----------------------------------
 Organization_Group_Code | 5
 Organization_Group      | Culture & Recreation
-RECORD 4----------------------------------
 Organization_Group_Code | 2
 Organization_Group      | Public Works, Tra...
-RECORD 5----------------------------------
 Organization_Group_Code | 7
 Organization_Group      | General City Resp...
-RECORD 6----------------------------------
 Organization_Group_Code | 3
 Organization_Group      | Human Welfare & N...
```

In [7]:
```
# Let's store it in a dictionary for future use
# Convert the result DataFrame into a dictionary
Organization_Group_Code_dict = dict(result.collect())
Organization_Group_Code_dict
```

Out[7]:
```
{4: 'Community Health',
 6: 'General Administration & Finance',
 1: 'Public Protection',
 5: 'Culture & Recreation',
 2: 'Public Works, Transportation & Commerce',
 7: 'General City Responsibilities',
 3: 'Human Welfare & Neighborhood Development'}
```

In [8]:
```
# Let's run a SQL query to understand the Job and Job Code mapping
temp_df = df.select("Job","Job Code" )
temp_df = temp_df.withColumn("Job_Code", df["Job Code"])
temp_df = temp_df.drop("Job Code")
temp_df.createOrReplaceTempView("temp_compensation")
result = spark.sql("SELECT Job_Code, Job FROM temp_compensation GROUP BY
result.show(n=5, vertical=True)
```

```
-RECORD 0-----------------------
 Job_Code | 9139
 Job      | Transit Supervisor
-RECORD 1-----------------------
 Job_Code | 1222
 Job      | Sr Payroll & Pers...
-RECORD 2-----------------------
 Job_Code | 5174
 Job      | Administrative En...
-RECORD 3-----------------------
 Job_Code | 2105
 Job      | Patient Svcs Fina...
-RECORD 4-----------------------
 Job_Code | 1071
 Job      | IS Manager
only showing top 5 rows
```

In [9]:
```
# Let's store it in a dictionary for future use
# Convert the result DataFrame into a dictionary
Job_Code_dict = dict(result.collect())
counter = 0
print(" Job Code, Job")
print("----------------")
for item in Job_Code_dict.keys():
    print(f" {item}, \t   {Job_Code_dict[item]} ")
    counter += 1
    if(counter==5):
        break
```

```
 Job Code, Job
----------------
 9139,     Transit Supervisor
 1222,     Sr Payroll & Personnel Clerk
 5174,     Administrative Engineer
 2105,     Patient Svcs Finance Tech
 1071,     IS Manager
```

In [10]:
```python
# Code cell 10
# Calculate the percentage of rows per column that have None values
total_rows = df.count()
for column in df.columns:
    null_rows = df.filter(col(column).isNull()).count()
    null_percentage = (null_rows / total_rows) * 100
    print(f"Column: {column}, Null Percentage: {null_percentage}%")
```

```
Column: Year Type, Null Percentage: 0.0%
Column: Year, Null Percentage: 0.0%
Column: Organization Group Code, Null Percentage: 0.0%
Column: Organization Group, Null Percentage: 0.0%
Column: Department Code, Null Percentage: 0.0%
Column: Department, Null Percentage: 0.0%
Column: Union Code, Null Percentage: 0.014734858219823524%
Column: Union, Null Percentage: 0.014734858219823524%
Column: Job Family Code, Null Percentage: 0.015420200462606013%
Column: Job Family, Null Percentage: 0.015420200462606013%
Column: Job Code, Null Percentage: 0.0%
Column: Job, Null Percentage: 0.0%
Column: Employee Identifier, Null Percentage: 0.0%
Column: Salaries, Null Percentage: 0.0%
Column: Overtime, Null Percentage: 0.0%
Column: Other Salaries, Null Percentage: 0.0%
Column: Total Salary, Null Percentage: 0.0%
Column: Retirement, Null Percentage: 0.0%
Column: Health/Dental, Null Percentage: 0.0%
Column: Other Benefits, Null Percentage: 0.0%
Column: Total Benefits, Null Percentage: 0.0%
Column: Total Compensation, Null Percentage: 0.0%
```

Remark for code cell 10

We can see that there are some missing values for the columns **Union Code, Union, Job Family Code, Job Family**

In [11]:
```python
# Dropping redundant features
df = df.drop("Organization Group","Department", "Union", "Job Family", "J
df.show(n=1, vertical=True)
```

```
-RECORD 0--------------------------
 Year Type                | Fiscal
 Year                     | 2016
 Organization Group Code  | 1
 Department Code          | DAT
 Union Code               | 311
 Job Family Code          | 8100
 Job Code                 | 8177
 Salaries                 | 114473.16
 Overtime                 | 0.0
 Other Salaries           | 1500.0
 Total Salary             | 115973.16
 Retirement               | 21025.98
 Health/Dental            | 13068.8
 Other Benefits           | 9368.71
 Total Benefits           | 43463.49
 Total Compensation       | 159436.65
only showing top 1 row
```

In [12]:
```
df.printSchema()
```

```
root
 |-- Year Type: string (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Organization Group Code: integer (nullable = true)
 |-- Department Code: string (nullable = true)
 |-- Union Code: integer (nullable = true)
 |-- Job Family Code: string (nullable = true)
 |-- Job Code: string (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Other Salaries: double (nullable = true)
 |-- Total Salary: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Health/Dental: double (nullable = true)
 |-- Other Benefits: double (nullable = true)
 |-- Total Benefits: double (nullable = true)
 |-- Total Compensation: double (nullable = true)
```

Let's convert the string types to numeric...

In [13]:
```
input_cols = ["Year Type","Job Family Code","Job Code","Department Code"]
output_cols = ["Year_Type_index", "Job_Family_Code_index", "Job_Code_inde

indexer = StringIndexer(inputCols=input_cols, outputCols=output_cols, han
df = indexer.fit(df).transform(df)
#df = df.drop("Year Type","Job Family Code","Job Code","Department Code")
df.show(n=1, vertical=True)
```

```
-RECORD 0--------------------------
 Year Type                | Fiscal
 Year                     | 2016
 Organization Group Code  | 1
 Department Code          | DAT
 Union Code               | 311
 Job Family Code          | 8100
 Job Code                 | 8177
 Salaries                 | 114473.16
 Overtime                 | 0.0
 Other Salaries           | 1500.0
 Total Salary             | 115973.16
 Retirement               | 21025.98
 Health/Dental            | 13068.8
 Other Benefits           | 9368.71
 Total Benefits           | 43463.49
 Total Compensation       | 159436.65
 Year_Type_index          | 0.0
 Job_Family_Code_index    | 16.0
 Job_Code_index           | 15.0
 Department_Code_index    | 19.0
only showing top 1 row
```

In [14]:
```
# Storing the encoding mapping of "Job Code" and "Job Code Index"
job_code_index_enc_dict = dict(df.select("Job_Code_index","Job Code").col
counter = 0
print("Mapping of original Job Code and indexes for Job Code created by s
print("Job C, Job Code index ")
print("--------------------------")
for item in job_code_index_enc_dict.keys():
    print(f" {job_code_index_enc_dict[item]}, \t {round(item,0)} ")
    counter += 1
    if(counter==5):
        break
```

```
Mapping of original Job Code and indexes for Job Code created by stringInd
exer:

Job C, Job Code index
--------------------------
 8177,   15.0
 1844,   135.0
 2903,   20.0
 2202,   332.0
 3279,   8.0
```

In [15]:
```
# Dropping the original columns
df = df.drop("Year Type","Job Family Code","Job Code","Department Code")
```

In [16]:
```
# Code cell 17
# Calculate the percentage of rows per column that have None values
total_rows = df.count()
for column in df.columns:
    null_rows = df.filter(col(column).isNull()).count()
    null_percentage = (null_rows / total_rows) * 100
    print(f"Column: {column}, Null Percentage: {null_percentage}%")
```

```
Column: Year, Null Percentage: 0.0%
Column: Organization Group Code, Null Percentage: 0.0%
Column: Union Code, Null Percentage: 0.0%
Column: Salaries, Null Percentage: 0.0%
Column: Overtime, Null Percentage: 0.0%

Column: Other Salaries, Null Percentage: 0.0%
Column: Total Salary, Null Percentage: 0.0%
Column: Retirement, Null Percentage: 0.0%
Column: Health/Dental, Null Percentage: 0.0%

Column: Other Benefits, Null Percentage: 0.0%
Column: Total Benefits, Null Percentage: 0.0%
Column: Total Compensation, Null Percentage: 0.0%
Column: Year_Type_index, Null Percentage: 0.0%
Column: Job_Family_Code_index, Null Percentage: 0.0%
Column: Job_Code_index, Null Percentage: 0.0%
Column: Department_Code_index, Null Percentage: 0.0%
```

Remark for code cell 17

Observe that missing values for the columns **Union Code, Union, Job Family Code, Job Family** are now 0%.

This is because StringIndexer in PySpark assigns a value to missing values (None or null values) in the column automatically without explicit handling. StringIndexer treats missing values as a separate category and assigns a unique index to them.

By default, StringIndexer uses the value -1 to represent missing values. However, we can specify a different value using the **setHandleInvalid()** method with the **"keep"** option.

3. Check basic statistics and perform necessary data preprocessing (Like removing negative amount)

In [17]:
```
# Checking basic statistics
df.describe().show(vertical=True)
```

```
[Stage 139:>                                                        (0 +
1) / 1]
```

```
-RECORD 0-------------------------------------
 summary                 | count
 Year                    | 291780
 Organization Group Code | 291780
 Union Code              | 291780
 Salaries                | 291780
 Overtime                | 291780
 Other Salaries          | 291780
 Total Salary            | 291780
 Retirement              | 291780
 Health/Dental           | 291780
 Other Benefits          | 291780
 Total Benefits          | 291780
 Total Compensation      | 291780
 Year_Type_index         | 291780
 Job_Family_Code_index   | 291780
 Job_Code_index          | 291780
 Department_Code_index   | 291780
-RECORD 1-------------------------------------
 summary                 | mean
 Year                    | 2014.3248029337171
 Organization Group Code | 2.9769175406127903
 Union Code              | 489.50702584138736
 Salaries                | 63217.50868436003
 Overtime                | 4407.446114332669
 Other Salaries          | 3781.503300431628
 Total Salary            | 71406.4580991163
 Retirement              | 12939.250722702001
 Health/Dental           | 8922.91011052773
 Other Benefits          | 4644.751855473425
 Total Benefits          | 26506.912688704226
 Total Compensation      | 97913.37078782043
 Year_Type_index         | 0.4260607306875043
 Job_Family_Code_index   | 10.908526972376448
 Job_Code_index          | 115.48635273151004
 Department_Code_index   | 6.8179141819178835
-RECORD 2-------------------------------------
 summary                 | stddev
 Year                    | 1.0321352604211558
 Organization Group Code | 1.57774295714257
 Union Code              | 333.76208303970617
 Salaries                | 44659.13274364933
 Overtime                | 11080.148890493894
 Other Salaries          | 7698.157206890118
 Total Salary            | 52223.09667479797
 Retirement              | 9784.921035538538
 Health/Dental           | 4899.9800540383385
 Other Benefits          | 3787.861521183913
 Total Benefits          | 16799.403469530953
 Total Compensation      | 67775.48233372133
 Year_Type_index         | 0.49450361225127504
 Job_Family_Code_index   | 10.610491274137415
 Job_Code_index          | 170.19448668236137
 Department_Code_index   | 9.04905460012686
-RECORD 3-------------------------------------
 summary                 | min
 Year                    | 2013
 Organization Group Code | 1
 Union Code              | 1
 Salaries                | -68771.78
```

```
 Overtime                | -12308.66
 Other Salaries          | -19131.1
 Total Salary            | -68771.78
 Retirement              | -30621.43
 Health/Dental           | -2940.47
 Other Benefits          | -10636.5
 Total Benefits          | -21295.15
 Total Compensation      | -74082.61
 Year_Type_index         | 0.0
 Job_Family_Code_index   | 0.0
 Job_Code_index          | 0.0
 Department_Code_index   | 0.0
-RECORD 4-------------------------------------
 summary                 | max
 Year                    | 2016
 Organization Group Code | 7
 Union Code              | 990
 Salaries                | 515101.8
 Overtime                | 227313.62
 Other Salaries          | 342802.63
 Total Salary            | 515101.8
 Retirement              | 105052.98
 Health/Dental           | 21872.8
 Other Benefits          | 35157.63
 Total Benefits          | 141043.64
 Total Compensation      | 653498.15
 Year_Type_index         | 1.0
 Job_Family_Code_index   | 55.0
 Job_Code_index          | 1132.0
 Department_Code_index   | 53.0
```

In [18]:
```
# Let's rename a few columns so it is easier to write sql queries
# Columns names with spaces in between make the query error prone
# so removing spaces from column names
df = df.withColumn("Other_Salaries", df["Other Salaries"])
df = df.withColumn("Total_Salary", df["Total Salary"])
df = df.withColumn("Other_Benefits", df["Other Benefits"])
df = df.withColumn("Total_Benefits", df["Total Benefits"])
df = df.withColumn("Total_Compensation", df["Total Compensation"])
df = df.withColumn("Organization_Group_Code", df["Organization Group Code
df = df.withColumn("Union_Code", df["Union Code"])
df = df.withColumn("Health_Dental", df["Health/Dental"])
df = df.drop("Other Salaries","Total Salary","Other Benefits","Total Bene
df.show(1, vertical=True)
```

```
-RECORD 0--------------------------
 Year                   | 2016
 Salaries               | 114473.16
 Overtime               | 0.0
 Retirement             | 21025.98
 Year_Type_index        | 0.0
 Job_Family_Code_index  | 16.0
 Job_Code_index         | 15.0
 Department_Code_index  | 19.0
 Other_Salaries         | 1500.0
 Total_Salary           | 115973.16
 Other_Benefits         | 9368.71
 Total_Benefits         | 43463.49
 Total_Compensation     | 159436.65
 Organization_Group_Code | 1
 Union_Code             | 311
 Health_Dental          | 13068.8
only showing top 1 row
```

In [19]:
```
# Let's register the dataframe as a view to run sql on
df.createOrReplaceTempView("compensation")
```

In [20]:
```
result = spark.sql("SELECT Salaries FROM compensation WHERE Salaries < 0
result.show(5)
```

```
+---------+
| Salaries|
+---------+
|-68771.78|
|-18437.73|
|-17635.32|
|  -7423.0|
|  -6622.5|
+---------+
only showing top 5 rows
```

In [21]:
```
result = spark.sql("SELECT Count(Salaries) FROM compensation WHERE Salari
result.show()
```

```
+---------------+
|count(Salaries)|
+---------------+
|             79|
+---------------+
```

Removing rows with negative salaries, as it is not possible to have negative salary & to avoid introducing any bias in dataset by imputting rows containing negative salaries with median salary.

In [22]:
```
# Filter out rows where salary is greater than or equal to 0
df = df.filter(col("Salaries") >= 0)
```

In [23]:
```
# Let's confirm if the rows containing negative rows have been removed
# Note we will have to replace the older view as the dataframe has been m
# Thus re-creating the view with new dataframe
```

```
df.createOrReplaceTempView("compensation")
result = spark.sql("SELECT Count(Salaries) as Count_of_Neg_Sal FROM compe
result.show()
```

```
+----------------+
|Count_of_Neg_Sal|
+----------------+
|               0|
+----------------+
```

Apart from salary, the following columns have negative values:

- Overtime,
- Other_Salaries,
- Total_Salary,
- Retirement,
- Health_Dental,
- Other_Benefits,
- Total_Benefits,
- Total_Compensation

In [24]:
```
# Calculate the median of the 'Overtime' column using a SQL query
median_overtime = spark.sql("SELECT percentile_approx(Overtime, 0.5) as m
median_overtime
```

Out[24]: 0.0

In [25]:
```
# Calculate the median of the 'Retirement' column using a SQL query
median_retirement = spark.sql("SELECT percentile_approx(Retirement, 0.5)
median_retirement
```

Out[25]: 13170.45

In [26]:
```
# Calculate the median of the 'Health_Dental' column using a SQL query
median_Health_Dental = spark.sql("SELECT percentile_approx(Health_Dental,
median_Health_Dental
```

Out[26]: 11971.43

In [27]:
```
# Calculate the median of the 'Other_Salaries' column using a SQL query
median_Other_Salaries = spark.sql("SELECT percentile_approx(Other_Salarie
median_Other_Salaries
```

Out[27]: 696.96

In [28]:
```
# Calculate the median of the 'Total_Salary' column using a SQL query
median_Total_Salary = spark.sql("SELECT percentile_approx(Total_Salary, 0
median_Total_Salary
```

Out[28]: 67870.98

In [29]:
```
# Calculate the median of the 'Other_Benefits' column using a SQL query
median_Other_Benefits = spark.sql("SELECT percentile_approx(Other_Benefit
median_Other_Benefits
```

Out[29]: 4350.63

In [30]:
```
# Calculate the median of the 'Total_Benefits' column using a SQL query
median_Total_Benefits = spark.sql("SELECT percentile_approx(Total_Benefit
median_Total_Benefits
```

Out[30]: 30319.5

In [31]:
```
# Calculate the median of the 'Total_Compensation' column using a SQL que
median_Total_Compensation = spark.sql("SELECT percentile_approx(Total_Com
median_Total_Compensation
```

Out[31]: 98061.92

In [32]:
```
# Fill in rows with negative values for the columns
df = df.withColumn("Overtime", when(col("Overtime") < 0, median_overtime)
df = df.withColumn("Retirement", when(col("Retirement") < 0, median_retir
df = df.withColumn("Health_Dental", when(col("Health_Dental") < 0, median
df = df.withColumn("Other_Salaries", when(col("Other_Salaries") < 0, medi
df = df.withColumn("Total_Salary", when(col("Total_Salary") < 0, median_T
df = df.withColumn("Other_Benefits", when(col("Other_Benefits") < 0, medi
df = df.withColumn("Total_Benefits", when(col("Total_Benefits") < 0, medi
df = df.withColumn("Total_Compensation", when(col("Total_Compensation") <
```

In [33]:
```
# Let's re-check if the negative values have been removed
df.describe().show(vertical=True)
```

```
[Stage 173:>                                                        (0 +
1) / 1]
```

```
-RECORD 0-------------------------------------
 summary                | count
 Year                   | 291701
 Salaries               | 291701
 Overtime               | 291701
 Retirement             | 291701
 Year_Type_index        | 291701
 Job_Family_Code_index  | 291701
 Job_Code_index         | 291701
 Department_Code_index  | 291701
 Other_Salaries         | 291701
 Total_Salary           | 291701
 Other_Benefits         | 291701
 Total_Benefits         | 291701
 Total_Compensation     | 291701
 Organization_Group_Code | 291701
 Union_Code             | 291701
 Health_Dental          | 291701
-RECORD 1-------------------------------------
 summary                | mean
 Year                   | 2014.3247949098563
 Salaries               | 63235.377997204574
 Overtime               | 4408.696255892116
 Retirement             | 12961.74011127825
 Year_Type_index        | 0.4261624060253479
 Job_Family_Code_index  | 10.908896438476384
 Job_Code_index         | 115.48220266642898
 Department_Code_index  | 6.81738835314243
 Other_Salaries         | 3781.088233190634
 Total_Salary           | 71426.63407352098
 Other_Benefits         | 4656.507952526867
 Total_Benefits         | 26556.62489686403
 Total_Compensation     | 98008.03568222291
 Organization_Group_Code | 2.9768632949492804
 Union_Code             | 489.4922883363444
 Health_Dental          | 8937.876481841937
-RECORD 2-------------------------------------
 summary                | stddev
 Year                   | 1.0321419259390108
 Salaries               | 44651.778830764975
 Overtime               | 11081.365239551971
 Retirement             | 9768.499681127409
 Year_Type_index        | 0.49451880456716707
 Job_Family_Code_index  | 10.610129622663045
 Job_Code_index         | 170.18710998805258
 Department_Code_index  | 9.04778133458641
 Other_Salaries         | 7695.647131885712
 Total_Salary           | 52216.358056814126
 Other_Benefits         | 3779.3469741036356
 Total_Benefits         | 16765.63392188047
 Total_Compensation     | 67716.2748254838
 Organization_Group_Code | 1.5777385715846854
 Union_Code             | 333.76335703328004
 Health_Dental          | 4890.740583561448
-RECORD 3-------------------------------------
 summary                | min
 Year                   | 2013
 Salaries               | 0.0
 Overtime               | 0.0
 Retirement             | 0.0
```

```
 Year_Type_index          | 0.0
 Job_Family_Code_index    | 0.0
 Job_Code_index           | 0.0
 Department_Code_index    | 0.0
 Other_Salaries           | 0.0
 Total_Salary             | 0.0
 Other_Benefits           | 0.0
 Total_Benefits           | 0.0
 Total_Compensation       | 0.0
 Organization_Group_Code  | 1
 Union_Code               | 1
 Health_Dental            | 0.0
-RECORD 4-----------------------------------
 summary                  | max
 Year                     | 2016
 Salaries                 | 515101.8
 Overtime                 | 227313.62
 Retirement               | 105052.98
 Year_Type_index          | 1.0
 Job_Family_Code_index    | 55.0
 Job_Code_index           | 1132.0
 Department_Code_index    | 53.0
 Other_Salaries           | 342802.63
 Total_Salary             | 515101.8
 Other_Benefits           | 35157.63
 Total_Benefits           | 141043.64
 Total_Compensation       | 653498.15
 Organization_Group_Code  | 7
 Union_Code               | 990
 Health_Dental            | 21872.8
```

Now there are no negative values present for the above mentioned columns

4. Perform Missing Value Analysis

In [34]:
```
df.select([count(when(isnull(c), c)).alias(c) for c in df.columns]).show(
```

```
[Stage 176:>                                                        (0 +
1) / 1]
```

```
-RECORD 0----------------------
 Year                    | 0
 Salaries                | 0
 Overtime                | 0
 Retirement              | 0
 Year_Type_index         | 0
 Job_Family_Code_index   | 0
 Job_Code_index          | 0
 Department_Code_index   | 0
 Other_Salaries          | 0
 Total_Salary            | 0
 Other_Benefits          | 0
 Total_Benefits          | 0
 Total_Compensation      | 0
 Organization_Group_Code | 0
 Union_Code              | 0
 Health_Dental           | 0
```

As observed in **remarks in Code cell 10 and 17**, there were a few missing values for Job_Family_Code and Union_Code - however **stringIndexer has assigned a unique values to the missing values implicitly** and I will be converting these columns to categorical columns through OneHotEncoding thereby treating missing values in these columns as a separate category. This is done to avoid imputation and to let the algorithm learn itself if there are any patterns in missing data.

5. Exploratory Data Analysis

5.1. Find top compensating organizations. Display using bar plot

In [35]:
```
df.printSchema()
```

```
root
 |-- Year: integer (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Year_Type_index: double (nullable = false)
 |-- Job_Family_Code_index: double (nullable = false)
 |-- Job_Code_index: double (nullable = false)
 |-- Department_Code_index: double (nullable = false)
 |-- Other_Salaries: double (nullable = true)
 |-- Total_Salary: double (nullable = true)
 |-- Other_Benefits: double (nullable = true)
 |-- Total_Benefits: double (nullable = true)
 |-- Total_Compensation: double (nullable = true)
 |-- Organization_Group_Code: integer (nullable = true)
 |-- Union_Code: integer (nullable = true)
 |-- Health_Dental: double (nullable = true)
```

In [36]:
```
df.createOrReplaceTempView("compensation")
result = spark.sql("SELECT Organization_Group_Code , avg(Total_Compensati
result.show()
```

```
[Stage 179:>                                                        (0 +
1) / 1]
+-----------------------+----------------------+
|Organization_Group_Code|Avg_Total_Compensation|
+-----------------------+----------------------+
|                      1|    142236.30949577756|
|                      2|     98802.65538117242|
|                      4|     95081.91639937599|
|                      6|     91155.60900121508|
|                      3|     66635.50288822156|
|                      5|    49302.622747364476|
|                      7|     17682.88197324415|
+-----------------------+----------------------+
```

In [37]:
```
# Convert the PySpark DataFrame to a Pandas DataFrame
org_compensation_df = result.toPandas()
org_compensation_df
```

Out[37]:

	Organization_Group_Code	Avg_Total_Compensation
0	1	142236.309496
1	2	98802.655381
2	4	95081.916399
3	6	91155.609001
4	3	66635.502888
5	5	49302.622747
6	7	17682.881973

In [38]:
```
org_compensation_df["Organization_Group_Code"] = org_compensation_df["Org
org_compensation_df
```

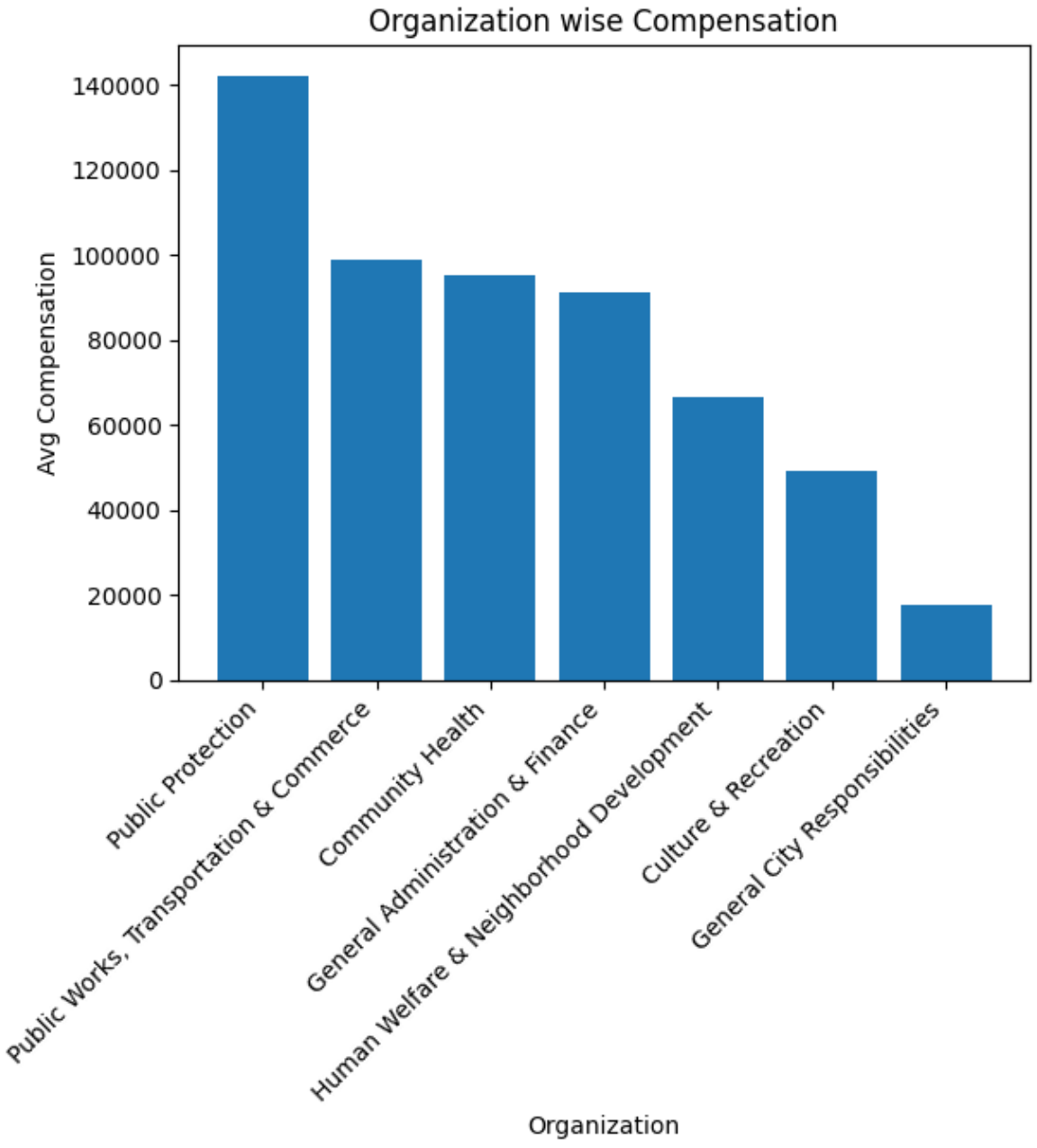
Out[38]:

	Organization_Group_Code	Avg_Total_Compensation
0	Public Protection	142236.309496
1	Public Works, Transportation & Commerce	98802.655381
2	Community Health	95081.916399
3	General Administration & Finance	91155.609001
4	Human Welfare & Neighborhood Development	66635.502888
5	Culture & Recreation	49302.622747
6	General City Responsibilities	17682.881973

In [39]:
```
# Plot the bar chart
fig, ax = plt.subplots()
ax.bar(org_compensation_df.Organization_Group_Code, org_compensation_df.A

# Set slanted x-axis labels
```

```
ax.set_xticklabels(org_compensation_df.Organization_Group_Code, rotation=

# Set plot title and labels
plt.title('Organization wise Compensation')
plt.xlabel('Organization')
plt.ylabel('Avg Compensation')

# Display the plot
plt.show()
```

```
/var/folders/97/vq6bhv0d5jd8spklkj7_6dl80000gn/T/ipykernel_45735/291381651
1.py:6: UserWarning: FixedFormatter should only be used together with Fixe
dLocator
  ax.set_xticklabels(org_compensation_df.Organization_Group_Code, rotation
=45, ha='right')
```



5.2. Find top Compensating Jobs. Display using bar plot

In [40]:
```
df.printSchema()
```

```
root
 |-- Year: integer (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Year_Type_index: double (nullable = false)
 |-- Job_Family_Code_index: double (nullable = false)
 |-- Job_Code_index: double (nullable = false)
 |-- Department_Code_index: double (nullable = false)
 |-- Other_Salaries: double (nullable = true)
 |-- Total_Salary: double (nullable = true)
 |-- Other_Benefits: double (nullable = true)
 |-- Total_Benefits: double (nullable = true)
 |-- Total_Compensation: double (nullable = true)
 |-- Organization_Group_Code: integer (nullable = true)
 |-- Union_Code: integer (nullable = true)
 |-- Health_Dental: double (nullable = true)
```

In [41]:
```
df.createOrReplaceTempView("compensation")
result = spark.sql("SELECT Job_Code_index , avg(Total_Compensation) as Av
result.show()

# Convert the PySpark DataFrame to a Pandas DataFrame
job_compensation_df = result.toPandas()
job_compensation_df
```

```
+--------------+----------------------+
|Job_Code_index|Avg_Total_Compensation|
+--------------+----------------------+
|        1050.0|    480653.56599999993|
|         924.0|     421244.0228571428|
|         922.0|     417736.6542857143|
|        1022.0|     393196.4685714286|
|         928.0|     371392.5457142857|
|         619.0|     358547.0466666667|
|         949.0|    358525.73285714287|
|         926.0|     349378.3085714286|
|         821.0|    343062.12400000007|
|         625.0|    342554.15190476197|
|        1008.0|    332883.26714285713|
|        1032.0|    329839.98000000004|
|        1007.0|     313132.2557142857|
|         798.0|    311706.67055555555|
|        1035.0|    308902.96714285715|
|        1006.0|     301998.3871428571|
|        1018.0|     299572.4985714286|
|         931.0|              295481.29|
|         222.0|     293472.3110344826|
|         959.0|              293040.69|
+--------------+----------------------+
only showing top 20 rows
```

Out[41]:

	Job_Code_index	Avg_Total_Compensation
0	1050.0	480653.566000
1	924.0	421244.022857
2	922.0	417736.654286
3	1022.0	393196.468571
4	928.0	371392.545714
...	...	...
1125	874.0	2092.302500
1126	200.0	1816.173889
1127	150.0	1815.471432
1128	1125.0	1777.550000
1129	198.0	328.411176

1130 rows × 2 columns

In [42]:
```
# Mapping the Job_code_index to Job
job_compensation_df["Job_Code_index"] = job_compensation_df["Job_Code_ind
job_compensation_df
```

Out[42]:

	Job_Code_index	Avg_Total_Compensation
0	Chief Investment Officer	480653.566000
1	Chief Of Police	421244.022857
2	Chief, Fire Department	417736.654286
3	Gen Mgr, Public Trnsp Dept	393196.468571
4	Mayor	371392.545714
...	...	...
1125	Manager I, MTA	2092.302500
1126	Bdcomm Mbr, Grp3,M=$50/Mtg	1816.173889
1127	Bdcomm Mbr, Grp5,M$100/Mo	1815.471432
1128	Cashier 3	1777.550000
1129	Bdcomm Mbr, Grp2,M=$25/Mtg	328.411176

1130 rows × 2 columns

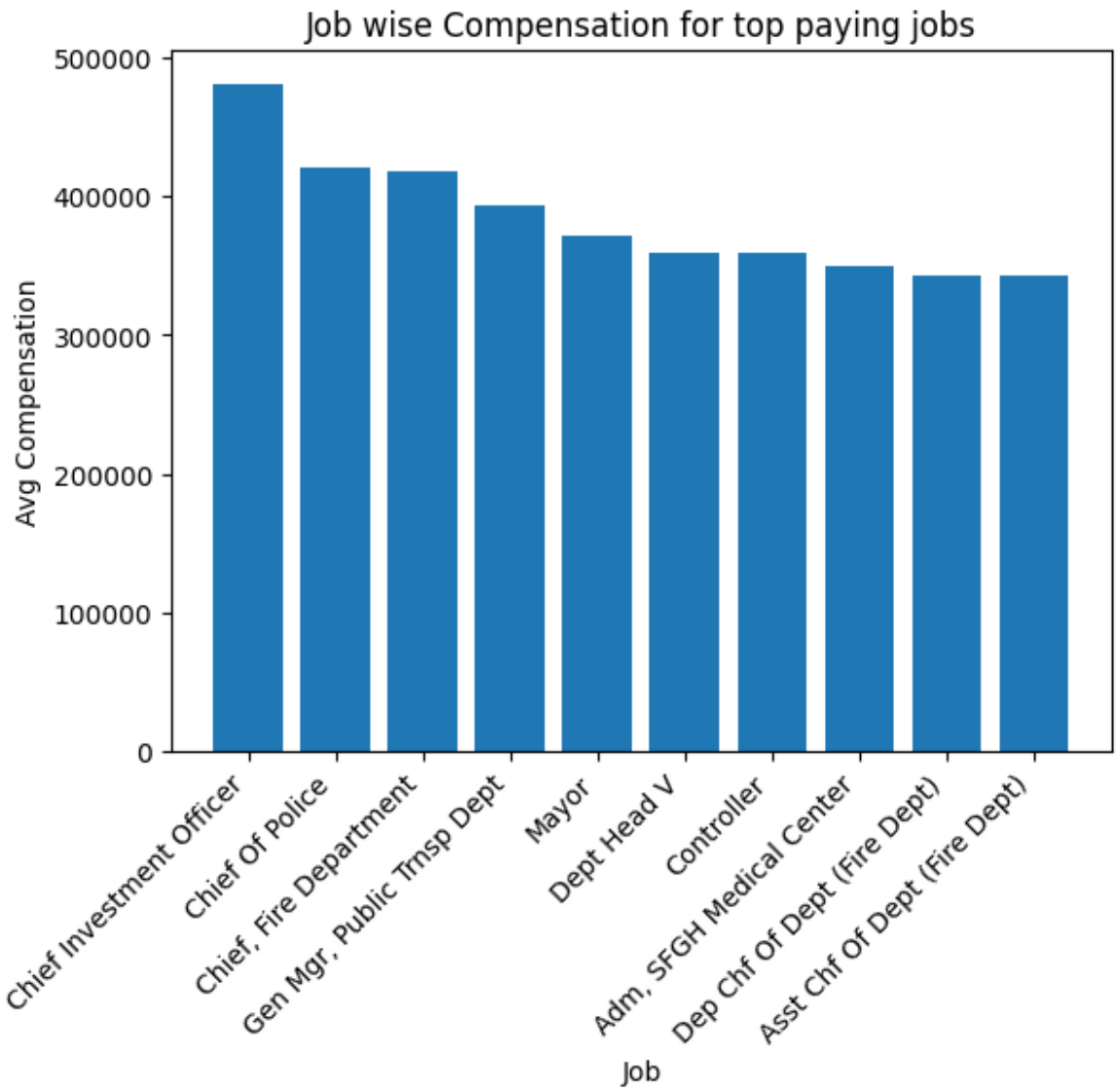
In [43]:
```
job_compensation_df_subset = job_compensation_df[:10]
job_compensation_df_subset
```

Out[43]:

	Job_Code_index	Avg_Total_Compensation
0	Chief Investment Officer	480653.566000
1	Chief Of Police	421244.022857
2	Chief, Fire Department	417736.654286
3	Gen Mgr, Public Trnsp Dept	393196.468571
4	Mayor	371392.545714
5	Dept Head V	358547.046667
6	Controller	358525.732857
7	Adm, SFGH Medical Center	349378.308571
8	Dep Chf Of Dept (Fire Dept)	343062.124000
9	Asst Chf Of Dept (Fire Dept)	342554.151905

In [44]:
```
# Plotting top 10 paying jobs using the bar chart
fig, ax = plt.subplots()
ax.bar(job_compensation_df_subset.Job_Code_index, job_compensation_df_sub

# Set slanted x-axis labels
ax.set_xticklabels(job_compensation_df_subset.Job_Code_index, rotation=45

# Set plot title and labels
plt.title('Job wise Compensation for top paying jobs')
plt.xlabel('Job')
plt.ylabel('Avg Compensation')

# Display the plot
plt.show()
```

```
/var/folders/97/vq6bhv0d5jd8spklkj7_6dl80000gn/T/ipykernel_45735/152267162
1.py:6: UserWarning: FixedFormatter should only be used together with Fixe
dLocator
  ax.set_xticklabels(job_compensation_df_subset.Job_Code_index, rotation=4
5, ha='right')
```



5.3. Check Correlation of Target Variable with Other Independent Variables. Plot Heatmap

In [45]:
```
df.printSchema()
```

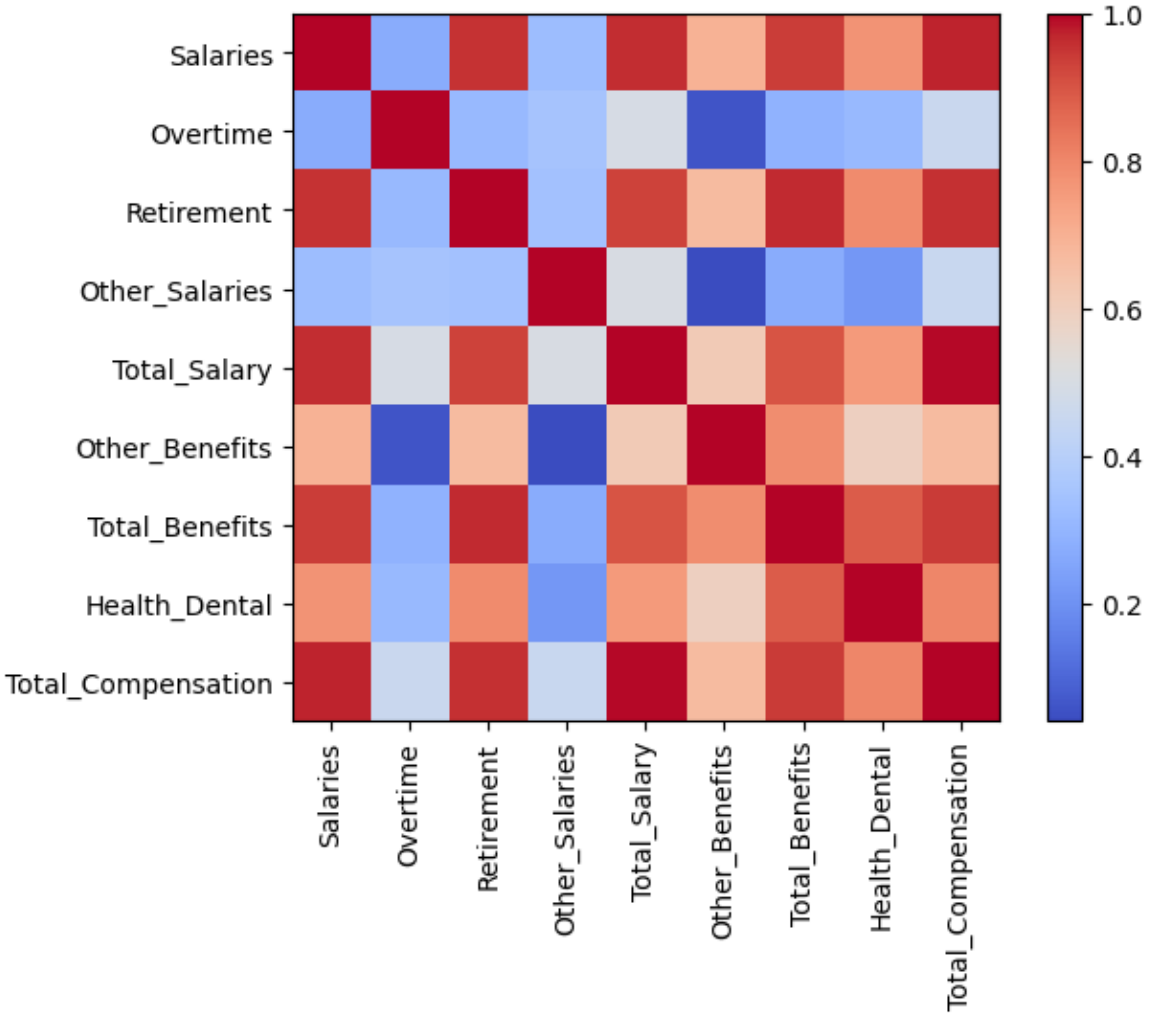
```
root
 |-- Year: integer (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Year_Type_index: double (nullable = false)
 |-- Job_Family_Code_index: double (nullable = false)
 |-- Job_Code_index: double (nullable = false)
 |-- Department_Code_index: double (nullable = false)
 |-- Other_Salaries: double (nullable = true)
 |-- Total_Salary: double (nullable = true)
 |-- Other_Benefits: double (nullable = true)
 |-- Total_Benefits: double (nullable = true)
 |-- Total_Compensation: double (nullable = true)
 |-- Organization_Group_Code: integer (nullable = true)
 |-- Union_Code: integer (nullable = true)
 |-- Health_Dental: double (nullable = true)
```

In [46]:
```
# Specifying the columns for which we want to calculate the correlation
columns = ['Salaries', 'Overtime', 'Retirement', 'Other_Salaries', 'Total
          'Total_Benefits', 'Health_Dental', 'Total_Compensation']

# Creating a VectorAssembler to combine the columns into a single vector
assembler = VectorAssembler(inputCols=columns, outputCol='features')
vectorized_df = assembler.transform(df).select('features')

# Compute the correlation matrix
correlation_matrix = Correlation.corr(vectorized_df, 'features').head()
```

```
23/07/16 21:14:47 WARN InstanceBuilder$NativeBLAS: Failed to load implemen
tation from:dev.ludovic.netlib.blas.JNIBLAS
23/07/16 21:14:47 WARN InstanceBuilder$NativeBLAS: Failed to load implemen
tation from:dev.ludovic.netlib.blas.ForeignLinkerBLAS
```

In [47]:
```
correlation_values = correlation_matrix[0].toArray()
```

In [48]:
```
# Creating a heatmap
plt.imshow(correlation_values, cmap='coolwarm', interpolation='nearest')
plt.colorbar()
plt.xticks(range(len(columns)), columns, rotation=90)
plt.yticks(range(len(columns)), columns)
plt.show()
```



6. Perform necessary data pre-processing and divide the data into train and test set

6.1 Categorise the attributes into its type (Use one hot encoding wherever required)

In [49]:
```
df.printSchema()
```

```
root
 |-- Year: integer (nullable = true)
 |-- Salaries: double (nullable = true)
 |-- Overtime: double (nullable = true)
 |-- Retirement: double (nullable = true)
 |-- Year_Type_index: double (nullable = false)
 |-- Job_Family_Code_index: double (nullable = false)
 |-- Job_Code_index: double (nullable = false)
 |-- Department_Code_index: double (nullable = false)
 |-- Other_Salaries: double (nullable = true)
 |-- Total_Salary: double (nullable = true)
 |-- Other_Benefits: double (nullable = true)
 |-- Total_Benefits: double (nullable = true)
 |-- Total_Compensation: double (nullable = true)
 |-- Organization_Group_Code: integer (nullable = true)
 |-- Union_Code: integer (nullable = true)
 |-- Health_Dental: double (nullable = true)
```

In [50]:
```
# Let's one-hot encode the categorical columns
input_cols = ["Organization_Group_Code", "Union_Code", "Job_Family_Code_i
output_cols = ["Organization_Group_Code_vec", "Union_Code_vec", "Job_Fami

encoder = OneHotEncoder(inputCols=input_cols, outputCols=output_cols)
df = encoder.fit(df).transform(df)
df.show(n=2, vertical=True)
```

```
-RECORD 0-----------------------------------------
 Year                          | 2016
 Salaries                      | 114473.16
 Overtime                      | 0.0
 Retirement                    | 21025.98
 Year_Type_index               | 0.0
 Job_Family_Code_index         | 16.0
 Job_Code_index                | 15.0
 Department_Code_index         | 19.0
 Other_Salaries                | 1500.0
 Total_Salary                  | 115973.16
 Other_Benefits                | 9368.71
 Total_Benefits                | 43463.49
 Total_Compensation            | 159436.65
 Organization_Group_Code       | 1
 Union_Code                    | 311
 Health_Dental                 | 13068.8
 Organization_Group_Code_vec   | (7,[1],[1.0])
 Union_Code_vec                | (990,[311],[1.0])
 Job_Family_Code_index_vec     | (55,[16],[1.0])
 Job_Code_index_vec            | (1132,[15],[1.0])
 Department_Code_index_vec     | (53,[19],[1.0])
 Year_vec                      | (2016,[],[])
 Year_Type_index_vec           | (1,[0],[1.0])
-RECORD 1-----------------------------------------
 Year                          | 2013
 Salaries                      | 84077.11
 Overtime                      | 0.0
 Retirement                    | 16587.3
 Year_Type_index               | 1.0
 Job_Family_Code_index         | 14.0
 Job_Code_index                | 135.0
 Department_Code_index         | 43.0
 Other_Salaries                | 0.0
 Total_Salary                  | 84077.11
 Other_Benefits                | 6931.91
 Total_Benefits                | 35976.94
 Total_Compensation            | 120054.05
 Organization_Group_Code       | 5
 Union_Code                    | 790
 Health_Dental                 | 12457.73
 Organization_Group_Code_vec   | (7,[5],[1.0])
 Union_Code_vec                | (990,[790],[1.0])
 Job_Family_Code_index_vec     | (55,[14],[1.0])
 Job_Code_index_vec            | (1132,[135],[1.0])
 Department_Code_index_vec     | (53,[43],[1.0])
 Year_vec                      | (2016,[2013],[1.0])
 Year_Type_index_vec           | (1,[],[])
only showing top 2 rows
```

In [51]:
```
# Now let's drop the original columns since we have obtained the one-hot
df = df.drop("Organization_Group_Code", "Union_Code", "Job_Family_Code_in
df.show(n=2, vertical=True)
```

```
-RECORD 0-----------------------------------------
 Salaries                    | 114473.16
 Overtime                    | 0.0
 Retirement                  | 21025.98
 Other_Salaries              | 1500.0
 Total_Salary                | 115973.16
 Other_Benefits              | 9368.71
 Total_Benefits              | 43463.49
 Total_Compensation          | 159436.65
 Health_Dental               | 13068.8
 Organization_Group_Code_vec | (7,[1],[1.0])
 Union_Code_vec              | (990,[311],[1.0])
 Job_Family_Code_index_vec   | (55,[16],[1.0])
 Job_Code_index_vec          | (1132,[15],[1.0])
 Department_Code_index_vec   | (53,[19],[1.0])
 Year_vec                    | (2016,[],[])
 Year_Type_index_vec         | (1,[0],[1.0])
-RECORD 1-----------------------------------------
 Salaries                    | 84077.11
 Overtime                    | 0.0
 Retirement                  | 16587.3
 Other_Salaries              | 0.0
 Total_Salary                | 84077.11
 Other_Benefits              | 6931.91
 Total_Benefits              | 35976.94
 Total_Compensation          | 120054.05
 Health_Dental               | 12457.73
 Organization_Group_Code_vec | (7,[5],[1.0])
 Union_Code_vec              | (990,[790],[1.0])
 Job_Family_Code_index_vec   | (55,[14],[1.0])
 Job_Code_index_vec          | (1132,[135],[1.0])
 Department_Code_index_vec   | (53,[43],[1.0])
 Year_vec                    | (2016,[2013],[1.0])
 Year_Type_index_vec         | (1,[],[])
only showing top 2 rows
```

In [52]:
```
features_col = df.columns
features_col.remove('Total_Compensation')

# Create the VectorAssembler object
assembler = VectorAssembler(inputCols= features_col, outputCol= "features
assembledDF = assembler.transform(df)
assembledDF.select("features").show(5, True)
```

```
23/07/16 21:14:50 WARN package: Truncated the string representation of a p
lan since it was too large. This behavior can be adjusted by setting 'spar
k.sql.debug.maxToStringFields'.
+--------------------+
|            features|
+--------------------+
|(4262,[0,2,3,4,5,...|
|(4262,[0,2,4,5,6,...|
|(4262,[0,3,4,5,6,...|
|(4262,[0,4,5,6,7,...|
|(4262,[0,3,4,5,6,...|
+--------------------+
only showing top 5 rows
```

In [53]:
```
assembledDF.show(n=1, vertical=True)
```

```
-RECORD 0-----------------------------------------
 Salaries                    | 114473.16
 Overtime                    | 0.0
 Retirement                  | 21025.98
 Other_Salaries              | 1500.0
 Total_Salary                | 115973.16
 Other_Benefits              | 9368.71
 Total_Benefits              | 43463.49
 Total_Compensation          | 159436.65
 Health_Dental               | 13068.8
 Organization_Group_Code_vec | (7,[1],[1.0])
 Union_Code_vec              | (990,[311],[1.0])
 Job_Family_Code_index_vec   | (55,[16],[1.0])
 Job_Code_index_vec          | (1132,[15],[1.0])
 Department_Code_index_vec   | (53,[19],[1.0])
 Year_vec                    | (2016,[],[])
 Year_Type_index_vec         | (1,[0],[1.0])
 features                    | (4262,[0,2,3,4,5,...
only showing top 1 row
```

In [54]:
```
final_data = assembledDF.select("features","Total_Compensation")
final_data.show(5, True)
```

```
+--------------------+------------------+
|            features|Total_Compensation|
+--------------------+------------------+
|(4262,[0,2,3,4,5,...|         159436.65|
|(4262,[0,2,4,5,6,...|         120054.05|
|(4262,[0,3,4,5,6,...|          13868.64|
|(4262,[0,4,5,6,7,...|            3718.5|
|(4262,[0,3,4,5,6,...|          10128.64|
+--------------------+------------------+
only showing top 5 rows
```

6.2 Split the data into train and test set

In [55]:
```
train_data , test_data = final_data.randomSplit([0.8,0.2])
```

In [56]:
```
train_data.describe().show()
```

```
[Stage 211:>                                                        (0 +
1) / 1]
+-------+------------------+
|summary|Total_Compensation|
+-------+------------------+
|  count|            233023|
|   mean| 97952.90933139446|
| stddev| 67693.72893331043|
|    min|               0.0|
|    max|         653498.15|
+-------+------------------+
```

In [57]:
```
test_data.describe().show()
```

```
[Stage 214:>                                                        (0 +
1) / 1]
+-------+------------------+
|summary|Total_Compensation|
+-------+------------------+
|  count|             58678|
|   mean| 98226.95431695088|
| stddev| 67805.87043346165|
|    min|               0.0|
|    max|         510574.44|
+-------+------------------+
```

7. Fit Linear Regression model on the data and check its performance

In [58]:
```
lr = LinearRegression(featuresCol="features" , labelCol="Total_Compensati
```

In [59]:
```
lr_model = lr.fit(train_data)
```

```
23/07/16 21:15:07 WARN BLAS: Failed to load implementation from: com.githu
b.fommil.netlib.NativeSystemBLAS
23/07/16 21:15:07 WARN BLAS: Failed to load implementation from: com.githu
b.fommil.netlib.NativeRefBLAS
```

In [60]:
```
test_results = lr_model.evaluate(test_data)
```

In [61]:
```
test_results.rootMeanSquaredError
```

Out[61]:
```
1758.067262371722
```

In [62]:
```
test_results.r2
```

Out[62]:
```
0.999327729918161
```

The **RMSE is approx 1760** which is **very good** considering that the **stddev of total_compensation is ~67,700**.

8. Fit Decision Tree Regression model on the data and check its performance (Optional)

In [63]:
```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Create a Decision Tree Regression model
dt = DecisionTreeRegressor(featuresCol ='features', labelCol = 'Total_Com

# Define the parameter grid for tuning
param_grid = ParamGridBuilder() \
```

```
    .addGrid(dt.maxDepth, [2, 4, 6]) \
    .build()

# Define the evaluator for the metric
evaluator = RegressionEvaluator(labelCol="Total_Compensation", prediction

# Create a cross validator
crossval = CrossValidator(estimator=dt,
                          estimatorParamMaps=param_grid,
                          evaluator=evaluator,
                          numFolds=3)

# Fit the cross validator to the training data
cv_model = crossval.fit(train_data)

# Get the best model from the cross validation
best_model = cv_model.bestModel

# Make predictions on the test data using the best model
predictions = best_model.transform(test_data)

# Evaluate the model's performance
rmse = evaluator.evaluate(predictions)

# Print the best model's maxDepth parameter
print("Best maxDepth:", best_model.getMaxDepth())
# Print the RMSE
print("Root Mean Squared Error (RMSE):", rmse)
```

```
[Stage 304:>                                                        (0 +
1) / 1]
23/07/16 21:15:23 WARN MemoryStore: Not enough space to cache rdd_679_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:15:23 WARN BlockManager: Persisting block rdd_679_0 to disk in
stead.
23/07/16 21:15:31 WARN MemoryStore: Not enough space to cache rdd_679_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:15:35 WARN MemoryStore: Not enough space to cache rdd_679_0 in
memory! (computed 294.1 MiB so far)
[Stage 313:>                                                        (0 +
1) / 1]
23/07/16 21:15:44 WARN MemoryStore: Not enough space to cache rdd_717_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:15:44 WARN BlockManager: Persisting block rdd_717_0 to disk in
stead.
23/07/16 21:15:51 WARN MemoryStore: Not enough space to cache rdd_717_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:15:55 WARN MemoryStore: Not enough space to cache rdd_717_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:15:59 WARN MemoryStore: Not enough space to cache rdd_717_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:03 WARN MemoryStore: Not enough space to cache rdd_717_0 in
memory! (computed 294.1 MiB so far)
```

```
[Stage 326:>                                                        (0 +
1) / 1]
23/07/16 21:16:08 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:16:08 WARN BlockManager: Persisting block rdd_756_0 to disk in
stead.
23/07/16 21:16:16 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:20 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:24 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:28 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:32 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:36 WARN MemoryStore: Not enough space to cache rdd_756_0 in
memory! (computed 294.1 MiB so far)
[Stage 343:>                                                        (0 +
1) / 1]
23/07/16 21:16:45 WARN MemoryStore: Not enough space to cache rdd_806_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:16:45 WARN BlockManager: Persisting block rdd_806_0 to disk in
stead.
23/07/16 21:16:53 WARN MemoryStore: Not enough space to cache rdd_806_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:16:57 WARN MemoryStore: Not enough space to cache rdd_806_0 in
memory! (computed 294.1 MiB so far)
[Stage 352:>                                                        (0 +
1) / 1]
23/07/16 21:17:06 WARN MemoryStore: Not enough space to cache rdd_844_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:17:06 WARN BlockManager: Persisting block rdd_844_0 to disk in
stead.
23/07/16 21:17:14 WARN MemoryStore: Not enough space to cache rdd_844_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:18 WARN MemoryStore: Not enough space to cache rdd_844_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:22 WARN MemoryStore: Not enough space to cache rdd_844_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:26 WARN MemoryStore: Not enough space to cache rdd_844_0 in
memory! (computed 294.1 MiB so far)
[Stage 365:>                                                        (0 +
1) / 1]
```

```
23/07/16 21:17:31 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:17:31 WARN BlockManager: Persisting block rdd_883_0 to disk in
stead.
23/07/16 21:17:39 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:43 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:47 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:51 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:17:55 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)
[Stage 375:>                                                        (0 +
1) / 1]
23/07/16 21:17:59 WARN MemoryStore: Not enough space to cache rdd_883_0 in
memory! (computed 294.1 MiB so far)
[Stage 382:>                                                        (0 +
1) / 1]
23/07/16 21:18:09 WARN MemoryStore: Not enough space to cache rdd_933_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:18:09 WARN BlockManager: Persisting block rdd_933_0 to disk in
stead.
23/07/16 21:18:16 WARN MemoryStore: Not enough space to cache rdd_933_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:18:21 WARN MemoryStore: Not enough space to cache rdd_933_0 in
memory! (computed 294.1 MiB so far)
[Stage 391:>                                                        (0 +
1) / 1]
23/07/16 21:18:30 WARN MemoryStore: Not enough space to cache rdd_971_0 in
memory! (computed 293.9 MiB so far)
23/07/16 21:18:30 WARN BlockManager: Persisting block rdd_971_0 to disk in
stead.
23/07/16 21:18:37 WARN MemoryStore: Not enough space to cache rdd_971_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:18:41 WARN MemoryStore: Not enough space to cache rdd_971_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:18:45 WARN MemoryStore: Not enough space to cache rdd_971_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:18:49 WARN MemoryStore: Not enough space to cache rdd_971_0 in
memory! (computed 294.1 MiB so far)

23/07/16 21:18:53 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 293.9 MiB so far)
23/07/16 21:18:53 WARN BlockManager: Persisting block rdd_1010_0 to disk i
nstead.
```

```
[Stage 404:>                                                        (0 +
1) / 1]
23/07/16 21:19:01 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:05 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:08 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:12 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:16 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:20 WARN MemoryStore: Not enough space to cache rdd_1010_0 i
n memory! (computed 294.1 MiB so far)
[Stage 421:>                                                        (0 +
1) / 1]
23/07/16 21:19:38 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 189.2 MiB so far)
23/07/16 21:19:38 WARN BlockManager: Persisting block rdd_1054_0 to disk i
nstead.
23/07/16 21:19:50 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:19:56 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:20:02 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:20:08 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:20:15 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)

23/07/16 21:20:21 WARN MemoryStore: Not enough space to cache rdd_1054_0 i
n memory! (computed 294.1 MiB so far)
[Stage 433:>                                                        (0 +
1) / 1]
Best maxDepth: 6
Root Mean Squared Error (RMSE): 6525.927023568768

```

Note: **I am still researching on how to mitigate these WARNINGs. It seems one option would be to specify more memory for pyspark. I am not sure if repartitioning it would help as I am working on a standalone machine. But would specifying partition size still make a difference? Like is that something one can tune to get better persormance? Any suggestions?**

Model Persistence (Optional)

Model persistence means saving your model to a disk. After you finalize your model for prediction depending upon the performance, you need to save the model to the disk. Let's say, you finalize 'lrmodel' to be used for in production environment i.e. in your application. We use the following code to save it.

Saving the model

In [64]:
```
# use save() method to save the model
# write().overwrite() is usually used when you want to replace the older
# It might happen that you wish to retrain your model and save it at the
lr_model.write().overwrite().save("/Users/harshit/Desktop/models/lrmodel"
```

Loading the model

In [ ]:
```
# import PipelineModel from pyspark.ml package
from pyspark.ml import PipelineModel

# load the model from the location it is stored
# The loaded model acts as PipelineModel
pipemodel = PipelineModel.load("/Users/harshit/Desktop/models/lrmodel")

# use the PipelineModel object to perform prediciton on test data.
# Use .transform() to perfrom prediction
# prediction = pipemodel.transform(test_data)

# print the results
# prediction.select('label', 'rawPrediction', 'probability', 'prediction'
# prediction.show(5, vertical=True)
```

Getting the following Error on running above cell:

PicklingError: Could not serialize object: IndexError: tuple index out of range

In [66]:
```
# Checking Python version
import sys

print("Python version:", sys.version)
```

```
Python version: 3.11.4 | packaged by conda-forge | (main, Jun 10 2023, 18:
10:28) [Clang 15.0.7 ]
```

In [67]:
```
# Checking PySpark version
import pyspark

print("PySpark version:", pyspark.__version__)
```

```
PySpark version: 3.3.1
```

As per:

https://stackoverflow.com/questions/75048688/picklingerror-could-not-serialize-object-indexerror-tuple-index-out-of-range

I will have to downgrade the python version to 3.10.x and below to resolve this error. However, that holds true for PySpark version 3.4 .. I'll try setting up a new environment and seeing if this error goes away.

Any Suggestions?