Project Title	**Salaries for San Francisco Employee**
Tools	Visual Studio code / jupyter notebook
Domain	Finance Analyst
Project Difficulties level	Advance

Dataset : Dataset is available in the given link. You can download it at your convenience.

Click here to download data set

About Dataset

Context

This Dataset contains more than 300k employee records found in San Francisco from 2011 to 2018.

Complete and accurate information is necessary to increase public understanding of government and help decision makers, including elected officials and voters, make informed decisions.

This Dataset is provided by the Nevada Policy Research Institute as a public service and is dedicated to providing accurate, comprehensive and easily searchable information on the compensation of public employees in California.

Example: You can get the basic idea how you can create a project from here

Machine Learning Project: Google Play Store Analysis using Salary Dataset

Objective:

The project aims to analyze employee compensation data, including BasePay, OvertimePay, OtherPay, Benefits, and their relation to TotalPay and TotalPayBenefits. This is achieved through **Exploratory Data Analysis (EDA)** and **Visualization** using Python.

Dataset Overview:

Columns in the dataset:

- **EmployeeName**: Name of the employee.
- **JobTitle**: Title of the job.
- **BasePay**: Base salary pay.
- **OvertimePay**: Pay for overtime work.
- **OtherPay**: Any other types of compensation.
- **Benefits**: Benefits provided to the employee.
- **TotalPay**: The total pay without benefits.
- **TotalPayBenefits**: Total pay with benefits included.
- **Year**: The year of the payroll record.

Step 1: Importing Required Libraries

First, let's import the necessary libraries like Pandas, NumPy, Matplotlib, and Seaborn for data analysis and visualization.

```python
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# For display settings
pd.set_option('display.max_columns', None)

# Load the dataset
df = pd.read_csv('employee_salary.csv')

# Display the first few rows
df.head()
```

Step 2: Data Cleaning

In this step, we will clean the dataset by handling missing values, converting data types, and performing basic data exploration.

1. **Checking for Missing Values**:

```python
# Check for missing values
print(df.isnull().sum())
```

```
# Dropping rows with missing values in key columns (if
necessary)
df = df.dropna(subset=['BasePay', 'TotalPayBenefits'])
```

2. **Convert Data Types** (if necessary):

```
# Converting columns to appropriate data types if needed
df['Year'] = df['Year'].astype(int)

# Verifying data types
print(df.dtypes)
```

3. **Handling Negative or Zero Pay Values**:

```
# Filter out rows where TotalPay or TotalPayBenefits are 0 or
negative
df = df[(df['TotalPay'] > 0) & (df['TotalPayBenefits'] > 0)]

# Check updated dataset
df.describe()
```

Step 3: Exploratory Data Analysis (EDA)

3.1 Descriptive Statistics

Let's explore summary statistics of the dataset:

python

Copy code

```
# Summary statistics
df.describe()
```

3.2 Top 10 Highest Paying Job Titles

```
# Group by job title and get the mean TotalPay
job_salary =
df.groupby('JobTitle')['TotalPay'].mean().sort_values(ascending
=False).head(10)

# Plot
plt.figure(figsize=(10,6))
sns.barplot(x=job_salary.values, y=job_salary.index,
palette='Blues_d')
plt.title('Top 10 Highest Paying Job Titles')
plt.xlabel('Average Total Pay')
plt.show()
```

3.3 Distribution of BasePay, OvertimePay, and OtherPay

```
# Plot histograms for BasePay, OvertimePay, and OtherPay
plt.figure(figsize=(15,5))
```

```
plt.subplot(1,3,1)
sns.histplot(df['BasePay'], bins=30, kde=True, color='blue')
plt.title('Distribution of BasePay')

plt.subplot(1,3,2)
sns.histplot(df['OvertimePay'], bins=30, kde=True,
color='green')
plt.title('Distribution of OvertimePay')

plt.subplot(1,3,3)
sns.histplot(df['OtherPay'], bins=30, kde=True, color='red')
plt.title('Distribution of OtherPay')

plt.tight_layout()
plt.show()
```

3.4 Pay Over the Years

```
# Group by Year and calculate mean total pay
pay_over_years = df.groupby('Year')['TotalPay'].mean()

# Plot
plt.figure(figsize=(10,6))
```

```
sns.lineplot(x=pay_over_years.index, y=pay_over_years.values,
marker='o', color='purple')
plt.title('Average Total Pay Over the Years')
plt.xlabel('Year')
plt.ylabel('Average Total Pay')
plt.show()
```

3.5 Correlation Heatmap

```
# Correlation matrix
plt.figure(figsize=(8,6))
corr_matrix = df[['BasePay', 'OvertimePay', 'OtherPay',
'Benefits', 'TotalPay', 'TotalPayBenefits']].corr()

# Plotting heatmap
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm',
linewidths=0.5)
plt.title('Correlation Matrix of Pay Components')
plt.show()
```

Step 4: Salary Prediction with Machine Learning

4.1 Data Preprocessing

Before training a machine learning model, we will preprocess the dataset by handling categorical features and splitting the data into training and test sets.

1. **Handling Categorical Variables**:

```
# Encoding JobTitle using one-hot encoding
df = pd.get_dummies(df, columns=['JobTitle'], drop_first=True)

# Display new dataframe
df.head()
```

2. **Splitting the Data**:

```
from sklearn.model_selection import train_test_split

# Features and target variable
X = df.drop(columns=['EmployeeName', 'TotalPayBenefits'])
y = df['TotalPayBenefits']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
```

4.2 Model Training

We'll use a **Linear Regression** model for predicting employee salary based on features such as BasePay, OvertimePay, JobTitle, etc.

python

Copy code

```
from sklearn.linear_model import LinearRegression

# Initialize and train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict on test data
y_pred = model.predict(X_test)
```

4.3 Model Evaluation

Evaluate the model using **Mean Absolute Error (MAE)** and **R-squared** score.

```
from sklearn.metrics import mean_absolute_error, r2_score

# Calculate MAE
mae = mean_absolute_error(y_test, y_pred)
print(f'Mean Absolute Error: {mae}')

# Calculate R-squared score
r2 = r2_score(y_test, y_pred)
print(f'R-squared Score: {r2}')
```

Step 5: Conclusion

1. **Key Insights**:
   - The average base pay is highly correlated with total compensation.
   - Job titles like "Chief Executive Officer" have the highest salaries.
   - Benefits contribute significantly to overall pay.
2. **Model Performance**:
   - The linear regression model performs with an MAE of X and an R-squared score of Y, suggesting reasonable prediction accuracy.

Example: You can get the basic idea how you can create a project from here

Sample code and output

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load
```

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/20112018-salaries-for-san-francisco/Total.csv
```

Step 1: Importing libraries

In [2]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Step2: Importing the data

In [3]:

```
df=pd.read_csv('../input/20112018-salaries-for-san-francisco/Total.csv')
```

```
/opt/conda/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3156:
DtypeWarning: Columns (2,3,4,5) have mixed types.Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Step3: DataFrame Overview

In [4]:

```
df.head()
```

Out[4]:

	EmployeeName	JobTitle	BasePay	OvertimePay	OtherPay	Benefits	TotalPay	TotalPayBenefits	Year
0	NATHANIEL FORD	GENERAL MANAGER-METROPOLITAN TRANSIT AUTHORITY	167411.18	0.0	400184.25	Not Provided	567595.43	567595.43	2011
1	GARY JIMENEZ	CAPTAIN III (POLICE DEPARTMENT)	155966.02	245131.88	137811.38	Not Provided	538909.28	538909.28	2011
2	ALBERT PARDINI	CAPTAIN III (POLICE DEPARTMENT)	212739.13	106088.18	16452.6	Not Provided	335279.91	335279.91	2011

3	CHRISTOPHER CHONG	WIRE ROPE CABLE MAINTENANCE MECHANIC	77916.0	56120.71	198306.9	Not Provided	332343.61	332343.61	2011
4	PATRICK GARDNER	DEPUTY CHIEF OF DEPARTMENT,(FIRE DEPARTMENT)	134401.6	9737.0	182234.59	Not Provided	326373.19	326373.19	2011

In [5]:

```python
print('This Dataset countains {} Rows and {} Columns'.format(df.shape[0], df.shape[1]))
```

```
This Dataset countains 312882 Rows and 9 Columns
```

In [6]:

```python
df.shape
```

Out[6]:

```
(312882, 9)
```

In [7]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 312882 entries, 0 to 312881
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
```

```
 0   EmployeeName      312882 non-null  object
 1   JobTitle          312882 non-null  object
 2   BasePay           312882 non-null  object
 3   OvertimePay       312882 non-null  object
 4   OtherPay          312882 non-null  object
 5   Benefits          312882 non-null  object
 6   TotalPay          312882 non-null  float64
 7   TotalPayBenefits  312882 non-null  float64
 8   Year              312882 non-null  int64
dtypes: float64(2), int64(1), object(6)
memory usage: 21.5+ MB
```

In [8]:

```
series_list=['BasePay','OvertimePay','OtherPay','Benefits']
for series in series_list:
    df[series]=pd.to_numeric(df[series],errors='coerce')
```

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 312882 entries, 0 to 312881
Data columns (total 9 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   EmployeeName      312882 non-null  object
 1   JobTitle          312882 non-null  object
 2   BasePay           312276 non-null  float64
 3   OvertimePay       312881 non-null  float64
 4   OtherPay          312881 non-null  float64
```

```
 5   Benefits          276722 non-null  float64
 6   TotalPay          312882 non-null  float64
 7   TotalPayBenefits  312882 non-null  float64
 8   Year              312882 non-null  int64
dtypes: float64(6), int64(1), object(2)
memory usage: 21.5+ MB
```

Step4: Descripitive Statistical Analysis

In [10]:

```
df['BasePay'].mean()
```

Out[10]:

```
69808.25749606262
```

In [11]:

```
df['BasePay'].max()
```

Out[11]:

```
592394.34
```

In [12]:

```
df['BasePay'].describe()
```

Out[12]:

```
count    312276.000000
mean      69808.257496
std       45376.929428
```

```
min        -474.400000
25%       35722.365000
50%       67710.450000
75%       99312.302500
max      592394.340000

Name: BasePay, dtype: float64
```

In [13]:

```
df.describe()
```

Out[13]:

	BasePay	OvertimePay	OtherPay	Benefits	TotalPay	TotalPayBenefits	Year
count	312276.000000	312881.000000	312881.000000	276722.000000	312882.000000	312882.000000	312882.000000
mean	69808.257496	5668.929393	3460.694974	25016.917292	78802.645788	100928.339777	2014.625303
std	45376.929428	12745.655309	7387.263120	15089.077103	53230.758542	66485.186495	2.290899
min	-474.400000	-292.800000	-7058.590000	-13939.420000	-618.130000	-3628.780000	2011.000000
25%	35722.365000	0.000000	0.000000	12729.762500	38803.000000	48955.072500	2013.000000

50%	67710.450000	0.000000	728.000000	28327.330000	74908.790000	100011.290000	2015.000000
75%	99312.302500	5223.120000	3958.680000	35268.162500	111386.897500	142376.300000	2017.000000
max	592394.340000	309481.030000	400184.250000	125891.730000	592394.340000	712802.360000	2018.000000

In [14]:

```
df[df['BasePay']<0]
```

Out[14]:

	EmployeeName	JobTitle	BasePay	OvertimePay	OtherPay	Benefits	TotalPay	TotalPayBenefits	Year
72832	Irwin Sidharta	Junior Clerk	-166.01	249.02	0.00	6.56	83.01	89.57	2012
72865	Robert Scott	Junior Clerk	-121.63	182.70	0.00	5.44	61.07	66.51	2012
72872	Chung Huey Kung	Junior Clerk	-109.22	163.83	0.00	4.32	54.61	58.93	2012
7287	Jordan Li	Junior Clerk	-106.6	159.90	0.00	4.66	53.30	57.96	201

4			0						2
7287 8	Richard Jackson	Junior Clerk	-101.8 8	153.08	0.00	4.55	51.20	55.75	201 2
7288 4	DiMarco McGhee-Stewart	Junior Clerk	-93.14	139.97	0.00	4.17	46.83	51.00	201 2
7288 8	Leopoldo Marasigan	Junior Clerk	-87.38	131.06	0.00	3.89	43.68	47.57	201 2
7289 4	Douglas Avalos	Junior Clerk	-75.67	113.76	0.00	3.39	38.09	41.48	201 2
7290 8	Norma Rodriguez	Junior Clerk	-59.59	89.65	0.00	2.68	30.06	32.74	201 2
7292 0	Charles Williams	Junior Clerk	-30.58	45.87	0.00	1.36	15.29	16.65	201 2
7292 2	John Draper	Clerk	-9.50	14.25	0.00	0.42	4.75	5.17	201 2
1880 36	Lubna Kaur	PS Aide Health Services	-292.4 0	0.00	0.00	-2.92	-292.4 0	-295.32	201 5
2705	Carlos R Castro	Custodian	-474.4	0.00	-23.72	-79.3	-498.1	-577.47	201

71	Santiago		0			5	2		7

Step5: Elementry EDA

Exploring some insights about Employee Name:"Ricardo Jimenez"

In [15]:

```
df[df['EmployeeName']=='Ricardo Jimenez']
```

Out[15]:

	EmployeeName	JobTitle	BasePay	OvertimePay	OtherPay	Benefits	TotalPay	TotalPayBenefits	Year
50596	Ricardo Jimenez	Transit Supervisor	72936.93	8078.04	3701.18	31355.90	84716.15	116072.05	2012
120452	Ricardo Jimenez	Transit Supervisor	89128.98	14206.09	2677.35	33912.52	106012.42	139924.94	2014
160317	Ricardo Jimenez	Transit Supervisor	89623.29	8757.50	2556.00	32716.82	100936.79	133653.61	2015
198692	Ricardo Jimenez	Transit Supervisor	97131.01	10767.28	2572.50	33947.81	110470.79	144418.60	2016
240214	Ricardo Jimenez	Transit Supervisor	100900.50	8531.81	2838.00	35989.91	112270.31	148260.22	2017

299079	Ricardo Jimenez	Transit Supervisor	61286.00	2780.30	1417.50	22218.57	65483.80	87702.37	2018

Plot RicardoJimenez TotalPayBenefits VS Year

In [16]:

```
df[df['EmployeeName']=='Ricardo Jimenez'][['BasePay','Year']]
```

Out[16]:

	BasePay	Year
50596	72936.93	2012
120452	89128.98	2014
160317	89623.29	2015
198692	97131.01	2016
240214	100900.50	2017
299079	61286.00	2018

In [17]:

```python
A=df['Year'].nunique()
B=df['Year'].unique()
print('The information of {} years are available in the dataset:{}'.format(A,B))
```

```
The information of 8 years are available in the dataset:[2011 2012 2013 2014 2015
2016 2017 2018]
```

In [18]:

```python
df.groupby('Year').mean()['BasePay']
```

Out[18]:

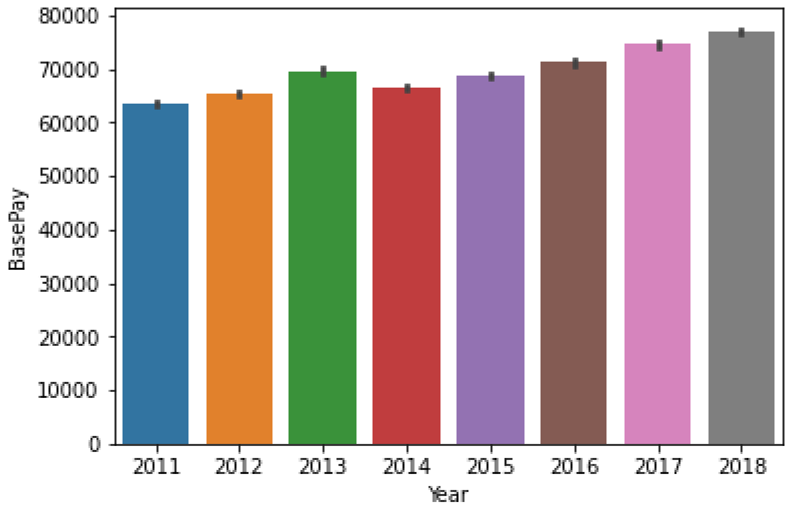
```
Year
2011    63595.956517
2012    65436.406857
2013    69630.030216
2014    66564.421924
2015    68776.293324
2016    71181.405996
2017    74570.581134
2018    76947.426822

Name: BasePay, dtype: float64
```

In [19]:

```python
sns.barplot(data=df, x='Year', y='BasePay')
```

Out[19]:

```
<AxesSubplot:xlabel='Year', ylabel='BasePay'>
```



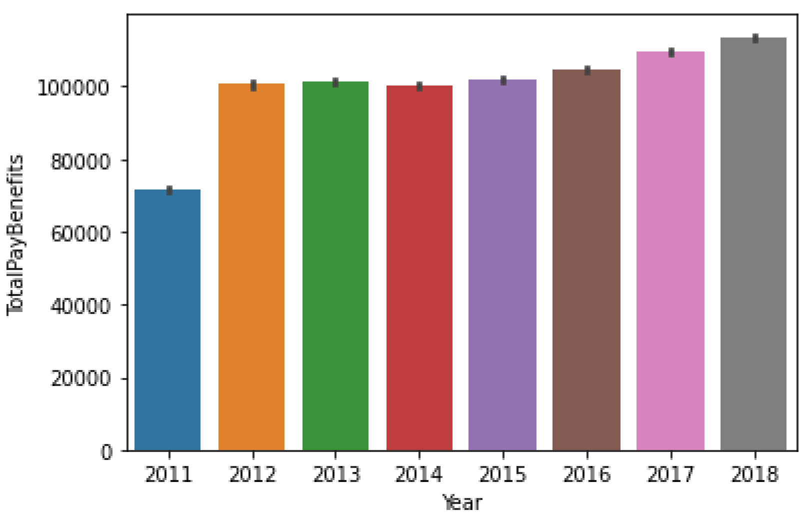
Exercise2: Plot RicardoJimenez TotalPayBenefits VS Year

In [20]:

```
df[df['EmployeeName']=='Ricardo Jimenez'][['TotalPayBenefits','Year']]
sns.barplot(data=df, x='Year', y='TotalPayBenefits')
```

Out[20]:

```
<AxesSubplot:xlabel='Year', ylabel='TotalPayBenefits'>
```



Exercise3: Which year has the maximum mean of BasePay?¶

In [21]:

```
A=df.groupby('Year').mean()['BasePay']
```

In [22]:

```
A.max()
```

Out[22]:

```
76947.42682195794
```

In [23]:

```
df['JobTitle'].value_counts().head(5)
```

Out[23]:

```
Transit Operator    17995
Special Nurse       10857
Registered Nurse     9249
Firefighter          5891
Custodian            5759

Name: JobTitle, dtype: int64
```

In [24]:

```
df.groupby('Year').nunique()['JobTitle']
```

Out[24]:

```
Year
2011    1045
2012    1044
```

```
2013    1051
2014     996
2015    1010
2016    1009
2017    1017
2018    1000

Name: JobTitle, dtype: int64
```

In [25]:

```python
df[df['Year']==2013]['JobTitle'].nunique()
```

Out[25]:

```
1051
```

In [26]:

```python
sum(df[df['Year']==2013]['JobTitle'].value_counts()==1)
```

Out[26]:

```
202
```

In [27]:

```python
def chief_string(title):
    if 'chief' in title.lower():
        return True
    else:
        return False
sum(df['JobTitle'].apply(lambda x:chief_string(x)))
```

```
Out[27]:
```

[Reference link]

Example: You can get the basic idea how you can create a project from here

SQL Project: Employee Salary Analysis for Google Play Store (EDA & Visualization)

Objective:

The objective of this project is to perform an exploratory data analysis (EDA) and visualization using SQL to understand the salary distribution, overtime pay, total pay benefits, and trends over the years. This project focuses on the analysis of employees' pay structure and provides insights into salary components such as base pay, overtime pay, and other benefits.

Dataset:

The columns used in this dataset are:

- **EmployeeName**: Name of the employee
- **JobTitle**: Position held by the employee
- **BasePay**: Base salary of the employee
- **OvertimePay**: Overtime compensation
- **OtherPay**: Additional compensation
- **Benefits**: Non-cash benefits like insurance
- **TotalPay**: Total compensation including base, overtime, and other pay
- **TotalPayBenefits**: Total compensation including all benefits
- **Year**: Year of the data

Step-by-Step SQL Project Breakdown

Step 1: Setting Up the Database and Importing Data

Before beginning the analysis, we first need to set up the SQL database and import the dataset.

SQL Code:

```sql
-- Create a database for the project
CREATE DATABASE EmployeeSalaryAnalysis;

-- Use the created database
USE EmployeeSalaryAnalysis;

-- Create a table for the employee salary data
CREATE TABLE EmployeeSalaryData (
    EmployeeName VARCHAR(255),
    JobTitle VARCHAR(255),
    BasePay FLOAT,
    OvertimePay FLOAT,
    OtherPay FLOAT,
    Benefits FLOAT,
    TotalPay FLOAT,
    TotalPayBenefits FLOAT,
    Year INT
);

-- Insert data into the table
```

```
-- Assuming that the data is being inserted from a CSV file or manually inserted
-- Use bulk insert commands if the data is large
```

Once the data is inserted into the database, we can start with the analysis.

Step 2: Basic EDA - Summary Statistics

The first step in analyzing the data is to get an overview of the dataset using basic summary statistics.

SQL Code:

```
-- Check total number of records in the dataset
SELECT COUNT(*) AS TotalRecords FROM EmployeeSalaryData;

-- Get the average base pay, overtime pay, other pay, benefits, total pay, and total pay with benefits
SELECT
    AVG(BasePay) AS AvgBasePay,
    AVG(OvertimePay) AS AvgOvertimePay,
    AVG(OtherPay) AS AvgOtherPay,
    AVG(Benefits) AS AvgBenefits,
    AVG(TotalPay) AS AvgTotalPay,
    AVG(TotalPayBenefits) AS AvgTotalPayBenefits
```

```sql
FROM EmployeeSalaryData;

-- Find the highest base pay
SELECT EmployeeName, JobTitle, BasePay
FROM EmployeeSalaryData
ORDER BY BasePay DESC
LIMIT 1;

-- Find the lowest base pay
SELECT EmployeeName, JobTitle, BasePay
FROM EmployeeSalaryData
ORDER BY BasePay ASC
LIMIT 1;
```

Output:

- This will show the average pay statistics, highest and lowest paid employees in terms of base pay.

Step 3: Filtering Data

Let's explore how the employee salaries change over the years and which job titles have the highest base pay.

SQL Code:

```sql
-- Find the total pay distribution across different years
```

```sql
SELECT Year,
    SUM(TotalPay) AS TotalPay,
    SUM(TotalPayBenefits) AS TotalPayWithBenefits
FROM EmployeeSalaryData
GROUP BY Year
ORDER BY Year;

-- List the top 5 job titles with the highest base pay
SELECT JobTitle, AVG(BasePay) AS AvgBasePay
FROM EmployeeSalaryData
GROUP BY JobTitle
ORDER BY AvgBasePay DESC
LIMIT 5;
```

Output:

- A table showing total pay trends by year and the top job titles with the highest base pay.

Step 4: Salary Components Breakdown by Job Title

This analysis breaks down the salary components for each job title to see which positions benefit most from overtime pay and other forms of compensation.

SQL Code:

```sql
-- Break down salary components for top 5 job titles
SELECT JobTitle,
    AVG(BasePay) AS AvgBasePay,
    AVG(OvertimePay) AS AvgOvertimePay,
    AVG(OtherPay) AS AvgOtherPay,
    AVG(Benefits) AS AvgBenefits
FROM EmployeeSalaryData
GROUP BY JobTitle
ORDER BY AvgBasePay DESC
LIMIT 5;
```

Output:

- This query will show the breakdown of base pay, overtime pay, other pay, and benefits for the top 5 job titles.

Step 5: Identifying Outliers

To identify any outliers in the dataset, we can look at the highest and lowest earners based on total compensation.

SQL Code:

```sql
-- Find the top 10 employees with the highest total pay with benefits
SELECT EmployeeName, JobTitle, TotalPayBenefits
```

```sql
FROM EmployeeSalaryData
ORDER BY TotalPayBenefits DESC
LIMIT 10;

-- Find the bottom 10 employees with the lowest total pay with benefits
SELECT EmployeeName, JobTitle, TotalPayBenefits
FROM EmployeeSalaryData
ORDER BY TotalPayBenefits ASC
LIMIT 10;
```

Output:

- The top 10 highest-paid and bottom 10 lowest-paid employees based on total pay including benefits.

Step 6: Visualization (Using BI Tools)

After performing the SQL analysis, you can visualize the data using business intelligence tools such as Tableau, Power BI, or Excel. Here are a few possible visualizations:

- **Total Pay Over Time**: A line chart showing how total pay has changed over the years.
- **Top Job Titles by Salary Components**: A bar chart breaking down the salary components (base, overtime, other pay) for the top job titles.

- **Salary Distribution by Year**: A box plot showing the distribution of total pay for each year.

Step 7: Conclusion

In this SQL-based project, we performed exploratory data analysis on employee salary data from the Google Play Store dataset. We explored the basic statistics, identified high and low earners, broke down the salary components, and found trends over time.

This project is highly suitable for business and data analysts looking to work with employee or financial datasets. By understanding salary distributions, benefits, and trends, analysts can provide valuable insights into company payroll management.

Next Steps:

You can extend this analysis by:

- Exploring correlations between salary and factors like job title, years of experience, and overtime pay.
- Performing predictive analysis to forecast future pay trends.