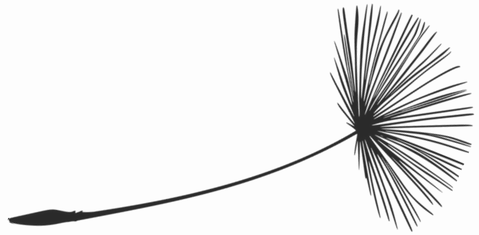
EMPLOYEE TURNOVER ANAYSIS

Machine Learning



SQL, Tableau, Python

Data Analyst: Phuong Pham

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ABOUT DATASET

Source: TAWFIK ELMETWALLY

This dataset contains information about employees in a company, including their educational backgrounds, work history, demographics, and employment-related factors. It has been anonymized to protect privacy while still providing valuable insights into the workforce.

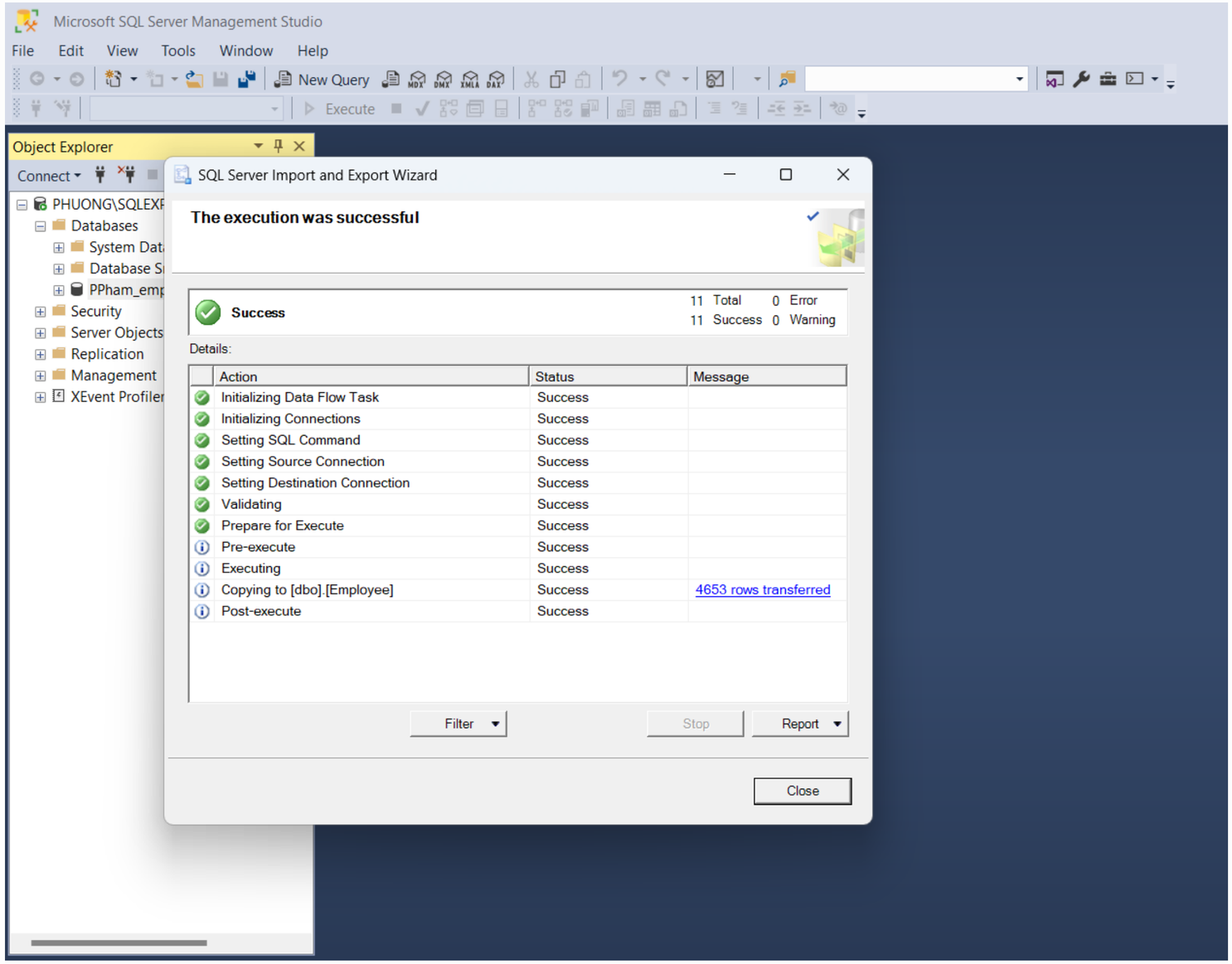
SQL SERVER

I use SQL to analyze and manage the dataset which contains **4,653** rows.

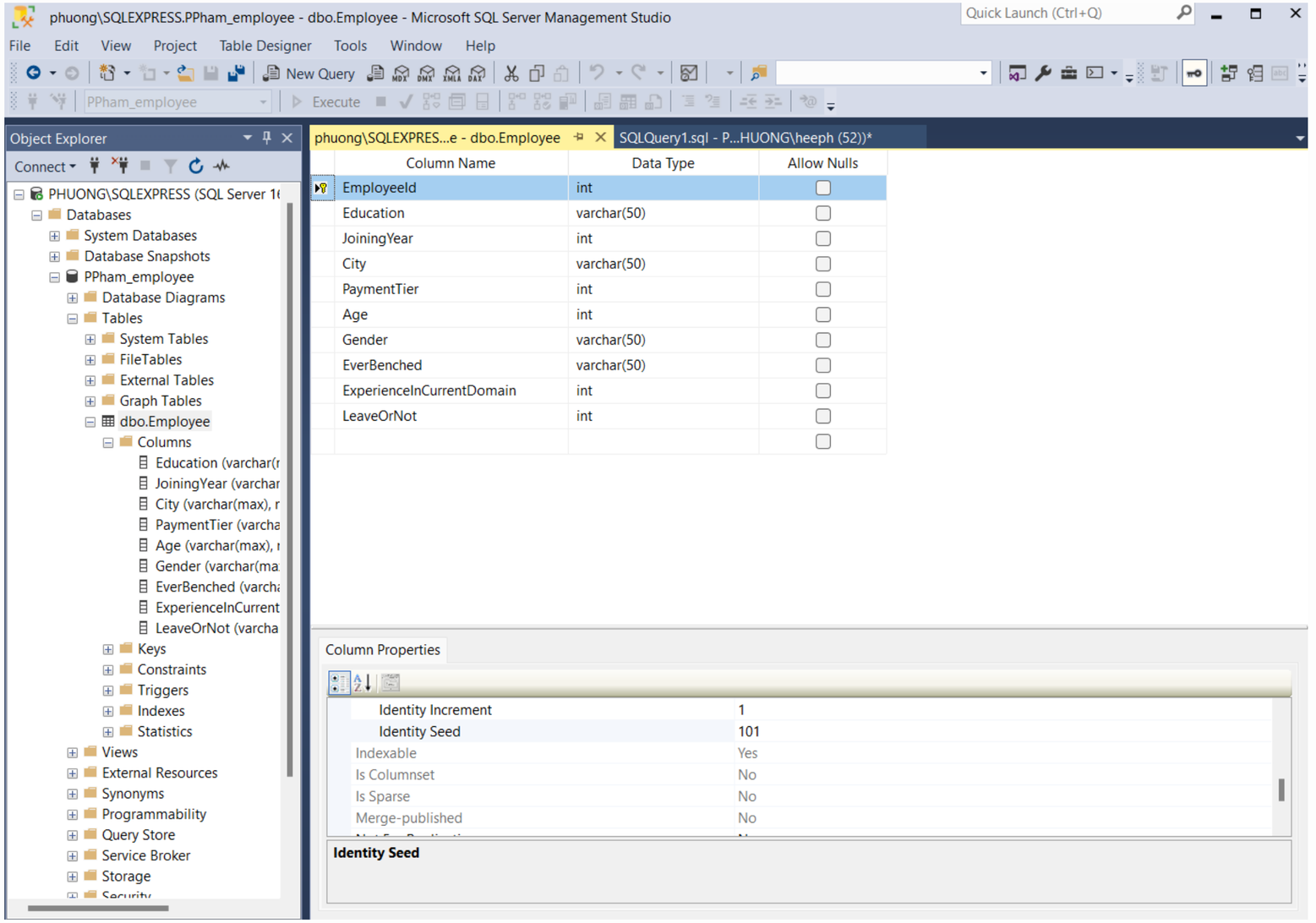
In this step, I want to find the relationship between variables that helps me answer the question:

What variables could relate to employee leaving their jobs?

I import the CSV file to SQL Server



Insert Primary Key for Employee Table



Count of Female Workers by Experience

- Female Workers with 2 years experience have the highest count

phuong\SQLEXPRES...e - dbo.Employee | SQLQuery1.sql - P...HUONG\heeph (52))*

```
SELECT * FROM Employee

SELECT Experience, COUNT(Gender) AS CountOfWomen
FROM Employee
WHERE Gender = 'Female'
GROUP BY Experience
ORDER BY Experience
```

100 %

Results | Messages

1	101	Bachelors	2017	Bangalore	3	34	Male	No	0	0
2	102	Bachelors	2013	Pune	1	28	Female	No	3	1
3	103	Bachelors	2014	New Delhi	3	38	Female	No	2	0
4	104	Masters	2016	Bangalore	3	27	Male	No	5	1
5	105	Masters	2017	Pune	3	24	Male	Yes	2	1
6	106	Bachelors	2016	Bangalore	3	22	Male	No	0	0
7	107	Bachelors	2015	New Delhi	3	38	Male	No	0	0
8	108	Bachelors	2016	Bangalore	3	34	Female	No	2	1

	Experience	CountOfWomen
1	0	142
2	1	227
3	2	447
4	3	321
5	4	367
6	5	365
7	6	2
8	7	4

Number of Employee Leaving by City

- Bangalore has the highest number of employee leaving

SQLQuery2.sql - P...HUONG\heeph (59))*

```
SELECT * FROM Employee

SELECT City, COUNT(LeaveOrNot) AS CountOfLeaving
FROM Employee
WHERE LeaveOrNot = 0
GROUP BY City
```

100 %

Results | Messages

	EmployeeId	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	Experience	LeaveOrNot
1	101	Bachelors	2017	Bangalore	3	34	Male	No	0	0
2	102	Bachelors	2013	Pune	1	28	Female	No	3	1
3	103	Bachelors	2014	New Delhi	3	38	Female	No	2	0
4	104	Masters	2016	Bangalore	3	27	Male	No	5	1
5	105	Masters	2017	Pune	3	24	Male	Yes	2	1
6	106	Bachelors	2016	Bangalore	3	22	Male	No	0	0
7	107	Bachelors	2015	New Delhi	3	38	Male	No	0	0
8	108	Bachelors	2016	Bangalore	3	34	Female	No	2	1
9	109	Bachelors	2016	Pune	3	23	Male	No	1	0
10	110	Masters	2017	New Delhi	2	37	Male	No	2	0

	City	CountOfLeaving
1	New Delhi	791
2	Pune	629
3	Bangalore	1633

SQLQuery2.sql - P...HUONG\heeph (59))*

```sql
SELECT * FROM Employee

SELECT EmployeeId, Age, Education
FROM Employee
WHERE Age > (SELECT AVG(Age)
FROM Employee e2
WHERE e2.Education = Employee.Education)
ORDER BY Age
```

100 %

Results | Messages

	EmployeeId	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	Experience	LeaveOrNot
1	101	Bachelors	2017	Bangalore	3	34	Male	No	0	0
2	102	Bachelors	2013	Pune	1	28	Female	No	3	1
3	103	Bachelors	2014	New Delhi	3	38	Female	No	2	0
4	104	Masters	2016	Bangalore	3	27	Male	No	5	1
5	105	Masters	2017	Pune	3	24	Male	Yes	2	1
6	106	Bachelors	2016	Bangalore	3	22	Male	No	0	0
7	107	Bachelors	2015	New Delhi	3	38	Male	No	0	0
8	108	Bachelors	2016	Bangalore	3	34	Female	No	2	1

	EmployeeId	Age	Education
1	2111	30	Bachelors
2	2115	30	Bachelors
3	2122	30	Masters
4	2128	30	Masters
5	2129	30	Bachelors
6	2131	30	Bachelors
7	2134	30	Bachelors

Query executed successfully. | PHUONG\SQLEXPRESS (16.0 RTM) | PHUONG\heeph (59) | PPham_emp

Return Employeeld, Age, and Eudcation who are older than Average Age

Relationship Between Gender and Employee Leaving Percentage

SQLQuery2.sql - P...HUONG\heeph (59))*

```sql
-- Percentage of Employee Leaving in the Company
SELECT SUM(IIF(LeaveOrNot=0,1,0))*100/COUNT(*) AS LeavingPercentage
FROM Employee

-- Percentage of Employee Leaving by Gender
SELECT Gender, SUM(IIF(LeaveOrNot=0,1,0)) * 100 / COUNT(*) AS LeavingPercentage
FROM Employee
GROUP BY Gender

--  Percentage of Male Employee Leaving when PaymentTier is 1
SELECT SUM(IIF(LeaveOrNot=0,1,0))*100/COUNT(*) As LeavingPercentage
FROM Employee
WHERE PaymentTier = 1 AND Gender = 'Male'
```

100 %

Results | Messages

	LeavingPercentage
1	65

	Gender	LeavingPercentage
1	Male	74
2	Female	52

	LeavingPercentage
1	82

- The total leaving percentage is 65%
- Male workers leave the company more than female workers
- Male workers who have Payment Tier 1 have very high chance of leaving the company - 82%

The relationship between Education, Gender, and Percentage of Employees Leaving

phuong\SQLEXPRES...e - dbo.Employee | SQLQuery1.sql - P...HUONG\heeph (52))*

```sql
SELECT * FROM Employee

SELECT Education,Gender, COUNT(LeaveOrNot) AS NumOfLeaving
FROM Employee
WHERE LeaveOrNot = 0
GROUP BY Education, Gender
ORDER BY COUNT(LeaveOrNot) ASC
```

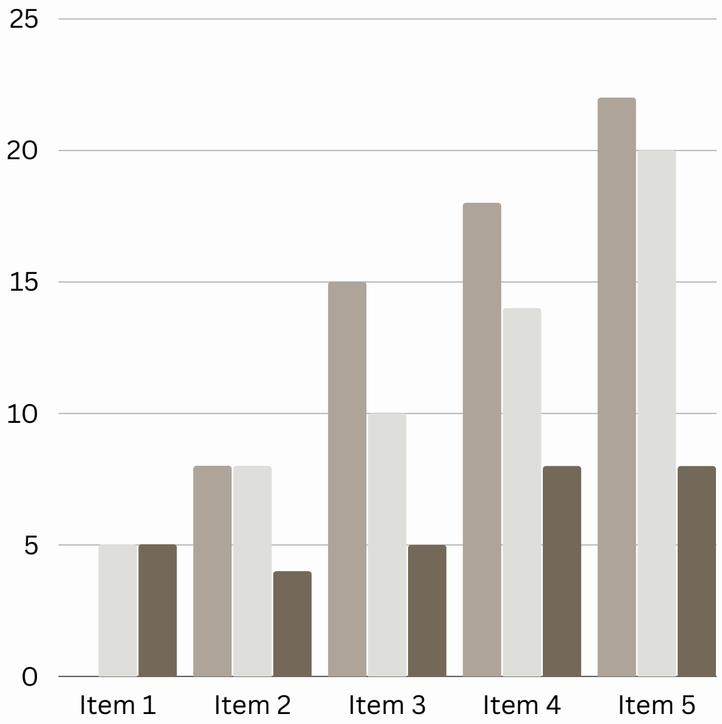
100 %

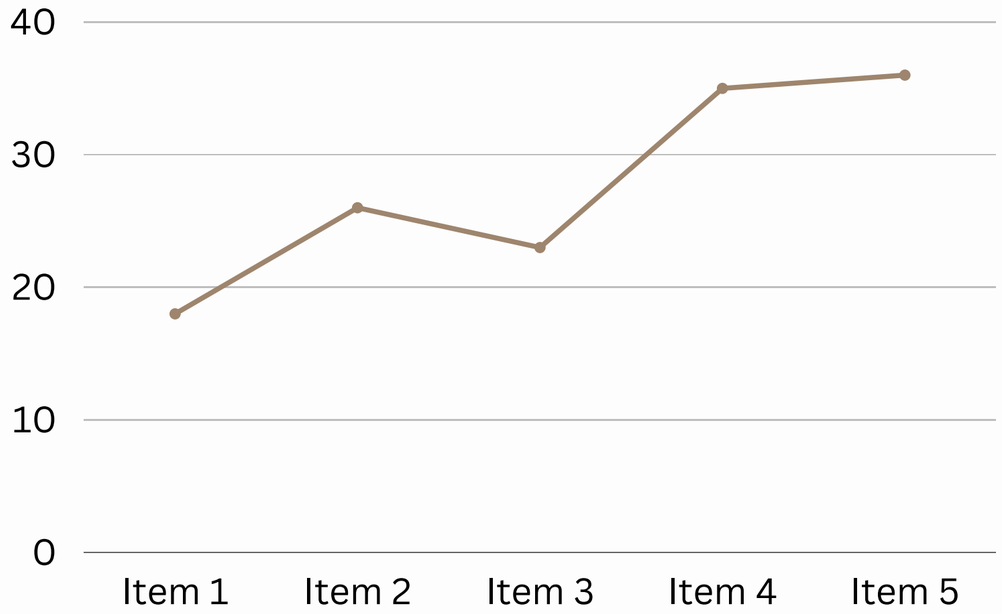
Results | Messages

	EmployeeId	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	Experience	LeaveOrNot
1	101	Bachelors	2017	Bangalore	3	34	Male	No	0	0
2	102	Bachelors	2013	Pune	1	28	Female	No	3	1
3	103	Bachelors	2014	New Delhi	3	38	Female	No	2	0
4	104	Masters	2016	Bangalore	3	27	Male	No	5	1
5	105	Masters	2017	Pune	3	24	Male	Yes	2	1
6	106	Bachelors	2016	Bangalore	3	22	Male	No	0	0
7	107	Bachelors	2015	New Delhi	3	38	Male	No	0	0
8	108	Bachelors	2016	Bangalore	3	34	Female	No	2	1

	Education	Gender	NumOfLeaving
1	PHD	Female	51
2	PHD	Male	83
3	Masters	Female	203
4	Masters	Male	244
5	Bachelors	Female	737
6	Bachelors	Male	1735

Male Workers who own Bachelor Degree
has the highest
number of leaving the company

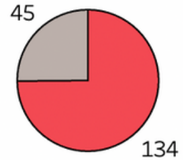

25
20
15
10
5
0
Item 1
Item 2
Item 3
Item 4
Item 5


40
30
20
10
0
Item 1
Item 2
Item 3
Item 4
Item 5

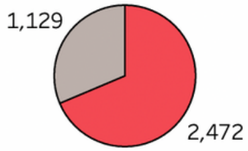
TABLEAU

Employee Leaving Dashboard

PHD



Bachelors



Master

Count of Employees leaving by Joining Year

Joining Year	LeaveOrNot	
2012	0	395
	1	109
2013	0	445
	1	224
2014	0	526
	1	173
2015	0	463
	1	318
2016	0	408
	1	117
2017	0	811
	1	297
2018	0	5
	1	362

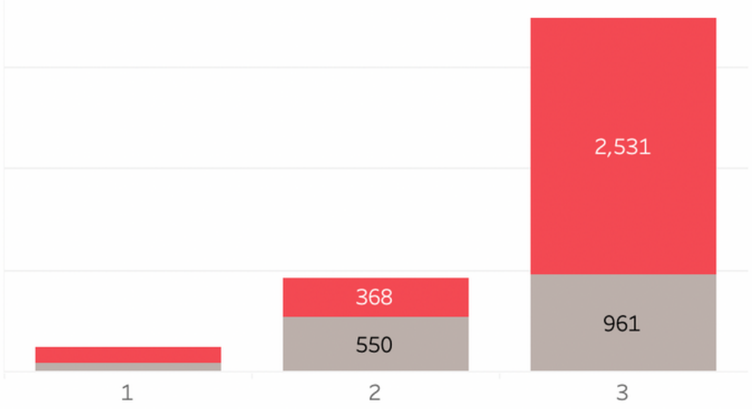
Count of Employees leaving by Gender

Gender	LeaveOrNot	
Female	0	991
	1	884
Male	0	2,062
	1	716

Employees Leaving Count by Ever Benched

Ever Bench..	LeaveOrNot	
No	0	2,792
	1	1,383
Yes	0	261
	1	217

Count of Employess Leaving or Not by Payment Tier



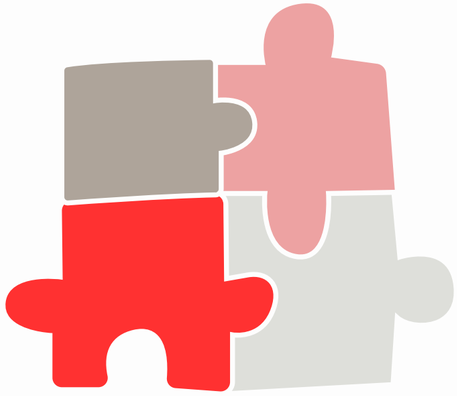
LeaveOrNot Count by City

City	LeaveOrNot	
Bangalore	0	1,633
	1	595
New Delhi	0	791
	1	366
Pune	0	629
	1	639

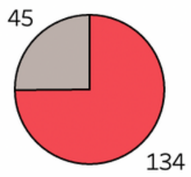
Red: leaving the company

Gray: staying with the company

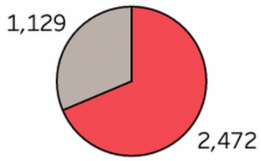
In this data visualization, I will mostly focus on red parts



PHD



Bachelors



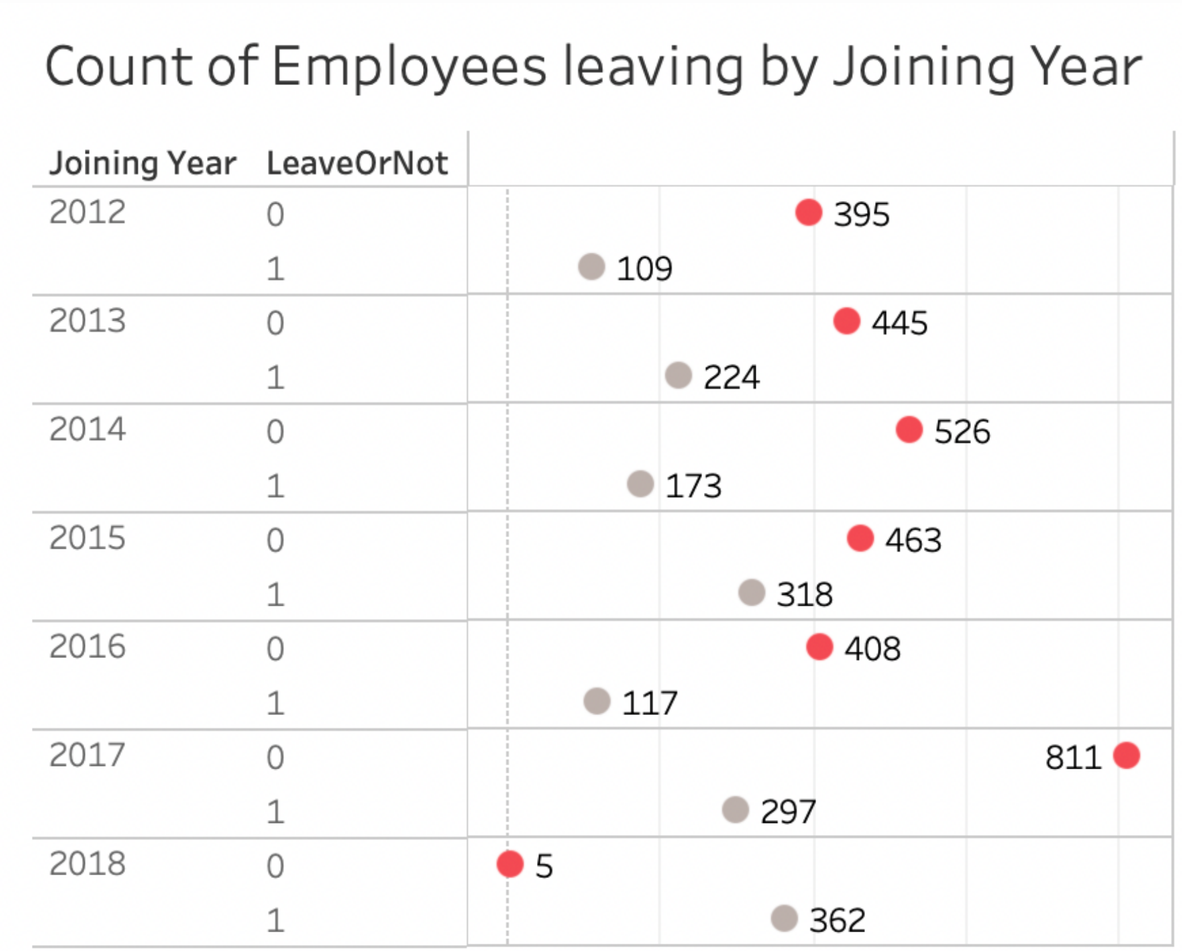
Master

Employees who earn PHD degree having the highest percentage of leaving the company

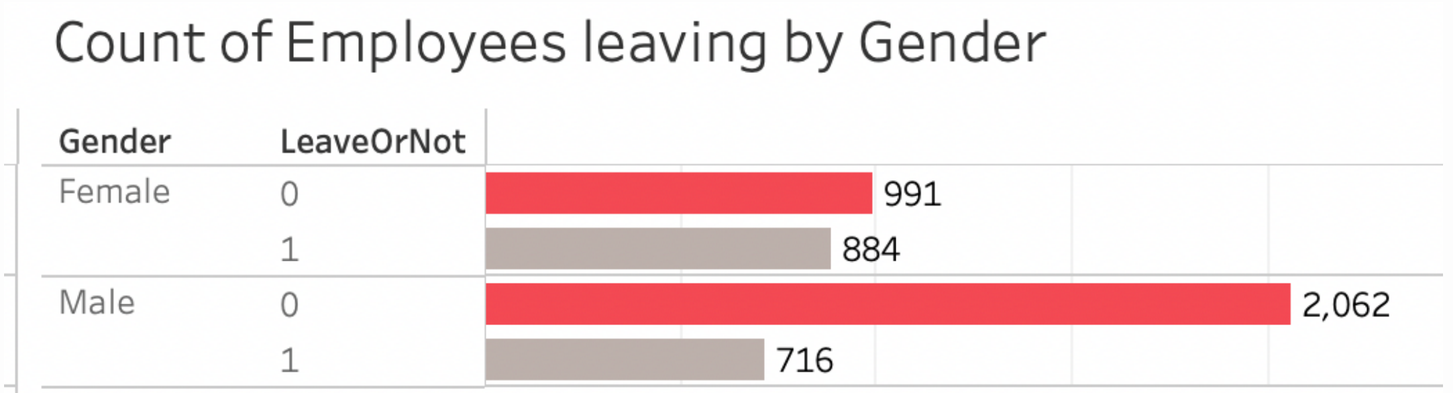
Employees who earn Master Degree having the lowest chance of leaving the company

The number of employees leaving the company is highest if they join in 2017 (811)

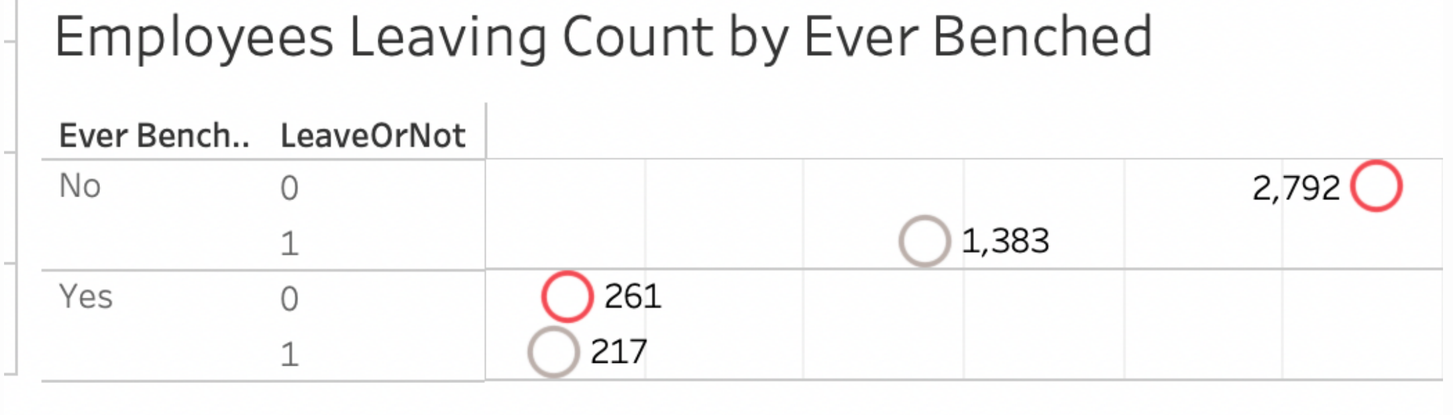
Employees who join the company next year, 2018, have the lowest number of leaving (5)



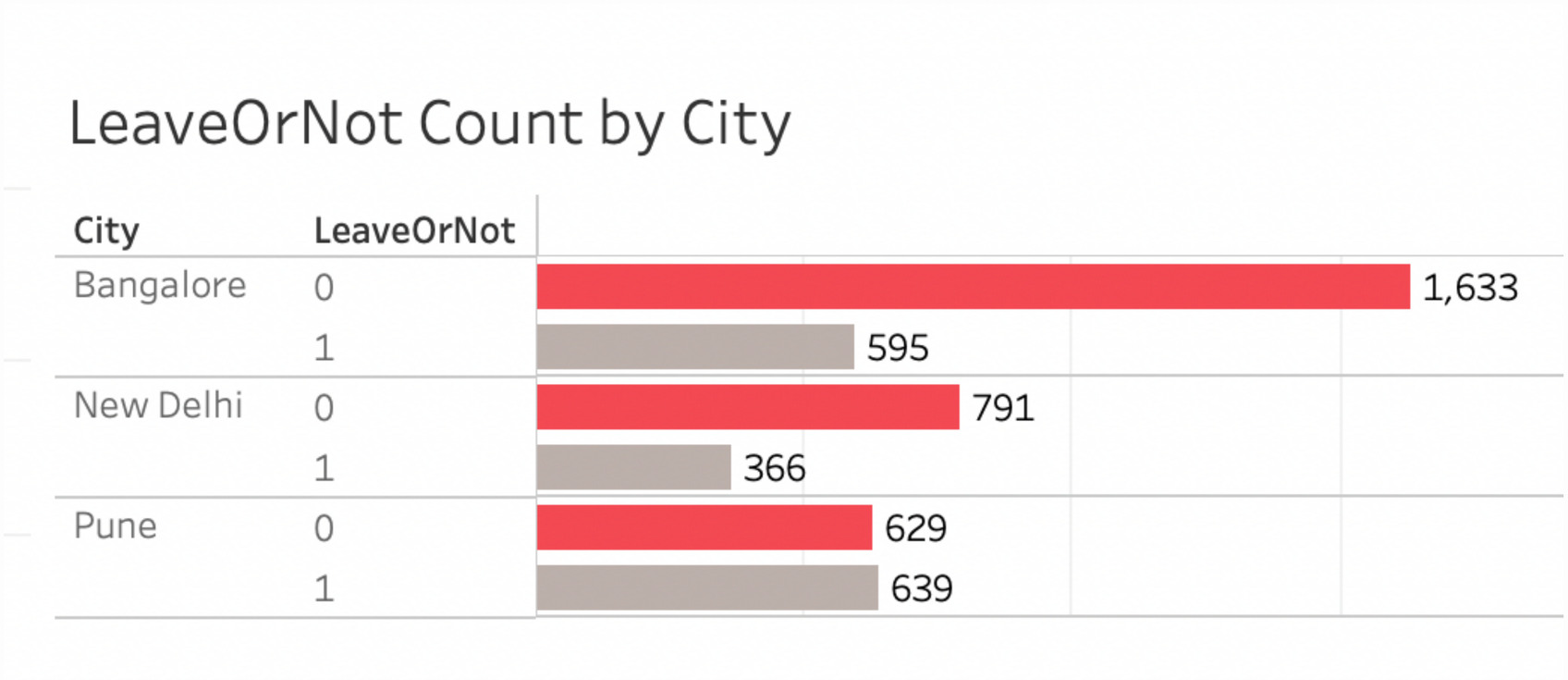
Male workers tend to leave the company



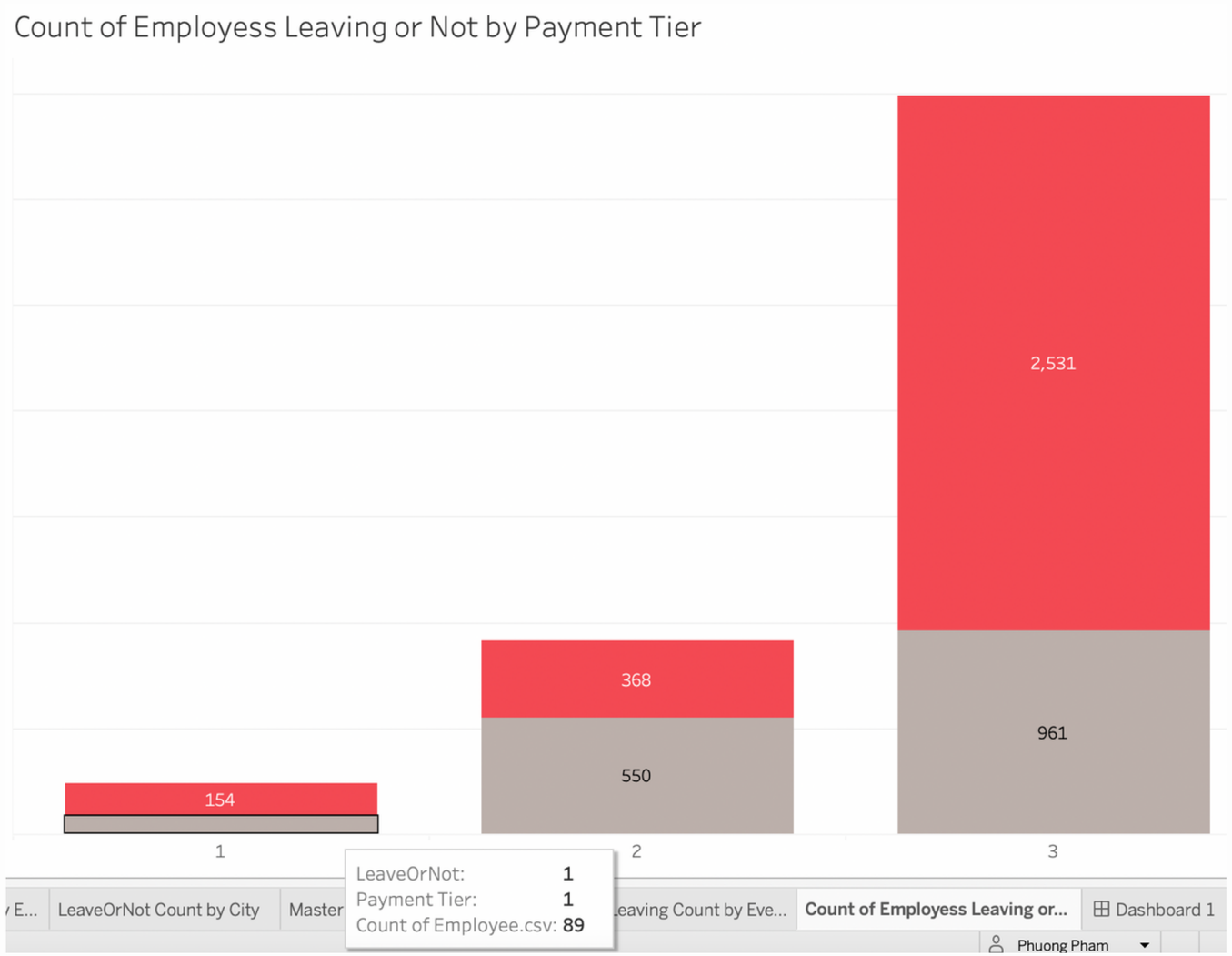
Employees who have been benched in the past have very high chance of leaving the company



Bangalor company location has a high number of employees leaving
1633 employees



Employees receiving Payment Tier 3 having high number of leaving the company



PYTHON

- Numpy
- Pandas
- Matplotlib
- Seaborn
- Plotly.express
- Sklearn

Obtaining dataset

In [1]:
```
#importing libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%matplotlib inline
```

In [2]:
```
#load dataset

df = pd.read_csv('Employee.csv')
```

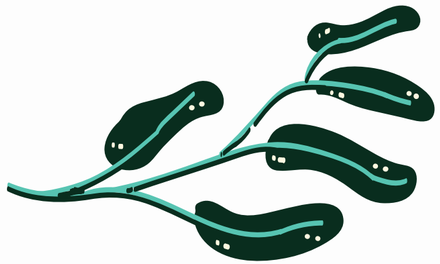
In [26]:
```
#check first 5 rows

df.head(5)
```

Out[26]:

	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	ExperienceInCurrentDomain	LeaveOrNot
0	0	2017	0	3	34	1	0	0	0
1	0	2013	2	1	28	0	0	3	1
2	0	2014	1	3	38	0	0	2	0
3	1	2016	0	3	27	1	0	5	1
4	1	2017	2	3	24	1	1	2	1

Exploratory Data Analysis

At this step. I investigation on data
to identify general patterns in the data



Get information about the data frame

In [4]:
```
#check information of columns

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4653 entries, 0 to 4652
Data columns (total 9 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Education                  4653 non-null   object
 1   JoiningYear                4653 non-null   int64 
 2   City                       4653 non-null   object
 3   PaymentTier                4653 non-null   int64 
 4   Age                        4653 non-null   int64 
 5   Gender                     4653 non-null   object
 6   EverBenched                4653 non-null   object
 7   ExperienceInCurrentDomain  4653 non-null   int64 
 8   LeaveOrNot                 4653 non-null   int64 
dtypes: int64(5), object(4)
memory usage: 327.3+ KB
```

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

Out[5]:

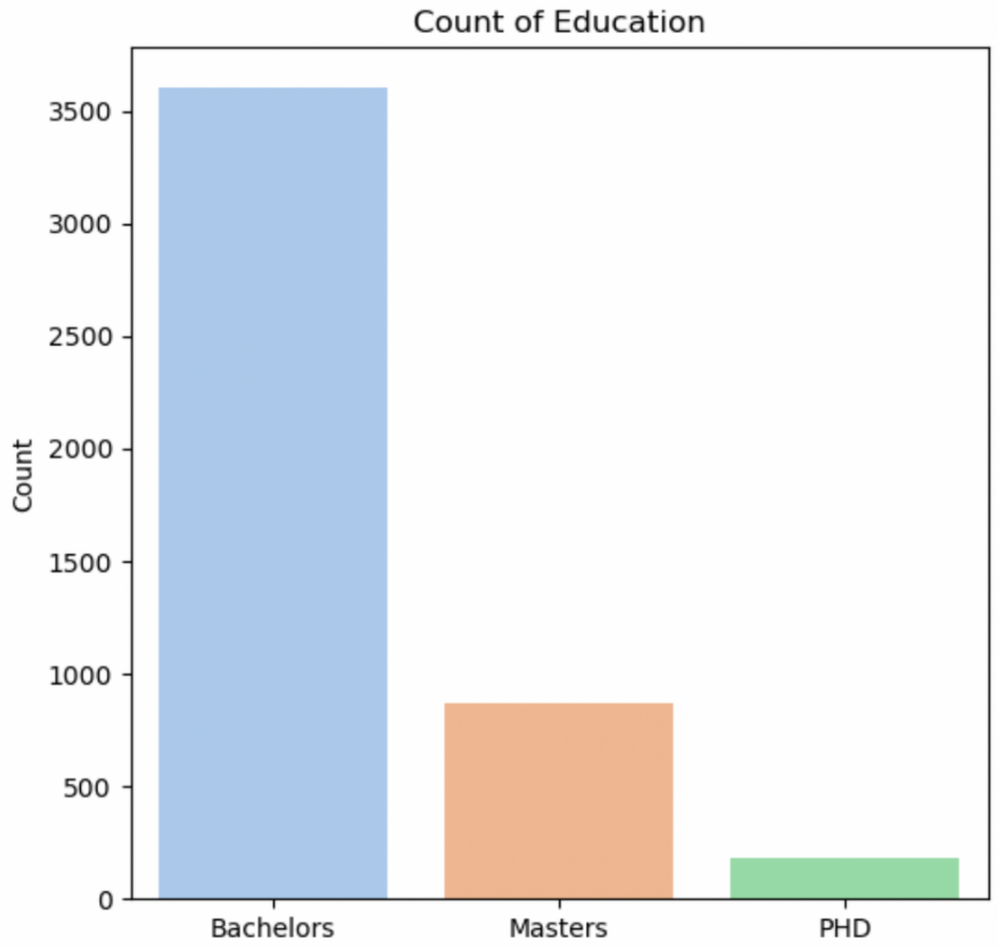
	JoiningYear	PaymentTier	Age	ExperienceInCurrentDomain	LeaveOrNot
count	4653.000000	4653.000000	4653.000000	4653.000000	4653.000000
mean	2015.062970	2.698259	29.393295	2.905652	0.343864
std	1.863377	0.561435	4.826087	1.558240	0.475047
min	2012.000000	1.000000	22.000000	0.000000	0.000000
25%	2013.000000	3.000000	26.000000	2.000000	0.000000
50%	2015.000000	3.000000	28.000000	3.000000	0.000000
75%	2017.000000	3.000000	32.000000	4.000000	1.000000
max	2018.000000	3.000000	41.000000	7.000000	1.000000

```
In [6]: #Check if the dataset has null value

        df.isnull().sum()
```

```
Out[6]: Education                   0
        JoiningYear                 0
        City                        0
        PaymentTier                 0
        Age                         0
        Gender                      0
        EverBenched                 0
        ExperienceInCurrentDomain   0
        LeaveOrNot                  0
        dtype: int64
```

No null values

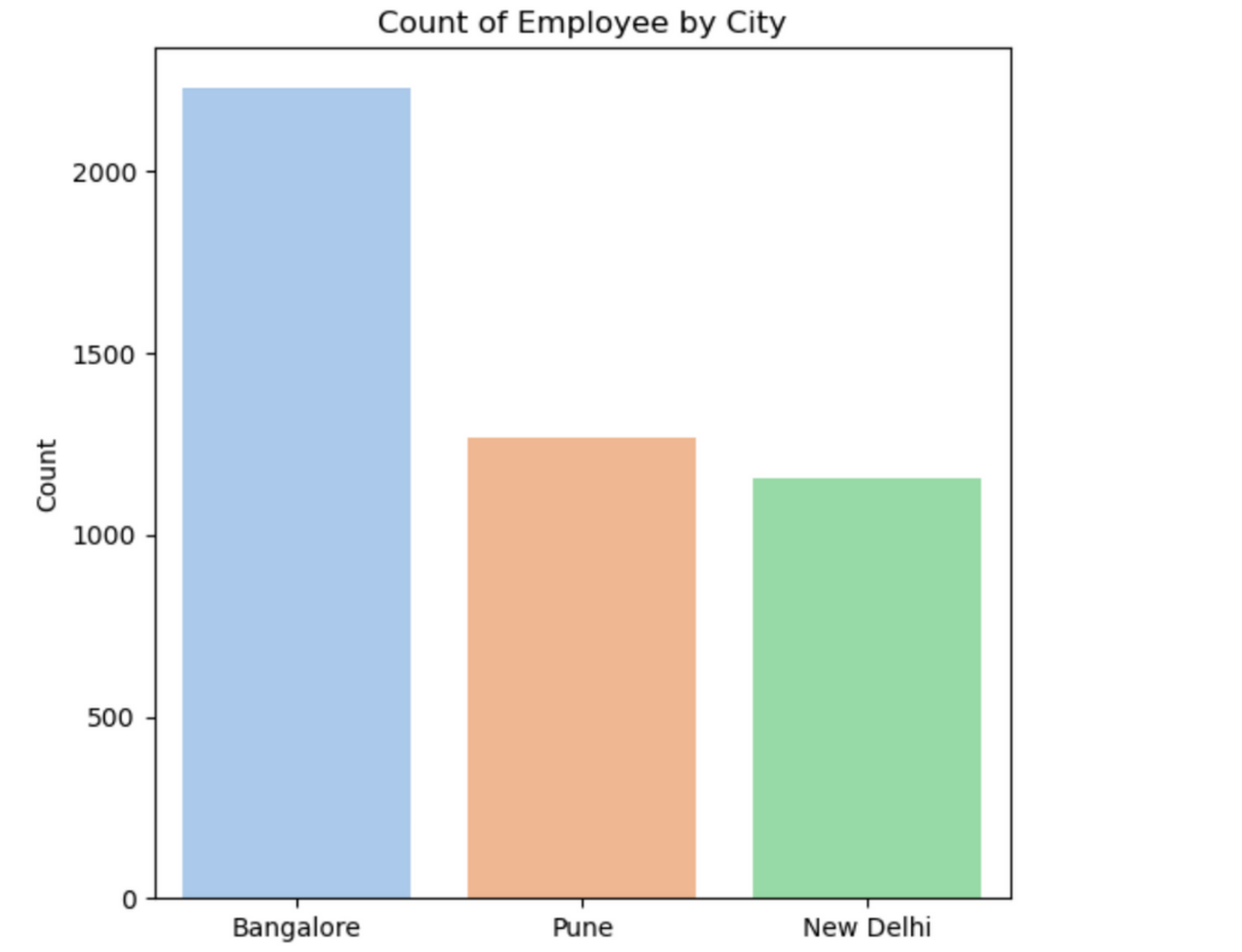
```
from matplotlib.pyplot import subplots
import seaborn as sns

#Creating bar graph for education counts

fig, ax = subplots(figsize=(6,6))
sns.countplot(x='Education',data=df,palette='pastel')
plt.xlabel('')
plt.ylabel('Count')
plt.title('Count of Education');
```



Counts of employees by Education Level

Most employees have Bachelors

```
#creating bar graph for city counts

fig, ax = subplots(figsize=(6,6))
sns.countplot(x='City',data=df,palette='pastel')
plt.xlabel('')
plt.ylabel('Count')
plt.title('Count of Employee by City');
```

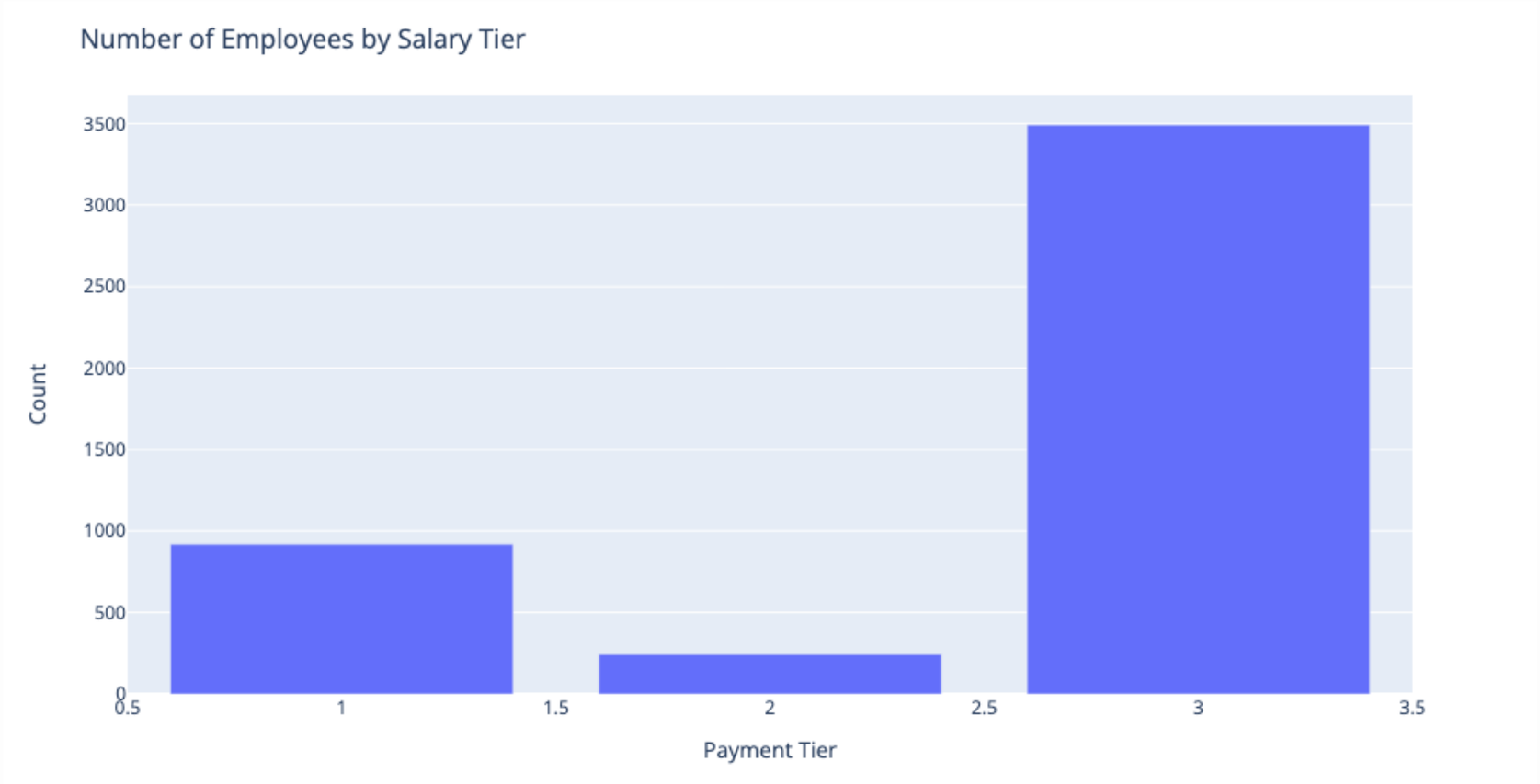


Counts of employees by City

Bangalore has highest number of employees

Count of employees by Payment Tier

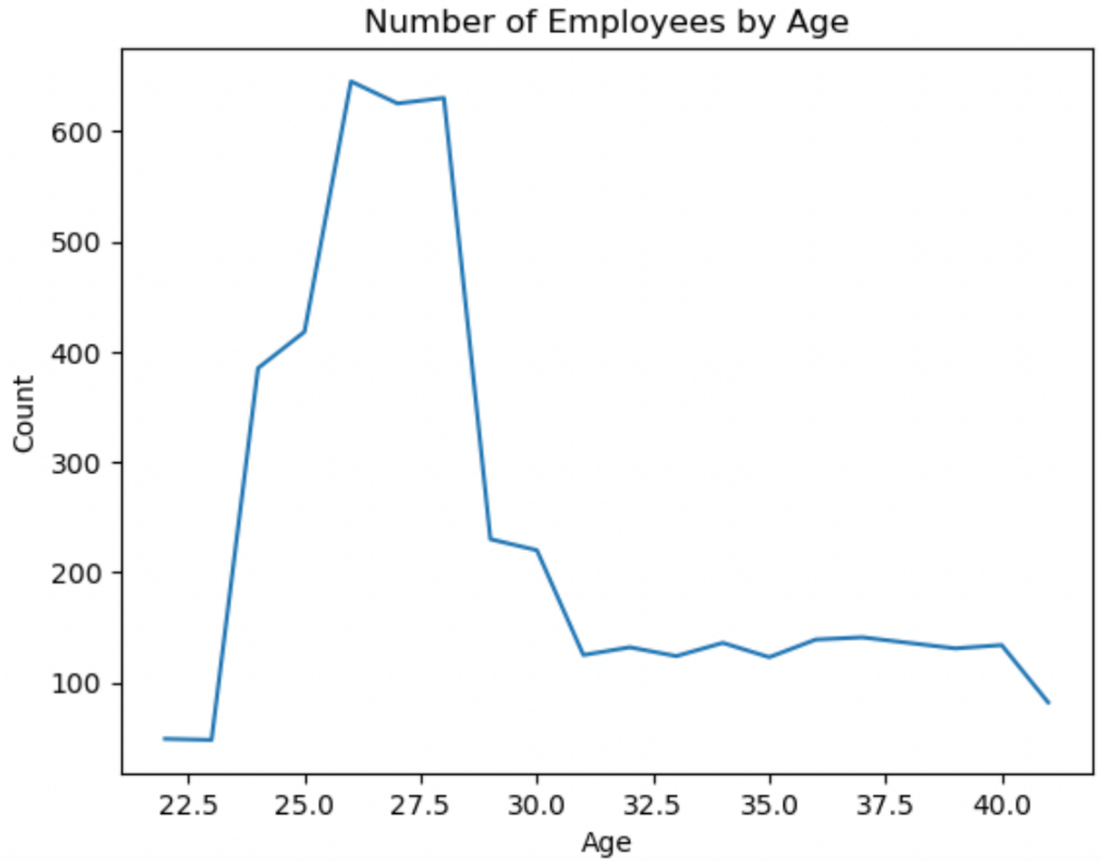
```
import plotly.express as px
fig = px.bar(df, df['PaymentTier'].unique(),df['PaymentTier'].value_counts())
fig.update_layout(title_text='Number of Employees by Salary Tier',
                  xaxis_title='Payment Tier',yaxis_title='Count')
fig.show()
```



Count of employees by Age

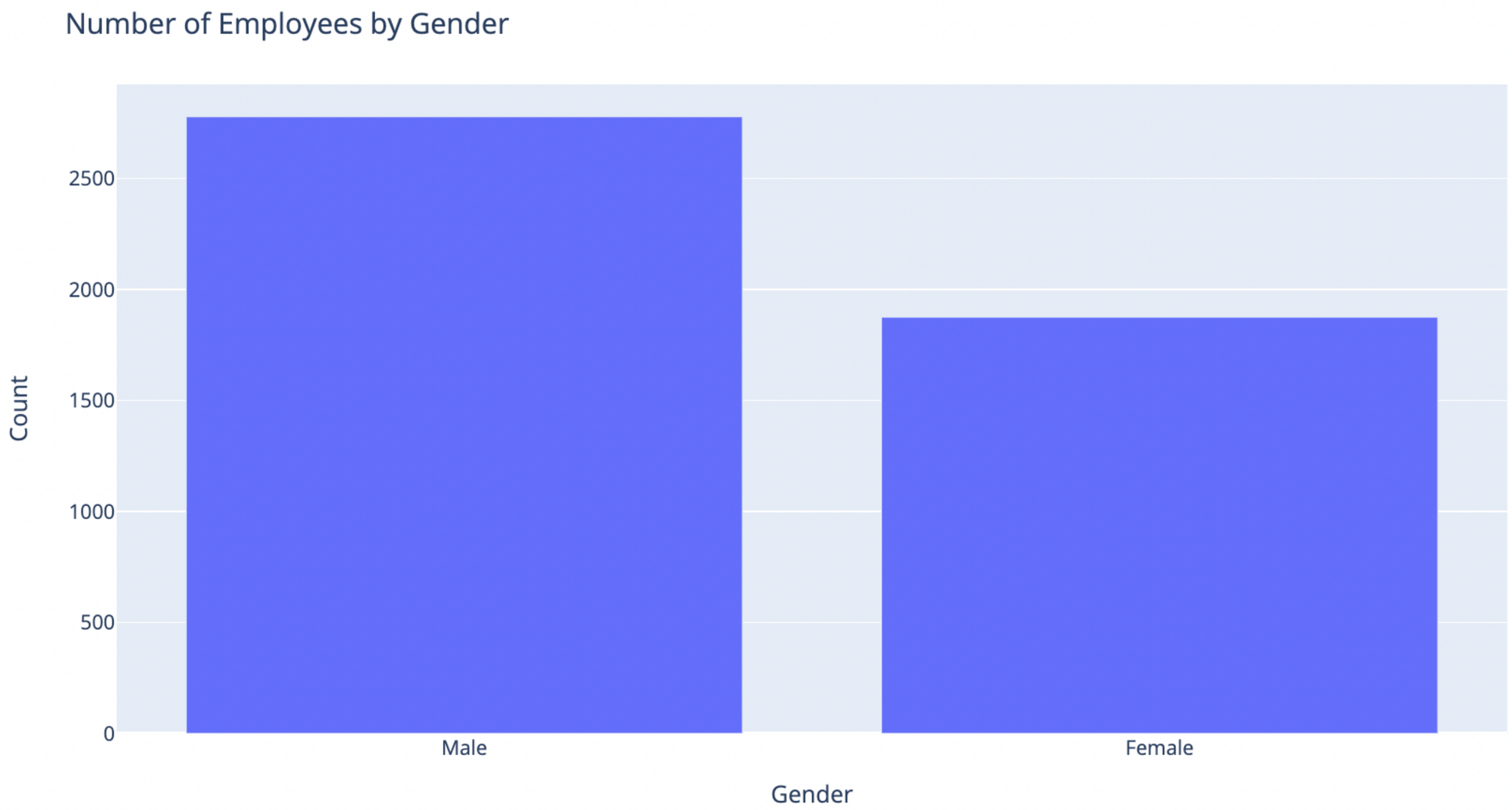
```
#creating a dataframe for counts of employees by age

Age = df['Age'].unique()
Age = df['Age'].value_counts().sort_values().reset_index()
```

```
#Creating line plot for the number of employees by Age

sns.lineplot(data=Age, x = 'index', y = 'Age')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Number of Employees by Age');
```



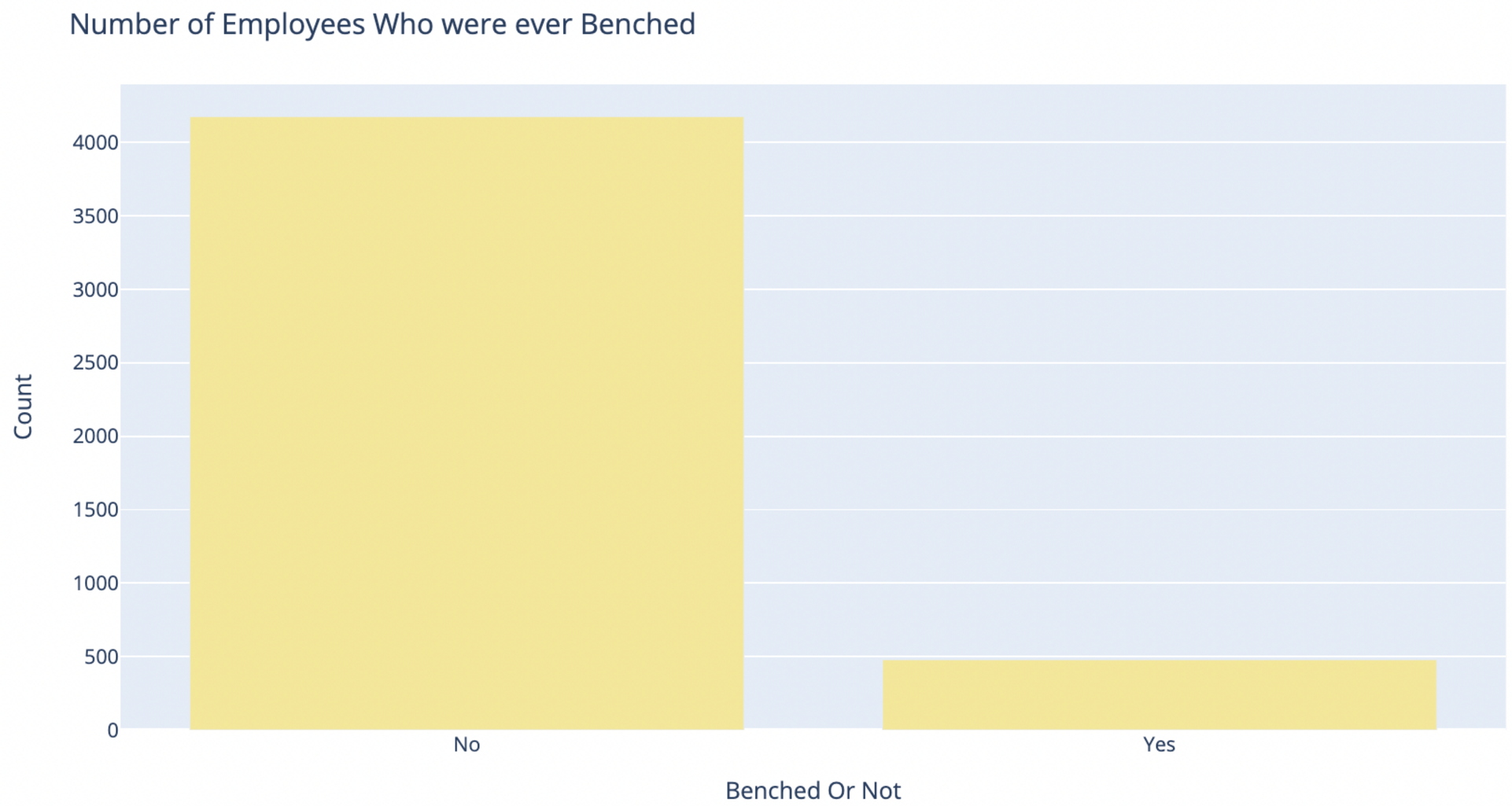
Count of Employees by Gender

```
fig = px.bar(df, df['Gender'].unique(), df['Gender'].value_counts())
fig.update_layout(title_text='Number of Employees by Gender',
                  xaxis_title='Gender',yaxis_title='Count')
```



Count of Employees by Ever Benched

```
fig = px.bar(df, df['EverBenched'].unique(), df['EverBenched'].value_counts(),
             color_discrete_sequence=px.colors.sequential.Sunset)
fig.update_layout(title_text='Number of Employees Who were ever Benched',
                  xaxis_title='Benched Or Not',yaxis_title='Count')
```



```python
#Encode target label with value 0 and n-1

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

#fit_transform function to fit label
df['Education'] = le.fit_transform(df['Education'])

df['Education']
```

```
0       0
1       0
2       0
3       1
4       1
       ..
4648    0
4649    1
4650    1
4651    0
4652    0
Name: Education, Length: 4653, dtype: int64
```

```python
#Fit label for other qualitative variables

df['Gender'] = le.fit_transform(df['Gender'])
df['City'] = le.fit_transform(df['City'])
df['EverBenched'] = le.fit_transform(df['EverBenched'])
```

Convert categorical columns into numerical values

Spliting data

```
target = ['LeaveOrNot']
X = df.drop(columns=target)
y = df[target]
```

```
X.head()
```

	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	ExperienceInCurrentDomain
0	0	2017	0	3	34	1	0	0
1	0	2013	2	1	28	0	0	3
2	0	2014	1	3	38	0	0	2
3	1	2016	0	3	27	1	0	5
4	1	2017	2	3	24	1	1	2

```
y.head()
```

	LeaveOrNot
0	0
1	1
2	0
3	1
4	1

Train the model

```
#split the data into training set and testing test

from sklearn.model_selection import train_test_split

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

```
#fitting the data and comparing it to test data

from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(350)
clf.fit(X_train,y_train.values.ravel())
y_pred = clf.predict(X_test)
```

Evaluate the model's performance

85% accuracy

```
#import metrics

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, classification_report
```

```
print(accuracy_score(y_test,y_pred))
```

```
0.8517191977077364
```

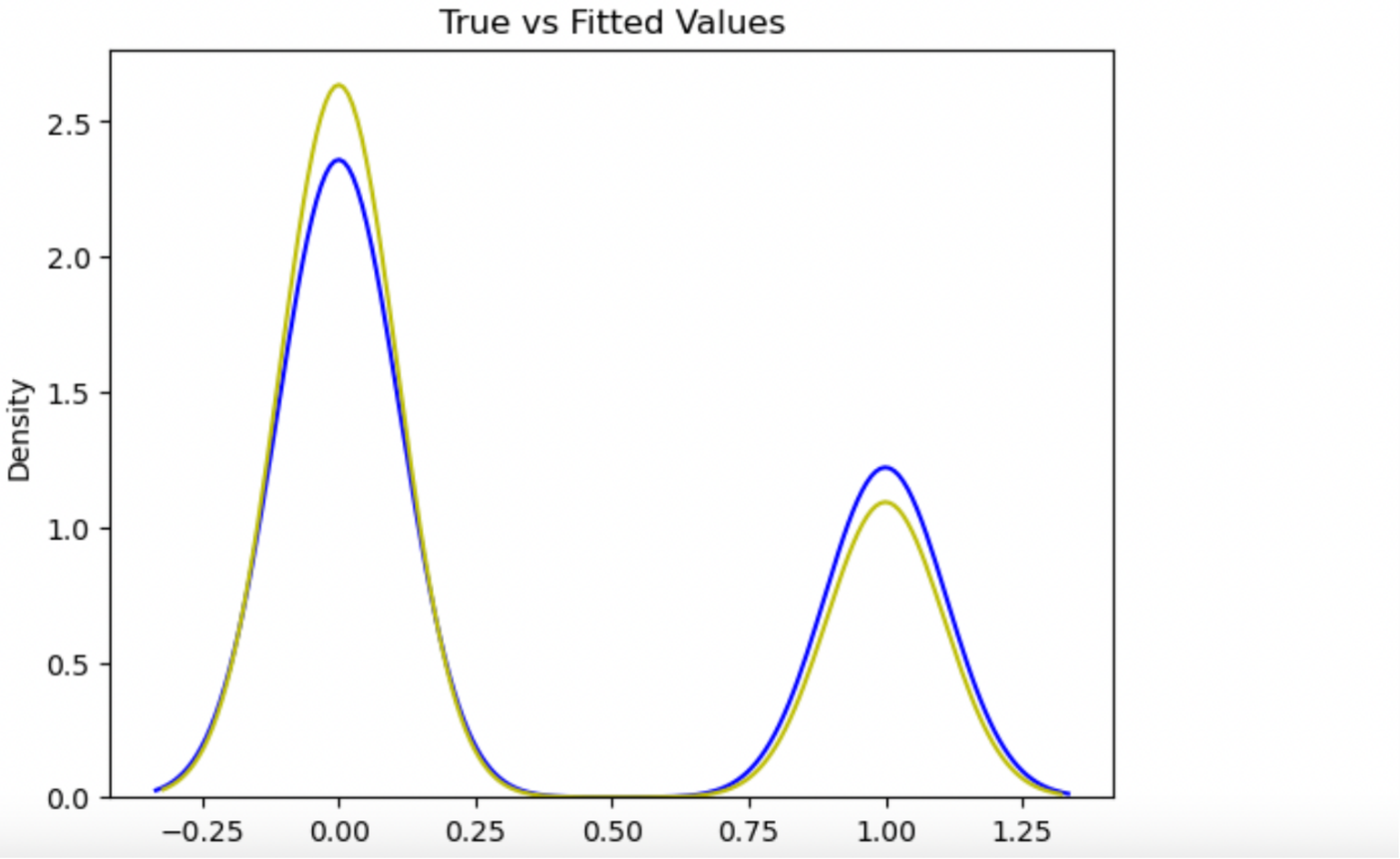
```
print('Confusion Matrix: \n', confusion_matrix(y_test,y_pred))
```

```
Confusion Matrix:
 [[850  70]
 [137 339]]
```

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.92      0.89       920
           1       0.83      0.71      0.77       476

    accuracy                           0.85      1396
   macro avg       0.85      0.82      0.83      1396
weighted avg       0.85      0.85      0.85      1396
```

```
import warnings
warnings.filterwarnings('ignore')

#Graphing Actual values and Fitted Values

ax1 = sns.distplot(y_test, hist=False, color="b", label="Actual")
sns.distplot(y_pred, hist=False, color="y", label="Fitted" , ax=ax1)


plt.title('True vs Fitted Values')

plt.show()
plt.close()
```



Graphing to compare the true value and predicted values

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