

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, mean_squared_error
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
```

```
import warnings
warnings.simplefilter(action="ignore")
```

```
df = pd.read_csv("/content/Employee.csv")
df.head()
```

| | Education | JoiningYear | City | PaymentTier | Age | Gender | EverBenched |
|---|-----------|-------------|-----------|-------------|-----|--------|-------------|
| 0 | Bachelors | 2017 | Bangalore | 3 | 34 | Male | I |
| 1 | Bachelors | 2013 | Pune | 1 | 28 | Female | I |
| 2 | Bachelors | 2014 | New Delhi | 3 | 38 | Female | I |
| 3 | Masters | 2016 | Bangalore | 3 | 27 | Male | I |
| 4 | Masters | 2017 | Pune | 3 | 24 | Male | Y |

Next steps:

[Generate code with df](#)[New interactive sheet](#)

```
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
```

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

| | 0 |
|----------------------------------|---|
| Education | 0 |
| JoiningYear | 0 |
| City | 0 |
| PaymentTier | 0 |
| Age | 0 |
| Gender | 0 |
| EverBenched | 0 |
| ExperienceInCurrentDomain | 0 |
| LeaveOrNot | 0 |

dtype: int64

```
df.describe()
```

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

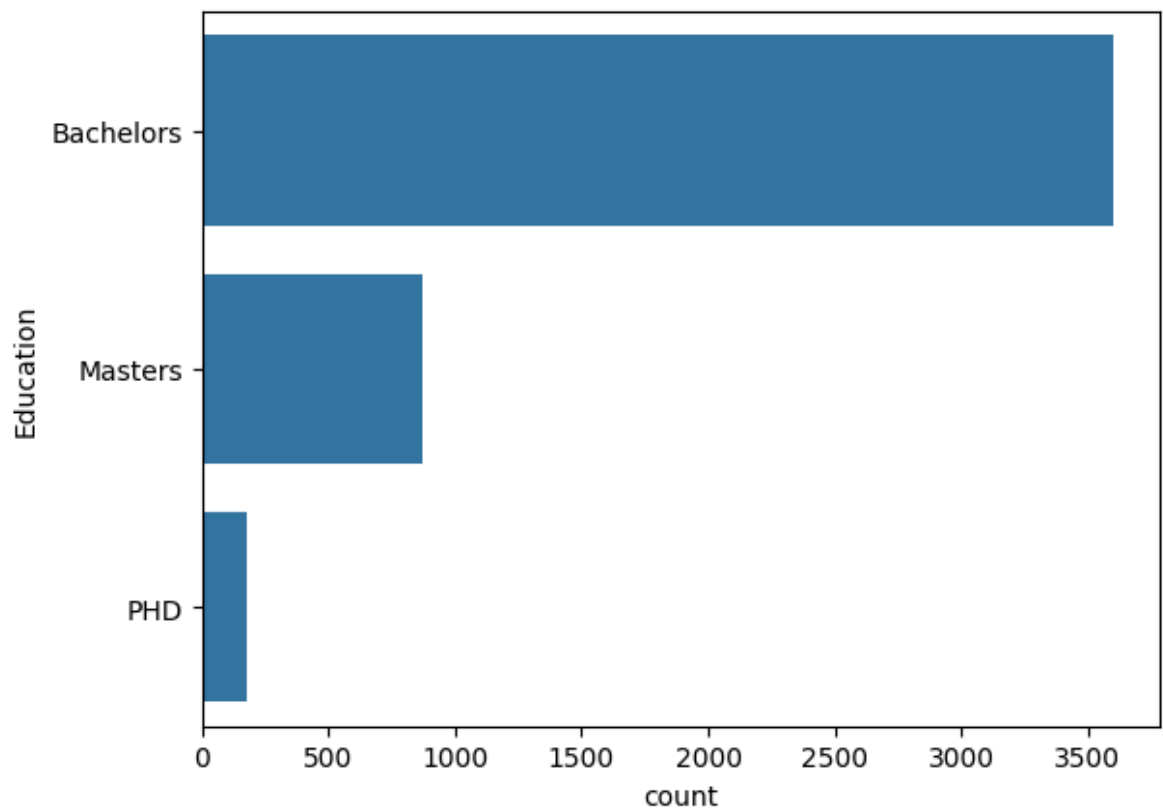
```
df["Education"].value_counts()
```

| | count |
|------------------|--------------|
| Education | |
| Bachelors | 3601 |
| Masters | 873 |
| PHD | 179 |

dtype: int64

```
sns.countplot(df["Education"])
```

<Axes: xlabel='count', ylabel='Education'>



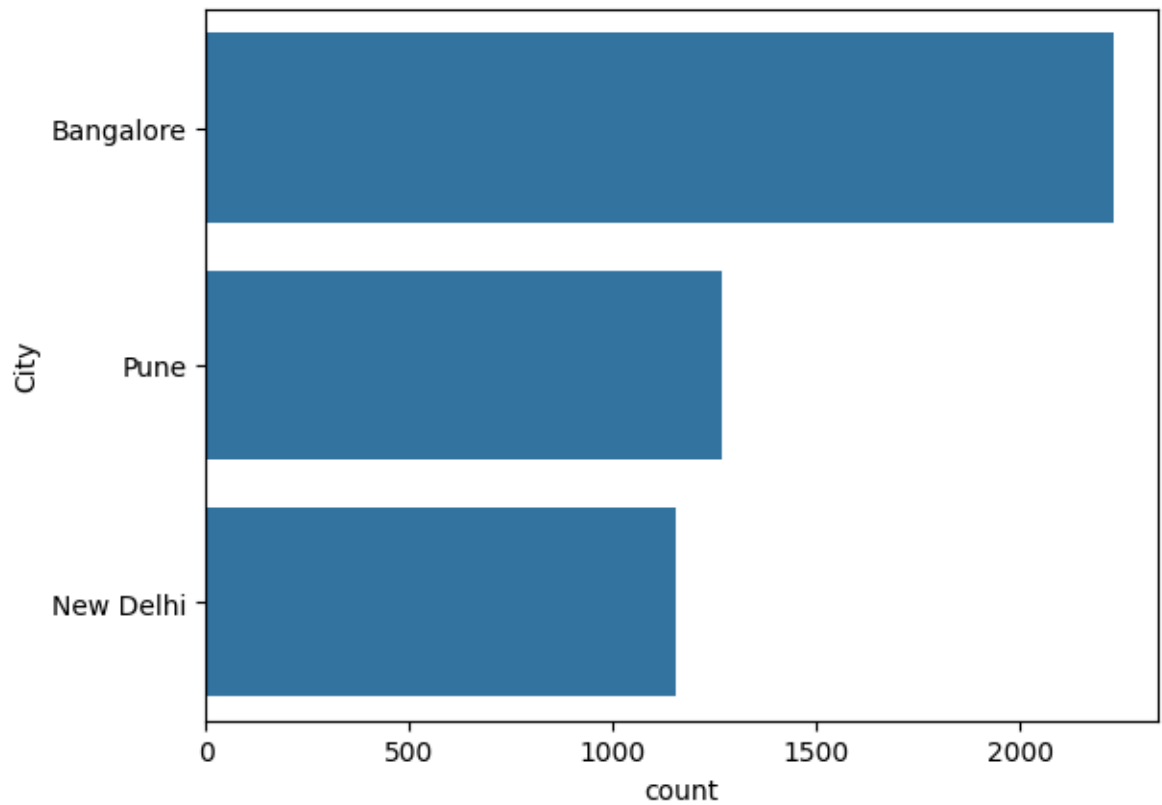
```
df["City"].value_counts()
```

| | count |
|-----------|-------|
| City | |
| Bangalore | 2228 |
| Pune | 1268 |
| New Delhi | 1157 |

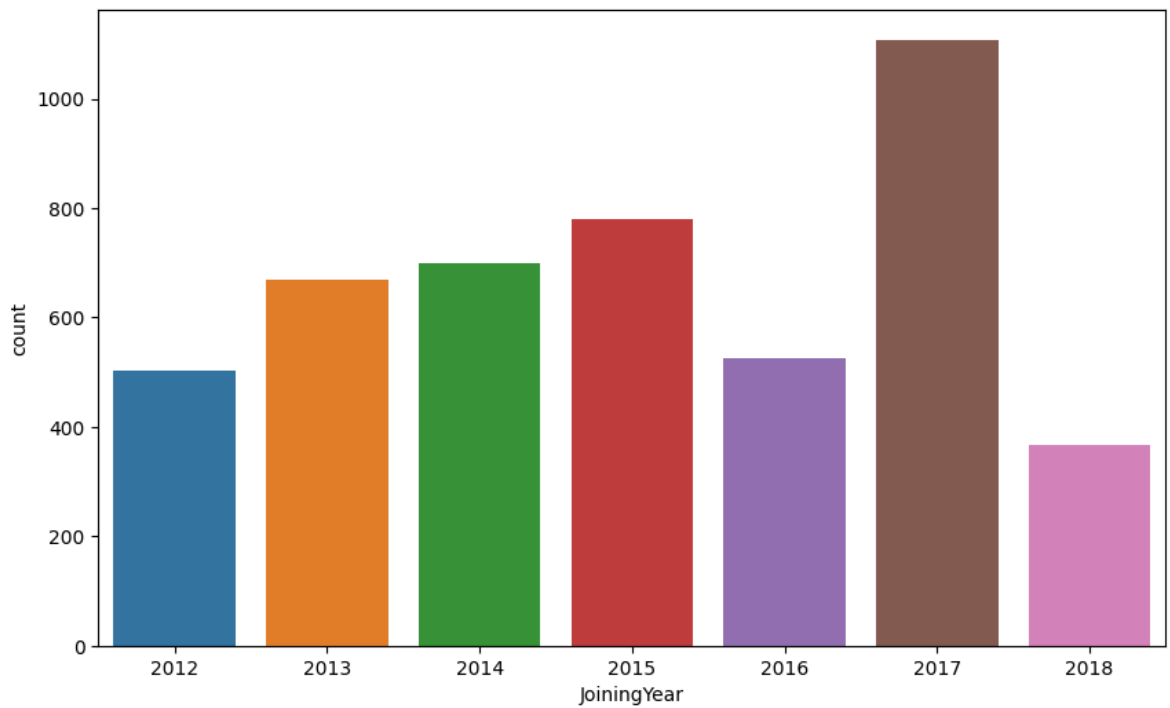
dtype: int64

```
sns.countplot(df["City"])
```

<Axes: xlabel='count', ylabel='City'>



```
plt.figure(figsize=(10,6))
sns.countplot(
    x="JoiningYear",
    data=df,
    hue="JoiningYear",
    palette="tab10",
    legend=False
)
plt.show()
```



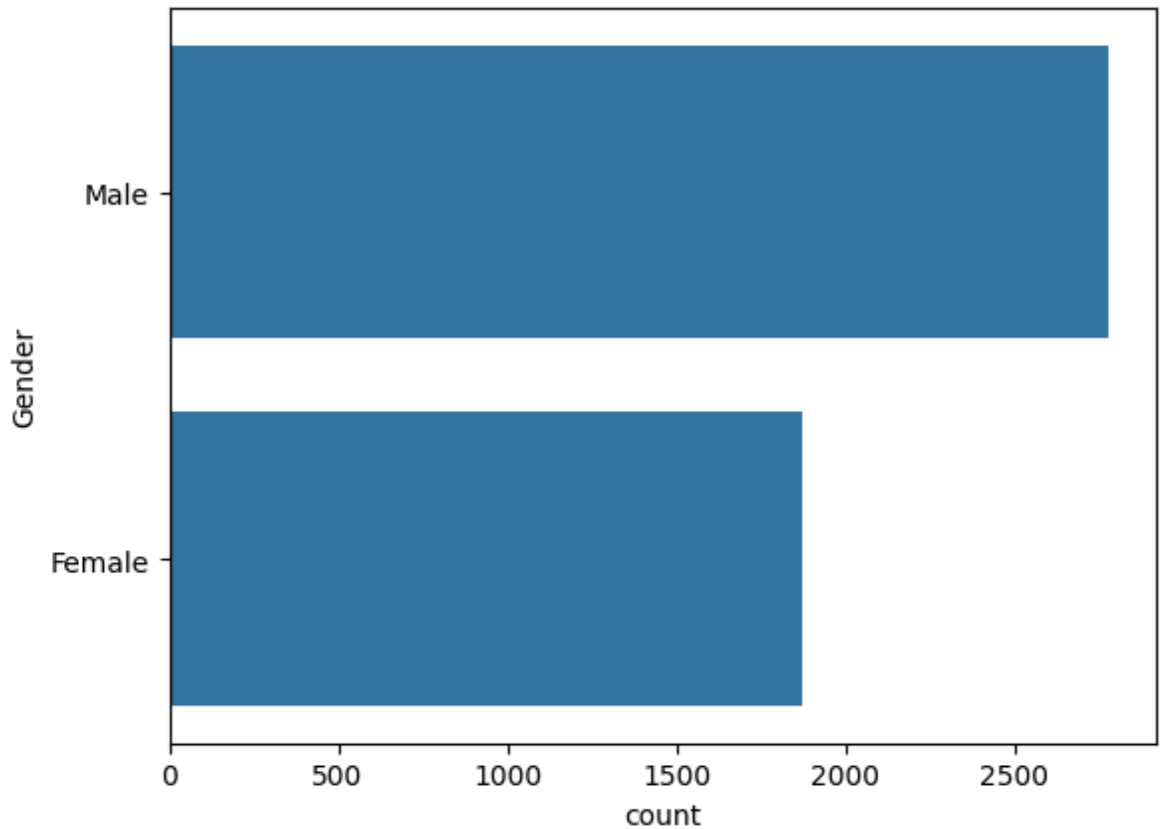
```
df["Gender"].value_counts()
```

| | count |
|--------|-------|
| Gender | |
| Male | 2778 |
| Female | 1875 |

dtype: int64

```
sns.countplot(df["Gender"])
```

<Axes: xlabel='count', ylabel='Gender'>

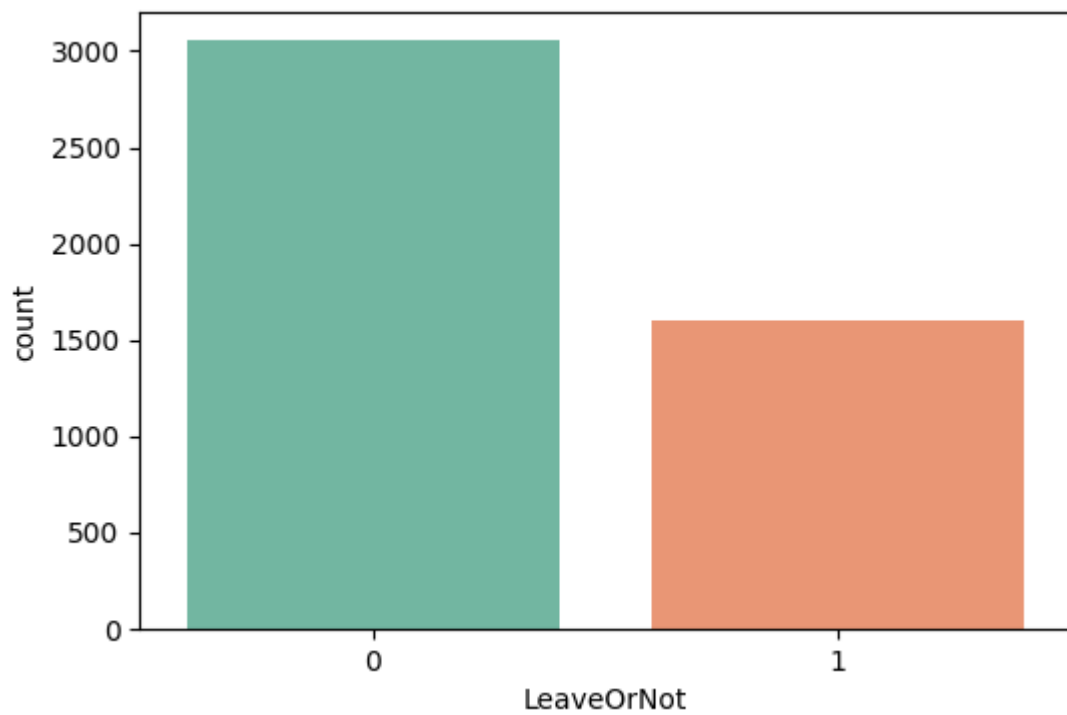


```
df["Leave0rNot"].value_counts()
```

| count | |
|------------|------|
| Leave0rNot | |
| 0 | 3053 |
| 1 | 1600 |

dtype: int64

```
plt.figure(figsize=(6,4))  
sns.countplot(x="Leave0rNot", data=df, hue="Leave0rNot", palette="Set1")  
plt.show()
```



```
df.head()
```

| | Education | JoiningYear | City | PaymentTier | Age | Gender | EverBenched |
|---|-----------|-------------|-----------|-------------|-----|--------|-------------|
| 0 | Bachelors | 2017 | Bangalore | 3 | 34 | Male | I |
| 1 | Bachelors | 2013 | Pune | 1 | 28 | Female | I |
| 2 | Bachelors | 2014 | New Delhi | 3 | 38 | Female | I |
| 3 | Masters | 2016 | Bangalore | 3 | 27 | Male | I |
| 4 | Masters | 2017 | Pune | 3 | 24 | Male | Y |

Next steps:

[Generate code with df](#)[New interactive sheet](#)

```
df = pd.get_dummies(df, ["Education", "City", "Gender", "EverBenched"])
```

```
df.head()
```

| | JoiningYear | PaymentTier | Age | ExperienceInCurrentDomain | LeaveOrNot |
|---|-------------|-------------|-----|---------------------------|------------|
| 0 | 2017 | | 3 | 34 | 0 |
| 1 | 2013 | | 1 | 28 | 3 |
| 2 | 2014 | | 3 | 38 | 2 |
| 3 | 2016 | | 3 | 27 | 5 |
| 4 | 2017 | | 3 | 24 | 2 |

Next steps:

[Generate code with df](#)[New interactive sheet](#)`df.head()`

| | JoiningYear | PaymentTier | Age | ExperienceInCurrentDomain | LeaveOrNot |
|---|-------------|-------------|-----|---------------------------|------------|
| 0 | 2017 | | 3 | 34 | 0 |
| 1 | 2013 | | 1 | 28 | 3 |
| 2 | 2014 | | 3 | 38 | 2 |
| 3 | 2016 | | 3 | 27 | 5 |
| 4 | 2017 | | 3 | 24 | 2 |

Next steps:

[Generate code with df](#)[New interactive sheet](#)

```
x = df.drop(["LeaveOrNot"], axis = 1)
y = df["LeaveOrNot"]
```

`x.head()`

| | JoiningYear | PaymentTier | Age | ExperienceInCurrentDomain | Education_ |
|---|-------------|-------------|-----|---------------------------|------------|
| 0 | 2017 | | 3 | 34 | 0 |
| 1 | 2013 | | 1 | 28 | 3 |
| 2 | 2014 | | 3 | 38 | 2 |
| 3 | 2016 | | 3 | 27 | 5 |
| 4 | 2017 | | 3 | 24 | 2 |

Next steps:

[Generate code with x](#)[New interactive sheet](#)


```
y.head()
```

| | Leave0rNot |
|---|------------|
| 0 | 0 |
| 1 | 1 |
| 2 | 0 |
| 3 | 1 |
| 4 | 1 |

dtype: int64

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2
```

```
x_train.shape
```

(3722, 14)

```
x_test.shape
```

(931, 14)

Logistic Regression

```
lr = LogisticRegression()  
lr.fit(x_train, y_train)
```

▼ LogisticRegression ⓘ ?
LogisticRegression()

```
y_pred = lr.predict(x_test)  
accuracy_score(y_pred, y_test)
```

0.7346938775510204

SVM (Support Vector Machine)

```
svm = SVC()  
svm.fit(x_train, y_train)
```