Github Repository URL

[Link to our repo]

Link to our live app

[Link to our live app]

1. Problem Statement

The Dunder Mifflin Paper Company, a well-known paper supplier situated in Scranton, Pennsylvania, is suffering a disturbing trend of excessive staff turnover, which is reducing operational efficiency and worker morale. We, the analytical team, are concerned about the company's high attrition rates, which we feel are damaging to its culture and performance. This research intends to use specific employee data, including tenure, income, work satisfaction, and departmental functions, to uncover major variables influencing employee turnover. We will create a prediction model based on detailed data analysis to put employees into three risk categories for leaving: extremely probable, moderately likely, and marginally likely. Our ultimate objective is to deliver actionable information that will assist in developing successful retention strategies to minimize turnover and improve overall employee engagement. Although the setting and data are fictitious and created for instructional reasons, the approaches used will closely resemble real-world analytical applications in human resource management, providing meaningful learning benefits.

2. Hypothesis Generation

We hypothesize that certain employee attributes and workplace conditions have a substantial impact on employee turnover at Dunder Mifflin Paper Company. We estimate that poorer job satisfaction, insufficient work-life balance, and longer travel lengths are highly related with increased risk of quitting the organization. Furthermore, we believe that employees with longer tenure, higher income, and recent promotions are less likely to quit, indicating that job stability and recognition are important determinants in employee retention. Our investigation aims to test these ideas by using predictive modelling approaches to categorize employees into distinct churn risk groups. By validating or disputing these assumptions, we will be able to pinpoint the most important areas for action to enhance retention methods and minimize staff turnover.

3. Prepare Data

Import the libraries

In [1]:

```
import numpy as np
import pandas as pd
```

Importing the dataset

https://www.kaggle.com/datasets/cocolicoq4/employee-churn-at-dunder-mifflin-paper-company

In [2]:

```
df = pd.read_csv('../../data/office_churn_dataset.csv')
```

```
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   EmployeeID                1543 non-null   int64  
 1   Branch                    1535 non-null   object 
 2   Tenure                    1534 non-null   float64
 3   Salary                    1534 non-null   float64
 4   Department                1543 non-null   object 
 5   JobSatisfaction           1515 non-null   float64
 6   WorkLifeBalance           1515 non-null   float64
 7   CommuteDistance           1543 non-null   object 
 8   MaritalStatus             1543 non-null   object 
 9   Education                 1543 non-null   object 
 10  PerformanceRating         1536 non-null   float64
 11  TrainingHours             1352 non-null   float64
 12  OverTime                  1443 non-null   object 
 13  NumProjects               1444 non-null   float64
 14  YearsSincePromotion       1542 non-null   float64
 15  EnvironmentSatisfaction   1515 non-null   float64
 16  ChurnLikelihood           1543 non-null   object 
dtypes: float64(9), int64(1), object(7)
memory usage: 205.1+ KB
None
```

Out[2]:

	EmployeeID	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus
0	1	San Francisco	4.0	63000.0	Legal	3.0	3.0	Long	Married
1	2	Chicago	14.0	72000.0	Accounting	4.0	4.0	Short	Single
2	3	Miami	4.0	40000.0	Quality Assurance	3.0	3.0	Medium	Single
3	4	Scranton	2.0	55000.0	Legal	3.0	3.5	Short	Married
4	5	Scranton	10.0	55500.0	Legal	3.0	3.0	Medium	Married

Understanding each feature

Dataset Features:

- **EmployeeID:** A unique identifier for each employee.
- **Branch:** The "Branch" feature represents the geographic location of each employee within one of the 12 Dunder Mifflin branches across the United States.
- **Tenure:** The number of years the employee has been with the company.
- **Salary:** The employee's annual salary.
- **Department:** The department in which the employee works (e.g., Sales, Accounting, Customer Service).
- **JobSatisfaction:** The employee's self-reported job satisfaction level (on a scale from 1 to 5, with 5 being highly satisfied).
- **WorkLifeBalance:** The employee's self-reported work-life balance rating (on a scale from 1 to 5, with 5 being excellent).
- **CommuteDistance:** The distance the employee commutes to work (e.g., Short, Medium, Long).
- **MaritalStatus:** The marital status of the employee (e.g., Single, Married, Divorced).
- **Education:** The highest level of education attained by the employee (e.g., High School, Bachelor's, Master's).
- **PerformanceRating:** The employee's performance rating (on a scale from 1 to 5, with 5 being excellent).
- **TrainingHours:** The number of hours of training the employee has received.
- **OverTime:** Whether the employee works overtime or not

- **OverTime:** Whether the employee works overtime or not.
- **NumProjects:** The number of projects the employee is currently working on.
- **YearsSincePromotion:** The number of years since the employee's last promotion.
- **EnvironmentSatisfaction:** The employee's self-reported environment satisfaction (on a scale from 1 to 5, with 5 being highly satisfied).

Classes (Target Variable): Employees will be classified into four classes based on their likelihood to leave the company:

- **Class A:** Highly likely to leave.
- **Class B:** Moderately likely to leave.
- **Class C:** Slightly likely to leave.

Remove irrelevant columns

In [3]:

```
irrelevant_features = ['EmployeeID']

df.drop(columns=irrelevant_features, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   1535 non-null   object 
 1   Tenure                   1534 non-null   float64
 2   Salary                   1534 non-null   float64
 3   Department               1543 non-null   object 
 4   JobSatisfaction          1515 non-null   float64
 5   WorkLifeBalance          1515 non-null   float64
 6   CommuteDistance          1543 non-null   object 
 7   MaritalStatus            1543 non-null   object 
 8   Education                1543 non-null   object 
 9   PerformanceRating        1536 non-null   float64
 10  TrainingHours            1352 non-null   float64
 11  OverTime                 1443 non-null   object 
 12  NumProjects              1444 non-null   float64
 13  YearsSincePromotion      1542 non-null   float64
 14  EnvironmentSatisfaction  1515 non-null   float64
 15  ChurnLikelihood          1543 non-null   object 
dtypes: float64(9), object(7)
memory usage: 193.0+ KB
```

4. Exploratory Data Analysis (EDA)

i) Univariate Analysis

Reading random records

In [4]:

```
df.sample(5)
```

Out[4]:

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Educatio
707	Chicago	10.0	54500.0	Quality Assurance	3.0	3.000000	Short	Married	Hig Schoo
1155	San Francisco	3.0	73500.0	Product Management	5.0	5.000000	Short	Divorced	Bachelo

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Educatio
	Francisco			Management					
638	Miami	8.0	55000.0	Human Resources	1.0	NaN	Medium	Single	Hig Schoo
531	Chicago	9.0	62500.0	Legal	4.0	3.609454	Long	Divorced	Bachelo
133	Denver	3.0	54000.0	Customer Service	4.0	3.000000	Medium	Single	Hig Schoo

Analysis of numerical attributes

In [5]:

```
df.describe()
```

Out[5]:

	Tenure	Salary	JobSatisfaction	WorkLifeBalance	PerformanceRating	TrainingHours	NumProjects	YearsSi
count	1534.000000	1534.000000	1515.000000	1515.000000	1536.000000	1352.000000	1444.000000	
mean	7.612125	66654.498044	3.421782	3.770770	3.493310	34.645646	3.500687	
std	4.123834	8473.622168	1.095047	0.481407	0.411208	22.970267	0.714107	
min	0.000000	40000.000000	1.000000	2.000000	1.639834	5.196002	1.505266	
25%	5.000000	61000.000000	3.000000	3.500000	3.333333	18.000000	3.000000	
50%	7.000000	66500.000000	3.000000	4.000000	3.363192	30.000000	3.618543	
75%	10.000000	72375.000000	4.000000	4.000000	3.666667	40.000000	4.000000	
max	27.000000	98000.000000	5.000000	5.000000	5.000000	96.000000	6.394718	

Visualization of the data

Importing Libraries for Visualization

In [6]:

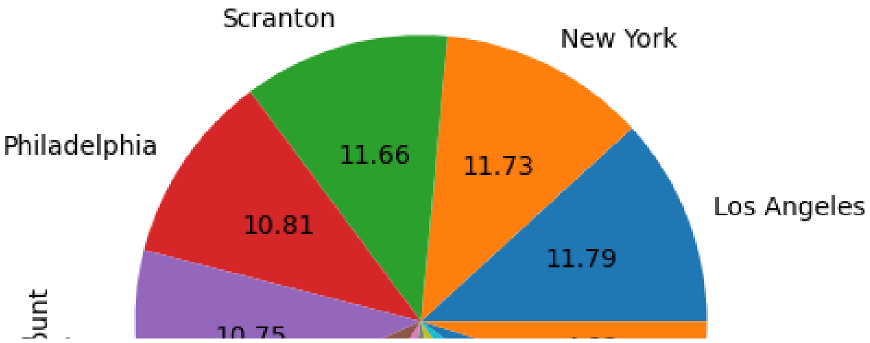
```
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

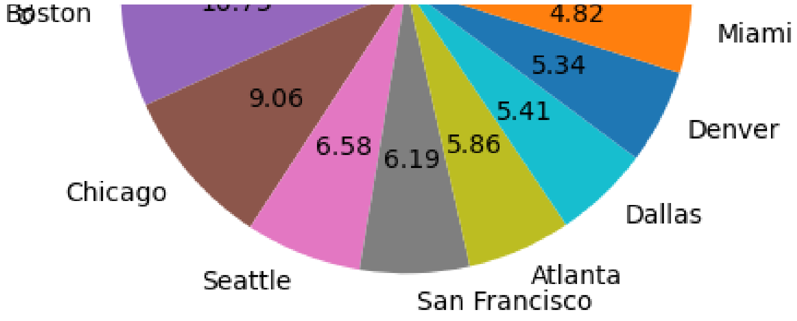
Categorical Visualization

Branch

In [7]:

```
df["Branch"].value_counts().plot(kind="pie",autopct='%.2f', figsize=(5, 8), y='',x='');
```

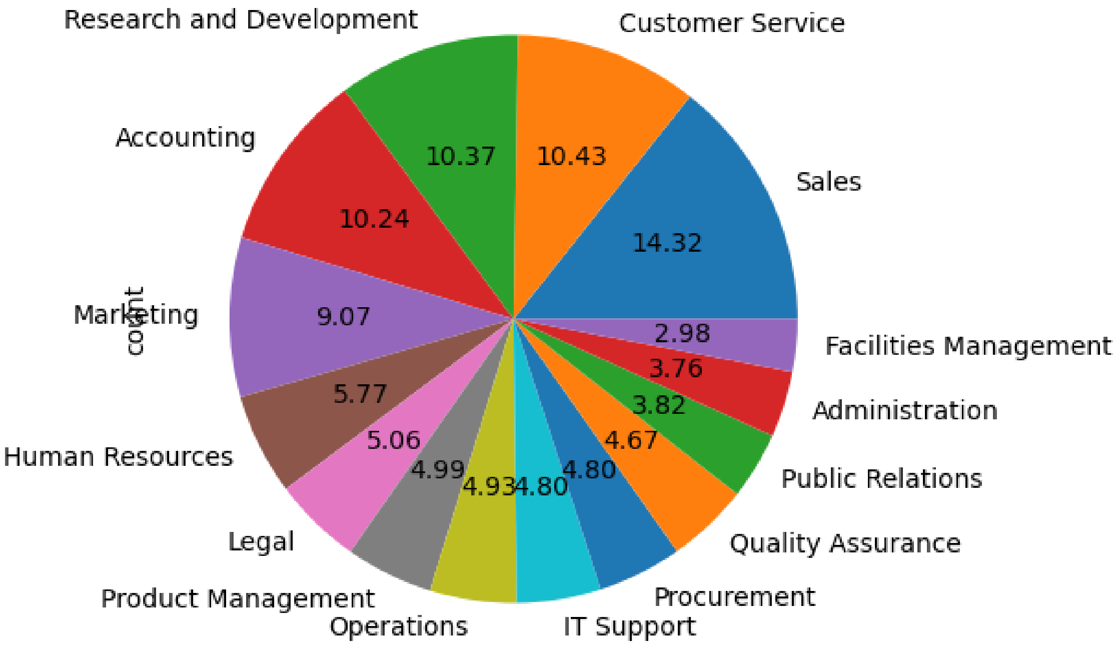




Department

In [8]:

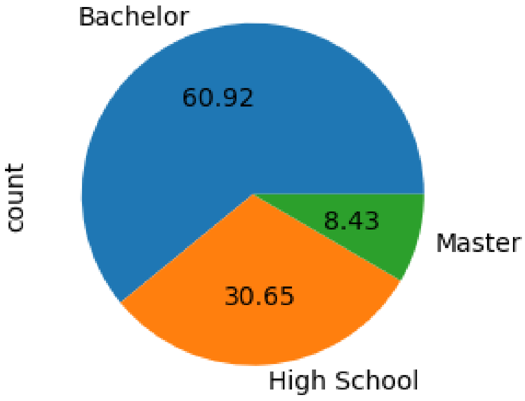
```
df["Department"].value_counts().plot(kind="pie",autopct='%.2f', figsize=(8, 5), y='',x='
');
```



Education

In [9]:

```
df["Education"].value_counts().plot(kind="pie",autopct='%.2f', figsize=(3, 5), y='',x=''
);
```

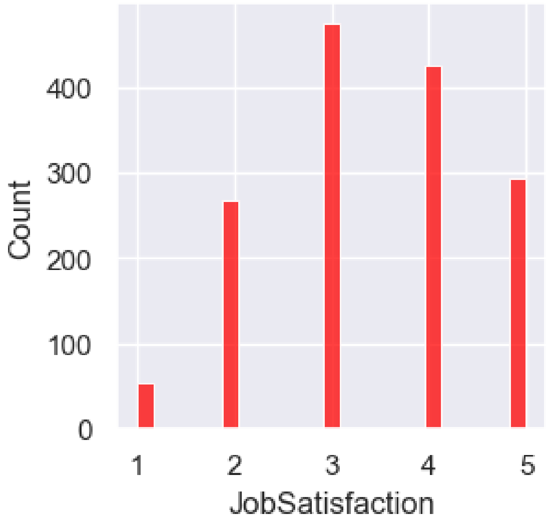


Job Satisfaction

In [10]:

```
sns.set_theme(rc={'figure.figsize':(3,3)})
sns.histplot(x="JobSatisfaction", data=df,color="red");
```

```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
nf_as_na option is deprecated and will be removed in a future version. Convert inf values
to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



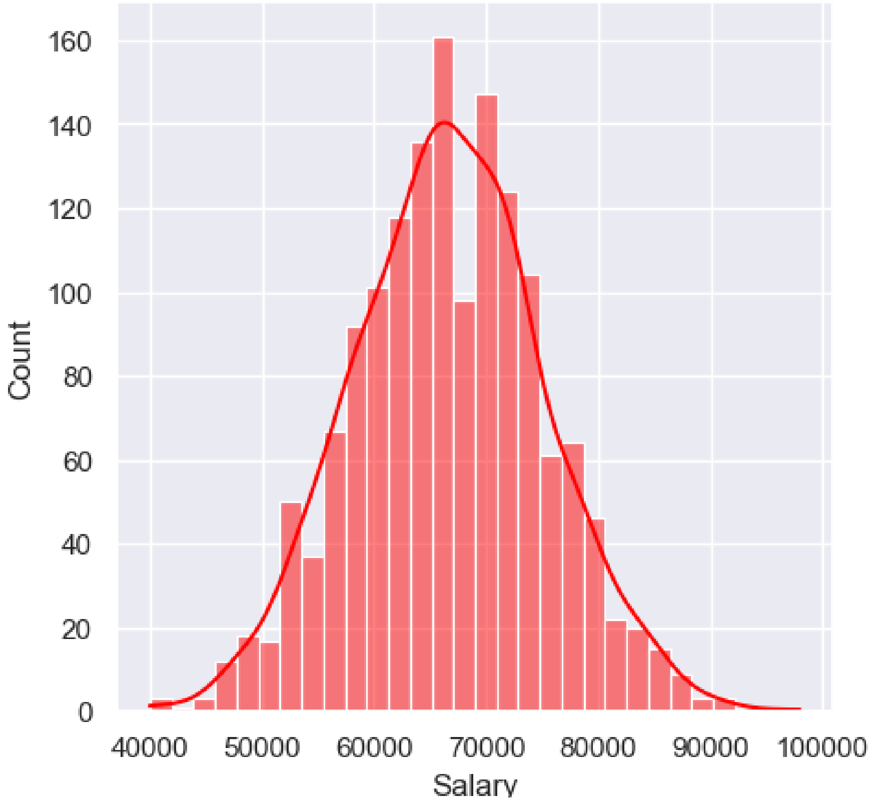
Numerical Visualization

Salary

In [11]:

```
sns.set_theme(rc={'figure.figsize':(5,5)})
sns.histplot(x="Salary", data=df, kde=True,color="red");
```

```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
nf_as_na option is deprecated and will be removed in a future version. Convert inf values
to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

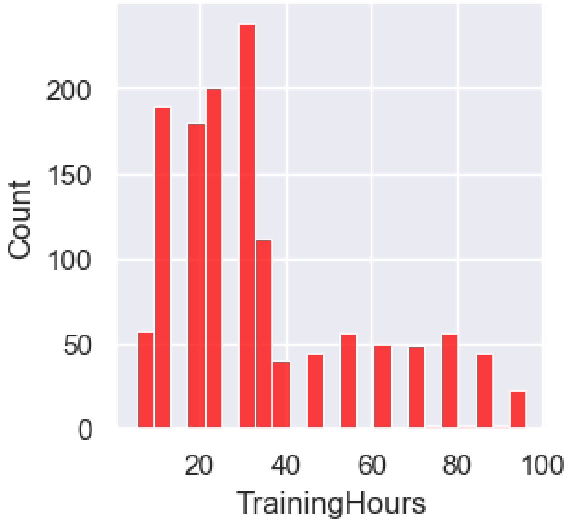


Training Hours

In [12]:

```
sns.set_theme(rc={'figure.figsize':(3,3)})
sns.histplot(x="TrainingHours", data=df, color="red");
```

```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
nf_as_na option is deprecated and will be removed in a future version. Convert inf values
to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Comparing Target Values for Categorical Imbalances

In [13]:

```
labels = (
    df['ChurnLikelihood']
    .astype('str')
    .str.replace('0','No', regex=True)
    .str.replace('1','Yes', regex=True)
    .value_counts()
)

fig = px.bar(
    data_frame=labels,
    x=labels.index,
    y=labels.values,
    title=f'Class Imbalance',
    color=labels.index
)

fig.update_layout(xaxis_title='Churn Status', yaxis_title='Number of Customers')
fig.show()
```

ii) Bivariate Analysis

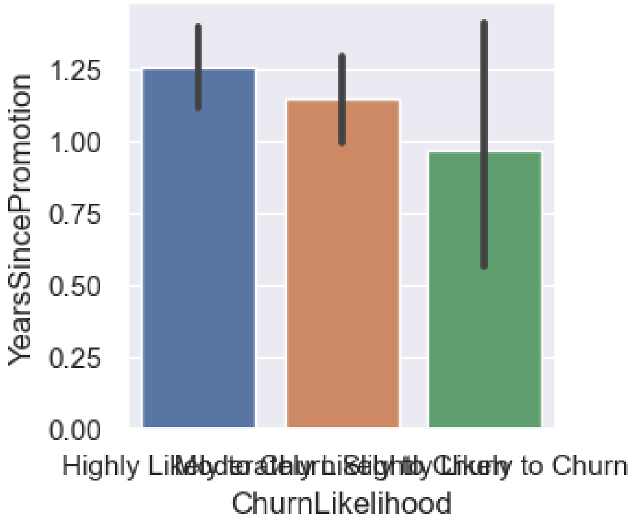
1. Years since promotion and Churn Likelihood

In [14]:

```
sns.barplot(x = 'ChurnLikelihood' , y ='YearsSincePromotion' , data=df)
```

Out[14]:

```
<Axes: xlabel='ChurnLikelihood', ylabel='YearsSincePromotion'>
```



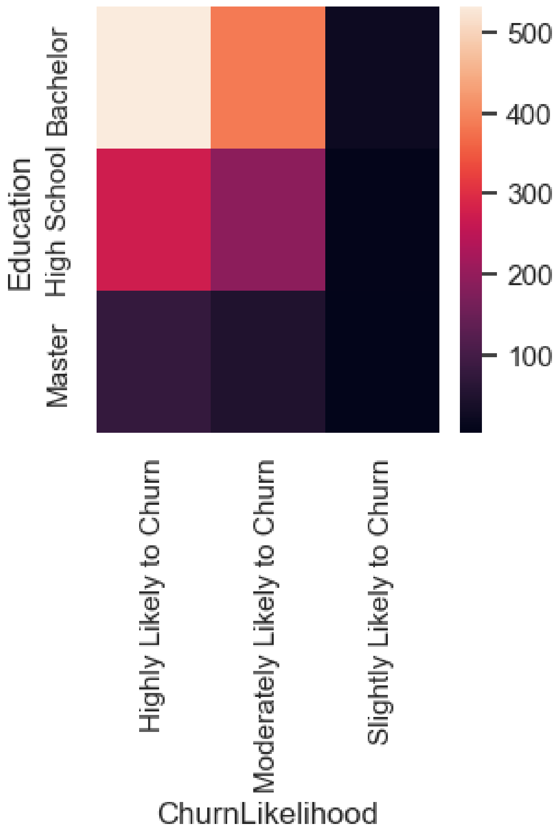
2 . Education and Churn likelihood

In [15]:

```
sns.heatmap(pd.crosstab(df['Education'] , df['ChurnLikelihood']))
```

Out[15]:

```
<Axes: xlabel='ChurnLikelihood', ylabel='Education'>
```



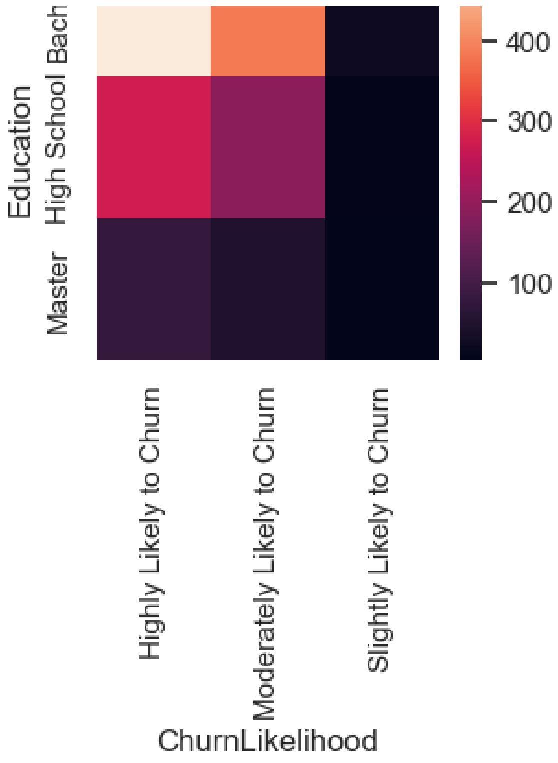
3. Department and Churn likelihood

In [16]:

```
sns.heatmap(pd.crosstab(df['Education'] , df['ChurnLikelihood']))
```

Out[16]:

```
<Axes: xlabel='ChurnLikelihood', ylabel='Education'>
```



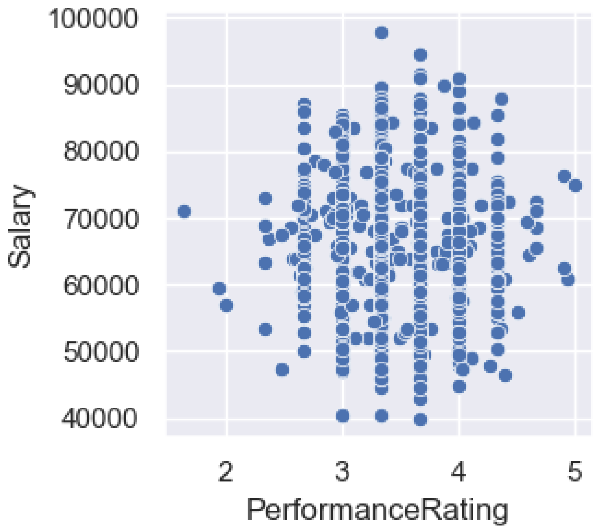
4. Performance rating and Salary

In [17]:

```
sns.scatterplot(x = 'PerformanceRating' , y = 'Salary' , data=df)
```

Out[17]:

```
<Axes: xlabel='PerformanceRating', ylabel='Salary'>
```



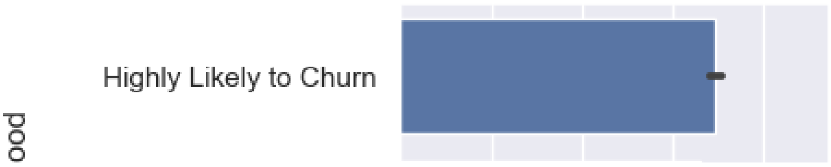
5. JobSatisfaction and ChurnLikelihood

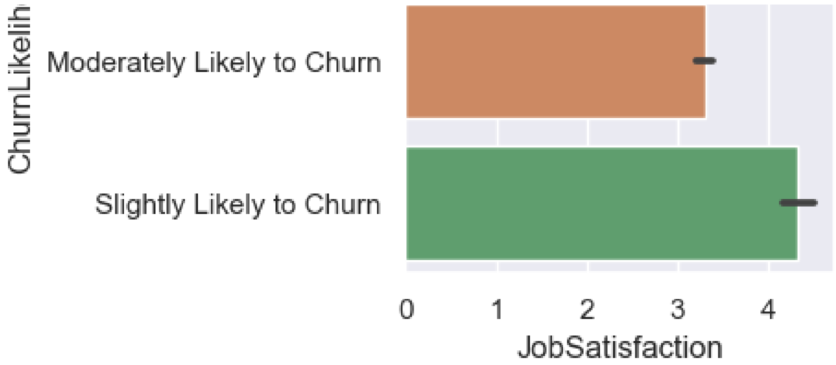
In [18]:

```
sns.barplot(x = 'JobSatisfaction' , y ='ChurnLikelihood' , data=df)
```

Out[18]:

```
<Axes: xlabel='JobSatisfaction', ylabel='ChurnLikelihood'>
```





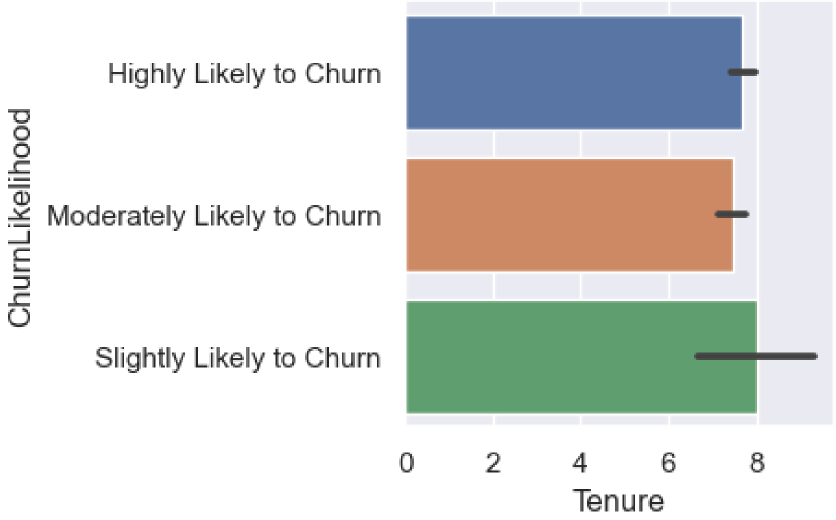
6. Tenure and ChurnLikelihood

In [19]:

```
sns.barplot(x = 'Tenure' , y ='ChurnLikelihood' , data=df)
```

Out[19]:

```
<Axes: xlabel='Tenure', ylabel='ChurnLikelihood'>
```



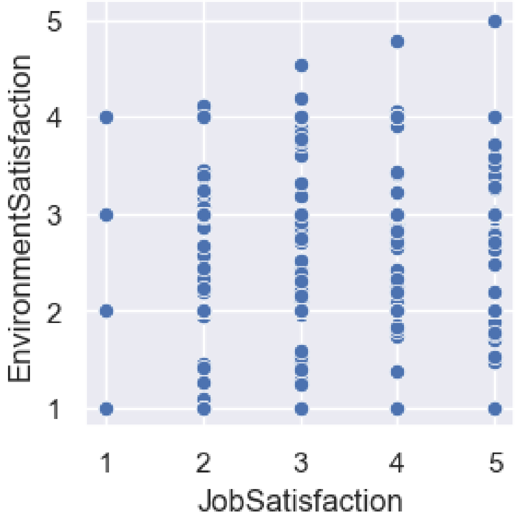
7. JobSatisfaction and EnvironmentSatisfaction

In [20]:

```
sns.scatterplot(x = 'JobSatisfaction' , y = 'EnvironmentSatisfaction' , data=df)
```

Out[20]:

```
<Axes: xlabel='JobSatisfaction', ylabel='EnvironmentSatisfaction'>
```



5. Preprocess Data

Analyze the data

In [21]:

```python
import skimpy as sk
sk.skim(df)
```

```
╭──────────────────────────────────────────────── skimpy summary ───────────────────────────────────────────────
│          Data Summary                Data Types                                                               │
│ ┏━━━━━━━━━━━━━━━━━━━┳━━━━━━━━┓ ┏━━━━━━━━━━━━━━┳━━━━━━━┓                                                      │
│ ┃ dataframe         ┃ Values ┃ ┃ Column Type  ┃ Count ┃                                                      │
│ ┡━━━━━━━━━━━━━━━━━━━╇━━━━━━━━┩ ┡━━━━━━━━━━━━━━╇━━━━━━━┩                                                      │
│ │ Number of rows    │ 1543   │ │ float64      │ 9     │                                                      │
│ │ Number of columns │ 16     │ │ string       │ 6     │                                                      │
│ └───────────────────┴────────┘ │ bool         │ 1     │                                                      │
│                                └──────────────┴───────┘                                                      │
│                                                   number                                                     │
│ ┏━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━┳━━━━━━━┳━━━━━━━━┳━━━━━━━┳━━━━━━━━┳━━━━━━━━┳━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━
┃ ┃ column_name            ┃ NA  ┃ NA %  ┃ mean   ┃ sd    ┃ p0     ┃ p25    ┃ p50    ┃
p75   ┃ p100   ┃ hist     ┃  │
│ ┡━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━╇━━━━━━━╇━━━━━━━━╇━━━━━━━╇━━━━━━━━╇━━━━━━━━╇━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━
━━━━━━╇━━━━━━━━╇━━━━━━━━━━┩  │
│ │ Tenure                 │   9 │  0.58 │    7.6 │   4.1 │      0 │      5 │      7 │
  10 │     27 │  ▆█▆▁    │  │
│ │ Salary                 │   9 │  0.58 │  67000 │  8500 │  40000 │  61000 │  66000 │ 7
2000 │  98000 │  ▂██▁    │  │
│ │ JobSatisfaction        │  28 │  1.81 │    3.4 │   1.1 │      1 │      3 │      3 │
   4 │      5 │ ▁▄ █▆    │  │
│ │ WorkLifeBalance        │  28 │  1.81 │    3.8 │  0.48 │      2 │    3.5 │      4 │
   4 │      5 │   ▄█▄    │  │
│ │ PerformanceRating      │   7 │  0.45 │    3.5 │  0.41 │    1.6 │    3.3 │    3.4 │
 3.7 │      5 │  ▁▂█▄    │  │
│ │ TrainingHours          │ 191 │ 12.38 │     35 │    23 │    5.2 │     18 │     30 │
  40 │     96 │ █▃▂▂▁    │  │
│ │ NumProjects            │  99 │  6.42 │    3.5 │  0.71 │    1.5 │      3 │    3.6 │
   4 │    6.4 │ ▁█ █▁    │  │
│ │ YearsSincePromotion    │   1 │  0.06 │    1.2 │   2.1 │      0 │      0 │      0 │
   2 │     16 │   █▂     │  │
│ │ EnvironmentSatisfactio │  28 │  1.81 │    2.5 │  0.69 │      1 │      2 │    2.8 │
   3 │      5 │ ▁█▁█▁    │  │
│ │ n                      │     │       │        │       │        │        │        │
     │        │          │  │
│ └────────────────────────┴─────┴───────┴────────┴───────┴────────┴────────┴────────┴────────────────────────
──────┴────────┴──────────┘  │
│                                                    bool                                                      │
│ ┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━
┏━━━━━━━━━━━━━━━━━━━━━━━━┓                                                                                    │
│ ┃ column_name                              ┃ true                 ┃ true_rate
│ ┃ column_name                       ┃ true             ┃ true rate
┃ hist                     ┃  │
│ ┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━
━━━━━━━━━━━━━━━━━━━━━━━━━━┩  │
│ │ OverTime                           │             1543 │                     1
           ▇              │  │
│ └────────────────────────────────────┴──────────────────┴──────────────────────
──────────────────────────┘  │
│                                             string
                              │
│ ┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━┳━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━
━━━━━━━━━━━━━━━━━━━━━━━━━━┓  │
│ ┃ column_name                     ┃ NA      ┃ NA %        ┃ words per row               ┃
total words              ┃  │
│ ┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━╇━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━
━━━━━━━━━━━━━━━━━━━━━━━━━━┩  │
│ │ Branch                          │       8 │        0.52 │                         1.3 │
                     1991 │  │
│ │ Department                      │       0 │           0 │                         1.6 │
                     2441 │  │
│ │ CommuteDistance                 │       0 │           0 │                           1 │
                     1543 │  │
│ │ MaritalStatus                   │       0 │           0 │                           1 │
                     1543 │  │
│ │ Education                       │       0 │           0 │                         1.3 │
                     2016 │  │
│ │ ChurnLikelihood                 │       0 │           0 │                           4 │
                     6172 │  │
│ └─────────────────────────────────┴─────────┴─────────────┴─────────────────────────────┴─
──────────────────────────┘  │
└─────────────────────────────────────────────────────────── End ───────────────────────────
──────────────────────────────┘
```

Handling rows without Churned

In [22]:

```
df.dropna(subset='ChurnLikelihood', inplace=True)

print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   1535 non-null   object 
 1   Tenure                   1534 non-null   float64
 2   Salary                   1534 non-null   float64
 3   Department               1543 non-null   object 
 4   JobSatisfaction          1515 non-null   float64
 5   WorkLifeBalance          1515 non-null   float64
 6   CommuteDistance          1543 non-null   object 
 7   MaritalStatus            1543 non-null   object 
 8   Education                1543 non-null   object 
 9   PerformanceRating        1536 non-null   float64
 10  TrainingHours            1352 non-null   float64
 11  OverTime                 1443 non-null   object 
 12  NumProjects              1444 non-null   float64
 13  YearsSincePromotion      1542 non-null   float64
 14  EnvironmentSatisfaction  1515 non-null   float64
 15  ChurnLikelihood          1543 non-null   object 
dtypes: float64(9), object(7)
memory usage: 193.0+ KB
None
```

Out[22]:

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education	P
0	San Francisco	4.0	63000.0	Legal	3.0	3.0	Long	Married	High School	
1	Chicago	14.0	72000.0	Accounting	4.0	4.0	Short	Single	Bachelor	
2	Miami	4.0	40000.0	Quality Assurance	3.0	3.0	Medium	Single	High School	
3	Scranton	2.0	55000.0	Legal	3.0	3.5	Short	Married	Bachelor	
4	Scranton	10.0	55500.0	Legal	3.0	3.0	Medium	Married	Bachelor	

Handling duplicate values

In [23]:

```
print(df.duplicated().value_counts())
df.drop_duplicates()
```

```
False    1543
Name: count, dtype: int64
```

Out[23]:

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Educatio
0	San Francisco	4.0	63000.0	Legal	3.0	3.000000	Long	Married	Hig Schoo
1	Chicago	14.0	72000.0	Accounting	4.0	4.000000	Short	Single	Bachelo
2	Miami	4.0	40000.0	Quality Assurance	3.0	3.000000	Medium	Single	Hig Schoo
3	Scranton	2.0	55000.0	Legal	3.0	3.500000	Short	Married	Bachelo
4	Scranton	10.0	55500.0	Legal	3.0	3.000000	Medium	Married	Bachelo
...	...	...	...	...	...	...	...	...	.
1538	Miami	6.0	58000.0	Research and Development	4.0	4.000000	Long	Married	Bachelo
1539	Boston	1.0	51500.0	Accounting	2.0	3.500000	Medium	Divorced	Hig Schoo
1540	San Francisco	11.0	77500.0	Human Resources	4.0	4.029174	Long	Married	Bachelo
1541	New York	NaN	81000.0	Research and Development	4.0	3.000000	Medium	Married	Maste
1542	Dallas	10.0	54500.0	Facilities Management	4.0	5.000000	Short	Married	Hig Schoo

1543 rows × 16 columns

Handling high and low cardinality features

In [24]:

```
# checking the cardinality of features
df.select_dtypes("object").nunique()
```

Out[24]:

```
Branch              12
Department          15
CommuteDistance      3
MaritalStatus        3
Education            3
OverTime             1
ChurnLikelihood      3
dtype: int64
```

Drop high cardinality features

In [25]:

```
high_cardinality = ['OverTime']

df.drop(columns=high_cardinality, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   1535 non-null   object 
 1   Tenure                   1534 non-null   float64
 2   Salary                   1534 non-null   float64
 3   Department               1543 non-null   object 
 4   JobSatisfaction          1515 non-null   float64
 5   WorkLifeBalance          1515 non-null   float64
 6   CommuteDistance          1543 non-null   object 
 7   MaritalStatus            1543 non-null   object 
 8   Education                1543 non-null   object 
 9   PerformanceRating        1536 non-null   float64
 10  TrainingHours            1352 non-null   float64
 11  NumProjects              1444 non-null   float64
 12  YearsSincePromotion      1542 non-null   float64
 13  EnvironmentSatisfaction  1515 non-null   float64
 14  ChurnLikelihood          1543 non-null   object 
dtypes: float64(9), object(6)
memory usage: 180.9+ KB
```

Handling empty cells

In [26]:

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

```
Branch                       8
Tenure                       9
Salary                       9
Department                   0
JobSatisfaction             28
WorkLifeBalance             28
CommuteDistance              0
MaritalStatus                0
Education                    0
PerformanceRating            7
TrainingHours              191
NumProjects                 99
YearsSincePromotion          1
EnvironmentSatisfaction     28
ChurnLikelihood              0
dtype: int64
```

In [27]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   1535 non-null   object 
 1   Tenure                   1534 non-null   float64
 2   Salary                   1534 non-null   float64
 3   Department               1543 non-null   object 
 4   JobSatisfaction          1515 non-null   float64
 5   WorkLifeBalance          1515 non-null   float64
 6   CommuteDistance          1543 non-null   object 
 7   MaritalStatus            1543 non-null   object 
 8   Education                1543 non-null   object 
 9   PerformanceRating        1536 non-null   float64
 10  TrainingHours            1352 non-null   float64
 11  NumProjects              1444 non-null   float64
 12  YearsSincePromotion      1542 non-null   float64
 13  EnvironmentSatisfaction  1515 non-null   float64
 14  ChurnLikelihood          1543 non-null   object 
dtypes: float64(9), object(6)
memory usage: 180.9+ KB
```

Fill categorical value(s)

In [28]:

```
for col in df.select_dtypes(include=['object']).columns:
    df[col]=df[col].fillna(df[col].mode()[0])

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

Out[28]:

```
Branch                       0
Tenure                       9
Salary                       9
Department                   0
JobSatisfaction             28
WorkLifeBalance             28
CommuteDistance              0
MaritalStatus                0
Education                    0
PerformanceRating            7
TrainingHours              191
NumProjects                 99
YearsSincePromotion          1
EnvironmentSatisfaction     28
ChurnLikelihood              0
dtype: int64
```

In [29]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   1543 non-null   object 
 1   Tenure                   1534 non-null   float64
 2   Salary                   1534 non-null   float64
 3   Department               1543 non-null   object 
 4   JobSatisfaction          1515 non-null   float64
 5   WorkLifeBalance          1515 non-null   float64
 6   CommuteDistance          1543 non-null   object 
 7   MaritalStatus             1543 non-null   object 
 8   Education                 1543 non-null   object 
 9   PerformanceRating         1536 non-null   float64
 10  TrainingHours             1352 non-null   float64
 11  NumProjects               1444 non-null   float64
 12  YearsSincePromotion       1542 non-null   float64
 13  EnvironmentSatisfaction   1515 non-null   float64
 14  ChurnLikelihood           1543 non-null   object 
dtypes: float64(9), object(6)
memory usage: 180.9+ KB
```

Fill numerical value(s)

In [30]:

```
for col in df.select_dtypes(include=['int64', 'float64']).columns:
    df[col].fillna(df[col].mean(), inplace=True)

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

Out[30]:

```
Branch                     0
Tenure                     0
Salary                     0
Department                 0
JobSatisfaction            0
WorkLifeBalance            0
CommuteDistance            0
MaritalStatus              0
Education                  0
PerformanceRating          0
TrainingHours              0
NumProjects                0
YearsSincePromotion        0
EnvironmentSatisfaction    0
ChurnLikelihood            0
dtype: int64
```

In [31]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1543 entries, 0 to 1542
Data columns (total 15 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Branch                    1543 non-null   object 
 1   Tenure                    1543 non-null   float64
 2   Salary                    1543 non-null   float64
 3   Department                1543 non-null   object 
 4   JobSatisfaction           1543 non-null   float64
 5   WorkLifeBalance           1543 non-null   float64
 6   CommuteDistance           1543 non-null   object 
 7   MaritalStatus             1543 non-null   object 
 8   Education                 1543 non-null   object 
 9   PerformanceRating         1543 non-null   float64
 10  TrainingHours             1543 non-null   float64
 11  NumProjects               1543 non-null   float64
 12  YearsSincePromotion       1543 non-null   float64
 13  EnvironmentSatisfaction   1543 non-null   float64
 14  ChurnLikelihood           1543 non-null   object 
dtypes: float64(9), object(6)
memory usage: 180.9+ KB
```

Outlier Treatment

Visualize the outliers of the numerical features

In [32]:

```
# Plot / Visualize the outliers of the numerical features
import matplotlib.pyplot as plt
import plotly.express as px

for col in df.select_dtypes(include=['int64', 'float64']).columns:
    fig = px.box(
        data_frame=df,
        x=col,
        orientation='h',
        title=f'Boxplot of the Target ({col}) - With Outliers'
    )
    fig.show()
```

Handling Outliers

Create a mask to filter out the outliers for 'Age'

In [33]:

```
mask_Tenure = df['Tenure'] <= 17

fig = px.box(
    data_frame=df[mask_Tenure],
    x='Tenure',
    orientation='h',
    title='Boxplot of the Target (Tenure) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'Salary'

In [34]:

```
mask_Salary1 = df['Salary'] >= 44_500
mask_Salary2 = df['Salary'] <= 88_000

fig = px.box(
    data_frame=df[mask_Salary1 & mask_Salary2],
    x='Salary',
    orientation='h',
    title='Boxplot of the Target (Salary) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'JobSatisfaction'

In [35]:

```
mask_JobSatisfaction = df['JobSatisfaction'] >= 2

fig = px.box(
    data_frame=df[mask_JobSatisfaction],
    x='JobSatisfaction',
    orientation='h',
    title='Boxplot of the Target (JobSatisfaction) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'WorkLifeBalance'

In [36]:

```
mask_WorkLifeBalance1 = df['WorkLifeBalance'] >= 2.840207
mask_WorkLifeBalance2 = df['WorkLifeBalance'] <= 4.712464

fig = px.box(
    data_frame=df[mask_WorkLifeBalance1 & mask_WorkLifeBalance2],
    x='WorkLifeBalance',
    orientation='h',
    title='Boxplot of the Target (WorkLifeBalance) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'PerformanceRating'

In [37]:

```
mask_PerformanceRating1 = df['PerformanceRating'] >= 2.835084
mask_PerformanceRating2 = df['PerformanceRating'] <= 4.13773

fig = px.box(
    data_frame=df[mask_PerformanceRating1 & mask_PerformanceRating2],
    x='PerformanceRating',
    orientation='h',
    title='Boxplot of the Target (PerformanceRating) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'TrainingHours'

In [38]:

```
mask_TrainingHours = df['TrainingHours'] <= 57

fig = px.box(
    data_frame=df[mask_TrainingHours],
    x='TrainingHours',
    orientation='h',
    title='Boxplot of the Target (TrainingHours) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'NumProjects'

In [39]:

```
mask_NumProjects = df['NumProjects'] <= 5.4

fig = px.box(
    data_frame=df[mask_NumProjects],
    x='NumProjects',
    orientation='h',
    title='Boxplot of the Target (NumProjects) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'YearsSincePromotion'

In [40]:

```
mask_YearsSincePromotion = df['YearsSincePromotion'] <= 2
```

```
fig = px.box(
    data_frame=df[mask_YearsSincePromotion],
    x='YearsSincePromotion',
    orientation='h',
    title='Boxplot of the Target (YearsSincePromotion) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Create a mask to filter out the outliers for 'EnvironmentSatisfaction'

In [41]:

```
mask_EnvironmentSatisfaction = df['EnvironmentSatisfaction'] <= 4.2

fig = px.box(
    data_frame=df[mask_EnvironmentSatisfaction],
    x='EnvironmentSatisfaction',
    orientation='h',
    title='Boxplot of the Target (EnvironmentSatisfaction) - Without Outliers')

fig.update_layout(xaxis_title='Target')
fig.show()
```

Filtering out the outliers

In [42]:

```
df = df[mask_Tenure & mask_Salary1 & mask_Salary2 & mask_JobSatisfaction & mask_WorkLifeBalance1 & mask_WorkLifeBalance2 & mask_PerformanceRating1 & mask_PerformanceRating2 & mask_TrainingHours & mask_NumProjects & mask_YearsSincePromotion & mask_EnvironmentSatisfaction]

print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 904 entries, 1 to 1541
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Branch                   904 non-null    object 
 1   Tenure                   904 non-null    float64
 2   Salary                   904 non-null    float64
 3   Department               904 non-null    object 
 4   JobSatisfaction          904 non-null    float64
 5   WorkLifeBalance          904 non-null    float64
 6   CommuteDistance          904 non-null    object 
 7   MaritalStatus            904 non-null    object 
 8   Education                904 non-null    object 
 9   PerformanceRating        904 non-null    float64
 10  TrainingHours            904 non-null    float64
 11  NumProjects              904 non-null    float64
 12  YearsSincePromotion      904 non-null    float64
 13  EnvironmentSatisfaction  904 non-null    float64
 14  ChurnLikelihood          904 non-null    object 
dtypes: float64(9), object(6)
memory usage: 113.0+ KB
None
```

Out[42]:

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education
1	Chicago	14.0	72000.0	Accounting	4.0	4.0	Short	Single	Bachelor
3	Scranton	2.0	55000.0	Legal	3.0	3.5	Short	Married	Bachelor

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education
4	Scranton	10.0	55500.0	Legal	3.0	3.0	Medium	Married	Bachelor
6	Boston	10.0	82000.0	Sales	5.0	3.0	Medium	Married	Bachelor
7	New York	6.0	59000.0	Administration	3.0	3.5	Short	Divorced	High School

Scaling

In [43]:

```
df['ChurnLikelihood'] = df['ChurnLikelihood'].map({'Slightly Likely to Churn' : 0, 'Mode
rately Likely to Churn' : 1, 'Highly Likely to Churn' : 2}).astype('int')
```

6. Modeling

Split Data

In [44]:

```
from sklearn.model_selection import train_test_split

X = df.drop(columns=['ChurnLikelihood'], inplace=False)
y = df['ChurnLikelihood']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

In [45]:

```
# print(X)
X.info()
```

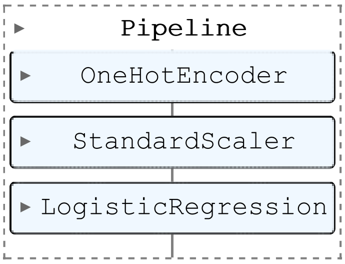
```
<class 'pandas.core.frame.DataFrame'>
Index: 904 entries, 1 to 1541
Data columns (total 14 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Branch                    904 non-null    object 
 1   Tenure                    904 non-null    float64
 2   Salary                    904 non-null    float64
 3   Department                904 non-null    object 
 4   JobSatisfaction           904 non-null    float64
 5   WorkLifeBalance           904 non-null    float64
 6   CommuteDistance           904 non-null    object 
 7   MaritalStatus             904 non-null    object 
 8   Education                 904 non-null    object 
 9   PerformanceRating         904 non-null    float64
 10  TrainingHours             904 non-null    float64
 11  NumProjects               904 non-null    float64
 12  YearsSincePromotion       904 non-null    float64
 13  EnvironmentSatisfaction   904 non-null    float64
dtypes: float64(9), object(5)
memory usage: 105.9+ KB
```

Build Model

In [46]:

```
from sklearn.pipeline import make_pipeline
from category_encoders import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

model_dt = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    DecisionTreeClassifier()) # build model

model_rf = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    RandomForestClassifier()) # build model

model_lr = make_pipeline(
    OneHotEncoder(use_cat_names=True), # encode cat features
    StandardScaler(), # imputation
    LogisticRegression()) # build model

# fit the model
model_dt.fit(X_train, y_train)
model_rf.fit(X_train, y_train)
model_lr.fit(X_train, y_train)
```

Out[46]:



Accuracy of Model

In [47]:

```
from sklearn.metrics import accuracy_score

y_pred = model_dt.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Decision Tree Accuracy:", (accuracy*100).__round__(4))

y_pred = model_rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Classifier:", (accuracy*100).__round__(4))

y_pred = model_lr.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Logistic Regression:", (accuracy*100).__round__(4))
```

```
Decision Tree Accuracy: 97.7901
Random Forest Classifier: 98.3425
Logistic Regression: 98.895
```

Evaluate

In [48]:

```
from sklearn.metrics import mean_absolute_error

# Decision Tree
# Predict the train data
y_pred_training = model_dt.predict(X_train)
y_pred_test = model_dt.predict(X_test)
```

```
# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Random Forest Regressor
# Predict the train data
y_pred_training = model_rf.predict(X_train)
y_pred_test = model_rf.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))

# Logistic Regression
# Predict the train data
y_pred_training = model_lr.predict(X_train)
y_pred_test = model_lr.predict(X_test)

# Compute MAE
print("Training MAE:", round(mean_absolute_error(y_train, y_pred_training),2))
print("Test data MAE:", round(mean_absolute_error(y_test, y_pred_test),2))
```

```
Training MAE: 0.0
Test data MAE: 0.02
Training MAE: 0.0
Test data MAE: 0.02
Training MAE: 0.01
Test data MAE: 0.01
```

The Logistic Regression Model will be used, seeing as it's accuracy is the highest and the MAE of the test data is lower/the same as the training MAE.

Feature Importance

Extract the feature names and importance from the model

In [49]:

```
features = model_lr.named_steps["onehotencoder"].get_feature_names()
coefs = model_lr.named_steps["logisticregression"].coef_[0]
```

```
C:\Users\hroux\AppData\Roaming\Python\Python311\site-packages\category_encoders\utils.py:
366: FutureWarning:

`get_feature_names` is deprecated in all of sklearn. Use `get_feature_names_out` instead.
```

In [50]:

```
import numpy as np

odds_ratios = pd.Series(np.exp(coefs), index=features).sort_values()
odds_ratios.head()
```

Out[50]:

```
Branch_Miami            0.519009
TrainingHours           0.596666
Branch_Atlanta          0.610408
Branch_Seattle          0.663997
Education_High School   0.671927
dtype: float64
```

Plot the Feature Importance

In [51]:

```
plt.Figure(figsize=(15,10))
fig = px.bar(
    data_frame=odds_ratios,
    x=odds_ratios[:10].values,
    y=odds_ratios[:10].index,
    title="Customer Churn Logistic Regression, Feature Importance (Odds Ratio)"
)

fig.update_layout(xaxis_title='Odds Ratio', yaxis_title='')
fig.show()
```

Predict

In [52]:

```
def make_prediction(row):

    data = {
        "Branch": row[1],
        "Tenure": row[2],
        "Salary": row[3],
        "Department": row[4],
        "JobSatisfaction": row[5],
        "WorkLifeBalance": row[6],
        "CommuteDistance": row[7],
        "MaritalStatus": row[8],
        "Education": row[9],
        "PerformanceRating": row[10],
        "TrainingHours": row[11],
        "NumProjects": row[12],
        "YearsSincePromotion": row[13],
        "EnvironmentSatisfaction": row[14]
    }

    df_predict = pd.DataFrame(data, index=[0])
    prediction_dt = model_dt.predict(df_predict)[0]
    prediction_rf = model_rf.predict(df_predict)[0]
    prediction_lr = model_lr.predict(df_predict)[0]

    return f"Decision Tree: {prediction_dt}; Random Forest: {prediction_rf} Logistic Regr
ession: {prediction_lr}"
```

In [53]:

```
print(make_prediction(pd.Series([1,'San Francisco',4.0,63000.0,'Legal',3.0,3.0,'Long','M
arried','High School',3.0,88.0,3.0,0.0,2.0]))) # Should output 2
print(make_prediction(pd.Series([2,'Chicago',14.0,72000.0,'Accounting',4.0,4.0,'Short','
Single','Bachelor',3.6666666666666665,30.0,3.0,2.0,3.0]))) # Should output 1
```

```
Decision Tree: 2; Random Forest: 2 Logistic Regression: 2
Decision Tree: 1; Random Forest: 1 Logistic Regression: 1
```

Save Model

In [54]:

```
import joblib
# Save Model
joblib.dump(model_dt, '../../artifacts/model.pkl')
```

Out[54]:

```
['../../artifacts/model.pkl']
```

Dash App

In [55]:

```python
import dash
from dash import dcc, html
from dash.dependencies import Input, Output
import joblib
import pandas as pd

# Load the trained model
model = joblib.load("../../artifacts/model.pkl")

# Initialize the Dash app
app = dash.Dash(__name__, external_stylesheets=['../../style.css'])

# Define the layout of the app
app.layout = html.Div([
    html.H1("Employee Churn Prediction", style={'color': 'blue', 'font-size': '24px'}),

    html.Label("Branch"),
    dcc.Dropdown(
        id="branch",
        options=[
            {'label': 'San Francisco', 'value': 'San Francisco'},
            {'label': 'Chicago', 'value': 'Chicago'},
            {'label': 'Miami', 'value': 'Miami'},
            {'label': 'Scranton', 'value': 'Scranton'},
            {'label': 'Boston', 'value': 'Boston'},
            {'label': 'New York', 'value': 'New York'},
            {'label': 'Philadelphia', 'value': 'Philadelphia'},
            {'label': 'Los Angeles', 'value': 'Los Angeles'},
            {'label': 'Seattle', 'value': 'Seattle'},
            {'label': 'Atlanta', 'value': 'Atlanta'},
            {'label': 'Denver', 'value': 'Denver'},
            {'label': 'Dallas', 'value': 'Dallas'}
        ],
        value='San Francisco'
    ),

    html.Label("Tenure"),
    dcc.Input(id="tenure", type="number", value=4.0),

    html.Label("Salary"),
    dcc.Input(id="salary", type="number", value=63000.0),

    html.Label("Department"),
    dcc.Dropdown(
        id="department",
        options=[
            {'label': 'Legal', 'value': 'Legal'},
            {'label': 'Accounting', 'value': 'Accounting'},
            {'label': 'Quality Assurance', 'value': 'Quality Assurance'},
            {'label': 'Customer Service', 'value': 'Customer Service'},
            {'label': 'Sales', 'value': 'Sales'},
            {'label': 'Administration', 'value': 'Administration'},
            {'label': 'Facilities Management', 'value': 'Facilities Management'},
            {'label': 'Research and Development', 'value': 'Research and Development'},
            {'label': 'Operations', 'value': 'Operations'},
            {'label': 'Marketing', 'value': 'Marketing'},
            {'label': 'Public Relations', 'value': 'Public Relations'},
            {'label': 'IT Support', 'value': 'IT Support'},
            {'label': 'Procurement', 'value': 'Procurement'},
            {'label': 'Product Management', 'value': 'Product Management'},
            {'label': 'Human Resources', 'value': 'Human Resources'}
        ],
        value='Legal'
    ),

    html.Label("JobSatisfaction"),
    dcc.Input(id="job", type="number", value=3.0),

    html.Label("WorkLifeBalance"),
    dcc.Input(id="balance", type="number", value=3.0),
    html.Label("CommuteDistance"),
    dcc.Dropdown(
        id="commute",
        options=[
            {'label': 'Short', 'value': 'Short'},
            {'label': 'Medium', 'value': 'Medium'},
            {'label': 'Long', 'value': 'Long'}
        ],
        value='Long'
    ),

    html.Label("MaritalStatus"),
    dcc.Dropdown(
        id="married",
        options=[
            {'label': 'Single', 'value': 'Single'},
            {'label': 'Married', 'value': 'Married'},
        ],
        value='Married'
    ),

    html.Label("Education"),
    dcc.Dropdown(
        id="education",
        options=[
            {'label': 'High School', 'value': 'High School'},
            {'label': 'Bachelor', 'value': 'Bachelor'},
            {'label': 'Master', 'value': 'Master'},
            {'label': 'Doctor', 'value': 'Doctor'}
        ],
        value='High School'
    ),

    html.Label("PerformanceRating"),
    dcc.Input(id="rating", type="number", value=3.0),

    html.Label("TrainingHours"),
    dcc.Input(id="training", type="number", value=88.0),

    html.Label("NumProjects"),
    dcc.Input(id="projects", type="number", value=3.0),

    html.Label("YearsSincePromotion"),
    dcc.Input(id="promotion", type="number", value=0.0),

    html.Label("EnvironmentSatisfaction"),
    dcc.Input(id="satisfaction", type="number", value=2.0),

    html.Button("Predict", id="predict_button", n_clicks=0),
    html.Div(id="prediction_output", style={'color': 'red'})
], style={'display': 'flex', 'flexDirection': 'column', 'gap': '1em'})

# Define callback to update prediction result
@app.callback(
    Output("prediction_output", "children"),
    [Input("predict_button", "n_clicks")],

    [Input("branch", "value"),
        Input("tenure", "value"),
        Input("salary", "value"),
        Input("department", "value"),
        Input("job", "value"),
        Input("balance", "value"),
        Input("commute", "value"),
        Input("married", "value"),
        Input("education", "value"),
        Input("rating", "value"),
        Input("training", "value"),
        Input("projects", "value"),
        Input("promotion", "value"),
        Input("satisfaction", "value")]
)
```

```python
def update_prediction(n_clicks, branch, tenure, salary, department, job, balance, commute, married, education, rating, training, projects, promotion, satisfaction):
    if n_clicks > 0:
        # Preprocess input data
        data = pd.DataFrame({
            "Branch": [branch],
            "Tenure": [tenure],
            "Salary": [salary],
            "Department": [department],
            "JobSatisfaction": [job],
            "WorkLifeBalance": [balance],
            "CommuteDistance": [commute],
            "MaritalStatus": [married],
            "Education": [education],
            "PerformanceRating": [rating],
            "TrainingHours": [training],
            "NumProjects": [projects],
            "YearsSincePromotion": [promotion],
            "EnvironmentSatisfaction": [satisfaction]
        })
        # Make prediction
        prediction = model.predict(data)[0]

        if prediction == 2:
            prediction_str = 'Highly Likely to Churn'
        elif prediction == 1:
            prediction_str = 'Moderately Likely to Churn'
        else:
            prediction_str = 'Slightly Likely to Churn'

        return html.Div(f"Churn Likelihood: {prediction_str}")
    else:
        return ""

# Run the app
if __name__ == "__main__":
    app.run_server(debug=True)
```