Employee Turnover Analytics pjt2

May 27, 2025

1 EMPLOYEE TURNOVER ANALYTICS

Prepared by: Vrinda Pillai Date: 27-May-2025 Objective: Predict Employee Turnover within the company by evaluating patterns in workstyle

1.1 1. Data Wrangling

Load and Inspect Data

[7]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler

#Load latest dataset for this project from Kaggle
df = pd.read_csv("HR_comma_sep.csv")
df.head()
```

[7]:
```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159

   time_spend_company  Work_accident  left  promotion_last_5years  sales  \
0                   3              0     1                      0  sales
1                   6              0     1                      0  sales
2                   4              0     1                      0  sales
3                   5              0     1                      0  sales
4                   3              0     1                      0  sales

   salary
0     low
1  medium
2  medium
3     low
4     low
```

[9]:
```
df.shape
```

[9]: (14999, 10)

[11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[13]:
```
df.describe()
```

[13]:
```
       satisfaction_level  last_evaluation  number_project  \
count        14999.000000     14999.000000    14999.000000
mean             0.612834         0.716102        3.803054
std              0.248631         0.171169        1.232592
min              0.090000         0.360000        2.000000
25%              0.440000         0.560000        3.000000
50%              0.640000         0.720000        4.000000
75%              0.820000         0.870000        5.000000
max              1.000000         1.000000        7.000000

       average_montly_hours  time_spend_company  Work_accident          left  \
count          14999.000000        14999.000000   14999.000000  14999.000000
mean             201.050337            3.498233       0.144610      0.238083
std               49.943099            1.460136       0.351719      0.425924
min               96.000000            2.000000       0.000000      0.000000
25%              156.000000            3.000000       0.000000      0.000000
50%              200.000000            3.000000       0.000000      0.000000
75%              245.000000            4.000000       0.000000      0.000000
max              310.000000           10.000000       1.000000      1.000000

       promotion_last_5years
count           14999.000000
```

```
mean                 0.021268
std                  0.144281
min                  0.000000
25%                  0.000000
50%                  0.000000
75%                  0.000000
max                  1.000000
```

[15]:
```
# Handling missing Data
df.isna().sum()
```

[15]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_montly_hours     0
time_spend_company       0
Work_accident            0
left                     0
promotion_last_5years    0
sales                    0
salary                   0
dtype: int64
```

Since there are no missing values, no further treatment is needed.

[17]:
```
df.drop_duplicates()
```

[17]:
```
       satisfaction_level  last_evaluation  number_project  \
0                    0.38             0.53               2
1                    0.80             0.86               5
2                    0.11             0.88               7
3                    0.72             0.87               5
4                    0.37             0.52               2
…                       …                …               …
11995                0.90             0.55               3
11996                0.74             0.95               5
11997                0.85             0.54               3
11998                0.33             0.65               3
11999                0.50             0.73               4

       average_montly_hours  time_spend_company  Work_accident  left  \
0                       157                   3              0     1
1                       262                   6              0     1
2                       272                   4              0     1
3                       223                   5              0     1
4                       159                   3              0     1
…                         …                   …              …     …
11995                   259                  10              1     0
```

```
11996                    266                   10              0      0
11997                    185                   10              0      0
11998                    172                   10              0      0
11999                    180                    3              0      0

       promotion_last_5years       sales  salary
0                          0       sales     low
1                          0       sales  medium
2                          0       sales  medium
3                          0       sales     low
4                          0       sales     low
…                        …           …     …
11995                      1  management    high
11996                      1  management    high
11997                      1  management    high
11998                      1   marketing    high
11999                      0          IT     low

[11991 rows x 10 columns]
```

1.2 2. Data Analysis

Identify the factors contributed most to employee turnover by EDA

[19]:

```python
# Correlation Matrix
import numpy as np
```

[21]:

```python
df_numeric = df.select_dtypes(include=np.number)
```

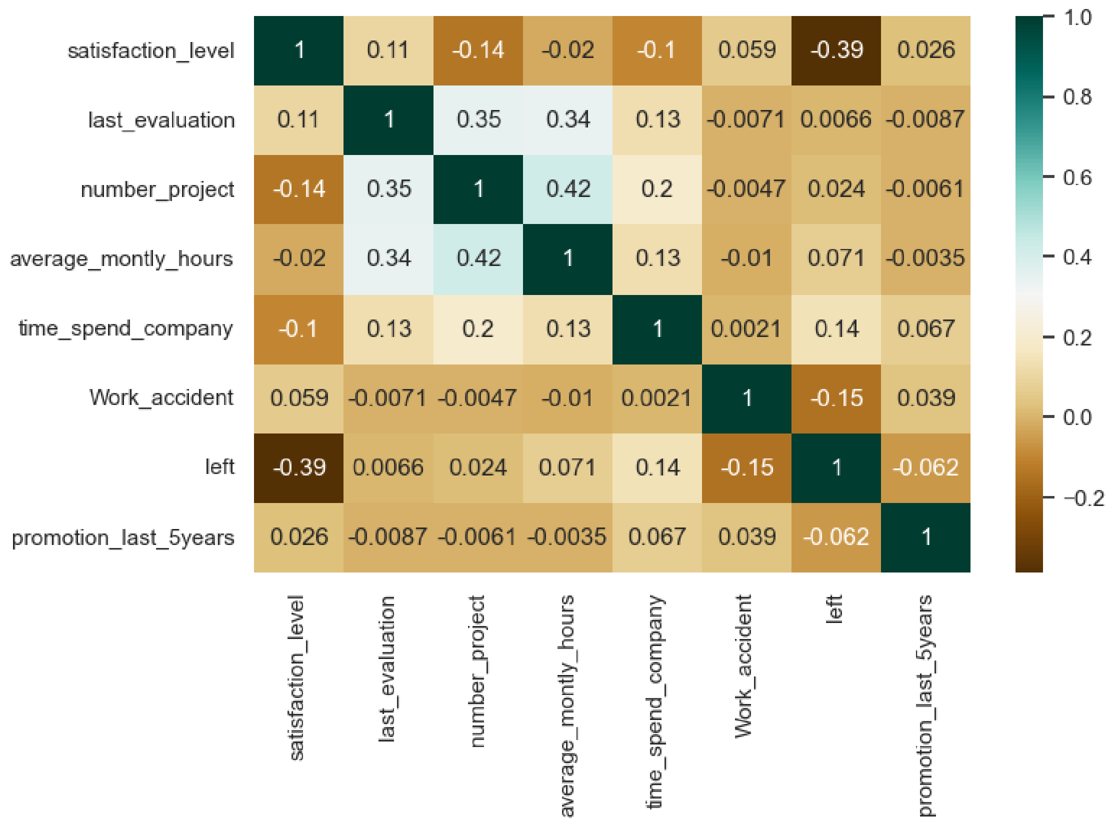
[23]:

```python
#relationship between variables using heatmap
corr = df_numeric.corr()
print(corr)
sns.set_theme(rc= {'figure.figsize':(8,5)})
sns.heatmap(corr,cmap='BrBG',annot=True)
```

```
                       satisfaction_level  last_evaluation  number_project  \
satisfaction_level               1.000000         0.105021       -0.142970
last_evaluation                  0.105021         1.000000        0.349333
number_project                  -0.142970         0.349333        1.000000
average_montly_hours            -0.020048         0.339742        0.417211
time_spend_company              -0.100866         0.131591        0.196786
Work_accident                    0.058697        -0.007104       -0.004741
left                            -0.388375         0.006567        0.023787
promotion_last_5years            0.025605        -0.008684       -0.006064

                       average_montly_hours  time_spend_company  \
satisfaction_level                -0.020048           -0.100866
last_evaluation                    0.339742            0.131591
```

```
number_project                   0.417211            0.196786
average_montly_hours             1.000000            0.127755
time_spend_company               0.127755            1.000000
Work_accident                   -0.010143            0.002120
left                             0.071287            0.144822
promotion_last_5years           -0.003544            0.067433

                       Work_accident       left  promotion_last_5years
satisfaction_level          0.058697 -0.388375               0.025605
last_evaluation            -0.007104  0.006567              -0.008684
number_project             -0.004741  0.023787              -0.006064
average_montly_hours       -0.010143  0.071287              -0.003544
time_spend_company          0.002120  0.144822               0.067433
Work_accident               1.000000 -0.154622               0.039245
left                       -0.154622  1.000000              -0.061788
promotion_last_5years       0.039245 -0.061788               1.000000
```

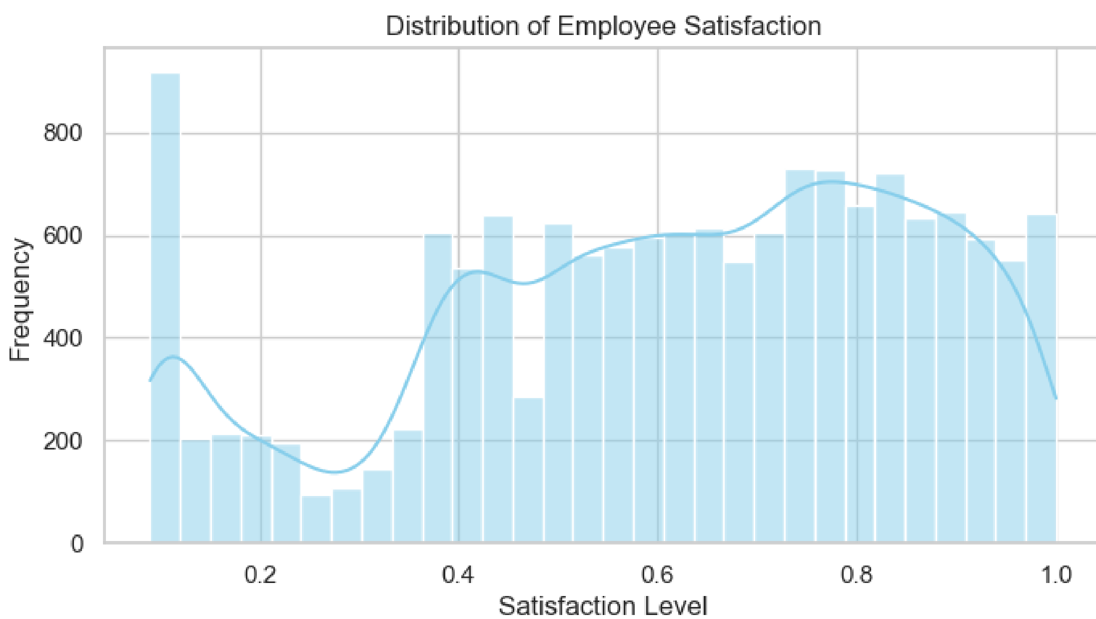
[23]: <Axes: >



1.As the Target variable in this case is 'left' there is a strong negative correlation between left and satisfaction level. Lower satisfaction is linked to employees leaving 2.time_spend_company: 0.14, Slight positive correlation: Longer tenure might be linked to higher attrition, possibly due to stagnation. 3.average_montly_hours: 0.071 Weak correlation, but slightly positive — may indicate overwork, though the correlation is not strong. 4.Work_accident: -0.15, Mild negative correlation: Employees who had accidents are less likely to leave (possibly due to retention efforts post-accident). 5.promotion_last_5years: -0.062, Very weak negative correlation: Those who got promoted were slightly less likely to leave. Not useful for predicting ‘left’: last_evaluation: 0.007 number_project: 0.024

feature-to-feature correlations: time spend in the company and number of projects are negatively correlated to satisfaction level. Which means satisfaction level decreases with more time spend and more number of projects. When employee is overloaded with work then satisfaction decreases and turn over increases Average monthly hours , time spend and number of projects are positively correlated to each other. last evaluation and satisfaction level are positively correlated

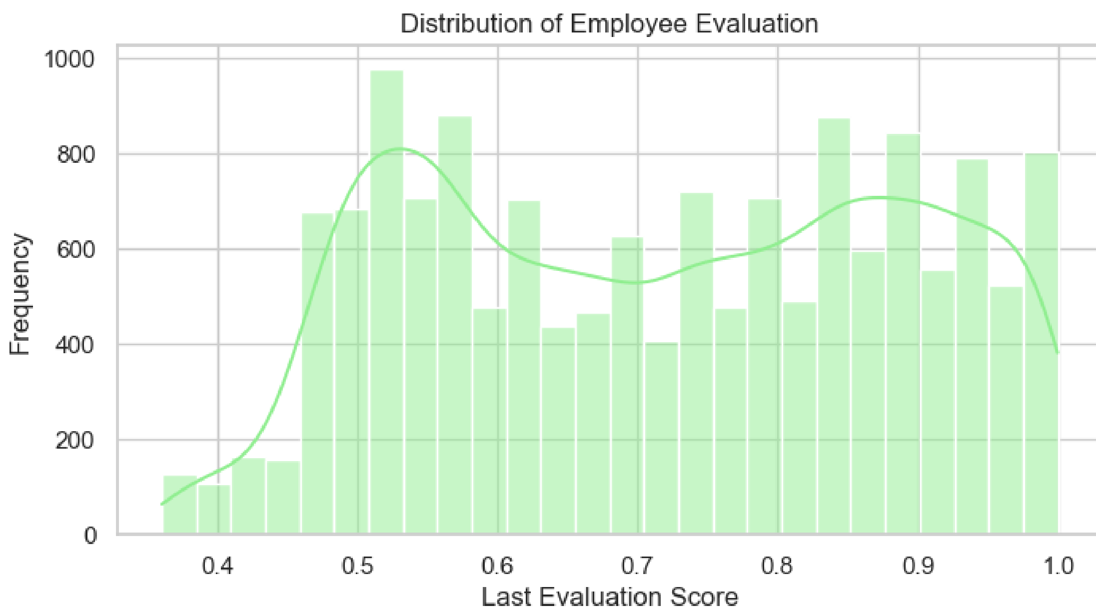
[25]:
```
#Distribution plots
sns.set(style="whitegrid")
# Plot 1: Employee Satisfaction
plt.figure(figsize=(8, 4))
sns.histplot(df['satisfaction_level'], kde=True, color='skyblue')
plt.title('Distribution of Employee Satisfaction')
plt.xlabel('Satisfaction Level')
plt.ylabel('Frequency')
plt.show()
```



The above plot shows spike at .1 which indicates very low satisfaction and spike at .7 to.9 which indicates high satisfaction This suggests that there are two distinct groups of employees: Highly dissatisfied employees (likely at risk of attrition). Highly satisfied employees (possibly stable or engaged). Gradual Increase from 0.4–0.8: The number of employees gradually increases in this range, forming a plateau before peaking again. Indicates a larger cluster of moderately to highly satisfied employees.

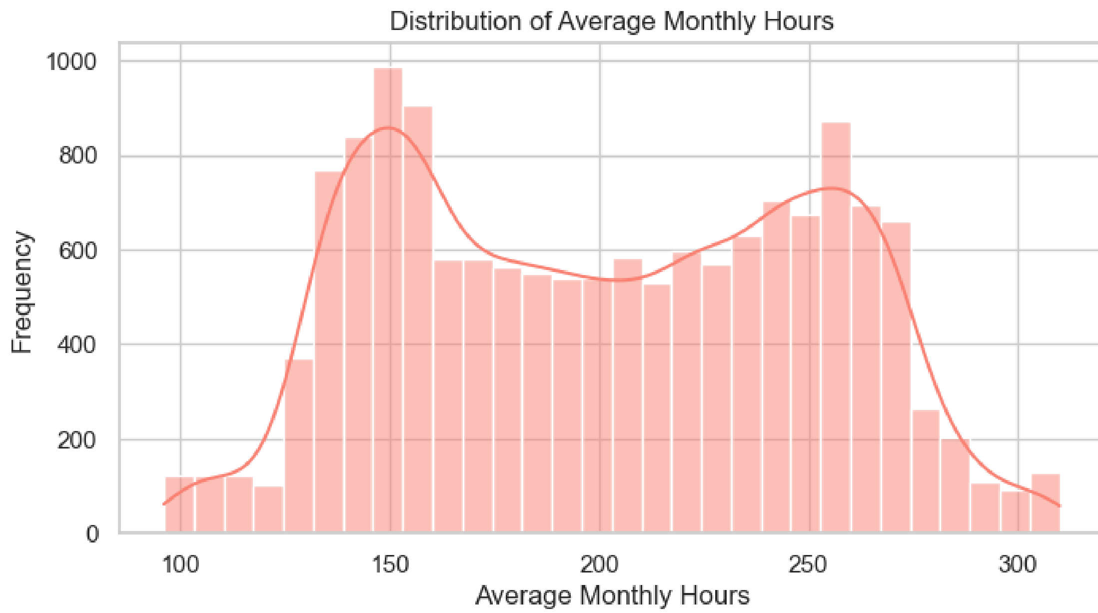
Skew and Spread: The distribution is spread across the full range (0 to 1). Slight right skew with concentration in the higher satisfaction zone (above 0.5).

[27]:
```
# Plot 2: Employee Evaluation
plt.figure(figsize=(8, 4))
sns.histplot(df['last_evaluation'], kde=True, color='lightgreen')
plt.title('Distribution of Employee Evaluation')
plt.xlabel('Last Evaluation Score')
plt.ylabel('Frequency')
plt.show()
```



Low Scores Are Rare: Very few employees have evaluation scores below 0.4. Implies underperformance is either rare or not tolerated, possibly leading to attrition or corrective action. A peak appears around 0.55–0.60, indicating that a large number of employees received average evaluation scores. After this peak, the distribution becomes more uniform or flat, particularly between 0.7 and 1.0, suggesting that many employees were evaluated highly.

[29]:
```
# Plot 3: Employee Average Monthly Hours
plt.figure(figsize=(8, 4))
sns.histplot(df['average_montly_hours'], kde=True, color='salmon')
plt.title('Distribution of Average Monthly Hours')
plt.xlabel('Average Monthly Hours')
plt.ylabel('Frequency')
plt.show()
```



The graph clearly shows two peaks:

Around 150 hours

Around 250 hours

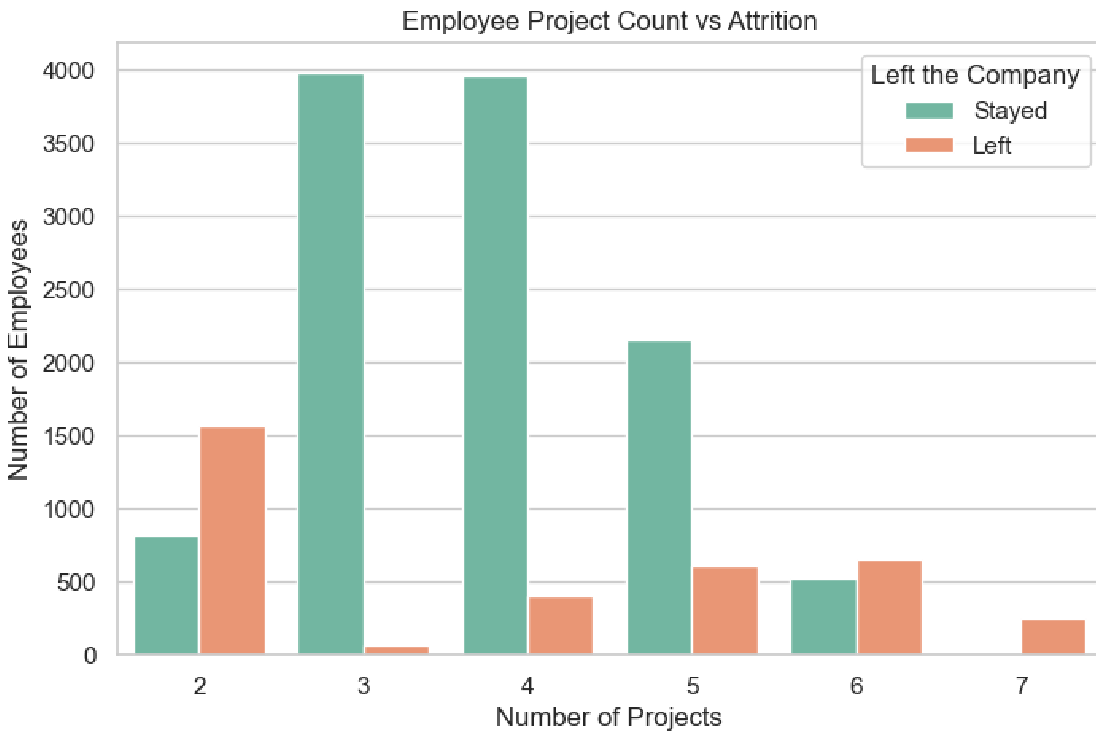
This suggests two distinct working patterns: One group of employees is working fewer hours (~150)

Another group is working very high hours (~250)

Middle Range (~200 hours): There is a dip in the number of employees working around 200 hours/month. Could indicate few employees have "average" workload—they're either under-loaded or overloaded.

Long Right Tail: A smaller number of employees work close to or beyond 300 hours per month. These could be overworked and may correlate with attrition or burnout.

[31]:
```
# Bar plot to show Employee project count of both employees who left and stayed␣
↪in organization
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='number_project', hue='left', palette='Set2')
plt.title('Employee Project Count vs Attrition')
plt.xlabel('Number of Projects')
plt.ylabel('Number of Employees')
plt.legend(title='Left the Company', labels=['Stayed', 'Left'])
plt.show()
```



When Project Count = 2:A higher number of employees left than stayed. Indicates that having too few projects may lead to dissatisfaction or underutilization.

When Project Count = 3 or 4:The majority of employees stayed. These are the safest project load levels with the highest retention.

When Project Count = 5: Still more employees stayed, but a noticeable rise in attrition. Indicates early signs of increasing workload stress.

When Project Count = 6:More employees left than stayed. Clear signal that high workload is becoming a cause for employee burnout or dissatisfaction.

When Project Count = 7: All employees with 7 projects left the company. Strong indication that extreme workload is directly linked to attrition.

Inference: There is a U-shaped relationship between project count and attrition: Low (2 projects) and high (6–7 projects) → Higher attrition. Moderate (3–4 projects) → Lower attrition and better retention. Actionable Insights: Ideal workload: Maintain employee project count around 3–4. Watch for extremes: Underworked (2 projects) might feel undervalued or unchallenged. Overworked (6–7 projects) are at high risk of leaving. HR and team leads should monitor project assignments to reduce both under- and over-utilization.

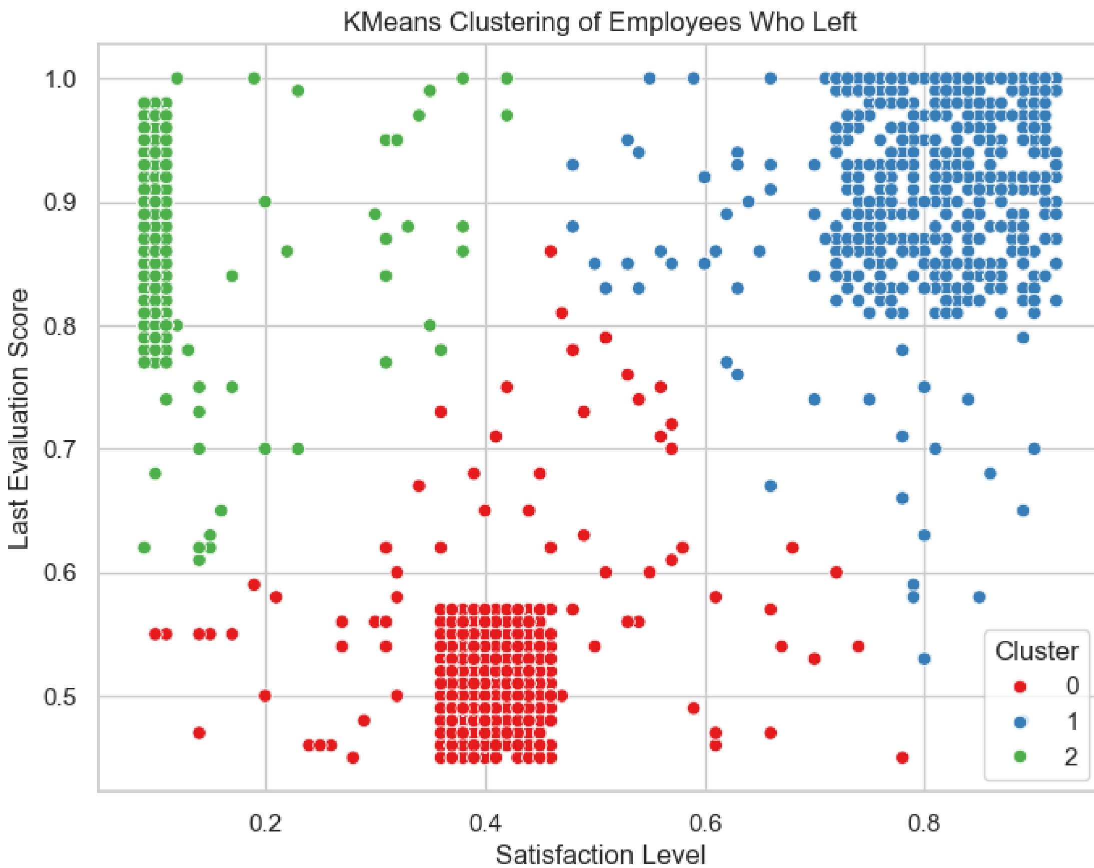
1.3 3. Data Clustering

[33]:
```python
from sklearn.cluster import KMeans
```

[35]:
```python
# Filter employees who left
df_left = df[df['left'] == 1][['satisfaction_level', 'last_evaluation']]
```

[37]:
```python
# Perform KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
df_left['Cluster'] = kmeans.fit_predict(df_left)
```

[39]:
```python
# Plot the clusters
plt.figure(figsize=(8,6))
sns.scatterplot(
    x='satisfaction_level',
    y='last_evaluation',
    hue='Cluster',
    data=df_left,
    palette='Set1'
)
plt.title('KMeans Clustering of Employees Who Left')
plt.xlabel('Satisfaction Level')
plt.ylabel('Last Evaluation Score')
plt.grid(True)
plt.show()
```



Cluster Summary: Cluster Satisfaction Evaluation Characteristics Possible Reasons for Attrition 0 (Red) Low–Medium Low–Medium Unhappy and underperforming Lack of engagement or development opportunities 1 (Blue) High High Happy and top-performing Burnout, no promotion, external offers 2 (Green)Very Low Very High Dissatisfied despite excellent performance Feeling undervalued,toxic work culture

Cluster 0: Low satisfaction, low evaluation — likely underperformers

Cluster 1: High satisfaction, high evaluation — critical loss of top talent

Cluster 2: Very low satisfaction, high evaluation — disengaged high performers

1.4 4. SMOTE technique

[41]:
```
pip install pandas scikit-learn imbalanced-learn
```

```
Requirement already satisfied: pandas in c:\users\vrinda\anaconda3\lib\site-
packages (2.2.2)
Requirement already satisfied: scikit-learn in
c:\users\vrinda\anaconda3\lib\site-packages (1.5.1)
Requirement already satisfied: imbalanced-learn in
c:\users\vrinda\anaconda3\lib\site-packages (0.12.3)
```

```
Requirement already satisfied: numpy>=1.26.0 in
c:\users\vrinda\anaconda3\lib\site-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\vrinda\anaconda3\lib\site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
c:\users\vrinda\anaconda3\lib\site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in
c:\users\vrinda\anaconda3\lib\site-packages (from pandas) (2023.3)
Requirement already satisfied: scipy>=1.6.0 in
c:\users\vrinda\anaconda3\lib\site-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in
c:\users\vrinda\anaconda3\lib\site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
c:\users\vrinda\anaconda3\lib\site-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\users\vrinda\anaconda3\lib\site-
packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[43]:

```
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
```

[45]:

```
X = df.drop('left', axis=1)
y = df['left']
```

[47]:

```
# Separate categorical and numeric variables
categorical_cols = X.select_dtypes(include=['object', 'category']).columns
numeric_cols = X.select_dtypes(include=['int64', 'float64']).columns
```

[49]:

```
# Apply get_dummies() to categorical variables
X_categorical = pd.get_dummies(X[categorical_cols], drop_first=True)
X_numeric = X[numeric_cols]
```

[51]:

```
# Combine categorical and numeric variables
X_processed = pd.concat([X_numeric, X_categorical], axis=1)
```

[53]:

```
# 4.2 Stratified split of the dataset (80:20)
X_train, X_test, y_train, y_test = train_test_split(
    X_processed, y, test_size=0.2, stratify=y, random_state=123
)
```

[55]:

```
# 4.3 Upsample the train dataset using SMOTE
smote = SMOTE(random_state=123)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

[57]:

```
# Check class distribution
print("Original training target class distribution:")
print(y_train.value_counts())
print("\nResampled training target class distribution:")
```

```python
print(y_train_resampled.value_counts())
```

```
Original training target class distribution:
left
0    9142
1    2857
Name: count, dtype: int64

Resampled training target class distribution:
left
0    9142
1    9142
Name: count, dtype: int64
```

Summary of the Result: Before SMOTE: Class 0: 9142 samples Class 1: 2857 samples (minority) After SMOTE: Class 0: 9142 samples Class 1: 9142 samples (upsampled to match class 0) output confirms that SMOTE has successfully handled the class imbalance in training data:

1.5 5-Fold cross-validation model training and performance evaluation

[62]:
```python
from sklearn.model_selection import StratifiedKFold, cross_val_predict
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import classification_report, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
```

[64]:
```python
# Reuse resampled data
X_cv, y_cv = X_train_resampled, y_train_resampled
```

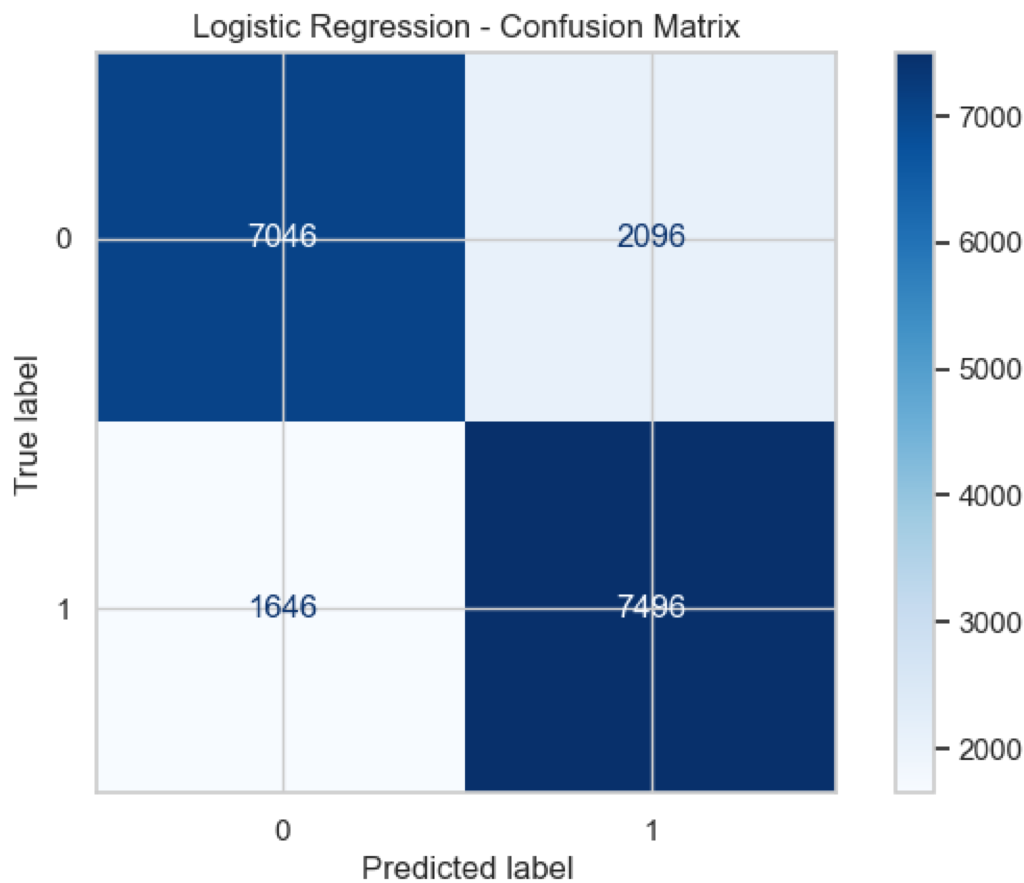
[66]:
```python
# Define models
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=123),
    'Random Forest': RandomForestClassifier(random_state=123),
    'Gradient Boosting': GradientBoostingClassifier(random_state=123)
}
```

[68]:
```python
# 5-Fold Stratified CV setup
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=123)
```

[70]:
```python
# Function to train and evaluate models
def evaluate_model(name, model, X, y):
    print(f"\n Model: {name}")

    # Cross-validated predictions
    y_pred = cross_val_predict(model, X, y, cv=cv)

    # Classification Report
    print("\nClassification Report:")
```

```python
    print(classification_report(y, y_pred))

    # Plot Confusion Matrix
    disp = ConfusionMatrixDisplay.from_predictions(y, y_pred, cmap="Blues")
    disp.ax_.set_title(f"{name} - Confusion Matrix")
    plt.show()

# Run evaluation for each model
for model_name, model in models.items():
    evaluate_model(model_name, model, X_cv, y_cv)
```

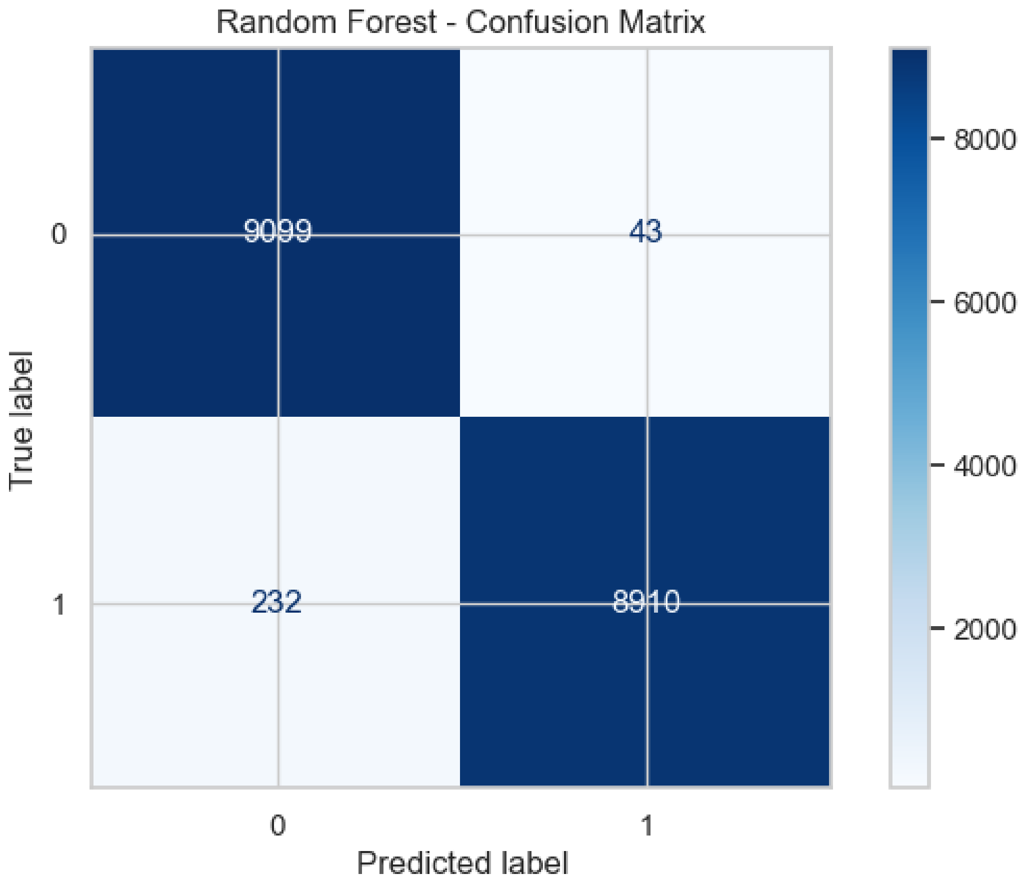
```
 Model: Logistic Regression

Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.77      0.79      9142
           1       0.78      0.82      0.80      9142

    accuracy                           0.80     18284
   macro avg       0.80      0.80      0.80     18284
weighted avg       0.80      0.80      0.80     18284
```



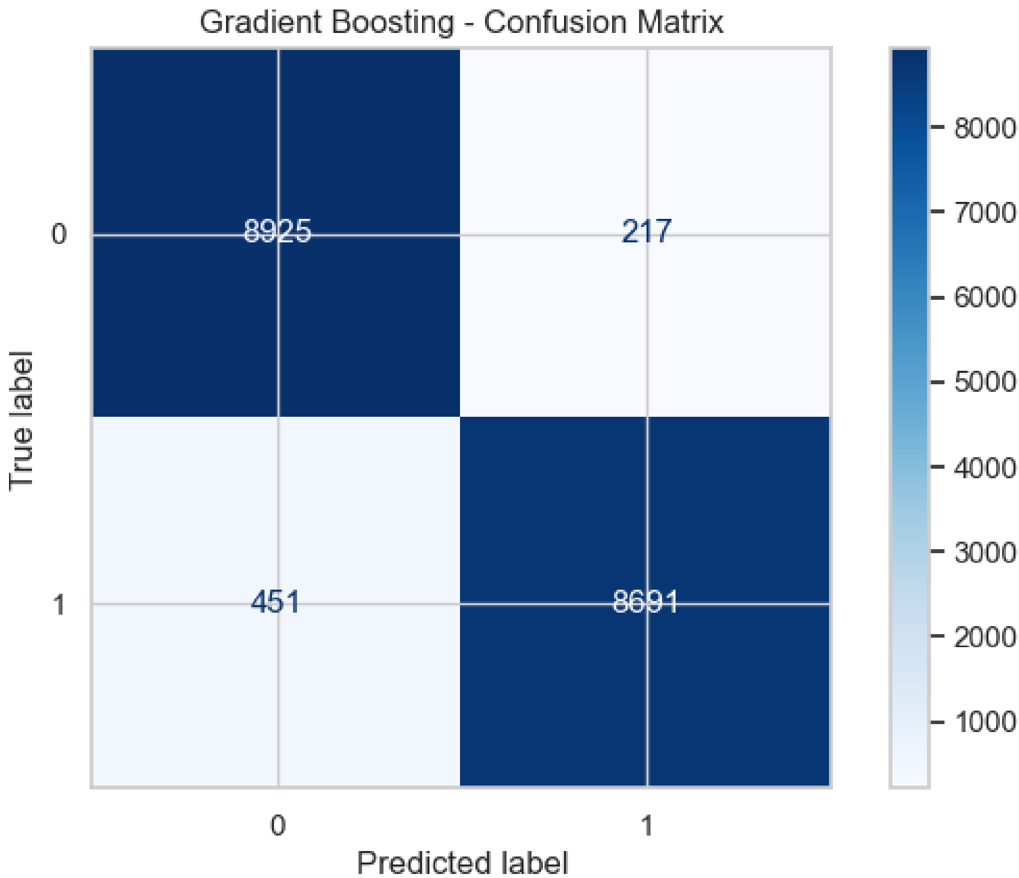
Model: Random Forest

Classification Report:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	9142
1	1.00	0.97	0.98	9142
accuracy			0.98	18284
macro avg	0.99	0.98	0.98	18284
weighted avg	0.99	0.98	0.98	18284




```
Model: Gradient Boosting

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.98      0.96      9142
           1       0.98      0.95      0.96      9142

    accuracy                           0.96     18284
   macro avg       0.96      0.96      0.96     18284
weighted avg       0.96      0.96      0.96     18284
```



1. Confusion Matrix Summary for Logistic regression: True Positives (TP) = 7496 → correctly predicted employees who left

True Negatives (TN) = 7046 → correctly predicted employees who stayed

False Positives (FP) = 2096 → predicted they would leave but they stayed

False Negatives (FN) = 1646 → predicted they would stay but they left High Recall for Class 1 (Left): 7496 / (7496 + 1646) 82% Good at catching employees who are likely to leave. Moderate False Alarm Rate: 2096 false positives — could affect interventions based on false attrition risks.

2.Confusion Matrix Summary for Random Forest: True Positives (TP) = 8910 → correctly predicted employees who left

True Negatives (TN) = 9099 → correctly predicted employees who stayed

False Positives (FP) = 43→ predicted they would leave but they stayed

False Negatives (FN) = 232 → predicted they would stay but they left

Interpretation: Accuracy = (TP + TN) / Total = (8910 + 9099) / 18284 98.3% Recall for class 1 (Left) = 8910 / (8910 + 232) 97.5% Precision for class 1 (Left) = 8910 / (8910 + 43) 99.5% Near-perfect prediction for employees who stayed. Strong performance for employees who left, with minimal false negatives. 3.Confusion Matrix Summary for Gradient Boosting: True Negatives (TN) = 8925 False Positives (FP) = 217 False Negatives (FN) = 451 True Positives (TP) = 8691

Key Calculations: Accuracy = (TP + TN) / Total = (8691 + 8925) / 18284 96% Precision (Class 1) = 8691 / (8691 + 217) 0.98 Recall (Class 1) = 8691 / (8691 + 451) 0.95 F1-Score (Class 1) 0.96

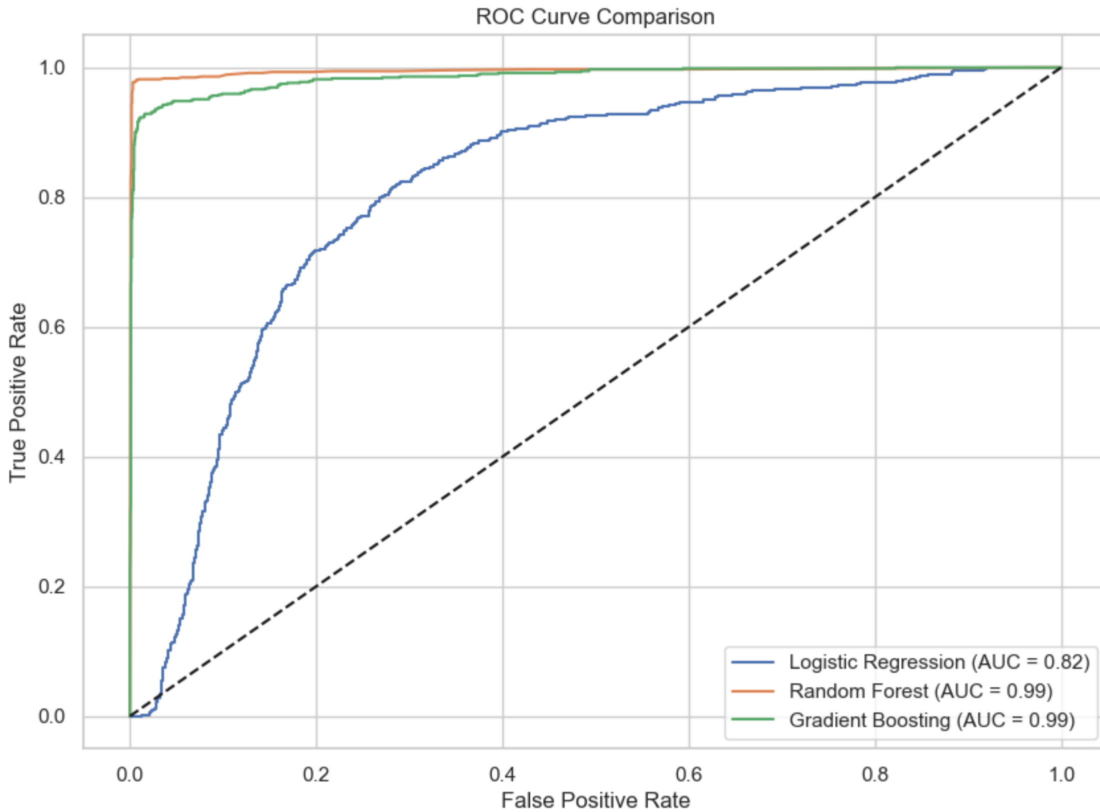
Interpretation: Very high precision for predicting attrition (class 1) — few false alarms. Slight drop in recall compared to Random Forest — missed more who actually left. Balanced performance, nearly matching classification report — solid second-best model.

Observations: Random Forest leads in almost every metric — especially precision and F1. Gradient Boosting is slightly more balanced but with a small dip in recall for "left" class. Logistic Regression lags behind — useful for interpretability but not optimal here.

1.6 6. ROC Curve

[73]:
```python
from sklearn.metrics import roc_curve, auc
```

[76]:
```python
# Plot ROC Curve
plt.figure(figsize=(10, 7))

for name, model in models.items():
    model.fit(X_train_resampled, y_train_resampled)
    y_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc:.2f})")

plt.plot([0, 1], [0, 1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve Comparison")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



ROC/AUC Curve Analysis: Logistic Regression: AUC = 0.82 Random Forest: AUC = 0.99 Gradient Boosting: AUC = 0.99

Higher AUC indicates better distinction between classes. Both Random Forest and Gradient Boosting show excellent class separation.

Precision vs Recall – Which Metric to Prioritize? Precision: Out of predicted positives, how many are actually positive?

Recall (Sensitivity): Out of actual positives, how many did we correctly identify?

In employee attrition prediction (as in this case with "left" as target): Recall is more critical, especially for class 1 (employee leaving). Missing an actual employee planning to leave (False Negative) is more costly than falsely predicting someone might leave (False Positive). Because high recall ensures fewer missed actual leavers, helping HR proactively intervene.

Best Model: Random Forest Classifier Justification: Highest Recall (0.97) and Precision (1.00) on class 1. Best AUC (0.99) — excellent at distinguishing between employees staying vs leaving. Lowest False Negatives (only 232) compared to others.

1.7 7. Probability prediction using Best Model and Retention strategies

[82]:
```python
best_model = RandomForestClassifier(n_estimators = 100,random_state = 42)
best_model.fit(X_train_resampled, y_train_resampled)
# Predict probabilities
y_probs = best_model.predict_proba(X_test)[:, 1]  # Probability of class 1␣
↪(employee will leave)
```

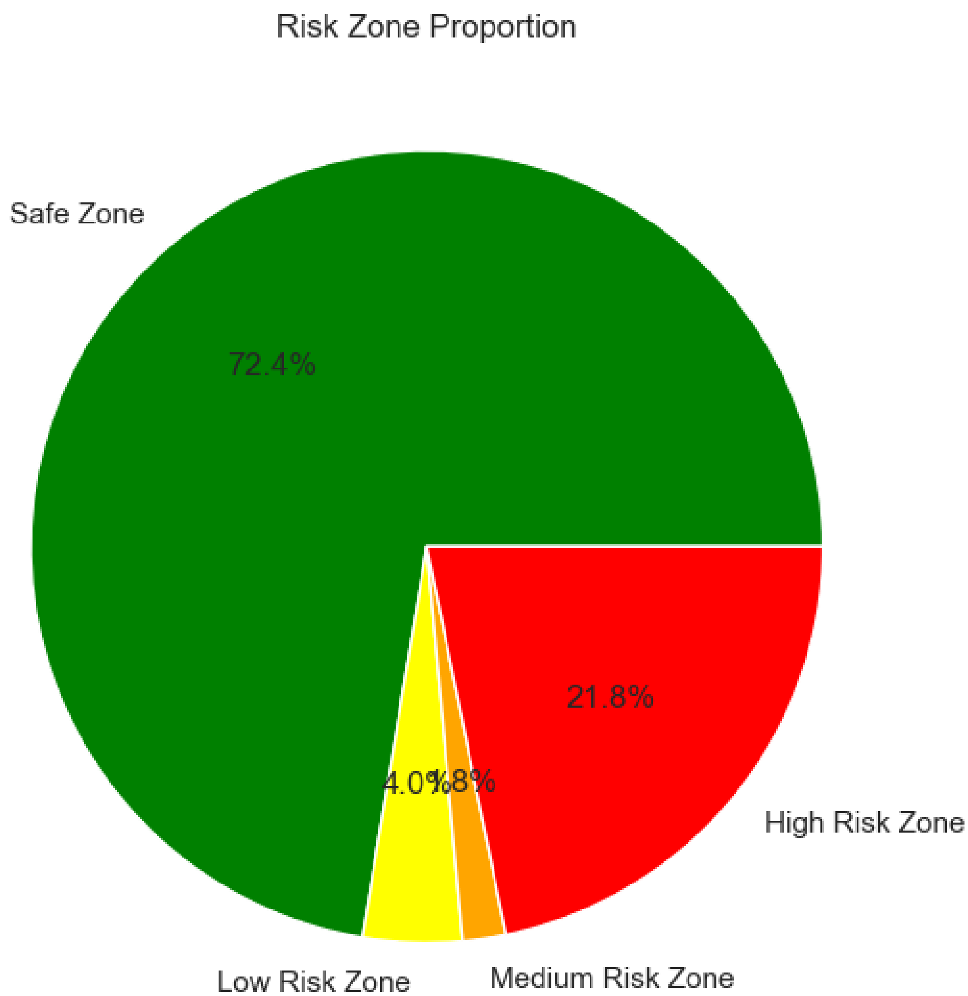
[88]:
```python
#Categorize probabilities into zones
def risk_zone(prob):
    if prob < 0.2:
        return 'Safe Zone'
    elif prob < 0.6:
        return 'Low Risk Zone'
    elif prob < 0.9:
        return 'Medium Risk Zone'
    else:
        return 'High Risk Zone'
# Create result data frame
results_df = X_test.copy()
results_df["Actual_Left"] = y_test.values
results_df["Leave_Probability"] = y_probs
results_df["Risk_Zone"] = results_df["Leave_Probability"].apply(risk_zone)
#Display results
print(results_df[["Leave_Probability","Risk_Zone"]].head(50))
```

```
       Leave_Probability       Risk_Zone
10627               0.00       Safe Zone
2703                0.59   Low Risk Zone
6059                0.04       Safe Zone
3258                0.00       Safe Zone
4565                0.00       Safe Zone
4991                0.02       Safe Zone
13976               0.00       Safe Zone
9427                0.00       Safe Zone
7173                0.02       Safe Zone
13412               0.02       Safe Zone
14892               1.00  High Risk Zone
11861               0.02       Safe Zone
1246                1.00  High Risk Zone
12932               0.00       Safe Zone
5997                0.00       Safe Zone
14278               1.00  High Risk Zone
3664                0.00       Safe Zone
4266                0.00       Safe Zone
13383               0.00       Safe Zone
12238               1.00  High Risk Zone
11072               0.01       Safe Zone
```

```
14859               1.00  High Risk Zone
2752                0.03       Safe Zone
5889                0.10       Safe Zone
10194               0.00       Safe Zone
10640               0.07       Safe Zone
12500               1.00  High Risk Zone
4181                0.19       Safe Zone
9779                0.00       Safe Zone
4483                0.00       Safe Zone
6420                0.11       Safe Zone
14703               1.00  High Risk Zone
233                 1.00  High Risk Zone
8857                0.08       Safe Zone
4324                0.03       Safe Zone
756                 0.98  High Risk Zone
14260               1.00  High Risk Zone
7947                0.00       Safe Zone
4228                0.01       Safe Zone
7009                0.00       Safe Zone
3675                0.13       Safe Zone
7321                0.00       Safe Zone
4534                0.47   Low Risk Zone
9908                0.09       Safe Zone
7338                0.00       Safe Zone
12268               1.00  High Risk Zone
5708                0.04       Safe Zone
14204               0.00       Safe Zone
8017                0.00       Safe Zone
12087               1.00  High Risk Zone
```

[90]:

```
zone_counts = results_df["Risk_Zone"].value_counts().reindex(['Safe Zone','Low␣
↪Risk Zone', 'Medium Risk Zone','High Risk Zone'])
plt.figure(figsize =(6,6))
zone_counts.plot.pie(autopct = '%1.1f%%',colors =␣
↪['green','yellow','orange','red'])
plt.title('Risk Zone Proportion')
plt.ylabel(" ")
plt.tight_layout()
plt.show()
```



Retention Strategies: Safe Zone - Maintain and motivate Keep engagement high by recognizing Good performance, career growth path feedback loop etc so that they wont slip into risk categories Critical Risk Zone : identify reason for dissatisfaction and act fast Identify overworked or under-appreciated employees , offer customized retention plan etc Low and Medium Risk Zone : Prevent then from slipping into critical zone Launch skill building programs, Check if they are overloaded or no work and allocate projects accordingly,offer small perks, keep communication transparent