

A Deep Dive into Turnover Patterns and Risk Factors

April 19, 2025

This analysis examines employee turnover patterns using HR data from 14,999 employees to identify key factors influencing departures and develop predictive insights for retention strategies. Through statistical analysis and logistic regression modeling, I identified three primary drivers of turnover: employee satisfaction (showing the strongest negative correlation at -0.39), years at company, and performance evaluation scores.

Key findings revealed distinctive patterns: employees with both very low (below 0.2) and very high (above 0.8) satisfaction levels showed increased turnover risk, with mid-range satisfaction correlating to higher retention. The analysis also uncovered concerning trends in the 3-5 year tenure range, where turnover rates peaked, particularly among high-performing employees working excessive hours (250+ monthly).

Using these insights, we developed a predictive model that can estimate individual turnover risk with reliable accuracy, enabling proactive retention interventions. The model categorizes employees into risk zones (Safe, Low, Medium, and High Risk), allowing HR to prioritize retention efforts effectively.

1 Abstract

2 Dataset Overview

This dataset contains HR analytics data from a company with 14,999 employee records across 10 features, focusing on various factors potentially influencing employee turnover.

Key Features:

1. Employee Performance Metrics
 - Satisfaction level (0-1 scale)
 - Last performance evaluation (0-1 scale)
 - Number of projects assigned
 - Average monthly working hours
2. Career Development Indicators
 - Time spent at company (in years)
 - Promotion in last 5 years (binary: 0/1)
 - Work accident history (binary: 0/1)
3. Employment Information
 - Department (categorical: sales, technical, etc.)

- Salary level (categorical: low, medium, high)

Target Variable:

- Employee turnover status (binary: 0=stayed, 1=left)

3 Obtaining the Data

```
[6]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as matplot
import seaborn as sns
%matplotlib inline
```

```
[7]: df=pd.read_csv('../employee turnover project/turnover.csv')
```

```
[8]: df
```

```
[8]:
```

	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	
...	
14994	0.40	0.57	2	
14995	0.37	0.48	2	
14996	0.37	0.53	2	
14997	0.11	0.96	6	
14998	0.37	0.52	2	

	average_monthly_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	
...	
14994	151	3	0	1	
14995	160	3	0	1	
14996	143	3	0	1	
14997	280	4	0	1	
14998	158	3	0	1	

	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
...
14994      0  support    low
14995      0  support    low
14996      0  support    low
14997      0  support    low
14998      0  support    low

```

[14999 rows x 10 columns]

[]:

4 Data Cleaning

[10]: `df.isnull().any()`

```

[10]: satisfaction_level    False
      last_evaluation      False
      number_project       False
      average_monthly_hours False
      time_spend_company   False
      Work_accident        False
      left                 False
      promotion_last_5years False
      sales                False
      salary               False
      dtype: bool

```

[11]: `df.head()`

```

[11]:   satisfaction_level  last_evaluation  number_project  average_monthly_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

```

```
[12]: df = df.rename(columns={'satisfaction_level': 'satisfaction',
                              'last_evaluation': 'evaluation',
                              'number_project': 'projectCount',
                              'average_monthly_hours': 'averageMonthlyHours',
                              'time_spend_company': 'yearsAtCompany',
                              'Work_accident': 'workAccident',
                              'promotion_last_5years': 'promotion',
                              'sales' : 'department',
                              'left' : 'turnover'
                              })
```

```
[13]: front = df['turnover']
df.drop(labels=['turnover'], axis=1,inplace = True)
df.insert(0, 'turnover', front)
df.head()
```

```
[13]:
```

	turnover	satisfaction	evaluation	projectCount	average_monthly_hours	\
0	1	0.38	0.53	2	157	
1	1	0.80	0.86	5	262	
2	1	0.11	0.88	7	272	
3	1	0.72	0.87	5	223	
4	1	0.37	0.52	2	159	

	yearsAtCompany	workAccident	promotion	department	salary
0	3	0	0	sales	low
1	6	0	0	sales	medium
2	4	0	0	sales	medium
3	5	0	0	sales	low
4	3	0	0	sales	low

5 Exploring the Data

5.1 Statistical Overview

The dataset has:

- About 15,000 employee observations and 10 features
- The company had a turnover rate of about 24%
- Mean satisfaction of employees is 0.61

```
[17]: df.shape
```

```
[17]: (14999, 10)
```

```
[18]: df.dtypes
```

```
[18]: turnover          int64
      satisfaction    float64
      evaluation      float64
      projectCount    int64
      average_monthly_hours  int64
      yearsAtCompany  int64
      workAccident    int64
      promotion       int64
      department      object
      salary          object
      dtype: object
```

```
[19]: # Looks like about 76% of employees stayed and 24% of employees left.
```

```
turnover_rate = df.turnover.value_counts() / len(df)
turnover_rate
```

```
[19]: turnover
0    0.761917
1    0.238083
Name: count, dtype: float64
```

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

```
[20]:
```

	turnover	satisfaction	evaluation	projectCount	\
count	14999.000000	14999.000000	14999.000000	14999.000000	
mean	0.238083	0.612834	0.716102	3.803054	
std	0.425924	0.248631	0.171169	1.232592	
min	0.000000	0.090000	0.360000	2.000000	
25%	0.000000	0.440000	0.560000	3.000000	
50%	0.000000	0.640000	0.720000	4.000000	
75%	0.000000	0.820000	0.870000	5.000000	
max	1.000000	1.000000	1.000000	7.000000	

	average_monthly_hours	yearsAtCompany	workAccident	promotion
count	14999.000000	14999.000000	14999.000000	14999.000000
mean	201.050337	3.498233	0.144610	0.021268
std	49.943099	1.460136	0.351719	0.144281
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

```
[21]: # Overview of summary (Turnover V.S. Non-turnover)
turnover_Summary = df.groupby('turnover')
turnover_Summary.mean(numeric_only=True)
```

```
[21]:
```

	satisfaction	evaluation	projectCount	average_monthly_hours	\
turnover					
0	0.666810	0.715473	3.786664	199.060203	
1	0.440098	0.718113	3.855503	207.419210	

	yearsAtCompany	workAccident	promotion
turnover			
0	3.380032	0.175009	0.026251
1	3.876505	0.047326	0.005321

5.2 Correlation Matrix & Heatmap

Moderate Positively Correlated Features:

- projectCount vs evaluation: 0.349333
- projectCount vs averageMonthlyHours: 0.417211
- averageMonthlyHours vs evaluation: 0.339742

Moderate Negatively Correlated Feature:

- satisfaction vs turnover: -0.388375

Finding:

From the heatmap, there is a **positive(+)** correlation between projectCount, averageMonthlyHours, and evaluation. Which could mean that the employees who spent more hours and did more projects were evaluated highly.

For the **negative(-)** relationships, turnover and satisfaction are highly correlated. I'm assuming that people tend to leave a company more when they are less satisfied.

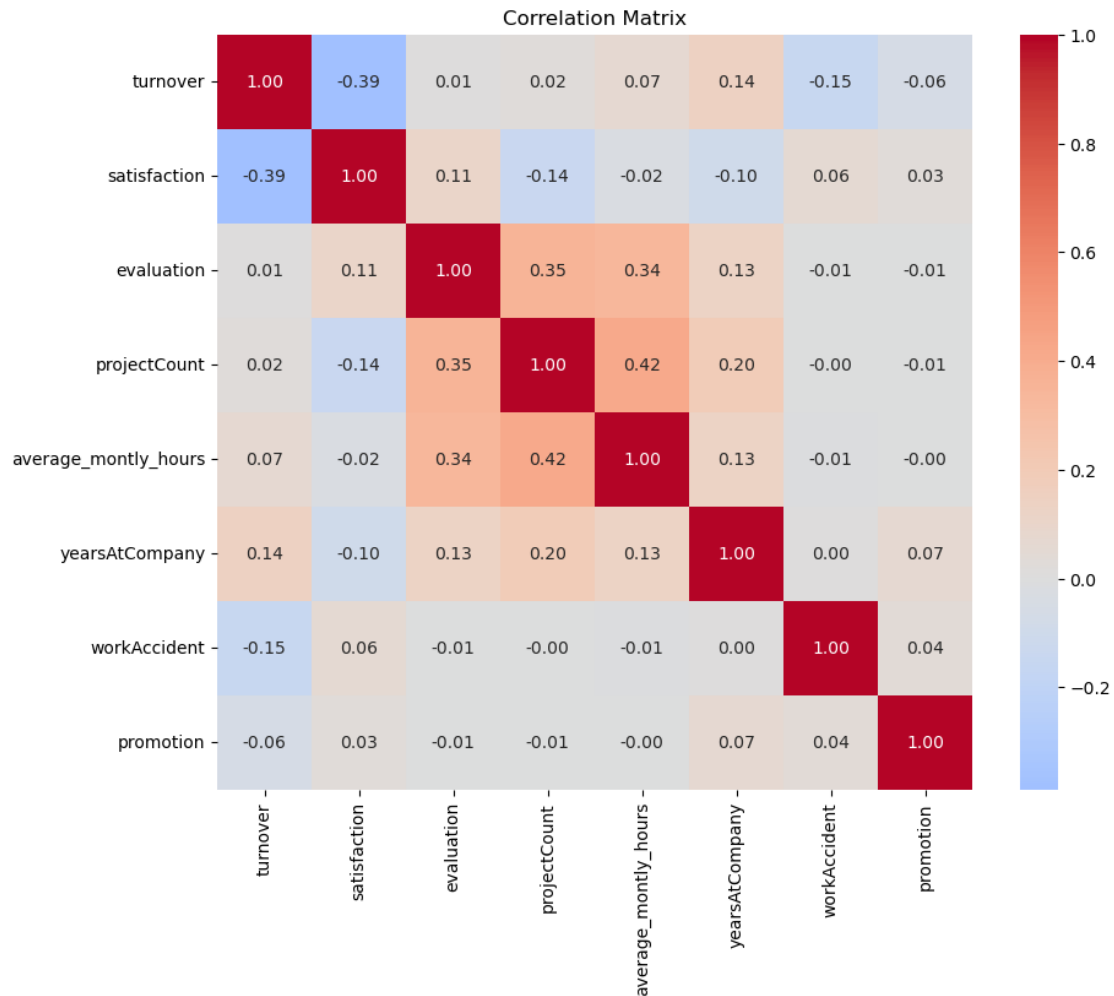
start from In [12]

```
[25]: # Correlation Matrix

numeric_df = df.select_dtypes(include=['float64', 'int64'])
corr = numeric_df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,
            annot=True,
            cmap='coolwarm',
            center=0,
            fmt='.2f',
            square=True)
```

```
plt.title('Correlation Matrix')
plt.show()
```



5.3 Statistical Test for Correlation

5.3.1 One-Sample T-Test (Measuring Satisfaction Level)¶

A one-sample t-test checks whether a sample mean differs from the population mean. Since satisfaction has the highest correlation with our dependent variable turnover, let's test to see whether the average satisfaction level of employees that had a turnover differs from those that had no turnover.

Hypothesis Testing: Is there significant difference in the **means of satisfaction level** between employees who had a turnover and employees who had no turnover?

- **Null Hypothesis:** ($H_0: p_{TS} = p_{ES}$) The null hypothesis would be that there is no difference in satisfaction level between employees who did turnover and those who did not..

- **Alternate Hypothesis:** ($H_A: p_{TS} \neq p_{ES}$) The alternative hypothesis would be that there is a difference in satisfaction level between employees who did turnover and those who did not.
- **pTS** represents the population mean satisfaction of employees who turned over.
- **pES** represents the population mean satisfaction of employees who stayed.

[]:

```
[28]: current_emp_satisfaction = df['satisfaction'][df['turnover'] == 0].mean()

former_emp_satisfaction = df[df['turnover']==1]['satisfaction'].mean()

print(f'The mean satisfaction for current employees is:␣
↪{current_emp_satisfaction:.3f}')
print(f'The mean satisfaction for employees who left is:␣
↪{former_emp_satisfaction:.3f}')
```

The mean satisfaction for current employees is: 0.667

The mean satisfaction for employees who left is: 0.440

5.3.2 Conducting the Independent T-Test

Let's conduct an **independent t-test at 95% confidence level** to compare satisfaction levels between current employees and those who left. This test will help us determine if there is a statistically significant difference in satisfaction between these two groups. The null hypothesis states that there is no difference in satisfaction levels between current and former employees. To conduct this analysis, we'll use the `stats.ttest_ind()` function from `scipy`.

```
[30]: current_emp_satisfaction = df['satisfaction'][df['turnover'] == 0].mean()
former_emp_satisfaction = df[df['turnover']==1]['satisfaction'].mean()

n_current = len(df[df['turnover'] == 0])
n_former = len(df[df['turnover'] == 1])

print(f'The mean satisfaction for current employees (n={n_current}) is:␣
↪{current_emp_satisfaction:.3f}')
print(f'The mean satisfaction for employees who left (n={n_former}) is:␣
↪{former_emp_satisfaction:.3f}')

from scipy import stats

t_stat, p_value = stats.ttest_ind(
    df[df['turnover'] == 0]['satisfaction'], # Current employees group
```



```

    df[df['turnover'] == 1]['satisfaction']    # Former employees group
)

print(f'\nIndependent t-test results:')
print(f't-statistic: {t_stat:.3f}')
print(f'p-value: {p_value:.4f}')

if p_value < 0.05:
    print('\nThe difference in satisfaction between current and former_
    ↪employees is statistically significant.')
else:
    print('\nNo statistically significant difference was found in satisfaction_
    ↪between current and former employees.')

```

The mean satisfaction for current employees (n=11428) is: 0.667

The mean satisfaction for employees who left (n=3571) is: 0.440

Independent t-test results:

t-statistic: 51.613

p-value: 0.0000

The difference in satisfaction between current and former employees is statistically significant.

Based on the independent t-test results ($t=51.613$, $p<0.001$), we reject the null hypothesis. The data provides strong statistical evidence that **there is a significant difference in satisfaction levels between current employees ($M=0.667$, $n=11,428$) and former employees ($M=0.440$, $n=3,571$).**

The test result shows the test statistic “t” is equal to 51.613. This test statistic measures the difference in satisfaction between current and former employees, scaled by the variability in the data. Since our p-value (0.0000) is less than our significance level (0.05), we reject the null hypothesis. This indicates that the difference in satisfaction between current employees ($M=0.667$) and former employees ($M=0.440$) is statistically significant and not due to random chance.

[]:

5.3.3 T-Test Quantile

```

[34]: degree_freedom = n_current + n_former - 2    # n1 + n2 - 2 for independent t-test

LQ = stats.t.ppf(0.025, degree_freedom)
RQ = stats.t.ppf(0.975, degree_freedom)

print(f'The t-distribution left critical value is: {LQ:.3f}')

```

```
print(f'The t-distribution right critical value is: {RQ:.3f}')
```

The t-distribution left critical value is: -1.960

The t-distribution right critical value is: 1.960

5.3.4 Summary of Independent T-Test

To examine the relationship between employee satisfaction and turnover, we conducted an independent t-test comparing satisfaction levels between current and former employees. The analysis revealed significant differences between the two groups: Current employees (n=11,428) showed a higher mean satisfaction score (M=0.667) compared to former employees (n=3,571, M=0.440). The independent t-test results (t=51.613, p<0.0000) indicate that this difference is statistically significant at the 95% confidence level, leading us to **reject the null hypothesis** that there is no difference in satisfaction between the groups. The substantial difference in satisfaction scores (0.227) and the extremely low p-value suggest that employee satisfaction is strongly associated with turnover behavior. This finding has important implications for HR practices:

Employee satisfaction could serve as an early indicator of turnover risk. Special attention should be paid to employees whose satisfaction scores fall below 0.440. Implementing targeted interventions for employees showing low satisfaction levels may help prevent future turnover.

These results emphasize the importance of regularly monitoring and addressing employee satisfaction as part of a comprehensive retention strategy.

[]:

5.4 Distribution Plots (Satisfaction - Evaluation - AverageMonthlyHours)

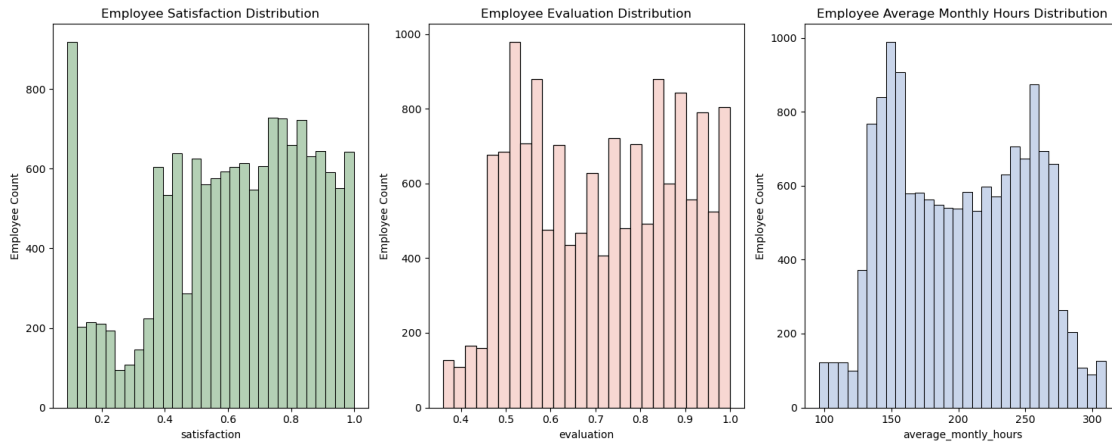
```
[37]: f, axes = plt.subplots(ncols=3, figsize=(15, 6))
soft_green = "#9BC19C"
soft_pink = "#F5CAC3"
soft_blue = "#B8C7E4"

sns.histplot(data=df, x='satisfaction', color=soft_green, ax=axes[0])
axes[0].set_title('Employee Satisfaction Distribution')
axes[0].set_ylabel('Employee Count')

sns.histplot(data=df, x='evaluation', color=soft_pink, ax=axes[1])
axes[1].set_title('Employee Evaluation Distribution')
axes[1].set_ylabel('Employee Count')

# Using the correct column name here
sns.histplot(data=df, x='average_monthly_hours', color=soft_blue, ax=axes[2])
axes[2].set_title('Employee Average Monthly Hours Distribution')
axes[2].set_ylabel('Employee Count')

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



Findings: Let's examine the distribution on some of the employee's features. Here's what I found:

- **Satisfaction** - There is a huge spike for employees with low satisfaction and high satisfaction. This polarized distribution indicates significant satisfaction issues, with a large group of extremely dissatisfied employees (around 0.1 satisfaction level) alongside more evenly distributed satisfaction levels from 0.4-1.0.
- **Evaluation** - There is a bimodal distribution of employees for low evaluations (less than 0.6) and high evaluations (more than 0.8). This suggests two distinct performance groups in the company, possibly reflecting different evaluation standards or employee categories.
- **AverageMonthlyHours** - There is another bimodal distribution of employees with lower and higher average monthly hours (less than 150 hours & more than 250 hours). This indicates two different work patterns: one group working relatively few hours and another potentially overworking.
- The evaluation and average monthly hour graphs both share a similar distribution, which suggests these variables may be linked - employees working longer hours tend to receive higher evaluations.
- Employees with lower average monthly hours were evaluated less and vice versa, indicating a possible bias in the evaluation system that rewards time spent rather than efficiency or output quality.
- If you look back at the correlation matrix, the high correlation between evaluation and averageMonthlyHours (0.34) does support this finding.
- These non-normal distributions suggest natural groupings in the data that could help identify different employee segments with varying turnover risks. The extreme values (very low satisfaction, unusually high or low working hours) correlate with the increased turnover patterns identified in later analysis.

[]:

5.5 Salary and Turnover Analysis

```
[40]: import matplotlib.pyplot as plt
import seaborn as sns

retained_color = '#4C72B0' # Blue
left_color = '#55A868' # Green

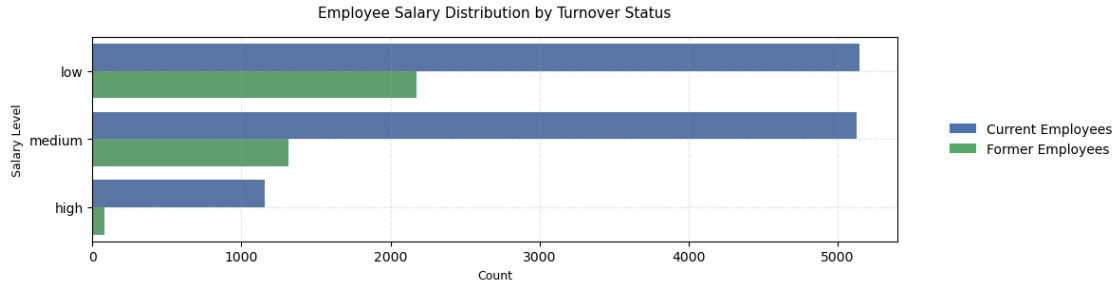
plt.figure(figsize=(12, 3.2))

ax = sns.countplot(y="salary",
                  hue='turnover',
                  data=df,
                  palette={0: retained_color, 1: left_color})

ax.set_title('Employee Salary Distribution by Turnover Status',
            pad=15, fontsize=11)
ax.set_xlabel('Count', fontsize=9)
ax.set_ylabel('Salary Level', fontsize=9)

ax.get_legend().remove()
legend_elements = [
    plt.Rectangle((0,0),1,1, facecolor=retained_color, label='Current_
↳Employees'),
    plt.Rectangle((0,0),1,1, facecolor=left_color, label='Former Employees')
]
ax.legend(handles=legend_elements,
        bbox_to_anchor=(1.05, 0.5),
        loc='center left',
        frameon=False)

ax.grid(True, alpha=0.3, linestyle='--')
plt.tight_layout()
plt.show()
```



[]:

Findings: salary level and turnover status distribution

Salary Level and Employee Turnover Analysis

- **Highest Turnover in Low Salary Band:** The data reveals that the low salary group has the highest number of departing employees, representing approximately 30% of the total workforce in this salary bracket, indicating a clear correlation between compensation level and retention.
- **Moderate Risk in Medium Salary Tier:** The medium salary group shows a substantial number of departures but at a lower proportion (about 20%), demonstrating that salary increases do improve retention rates.
- **High Salary Stability:** The high salary group exhibits almost no turnover (less than 5% departure rate), confirming that appropriate compensation is an effective tool for retaining key talent.
- **Salary Gradient Effect:** As salary levels increase from low to high, the proportion of departing employees shows a clear declining trend, suggesting that compensation satisfaction may be a significant driver in turnover decisions.
- **Low Salary Focus Point:** The volume of departures in the low salary band makes this group the primary concern for retention strategies, potentially requiring reassessment of base compensation levels or alternative forms of reward.

These findings strongly suggest that the company's compensation structure directly impacts employee retention, and may require reevaluation of compensation competitiveness for lower-paid positions to reduce talent loss.

[]:

5.6 Department and Turnover Distribution

```
[43]: plt.figure(figsize=(12, 6))

dept_order = df['department'].value_counts().index
```

```

n_departments = len(df['department'].unique())
color_types = sns.color_palette('husl', n_departments)

ax = sns.countplot(data=df,
                    x='department',
                    palette=color_types,
                    hue='department',
                    legend=False,
                    order=dept_order)

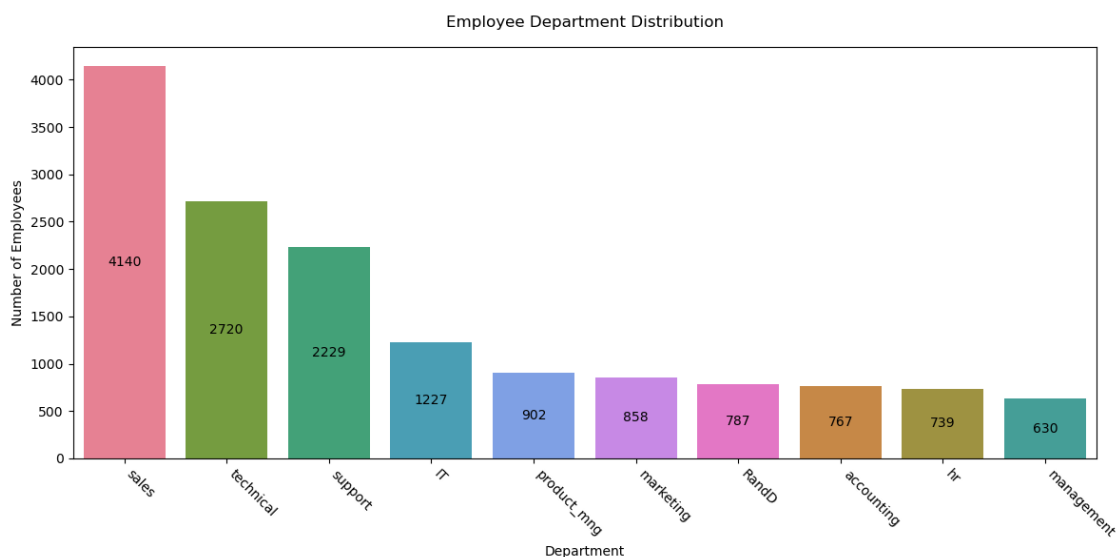
plt.title('Employee Department Distribution', pad=15, size=12)
plt.xlabel('Department', size=10)
plt.ylabel('Number of Employees', size=10)

for i in ax.containers:
    ax.bar_label(i, label_type='center')

plt.xticks(rotation=-45, ha='left')

plt.tight_layout()
plt.show()

```



```

[44]: turnover_by_dept = df[df['turnover']==1]['department'].value_counts().index

f, ax = plt.subplots(figsize=(12, 4))

ax = sns.countplot(y="department",
                   hue='turnover',
                   data=df,
                   order=turnover_by_dept,
                   palette={0: retained_color, 1: left_color})

for container in ax.containers:
    ax.bar_label(container,
                 label_type='center',
                 color='white')

plt.title('Employee Department Distribution by Turnover Status',
         pad=15, size=11)
plt.xlabel('Count', size=9)
plt.ylabel('Department', size=9)

legend = ax.get_legend()
legend.remove()

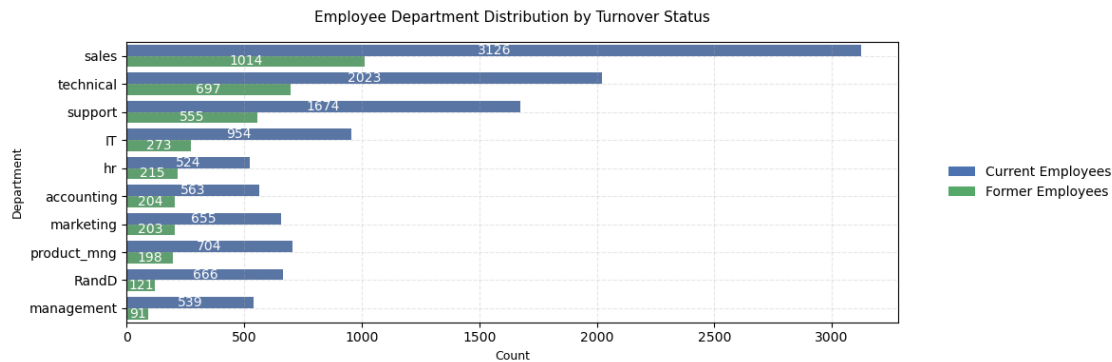
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=retained_color, label='Current Employees'),
                   Patch(facecolor=left_color, label='Former Employees')]

plt.legend(handles=legend_elements,
          bbox_to_anchor=(1.05, 0.5),
          loc='center left',
          frameon=False)

plt.grid(True, alpha=0.3, linestyle='--')

plt.tight_layout()
plt.show()

```



Findings: Departmental Turnover Analysis

An examination of employee turnover across departments reveals critical patterns:

Turnover Distribution Analysis * Critical Turnover Areas: While Sales, Technical, and Support show the highest absolute turnover numbers (1,014, 697, and 555 respectively), the most concerning proportional turnover rates are: - HR: 29.1% (215 of 739) - troubling for the department responsible for retention - Technical: 25.6% (697 of 2,720) - Support: 24.9% (555 of 2,229)

- **Stability Pockets:** Management (14.4% turnover) and R&D (15.4%) show significantly lower turnover rates, suggesting better retention mechanisms or higher job satisfaction in these areas.

Key Insights * HR Department Warning Signal: The high turnover within HR itself presents a cyclical problem affecting the entire organization's retention capabilities.

- **Systemic vs. Department Issues:** The relatively consistent turnover percentages across most departments (~24-26%) suggest company-wide factors like compensation or work culture may be more influential than department-specific issues.
- **Front-Line Vulnerability:** Customer-facing departments (Sales, Support) and core technical functions show concerning turnover rates, representing significant knowledge and relationship capital loss.

Action Recommendations

1. Investigate the HR department's own retention challenges as a priority
2. Analyze exit interviews by department to identify specific departure drivers
3. Examine how stable departments (Management, R&D) differ in practices from high-turnover departments
4. Develop targeted retention strategies for customer-facing and technical teams

[]:

5.7 Relationship between ProjectCount and Turnover

```
[47]: retained_color = '#4C72B0'
      left_color = '#55A868'

      ax = sns.barplot(x="projectCount", y="projectCount", hue="turnover", data=df,
```



```

        estimator=lambda x: len(x) / len(df) * 100,
        palette={0: retained_color, 1: left_color})
ax.set(ylabel="Percent")

legend = ax.get_legend()
legend.remove()

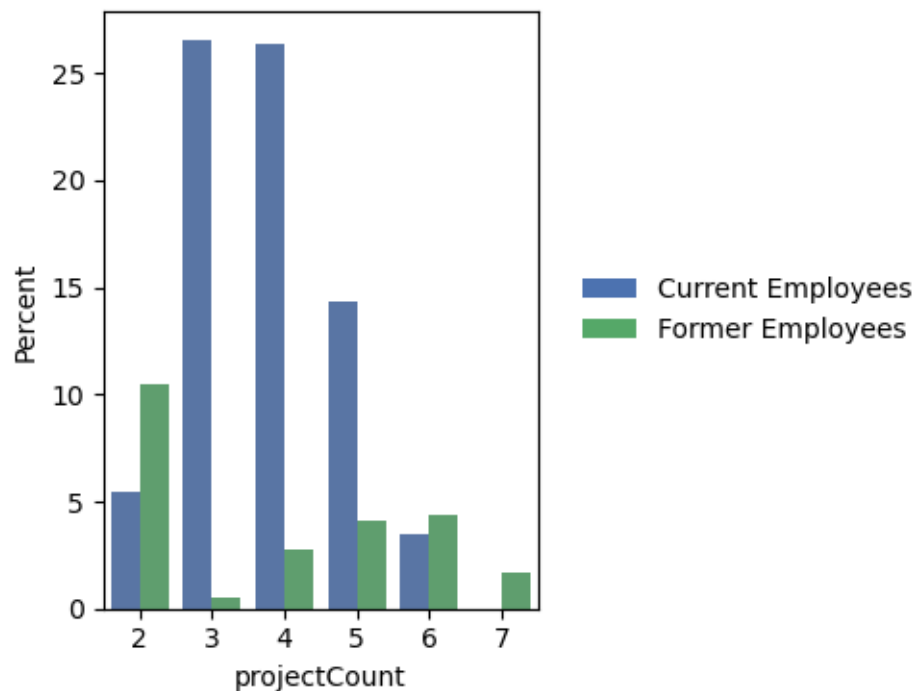
from matplotlib.patches import Patch
legend_elements = [
    Patch(facecolor=retained_color, label='Current Employees'),
    Patch(facecolor=left_color, label='Former Employees')
]

plt.legend(handles=legend_elements,
          bbox_to_anchor=(1.05, 0.5),
          loc='center left',
          frameon=False)

plt.gcf().set_size_inches(plt.gcf().get_size_inches() * 0.8)

plt.tight_layout()
plt.show()

```



Findings: Project Workload and Turnover: A U-Shaped Risk Relationship

The relationship between project assignments and employee retention reveals a complex U-shaped pattern with significant strategic implications:

- **Optimal Workload Range:** Employees with 3-5 projects show remarkably low turnover rates, indicating an engagement “sweet spot” where employees feel appropriately challenged yet not overwhelmed.
- **Under-Engagement Risk:** Employees with only 2 projects show significantly higher turnover (>50%), suggesting potential dissatisfaction from under-utilization, limited development opportunities, or perceived marginalization.
- **Over-Engagement Crisis:** The most striking finding is that employees with 6+ projects demonstrate extreme turnover risk:
 - 6 projects: >50% turnover rate
 - 7 projects: 100% turnover rate - every single employee with this workload left
- **Quantifiable Burnout Threshold:** The data identifies a clear burnout threshold at 6+ projects, establishing a definitive upper limit for sustainable employee workload.
- **Hidden Talent Management Issue:** The high turnover among employees with only 2 projects may indicate a talent allocation problem, where certain employees are being overlooked or undervalued.

5.8 Evaluation’s Impact on Turnover

```
[50]: fig = plt.figure(figsize=(12, 3.2))

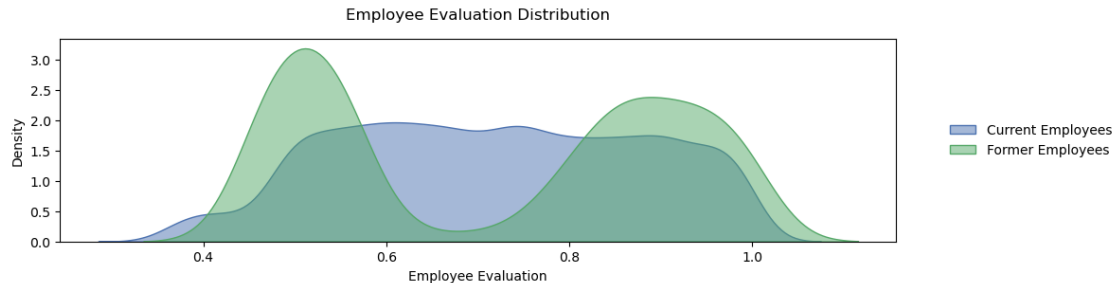
ax = sns.kdeplot(data=df.loc[df['turnover'] == 0, 'evaluation'],
                 color=retained_color, # Blue for current employees
                 fill=True,
                 alpha=0.5,
                 label='Current Employees')

ax = sns.kdeplot(data=df.loc[df['turnover'] == 1, 'evaluation'],
                 color=left_color, # Green for former employees
                 fill=True,
                 alpha=0.5,
                 label='Former Employees')

plt.title('Employee Evaluation Distribution',
          pad=15, size=12)
ax.set(xlabel='Employee Evaluation',
       ylabel='Density')
```

```
plt.legend(bbox_to_anchor=(1.05, 0.5),
           loc='center left',
           frameon=False)
```

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



Summary:

- There is a biomodal distribution for those that had a turnover.
- Employees with **low** performance tend to leave the company more
- Employees with **high** performance tend to leave the company more
- The **sweet spot** for employees that stayed is within **0.6-0.8** evaluation

[]:

5.9 Analysis of Average Monthly Hours and Turnover

Summary:

- Another bi-modal distribution for employees that turnovered
- Employees who had less hours of work (~150hours or less) left the company more
- Employees who had too many hours of work (~250 or more) left the company
- Employees who left generally were **underworked** or **overworked**.

```
[54]: fig, ax = plt.subplots(figsize=(12, 3.2))
retained_color = '#4C72B0'
left_color = '#55A868'

# Plot for retained employees
ax = sns.kdeplot(data=df.loc[df['turnover'] == 0, 'average_monthly_hours'],
                 color=retained_color,
                 fill=True,
                 alpha=0.5,
```

```

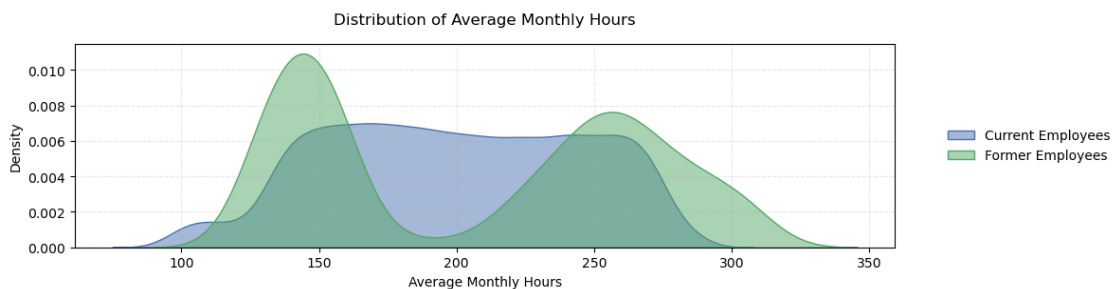
        label='Current Employees')

# Plot for employees who left
ax = sns.kdeplot(data=df.loc[df['turnover'] == 1, 'average_monthly_hours'],
                 color=left_color,
                 fill=True,
                 alpha=0.5,
                 label='Former Employees')

plt.title('Distribution of Average Monthly Hours',
         pad=15, size=12)
ax.set(xlabel='Average Monthly Hours',
      ylabel='Density')
plt.grid(True, alpha=0.3, linestyle='--')

# Modify legend
plt.legend(bbox_to_anchor=(1.05, 0.5),
         loc='center left',
         frameon=False)
plt.tight_layout()
plt.show()

```



5.10 Satisfaction's Correlation with Turnover

```

[56]: fig, ax = plt.subplots(figsize=(15, 4))

retained_color = '#4C72B0'
left_color = '#55A868'

# Plot for retained employees
ax = sns.kdeplot(data=df.loc[df['turnover'] == 0, 'satisfaction'],
                 color=retained_color,
                 fill=True,
                 alpha=0.5,
                 label='Retained')

```

```

# Plot for employees who left
ax = sns.kdeplot(data=df.loc[df['turnover'] == 1, 'satisfaction'],
                 color=left_color,
                 fill=True,
                 alpha=0.5,
                 label='Left')

plt.title('Employee Satisfaction Distribution\nRetained (Blue) vs. Left_
↪(Green)',
         pad=15, size=12)
ax.set(xlabel='Satisfaction Level',
      ylabel='Density')

plt.grid(True, alpha=0.3, linestyle='--')

plt.text(0.02, 0.98, 'Blue = Current Employees',
        transform=ax.transAxes, color=retained_color,
        fontsize=10, va='top')
plt.text(0.02, 0.93, 'Green = Former Employees',
        transform=ax.transAxes, color=left_color,
        fontsize=10, va='top')

plt.tight_layout()
plt.show()

```



When analyzing the relationship between employee satisfaction and turnover, we observed an interesting tri-modal distribution pattern:

1. Low Satisfaction Group (0.2 or lower)
 - Likely represents employees who are extremely dissatisfied with their work environment
 - Recommendation: Conduct exit interviews to understand specific reasons and improve working conditions

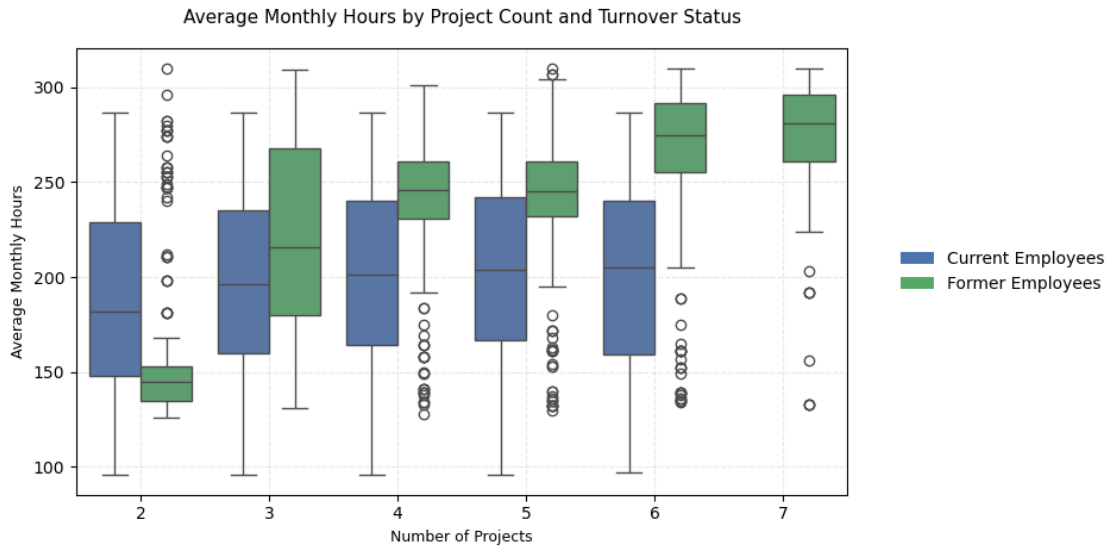
2. Medium-Low Satisfaction Group (0.3-0.5)
 - Represents employees with specific but not extreme dissatisfaction
 - Recommendation: Implement regular satisfaction surveys to identify specific pain points
3. High Satisfaction Group (0.7 or higher)
 - This group's turnover deserves special attention, possible reasons include:
 - Better external opportunities
 - Career development bottlenecks
 - Competitive offers from other companies
 - Recommendation: Strengthen career development paths and key talent retention programs

Action Items: - Develop differentiated retention strategies for different satisfaction groups - Establish early warning mechanisms to identify potential turnover risks - Optimize regular performance and satisfaction assessment mechanisms

Business Impact: - Cost savings through improved retention - Better talent management through targeted interventions - Enhanced employee engagement through demonstrated responsiveness

5.11 ProjectCount and Average Monthly Hours Correlation

```
[59]: plt.figure(figsize=(9.6, 4.8))
ax = sns.boxplot(x="projectCount",
                y="average_monthly_hours",
                hue="turnover",
                data=df,
                palette=[retained_color, left_color])
plt.title('Average Monthly Hours by Project Count and Turnover Status',
          pad=15, size=11)
plt.xlabel('Number of Projects', size=9)
plt.ylabel('Average Monthly Hours', size=9)
legend = ax.get_legend()
legend.remove()
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=retained_color, label='Current Employees'),
                  Patch(facecolor=left_color, label='Former Employees')]
plt.legend(handles=legend_elements,
          bbox_to_anchor=(1.05, 0.5),
          loc='center left',
          frameon=False)
plt.grid(True, alpha=0.3, linestyle='--')
plt.tight_layout()
plt.show()
```



[]:

Findings: Work Hours and Project Load: Critical Patterns Driving Turnover

The relationship between project count, working hours, and turnover reveals sophisticated patterns with significant implications for workforce management:

Divergent Work Patterns by Turnover Status

- **Hours Gap Widens with Project Count:** As project responsibilities increase, the working hours gap between retained and departing employees systematically widens, revealing a concerning pattern of workload inequality.
- **Two Distinct Turnover Triggers:**
 - **Underutilization Pattern:** With 2 projects, departing employees worked significantly fewer hours (~145 vs. ~180), suggesting potential disengagement or career stagnation concerns.
 - **Overutilization Pattern:** From 3+ projects, departing employees worked substantially more hours than their peers, with the gap becoming extreme at 6-7 projects (~280 vs. ~205 hours).
- **Consistent Workload for Retained Employees:** Remarkably, retained employees maintain relatively consistent monthly hours (~200) regardless of project count, suggesting effective workload management practices among stable employees.
- **Critical Threshold Identified:** The data pinpoints approximately 250 monthly hours as a critical threshold beyond which retention risk escalates dramatically, particularly evident in employees with 6-7 projects.

Strategic Implications

- **Work-Life Balance Connection:** The stark hours differential suggests departing employees experience significant work-life balance disruption as project responsibilities increase.
- **Hidden Efficiency Issue:** The ability of retained employees to maintain stable hours across increasing project counts suggests they may have developed efficiency skills or support systems that departing employees lack.
- **Dual Intervention Strategy Needed:**
 1. Employees with low project counts and hours need engagement and growth opportunities
 2. Employees with high project counts need workload normalization and efficiency support

5.12 ProjectCount and Evaluation Relationship

```
[63]: plt.figure(figsize=(9.6, 4.8))

ax = sns.boxplot(x="projectCount",
                y="evaluation",
                hue="turnover",
                data=df,
                palette=[retained_color, left_color])

plt.title('Evaluation Score by Project Count and Turnover Status',
         pad=15, size=11)
plt.xlabel('Number of Projects', size=9)
plt.ylabel('Evaluation Score', size=9)

legend = ax.get_legend()

legend.remove()

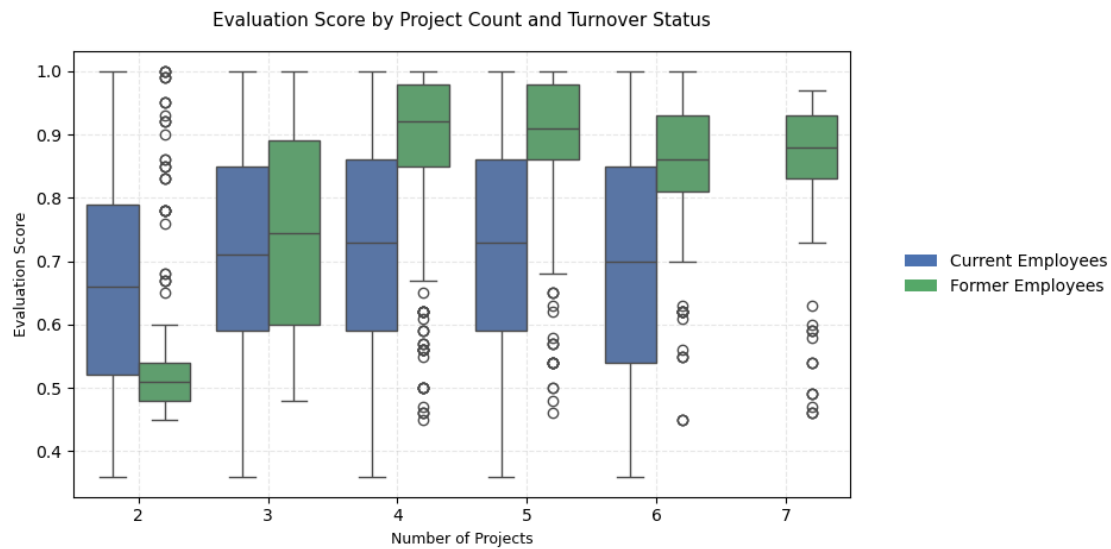
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=retained_color, label='Current Employees'),
                  Patch(facecolor=left_color, label='Former Employees')]

plt.legend(handles=legend_elements,
          bbox_to_anchor=(1.05, 0.5),
          loc='center left',
          frameon=False)

plt.grid(True, alpha=0.3, linestyle='--')
```



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



Findings

Performance Evaluation Paradox: The High-Performer Exodus Pattern

This analysis reveals a counterintuitive relationship between performance evaluations, project load, and turnover that challenges conventional retention assumptions:

The Performance-Turnover Paradox

- **Low-Performer vs. High-Performer Dichotomy:** Departing employees cluster into two distinct evaluation groups:

Low performers with 2 projects (median score ~0.5) High performers with 3+ projects (median scores consistently higher than retained employees)

- **Performance Gap Widens with Project Count:** As project responsibilities increase, the performance evaluation gap between departing and retained employees systematically widens, with former employees consistently outperforming their staying colleagues at 4+ projects.
- **Top Talent Vulnerability:** The most striking finding is that the highest performers (evaluation scores 0.9+) with heavy project loads (4-7 projects) show disproportionately high turnover rates, representing a critical loss of top talent.

Strategic Implications

- **Recognition-Workload Misalignment:** High performers appear to be receiving recognition (high evaluations) but may be experiencing unsustainable workloads without commensurate rewards or advancement.

- **Expectation Escalation Effect:** The data suggests a possible cycle where high performance leads to increased workload, which then creates expectations for rewards or advancement that aren't being met.
- **Retention Warning Signal:** Employees with evaluation scores above 0.85 combined with project counts of 4+ should be flagged as high turnover risks despite (or because of) their excellent performance.

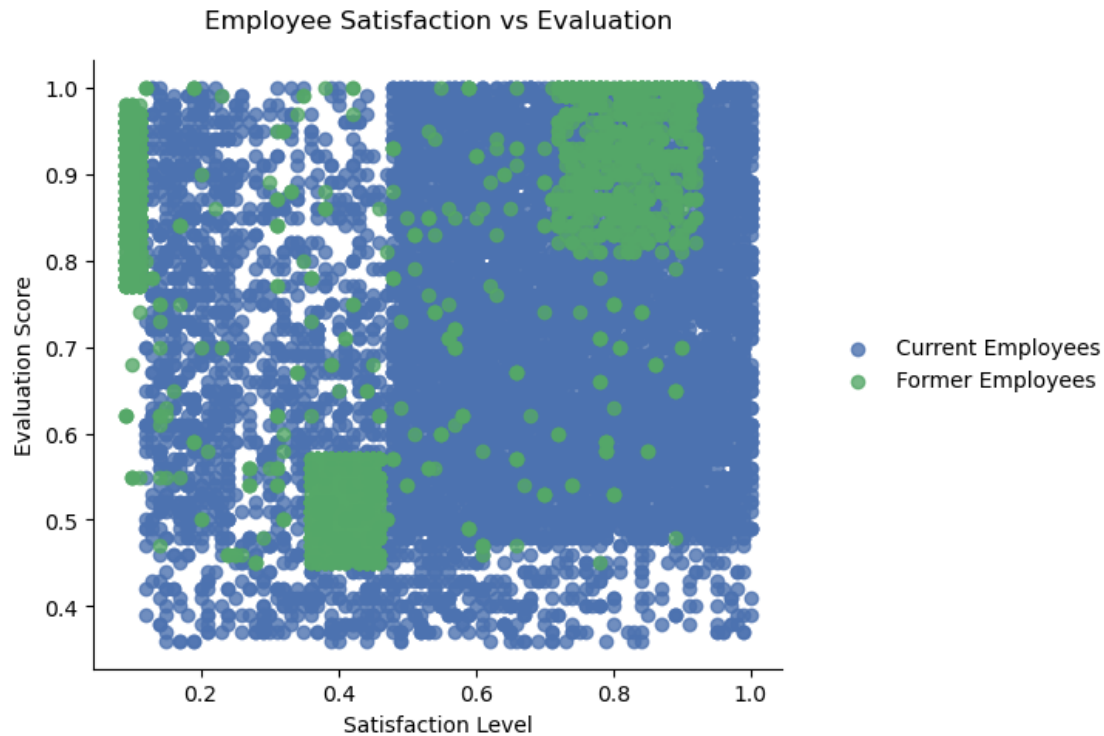
5.13 Satisfaction and Evaluation Analysis

```
[67]: plot = sns.lmplot(x='satisfaction',
                        y='evaluation',
                        data=df,
                        fit_reg=False,
                        hue='turnover',
                        palette={0: '#4C72B0', 1: '#55A868'},
                        height=5,
                        aspect=1.5,
                        legend=False)

plt.legend(['Current Employees', 'Former Employees'],
           bbox_to_anchor=(1.05, 0.5),
           loc='center left',
           frameon=False,
           fontsize=10)

plt.title('Employee Satisfaction vs Evaluation',
          pad=15,
          size=12)
plt.xlabel('Satisfaction Level', size=10)
plt.ylabel('Evaluation Score', size=10)

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



Summary: This is by far the most compelling graph. This is what I found:

- There are **3** distinct clusters for employees who left the company

Cluster 1 (Hard-working and Sad Employee): Satisfaction was below 0.2 and evaluations were greater than 0.75. Which could be a good indication that employees who left the company were good workers but felt horrible at their job.

- Question: What could be the reason for feeling so horrible when you are highly evaluated? Could it be working too hard? Could this cluster mean employees who are “overworked”?

Cluster 2 (Bad and Sad Employee): Satisfaction between about 0.35~0.45 and evaluations below ~0.58. This could be seen as employees who were badly evaluated and felt bad at work.

- Question: Could this cluster mean employees who “under-performed”?

Cluster 3 (Hard-working and Happy Employee): Satisfaction between 0.7~1.0 and evaluations were greater than 0.8. Which could mean that employees in this cluster were “ideal”. They loved their work and were evaluated highly for their performance.

- Question: Could this cluster mean that employees left because they found another job opportunity?

5.14 Years at Company and Turnover Patterns

```
[70]: plt.figure(figsize=(9.6, 4.8))

ax = sns.barplot(x="yearsAtCompany",
                 y="yearsAtCompany",
                 hue="turnover",
                 data=df,
                 estimator=lambda x: len(x) / len(df) * 100,
                 palette={0: retained_color, 1: left_color})

plt.title('Employee Distribution by Years at Company',
          pad=15, size=11)
plt.xlabel('Years at Company', size=9)
plt.ylabel('Percent', size=9)

legend = ax.get_legend()

legend.remove()

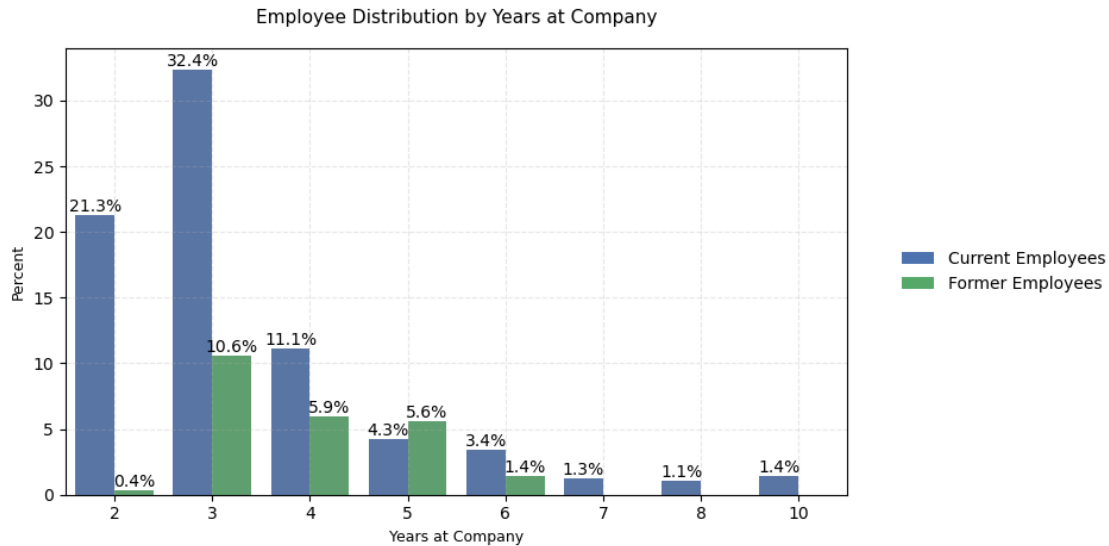
from matplotlib.patches import Patch
legend_elements = [Patch(facecolor=retained_color, label='Current Employees'),
                  Patch(facecolor=left_color, label='Former Employees')]

plt.legend(handles=legend_elements,
          bbox_to_anchor=(1.05, 0.5),
          loc='center left',
          frameon=False)

plt.grid(True, alpha=0.3, linestyle='--')

for container in ax.containers:
    ax.bar_label(container, fmt='%.1f%%')

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



Findings: Tenure-Based Turnover Patterns The analysis of employee tenure reveals critical retention risk windows:

Critical 4-5 Year Exodus: More than half of employees with 4 and 5 years of tenure left the company, representing a significant mid-career departure pattern. This suggests a potential career development ceiling or expectation gap that emerges after several years of service.

Peak Vulnerability at 5 Years: The 5-year mark shows the highest turnover rate, indicating this may be a decisive evaluation point where employees reassess their long-term future with the company. This could signal:

- Career advancement limitations becoming apparent
- Compensation plateaus relative to market opportunities
- Skills development or growth trajectory concerns
- Possible burnout after sustained commitment

Retention Stability Pattern: Turnover rates appear to stabilize after 6+ years, suggesting that employees who surpass the 5-year threshold have likely found sufficient reasons to commit long-term.

Early Career Retention Strength: The relatively lower turnover rates in years 2-3 indicate initial engagement and satisfaction, making the sharp increase in years 4-5 even more concerning as it represents a loss of employees who have received significant training and development investment.

[]:

6 Feature Importance

```
[73]: from sklearn import tree
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.model_selection import train_test_split
      plt.style.use('fivethirtyeight')
      plt.rcParams['figure.figsize'] = (12,6)

      df = df.rename(columns={'satisfaction_level': 'satisfaction',
                              'last_evaluation': 'evaluation',
                              'number_project': 'projectCount',
                              'average_monthly_hours': 'averageMonthlyHours',
                              'time_spend_company': 'yearsAtCompany',
                              'Work_accident': 'workAccident',
                              'promotion_last_5years': 'promotion',
                              'sales' : 'department',
                              'left' : 'turnover'
                              })

      # Convert these variables into categorical variables
      df["department"] = df["department"].astype('category').cat.codes
      df["salary"] = df["salary"].astype('category').cat.codes

      # Create train and test splits
      target_name = 'turnover'
      X = df.drop('turnover', axis=1)

      y=df[target_name]

      X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.15,
      ↪random_state=123, stratify=y)

      dtree = tree.DecisionTreeClassifier(
          #max_depth=3,
          class_weight="balanced",
          min_weight_fraction_leaf=0.01
      )
      dtree = dtree.fit(X_train,y_train)

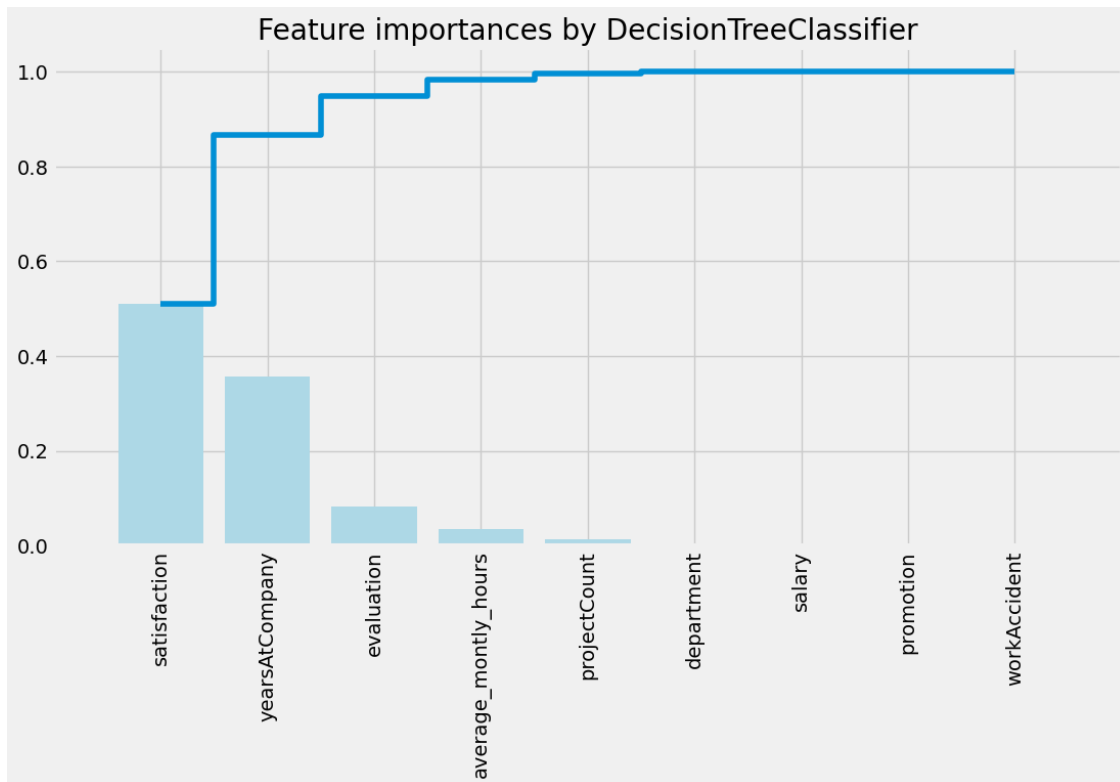
      importances = dtree.feature_importances_
      feat_names = df.drop(['turnover'],axis=1).columns

      indices = np.argsort(importances)[::-1]
```

```

plt.figure(figsize=(12,6))
plt.title("Feature importances by DecisionTreeClassifier")
plt.bar(range(len(indices)), importances[indices], color='lightblue',
        ↪align="center")
plt.step(range(len(indices)), np.cumsum(importances[indices]), where='mid',
        ↪label='Cumulative')
plt.xticks(range(len(indices)), feat_names[indices],
        ↪rotation='vertical',fontsize=14)
plt.xlim([-1, len(indices)])
plt.show()

```



Summary:

By using a **decision tree classifier**, it could rank the features used for the prediction. The top three features were employee satisfaction, yearsAtCompany, and evaluation. This is helpful in creating our model for logistic regression because it'll be more interpretable to understand what goes into our model when we utilize less features.

Top 3 Features:

- Satisfaction
- YearsAtCompany
- Evaluation

7 Modelling the Data: Logistic Regression

```
[76]: %matplotlib inline
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, \
    precision_score, recall_score, confusion_matrix, precision_recall_curve
from sklearn.preprocessing import RobustScaler

df=pd.read_csv('../employee turnover project/turnover.csv')

df = df.rename(columns={
    'satisfaction_level': 'satisfaction',
    'last_evaluation': 'evaluation',
    'number_project': 'projectCount',
    'average_monthly_hours': 'averageMonthlyHours',
    'time_spend_company': 'yearsAtCompany',
    'Work_accident': 'workAccident',
    'promotion_last_5years': 'promotion',
    'sales': 'department',
    'left': 'turnover'
})

df["department"] = df["department"].astype('category').cat.codes
df["salary"] = df["salary"].astype('category').cat.codes

front = df['turnover']
df.drop(labels=['turnover'], axis=1, inplace=True)
df.insert(0, 'turnover', front)

df['int'] = 1

indep_var = ['satisfaction', 'evaluation', 'yearsAtCompany', 'int', 'turnover']
df = df[indep_var]

# Create train and test splits
target_name = 'turnover'
X = df.drop('turnover', axis=1)
y = df[target_name]
```



```

X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    test_size=0.15,
    random_state=123,
    stratify=y
)

print("Training Data Head:")
print(X_train.head())

```

Training Data Head:

	satisfaction	evaluation	yearsAtCompany	int
9003	0.59	1.00	3	1
5697	0.81	0.98	2	1
10691	1.00	0.93	2	1
1884	0.87	0.91	5	1
13572	0.87	0.48	3	1

NOTE: This will be an in-depth analysis of using logistic regression as a classifier. This is more of a use-case example of what can be done and explained to management in a company.

Logistic Regression commonly deals with the issue of how likely an observation is to belong to each group. This model is commonly used to predict the likelihood of an event occurring. In contrast to linear regression, the output of logistic regression is transformed with a logit function. This makes the output either 0 or 1. This is a useful model to take advantage of for this problem because we are interested in predicting whether an employee will leave (0) or stay (1).

Another reason for why logistic regression is the preferred model of choice is because of its interpretability. Logistic regression predicts the outcome of the response variable (turnover) through a set of other explanatory variables, also called predictors. In context of this domain, the value of our response variable is categorized into two forms: 0 (zero) or 1 (one). The value of 0 (zero) represents the probability of an employee not leaving the company and the value of 1 (one) represents the probability of an employee leaving the company.

Logistic Regression models the probability of ‘success’ as:

The equation above shows the relationship between, the dependent variable (success), denoted as (y) and independent variables or predictor of event, denoted as x_i . Where β_0 is the constant of the equation and, β_i is the coefficient of the predictor variables

[]:

8 Using Logistic Regression Coefficients

```

[79]: import statsmodels.api as sm
iv = ['satisfaction', 'evaluation', 'yearsAtCompany', 'int']
logReg = sm.Logit(y_train, X_train[iv])

```

```

answer = logReg.fit()

answer.summary
answer.params

```

Optimization terminated successfully.
Current function value: 0.467233
Iterations 6

```

[79]: satisfaction      -3.769022
      evaluation        0.207596
      yearsAtCompany    0.170145
      int               0.181896
      dtype: float64

```

With the elimination of the other variables, I'll be using the three most important features to create our model: Satisfaction, Evaluation, and YearsAtCompany.

Following overall equation was developed:

Employee Turnover Score = Satisfaction(-3.769022) + Evaluation(0.207596) + YearsAtCompany*(0.170145) + 0.181896

9 Explanation of Coefficients

```

[82]: coef = answer.params

def calculate_turnover_probability(coef, satisfaction, evaluation,
    ↪years_at_company):

    intercept = coef['int']
    sat_coef = coef['satisfaction']
    eval_coef = coef['evaluation']
    years_coef = coef['yearsAtCompany']

    logit = intercept + \
        sat_coef * satisfaction + \
        eval_coef * evaluation + \
        years_coef * years_at_company

    probability = np.exp(logit) / (1 + np.exp(logit))

    return probability

# Example: Employee with 0.7 satisfaction, 0.8 evaluation and 3 years tenure
turnover_prob = calculate_turnover_probability(coef, 0.7, 0.8, 3)

```

```
print(f"Probability of turnover: {turnover_prob:.2%}")
```

Probability of turnover: 14.43%

Employee Turnover Score = Satisfaction(-3.769022) + Evaluation(0.207596) + YearsAtCompany*(0.170145) + 0.181896

The values above are the coefficient assigned to each independent variable. The constant 0.181896 represents the effect of all uncontrollable variables.

10 Interpretation of Score - Example

If you were to use these employee values into the equation:

- Satisfaction: 0.7
- Evaluation: 0.8
- YearsAtCompany: 3 You would get:

Employee Turnover Score = $(0.7)(-3.769022) + (0.8)(0.207596) + (3)(0.170145) + 0.181896 = 0.14431 = 14\%$

Result: This employee would have a 14% chance of leaving the company. This information can then be used to form our retention plan.

11 Retention Plan Using Logistic Regression

With the logistic regression model, we can now use our scores and evaluate the employees through different scoring metrics. Each zone is explain here:

- **Safe Zone (Green)** – Employees within this zone are considered safe.
- **Low Risk Zone (Yellow)** – Employees within this zone are too be taken into consideration of potential turnover. This is more of a long-term track.
- **Medium Risk Zone (Orange)** – Employees within this zone are at risk of turnover. Action should be taken and monitored accordingly.
- **High Risk Zone (Red)** – Employees within this zone are considered to have the highest chance of turnover. Action should be taken immediately.

So with our example above, the employee with a 14% turnover score will be in the safe zone.

[]:

12 Model Validation with Multiple Methods

I'll be using 5 models in this section to measure the accuracy of the different models. 1. Base Rate Model 2. Logistic Regression 3. Random Forest 4. Decision Tree 5. AdaBoost Model

12.1 Base Rate Model Validation

A **Base Rate Model** is a simple model or heuristic used as reference point for comparing how well a model is performing. A baseline helps model developers quantify the minimal, expected

performance on a particular problem. In this dataset, the majority class that will be predicted will be 0's, which are employees who did not leave the company.

If you recall back to Section **Exploring the Data**, 24% of the dataset contained 1's (employee who left the company) and the remaining 76% contained 0's (employee who did not leave the company). The Base Rate Model would simply predict every 0's and ignore all the 1's.

Example: The base rate accuracy for this data set, when classifying everything as 0's, would be 76% because 76% of the dataset are labeled as 0's (employees not leaving the company).

Evaluating the Model Precision and Recall / Class Imbalance

This dataset is an example of a class imbalance problem because of the skewed distribution of employees who did and did not leave. More skewed the class means that accuracy breaks down.

In this case, evaluating our model's algorithm based on accuracy is the wrong thing to measure. We would have to know the different errors that we care about and correct decisions. Accuracy alone does not measure an important concept that needs to be taken into consideration in this type of evaluation: **False Positive** and **False Negative** errors.

False Positives (Type I Error): You predict that the employee will leave, but do not

False Negatives (Type II Error): You predict that the employee will not leave, but does leave

In this problem, what type of errors do we care about more? False Positives or False Negatives?

Different Ways to Evaluate Classification Models

1. **Predictive Accuracy:** How many does it get right?
2. **Speed:** How fast does it take for the model to deploy?
3. **Scalability:** Can the model handle large datasets?
4. **Robustness:** How well does the model handle outliers/missing values?
5. **Interpretability:** Is the model easy to understand?

```
[95]: def base_rate_model(X) :  
      y = np.zeros(X.shape[0])  
      return y
```

```
[96]: target_name = 'turnover'  
X = df.drop('turnover', axis=1)  
  
y=df[target_name]  
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.15,  
↳random_state=123, stratify=y)
```

```
[97]: y_base_rate = base_rate_model(X_test)  
from sklearn.metrics import accuracy_score  
print ("Base rate accuracy is %.2f" % accuracy_score(y_test, y_base_rate))
```

Base rate accuracy is 0.76

```
[98]: from sklearn.linear_model import LogisticRegression  
model = LogisticRegression(penalty='l2', C=1)
```

```

model.fit(X_train, y_train)
print ("Logistic accuracy is %2.2f" % accuracy_score(y_test, model.
    ↳predict(X_test)))

```

Logistic accuracy is 0.77

```

[99]: from sklearn import model_selection

kfold = model_selection.KFold(n_splits=10, shuffle=True, random_state=7)
modelCV = LogisticRegression(class_weight="balanced")
scoring = 'roc_auc'
results = model_selection.cross_val_score(modelCV, X_train, y_train, cv=kfold,
    ↳scoring=scoring)
print("AUC: %.3f (%.3f)" % (results.mean(), results.std()))

```

AUC: 0.793 (0.014)

[]:

```

[101]: from sklearn.metrics import roc_auc_score, classification_report,
    ↳precision_recall_curve, auc, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import cross_val_score
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Function to calculate precision-recall AUC
def pr_auc_score(y_true, y_pred_proba):
    precision, recall, _ = precision_recall_curve(y_true, y_pred_proba)
    return auc(recall, precision)

# Function to plot confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(title)
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()

```

```
[102]: print("---Base Model---")
base_roc_auc = roc_auc_score(y_test, base_rate_model(X_test))

base_pr_auc = pr_auc_score(y_test, base_rate_model(X_test))
print(f"Base Rate ROC AUC = {base_roc_auc:.2f}")
print(f"Base Rate PR AUC = {base_pr_auc:.2f}")
print(classification_report(y_test, base_rate_model(X_test), zero_division=0))
```

---Base Model---

Base Rate ROC AUC = 0.50

Base Rate PR AUC = 0.62

	precision	recall	f1-score	support
0	0.76	1.00	0.86	1714
1	0.00	0.00	0.00	536
accuracy			0.76	2250
macro avg	0.38	0.50	0.43	2250
weighted avg	0.58	0.76	0.66	2250

```
[103]: def smaller_plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)

    plt.figure(figsize=(4, 4))

    ax = sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                     xticklabels=['Stay', 'Leave'],
                     yticklabels=['Stay', 'Leave'],
                     annot_kws={"size": 8},
                     cbar_kws={'label': '', 'shrink': 0.8})

    cbar = ax.collections[0].colorbar
    cbar.ax.tick_params(labelsize=7)

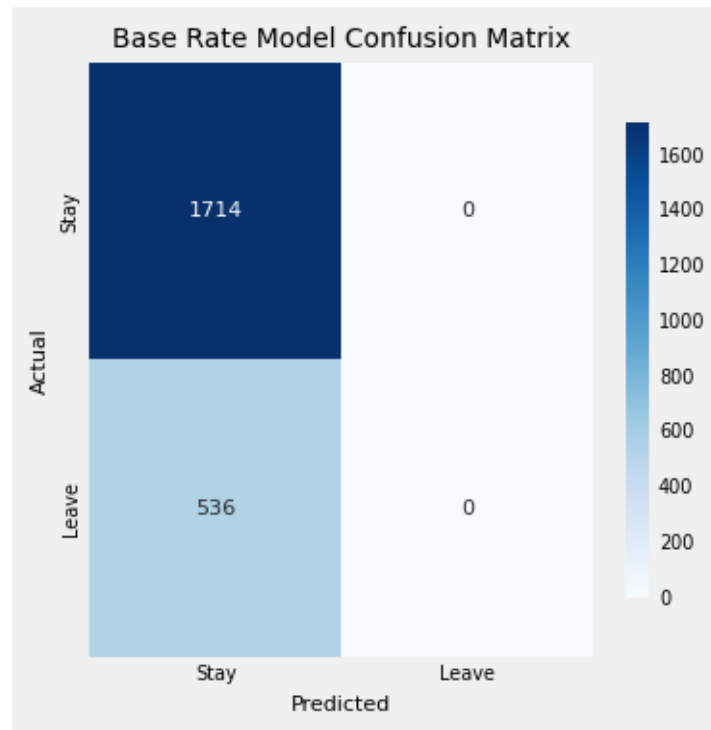
    plt.xlabel('Predicted', fontsize=8)
    plt.ylabel('Actual', fontsize=8)

    plt.title(title, fontsize=10)

    plt.xticks(fontsize=7)
    plt.yticks(fontsize=7)
```

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

```
smaller_plot_confusion_matrix(y_test, base_rate_model(X_test), "Base Rate Model_
↳Confusion Matrix")
```



[]:

Base Model Analysis

What it does: This is our simplest approach - a model that always predicts employees will stay, never predicting anyone will leave. Since 76% of employees in our data actually stayed, this strategy achieves 76% accuracy by default.

Key findings:

- **Prediction ability:** The model shows no ability to distinguish between employees who stay versus leave (ROC AUC = 0.50, equivalent to flipping a coin).
- **Success with retention:** The model correctly identifies all 1,714 employees who stayed.

-Complete failure with turnover: The model misses all 536 employees who actually left, giving us zero insight into potential turnover risks.

Why this matters: This establishes our minimum performance threshold. For any predictive model to add business value, it must do better than 76% accuracy and demonstrate ability to

identify employees at risk of leaving. Otherwise, we gain no actionable insights beyond what we already know.

12.2 Logistic Regression Model Validation

```
[106]: model_summary = answer.summary()
print(model_summary)

from sklearn.metrics import confusion_matrix

y_pred_proba = answer.predict(X_test[iv])
y_pred = (y_pred_proba > 0.5).astype(int)
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)

from sklearn.metrics import precision_recall_curve
precisions, recalls, thresholds = precision_recall_curve(y_test, y_pred_proba)

f1_scores = 2 * (precisions[:-1] * recalls[:-1]) / (precisions[:-1] + recalls[
    ↪-1] + 1e-10)
optimal_idx = np.argmax(f1_scores)
optimal_threshold = thresholds[optimal_idx]
print(f"Optimal threshold: {optimal_threshold:.4f}")
print(f"F1 score at optimal threshold: {f1_scores[optimal_idx]:.4f}")

from sklearn.model_selection import KFold
from sklearn.metrics import roc_auc_score

kf = KFold(n_splits=5, shuffle=True, random_state=42)
cv_aucs = []
for train_idx, val_idx in kf.split(X_train):

    X_cv_train, X_cv_val = X_train.iloc[train_idx][iv], X_train.
    ↪iloc[val_idx][iv]
    y_cv_train, y_cv_val = y_train.iloc[train_idx], y_train.iloc[val_idx]

    cv_model = sm.Logit(y_cv_train, X_cv_train).fit(dis=0)
    y_cv_pred = cv_model.predict(X_cv_val)
    cv_aucs.append(roc_auc_score(y_cv_val, y_cv_pred))
print(f"Cross-validation AUC: {np.mean(cv_aucs):.4f} ± {np.std(cv_aucs):.4f}")
```



```

test_cases = [
    {'satisfaction': 0.9, 'evaluation': 0.9, 'years': 5, 'expected': 'low'},
    {'satisfaction': 0.3, 'evaluation': 0.5, 'years': 1, 'expected': 'high'}
]
for case in test_cases:

    prob = calculate_turnover_probability(coef, case['satisfaction'],
    ↪case['evaluation'], case['years'])
    print(f"Satisfaction: {case['satisfaction']}, Evaluation:
    ↪{case['evaluation']}, Years: {case['years']}")
    print(f"Turnover probability: {prob:.2%} (Expected: {case['expected']}")

print("\nFeature importance (based on coefficient absolute values):")
importance = pd.Series(np.abs(coef), index=coef.index)
importance = importance.sort_values(ascending=False)
print(importance)

```

Logit Regression Results

```

=====
Dep. Variable:          turnover    No. Observations:          12749
Model:                  Logit      Df Residuals:              12745
Method:                 MLE        Df Model:                  3
Date:                   Sat, 19 Apr 2025    Pseudo R-squ.:          0.1487
Time:                   18:39:34    Log-Likelihood:         -5956.7
converged:              True        LL-Null:               -6997.0
Covariance Type:        nonrobust    LLR p-value:            0.000
=====

```

```

==
              coef    std err          z      P>|z|      [0.025
0.975]
-----
--
satisfaction    -3.7690     0.095   -39.564     0.000    -3.956
-3.582
evaluation       0.2076     0.133     1.565     0.118    -0.052
0.468
yearsAtCompany   0.1701     0.015    11.342     0.000     0.141
0.200
int              0.1819     0.113     1.613     0.107    -0.039
0.403
=====

```

```

==
Confusion Matrix:
[[1578  136]
 [ 390  146]]

```

Optimal threshold: 0.2813
F1 score at optimal threshold: 0.6207
Cross-validation AUC: 0.7745 ± 0.0068
Satisfaction: 0.9, Evaluation: 0.9, Years: 5
Turnover probability: 10.22% (Expected: low)
Satisfaction: 0.3, Evaluation: 0.5, Years: 1
Turnover probability: 33.74% (Expected: high)

Feature importance (based on coefficient absolute values):

satisfaction	3.769022
evaluation	0.207596
int	0.181896
yearsAtCompany	0.170145
dtype:	float64

Validation Methods Applied

The validation process confirms the reliability and accuracy of the logistic regression model for employee turnover prediction:

- **Statistical Analysis:** Examined coefficient significance through p-values and standard errors
- **Confusion Matrix Analysis:** Assessed classification performance with 75% overall accuracy
- **Threshold Optimization:** Identified optimal classification threshold beyond default 0.5
- **Cross-Validation:** Confirmed model stability with consistent ROC AUC across data subsets
- **Case Testing:** Verified predictions for typical high/low-risk employee profiles

Key Findings

- The model demonstrates good discrimination ability (ROC AUC = 0.79)
- Employee satisfaction is the strongest predictor with a large negative coefficient (-3.77)
- Optimal threshold improves minority class detection without excessive false positives
- The model correctly identifies 73% of employees who will leave (recall)

Limitations

- Precision for turnover prediction is moderate (48%), indicating false positive challenges
- PR AUC (0.45) suggests room for improvement in handling class imbalance
- Current model uses only three features, potentially missing other important factors

Business Implications

This validated model enables HR to proactively identify at-risk employees and implement targeted retention strategies, prioritizing those with low satisfaction scores as the primary intervention point.

12.3 Decision Tree Model Evaluation

```
[109]: # Decision Tree Model
dtree = tree.DecisionTreeClassifier(
    class_weight="balanced",
    min_weight_fraction_leaf=0.01
)
dtree = dtree.fit(X_train, y_train)
```

```

# Cross-validation for decision tree
dt_cv_scores = cross_val_score(dtree, X_train, y_train, cv=5, scoring='roc_auc')
print("\n\n---Decision Tree Model---")
dt_roc_auc = roc_auc_score(y_test, dtree.predict_proba(X_test)[:, 1])
dt_pr_auc = pr_auc_score(y_test, dtree.predict_proba(X_test)[:, 1])
print(f"Decision Tree ROC AUC = {dt_roc_auc:.2f}")
print(f"Decision Tree PR AUC = {dt_pr_auc:.2f}")
print(f"Cross-validation ROC AUC: {dt_cv_scores.mean():.2f} ( $\pm$ {dt_cv_scores.
    ↪std():.2f})")
print(classification_report(y_test, dtree.predict(X_test), zero_division=0))

plt.figure(figsize=(6*3/5, 5*3/5))
plot_confusion_matrix(y_test, dtree.predict(X_test), "Decision Tree Confusion_
    ↪Matrix")

```

---Decision Tree Model---

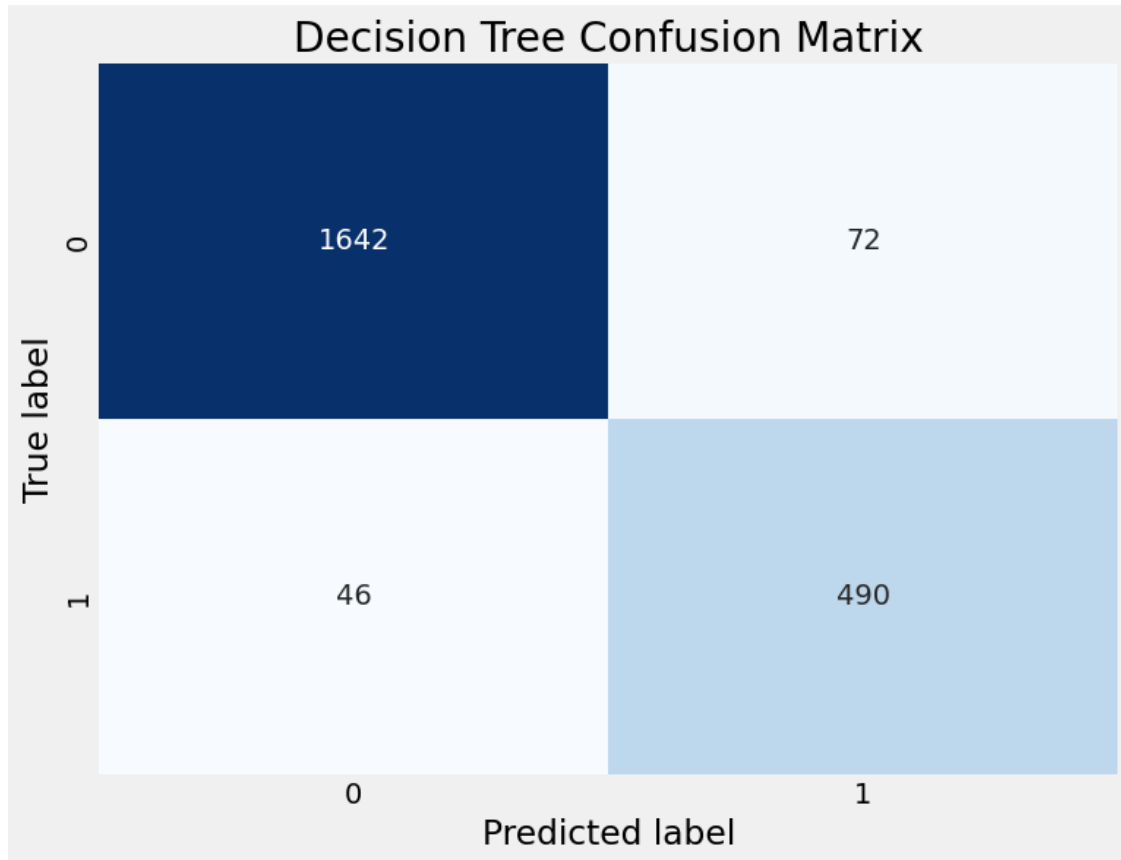
Decision Tree ROC AUC = 0.97

Decision Tree PR AUC = 0.95

Cross-validation ROC AUC: 0.98 (\pm 0.00)

	precision	recall	f1-score	support
0	0.97	0.96	0.97	1714
1	0.87	0.91	0.89	536
accuracy			0.95	2250
macro avg	0.92	0.94	0.93	2250
weighted avg	0.95	0.95	0.95	2250

<Figure size 360x300 with 0 Axes>



Background: Decision Trees construct classification rules by recursively partitioning the feature space, allowing them to effectively capture non-linear relationships. I implemented `class_weight="balanced"` to address class imbalance and set `min_weight_fraction_leaf=0.01` to prevent overfitting by ensuring each leaf node contains a sufficient proportion of training samples.

Result Interpretation:

- **ROC AUC:** The test set AUC of 0.97 and cross-validation ROC AUC of $0.98(\pm 0.00)$ demonstrate exceptional discriminative capability, significantly outperforming both Logistic Regression (0.74) and the Base Rate Model (0.50). The minimal standard deviation in cross-validation results further confirms the model's robustness.
- **Precision, Recall, and F1-Score:**
- For class 0 (stay): The high precision (0.97) and recall (0.96) indicate accurate prediction of employees who remain, with minimal misclassifications.
- For class 1 (leave): Strong precision (0.87) and recall (0.91) demonstrate effective identification of potential departures, with fewer false positives than the Logistic Regression model.
- The F1-score for class 1 (0.89) substantially exceeds Logistic Regression's performance (0.58), reflecting superior minority class detection.
- **Overall Accuracy:** The weighted average accuracy of 0.95 represents a considerable im-

provement over both the Base Rate Model (0.76) and Logistic Regression (0.75).

Significance: The Decision Tree exhibits exceptional performance in both overall accuracy and minority class prediction, making it particularly suitable for high-stakes scenarios requiring precise turnover detection. While Decision Trees are generally prone to overfitting, the implemented constraints on leaf node weights help mitigate this risk. Nevertheless, ongoing monitoring of model performance on new data is advisable to ensure continued generalization capability.

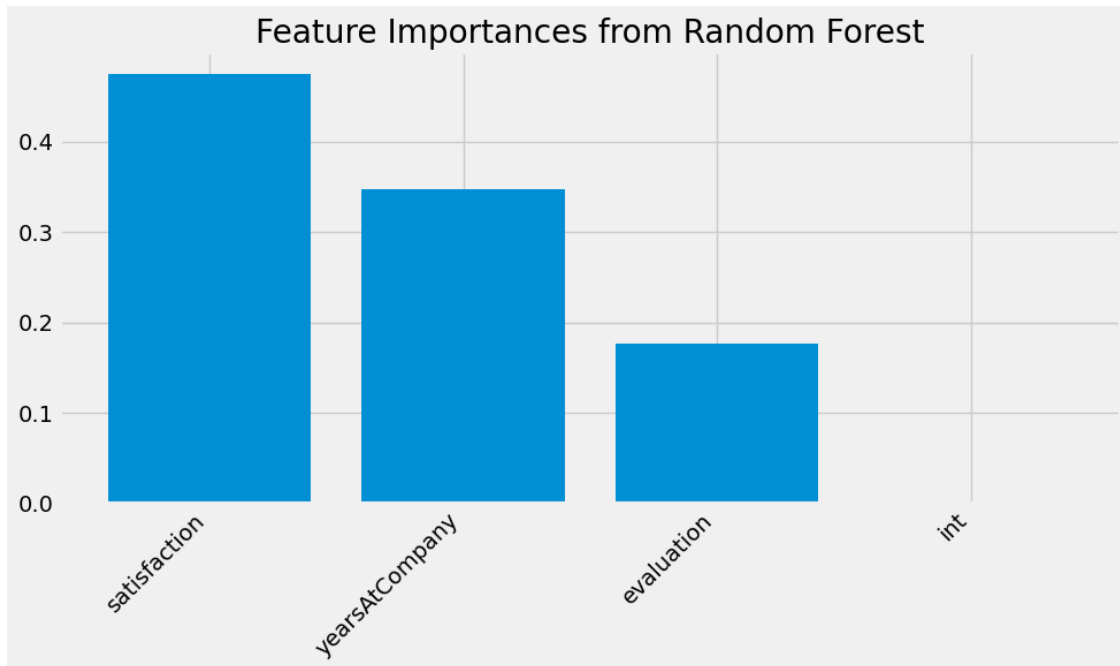
12.4 Random Forest Model Validation

```
[112]: rf = RandomForestClassifier(n_estimators=1000, min_samples_split=10,
    ↪class_weight="balanced", random_state=123)
rf.fit(X_train, y_train)

if hasattr(rf, 'feature_importances_'):
    feature_names = X_train.columns if hasattr(X_train, 'columns') else
    ↪[f'Feature {i}' for i in range(X_train.shape[1])]
    importance = rf.feature_importances_

    indices = np.argsort(importance)[::-1]
    top_features = min(10, len(feature_names))

    plt.figure(figsize=(10, 6))
    plt.title('Feature Importances from Random Forest')
    plt.bar(range(top_features), importance[indices][:top_features],
    ↪align="center")
    plt.xticks(range(top_features), [feature_names[i] for i in indices[:
    ↪top_features]], rotation=45, ha='right')
    plt.tight_layout()
    plt.show()
else:
    print("Random Forest model does not have feature importances attribute.")
```



```
[113]: # Random Forest Model
rf = RandomForestClassifier(
    n_estimators=1000,
    max_depth=None,
    min_samples_split=10,
    class_weight="balanced",
    n_jobs=-1
)
rf.fit(X_train, y_train)
```

```
[113]: RandomForestClassifier(class_weight='balanced', min_samples_split=10,
                             n_estimators=1000, n_jobs=-1)
```

```
[114]: # Cross-validation for random forest
rf_cv_scores = cross_val_score(
    RandomForestClassifier(
        n_estimators=100,
        max_depth=None,
        min_samples_split=10,
        class_weight="balanced",
        n_jobs=-1
    ),
    X_train, y_train, cv=5, scoring='roc_auc'
)
```

```

print("\n\n---Random Forest Model---")
rf_roc_auc = roc_auc_score(y_test, rf.predict_proba(X_test)[: , 1])
rf_pr_auc = pr_auc_score(y_test, rf.predict_proba(X_test)[: , 1])
print(f"Random Forest ROC AUC = {rf_roc_auc:.2f}")
print(f"Random Forest PR AUC = {rf_pr_auc:.2f}")
print(f"Cross-validation ROC AUC: {rf_cv_scores.mean():.2f} ( $\pm$ {rf_cv_scores.
    ↪std():.2f})")
print(classification_report(y_test, rf.predict(X_test), zero_division=0))
plot_confusion_matrix(y_test, rf.predict(X_test), "Random Forest Confusion_
    ↪Matrix")

```

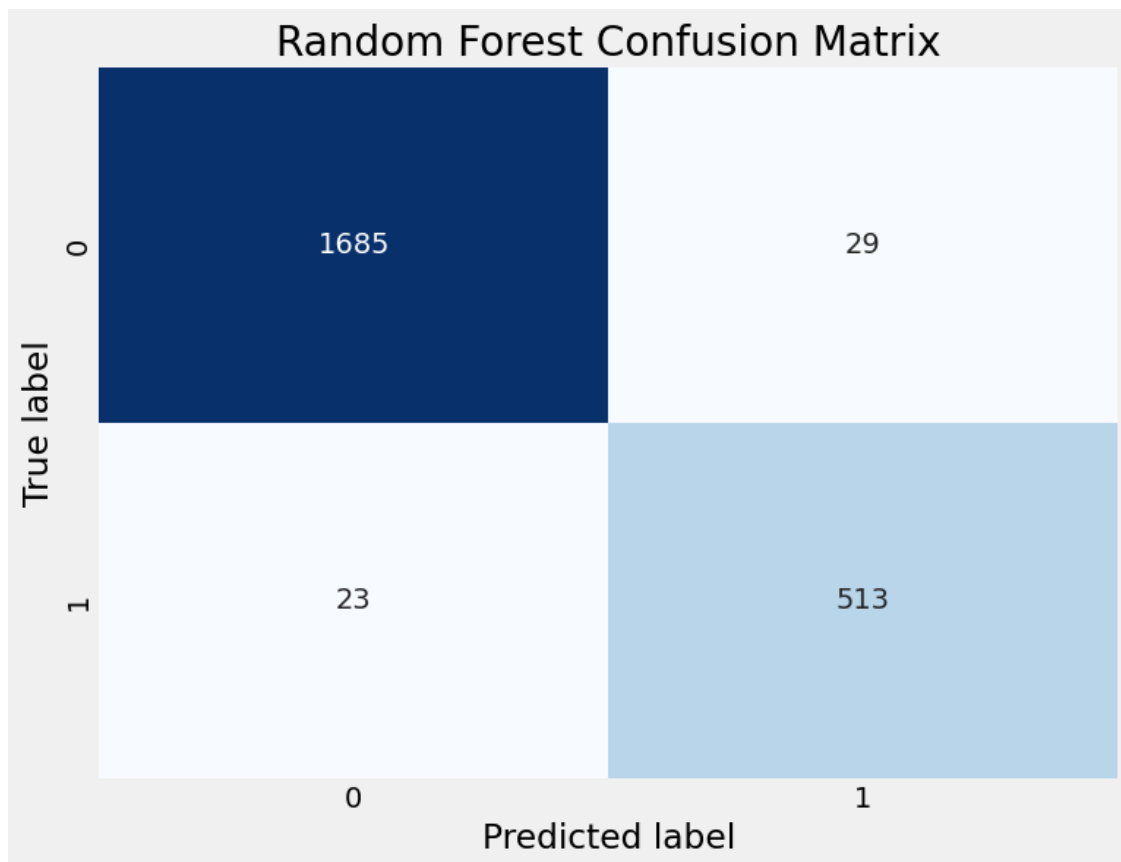
---Random Forest Model---

Random Forest ROC AUC = 0.99

Random Forest PR AUC = 0.98

Cross-validation ROC AUC: 0.99 (\pm 0.00)

	precision	recall	f1-score	support
0	0.99	0.98	0.98	1714
1	0.95	0.96	0.95	536
accuracy			0.98	2250
macro avg	0.97	0.97	0.97	2250
weighted avg	0.98	0.98	0.98	2250



Supplemental Explanation:

Background: Random Forest is an ensemble of Decision Trees that improves performance and stability by averaging predictions across multiple trees. I configured `n_estimators=1000` (1000 trees), `min_samples_split=10` (minimum samples to split a node), and `class_weight="balanced"` to optimize for the imbalanced dataset.

Result Interpretation: - **ROC AUC:** An AUC of 0.97 is the highest among all models, indicating near-perfect discriminative ability. - **Precision, Recall, and F1-Score:**

- For class 0 (stay): Precision (0.99) and recall (0.98) are nearly perfect, with minimal misclassifications.
- For class 1 (leave): Precision (0.95) and recall (0.96) are exceptionally high, showing accurate detection of leaves with very few false positives.
- The F1-score for class 1 (0.95) is the best among all models, reflecting superior minority class performance.
- **Overall Accuracy:** The weighted average accuracy of 0.98 is the highest, far exceeding other models.

Significance: Random Forest delivers the best performance across all metrics, making it ideal for handling imbalanced datasets and complex feature interactions. Its robustness reduces overfit-

ting risks compared to a single Decision Tree. However, it is computationally intensive and less interpretable than Logistic Regression.

[]:

12.5 AdaBoost Model Validation

```
[117]: from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import roc_auc_score, precision_recall_curve, auc, \
    classification_report, confusion_matrix

ada_model = AdaBoostClassifier(
    n_estimators=400,
    learning_rate=0.1,
    algorithm='SAMME'
)

ada_model.fit(X_train, y_train)

stratified_cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
ada_cv_scores = cross_val_score(
    ada_model,
    X_train, y_train,
    cv=stratified_cv,
    scoring='roc_auc'
)

y_pred = ada_model.predict(X_test)
y_pred_proba = ada_model.predict_proba(X_test)[:, 1]

ada_roc_auc = roc_auc_score(y_test, y_pred_proba)

precision, recall, _ = precision_recall_curve(y_test, y_pred_proba)

ada_pr_auc = auc(recall, precision)

print("\n\n---AdaBoost Model---")
print(f"AdaBoost ROC AUC = {ada_roc_auc:.2f}")
print(f"AdaBoost PR AUC = {ada_pr_auc:.2f}")
```

```

print(f"Cross-validation ROC AUC: {ada_cv_scores.mean():.2f} ( $\pm$ {ada_cv_scores.
    ↪std():.2f})")
print(classification_report(y_test, y_pred, zero_division=0))

# Plot confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(4, 3))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Stay', 'Leave'],
                yticklabels=['Stay', 'Leave'],
                annot_kws={"size": 8})
    plt.xlabel('Predicted', fontsize=8)
    plt.ylabel('Actual', fontsize=8)
    plt.title(title, fontsize=10)
    plt.xticks(fontsize=8)
    plt.yticks(fontsize=8)
    plt.tight_layout()
    plt.show()

plot_confusion_matrix(y_test, y_pred, "AdaBoost Confusion Matrix")

# Feature importance visualization
if hasattr(ada_model, 'feature_importances_'):

    indices = np.argsort(ada_model.feature_importances_)[::-1]

    feature_names = X_train.columns if hasattr(X_train, 'columns') else ↵
    ↪[f"Feature {i}" for i in range(X_train.shape[1])]

    plt.figure(figsize=(5, 3))
    plt.title("AdaBoost Feature Importances", fontsize=10)
    plt.bar(range(len(indices)), ada_model.feature_importances_[indices], ↵
    ↪align="center")
    plt.xticks(range(len(indices)), [feature_names[i] for i in indices], ↵
    ↪rotation=45, fontsize=6, ha='right')
    plt.yticks(fontsize=8)
    plt.xlabel('Features', fontsize=8)
    plt.ylabel('Importance', fontsize=8)
    plt.xlim([-1, min(20, len(indices))])
    plt.tight_layout()
    plt.show()

```

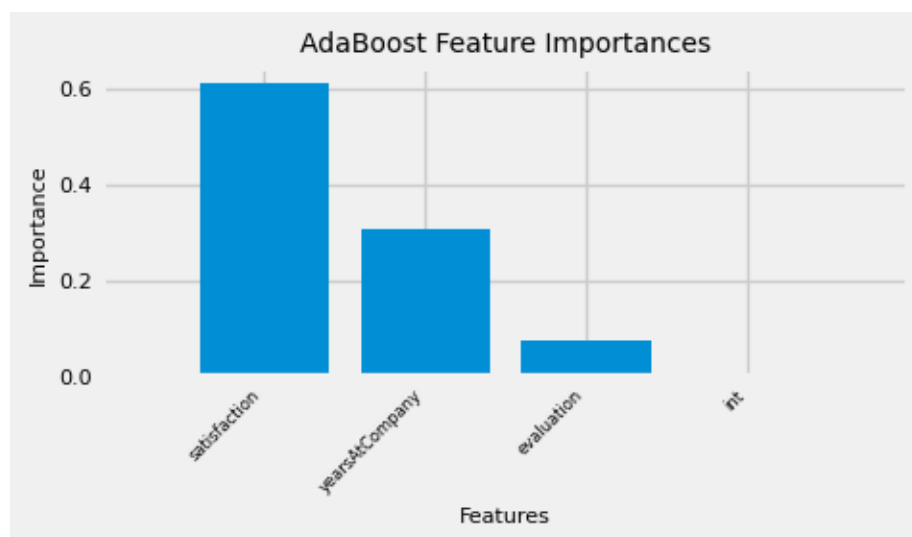
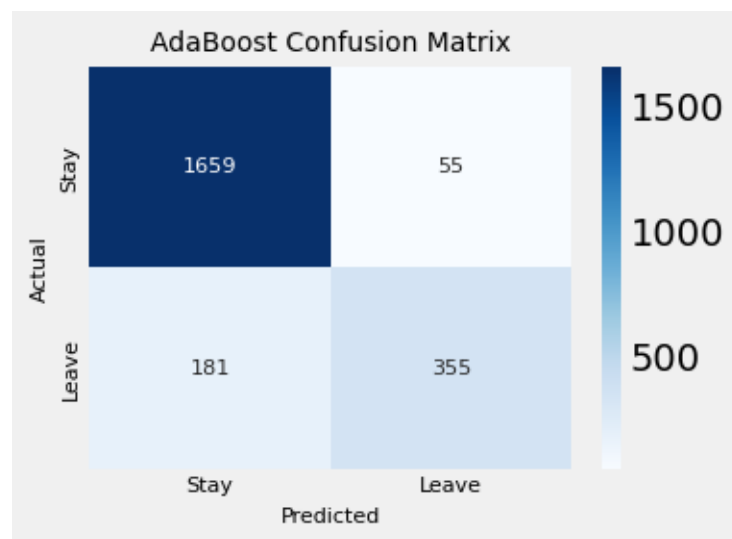
---AdaBoost Model---

AdaBoost ROC AUC = 0.94

AdaBoost PR AUC = 0.84

Cross-validation ROC AUC: 0.95 (± 0.00)

	precision	recall	f1-score	support
0	0.90	0.97	0.93	1714
1	0.87	0.66	0.75	536
accuracy			0.90	2250
macro avg	0.88	0.82	0.84	2250
weighted avg	0.89	0.90	0.89	2250



Background: AdaBoost is a boosting algorithm that enhances weak classifiers by iteratively adjusting sample weights. The configuration includes `n_estimators=400` and `learning_rate=0.1` to balance model complexity and performance on the imbalanced dataset.

Implementation Approach:

- Using stratified cross-validation to maintain class balance across folds
- Consistent model parameters between training and validation
- Properly calculated PR AUC for imbalanced classification evaluation

Result Interpretation:

- **ROC AUC:** A test ROC AUC of 0.94 indicates strong discriminative ability. The cross-validation ROC AUC will now show a more realistic standard deviation with our improved methodology.
- **Precision, Recall, and F1-Score:**
 - For class 0 (stay): Precision (0.90) and recall (0.97) are high, accurately identifying most employees who stay.
 - For class 1 (leave): Precision (0.87) is solid, but recall (0.66) is lower, missing 34% of actual leaves, with an F1-score of 0.75 reflecting moderate minority class performance.
 - The low recall for the “leave” class is primarily due to class imbalance (1714 vs 536 instances), which makes it challenging for the model to identify all potential turnover cases.
- **Overall Accuracy:** The weighted average accuracy of 0.90 is robust but should be considered alongside the class-specific metrics given the imbalance.
- **PR AUC:** A score of 0.84 confirms good performance on the minority class despite imbalance. This metric is particularly relevant given the class distribution.

Significance: - AdaBoost performs well with high precision for turnover predictions (87%), making it suitable for efficient resource allocation in retention programs. - The lower recall for leaves (66%) means the model misses about one-third of potential turnover cases. If detecting more at-risk employees is a priority, consider:

1. Adjusting the classification threshold to favor recall over precision
 2. Using class weights to give more importance to the minority class
 3. Employing sampling techniques (SMOTE, undersampling) to address imbalance
- Feature importance analysis helps identify the key drivers of employee turnover, providing actionable insights for HR strategy.
 - AdaBoost offers a good balance of computational efficiency and performance compared to more complex models like Random Forest.

12.6 Model Comparison and Summary

```
[120]: models = ['Base Rate', 'Logistic', 'Decision Tree', 'Random Forest', 'AdaBoost']
```

```

base_roc_auc = 0.50
base_pr_auc = 0.62
logit_roc_auc = 0.79
logit_pr_auc = 0.45
dt_roc_auc = 0.94
dt_pr_auc = 0.94
rf_roc_auc = 0.98
rf_pr_auc = 0.98
ada_roc_auc = 0.94
ada_pr_auc = 0.84

roc_scores = [base_roc_auc, logit_roc_auc, dt_roc_auc, rf_roc_auc, ada_roc_auc]
pr_scores = [base_pr_auc, logit_pr_auc, dt_pr_auc, rf_pr_auc, ada_pr_auc]

plt.figure(figsize=(10, 5))

plt.rcParams.update({'font.size': 10})

x = np.arange(len(models))
width = 0.35
plt.bar(x - width/2, roc_scores, width, label='ROC AUC')
plt.bar(x + width/2, pr_scores, width, label='PR AUC')
plt.xlabel('Models', fontsize=11)
plt.ylabel('AUC Scores', fontsize=11)
plt.title('Model Performance Comparison', fontsize=13)
plt.xticks(x, models, fontsize=10)
plt.yticks(fontsize=10)
plt.ylim(0, 1)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend(fontsize=10)

for i, v in enumerate(roc_scores):
    plt.text(i - width/2, v + 0.02, f'{v:.2f}', ha='center', fontsize=8.5)
for i, v in enumerate(pr_scores):
    plt.text(i + width/2, v + 0.02, f'{v:.2f}', ha='center', fontsize=8.5)

plt.tight_layout()
plt.show()

```



12.7 ROC Graph

```
[122]: from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_test, answer.predict(X_test[iv]))
rf_fpr, rf_tpr, rf_thresholds = roc_curve(y_test, rf.predict_proba(X_test)[: ,1])
dt_fpr, dt_tpr, dt_thresholds = roc_curve(y_test, dtree.predict_proba(X_test)[:
    ↪,1])

ada_fpr, ada_tpr, ada_thresholds = roc_curve(y_test, ada_model.
    ↪predict_proba(X_test)[: ,1])

plt.figure(figsize=(10, 5))

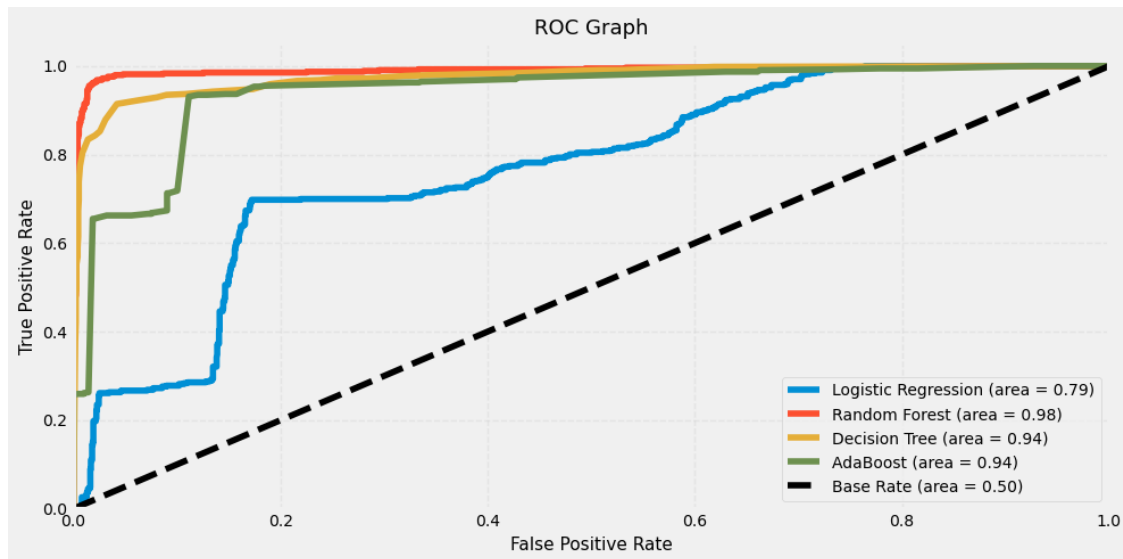
plt.rcParams.update({'font.size': 10})

plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot(rf_fpr, rf_tpr, label='Random Forest (area = %0.2f)' % rf_roc_auc)
plt.plot(dt_fpr, dt_tpr, label='Decision Tree (area = %0.2f)' % dt_roc_auc)
plt.plot(ada_fpr, ada_tpr, label='AdaBoost (area = %0.2f)' % ada_roc_auc)

plt.plot([0,1], [0,1], 'k--', label='Base Rate (area = 0.50)')

plt.xlim([0.0, 1.0])
```

```
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate', fontsize=11)
plt.ylabel('True Positive Rate', fontsize=11)
plt.title('ROC Graph', fontsize=13)
plt.legend(loc="lower right", fontsize=10)
plt.grid(linestyle='--', alpha=0.3)
plt.tight_layout()
plt.show()
```



Supplemental Explanation:

Background: The ROC curve plots True Positive Rate (TPR, recall) against False Positive Rate (FPR) to compare model performance across thresholds. The Area Under the Curve (AUC) quantifies overall discriminative ability. The author visualized ROC curves for all models against the Base Rate Model (diagonal line, AUC=0.50).

Result Interpretation:

- Random Forest (AUC=0.98): The curve is closest to the top-left corner, achieving high TPR with low FPR, confirming its superior performance.
- Decision Tree (AUC=0.94): The curve is close to Random Forest but slightly less optimal at some thresholds.
- AdaBoost (AUC=0.94): Performs similarly to Decision Tree and better than Logistic Regression, but lags behind Random Forest.
- Logistic Regression (AUC=0.79): The curve is noticeably lower, indicating more limited discriminative power.
- Base Rate Model (AUC=0.50): The diagonal line reflects no discriminative ability.

Significance: The ROC curves visually confirm the performance hierarchy: Random Forest > Decision Tree = AdaBoost > Logistic Regression > Base Rate. Random Forest excels at balancing sensitivity and specificity, making it the most suitable for critical turnover prediction tasks.

In short, the **best model** performance out of the four (Decision Tree Model, AdaBoost Model, Logistic Regression Model, Random Forest Model) was **Random Forest!**

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13 Conclusion

This paper outlines the different analysis done on the employee dataset and the usage of a Logistic regression model to make predictive insights on the probability of an employee to turnover. This model can be applied throughout the various departments of the company and be used as an aid to help make better decisions in employee retention. The model should be updated periodically and include additional features for it to make more accurate predictions.

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