Employee Turnover Analysis

[1]:

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import (accuracy_score, precision_score, recall_score, f1_score,
                             roc_auc_score, classification_report, confusion_matrix)
from sklearn.cluster import KMeans
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
sns.set_style('whitegrid')
print("Libraries loaded successfully.")
```

```
Libraries loaded successfully.
```

1. Load Data & Data Quality Checks

Load HR dataset and check for missing values.

[4]:

```
# Load dataset (use path relative to notebook location)
df = pd.read_csv('HR_comma_sep.csv')
print("Dataset shape:", df.shape)
print("\nFirst 5 rows:")
df.head()
```

```
Dataset shape: (14999, 10)

First 5 rows:
```

[4]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

[6]:

```python
# Data quality checks - Missing values
print("=== DATA QUALITY CHECKS ===\n")
print("Missing values per column:")
print(df.isnull().sum())
print("\nTotal missing values:", df.isnull().sum().sum())
print("\nData types:\n", df.dtypes)
print("\nBasic statistics:")
df.describe()
```

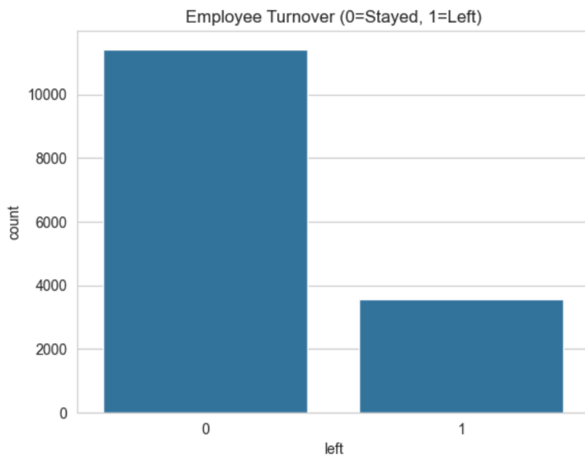
```
=== DATA QUALITY CHECKS ===

Missing values per column:
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

Total missing values: 0

Data types:
 satisfaction_level       float64
last_evaluation          float64
number_project             int64
average_montly_hours       int64
time_spend_company         int64
Work_accident              int64
left                       int64
promotion_last_5years      int64
sales                     object
salary                    object
dtype: object

Basic statistics:
```

[6]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years
count	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000
mean	0.612834	0.716102	3.803054	201.050337	3.498233	0.144610	0.238083	0.021268
std	0.248631	0.171169	1.232592	49.943099	1.460136	0.351719	0.425924	0.144281
min	0.090000	0.360000	2.000000	96.000000	2.000000	0.000000	0.000000	0.000000
25%	0.440000	0.560000	3.000000	156.000000	3.000000	0.000000	0.000000	0.000000
50%	0.640000	0.720000	4.000000	200.000000	3.000000	0.000000	0.000000	0.000000
75%	0.820000	0.870000	5.000000	245.000000	4.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	7.000000	310.000000	10.000000	1.000000	1.000000	1.000000

[8]:
```python
# Class distribution (target: left)
print("Target 'left' distribution:")
print(df['left'].value_counts())
print("\nPercentage:")
print(df['left'].value_counts(normalize=True).round(3) * 100)
sns.countplot(data=df, x='left')
plt.title('Employee Turnover (0=Stayed, 1=Left)')
plt.show()
```

```
Target 'left' distribution:
left
0    11428
1     3571
Name: count, dtype: int64

Percentage:
left
0    76.2
1    23.8
Name: proportion, dtype: float64
```

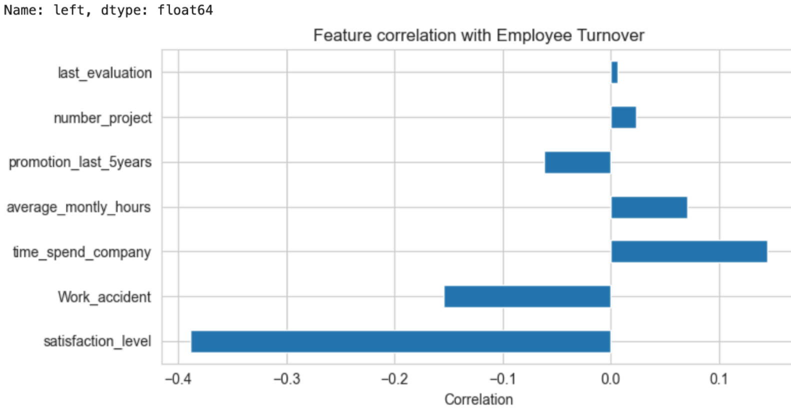


2. Exploratory Data Analysis - Factors Contributing to Turnover

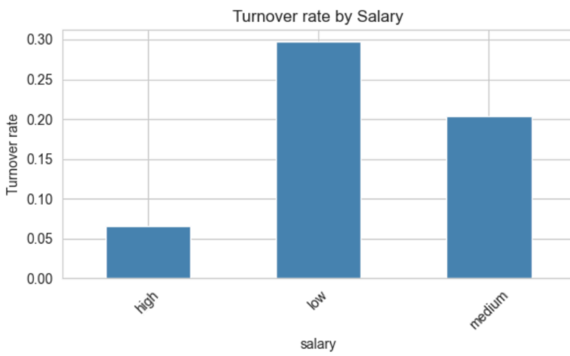
Understand which factors contribute most to employee turnover.

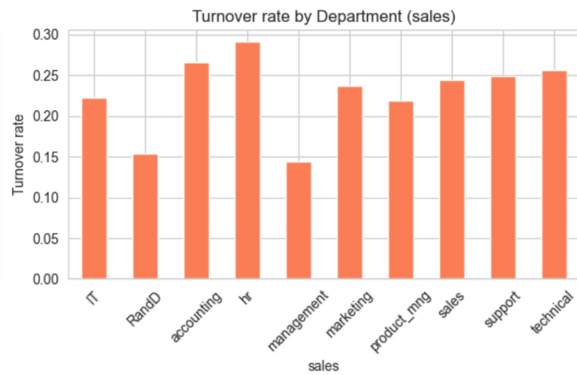
[11]:
```python
# Correlation with target
df_numeric = df.select_dtypes(include=[np.number])
corr_with_left = df_numeric.corr()['left'].drop('left').sort_values(key=abs, ascending=False)
print("Correlation with 'left' (absolute):\n", corr_with_left)
corr_with_left.plot(kind='barh', figsize=(8,4))
plt.title('Feature correlation with Employee Turnover')
plt.xlabel('Correlation')
plt.tight_layout()
plt.show()
```

```
Correlation with 'left' (absolute):
 satisfaction_level      -0.388375
Work_accident           -0.154622
time_spend_company       0.144822
average_montly_hours     0.071287
promotion_last_5years   -0.061788
number_project           0.023787
last_evaluation          0.006567
Name: left, dtype: float64
```



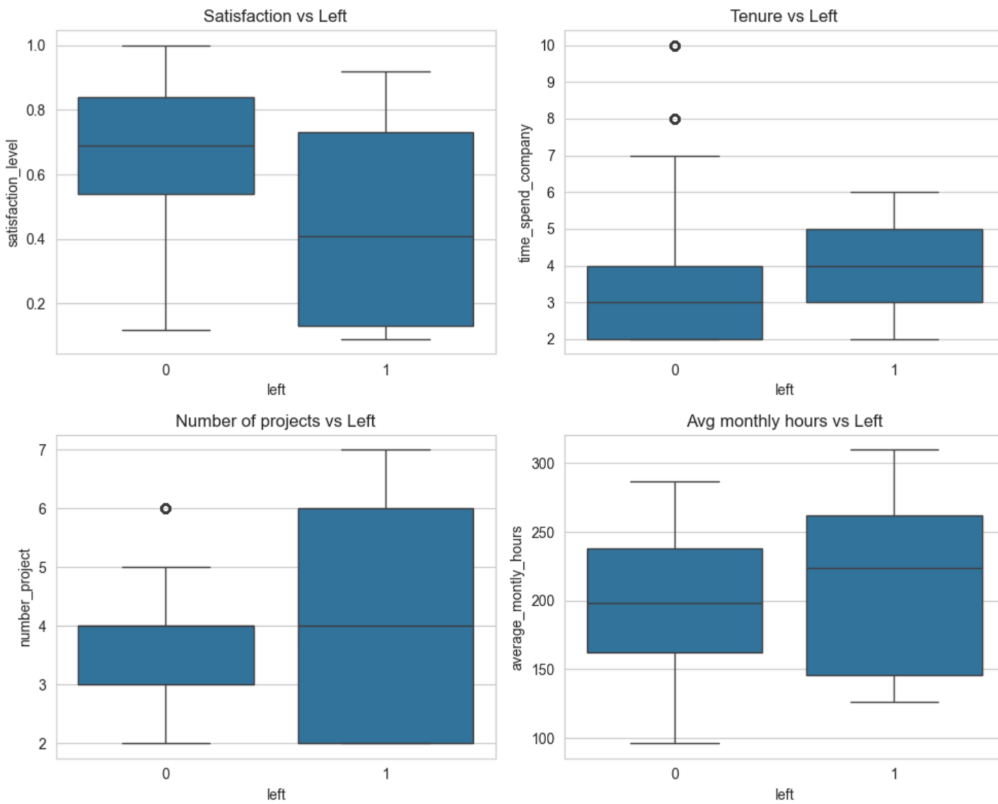
[13]:
```
# Turnover rate by categorical features
fig, axes = plt.subplots(1, 2, figsize=(12, 4))
df.groupby('salary')['left'].mean().plot(kind='bar', ax=axes[0], color='steelblue')
axes[0].set_title('Turnover rate by Salary')
axes[0].set_ylabel('Turnover rate')
axes[0].tick_params(axis='x', rotation=45)
df.groupby('sales')['left'].mean().plot(kind='bar', ax=axes[1], color='coral')
axes[1].set_title('Turnover rate by Department (sales)')
axes[1].set_ylabel('Turnover rate')
axes[1].tick_params(axis='x', rotation=45)
plt.tight_layout()
plt.show()
```





[15]:

```python
# Key numeric factors: satisfaction_level, time_spend_company, number_project
fig, axes = plt.subplots(2, 2, figsize=(10, 8))
sns.boxplot(data=df, x='left', y='satisfaction_level', ax=axes[0,0])
axes[0,0].set_title('Satisfaction vs Left')
sns.boxplot(data=df, x='left', y='time_spend_company', ax=axes[0,1])
axes[0,1].set_title('Tenure vs Left')
sns.boxplot(data=df, x='left', y='number_project', ax=axes[1,0])
axes[1,0].set_title('Number of projects vs Left')
sns.boxplot(data=df, x='left', y='average_montly_hours', ax=axes[1,1])
axes[1,1].set_title('Avg monthly hours vs Left')
plt.tight_layout()
plt.show()
print("\nEDA Summary: Low satisfaction, longer tenure, high hours and project count associate with higher turnover.")
```

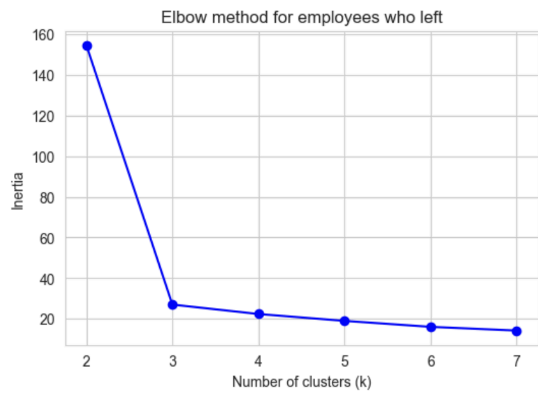



```
EDA Summary: Low satisfaction, longer tenure, high hours and project count associate with higher turnover.
```

3. Clustering of Employees Who Left (Satisfaction & Evaluation)

Cluster employees who left based on satisfaction_level and last_evaluation.

[18]:
```
# Subset: employees who left
df_left = df[df['left'] == 1][['satisfaction_level', 'last_evaluation']].copy()
# Elbow method for optimal k
inertias = []
K = range(2, 8)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(df_left)
    inertias.append(kmeans.inertia_)
plt.figure(figsize=(6, 4))
plt.plot(K, inertias, 'bo-')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow method for employees who left')
plt.show()
```



[20]:
```
# K-Means clustering with k=3 (typical elbow around 3)
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
df_left['cluster'] = kmeans.fit_predict(df_left)
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df_left, x='satisfaction_level', y='last_evaluation', hue='cluster', palette='Set1')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=200, c='black', marker='X', label='Centroids')
plt.title('Clustering of employees who left (Satisfaction vs Evaluation)')
plt.legend()
plt.show()
print("Cluster sizes:", df_left['cluster'].value_counts().sort_index())
```


```
Cluster sizes: cluster
0    1650
1     977
2     944
Name: count, dtype: int64
```

4. Data Preprocessing & SMOTE for Class Imbalance

Encode categoricals, scale features, and apply SMOTE to balance the 'left' class.

4. Data Preprocessing & SMOTE for Class Imbalance

Encode categoricals, scale features, and apply SMOTE to balance the 'left' class.

[23]:
```python
# Encode categorical columns
df_ml = df.copy()
le_sales = LabelEncoder()
le_salary = LabelEncoder()
df_ml['sales_enc'] = le_sales.fit_transform(df_ml['sales'])
df_ml['salary_enc'] = le_salary.fit_transform(df_ml['salary'])
# Features and target
feature_cols = ['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hours',
                'time_spend_company', 'Work_accident', 'promotion_last_5years', 'sales_enc', 'salary_enc']
X = df_ml[feature_cols]
y = df_ml['left']
# Train-test split first (SMOTE only on training set)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
print("Before SMOTE - Train:", y_train.value_counts().to_dict())
```

```
Before SMOTE - Train: {0: 9142, 1: 2857}
```

[25]:
```python
# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Apply SMOTE on training data only
smote = SMOTE(random_state=42, k_neighbors=5)
X_train_bal, y_train_bal = smote.fit_resample(X_train_scaled, y_train)
print("After SMOTE - Train:", pd.Series(y_train_bal).value_counts().to_dict())
```

```
After SMOTE - Train: {0: 9142, 1: 9142}
```

5. K-Fold Cross-Validation & Model Training

Train multiple classifiers with stratified k-fold CV and evaluate performance.

[28]:
```python
# Stratified 5-fold cross-validation
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, random_state=42)
}
cv_results = {}
for name, model in models.items():
    scores_acc = cross_val_score(model, X_train_bal, y_train_bal, cv=cv, scoring='accuracy')
    scores_f1 = cross_val_score(model, X_train_bal, y_train_bal, cv=cv, scoring='f1')
    scores_roc = cross_val_score(model, X_train_bal, y_train_bal, cv=cv, scoring='roc_auc')
    cv_results[name] = {'accuracy': scores_acc.mean(), 'f1': scores_f1.mean(), 'roc_auc': scores_roc.mean()}
    print(f"{name}: CV Accuracy={scores_acc.mean():.3f}, F1={scores_f1.mean():.3f}, ROC-AUC={scores_roc.mean():.3f}")
cv_df = pd.DataFrame(cv_results).T
cv_df
```

```
Logistic Regression: CV Accuracy=0.762, F1=0.768, ROC-AUC=0.817
Random Forest: CV Accuracy=0.990, F1=0.990, ROC-AUC=0.999
Gradient Boosting: CV Accuracy=0.966, F1=0.965, ROC-AUC=0.993
```

[28]:

	accuracy	f1	roc_auc
Logistic Regression	0.761978	0.767872	0.816927
Random Forest	0.989827	0.989756	0.998775
Gradient Boosting	0.965653	0.965218	0.993267

[35]:
```python
# Train final models on full balanced train set and evaluate on test set (no SMOTE)
results = []
for name, model in models.items():
    model.fit(X_train_bal, y_train_bal)
    y_pred = model.predict(X_test_scaled)
    results.append({
        'Model': name,
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred, zero_division=0),
        'Recall': recall_score(y_test, y_pred, zero_division=0),
        'F1-Score': f1_score(y_test, y_pred, zero_division=0),
        'ROC-AUC': roc_auc_score(y_test, model.predict_proba(X_test_scaled)[:, 1])
    })
results_df = pd.DataFrame(results)
results_df
```

[35]:

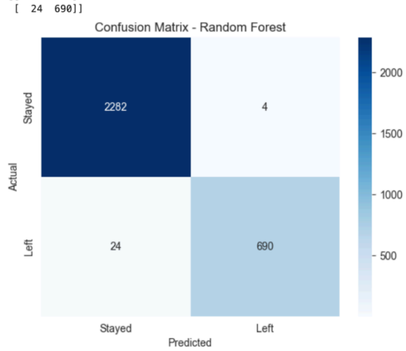
	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
0	Logistic Regression	0.762000	0.500000	0.778711	0.608981	0.822411
1	Random Forest	0.990667	0.994236	0.966387	0.980114	0.992312
2	Gradient Boosting	0.965667	0.921379	0.935574	0.928423	0.989849

6. Best Model Selection & Evaluation Metrics Justification

We use **F1-Score** and **ROC-AUC** as primary metrics because turnover is a class-imbalanced problem: we care about correctly identifying employees who will leave (minority class) without excessive false positives. Accuracy alone can be misleading.

[31]:
```python
# Best model by F1 (and ROC-AUC for robustness)
best_by_f1 = results_df.loc[results_df['F1-Score'].idxmax()]
print("Best model (by F1-Score):", best_by_f1['Model'])
print(best_by_f1)
best_model_name = best_by_f1['Model']
best_model = models[best_model_name]
best_model.fit(X_train_bal, y_train_bal)
y_pred_best = best_model.predict(X_test_scaled)
print("\nClassification Report (Best Model):")
print(classification_report(y_test, y_pred_best, target_names=['Stayed', 'Left']))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_best))
sns.heatmap(confusion_matrix(y_test, y_pred_best), annot=True, fmt='d', cmap='Blues',
            xticklabels=['Stayed', 'Left'], yticklabels=['Stayed', 'Left'])
plt.title(f'Confusion Matrix - {best_model_name}')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```

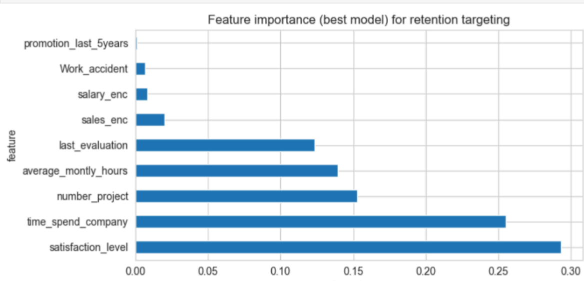
```
Best model (by F1-Score): Random Forest
Model        Random Forest
Accuracy          0.990667
Precision         0.994236
Recall            0.966387
F1-Score          0.980114
ROC-AUC           0.992312
Name: 1, dtype: object

Classification Report (Best Model):
              precision    recall  f1-score   support

      Stayed       0.99      1.00      0.99      2286
        Left       0.99      0.97      0.98       714

    accuracy                           0.99      3000
   macro avg       0.99      0.98      0.99      3000
weighted avg       0.99      0.99      0.99      3000

Confusion Matrix:
[[2282    4]
 [  24  690]]
```



7. Retention Strategies for Targeted Employees

Based on EDA and clustering, we recommend the following retention strategies for employees at risk of leaving:

[33]:
```python
# Feature importance (for tree-based best model) to target interventions
if hasattr(best_model, 'feature_importances_'):
    imp = pd.DataFrame({'feature': feature_cols, 'importance': best_model.feature_importances_})
    imp = imp.sort_values('importance', ascending=False)
    imp.plot(x='feature', y='importance', kind='barh', legend=False, figsize=(8, 4))
    plt.title('Feature importance (best model) for retention targeting')
    plt.xlabel('Importance')
    plt.tight_layout()
    plt.show()
    print(imp)
```




```
                 feature  importance
0     satisfaction_level    0.293491
4     time_spend_company    0.254973
2         number_project    0.153020
3   average_montly_hours    0.139348
1        last_evaluation    0.123520
7              sales_enc    0.020054
8             salary_enc    0.008201
5          Work_accident    0.006514
6  promotion_last_5years    0.000879
```

RETENTION STRATEGIES (Targeted by risk factors):

1. LOW SATISFACTION: Conduct stay interviews and pulse surveys; address workload, recognition, and work-life balance.
2. HIGH TENURE + BURNOUT: Offer sabbaticals, role rotation, or project variety; review promotion and growth paths.
3. HIGH HOURS / OVERLOAD: Cap overtime, redistribute projects, and hire to reduce average_montly_hours.
4. LOW SALARY (vs market): Benchmark compensation; consider raises or bonuses for high performers.
5. NO PROMOTION (promotion_last_5years=0): Clear career ladder and internal mobility programs.
6. DEPARTMENT-SPECIFIC: Tailor interventions by sales/technical/support (e.g., sales: quotas and incentives; technical: learning budget).

Using the model: Score current employees; target retention efforts on those predicted as 'left' with highest probability.