Group Final Project: Employee Churn at Dunder Mifflin Paper Company

Import data

In [297…

```
# Install Required Libraries
!pip install mlxtend --quiet
```

In [298…

```
# Import Libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt
import seaborn as sns
import networkx as nx

from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
```

In [299…

```
#Load Dataset
df = pd.read_csv("office_churn_dataset.csv")
print("Initial Shape:", df.shape)
df.head()
```

```
Initial Shape: (1543, 17)
```

Out[299…

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

Data Preprocessing

In [300…

```
# Display the number of missing values per column
missing_values = df.isnull().sum()

# Determine data types: 'numeric' or 'character'
data_types = df.dtypes.apply(lambda x: 'numeric' if pd.api.types.is_numeric_dtype(x) else 'character')

# Combine both into one table
summary = pd.DataFrame({
    'Missing Values': missing_values,
    'Data Type': data_types
})
summary
```

Out[300…

	Missing Values	Data Type
EmployeeID	0	numeric
Branch	8	character
Tenure	9	numeric
Salary	9	numeric
Department	0	character
JobSatisfaction	28	numeric
WorkLifeBalance	28	numeric
CommuteDistance	0	character
MaritalStatus	0	character
Education	0	character
PerformanceRating	7	numeric
TrainingHours	191	numeric
OverTime	100	character
NumProjects	99	numeric
YearsSincePromotion	1	numeric
EnvironmentSatisfaction	28	numeric
ChurnLikelihood	0	character

In [301…

```
# Handle missing values - with some needed column

# Fill numerical columns with median/mean
df['TrainingHours'] = df['TrainingHours'].fillna(df['TrainingHours'].median())
df['NumProjects'] = df['NumProjects'].fillna(df['NumProjects'].median())
df['PerformanceRating'] = df['PerformanceRating'].fillna(df['PerformanceRating'].mean())

# Fill OverTime with 'False' and convert to binary
df['OverTime'] = df['OverTime'].fillna('False')  # Fill missing with 'False'
df['OverTime'] = df['OverTime'].astype(str).str.strip().str.capitalize()  # Clean and standardize
df['OverTime'] = df['OverTime'].replace({'True': 1, 'False': 0})
df['OverTime'] = df['OverTime'].infer_objects(copy=False).astype(int)  # Convert to binary

# Fill satisfaction scores with mode
```

```python
satisfaction_cols = ['JobSatisfaction', 'WorkLifeBalance', 'EnvironmentSatisfaction']
for col in satisfaction_cols:
    df[col] = df[col].fillna(df[col].mode()[0])
df.head()
```

```
/tmp/ipython-input-1755539486.py:11: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['OverTime'] = df['OverTime'].replace({'True': 1, 'False': 0})
```

Out[301…

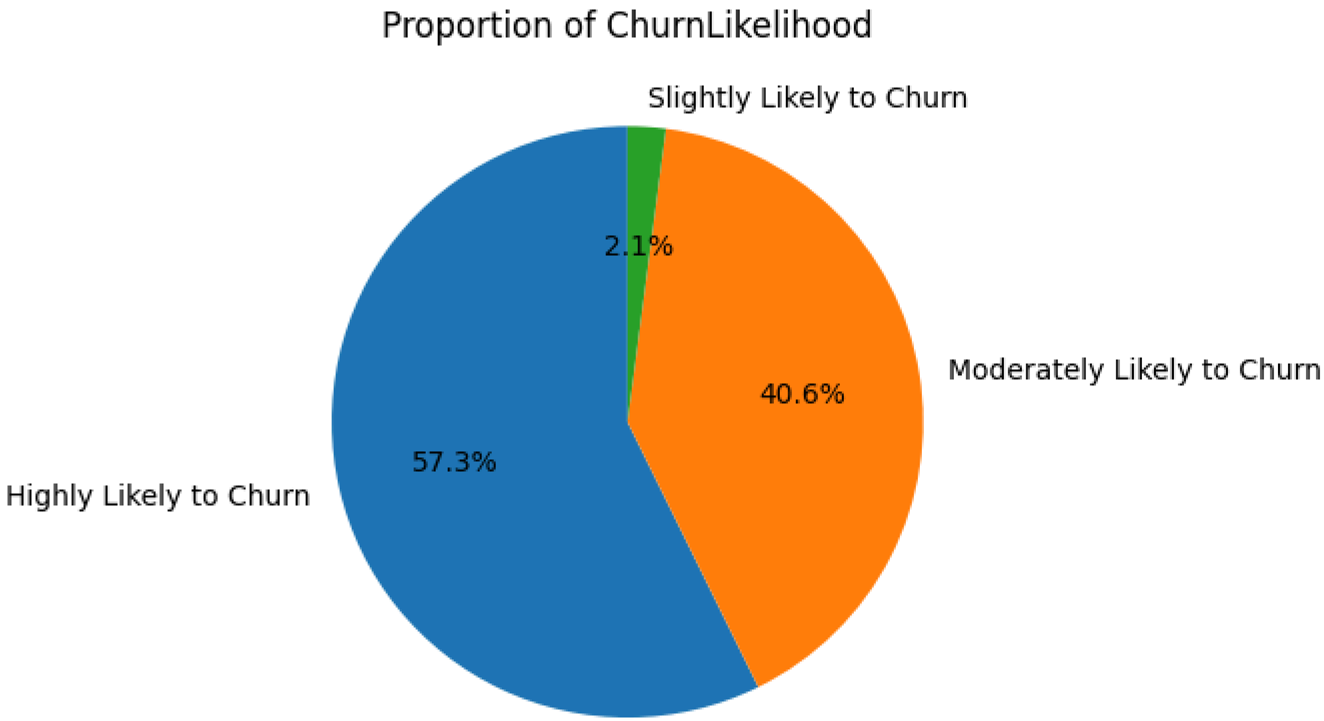
	EmployeeID	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education	Per
0	1	San Francisco	4.0	63000.0	Legal	3.0	3.0	Long	Married	High School	
1	2	Chicago	14.0	72000.0	Accounting	4.0	4.0	Short	Single	Bachelor	
2	3	Miami	4.0	40000.0	Quality Assurance	3.0	3.0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

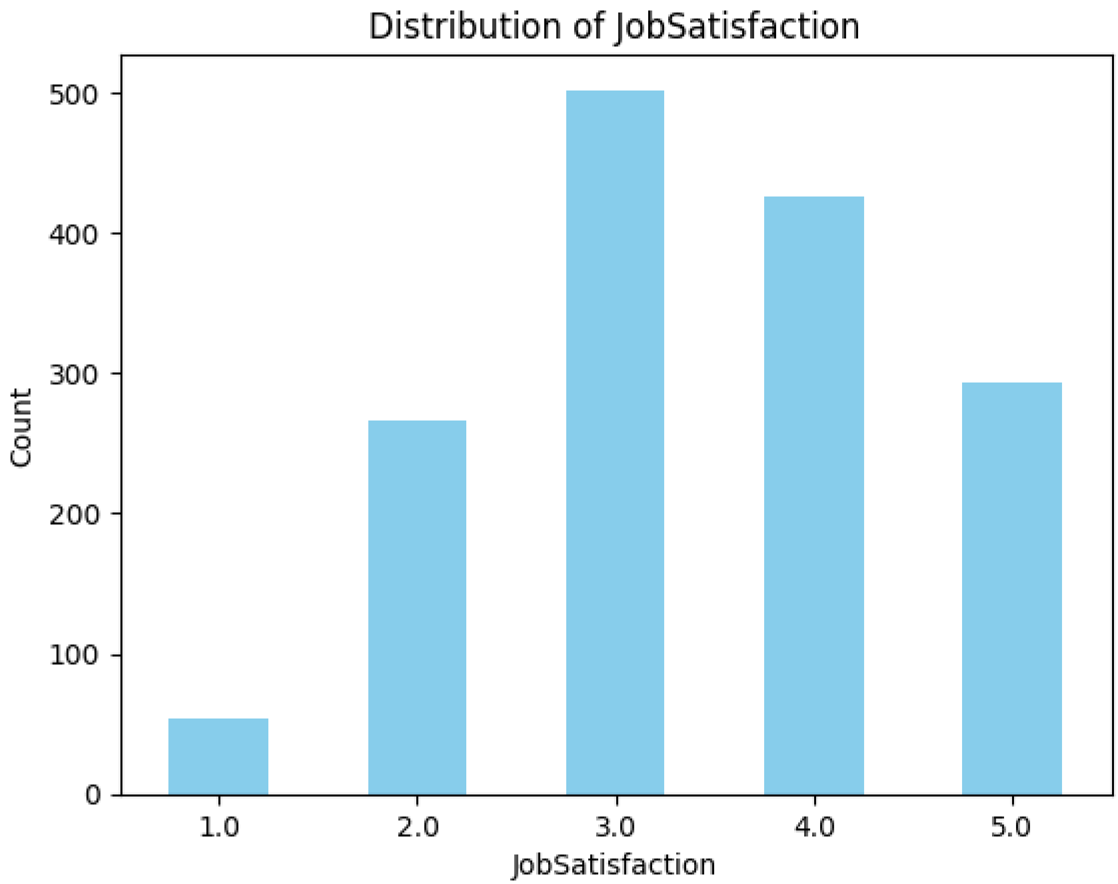
Exploratory Data Analysis

In [302…

```python
# Pie chart for ChurnLikelihood
churn_counts = df['ChurnLikelihood'].value_counts()
churn_counts.plot(kind='pie', autopct='%1.1f%%', startangle=90)
plt.title('Proportion of ChurnLikelihood')
plt.ylabel('')  # Hide y-label for pie chart
plt.show()

# Plot JobSatisfaction distribution
df['JobSatisfaction'].value_counts().sort_index().plot(kind='bar',color='skyblue')
plt.title('Distribution of JobSatisfaction')
plt.xlabel('JobSatisfaction')
plt.ylabel('Count')
```

```
plt.xticks(rotation=0)
plt.show()
```





In [303…

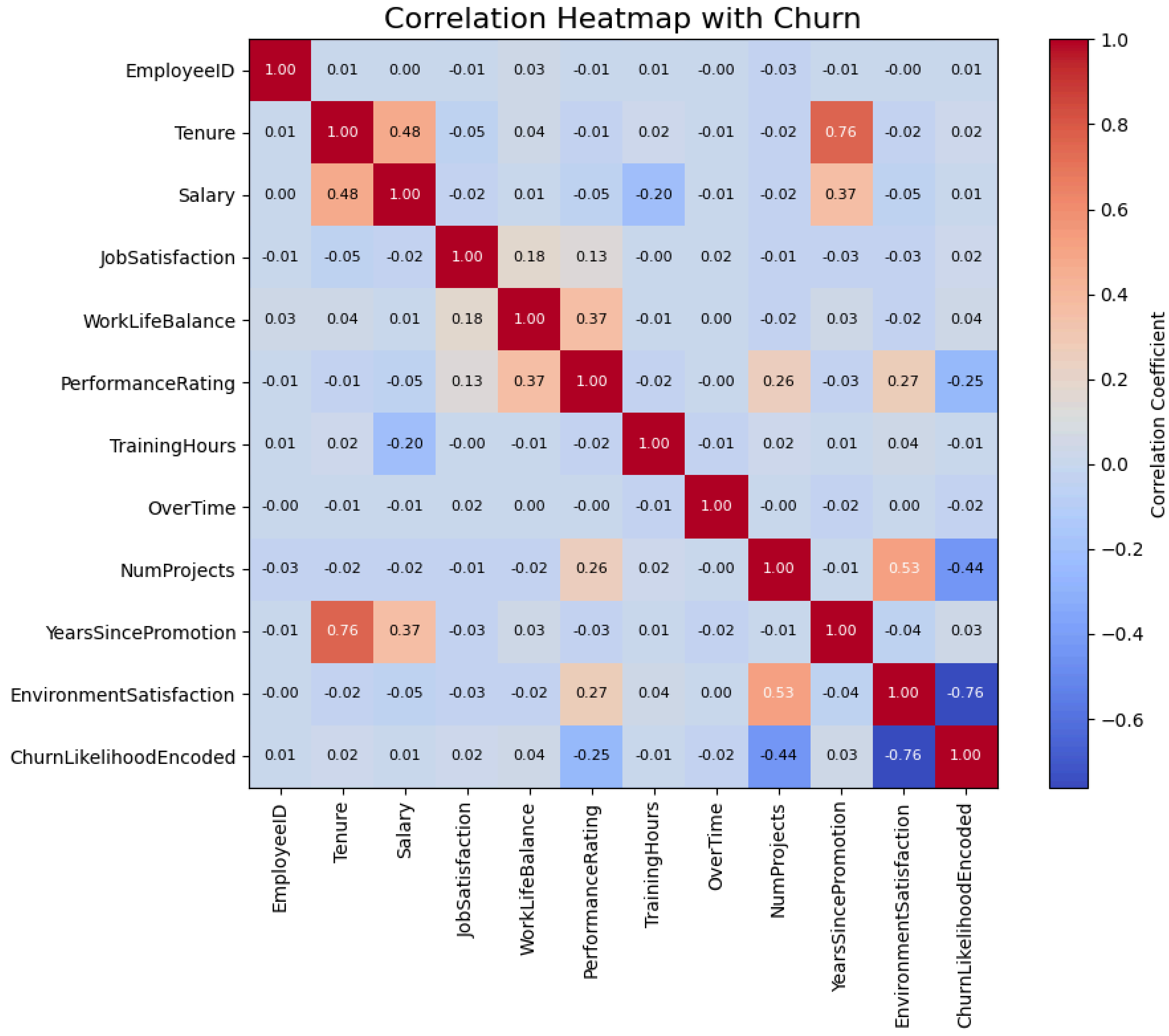
```
# Plot the heatmap to see correlation among variables
import pandas as pd
import matplotlib.pyplot as plt

churn_mapping = {'Slightly Likely to Churn': 0, 'Moderately Likely to Churn': 1, 'Highly Likely to Churn': 2}
df['ChurnLikelihoodEncoded'] = df['ChurnLikelihood'].map(churn_mapping)
df[['ChurnLikelihood', 'ChurnLikelihoodEncoded']].head()
```

Out[303…

	ChurnLikelihood	ChurnLikelihoodEncoded
0	Highly Likely to Churn	2
1	Moderately Likely to Churn	1
2	Highly Likely to Churn	2
3	Moderately Likely to Churn	1
4	Moderately Likely to Churn	1

In [304…

```python
# Compute correlation matrix
corr = df.corr(numeric_only=True)

# Plot the heatmap
plt.figure(figsize=(10, 8))
plt.imshow(corr, cmap='coolwarm', interpolation='nearest')
plt.colorbar(label='Correlation Coefficient')
# Add correlation numbers inside the heatmap
for i in range(len(corr.columns)):
    for j in range(len(corr.columns)):
        plt.text(j, i, f"{corr.iloc[i, j]:.2f}",
                 ha='center', va='center',
                 color='black' if abs(corr.iloc[i, j]) < 0.5 else 'white',
                 fontsize=8)
# Add labels
plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
plt.yticks(range(len(corr.columns)), corr.columns)

plt.title("Correlation Heatmap with Churn", fontsize=16)
plt.tight_layout()
plt.show()
```


Correlation Heatmap with Churn
EmployeeID
Tenure
Salary
JobSatisfaction
WorkLifeBalance
PerformanceRating
TrainingHours
OverTime
NumProjects
YearsSincePromotion
EnvironmentSatisfaction
ChurnLikelihoodEncoded
1.00 0.01 0.00 -0.01 0.03 -0.01 0.01 -0.00 -0.03 -0.01 -0.00 0.01
0.01 1.00 0.48 -0.05 0.04 -0.01 0.02 -0.01 -0.02 0.76 -0.02 0.02
0.00 0.48 1.00 -0.02 0.01 -0.05 -0.20 -0.01 -0.02 0.37 -0.05 0.01
-0.01 -0.05 -0.02 1.00 0.18 0.13 -0.00 0.02 -0.01 -0.03 -0.03 0.02
0.03 0.04 0.01 0.18 1.00 0.37 -0.01 0.00 -0.02 0.03 -0.02 0.04
-0.01 -0.01 -0.05 0.13 0.37 1.00 -0.02 -0.00 0.26 -0.03 0.27 -0.25
0.01 0.02 -0.20 -0.00 -0.01 -0.02 1.00 -0.01 0.02 0.01 0.04 -0.01
-0.00 -0.01 -0.01 0.02 0.00 -0.00 -0.01 1.00 -0.00 -0.02 0.00 -0.02
-0.03 -0.02 -0.02 -0.01 -0.02 0.26 0.02 -0.00 1.00 -0.01 0.53 -0.44
-0.01 0.76 0.37 -0.03 0.03 -0.03 0.01 -0.02 -0.01 1.00 -0.04 0.03
-0.00 -0.02 -0.05 -0.03 -0.02 0.27 0.04 0.00 0.53 -0.04 1.00 -0.76
0.01 0.02 0.01 0.02 0.04 -0.25 -0.01 -0.02 -0.44 0.03 -0.76 1.00
Correlation Coefficient
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

Association Rule Mining

In [305…

```
# Bin training hours into categories
df['TrainingCategory'] = pd.cut(df['TrainingHours'],
                                bins=[-np.inf, 20, 40, 60, np.inf],
                                labels=['Low', 'Moderate', 'High', 'Very High'])

df[['EmployeeID','TrainingHours','TrainingCategory']].head()
```

Out[305…

	EmployeeID	TrainingHours	TrainingCategory
0	1	88.0	Very High
1	2	30.0	Moderate
2	3	64.0	Very High
3	4	30.0	Moderate
4	5	18.0	Low

In [306…

```
# Select features for Association Rule Mining
arm_df = df[['TrainingCategory', 'OverTime', 'Department', 'JobSatisfaction', 'ChurnLikelihood']].dropna()

# Convert each row into a transaction
transactions = arm_df.apply(lambda row: [f"{col}={val}" for col, val in row.items()], axis=1)

# Encode transactions
te = TransactionEncoder()
te_array = te.fit_transform(transactions)
df_encoded = pd.DataFrame(te_array, columns=te.columns_)
df_encoded.head()
```

Out[306…

	ChurnLikelihood=Highly Likely to Churn	ChurnLikelihood=Moderately Likely to Churn	ChurnLikelihood=Slightly Likely to Churn	Department=Accounting	Department=Administration
0	True	False	False	False	False
1	False	True	False	True	False
2	True	False	False	False	False
3	False	True	False	False	False
4	False	True	False	False	False

5 rows × 29 columns

In [307…

```
# Run Apriori and generate rules
frequent_itemsets = apriori(df_encoded, min_support=0.05, use_colnames=True)
frequent_itemsets.head()
```

Out[307…

	support	itemsets
0	0.572910	(ChurnLikelihood=Highly Likely to Churn)
1	0.406351	(ChurnLikelihood=Moderately Likely to Churn)
2	0.102398	(Department=Accounting)
3	0.104342	(Department=Customer Service)
4	0.057680	(Department=Human Resources)

In [308…

```
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.6)
rules.head()
```

Out[308...

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	levera
0	(Department=Accounting)	(ChurnLikelihood=Highly Likely to Churn)	0.102398	0.572910	0.061568	0.601266	1.049495	1.0	0.0029
1	(JobSatisfaction=5.0)	(ChurnLikelihood=Highly Likely to Churn)	0.190538	0.572910	0.115360	0.605442	1.056784	1.0	0.0061
2	(ChurnLikelihood=Highly Likely to Churn)	(OverTime=1)	0.572910	0.935191	0.532728	0.929864	0.994304	1.0	-0.0030
3	(TrainingCategory=Low)	(ChurnLikelihood=Highly Likely to Churn)	0.278030	0.572910	0.167855	0.603730	1.053795	1.0	0.0085
4	(ChurnLikelihood=Moderately Likely to Churn)	(OverTime=1)	0.406351	0.935191	0.383668	0.944179	1.009610	1.0	0.0036

In [309...

```python
# Show only rules that lead to churn
churn_rules = rules[rules['consequents'].apply(lambda x: any('ChurnLikelihood' in i for i in x))]
churn_rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']]
```

Out[309...

	antecedents	consequents	support	confidence	lift
0	(Department=Accounting)	(ChurnLikelihood=Highly Likely to Churn)	0.061568	0.601266	1.049495
1	(JobSatisfaction=5.0)	(ChurnLikelihood=Highly Likely to Churn)	0.115360	0.605442	1.056784
3	(TrainingCategory=Low)	(ChurnLikelihood=Highly Likely to Churn)	0.167855	0.603730	1.053795
25	(JobSatisfaction=3.0, TrainingCategory=Low)	(ChurnLikelihood=Highly Likely to Churn)	0.060920	0.652778	1.139407
28	(JobSatisfaction=5.0, OverTime=1)	(ChurnLikelihood=Highly Likely to Churn)	0.109527	0.612319	1.068787
30	(OverTime=1, TrainingCategory=Low)	(ChurnLikelihood=Highly Likely to Churn)	0.160726	0.607843	1.060975
49	(JobSatisfaction=3.0, OverTime=1, TrainingCate...	(ChurnLikelihood=Highly Likely to Churn)	0.058976	0.659420	1.151002
50	(JobSatisfaction=3.0, TrainingCategory=Low)	(ChurnLikelihood=Highly Likely to Churn, OverT...	0.058976	0.631944	1.186241

Comments: It only shows rules leading to 'highly likely to churn', there is too small data to find the rules of 'low likely to churn'.

If Department = Accounting, ChurnLikelihood = Highly Likely to Churn

support = 6.16% → About 6% of employees are in this situation

confidence = 60.1% → 60% of Accounting employees are highly likely to churn

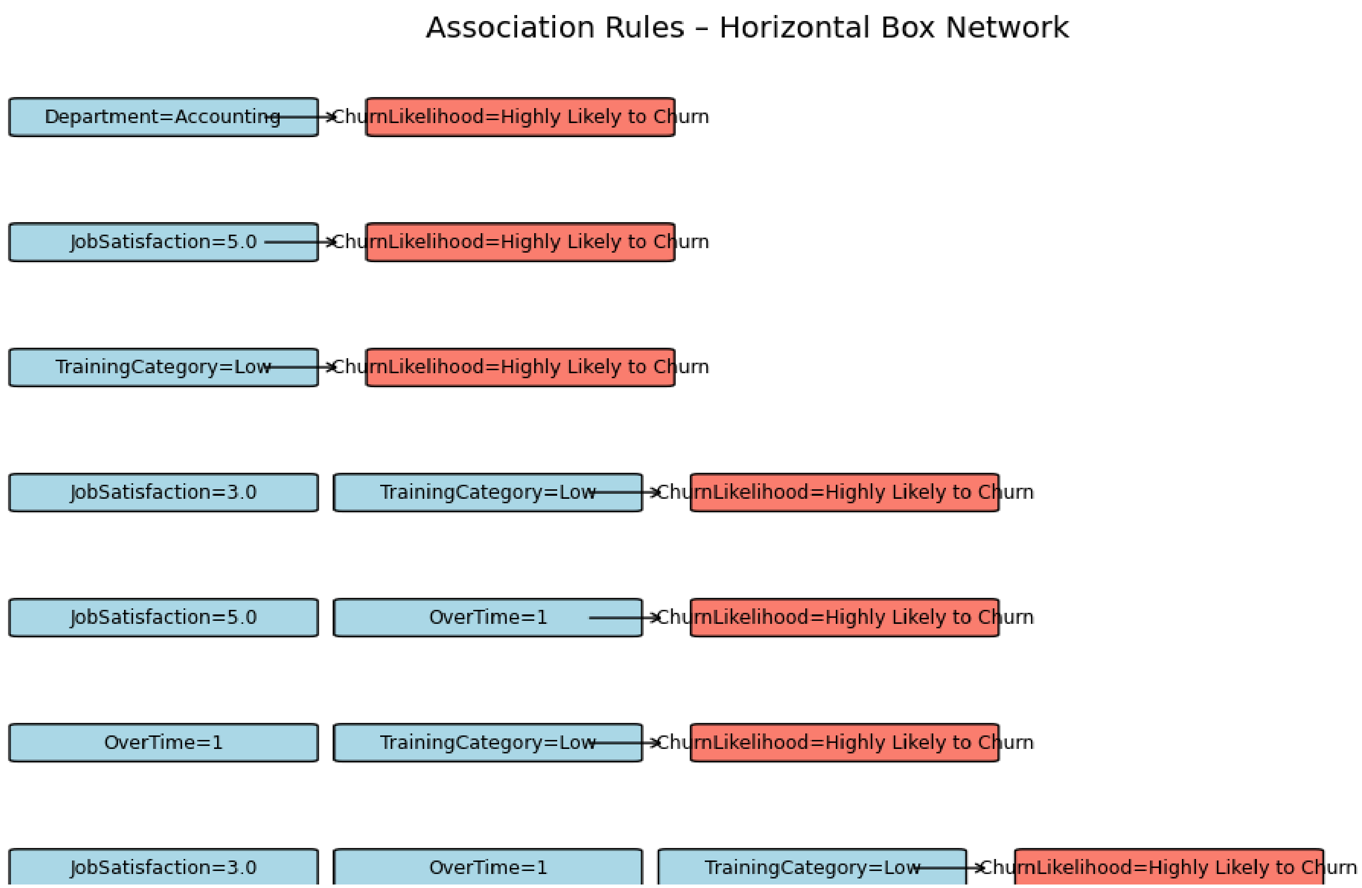
lift = 1.05 → Slightly more likely than average (5% more)

There is a slightly elevated churn risk in the Accounting department. This may suggest dissatisfaction or role mismatch in that team.

In [310…

```
# visualize some above rules
import matplotlib.patches as patches

# churn rules (antecedents → consequent)
visualize_rules=[
    ({"Department=Accounting"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"JobSatisfaction=5.0"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"TrainingCategory=Low"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"JobSatisfaction=3.0", "TrainingCategory=Low"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"OverTime=1", "JobSatisfaction=5.0"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"TrainingCategory=Low", "OverTime=1"}, "ChurnLikelihood=Highly Likely to Churn"),
    ({"JobSatisfaction=3.0", "TrainingCategory=Low", "OverTime=1"}, "ChurnLikelihood=Highly Likely to Churn"),
]

# Create a horizontal box network-style visualization
fig, ax = plt.subplots(figsize=(12, 6))

y_level = 0
box_width = 1.8
box_height = 0.8
spacing = 3

for idx, (antecedents, consequent) in enumerate(visualize_rules):
    # Draw antecedent boxes
    x = 0
    for ant in antecedents:
        rect = patches.FancyBboxPatch(
            (x, y_level), box_width, box_height,
            boxstyle="round,pad=0.05", edgecolor='black', facecolor='lightblue'
        )
        ax.add_patch(rect)
        ax.text(x + box_width / 2, y_level + box_height / 2, ant, ha='center', va='center', fontsize=9)
        x += box_width + 0.2

    # Draw arrow to consequent
    ax.annotate('', xy=(x, y_level + box_height / 2), xytext=(x - 0.5, y_level + box_height / 2),
                arrowprops=dict(facecolor='gray', arrowstyle='->'))

    # Draw consequent box
    rect = patches.FancyBboxPatch(
        (x + 0.2, y_level), box_width, box_height,
```

```python
        boxstyle="round,pad=0.05", edgecolor='black', facecolor='salmon'
    )
    ax.add_patch(rect)
    ax.text(x + box_width / 2 + 0.2, y_level + box_height / 2, consequent, ha='center', va='center', fontsize=9)

    y_level -= spacing

# Format plot
ax.set_xlim(-1, 10)
ax.set_ylim(y_level + spacing, 2)
ax.axis('off')
plt.title("Association Rules – Horizontal Box Network", fontsize=14)
plt.tight_layout()
plt.show()
```



Data Cleaning for Clustering

In [311...

```
df_clustering = df.copy()

# Drop irrelevant columns
df_clustering = df_clustering.drop(columns=['EmployeeID'], errors='ignore')
df_clustering.head(2)
```

Out[311...

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education	Performance
0	San Francisco	4.0	63000.0	Legal	3.0	3.0	Long	Married	High School	3.
1	Chicago	14.0	72000.0	Accounting	4.0	4.0	Short	Single	Bachelor	3.

In [312...

```
missing_cols = df_clustering.isnull().sum()
missing_cols = missing_cols[missing_cols > 0]
missing_cols
```

Out[312...

	0
Branch	8
Tenure	9
Salary	9
YearsSincePromotion	1

dtype: int64

In [313...

```
# Fill categorical NaNs with most frequent value
for col in ['Branch']:
    df_clustering[col] = df_clustering[col].fillna(df_clustering[col].mode()[0])

# Fill numeric NaNs with median
num_cols = df_clustering.select_dtypes(include=[np.number]).columns
for col in num_cols:
    df_clustering[col] = df_clustering[col].fillna(df_clustering[col].median())
```

Divide into 2 groups: High churn risk and Moderate churn risk

In [314…
```python
df_high_risk = df_clustering[df_clustering['ChurnLikelihoodEncoded'] == 2].copy()
df_moderate_risk = df_clustering[df_clustering['ChurnLikelihoodEncoded'] == 1].copy()
```

In [315…
```python
from sklearn.preprocessing import OneHotEncoder, StandardScaler
def preprocess(df, categorical_cols):
    # One-hot encode categorical columns
    encoder = OneHotEncoder(drop='first',sparse_output=False)
    encoded = encoder.fit_transform(df[categorical_cols])
    encoded_df = pd.DataFrame(encoded, columns=encoder.get_feature_names_out(categorical_cols))
    # Numeric columns only (exclude some columns)
    df_num = df.drop(columns=categorical_cols + ['ChurnLikelihood', 'ChurnLikelihoodEncoded'], errors='ignore').reset_index
    # Combine numeric and encoded columns
    combined = pd.concat([df_num, encoded_df], axis=1)
    # Scale all features
    scaler = StandardScaler()
    scaled = scaler.fit_transform(combined)
    return scaled, combined
```

In [316…
```python
from sklearn.cluster import KMeans

def cluster(df, scaled_data, n_clusters=3):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    clusters = kmeans.fit_predict(scaled_data)
    df['Cluster'] = clusters
    return df
```

Clustering for each group

In [317…
```python
categorical_columns = ['Branch', 'MaritalStatus', 'Education', 'Department', 'CommuteDistance','TrainingCategory']

# High risk group
scaled_high, combined_high = preprocess(df_high_risk, categorical_columns)
df_high_risk = cluster(df_high_risk, scaled_high, n_clusters=3)

# Moderate risk group
scaled_moderate, combined_moderate = preprocess(df_moderate_risk, categorical_columns)
df_moderate_risk = cluster(df_moderate_risk, scaled_moderate, n_clusters=3)
```

Because the low likelihood group contains only 2.1% of the total employees, it represents a very small sample size.

From a clustering perspective, this presents several problems:

Insufficient data for reliable patterns – Clustering algorithms (e.g., K-Means) rely on detecting structure in the data. When a group has very few observations, the algorithm cannot form stable, meaningful clusters for that group.

In [318...
```
df_high_risk.head(2)
```

Out[318...

	Branch	Tenure	Salary	Department	JobSatisfaction	WorkLifeBalance	CommuteDistance	MaritalStatus	Education	Performan
0	San Francisco	4.0	63000.0	Legal	3.0	3.0	Long	Married	High School	
2	Miami	4.0	40000.0	Quality Assurance	3.0	3.0	Medium	Single	High School	

In [319...
```
df_moderate_risk.head(2)
```

Out[319...

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

Visualize Clusters with PCA

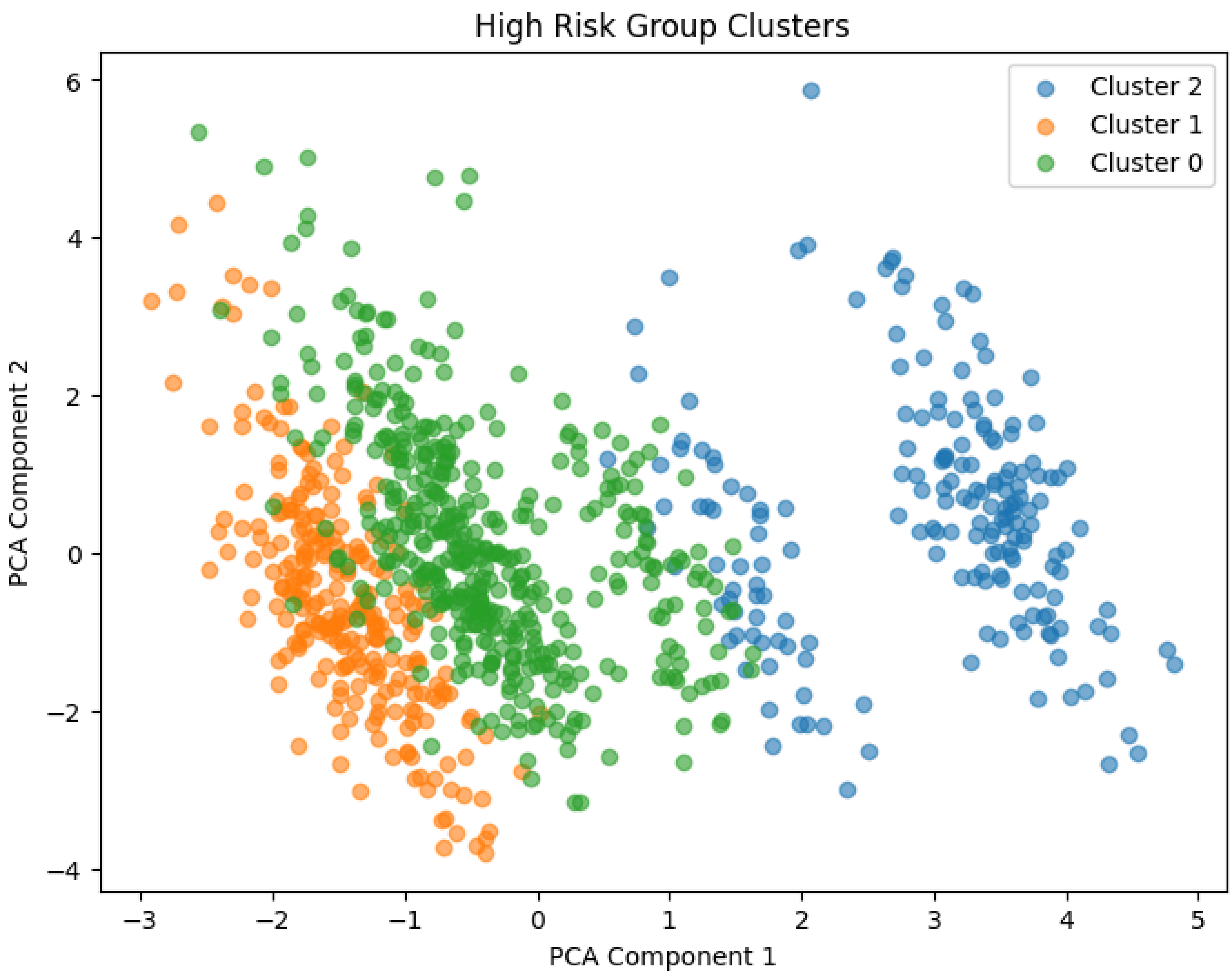
In [320...
```
def plot_clusters(df, scaled_data, title):
    # Reduce dimensions to 2D for plotting
    pca = PCA(n_components=2)
    reduced_data = pca.fit_transform(scaled_data)

    plt.figure(figsize=(8,6))

    # Plot each cluster with different color
    clusters = df['Cluster'].unique()
    for cluster in clusters:
        idx = df['Cluster'] == cluster
```

```
        plt.scatter(reduced_data[idx, 0], reduced_data[idx, 1], label=f'Cluster {cluster}', alpha=0.6)

    plt.title(title)
    plt.xlabel('PCA Component 1')
    plt.ylabel('PCA Component 2')
    plt.legend()
    plt.show()
```

Analyzing High Risk Group

In [321…

```
plot_clusters(df_high_risk, scaled_high, 'High Risk Group Clusters')
```



In [322…

```
print("Numeric feature means per cluster:")
print(df_high_risk.groupby('Cluster').mean(numeric_only=True))
```

```
Numeric feature means per cluster:
           Tenure        Salary  JobSatisfaction  WorkLifeBalance  \
Cluster
0        7.662844  67478.211009         3.408257         3.793119
1        7.729730  68081.081081         3.509653         3.818976
2        7.698413  63412.698413         3.523810         3.779645

         PerformanceRating  TrainingHours  OverTime  NumProjects  \
Cluster
0                 3.392193      29.867255  0.912844     3.242277
1                 3.444174      13.445247  0.957529     3.251148
2                 3.404725      70.698009  0.931217     3.267081

         YearsSincePromotion  EnvironmentSatisfaction  ChurnLikelihoodEncoded
Cluster
0                   1.298165                 2.051146                     2.0
1                   1.196911                 2.051650                     2.0
2                   1.227513                 2.167249                     2.0
```

Interpretation:

Cluster 2 stands out with lower salary, higher training hours, and slightly better job & environment satisfaction. This might indicate employees who get more training but still have lower pay — possibly newer or less senior staff feeling somewhat supported but still at risk.

Cluster 1 shows highest salary, highest performance rating, and most overtime work. These employees might be high performers working hard but potentially stressed by overtime.

Cluster 0 is intermediate but has longest time since promotion, which could signal stagnation or lack of advancement, possibly contributing to churn risk.

The OverTime values suggest a majority in all clusters work overtime, but cluster 1 more so.

Job satisfaction and work-life balance vary only slightly, so these factors might not differentiate clusters strongly here.

Consider targeted interventions:

Cluster 2: Focus on salary review or career path support.

Cluster 1: Manage overtime or burnout risk.

Cluster 0: Address promotion and career growth opportunities.

In [323…

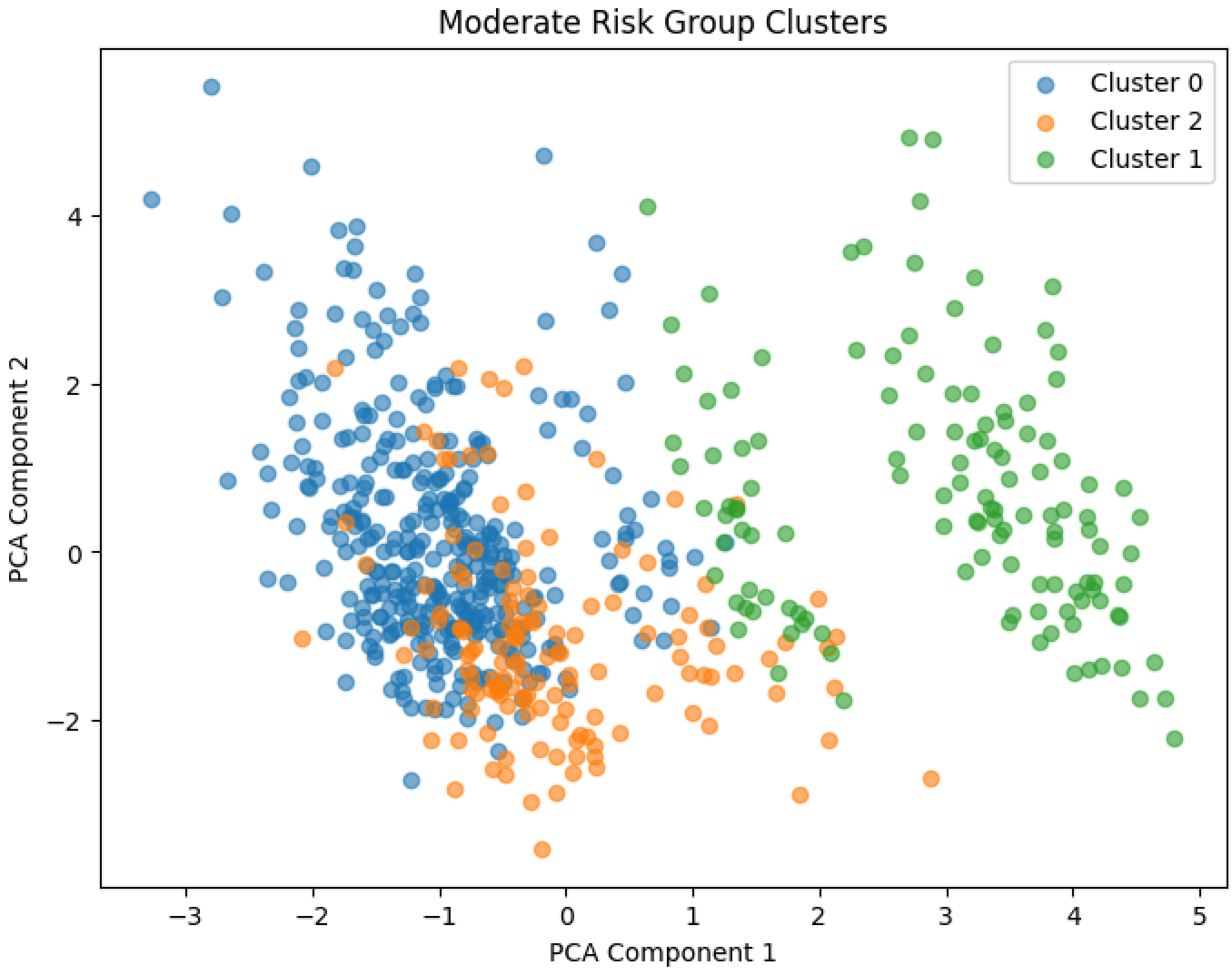
```python
categorical_columns = ['Branch', 'MaritalStatus', 'Education', 'Department', 'CommuteDistance']

print("\nMost common category per cluster:")
for col in categorical_columns:
    mode_per_cluster = df_high_risk.groupby('Cluster')[col].agg(lambda x: x.mode()[0] if not x.mode().empty else 'None')
    print(f"\n{col}:")
    print(mode_per_cluster)
```

```
Most common category per cluster:

Branch:
Cluster
0    Los Angeles
1    Los Angeles
2       Scranton
Name: Branch, dtype: object

MaritalStatus:
Cluster
0    Married
1    Married
2    Married
Name: MaritalStatus, dtype: object

Education:
Cluster
0       Bachelor
1       Bachelor
2    High School
Name: Education, dtype: object

Department:
Cluster
0         Sales
1         Sales
2    Accounting
Name: Department, dtype: object

CommuteDistance:
Cluster
0    Medium
1     Short
2    Medium
Name: CommuteDistance, dtype: object
```

Analyzing Moderate Risk Group

In [324…

```
plot_clusters(df_moderate_risk, scaled_moderate, 'Moderate Risk Group Clusters')
```



In [325…

```
print("Numeric feature means per cluster:")
print(df_moderate_risk.groupby('Cluster').mean(numeric_only=True))
```

```
Numeric feature means per cluster:
            Tenure        Salary  JobSatisfaction  WorkLifeBalance  \
Cluster
0         7.722222  69947.222222         3.213889         3.716429
1         7.703125  63207.031250         3.304688         3.808782
2         6.611511  60061.151079         3.525180         3.717572

         PerformanceRating  TrainingHours  OverTime  NumProjects  \
Cluster
0                 3.584126      24.667763  0.938889     3.854429
1                 3.598588      70.274335  0.953125     3.802964
2                 3.600214      27.422625  0.949640     3.799936

         YearsSincePromotion  EnvironmentSatisfaction  ChurnLikelihoodEncoded
Cluster
0                   1.283333                 3.047274                     1.0
1                   1.093750                 3.055854                     1.0
2                   0.827338                 3.041713                     1.0
```

Cluster 0 — Higher Salary & More Balanced Workload Salary: Highest among the three (~69,947).

Job Satisfaction: Slightly lower than Cluster 2, but still decent.

Training Hours: Moderate (~24.7 hours), which might indicate they receive enough skill development without feeling overwhelmed.

NumProjects: Slightly higher (~3.85), suggesting they handle more tasks but not necessarily at the cost of satisfaction.

Possible interpretation: These employees are paid well and have a stable workload, but their job satisfaction isn't the highest — so salary alone may not prevent churn.

Cluster 1 — Heavy Training Load Salary: Mid-range (~63,207).

Training Hours: Extremely high (~70.27 hours) — much higher than the other clusters.

Job Satisfaction: Slightly lower than Cluster 2 despite high training, which may mean the training is either mandatory or stressful.

OverTime: High (95%), which might compound stress.

Possible interpretation: This group may be at risk of burnout due to intense training and overtime, despite their salary being fair.

Cluster 2 — Shorter Tenure & Higher Job Satisfaction Tenure: Shortest (~6.6 years).

Job Satisfaction: Highest (~3.53).

Salary: Lowest (~60,061).

YearsSincePromotion: Lowest (~0.83), meaning they may have been promoted recently, boosting morale.

Possible interpretation: This group is newer, recently rewarded (promotion), and still enthusiastic. But low salary could become an issue over time.

(This cluster is smaller and is located in the middle, overlapping significantly with the blue Cluster 0. It's less distinct than the other two, suggesting that individuals in this group share some characteristics with Cluster 0, but are different enough to be classified separately.)

In [326...

```
categorical_columns = ['Branch', 'MaritalStatus', 'Education', 'Department', 'CommuteDistance']

print("\nMost common category per cluster:")
for col in categorical_columns:
    mode_per_cluster = df_moderate_risk.groupby('Cluster')[col].agg(lambda x: x.mode()[0] if not x.mode().empty else 'No
    print(f"\n{col}:")
    print(mode_per_cluster)
```

```
Most common category per cluster:

Branch:
Cluster
0     Los Angeles
1    Philadelphia
2        Scranton
Name: Branch, dtype: object

MaritalStatus:
Cluster
0    Married
1    Married
2    Married
Name: MaritalStatus, dtype: object

Education:
Cluster
0       Bachelor
1    High School
2       Bachelor
Name: Education, dtype: object

Department:
Cluster
0         Sales
1         Sales
2    Operations
Name: Department, dtype: object

CommuteDistance:
Cluster
0     Short
1     Short
2    Medium
Name: CommuteDistance, dtype: object
```