Data-Driven Analysis

Answer Predictive Questions

For HR Data Analysis

DATA DYNAMOS

Harnessing the Power of Data to Drive Innovation

Data-Driven Analysis

This report analyzes employee data from "HrData.xlsx" to support HR decision-making , In a competitive business environment, effective human resource management is crucial for sustaining performance and growth. This report leverages employee data to uncover key insights into individual performance, organizational talent potential, and HR strategy efficiency. By using data analysis techniques in Python, we aim to support smarter decision-making in training, promotion, and retention strategies.

Overview of the Code Structure

This report analyzes employee data from a structured Excel file to evaluate performance, potential, and HR effectiveness. The insights are drawn using Python-based analytics and aim to guide data-driven decisions in talent management.

Three core frameworks were applied:

1. **GAP Analysis**
2. **9-Box Grid Analysis**
3. **Balanced Scorecard Analysis**

The dataset includes employee demographics, performance reviews, training history, satisfaction levels, and career progression indicators.

Stage 1: Data Loading and Preprocessing

Excel File Structure

The Excel file used in this analysis contains five sheets with structured information:

- **Employee Sheet:** Includes demographics, job details, and career progression fields (e.g., EmployeeID, JobRole, Department, Salary, HireDate, Attrition, etc.)
- **PerformanceRating Sheet:** Historical reviews including ManagerRating, satisfaction scores, training participation, and WorkLifeBalance.
- **EducationLevel / RatingLevel / SatisfiedLevel Sheets:** Contain reference data to decode categorical fields like education and satisfaction levels.

What the Code Does:

- The data was imported using **Pandas.**
- Each sheet was loaded into a dedicated **DataFrame.**
- Data types were adjusted (e.g., dates parsed correctly), and columns were renamed or merged as necessary for consistency across sheets.
- Filtering and sorting were applied to ensure only the most recent performance reviews were considered where needed.

Results

- This structured loading process enabled clean, reliable analysis across the subsequent stages: GAP Analysis, 9-Box Grid, and Balanced Scorecard.

```python
# Step 2: Load the Data

# Define file path
file_path = 'HrData.xlsx'

# Load sheets into DataFrames
employee_df = pd.read_excel(file_path, sheet_name='Employee')
performance_df = pd.read_excel(file_path, sheet_name='PerformanceRating')
education_level_df = pd.read_excel(file_path, sheet_name='EducationLevel')
rating_level_df = pd.read_excel(file_path, sheet_name='RatingLevel')
satisfied_level_df = pd.read_excel(file_path, sheet_name='SatisfiedLevel')

# Convert ReviewDate to datetime
performance_df['ReviewDate'] = pd.to_datetime(performance_df['ReviewDate'])

# Display previews
print('Employee Data:')
print(employee_df.head())

print('\nPerformance Rating Data:')
print(performance_df.head())
```

```
Employee Data:
  EmployeeID   FirstName LastName      Gender  Age BusinessTravel  \
0  3012-1A41    Leonelle    Simco      Female   30    Some Travel
1  CBCB-9C9D     Leonerd    Aland        Male   38    Some Travel
2  95D7-1CE9       Ahmed    Sykes        Male   43    Some Travel
3  47A0-559B  Ermentrude   Berrie  Non-Binary   39    Some Travel
4  42CC-040A       Stace   Savege      Female   29    Some Travel

        Department  DistanceFromHome State                Ethnicity  ...  \
0            Sales                27    IL                    White  ...
1            Sales                23    CA                    White  ...
2  Human Resources                29    CA  Asian or Asian American  ...
3       Technology                12    IL                    White  ...
4  Human Resources                29    CA                    White  ...

   MaritalStatus  Salary StockOptionLevel OverTime   HireDate  Attrition  \
0       Divorced  102059                1       No 2012-01-03         No
1         Single  157718                0      Yes 2012-01-04         No
2        Married  309964                1       No 2012-01-04         No
3        Married  293132                0       No 2012-01-05         No
4         Single   49606                0       No 2012-01-05        Yes

  YearsAtCompany YearsInMostRecentRole YearsSinceLastPromotion  \
0             10                    4                       9
1             10                    6                      10
...
1             Valid
2             Valid
3             Valid
4             Valid
```

Stage 2: GAP Analysis

Objective

Identify performance discrepancies between employees and the benchmark for their job roles.

Process

- Extracted the most recent **ManagerRating** per employee.
- Calculated the **average rating** for each **JobRole**.
- Computed a **performance gap** for each employee (Employee Rating – JobRole Average).

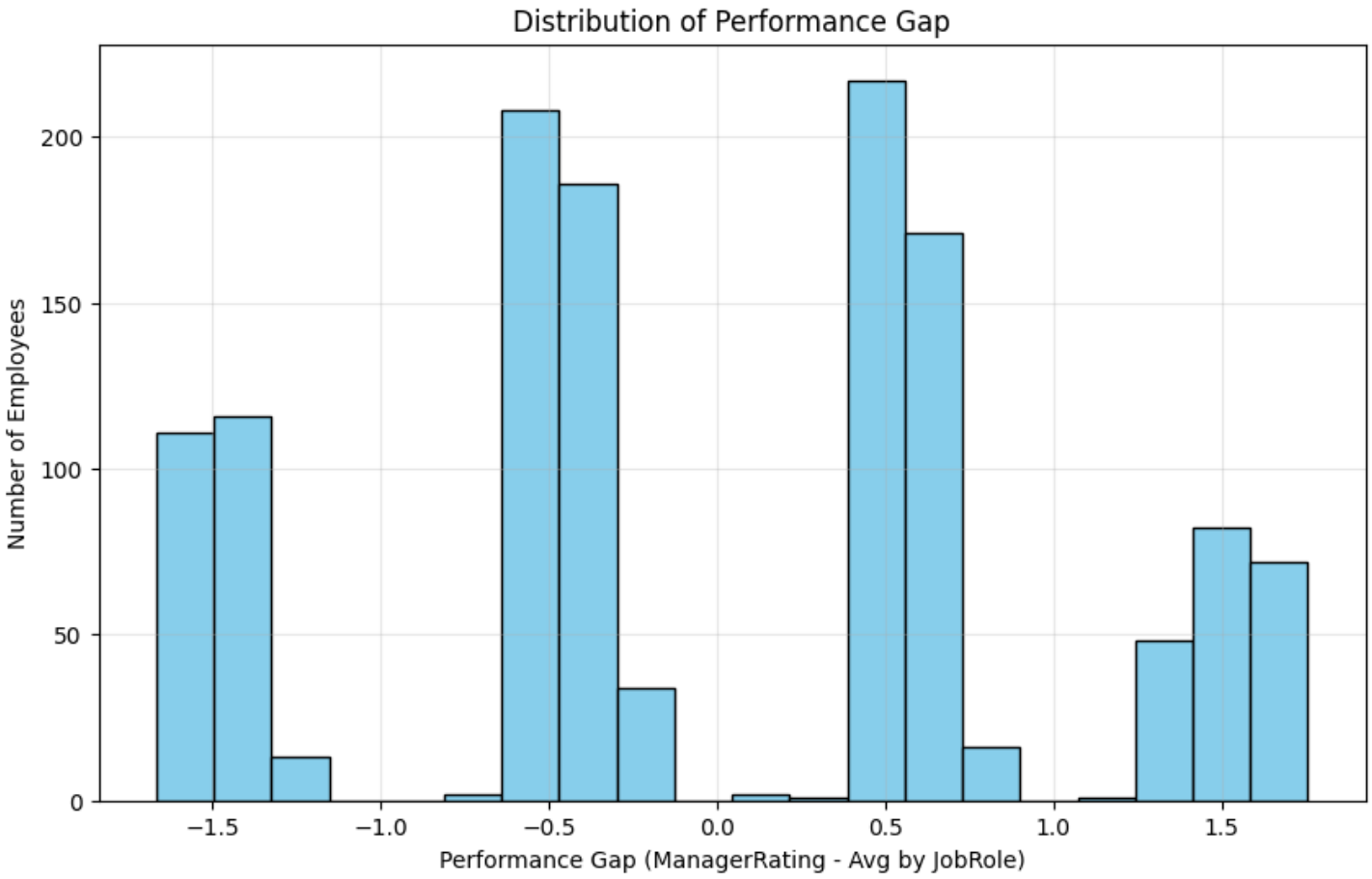
Interpretation:

- **Negative gaps** indicate underperformance relative to the expected standard for that role.
- A correlation was analyzed between **TrainingOpportunitiesTaken** and **performance gaps**, providing insight into the impact of training.

Insight:

Employees falling below their role average should be prioritized for development plans. This also highlights the importance of personalized learning interventions.

```python
# Step 3: Performance GAP Analysis

# Objective: Identify the gap between current and desired performance.
# Here we use the latest performance review per employee and compare
# each employee's ManagerRating to the average for their JobRole.

# Get the most recent performance review per employee
latest_performance = performance_df.loc[performance_df.groupby('EmployeeID')['ReviewDate'].idxmax()]

# Merge the latest performance review with employee data
merged_df = pd.merge(employee_df, latest_performance, on='EmployeeID', how='left')

# Calculate average ManagerRating per JobRole
avg_rating_by_role = merged_df.groupby('JobRole')['ManagerRating'].mean()

# Compute the performance gap per employee (ManagerRating - average for their job role)
merged_df['Gap'] = merged_df['ManagerRating'] - merged_df['JobRole'].map(avg_rating_by_role)

# Visualize the distribution of performance gaps
plt.figure(figsize=(10, 6))
plt.hist(merged_df['Gap'].dropna(), bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Performance Gap')
plt.xlabel('Performance Gap (ManagerRating - Avg by JobRole)')
plt.ylabel('Number of Employees')
plt.grid(True, alpha=0.3)
plt.show()

# Calculate percentage of employees with a negative gap
negative_gap_pct = (merged_df['Gap'] < 0).mean() * 100
print(f"Percentage of employees performing below their job role average: {negative_gap_pct:.2f}%")

# Explore correlation with training opportunities taken (if column exists in performance_df)
if 'TrainingOpportunitiesTaken' in merged_df.columns:
    correlation = merged_df['Gap'].corr(merged_df['TrainingOpportunitiesTaken'])
    print(f"Correlation between Performance Gap and TrainingOpportunitiesTaken: {correlation:.2f}")
else:
    print("Column 'TrainingOpportunitiesTaken' not found in merged data.")
```




```
Percentage of employees performing below their job role average: 45.58%
Correlation between Performance Gap and TrainingOpportunitiesTaken: 0.01
```

2: Training GAP Analysis

Objective

Calculate the gap between the training opportunities available and those attended, and identify the top 10 employees who need more training.

Methodology:

1. Gap Calculation:

Compute TrainingGap as the difference between TrainingOpportunitiesWithinYear and TrainingOpportunitiesTaken.

2. Summary Statistics:

Use descriptive statistics to summarize the training gap.

3. Top 10 Employees Extraction:

Identify employees with the largest training gap and merge with their personal details.

```python
# Step 4: Training GAP Analysis

# Objective: Calculate the gap between available and attended training opportunities
# and identify the top 10 employees with the largest training gaps.

# Calculate the training gap
performance_df['TrainingGap'] = performance_df['TrainingOpportunitiesWithinYear'] - performance_df['TrainingOpportunitiesTaken']

# Summarize training gaps
gap_summary = performance_df['TrainingGap'].describe()
print('\nTraining Gap Statistics:\n', gap_summary)

# Extract employees with the largest training gaps (Top 10)
top_training_gaps = performance_df.sort_values(by='TrainingGap', ascending=False).head(10)

# Retrieve their details from the Employee table
df_employee_selected = employee_df[employee_df['EmployeeID'].isin(top_training_gaps['EmployeeID'])]

# Merge performance data with employee details
df_gap_analysis = pd.merge(top_training_gaps, df_employee_selected, on='EmployeeID', how='left')

# Select important columns
df_gap_analysis = df_gap_analysis[['EmployeeID', 'FirstName', 'LastName', 'Department',
                                   'TrainingOpportunitiesWithinYear', 'TrainingOpportunitiesTaken', 'TrainingGap']]

# Display the top 10 employees in need of training
print('\nTop 10 Employees in Need of Training:\n', df_gap_analysis)
```

```
Training Gap Statistics:
 count    6709.000000
mean        1.147116
std         1.014636
min         0.000000
25%         0.000000
50%         1.000000
75%         2.000000
max         3.000000
Name: TrainingGap, dtype: float64

Top 10 Employees in Need of Training:
   EmployeeID FirstName    LastName       Department  \
0  3EB2-9111    Ginger      Blinde       Technology
1  2E72-4BF1     Grace      Gohier            Sales
2  5468-EEE1    Forbes     Toretta       Technology
3  10E9-4C86  Ignacius    Dockrill       Technology
4  D676-4ECC  Florenza      Nesbit       Technology
5  2B7A-9C73   Bryanty  Wickersley       Technology
6  B6EC-313E    Corbin      Gooddy  Human Resources
7  7749-B277     Caryl    Roycroft  Human Resources
8  1799-5B3F     Howey      Woolis            Sales
9  819A-2C9C   Hillary      Atchly       Technology
...
6                              3                          0           3
7                              3                          0           3
8                              3                          0           3
9                              3                          0           3
```

3: 9-Box Grid Analysis

Objective:

Map employees based on **Current Performance** and **Future Potential** to inform leadership development and succession planning.

Process

- **Performance:** Defined by latest ManagerRating (1–2 = Low, 3 = Average, 4–5 = High).
- **Potential:** Estimated by calculating the **trend (slope)** of ManagerRating over time.
- Employees were placed into a **3x3 matrix** based on these two factors.

Steps in the Code:

1. Calculate Slope (Trend): Use linear regression to estimate the trend (slope) of the ManagerRating over time for each employee. This slope acts as a proxy for future potential.

2. Categorize Performance: Employees are categorized into 'Low', 'Average', or 'High' based on their current ManagerRating.

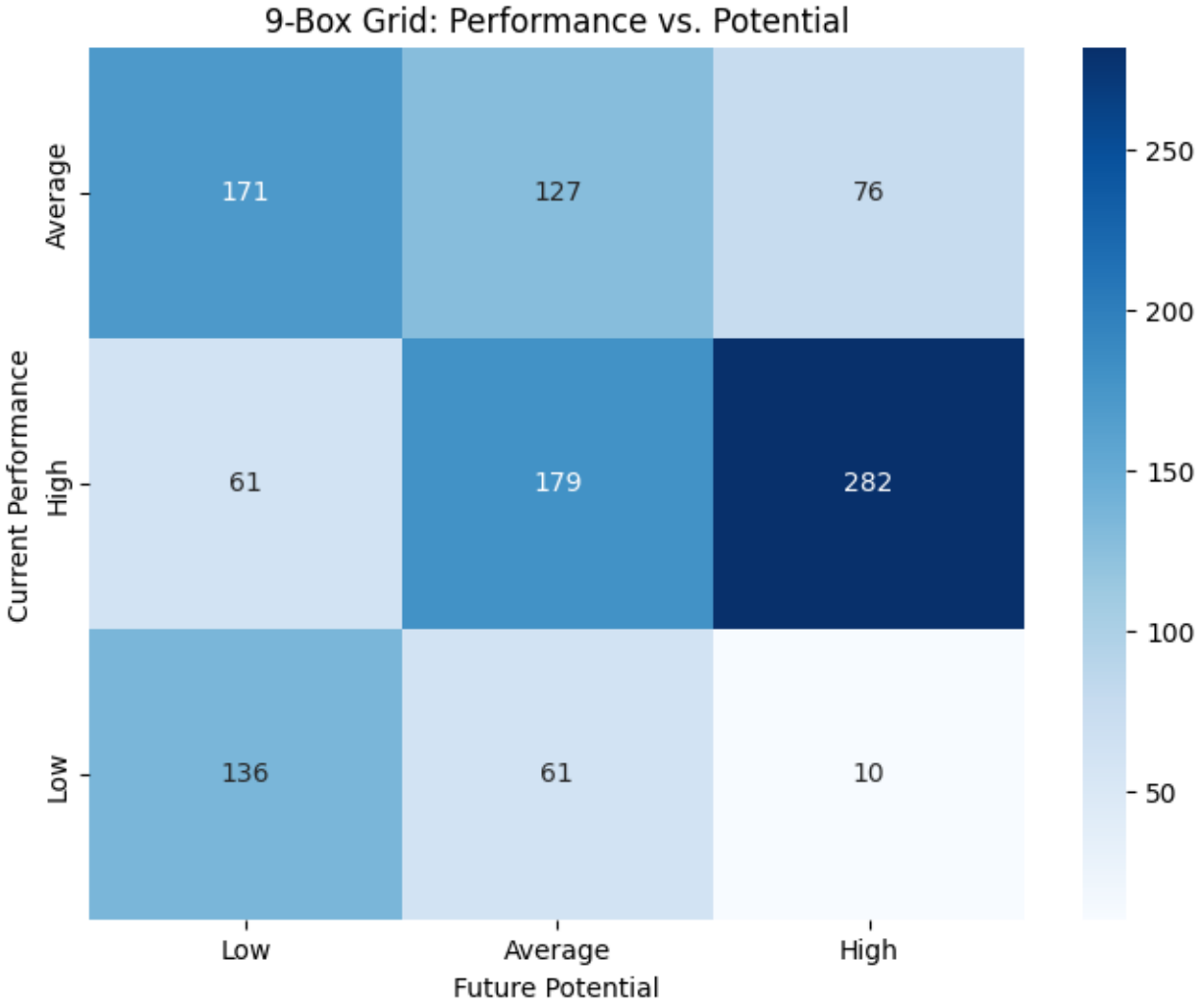
3. Categorize Potential: For employees with valid slope values, quantile-based categorization is applied to assign them into potential categories.

4. Create & Visualize Grid: Construct a crosstab of performance vs. potential and visualize it using a heatmap

Expected Output::

- A printed table (crosstab) showing the distribution of employees across the 9-box grid.
- A heatmap that visually represents this distribution, making it easy to identify clusters of talent.

```python
# Step 5: 9-Box Grid Analysis

# Objective: Place employees in a 3x3 grid based on their current performance
# and future potential.
# For current performance we use ManagerRating; for future potential,
# we compute the trend (slope) of ManagerRating over time using linear regression.

# Function to calculate the slope of ManagerRating over time for each employee
def calculate_slope(group):
    if len(group) < 2:  # Need at least 2 points to calculate a trend
        return np.nan
    X = (group['ReviewDate'] - group['ReviewDate'].min()).dt.days.values.reshape(-1, 1)
    y = group['ManagerRating'].values
    model = LinearRegression().fit(X, y)
    return model.coef_[0]

# Calculate slopes for each employee based on their performance reviews
slopes = performance_df.groupby('EmployeeID').apply(calculate_slope)
merged_df['Slope'] = merged_df['EmployeeID'].map(slopes)

# Categorize current performance based on ManagerRating
def categorize_performance(rating):
    if pd.isna(rating):
        return np.nan
    elif rating <= 2:
        return 'Low'
    elif rating == 3:
        return 'Average'
    else:
        return 'High'

merged_df['PerformanceCategory'] = merged_df['ManagerRating'].apply(categorize_performance)

# Filter employees with valid slope values and then categorize potential into 3 quantiles
valid_df = merged_df.dropna(subset=['Slope'])
valid_df['PotentialCategory'] = pd.qcut(valid_df['Slope'], 3, labels=['Low', 'Average', 'High'])

# Create the 9-box grid as a crosstab of Performance vs. Potential
grid = pd.crosstab(valid_df['PerformanceCategory'], valid_df['PotentialCategory'])
print('9-Box Grid Distribution:')
print(grid)

# Visualize the 9-box grid using a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(grid, annot=True, fmt='d', cmap='Blues')
plt.title('9-Box Grid: Performance vs. Potential')
plt.xlabel('Future Potential')
plt.ylabel('Current Performance')
plt.show()
```




```
9-Box Grid Distribution:
PotentialCategory    Low  Average  High
PerformanceCategory
Average              171      127    76
High                  61      179   282
Low                  136       61    10
```

3: KPIs & Turnover Analysis-

Objective:

Calculate key HR metrics (KPIs) such as turnover rate, average satisfaction, and average tenure. Additionally, analyze turnover by department, salary, and years of service.

Methodology:

1.Turnover Rate Calculation: **Determine the percentage of employees who have left the organization.**

2. Satisfaction Analysis: **Convert categorical satisfaction ratings into numerical values, then compute the overall average satisfaction.**

3. Tenure Analysis: **Calculate the average years employees have been with the company.**

4. Turnover Breakdown: **Filter data for ex-employees and analyze turnover by department, median salary, and median years at the company.**

Expected Output::

- Printed KPIs including turnover rate, average satisfaction, and average tenure.
- A breakdown of turnover statistics by department, median salary, and median experience.

```python
# Step 6: KPIs & Turnover Analysis

# Objective: Calculate key HR metrics including employee turnover rate, average satisfaction, and average tenure.
# Then, analyze turnover by department, salary, and experience.

# 1. Employee Turnover Rate
turnover_rate = employee_df['Attrition'].value_counts(normalize=True).get('Yes', 0) * 100

# 2. Convert satisfaction levels to numerical values
satisfaction_mapping = {
    "Very Dissatisfied": 1,
    "Dissatisfied": 2,
    "Neutral": 3,
    "Satisfied": 4,
    "Very Satisfied": 5
}
satisfied_level_df['SatisfactionLevelNumeric'] = satisfied_level_df['SatisfactionLevel'].map(satisfaction_mapping)

# Calculate the average employee satisfaction
avg_satisfaction = satisfied_level_df['SatisfactionLevelNumeric'].mean()

# 3. Average tenure of employees in the company
avg_hiring_time = employee_df['YearsAtCompany'].mean()

# Aggregate KPI Results
kpi_results = {
    "Turnover Rate (%)": turnover_rate,
    "Average Satisfaction Level": avg_satisfaction,
    "Average Hiring Time (Years)": avg_hiring_time
}

# Turnover Analysis
df_turnover = employee_df[employee_df['Attrition'] == 'Yes']
turnover_by_department = df_turnover['Department'].value_counts()
turnover_by_income = df_turnover['Salary'].median()
turnover_by_experience = df_turnover['YearsAtCompany'].median()

turnover_results = {
    "Turnover by Department": turnover_by_department.to_dict(),
    "Median Salary of Ex-Employees": turnover_by_income,
    "Median Experience of Ex-Employees (Years)": turnover_by_experience
}

# Print KPIs Analysis results
print('=== KPIs Analysis ===')
for key, value in kpi_results.items():
    print(f"{key}: {value}")

print('\n=== Turnover Analysis ===')
for key, value in turnover_results.items():
    print(f"{key}: {value}")
```

```
=== KPIs Analysis ===
Turnover Rate (%): 16.122448979591837
Average Satisfaction Level: 2.75
Average Hiring Time (Years): 4.562585034013606

=== Turnover Analysis ===
Turnover by Department: {'Technology': 133, 'Sales': 92, 'Human Resources': 12}
Median Salary of Ex-Employees: 50660.0
Median Experience of Ex-Employees (Years): 1.0
```

4: Balanced Scorecard Analysis-

Objective:

Assess HR effectiveness across four strategic pillars:

Dimension	Metric
Financial	Attrition Rate (employee turnover as a cost indicator)
Employee Satisfaction	Average of Environment, Job, and Relationship Satisfaction scores
Internal Processes	Training utilization, promotion frequency, and years in current roles
Learning & Growth	Training participation and recent promotion percentage

Methodology:

Each perspective is evaluated by:

1. Financial Perspective:

Calculate the attrition rate.

2. Employee Satisfaction:

Compute overall satisfaction by averaging various satisfaction measures.

3. Internal Processes:

Calculate training utilization (ratio of training taken to available training opportunities) and average years since last promotion.

4. Learning and Growth:

Determine the average training opportunities taken and the percentage of employees promoted in the last year.

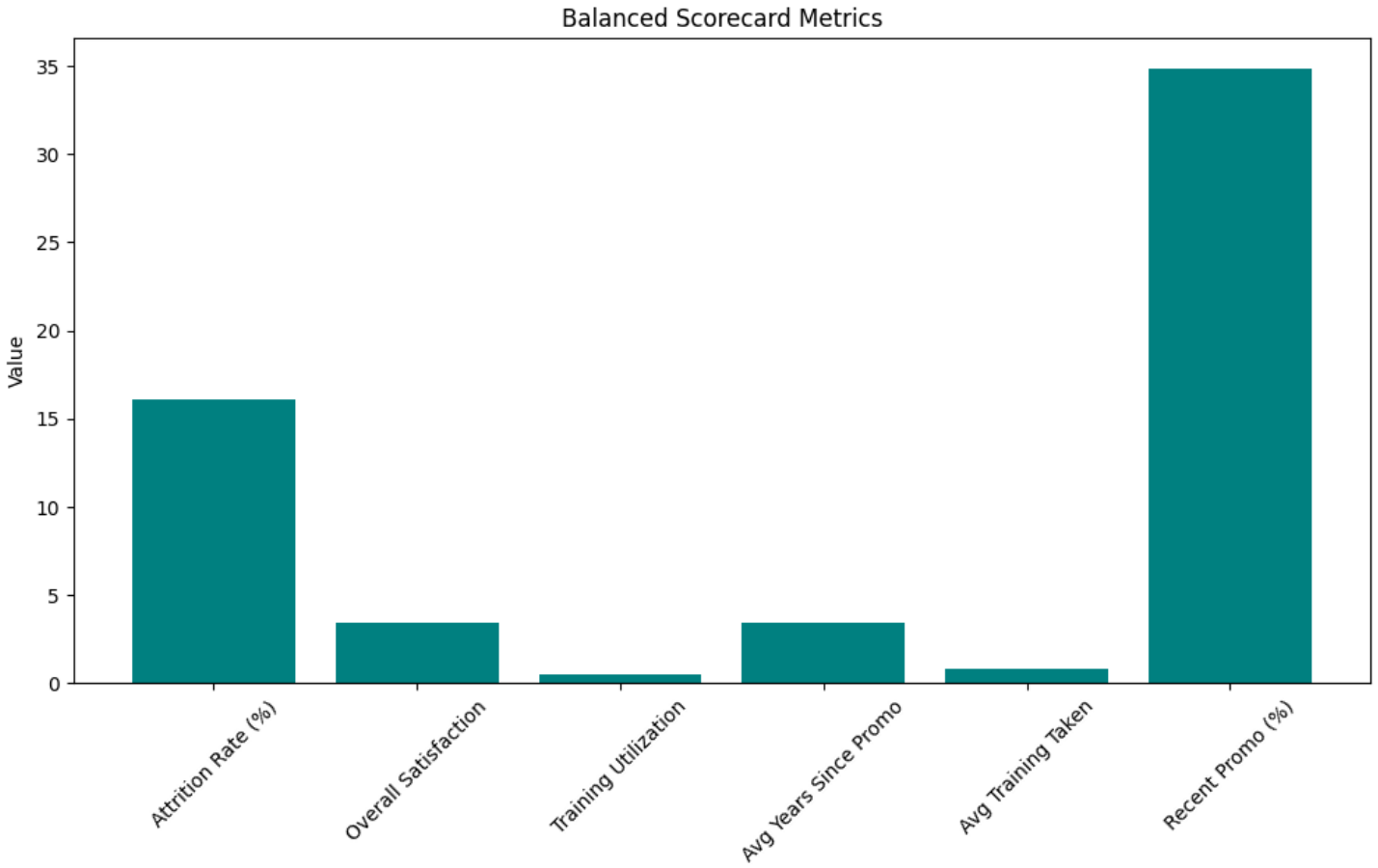
5. Visualization:

Display the key metrics using a bar chart.

Expected Output::

- Printed metrics including attrition rate, overall satisfaction, training utilization, years since last promotion, average training taken, and percentage of recent promotions.
- A bar chart visualizing these balanced scorecard metrics.

```python
# Step 7: Balanced Scorecard Analysis

# Objective: Evaluate HR performance across multiple perspectives:

# - **Financial Performance:** Attrition rate as a cost indicator.
# - **Employee Satisfaction:** Average satisfaction scores.
# - **Internal Processes:** Training utilization and promotion frequency.
# - **Learning and Growth:** Training participation and recent promotions.

# Financial Perspective: Attrition Rate
attrition_rate = (employee_df['Attrition'] == 'Yes').mean() * 100
print(f"Attrition Rate: {attrition_rate:.2f}%")

# Employee Satisfaction: Average satisfaction scores
satisfaction_cols = ['EnvironmentSatisfaction', 'JobSatisfaction',
                     'RelationshipSatisfaction', 'WorkLifeBalance']

# Some satisfaction columns might be in the performance_df or employee_df; adjust as needed
if set(satisfaction_cols).issubset(latest_performance.columns):
    latest_performance['OverallSatisfaction'] = latest_performance[satisfaction_cols].mean(axis=1)
    overall_satisfaction = latest_performance['OverallSatisfaction'].mean()
    print(f"Overall Average Satisfaction (1-5 scale): {overall_satisfaction:.2f}")
else:
    print("Satisfaction columns not found in latest performance data.")

# Internal Processes: Training Utilization and Years Since Last Promotion
if 'TrainingOpportunitiesWithinYear' in latest_performance.columns and 'TrainingOpportunitiesTaken' in latest_performance.columns:
    latest_performance['TrainingUtilization'] = (latest_performance['TrainingOpportunitiesTaken'] / latest_performance['TrainingOpportunitiesWithinYear'])
    avg_training_utilization = latest_performance['TrainingUtilization'].mean()
    print(f"Average Training Utilization: {avg_training_utilization:.2f}")
else:
    print("Training data not found in latest performance data.")

if 'YearsSinceLastPromotion' in employee_df.columns:
    avg_years_since_promo = employee_df['YearsSinceLastPromotion'].mean()
    print(f"Average Years Since Last Promotion: {avg_years_since_promo:.2f}")
else:
    print("Column 'YearsSinceLastPromotion' not found in employee data.")

# Learning and Growth: Training Opportunities Taken and Recent Promotions
if 'TrainingOpportunitiesTaken' in latest_performance.columns:
    avg_training_taken = latest_performance['TrainingOpportunitiesTaken'].mean()
    print(f"Average Training Opportunities Taken: {avg_training_taken:.2f}")
else:
    print("Column 'TrainingOpportunitiesTaken' not found in latest performance data.")

if 'YearsSinceLastPromotion' in employee_df.columns:
    recent_promo_pct = (employee_df['YearsSinceLastPromotion'] <= 1).mean() * 100
    print(f"Percentage of Employees with Promotion in Last Year: {recent_promo_pct:.2f}%")
else:
    print("Column 'YearsSinceLastPromotion' not found in employee data.")

# Optional: Visualize key metrics
metrics = {
    'Attrition Rate (%)': attrition_rate,
    'Overall Satisfaction': overall_satisfaction if 'overall_satisfaction' in locals() else np.nan,
    'Training Utilization': avg_training_utilization if 'avg_training_utilization' in locals() else np.nan,
    'Avg Years Since Promo': avg_years_since_promo if 'avg_years_since_promo' in locals() else np.nan,
    'Avg Training Taken': avg_training_taken if 'avg_training_taken' in locals() else np.nan,
    'Recent Promo (%)': recent_promo_pct if 'recent_promo_pct' in locals() else np.nan
}

plt.figure(figsize=(12, 6))
plt.bar(metrics.keys(), metrics.values(), color='teal')
plt.title('Balanced Scorecard Metrics')
plt.ylabel('Value')
plt.xticks(rotation=45)
plt.show()
```




```
Attrition Rate: 16.12%
Overall Average Satisfaction (1-5 scale): 3.46
Average Training Utilization: 0.46
Average Years Since Last Promotion: 3.44
Average Training Opportunities Taken: 0.83
Percentage of Employees with Promotion in Last Year: 34.83%
```

Conclusion

Through the use of Python and structured data analysis, the organization gains:

- ✅ A clear view of **performance gaps** by role
- ✅ A strategic **talent map** to guide promotions and succession
- ✅ A holistic **HR performance dashboard** to guide decision-making

Final Remarks Analysis Summary:

GAP Analysis: Identifies performance gaps relative to job role averages. The analysis reveals which employees are underperforming relative to their peers.

Training Gap Analysis: Calculates the discrepancy between available and attended training opportunities. The top 10 employees with the largest gaps are highlighted, enabling targeted training interventions.

9-Box Grid Analysis: Maps employees according to current performance and future potential. This tool helps in talent management by visualizing where employees stand and informing succession planning.

KPIs & Turnover Analysis: Provides key HR metrics, including employee turnover, satisfaction, and tenure. It also breaks down turnover by department and other key dimensions.

Balanced Scorecard: Integrates multiple HR dimensions (financial, satisfaction, internal processes, learning & growth) into a holistic view, enabling strategic decision-making.

Data Dynamos