Step 1: Import Required Libraries

This cell imports all necessary libraries for data manipulation, visualization, and modeling.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

Step 2: Load the Data

Load all sheets from the Excel file and display a preview of key datasets.

```
# 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
2             10                     6                      10
3             10                    10                      10
4              6                     1                       1

   YearsWithCurrManager
0                     7
1                     0
2                     8
3                     0
4                     6

[5 rows x 23 columns]

Performance Rating Data:
  PerformanceID EmployeeID ReviewDate  EnvironmentSatisfaction  \
0          PR01  79F7-78EC 2013-02-01                        5
1          PR02  B61E-0F26 2013-03-01                        5
2          PR03  F5E3-48BB 2013-03-01                        3
```

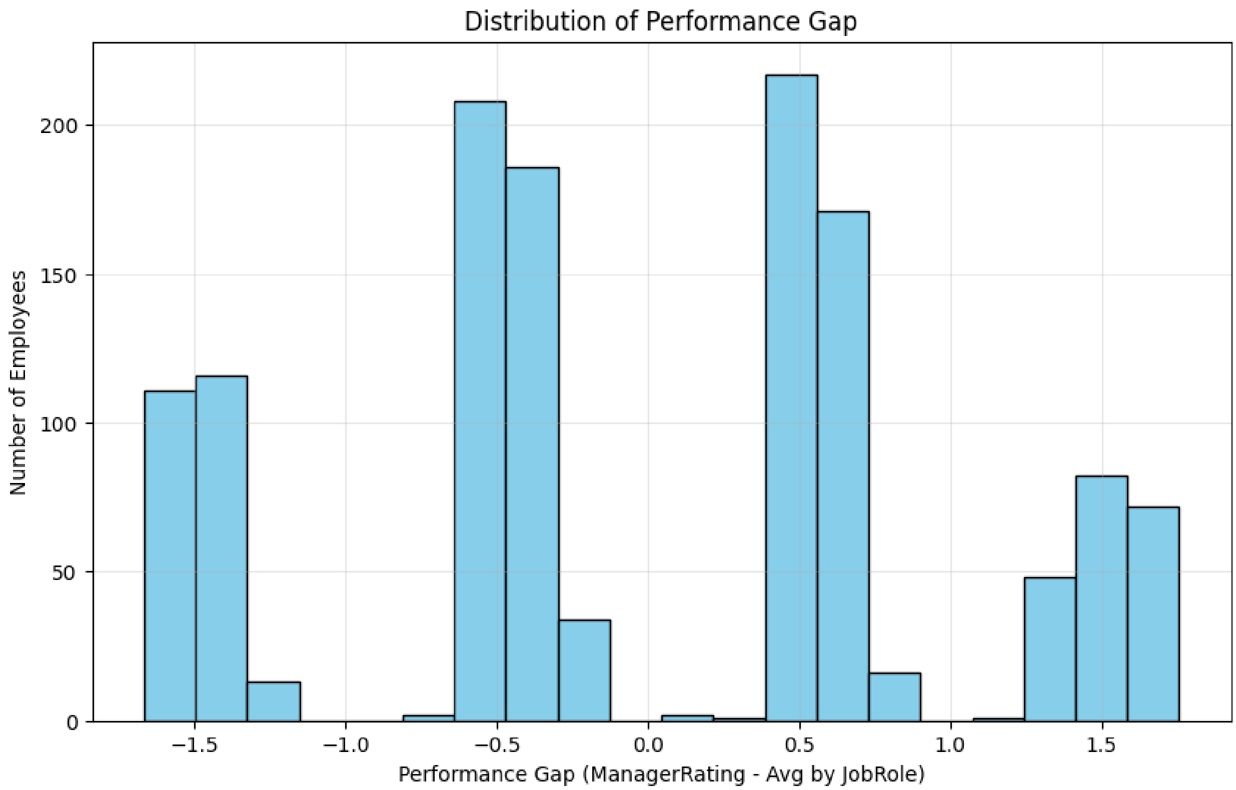
```
3          PR04  0678-748A 2013-04-01                       5
4          PR05  541F-3E19 2013-04-01                       5

   JobSatisfaction  RelationshipSatisfaction  
TrainingOpportunitiesWithinYear  \
0                4                         5   
1  
1                4                         4   
1  
2                4                         5   
3  
3                3                         2   
2  
4                2                         3   
1  

   TrainingOpportunitiesTaken  WorkLifeBalance  SelfRating  
ManagerRating  \
0                           0                4           4   
4  
1                           1                4           4   
3  
2                           2                3           5   
4  
3                           0                2           3   
2  
4                           0                4           4   
3  

  DataQualityStatus  
0             Valid  
1             Valid  
2             Valid  
3             Valid  
4             Valid  
```

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()]
```

```python
# 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
```

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.

```
# 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()
```

```python
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['Employee
ID'])]

# 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

   TrainingOpportunitiesWithinYear  TrainingOpportunitiesTaken
```

```
TrainingGap
0                                3                           0
3
1                                3                           0
3
2                                3                           0
3
3                                3                           0
3
4                                3                           0
3
5                                3                           0
3
6                                3                           0
3
7                                3                           0
3
8                                3                           0
3
9                                3                           0
3
```

Step 5: 9-Box Grid Analysis

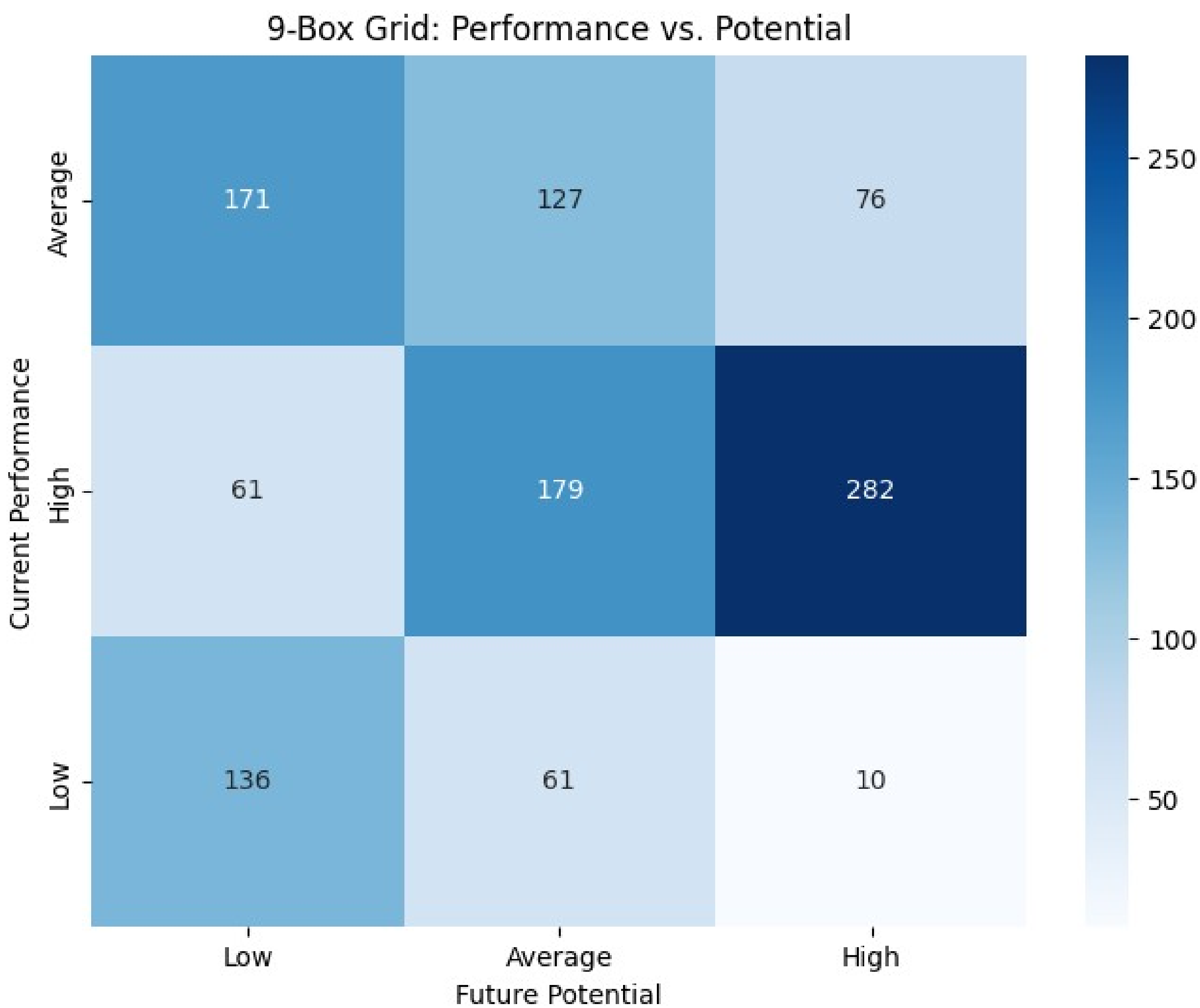
Objective: Place employees in a 3x3 grid based on their current performance and future potential. For current performance we use ManagerRating; for future potential, we compute the trend (slope) of ManagerRating over time using linear regression.

```
# 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()
```

```
/tmp/ipykernel_872422/3655308779.py:11: DeprecationWarning:
DataFrameGroupBy.apply operated on the grouping columns. This behavior
is deprecated, and in a future version of pandas the grouping columns
will be excluded from the operation. Either pass
`include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  slopes = performance_df.groupby('EmployeeID').apply(calculate_slope)
/tmp/ipykernel_872422/3655308779.py:29: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid_df['PotentialCategory'] = pd.qcut(valid_df['Slope'], 3,
labels=['Low', 'Average', 'High'])

9-Box Grid Distribution:
PotentialCategory    Low  Average  High
```

```
PerformanceCategory
Average                    171       127    76
High                        61       179   282
Low                        136        61    10
```



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
```

```python
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
```

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')
```

```python
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%
```