Friedrich-Alexander-Universität
Rechts- und Wirtschafts-
wissenschaftliche Fakultät

DIGITALISIERUNG
Schöller-Stiftungslehrstuhl

People Analytics

Project Report

at the Faculty of Business, Economics, and Law
Friedrich-Alexander-Universität Erlangen-Nürnberg
Schöller Endowed Chair for Information Systems
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Content

1 Personnel Planning

1.1 HR Staffing Model Application *(5 Points)*

With the HR Staffing Model, we can calculate the future demand for new employees. For this purpose, we calculate the total gross employee requirements (GER) demand for employees from the net (NER) and reserve (RER) demand.

Differences between Future No. of Employees and Gross Employee Requirements (GER) are shown below:

Future No. of Employees	Gross Employee Requirements (GER)
It represents the actual expected number of employees, considering the current number of employees, employee attrition(**EA**), and expected hires(**EH**).	It is calculated from the net (NER) and reserve (RER) requirements.GER is the sum total of the number of employees needed, taking into consideration the requirement of the planned workforce plus a buffer (reserve) to take care of unforeseen or temporary events like absenteeism.
It is calculated as follows: **Future No. of Employees**= Current Employees **-** EA + EH	It is calculated as follows: **GER**= NER + RER

Calculation of Future No. of Employees and GER for each of the job positions:

We know the following information:

Current Employees	Employee Attrition(EA)	Expected Hires(EH)	Additional Reserve for Absenteeism
Conductors: 5	Conductors: 2	Conductors: 3	Conductors: 1
Bus Drivers: 8	Bus Drivers: 2	Bus Drivers: 3	Bus Drivers: 2
Technicians: 4	Technicians: 1	Technicians: 2	Technicians: 1

For Future No. of Employees:

Conductors**=**Current Employees - EA + EH = 5-2+3= 6, Bus Drivers**=** 9, Technicians=5

For Gross Employee Requirements (GER):

Conductors=NER (EA)+ RER= 2+1=3, Bus Drivers=4**,** Technicians=2.

1.2 Optimal Staff Need *(5 Points)*

In order to find out the ideal number of bus conductors to work per 6 hour per shift at the intercity buses of the FAU Transline, I applied linear optimization programming. The buses are exposed to four shifts of operation a day (00:00-06:00, 06:00-12:00, 12:00-18:00, 18:00-00:00), and each conductor is able to serve up to 10 people an hour. The objective is to have a minimum total wage bill between the shifts in terms of shifting wage rate that varies in every shift.

Approach:

- **Decision Variables**: The number of bus conductors to be hired per shift.
- **Goal**: Reduce the total wages

- **Constraints:** In every shift, make sure that capacity overcomes demand in each hourly time. A conductor covers a maximum of 10 passengers per hour ensuring quality service.

Steps:

1. Import libraries (pandas, math).
2. Load the data(CSV) and read fau_staffing_conductors.csv.
3. Define decision variables.
4. Set objective function to reduce total wages.
5. Add constraints for sufficient staff coverage.
6. Solve with prob.solve().

Code & Result:

```
# Load dataset
df = pd.read_csv(r'C:\Users\Maisha Fahmida\Desktop\PA\CSV file\fau_staffing_conductors.csv')

# Separate passenger demand and wage rate
passenger_df = df.iloc[:-1].copy()
passenger_df['Avg_Passenger_Number'] = passenger_df['Avg_Passenger_Number'].astype(float)
wage_row = df.iloc[-1]
wage_rates = {i: float(wage_row[f'Shift {i}']) for i in range(1,5)}

# Compute required conductors and cost per shift
results = []
for i in range(1,5):
    shift_label = f'Shift {i}'
    subset = passenger_df[passenger_df[shift_label] == 'X']
    max_demand = subset['Avg_Passenger_Number'].max()
    conductors = math.ceil(max_demand / 10)
    cost = conductors * wage_rates[i]
    results.append({'Shift': i, 'Max_Demand': max_demand, 'Conductors': conductors, 'Wage_Rate': wage_rates[i], 'Cost': cost})
results_df = pd.DataFrame(results)
print(results_df)
total_cost = results_df['Cost'].sum()
print(f"\nTotal Daily Wage Cost: €{total_cost}")
```

```
   Shift  Max_Demand  Conductors  Wage_Rate   Cost
0      1        91.0          10       60.0  600.0
1      2        46.0           5       45.0  225.0
2      3        42.0           5       45.0  225.0
3      4         8.0           1       70.0   70.0
```

The findings shows that for Shift 1 (06:00–12:00): Peak 91 passengers ⇒ 10 conductors, Shift 2 (12:00–18:00): Peak 46 passengers ⇒ 5 conductors, Shift 3 (18:00–00:00): Peak 42 passengers ⇒ 5 conductors, Shift 4 (00:00–06:00): Peak 8 passengers ⇒ 1 conductor.

1.3 Reskilling vs. External Hiring (*4 Points*)

Trade-Offs Between Reskilling and External Hiring in the context of public transportation are shown below:

- **Cost of labor & salary**
  External employees are paid 20 % more than their internal counterparts who have been upskilled.
- **On-boarding & time-to competency**
  New recruits must be inducted into the safety standards and culture of FAU Transline completely. On the other hand, Reskilled workers have the advantage of having core operations knowledge and therefore ramp time is reduced.
- **Morale of the employees & retention**
  Investment in the development of the existing employees increases participation and decreases turnover. In contrast, Pure outside recruitment can be considered as failure to recognize internal talent.
- **Skill-Specific Challenges**
  Reskilling encounters some obstacles such as motivation of the employees, technophobia and selecting applicable skills.However, by employing, they can guarantee immediate expertise, although it might not cover long-term skills deficiencies.

A hybrid approach is recommended for FAU Transline because of a good combination of cost, time, and quality. Reskilling existing operations staff where significant domain knowledge is required, and recruiting niche technical staff from outside.

2 Sourcing and Acquisition

2.1 Personnel selection process *(4 Points)*

At FAU Transline, a requirements analysis can be done by using:

- o **Experience-Based Approach**:
    - o Benefits of professional understanding and instincts of HR practitioners and managers.
    - o Refers to experience by using informal techniques (discussions, interviews) to determine the successful traits of the employee.
- o **Empirical Approach:**
    - Workplace-Analytical: Employs the consistent application of analytical work-based tools (e.g. questionnaires) to determine which competencies are necessary.
    - Personal- Empirical: Uses statistical profiling of current employees to discover job outcomes linked variables (e.g. decision trees, association analyses).

When both of the approaches are combined, FAU Transline will be able to make an effective balance between expert intuition and strict statistical verification, thereby increasing the reliability and accuracy of their personnel selection process.

2.2 Data driven recruitment *(7 Points)*

The potential benefits of using data-driven tools to select applicants **:**

Cost Reduction: Automation saves significantly on the cost of hiring since it simplifies the processes of sifting through resumes and using first-level filters.

Objectivity: Data-driven tools improve objectivity in making staffing decisions as data-based judgment is used instead of subjective assessment.

Better Fit: Based on past recruitment data Algorithms are able to find candidates whose profile best fits and matches the job requirements.

Efficiency: Eliminates long time used to hire people because of filtration and ranking of the candidates automatically.

Improved Hiring Source: Predictive models also allow you to determine which applications are likely to perform well, based on historical performance data of the employeespeople Analytics.

Scalability: Automation enables one to take the large numbers of applications easily and not to sacrifice quality.

By automating some processes in recruitment, the FAU Transline will be able to cut down the cost of selection of personnel since it does not have to undertake manual screening and administrative expenses in personnel selection. At the same time, the employment process can be improved with prediction analytics and individual models to increase the likelihood of hiring only qualified employees. This lessens the possibility and the costs of bad hiring practices and allows finding the ideal candidates in a shorter time with more confidence.

FAU Transline wants to automate parts of its recruitment procedure into the intercity bus driver role through using the history of applicant data. An association rule mining algorithm was applied on the fau_transline_recruitment.csv set of data that includes the background characteristics, qualifications, and recruitment results of the transportation posts of past candidates. Below are **the steps** taken to identify the relevant **association rules**:

Data Preprocessing:

- **Filtering:** Just screened the candidates who had applied to the post of intercity bus driver.
- **Numeric Discretization:** The continuum variables (years of experience, number of previous companies, distance) were changed into a high/low flag at a median; skill scores (safe driving, customer service, navigation) were set in the binned (low, high) 75).
- **Target Variable:** turned the hiring_decision variable that is a boolean into the hired column that is a binary variable.
- **Cleaning:** Dropped raw numeric columns and the others columns(depot_driver, city_bus_driver), and also dropped the columns with missing data.

Association Analysis:

- **Frequent Itemsets:** The **Apriori algorithm** was applied, min_support=0.1, which identifies sets of items, which occur in at least 10 percent of the cases.
- **Filtering:** Association Rules were generated where lift 1 (positive association) and confidence 0.5 (more likely than chance).
- **Ranking:** A filter that ranks the rules in descending order of lift (the ranking then by confidence) in order to determine the most predictive rules.

The key skills that are linked to being hired for the intercity bus driver role:

- Above-Median Years of Experience (experience_high == 1)
- Strong Navigation Skills (navigation_high == 1)
- High Safe Driving Skills (safe_driving_high == 1)
- Excellent Customer Service Skills (customer_service_high == 1)
- Specific Recruitment Strategy (e.g., strategy_aggressive == 1)

The top rule is (**edu_no_degree, strategy_aggressive**)→ (hired=1), which implies that candidates with these two are most likely to be employed as an intercity bus driver.

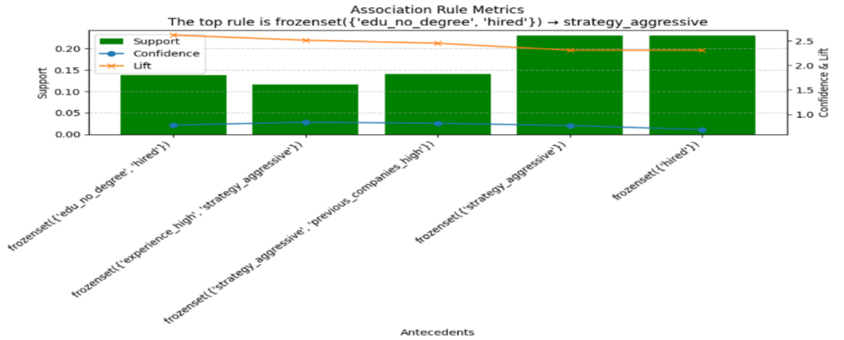
Rule Metrics: For the top rule (edu_no_degree, strategy_aggressive)→ **(hired=1)**:

- **Support**: 0.14 (A proportion of 14 % of intercity-bus-driver applicants meet the criteria of high safe-driving)
- **Confidence**: 0.78 (78 percent of possibility of getting hired based on those two qualities)
- **Lift**: 2.62 (In comparison, candidates who have both skills stand a 2.62 increase in the chance of being hired in comparison to chance alone)

[27]:

```
first = rules_sorted.iloc[0]
ante = ', '.join(first['antecedents'])
cons = next(iter(first['consequents']))
sup = first['support']
conf = first['confidence']
lf = first['lift']
print(f"Top rule: ({ante}) → ({cons})")
print(f"Support: {sup:.2f} ({sup*100:.0f}%)")
print(f"Confidence: {conf:.2f} ({conf*100:.0f}%)")
print(f"Lift: {lf:.2f}")
```

```
Top rule: (edu_no_degree, hired) → (strategy_aggressive)
Support: 0.14 (14%)
Confidence: 0.78 (78%)
Lift: 2.62
```



2.3 Ethical Risks in automation *(4 Points)*

Ethical and legal risks of AI-based hiring tools at FAU Transline:

Algorithmic Bias: AI judgments are strongly reliant on the quality of training data, which can unfairly discriminate against groups (e.g. age, gender discrimination, refuse people over 50, or women over 35, despite qualifications).

Transparency Problems ("Black Box Problem"): Algorithms of a complex kind are frequently inexplicable, and overcoming this can present issues with regard to the comprehending of hiring decisions, which in turn, can lead to social and lawful complications.

Examples:

Hiring model based on decision tree (intentionally exclude older, female candidates and basically hire based on previous hiring patterns).

Ways to reduce potential bias in automated hiring

1.Quality Training Data:

The AI models should be learned by precise and representative data. Any algorithm trained on poor-quality data or biased data may induce systematic discrimination against a certain group of people, like rejection of older applicants or women unfairly. Such biases can be avoided by ensuring that data is high in quality.

2. Data Mining: Discrimination Aware:

The inference can be attained without necessarily using sensitive attributes in a clear way. Discrimination-sensible approaches examine patterns to identify and cleanse implicit prejudice and guarantee reasonable treatment across demographic borders of automatic judgments.

3. XAI (explainable AI):

The AI decision-making must be viable and open to interpretation. Explainable AI methods make hiring suggestions also more understandable, therefore, making control simpler and decreasing the possibility of any legal or ethical problems.

3 Onboarding and Performance

3.1 A new hire *(5 Points)*

Socialization plays a crucial role in the process of onboarding since it tailors personal values of the new employees to the mission, vision, and culture of the organization. Such harmonization promotes a stronger feeling of purpose and existence, which encourages employees to make a difference. It is during the initial periods that socialization is particularly critical as it assists new employees to fit in and become productive members of the organizations. It has direct connection with greater organizational commitment, job involvement, and tenure. Positive socialization enhances clear understanding of roles, belief in self ability, and acceptance of society which are the key drivers of early adjustment and long-term success.

Based on academic research, the four key components of effective onboarding:

- **Compliance**: Adherence to rules of law, safety and organization.

FAU Transline Action: Conduct planned briefings and online courses on transport safety and HR policies on the first week.

- **Clarification**: Clear definition of role and expectations.

FAU Transline Action: Provide bus drivers, train conductors and the technicians that perform maintenance with rolespecific trainings and questionanswer sessions.

- **Culture**: Introductions to formal and informal corporate rules.

FAU Transline Action: Reorganize on-boarding tours, narration of senior workers and informal meetings.

- **Connection**: developing in-house connections and networks.

FAU Transline Action: Adopt a recommender system and match the new hires with those who share their interests.

The following tactics of socialization should be embraced by FAU Transline:

- **Formal and group onboarding** to learn and identify with each other.
- **Fixed and sequential training** to curtail uncertainty.
- **Serial and investiture method**- assigns mentors and positively reinforces on the way to integration.

The **possible outcomes** that successful onboarding could have on employee performance, satisfaction, and organizational commitment:

- Increased role clarity and confidence increasing the level of job performance.
- There will be more job satisfaction due to cultural fit and social acceptance.
- Greater organizational commitment, lowered turnover and augmented engagement and retention

An external study supports this, noting that employees improve when they receive regular feedback, aligned goals, and peer collaboration opportunities.

3.2 Recommender System *(4 Points)*

The recommender system of matching new employees with the existing ones in terms of common interests presupposes the calculation of similarity scores based on the team affiliations, previous experience, interests, sports, as well as the personalities. This is necessary in generating social ties in the workplace which would help new employees to integrate easily because they would be linked with other sharing similar interests.

To implement this, we follow these steps:

1. Load & clean data
2. Build profile "soup"
3. Vectorize & score
4. Map IDs to indices
5. Recommend top 3

[19]:
```
def get_recommendations(emp_id, cosine_sim=cosine_sim):
    idx = indices[emp_id]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)[1:4]
    emp_indices = [i[0] for i in sim_scores]
    return df.iloc[emp_indices][['id', 'teams', 'previous_experience', 'hobbies', 'sports', 'personality_traits']]
```

[21]:
```
recommendations = get_recommendations('klara_007')
recommendations
```

[21]:

	id	teams	previous_experience	hobbies	sports	personality_traits
41	emma_042	team_03	Advanced beginner	walking, journaling, listening to podcasts	table tennis	empathetic,innovator
48	christian_049	team_03	Competent	listening to podcasts, journaling, puzzle-solving	table tennis	cooperative,empathetic
0	simon_001	team_02	Expert	reading maps, walking, listening to podcasts	table tennis	curious,energetic

Findings discussion:

- Communal team and experience: Emma_042 and Christian_049 are on team_03 where Klara is in, and have the same Advanced beginner / Competent experience level that can facilitate cooperation due to shared work processes and vocabulary.
- Overlapping interests: The three recommended professional colleagues have interests such as listening to podcasts and table tennis, two hobbies clearly shared by Klara, which can support the creation of natural, informal contact at breaks or social gatherings.
- Auxiliary character traits: The presence of empathetic and collaborative characteristics (Emma, Christian) and curious and energetic characters (Simon) indicates that these colleagues not only can assist Klara in an emotional sense but also keep her busy, which creates a healthy and beneficial atmosphere during onboarding

In sum, such relationships are bound to make Klara feel welcome (Connection), learn norms and workflows (Clarification), and gain confidence (Self-efficacy) in a shorter amount of time, which are some of the most important short-term onboarding and long-term retention success factors.

3.3 Factors that affect employee performance *(4 Points)*

What went wrong and Why?

Despite the fact that there was an appropriate welcome and training of the maintenance technician, this was a major shortcoming due to the absence of clear leadership. Studies in academia show that transformational leadership which is typified by vision, support, motivation, and ethical practice is critical in performance and retention. This kind of lack of it probably contributed to the low-motivation, disconnection and early turnover of a three-month turnover of the technician.

Organizational Effects:

1. wastage of Investment in recruiting and training.
2. Negative impact on team performance and morale, since people may walk and leave, demoralizing those who are still in the workplace.
3. High employee turnover expenses and fluctuation.
4. Interference in the onboarding quality that hinders socialization and role definition.

Factors that most affect employee performance at FAU Transline:

- Leadership style - Transformational leadership enhances job satisfaction and performance.
- Job related considerations Role clarity and autonomy is crucial.
- Socialization - Indoctrination into the group and the culture enhances performance.
- Employee related factors - Factors which affect performance.

The practical actions that FAU Transline can take to strengthen employee performance during the first year:

- To equip train supervisors with transformational leadership skills, in order to give the vision, feedback, and motivation.
- Make sure that the role and what is expected of them is clearly defined during onboarding.
- Encourage team relationships with mentoring or recommendation system.
- Foster the practice of integrating culture by ensuring frequent meetings of groups and support by peers.

3.4 Employee performance analysis *(8 Points)*

Objective:

This project is aimed to analyzes the current employee data, in order to identify some underlying reasons of performance issues at FAU Transline:

- Undertake performance analysis based on the job role.
- Determine key factors influencing employee performance.
- Develop a trained machine learning model that can predict employee performance

Step-by-Step Analysis:

Data Loading and Exploring :

We loaded the employee_performance.csv file in the Pandas DataFrame and analyzed the structure of the file using the commands df.head() and df.info(). This showed 632 records and 18 columns, which contained the unique identifier EmpNumber and the target PerformanceRating.

```
# 1. Load data
df = pd.read_csv(r'C:\Users\Maisha Fahmida\Desktop\PA\CSV file\employee_performance.csv')
df.head()
df.info()
```

Checking for Missing Values:

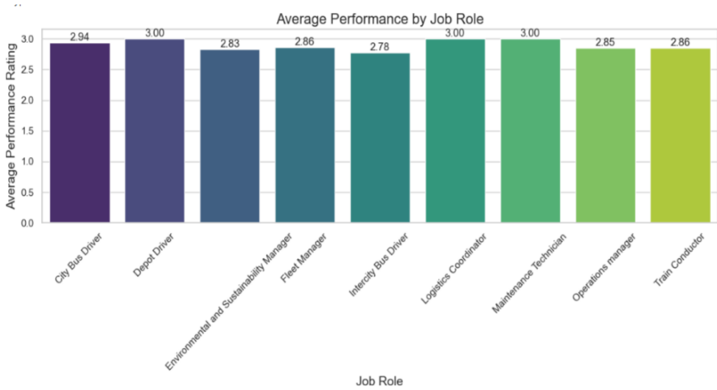
We should deal with missing data since they may affect the quality of our analysis.So, df.isnull().sum() is used to identify any missing values .In this case, No missed value was detected hence there was no imputation to be done.

Employees' performance Analysis Based on Job Role:

The main goals of the project that had to analyze the performance of the employees basing it on their job roles. Firstly, we clustered the data according to the EmpJobRole column and then we extracted the mean. Each job role should be rated in its performance. A visual representation is used in this case, depicted with a bar plot to analyze this. demonstrate the performance rating distribution through the number of job positions.

```python
# Performance by Job Role
if 'EmpJobRole' in df.columns:
    avg_perf = df.groupby('EmpJobRole')['PerformanceRating'].mean().reset_index()
    plt.figure(figsize=(12, 6))
    bars = sns.barplot(
        x='EmpJobRole',
        y='PerformanceRating',
        hue='EmpJobRole',
        data=avg_perf,
        palette='viridis',
        legend=False
    )
```

The mean on the performance rating can be represented as shown in the bar plot below in every job position. It emphasizes the difference in the performance ratings among job functions in the FAU Transline.



Redundant Features Identification and Dropping :

To diminish the noise and the multicollinearity we exclude features that we recognize to be overlapping, or irrelevant to the target,

- Attrition
- ExperienceYearsInCurrentRole
- YearsWithCurrManager

```python
drop_cols = ['Attrition', 'ExperienceYearsInCurrentRole', 'YearsWithCurrManager']
df.drop(columns=[c for c in drop_cols if c in df.columns], inplace=True)
df.shape
```

This reduces the complexity of the set of data without compromising the predictive value.

Encoding Categorical into Numerical:

Machine learning algorithms can process only numerical data, so categorical data was converted into numerical ones. We simply label-encode EmpJobRole so that each different job role corresponds to a number in an integer range that is suitable to model.

```python
# Label encoding categorical columns
le = LabelEncoder()
for col in ['EmpJobRole']:
    if col in df.columns:
        df[col] = le.fit_transform(df[col])

df.dtypes
```

Creating the Correlation Heatmap:

We calculated a correlation table to learn more about interrelationships among the features. and mapped it in the form of a heatmap. Some variables turned out to be revealed by the heatmap, those were highly correlated.It was associated with the dependent variable PerformanceRating.

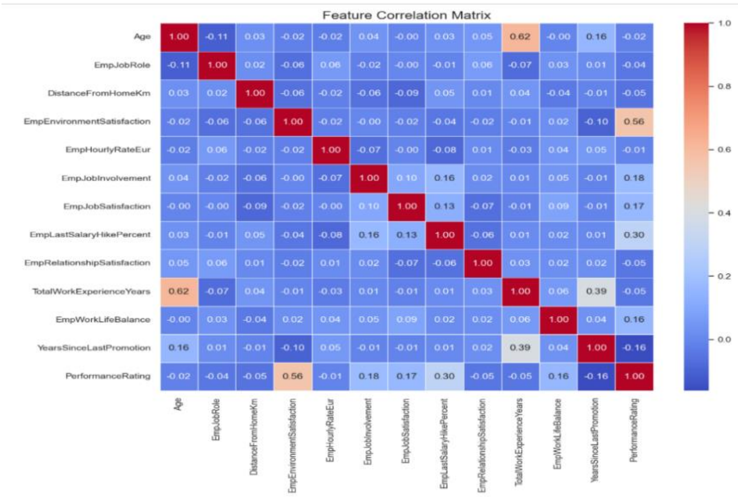
Key correlations:

- EmpEnvironmentSatisfaction ↔ PerformanceRating
- EmpLastSalaryHikePercent ↔ PerformanceRating

- EmpWorkLifeBalance ↔ PerformanceRating

```
# Compute correlation matrix
corr = numeric_df.corr()
# Plot heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(
    corr,
    annot=True,
    fmt='.2f',
    cmap='coolwarm',
    linewidths=0.5,
    square=True
)
```

Correlation Heatmap: As depicted in the heatmap below, there is a correlation among different features. the dataset. High relations can be observed between the satisfaction with work environment and salary hikes, work-life balance and PerformanceRating.



Data Division in Training Models:

We treat predictors (X) and target (y) as separate, and we divide them into training (80%) and test (20%) sets, with only numeric columns involved.

```
X = numeric_df.drop('PerformanceRating', axis=1)
y = numeric_df['PerformanceRating']
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
```

This reserves an unseen portion of the tests to test unbiasedly.

Machine Learning Models Training and Evaluation:

Three machine learning models have been trained :

- Random Forest Classifier
- Support Vector Machine (SVM)
- Logistic Regression

We considered three measures of performance to analyze the results of every model:

- Accuracy: The ratio of the right predictions.
- Precision: The true percentage of predictions which are positive.
- Recall: Rate of true positive being identified by the model.

The outcomes of every model were analyzed and printed:

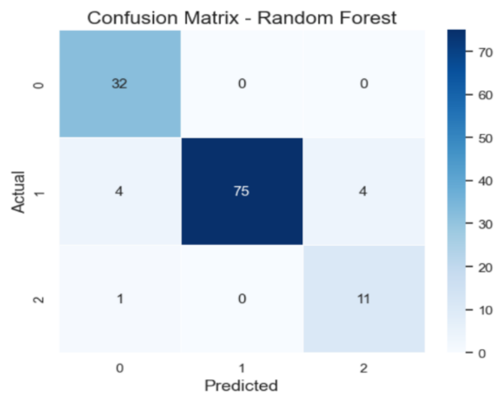
```
[15]: models = {
          'Random Forest': RandomForestClassifier(random_state=42),
          'SVM': SVC(),
          'Logistic Regression': LogisticRegression(max_iter=1000)
      }
      results = {}
      for name, model in models.items():
          model.fit(X_train, y_train)
          preds = model.predict(X_test)
          results[name] = {
              'accuracy': accuracy_score(y_test, preds),
              'precision': precision_score(y_test, preds, average='weighted', zero_division=0),
              'recall': recall_score(y_test, preds, average='weighted')
          }
      results
```

The best performer is Random Forest as it gained the most balance between accuracy, precision, and recall.

Confusion Matrix model Evaluation:

In order to give a better assessment of the Random Forest Classifier performance, we also gave a confusion matrix. The figures indicate in this matrix on how many people were correctly or incorrectly tested. predictions at every individual class giving a clearer picture on how the model performed.

```
# Confusion matrix
best_model = models['Random Forest']
preds = best_model.predict(X_test)
cm = confusion_matrix(y_test, preds)
plt.figure(figsize=(6, 5))
sns.heatmap(
    cm,
    annot=True,
    fmt='d',
    cmap='Blues',
    linewidths=0.5,
    square=True
)
plt.title('Confusion Matrix - Random Forest', fontsize=16)
plt.xlabel('Predicted', fontsize=14)
plt.ylabel('Actual', fontsize=14)
plt.tight_layout()
plt.show()
```



Based on the analysis we drew the conclusion that the Random Forest Classifier is an optimal model. Foresight into the employee performance with maximum accuracy and carefulness of balance between precision and recall. The factors that were found to be the most important in determining performance ratings were:

1. EmpWorkLifeBalance
2. EmpEnvironmentSatisfaction
3. EmpLastSalaryHikePercent

```
[15]: {'Random Forest': {'accuracy': 0.9291338582677166,
        'precision': 0.9407533517769738,
        'recall': 0.9291338582677166},
       'SVM': {'accuracy': 0.6535433070866141,
        'precision': 0.42711885423770846,
        'recall': 0.6535433070866141},
       'Logistic Regression': {'accuracy': 0.8503937007874016,
        'precision': 0.8564835178450845,
        'recall': 0.8503937007874016}}
```

References

[1] https://elearningindustry.com/practical-ways-to-improve-employee-performance

[2] Lecture Note from studon

[3] Data set from studon

Declaration of Academic Integrity at the Schöller Endowed Chair for Information Systems

I hereby certify that I have prepared the submitted work independently, and without the unauthorized assistance of third parties, as well as without the use of unauthorized aids. The work has not been submitted in the same or similar form to any other examination authority, nor has it been accepted by any other examination authority as part of an examination.

The passages in the work, which have been taken from other sources in terms of wording or meaning, are identified by indicating the origin. This also applies to drawings, sketches, picture representations and sources from the Internet.

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Violations of the above-mentioned rules are to be qualified as deception or attempted deception and lead to an assessment of the examination with "failed". Further sanctions are possible in the case of multiple or particularly drastic violations of the rules by the examination board.

Maisha

Maisha Fahmida | Example City, 2025-06-22