People Analytics

Project Report

at the Faculty of Business, Economics, and Law
Friedrich-Alexander-Universität Erlangen-Nürnberg
Schöller Endowed Chair for Information Systems
Prof. Dr. Sven Laumer

Presented by: Md Abdullah Al Mahmud Khosru
Hauptstrasse 91
Erlangen, 91054
+49 15754650982
md.khosru@fau.de
23070520

Final Date of Submission: 2024-12-20

Content

1 Personnel Planning

1.1 Future workforce needs *(4 Points)*

To identify future workforce needs, FAU Clinic should follow the workforce planning process. Here's a step-by-step approach based on the methodology discussed. First of all, FAU Clinic needs to align its workforce needs with the strategic goal of opening a new emergency room. The clinic must assess the required skill set and headcount based on anticipated patient flow and the need for medical assistants in the new facility. Next, The FAU clinic should consider internal and external factors like current workforce capabilities, skill shortages, regional population growth, patient demand, and healthcare trends

After that, analyze the actual existing medical staff, including the number of medical assistants currently employed and their distribution across the all shifts. It could be done using our existing HR data. Then, given the expansion, the clinic can project the number of medical assistants needed per shift based on patient volume and the hours of operation. For example, a historical patient-to-assistant ratio can help determine the ideal staffing levels.

It's very important to identify the gaps between future needs and current capabilities. The clinic should develop strategies to address these gaps. And it can be done in various ways like targeted recruitment, training programs, and educational partnerships. And at the end it's really important to regularly monitor the effectiveness of these flows and strategies. make adjustments based on feedback and changing conditions to ensure the workforce meets the clinic's goals.

1.2 Recruiting new hires *(4 Points)*

We know that **passive recruiting** is a process to hire new employees by job posting in a different social platform and make a strong employer brand and Fau clinic can be attractive to potential candidates through this process. The candidates can trust and apply voluntarily. On the other hand, **active sourcing** is a process where organizations actively approach potential candidates and it could directly reach out to the skilled professionals, even if they are not actively job hunting. the organizations are in a weaker negotiating position here.

For hiring skilled medical assistants and critical care nurses for the new emergency room, **active sourcing** should be prioritized. This method enables the clinic to directly identify and recruit candidates with specific qualifications and experience. In addition, FAU Clinic should adopt a **blended strategy** by combining active sourcing with passive recruiting. This approach will enhance visibility and attract a broader talent pool, ensuring both immediate and long-term staffing needs are met effectively.

To recruit new hires, FAU Clinic can utilize various channels to ensure effective staffing. Posting job descriptions on healthcare job boards and the clinic's website can attract active job seekers. Platforms like LinkedIn allow direct outreach to qualified professionals, especially for specialized roles such as medical assistants and critical care nurses. Recruitment agencies specializing in healthcare can streamline the hiring process, while participation in healthcare job fairs and industry events enables face-to-face engagement with potential candidates. These channels collectively ensure a strong pool of talent to meet the clinic's staffing needs for its new emergency room.

1.3 Optimal Staff Need *(7 Points)*

To determine the optimal number of medical assistants required per 8-hour shift in the emergency room, ensuring efficient care for all patients while adhering to the service level of 4 patients per assistant per hour. The following steps were performed to calculate the staffing requirements:

01. **Data Preparation**: Loaded the fau_medical_staff.csv dataset, replaced "X" with 1 to mark active shifts, filled NaNs with 0, and extracted patient numbers and shift activity data.

02. **Wage Rates and Service Level**: Assigned wage rates of $45 for Shifts 1 and 2, and $60 for Shift 3. Defined a service level of 1 worker per 4 patients to calculate staffing needs.

03. **Optimization Model**: Created a linear programming model to minimize total wage costs, using decision variables for the number of workers per shift.

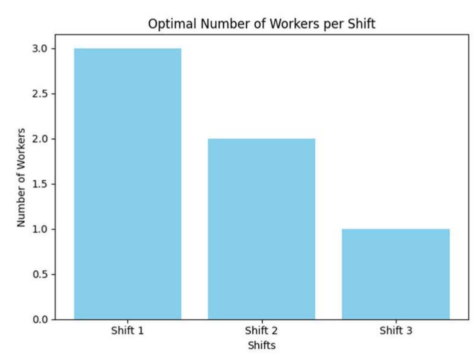
04. **Constraints and Solution**: Added constraints to ensure sufficient workers for active shifts based on patient demand and solved the optimization model to determine the optimal staffing levels.

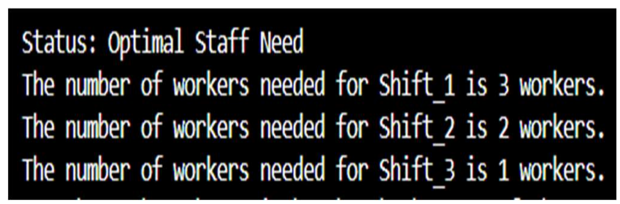
05. **Visualization and Results**: Results are showend using a bar chart.

Findings: Based on the **optimization results** provided through Linear Programming (LP), the number of workers needed for each shift at FAU Clinic is determined as follows:

- **Shift 1**: **3 workers**
- **Shift 2**: **2 workers**
- **Shift 3**: **1 worker**

The allocation is based on the **service level constraint**, which states that **one medical assistant can handle up to 4 patients per hour**. In Shift 1, The time slot **12:00 PM – 1:00 PM** has the **maximum patient load** of **11 patients** in one hour. Since 1 worker can handle 4 patients/hour. So we need 3 workers. In shift 2, The time slot **3:00 PM – 4:00 PM** has the **maximum patient load** of **8 patients** in one hour. So we need 2 workers and In shift 3, The **maximum patient load** of **4 patients** in one hour. So it can handle 1 worker as he has 8h shift and can manage 4 patient in each hour. The LP optimization is an effective method to allocate workers to shifts efficiently while meeting patient demand. It considers critical factors such as the average number of patients per hour and the service level constraint (1 worker can handle 4 patients per hour) to determine the optimal number of workers required for each shift. This ensures that staffing levels are sufficient to meet patient needs while avoiding overstaffing and maintaining operational efficiency.





Reliability of Results: The results are based on observed patient flow data from an existing emergency department, making them reliable for planning purposes. However, factors such as sudden surges in patient numbers or differences in patient complexity may require adjustments. Regular monitoring of patient flow and assistant workload is recommended to maintain service quality

Discussion: The required assistants are rounded up to ensure sufficient staffing for all shifts. The results indicate that the highest staffing demand is for Shift 1 (day shift), which experiences the largest patient volume. Shift 3 (night shift) has the lowest patient volume but remains the most expensive due to higher night-shift pay rates. By adhering to this staffing plan, FAU Clinic can maintain efficient and high-quality patient care while avoiding understaffing or overstaffing

2 Sourcing and Acquisition

2.1 Automation of personnel recruitment *(5 Points)*

Motivations for Automating Recruitment: FAU clinic can automate its hiring process and it could be beneficial in different ways, it will save cost and reduce manual work, streamline candidate screening, Applicant Tracking Systems (ATS) efficiently manage candidate pipelines, and allow HR to focus on strategic priorities. Also, it minimize human bias and lengthy process.

Strategy for Implementation: FAU Clinic could adopt an **AI-driven ATS** to screen resumes, rank candidates, and track applications. To implement this: At first, Identify key job-specific skills for training the ATS. After that Pilot-test the system using past recruitment data to refine its performance. Then, Combine automation outputs with human oversight for cultural and interpersonal evaluations. And continuously monitor and improve the system.

Drawbacks of Data-Driven Approaches: There are many disadvantages to data-driven approaches like algorithmic bias could be an issue, black box problem because it difficult to understand how decision made, over-reliance on quantitative data and reduced human interaction. Mismanaged automation can also lead to poor candidate experience.

Solutions: Use diverse training datasets, combine automation with human oversight, and regularly audit algorithms to mitigate bias and ensure fairness.

2.2 Data-driven recruitment *(6 Points)*

To determine the likelihood of an upcoming application being considered for the critical care nursing position, an association analysis was conducted on the dataset fau_clinic_recruitment.csv, which contains details of applicants who were either hired or declined, along with their skills and qualifications. Let’s have a look at the detailed analysis:

1. **Data Loading**: At the very beginning we Loaded the dataset to identify columns related to applicant attributes (empathy, patience, education, skills, qualifications, outcomes like hired or declined).

2. **Preprocessing**: And now I converted the experience column into ranges ([0,8), [8,20], [20,inf)), allowing for better categorical analysis And I used get_dummies to do that. Then, I used one-hot encoding to transform gender and education columns into binary format. To work with the Apriori algorithm effectively I had to ensure all data was into binary format.

3. **Applying Apriori Algorithm**: Generated frequent combinations of attributes with a minimum support of **2%**. This step identifies recurring patterns in the dataset, such as which skills or qualifications are commonly associated with critical care nursing hires. I used num_itemsets' argument for older mlxtend versions.

4. **Generating Association Rules**: Association rules were generated with a confidence threshold of **25%**. These rules predict outcomes (e.g., critical care nursing) based on antecedent attributes (e.g., skills, experience). Focused on rules where the **rhs** was critical_care_nursing. .

5.**Filtering Rules by Lift**: Added all columns like coverage, count, lift, support, confidence. Reset the index to start from 1. Rules were filtered and sorted by **lift** to prioritize statistically significant and impactful relationships. **High Lift (>1)**: Indicates that the antecedent attributes strongly predict the consequent.

Key Rule Identified: After sorting the rules by lift, the first rule identified was:

{gender_m, empathy, professional, patience} → {critical_care_nursing}

```
Top 10 Rules for Critical Care Nursing:
                                                   lhs                      rhs   support  confidence  coverage      lift  count
1                 (gender_m, empathy, professional, patience)  (critical_care_nursing)  0.024667    0.560606  0.044000  5.759651   37.0
2            (gender_m, empathy, patience, education_master)  (critical_care_nursing)  0.028667    0.494253  0.058000  5.077940   43.0
3                        (gender_m, empathy, professional)  (critical_care_nursing)  0.029333    0.483516  0.060667  4.967635   44.0
4  (gender_m, empathy, experience_range_[8,20], education_master)  (critical_care_nursing)  0.020667    0.455882  0.045333  4.683723   31.0
5                  (gender_m, empathy, patience, confidence)  (critical_care_nursing)  0.022000    0.452055  0.048667  4.644399   33.0
6                        (empathy, professional, patience)  (critical_care_nursing)  0.025333    0.441860  0.057333  4.539662   38.0
7        (gender_m, empathy, experience_range_[8,20], patience)  (critical_care_nursing)  0.038000    0.431818  0.088000  4.436488   57.0
8                       (gender_m, professional, patience)  (critical_care_nursing)  0.024667    0.420455  0.058667  4.319738   37.0
9                    (gender_m, empathy, education_master)  (critical_care_nursing)  0.034667    0.409449  0.084667  4.206666   52.0
10                         (empathy, patience, confidence)  (critical_care_nursing)  0.025333    0.408602  0.062000  4.197967   38.0
PS C:\Users\USER\OneDrive\Desktop\PA\Report_of_Khosru_Part_1>
```

Metrics: Support: 0.02667 means About 2.67% of applicants possess the antecedent attributes (e.g., male, empathetic, professional, and patient), making this rule relevant for a focused subset. **Confidence: 0.56606** means 56.61% chance that the applicant is considered for critical care nursing when the antecedent attributes are true, indicating a moderately strong association. **Lift: 5.75963** means Antecedents make the consequent (critical care nursing) **5.76 times more likely**, reflecting a statistically significant and impactful relationship

Key Skills Required for Critical Care Nursing: From the analysis, the following attributes were identified as critical for hiring candidates for the role:

Field Knowledge: Expertise in critical care nursing.

1. **Education**: Relevant qualifications and certifications.
2. **Soft Skills**: **Empathy**: The ability to connect with and care for patients. **Patience**: Managing stressful and critical situations calmly.
3. **Commitment to Location**: Willingness to work in the clinic's specific regional context.

Significance of Metrics: **Support**: Measures how frequently the rule applies to the dataset. Higher support reflects common patterns, while lower support indicates niche but valuable insights. **Confidence**: Indicates how reliably the antecedents predict the consequents. High confidence means the rule is trustworthy for decision-making. **Lift**: Evaluates the strength of the rule compared to random chance. High lift (>1) highlights statistically significant and impactful relationships.

Actionable Insights: Focus on High-Lift Rules: Use rules like {gender_m, empathy, professional, patience} → {critical_care_nursing} to prioritize candidates with the most relevant skills. Empathy and patience are essential attributes for handling stressful situations in critical care. Leverage these rules to automate initial screening, filtering applications based on attributes aligned with successful hires

2.3 Address the issue *(4 Points)*

Identified Issue: The analysis of the dataset suggests the possibility of **bias in hiring decisions** for the critical care nursing position. Applicants with key qualifications like critical_care_nursing and education may still face challenges if: **Soft Skills Overemphasis**: Traits like patience or empathy are heavily weighted, potentially overshadowing technical qualifications. **Regional or Gender Bias**: Patterns like higher hiring rates for specific genders or locations may indicate bias. **Incomplete Candidate Screening**: Applicants with sufficient technical qualifications but lacking minor soft skills may be overlooked.

Mitigation Strategies: **1. Ensure Equal Opportunity**: Use data-driven hiring tools to standardize candidate evaluation based on weighted scores for both technical and soft skills. Regularly monitor hiring data for patterns of bias.

1. **Refine Screening Criteria**: Focus on critical qualifications (e.g., critical_care_nursing, education) while balancing the importance of soft skills. Avoid overemphasis on subjective traits that might introduce bias.
2. **Promote Diversity**: Implement measures to ensure fair consideration for all applicants, irrespective of gender, location, or background.
3. **Continuous Feedback**:Use historical data and post-hiring performance reviews to refine hiring rules and avoid excluding qualified candidates.

3 Onboarding and Performance

3.1 A new hire *(5 Points)*

Socialization during onboarding is crucial as it helps new hires integrate into the organization's culture, clarify their roles, build relationships with colleagues, reducing stress and improving engagement. **The Main Factors for Successful onboarding** requires clear role expectations and responsibilities, cultural integration, relationship building, and a structured process. **For Socialization Approach** I would say FAU Clinic should adopt a proactive socialization model, that encouraging the new hire to seek information and connections, adapting to their roles while providing structured activities. **Recommended events** include a welcome session to introduce the team and provide an overview of the clinic's mission, values, and culture. Then, assigning a mentor for guidance, hosting an informal team lunch to foster rapport, and implementing a shadowing program which will allow the new hire to shadow experienced nurses during their initial shifts to learn best practices and workflows.

Successful onboarding brings long-term benefits for both the company and the employee. *For the company*, it improves retention by encouraging employees to stay, enhances productivity as new hires adapt quickly and contribute effectively, and boosts the organization's reputation through positive onboarding experiences. *For the employee*, it increases engagement by fostering a welcoming and supportive environment, facilitates career development with clear guidance and mentorship, and promotes job satisfaction by building loyalty and a positive perception of the organization.

3.2 Recommender System *(4 Points)*

To help new employees build strong social connections, FAU Clinic developed a recommendation system that identifies existing employees with shared team affiliations, hobbies, and favorite sports. Using the dataset fau_clinic_recommender_system.csv, a cosine similarity approach was applied to calculate the similarities between the new hire **(ID: emp_050)** and all other employees.

Findings and Discussion: The top 3 employees most similar to emp_050 are: **emp_042, emp_014 and emp_033.** The recommendation system highlights the most suitable colleagues for emp_050 based on shared attributes: **01.Team Affiliations**: Employees emp_042 and emp_033 belong to **team_03**, promoting team-based collaboration. 02. **Hobbies**: 042 and 014 are likely common hobbies such as **fitness**, **running**, and **cooking** providing opportunities for informal connections and shared activities. 3. **Sports**: While sports preferences vary, overlaps in hobbies and teams strengthen the likelihood of forming strong relationships. The recommendation system supports personalized connections and smoother integration, enhances teamwork, and improves onboarding.

```
Top 3 Recommendations for emp_050:
        id    teams                          hobbies      sports
41  emp_042  team_03       fitness, running, cooking    football
13  emp_014  team_04       fitness, running, cooking    swimming
32  emp_033  team_03  fitness, yoga, cooking, baking  volleyball
```

3.3 Factors that affect employee performance *(3 Points)*

Employee performance is critical for organizational success, and scientific theories provide valuable insights into improving it. The main factors influencing employee performance are outlined below:

Management Support enhances job satisfaction and productivity by fostering trust and feedback *(Pulakos, 2004; Armstrong, 2012)*.

Organizational Climate A positive work environment improves attitudes, adaptability, and proactivity in employees *(Lepak et al., 2006; Erkutlu, 2012)*.

Job Autonomy empowers employees by increasing job satisfaction, innovation, and commitment *(Parker et al., 2006)*.

Training and Development equips employees with new skills to handle challenges effectively and boost performance *(Dermol & Cater, 2013; Hale, 2002)*.

Lastly, **Intrinsic Motivation**, driven by internal satisfaction, is a strong predictor of performance *(Boxall & Purcell, 2011).*

Recommendations for FAU Clinic: To enhance employee performance, FAU Clinic should provide strong management support through regular feedback and recognition. Creating a positive work environment with open communication and teamwork will improve morale. Empowering employees with autonomy and decision-making authority will boost satisfaction and innovation. Implementing regular training programs to upskill employees and aligning roles with their career interests will improve performance. Lastly, fostering intrinsic motivation through rewards and encouraging proactive behaviors will ensure long-term engagement and productivity.

3.4 Employee Performance Analysis *(8 Points)*

A structured approach involving data exploration, preprocessing, correlation analysis, and machine learning model training was undertaken to analyze employee performance for FAU Clinic. All steps are given below:

1. Exploratory Data Analysis (EDA):

Dataset loaded: The dataset clinic_performance.csv was loaded, and an initial review of the structure, column types, and summary statistics was performed.

Handling Missing Values: No missing values were detected. The dataset was clean for further processing. Attached the screenshot.

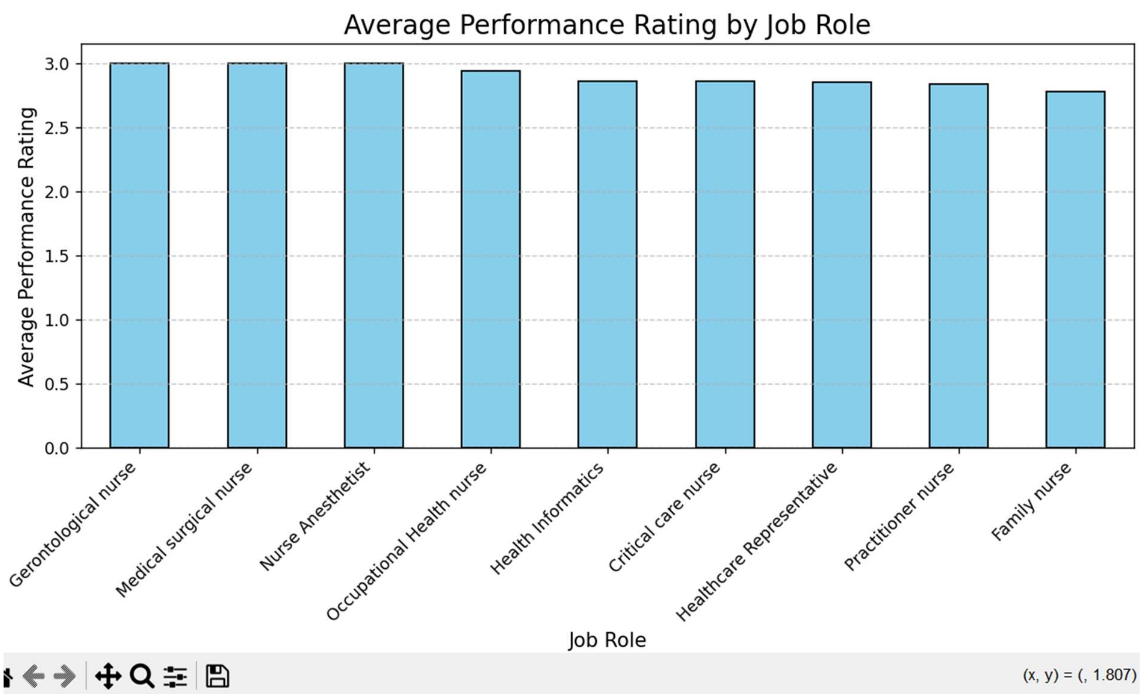
```
# Check for missing values
print("\nMissing Values:")
print(data.isnull().sum())
```

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMI

4  E1001010   60   Male        Single

[5 rows x 19 columns]

Missing Values:
EmpNumber                      0
Age                            0
Gender                         0
MaritalStatus                  0
EmpJobRole                     0
DistanceFromHomeKm             0
EmpEnvironmentSatisfaction     0
EmpHourlyRate                  0
EmpJobInvolvement              0
EmpJobSatisfaction             0
OverTime                       0
EmpLastSalaryHikePercent       0
EmpRelationshipSatisfaction    0
TotalWorkExperienceInYears     0
EmpWorkLifeBalance             0
ExperienceYearsInCurrentRole   0
YearsSinceLastPromotion        0
Attrition                      0
PerformanceRating              0
dtype: int64
```

Dropping Irrelevant Columns: The column **EmpNumber** was dropped as it did not contribute to performance prediction.

Identify Categorical Columns and Convert to Numerical: Columns like Gender, EmpJobRole, and MaritalStatus Identified as Categorical and were converted into numerical values using one-hot encoding (get_dummies). This transformation ensured the data was in the appropriate format for machine learning.

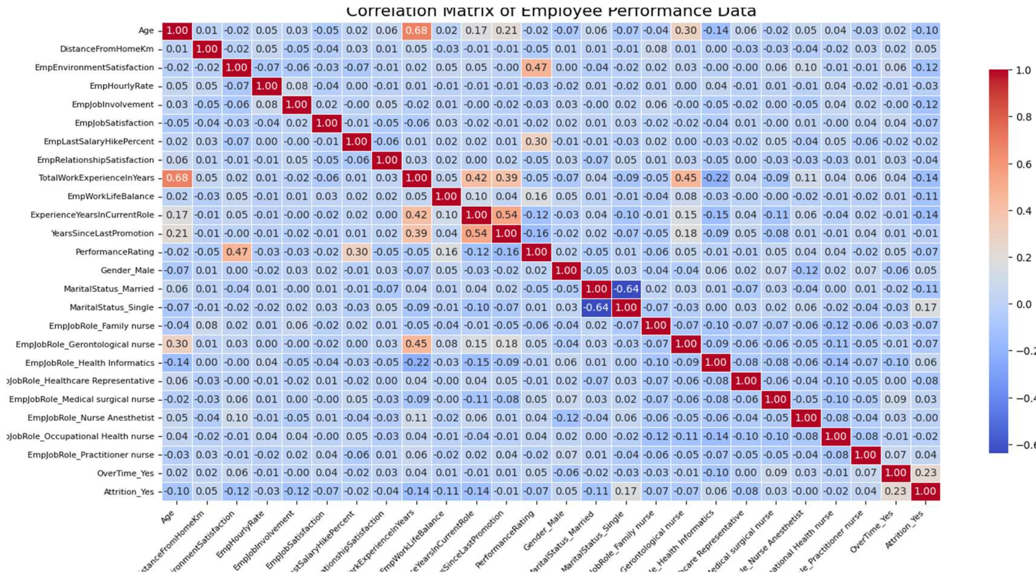
2. Performance Analysis by Job Role: The average performance ratings were grouped by EmpJobRole to analyze performance variations across roles. After doing all of the steps, Here is the performance analysis Job Role wise.




```
Average Performance Rating by Job Role:
EmpJobRole
Gerontological nurse         3.000000
Medical surgical nurse       3.000000
Nurse Anesthetist            3.000000
Occupational Health nurse    2.936170
Health Informatics           2.859375
Critical care nurse          2.855556
Healthcare Representative    2.848485
Practitioner nurse           2.833333
Family nurse                 2.775510
```

It shows Gerontological nurse, Medical surgical nurse and Nurse Anesthetist role has 3 rating that meas Excellent and then Occupational Health nurse role has 2.9 rating and so on.

3: Correlation analysis: Correlation matrix is used to see how all the numerical variables relate to each other. This matrix will help us understand the strength and direction of the relationships between different factors. Here is the correlation matrix:



From the correlation matrix we can see the most important factors(columns) which are responsible for the performance rating. A Highly correlated variables (for example: EmpEnvironmentSatisfaction, EmpLastSalaryHikePercent) were identified as strong performance influencers.

```
# Correlation of features with 'PerformanceRating' and sorting
important_factors = correlation_matrix['PerformanceRating'].sort_values(ascending=False)[1:11]
print("Top 10 Important Factors (Correlation):")
print(important_factors)
```

C:\Windows\System32\cmd.exe - python performance.py

```
[5 rows x 26 columns]
Top 10 Important Factors (Correlation):
EmpEnvironmentSatisfaction            0.466283
EmpLastSalaryHikePercent              0.296237
EmpWorkLifeBalance                    0.163075
EmpJobRole_Gerontological nurse       0.054290
EmpJobRole_Medical surgical nurse     0.052791
OverTime_Yes                          0.049486
EmpJobRole_Occupational Health nurse  0.040250
EmpJobRole_Nurse Anesthetist          0.040204
Gender_Male                           0.017087
MaritalStatus_Single                  0.005872
```

After applying the machine learning algorithm, there is another way to the observe the columns that are the most responsible for the prediction.

```
feature_importance = pd.DataFrame({
'Column_Name': X_train.columns,'Importance Correlation': model.feature_importances_})
feature_importance_sorted = feature_importance.sort_values(by='Importance Correlation', ascending=False)[1:6]
print("\nTop 5 Important Features (Random Forest):")
print(feature_importance_sorted)
```

C:\Windows\System32\cmd.exe

```
Top 5 Important Features (Random Forest):
                   Column_Name  Importance Correlation
6       EmpLastSalaryHikePercent              0.190935
11       YearsSinceLastPromotion              0.115346
3                  EmpHourlyRate              0.064027
10  ExperienceYearsInCurrentRole              0.060285
0                            Age              0.055651
```

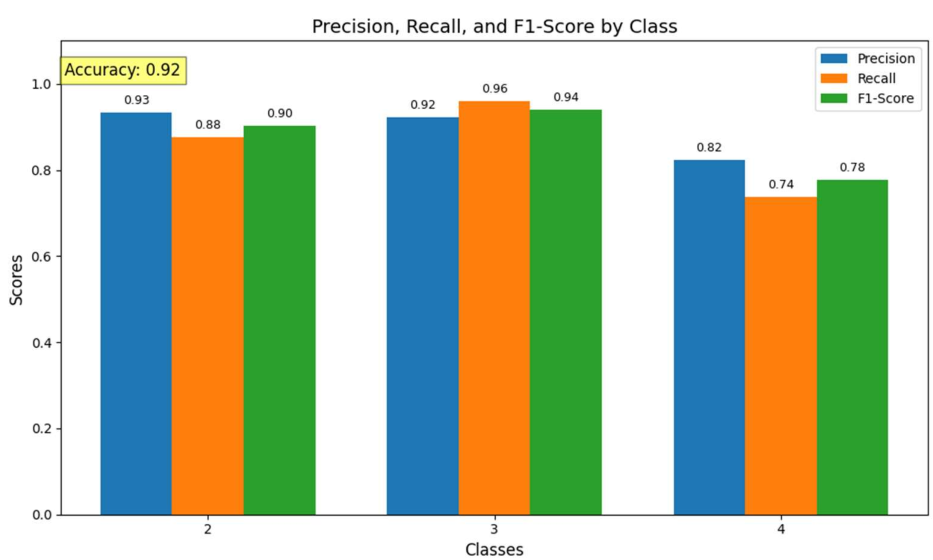
4. Train a Machine learning model:

For the machine leaning model I have choose the Random Forrest Algorithm. With this algorithm I have 92% of the accuracy. PerformanceRating was set as the target variable, and other attributes were used as features.

Class	Precision	Recall	F1-Score
2	0.93	0.88	0.90
3	0.92	0.96	0.94
4	0.82	0.74	0.78

```python
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
report = classification_report(y_test, y_pred, output_dict=True)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           2       0.93      0.88      0.90        48
           3       0.92      0.96      0.94       123
           4       0.82      0.74      0.78        19

    accuracy                           0.92       190
   macro avg       0.89      0.86      0.87       190
weighted avg       0.91      0.92      0.91       190
```



Random Forest is an excellent choice for predicting employee performance at FAU Clinic for several reasons. Firstly, it effectively handles the complexity of employee performance, which is influenced by multiple interacting factors such as job satisfaction, salary hikes, work-life balance, and employee engagement. By combining the outputs of multiple decision trees, Random Forest captures these intricate relationships and provides robust, reliable predictions.

A key advantage of Random Forest is its ability to prevent overfitting. By averaging the outputs of numerous trees, it generalizes well to unseen data, ensuring the model performs accurately on both training and test datasets. This means we can trust its predictions, making it a dependable tool for decision-making. Additionally, it provides valuable insights by identifying the most important factors influencing employee performance. For example, features like environment satisfaction, salary growth, and overtime can be analyzed to determine their impact on performance ratings, offering actionable insights for HR decision-makers.

Moreover, Random Forest is highly scalable and efficient, capable of handling large datasets with numerous features. Its versatility is particularly beneficial for FAU Clinic, as it seamlessly handles both numerical and categorical data while efficiently managing missing values and mitigating the effects of outliers. This ensures that the model works effectively even when dealing with imperfect or incomplete data.

Random Forest's resilience and flexibility are two more important advantages. Because of its ensemble nature, it is more robust to noise in the dataset and can function with a variety of employee data formats, both structured and unstructured. Because of its flexibility, FAU Clinic can use the model to evaluate different aspects of employee performance and make evidence-based choices that will enhance results..

In conclusion, Random Forest’s ability to handle complex data relationships, prevent overfitting, identify key performance drivers, and deliver reliable, accurate predictions makes it an ideal tool for analyzing and predicting employee performance at FAU Clinic. By leveraging this model, FAU Clinic can gain deeper insights, optimize HR strategies, and enhance overall employee satisfaction and productivity.

References

01. *Pulakos, E. D. (2004). Performance Management: A New Approach for Driving Business Results. Wiley.*

02. *Lepak, D. P., Takeuchi, R., & Snape, E. (2006). Employment Systems and Performance: A Multilevel Analysis. Academy of Management Journal, 49(4), 643–660.*

03. *Parker, S. K., Williams, H. M., & Turner, N. (2006). Modeling the antecedents of proactive behavior at work. Journal of Applied Psychology, 91(3), 636–652.*

04. *Dermol, V., & Cater, T. (2013). The influence of training and training transfer factors on organizational learning and performance. Personnel Review, 42(3), 324–338. https://doi.org/10.1108/00483481311320435*

05. *Hale, J. (2002). Performance-Based Evaluation: Tools and Techniques to Measure the Impact of Training. Jossey-Bass.*

06. *Armstrong, M. (2012). Armstrong's Handbook of Human Resource Management Practice. Kogan Page Publishers.*

07. *Chatman, J. A., Caldwell, D. F., O'Reilly, C. A., & Doerr, B. (2014). Parsing organizational culture: How the norm for adaptability influences the relationship between culture consensus and financial performance in high-technology firms. Journal of Organizational Behavior, 35(6), 785–808. https://doi.org/10.1002/job.1928*

08. *Boxall, P., & Purcell, J. (2011). Strategy and Human Resource Management. Palgrave Macmillan.*

09. *Erkutlu, H. (2012). The impact of organizational climate on the relationship between shared leadership and team proactivity. Team Performance Management, 18(1/2), 102–119. https://doi.org/10.1108/13527591211207785*

10. *Morrison, E. W., & Phelps, C. C. (1999). Taking charge at work: Extra-role efforts to initiate workplace change. Academy of Management Journal, 42(4), 403–419.*

11. *Noe, R. A., Hollenbeck, J. R., Gerhart, B., & Wright, P. M. (2006). Human Resource Management: Gaining a Competitive Advantage. McGraw-Hill.*

12. *Delaney, J. T., & Huselid, M. A. (1996). The impact of human resource management practices on perceptions of organizational performance. Academy of Management Journal, 39(4), 949–969.*

13. *Ochmann, J., Michels, L., Zilker, S., Tiefenbeck, V., & Laumer, S. (2020). The influence of algorithm aversion and anthropomorphic agent design on the acceptance of AI-based job recommendations. 17.*

14. *People Analytics - V04 - EN - Personnel Planning Analytics – Notes, People Analytics - V05 - EN - Sourcing and Acquisition Analytics and People Analytics - V06 - EN - Onboarding and Performance Analytics*

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.

I am aware that the use of artificial intelligence is permitted for work at the Schöller Endowed Chair of Information Systems, Digitalization in Business and Society (esp. to improve the text written by myself). However, the intellectual core of the respective work has been developed by me, and the scientific methods that are part of the work have been carried out by myself. Furthermore, I have transparently communicated the aids used in the work.

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.

Md Abdullah Al Mahmud Khosru Erlangen, 2024-12-20