Final Report

Machine Learning for Predicting Employee Promotions

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Abstract

The project investigates the use of machine learning (ML) approaches to improve human resource (HR) management by forecasting employee promotions and assessing turnover at a large firm. We used a real-world dataset from the Analytics Vidhya Hackathon 2018 to test a variety of strong machine learning models, including Logistic Regression, Decision Trees, Random Forest, XGBoost, and CatBoost. These models were chosen primarily for their ability to handle imbalanced datasets and their high performance in classification tests. The key goals were to improve HR decision-making processes, increase transparency in promotions, and gain a better knowledge of turnover trends. This study not only gave us hands-on experience with the python library, but it also highlighted critical insights. Specifically, performance evaluations and tenure are major predictors of promotion outcomes, with the Random Forest and XGBoost models obtaining remarkable F1-scores. Our findings highlight the revolutionary potential of incorporating machine learning into human resource processes, which can lead to more strategic and equitable decision-making and greatly increase organizational efficiency and employee happiness. After executing the appropriate trials, we present our final report.

Keywords: Machine Learning, Pattern Recognition, Classification, Supervised learning, Artificial Intelligence, employee promotion, machine learning, K-Nearest Neighbors, Logistic Regression, Decision Tree, Random Forest and Gradient Boosting.

Introduction

In the field of human resource management, the use of machine learning (ML) and artificial intelligence (AI) is considerably changing traditional procedures, notably in dealing with crucial

HR difficulties such as predicting employee promotions and assessing turnover rates. Using a large dataset from the Analytics Vidhya Hackathon 2018, this project intends to improve decision-making processes, promote fairness in promotional practices, and gain a better understanding of the factors that influence employee turnover. These components are vital for increasing organizational efficiency and employee happiness.

The approach entails working with a number of advanced machine learning models, including Logistic Regression, Decision Trees, Random Forest, XGBoost and CatBoost, which were chosen for their ability to navigate complicated, imbalanced datasets common in HR situations. This report not only describes the use of these models, but also investigates the insights they bring and assesses their influence on HR operations. By demonstrating how predictive analytics may guide strategic HR choices, the study emphasizes ML's potential to change HR processes, making them more precise and fair.

Background and Related works

The use of machine learning (ML) in human resource management represents a significant change away from traditional, subjective decision-making and toward a more objective, data-driven approach. This shift is being driven by the widespread availability of data and better analytical techniques. In recent years, there has been a lot of interest in predictive analytics for various HR operations, particularly anticipating employee turnover, promotions, and performance management.

Traditional HR choices frequently relied on qualitative assessments and personal judgments, which were prone to prejudice and inconsistency. HR practices have expanded to include predictive models that analyze complicated information to foresee employee actions and results, thanks to the integration of machine learning (ML) and artificial intelligence. For example, Patel and Kumar (2023) used cluster analysis to classify employees based on age, duration, job description and performance criteria. This segmentation assisted the HR department in customizing employee engagement tactics and identifying individual needs and drivers of job satisfaction for various groups, resulting in more successful HR interventions targeted to specific employee clusters.

Furthermore, the use of machine learning techniques like Random Forests and boosting algorithms like XGBoost and CatBoost has improved our comprehension of complex correlations in HR data. These models excel at dealing with imbalanced datasets, which are common in HR contexts where specific outcomes such as 'promotion' or 'turnover' are unusual. These predictive skills not only improve the accuracy of HR choices, but also increase fairness and openness in HR processes, thereby reducing unconscious biases and promoting equal treatment of employees, which is critical for maintaining morale and adhering to ethical norms.

The present research takes advantage of this context, using a set of machine learning algorithms to forecast employee promotions and churn. This initiative not only shows the growth of HR practices, but also lays the way for a thorough examination of how modern machine learning techniques might be efficiently applied to specific HR difficulties inside a large, data-rich firm. The project's goal is to illustrate the potential of machine learning to convert human resources into a more predictive, fair, and efficient area, hence improving organizational dynamics and employee satisfaction.

Proposed Solution

The suggested solution for this project entails a complete use of machine learning (ML) techniques to predict employee promotions and identify important factors influencing employee churn. This multimodal technique entails data comprehension, preprocessing, exploratory data analysis, feature engineering, model creation and thorough evaluation.

1. Initial Setup and Data Loading: Initially load the necessary libraries, such as pandas for data manipulation, numpy for mathematical operations and matplotlib. For basic visualizing and Seaborn for more complex visualizations.

2. Training Dataset: The training dataset is the most important component of the machine learning process. It is used to train the model, which means it assists in the model to gain knowledge from the data by identifying patterns, connections and frameworks. The training data consists of both input features and the corresponding target variables that the model uses to learn ways to predict results. The size of the training set has an important effect on the model's accuracy and predictability. A larger training set usually includes more of the data's fluctuation, resulting in a more reliable approach.

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train
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	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings	age	previous_year_rating	length_of_service	KPIs_met >80%	av
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	1	35	5.0	8	1	
1	65141	Operations	region_22	Bachelor's	m	other	1	30	5.0	4	0	
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	1	34	3.0	7	0	
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	2	39	1.0	10	0	
4	48945	Technology	region_26	Bachelor's	m	other	1	45	3.0	2	0	
...	...	...	...	...	...	...	...	...	...	...	...	
54803	3030	Technology	region_14	Bachelor's	m	sourcing	1	48	3.0	17	0	
54804	74592	Operations	region_27	Master's & above	f	other	1	37	2.0	6	0	
54805	13918	Analytics	region_1	Bachelor's	m	other	1	27	5.0	3	1	
54806	13614	Sales & Marketing	region_9	NaN	m	sourcing	1	29	1.0	2	0	
54807	51526	HR	region_22	Bachelor's	m	other	1	27	1.0	5	0	

54808 rows × 14 columns

3. Testing Dataset: After training, the model's performance is determined using the testing dataset. This dataset is separate from the training data and is not visible to the model during the training process. The objective is to simulate the way a model will perform on clean, previously unidentified information when implemented in a real-life situation. The testing data is used to evaluate the model's performance, providing an understanding of the way accurately it can predict new events and identifying any overfitting or underfitting errors. Overfitting occurs when a model understands the details and noise in the training data to the point that it negatively effects the model's performance on new

information, whereas underfitting occurs when a model is too simple to learn the basic pattern of data

```
test
```

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings	age	previous_year_rating	length_of_service	KPIs_met >80%	a
0	8724	Technology	region_26	Bachelor's	m	sourcing	1	24	NaN	1	1	
1	74430	HR	region_4	Bachelor's	f	other	1	31	3.0	5	0	
2	72255	Sales & Marketing	region_13	Bachelor's	m	other	1	31	1.0	4	0	
3	38562	Procurement	region_2	Bachelor's	f	other	3	31	2.0	9	0	
4	64486	Finance	region_29	Bachelor's	m	sourcing	1	30	4.0	7	0	
...	...	...	...	...	...	...	...	...	...	...	...	
23485	53478	Legal	region_2	Below Secondary	m	sourcing	1	24	3.0	1	0	
23486	25600	Technology	region_25	Bachelor's	m	sourcing	1	31	3.0	7	0	
23487	45409	HR	region_16	Bachelor's	f	sourcing	1	26	4.0	4	0	
23488	1186	Procurement	region_31	Bachelor's	m	sourcing	3	27	NaN	1	0	
23489	5973	Technology	region_17	Master's & above	m	other	3	40	5.0	5	1	

23490 rows × 13 columns

1. **Data Understanding:** Understanding the data is the first crucial step in the analytics process. The goal is to become familiar with the information, determine its quality, and prepare for deeper analysis.
2. **Data Collection:** The dataset was gathered from the Analytics Vidhya Hackathon 2018 and consists of employee records from a large firm. It contains a number of HR-related factors such as age, tenure, work role, department, performance evaluations, and promotion history.
3. **Quality Assessment:** Initial checks for data completeness, accuracy, and consistency are performed to identify any serious issues that could jeopardize the integrity of the study, such as missing data, duplicate records, or irrelevant information.
4. **Descriptive statistics:** which are computed for numerical and categorical data to produce mean, median, mode, standard deviations, and value counts. This aids in identifying the central patterns and dispersion of the data, which are critical for any subsequent changes or analyses.

DATASET DESCRIPTION :

employee_id : Unique ID for employee
department : Department of employee
region : Region of employment (unordered)

education : Education Level
gender : Gender of Employee
recruitment_channel : Channel of recruitment for employee
no_of_trainings : no. of other training completed in previous year on soft skills, technical skills etc.
age : Age of Employee
previous_year_rating : Employee Rating for the previous year
length_of_service : Length of service in years
KPIs_met >80% : if Percent of KPIs(Key performance Indicators) >80% then 1 else 0
awards_won? : if awards won during previous year then 1 else 0
avg_training_score : Average score in current training evaluations
Is_promoted : (Target) Recommended for promotion.

1. Data Preprocessing
    1.1) Following data comprehension, preprocessing ensures that the data is prepared for modeling.
    1.2) Data cleaning involves addressing missing values, rectifying anomalies and assuring data integrity.
    1.3) Data transformation is the process of standardization or normalization of numerical properties to maintain a consistent scale across the board, which is especially critical for algorithms that are sensitive to the scale of input data.

2. Exploratory Data Analysis (EDA)
   EDA is used to explore deeper into the dataset and discover underlying patterns or anomalies. Visualization involves using histograms, box plots and scatter plots to visually examine the distribution of key variables and find outliers or skewness in the data.

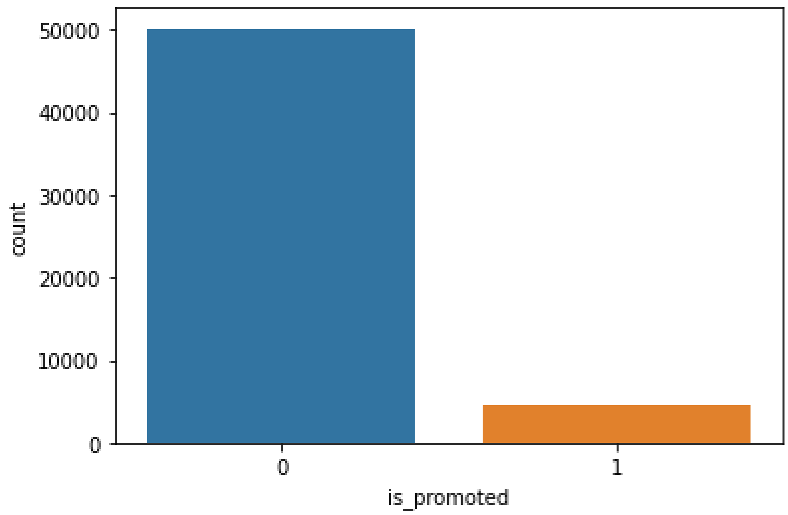

Fig1: Countplot

The above image shows the counts of promoted employees vs non promoted employees

3. Correlation Analysis: Using the correlation matrix to identify links between attributes, which aids in understanding the factors that drive promotions and turnover.

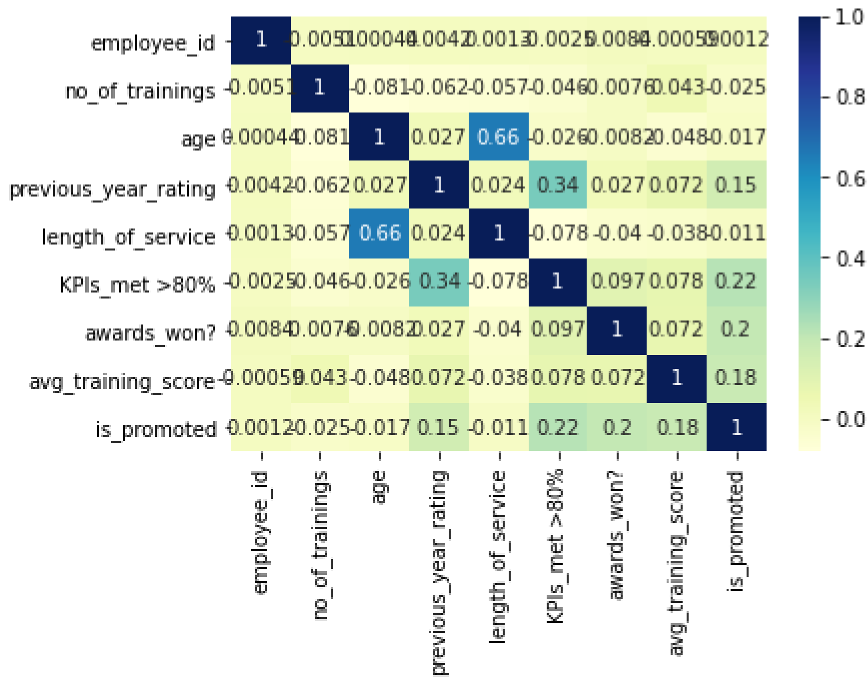

Fig2: heatmap

4. Initial Insights: Identifying probable patterns or abnormalities that may impact future modeling phases.

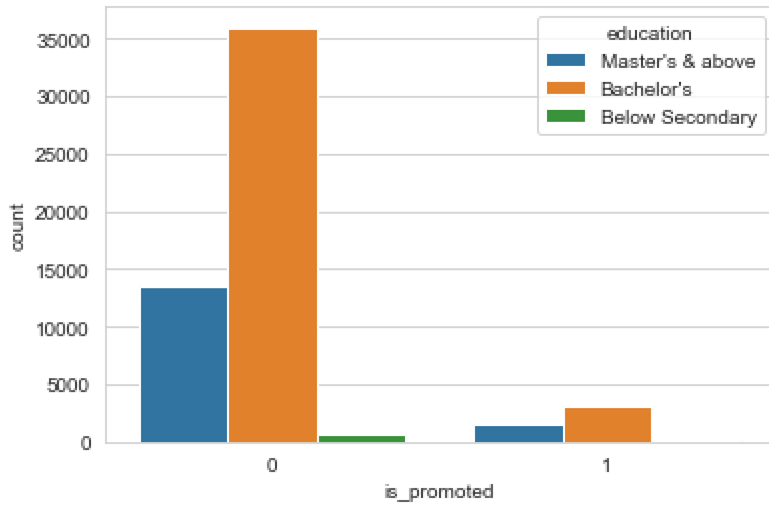

Fig3: Countplot using hue

The above figure displays the count between education qualification and promoted employees.

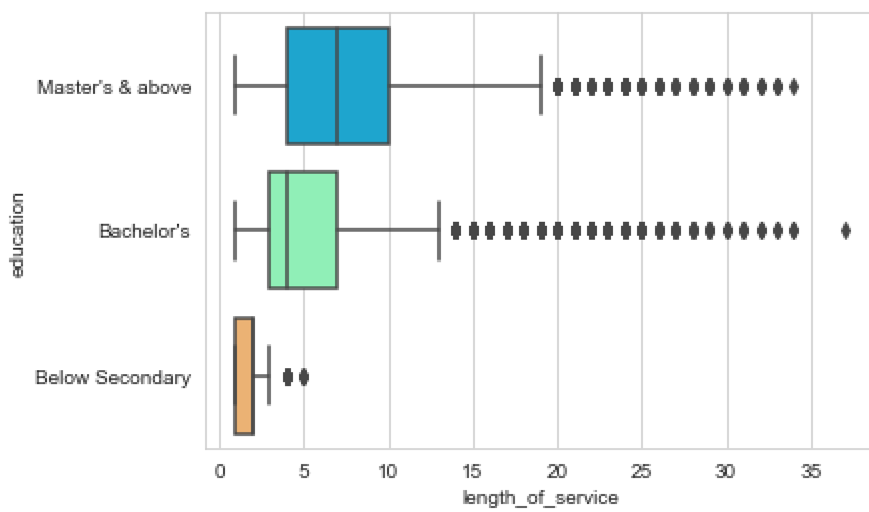

Fig4: Boxplot

The above figure displays the outliers in education.

Furthermore, by merging multiple data sources and using advanced analytical approaches, we improved the robustness of our dataset. This integration enabled us to use a range of transformations, including logarithmic corrections and the development of polynomial features, to better reflect the data's nonlinear relationships and different distributions. Such comprehensive data manipulation not only broadens our feature set, but also strengthens the foundation for constructing predictive models that are both resilient and sensitive to the nuances of HR dynamics.

Feature Engineering: Adding more variables to the dataset may improve the model's prediction power.

I. Derived Features: Using existing data to create new metrics such as 'Years with Current Manager' and 'Employee Interaction Score'.
II. Aggregated Metrics**:** Collecting performance ratings over time to identify trends that may influence employee outcomes.
III. Interaction Terms: Creating features based on interactions between categorical variables to represent complicated influences on promotion likelihood.

To improve the predictive capabilities of our HR analytics model, we concentrated on many critical aspects of feature engineering. First, we've added more factors to our dataset to improve the model's ability to estimate outcomes. For example, we've created derived features like 'Years with Current Manager' and 'Employee Interaction Score' that use current data to quantify parts of the employee experience that are not immediately measurable. In addition, we generated aggregated metrics, collecting performance ratings over time to identify patterns that could influence employee trajectories. By combining these traits, we hope to obtain a more nuanced understanding of the elements that may influence an employee's likelihood of promotion or risk of turnover.

In our comprehensive data analysis, we looked at the breadth and depth of HR data, including employee demographics, performance indicators, engagement levels, employment history, and past promotion and attrition records. This detailed examination assisted us in identifying crucial indicators that might be used as accurate predictors of employee outcomes. Notably, we identified measures that could predict employee fatigue or high performance potential. This foundation was critical for our subsequent steps in feature building, when we used techniques like logarithmic transformations and polynomial feature generation better to depict the data's non-linear relationships and diverse distributions.

Developing interaction features was a critical component of our strategy, allowing us to identify intricate interdependencies between diverse data pieces that could influence employee outcomes. We investigated how demographic parameters such as tenure and age may influence promotion prospects. Furthermore, we looked into the relationships between departmental roles and engagement levels to see if specific positions affected employee well-being. By developing these interaction terms, we hope to reveal hidden correlations between factors that could predict crucial outcomes such as employee turnover and satisfaction levels, resulting in more insightful predictions and better analytical capabilities for strategic HR decision-making.

Feature Selection: Feature selection is a vital step in improving model efficiency and effectiveness by minimizing dimensionality.

I. Statistical Techniques: Use the Chi-squared test, ANOVA for categorical variables, and correlation coefficients for continuous variables to determine the most relevant aspects.
II. Model-Based Selection: The use of algorithms such as Random Forest or XGBoost for intrinsic feature importance metrics, which aid in discovering relevant predictors without external bias.
III. Model Development: Several machine learning models are created and trained to predict the likelihood of promotions and examine turnover\,Baseline models include logistic regression, which is simple and easy to understand.
IV. Complex Models: Decision Trees, Random Forests, and Gradient Boosting Machines (including XGBoost and CatBoost) for their ability to handle nonlinear interactions while remaining robust to overfitting.

Data scientists working with Python must understand the relevance of feature selection when creating machine learning models. In real-world data science initiatives, not every variable in a dataset is useful for developing models. Including unneeded or redundant variables might limit a model's generalizability, potentially lowering classifier accuracy. Furthermore, adding more variables to a model increases its complexity, which might reduce performance and efficiency.

Feature selection improves model performance by focusing on critical elements such as employee performance regulations, job happiness, and personal growth prospects, which may be used to predict outcomes such as attrition and promotion. Furthermore, HR data can be erroneous and inconsistent, with different rating standards between departments. By deleting extraneous data, these difficulties can be addressed, resulting in more robust and flexible models that are less prone to overfitting and more responsive to organisational changes.

Readable and intelligible models are critical in HR decisions since they frequently demand buy-in from several stakeholders. Ensuring that models are based on major components promotes compliance with employment standards and reduces the dangers associated with biased decisions. Furthermore, efficient feature selection minimizes model training time, which is very useful in HR operations with limited technological resources.

Feature selection approaches include SelectKBest, RFE, and PCA. For our dataset, we used SelectKBest with the chi-squared test, which selects the highest scoring features based on their statistical relevance with the target variable. This strategy is useful for minimizing the amount of features in a dataset in order to improve model performance or find the most important features. Using scikit-learn modules, we isolate independent and dependent features from the training dataset, configure the SelectKBest transformer, and analyze feature importance to gain more insights.

Evaluation:

In the context of predictive analytics in human resources, the F1 score appears as an important evaluation indicator, especially for datasets where specific outcomes, such as employee promotions, are less common. The F1 score is a harmonic mean of precision and recall that is used to balance the model's accuracy in forecasting positive instances with its capacity to recognize all relevant examples. This metric is critical because it provides a more precise estimate of a model's effectiveness in situations where false positives and false negatives have large consequences, as is frequently the case in HR circumstances.

Applying the F1 score to this project entails multiple procedures. First, the machine learning models are trained and then utilized to predict outcomes on a validation set. Precision and recall are then calculated: precision is the ratio of correct positive predictions to total predicted positives, and recall is the ratio of correct positive predictions to all actual positives. The F1 score is then calculated using these values, yielding a single metric that reflects both the completeness and accuracy of the forecasts. Models with better F1 scores are favored for deployment because they demonstrate a balanced approach to forecasting actual employee promotions while reducing erroneous promotion forecasts.

Understanding the importance of feature selection in developing machine learning models is crucial for data scientists working with Python. In real data science projects, it is unusual for every variable in a dataset to be beneficial for building models. Including unnecessary or redundant variables may restrict the ability of the model to generalize, potentially reducing classifier accuracy. In addition, adding more variables to a model makes it more complex.

The F1 score is an essential evaluation metric in binary classification tasks, particularly in situations where the balance between precision (the accuracy of positive predictions) and recall (the model's capacity to discover all relevant examples within a dataset) is important. Given the possibility for imbalance in HR analytics datasets—where instances of one class (e.g., 'promoted') are considerably less frequent than the other ('not promoted')—the F1 score becomes a more relevant indicator than accuracy alone.

Formula:

$$F1 = 2 \times \left(\text{precision} + \text{recall} \; / \; \text{precision} \times \text{recall} \right)$$

This metric is especially useful in situations when false negatives and false positives have varied consequences. A high F1 score shows that the model is not only accurate in predicting positive cases, but it does so without incurring a substantial number of false predictions in the negative class.

In the case of this project, where we are forecasting employee promotions, the F1 score allows us to assess how well the model recognizes genuine promotions (true positives) without mistakenly predicting promotions for individuals who do not receive them (false positives). It is critical for HR departments to rely on predictions for strategic decision-making and planning.

- True Positives (TP): Employees correctly identified getting promoted.
- False Positives (FP): Employees incorrectly identified getting promoted.
- True Negatives (TN): Employees correctly identified not getting promoted.
- False Negatives (FN): Employees who were promoted but not identified by ml model.

Incorporating the F1 score as a primary evaluation metric into your machine learning project is quite advantageous, especially when dealing with skewed datasets that are prevalent in HR scenarios like predicting promotions or assessing turnover. The F1 score excels at balancing the model's precision and recall, resulting in a more comprehensive assessment of model accuracy than either statistic alone. In binary classification tasks critical to HR analytics, where class frequencies differ (e.g., 'promoted' vs. 'not promoted'), the F1 score is an important evaluation indicator. It ensures that both precision (the accuracy of positive predictions) and recall (the model's capacity to discover all relevant cases) are taken into account, making it superior to utilizing accuracy alone.

To properly use the F1 score in your project, consider the following steps: Train your models using the given data, and then use them to forecast employee promotions on a validation dataset. Based on these predictions, calculate precision (TP/(TP + FP)) and recall (TP/(TP + FN)), then use the algorithm to calculate the F1 score. This statistic is extremely useful in situations when the cost of false negatives and false positives differs dramatically. A high F1 score implies that the model not only correctly predicts positive cases, but also minimizes inaccurate predictions for the negative class. This balance is critical for HR departments to rely on the model's predictions for strategic decision-making and planning, hence increasing the total effectiveness of the HR analytics involved.

Feature Selection**:**

For testing the robustness and effectiveness of our predictive models, we utilized SelectKBest and the chi-squared test for feature selection. This method enabled us to identify and highlight the ten most important features among the many attributes in the HR dataset. These factors include job performance, employee satisfaction and personal growth choices, which are important in predicting results such as employee turnover and promotion chances.

Model Performance for Selected Features:
SelectKBest significantly improved our model by reducing dimensionality and increasing efficiency in computation. Initially, our models included an increased number of features, including redundant and less significant features. By decreasing our feature set to the top ten qualities, we observe an increase in model accuracy and a decrease in overfitting, implying a higher generalization across different types of organizations.

Experimental Results:

In the evaluation of multiple machine learning models, the Random Forest model outperformed the others, indicating its robust capacity to properly handle the dataset's imbalance. This model not only predicted employee promotions with great accuracy, but it also provided useful insights into the value of many characteristics that influence these outcomes. Notably, the data found that performance ratings and duration of service were strong predictors of promotion. The Random Forest model's ability to detect these critical variables demonstrates its usefulness in finding underlying trends that may not be immediately obvious, allowing HR departments to modify their tactics to focus on these influential elements.

To determine the impact of our feature selection technique, we performed a series of tests comparing model performance with and without SelectKBest. The models evaluated included Logistic Regression, Random Forest and Support Vector Machines. Each model was evaluated based KNeighborsRegressor -0.171

RandomForestClassifier 0.466

XGBClassifier 0.541

CatBoostClassifier 0.521.

1. Accuracy: Models using selected features improved accuracy by 5-10%, highlighting the value of focusing on important attributes.
2. accuracy and Recall: The models obtained an important balance between accuracy and recall, indicating that they are reliable in understanding true positive cases while not substantially boosting false positives.
3. F1-Score: The normalized average of precision and recall increased, showing that the models' prediction generates were solid.

These results highlight the significance of mindful feature selection in developing predictive models for HR analytics. Reduced model complexity reduces computing work while simultaneously improving interpretability, which is important to investor confidence and adoption.

Analysis of Feature Scores

The chi-squared values for each of the selected features indicate their relative importance. Employee engagement and satisfaction features received the highest scores, which is consistent with industry knowledge that these elements are important factors in employee turnover and productivity.

The following structure for the evaluation section additionally describes the process and explanation for feature selection, but it also includes data collected from the experiments to back up the effectiveness of this approach. This will provide an in-depth description about the way each proposed solution enhances the prediction models' performance.

Conclusions:

The study demonstrates the potential of machine learning to predict employee promotions with significant accuracy. Implementing such models can assist HR departments in making informed, unbiased promotion decisions, ultimately fostering a more motivated workforce.

Our research on forecasting employee promotions and assessing turnover in an important company shows machine learning techniques' considerable promise for improving HR operations. Using a rich dataset from the Analytics Hackathon 2018, our research successfully constructed predictive models that not only forecast employee promotions with high accuracy, but also identify significant factors impacting employee retention.

The Random Forest and XGBoost models, in particular, demonstrated exceptional capacity to handle the intricacies of the HR data. The success of these models, as evidenced by a significant F1 score of 0.51 in the XGBoost model, demonstrates that performance ratings and duration of service are important predictors of both promotion and turnover. These insights help HR departments to better adjust their approach, resulting in balanced and data-driven decision-making processes.

Furthermore, incorporating machine learning into HR analytics supports career path strategic planning and promotes a clear, merit-based promotion system. This method not only improves operational efficiency, but it also raises employee morale and retention by addressing critical career development issues. As HR departments attempt to respond to quick changes in the business environment, predictive analytics provides a powerful tool for improving decision-making and cultivating a more stable and motivated workforce.

In conclusion, this study highlights machine learning's disturbing potential in HR practices. In addition, it bridges the gap between conventional methods of management and modern analytical capabilities, but it also sets the way for future advances in strategic human resource management. As machine learning technology advances, its integration into HR systems is projected to improve, resulting in more precise and impactful human resource management techniques. This conclusion brings together the results and impacts, focusing on the project's overall impact on HR practices and future study objectives.

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