

University of Siegen Faculty III: School of Economic

Master Program in Economic Policy

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Seminar Project

Which employee will leave the company next?

Seminar: Solving Big Data Problems

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Siegen



Content

- Business problem
- Variables Description
- 3. Data investigation and analysis
- 4. Emprical Framework
- 5. Linear regression
- 6. Other ML algorithms and their Hyper-parameter tuning: optimal model selection
- 7. Conclusions



Business problem

- Corporation X with 14999 data on employees (anonymous data)
- Why are the best and the most experienced employees leaving prematurely?
- TASK: How to predict that an employee leaves the company before it happens?
- SOLUTION: Collect the data on employees and apply ML algorithm



- In ML framework this is Binary Classification task: 2 groups of employees
 - → Leave vs. Don't Leave



Variables Description

Variable Name	Description	Type of Variable
satisfaction_level	Satisfaction	Numeric, continuous
last_evaluation	Last review	Numeric, continuous
number_project	Number of projects done by employees	Numeric, discreate
average_montly_hours	Average working hours per month	Numeric, discreate
time_spend_company	Years from entry time	Numeric, discreate
work_accident	Whether there is a work accident	Binary -> Dummy
promotion_last_5years	Have you been promoted in the last five years	Binary -> Dummy
department	Staff department	Categorical -> Dummy
salary	Salary level	Categorical -> Dummy
left	Resign	Categorical -> Dummy



There are 14999 observations in 10 columns with no missing values

```
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
                          Non-Null Count Dtype
    Column
   satisfaction_level 14999 non-null float64
last_evaluation 14999 non-null float64
                      14999 non-null int64
    number project
    average monthly hours 14999 non-null int64
    time spend company 14999 non-null int64
    Work_accident 14999 non-null int64
                          14999 non-null int64
    left
    promotion last 5years 14999 non-null int64
    department 14999 non-null object
    salarv
                14999 non-null object
dtypes: float64(2), int64(6), object(2)
```



Descrip	otive Statistics			
Variables	mean	std	min	max
satisfaction_level	0.61	0.25	0.09	1
last_evaluation	0.72	0.17	0.36	1
number_project	3.80	1.23	2	7
average_monthly_hours	201.05	49.94	96	310
time_spend_company	3.50	1.46	2	10
Work_accident	0.14	0.35	0	1
left	0.24	0.43	0	1
promotion_last_5years	0.02	0.14	0	1

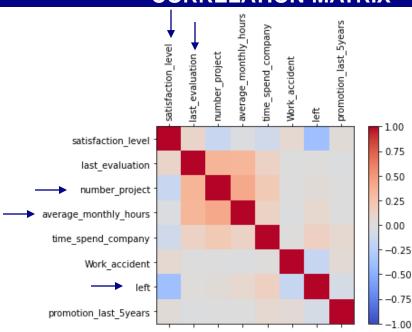
⁺ Investigation of distribution plots and histograms*

Key insights

- Despite the fact that 55% of employees have level satisfaction (> 0.6), 13% have the level of satisfaction (<0.3)
- Working extra hours was a norm in the company: on average employees do ~ 16 extra hours per month (if norm = 184 hours = 23 full days per month). 59% of all employees work more than 184 hours per month, 31% more than 201 hours per month. It is unclear if those extra hours are paid
- On average an employee is assigned to 3-4 projects, but at least to 2
- Level of promotion is extremely low: 2%
- After 6 years the probability that an employee leaves the company is low
- > 49% get low salary and 43% medium salary. Only 8% get high salary. However, thresholds of the salary are not given.
- > 41% of all employees work in Technical, Support and IT departments, 28% in sales







Key insights:

- Strong negative correlation of satisfaction level, number of projects and decision to leave. → The more employees were working and the lower was the satisfaction level, more often they decided to leave the company
- Positive correlation of high last evaluation and number of projects and average monthly hours → The more employees were working, the higher they were evaluated



Empirical framework

- Predicted variable: Y = df.left → decision to leave the company, either 1 or 0
- Predictable variables: X = df.drop(['left'], axis = 1) → all other variables
- Split of the data on test and train: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.30, stratify=y, random_state=101) → 10499 for Train set and 4500 for Test set
- Standardize the variables
- Initiate the model → LinearRegression(), LogisticRegression(), DecisionTreeClassifier(), RandomForestClassifier(), XGBClassifier()
- Fit the model → Make predictions → Calculate Accuracy, Precision, Recall, and
 F1 and AUC scores → Display Confusion Matrix
- Perform Hyper Parameter Tuning: GridSearchCV and RandomizedSearchCV
- Choose the best model:
 - Situation: The company wants to find a balance between Precision and Recall, resources are limited → best AUC score



Why linear regression is not suitable?

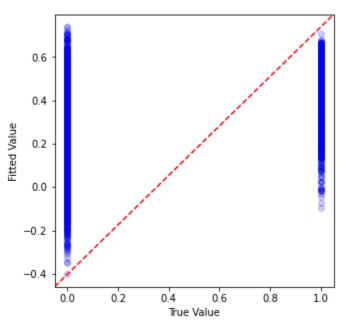
- Problem #1: Predicted value is continuous, not probabilistic
- Problem #2: Sensitive to imbalance data:
 - 0 11428
 - **1** 3571
- Fit the model to the train dataset
- Predict Y on the test dataset
- Look at the key metrics:

$$\rightarrow R^2 = 0.205$$
, MSE = 0.1439

► → Linear Regression is not the best fit for the binary classification task

True vs. Fitted Values

Linear Regression on Decision to Leave



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Models Comparison

Logistic Regression

Decision Tree

Models' Scores: Selection Criteria - AUC Score

Random Forest

XGBoost

Accuracy: 0.792
Precision: 0.604
Recall: 0.366
F1 score: 0.456

Default Model

Tuned model

AUC score: 0.822

Accuracy: 0.802

Precision: 0.729

• Recall : 0.264

• F1 score : 0.388

AUC score: 0.764

Accuracy: 0.969

Precision: 0.918

Recall: 0.957
F1 score: 0.937

AUC score: 0.965

Accuracy: 0.975

Precision: 0.965

• Recall: 0.928

• F1 score: 0.946

AUC score: 0.974

Accuracy: 0.985

Precision: 0.980

Recall : 0.957

F1 score: 0.968

AUC score: 0.991

Accuracy: 0.983

Precision: 0.977

• Recall : 0.952

F1 score : 0.965

AUC score: 0.990

Accuracy: 0.981

Precision: 0.970

Recall : 0.949

F1 score: 0.959

AUC score: 0.989

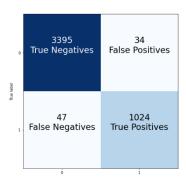
Accuracy: 0.983

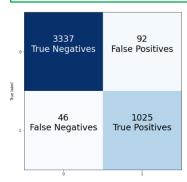
Precision: 0.972

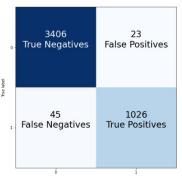
Recall : 0.955

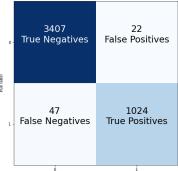
F1 score: 0.963

AUC score: 0.991







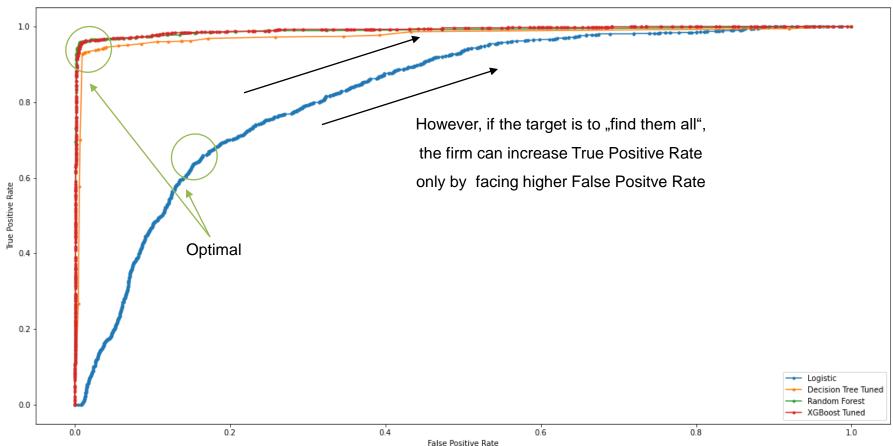


→ Random Forest and XGBoost produce the highest AUC score, however, other parameters in Random Forest are slightly higher



Models Comparison

AUC Curves for the Models with the best parameters



Best models: Random Forest, XGBoost hyper-parameter tuned



Conclusions

- Applying ML the company can identify up to 96% of all employees who are most likely leave the company and undertake particular measures to avoid this scenario
- In the context of this company the algorithms with the highest performance are Random Forest and XGBoost
- If the company wants to be able to identify all employees who are going to leave the company, it has face high False Positive Rate
- The company can also undertake preventive measures and change its policies in order to reduce staff turnover such as, e.g. ensuring healthy work-life-balance and avoiding to evaluate employees with higher extra hours higher than others
- If any major changes in human resources policy of the company will take place, it is recommended to evaluate model once again



Thank you!

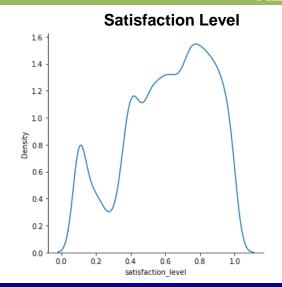


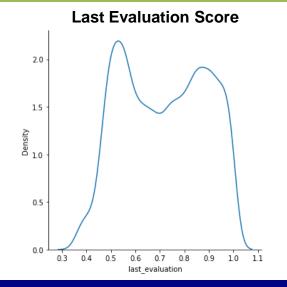
Back- up slides

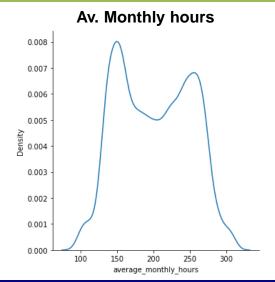


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KEY VARIABLES VIZUALIZATION



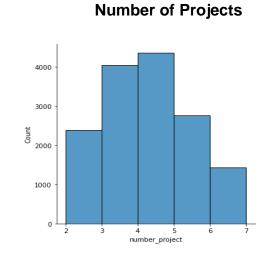


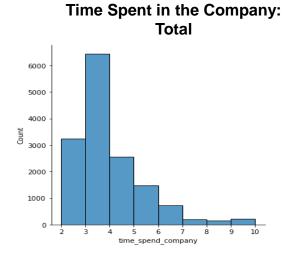


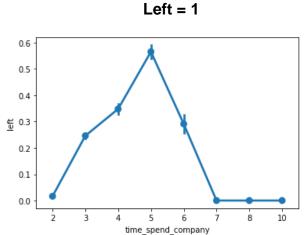


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KEY VARIABLES VIZUALIZATION







Time Spent in the Company:



KEY VARIABLES VIZUALIZATION

Number of Employees by Salary Level

9000 8000 7316 7000 6446 6000 5000 4000 3000 2000 1237 1000 high low medium salary level

Number of Employees by Department

sales	4140
technical	2728
support	2229
IT	1227
product_mng	902
marketing	858
RandD	787
accounting	767
hr	739
management	638