



Turnover prediction (POC)

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Agenda

1. Introduction

Why we're doing that?

2. Data analysis

- Data preprocessing
- Features engineering

3. Modeling

- Algorithms
- Evaluation metrics

4. Results

- Model testing
- 5. Improvements
 - Next steps





Introduction

Retaining your talent is one of the most essential aspect of building a thriving business. The key element to avoid turning is to **spot the "red flags" at the right time**. Companies struggle with timing of taking proper actions to prevent employee turnover. And that's why we're exploring possibilities in that area. The main goal of turnover prediction analysis is to identify problem areas and **take preventive steps to retain your employees**.





Data analysis

Data source:

SR-Bank

Data filtering:

- Keeping only regular "full-time" employees
- Keeping only "Ordinært" form of employment
- Testing on data that were not seen by the model during the training phase

Data cleaning:

Drop not relevant information from data

• Data transformation:

 All columns in data needs to be in numeric format, because computers understand only numbers, right ? :)





Feature engineering

New fields derived from input data

- Employee groups based on salary and age
- Movement score how many position codes has employee had
- Average salary on position, in position group, in age group etc...
- Average employee age on position, average job duration etc..

Dropped fields

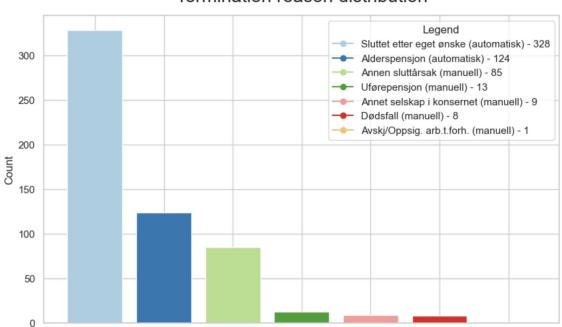
- Unique columns (addresses, IDs)
- Constant columns
- Datetime columns





Why do employees leave?

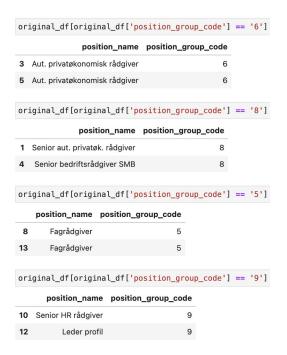
Termination reason distribution



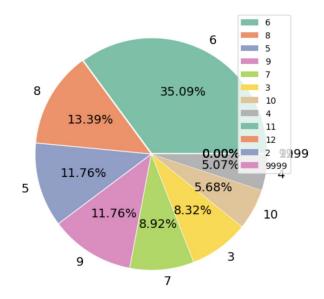




Which ones leave the most?



Most fluctuated position groups







ML problem definition

Classification

- Will employee quit in next 6 months?
 - output: decision (yes/no)
- What is a confidence level of that prediction?
- Goal is to classify case as:
 - Positive employee will quit in next 6 months
 - Negative employee will stay in next 6 months





Classification model

Goal:

Predict if employee will quit in next 6 months

Algorithms that we used:

- Decision tree
- Random forest
- XGBoost

Evaluation metrics that we used:

- Confusion matrix Performance measurement for classification model
- Balanced accuracy How well a classifier identifies or excludes leaving employees
- **Precision** probability of employee to leave in case of positive case classification
- Recall probability of leaving employee detection
- **F1** harmonic mean of precision and recall





What have we tested on?

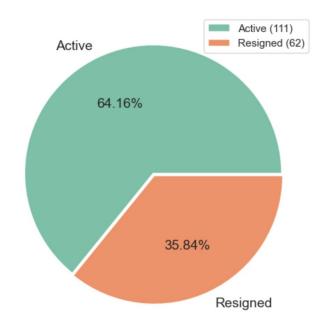
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	0 6	62	9	4	11560	6	11032	2	529	527182.0	5	571260	47	1
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What have we tested on?

173 separated cases that were not used during a training phase of the model

Employees distribution - Test data







Classification - Decision tree

Confusion Matrix (Decision tree - testing)

True Negative ("correct rejection") 105 60.69%

0

False Positive ("false alarm")

6 3.47%

False Negative ("miss") 12 6.94%

True Positive ("hit")

28.90%

- 60

- 40

- 20

Classification Score Table (Decision tree - testing)

Metric	Score
Balanced accuracy	0.876
Precision	0.893
Recall	0.806
F1	0.847



0

Classification - Random forest

- 100

- 60

- 40

- 20

Confusion Matrix (Random forest - testing)

True Negative False Positive ("correct rejection") ("false alarm") 0 110 63.58% 0.58% False Negative True Positive ("miss") ("hit") 14 48 8.09% 27.75%

Classification Score Table (Random forest - testing)

Metric	Score
Balanced accuracy	0.883
Precision	0.98
Recall	0.774
F1	0.865



0

Classification - XGBoost

- 60

- 40

- 20

Confusion Matrix (XGboost - testing)

True Negative False Positive ("correct rejection") ("false alarm") 110 63.58% 0.58% False Negative True Positive ("miss") ("hit") 10 52 5.78% 30.06%

Classification Score Table (XGboost - testing)

Metric	Score
Balanced accuracy	0.915
Precision	0.981
Recall	0.839
F1	0.904



0

What to do next?

• Improvements:

- Data from external sources How many similar open positions are available at the moment in specific region?
- More customer data larger dataset = more information to train model on (should result in better model)

Needs to be clarified:

- What exactly we want to predict?
 - Define unambiguous requirements on the solution
 - By being clear on this we'll be able to decide how to proceed and what techniques to use
- What is acceptable accuracy of model?







Respect Reliability Innovation Competence Team spirit

