



# Introduction to HR analytics

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#### What is HR analytics?

- Also known as People analytics
- Is a data-driven approach to managing people at work.



#### Problems addressed by HR analytics

- Hiring/Assessment
- Retention
- Performance evaluation

- Learning and Development
- Collaboration/team composition
- Other (e.g. absenteeism)



#### Employee turnover

- Employee turnover is the process of employees leaving the company
- Also known as employee attrition or employee churn
- May result in high costs for the company
- May affect company's hiring or retention decisions



#### Course structure

- 1. Describing and manipulating the dataset
- 2. Predicting employee turnover
- 3. Evaluating and tuning prediction
- 4. Selection final model



#### The Dataset

```
[1]: import pandas as pd
In
       data = pd.read csv("turnover.csv")
   [2]: data.info()
Out [2]:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
satisfaction level 14999 non-null float64
last evaluation 14999 non-null float64
time_spend_company 14999 non-null int64
              14999 non-null int64
work accident
                  14999 non-null int64
churn
promotion last 5years 14999 non-null int64
          14999 non-null object
department
salary
                     14999 non-null object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```



#### The Dataset (cont'd)

In [1]: data.head()

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	work_accident	churn	promotion_last_5years	department	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.8	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low



#### Unique values

```
In [1]: print(data.salary.unique())
array(['low', 'medium', 'high'], dtype=object)
```





# Let's practice!





# Transforming categorical variables

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#### Types of categorical variables

- Ordinal variables with two or more categories that can be ranked or ordered
  - Our example: salary
  - Values: low, medium, high
- Nominal variables with two or more categories with do not have an instrinsic order
  - Our example: department
  - Values: sales, accounting, hr, technical, support, management, IT, product mng, marketing, RandD



#### Encoding categories (salary)

Old values	New values
low	0
medium	1
high	2



### Getting dummies

```
In [1]: # Get dummies and save them inside a new DataFrame
    departments = pd.get_dummies(data.department)
```

#### Example output

IT	RandD	accounding	hr	management	marketing	product_mng	sales	support	technical
0	0	0	0	0	0	0	0	0	1



#### Dummy trap

```
In [1]: departments.head()
```

IT	RandD	accounding	hr	management	marketing	product_mng	sales	support	technical
0	0	0	0	0	0	0	0	0	1

```
In [1]: departments = departments.drop("technical", axis = 1)
```

In [2]: departments.head()

ΙΤ	RandD	accounding	hr	management	marketing	product_mng	sales	support
0	0	0	0	0	0	0	0	0





# Let's practice!





#### **Descriptive Statistics**

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#### Turnover rate

#### Summary

Stayed	Left
76.19%	23.81%



#### Correlations

```
In [1]: import matplotlib.pyplot as plt
In [2]: import seaborn as sns
In [3]: corr_matrix = data.corr()
In [4]: sns.heatmap(corr_matrix)
In [5]: plt.show()
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	work_accident	churn	promotion_last_5years	salary
satisfaction_level	1	0.11	-0.14	-0.02	-0.10	0.06	-0.39	0.03	0.05
last_evaluation	0.11	1	0.35	0.34	0.13	-0.01	0.01	-0.01	-0.01
number_project	-0.14	0.35	1	0.42	0.20	0.00	0.02	-0.01	0.00
average_montly_hours	-0.02	0.34	0.42	1	0.13	-0.01	0.07	0.00	0.00
time_spend_company	-0.10	0.13	0.20	0.13	1	0.00	0.14	0.07	0.05
work_accident	0.06	-0.01	0.00	-0.01	0.00	1	-0.15	0.04	0.01
churn	-0.39	0.01	0.02	0.07	0.14	-0.15	1	-0.06	-0.16
promotion_last_5years	0.03	-0.01	-0.01	0.00	0.07	0.04	-0.06	1	0.10
salary	0.05	-0.01	0.00	0.00	0.05	0.01	-0.16	0.10	1





# Let's practice!





### Splitting the data

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#### Target and features

- target = churn
- features = everything else



#### Train/test split

- train the component used to develop the model
- test the component used to validate the model



#### Overfitting

an error that occurs when model works well enough for the dataset it was developed on (train) but is not useful outside of it (test)





# Let's practice!





# Introduction to Decision Tree -classification

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#### Classification in Python

#### Classification algorithms

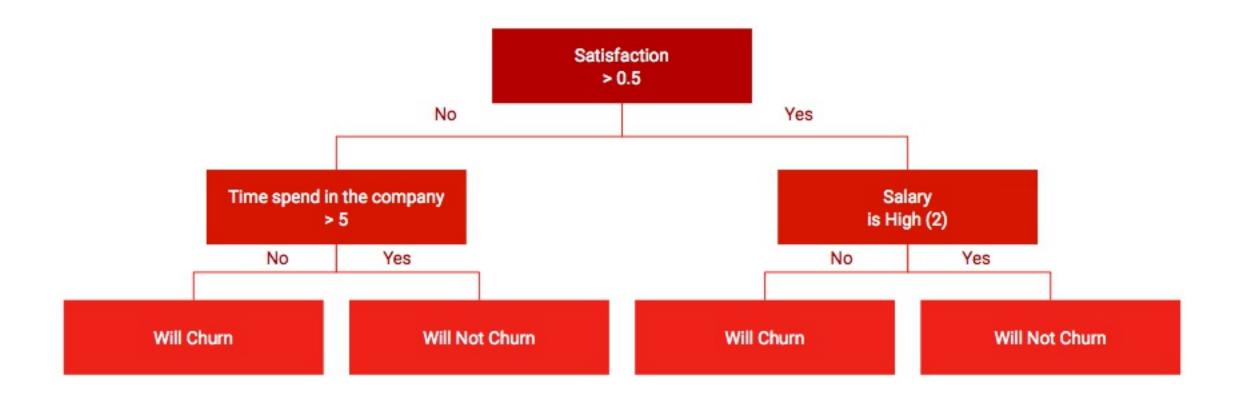
- Logistic regression
- Support Vector Machines
- Neural Networks
- Other algorithms

#### Algorithm we will use

Decision Tree



#### Decision Tree Classification





#### Splitting rule

#### Splitting rules:

- Gini: 2\*p\*(1-p)
- Entropy: -p\*log(p) (1-p)\*log(1-p)



#### Decision Tree splitting: hypothetical example

Total set: 100 observations, 40 left, 60 stayed

• Gini: 2\*0.4\*0.6 = 0.48

Splitting rule: satisfaction > 0.8

- Left branch (YES) 50 people: all stayed
- Gini: 2\*1\*0 = 0
- Right branch (NO) 50 people: 40 left, 10 stayed
- Gini: 2\*0.4\*0.1 = 0.08





# Let's practice!





# Predicting employee churn using decision trees

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#### Decision Tree in Python

```
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier(random_state=42)
model.fit(features_train,target_train)
model.score(features_test,target_test)*100
```





# Let's practice!





# Interpretation of the decision tree

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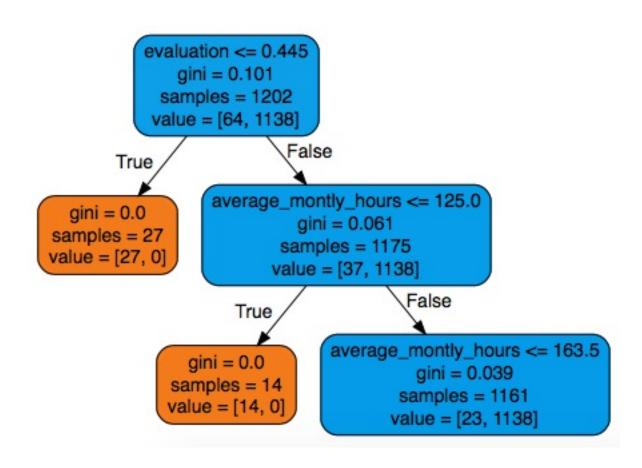


#### Visualization

- 1. Export
- 2. Copy content
- 3. Paste it in www.webgraphviz.com



#### Interpretation











# Tuning employee turnover classifier

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## Overfitting

#### Existance of overfitting:

- Training accuracy: 100%
- Testing accuracy: 97.23%

#### Methods to fight it:

- Limiting tree maximum depth
- Limiting minimum saple size in leafs



## Pruning the tree

#### Limiting Depth

#### **Limiting Samples**









## **Evaluating the model**

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## Prediction errors

Confusio	n Matrix	Reality			
Confusion Matrix		0	1		
Predicted	0	TN	FN		
	1	FP	TP		



#### Evaluation metrics 1

- If target is leavers, focus on FN
  - Recall score = TP/(TP+FN)
  - Lower FN, higher Recall score
  - Recall score % of correct predictions among 1s (leavers)
- If target is stayers, focus on FP
  - Specificity = TN/(TN+FP)
  - Lower FP, higher Specificity,
  - Specificity % of correct predictions among 0s (stayers)



#### Evaluation metrics 2

- Even if target is leavers, you may still focus on FP:
  - Precision score = TP/(TP+FP)
  - Lower FP, higher Recall score
  - Precision score % of leavers in reality, among those predicted to leave



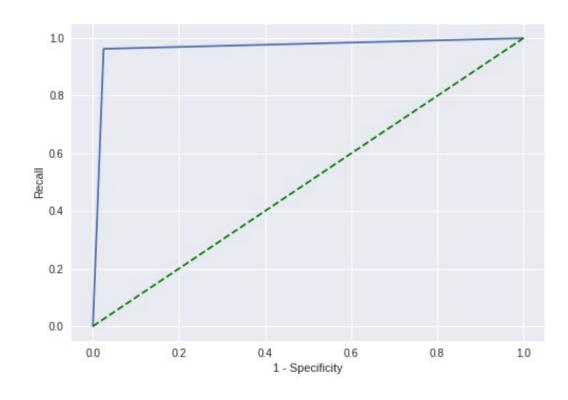






# Targeting both leavers and stayers

#### AUC score



- Vertical axis: Recall
- Horizontal axis: 1 Specificity
- Blue line: ROC
- Green line: baseline
- Area between blue and green:

AUC









#### Class Imbalance

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## Prior probabilities

#### Without balance

- $P_0 = 0.76$
- $P_1 = 0.24$
- Gini = 0.36

#### With balance

• 
$$P_0 = 0.5$$

• 
$$P_1 = 0.5$$

• 
$$Gini = 0.5$$









## Hyperparameter tuning

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### GridSearch

#### Values for minimum samples in the leaf

	50	100	150	200	250	300	350	400	450
5	5, 50	5, 100	5, 150	5, 200	5, 250	5, 300	5, 350	5, 400	5, 450
6	6, 50	6, 100	6, 150	6, 200	6, 250	6, 300	6, 350	6,400	6, 450
7	7, 50	7, 100	7, 150	7, 200	7, 250	7, 300	7, 350	7,400	7, 450
8	8,50	8, 100	8, 150	8, 200	8, 250	8, 300	8, 350	8,400	8, 450
9	9,50	9, 100	9, 150	9, 200	9, 250	9, 300	9, 350	9,400	9, 450
10	10,50	10, 100	10, 150	10, 200	10, 250	10, 300	10, 350	10, 400	10, 450
11	11,50	11, 100	11, 150	11, 200	11, 250	11, 300	11, 350	11, 400	11, 450
12	12,50	12, 100	12, 150	12, 200	12, 250	12, 300	12, 350	12, 400	12, 450
13	13,50	13, 100	13, 150	13, 200	13, 250	13, 300	13, 350	13, 400	13, 450
14	14,50	14, 100	14, 150	14, 200	14, 250	14, 300	14, 350	14, 400	14, 450
15	15,50	15, 100	15, 150	15, 200	15, 250	15, 300	15, 350	15, 400	15, 450
16	16,50	16, 100	16, 150	16, 200	16, 250	16, 300	16, 350	16, 400	16, 450
17	17,50	17, 100	17, 150	17, 200	17, 250	17, 300	17, 350	17, 400	17, 450
18	18,50	18, 100	18, 150	18, 200	18, 250	18, 300	18, 350	18, 400	18,450
19	19,50	19, 100	19, 150	19, 200	19, 250	19, 300	19, 350	19, 400	19, 450
20	20, 50	20, 100	20, 150	20, 200	20, 250	20, 300	20, 350	20, 400	20, 450

Values for maximum depth



#### **Cross-Validation**

Fold 1

Fold 2

Fold 3

Fold 4

Fold 5

Test Train Train

Train

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# Important features for predicting attrition



### Feature Importances

- Importance is calculated as relative decrease in Gini due to the selected feature.
- Importances are scaled to sum up to 100%.
- Higher percentage, higher importance.









## Final thoughts

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#### Alternative methods

- Logistic Regression
- Tree based
  - Random Forest
  - Gradient Boosting
- Neural Networks





### The End