# Tuning employee turnover classifier

**HUMAN RESOURCES ANALYTICS: PREDICTING EMPLOYEE CHURN IN PYTHON** 



#### **Hrant Davtyan**



## Overfitting

Existence of overfitting:

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

Methods to fight it:

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



### Pruning the tree

#### Limiting Depth

#### **Limiting Samples**



# Evaluating the model

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### **Prediction errors**

Confusion Matrix		Reality	
		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

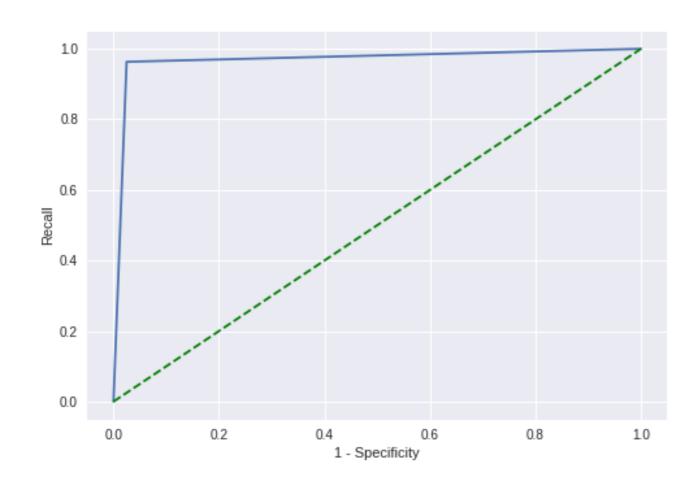
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#### **AUC** score



- 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

• 
$$P_0 = 0.5$$

• 
$$P_1 = 0.5$$

• 
$$Gini = 0.5$$

