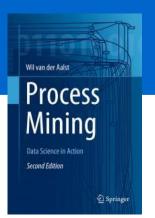
Process Mining: Data Science in Action

Evaluating Mining Results



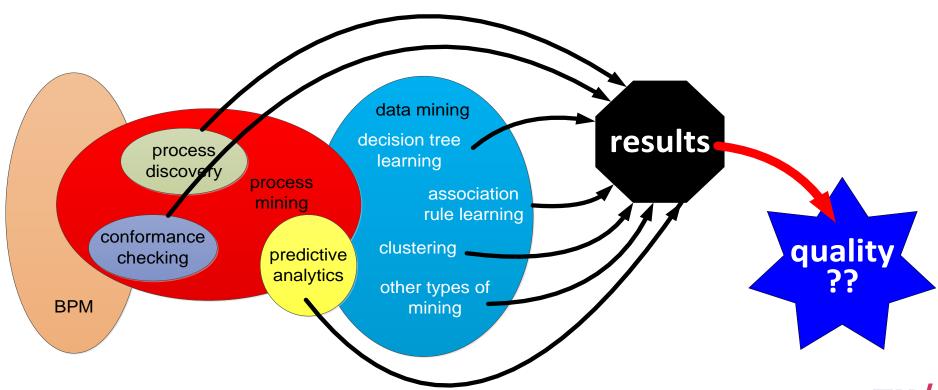
prof.dr.ir. Wil van der Aalst www.processmining.org

TU



Where innovation starts

Evaluating (data/process) mining results



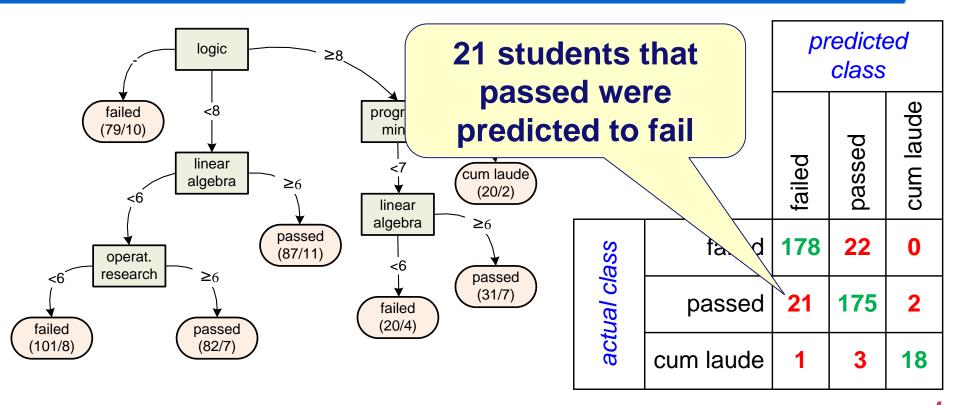
Confusion matrix and related measures



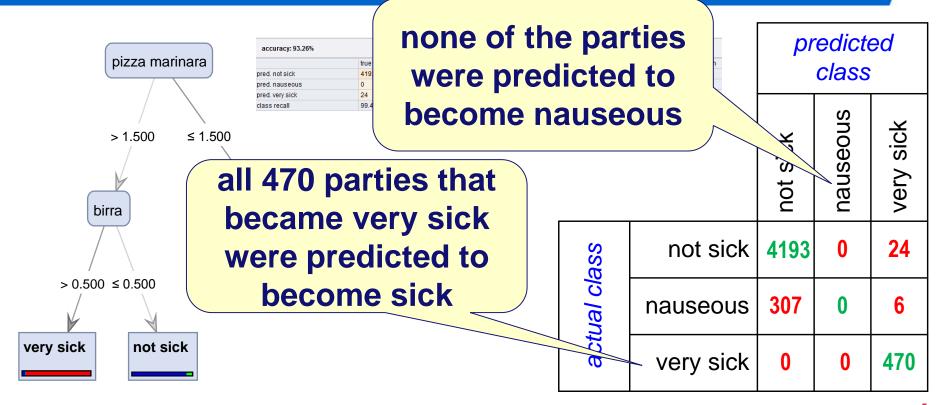
Straight Ahead



Confusion matrix for decision tree

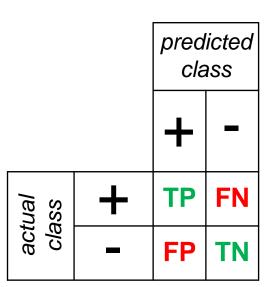


Another example



Confusion matrix for binary classification

- True Positives (TP): positive instances predicted to be positive.
- True Negatives (TN): negative instances predicted to be negative.
- False Positives (FP): negative instances predicted to be positive.
- False Negatives (FN): positive instances predicted to be negative.

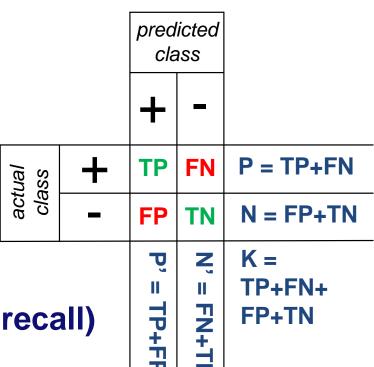




Quality measures

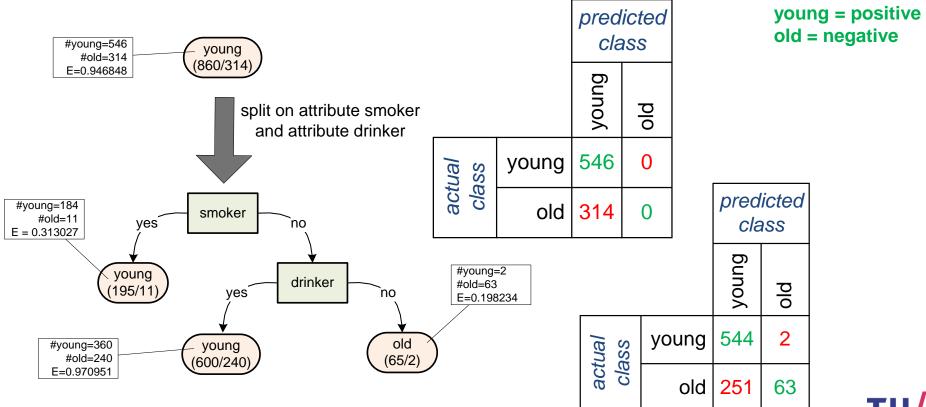
(based on confusion matrix)

- error = (FP+FN)/K
- accuracy = (TP+TN)/K
- precision = TP/P' = TP/(TP+FP)
- recall = TP/P = TP/(TP+FN)
- F1-score =
 (2 x precision x recall)/(precision + recall)
 (harmonic mean of precision and recall)





Question: Compute precision, recall, and the F1-score before and after splitting





Answer

precision = 546/(546+314) = 0.635recall = 546/(546+0) = 1.000F1-score = 0.777

		predicted class	
		young	old
actual class	young	546	0
	old	314	0

		predicted class	
		young	old
actual class	young	544	2
	old	251	63

Cross-validation

Evaluation

Straight Ahead



Consider your 10 best friends

You can create a decision tree that accurately predicts the length of a friend based on his/her birth date and eye color.

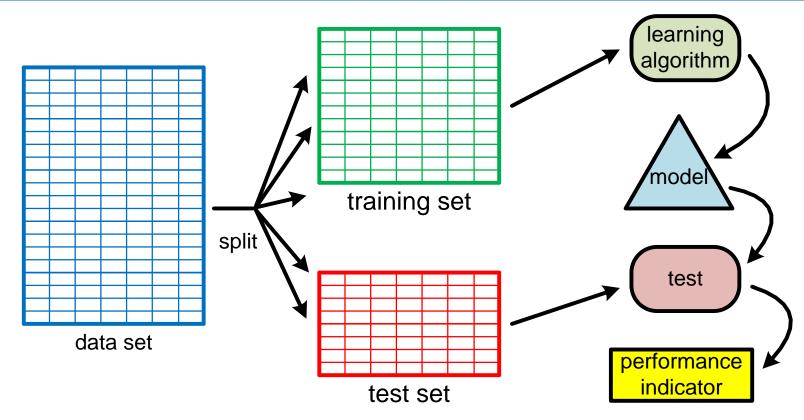
... but the model will be overfitting the data set and will most likely not apply to any new friends.

Overfitting and underfitting

- Overfitting: the model is too specific for the data set used to learn the model and performs poorly on new instances.
 - If birth date = 16-05-1998 and eye color = blue,
 then length = 172.8 cm.
- Underfitting: the model is too general and does not exploit the data.
 - If gender = male, then length > 1 meter.

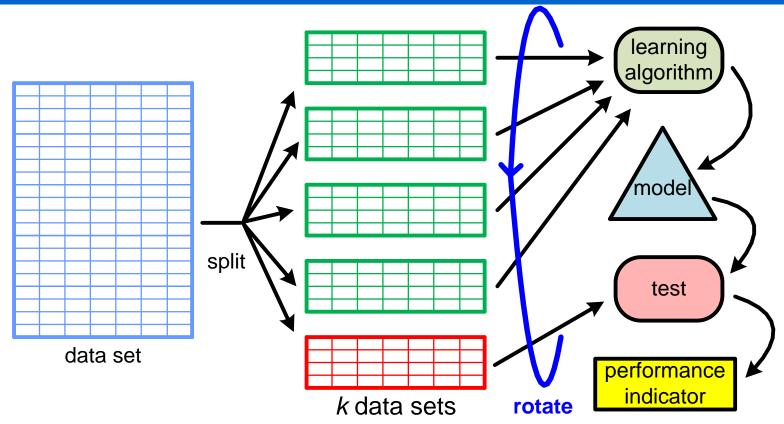


Cross-validation





k-fold cross-validation



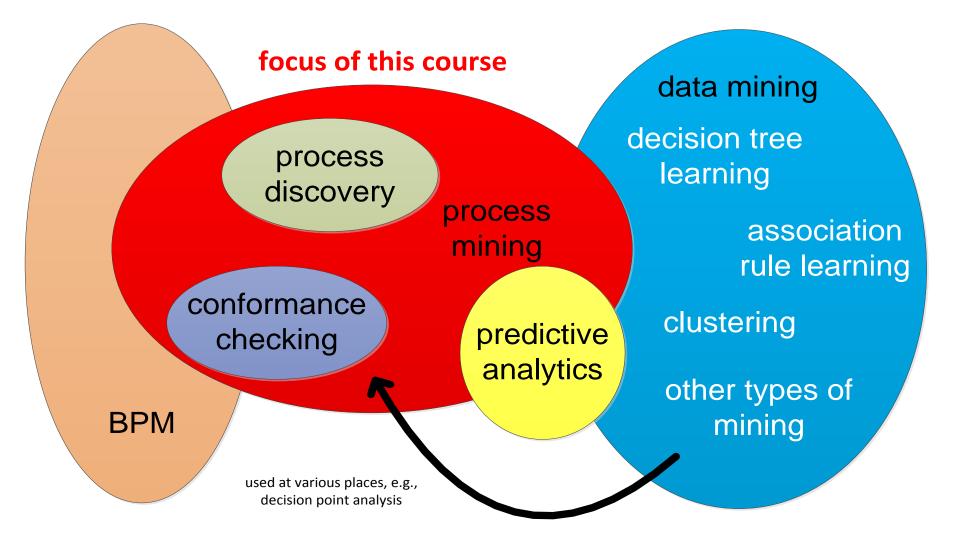


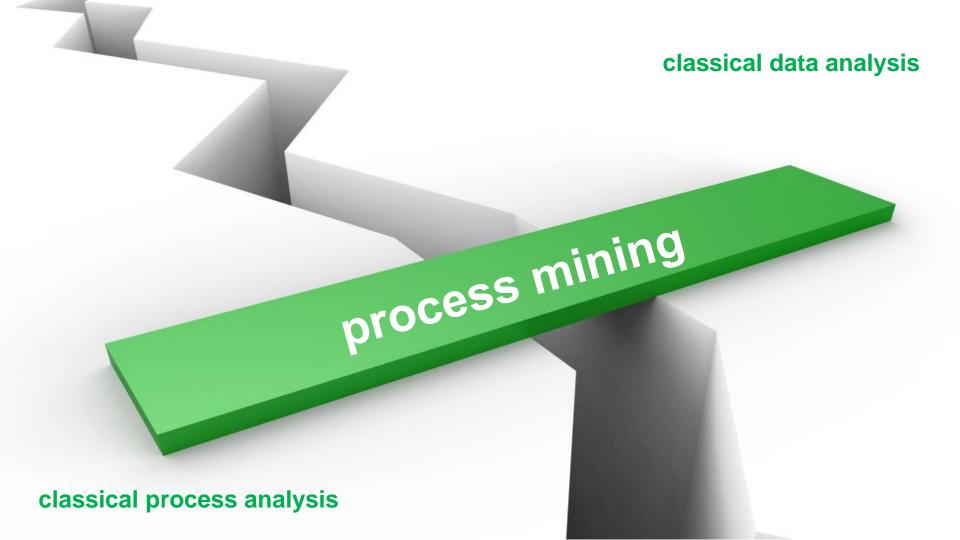
Possible complications

- Concept drift (model should change over time).
- No negative examples (we only know about sick customers that complained afterwards).

• ...







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Chapter 2 Process Mining: The Missing Link

Part II: Preliminaries

Chapter 3 Process Modeling

and Analysis

Chapter 4
Data Mining

Part III: From Event Logs to Process Models

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Chapter 6 Process Discovery: An Introduction

Chapter 7

Advanced Process
Discovery Techniques

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Chapter 14

Analyzing "Spaghetti Processes"





Process

Mining

Second Edition

Wil van der Aalst

