Machine Learning Applications

Wintersemester 2019/2020

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Agenda

Agenda

AI in the company

Quality assurance and related processes

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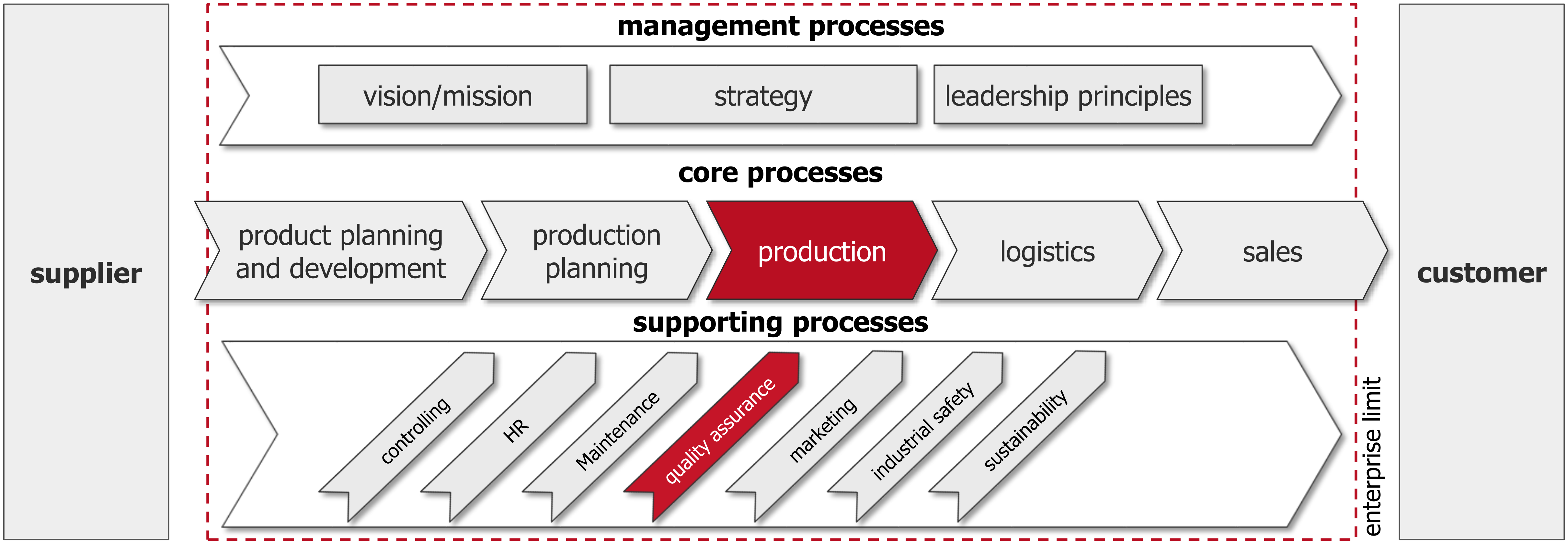
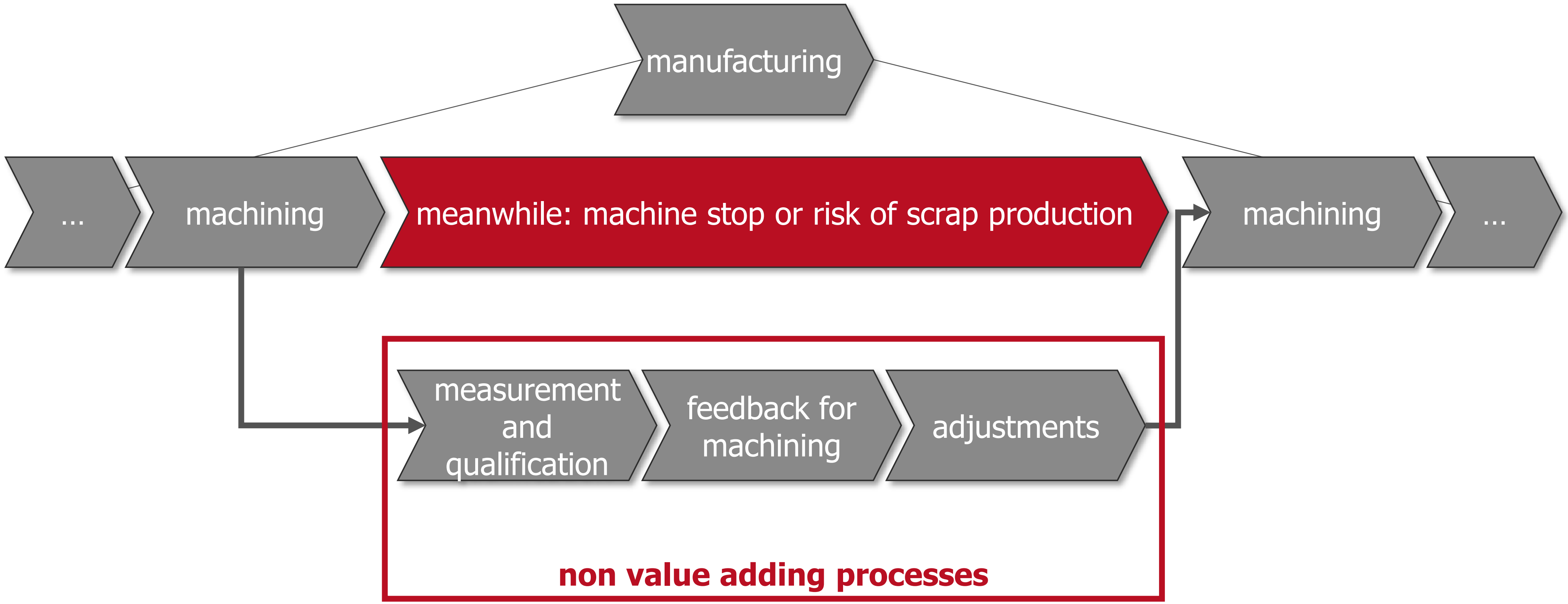


Quelle: in Anlehnung an REFA

Predictive quality
Process



Idea: Production optimisation through reduction of non value adding processes

Predictive quality

Approach

predictive quality

Determination of quality indicators on the basis of data without a dedicated measuring operation.

conventional

machining → measurement of produced part to determine product quality

- ⊖ time consuming
- ⊖ equipment and staff necessary (investment and maintenance)
- ⊕ conventional documentation possible

predictive quality

machining

analysis of machining data to determine product quality

- ⊕ trained models allow fast analysis and feedback
- ⊕ server maintenance cost < measuring equipment maintenance cost
- ⊖ conventional documentation not possible

Agenda

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DMME Process for AI projects in production technology

Data Mining Methodology for Engineering Applications

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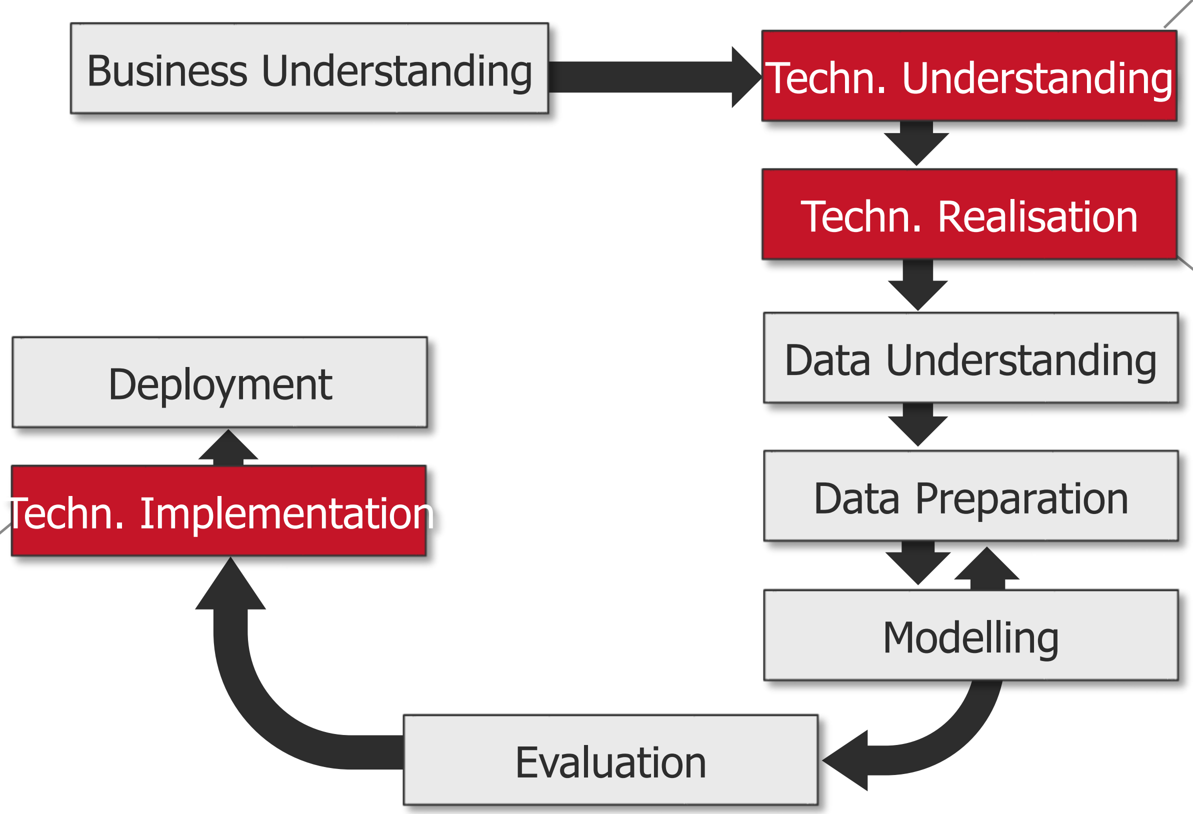
- Measurable technical targets
- Domain knowledge
- Experimental design

- Measuring concept
- Conduct Experiments



- Adapt sensor concept to production environment
- Software integration

DMME process

Business understanding

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example: start 1 – business case

business objective:

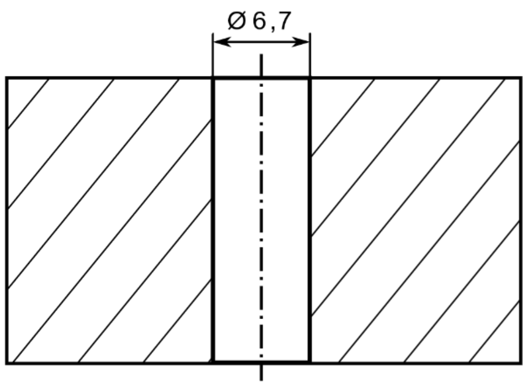
- increase production efficiency, avoid waste
- enable quality control based on machine data, avoid physical measurements

data mining target:

- identify product quality based on data

pitfalls

- early identification and involvement of involved parties and stakeholders
- identify evaluation variables for project success



Result **Clarity about the underlying objective achieved.**

Quality assurance in production

Potential errors

roundness

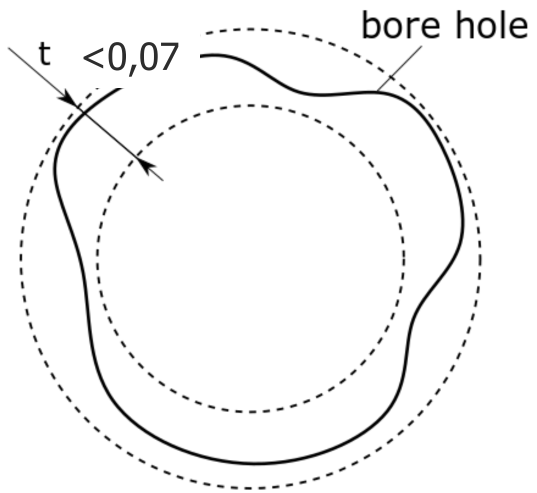
shape of bore hole

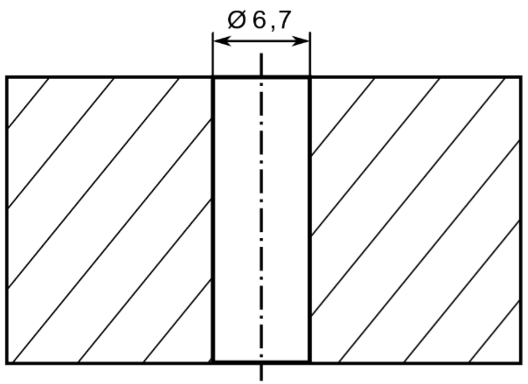
- bore hole not round due to weak tool guidance

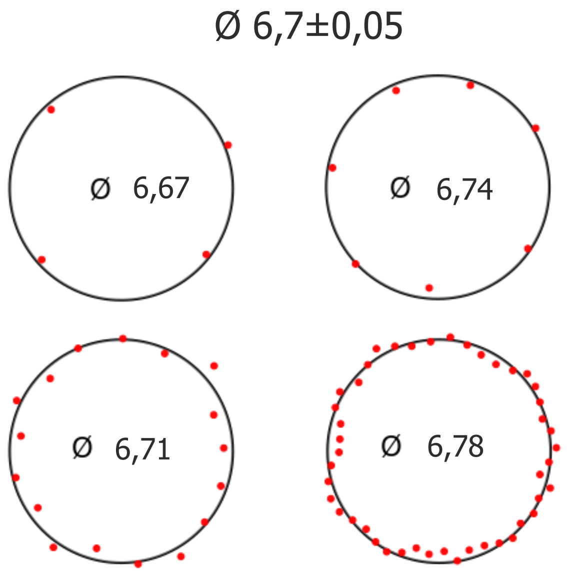
diameter

measured diameter

- rough bore hole wall due to worn tool







DMME process
Technical understanding

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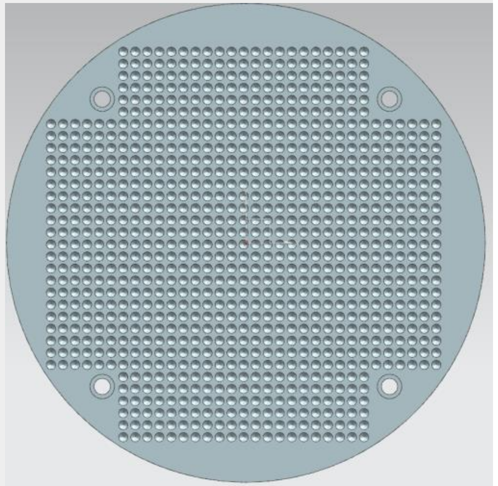
procedure

How can the quality characteristics be produced?

- determine framework conditions (e.g. machine tool selection)
- perform technical system analysis
- identify relevant parameters
- create measurement concept
- create experimental design



use case

Scope:

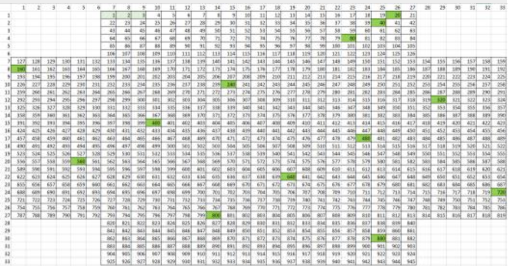
Machine tool, measuring machine, tool cycle

Analysis of the relevant parameters using domain knowledge about the machining process (spindle current, axis position, rpm)

In this step process knowledge is indispensable so far!

Experimental design:

- G code
- material & tools
- No. and arrangement of bores



Result | **Clarity about the experimental design achieved.**

DMME process

Technical realisation

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procedure	use case

▪ set up experimental design
▪ conduct an experiment
▪ documentation
	▪ machine tool: Hermle
	  ▪ machine tool setup and conduction
	  ▪ problem of machine data acquisition
	▪ coordinate measuring machine
	  ▪ setup measuring programme

Open Research:

Required frequency

- required frequency strongly depends on underlying business case

Required parameter

- ML aims for finding correlations that go beyond expert knowledge ->the more parameters the better

Approach: Use max. option and reduce in deployment

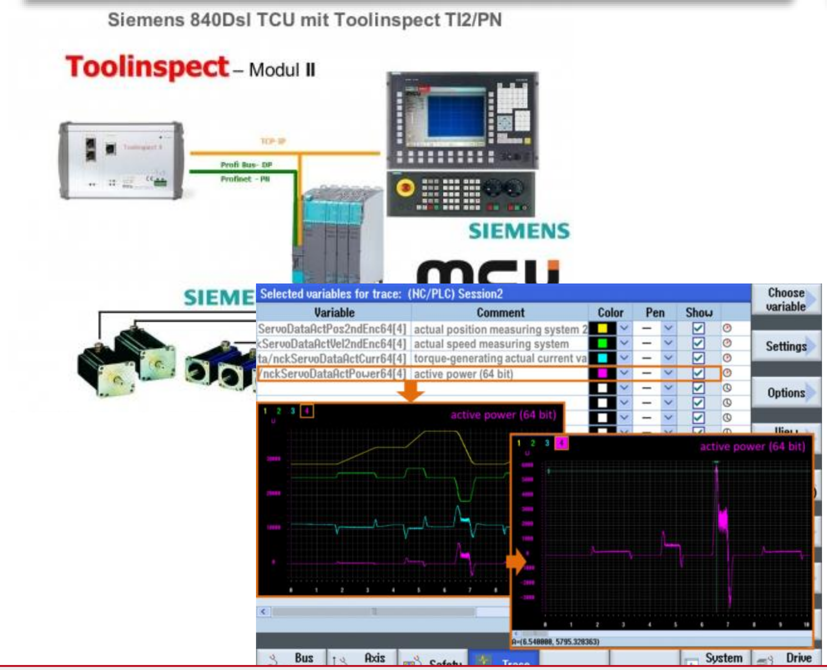
Problem: Technical restrictions result in a trade-off between frequency and number of recorded parameters

-> Generalised findings are still subject of research

DMME process

Technical realisation

machining | data acquisition | measurement



Result **Test conducted and documented.**

DMME process
Data understanding

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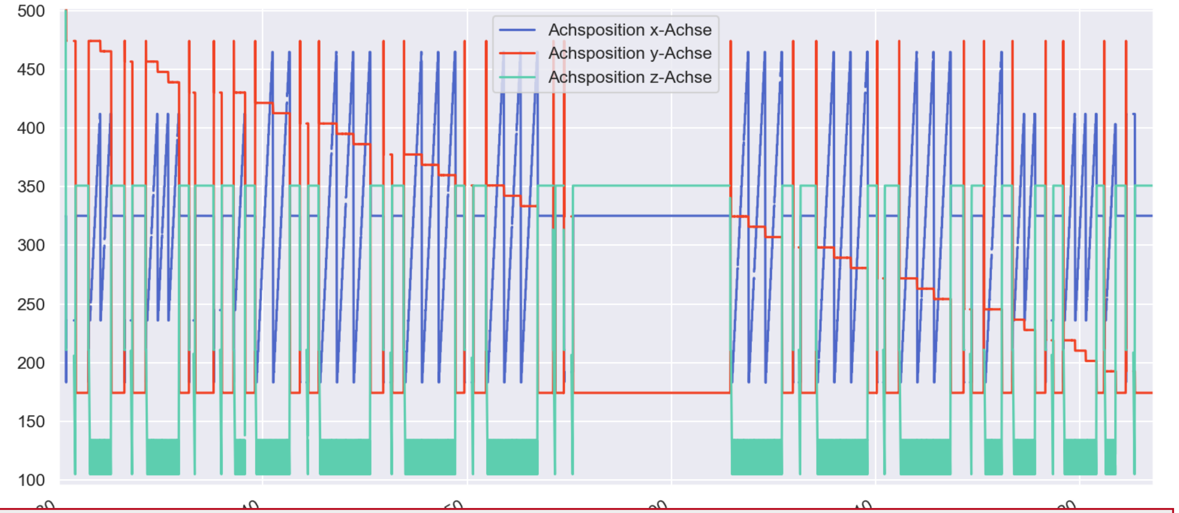
procedure

- reading the data into the analysis software
- first view into the recorded data
  - result:
    – Trace: high frequency but incomplete data
    – Edge device: low frequency but complete data
    – KMM: Complete data record
  - plausibility checks:
    – trajectories do not match data
    – → G-Code structure leads to double approaching of some bore holes
    – → attention, those cases distort the database

use case

- Python as data analysis tool
- attention: time and effort for data integration



Result **Data understood, ambiguities identified and understood.**

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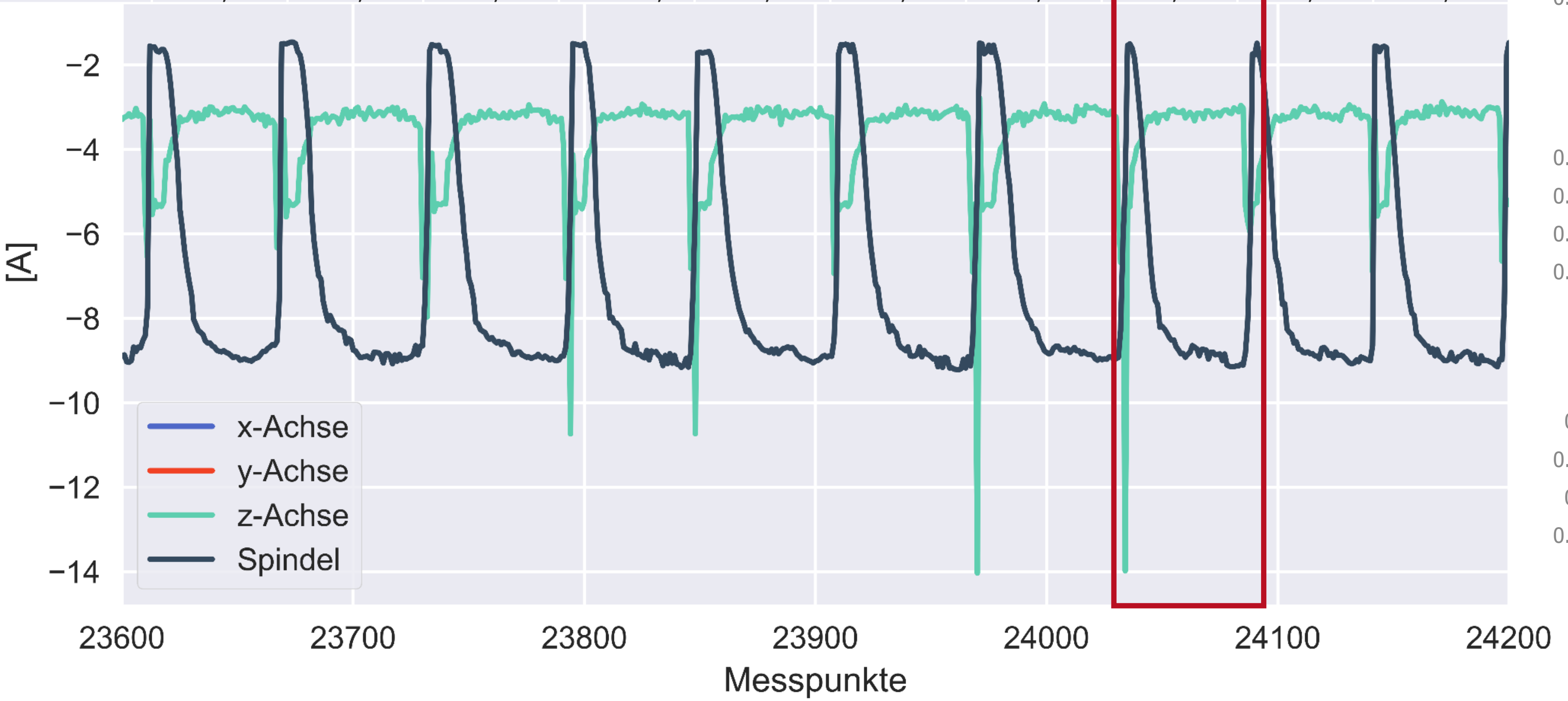
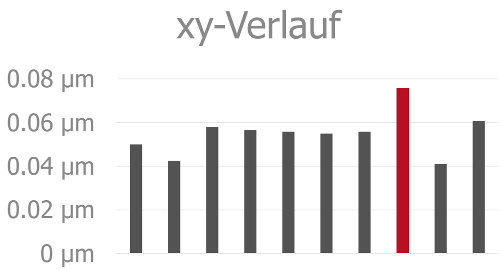
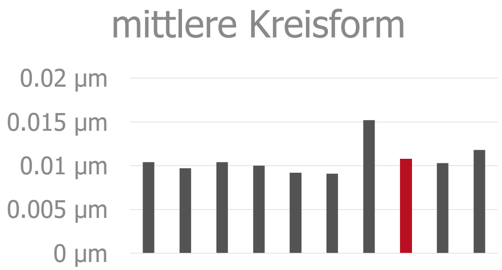
DMME process

Data preparation

Bohrung	1346	1347	1348	1349	1350	1351	1352	1353	1354	1355
mittlerer Durchmesser	6,7254	6,7253	6,7246	6,7246	6,7255	6,7242	6,7246	6,7255	6,7245	6,7239
xy-Verlauf	0,05	0,0426	0,058	0,0566	0,0559	0,055	0,0559	0,0759	0,0411	0,0608
mittlere Kreisform	0,0104	0,0097	0,0104	0,01	0,0092	0,0091	0,0152	0,0108	0,0103	0,0118







DMME process

Data preparation

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procedure	use case
combine data from different sources ▪ data of different frequencies → How to connect? ensuring data quality ▪ how to fill vacancies? facilitate data handling ▪ adapt memory formats ▪ indexing for the selection of test periods	**linking of machine data with quality data** ▪ identification of drilling operations based on G-code ▪ demarcation of the bore holes by abruptly changing the z-position → numerical differentiation ▪ insert the meta information "hole number". ▪ linking of quality data, linear interpolation to eliminate defects

Result **Cleaned and complete database for modelling created.**

DMME process

Modelling

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procedure

- selection of the ML algorithm
    - regression/classification/cluster?

- analysis of possible methods
- checking the requirements
- derivation of data features to extend the data basis
- splitting into train and test data
- implementing the algorithm
- evaluation and adjustment

use case

- classification model selected
- raw values and features used for training
- train/test set randomly selected

Result | **ML algorithm chosen and implemented.**

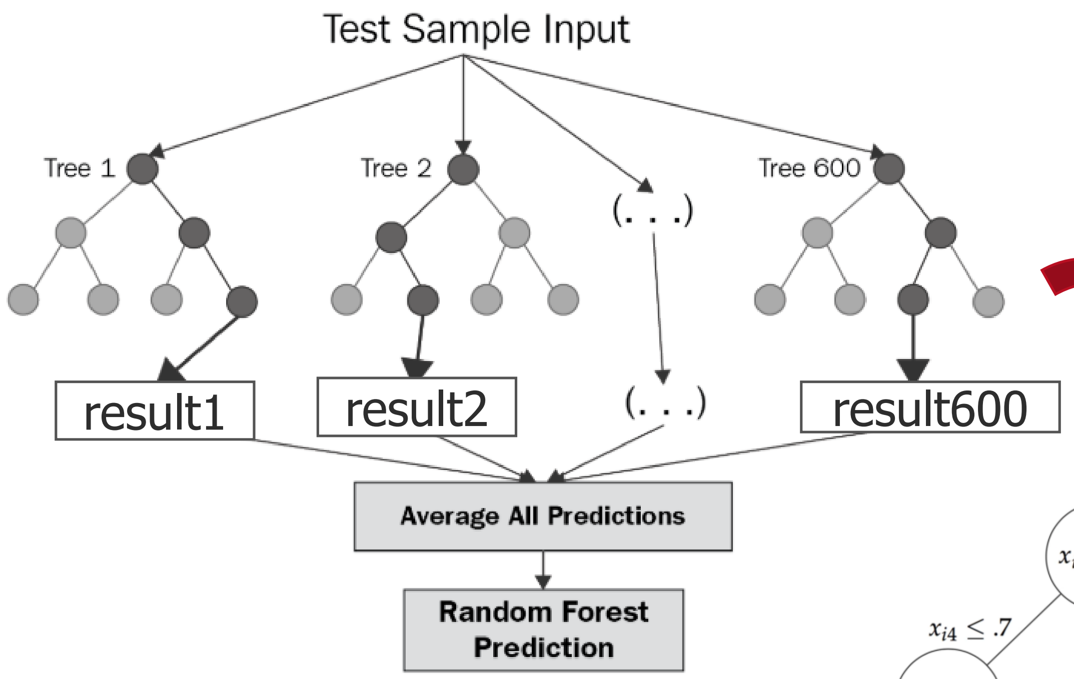
Classifier
Random Forest

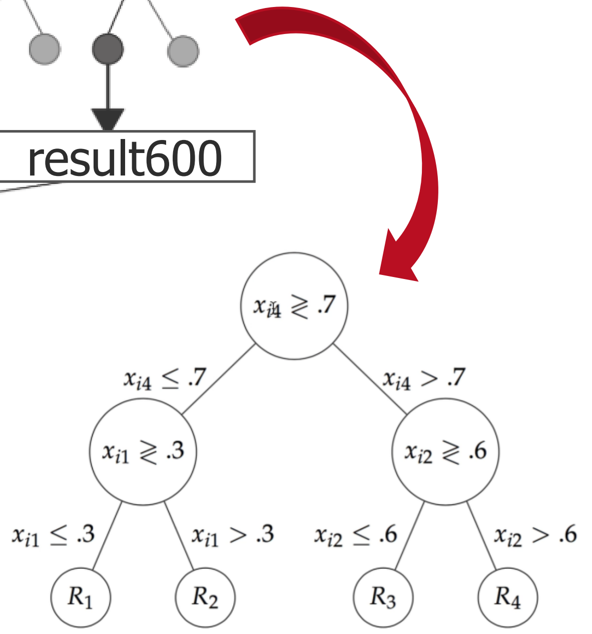
→ supervised learning
→ classification and regression

Training phase: Creation of decision trees.

Output: Mean value of the forecast of the individual trees.

Hyperparameters:
n_estimators: No. of trees
random_state: The seed used by the random number generator (used to draw a random sample from the data set when generating its splits)
max_depth: No. of nodes
...





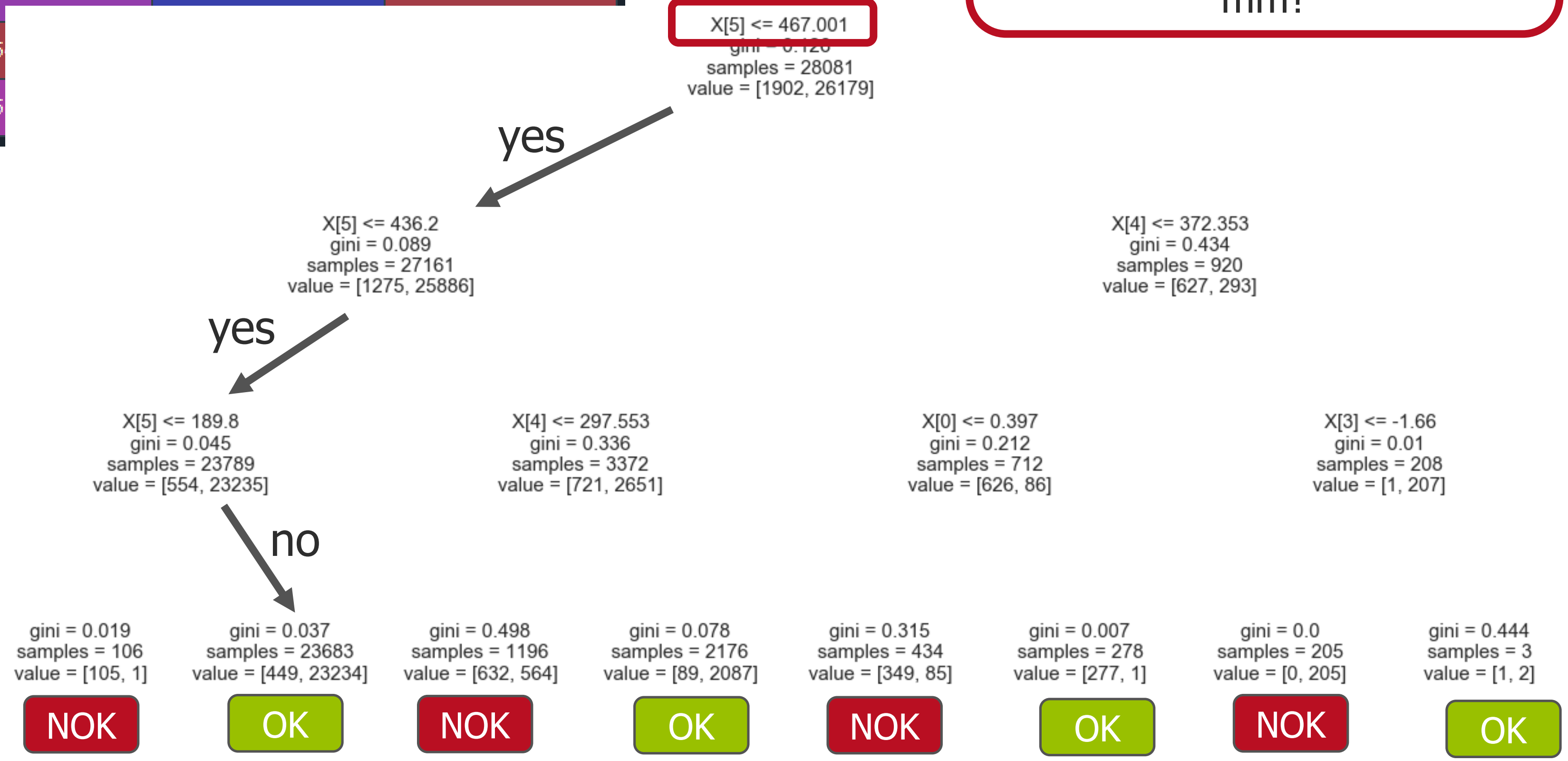
Quelle: [11]

Classifier

Random Forest

Strom x-Achse	Strom y-Achse	Strom z-Achse	Strom Spindel	Achsposition x-Achse	Achsposition y-Achse	Achsposition z-Achse
0.41391	0.381348	-2.95477	-9.2395	350.354	330.601	116.369
0.41391	0.338379	-2.40189	-11.0237	279.955	216.201	119.814
0.419952	0.386719	-3.19043	-7.34204	315.153	445.001	109.938
0.386719	0.39209	-5.37177	-1.64966	271.15		
0.386719	0.354492	-3.29013	-7.38452	306.35		

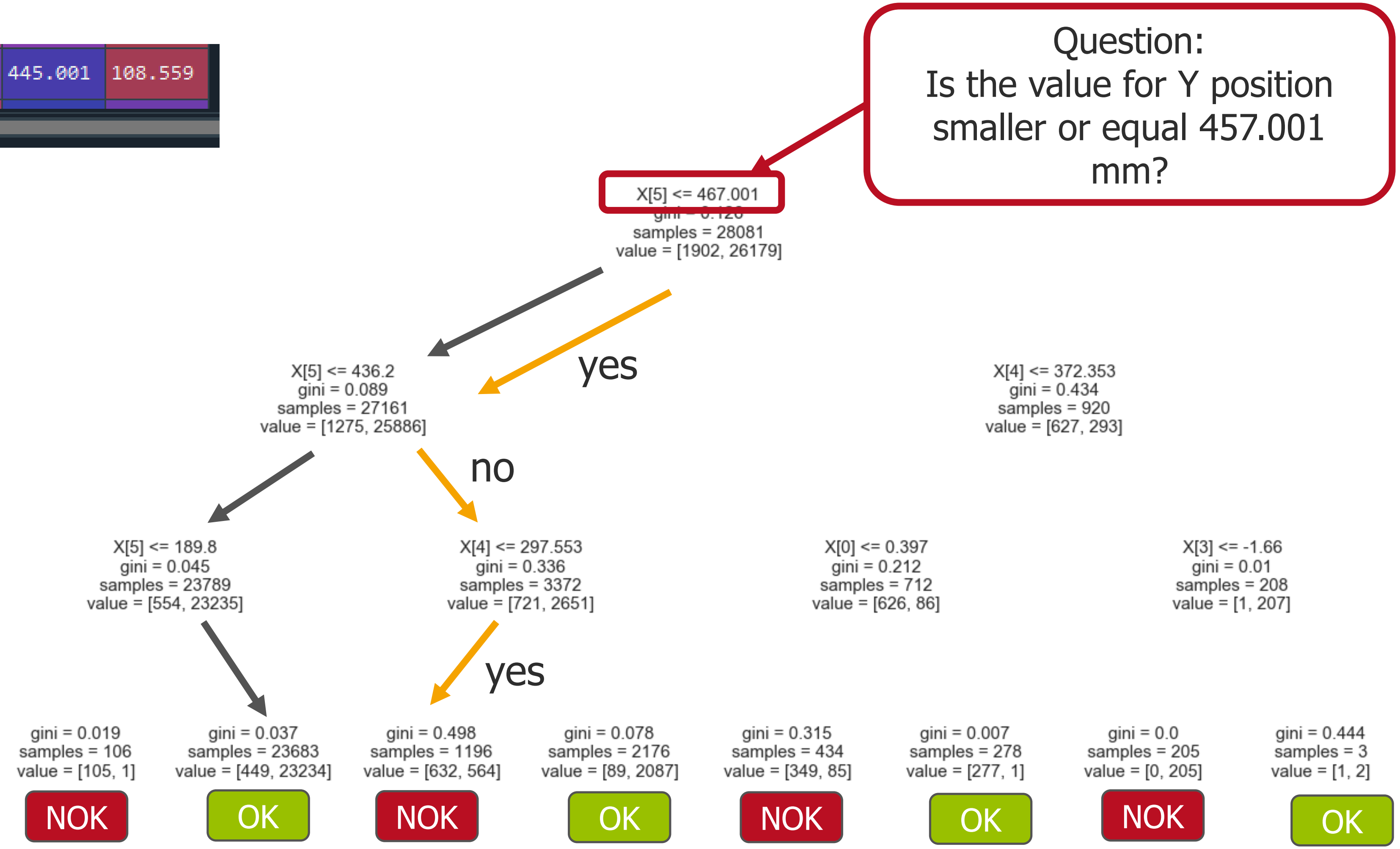
Question:
Is the value for Y position smaller or equal 457.001 mm?



X[0]	'Strom x-Achse'
X[1]	'Strom y-Achse'
X[2]	'Strom z-Achse'
X[3]	'Strom Spindel'
X[4]	'Achsposition x-Achse'
X[5]	'Achsposition y-Achse'
X[6]	'Achsposition z-Achse'
gini	impurity
samples	data set considered per node
values	amt. of sample each category

Classifier
Random Forest

0.489441	0.354492	-3.24481	-6.99512	394.353	445.001	108.559



X[0]	'Strom x-Achse'
X[1]	'Strom y-Achse'
X[2]	'Strom z-Achse'
X[3]	'Strom Spindel'
X[4]	'Achsposition x-Achse'
X[5]	'Achsposition y-Achse'
X[6]	'Achsposition z-Achse'
gini	impurity
samples	data set considered per node
values	amt. of sample each category

Metrics and scoring

Quantifying the quality of predictions

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accuracy

$$accuracy = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(\hat{y}_i = y_i)$$

Number of correct predictions divided by the total number of predictions.

The prediction accuracy of coin flipping is 50 percent for binary classification, according to the probability theory.

It does not tell you the underlying distribution of response values and what "types" of errors your classifier is making.

precision

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

If a positive value is predicted, how often is the prediction correct?

Precision helps if the costs of false positives are high.

Example for **high precision** necessary: A diagnosis might be better with a few false positives rather than let anyone with the actual disease slip through and neglect for treatment.

recall

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

If the actual value is positive, how often is the prediction correct?

Recall helps if the cost of false negatives is high.

Example for **high recall** necessary: It's more acceptable to have a few spam emails in the users inbox than it is to classify important emails as junk.

MAE, MSE

$$Mean\ average\ error = \frac{1}{n_{samples}} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

Finds the average absolute distance between predicted and target values. Usually used when the performance is measured on continuous variable data.

$$Mean\ squared\ error = \frac{1}{n_{samples}} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

MSE is more robust to the outliers than MAE. Useful when a single bad prediction would ruin the entire model's predicting abilities, i.e when the dataset contains a lot of noise.

Quelle: [13], [18], [19], [20]

DMME process
Evaluation

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procedure

- scoring with different evaluation metrics
  - MAE
  - RMSE
  - …

use case

- confusion matrix

```
Out[86]:
array([[   487,    329],
       [    30, 11189]],
```

		predicted class	
true class		NOK	OK
	NOK	487	329
	OK	30	11189

```
In [95]: score_prec
Out[95]: array([0.94197292, 0.97143601])
```

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Precision_{ok} = \frac{11189}{11189 + 30} = 0.971$$

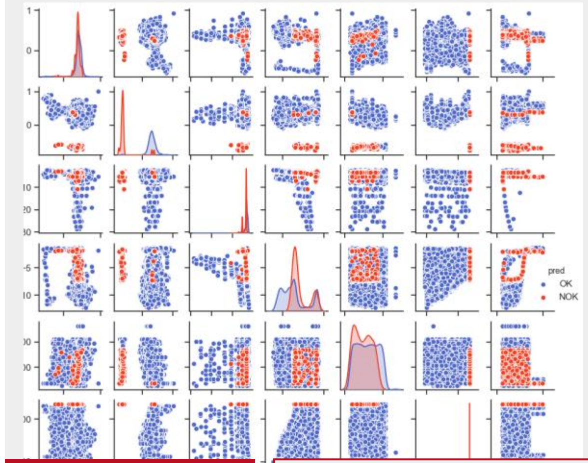
Result **Evaluation and selection of the appropriate model for the application.**

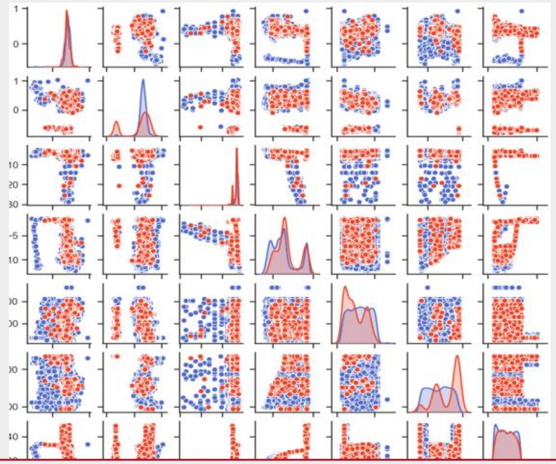
DMME process
Evaluation

procedure

- evaluation of the quality of the models used
    - attention: informational value of evaluation variables controversial and dependent on business case
- if necessary, loop to the model
- selection

predicted

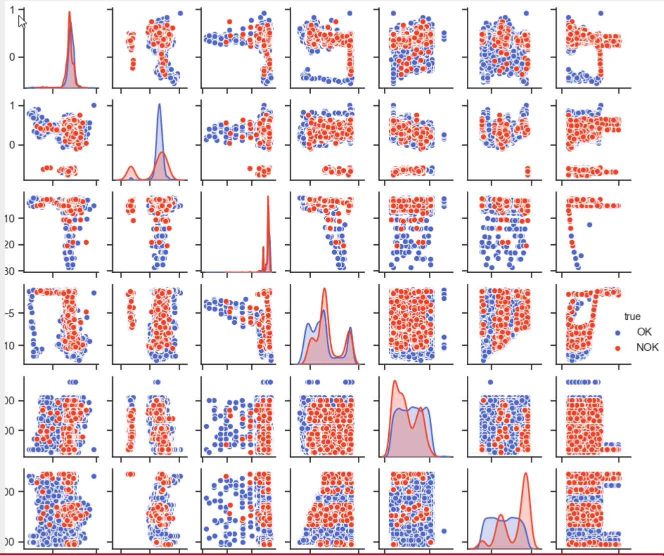




use case

- many influencing factors, e.g. inhomogeneous material, machine/tool condition, etc. require larger amounts of data or more targeted investigations.

true



Result **Evaluation and selection of the appropriate model for the application.**

DMME process

Technical implementation

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procedure

- implementation of the procedure in the company
  - transition from experiment to ongoing recording and analysis
  - IT infrastructure
  - automation of analysis processes
  - protection against standstills, failures, etc.
  - synchronization of time servers

pitfalls

- In particular, data transmission poses a problem here. If necessary, the data must be selected specifically for the application.
  - Consequence: Further information is lost.
- In practice, the extension of the infrastructure is associated with problems.
  - IT and security guidelines, especially for WIFI connections
  - Involve stakeholders at an early stage!

Result | **Technical framework conditions for long-term analysis created.**

DMME process
Deployment

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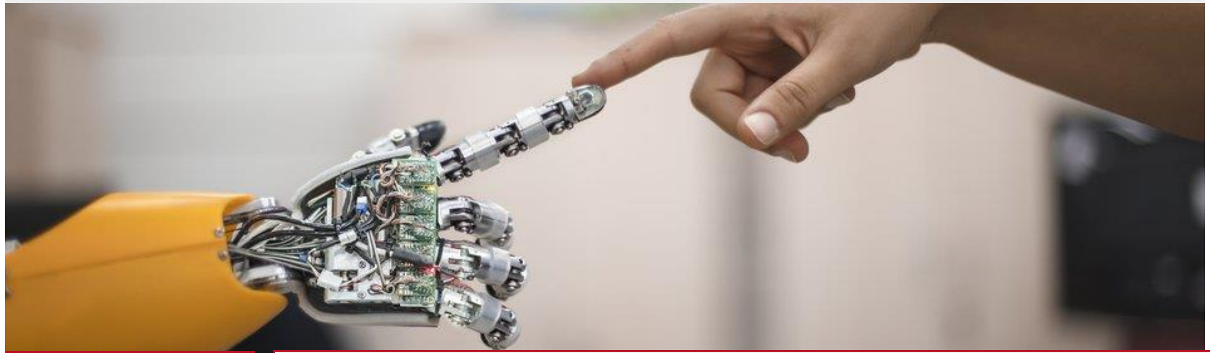
procedure

- deployment of ML analysis results in practice



pitfalls

organisational and legal issues to be considered

- organisational:
  - What consequences does the employee draw from the results of the analysis?
  - Which business processes are affected and need to be redefined?
- legally:
  - Do legal questions stand in the way of machine analysis?
  - Do certain tests still have to be physically performed and documented?
  - Can automated (black box) procedures be used? → warranty

Result **ML in practice has been established.**

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What to take with you?

LEARNING OUTCOMES

Key findings

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- **Machine learning in production: Predictive quality**
  - digitalization enables to rethink established processes
  - combination of existing databases enable new solution approaches
- **CRISP-DM:** specialised adaptions of the standard model exist in different areas of application
  - Business understanding: business case is basis for all following steps
  - Technical understanding: deep domain knowledge is necessary
  - Technical realisation: wide variety of technical infrastructure in production and lack of standardisation
  - Data understanding & preparation: hardest part of a real world project in production (domain knowledge is vital)
  - Modelling: start with simple models, use advanced ones once the data and process are fully understood
  - Evaluation: understandability and determination of model performance -> adjust based on business model
  - Technical implementation and deployment: highly individual, technical restrains, stakeholders to be included

References

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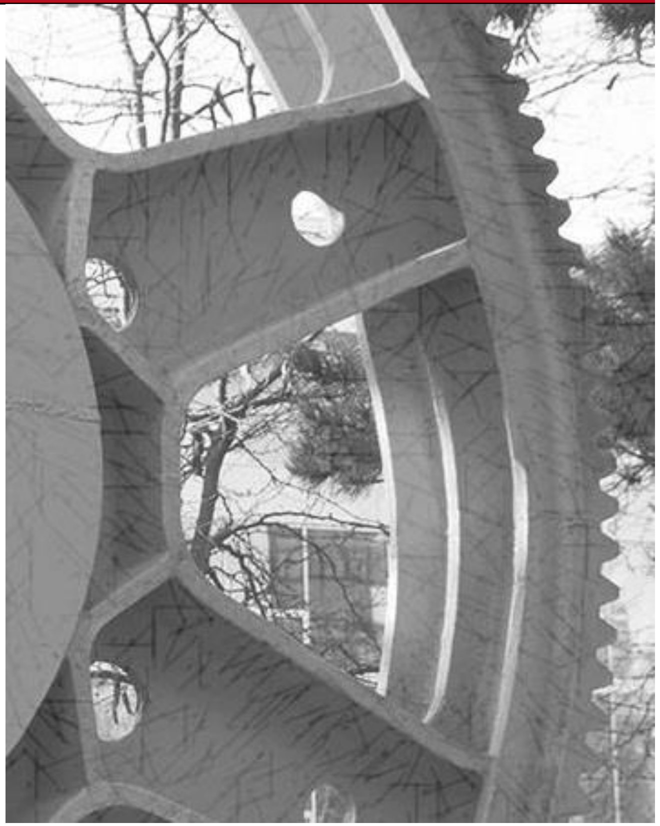
Thank you for your kind attention!!

If you have any questions, do not hesitate to contact us.



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