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Analytical Challenges for Data-Driven Fault Diagnosis in End-of-Line Testing of Complex Products

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Agenda

| Motivation

| Analytical Challenges

| Evaluation

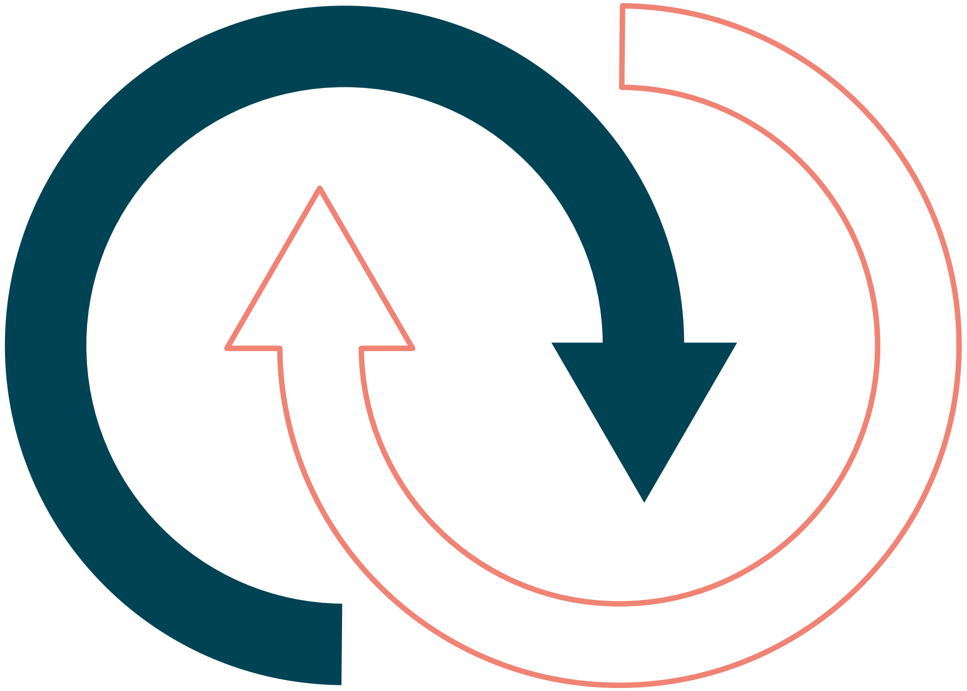
| Conclusion

[Daimler 2019]

Machine Learning – promising potential for fault diagnosis

Potential

- Improving quality control in manufacturing systems [1,2,3,4,5,6]
- Manufacturing data is often labeled with expert feedback [7]



Limitation(s)

- Real-world manufacturing data is imprecise, uncertain and vague [5,6,8]
- Data characteristics have critical effect on data-driven approaches [1,6,20,30]

Decision support in fault diagnosis via classification techniques

Inherent data characteristics are not discussed in literature [2,4]

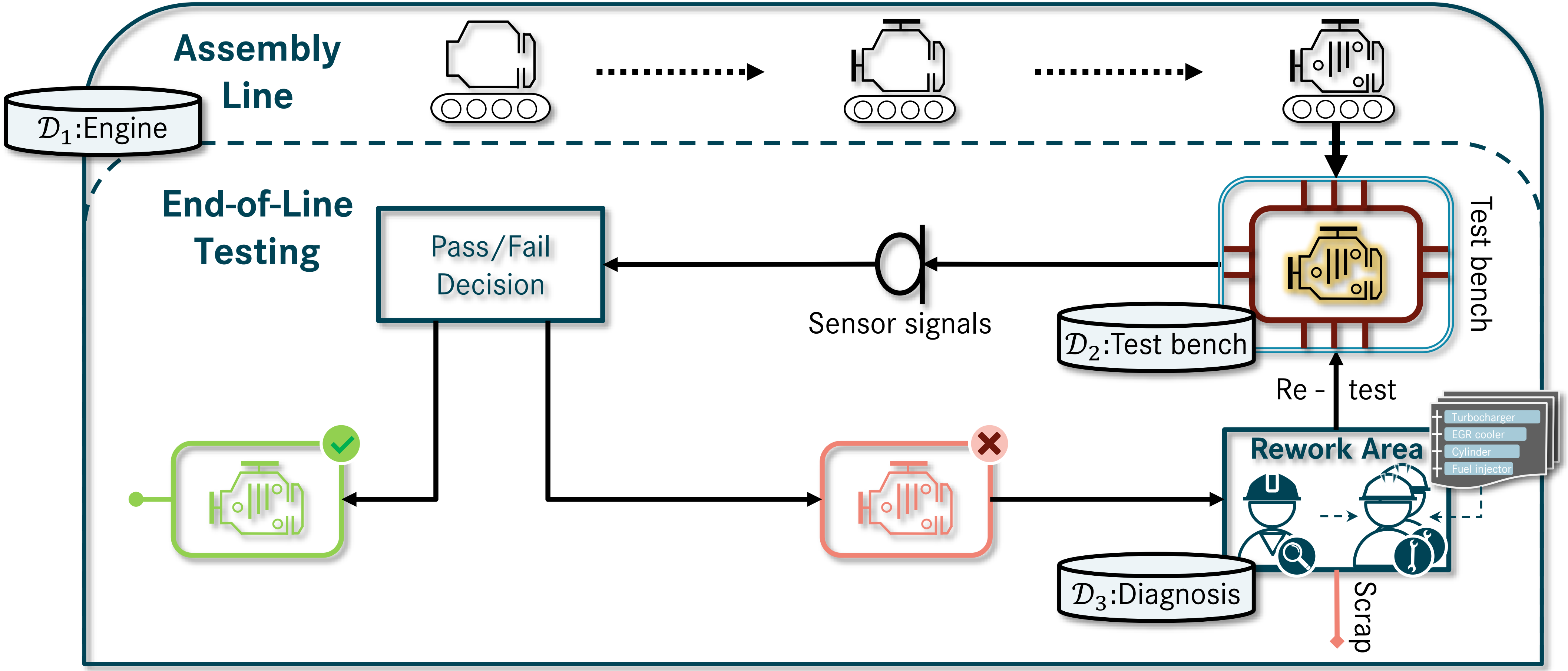
Use case: powertrain aggregates of commercial vehicles

Development → Procurement → Production → Distribution → After Sales

Forming | Machining | Assembly

[Daimler 2019]

End-of-Line testing of complex products; aim is to reduce the number of rework attempts and relieve the quality engineer



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Data-driven recommendation system must consider all four challenges (C)

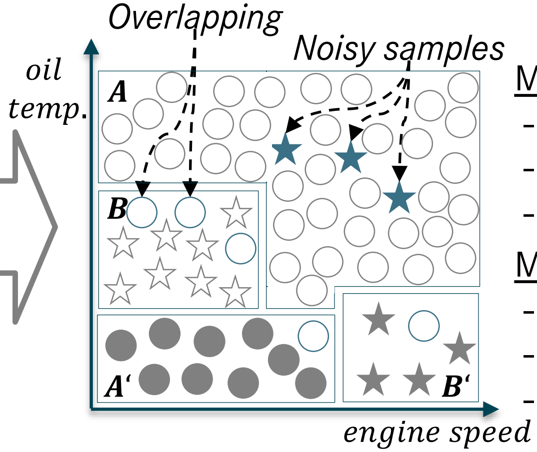
C1
Small size of sample set $\mathcal{X}$

- 1,050 samples with 84 classes and 115 features makes learning a concept difficult

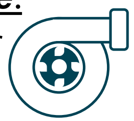
C2
Class imbalance

- Reduce the number of faulty components that can be predicted

Content in figure:		**#**	**C**
- classes		2	-
- majority samples	○ ●	50	C2
- minority samples	☆ ★	15	C2
- concepts		2	C3
- sub-concepts		2	C3
- overlapping samples	○	5	C4
- noisy samples	★	3	C4



<u>Majority class *circle*</u>:
- e.g., *turbocharger*
- $\boldsymbol{A}$: concept
- $\boldsymbol{A'}$: sub-concept



<u>Minority class *star*</u>:
- e.g., *fuel injector*
- $\boldsymbol{B}$: concept
- $\boldsymbol{B'}$: sub-concept

C3
Heterogenic product space

- Inconsistent sensor signals for different product variants

Set	**Name**	**Topic**	**Sample feature**	N^*	M^*
$\mathcal{D}_1$	Engine	Spec sheet	- Engine type - Engine design	519,214	22
$\mathcal{D}_2$	Test bench	Test runs	- Sensor signals	621,689	383
$\mathcal{D}_3$	Diagnostic	Faults	- Error codes	20,631	77

* Raw data from source systems, where N is the amount of observations and M of features

C4
Noise and overlapping samples

- Severe issue for algorithms to distinct between classes properly

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Interim conclusions of a theoretical investigation of methods to deal with analytical challenges

Ensemble procedures

- *AdaBoost*: sensitive to noise (focuses on it)
- *Random Forest:* handles all analytical challenges to a certain degree

Binarization strategy

- *One-Vs-All (OvA):* intensives class imbalance

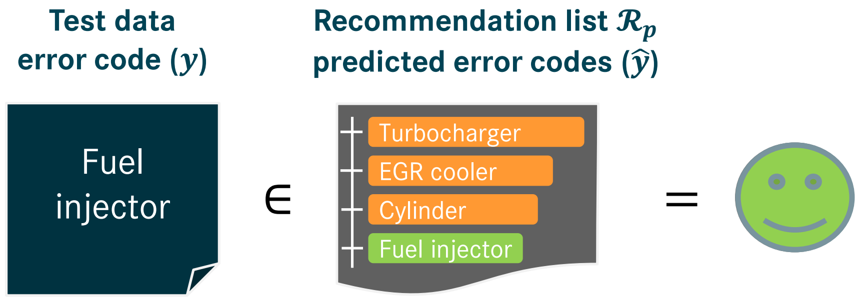
Sampling strategies

- *Random undersampling (RUS):* concepts are not recognized
- *Random oversampling (ROS):* decision boundaries become too tailored (overfitting)
- *Synthetic minority oversampling technique (SMOTE):* introduces “artificial” noise

Feature selection

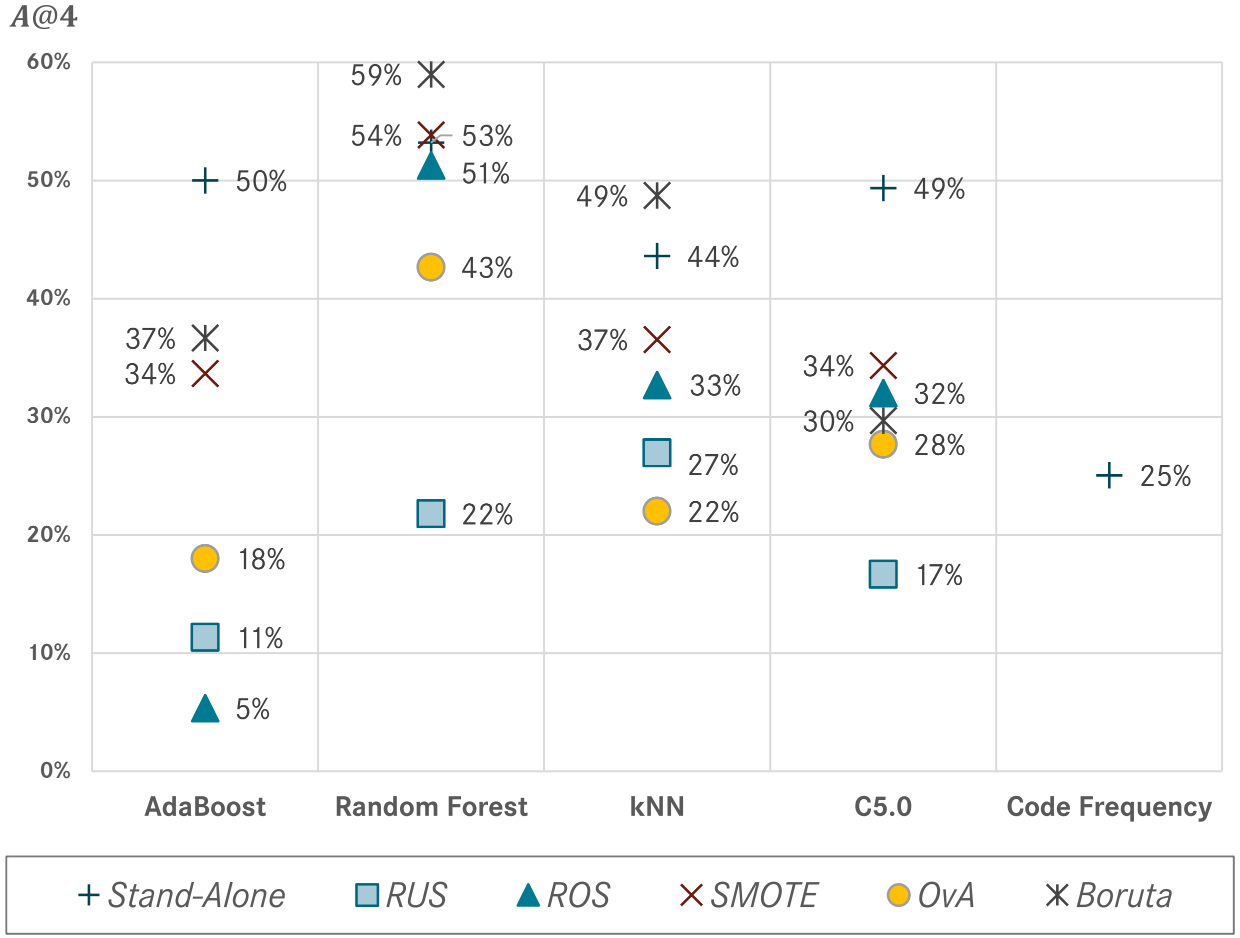
- *Boruta:* concepts to characterize faulty components are rather complex

Technical evaluation of examined methods; results for recommendation list $\mathcal{R}_p$ of length four



Accuracy@p ($A@p$):

- $A@p$ measures the portion of correctly predicted error codes among the first p elements of the list $\mathcal{R}_P$
- $\mathcal{R}_4$ is limited to **four** error codes, as quality engineers need in average four attempts to identify the faulty component



RUS: Random oversampling | ROS: Random undersampling | SMOTE: Synthetic minority oversampling technique | kNN: k-Nearest-Neighbors

Prediction performance and the amount of estimated rework attempts; comparison with an experienced quality engineer

	Recommendation list $\mathcal{R}_p$				Estimated Ø rework attempts
	$A@1$	$A@2$	$A@3$	$A@4$	
(1) Random Forest + Boruta	33%	42%	49%	59%	~1.9
(2) Experienced quality engineer	subjective experiences (100%)				~4.0

Key message(s):

- Operators can solve the quality issue by themselves:
  - in 1/3 of all cases with only one repair attempt
  - in 6 out of 10 cases, by working through the list (ca. 2 repair attempts required)
- Increase efficiency of the workforce, because:
  - Operators can carry out rework attempts without involving the quality engineer
  - Quality engineer needs to be consulted in only 41% of all required rework attempts

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Conclusion and future work

Summary:

- We can found similar data characteristics i.e., analytical challenges, in other use cases as well
- Methods from the area of data analytics, e.g., sampling, are associated with tradeoffs with an effect on the challenges
- With a score A@4 of about 59%, we can achieve improvements in the practical application

Next steps:

- Domain-specific approach in order to increase further the prediction performance by incorporating domain knowledge
- Where the system is uncertain, incorporating cost aspects in order to adjust the order of the components
- Automatic adaption of the system, since the manufacturing domain is non-stationary

[Daimler 2019]

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References

[1] Ying Cheng, Ken Chen, Hemeng Sun, Yongping Zhang, and Fei Tao. 2017. Data and Knowledge Mining with Big Data towards Smart Production. Journal of Industrial Information Integration (2017). https://doi.org/10.1016/j.jii.2017.08.001

[2] A. K. Choudhary, J. A. Harding, and M. K. Tiwari. 2009. Data mining in manufacturing: A review based on the kind of knowledge. Journal of Intelligent Manufacturing 20, 5 (2009). https://doi.org/10.1007/s10845-008-0145-x

[3] A. Harding, M. Shahbaz, Srinivas, and A. Kusiak. 2006. Data Mining in Manufacturing: A Review. Journal of Manufacturing Science and Engineering 128, 4 (2006). https://doi.org/10.1115/1.2194554

[4] Gülser Köksal, İnci Batmaz, and Murat Caner Testik. 2011. A review of data mining applications for quality improvement in manufacturing industry. Expert Systems with Applications 38, 10 (2011). https://doi.org/10.1016/j.eswa.2011.04.063

[5] Keqin Wang, Shurong Tong, Benoit Eynard, Lionel Roucoules, and Nada Matta. 2007. Review on Application of Data Mining in Product Design and Manufacturing. In FSKD 2007, Jingsheng Lei, Jian Yu, and Shuigeng Zhou (Eds.). IEEE, Los Alamitos, California. https://doi.org/10.1109/FSKD.2007.482

[6] Thorsten Wuest, Daniel Weimer, Christopher Irgens, and Klaus-Dieter Thoben. 2016. Machine learning in manufacturing: Advantages, challenges, and applications. Production & Manufacturing Research 4, 1 (2016). https://doi.org/10.1080/21693277.2016.1192517

[7] Stephen C-Y. Lu. 1990. Machine learning approaches to knowledge synthesis and integration tasks for advanced engineering automation. Computers in Industry 15, 1-2 (1990). https://doi.org/10.1016/0166-3615(90)90088-7

[8] Michał Woźniak, Manuel Graña, and Emilio Corchado. 2014. A survey of multiple classifier systems as hybrid systems. Information Fusion 16 (2014). https://doi.org/10.1016/j.inffus.2013.04.006

[9] Ethem Alpaydin. 2010. Introduction to machine learning (2nd ed. ed.). MIT Press, Cambridge, Mass. http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=307676