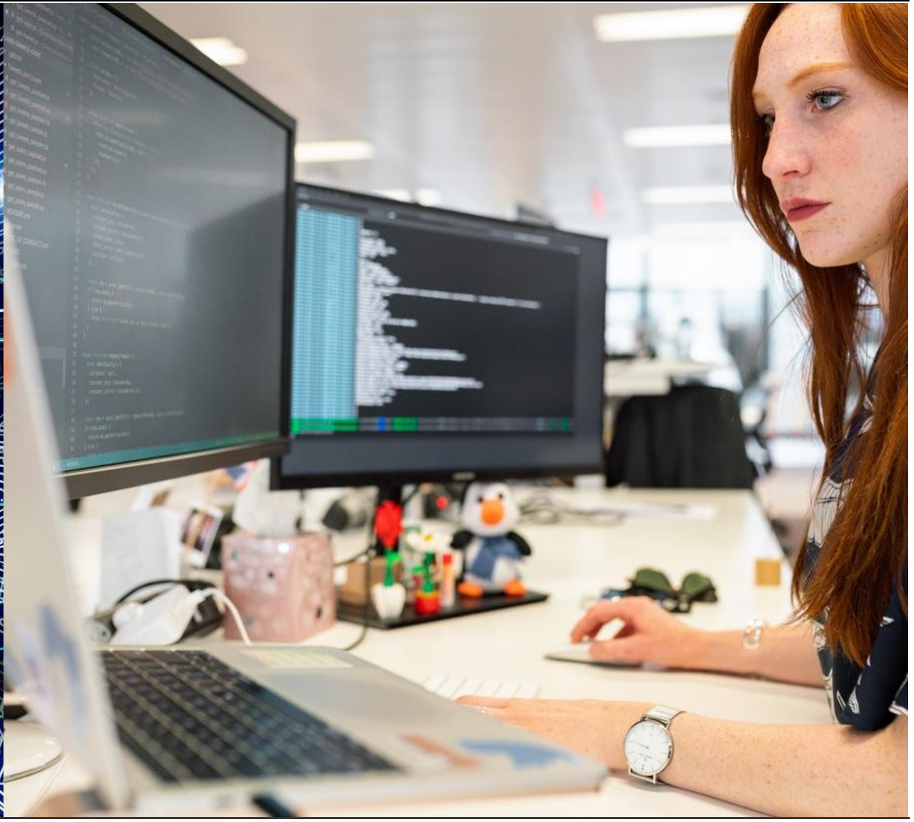
Software Engineering for Artificial Intelligence

Basics and Challenges



Outline

- Intelligent Systems
- When to Use Intelligent Systems
- Challenges of Intelligent Systems
  - Good Goals
  - SE Workflow
  - Technical Debt

Let‘s talk about Toast

Intelligent Systems [2]

Artificial Intelligence ← Intelligent System → User

Successful Intelligent Systems have:

Objective
- Meaningful to user
- Achievable

Experience

Intelligence Creation
- Through anything from simple heuristics to complex ML

Intelligent Experience [2]

- Achieve system‘s objective
- Present intelligence to users
  - Balance quality with forcefulness
  - Key actions: automate, prompt, organize and annotate
- Minimize intelligence flaws
  - Experience can avoid risky decisions
  - Experience can control the number of user interactions
  - Experience can use less forceful actions in risky situations
- Create data for system growth
  - Experience must know the interaction context, the action taken by the user, and the outcome

Intelligent Systems [2]

TECHNISCHE UNIVERSITÄT DARMSTADT

Artificial Intelligence ← **Intelligent System** → **User**

Successful Intelligent Systems have:

Objective
- Meaningful to user
- Achievable

Implementation

Experience
- Presents output to the user
- Minimizes mistakes
- Must collect feedback

Intelligence Creation
- Through anything from simple heuristics to complex ML

Orchestration
- Controlling system changes
- Keep experience in sync with intelligence quality
- Involves dealing with mistakes, controlling risks and defusing abuse

Intelligence Implementation [2]

- Intelligence Runtime: executes the intelligence and gathers the context of the interaction
- Intelligence Management: deploying new versions of the intelligence
- Monitoring and Telemetry Pipeline: what and how to observe, sample, and summarize what is going on
- Intelligence Creation Environment: intelligence creator must be able to recreate runtime context to create accurate intelligence
- Intelligence Orchestration: controlling the system, i.e., when the intelligence evolves, runs into problems

Intelligent Systems [2]

Artificial Intelligence ← Intelligent System → User

Successful Intelligent Systems have:

Objective
- Meaningful to user
- Achievable

Implementation
- Executing system
- Includes telemetry and feedback

Experience
- Presents output to the user
- Minimizes mistakes
- Must collect feedback

Intelligence Creation
- Through anything from simple heuristics to complex ML

Orchestration
- Controlling system changes
- Keep experience in sync with intelligence quality
- Involves dealing with mistakes, controlling risks and defusing abuse

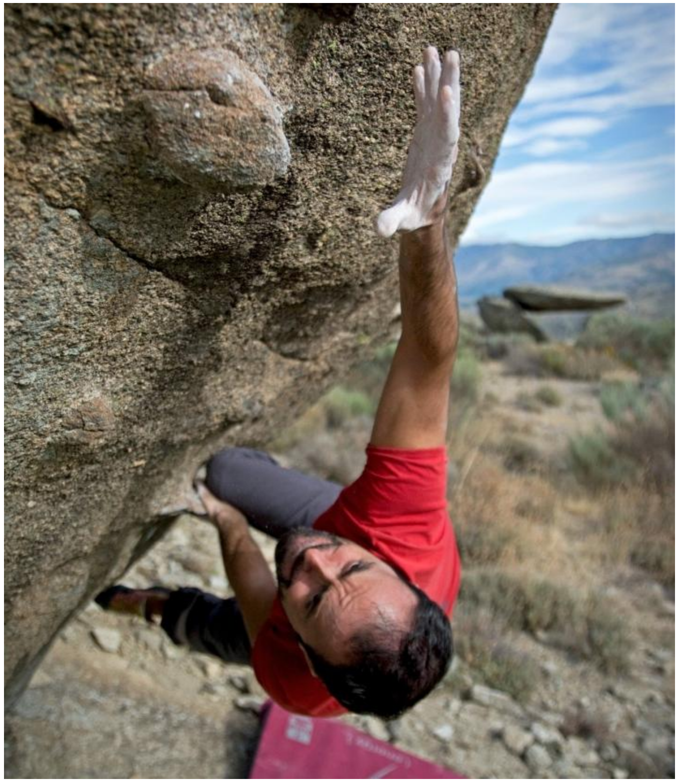
When to Use Intelligent Systems [2]

Intelligent systems should be only used for complex problems

- Complex problems: *big, open-ended, time-changing* or *intrinsically hard*
- Requirements for intelligent systems
  - Partial solution must be viable and interesting
  - Usage data must be recordable (to improve the system)
  - Ability to influence meaningful objective
    - Objective should be *directly* and *quickly* affectable; taken actions should be *measurable* in the outcome
  - Problem must justify effort
    - Intelligence creation is cheaper than in other methods, but the overhead is very expensive

Challenges

ML challenges remain, but the SE challenges of intelligent systems are much broader



General ML Challenges [1]

- Insufficient Quantity of Training Data
- Nonrepresentative Training Data
- Poor-Quality Data
- Irrelevant Features
- Overfitting the Training Data
- Underfitting the Training Data

Challenges: Good Goals [2]

TECHNISCHE UNIVERSITÄT DARMSTADT

Intelligent System

Intelligence + **Experience** → **Outcome**

Targeted at right problem

Encourages correct user behavior

Achievable

Challenges: Good Goals [2]

- **Communicate desired outcome** to everyone with clear importance and understanding of success
- **Are achievable,** meaning there is an explainable approach and a likely chance of success
- **Are measurable**, optimizing for non-measurable goals is impossible

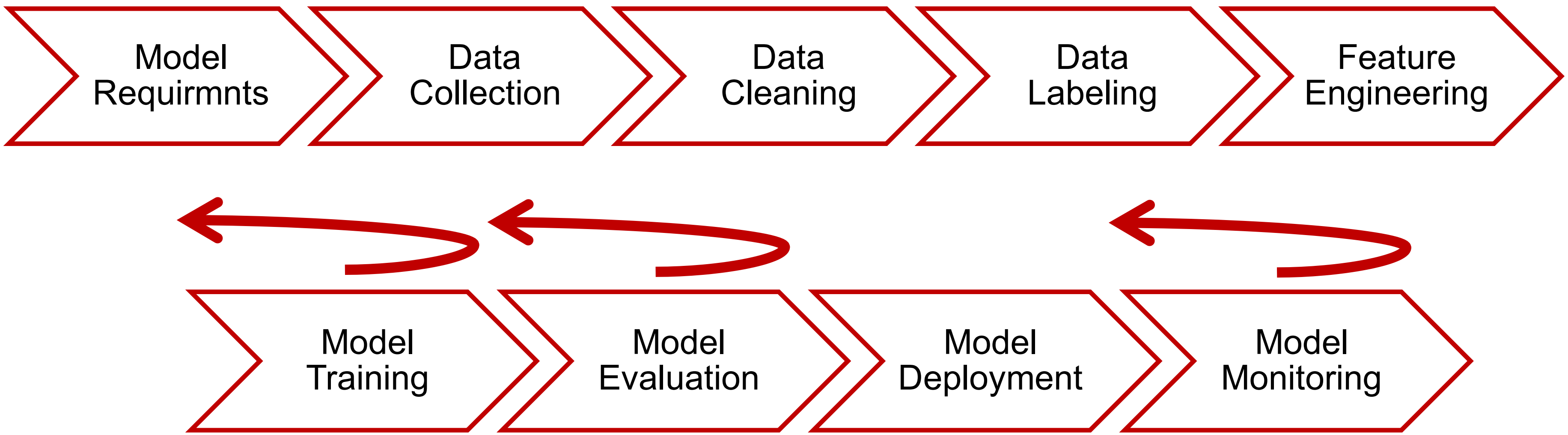
Abstract goals | Very concrete

organizational objectives | leading indicators | user outcomes | model properties

Effective goal sets tie usually goals of various types together

SE Workflow [4]

- Case study at Microsoft: 9 stages ML workflow with big feedback loops



- Big difference to „traditional software“: Very data centric & more loops

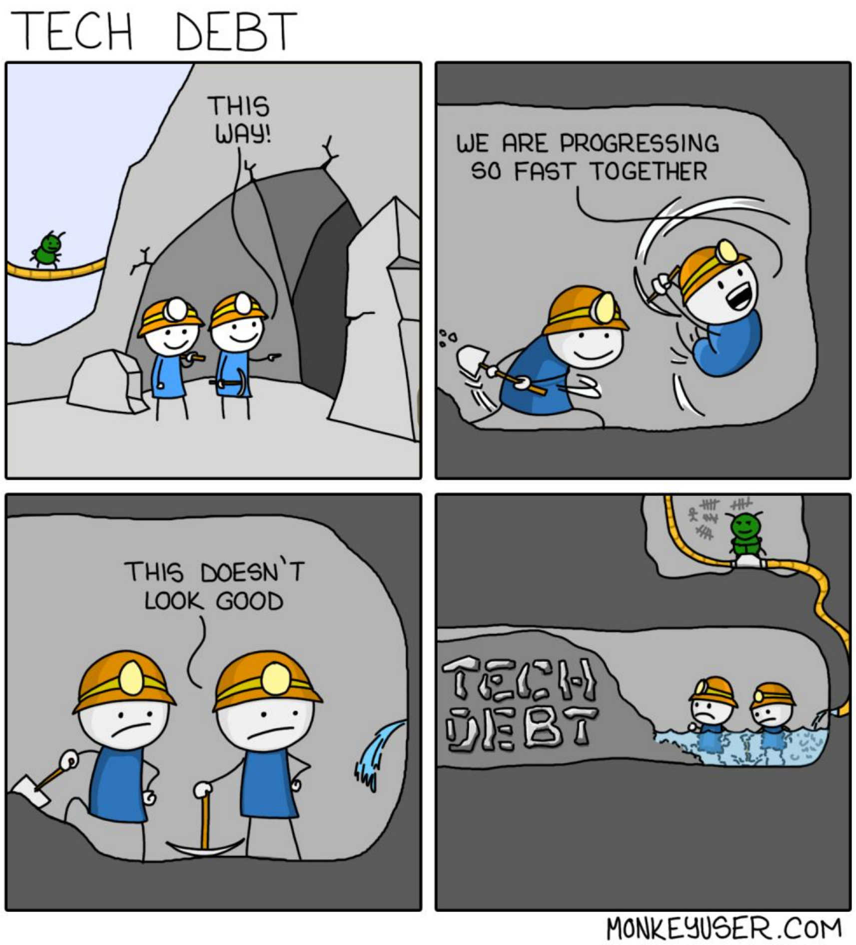
SE Workflow: Fundamental Differences [4]

TECHNISCHE UNIVERSITÄT DARMSTADT

- SE is about software code, ML is all about data for learning models
  - Software has specifications, datasets usually do not have specifications
  - Specifications change rarely, data schemas may change very frequently
  - No mature tools for data versioning and meta-data management, while for code these systems exist
- Customization and reuse of models is harder than of code
  - Even a slight variation in the usage scenario may require deep changes to the model, training data or the executing system
- Modularity in ML and strict boundaries between models are difficult
  - Models are not easily extensible
  - Models interact in non-obvious ways: model results affect others training and tuning processes; isolated development is hard

Technical Debt

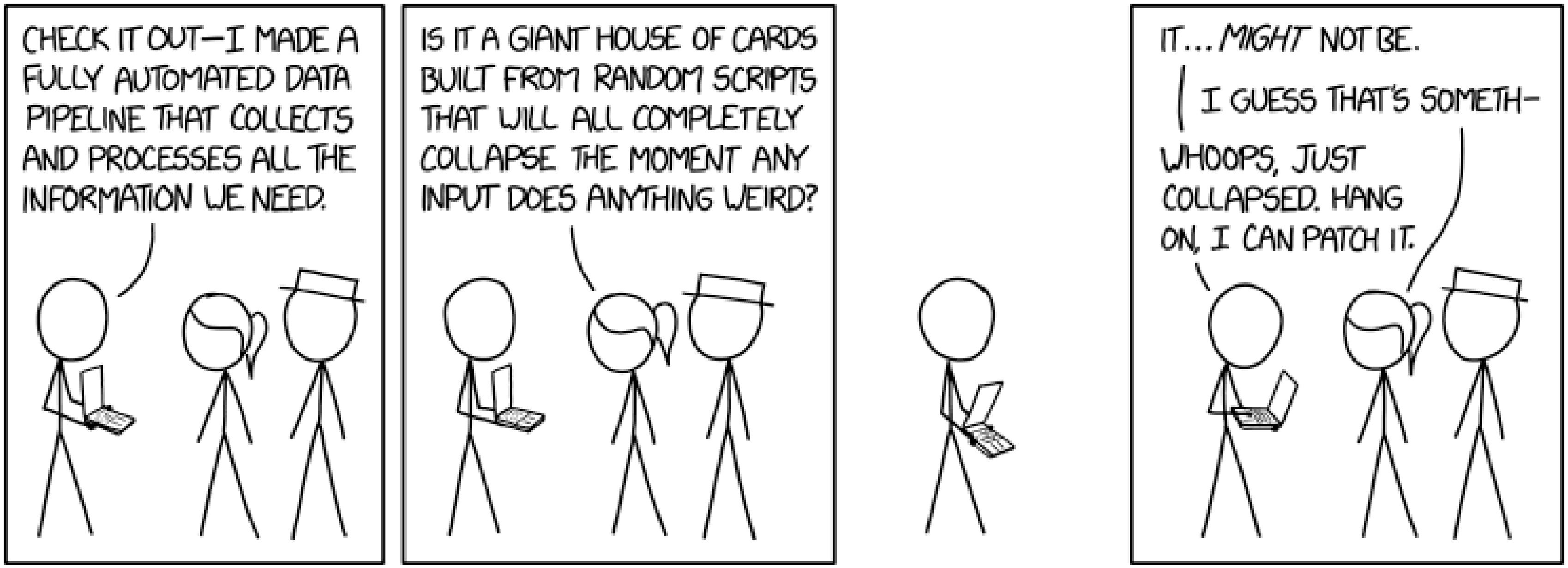
- SE is all about making **qualified decisions** based on tradeoffs
- Sometimes decision are knowingly taken, which are good in the short run, but will cause more work in future: „technical debt“



https://www.monkeyuser.com/2018/tech-debt/
(accessed on 04.05.2020)

Technical Debt

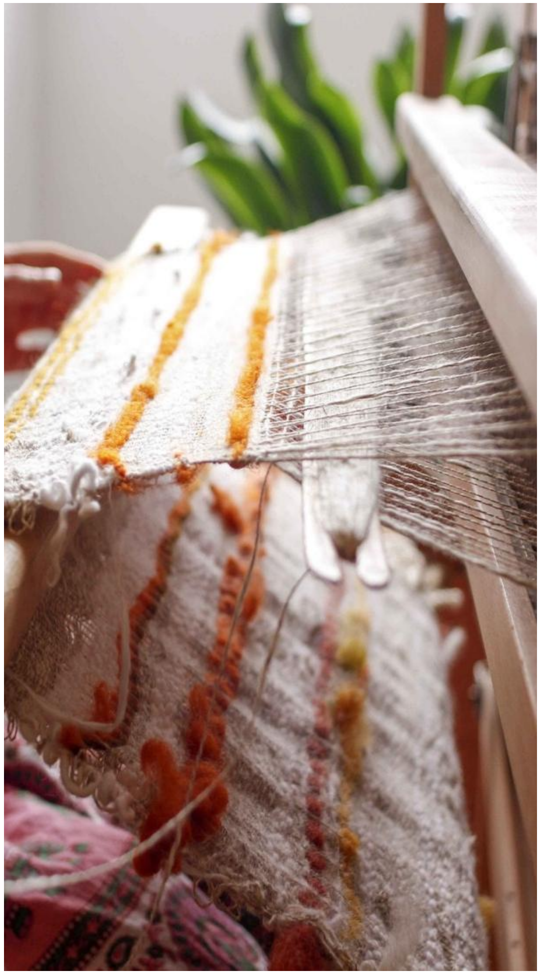
Sources of technical debt are ubiquitous in today‘s ML



https://xkcd.com/2054/ (accessed in 04.05.2020)

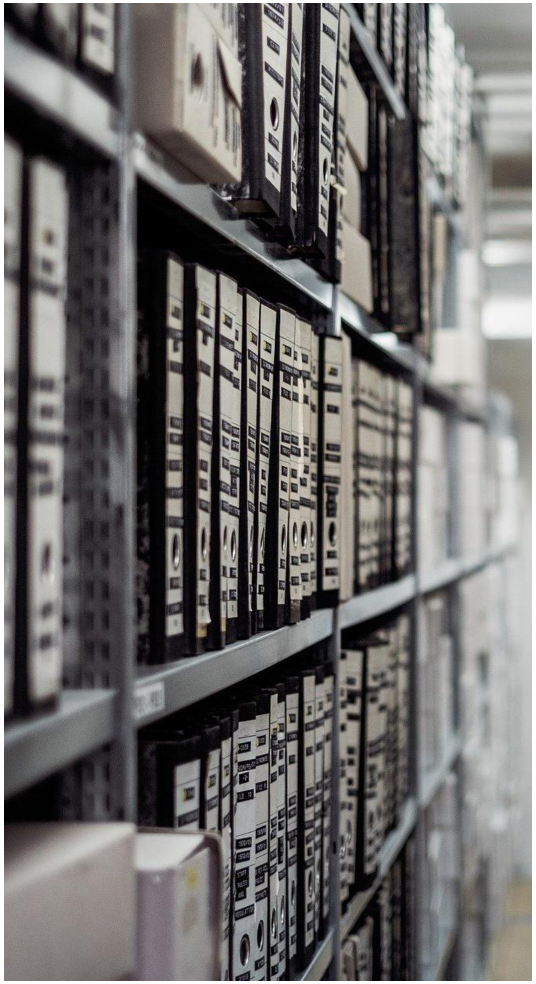
Hidden Technical Debt in ML Systems [3]
1. Model Complexity

- Entanglement: ML mixes many different external and internal signales; isolated improvement is impossible, wherefore changes are expensive
- Correction Cascades: For reuse it is tempting to add a new tiny AI on top of a existing one, but this makes analysis and improvement much more expensive
- Undeclared Consumers: Opening AI results is great for re-use, but makes overall progress much more expensive



Hidden Technical Debt in ML Systems [3]
2. Data Dependencies

- Data dependencies cause **dependency debt**, which is hard to detect; code dependencies are easily traceable through static analysis
- Unstable Data Dependencies: Some sources might vary in quality and quantity of provided data
- Underutilized Data Dependencies: Some data sources might not really be relevant to the outcome of the intelligence, however, they still increase complexity



Hidden Technical Debt in ML Systems [3]
3. Feedback Loops

- Intelligent systems offten influence their own behavior through feedback loops
- Causes **analysis debt**: behavior after release is hard to, if it depends on the sexecution
- Direct Feedback Loops: Explicitly build in loops, e.g., for selection of future training data
- Hidden Feedback Loops: Implicit feedback loops, e.g., through reactions of users
  - Example: ML-based stock market agents: developed separately, but through shared market they influence each other and themselves

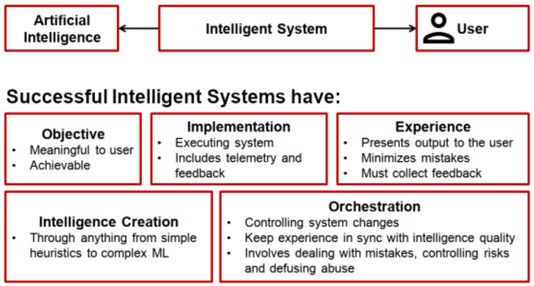
Hidden Technical Debt in ML Systems [3]
4. Others

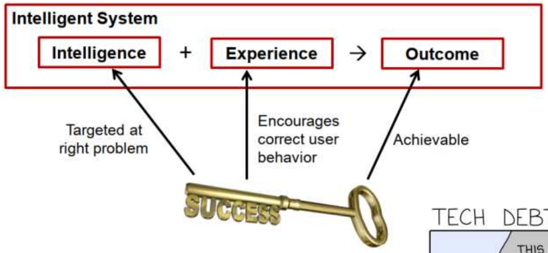
TECHNISCHE UNIVERSITÄT DARMSTADT

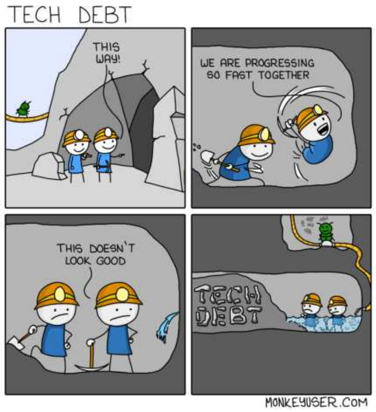
- Anti-patterns
  - Glue Code: big support code makes the system heavy
  - Pipeline Jungles: special kind of glue code; expensive to test
  - Dead Experimental Codepaths: common source of sudden errors
- Common Smells
  - Plain-old-data type smell
  - Multiple-language smell: Increases testing complexity and makes ownership transition often harder
  - Prototype smell

Summary

- Intelligent systems connect AI and users
  - Objective, intelligence creation, implementation, experience, and orchestration
- Intelligent systems should be only used for complex problems
- Challenges include:
  - Definition of Goals
  - Differences between SE for 4ML and traditional SE methods
  - Ubiquitous sources of technical debt in ML







Literature

- [1] Géron, Aurélien. **Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems**. 2nd edition. O'Reilly. 2019. https://ebookcentral.proquest.com/lib/ulbdarmstadt/detail.action?docID=5892320
- [2] Chapter 1, 2, 4, 5 and 11 of Hulten, Geoff. **Building Intelligent Systems: A Guide to Machine Learning Engineering**. Apress. 2018. https://hds.hebis.de/ulbda/Record/HEB461642786
- [3] Sculley, David, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, and Dan Dennison. **Hidden Technical Debt in Machine Learning Systems**. In Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2, pp. 2503 - 2511. 2015. http://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf
- [4] Amershi, Saleema, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann. **Software Engineering for Machine Learning: A Case Study**. In 2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP), pp. 291-300. 2019. https://ieeexplore.ieee.org/document/8804457

Discussion

Acknowledgements & License

TECHNISCHE UNIVERSITÄT DARMSTADT

- Material Design Icons, by Google under Apache-2.0
- Other images are either by the authors of these slides, attributed where they are used, or licensed under Pixabay or Pexels

- These slides are made available by the authors (Daniel Sokolowski, Guido Salvaneschi) under CC BY 4.0