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Requirements and Risks

Overview

1. AI makes mistakes
2. Requirements
3. Risks
4. Risks mitigation ideas
   - Feature selection
   - Testing
   - Monitoring
5. Conclusion

AI makes mistakes

The mistakes intelligence makes:

- Aren’t necessarily intuitive.
- Aren’t the same from day to day.
- Aren’t easy to find ahead of time.
- Aren’t possible to fix with “just a little more work on intelligence.”

Different types of mistakes

The Intelligence says some is

Someone actually is		There	Not there
	There	True positive	False negative
	Not There	False positive	True negative

AI Changes

- If it learns something new, it maybe changes the result.
  - …but in which way?
- We control the way AI changes

Humanfactor

- Confusion
- Distrust
- Lack of confidence
- Fatigue
- Creep Factor

Intelligence Quality

- What makes an AI a good AI?
  - It depends on the use case
- A better Intelligence can support more forceful, frequent experiences
- Change comes from improved intelligence

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Requirements Engineering

- The Process of defining the Specifications of the Software
- A lot of definitions and standards (e.g. IEEE 830)

Types of Requirements

- Functional requirements
  - What the system should do in terms of functionality
  - Input & output, response to events
- Quality (non-functional) requirements
  - How well the system delivers its functionality
  - Performance, reliability, security, safety, availability...

Specification in AI

Hard specifications are difficult

- Available Data is often small or partially describe the wanted AI model
- Accuracy is often not the requirement in an AI system (it’s quite okay if the model makes wrong predictions)

Importance of Context

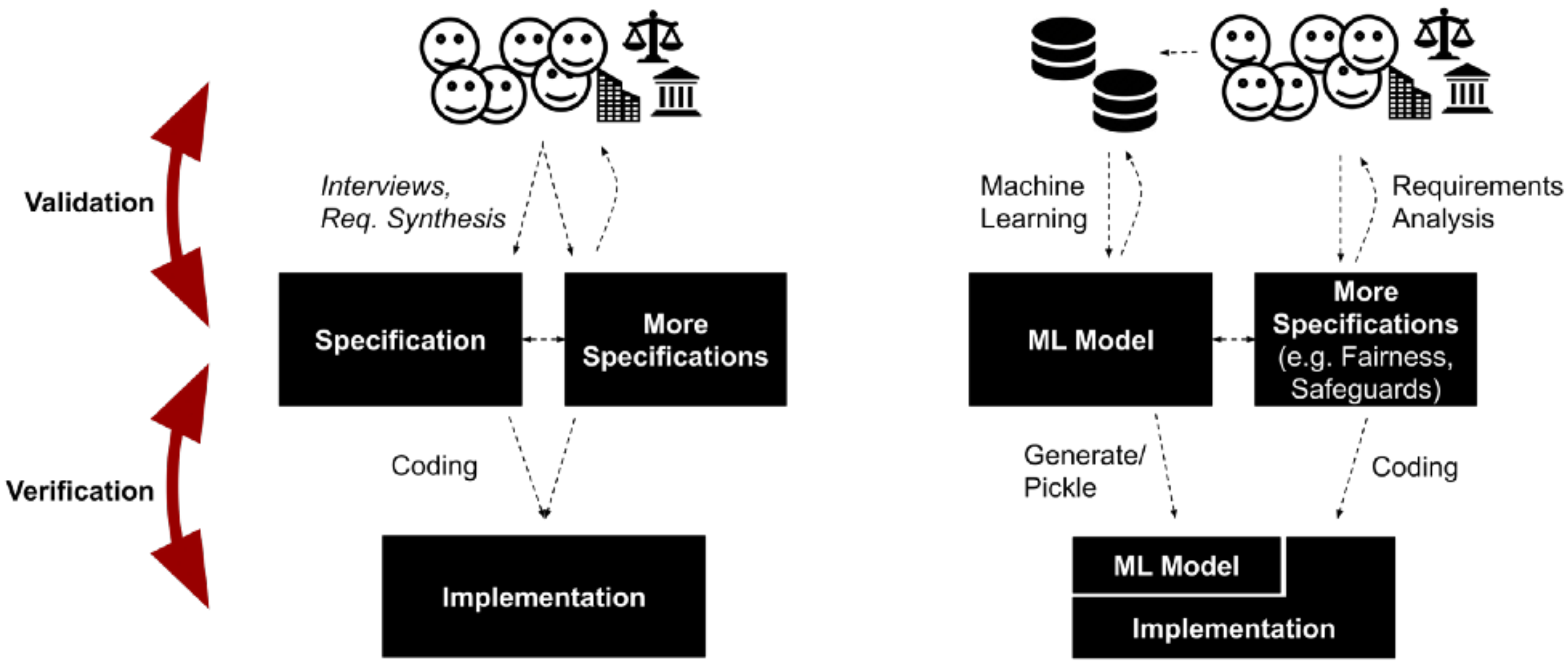
Too many parameters, features, sensors and the human factor (complex problem)

- Slicing context to simple smaller problems
- Monitoring user activities
- Training AI to target smaller problems
- Continual verification

AI Models are specifications

- The AI Model is just a Specification
  - What should it do?
- If the implementation is correct but the result is wrong, it could be the wrong Model

Machine learning is like requirements engineering



Machine Learning as Requirements Engineering (Source [1])

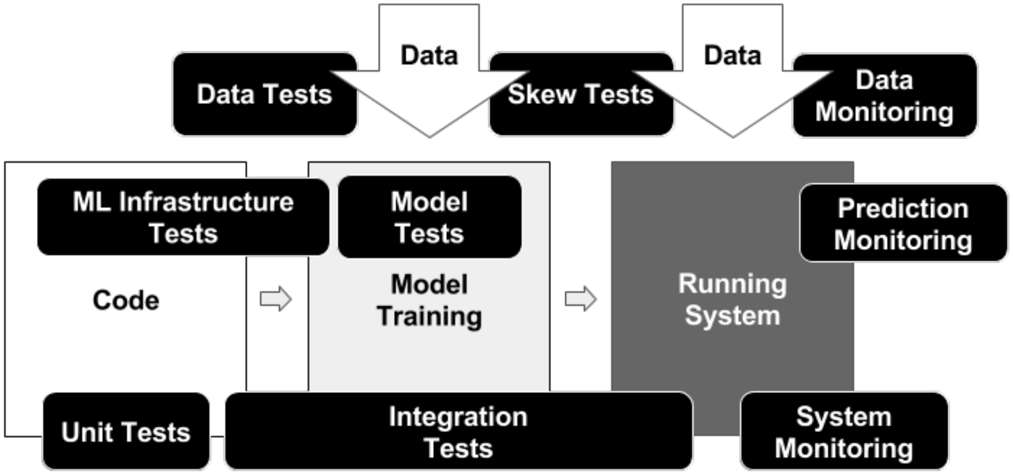
Machine learning is like requirements engineering

Assuming AI models are specifications

- We need to identify relevant and representative data
- In both machine learning and requirements engineering, we may need to compromise user-desired functionality with laws governing privacy, fairness, or security
- When we identify that the specification does not fit, we have often gained valuable insights and in some cases learn something immediately actionable

Intelligent Experiences are Complex

- Understanding AI mistakes is not intuitive
- Unmitigated mistakes may result in system distrust
- False positives and false negatives may result in confusion



ML-Based Testing and Monitoring (Source [2])

→ Lack of confidence, safety and reliability in the system

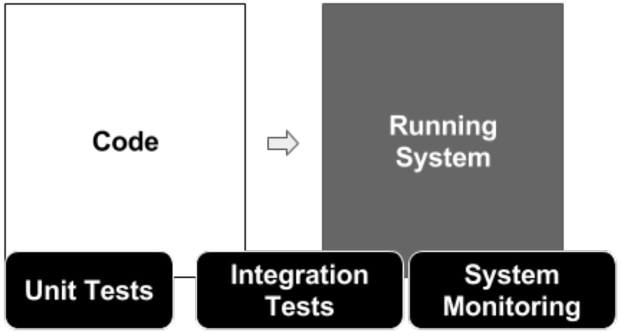
Risks Mitigation

❖ Complex AI systems require constant testing and monitoring

→ **Large technical debt**

❖ Traditional ways of paying debt

1. Code refactoring
2. Increasing coverage of unit tests
3. Reduce dependencies
4. Improving documentation



Traditional System Testing and Monitoring (Source [2])

→ **Code and system-level complexity for ML**

Data and Feature Selection

1. Identify expected features from the training data in schemas with help of statistics for future analysis
2. Understanding the value of every feature
3. Reduce the feature set to the features that add the most predictive benefit
4. The training data has appropriate privacy controls

Testing

1. Version control for the model code and training data
2. Use A/B testing to understand online vs. offline result evaluation and model’s staleness
3. Use data slicing to understand model quality
4. Enforce ML faireness
5. Implement unit test for API usage
6. Implement assertions to verify the ML’s algorithmic sub-computations

Monitoring

It’s important verify that the ML system is working over time

→ In case of an incident that ML system code can be rolled back

How?

1. Notify on dependency changes
2. Log traffic and label data of new evolving features for future analysis
3. Measure statistical bias in predictions to monitor prediction quality

Conclusion

- AI makes different and unpredictable mistakes
- Undestanding AI mistakes isn’t intuitive
- AI changes over time
- Understanding context is a complex task
- Requirements engineering produces large amount of technical debt
- Possible mitigations:
    1. Data and Feature Selection
    2. Testing
    3. Monitoring

Questions

THANK YOU FOR YOUR ATTENTION!

References

[1] Kaestner, C., “*Machine Learning is Requirements Engineering — On the Role of Bugs, Verification, and Validation in Machine Learning*”, https://medium.com/analytics-vidhya/machine-learning-is-requirements-engineering-8957aee55ef4, 2020 (visited 07.06.2020).

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[3] Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V. & Young, M., “*Machine Learning: The High Interest Credit Card of Technical Debt*”, SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop), 2014.

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