Iowa State University

COMS 509

Requirements Engineering for Machine Learning: Perspectives from Data Scientists

Vogelsang, Andreas, and Markus Borg.

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Overview

1. Where does the problem start?
2. Types of ML Approaches
3. High-Level Idea of different ML approaches
4. The Problem
5. Contribution of the paper
6. Suggested RE-process for ML Systems
7. An interesting study by Microsoft team
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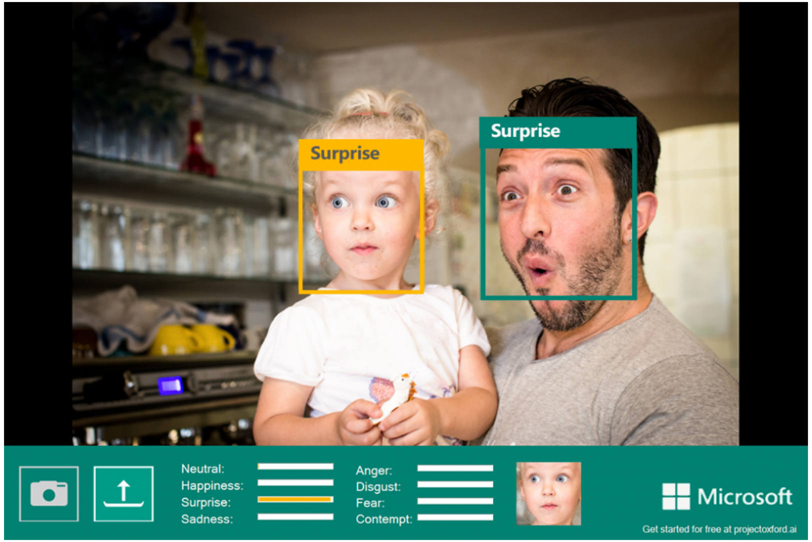
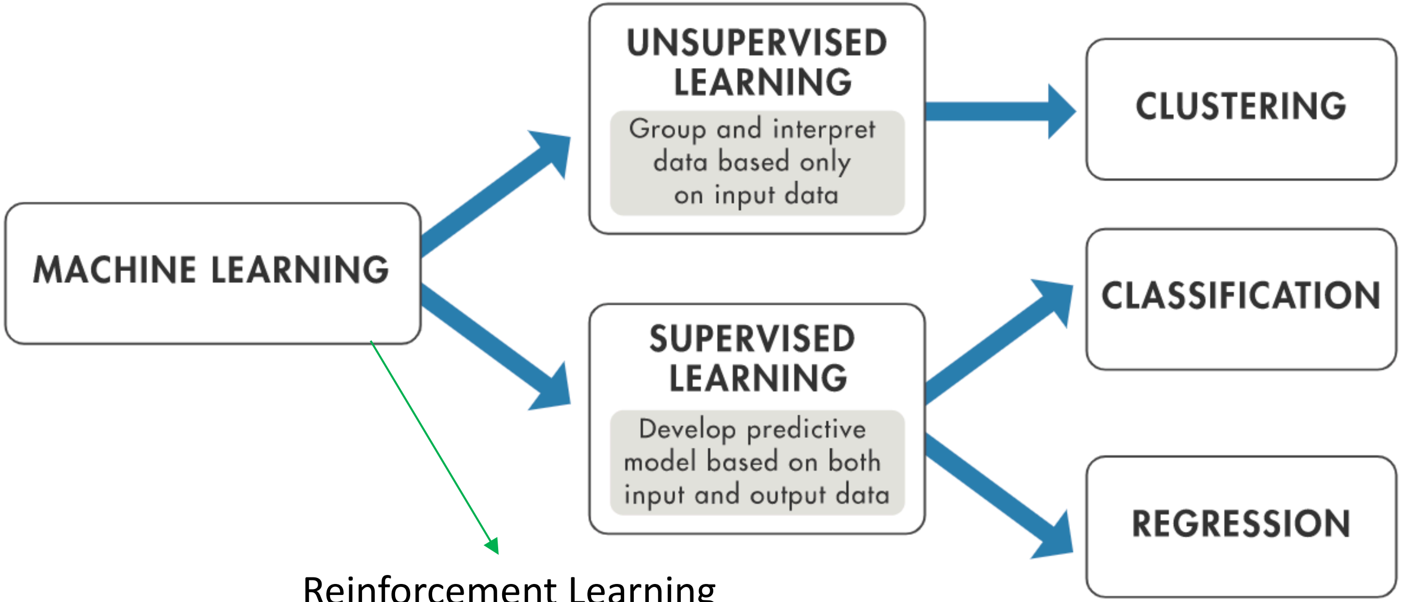
Where does the Problem start?

- Machine Learning (ML) has accomplished major technical breakthroughs in image recognition, natural language processing, and beating humans in complex games.
- This is made possible by
  - Improved computational power of modern processors (GPUs)
  - Large availability of data
  - Accessibility of these complex technologies by rather simple-to-use frameworks and libraries
- Many companies started using ML to improve their products and processes.

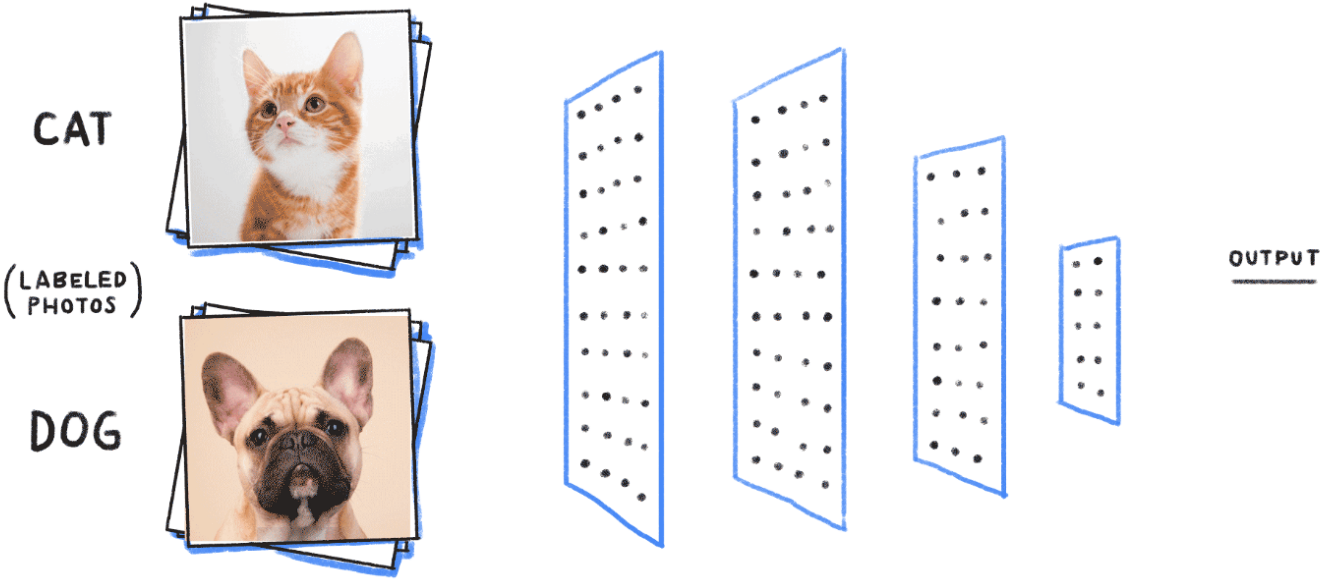


Types of ML approaches

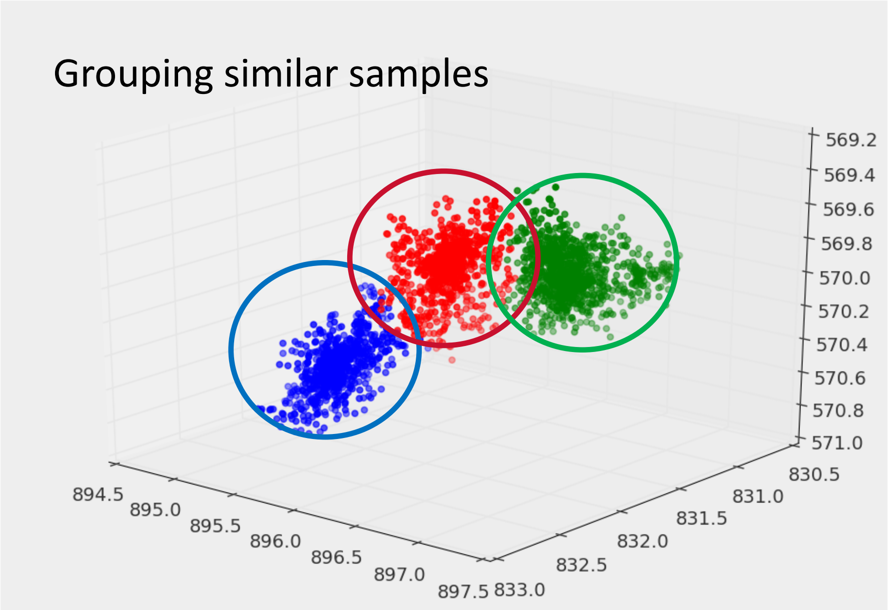


Reinforcement Learning

How does ML work? An Example of Supervised Learning - Classification



Clustering and Regression



Clustering

Effect

Cause

$$y = a + bx$$

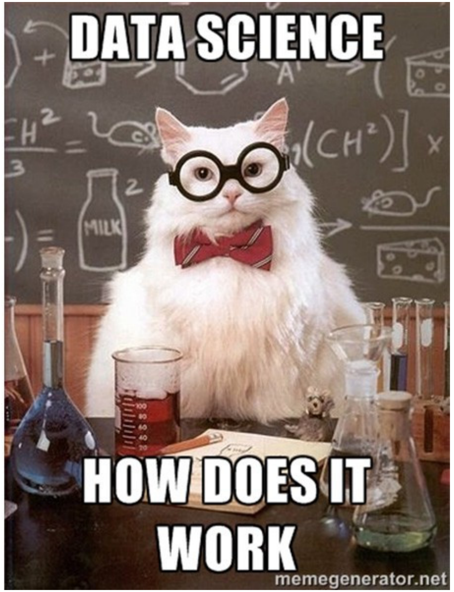
Income

Education

Linear Regression

The Problem – Paradigm shift

- A paradigm shift compared to conventional software engineering.
- In this paper, the authors share results that indicate that RE must evolve to match the specifics of ML systems.
- Right now, Data Scientists decide the **definition of the fitness functions, the selection and preparation of data, and the quality assurance**.
- However, these decisions should be based on the understanding of the business domain and the stakeholder needs.



Contribution of the paper

- Conducted interviews with four data scientists to explore their perceptions on RE.
- The interviews covered specific requirements for ML systems, challenges involved in RE for ML, and how the RE process needs to evolve.
- We were interested in the following research questions:
  - **RQ1:** How do data scientists elicit, document, and analyze requirements for ML systems?
  - **RQ2:** What processes do data scientists follow and which parts relate to requirements?
  - **RQ3:** What are requirements-related challenges that data scientists face?

A. Quantitative Targets a.k.a. Functional Requirements

- Just like for conventional software products, it is **hard to satisfy a client without making expectations explicit**.
- Interviewees mentioned measures to quantify the predictive power including accuracy, precision, and recall. P3: "**The customers don't understand the performance measures**."
- **Selecting and interpreting performance measures appropriately** is crucial for the acceptance of ML systems.
- Interviewees stressed that data scientists need skills to help a client set **reasonable targets**, including domain understanding, statistics, and computer science.
- **In ML systems, the quality of the resulting predictions can be considered a functional requirement**

B. Explainability

- ML systems are **hard to understand for human analysts** since models are adjusted to fit **specific data**.
- The **ability to explain decisions** in ML systems depends on the used technology.
- **A Requirements Engineer should elicit explainability requirements from a user's point of view**

Difference in Performance Measures

Classification

Performance Metric – Accuracy, Precision, Recall

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{1 + 90}{1 + 90 + 1 + 8} = 0.91$$

Regression

Performance Metrics - RMSE/MAE/MAPE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative
RMSE – Root Mean Square Error, MAE – Mean Absolute Error, MAPE – Mean Absolute Percentage Error

C. Freedom from Discrimination

- ML systems are designed to discriminate - identify recurring patterns in data (i.e., stereotypes) and apply these patterns to judge about unseen data.
- Some forms of discrimination are considered as unacceptable by our society or by law (e.g., race or gender)
- Introduced by unrepresentative training data
- Availability of tools and algorithms that can balance discrimination
- Need to know which attributes you must balance
- **Hence, a requirements engineer must elicit and identify the “protected” characteristics that must not be used by the ML algorithm to discriminate samples.**

D. Legal and Regulatory Requirements

- An example is how the General Data Protection Regulation (GDPR) constrains that personal data can only be used in ways specified by an explicit consent.
- Revoked Consent leads to retraining of the whole model
- **Requirements engineers working on ML systems must stay on top of legal requirements, to ensure no illegal features have influenced the final dataset used for training the ML models**

E. Data Requirements

- Training data is an integral part of any ML system.
- Training data need specified and validated requirements like code
- **Data Quantity and Data Quality**
- Requirements on data quantity should not be specified on the number of examples but rather on the **diversity of the examples**
- The **higher the quality** of the data, the better the application will work.

RE-PROCESS FOR ML SYSTEMS

A. Elicitation
B. Analysis
C. Specification
D. Verification and Validation (V & V)

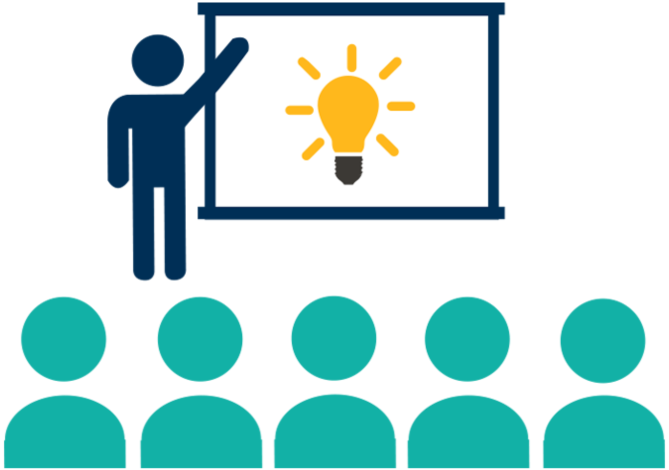
TABLE I
RE FOR ML: IMPACT ON RE ACTIVITIES

Elicitation	Analysis	Specification	V&V
• Elicit additional data sources • Important stakeholders: Data scientists and legal experts • "Protected" characteristics?	• Discuss performance measures • Discuss conditions for data preparation, definitions of outliers, and derived data	• Quantitative targets • Data requirements • Explainability • Freedom from discrimination • Legal and regulatory constraints	• Analyze operational data • Look for bias in data • Retrain ML models • Detect data anomalies

A few more observation from a study by Microsoft team[2]

- More education and training
- **ML modularity is not the same as software modularity** –
  - Need for maintaining strict module boundaries
  - Each model's results will affect one another's training and tuning processes
- **Customization and Reuse** –
  - straightforward only in similar domain
  - model may require retraining, or worse, may need to be replaced with another model
- **Data Discovery and management –**
  - Engineers must find, collect, curate, clean, and process data for use in model training and tuning.
  - While there are very well-designed technologies to version code, the same is not true for data

Evaluation



- If these changes are made, it would benefit significantly
- One of the main challenges will be to provide training to the Requirement Engineers.
- Knowledge transfer
- Hyperparameter Tuning
- REs would need substantial experience to understand where to look to find out requirements.
- And of course, more communication should be encouraged between the REs and the Data Scientists.

References

[1] Vogelsang, Andreas, and Markus Borg. "Requirements Engineering for Machine Learning: Perspectives from Data Scientists." *2019 IEEE 27th International Requirements Engineering Conference Workshops (REW)*. IEEE, 2019.

[2] Amershi, Saleema, et al. "Software engineering for machine learning: A case study." *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE, 2019.

Questions