

University of Applied Sciences and Arts Northwestern Switzerland School of Business

Combining Machine Learning and Knowledge Engineering



Challenges for Data Driven Solutions

- Consistency of Past and Future
- Cold Start/ New Products
- Explanations
- Compliance

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A Temporal View



Prof. Dr. Knut Hinkelmann

Time

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Consistency of Past and Future

Example: Changes in Customer Behaviour because of climate change and Pandemic



Consistency between Data and Intent

Customers also bought



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Talisker Skye Single Malt Scotch Whisky 70cl mit Etui und 2 Rocking Gläsern

CHF 58.00



The Ultimate Mortlach 2008 Single Malt Scotch Whisky 70cl

CHF 68.00



Talisker Port Ruighe Single Malt Scotch Whisky 70cl mit Etui

CHF 65.00



Kopfgetriebeöl 10T30 Nuss-Karamell Likör 50cl

CHF 24.90



Cold Start: New or Limited Products

Limited Editions







New Distilleries/Brands



Small Batch



Explanations

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Can decisions without explanation be intelligent?



Trust Compliance Traceability

In particular for subsymbolic learning (neural networks) $\mathbf{n}|_{\mathcal{U}}$

Diagnosis







Compliance with Regulations

Example: Autonomous Driving

 Machine Learning: Driving Behaviour





Knowledge Engineering: Traffic Rules n

Compliance Rules

Example: Eligibility Decision for Insurance



Accept yes/no

Combining Machine Learning and Knowledge Engineering for Eligibility Decisions (1/2)

Example: Application of health insurance

Machine Learning: data records about risks of clients

| | Age | surgery | docvisit | allergy | med | disieases | bmi | class |
|---|-----|---------|----------|---------|-----|-------------|-----|-------|
| 1 | 20 | 0 | 2 | no | no | cholesterol | 28 | low |
| | 21 | 0 | 4 | no | no | no | 23 | low |
| | 49 | 2 | 12 | yes | yes | heart | 34 | high |
| | 22 | 0 | 3 | no | no | no | 23 | low |
| | 51 | 2 | 2 | yes | yes | diabetes | 26 | high |
| | 52 | 2 | 8 | no | no | heart | 31 | high |
| | 52 | 0 | 3 | yes | no | no | 22 | low |
| | 52 | 2 | 12 | yes | yes | diabetes | 27 | high |
| | 52 | 0 | 11 | yes | no | cholesterol | 29 | high |
| | 23 | 0 | 3 | no | no | no | 23 | low |

• Engineered knowledge: eligibility and compliance

Applicants from Switzerland are eligible. A person younger than 21 year is not able to apply





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Combining Machine Learning and Knowledge Engineering for Eligibility Decisions (2/2)

Examples of learned rules:

| risk (Person, high) :- | age(Person,A), A > 50, | | | |
|------------------------|-----------------------------|--|--|--|
| | bmi(Person, Bmi), Bmi =<25, | | | |
| | disease(Person, diabetes). | | | |
| risk (Person, low) :- | age(Person,A), A =< 29. | | | |
| | | | | |

Examples of engineered rules:

eligible(Person, no) :- age(Person,A), A =< 21. eligible(Person,no) :- country(Person,C), C =/= switzerland.

Combining engineered and learned rules:

accept(Person, yes) :- eligible(Person, yes), risk(Person, low).
accept(Person, yes) :- eligible(Person, yes), risk(Person, medium).
accept(Person, no) :- eligible(Person, no).
accept(Person, no) :- risk(Person, high)

Learned Knowledge Engineered Knowledge



Combining Machine Learning and KnowledgeBaseMachine LearningKnowledge Base



- Tacit or unknown knowledge
- Stable knowledge

- Knowledge we are aware of
- Knowledge that must be correct
- Explanations

Summary: Creating Knowledge Bases

- **Knowledge Engineering:** Human experts build knowledge base
 - For knowledge we are aware of
 - For knowledge that must be correct (e.g. compliance rules)
 - Inferences are explainable (trust)

Machine Learning: automatic creation of knowledge from example data

- Can solve complex tasks for which
 - knowledge is not known
 - knowledge is tacit
- For stable world, where future can be predicted from past
- Reliance on real-world data instead of pure intuition
- Requires large sets of data



