

integreat

The Norwegian centre for knowledge- driven machine learning

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Challenges of contemporary machine learning:

- Algorithms are fragile and lack robustness
- Most methods lack transparency and explainability
- Data and loss functions/rewards might be biased and discriminating
- Uncertainty around results are not, or poorly, quantified
- Algorithms depend on huge amounts of curated data
- Algorithms require excessive energy to train and run (and store)
- ++

Integreat will transform machine learning to address these challenges

Today

Machine learning is mostly data centric and has difficulties in incorporating existing knowledge

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Knowledge-driven and data informed machine learning

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Knowledge-driven and
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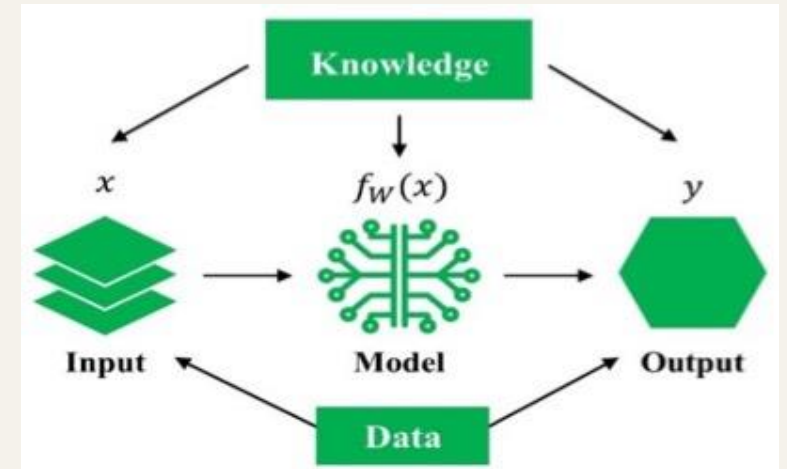


- Accurate
- Sustainable
- Explainable and trustworthy
- With quantified uncertainty

Knowledge-driven?

Knowledge about

- structures, processes and dynamics of the system
- data generating mechanisms



Knowledge might be

- exact (in the form of must-links and cannot relationships, logical formalisations and formal ontologies, mathematical models)
- more imprecise, soft or subjective (in the form of most-likely-links, prior beliefs and stochastic relations)

Accurate

Knowledge can compensate for bad data:

- Makes it possible to solve problems that otherwise would not be solved, due to bad data, small data, or lack of (enough) labelled data

Sustainable

Knowledge-driven ML saves energy:

- Reuseing and integrating data, exploiting transfer learning and causal inference, using more parsimonious models
- Storage also consumes energy: Knowledge-driven methods to compress, project and reduce data, while controlling the loss of information

Quantifying uncertainty

Data are incomplete, noisy and inconsistent; knowledge and models are imperfect; algorithms are approximate. Therefore, estimates, predictions and decisions are uncertain:

- Represent and model multiple sources of uncertainty probabilistically
- Uncertainty quantification can reveal disagreement between data and knowledge, as well as between different data sources
- Develop methods that automatically alert of such discrepancies
- By combining knowledge and data, we reduce the uncertainty of solutions

Explainable and trustworthy

- Declaring knowledge allows its critique
- Using knowledge to de-bias datasets and models
- Understand the inner-workings of black- and grey-boxes, by augmenting them with knowledge-based explainable white-box components

Others already do

- physics-informed deep learning
- hybrid modelling

We integrate ML, statistics and logic

- **ML** is inductive, learns about the world by examples
- **Logic** is deductive, with rules, principles and reasoning describing and representing knowledge
- **Statistics** is inferential, learns models, quantifies uncertainty

Example: Learning from inconsistent preference data

Preference learning

- Users compare items in pairs: which is preferred?
- Used in psychology, social sciences, marketing ...

Some comparisons of 300 items

1 million users

```
{( A3 < A5 ), ( A7 < A5 )}  
{( A2 < A9 ), ( A6 < A5 ), ( A6 < A10 ), ( A8 < A1 ), ( A8 < A7 )}  
{( A1 < A9 ), ( A4 < A5 ), ( A4 < A10 ), ( A8 < A7 ), ( A9 < A2 )}  
{( A1 < A4 ), ( A2 < A9 ), ( A3 < A4 ), ( A7 < A4 ), ( A9 < A1 )}  
{( A4 < A3 ), ( A4 < A7 ), ( A7 < A3 ), ( A7 < A10 )}  
{( A2 < A8 ), ( A1 < A2 ), ( A8 < A1 )}  
{( A4 < A1 ), ( A9 < A3 ), ( A10 < A5 )}  
{( A2 < A4 ), ( A8 < A4 ), ( A9 < A5 )}  
{( A1 < A7 ), ( A5 < A9 ), ( A10 < A4 ), ( A10 < A8 ), ( A10 < A9 )}  
{( A1 < A10 ), ( A2 < A4 ), ( A3 < A4 ), ( A3 < A5 )}  
{( A1 < A8 ), ( A9 < A6 )}  
{( A1 < A5 ), ( A7 < A5 ), ( A8 < A7 ), ( A9 < A7 ), ( A10 < A3 )}  
{( A2 < A10 ), ( A4 < A7 ), ( A4 < A9 ), ( A6 < A3 ), ( A6 < A5 )}  
{( A1 < A4 ), ( A1 < A9 )}  
{( A2 < A8 ), ( A3 < A10 ), ( A5 < A6 ), ( A7 < A8 ), ( A9 < A1 )}
```



Estimate individual preference

{(A3 < A5), (A7 < A5)}
 {(A2 < A9), (A6 < A5), (A6 < A10), (A8 < A1), (A8 < A7)}
 {(A1 < A9), (A4 < A5), (A4 < A10), (A8 < A7), (A9 < A2)}
 {(A1 < A4), (A2 < A9), (A3 < A4), (A7 < A4), (A9 < A1)}
 {(A4 < A3), (A4 < A7), (A7 < A3), (A7 < A10)}
 {(A2 < A8), (A1 < A2), (A8 < A1)}
 {(A4 < A1), (A9 < A3), (A10 < A5)}
 {(A2 < A4), (A8 < A4), (A9 < A5)}
 {(A1 < A7), (A5 < A9), (A10 < A4), (A10 < A8), (A10 < A9)}
 {(A1 < A10), (A2 < A4), (A3 < A4), (A3 < A5)}
 {(A1 < A8), (A9 < A6)}
 {(A1 < A5), (A7 < A5), (A8 < A7), (A9 < A7), (A10 < A3)}
 {(A2 < A10), (A4 < A7), (A4 < A9), (A6 < A3), (A6 < A5)}
 {(A1 < A4), (A1 < A9)}
 {(A2 < A8), (A3 < A10), (A5 < A6), (A7 < A8), (A9 < A1)}

A7	A2	A5	A1	A10	A8	A2	A9	A6	A3
A1	A3	A5	A7	A10	A8	A2	A6	A9	A4
A1	A7	A3	A5	A10	A8	A9	A6	A2	A4

⋮

A2	A3	A1	A7	A5	A9	A8	A4	A6	A10
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Consistent comparisons?

- Consistent user, transitive preferences

$A1 > A2$ and $A2 > A3$ and $A1 > A3$

- Non-consistent user

$A1 > A2$ and $A2 > A3$ but $A1 < A3$

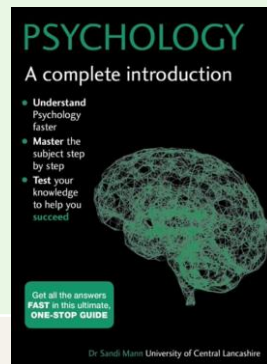
- Non-consistent user

$A1 > A2$ and $A1 < A2$

What to do with inconsistent users?

$A1 > A2$ and $A1 < A2$

Knowledge	Model
<ul style="list-style-type: none">User confused, no information in this data	<ul style="list-style-type: none">Drop both preferences $A1 > A2$ and $A1 < A2$
<ul style="list-style-type: none">Similar users share preferences to some degree	<ul style="list-style-type: none">A measure of similarity of usersUse only one of $A1 > A2$ or $A1 < A2$, the one expressed by similar users
<ul style="list-style-type: none">Similar users share preferences to some degreeIt is easier to be uncertain when comparing similar items	<ul style="list-style-type: none">A measure of similarity of usersUse only one of $A1 > A2$ or $A1 < A2$, the one expressed by similar users$A1$ and $A2$ are close in preference for this user



The new centre...

- builds on a team of **statisticians, logicians, machine learning researchers and ethicists**
- will develop theories, methods, models and algorithms which exploit **knowledge together with data**
- will solve important **real-world problems** in science, industry and society together with domain experts

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Thank you!

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