Explaining AI systems

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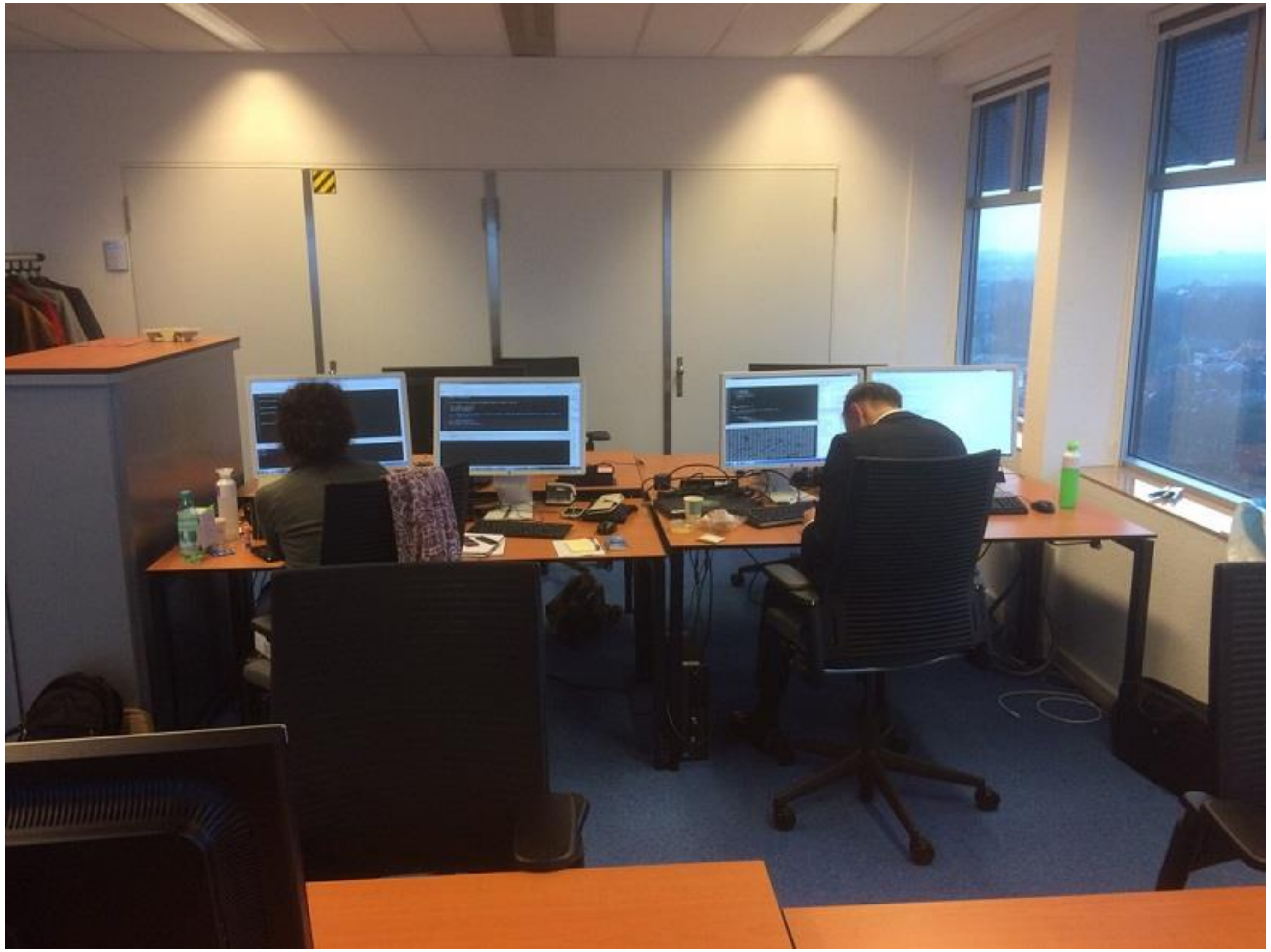
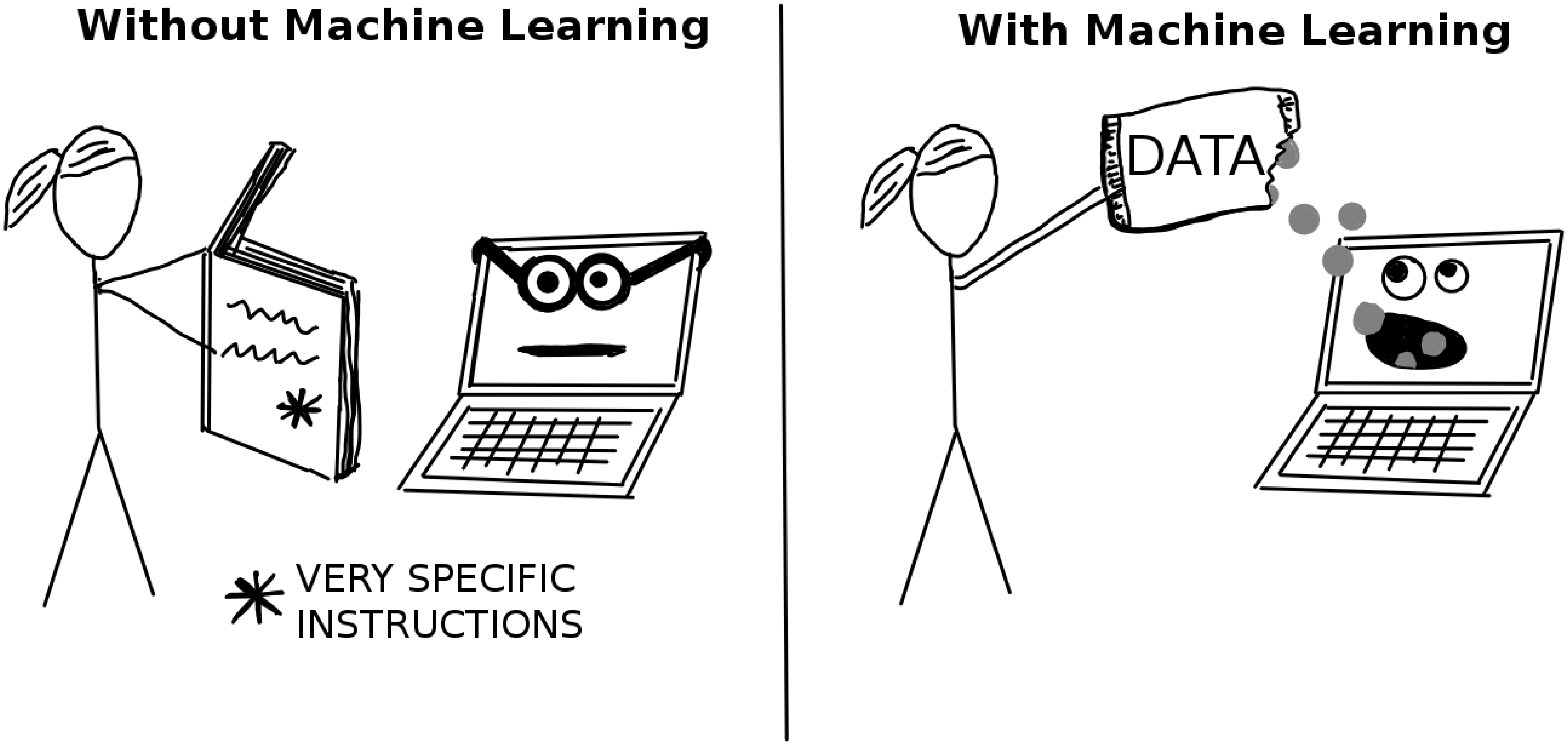
Artificial Intelligence (AI)

Retrieved from Google image search - June 17th 2019

In real life

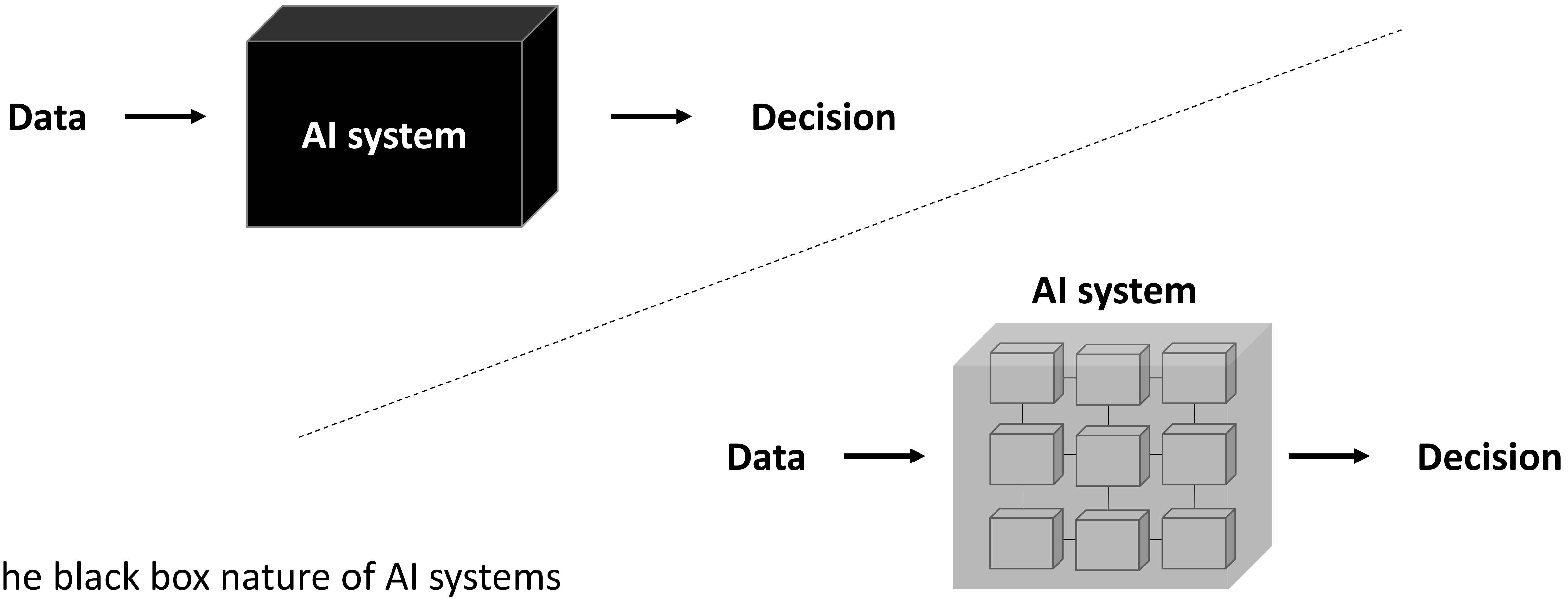


Machine learning



Source: https://christophm.github.io/interpretable-ml-book/

Black box metaphor



The black box nature of AI systems comes from the interaction of many simple components

AI & Explanations: debate

Against

- Not compatible with the purpose of AI systems to begin with
- Holding AI to above humans standards is unrealistic
- Explainability sacrifices performance for user-trust

In favor

- Transparency helps improve the AI-system
- Explanations help users trust AI-driven systems
- Compliance with regulations (Europe)

Explaining AI: why bother?

Compliance with General Data Protection Regulation (GDPR – 2018) – articles 13-15

“Data subjects have a right to “meaningful information about the logic involved” and to “the significance and the envisaged consequences” of automated decision-making”

An example: SPUI25 Forecaster

Prediction Task How many people will attend an event at SPUI 25?

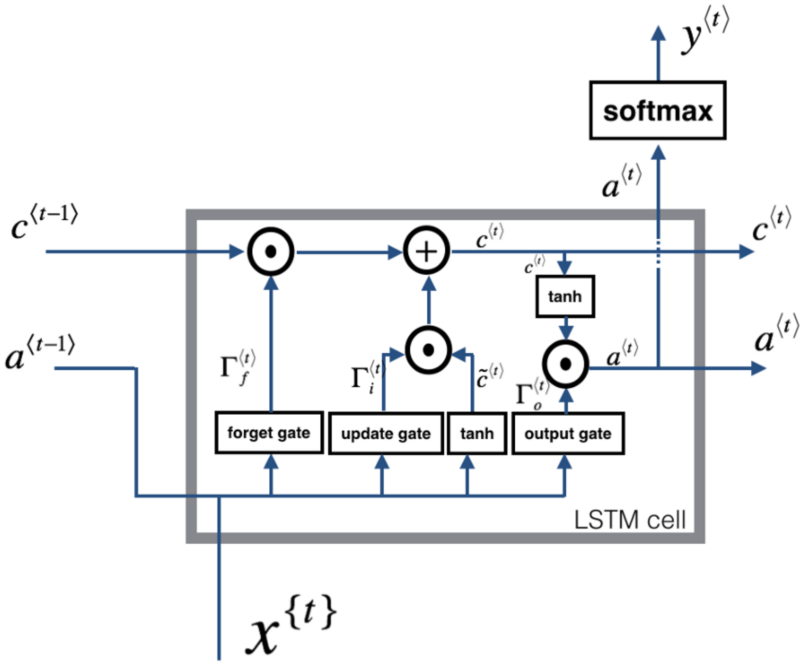
SPUI25 Forecaster

An example: SPUI25 Forecaster

Data

- Past experience at SPUI 25
- Weather on Thursday night?
- Is it raining?
- Free drinks afterwards?
- Is there football tonight?
- Subject popularity score
- Speakers popularity score
- ….

Model



. . .

$$\Gamma_f^{\langle t\rangle} = \sigma(W_f[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_f)$$
$$\Gamma_u^{\langle t\rangle} = \sigma(W_u[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_u)$$
$$\tilde{c}^{\langle t\rangle} = \tanh(W_C[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_C)$$
$$c^{\langle t\rangle} = \Gamma_f^{\langle t\rangle} \circ c^{\langle t-1\rangle} + \Gamma_u^{\langle t\rangle} \circ \tilde{c}^{\langle t\rangle}$$
$$\Gamma_o^{\langle t\rangle} = \sigma(W_o[a^{\langle t-1\rangle}, x^{\langle t\rangle}] + b_o)$$
$$a^{\langle t\rangle} = \Gamma_o^{\langle t\rangle} \circ \tanh(c^{\langle t\rangle})$$

Long Short-Term Memory (LSTM) cell structure

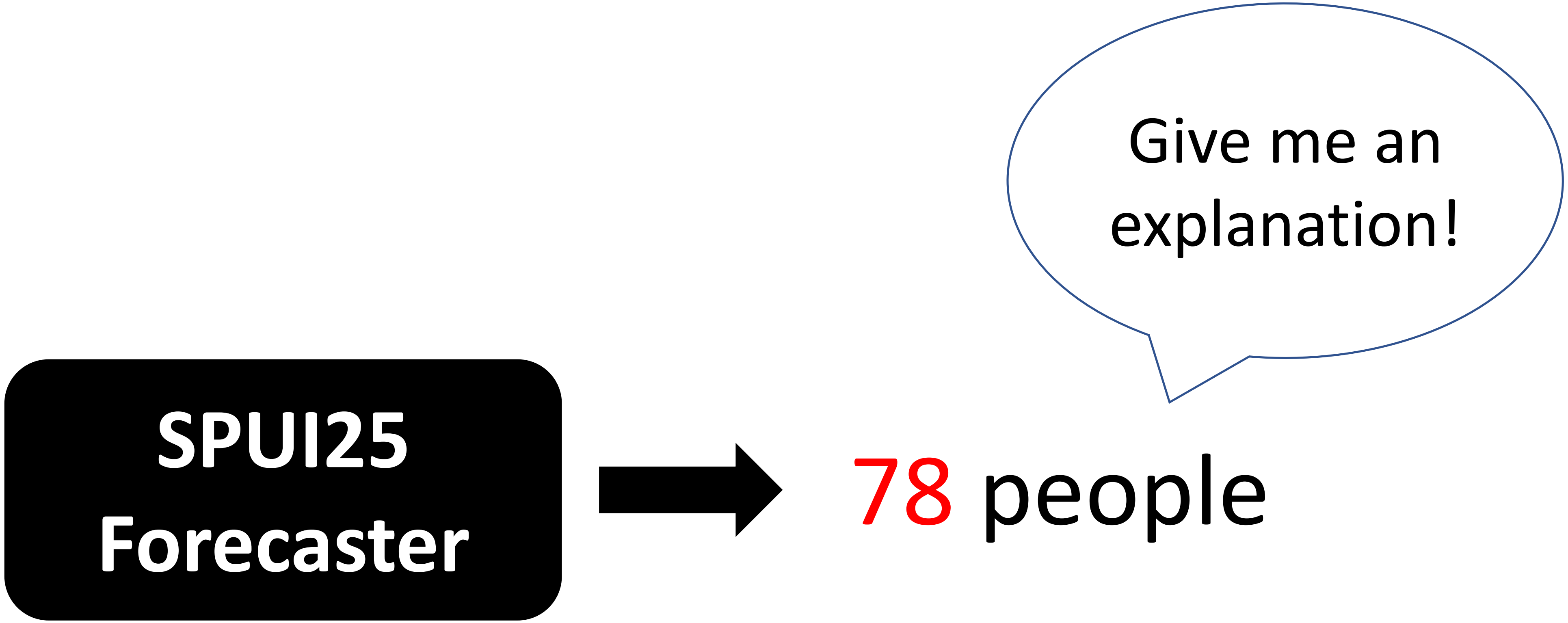
Source: https://iitmcvg.github.io/

An example: the SPUI25 Forecaster

Prediction How many people will attend tonight's event at SPUI 25?

SPUI25 Forecaster → 78 people

An example: the SPUI25 Forecaster



What is an explanation?

An explanation is the answer to a why-question (Miller 2017)

- Why this book recommendation?
- Why does this shopping app think I am pregnant?
- Why did I not get the loan?
- Why did the car crash?

What is a good explanation?

Research shows that people do not explain the causes for an event, but explain the cause of an event relative to some other event that did not occur; that is, an explanation is always of the form:

“Why A and not B”

This is called a contrastive explanation

T. Miller (2017)

Generating contrastive explanations

Counterfactual examples

describes the smallest change to the feature values that changes the prediction to a predefined output

how would the prediction have been if input X had been different?

Surrogate models

simplified local version of the black box model

features that influenced the predictions vs. those that were absent

Contrastive explanations

SPUI25
Forecaster

Which feature values **must be changed** to increase the number of people to 100?

- If the temperature was increased by 10 degrees, the prediction would be 100 people
- If the speaker popularity score was up by 7 points, the prediction would be 100 people

Which features **were not important** for the prediction?

- Number of free drinks after the talk

Limitations

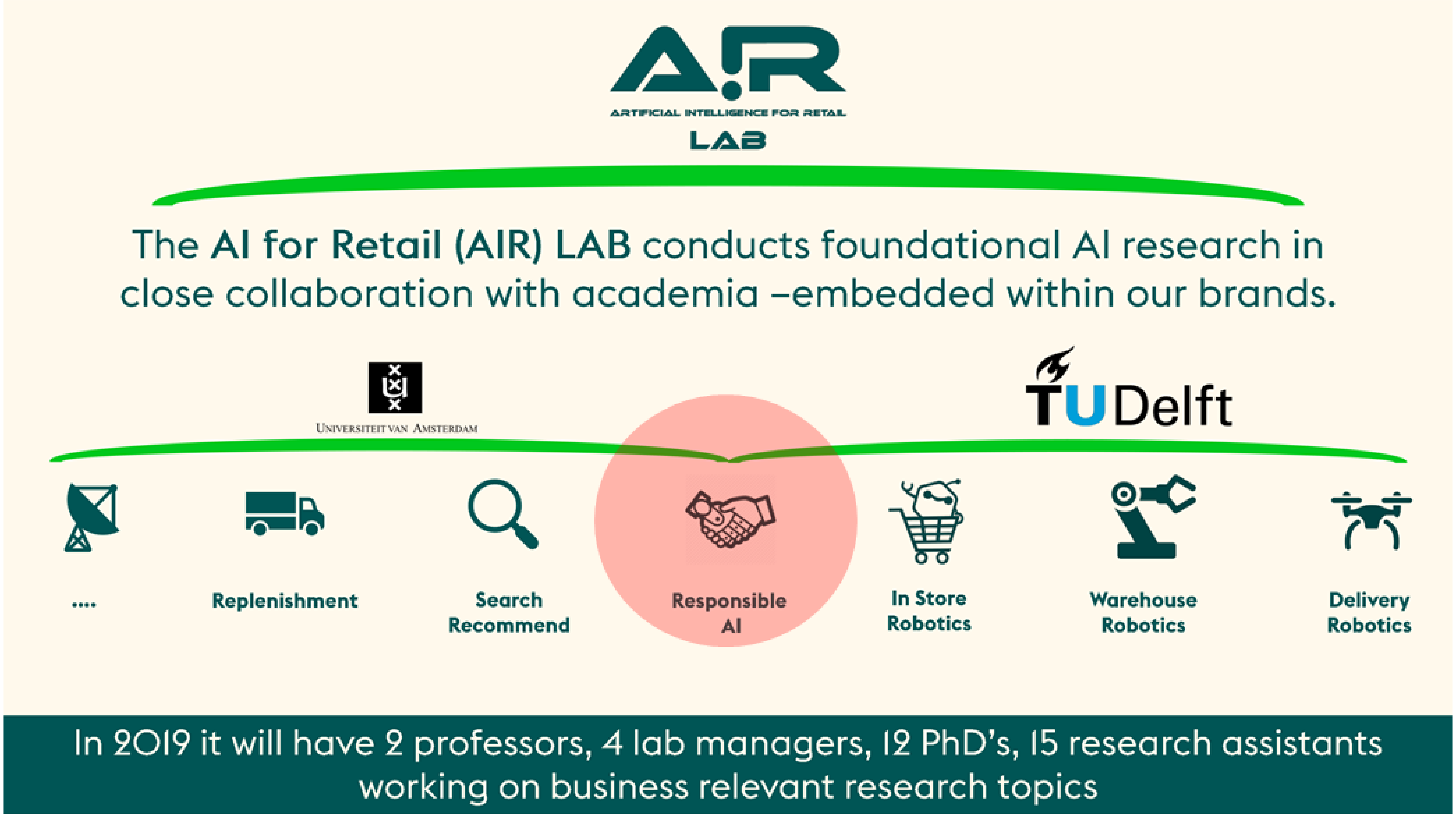
- We can find multiple contrastive explanations for the same prediction: how do we choose?
- It might not always be possible to find contrastive explanations
- Explanations can be very instable
- The explanations might not be actionable

Algorithmic aversion is a thing!

"We show that people are especially averse to algorithmic forecasters after seeing them perform, even when they see them outperform a human forecaster. This is because people more quickly lose confidence in algorithmic than human forecasters after seeing them make the same mistake"

Dietvorst et al (2015)

Ongoing research



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What WE want

- Have some idea of what the system does
  - How do the personalized recommendations work?
- Able to challenge the system
  - What can I do to change my application's outcome?
- Able to understand when the system make
  - How do I trust the self-driving car?