

Causes and Explanations in Practical Applications

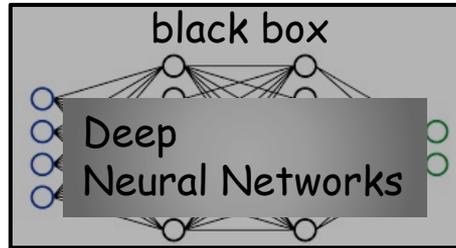
Hana Chockler



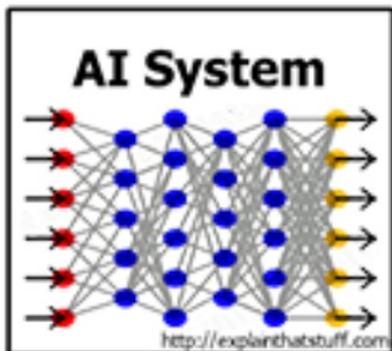
Modern computerized systems are
huge and difficult to understand



Modern computerized systems are
huge and difficult or even impossible
to understand



From DARPA:



- We are entering a new age of AI applications
- Machine learning is the core technology
- Machine learning models are opaque, non-intuitive, and difficult for people to understand



- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

GDPR right to explanation

[For organisations](#) / [Guide to Data Protection](#) / [Key DP themes](#) / [Explaining decisions made with Artificial Intelligence](#)

Explaining decisions made with AI



Brussels, 19.2.2020
COM(2020) 65 final

WHITE PAPER

On Artificial Intelligence - A European approach to excellence and trust

Who is the recipient of explanations?

Laypeople



- ◆ Why did you do that?
- ◆ Can I trust you?

Experts



- ◆ Why not something else?
- ◆ What if...?

Developers

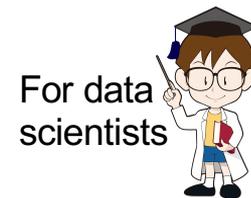


- ◆ When does the system succeed?
- ◆ When does it fail?
- ◆ How can I correct an error?



Build Causal AI

The new data science workflow



Causal Graph Discovery

Proprietary framework to discover causal drivers from raw data and filter spurious correlations.

Can incorporate domain knowledge & constraints into the causal graph.



Causal AI Model Discovery

Proprietary implementations that take a causal graph & its constraints as input to build a causal model.



Business Interventions & Simulations

Proprietary implementations that recommending actions which lead to the desired outcome.

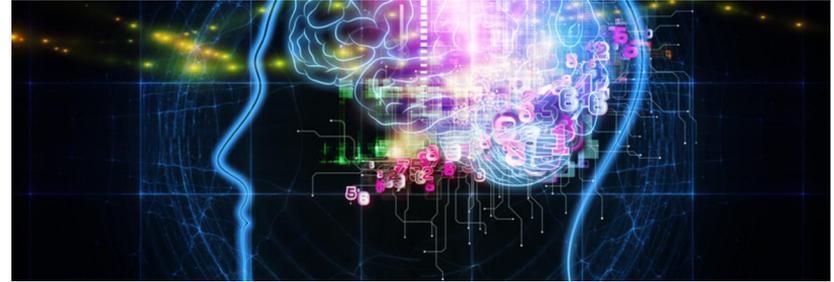
Proprietary modelling of what-if questions and scenario planning

Causal AI is able to ‘imagine’ counterfactual scenarios



Answer ‘Why’ and ‘What-if’ questions

Causal AI can explore potentialities that never actually happened — “counterfactuals” — while maintaining a connection with reality. It can reimagine the past, explaining why events unfolded as they did.



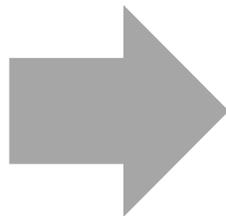
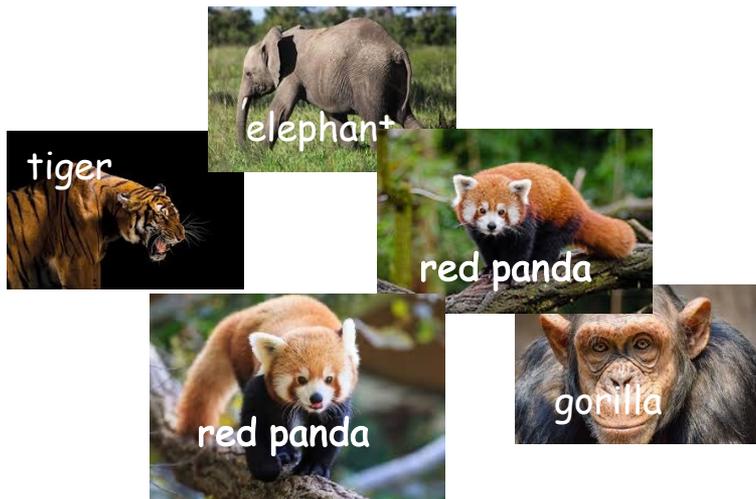
- Why are our factory’s solar panels failing with heat spots? What’s the root cause?
- How would growth stocks have been impacted this past quarter had consumer price inflation risen by 1%?
- What would have happened to quarterly sales had we not increased advertising spend?

Deep Neural Networks for image classification



For developers

Training phase



**DNN for
classifying animals**

After sufficient training...
?

Deep Neural Networks for image classification

Classification phase



DNN for
classifying animals



red panda

How can we
trust DNN's
output?

Explanations for Deep Neural Network's decisions



DNN for
classifying animals



red panda



Explanation:
minimal, sufficient,
non-trivial subset
of highest-ranked
causes

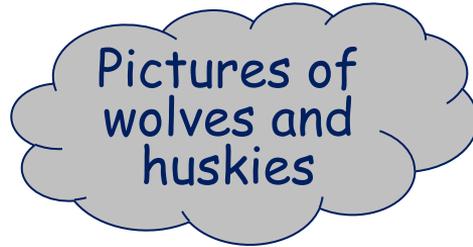
Because
of this part:



How to detect misclassification?

Example: wolves vs huskies

Training phase:



Classification phase:



(husky)



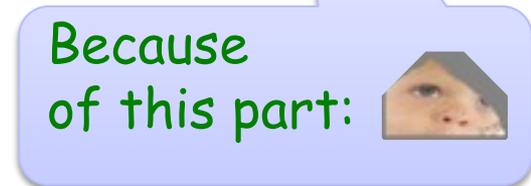
Subtle misclassification - uncovered by explanations



DNN for
classifying images



cowboy hat



Explanations for DNN's decisions -Based on ranking of causes



DNN for
classifying animals



red panda

Because
of this part:



How to compute a
minimal and
sufficient subset
of causes
efficiently?

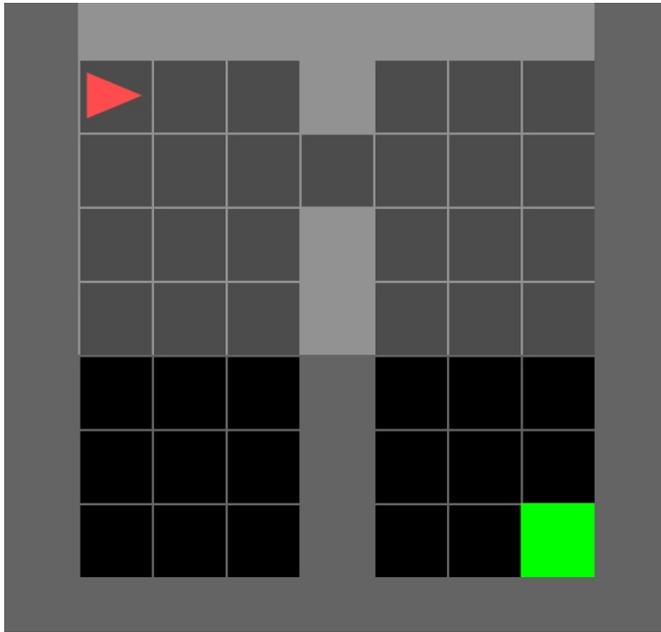
causality



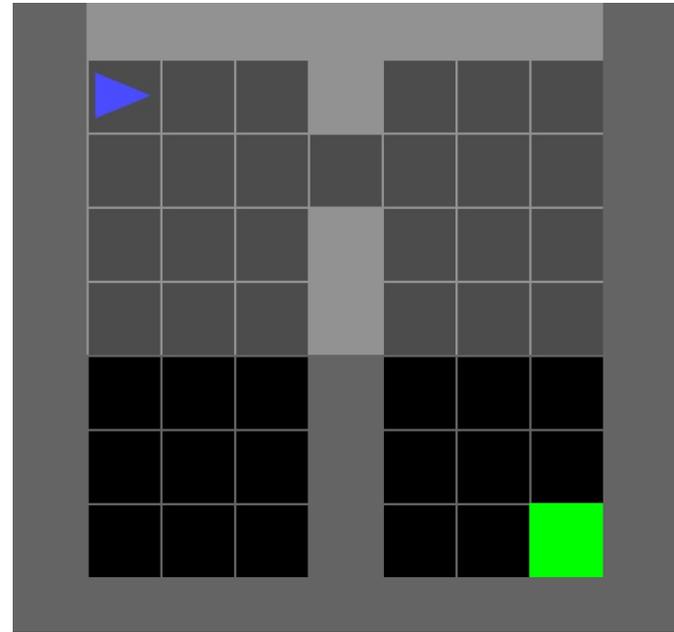
Use causal
analysis for
ranking

Explanations of Reinforcement Learning Policies

Original RL policy



Policy with only the top-ranked decisions





causaLens

We are hiring!

- Research Scientist - Machine Learning and Causality
- Director of Applied Data Science
- VP of Engineering
- Engineering Team Lead

Please email join@causaLens.com for more information

