## PAMI Seminar SS 19

Focus of Papers/Theme: Explainable Al

Prof. Dr. Nils Bertschinger and Prof. Dr. Visvanathan Ramesh

#### "Why Should I Trust You?" Explaining the Predictions of Any Classifier

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## This looks like that: deep learning for interpretable image recognition

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#### Abstract

#### Deep Learning for Case-Based Reasoning through Prototypes: A Neural Network that Explains Its Predictions

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#### Transparency by Design: Closing the Gap Between Performance and Interpretability in Visual Reasoning

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# Explanations based on the Missing: Towards Contrastive Explanations with Pertinent Negatives\*

Amit Dhurandhar<sup>†1</sup>, Pin-Yu Chen<sup>†1</sup>, Ronny Luss<sup>1</sup>, Chun-Chen Tu<sup>2</sup>, Paishun Ting<sup>2</sup>, Karthikeyan Shanmugam<sup>1</sup> and Payel Das<sup>1</sup>

February 22, 2018

#### The Mythos of Model Interpretability

Zachary C. Lipton 1

#### On the Robustness of Interpretability Methods

David Alvarez-Melis <sup>1</sup> Tommi S. Jaakkola <sup>1</sup>

#### AI in Education needs interpretable machine learning: Lessons from Open Learner Modelling

Cristina Conati 1 Kaśka Porayska-Pomsta 2 Manolis Mavrikis 2

#### Building Machines That Learn and Think Like People

Brenden M. Lake,<sup>1</sup> Tomer D. Ullman,<sup>2,4</sup> Joshua B. Tenenbaum,<sup>2,4</sup> and Samuel J. Gershman<sup>3,4</sup>

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### Causality

#### Introduction to Judea Pearl's Do-Calculus

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## Snorkel: Rapid Training Data Creation with Weak Supervision

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