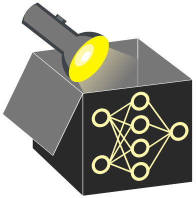
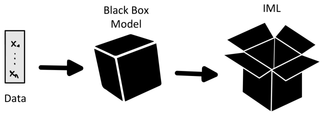
Interpretable Machine Learning



Interpretation Goals

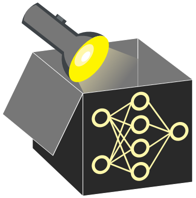


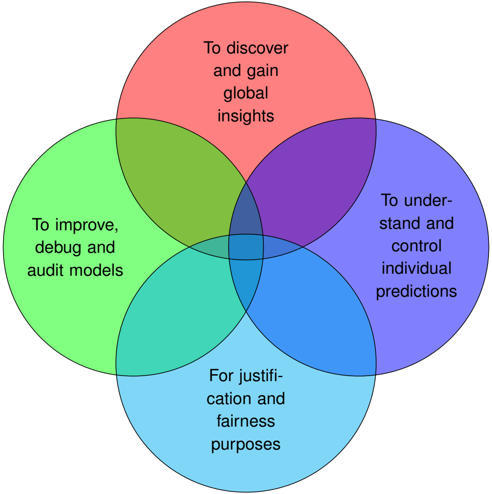
Learning goals

Understand Interpretation Goals:

- Global insights (discovery)
- Improve model (debug and audit)
- Understand and control individual predictions
- Justification and fairness

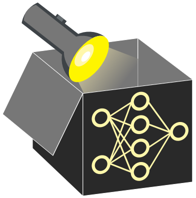
POTENTIAL INTERPRETATION GOALS





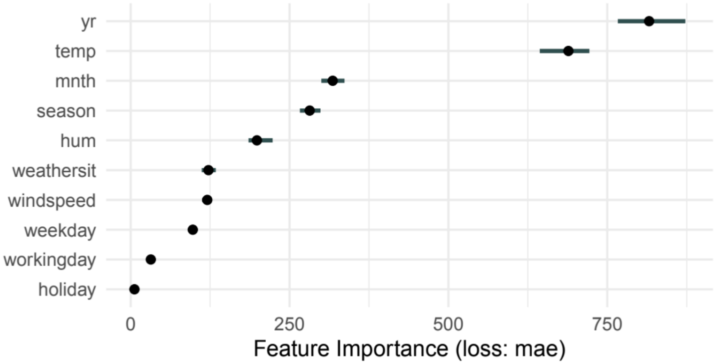
A related presentation can be found in ▸ Adadi and Berrada 2018.

DISCOVER AND GAIN GLOBAL INSIGHTS



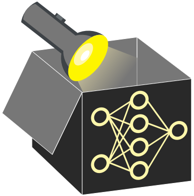
$\rightsquigarrow$ Gain insights about data, distribution and model

Example: Bike Sharing Dataset (predict number of bike rentals per day)
Exemplary question: Which feature influences the model performance and to what extent?



- Year (`yr`) and Temperature (temp) most important features
- Holiday (`holiday`) less important (Can we drop it?)

IMPROVE, DEBUG AND AUDIT MODELS



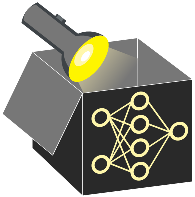
⇝ Insights help to identify flaws (in data or model), which can be corrected

Example: Neural Net Tank ▸ gwern.net

A cautionary tale (never actually happened):

- Train a neural network to detect tanks
- Good fit on training data
- Application outside training data: failure

IMPROVE, DEBUG AND AUDIT MODELS



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  ⇝ NN based decision on irrelevant points

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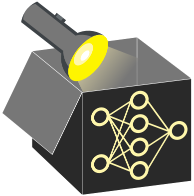

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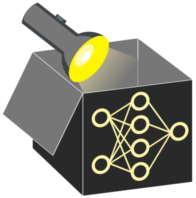
- Reasons vary depending on input
  ⇝ NN based decision on irrelevant points
- E.g. model detects weather based on sky:
  ⇝ All photos with tanks show cloudy sky
  ⇝ Photos without tanks show sunny sky

IMPROVE, DEBUG AND AUDIT MODELS



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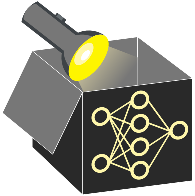
Comment on tank example:

"We made exactly the same mistake in one of my projects on insect recognition. We photographed 54 classes of insects. Specimens had been collected, identified, and placed in vials. Vials were placed in boxes sorted by class. I hired student workers to photograph the specimens. Naturally they did this one box at a time; hence, one class at a time. Photos were taken in alcohol. Bubbles would form in the alcohol. Different bubbles on different days. The learned classifier was surprisingly good. But a saliency map revealed that it was reading the bubble patterns and ignoring the specimens. I was so embarrassed that I had made the oldest mistake in the book (even if it was apocryphal). Unbelievable. Lesson: always randomize even if you don't know what you are controlling for!"

▸ Thomas G. Dietterich

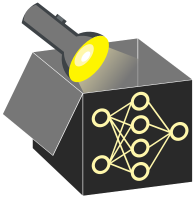
DEBUG AND AUDIT



- Nearly all computer programs have bugs
  - $\rightsquigarrow$ Minimizing such bugs extremely relevant
- Process with multiple steps to locate, understand and solve a problem
  - $\rightsquigarrow$ Classical debugging
- **In ML** we have a program (learner) writing another program (model)
- How to debug or audit programs which contain ML models?
- Based on a single cross-val score?

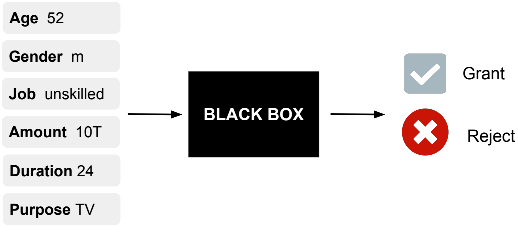
$\rightsquigarrow$ Being able to interpret your model will always be helpful – if possible!

UNDERSTAND & CONTROL INDIVIDUAL PREDICTIONS



⇝ Explaining individual decisions can prevent unwanted actions based on the model

Example: Credit Risk Application
x: customer and credit information; *y*: grant or reject credit



Questions:

- Why was the credit rejected?
- Is it a fair decision?
- **How should x be changed so that the credit is accepted?**

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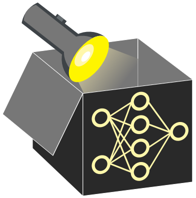

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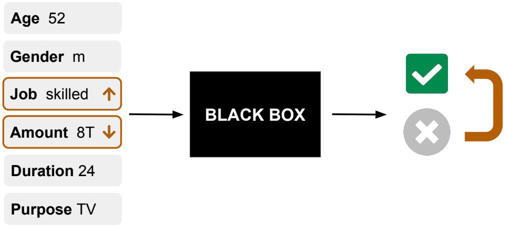
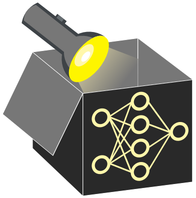


“If the person was more skilled and the credit amount had been reduced to $8.000, the credit would have been granted."

JUSTIFICATION AND FAIRNESS



⇝ Investigate if and why biased, unexpected or discriminatory predictions were made

Example: COMPAS

- Correctional Offender Management Profiling for Alternative Sanctions (COMPAS)
- Commercial algorithm used by judges to assess defendant's likelihood of re-offending

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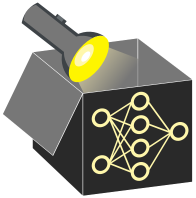

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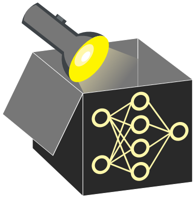
Example: COMPAS

- Correctional Offender Management Profiling for Alternative Sanctions (COMPAS)
- Commercial algorithm used by judges to assess defendant's likelihood of re-offending
- Predict recidivism risk
  - i.e., criminal re-offense after previous crime, resulting in jail booking
  - different risk levels: high risk, medium risk or low risk
- Evaluate risk of recidivism based on questionnaire answered by the defendant

JUSTIFICATION AND FAIRNESS: COMPAS ▸ Larson et al. 2016



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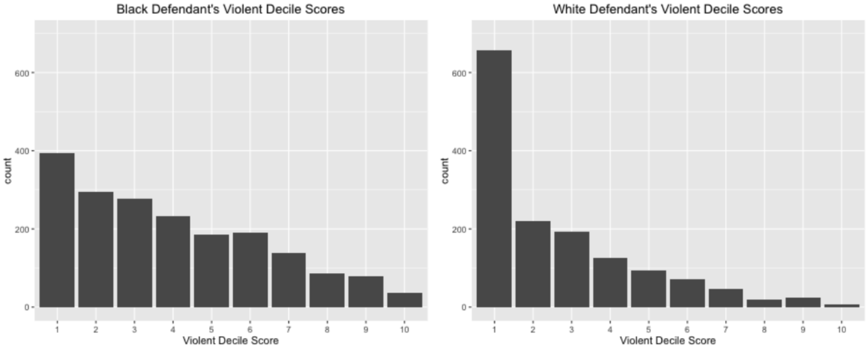
Descriptive data analysis:



Decile score: 1 (low risk) to 10 (high risk)

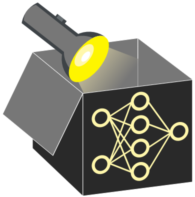
⇝ Model skewed towards low risk for white defendants

⇝ Strong indication that the model is discriminating black defendants

⇝ Use IML to investigate if and how much the model uses the defendants' origin.

JUSTIFICATION AND FAIRNESS: COMPAS

▸ Alvarez-Melis and Jaakkola 2018



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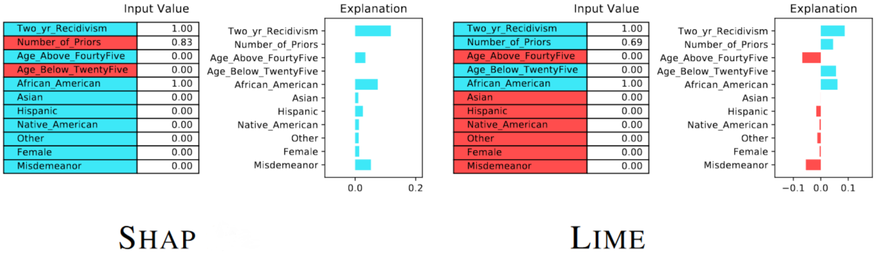
- Feature effects analysis for two exemplary defendants, using different interpretation methods (SHAP and LIME):



⇝ Methods give for every feature a number mirroring the impact on violence score.

⇝ Race (african american) has a noticeable positive impact on violent score