AI: Strategy + Marketing (MGT 853)

The AI $\Longleftrightarrow$ Human Interface (Session 5)

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Agenda for Today's Session

- Driving as an ML Problem

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- Explainability, Interpretability and Transparency

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- Research on Interpretable ML models

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Autonomous Vehicles


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Autonomous Vehicles

Three Waves

First-wave used mechanical control (1970s)

Mechanical Control

- Works in very limited way
- No flexibility if environment is changed even a bit

Autonomous Vehicles

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If condition X, Then do Y

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Autonomous Vehicles

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First-wave used mechanical control (1970s) → **Expert Systems** Second-wave used computer programming (1980s to early 2000s) → **Prediction Models** Third-wave uses (2007 – current)

Mechanical Control

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If condition X, Then do Y

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Predictive Model

- AI system learns and builds the model and delivers better (more accurate prediction) as more data is generated

Converting to Prediction Problem (In class exercise)

Autonomous Vehicles

- Consider the role of prediction in autonomous driving
- Let's walk through the AI Decision Framework

Questions to Ponder

0) What sources of data should the system use?
1) What are the possible predictive problems one might encounter?
2) How should we measure performance?
3) What are appropriate ML algorithms in our toolbox to solve them?
4) What role does judgment play in this problem?

ML Pipeline

Where do humans interface?

ML Pipeline

0. Data Sources
   - First Party
   - Data Broker
   - External Survey
   - Sensors
   - Modality
     Video Text ...

1. Pre-processing
   - Collect & Connect
   - Cleaning & Filtering
   - Outliers
   - Standardization
   - Format → Analysis

2. Visualization
   - Bar Charts
   - Initial insights
   - Correlations
   - Distribution

3. Feature Engineering
   - No new data
   - New feature

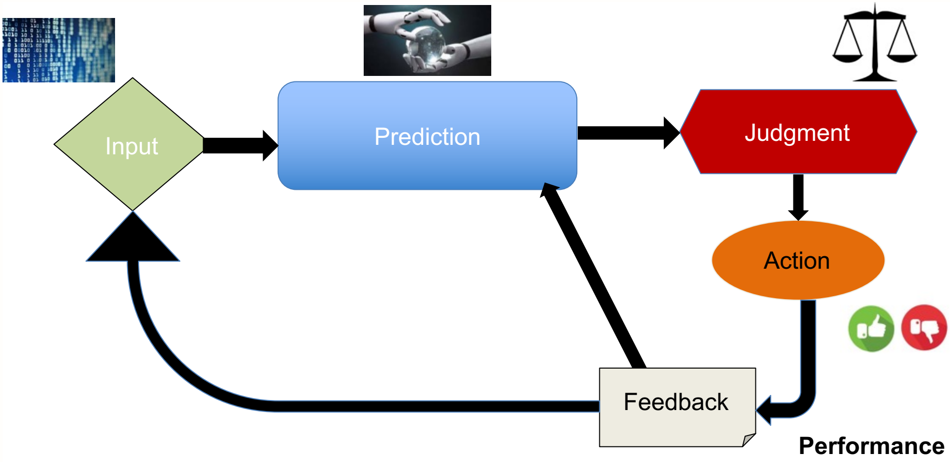
4. Data Splitting
   Train | Test
   Validation

5. Model
   - Accuracy
   - Dependent Variable
   - Explainable
   - Gen or Predict
   - Cost / Time
   - Data

6. Hyperparameter
   - Human designer selects

7. Learning (Training) 8. Validation 9. Testing

AI Decision-Making Framework



Does Feedback also inform Judgment?

Why worry about Black Box?

What if we get very high accuracy?

- 95

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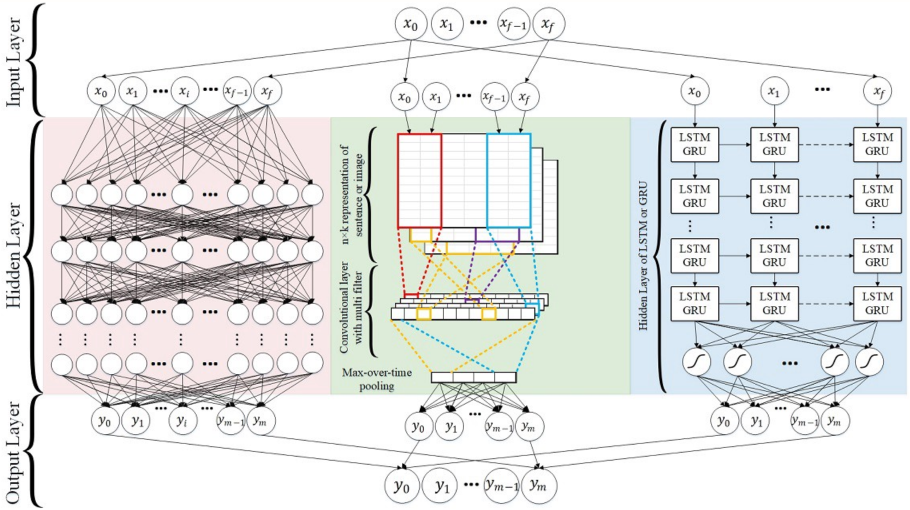
- 100

Can we understand this?



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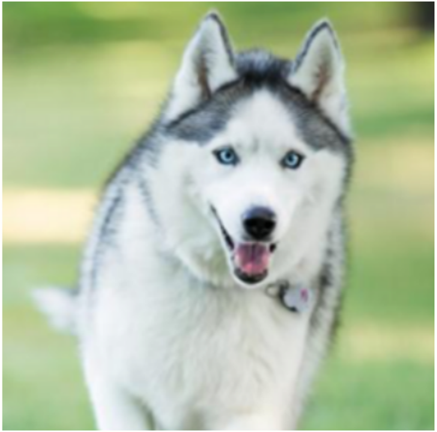
Wolf or Husky?



Source: Why Should I Trust You? Explaining the predictions of any classifier

Even 100% accuracy may not be enough
Need to understand why the model works

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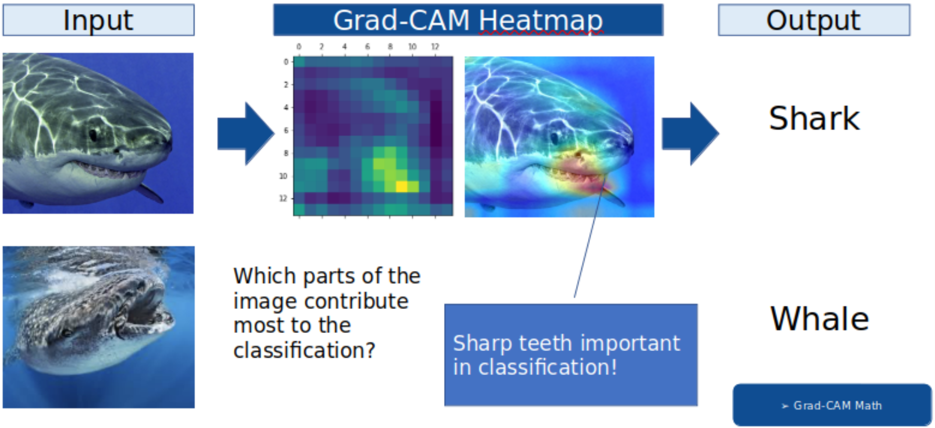
- May not be easy for all models

Explainability in Complex Models

Shark or Whale?

Explainability in Complex Models



Source: Understand your Algorithm with Grad-CAM

Grad-CAM

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Explainability $\Longrightarrow$ Interpretability

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nature > nature machine intelligence > perspectives > article

Perspective | Published: 13 May 2019

Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead

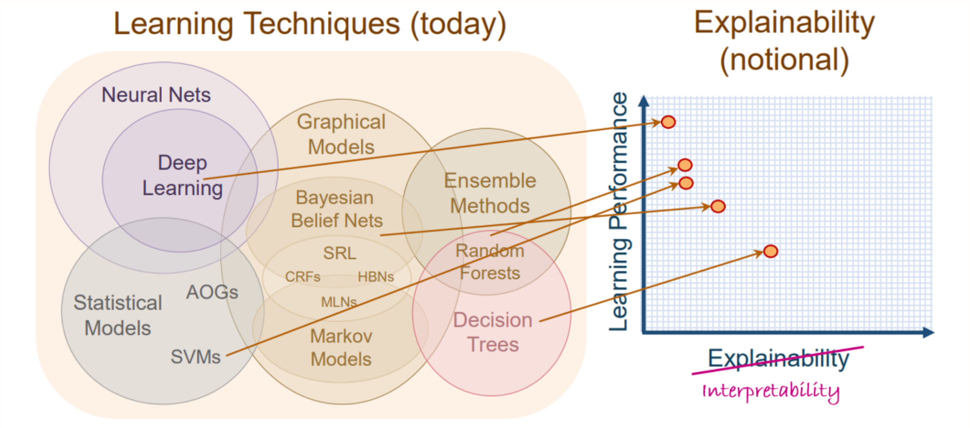
Cynthia Rudin

Nature Machine Intelligence **1**, 206–215 (2019) | Cite this article

Abstract

Black box machine learning models are currently being used for high-stakes decision making throughout society, causing problems in healthcare, criminal justice and other domains. Some people hope that creating methods for explaining these black box models will alleviate some of the problems, but trying to explain black box models, rather than creating models that are interpretable in the first place, is likely to perpetuate bad practice and can potentially cause great harm to society. The way forward is to design models that are inherently

Performance $\Longleftrightarrow$ Transparency Tradeoff?



https://www.researchgate.net/figure/
Current-Machine-Learning-Techniques-and-Notional-Explainability-Source-1

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- Transparency, Explainability and Interpretability can be very important for application
    - Often critically important to helping humans understand why AI makes the decisions it does
- Without that, we're guessing at how a "well performing" black box is doing its job
- Broadly, many applications of interpretability, e.g. with cars or watches, why are some products visually appealing?

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