AI: Strategy + Marketing (MGT 853)

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

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Spring 2024

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


HYSTER
80 HYSTER
XL2
24

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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Prediction Models
Third-wave uses (2007 – current)

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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?

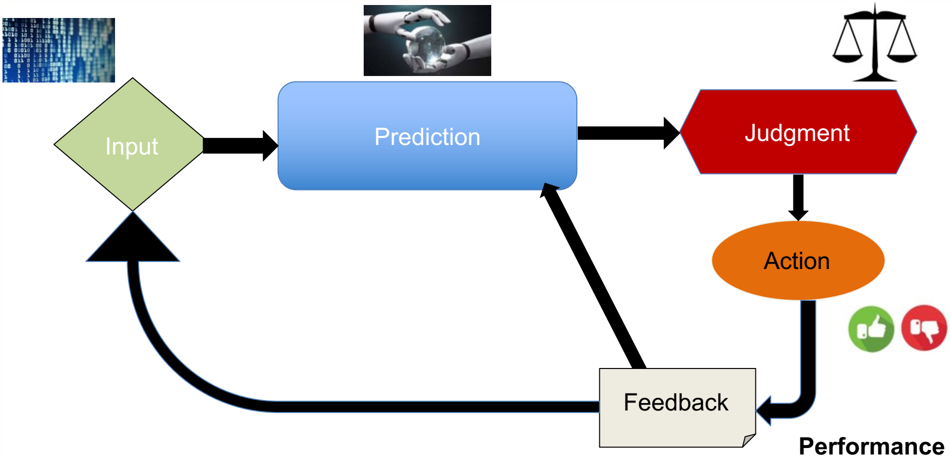
ML Pipeline

Where do humans interface?

ML Pipeline:

0. Identify Data (y, x)
1. Pre-processing
   Centering, Missing Data/Quality, Outliers, Normalization
2. Data Visualization
   Correlation, Distribution, Model
3. Data Splitting — Test
   Training, Validation
4. Feature Engineering
5. Model Selection
6. Hyperparameter Selection
   Human Analyst Decides
7. Learning (Training)
   $y = f(x)$
8. Validation
9. Interpretation
10. Testing ...

AI Decision-Making Framework



Does Feedback also inform Judgment?

Why not have a black box model?
What about Digit Classification?

Why worry about Black Box?

What if we get very high accuracy?

- 95

Why worry about Black Box?

What if we get very high accuracy?

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- 99.x?

Why worry about Black Box?

What if we get very high accuracy?

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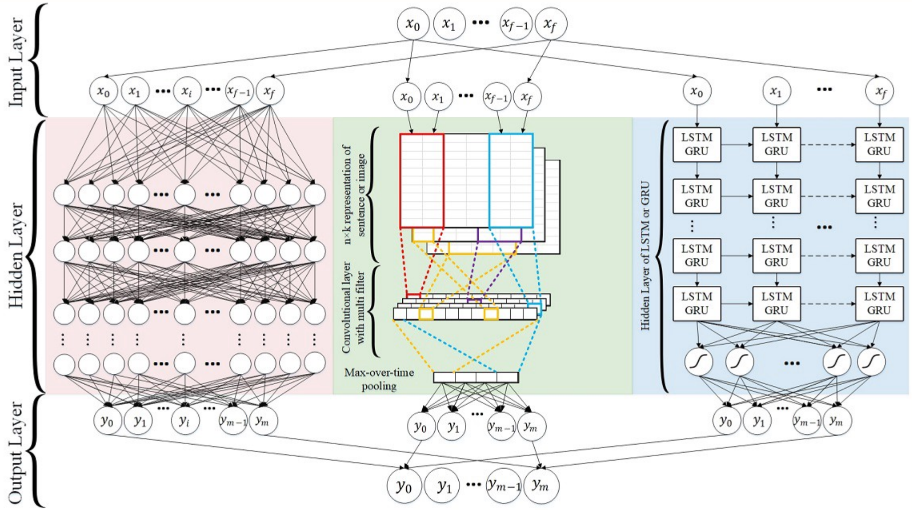
- 100

Why worry about Black Box?

Wolf or Husky?

Can we understand this?



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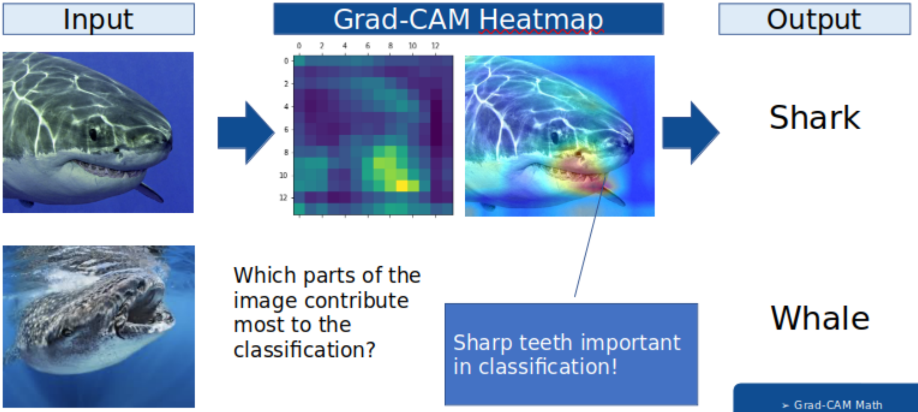
- Model produces constructs with meanings known to humans
- May not be easy for all models

Explainability in Complex Models

Shark or Whale?

Explainability in Complex Models



Grad-CAM Math

Source: Grad-CAM Details (Technical)

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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

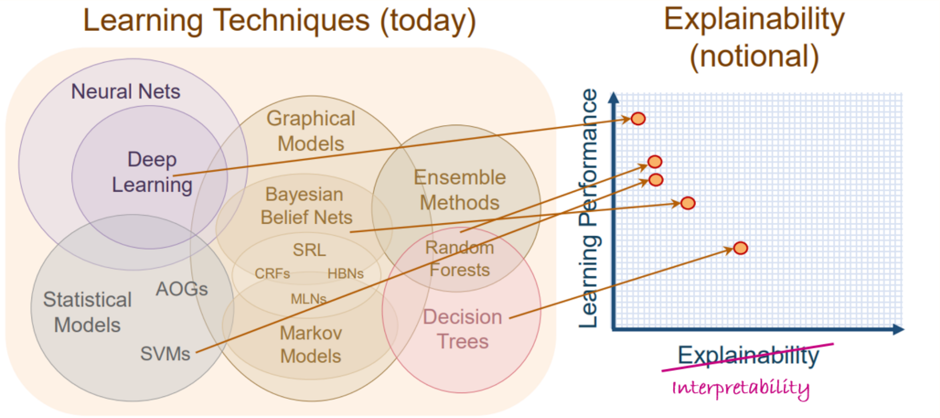
A preprint version of the article is available at arXiv.

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

Research

Performance $\Longleftrightarrow$ Transparency Tradeoff?



Converting to Prediction Problems (In class exercise *if we have time*)

Let's try this in Groups

- Choose one of (1), (2) or (3). Tell the class what you have chosen before you get started.
  $\geq$ 2 groups for each.

3 Cases – Chose ONE

1) Social media (Instagram) – increase engagement
2) Content firm (Spotify) – recommend new content to its users
3) Apparel retailer – improve its product assortment

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- Role of Transparency, Interpretability and Explainability

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- Broadly, many applications of interpretability, e.g. with cars or watches, why are some products visually appealing?
- What visual features contribute most to value?

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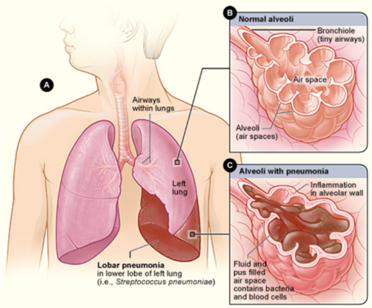

Research Presentation