



Lady Ada Lovelace

AI for Decision Making

Phanish Puranam, INSEAD

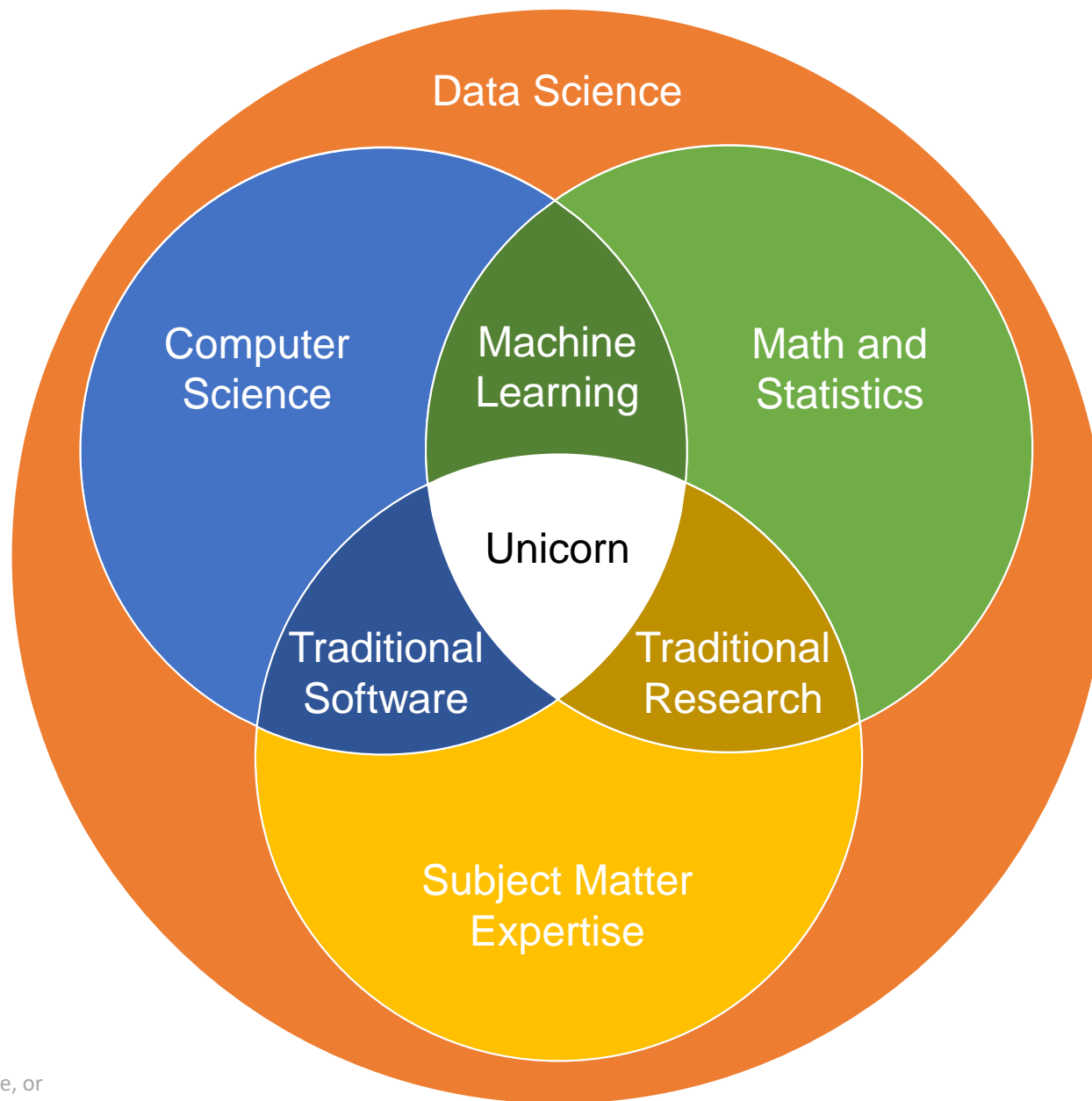
Phanish Puranam



The Roland Berger Chaired Professor of Strategy and Organisation Design

- PhD in Management from the Wharton School of the University of Pennsylvania
- Served as the Academic Director for the PhD Program at both London Business School and INSEAD
- Expertise: Organization Design & Strategy
- Current research: Organizations & Algorithms, Remote Collaboration

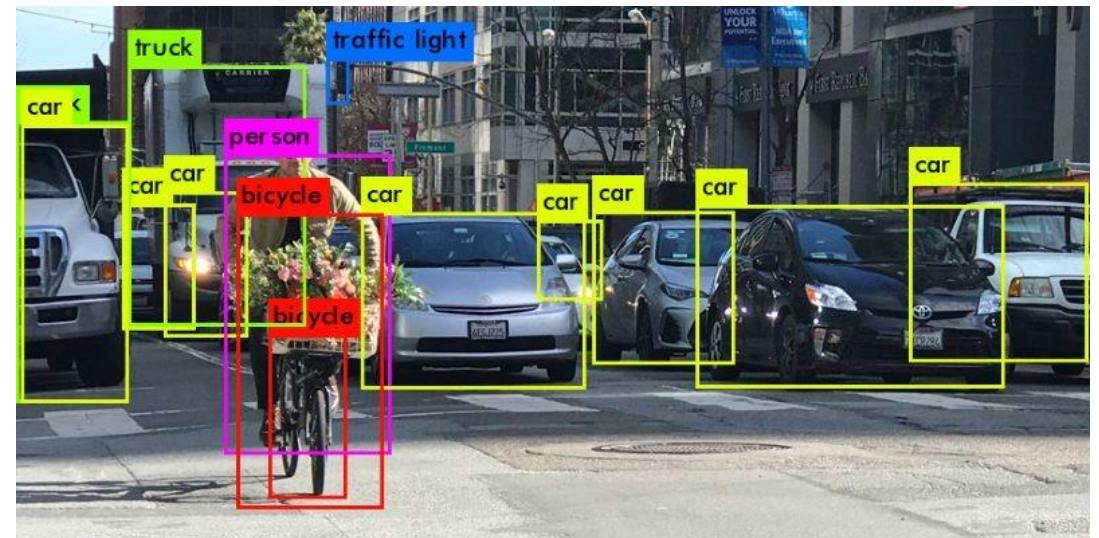
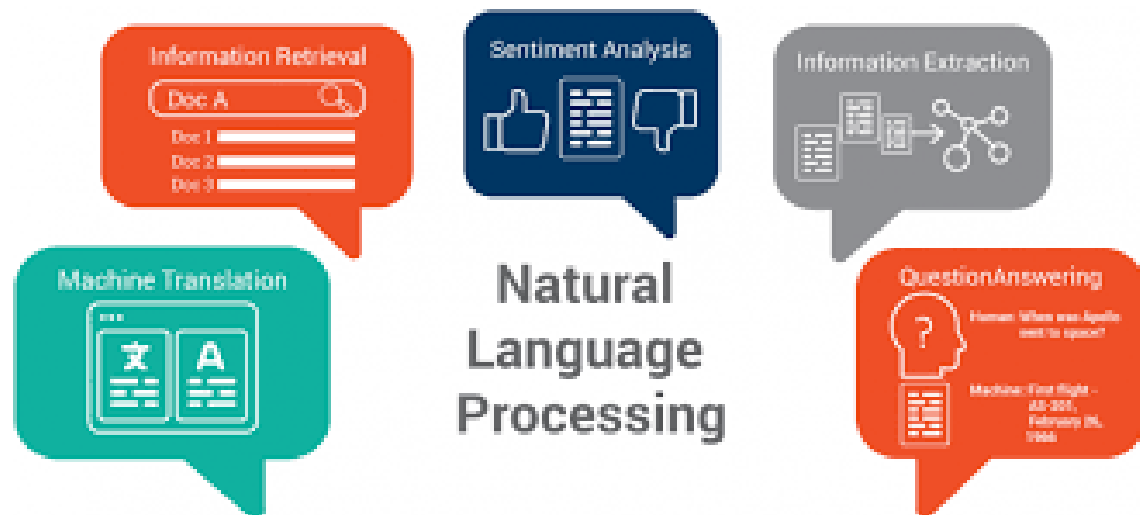
What does it take to master AI?



What's the most impressive accomplishment of AI to date (in *your* view)?

- Please enter into our Shared Google Doc- do check for redundancy with what others are typing!
- 3 minutes

What's the most impressive accomplishment of AI to date (in *your* view)?



Can AI be creative?



Figure 5: 1024×1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.



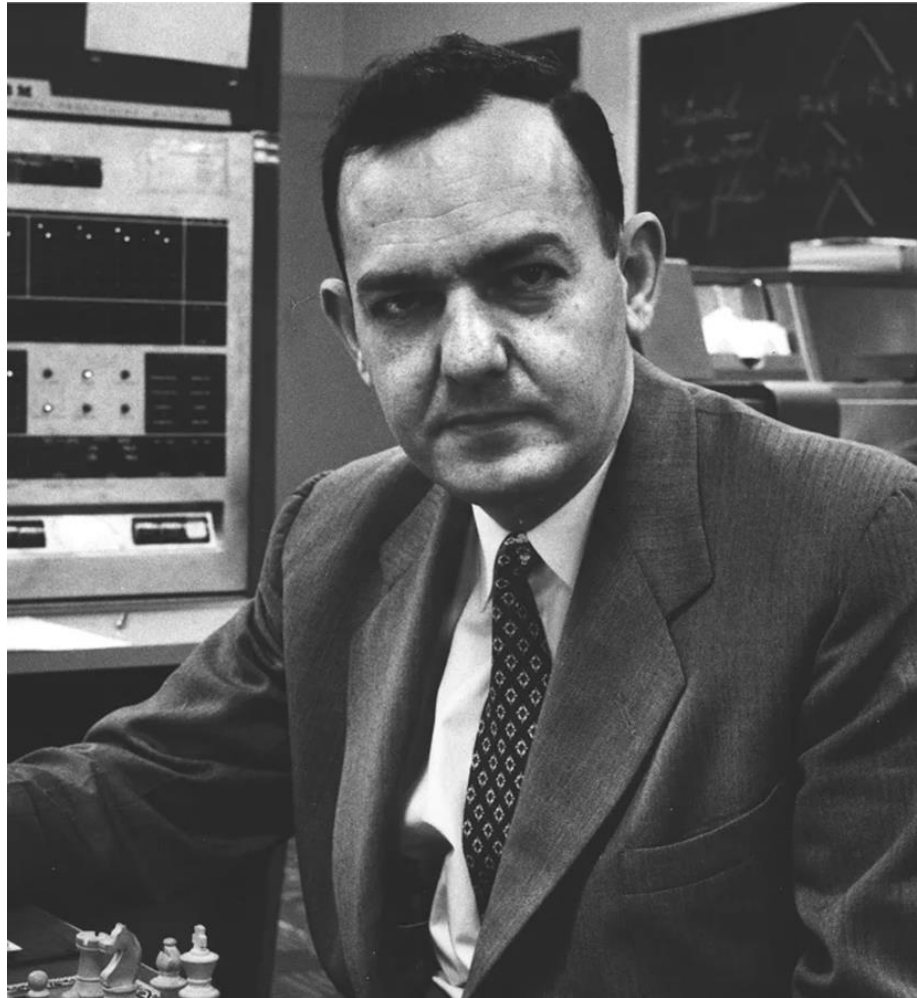
1959



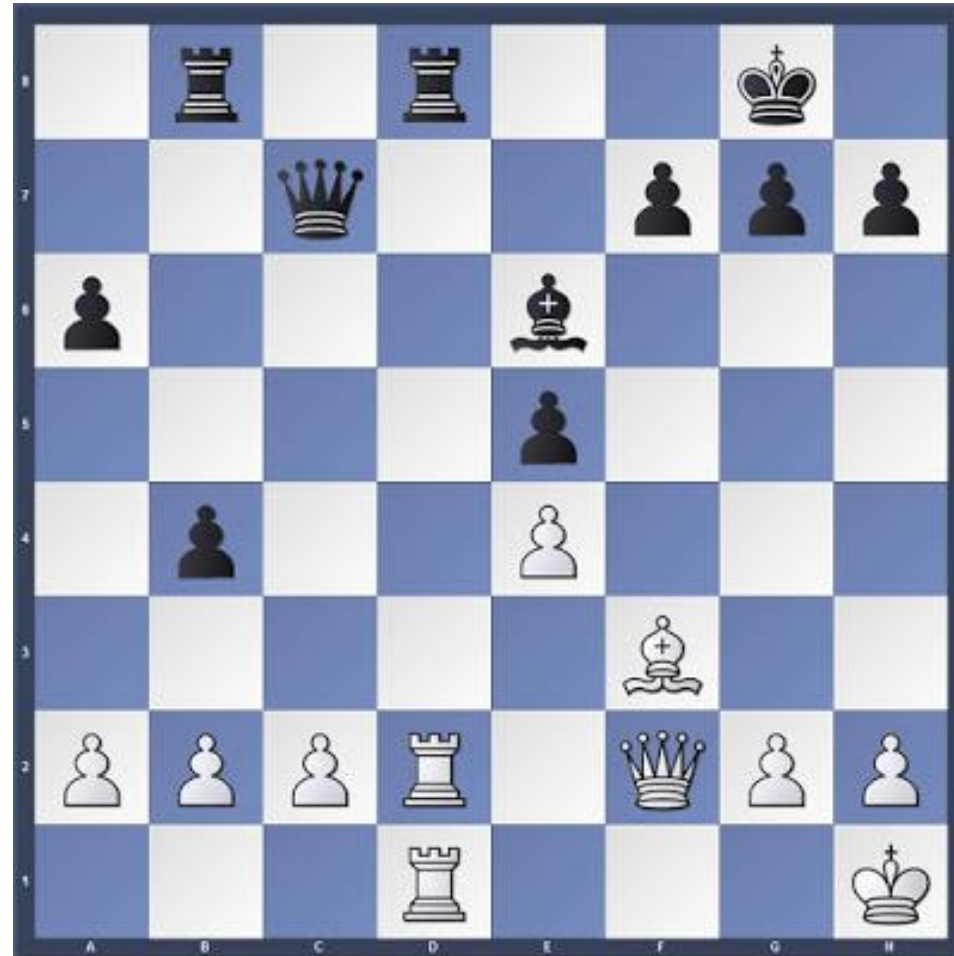
1997



2016



Herbert Simon (joint work with W.G. Chase, 1973)



HUMAN EXPERTISE= INTELLIGENT BEHAVIOR IN A CONTEXT= PATTERN RECOGNITION !

$$\begin{array}{r} 2 \\ 15 \overline{) 3640} \\ \underline{- 30} \\ 6 \end{array}$$

15 into 3 doesn't go, so look at the next digit.

15 goes into 36 two times, so put a 2 above the 6.
 $15 \times 2 = 30$

Take that 30 away from the 36 to get your remainder.
 $36 - 30 = 6$

$$\begin{array}{r} 24 \\ 15 \overline{) 3640} \\ \underline{- 30} \\ 64 \\ \underline{- 60} \\ 4 \end{array}$$

Next, carry the 4 down to make 64.
 15 goes into 64 four times, so put a 4 above the 4.
 $15 \times 4 = 60$

Take 60 from the 64 to get your remainder.
 $64 - 60 = 4$

$$\begin{array}{r} 242 \\ 15 \overline{) 3640} \\ \underline{- 30} \\ 64 \\ \underline{- 60} \\ 40 \\ \underline{- 30} \\ 10 \end{array}$$

Carry the 0 down to make 40.
 15 goes into 40 two times, so put a 2 above the 0.
 $15 \times 2 = 30$

Take 30 from the 40 to get your remainder.
 $40 - 30 = 10$





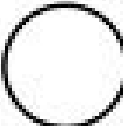



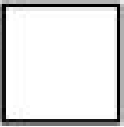

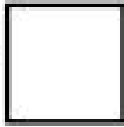


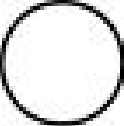
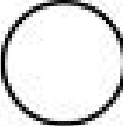

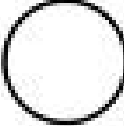






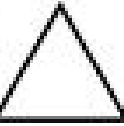
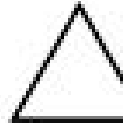

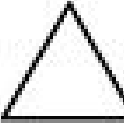
OLD AI: EXECUTES RULES

NEW AI: LEARNS PATTERNS FROM DATA

Name: _____

Complete the Pattern

Look at each pattern below and then use the box on the right to complete the pattern.

Pattern recognition & application

- Learning to recognize and apply patterns is the heart of intelligence
- That's what Machine Learning does
- Lots of data + processing power makes it easier to recognize (even complex) patterns
- A pattern= a “function” – which associates inputs to *unique* outputs.
- Pattern recognition in humans = function approximation in algorithms



Machine learning \subseteq artificial intelligence

ARTIFICIAL INTELLIGENCE

Design an intelligent agent that perceives its environment and makes decisions to maximize chances of achieving its goal.

Subfields: vision, robotics, machine learning, natural language processing, planning, ...

MACHINE LEARNING

Gives "computers the ability to learn without being explicitly programmed" (Arthur Samuel, 1959)

SUPERVISED LEARNING

Classification, regression

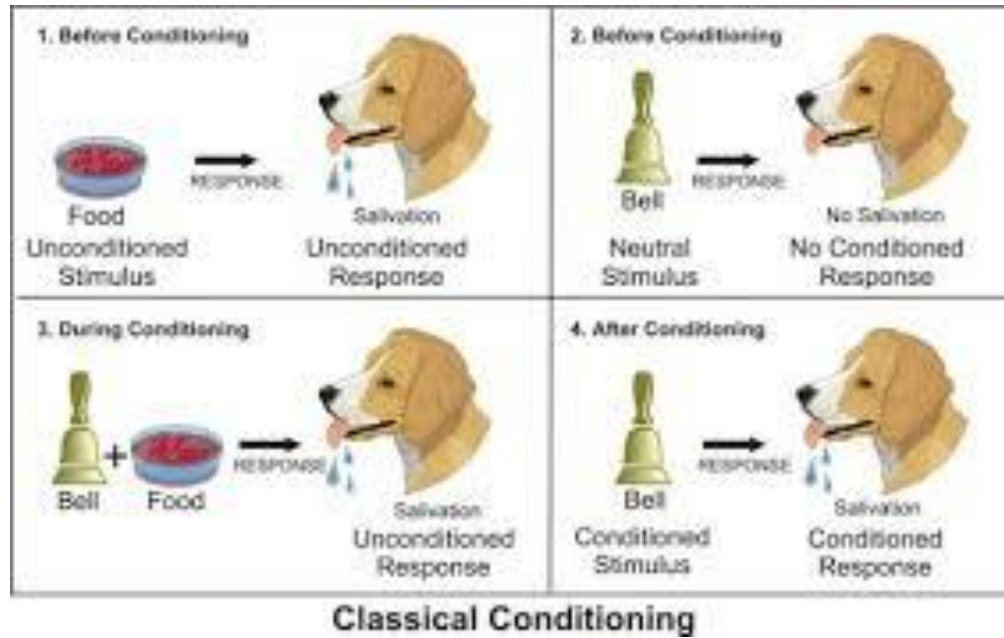
UNSUPERVISED LEARNING

Clustering, dimensionality
reduction, recommendation

REINFORCEMENT LEARNING

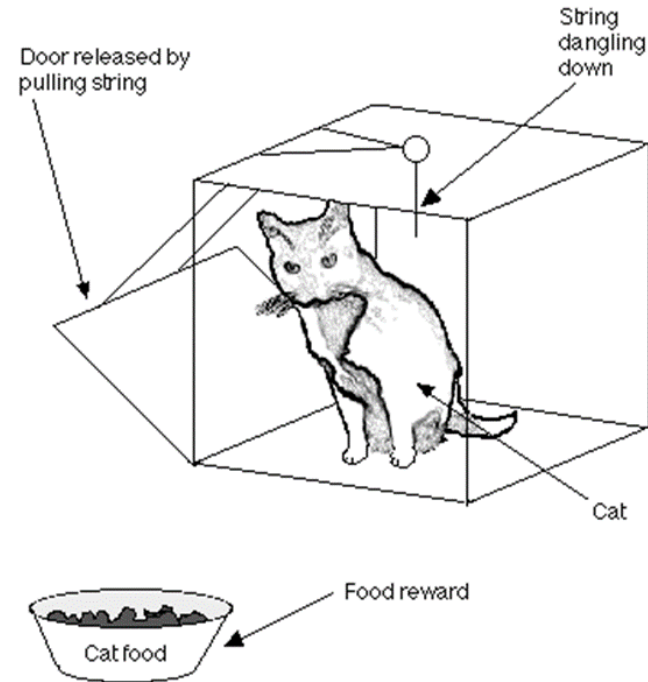
Reward maximization

A STORY OF DOGS AND CATS



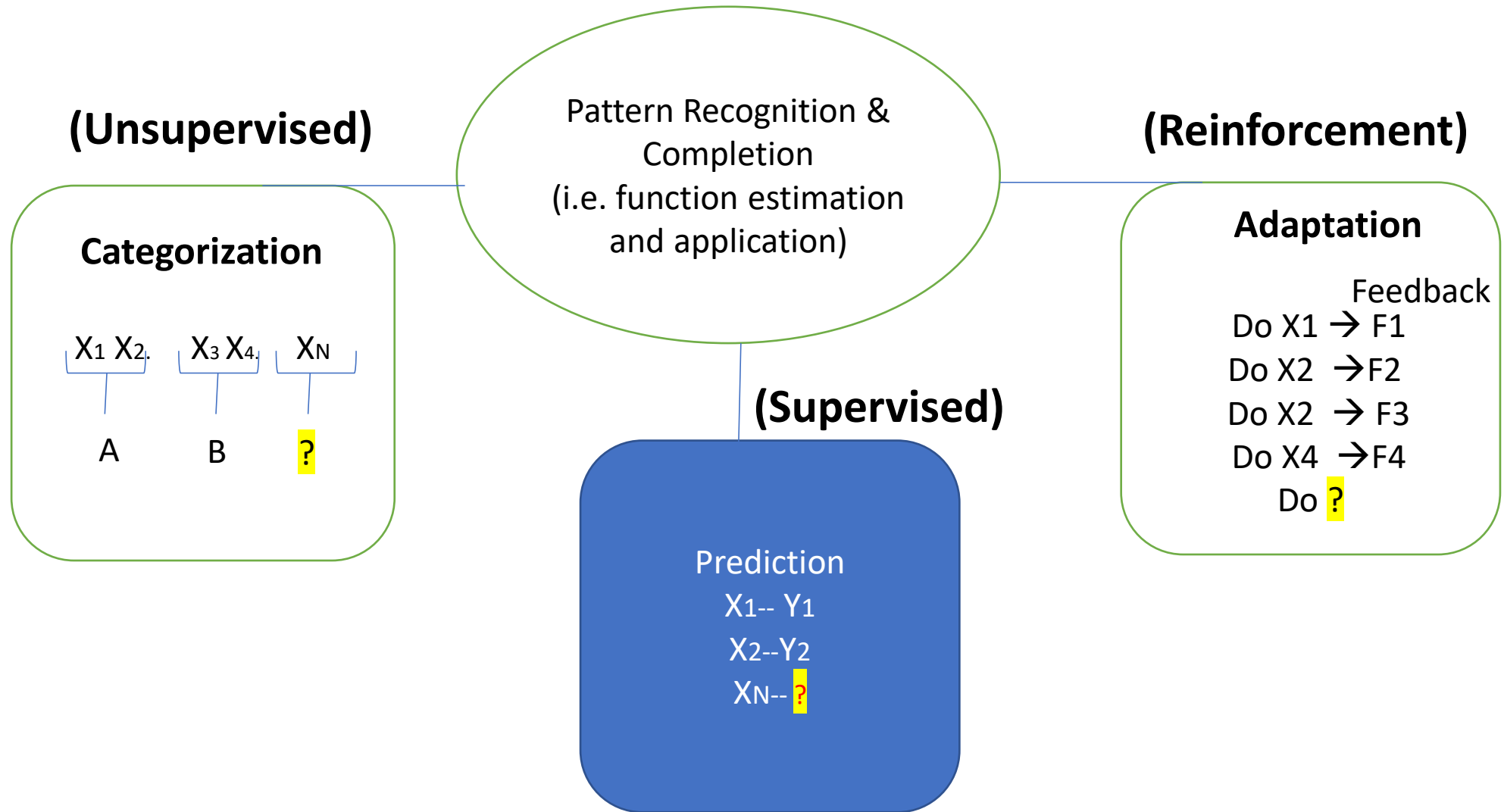
Supervised & Unsupervised Learning

Figure 18.2 Thorndike's puzzle box



Reinforcement Learning

ML algorithms work through pattern recognition & completion



Patterns → Predictions → Decisions

- All decisions require prediction
- Decisions can be “standalone” vs. “embedded”

AI ~ ML ~ Pattern Detection: Standard use cases today



Transaction features ---- Fraud



Customer attributes---- Churn likelihood



Inkdots ---- Words

AI ~ ML ~ Pattern Detection: Standard use cases today



Pixel ----- Image



Sound ----- Words in speech

<https://www.youtube.com/watch?v=D5VN56jQMWM&t=127s>



State of play ----- Optimal next move in game

<https://www.eff.org/ai/metrics#Abstract-Strategy-Games>

AI ~ ML~ Pattern Detection : Emerging Use cases



Employee attributes----Exit likelihood



CV attributes ---- Good hire



Project characteristics ---- Good investment

AI ~ ML~ Pattern Detection : Emerging Use cases



Text and word use ----- Cultural values



Company characteristics----- Strategic moves



Hans Moravec's landscape, in Tegmark (2018)

Dominance or Co-existence?



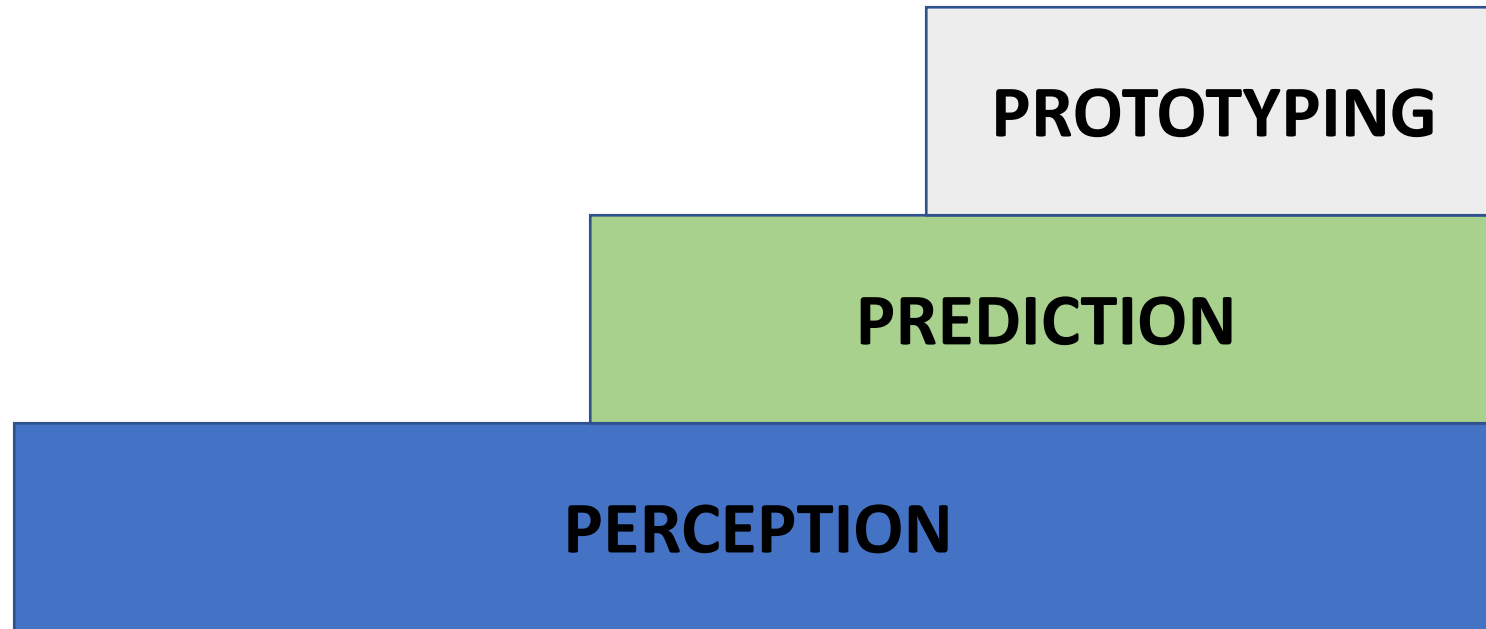
8 - 15 March 2016



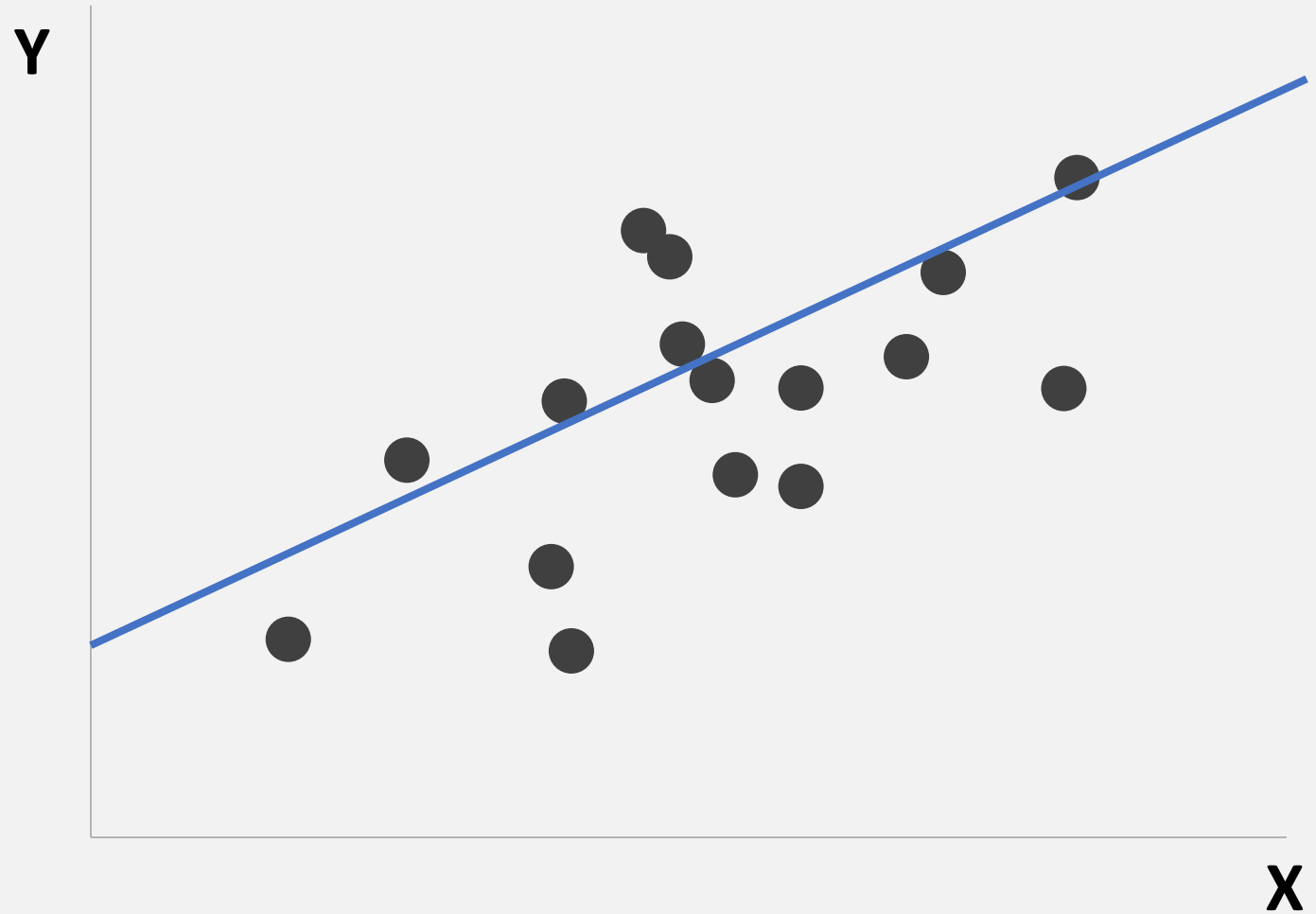
HOW TO KEEP UPTODATE ON WHAT AI IS DOING (WELL)

<https://www.eff.org/ai/metrics>

Levels of sophistication in using Data in Business



Data
Continuous
Outcome



PERCEPTION *vs.* PREDICTION

- Perception through Hypothesis testing:

- Does this association exist in the data?
 - We have a hunch (hypothesis) about an explanation
 - **Null Hypothesis Significant Testing** tells us the probability (across many samplings) of observing the association we see merely by chance, even if the true association in the population is zero.
 - **p-value**

- Prediction through Data mining:

- What associations exist in the data?
 - We have no or minimal hunches, we “let the data speak” to make a prediction
 - **Data mining** involves algorithms that hunt for useful associations in the data that can be summarized in a model.
 - **Predictive accuracy**

Prediction What's going to happen?



- Different algorithms

- Tree induction
- LASSO
- Random forest
- OLS
- Logistic
- Deep learning

- Common to all:

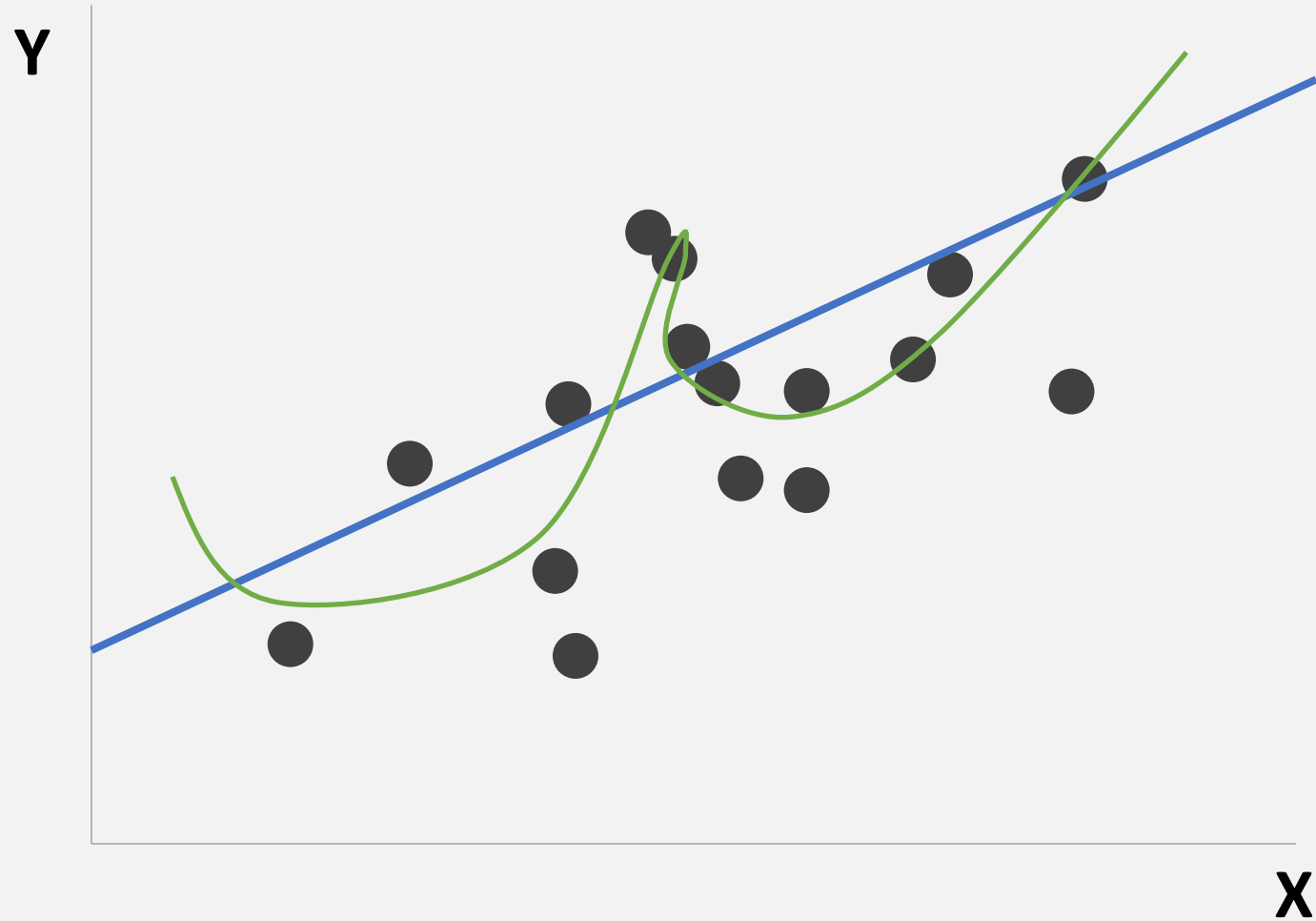
- Use past data to predict
- future outcomes

How can more advanced ML algorithms improve on what we just did?

Past Data Continuous Outcome

Key issue: build models that fit current data well but also predict future data well

—



Overfitting + Generalization

- **Problem:**

- Every sample is truth + error. The model may learn too much about the error in a particular sample by adding too many parameters.

- **Solutions:**

- 1. Penalizing predictive accuracy for model complexity**

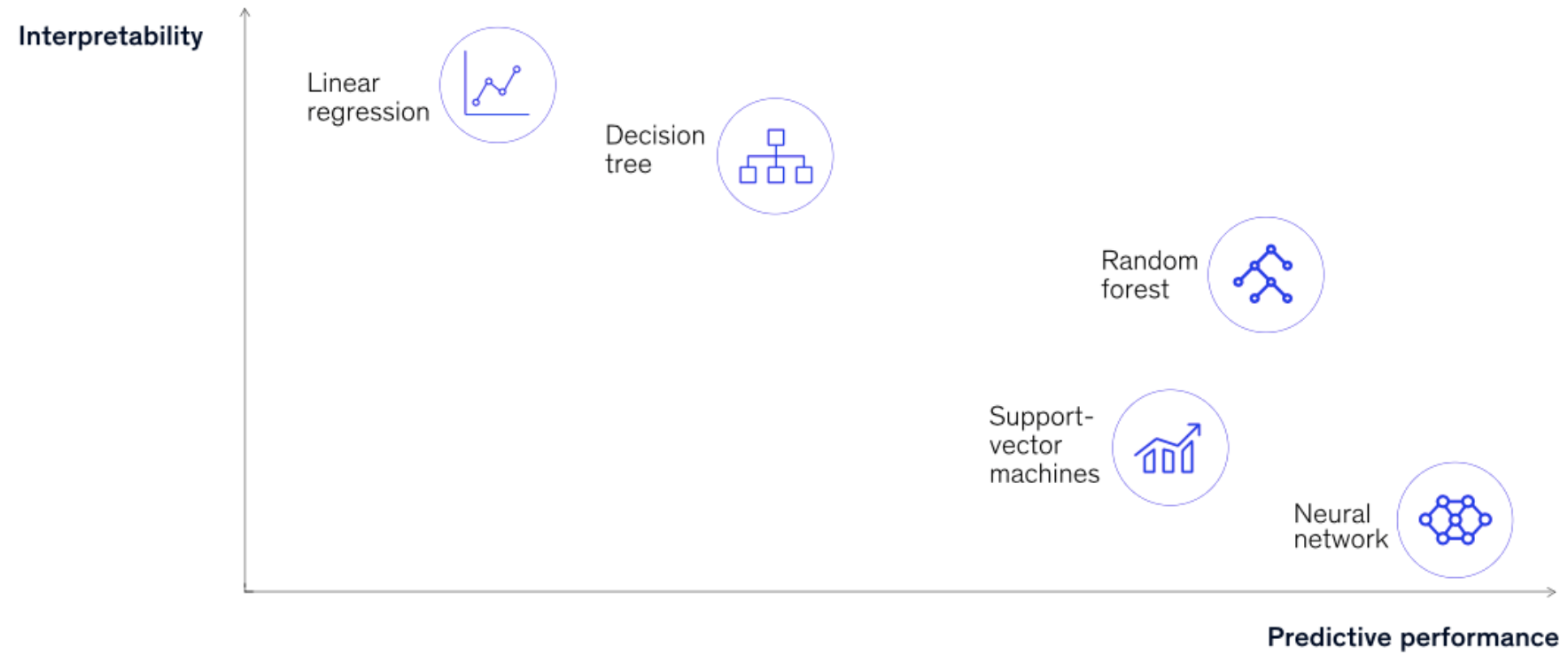
1. Regularization (constraint on parameters)

- 2. Partition training data into training and test data**

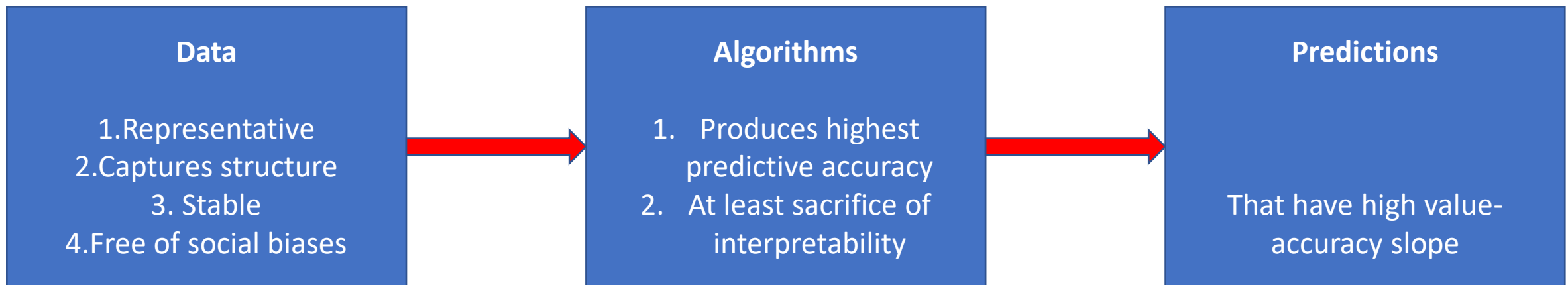
1. K-fold validation

- 3. Both!**

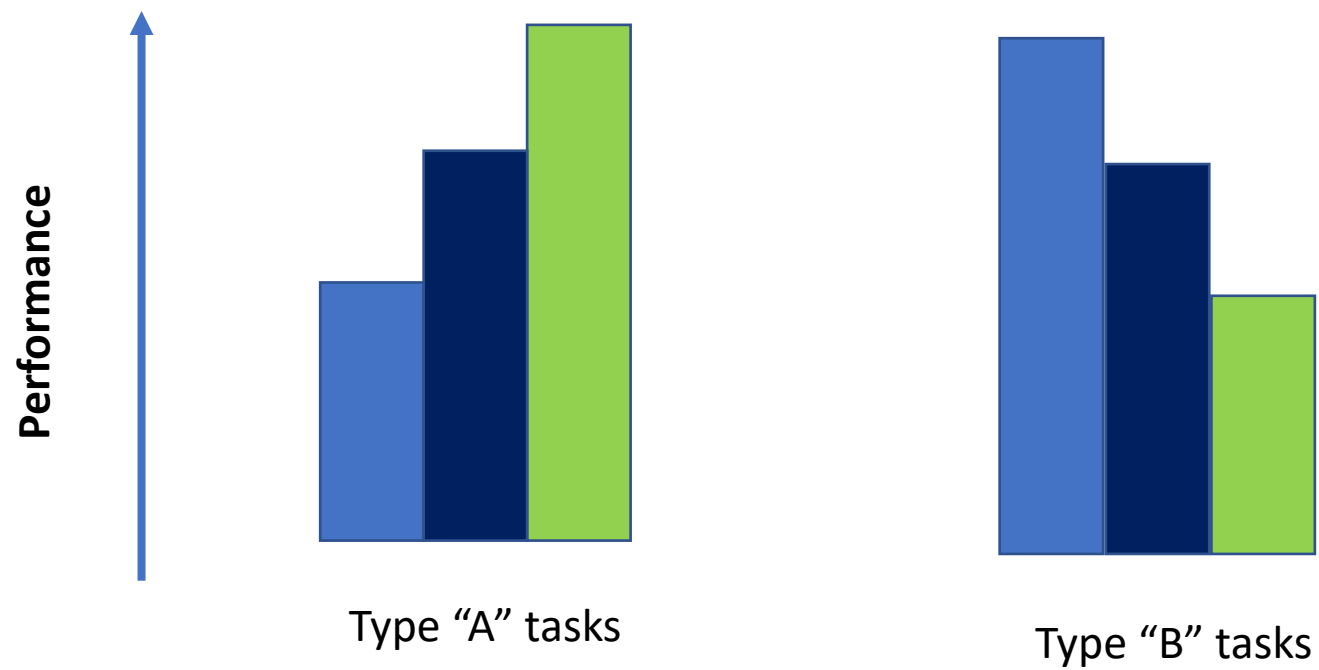
Models with more predictive power are often more opaque.



Components of a prediction machine



<https://knowledge.insead.edu/blog/insead-blog/where-ai-can-help-your-business-and-where-it-cant-13136>



Division of Labour + Integration of Effort

