

# Introduction to Pattern Recognition (PR) and Machine Learning (ML)

B. Ravindran

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PRML Aug-Nov 2021 (BR section)

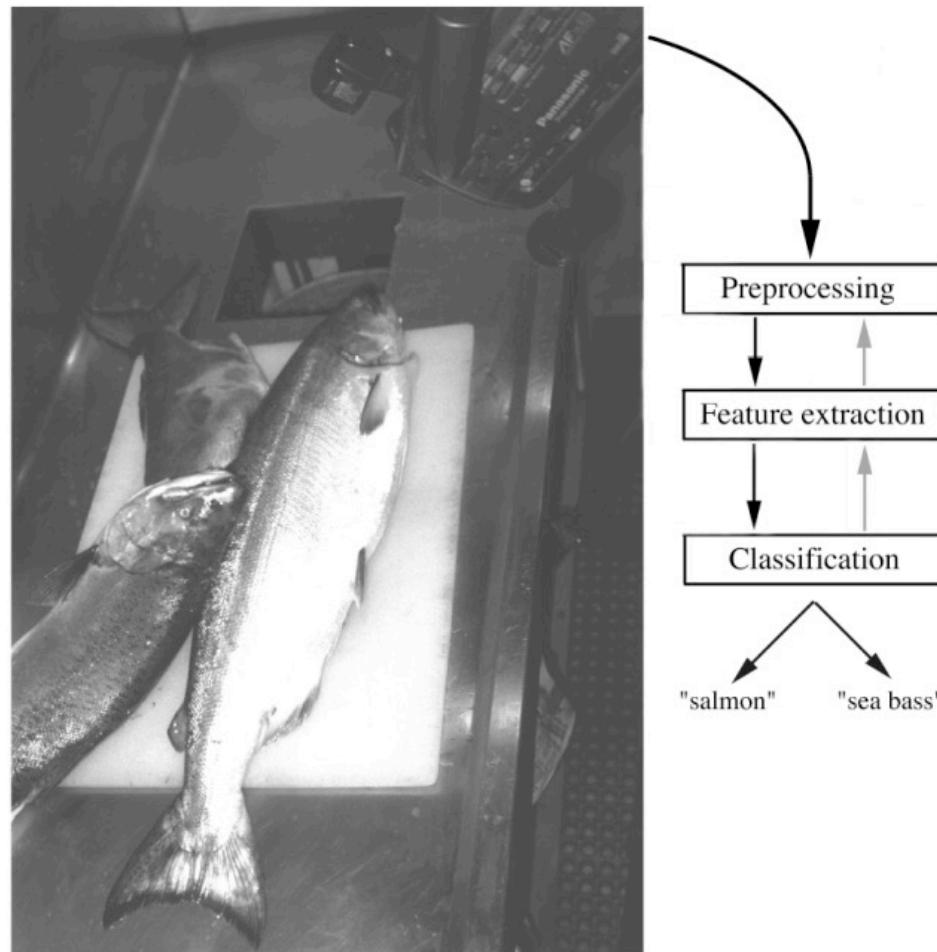
# Acknowledgment of Sources

- Slides based on content from related
  - Courses:
    - IITM – Profs. Arun/Harish/Manikandan/Chandra’s PRML offerings (slides, quizzes, notes, etc.).
    - India – NPTEL PR course by IISc Prof. PS. Sastry (slides, etc.)
  - Books:
    - PRML by Bishop. (content, figures, slides, etc.) – cited as [CMB]
    - Pattern Classification by Duda, Hart and Stork. (content, figures, etc.) – [DHS]
    - Elements of Statistical Learning by Hastie, Tibshirani, Friedman (content, figures, etc.) – [ESL]
    - Mathematics for ML by Deisenroth, Faisal and Ong. (content, figures, etc.) – [DFO]

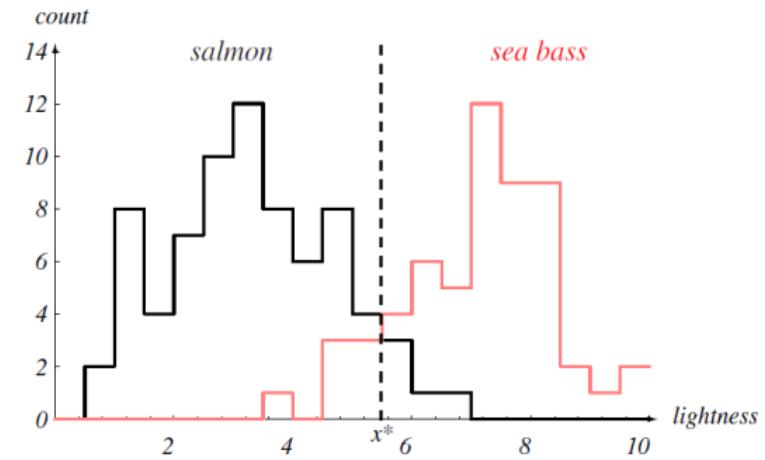
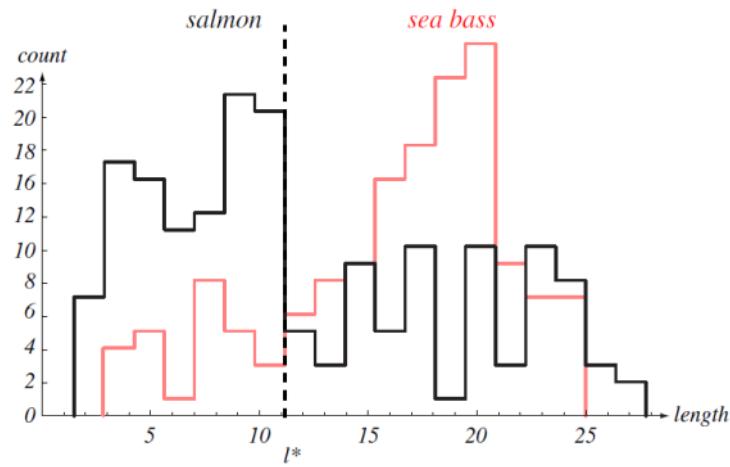
# What is a (real-world) PR task?

- Humans routinely categorize sensory inputs (i.e., recognize patterns in sensory inputs).
  - Read facial expressions
  - Recognize speech
  - Read a document
  - Diagnose disease from medical image
- Build a machine (system) to recognize
  - Recognize a person by fingerprints
  - Recognize different types of fruits from an image
  - Predict if a particular region would suffer from a COVID outbreak in the next month.
  - Find relevant movies for you in Netflix based on movies you've watched.

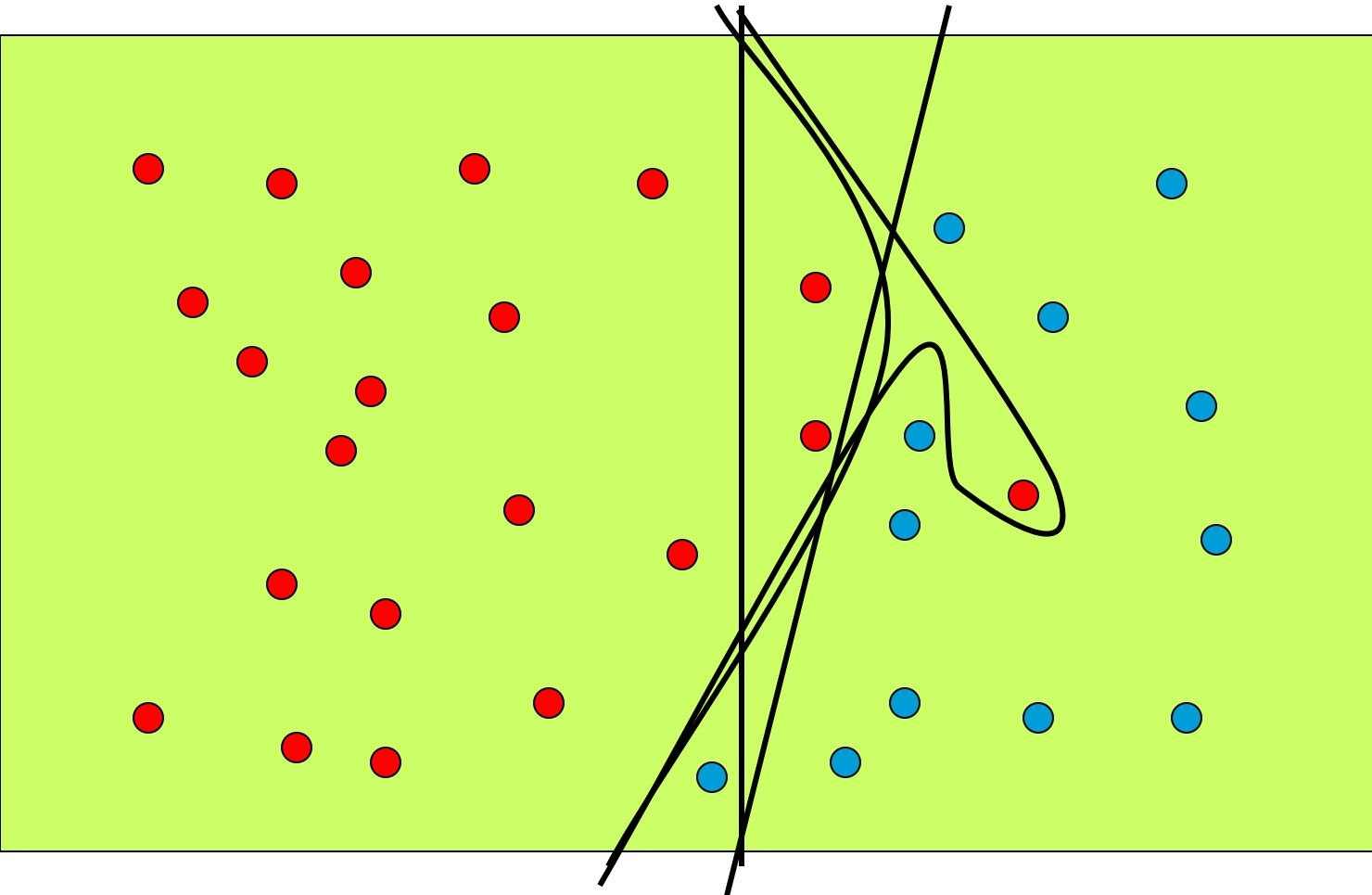
# How does a system for a PR task look like?



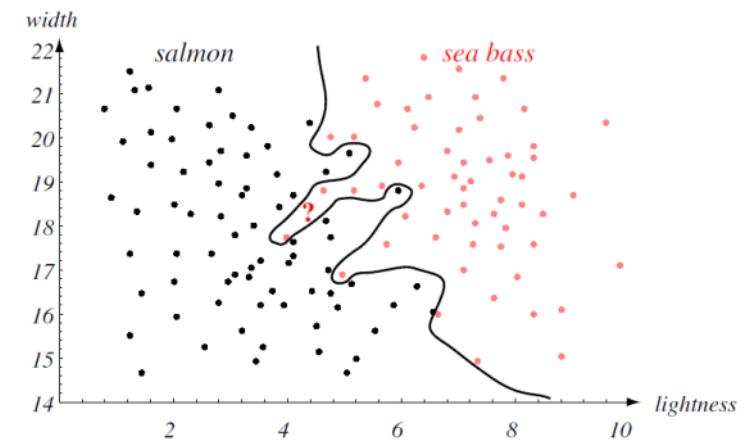
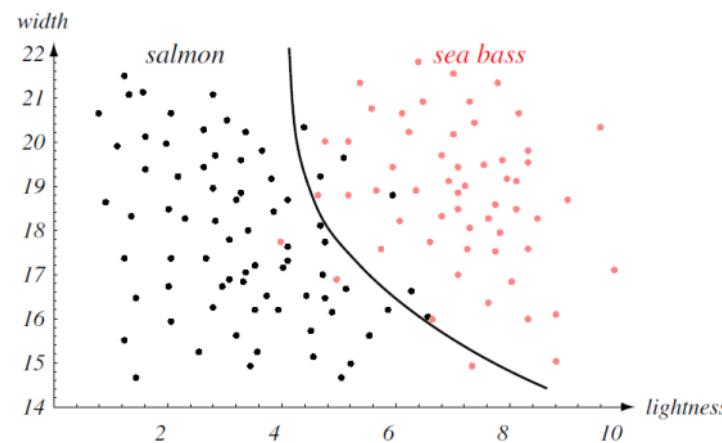
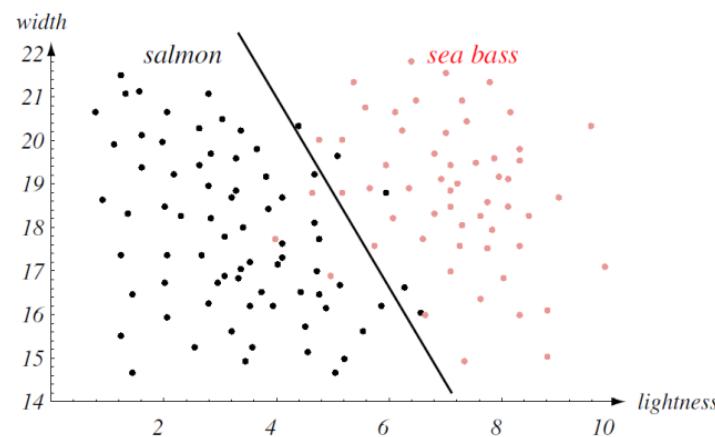
# Feature extraction/selection



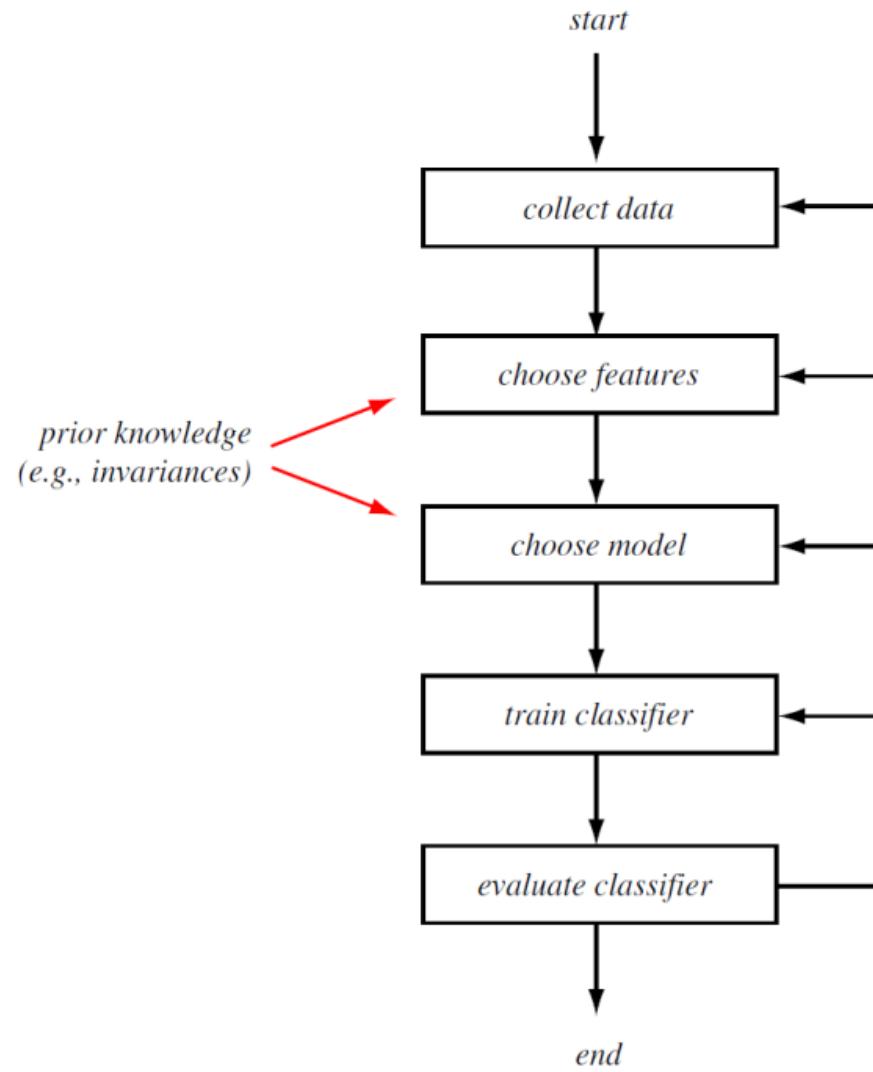
# Decision Boundaries



# Decision boundary – from simple to complex



# The Design Cycle



# What is a PR problem?

- Formulation of the PR task as an abstract computational problem with given input (features) and desired outputs/actions.
- Major classes of PR problems:
  - Clustering
  - Classification
  - Regression
  - ...
- How do we solve a PR problem?
  - Logic/Data-driven approaches

# What is a ML algorithm?

- An algorithm is
  - "... said to learn from experience with respect to some class of tasks, and a performance measure P, if [the learner's] performance at tasks in the class, as measured by P, improves with experience.". [Tom Mitchell 1997]
- In our context of solving a PR task, an ML algorithm recognizes a pattern by:
  - learning it from examples (*training* data provided by a teacher/oracle),
  - so that it can *generalize* to *unseen* (*test*) data.

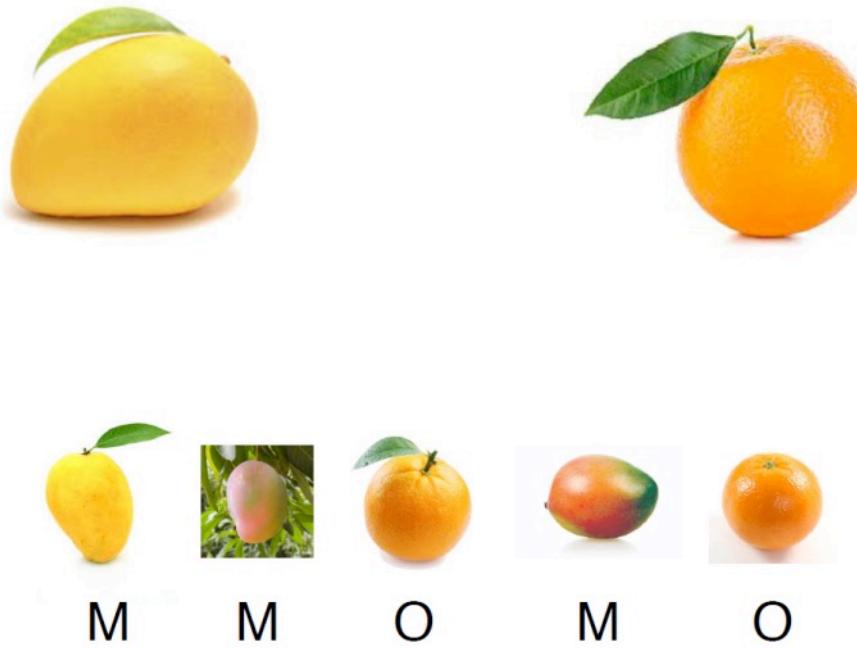
# Example PR problem

- Identify a given image as mango or orange.



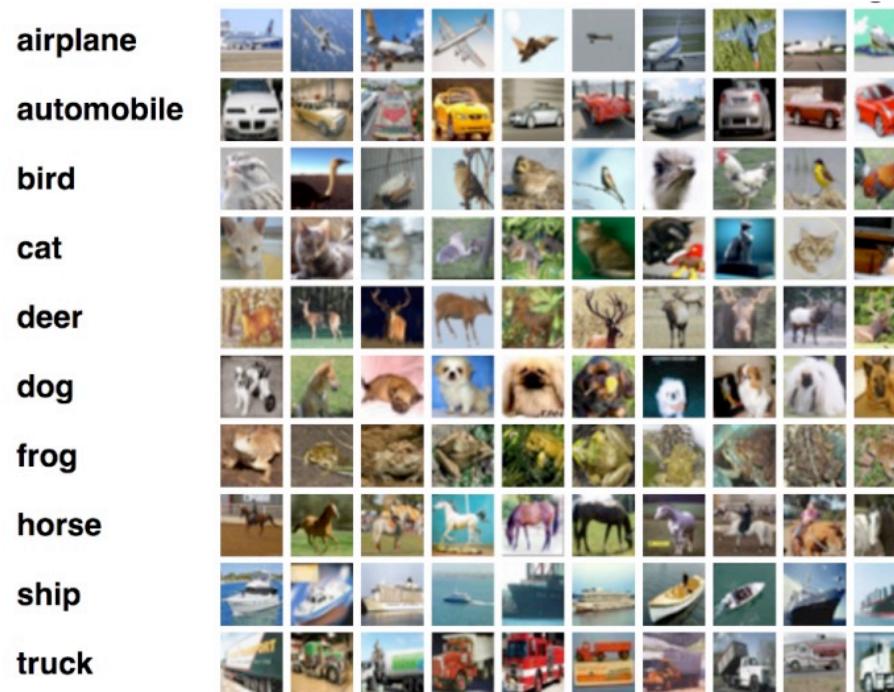
# Example ML approach

- Identify a given image as mango or orange, given many example images of mango and orange.



# Example PR/ML problem

Classify an image into one of 10 classes,  
given a “training set” of images with classes.



<course logistics begin>

# Get to know you - poll

- Level of comfort with prereqs.:

	Moderate	Poor	Very Good
Probability			
Linear algebra			
Calculus			
Optimization			
Programming			

# Get to know the TAs

- Rahul Vashisht – Lead TA. Will announce the rest of the TAs shortly.
  - cs18d006@smail.iitm.ac.in

# Planned syllabus (tentative)

**Subset of topics below to be covered** (not necessarily in the same order):

1. Overview of PR/ML problems/algorithms (PR tasks/systems, ML paradigms)
2. Bayesian decision theory (Bayes classifier, loss functions)
3. Density estimation (Maximum likelihood, Bayesian estimation, Expectation Maximization (EM) for mixture density estimation, Non-parametric methods)
4. Linear models for classification and regression (Linear discriminant analysis (hyperplanes), Linear/polynomial regression, Bayesian regression)
5. Non-linear models for classification and regression (Support Vector Machines and kernel methods, Neural networks)
6. Combining models (Ensemble methods like boosting and bagging, Tree-based models)
7. Unsupervised learning methods for clustering and dimensionality reduction (E.g., hard/soft k-means clustering, Principal Component Analysis (PCA))
8. Select advanced topics based on time available (E.g., a subset of computational learning theory, algorithms for sequential data (Hidden Markov Models HMM), or graph-structured data; probabilistic graphical models).

A big question is:

**WHY???**

learn so many models/methods, if only one of the methods is all you hear about everywhere?

On a different context, always ask WHY you are taking this course? I hope it is not only campus placement opportunities or hype around ML, but also a general interest in understanding how you can take this field forward with your own creativity and internal ethical compass.

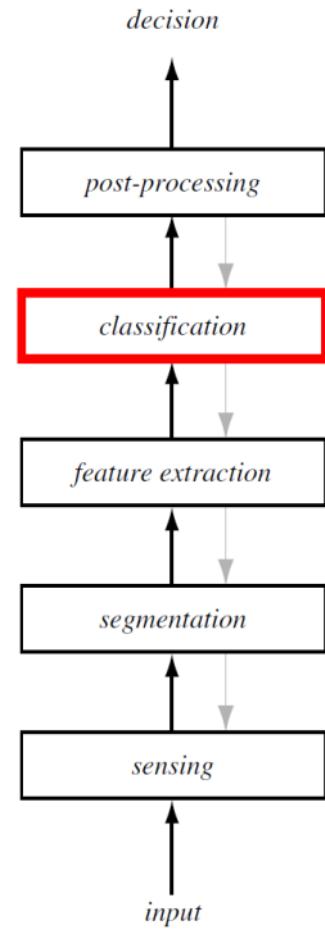
# Evaluation scheme (tentative)

- Aka “Help us help you learn”
- 30% Homework assignments (2 problems/programming-based assignments; done in teams of two students)
- 25% (Real-world) Data contest and writeup (done in teams of two students)
- 5% Tutorial participation – solving problems and interactions during tutorials
- 40% Quiz-I and Quiz-II
  - Proctored, closed-book, online live exam
  - F slot Quiz-II date and F slot EndSem date
- Above amounts to ~6 activities in total – roughly one activity per two weeks.

<course logistics end>

# So far: PR system

- PR task and problem
- ML problem
- ML algorithm

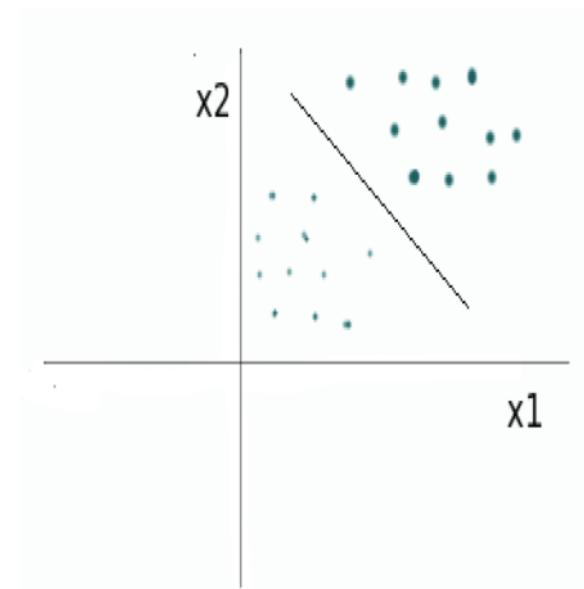


# ML Paradigms

- Supervised Learning (informally aka curve-fitting or function learning)
  - Learn an input and output map (features to target(s))
    - Classification: categorical output
    - Regression: continuous output
- Unsupervised Learning (informally aka pattern discovery)
  - Discover/uncover patterns in the data (without target/response variable(s))
    - Clustering: cohesive grouping
    - Dimensionality reduction: represent features in low-dimensional space
    - Density estimation: learning model parameters
    - Association: frequent co-occurrence
- Reinforcement Learning
  - Learning control (maximize reward in the long run, via optimal explore-exploit policy)
    - Agent interacting with an environment iteratively via a set of “controlling” actions, and getting information about environment’s state/reward to decide next action.
- Other paradigms/categorizations
  - Other paradigms: semi-supervised, online, etc.
  - Other categorizations: linear vs. non-linear models, single vs. ensemble models, methods for independent vs. time-dependent vs. graph-structured data, etc.

# Example (linear) classification problem

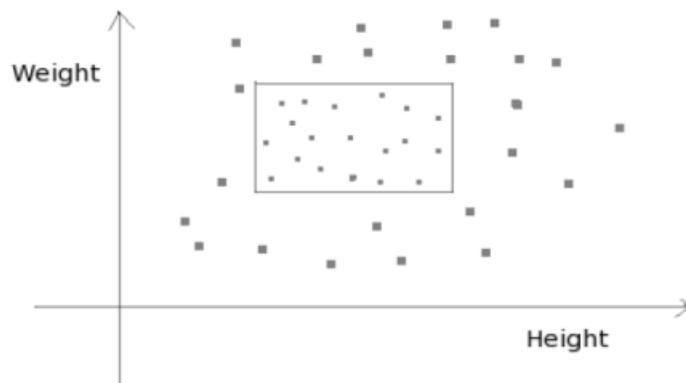
- Problem: ‘Spot the Right Candidate’
- Features:
  - $x_1$ : Marks based on academic record
  - $x_2$ : Marks in the interview
- A Classifier:  $ax_1 + bx_2 > c \Rightarrow \text{‘Good’}$   
We have chosen a specific form for the classifier.
- Design of classifier: What values to use for  $a, b, c$ ?
- Information available: ‘experience’ – history of past candidates



# Example (non-linear) classification problem

- Problem: recognize persons of ‘medium build’
- Features: Height and Weight

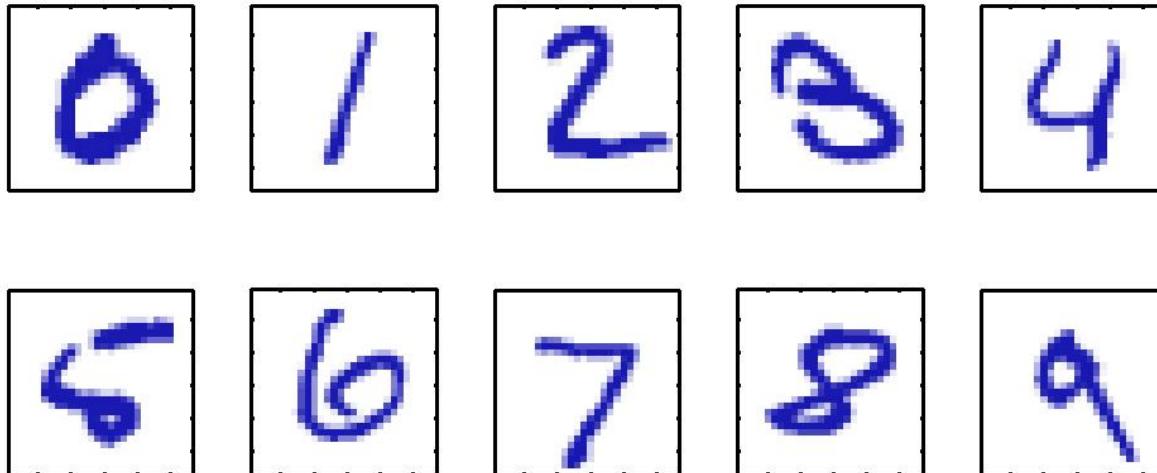
$$f(ax+by) = af(x) + bf(y)$$



The classifier is ‘nonlinear’ here

# Example classification problem

- Handwritten Digit Recognition:
  - Take a digit's  $28 \times 28$  pixel image, represented by a vector of 784 real numbers, as input feature vector  $\mathbf{x}$ , and output the identify of the digit 0,...,9.
  - Non-trivial problem due to the wide variability of handwriting.

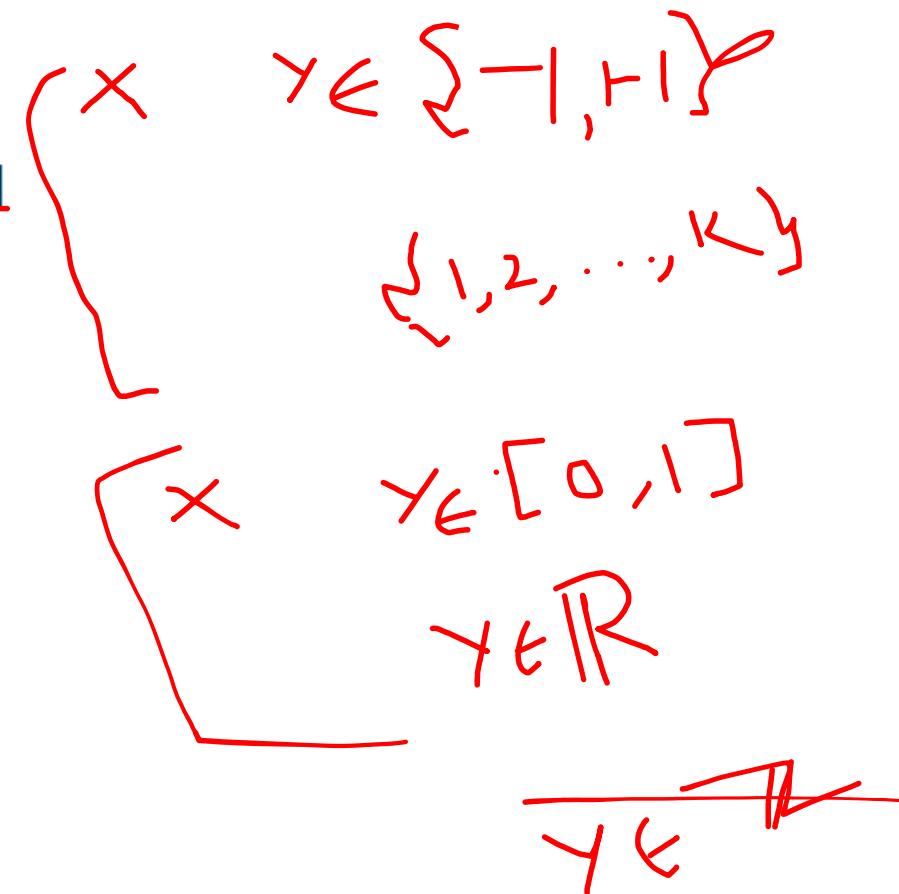


# Classification Applications

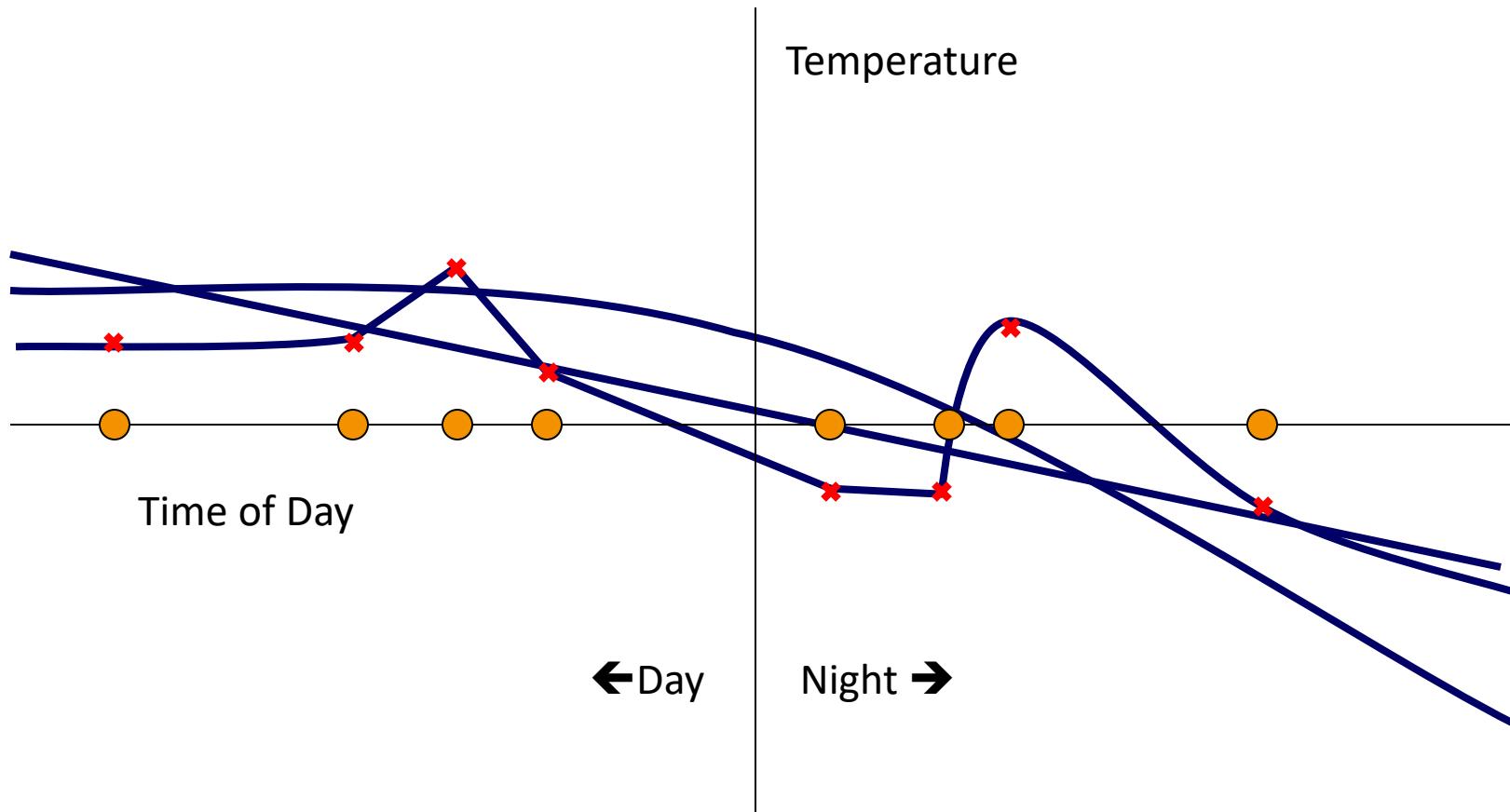
- Credit Card fraud detection
  - Valid transaction or not
- Sentiment Analysis
  - Opinion mining; buzz analysis; etc.
- Churn prediction
  - Potential chunner or not
- Medical diagnoses
  - Risk analysis

# Regression (vs. classification) problem

- Closely related problem. Output is continuous-valued rather than discrete as in classifiers.
- Here training set examples could be  $\{(X_i, y_i), i = 1, \dots, \ell\}, X_i \in \mathcal{X}, y_i \in \mathbb{R}$ .
- The prediction variable,  $y$ , is continuous; rather than taking finitely many values. ( There can be noise in examples).
- Similar learning techniques needed to infer the underlying functional relationship between  $X$  and  $y$ . (Regression function of  $y$  on  $X$ ).



# Prediction or Regression



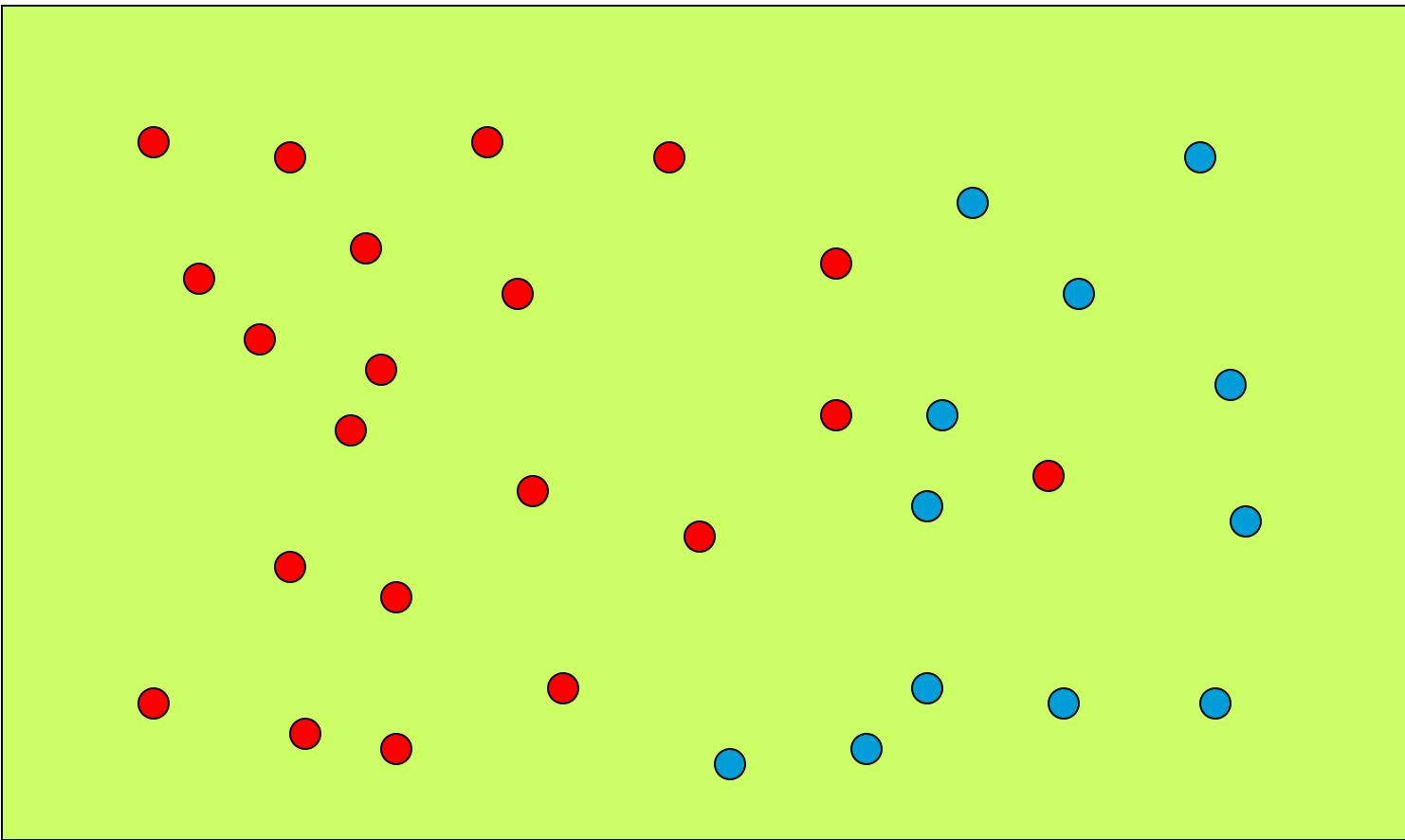
# Example regression problems

- Time series prediction: Given a series  $x_1, x_2, \dots$ , find a function to predict  $x_n$ .
- Based on past values: Find a ‘best’ function
$$\hat{x}_n = h(x_{n-1}, x_{n-2}, \dots, x_{n-p})$$
  - Predict stock prices, exchange rates etc.
  - Linear prediction model used in speech analysis
- More general predictors can use other variables also.
  - Predict rainfall based on measurements and (possibly) previous years’ data.
  - In general, System Identification. (An application: smart sensors)

# ML Paradigms

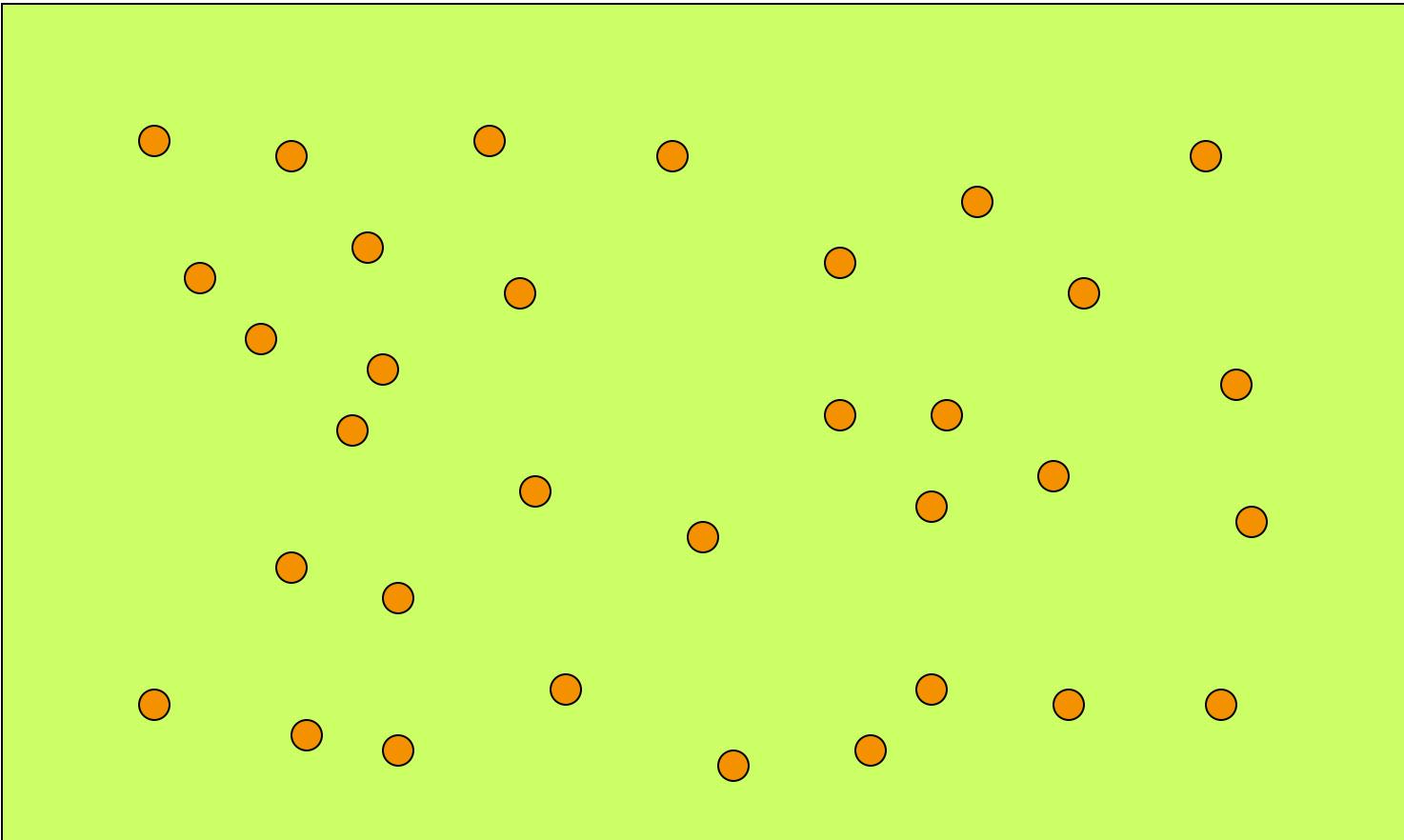
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# Labeled Training Data

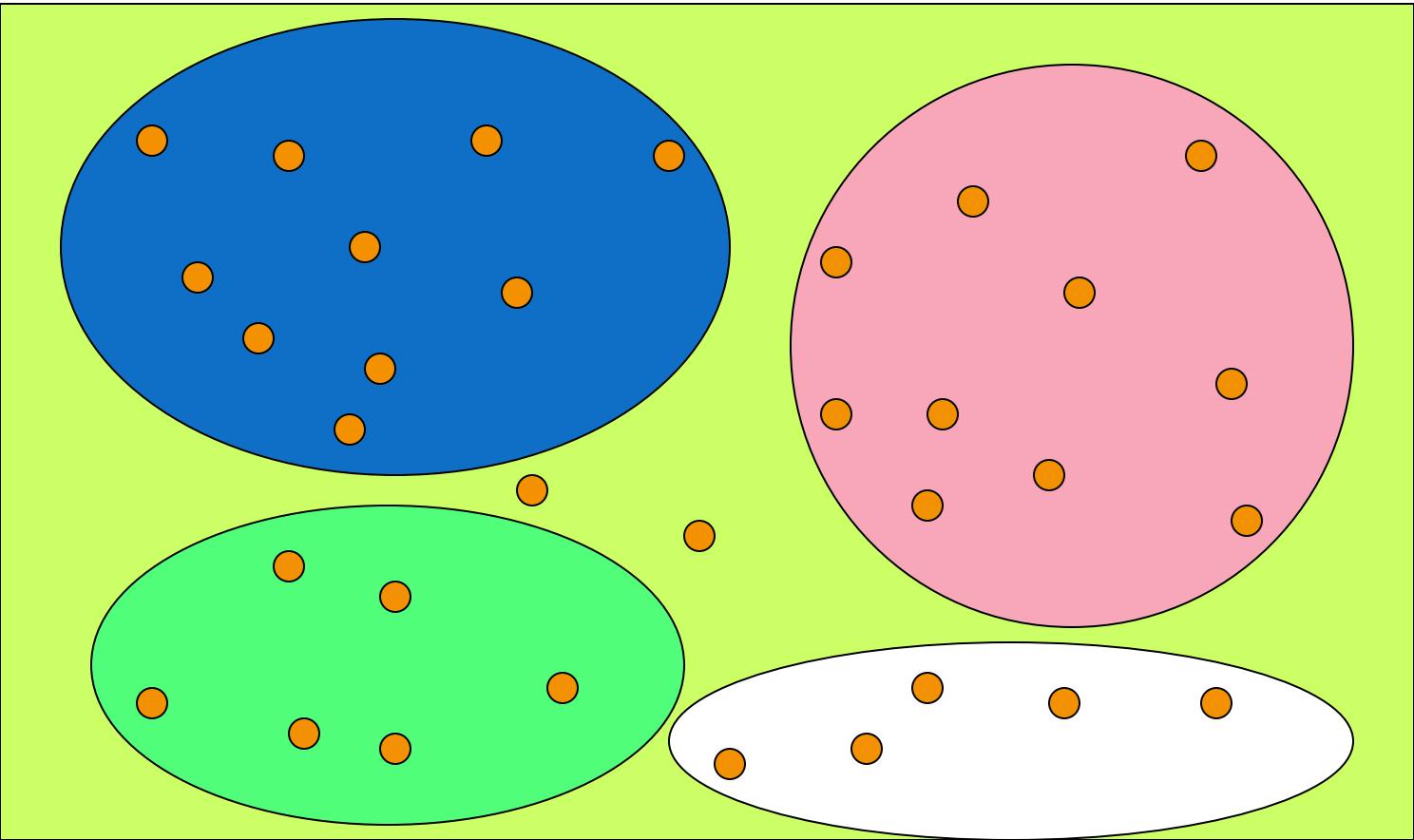


# Unlabelled Training Data

## Clustering



# Possible Clusters



# Clustering Applications

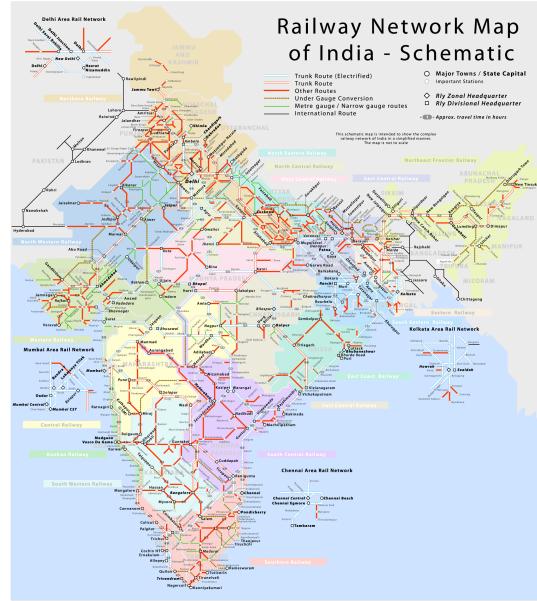
- Customer Data
  - Discover classes of customers
- Image pixels
  - Discover regions
- Biomarkers
  - Genes or proteins vs. disease
- Transportation Networks
  - Zones



Image Courtesy: <http://cs.brown.edu/~pff/segment/>

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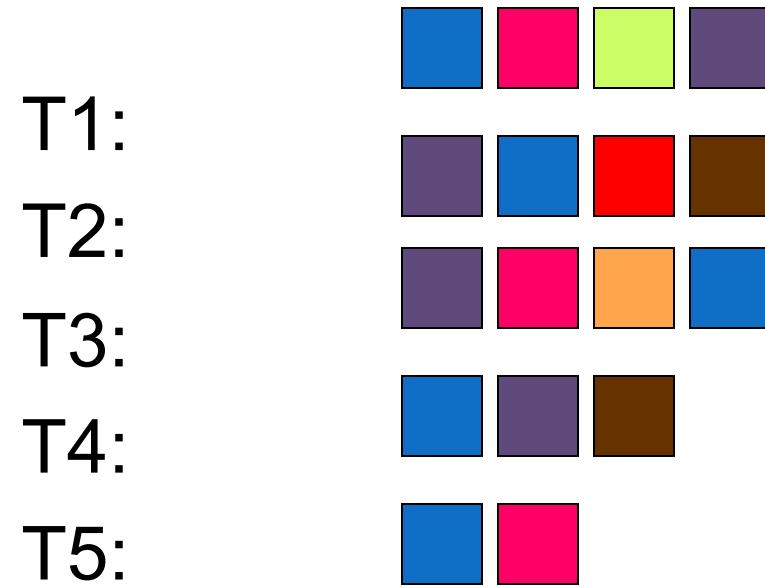
# Association Rule Mining

- Mining frequent patterns and rules
- Association rules: conditional dependencies
- Two stages
  - Find frequent patterns
  - Derive associations ( $A \Rightarrow B$ ) from frequent patterns
- Find patterns in
  - Sequences (time series data, fault analysis)
  - Transactions (market basket data)
  - Graphs (social network analysis)

# Mining Transactions

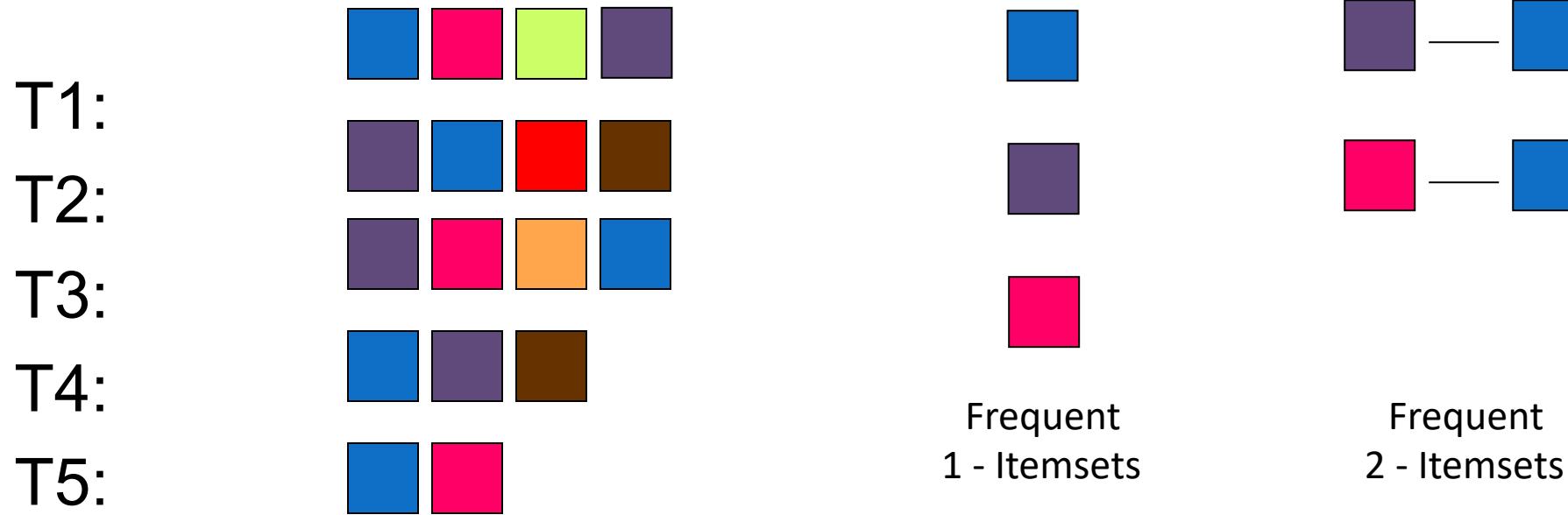
- Transaction is a collection of items bought together
  - A (sub)set of items is called an itemset
- Find frequent itemsets
- Itemset  $A \Rightarrow$  itemset  $B$ , if both  $A$  and  $A \cup B$  are frequent itemsets.

# Transaction data bases



Frequency Threshold: 3

# Frequent Pattern Mining

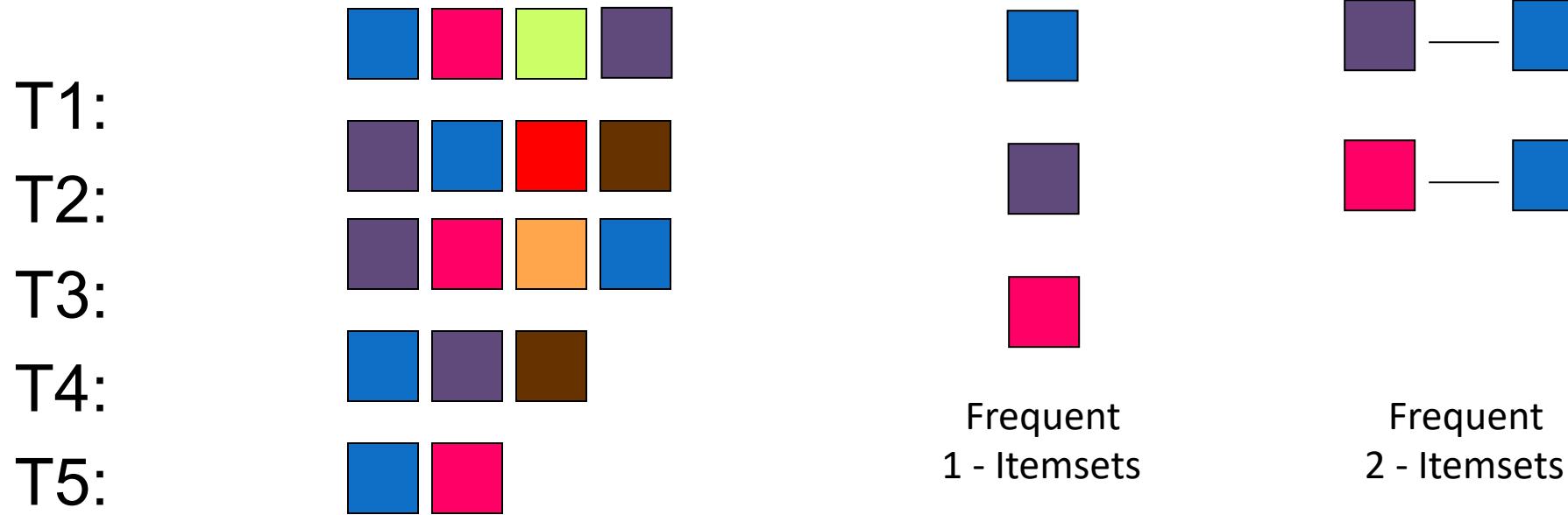


Frequency Threshold: 3

# Mining Transactions

- Transaction is a collection of items bought together
  - A (sub)set of items is called an itemset
- Find frequent itemsets
- Itemset  $A \Rightarrow$  itemset  $B$ , if both  $A$  and  $A \cup B$  are frequent itemsets.
- Support of a rule is the percentage of itemsets containing  $A \cup B$
- Confidence of a rule is the percentage of itemsets containing  $A$  that also contain  $A \cup B$
- We look for rules with both high support and confidence
  - Can be determined from the frequent itemsets; hence more effort focused on that

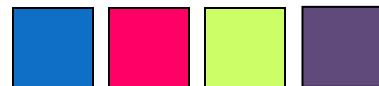
# Frequent Pattern Mining



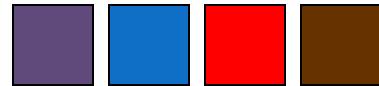
Frequency Threshold: 3

# Association Rules

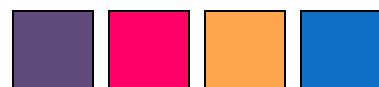
T1:



T2:



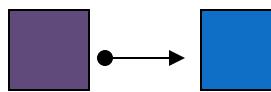
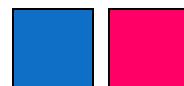
T3:



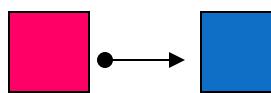
T4:



T5:



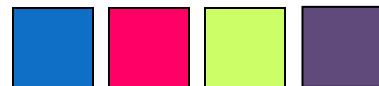
Support: 4/5; Conf: 1



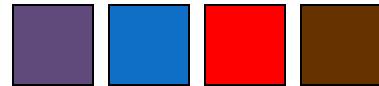
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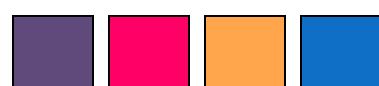
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T2:



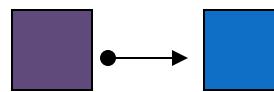
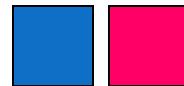
T3:



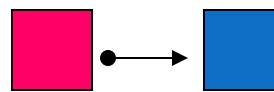
T4:



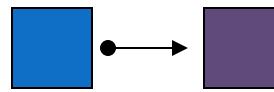
T5:



Support: 4/5; Conf: 1



Support: 3/5; Conf: 1



Support: 4/5; Conf: 4/5

# Association Mining Applications

- Market Basket analysis
- Topic identification
  - co-occurrence of words
- Plagiarism Detection!
- Biomarkers
  - Genes or proteins vs. disease
- Time series analysis!
  - Trigger Events

# ML Paradigms

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# Learning to Control

- Familiar models of machine learning
  - Learning from data.
- How did you learn to cycle?
  - Not from Data!
  - Trial and error!
  - Falling down hurts!
  - Learn from Evaluation!

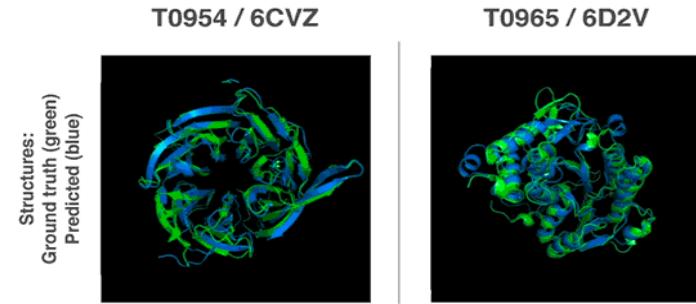
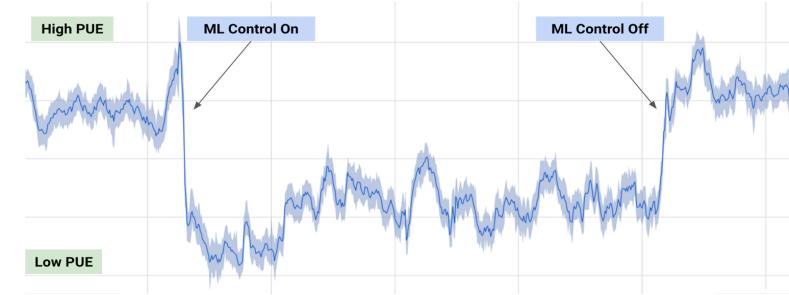


# Learning to Control

- Familiar models of machine learning
  - Learning from data.
- How did you learn to cycle?
  - Not from Data!
  - Trial and error!
  - Falling down hurts!
  - Learn from Evaluation!
- Walking, Talking, etc.

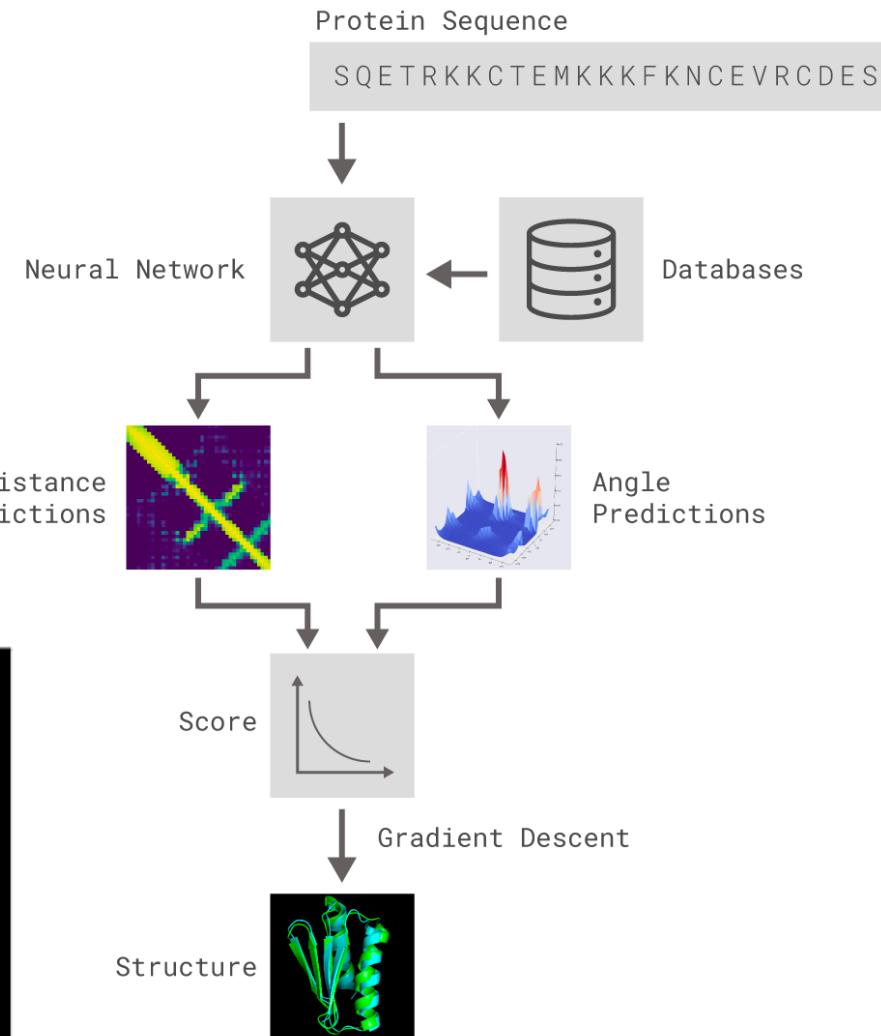
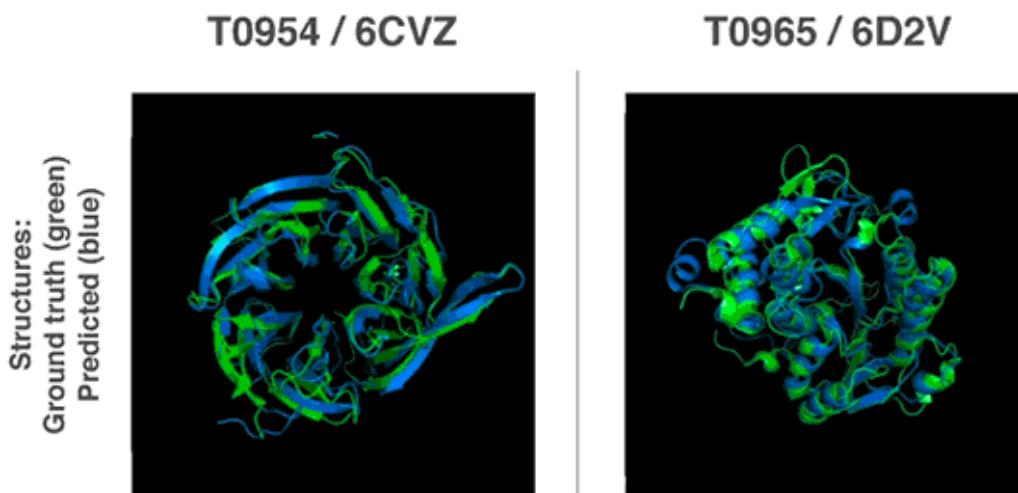


# Reinforcement Learning Works!



# AlphaFold

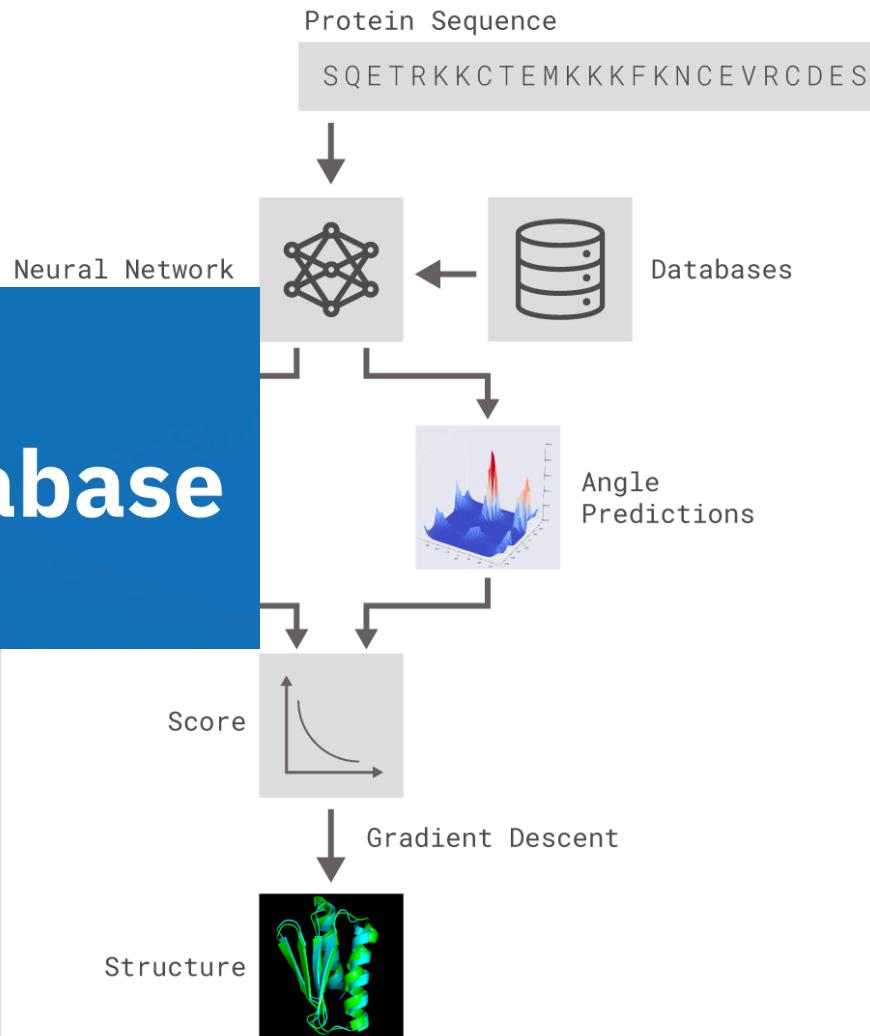
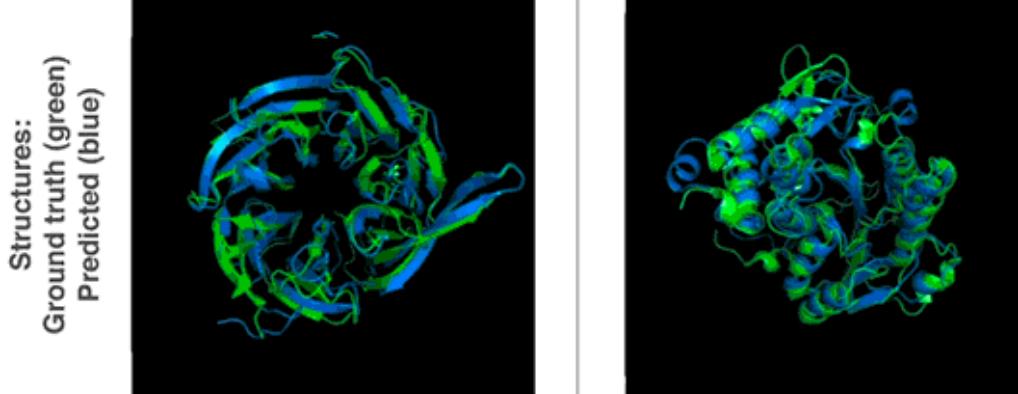
- Protein Folding: One of the hardest problems in biology
- An AI agent achieved 25% improvement over best human effort



# AlphaFold 2.0

- Protein Folding: One of the hardest problems in biology

**SOLVED?**



# Get to know the TAs

- Rahul Vashisht – Lead TA. Will announce the rest of the TAs shortly.
  - cs18d006@smail.iitm.ac.in