ITCS 6156/8156 Machine Learning

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Class Meeting: Mon & Wed, 4:00 PM – 5:15 PM, Denny 109

UNIVERSITY OF NORTH CAROLINA CHARLOTTE

How to Automate Solutions to Computational Problems

- Spam email classification:
  - Binary classification of emails:
    Spam vs. Ham (Legitimate message)

- Expert Systems approach (Rule-based)
  - A group of experts write rules determining whether an email is spam or not.
  - A programmer implement the rules into computer code

- Example rules:
  - Classify the email as spam in “Money” appears in the text.
  - What if the email is sent by your parents?

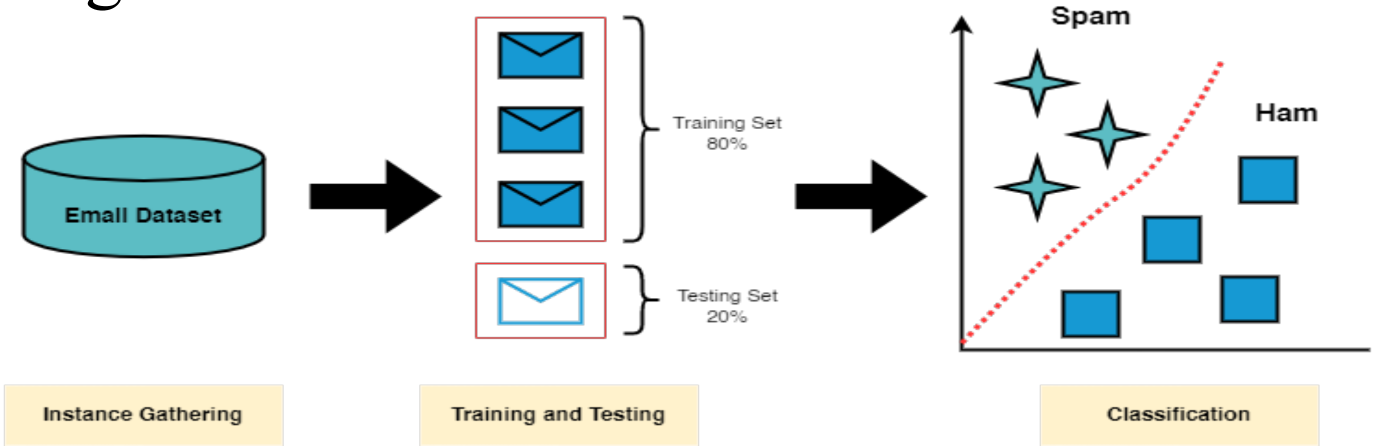
How to Automate Solutions to Computational Problems

- Cons of **Expert Systems** approach (Rule-based)
  - **Cognitively demanding**: Difficult for humans to reason with many useful but imprecise features that are indicative (signals) of spam or not spam:
    - Words, phrases, images, meta-data, time series, …
    - Need to combine a large number of signals, figure out their relative importance in determining spam vs. ham label.
  - **Brittle**: Always going to miss some usef features or patterns
    - Spam filtering is adversarial, new features need be added over time.

Expert (Rule-based) Systems

Why Machine Learning?

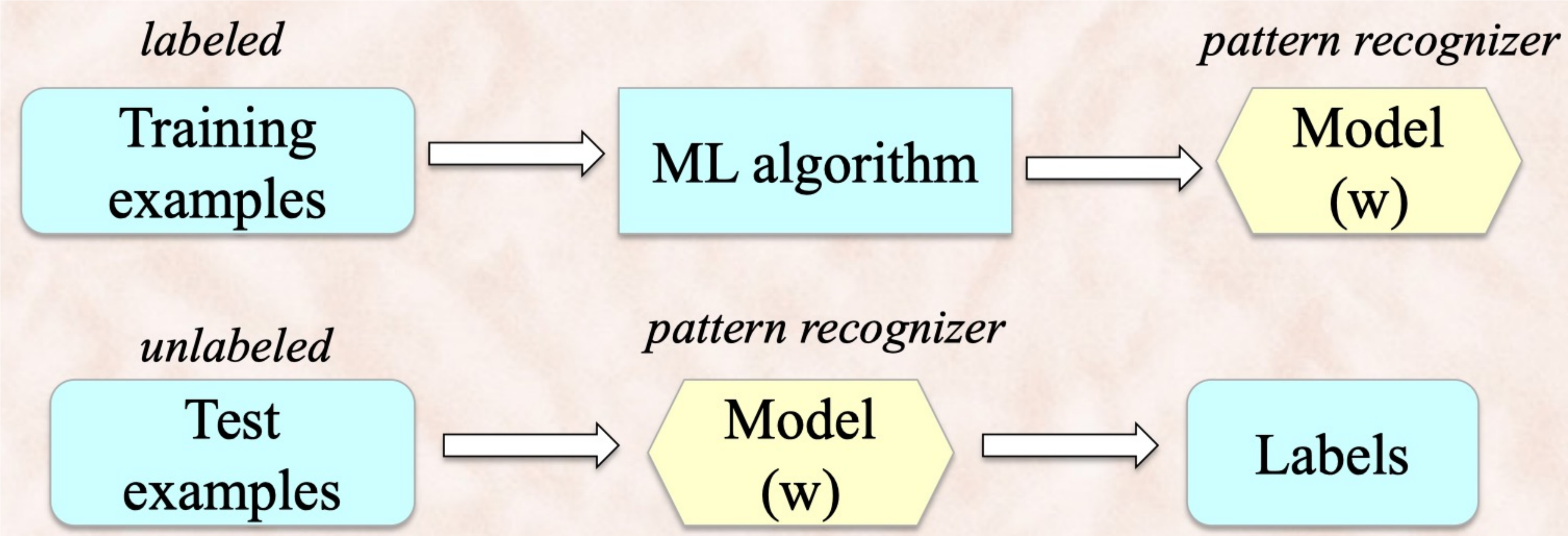
- Machine Learning algorithms can automatically learn the weights to combine features.



- A typical Machine Learning (ML) approach:
  1. Acquire a large enough dataset of labeled examples:
     - Each email is an instance, the label is spam (+1) vs. not spam (-1).
  2. Represent emails as feature vectors:
     - Each feature has a weight, the sign of the weighted sum of features should match the label.
       - Traditional ML: Engineer the features.
       - Deep ML: Learn the features
  3. Learn the weights so that the model (weighted combination of features) does well on labeled examples.

What's Machine Learning?

- **Machine Learning** is to construct computer programs that learn from experience to perform well on a given task.
  - **Supervised Learning**: discover patterns from labeled examples that enable predictions on (previously unseen) unlabeled examples.



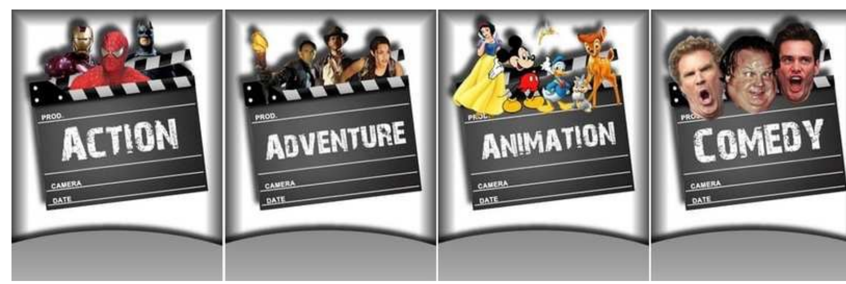
Topics of This Class

Machine Learning

- Function is everywhere!
  - Function → f ; Input instance → x; Output Targe → y

$f($  $)$ → 

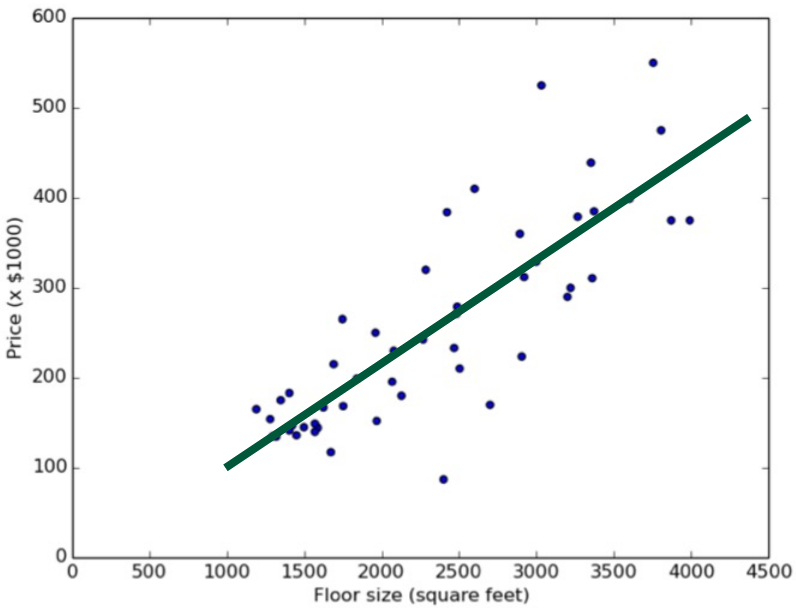
$f($ 

$)$ → 

- Machine Learning Task:
  - learn an (unknown) function $f: X \rightarrow Y$ that maps input instances x $\in X$ to output targets $f(x) \in Y$.

Linear Regression

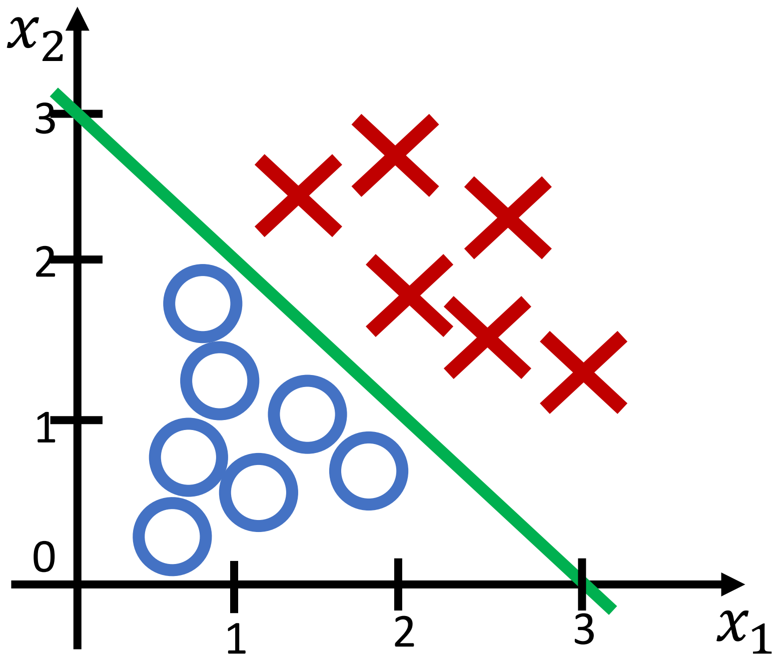
- Given the floor size in square feet, predict the selling price:
  - Input x: the floor size of the house
  - Output y: the selling price of the house
  - Need to learn a function h such that $h(x) \approx f(x)$

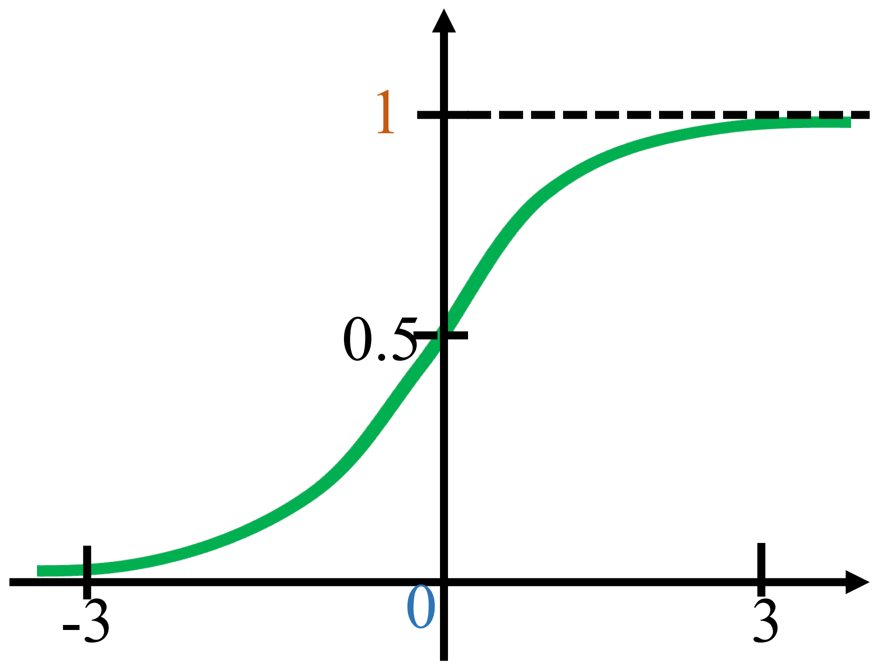


- Assumption: the prediction results are the linear combination of input attributes (features).

Logistic Regression

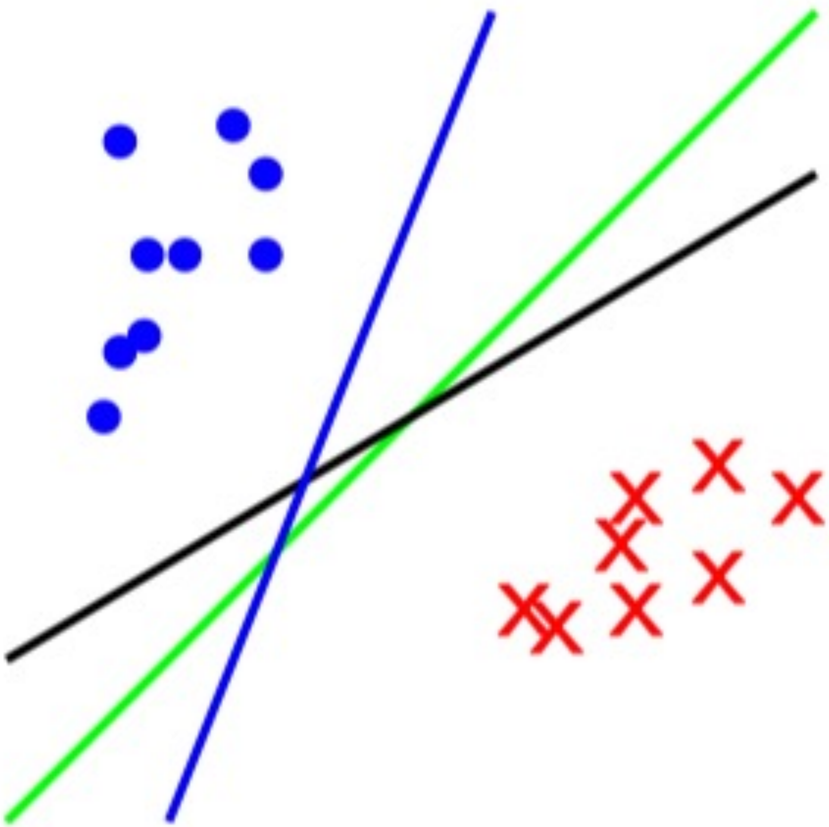
- Objective: To accurately determine the likelihood (probability) of each data instance being classified into a designated category.





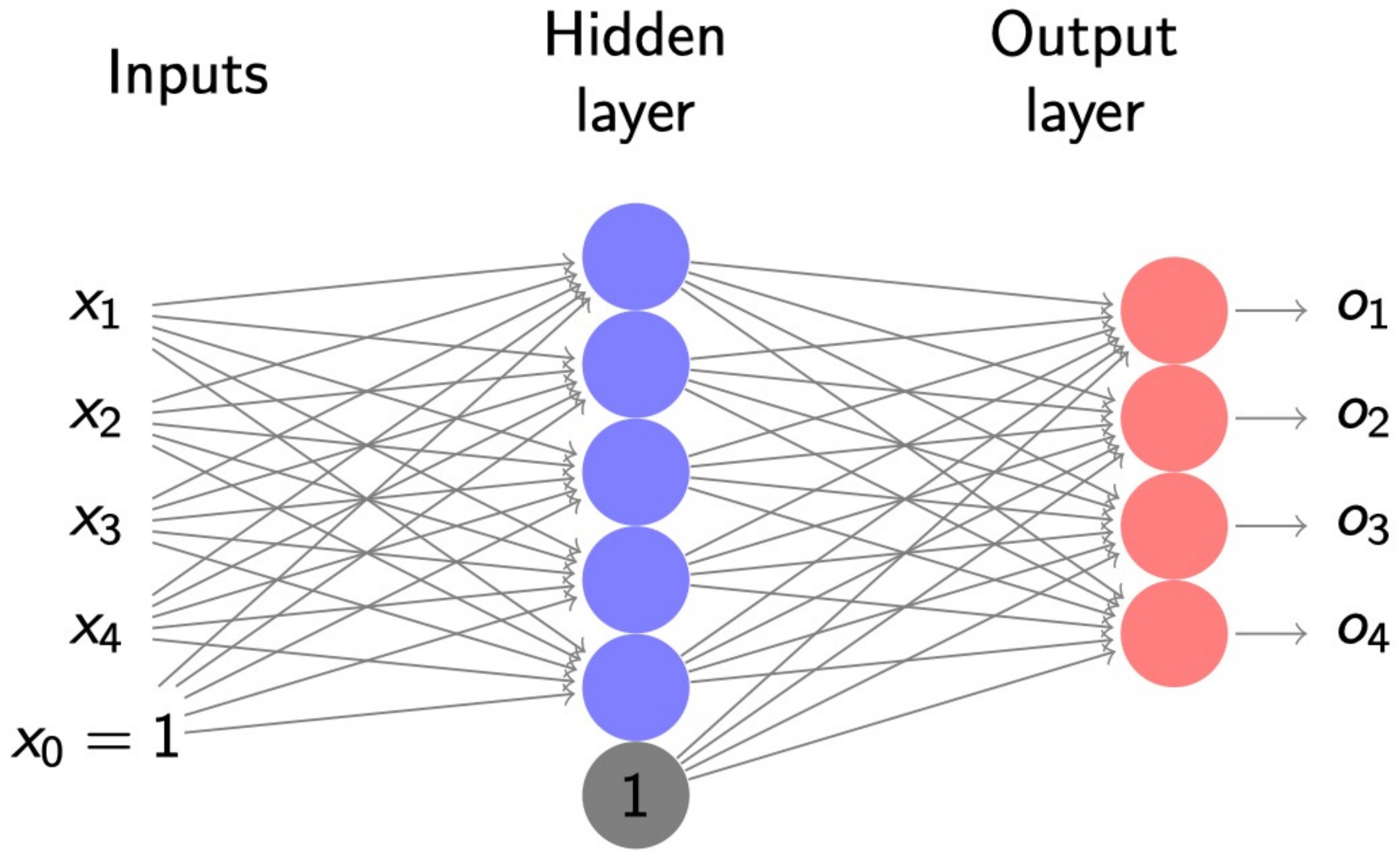
Support Vector Machine

- Objective: to find the optimal hyperplane that maximally separates classes of data points in a feature space.



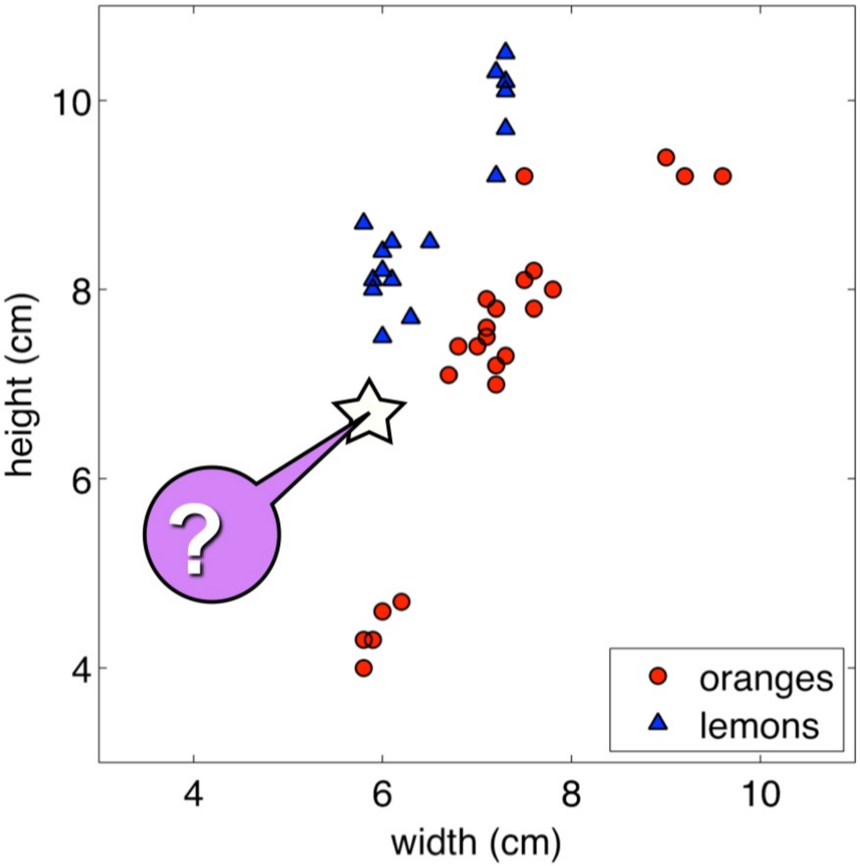
Neural Networks

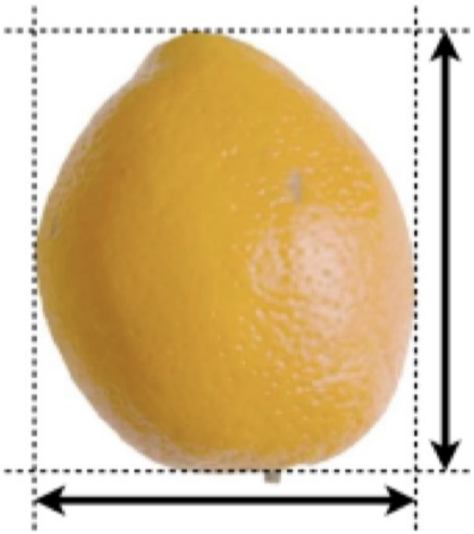
- Assumption: complex patterns and relationships in data can be approximated and learned through a series of interconnected layers of simple computational units (neurons).



k-Nearest Neighbor

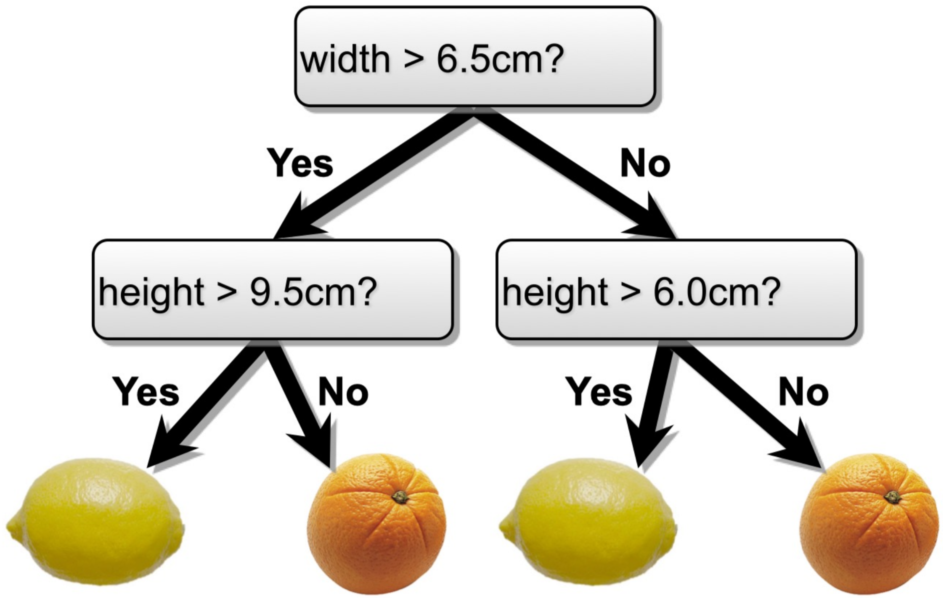
- Assumption: similar data points are likely to belong to the same class, with proximity measured by a distance metric in the feature space.

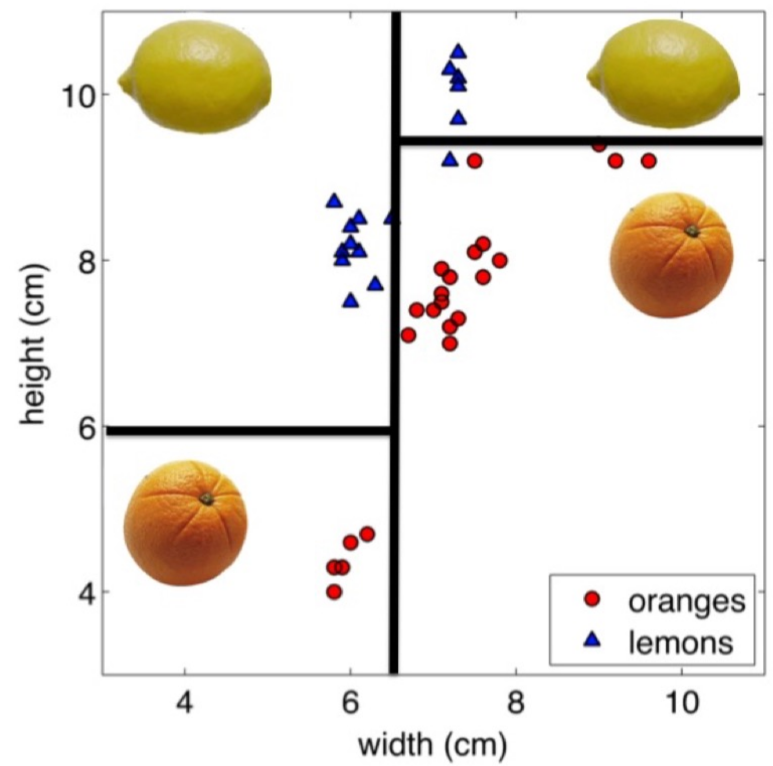




Decisions Trees

- Assumption: complex decisions can be modeled through a series of simple, hierarchical decision rules based on the input features.





Generative Models for Classification

How about this approach: build a model of “how data for a class looks like”

- **Generative** classifiers try to model $p(\mathbf{x}|y)$
- Classification via Bayes rule (thus also called Bayes classifiers)

(prob. of features given label) (class label)

$p(\mathbf{x}|y) \longleftarrow y$

e.g:
- height
- weight
- color

elefant

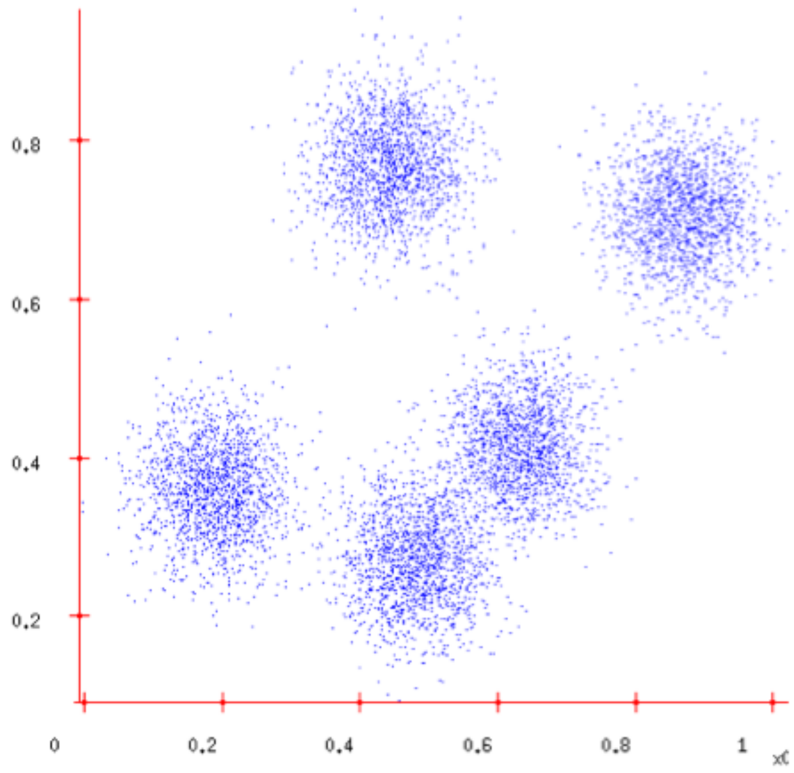
bear

Tries to model:
- How does data look like for a class?

Classification (How?)

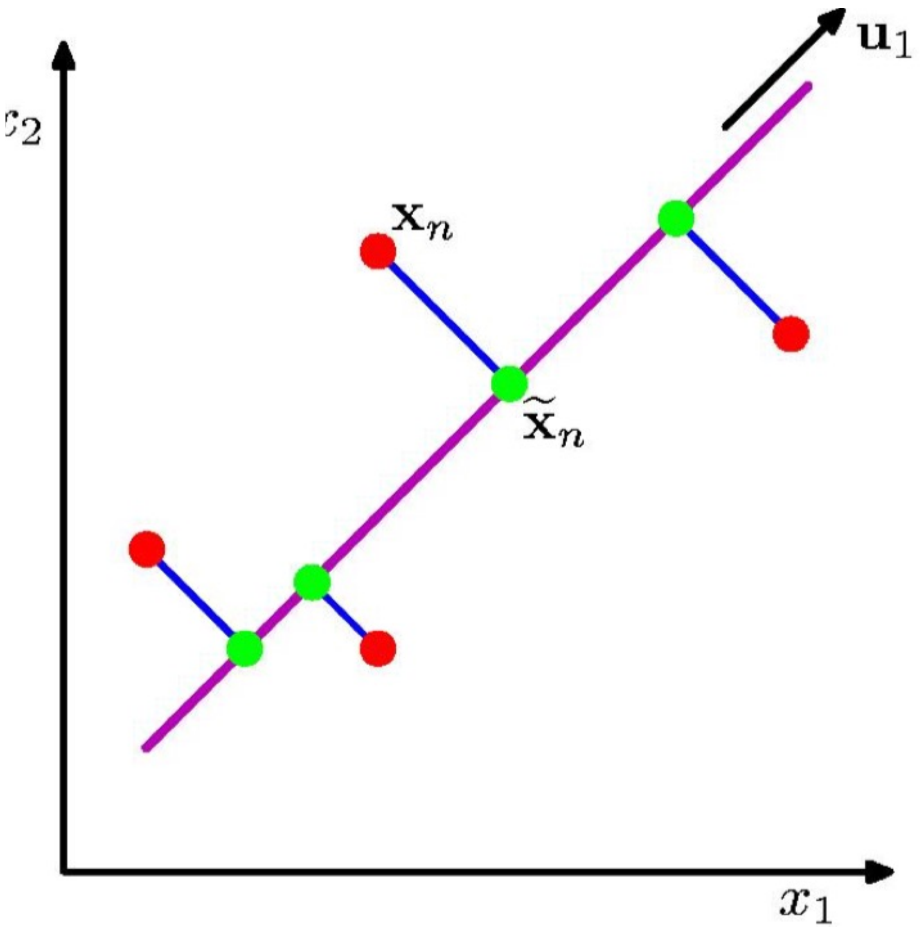
Clustering

- Objective: partition a dataset into k distinct clusters without supervision.



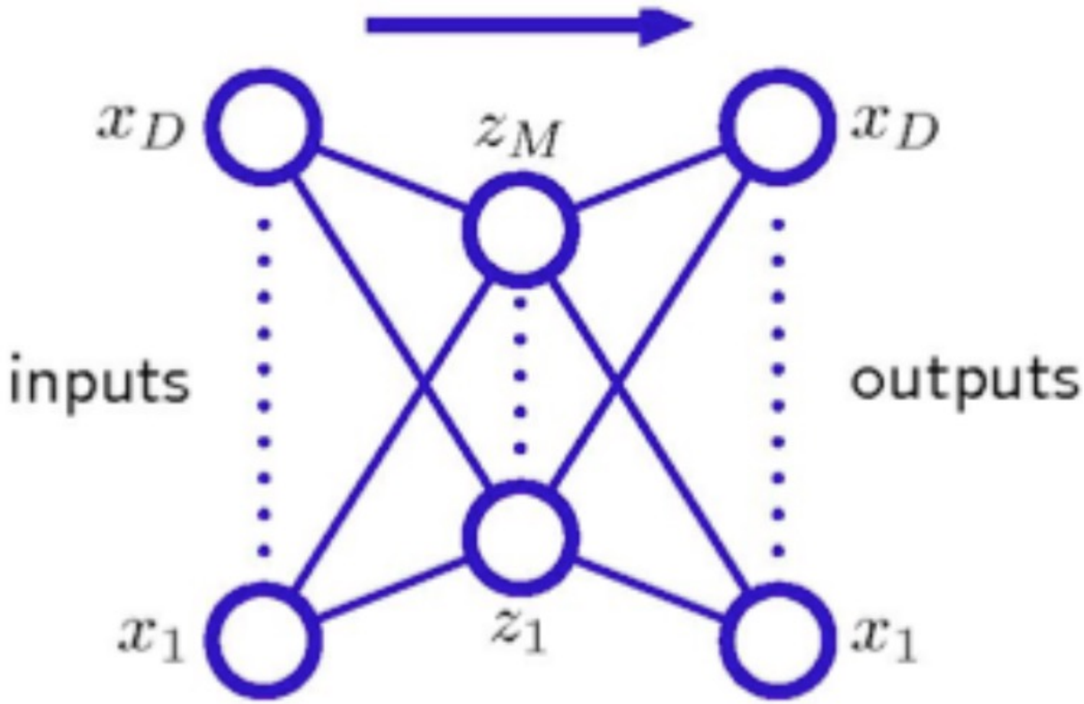
Principal Component Analysis

- Objective: to reduce the dimensionality of a dataset by transforming it into a new set of variables (principal components).



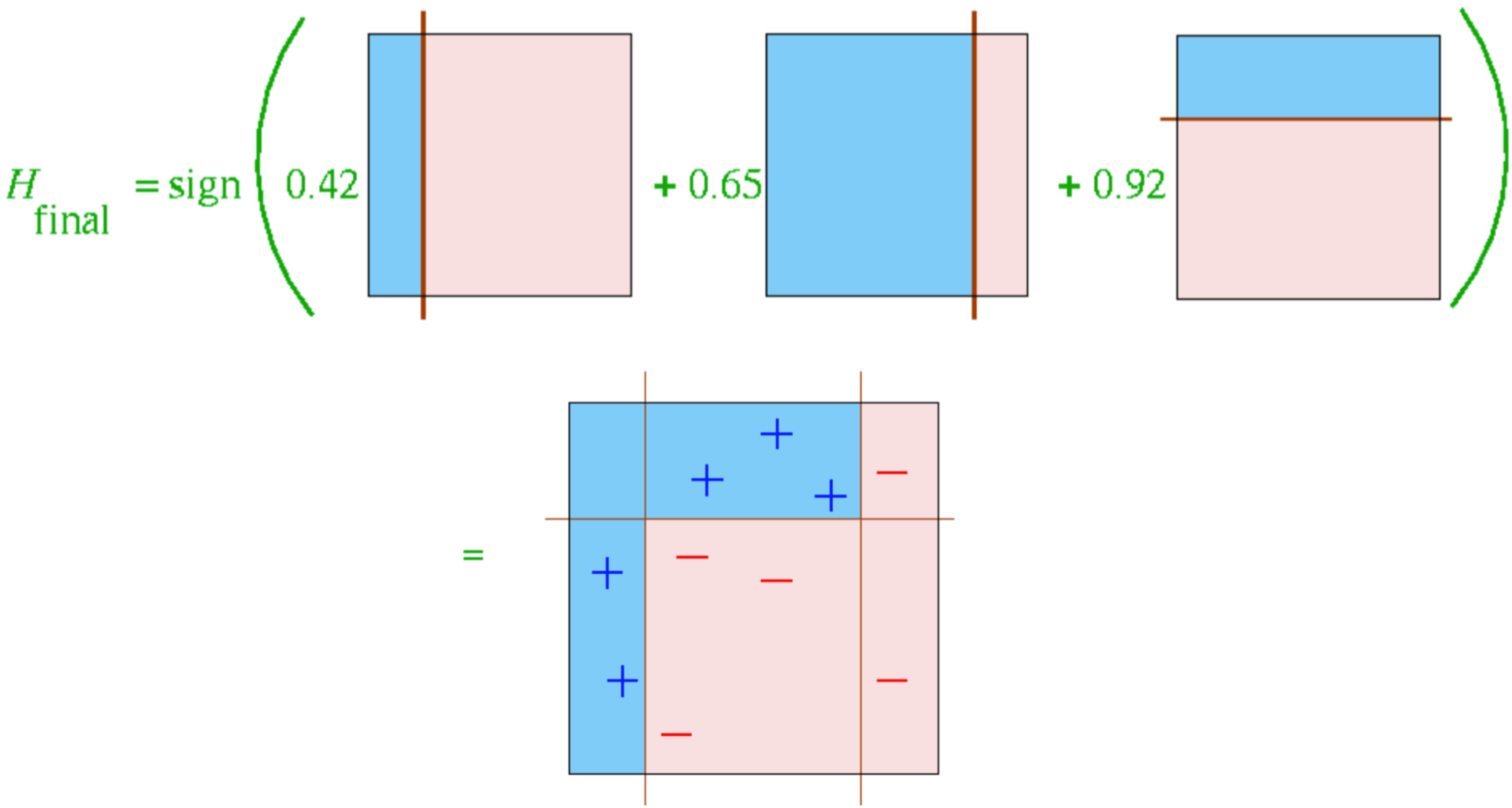
Autoencoders

- Objective: to learn a compressed, low-dimensional representation of input data by encoding it into a latent space and then reconstructing the original input.



Ensemble Methods

- Assumption: Combining multiple diverse models or algorithms can yield more accurate and robust predictions than any single model alone.



Netflix Prize 2007

- The Netflix Prize was an open competition for the best collaborative filtering algorithm to predict user ratings for films, based on previous ratings without any other information about the users or films.

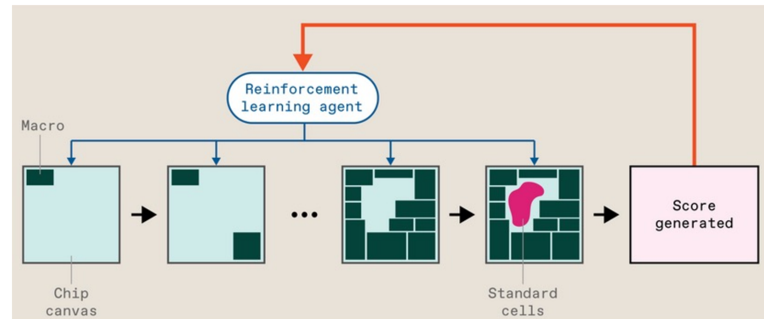
- Rewarded $50,000 in 2007.

- Original progress prize winner (BellKor) was ensemble of 107 models!
  - *"Our experience is that most efforts should be concentrated in deriving substantially different approaches, rather than refining a simple technique."*
  - *"We strongly believe that the success of an ensemble approach depends on the ability of its various predictors to expose different complementing aspects of the data. Experience shows that this is very different than optimizing the accuracy of each individual predictor."*

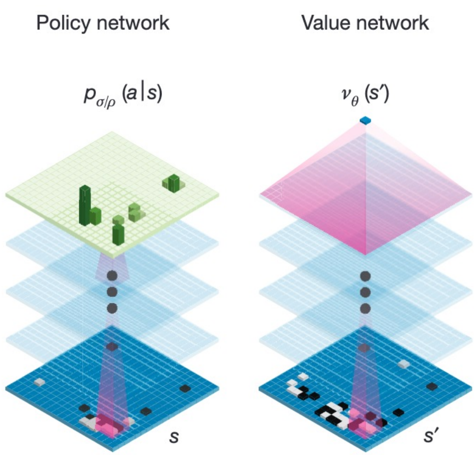
Reinforcement Learning

- Assumption: An agent can learn optimal behavior or policies by interacting with an environment, receiving feedback in the form of rewards or punishments for its actions.

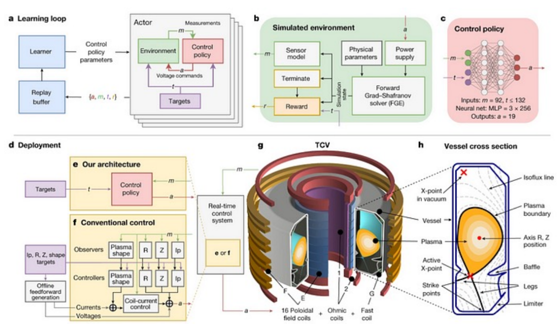
Play Dota



Chip Design



AlphaGo

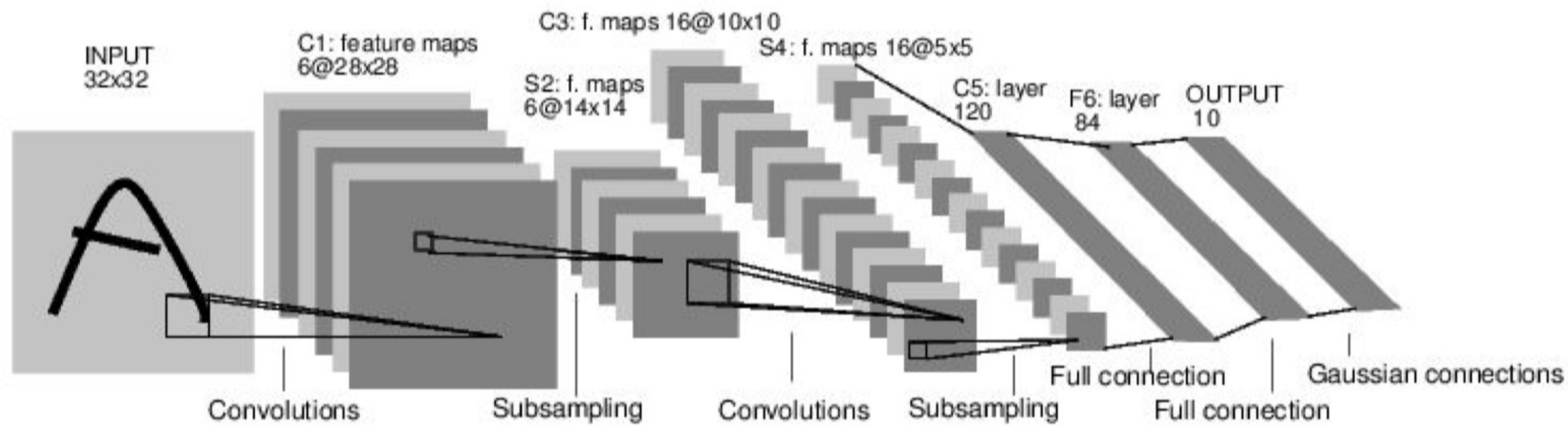


Nuclear Fusion

AWS Deep Racer

Convolutional Neural Networks

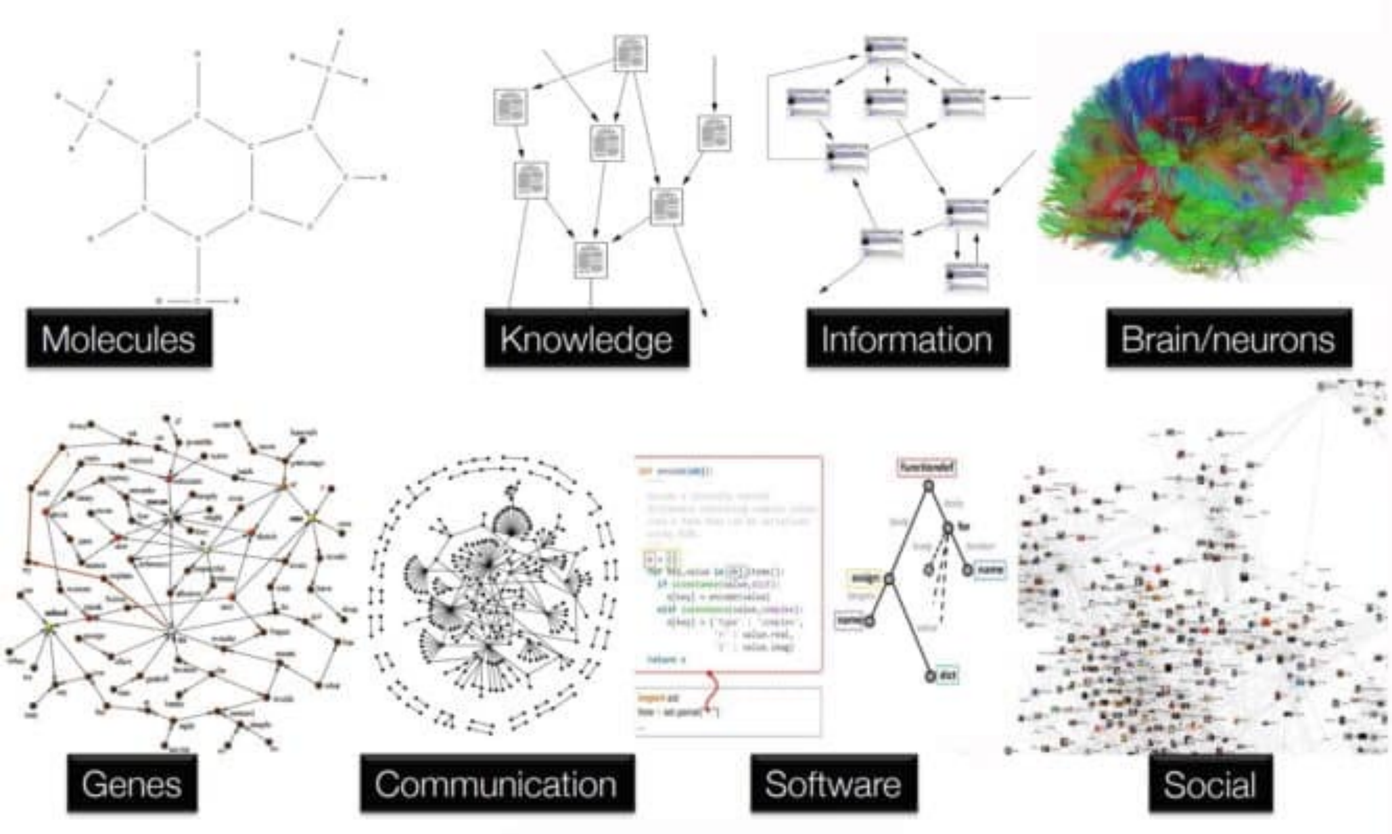
- Assumption: Input data, particularly images, can be effectively processed and analyzed using spatial hierarchies of patterns through localized and parameter-efficient convolutions.



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Graph Neural Networks

- Assumption: Data represented as graphs can be effectively analyzed by capturing dependencies and relationships between nodes through message passing or aggregation mechanisms.

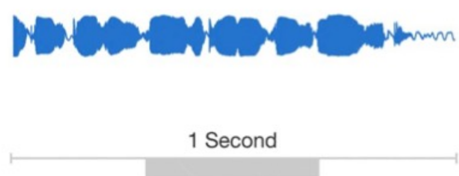


Recurrent Neural Networks

- Assumption: Sequential data has an inherent order, and understanding each element requires knowledge from its previous elements in the sequence.

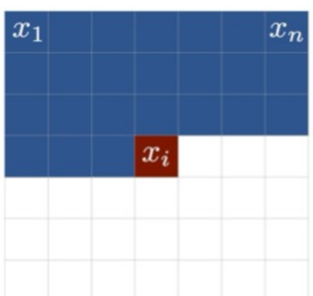
“Sequences really seem to be everywhere! We should learn how to model them. What is the best way to do that? Stay tuned!”

Words, letters

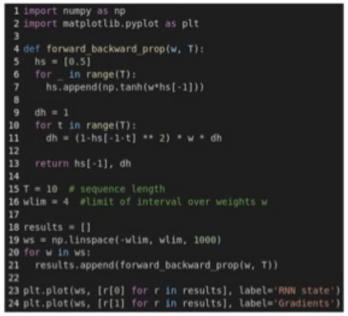


Speech

Videos

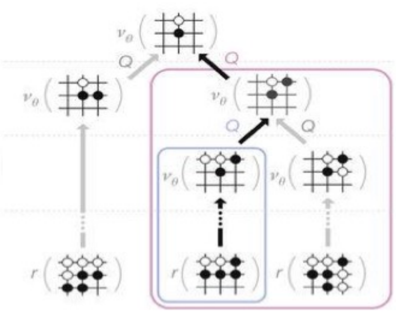


Images



```
import numpy as np
import matplotlib.pyplot as plt

def forward_backward_prop(w, T):
  hs = [0.5]
  for _ in range(T):
    hs.append(np.tanh(w*hs[-1]))

  dh = 1
  for t in range(T):
    dh = (1-hs[-1-t] ** 2) * w * dh

  return hs[-1], dh

T = 10  # sequence length
wlim = 4  #limit of interval over weights w

results = []
ws = np.linspace(-wlim, wlim, 1000)
for w in ws:
  results.append(forward_backward_prop(w, T))

plt.plot(ws, [r[0] for r in results], label='RNN state')
plt.plot(ws, [r[1] for r in results], label='Gradients')
```

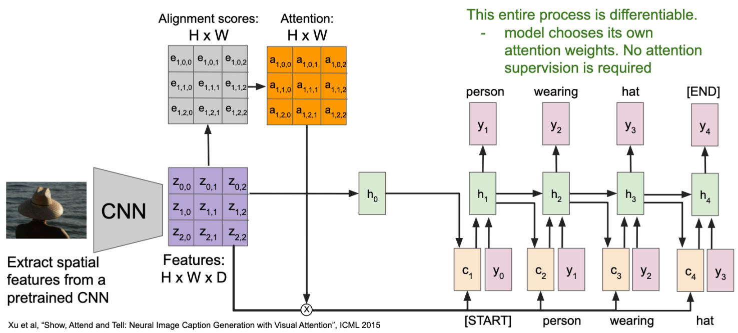
Programs



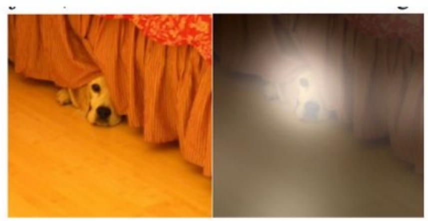
Decision making

Attention & Transformers

- Assumption: It's beneficial to selectively focus on certain parts of the input while processing others, thereby dynamically prioritizing information based on its relevance.

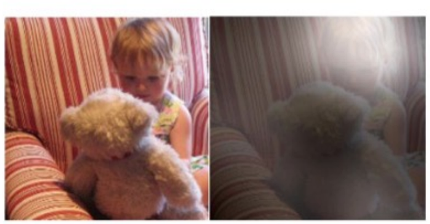


A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.

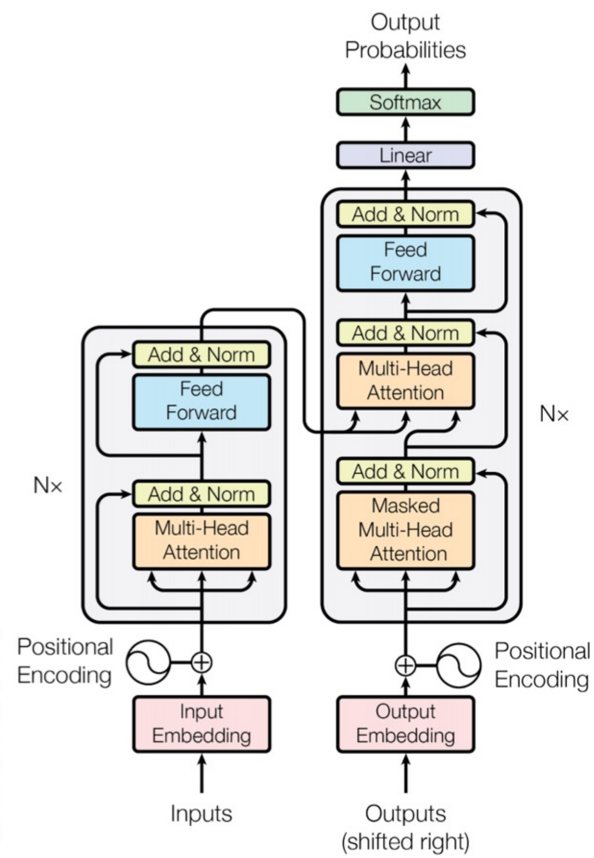
A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.

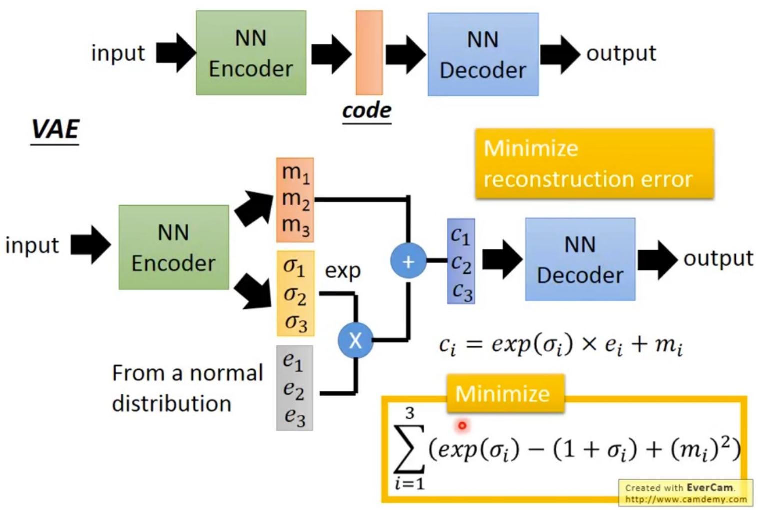
A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

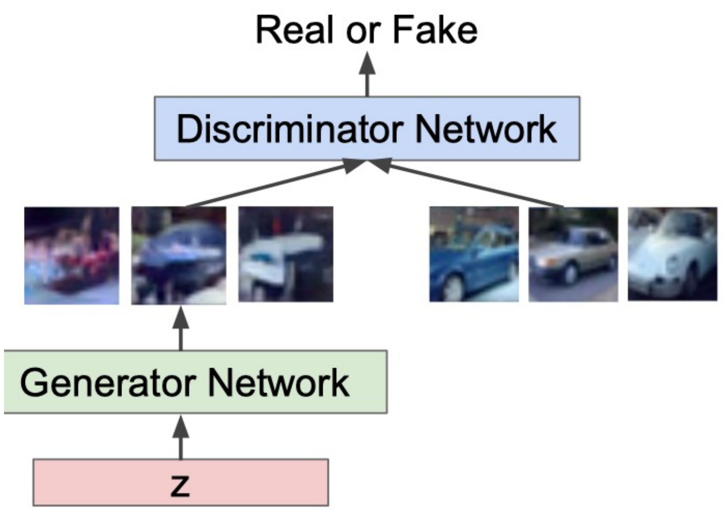


Deep Generative Models

- Variational Autoencoders:



- Generative Adversarial Networks:



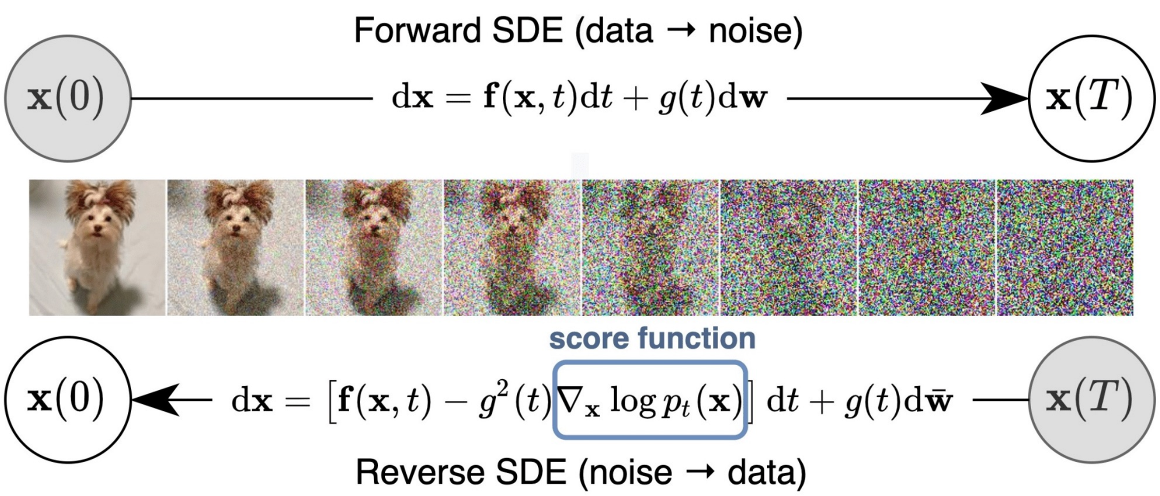
Deep Generative Models

- Diffusion Models:

A transparent sculpture of a duck made out of glass.

A raccoon wearing cowboy hat and black leather jacket is behind the backyard window. Rain droplets on the window.

A bucket bag made of blue suede. The bag is decorated with intricate golden paisley patterns. The handle of the bag is made of rubies and pearls.



My Research:
Wireless Human Sensing

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Internet of things
IOT

Research Overview

Human Activity Recognition

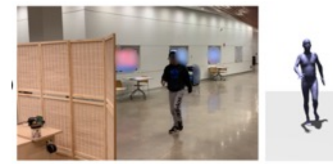
UbiComp’20] Multi-View Deep Learning for Environment-independent Device-Free Haman Activity Recognition

[MobiHoc’19] A Deep Learning Framework for the Fusion of Heterogeneous Sensory Data

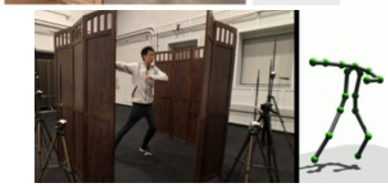
3D Skeleton/Mesh Reconstruction

[SenSys’22] Multi-subject 3D Human Mesh Construction Using Millimeter-wave

[MobiSys’21] 3D Real-Time Human Mesh Construction Using Millimeter-wave

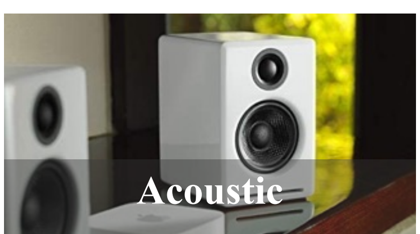


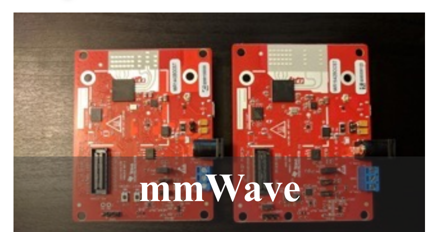
[MobiCom’20] 3D Human Pose Construction Using Commercial WiFi Devices



Deep Learning

Commercial Wireless Devices in IoT Systems



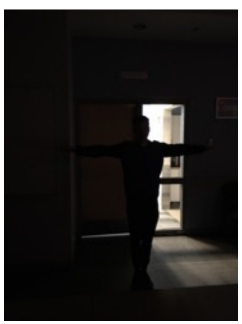


Why we need Wireless Sensing

Advantages of Wireless Sensing Systems:

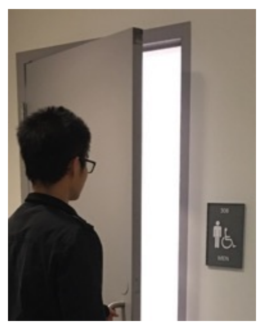
- Easy to deploy using existing IoT wireless devices for communication.
- Function well under the conditions of bad lighting and occlusions.
- Have little privacy issue since the wireless signal data is not human-readable.
- Exempt people from extra burdens and discomfort caused by wearable devices.

Ubiquity of Wireless Infrastructures



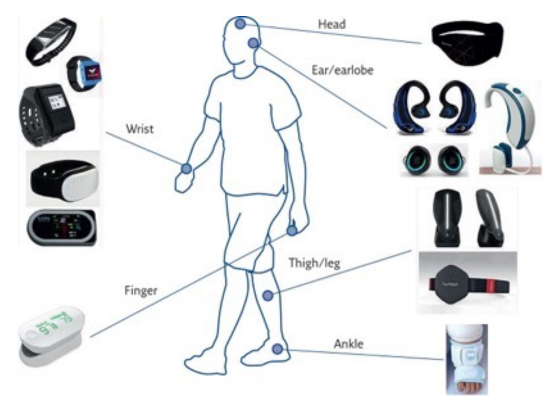
Bad Lighting

Occlusions



Privacy

Challenges of Vision-based Solutions



Challenges of Using Wearable Devices

Applications

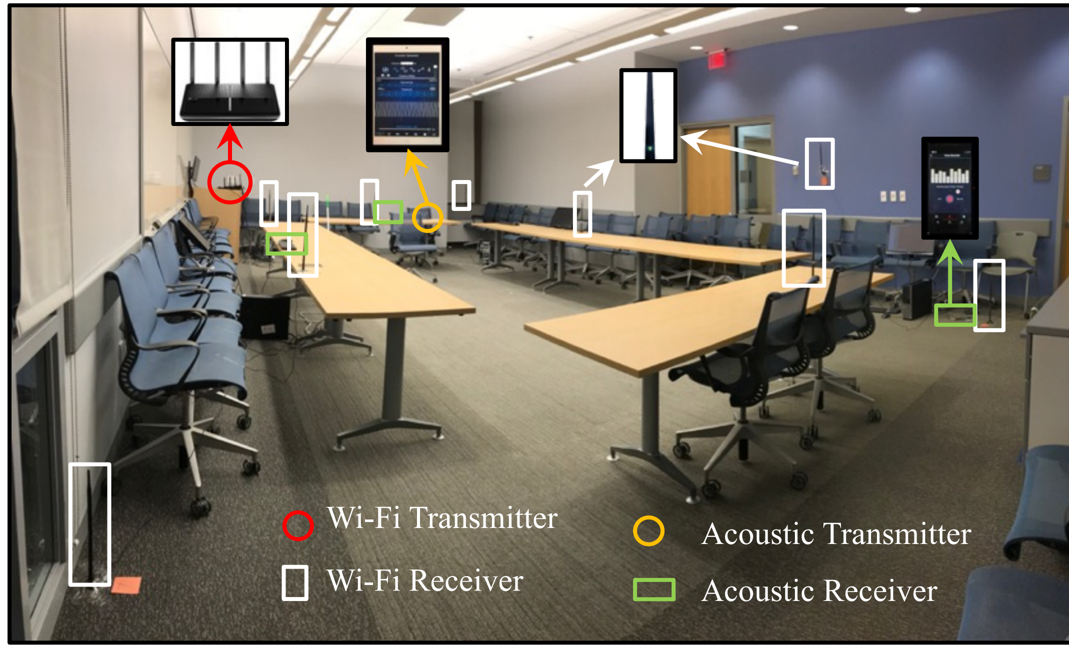
Experiment on Wireless Dataset

- ## Device-Free Human Activity Dataset

  - Heterogeneous Dataset

4 Wi-Fi Sensors

3 Acoustic Sensors



- ## Results

Model	Accuracy WiFi	Accuracy Acoustic	Accuracy Heterogeneous
SVM	0.450	0.410	0.528
SR+Avg	0.713	0.623	0.833
SR+WC	0.795	0.635	0.835
DeepFusion	0.813	0.633	**0.885**

[MobiHoc'19] DeepFusion

WiFi-based Human Skeleton Reconstruction

- **YouTube Link:**
  - https://www.youtube.com/watch?v=puU4EvBTPxA

mmWave-based Real-time Human Mesh Reconstruction

- **YouTube Link:**
  - https://www.youtube.com/watch?v=xW4ZlmxEu9Q

Questions?

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