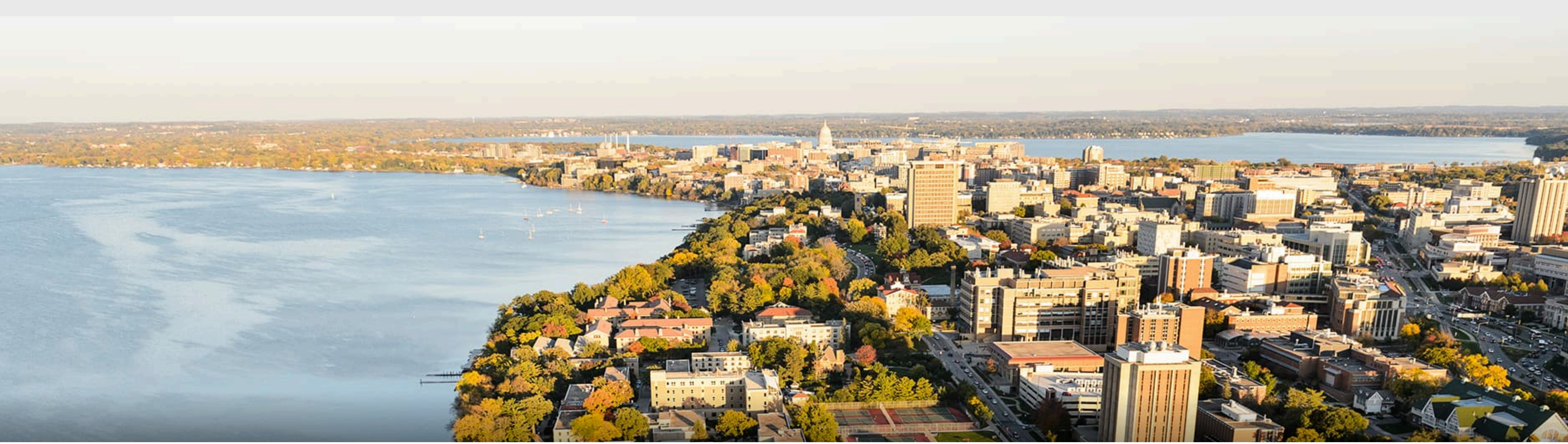

# CS 760: Machine Learning
# **ML Overview**

Josiah Hanna
University of Wisconsin-Madison

**9/12/2023**

# Announcements

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- Enrollment:
  - Waitlist is beginning to clear. Email me Thursday if you’re still on it AND have a reason for additional priority.
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- Homework 1 is due at 9:30 AM on Tuesday, September 19.

# Office Hours

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- My office hours are Tuesdays from 11 — 12pm in CS 5391.
  - Or by appointment.
  - I will meet students in the hall after lecture at 10:45 for quick questions and then walk back to my office.
  - If you need a longer discussion, please wait to either walk with me or meet me at my office.

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- **After today’s lecture:**
  - You will be able to explain the key aspects of a supervised learning problem.
  - Provide examples of unsupervised learning problems and explain why these are not supervised learning problems.
  - Explain key challenges of reinforcement learning problems.

# Outline

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- **Review from last time**

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# **Review: ML Overview**: Definition

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What is machine learning?

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What is machine learning?

"A computer program is said to learn from experience **E** with respect to some class of tasks **T** and performance measure **P**, if its performance at tasks in **T** as measured by **P**, improves with experience **E**." *Machine Learning*, Tom Mitchell, 1997

# **ML Overview**: Flavors

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## Supervised Learning

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**Supervised Learning**

- Learning from labelled examples.

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  - Collect a set of examples {data point, label}: **training set**
  - “**Train**” a model to match data points to labels.
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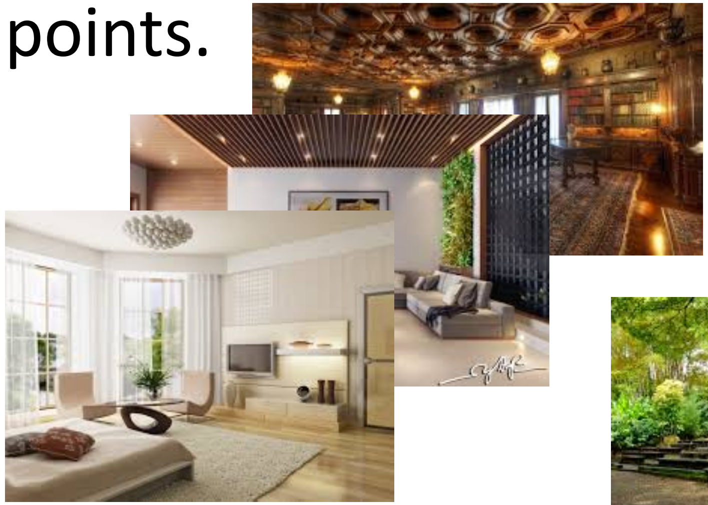
- **Image classification**:



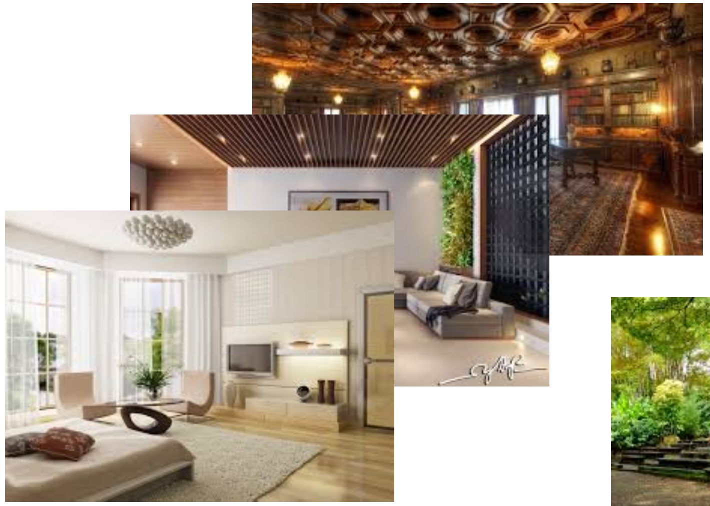
indoor

outdoor

# **ML Overview**: Flavors

## Supervised Learning

- **Example: Image classification**



indoor

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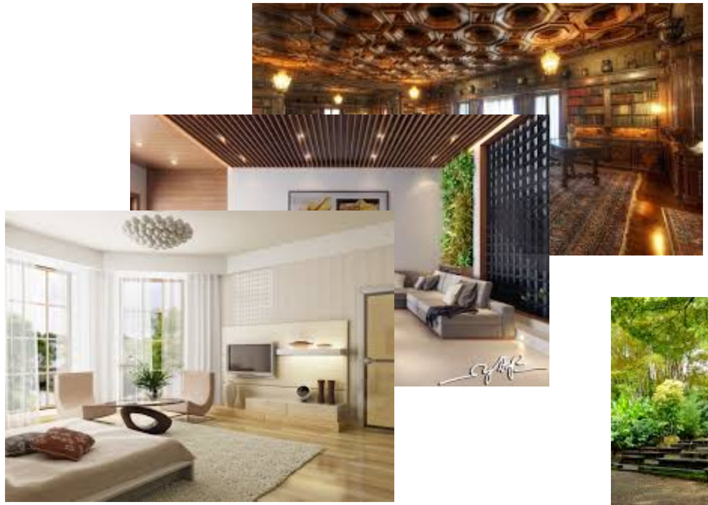
- **Example: Image classification**
- Recall **T**ask/**P**erformance measure/**E**xperience definition



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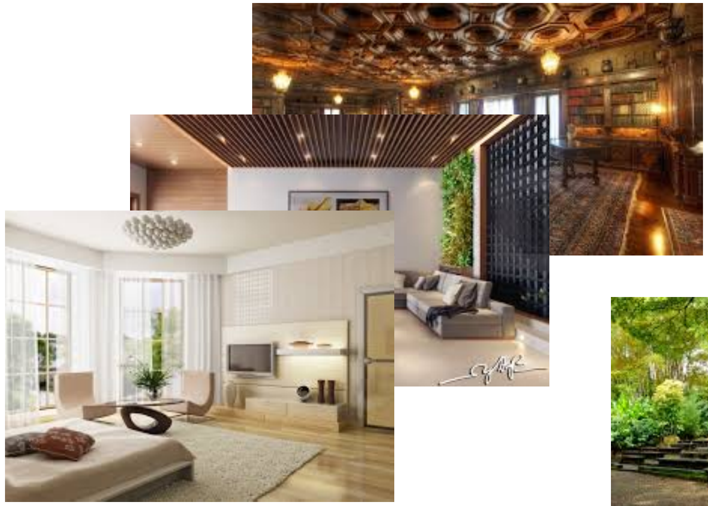

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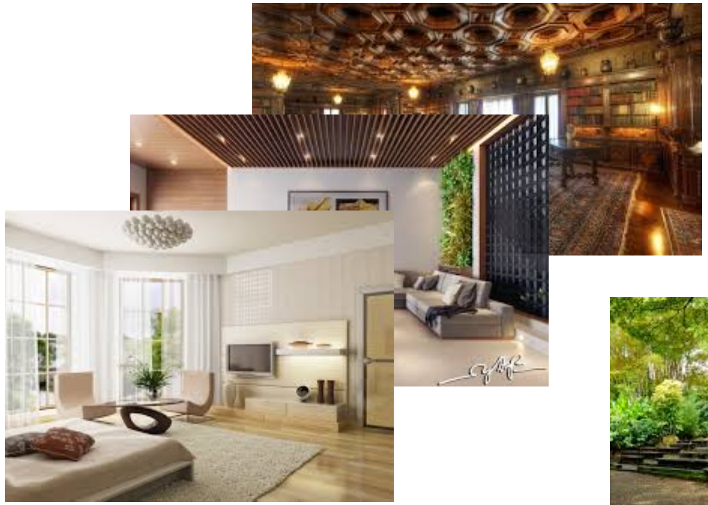

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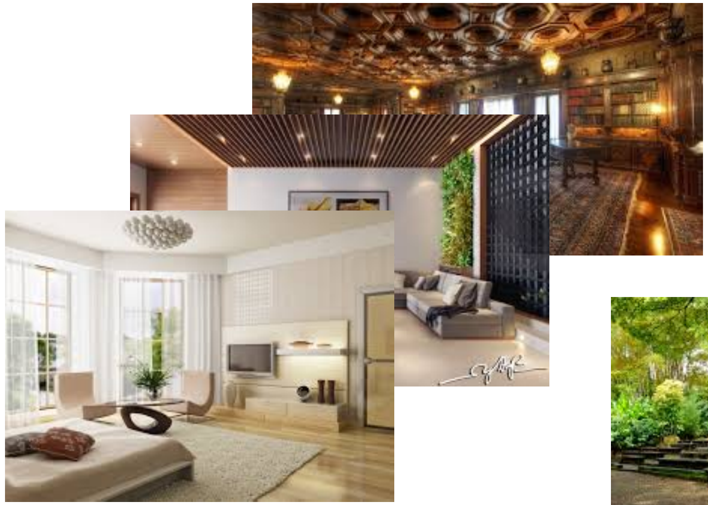
  - **E**xperience: labeled examples



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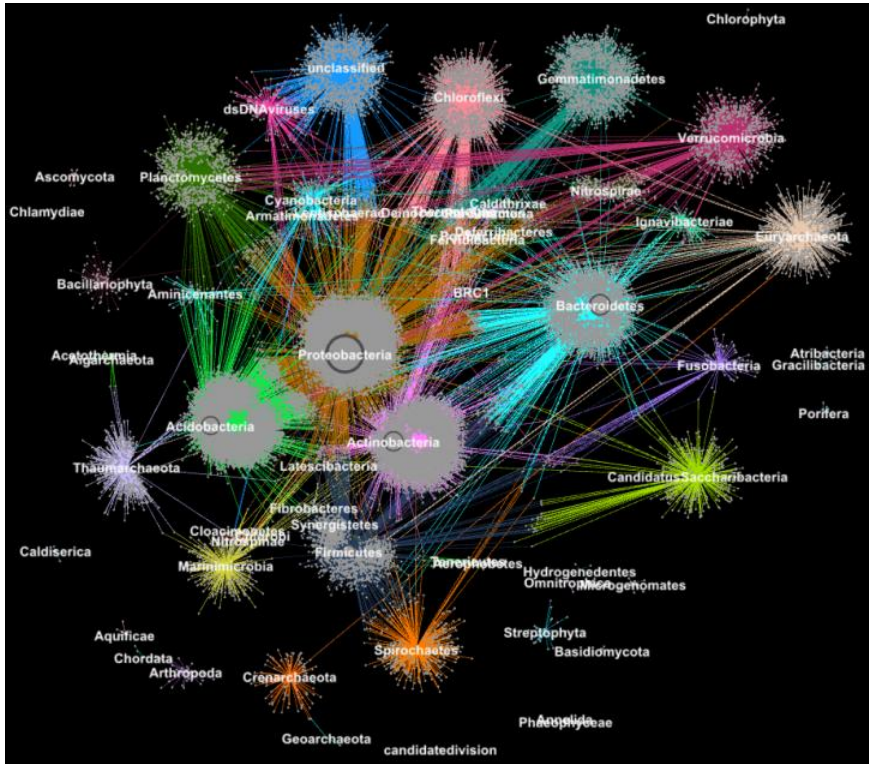

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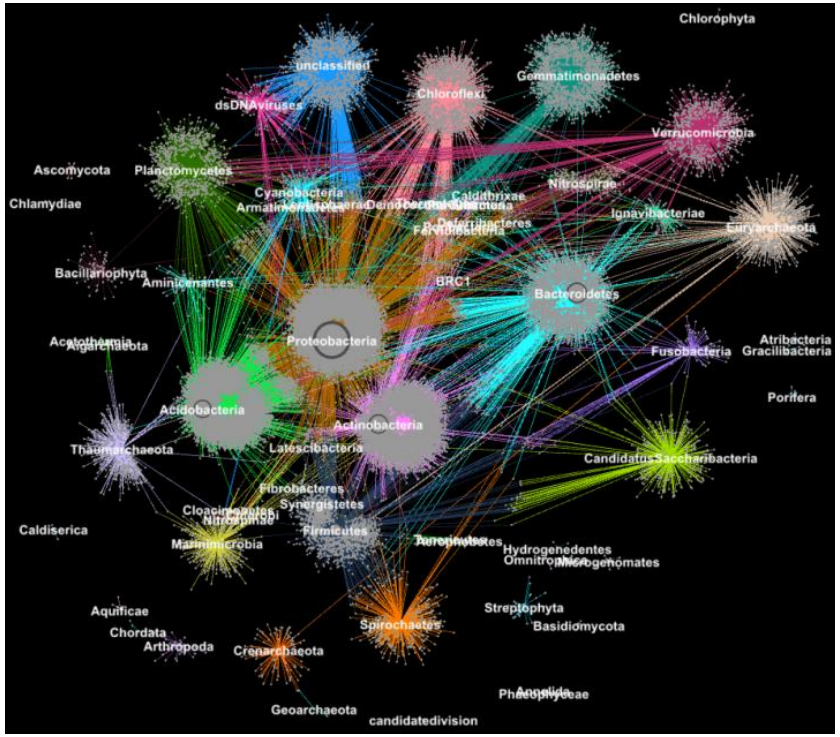

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## Unsupervised Learning

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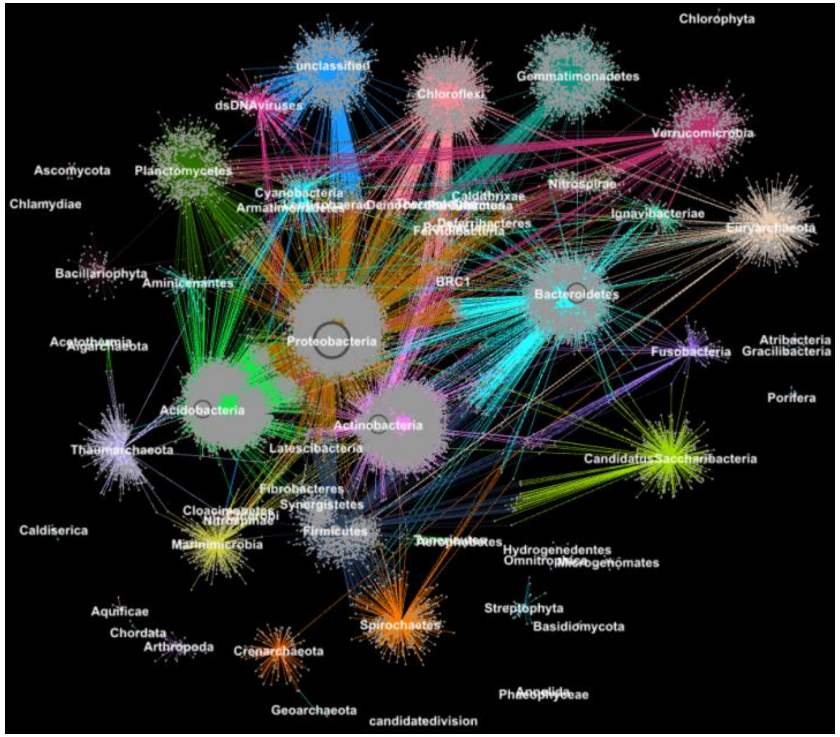

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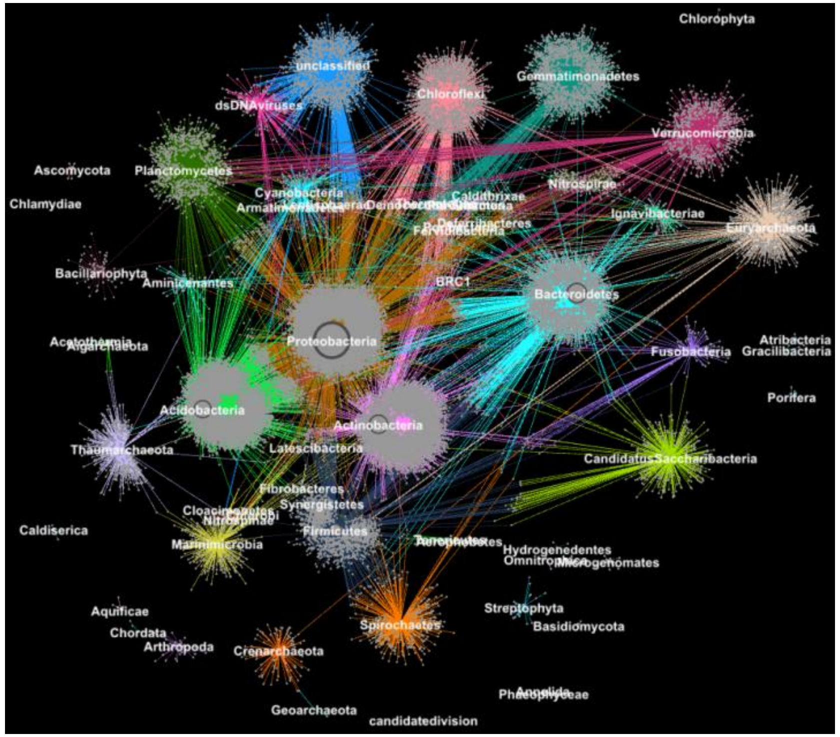

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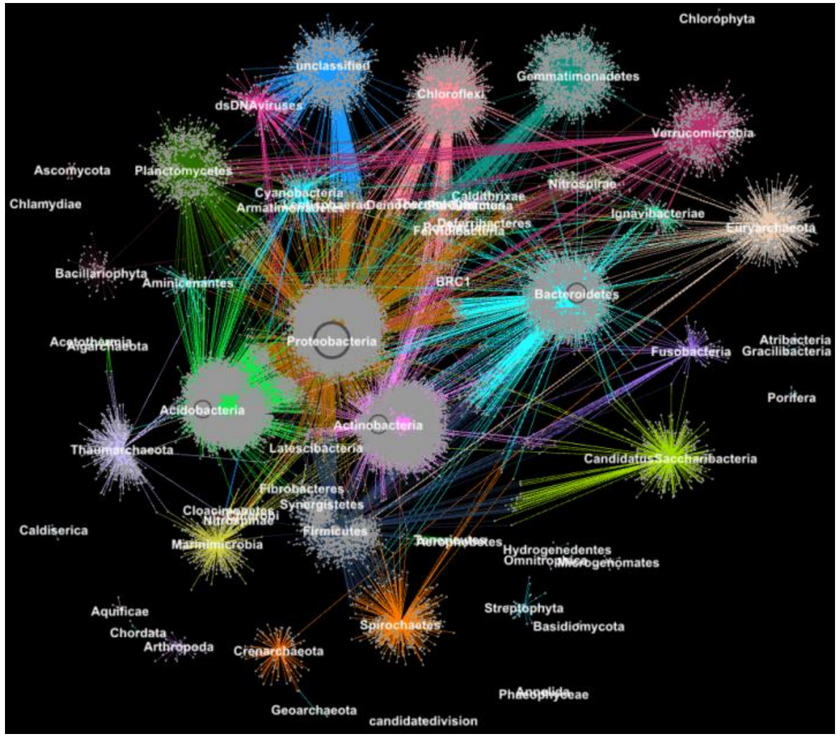

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  - **Deploy** in new environment

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- **Example: Controlling aircraft**

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# Break & Quiz

Q1-1: Which of the following is generally NOT a supervised learning task?

1. Predicting house prices from past home sales.
2. Email spam detection
3. Handwriting recognition
4. Eigenvalue calculation

Q1-1: Which of the following is generally NOT a supervised learning task?

1. Predicting house prices from past home sales.
2. Email spam detection
3. Handwriting recognition
4. **Eigenvalue calculation**

**Eigenvalue calculation is a mathematical problem, and we do not have any labels for this problem.**

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- Can I eat this?
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- How to decide?

# **Supervised Learning:** Training Instances

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- I know about other mushrooms:

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**Given:**

- Training set of instances for unknown target function, where $y^{(i)} \approx f(x^{(i)})$

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**Goal**: model *h* that best approximates *f*

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**Three types of sets**

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## Three types of sets

- Input space, output space, hypothesis class

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- **Examples**:
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**safe** **poisonous**

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- **Examples**:
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- For each instance, store features as a vector.

# **Input Space:** Feature Vectors

- Need a way to represent instance information:

$$\begin{array}{c} \text{cap-shape} \quad \text{cap-surface} \quad \text{cap-color} \quad \text{bruises?} \quad \text{odor} \\ x^{(1)} = \langle \texttt{bell}, \texttt{fibrous}, \texttt{gray}, \texttt{false}, \texttt{foul} \rangle \end{array}$$

safe

- For each instance, store features as a vector.
  - What kinds of features can we have?

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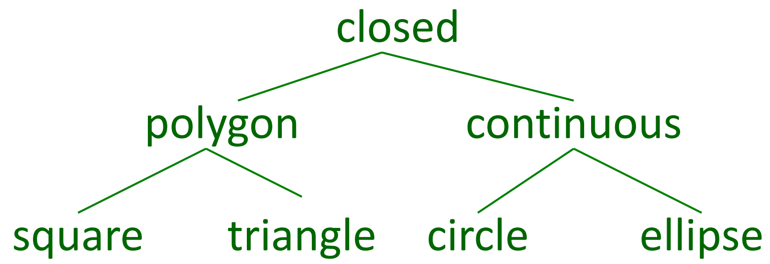
- *hierarchical*
  - possible values are partially *ordered* in a hierarchy, e.g. *shape*



# **Input Space**: Features Example


***sunken* is one possible value of the *cap-shape* feature**

**Mushroom features (UCI Repository)**

cap-shape: bell=b,conical=c,convex=x,flat=f, knobbed=k,sunken=s
cap-surface: fibrous=f,grooves=g,scaly=y,smooth=s
cap-color: brown=n,buff=b,cinnamon=c,gray=g,green=r, pink=p,purple=u,red=e,white=w,yellow=y
bruises?: bruises=t,no=f
odor: almond=a,anise=l,creosote=c,fishy=y,foul=f, musty=m,none=n,pungent=p,spicy=s
gill-attachment: attached=a,descending=d,free=f,notched=n
gill-spacing: close=c,crowded=w,distant=d
gill-size: broad=b,narrow=n
gill-color: black=k,brown=n,buff=b,chocolate=h,gray=g, green=r,orange=o,pink=p,purple=u,red=e, white=w,yellow=y
stalk-shape: enlarging=e,tapering=t
stalk-root: bulbous=b,club=c,cup=u,equal=e, rhizomorphs=z,rooted=r,missing=?
stalk-surface-above-ring: fibrous=f,scaly=y,silky=k,smooth=s
stalk-surface-below-ring: fibrous=f,scaly=y,silky=k,smooth=s
stalk-color-above-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o, pink=p,red=e,white=w,yellow=y
stalk-color-below-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o, pink=p,red=e,white=w,yellow=y
veil-type: partial=p,universal=u
veil-color: brown=n,orange=o,white=w,yellow=y
ring-number: none=n,one=o,two=t
ring-type: cobwebby=c,evanescent=e,flaring=f,large=l, none=n,pendant=p,sheathing=s,zone=z
spore-print-color: black=k,brown=n,buff=b,chocolate=h,green=r, orange=o,purple=u,white=w,yellow=y
population: abundant=a,clustered=c,numerous=n, scattered=s,several=v,solitary=y
habitat: grasses=g,leaves=l,meadows=m,paths=p, urban=u,waste=w,woods=d

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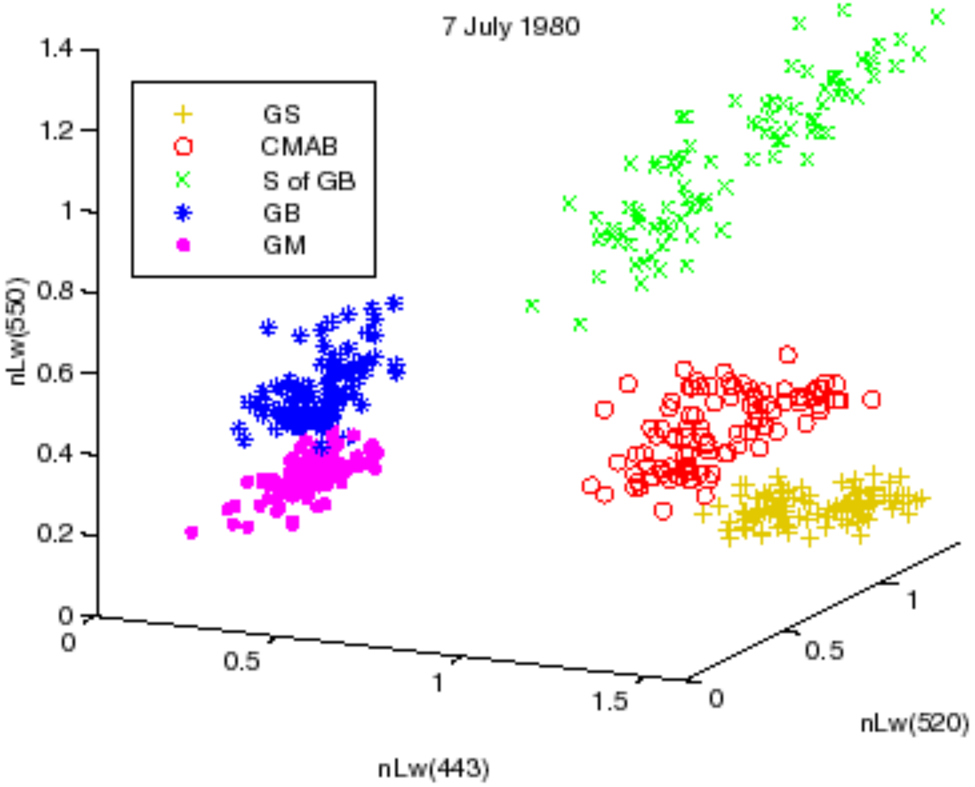


- **Example**: optical properties of oceans in three spectral bands

[Traykovski and Sosik, *Ocean Optics XIV Conference Proceedings*, 1998]

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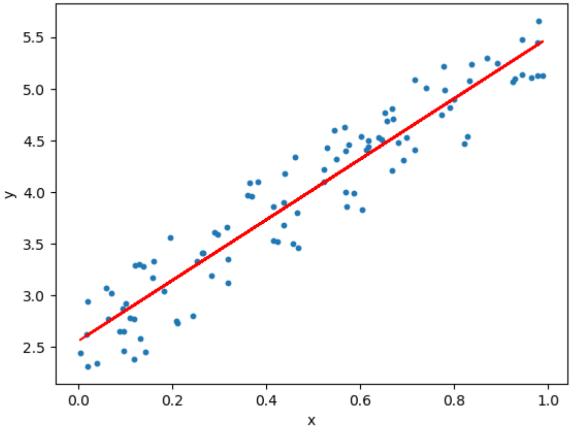

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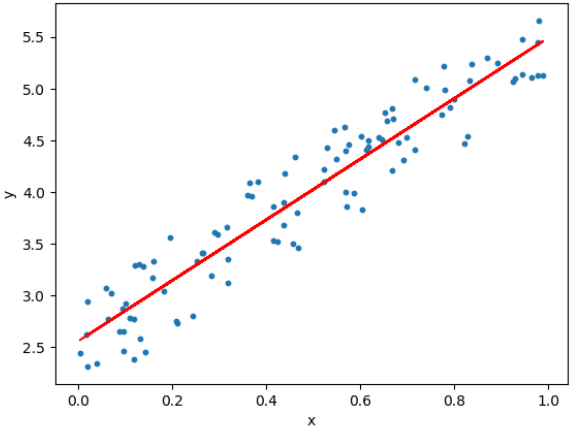


- There are other types…

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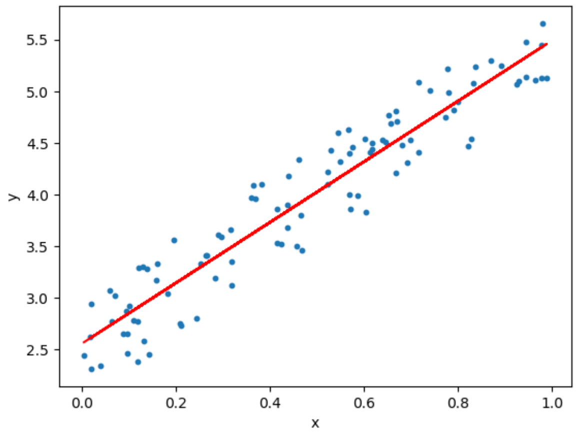


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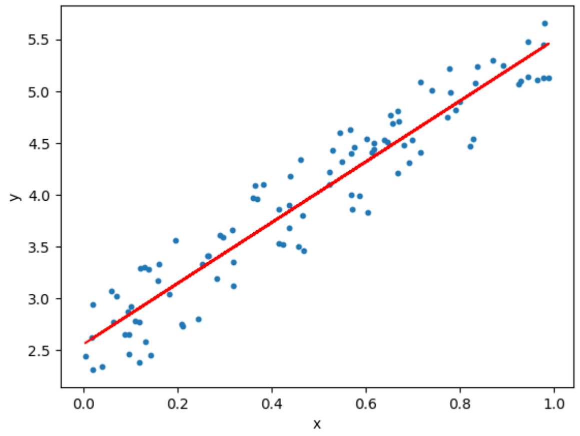

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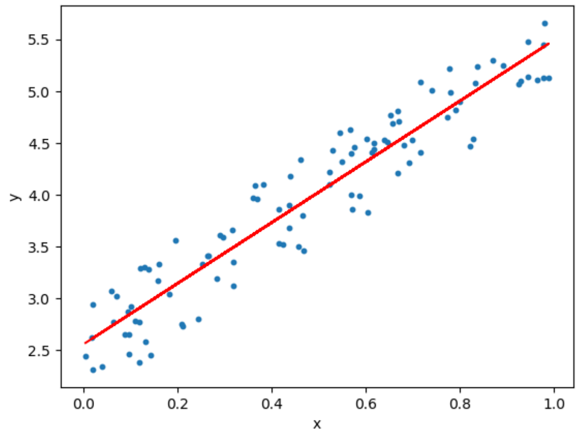

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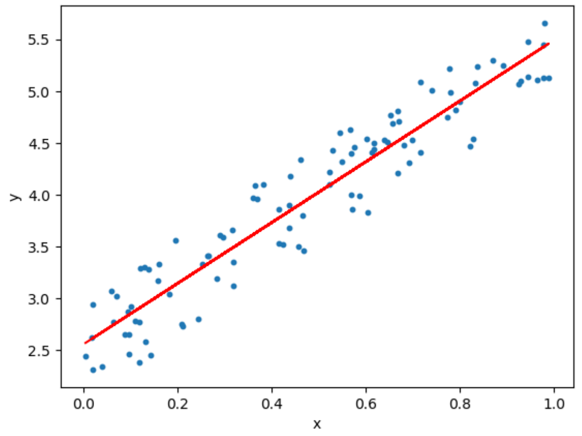


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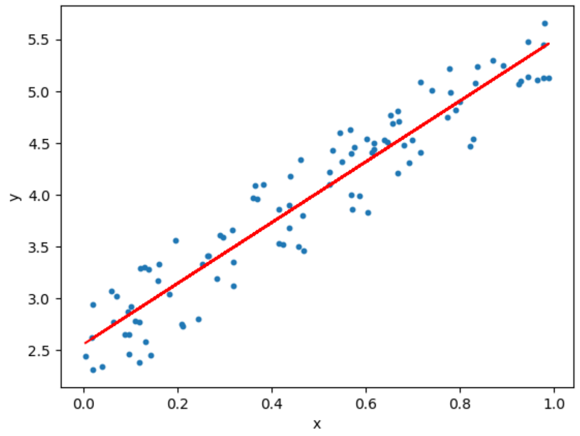


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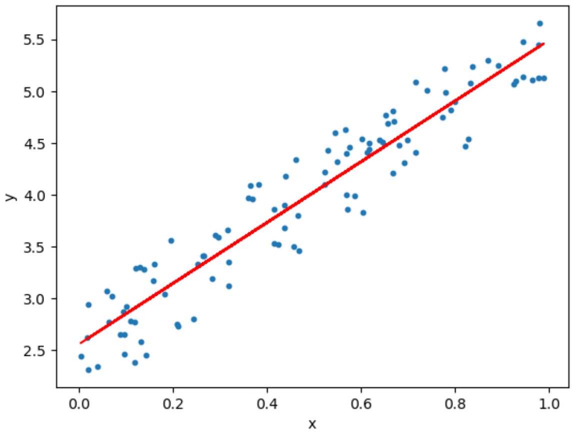


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**Parameters (weights)**

**Features**

- How many linear functions are there?
  - Can any function be fit by a linear model?

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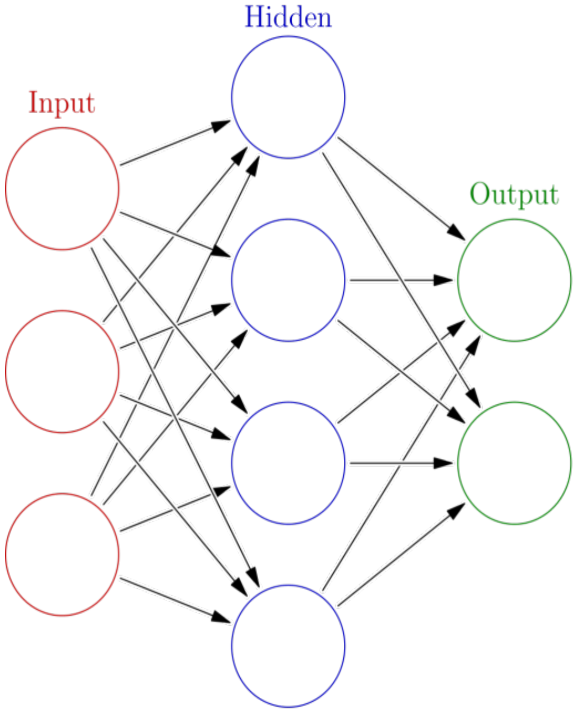


Wikipedia

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**Example** classes of models: neural networks

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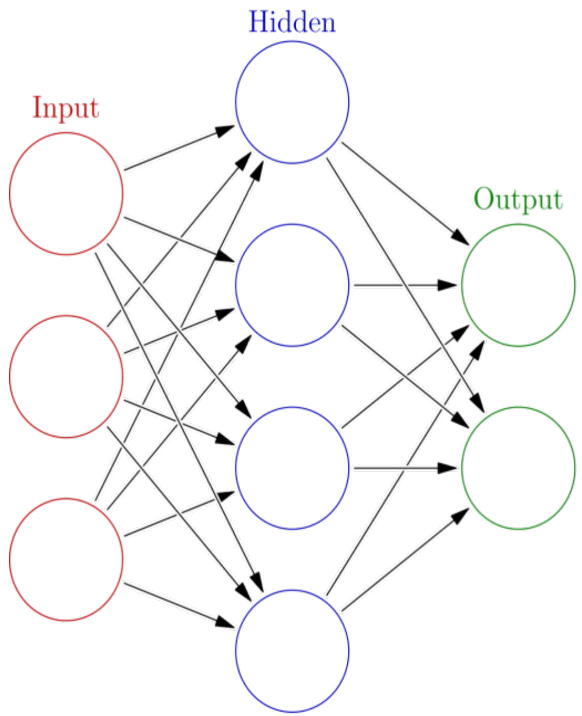


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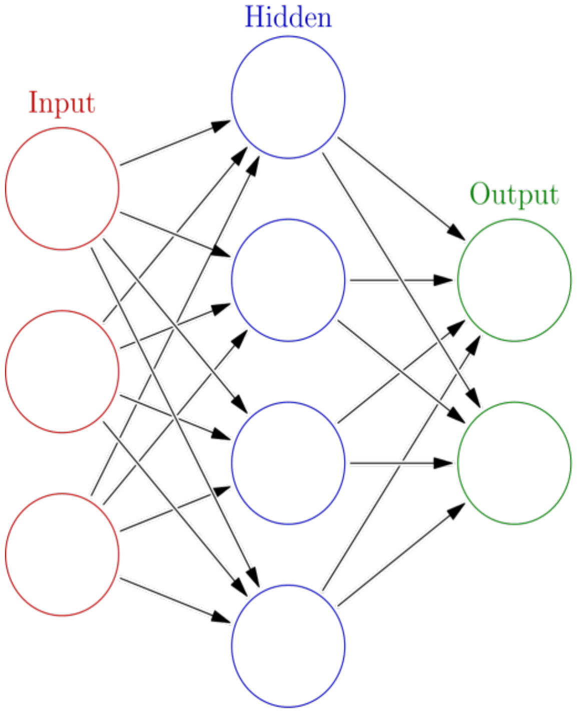


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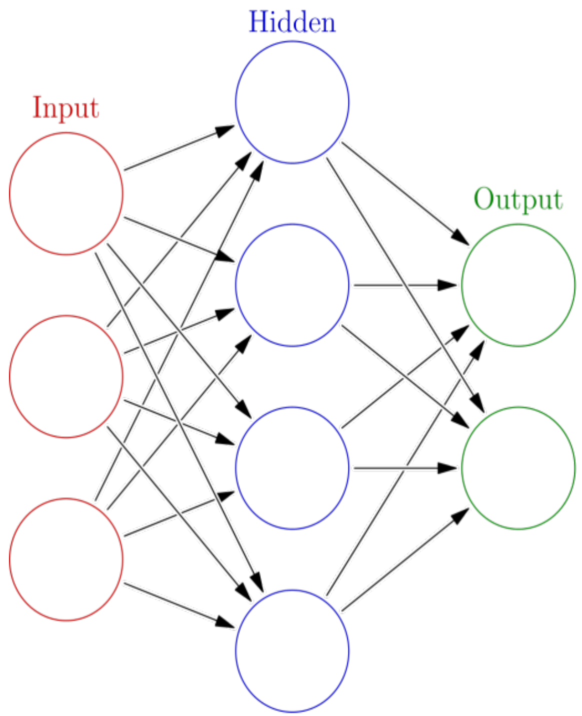


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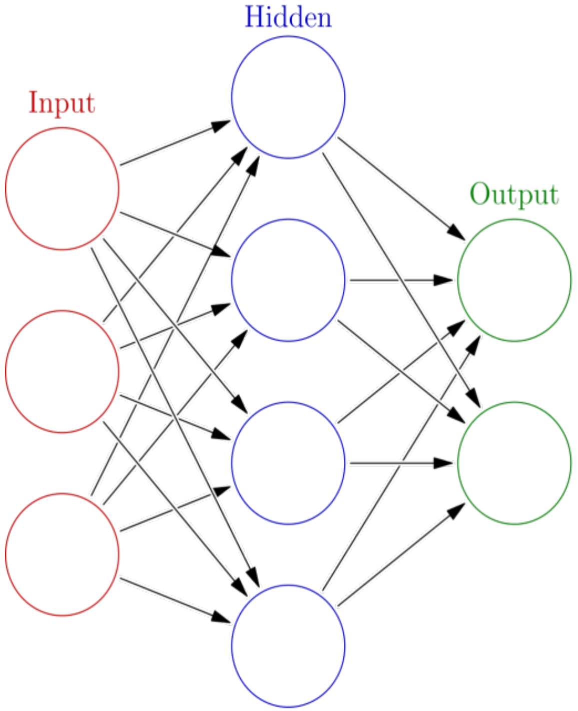


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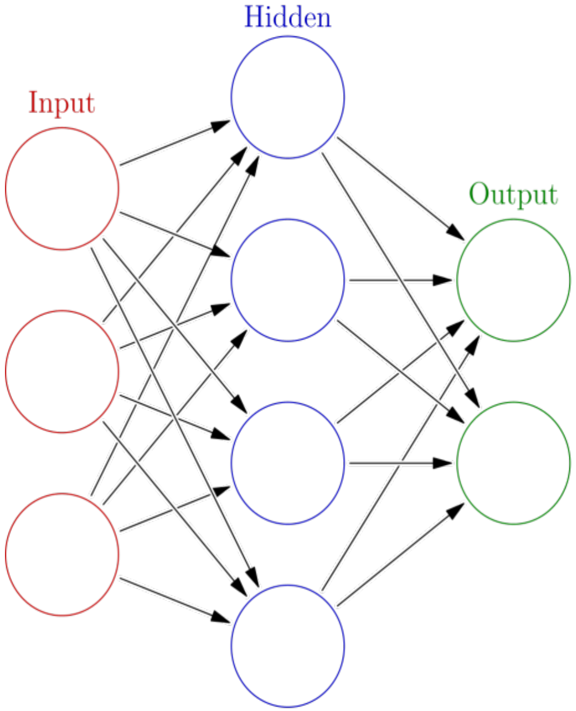


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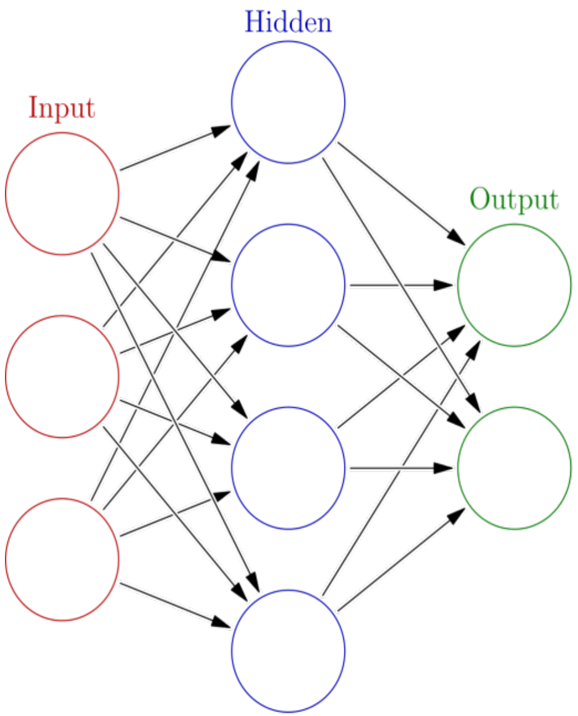


Wikipedia

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  - What are the parameters here?

# **Back to** Formal Setup

**Problem setting**

- Set of possible instances $\mathcal{X}$ ✓
- Unknown *target function* $f : \mathcal{X} \rightarrow \mathcal{Y}$ ✓
- Set of *models* (a.k.a. *hypotheses*) $\mathcal{H} = \{h | h : \mathcal{X} \rightarrow \mathcal{Y}\}$ ✓

**Get**

- Training set of instances for unknown target function *f*,

$$(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(n)}, y^{(n)})$$ ✓

**Goal: model *h* that best approximates *f***

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Loss function: how far is the prediction from the label?

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$\mathbf{x} = \langle \text{bell, fibrous, brown, false, foul, ...} \rangle$

```
odor = a: e (400.0)
odor = c: p (192.0)
odor = f: p (2160.0)
odor = l: e (400.0)
odor = m: p (36.0)
odor = n
|   spore-print-color = b: e (48.0)
|   spore-print-color = h: e (48.0)
|   spore-print-color = k: e (1296.0)
|   spore-print-color = n: e (1344.0)
|   spore-print-color = o: e (48.0)
|   spore-print-color = r: p (72.0)
|   spore-print-color = u: e (0.0)
|   spore-print-color = w
|   |   gill-size = b: e (528.0)
|   |   gill-size = n
|   |   |   gill-spacing = c: p (32.0)
|   |   |   gill-spacing = d: e (0.0)
|   |   |   gill-spacing = w
|   |   |   |   population = a: e (0.0)
|   |   |   |   population = c: p (16.0)
|   |   |   |   population = n: e (0.0)
|   |   |   |   population = s: e (0.0)
|   |   |   |   population = v: e (48.0)
|   |   |   |   population = y: e (0.0)
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safe or poisonous

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$$\hat{f} = \underbrace{\arg\min_{h \in \mathcal{H}}}_{\text{Hypothesis Class}} \frac{1}{n} \sum_{i=1}^{n} \underbrace{\ell}_{\text{Loss function}}(\underbrace{h(x^{(i)})}_{\text{Model prediction}}, y^{(i)})$$

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- We can get a perfect fit by setting d to be very large.
  - E.g. In 1D, set d = n-1

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Another class of models: polynomials:

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# Break & Quiz

# Q2-1: Which of the following is a NOMINAL feature as introduced in the lecture?

1. Cost $\in [0, 100]$
2. Awarded $\in \{\text{True}, \text{False}\}$
3. Steak

   $\in \{\text{Rare}, \text{Medium Rare}, \text{Medium}, \text{Medium Well}, \text{Well Done}\}$
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# Q2-2: What is the dimension of the following feature space?

The CIFAR-10 dataset contains 60,000 32x32 **color** images in 10 different classes.
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**Every color image has 3 channels (RGB) and 32*32 pixels, so the dimension is 3*32*32=3072.**

Q2-3: Are these statements true or false?
(A) Instances from time series are independent and identically distributed.
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**(A) Instances from time series usually have dependencies on the previous instances.**
**(B) The primary objective of supervised learning is to find a model that generalizes.**

# Outline

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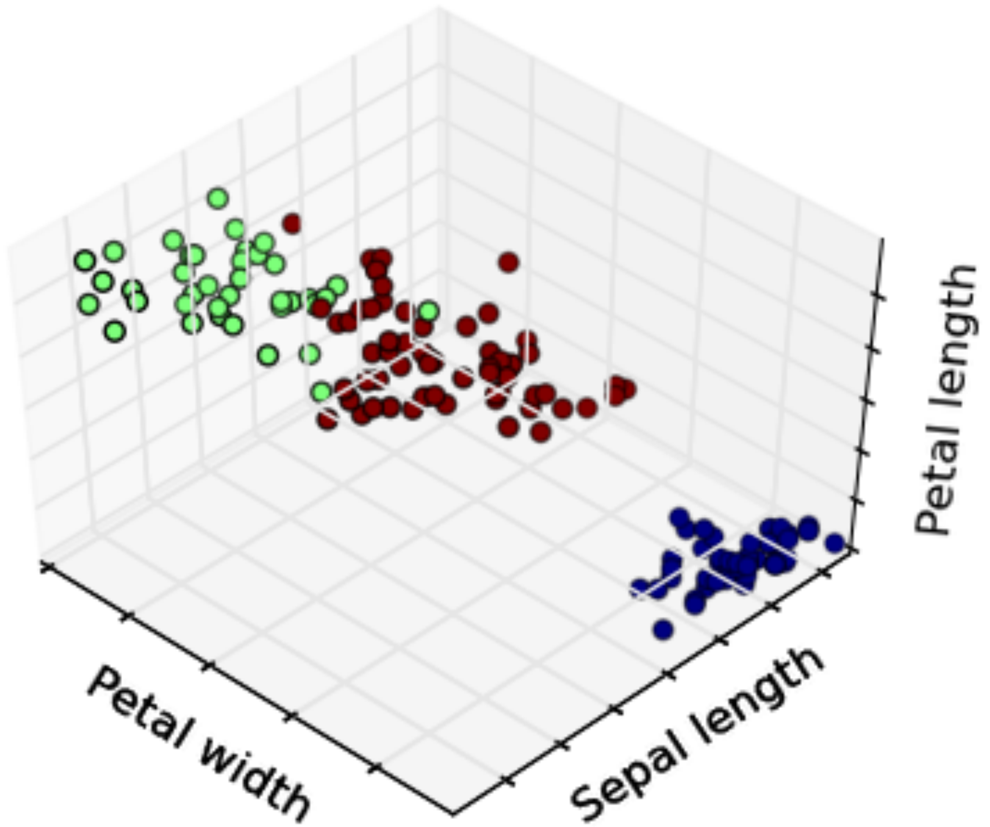

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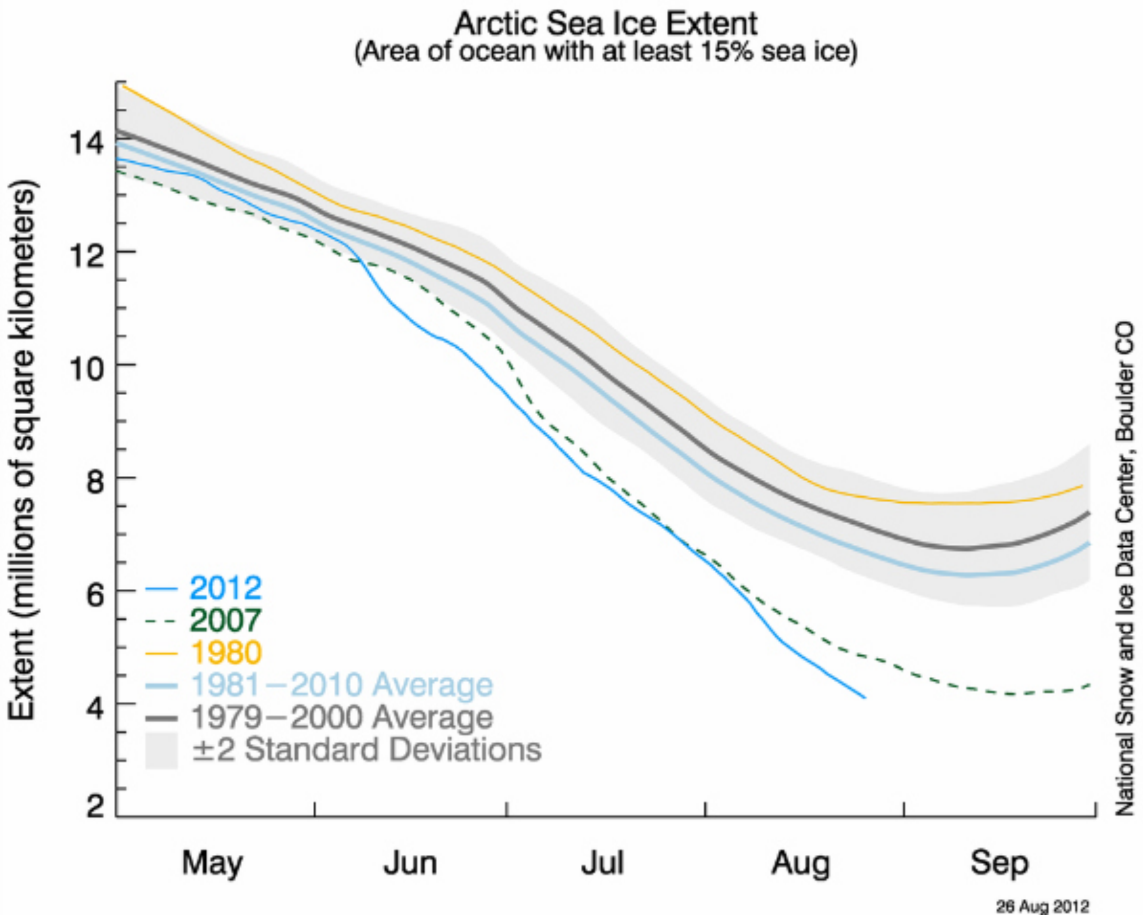

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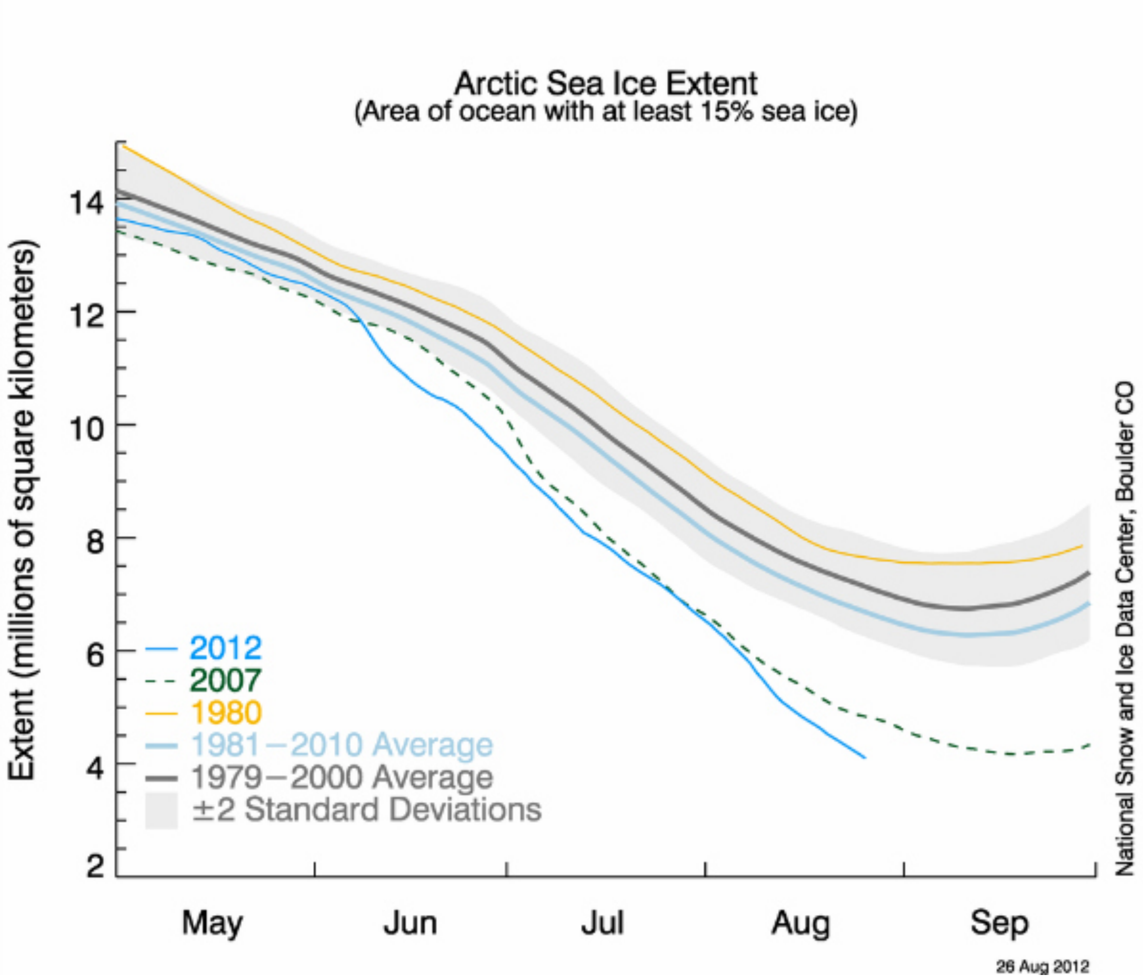
Let's say our model is represented by:
  1979-2000 average, ±2 stddev

Does the data for 2012 look anomalous?



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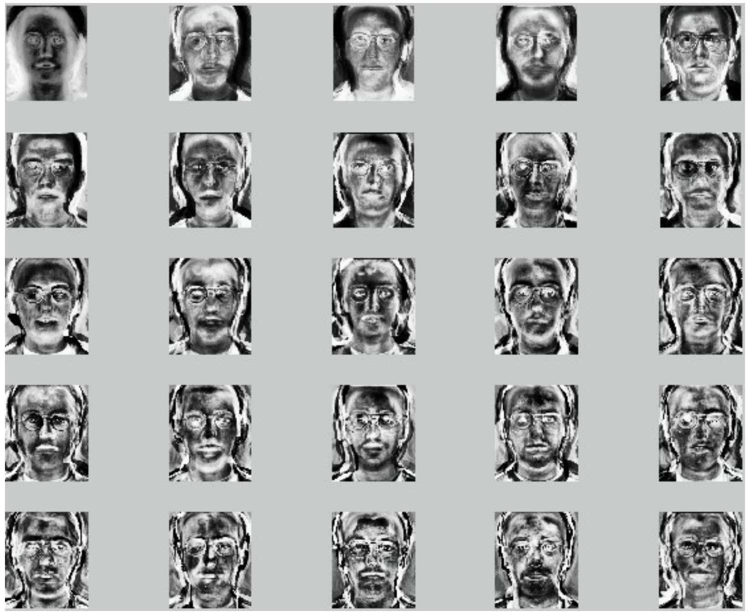

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What dimension are we using now?

# Q3-1: Which generally is NOT an unsupervised learning task?

1. Principal component analysis
2. Fraud detection
3. CIFAR-10 image classification
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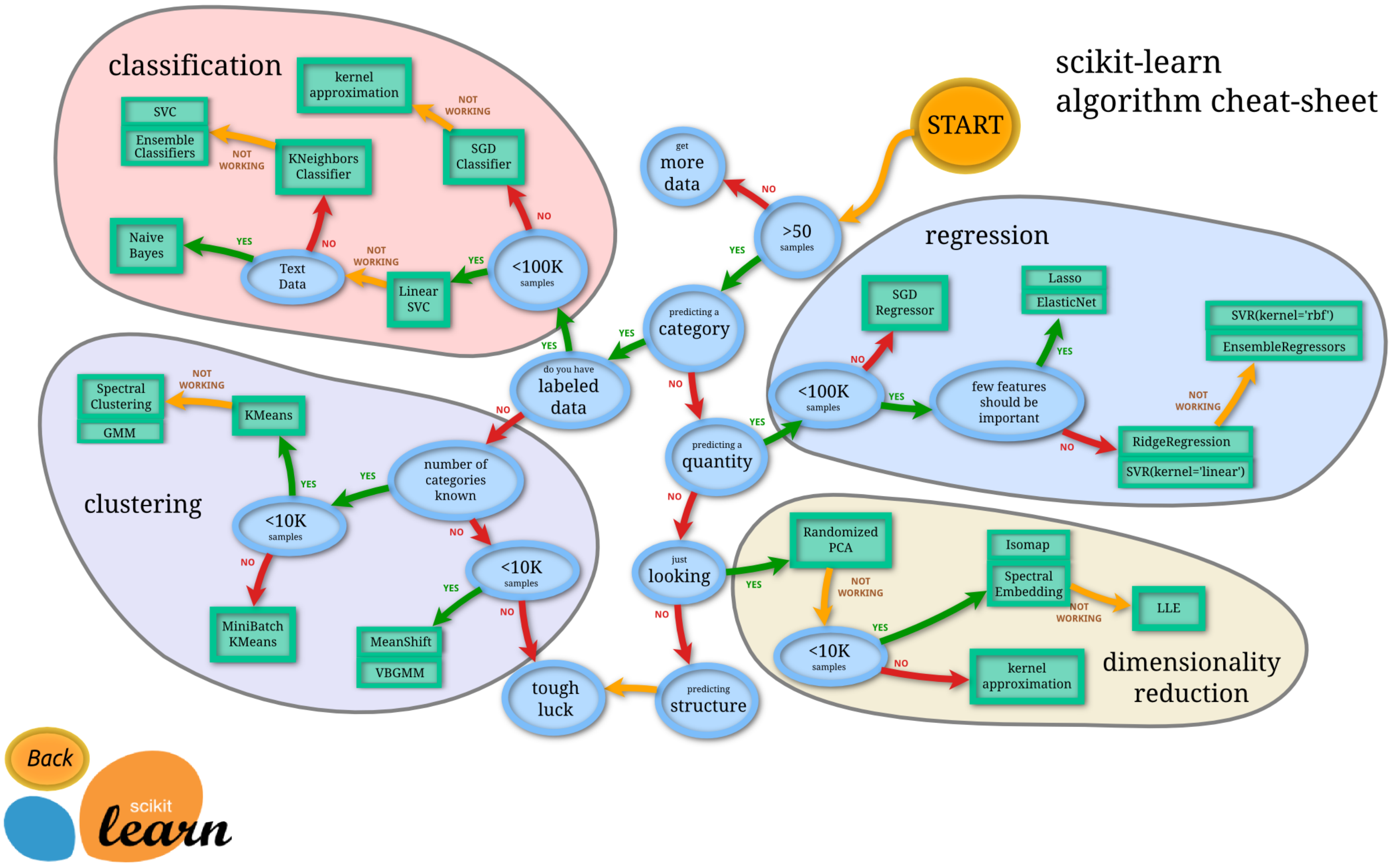
**1. Principal component analysis is a problem of dimensionality reduction.**
**2. You can think fraud detection as an anomaly detection problem.**
**3. CIFAR-10 image classification is a classification task for labeled image data.**
**4. Community detection is some clustering problem.**

# Model Zoo

Lots of models!



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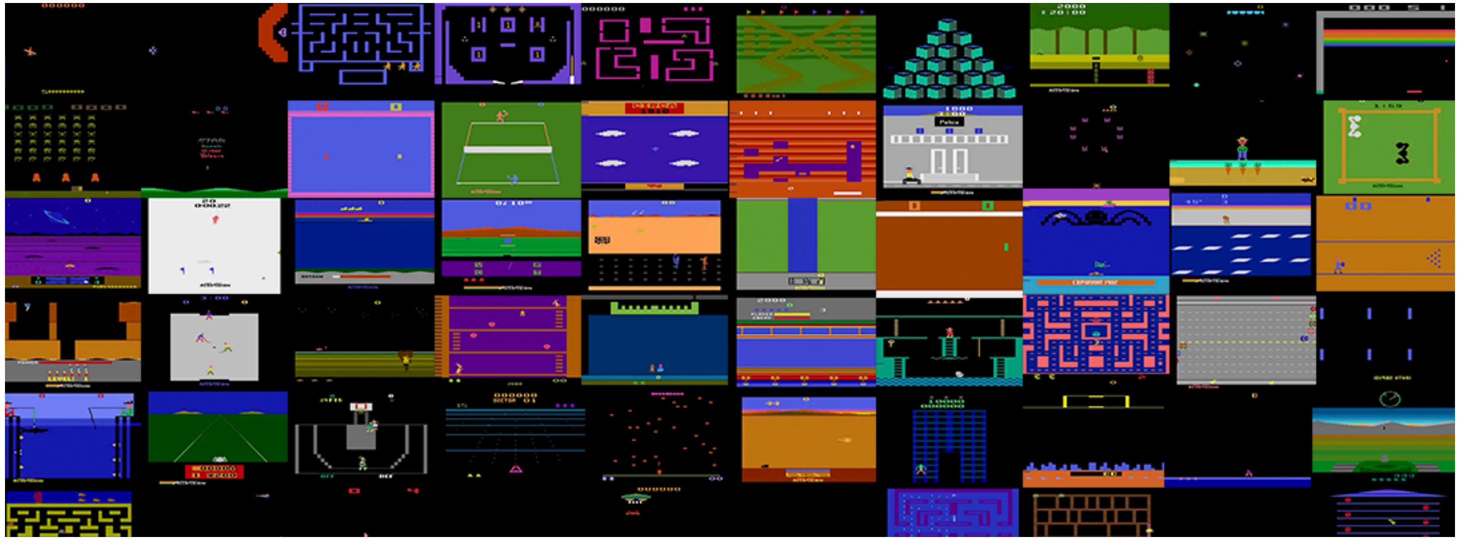

Google Deepmind

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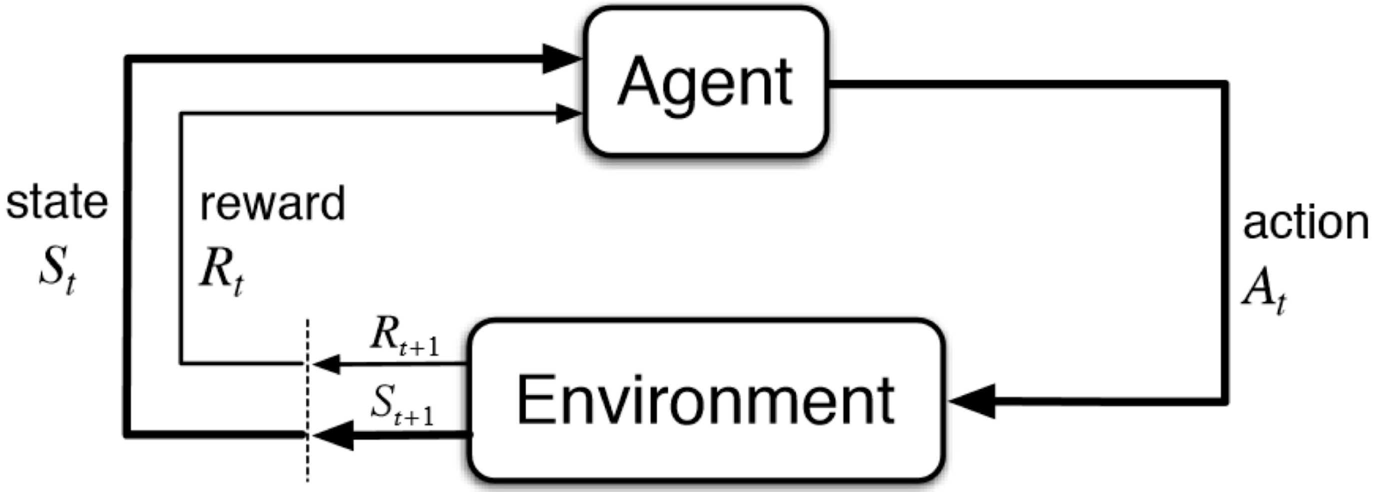

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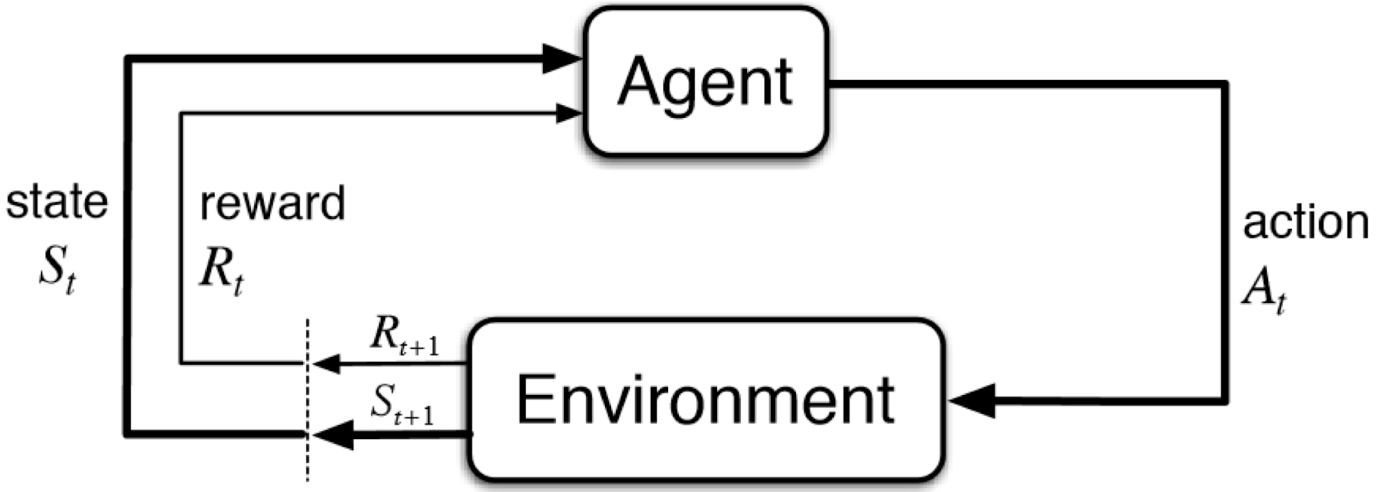


Agent collects data $s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T, a_T, r_T$ .

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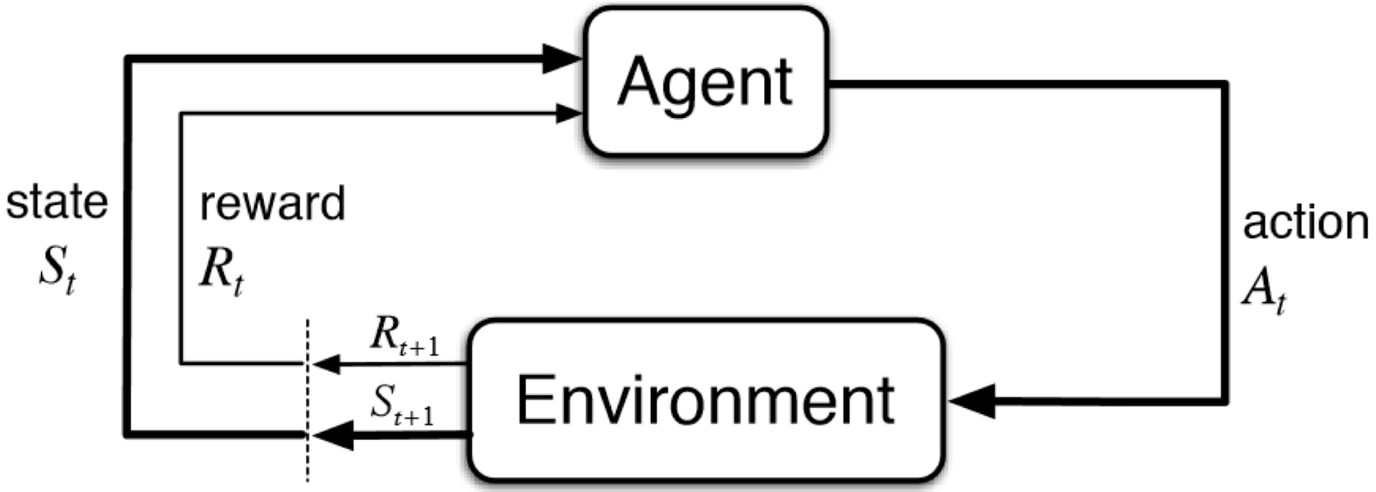


Agent collects data $s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T, a_T, r_T$ .

Learn *policy* $\pi : \mathcal{S} \rightarrow \mathcal{A}$ that maximizes $\sum_{t=0}^{\infty} \gamma^t r_t$.

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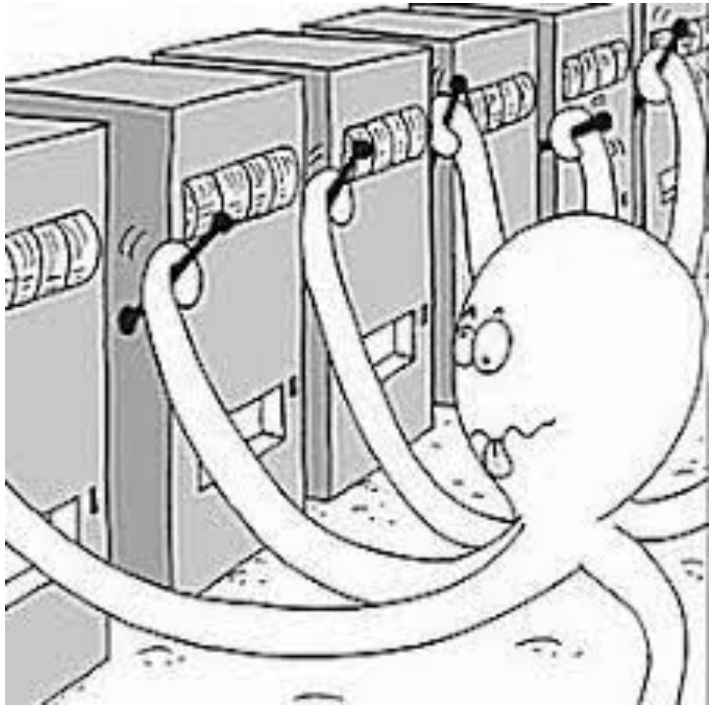

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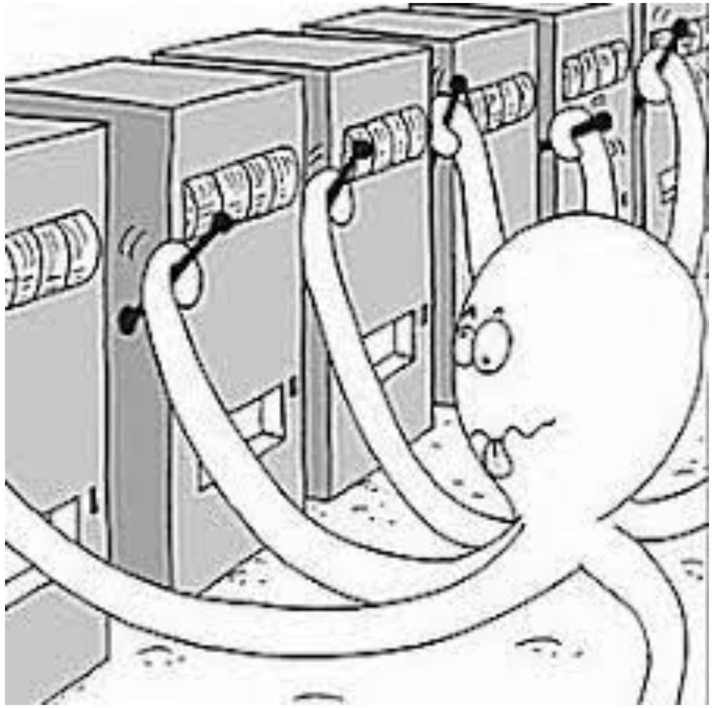
"..the problem [exploration-exploitation] was proposed [by British scientist] to be dropped over Germany so that German scientists could also waste their time on it."

- Peter Whittle



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# Learning Outcomes

- **After today's lecture:**
  - You will be able to explain the key aspects of a supervised learning problem.
  - Provide examples of unsupervised learning problems and explain why these are not supervised learning problems.
  - Explain key challenges of reinforcement learning problems.

# Thanks Everyone!

Some of the slides in these lectures have been adapted/borrowed from materials developed by Mark Craven, David Page, Jude Shavlik, Tom Mitchell, Nina Balcan, Elad Hazan, Tom Dietterich, Pedro Domingos, Jerry Zhu, Yingyu Liang, Volodymyr Kuleshov, and Fred Sala