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Learning

- Adapt through interaction with the world: rote memory to developing a complex strategy
- Types of learning:
  1. Supervised learning (dense feedback)
  2. Unsupervised learning (no feedback)
  3. Reinforcement learning (sparse feedback, environment altering), etc.
- Advantages (two, among many):
  1. Fault tolerance ✓
  2. No need for a complete specification to begin with ✓
- Becoming a central focus of AI.

1990 ~ 2000

ML.

2005~2010

Deep Learning

Not specifically related to deep learning, but anyway, so it's machine learning is really one of the most popular and powerful technologies

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What Is Machine Learning?

dominating the field.

- A subfield of AI that is rapidly growing in importance.
- Performance of a system is improved based on learning experience.
- Learning from data.

What Is Machine Learning?

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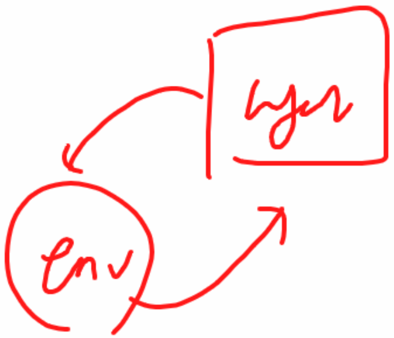
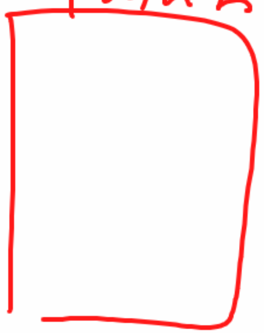


Data file



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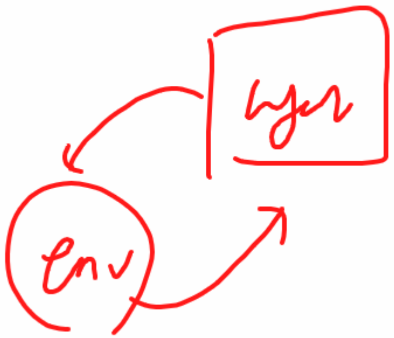

So all of these are different forms of experience. So learning from data is basically one form of experience

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Huge amount of data

"Big Data"

Why Machine Learning?

- Abundance of data: the data deluge.
  - Scientific instruments.
  - Data acquisition devices.
  - Internet and the web.
  - All sectors of human society producing and digitizing data (e.g., your cell phone).
- Not enough human expertise or human power to make sense of such huge amounts of data.

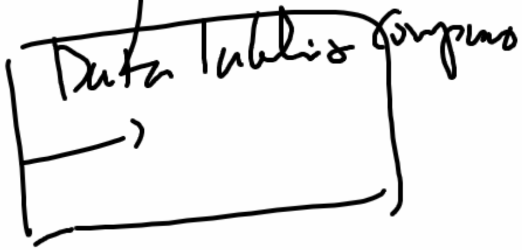
ML

Amazon's Mechanical Turk

¢

label

requires human effort



Machine Learning in the News

IBM's Watson   Google DeepMind's AlphaGo

- IBM's Watson beats human champions: Jeopardy (game show)
- Google detects cats from YouTube videos.
- Google Glass app recognizes people it sees.
- Legal, medical, financial applications.
- Google DeepMind: Atari 2600 game playing, AlphaGo, AlphaStar

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2015

Deep R.L

I

Atari 2600

Machine Learning in the News

2016

IBM's Watson   Google DeepMind's AlphaGo

Google Deepmind

UK

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alpha goal, and then applied that to atari, 26, 3,600 games

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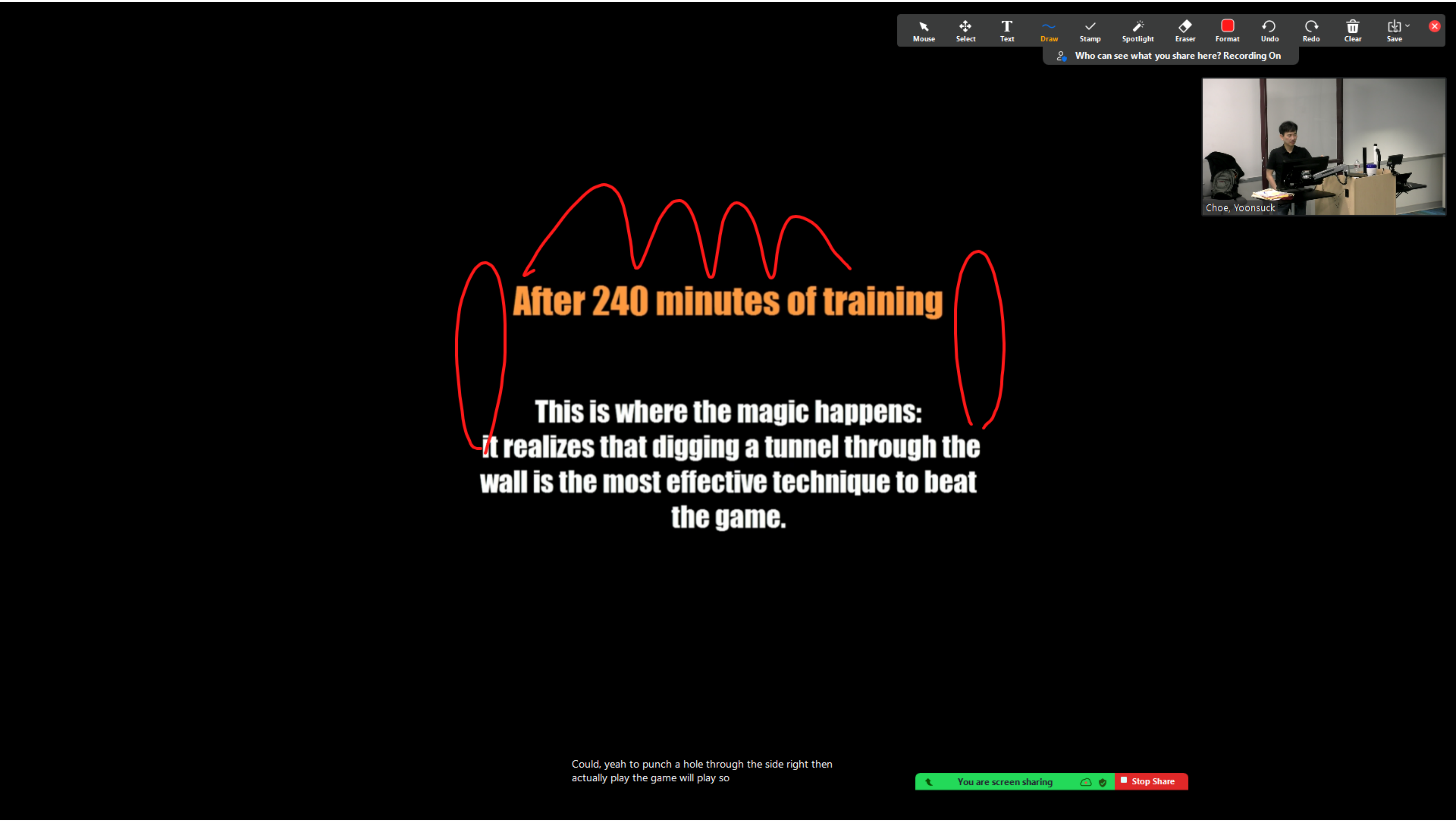
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Who can see what you share here? Recording On
Choe, Yoonsuck
After 240 minutes of training
This is where the magic happens:
it realizes that digging a tunnel through the
wall is the most effective technique to beat
the game.
Could, yeah to punch a hole through the side right then
actually play the game will play so
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Machine Learning in the News

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$P(\text{Earthquake} \mid \text{HouseShaking}) = 0.9$

observation

Probabilistic Inference

- **Diagnostic inferences**: $P(Cause|Effect)$
- **Causal inferences**: $P(Effect|Cause)$
- **Intercausal inferences**: causes of a common effect (**explaining away**: cause has already been found)

  $P(Cause|Effect) >> P(Cause|Effect \wedge OtherCause)$

- **Mixed inferences**: combining two or more of the above

  $P(A|CauseOfA \wedge EffectOfA)$

Construction

$P(\text{Earthquake} \mid \text{House shaking, Construction}) = 0.2$

Machine Learning in the News

IBM's Watson   Google DeepMind's AlphaGo

Deep Q Network

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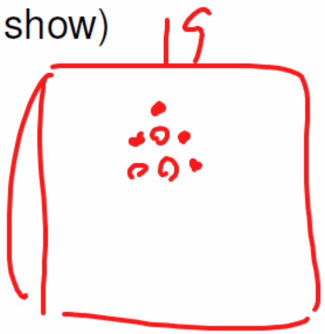

Machine Learning in the News

IBM's Watson   Google DeepMind's AlphaGo

Deep Network

15

15

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Network, combined with something called Monte Carlo. 3
search has been able to actually beat this former champion

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Machine Learning in the News

IBM's Watson   Google DeepMind's AlphaGo

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And he's just thing the game dictated by Alpha go

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Machine Learning in the News

IBM's Watson Google DeepMind's AlphaGo

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ACM Turing Award 2018: Deep Learning

Association for Computing Machinery

ACM

ACM recognizes excellence

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Awards Home | ACM A.M. Turing Award | Spotlight on Turing Laureates | ACM Prize in Computing

Home > Latest Awards News > 2018 Turing Award

Fathers of the Deep Learning Revolution Receive ACM A.M. Turing Award

Bengio, Hinton and LeCun Ushered in Major Breakthroughs in Artificial Intelligence

Communications of the ACM

- ACM Turing Award 2018 goes to Deep Learning pioneers!

So this is a good way to find your research interested to int

What Does It Take to do ML?

A lot of math:

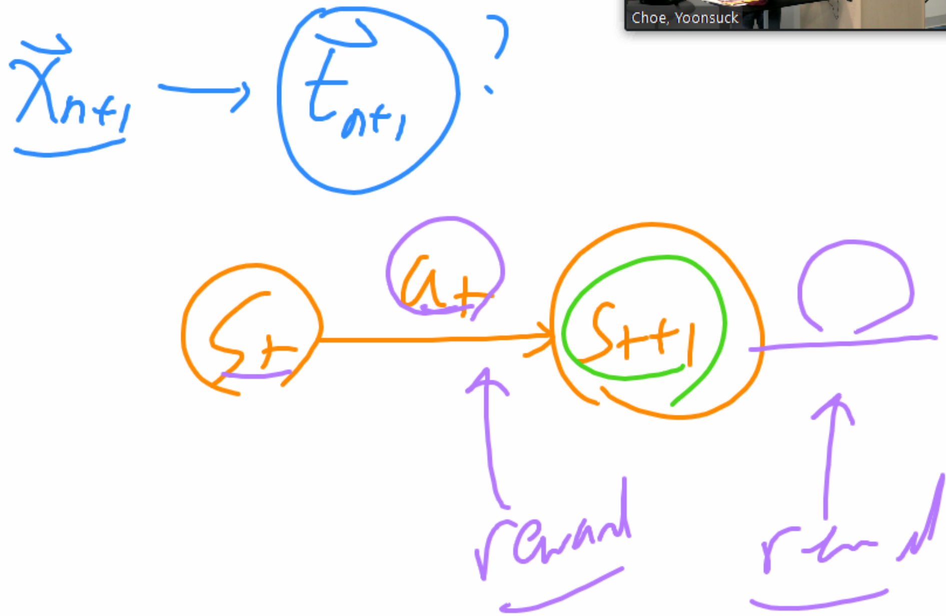
- Linear algebra
- Calculus
- Probability and statistics
- Differential geometry
- Numerical methods

$A \cdot B \quad (A)^{-1}$

$$\begin{cases} (\bigcirc * \bigcirc) + \bigcirc \\ \bigcirc + (\bigcirc * \bigcirc) \end{cases}$$

Types of Machine Learning

1. Supervised learning
   - Input-Target pairs
   - $\{\langle \vec{x}_i, \vec{t}_i \rangle | i = 1, 2, .., n\}$
2. Unsupervised learning
   - A bunch of inputs (unlabeled)
   - $\{\vec{x}_i | i = 1, 2, ..., n\}$
3. Reinforcement learning
   - state$_1$ $\xrightarrow{\text{action}_1}$ state$_2$ $\xrightarrow{\text{action}_2}$ state$_3$, ... , reward
   - $s_{t+1} = \underbrace{\delta(s_t, a_t)}_{\text{env}}$, $r_{t+1} = \underbrace{\rho(s_t, a_t)}_{\text{env}}$



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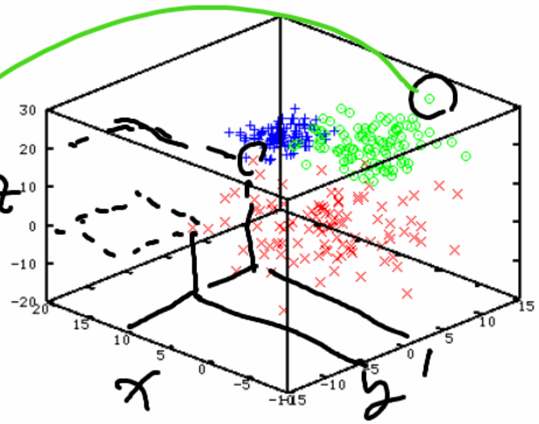
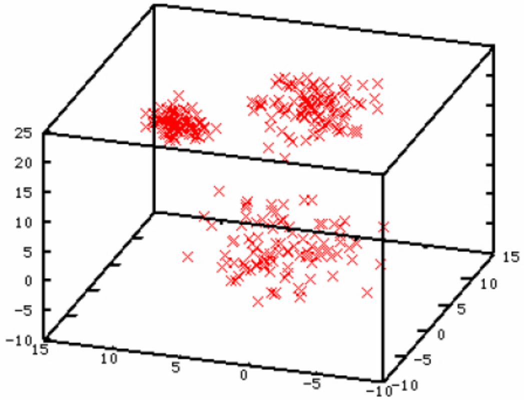
3. Reinforcement learning
   - $\text{state}_1 \xrightarrow[\text{action}_1]{} \text{state}_2 \xrightarrow[\text{action}_2]{} \text{state}_3$, ... , reward
   - $s_{t+1} = \delta(s_t, a_t), r_{t+1} = \rho(s_t, a_t)$

So you're the local reward would actually go down. But then you get a good grade. Then that that actually give you a much more

Example Data

x	y	z	Color
10	5	0	×
10	1	20	+
			O





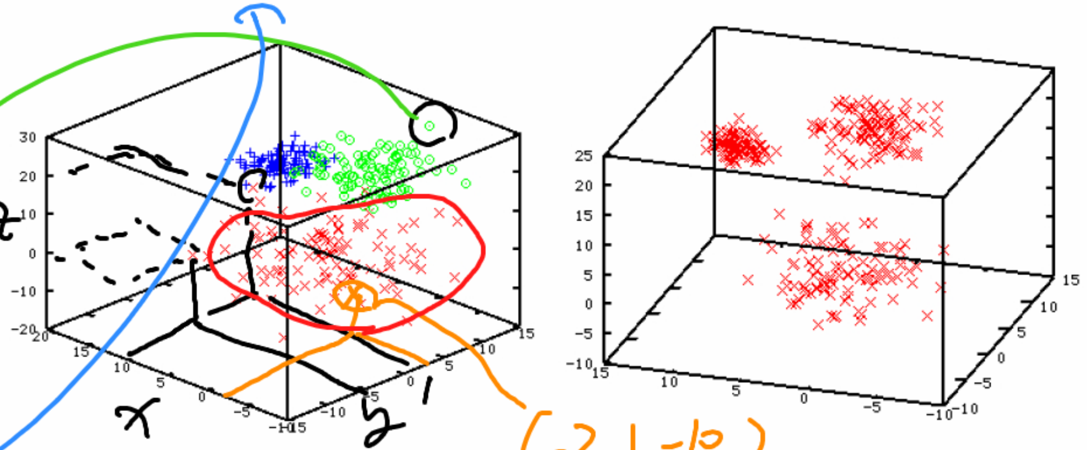
- Left: supervised
- Right: unsupervised
- Typically very high dimensional (10,000, 1 million [or more]).

Example Data

"X"

x	y	z	color
10	5	0	X
10	1	20	+
			O
			⋮
-2, 1, -10			X ?

1ᴺ4



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- Right: unsupervised
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cond. indep

$P(\text{Ache} \mid \text{Cav}, \text{Catch})$

cause

cause

Probabilistic Inference

- **Diagnostic inferences**: $P(Cause|Effect)$
- **Causal inferences**: $P(Effect|Cause)$
- **Intercausal inferences**: causes of a common effect (**explaining away**: cause has already been found)

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Intercausal Inference

- **Mixed inferences**: combining two or more of the above

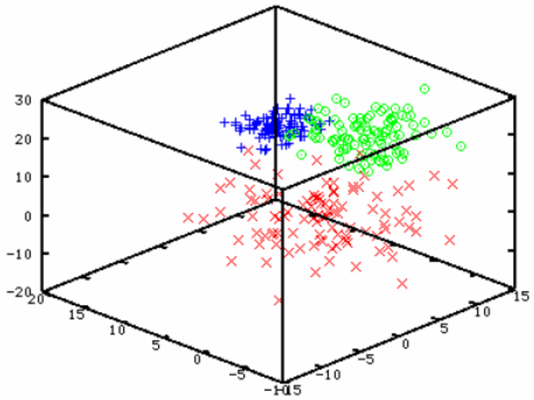
  $P(A|CauseOfA \land EffectOfA)$

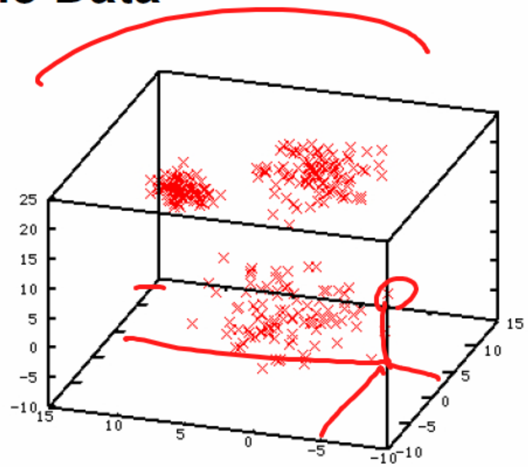
$P(\text{Earthquake} \mid \text{Houseshaking}, \text{Construction})$

cause

cause

Example Data





~~target~~

-5, 2 10

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- Right: unsupervised
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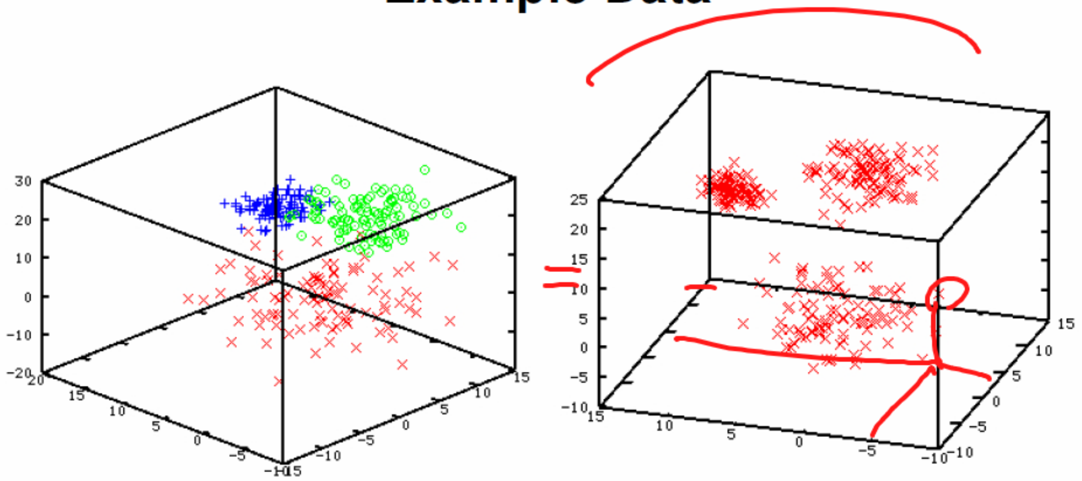
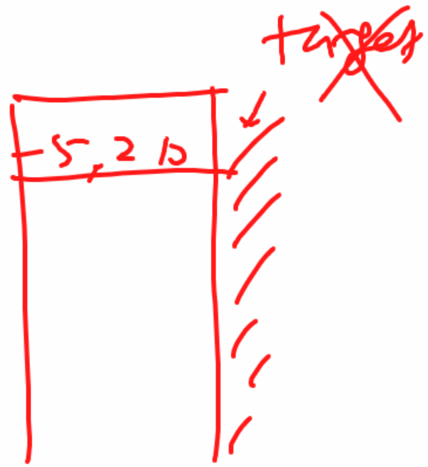
Example Data





- Left: supervised
- Right: unsupervised
- Typically very high dimensional (10,000, 1 million [or more]).

So, in fact, these 2 are the same data set. but here I just removed the label on the target value

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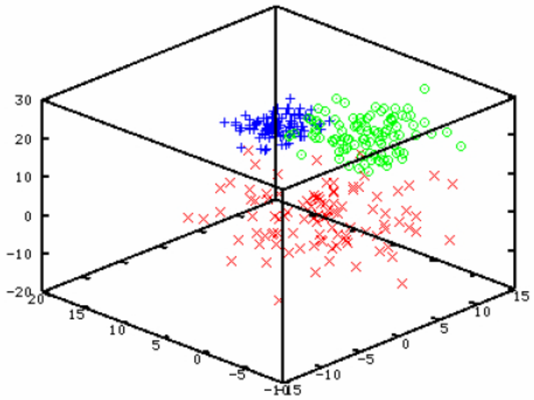
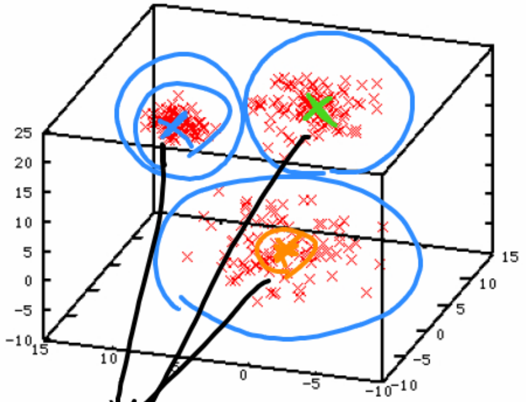
Example Data





features

clusters. - - structure.

- Left: supervised
- Right: unsupervised
- Typically very high dimensional (10,000, 1 million [or more]).

So there's something that you can say about this kind of data set

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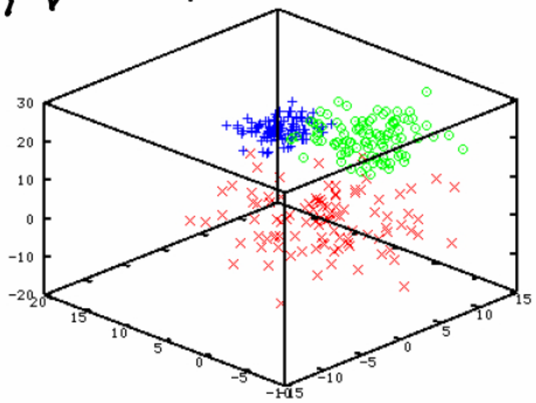
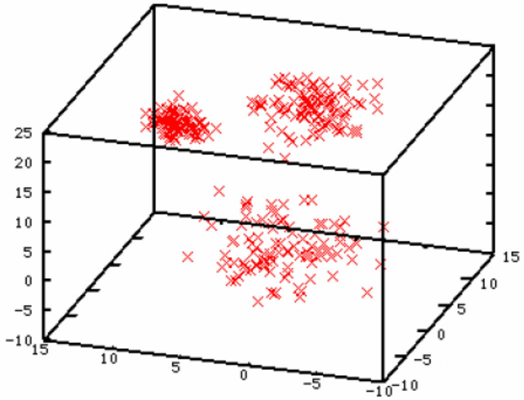
Example Data

3 D input.

x	y	z





x	y	z

3 D

- Left: supervised
- Right: unsupervised
- Typically very high dimensional (10,000, 1 million [or more]).

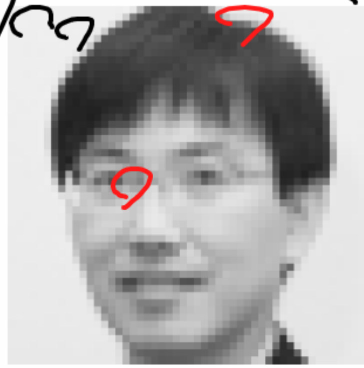
Can you imagine that this kind of data exist

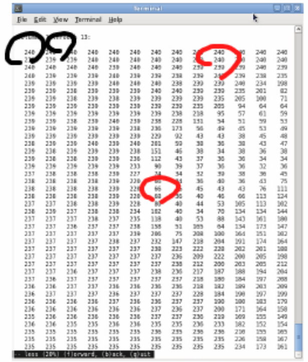
$\rightarrow$ 2500 Values

High-dimensional Data

50

50





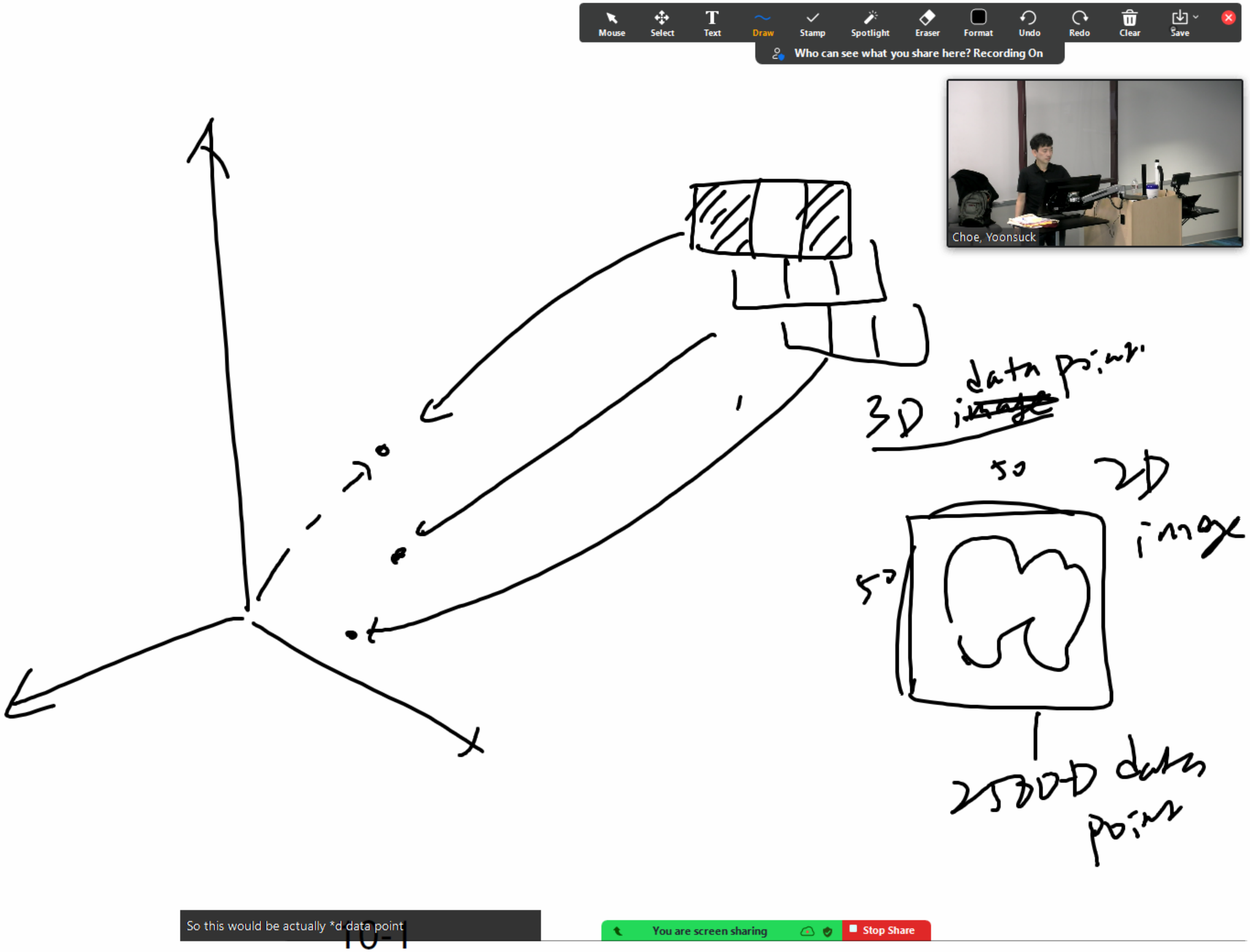
50

50

ML → "Choe"

$$\longrightarrow \underbrace{[240, 240, \ldots, 232, \ldots.]}_{\text{2,500-D vector}}$$

- Images: these are 2D images, but ...
- These are 50×50 = 2,500-dimensional vectors.
  - Each such image is a single point in 2,500-dimensional space.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Who can see what you share here? Recording On
Choe, Yoonsuck
3D ~~image~~ data point
50
2D image
50
2500-D data point
So this would be actually *d data point
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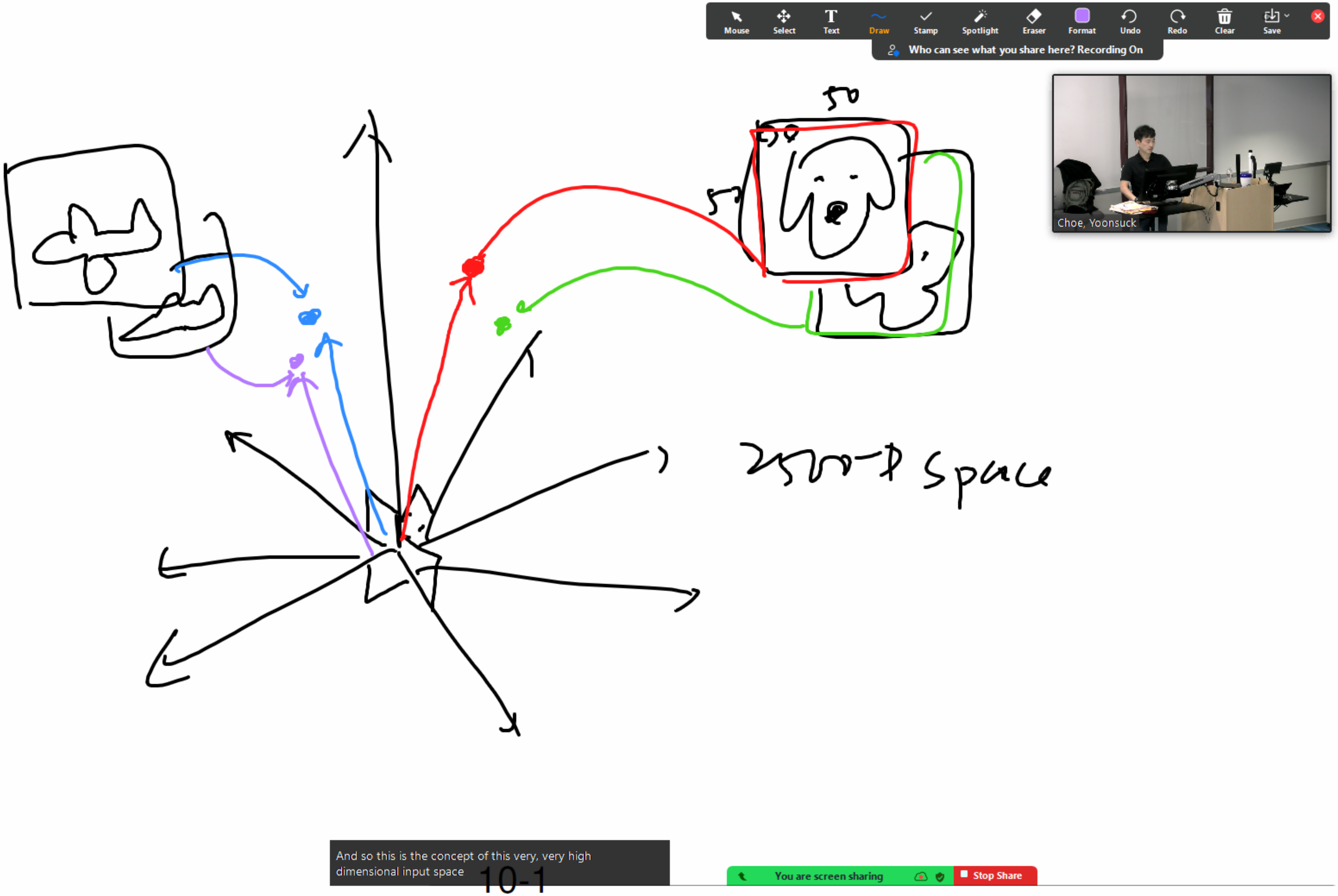
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Redo
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Who can see what you share here? Recording On
Choe, Yoonsuck
50
50
2500-D space
And so this is the concept of this very, very high dimensional input space
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Supervised Learning

① Supervised learning

- Regression: approximating $y = f(x)$
- Classification: face recognition, hand-written character recognition, credit risk assessment, etc.
- Techniques:
  - Neural networks
  - Decision tree learning
  - Support vector machines
  - Radial basis functions
  - Naive Bayes learning
  - k-nearest neighbor

② Unsupervised learning

③ Reinforcement learning

input	$\mathbb{R}$
x_1	y_1
x_2	y_2
	⋮

input target

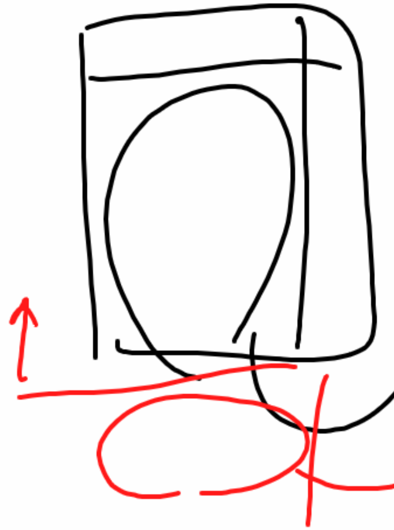
input	target
	"cat"
	"dog"

input target

ML → error

Supervised Learning Issues

error

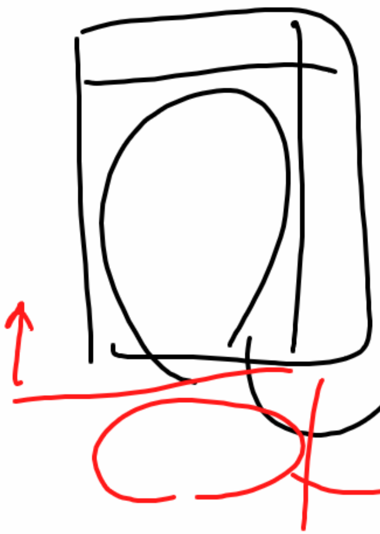


- How well will it do on training inputs?
- How well will it do on novel inputs?
  - Generalization.
- How many samples needed for sufficient performance and generalization?
  - Sample complexity
  - Curse of dimensionality
  - Computational learning theory
- Catastrophic forgetting (online learning hard).

ML → error

Supervised Learning Issues

error



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cond. indep

P(Ache | Cav, Catch)

cause

cause

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Intercausal Inference

- **Mixed inferences**: combining two or more of the above

  $P(A|CauseOfA \wedge EffectOfA)$

P(Earthquake | Houseshaking, Construction)

cause

cause

Supervised Learning Issues

D1 D2 ML 98.5% 90.2% 98%

D1 D2 ML 98% 98.5% 97.5%

Expensive

- How well will it do on training inputs?
- How well will it do on novel inputs?
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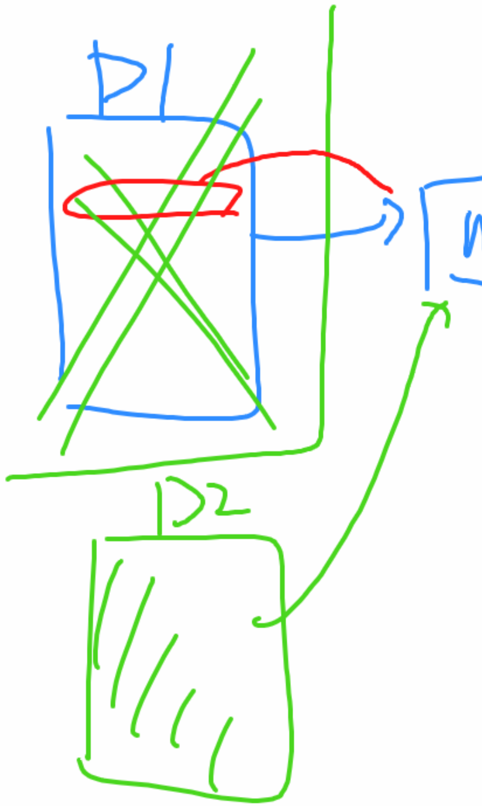
Supervised Learning Issues



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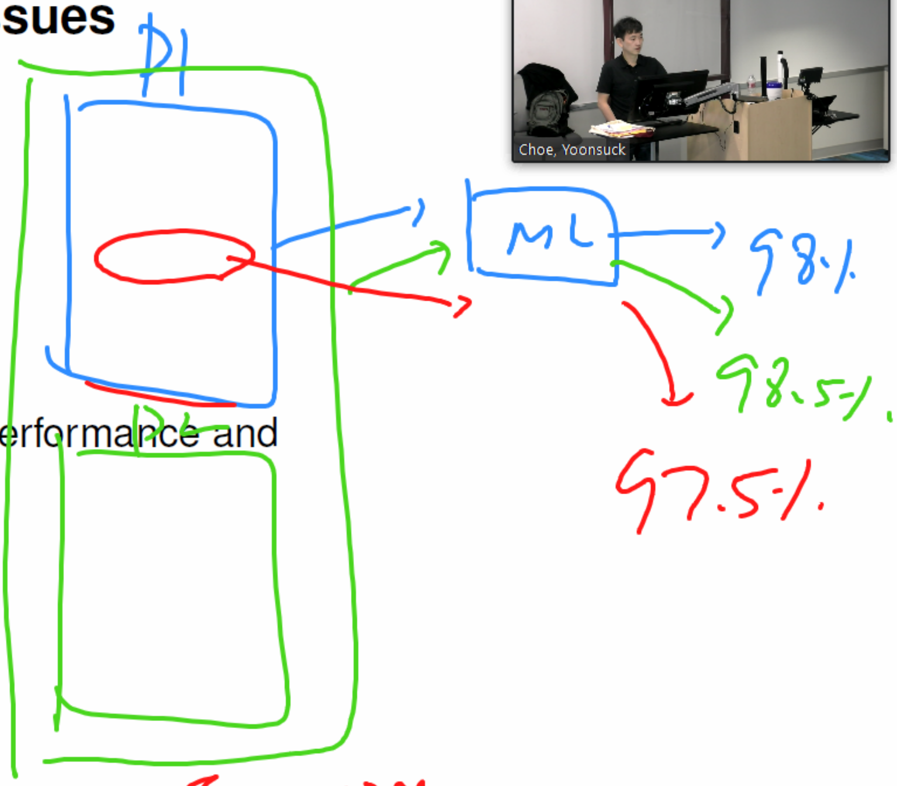


Expensive

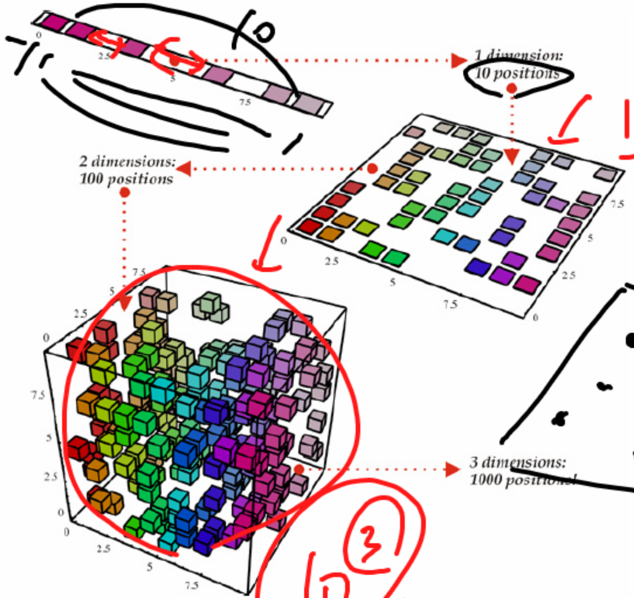
Continual learning

That came out to overcome this kind of issue, and this is called continual learning.

Addendum: Curse of Dimensionality

X

1D 10 10^2 2D



10^3

10^{2500}

X b

n=10

sparse

From: Yoshua Bengio's page

- Exponentially many points needed to achieve same density of training samples.

Probabilistic Inference

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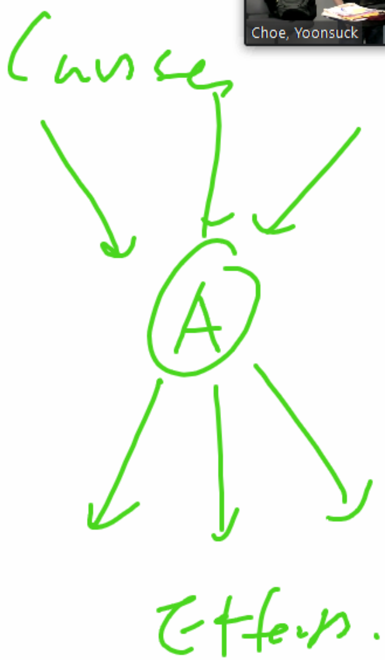
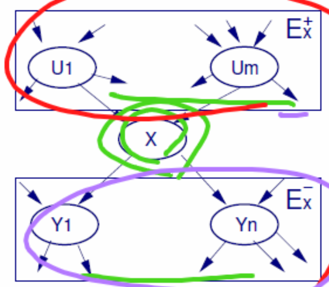


Answering Queries: A Brief Outline



Given a set of evidence E, find the conditional probability $\mathbf{P}(X|E)$ where X is the query.

- Recursively deterimine the **causal support** E_X^+ for X.
- Recursively deterimine the **evidential support** E_X^- for X.

Note: This is only when the graph is **singly connected**.

So. And there are certain conditions. For example, the graph has to be singular

Using Belief Networks and Probabilistic Inference

- Making decisions based on the derived probabilities and an agent's utility function.
- Deciding which additional variables to include in the model.
- Performing **sensitivity analysis** to find out which node is most important and thus should be more accurate.
- Explaining the results of reasoning.

$p(X \mid E)$

$\text{Utility}(X = x_i)$

$\rightarrow$ decision

Using Belief Networks and Probabilistic Inference

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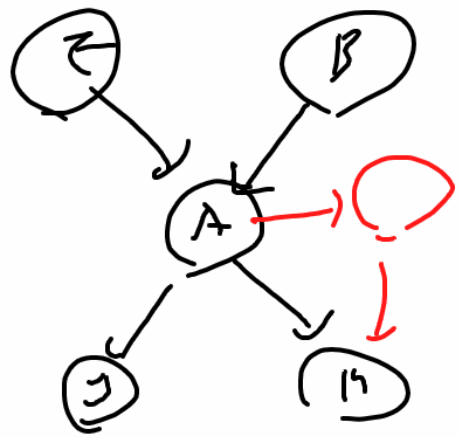

Knowledge Engineering for Uncertain Reasoning

- Decide what to talk about (i.e. what to be included in the model). Gradually add more factors that can influence the current collection of events.
- Determine the variables to use and the range of the values.
- Encode general knowledge about the dependence between variables:
  1. qualitative: which variable depends on some other variable
  2. quantitative: probability value of the dependence (from experience, or from data gathered from a sample space)

graph

cond. prob.

- Encode a description of the specific problem instance: assign values to the variables.

$p(X=?\mid E=?)$

- Pose queries to the inference procedure and get answers: what is the probability of X? how sensitive are the values in the conditional probability tables to perturbations?

Learning

- Adapt through interaction with the world: rote memory to developing a complex strategy
- Types of learning:
  1. Supervised learning (dense feedback)
  2. Unsupervised learning (no feedback)
  3. Reinforcement learning (sparse feedback, environment altering), etc.
- Advantages (two, among many):
  1. Fault tolerance
  2. No need for a complete specification to begin with
- Becoming a central focus of AI.