

# INTRODUCTION TO DEEP LEARNING

Seminar @ UPC TelecomBCN Barcelona (3rd edition). 22-28 January 2020.



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<http://bit.ly/idl2020>

## Day 1 Lecture 2

# Machine Learning Basics



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# Acknowledgements



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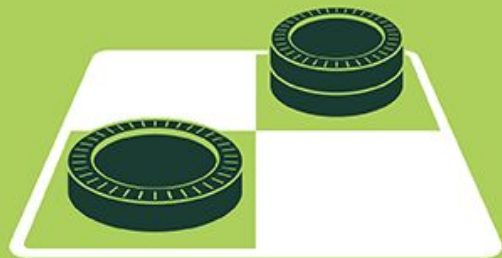
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# ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



# MACHINE LEARNING

Machine learning begins to flourish.



# DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

1990's

2000's

2010's

# Types of Machine Learning

Yann Lecun's Black Forest cake

## ■ "Pure" Reinforcement Learning (cherry)

- ▶ The machine predicts a scalar reward given once in a while.
- ▶ **A few bits for some samples**

## ■ Supervised Learning (icing)

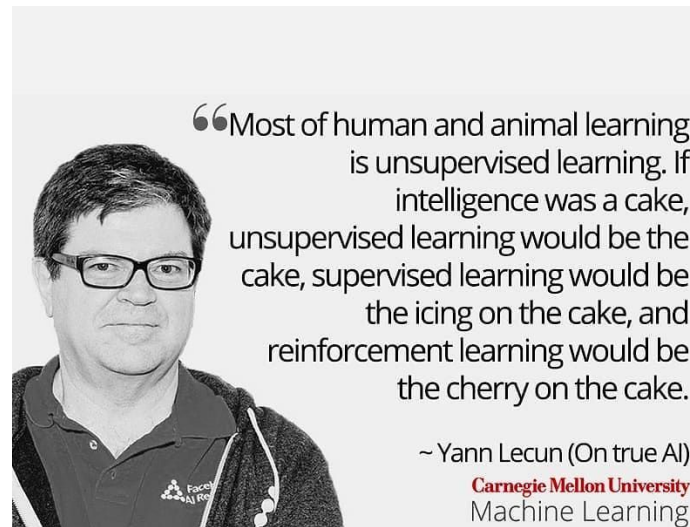
- ▶ The machine predicts a category or a few numbers for each input
- ▶ Predicting human-supplied data
- ▶ **10→10,000 bits per sample**

## ■ Unsupervised/Predictive Learning (cake)

- ▶ The machine predicts any part of its input for any observed part.
- ▶ Predicts future frames in videos
- ▶ **Millions of bits per sample**



■ (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)



	...with a teacher	...without a teacher
Active agent...	Reinforcement learning (with extrinsic reward)	Intrinsic motivation / Exploration.
Passive agent...	Supervised learning	Unsupervised learning



Slide inspired by Alex Graves (Deepmind) at  
[“Unsupervised Learning Tutorial”](#) @ NeurIPS 2018.

# Machine Learning

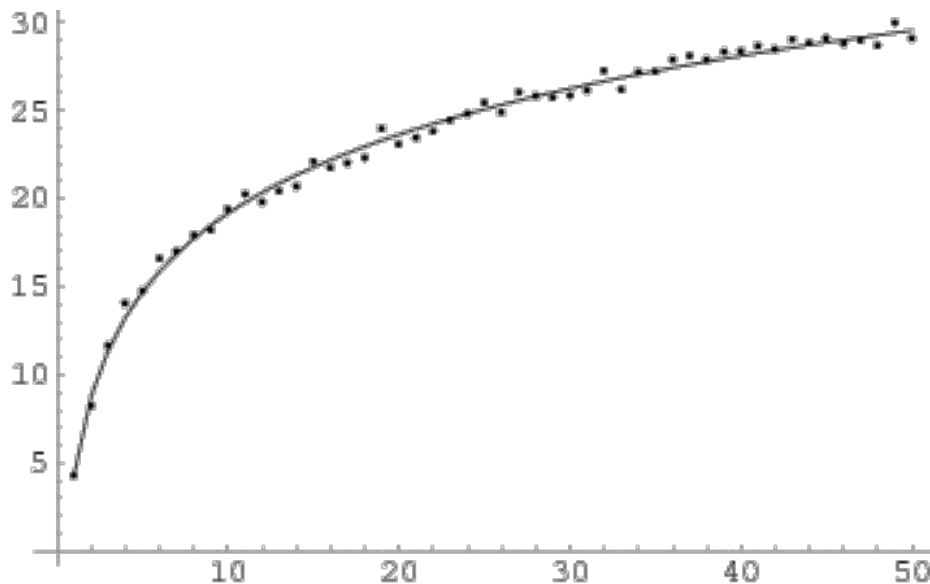
	...with a teacher	...without a teacher
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# Supervised learning

Fit a function:  $y = f(\mathbf{x})$ ,  $\mathbf{x} \in \mathbb{R}^m$

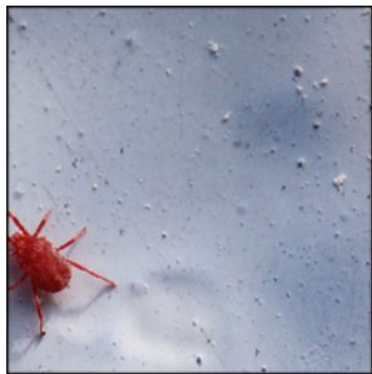
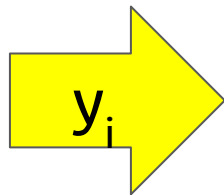
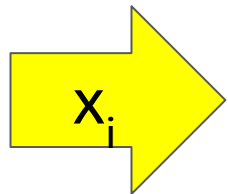




# Supervised learning

Fit a function:  $\mathbf{y} = f(\mathbf{x})$ ,  $\mathbf{x} \in \mathbb{R}^m$

Given paired training examples  $\{(\mathbf{x}_i, \mathbf{y}_i)\}$



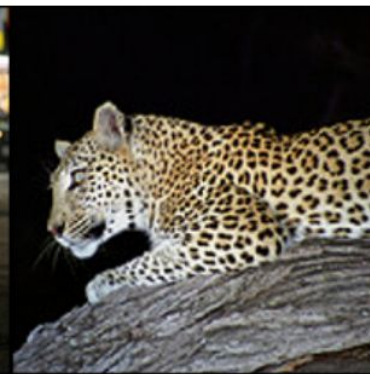
**mite**



**container ship**



**motor scooter**



**leopard**



# Supervised learning

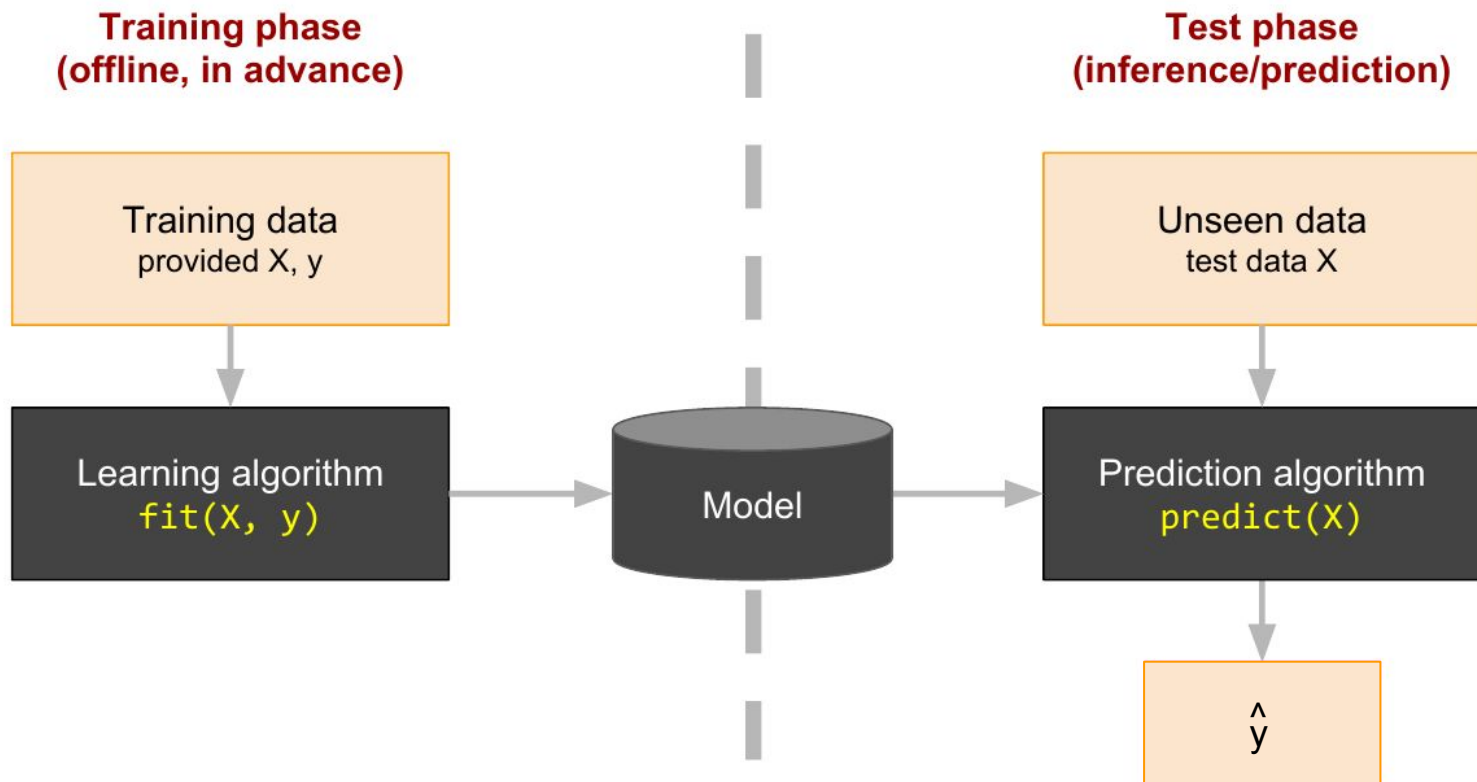
Fit a function:  $\mathbf{y} = f(\mathbf{x})$ ,  $\mathbf{x} \in \mathbb{R}^m$

Given paired training examples  $\{(\mathbf{x}_i, \mathbf{y}_i)\}$

Key point: **generalize well to unseen examples**



# Black box abstraction of supervised learning



# Regression vs Classification

Depending on the type of target  $y$  we get:

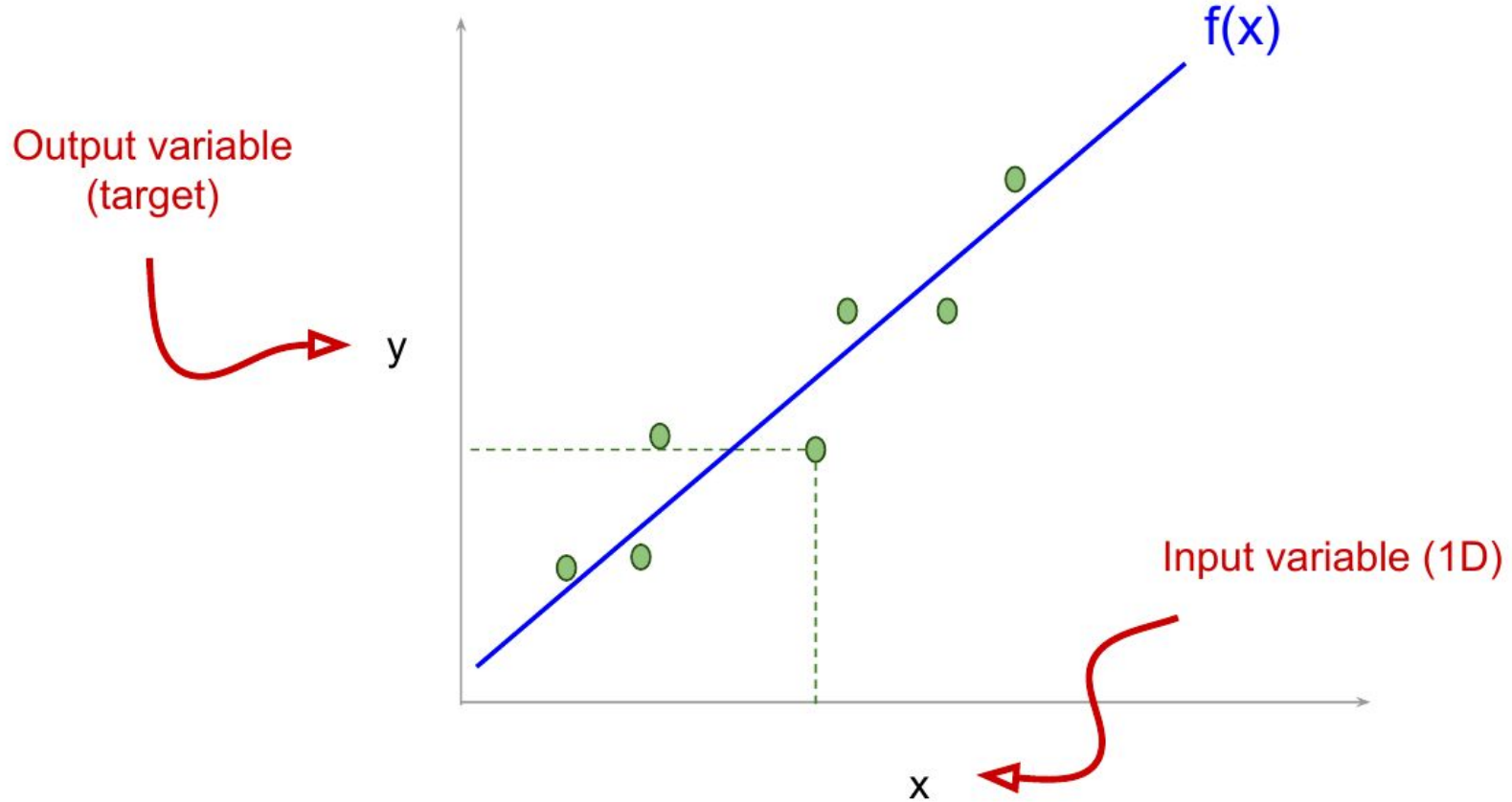
- **Regression**:  $y \in \mathbb{R}^N$  is continuous (e.g. temperatures  $y = \{19^\circ, 23^\circ, 22^\circ\}$ )
- **Classification**:  $y$  is discrete (e.g.  $y = \{\text{"dog"}, \text{"cat"}, \text{"ostrich"}\}$ ).

# Regression vs Classification

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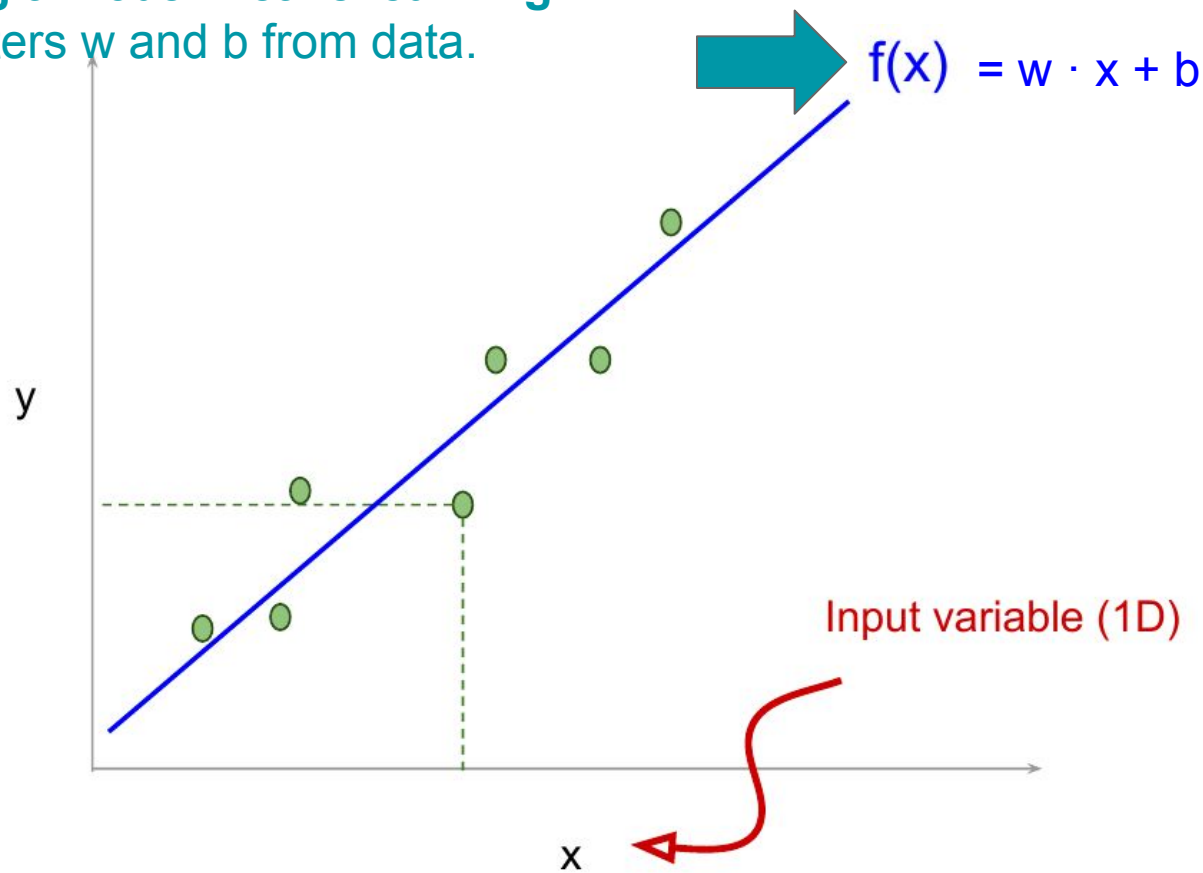
- **Regression**:  $y \in \mathbb{R}^N$  is **continuous** (e.g. temperatures  $y = \{19^\circ, 23.2^\circ, 22.8^\circ\}$ )
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# Linear Regression (eg. 1D input - 1D output)



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Training a model means learning parameters  $w$  and  $b$  from data.



# Linear Regression (M-D input)

Input data can also be M-dimensional with vector  $\mathbf{x}$ :

$$\boxed{y = \mathbf{w}^T \cdot \mathbf{x} + b} = w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + \dots + w_M \cdot x_M + b$$

e.g. we want to predict the **price of a house (y)** based on:

$x_1$  = square-meters (sqm)

$x_{2,3}$  = location (lat, lon)

$y$  = price =  $w_1 \cdot (\text{sqm}) + w_2 \cdot (\text{lat}) + w_3 \cdot (\text{lon}) + b$



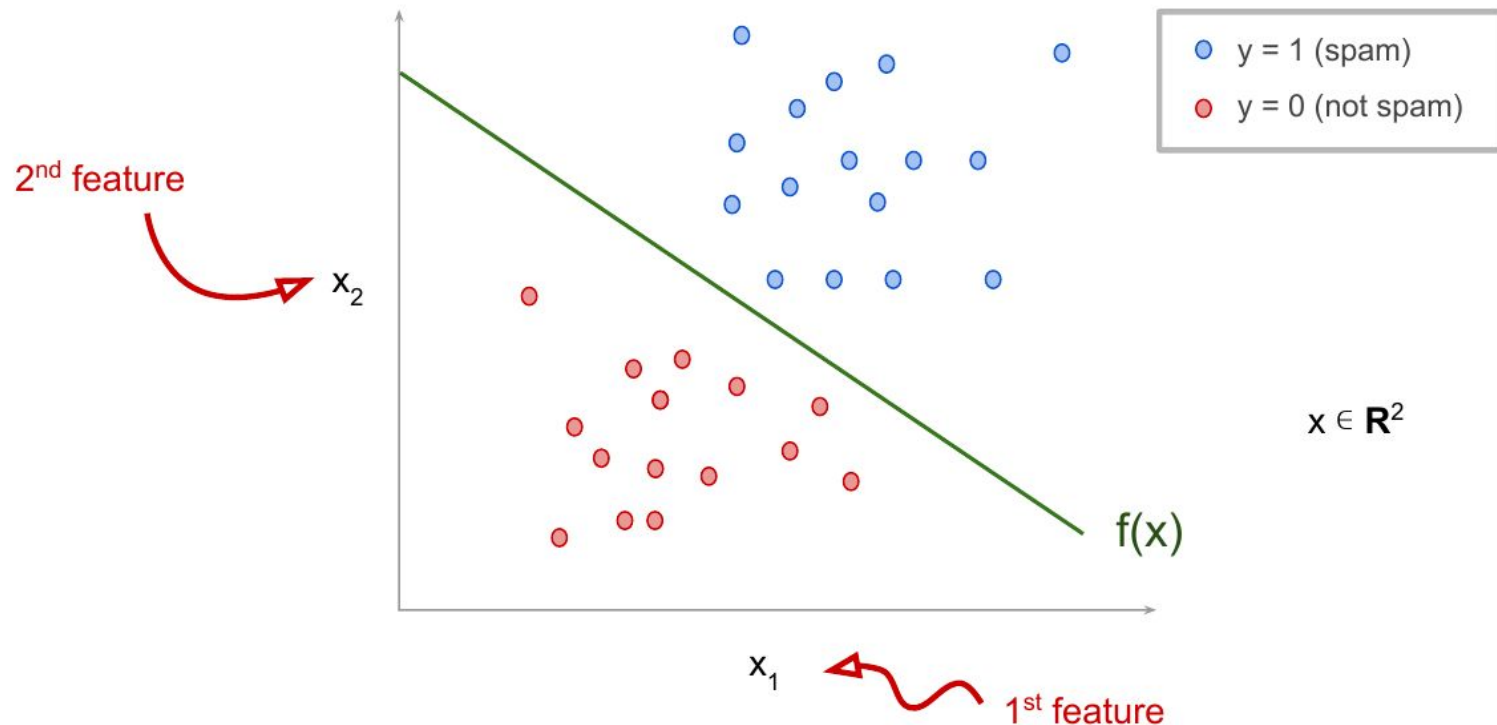


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# Binary Classification (eg. 2D input, 1D output)

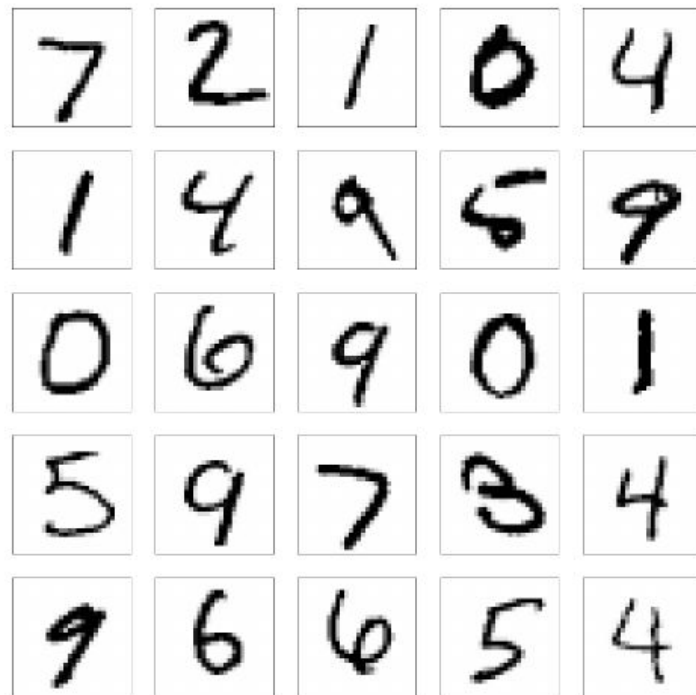


# Multi-class Classification

Produce a classifier to map from pixels to the digit.

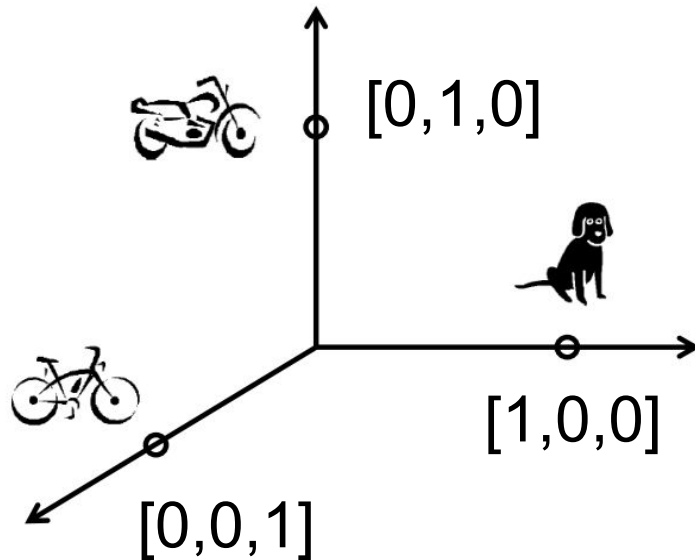
- ▶ If images are grayscale and  $28 \times 28$  pixels in size, then  $\mathbf{x}_i \in \mathbb{R}^{784}$
- ▶  $y_i \in \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

Example of a **multi-class classification** task.



# Multi-class Classification

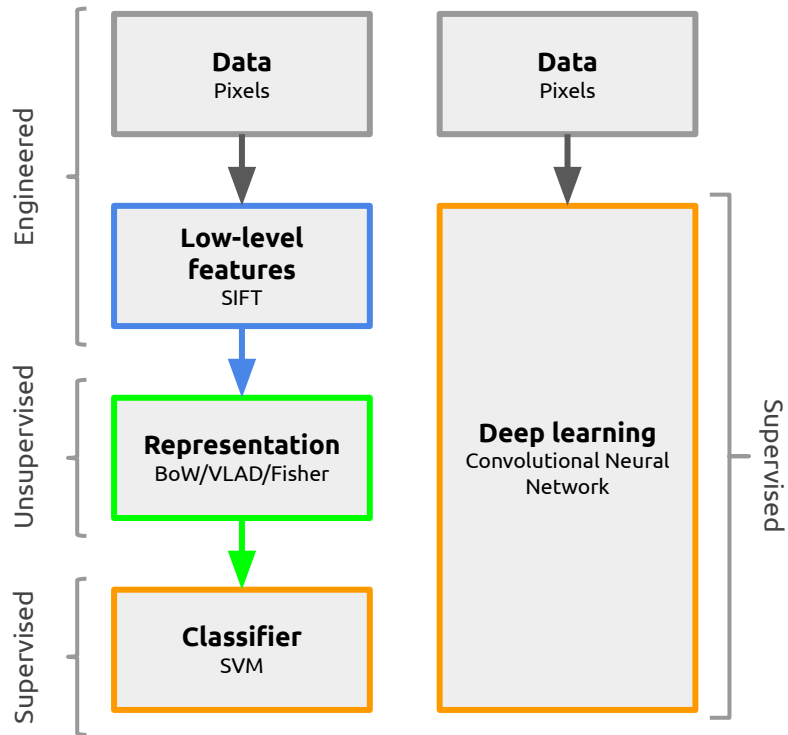
- **Classification:**  $y$  is **discrete** (e.g.  $y = \{\text{"dog"}, \text{"cat"}, \text{"ostrich"}\}$ ).
  - Classes are often coded as **one-hot vector** (each class corresponds to a different dimension of the output space)



One-hot  
representations

# End-to-end Learning

- Old style machine learning:
  - Engineer features (by some unspecified method)
  - Create a representation (descriptor)
  - Train shallow classifier on representation
- Example:
  - SIFT features (engineered)
  - BoW representation (engineered + unsupervised learning)
  - SVM classifier (convex optimization)
- **Deep learning**
  - Learn layers of features, representation, and classifier in one go based on the data alone
  - Primary methodology: deep neural networks (non-convex)



# Multi-class Classification

What is the dimensionality of a one-hot representation of the MNIST classes ?

- A. 1
- B. 28
- C. 10
- D. 784

# Multi-class Classification

What is the dimensionality of a one-hot representation of the MNIST classes ?

- A. 1
- B. 28
- C. 10**
- D. 784



# Regression vs Classification

Should you treat these three problems as classification or as regression problems?

Problem	Regression ?	Classification ?
Predicting whether stock price of a company will increase tomorrow		
Predict the number of copies a music album will be sold next month		
Predicting the gender of a person by his/her handwriting style		

# Regression vs Classification

Should you treat these three problems as classification or as regression problems?

Problem	Regression ?	Classification ?
Predicting whether stock price of a company will increase tomorrow		✓
Predict the number of copies a music album will be sold next month	✓	
Predicting the gender of a person by his/her handwriting style		✓

# Discussion

Can intelligence be modelled by curve fitting ?  
(read the thread discussion for arguments)



michael\_nielsen  
@michael\_nielsen



Whenever I see this kind of headline, I always think "But what if intelligence is mostly about curve-fitting, and we're merely too un-self-aware to notice?"

**AI today and tomorrow is mostly  
about curve fitting, not intelligence**

9:16 PM · Nov 23, 2019 · [Twitter Web App](#)

# Questions ?

## Undergradese

What undergrads ask vs. what they're REALLY asking

"Is it going to be an open book exam?"

Translation: "I don't have to actually memorize anything, do I?"

"Hmm, what do you mean by that?"

Translation: "What's the answer so we can all go home."

"Are you going to have office hours today?"

Translation: "Can I do my homework in your office?"

"Can i get an extension?"

Translation: "Can you re-arrange your life around mine?"

"Is this going to be on the test?"

Translation: "Tell us what's going to be on the test."

"Is grading going to be curved?"

Translation: "Can I do a mediocre job and still get an A?"

JORGE CHAM © 2008

