Pengenalan Kecerdasan Buatan

AI for everyone[1]

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[1] https://www.coursera.org/learn/ai-for-everyone/home/welcome

Outline

Outline

Introduction

Figure 1: Source: McKinsey Global Institute (Ng, 2019)

$$\begin{aligned}
\$13 \text{ trillion} &= \$13 \times 10^{12} \\
&= \text{Rp}183.000.000.000.000.000,- \\
&= 183 \text{ billiard.}
\end{aligned}$$

Demystifying AI

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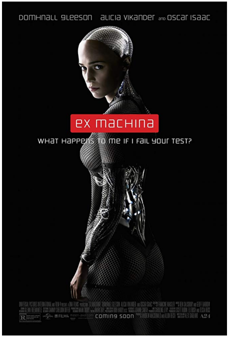
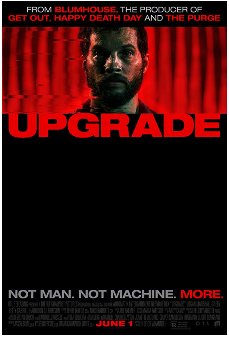
- **ANI** $\Rightarrow$ *Artificial Narrow Intelligence*.
  Examples: smart speaker, self-driving car, web search, AI in farming and factories.

- **AGI** $\Rightarrow$ *Artificial General Intelligence*.
  Examples: Do anything or **even more** than a human can do.





Outline

AI has many tools

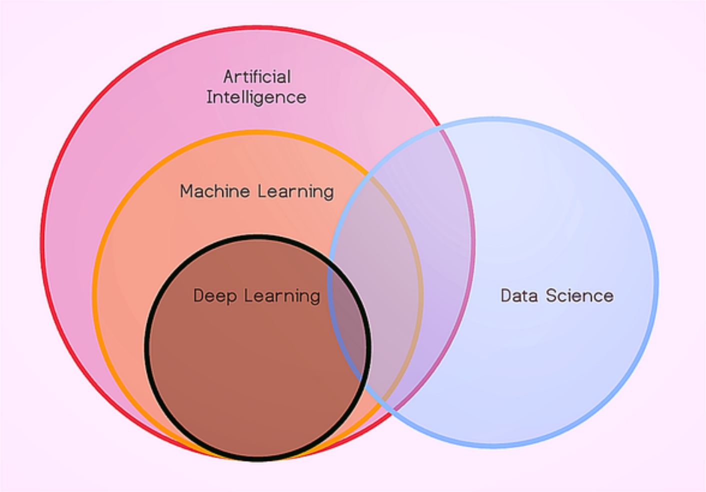


Figure 2: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Machine Learning (1/2)

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- One of the tools that drive the significant progress of AI is **Machine Learning** (ML).

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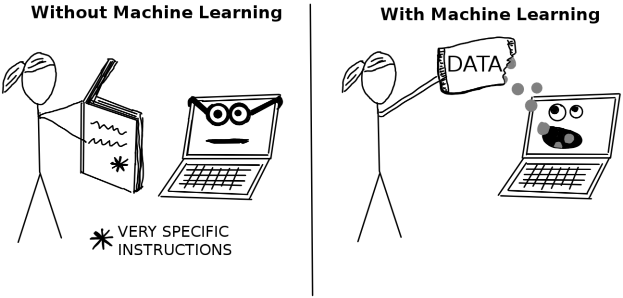

Machine Learning (2/2)

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Supervised Learning (1/2)

- A common type of of Machine Learning is a type of AI that learns from A to B or is often called ***Supervised Learning***.

$$\underset{\text{input}}{A} \longrightarrow \underset{\text{output}}{B}$$

Supervised Learning (2/2)

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(*input A* in **bold** and *output B* in italic) (Trask, 2019):

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- Using **weather sensor data** to predict the *probability of rain*
- Using **car engine sensors** to predict the optimal tuning *settings*
- Using **news data** to predict tomorrow's stock *price*
- Using a raw **audio file** to predict a *transcript* of the audio.

Supervised Learning (2/2)

Input (A)	Output (B)	Application

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Input (A)		Output (B)	Application
email	$\longrightarrow$	spam? (0/1)	**spam filtering**

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image, radar info	$\longrightarrow$	position of other cars	**self-driving car**

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image, radar info	$\longrightarrow$	position of other cars	**self-driving car**
image of phone	$\longrightarrow$	defect? (0/1)	**visual inspection**

Why Now?

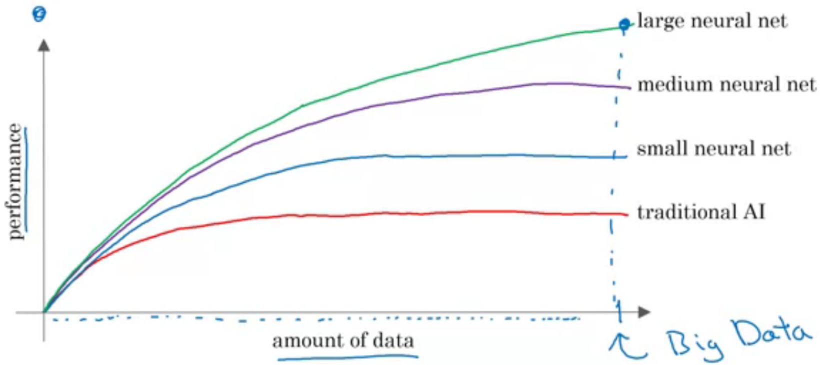

Figure 3: Large neural net + Big Data = High Performance (Ng, 2019)

Outline

Example of a Table of Data (Dataset) (1/3)

size of house (square feet)		price (1000$)
523		115
645		150
708		210
1034		280
2290		355
2545		440

A B

$A \longrightarrow B$

Table 1: House prices dataset (Ng, 2019)

Example of a Table of Data (Dataset) (2/3)

size of house (square feet)	# of bedrooms	price (1000\$)
523	1	115
645	1	150
708	2	210
1034	3	280
2290	4	355
2545	4	440

A B

$A \longrightarrow B$

Table 2: House prices dataset (Ng, 2019)

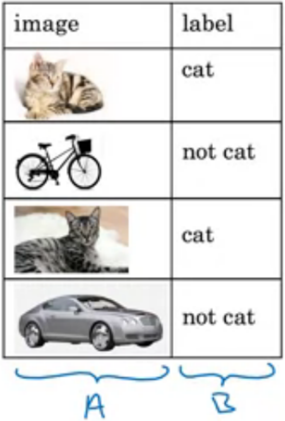

image	label
	cat
	not cat
	cat
	not cat

Table 3: Cat images dataset (Ng, 2019)

Acquiring data

Acquiring data

- Manual labeling

cat

not cat

cat

not cat

Acquiring data

- Manual labeling


cat


not cat


cat


not cat

- From observing behaviors

user ID	time	price ($)	purchased
4783	Jan 21 08:15.20	7.95	yes
3893	March 3 11:30.15	10.00	yes
8384	June 11 14:15.05	9.50	no
0931	Aug 2 20:30.55	12.90	yes

machine	temperature (°C)	pressure (psi)	machine fault
17987	60	7.65	N
34672	100	25.50	N
08542	140	75.50	Y
98536	165	125.00	Y

A B

Acquiring data

- Manual labeling


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A B

- Download from websites / partnerships

Data is Messy

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- Garbage in, garbage out

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- Data problems: *incorrect labels* and *missing values*

size of house (square feet)	# of bedrooms	price (1000$)
523	1	115
645	1	0.001
708	unknown	210
1034	3	unknown
unknown	4	355
2545	unknown	440

Data is Messy

- Garbage in, garbage out
- Data problems: *incorrect labels* and *missing values*

size of house (square feet)	# of bedrooms	price (1000$)
523	1	115
645	1	0.001
708	unknown	210
1034	3	unknown
unknown	4	355
2545	unknown	440

- Multiple types of data
  images, *audio*, *text* ⇒ **unstructured data**

Outline

Machine Learning vs. Data Science (1/2)

size of house (square feet)	# of bedrooms	# of bathrooms	newly renovated	price (1000$)
523	1	2	N	115
645	1	3	N	150
708	2	1	N	210
1034	3	3	Y	280
2290	4	4	N	355
2545	4	5	Y	440

A B

Figure 4: Home prices (Ng, 2019)

Machine Learning vs. Data Science (1/2)

size of house (square feet)	# of bedrooms	# of bathrooms	newly renovated	price (1000$)
523	1	2	N	115
645	1	3	N	150
708	2	1	N	210
1034	3	3	Y	280
2290	4	4	N	355
2545	4	5	Y	440
		A		B

Figure 4: Home prices (Ng, 2019)

- **According to *Machine Learning***:
  $A \longrightarrow B$: Running AI system (e.g., websites / mobile app)

Machine Learning vs. Data Science (1/2)

size of house (square feet)	# of bedrooms	# of bathrooms	newly renovated	price (1000$)
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A

B

Figure 4: Home prices (Ng, 2019)

- **According to *Machine Learning***:
  $A \longrightarrow B$: Running AI system (e.g., websites / mobile app)
- **According to *Data Science***:
  Homes with 3 bedrooms are more expensive than homes with 2 bedrooms of a similar size.
  Newly renovated homes have a 15% premium.

Machine Learning vs. Data Science (2/2)

Machine Learning

Data Science

Machine Learning vs. Data Science (2/2)

Machine Learning

"Field of study that gives computers the ability to learn without being explicitly programmed."
$\longrightarrow$ **software**
-Arthur Samuel (1959)

Data Science

Machine Learning vs. Data Science (2/2)

Machine Learning	**Data Science**
"Field of study that gives computers the ability to learn without being explicitly programmed." $\longrightarrow$ **software** -Arthur Samuel (1959)	*Science of extracting knowledge and insights from data.* $\longrightarrow$ **slide presentation** or **report**

Outline

AI has many tools

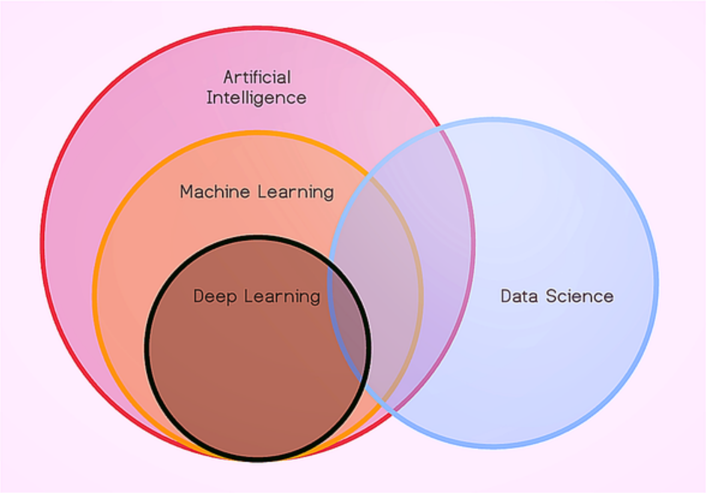

Figure 5: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Dataset: Home Prices

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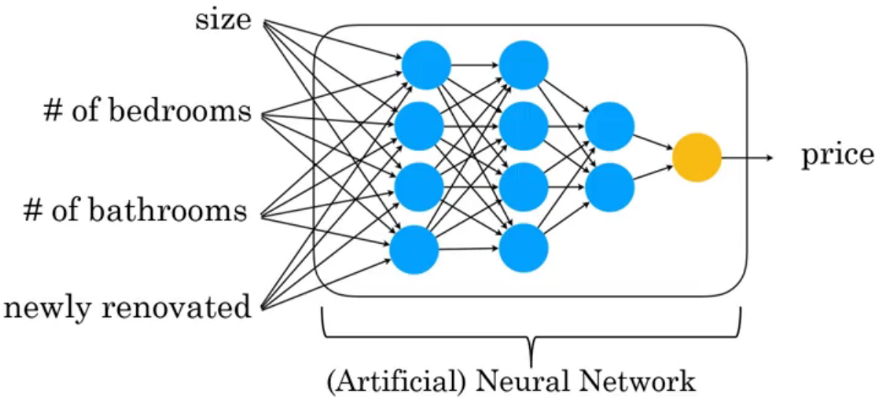
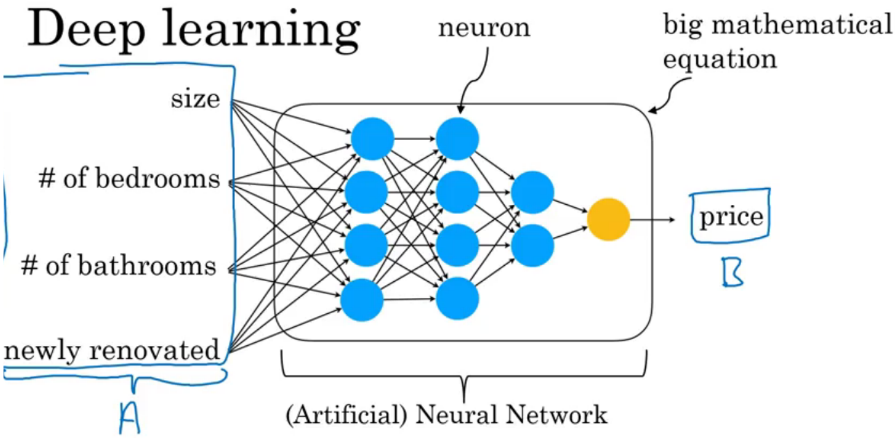
A B

Figure 6: Home prices (Ng, 2019)

Deep Learning (1/2)



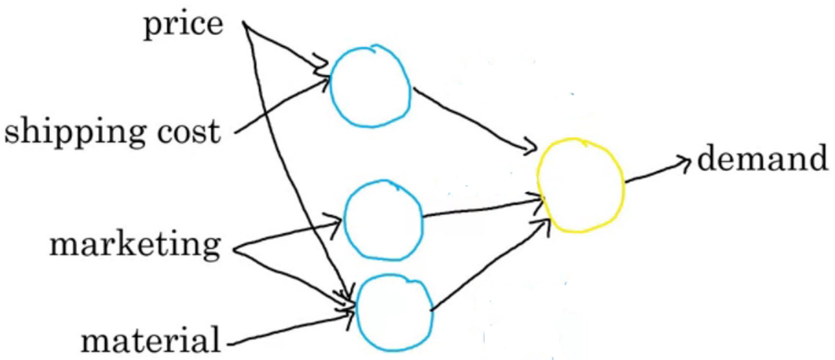

Deep learning
neuron
big mathematical equation
size
# of bedrooms
# of bathrooms
newly renovated
A
price
B
(Artificial) Neural Network

Outline

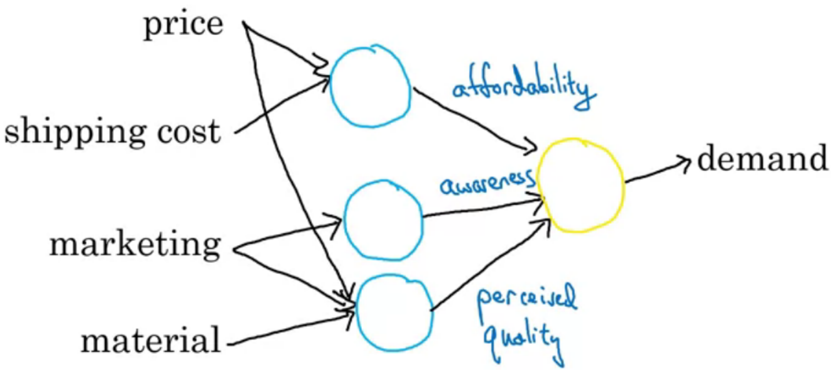
Demand prediction (1/2)

Demand prediction (2/2)

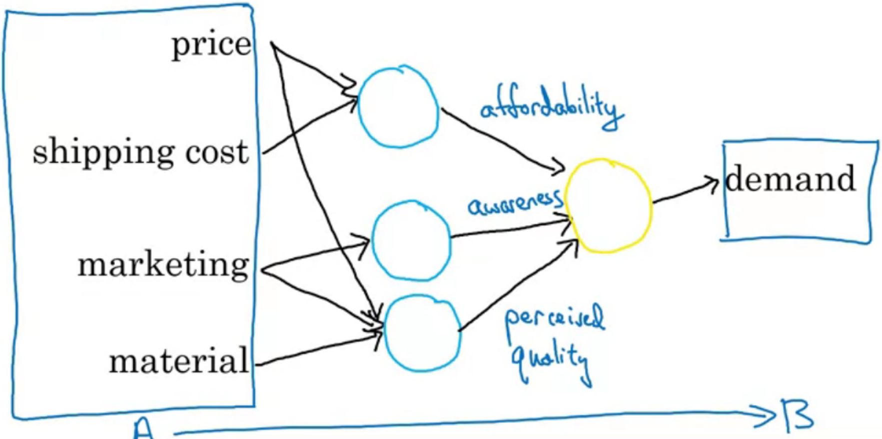
Demand prediction: a little bit more complex (1/4)



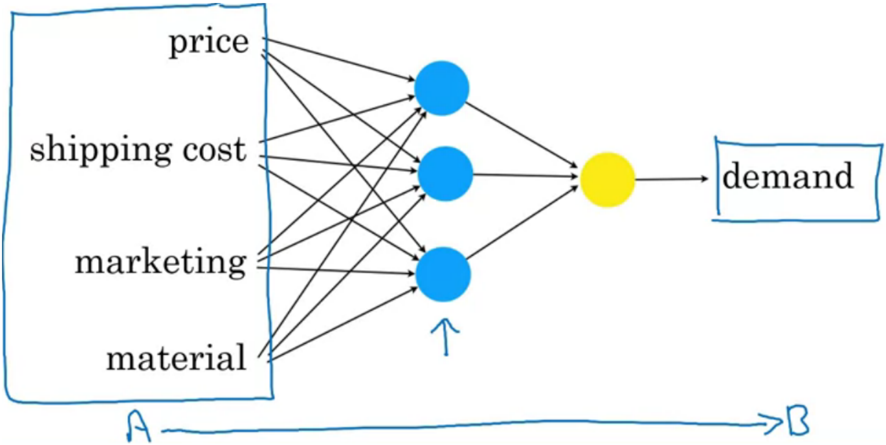
Demand prediction: a little bit more complex (2/4)



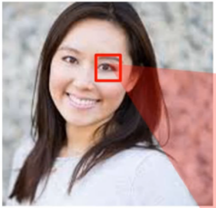
Demand prediction: a little bit more complex (3/4)



Demand prediction: a little bit more complex (4/4)



We want to build a system that recognizes people from pictures.



30	32	22	12	10	10	12	33	35	30
12	11	12	234	170	176	13	15	12	12
234	222	220	230	200	222	230	234	56	78
190	220	186	112	110	110	112	180	30	32
49	250	250	250	4	2	254	200	44	6
55	250	250	250	3	1	250	245	25	3
189	195	199	150	110	110	182	190	199	55
200	202	218	222	203	200	200	208	215	222
219	215	220	220	222	214	215	210	220	220
220	220	220	220	221	220	221	220	220	222

Figure 7: What a computer sees from an image (assume the picture is grayscale) (Ng, 2019)

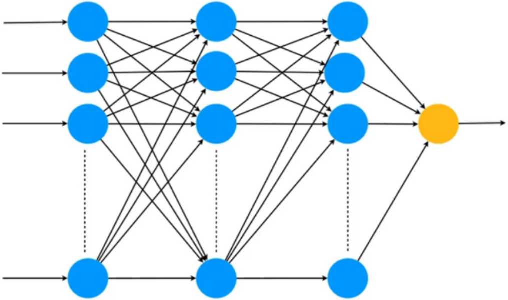
NN Application: Face recognition (2/3)

1000

1000

1,000,000

3,000,000



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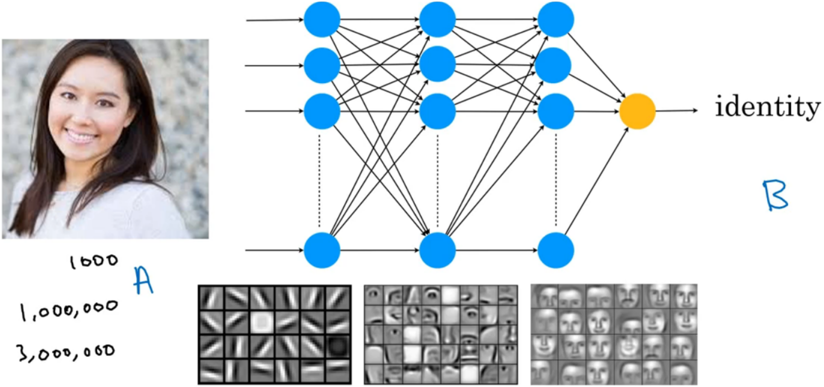

1000

1600

A

B

1,000,000

3,000,000

How Does a Neural Network Learn?

Watch a Demo by Phiresky (2017).

Outline

Supervised Learning

Input (A)	Output (B)	Application
email	spam? (0/1)	spam filtering
audio	text transcripts	speech recognition
English	Chinese	machine translation
ad, user info	click? (0/1)	online advertising
image, radar info	position of other cars	Self-driving car
image of phone	defect? (0/1)	visual inspection

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Anything you can do with 1 second of thought, we can probably now or soon automate.

What machine learning today can and cannot do

You ordered a toy. The toy arrived late. Therefore, you write an email:

The toy arrived two days late, so I wasn't able to give it to my niece for her birthday.
Can I return it?

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Machine Learning Can Do:
$\longrightarrow$ "*Refund request*"
Input text $\longrightarrow$ Refund/Shipping/Other
$A \longrightarrow B$

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Machine Learning Can Do:
$\longrightarrow$ "*Refund request*"
Input text $\longrightarrow$ Refund/Shipping/Other
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Machine Learning Cannot Do Elegantly Yet:
$\longrightarrow$ "*Oh, sorry to hear that. I hope your niece had a good birthday. Yes, we can help with ...*"

What happens if you try?

Input (A) $\longrightarrow$ **Output (B)**
User email 2-3 paragraph response

Train Data: 1000 examples

What happens if you try?

Input (A) $\longrightarrow$ **Output (B)**
User email — 2-3 paragraph response

Train Data: 1000 examples

"My box was damaged" $\longrightarrow$ Thank you for your email.

What happens if you try?

Input (A) $\longrightarrow$ **Output (B)**
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Train Data: 1000 examples

"My box was damaged" $\longrightarrow$ Thank you for your email.

"Where do I write a review?" $\longrightarrow$ Thank you for your email.

What happens if you try?

Input (A)	$\longrightarrow$	**Output (B)**
User email		2-3 paragraph response

Train Data: 1000 examples

"My box was damaged"	$\longrightarrow$	Thank you for your email.
"Where do I write a review?"	$\longrightarrow$	Thank you for your email.
"What's the return policy"	$\longrightarrow$	Thank you for your email.

What happens if you try?

Input (A)	$\longrightarrow$	**Output (B)**
User email		2-3 paragraph response

Train Data: 1000 examples

"My box was damaged"	$\longrightarrow$	Thank you for your email.
"Where do I write a review?"	$\longrightarrow$	Thank you for your email.
"What's the return policy"	$\longrightarrow$	Thank you for your email.
"When is my box arriving?"	$\longrightarrow$	Thank yes now your....

What makes an ML problem easier

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1. Learning a "simple" concept

$$\leq 1 \text{ sec}$$

What makes an ML problem easier

1. Learning a "simple" concept

$$\leq 1 \text{ sec}$$

2. Lots of data available

$$\underset{\text{input}}{A} \longrightarrow \underset{\text{output}}{B}$$

Outline

Self-driving car

Self-driving car

Can do

$A \longrightarrow B$

Self-driving car

Can do

A $\longrightarrow$ B

Cannot do

stop

hitchhiker

bike turn left signal

A $\longrightarrow$ B

Self-driving car

Can do

$A \longrightarrow B$

Cannot do

stop

hitchhiker

bike turn left signal

$A \longrightarrow B$

1. Data

Self-driving car

Can do

$A \longrightarrow B$

Cannot do

stop

hitchhiker

bike turn
left signal

$A \longrightarrow B$

1. Data
2. Need high accuracy

X-ray diagnosis

Can do | **Cannot do**

X-ray diagnosis

Can do	**Cannot do**
Diagnose pneumonia from ~10,000 labeled images	

X-ray diagnosis

Can do	**Cannot do**
Diagnose pneumonia from ∼10,000 labeled images	Diagnose pneumonia from 10 images of medical textbook chapter explaining pneumonia

Strengths and weaknesses of machine learning

ML tends to work well when:

ML tends to work poorly when:

Strengths and weaknesses of machine learning

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Strengths and weaknesses of machine learning

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ML tends to work poorly when:

1. Learning complex concepts from small amounts of data

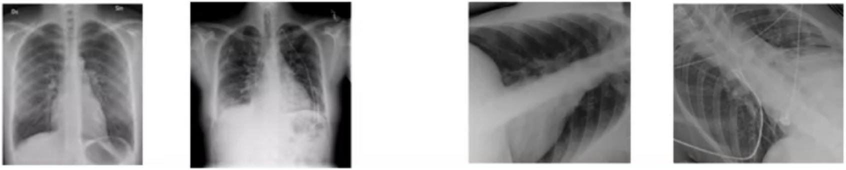
Strengths and weaknesses of machine learning

ML tends to work well when:

1. Learning a "simple" concept
2. There are lots of data available

ML tends to work poorly when:

1. Learning complex concepts from small amounts of data
2. It is asked to perform on new types of data



Outline

Computer Vision (1/3)

- Image classification/Object recognition

cat

Computer Vision (1/3)

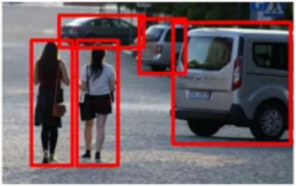
- Image classification/Object recognition

- Face recognition

- Object detection

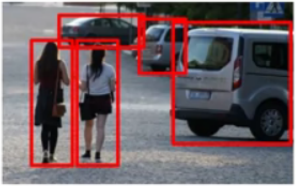
Computer Vision (2/3)

- Object detection



Computer Vision (2/3)

- Object detection



Computer Vision (3/3)

- Image Segmentation

Computer Vision (3/3)

- Image Segmentation

Computer Vision (3/3)

- Image Segmentation


- Tracking

Natural Language Processing (1/7)

- Text Classification

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  Email $\longrightarrow$ Spam/Non-Spam

Natural Language Processing (1/7)

- Text Classification

Email	$\longrightarrow$	Spam/Non-Spam
Product description	$\longrightarrow$	Product category

Natural Language Processing (1/7)

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Email	$\longrightarrow$	Spam/Non-Spam
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  - Sentiment recognition

    "The food was good" $\longrightarrow$ 

Natural Language Processing (1/7)

- Text Classification

Email	$\longrightarrow$	Spam/Non-Spam
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    "The food was good" $\longrightarrow$ 

    "Service was horrible" $\longrightarrow$ 

Natural Language Processing (1/7)

- Text Classification

  Email $\longrightarrow$ Spam/Non-Spam

  Product description $\longrightarrow$ Product category

  - Sentiment recognition

    "The food was good" $\longrightarrow$ 

    "Service was horrible" $\longrightarrow$ 

- Information retrieval
  - E.g., web search

- **Name entity recognition**

  "Queen Elizabeth II knighted Sir Paul McCartney for his services to music at the Buckingham Palace."

Natural Language Processing (2/7)

- **Name entity recognition**

"Queen Elizabeth II knighted Sir Paul McCartney for his services to music at the Buckingham Palace."

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Natural Language Processing (2/7)

- **Name entity recognition**

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Natural Language Processing (2/7)

- **Name entity recognition**

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- **Machine translation**

  "AI adalah listrik baru" $\Longrightarrow$ "AI is new electricity"

Natural Language Processing (3/7)

- Others: parsing, part-of-speech tagging

The cat on the mat

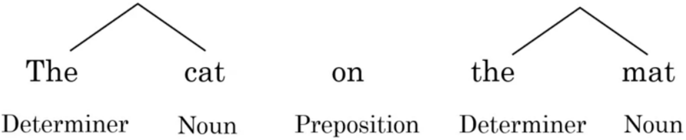
Natural Language Processing (4/7)

- Others: parsing, part-of-speech tagging

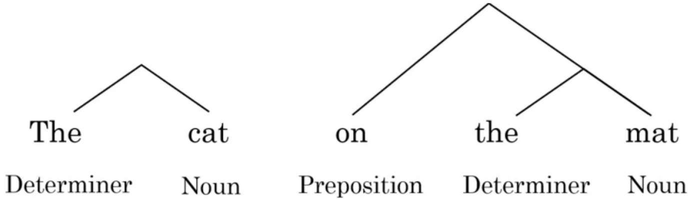
The	cat	on	the	mat
Determiner	Noun	Preposition	Determiner	Noun

Natural Language Processing (5/7)

- Others: parsing, part-of-speech tagging

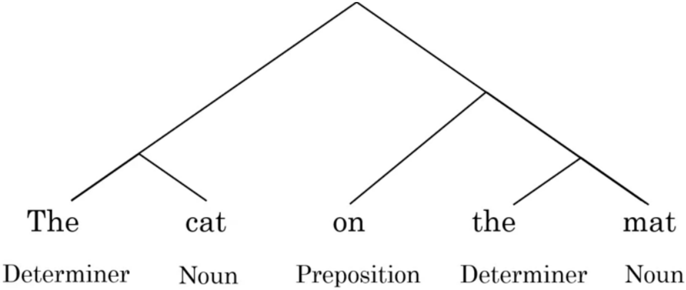


- Others: parsing, part-of-speech tagging



Natural Language Processing (7/7)

- Others: parsing, part-of-speech tagging



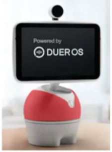
Speech (1/2)

- Speech recognition (speech-to-text)

Amazon
Echo / Alexa

Google
Home

Apple
Siri



Baidu
DuerOS

Speech (1/2)

- Speech recognition (speech-to-text)

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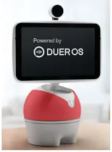


Baidu
DuerOS

- Trigger word/wakeword detection
  Audio $\longrightarrow$ "Hey device"? (0/1)

Speech (2/2)

- Speaker ID

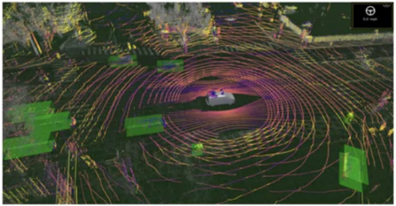
Speech (2/2)

- Speaker ID
- Speech synthesis (text-to-speech, TTS)

  `The quick brown fox jumps over the lazy dog.`

Robotics

- Perception: figuring out what's in the world around you.



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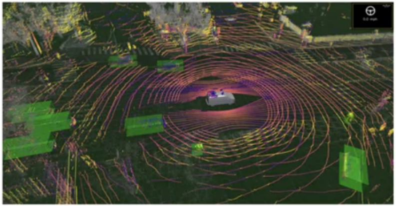

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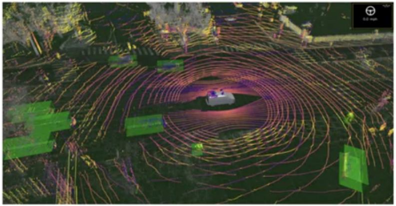
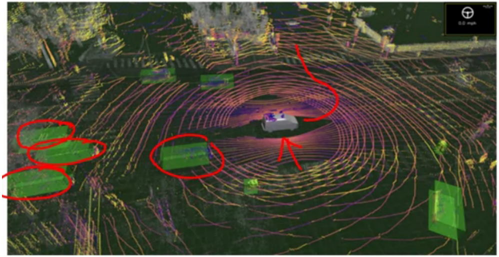



- Motion planning: finding a path for the robot to follow.



Robotics

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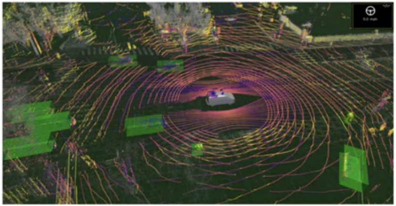

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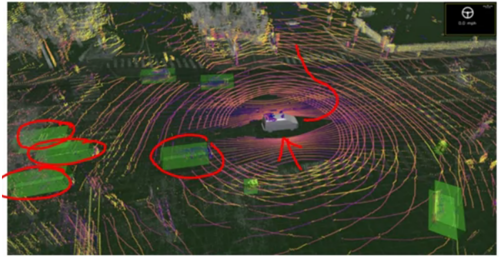
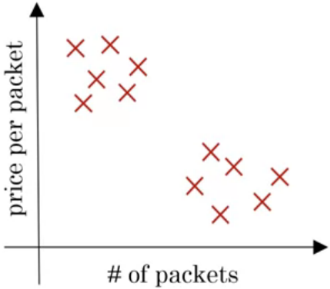


- Control: sending commands to the motors to follow a path

Unsupervised learning (1/2)

Clustering potato chip sales



Unsupervised learning (1/2)

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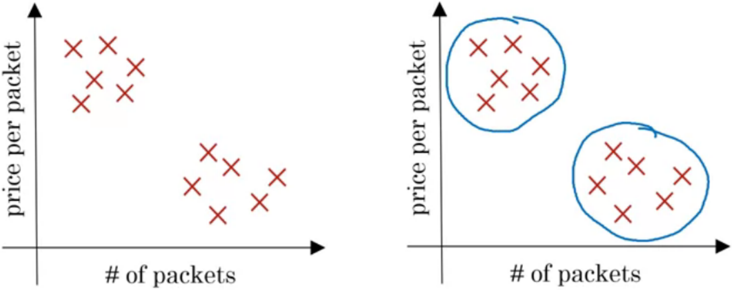


Unsupervised learning (2/2)

Unsupervised learning:

Given data (without any specific desired output labels), find something interesting about the data.

Another example of unsupervised learning:

Unsupervised learning:

Given data (without any specific desired output labels), find something interesting about the data.

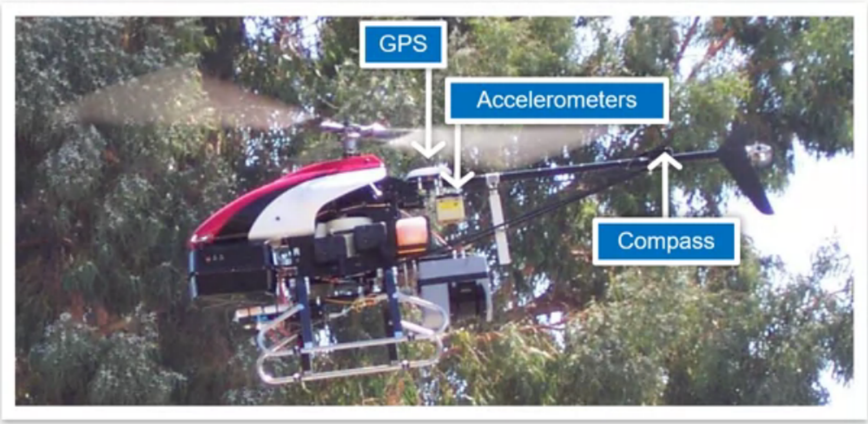
Another example of unsupervised learning:

Finding cats from unlabeled YouTube videos

Transfer learning

Learn from task A, and use knowledge to help on task B

Reinforcement learning (1/2)



Use a "reward" signal to tell the AI when it is doing well or poorly. It automatically learns to maximize its rewards.

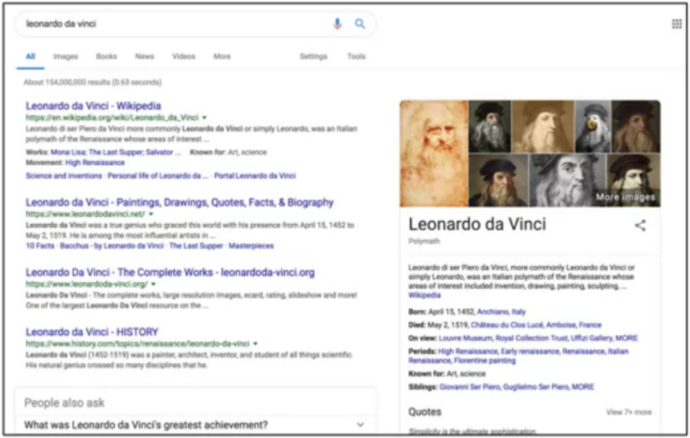
Reinforcement learning (2/2)

Use a "reward" signal to tell the AI when it is doing well or poorly. It automatically learns to maximize its rewards.

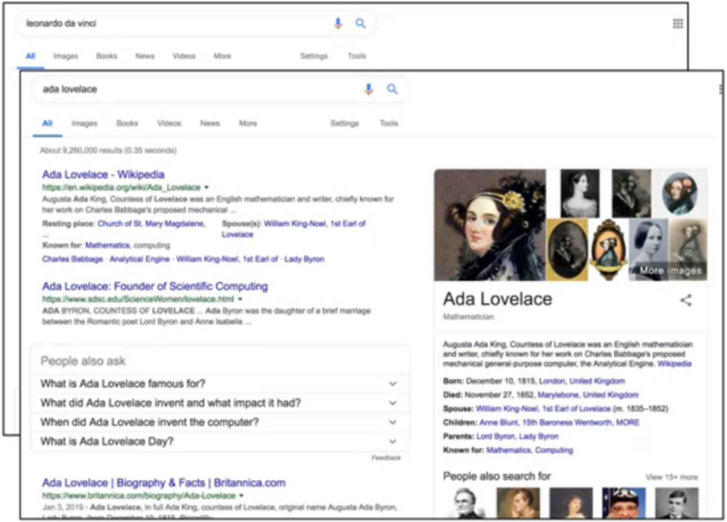
GANs (Generative Adversarial Network)

Synthesize new images from scratch (Karras et al., 2017)

Knowledge Graph (1/4)



Knowledge Graph (2/4)



Knowledge Graph (3/4)

Ada Lovelace	
Born	Dec 10, 1815
Died	Nov 27, 1852
Bio	English mathematician and writer...

Knowledge Graph (4/4)

Northern Rooster Hotel	
Address	45 Rooster St, LA
Phone	(650) 555-3992
Wifi	yes
Pool	no

Daftar Pustaka I

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