

Pengenalan Kecerdasan Buatan

AI for everyone¹

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December 4, 2021



¹<https://www.coursera.org/learn/ai-for-everyone/home/welcome>

Outline

- 1 Introduction
- 2 Machine Learning
- 3 What is Data?
- 4 Machine Learning vs. Data Science
- 5 Deep Learning
- 6 Non-technical explanation of deep learning
- 7 What Machine Learning Can and Cannot Do
- 8 More examples of what ML can and cannot do
- 9 Survey of major AI application areas

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Introduction

AI value creation
by 2030

\$13
trillion

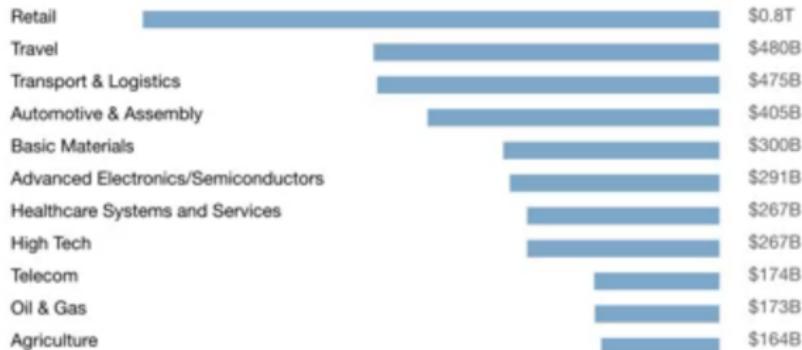


Figure 1: Source: McKinsey Global Institute (Ng, 2019)

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

Demystifying AI

Artificial Intelligence or **AI** can be divided into 2 as follows:



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- **ANI** ⇒ *Artificial Narrow Intelligence.*

Examples: smart speaker, self-driving car, web search, AI in farming and factories.



Demystifying AI

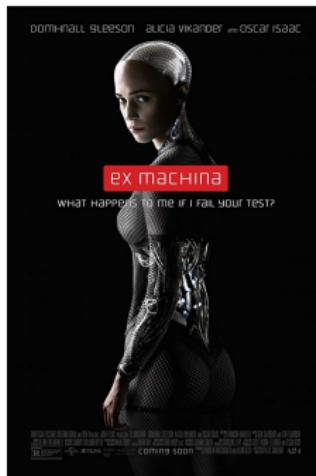
Artificial Intelligence or **AI** can be divided into 2 as follows:

- **ANI** ⇒ *Artificial Narrow Intelligence.*

Examples: smart speaker, self-driving car, web search, AI in farming and factories.

- **AGI** ⇒ *Artificial General Intelligence.*

Examples: Do anything or **even more** than a human can do.



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AI has many tools

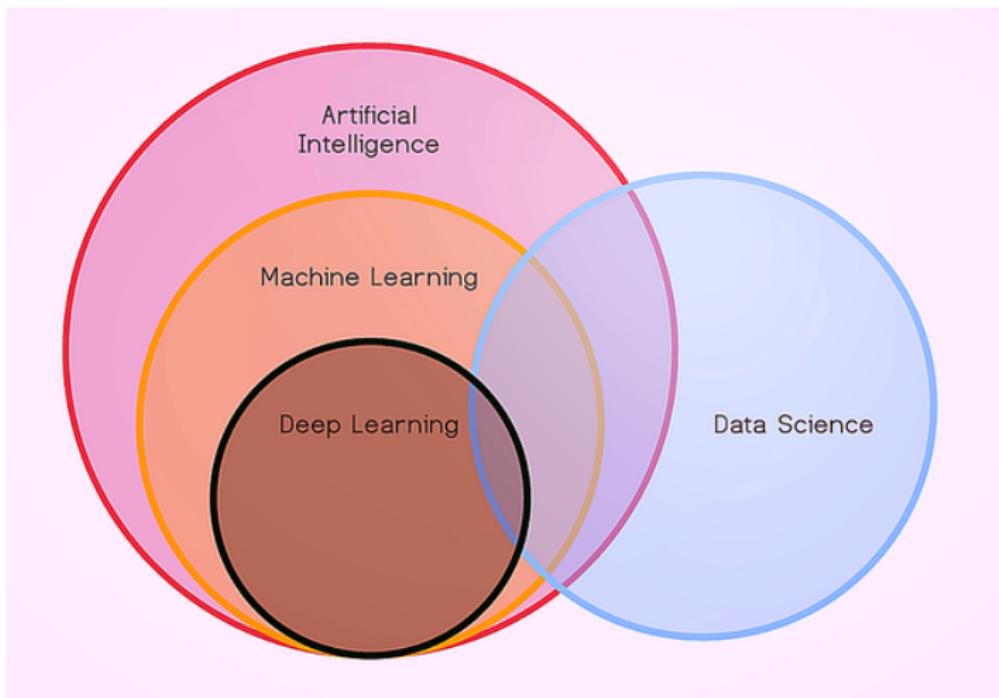


Figure 2: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Machine Learning (1/2)

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

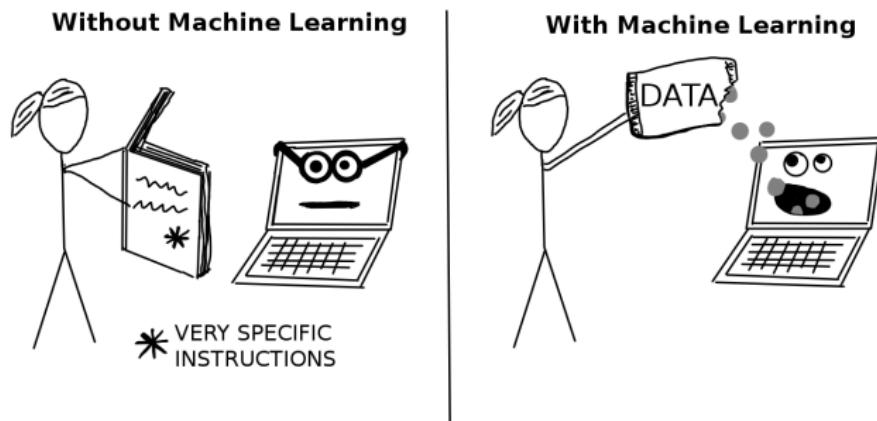
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- **Machine Learning** is a set of methods that allow computers to *learn from data to make and improve predictions*, e.g., cancer, weekly sales, credit default (Molnar, 2019).



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Machine Learning (2/2)

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Supervised Learning (1/2)

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

$$A \longrightarrow B$$

input output



Supervised Learning (2/2)

Consider the following examples

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



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- Using the **movies you've liked** to predict more *movies you may like*



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- Using **news data** to predict tomorrow's stock *price*



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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



Supervised Learning (2/2)

Input (A)	Output (B)	Application
email	spam? (0/1)	spam filtering

Supervised Learning (2/2)

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image of phone	→ defect? (0/1)	visual inspection 

Why Now?

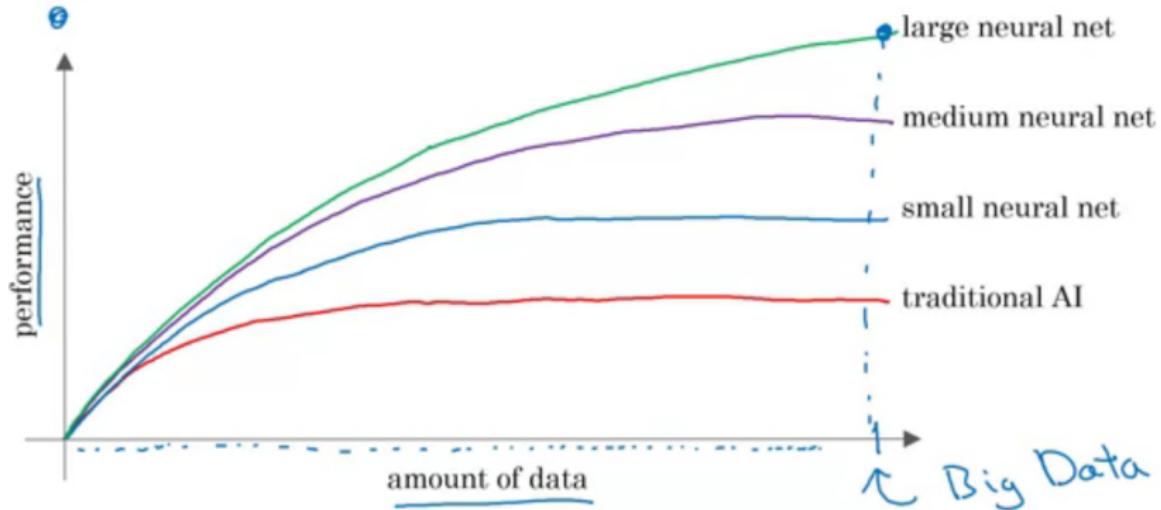


Figure 3: Large neural net + Big Data = High Performance (Ng, 2019)

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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

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


 $A \longrightarrow B$

Table 2: House prices dataset (Ng, 2019)

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

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

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cat



not
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cat



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

size of house (square feet)	# of bedrooms	price (1000\$)
523	1	115
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708	unknown	210
1034	3	unknown
unknown	4	355
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Data is Messy

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size of house (square feet)	# of bedrooms	price (1000\$)
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- Multiple types of data
images, audio, text ⇒ **unstructured data**

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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\$)
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Figure 4: Home prices (Ng, 2019)

- According to **Machine Learning**:

$A \rightarrow B$: Running AI system (e.g., websites / mobile app)

Machine Learning vs. Data Science (1/2)

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Figure 4: Home prices (Ng, 2019)

- According to **Machine Learning**:

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- 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

Data Science

"Field of study that gives computers the ability to learn without being explicitly programmed."

→ **software**

-Arthur Samuel (1959)



Machine Learning vs. Data Science (2/2)

Machine Learning

"Field of study that gives computers the ability to learn without being explicitly programmed."

→ **software**

-Arthur Samuel (1959)

Data Science

Science of extracting knowledge and insights from data.

→ **slide presentation or report**



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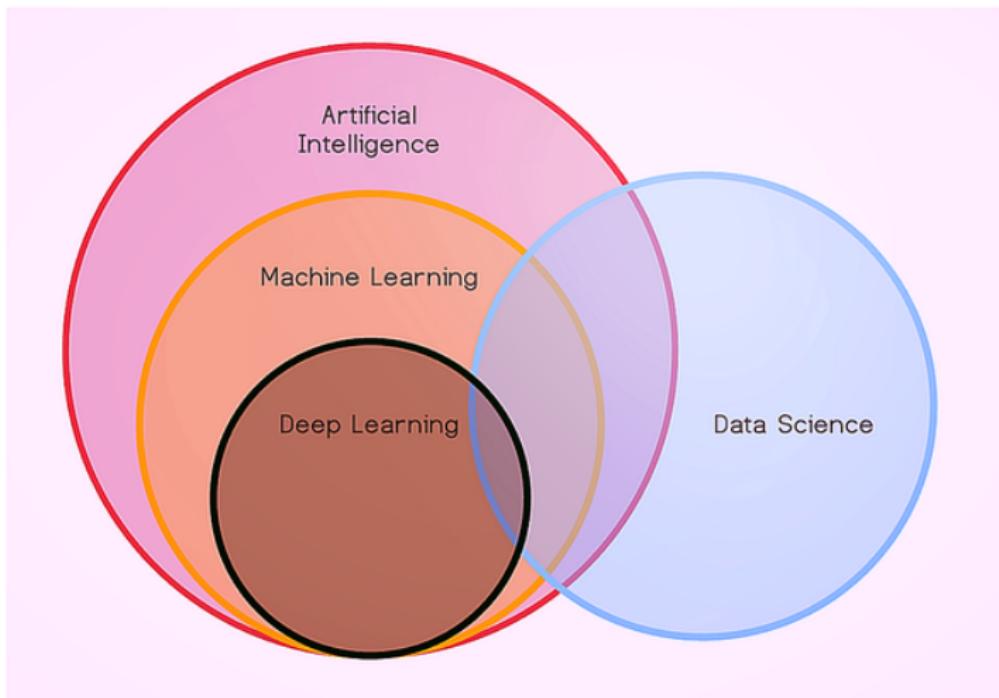


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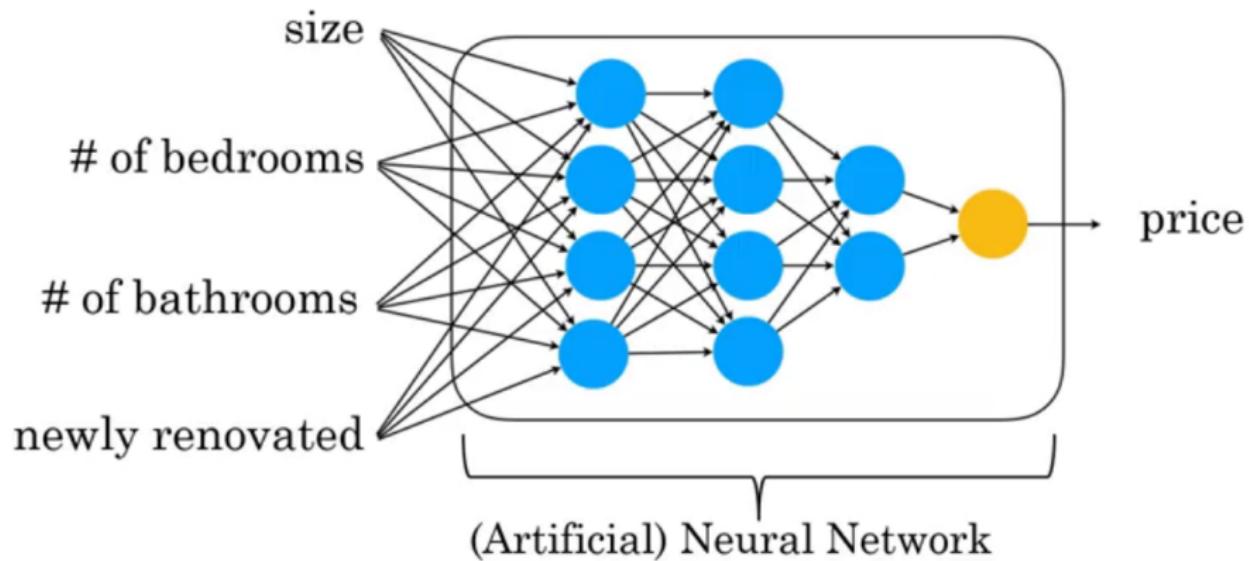
Dataset: Home Prices

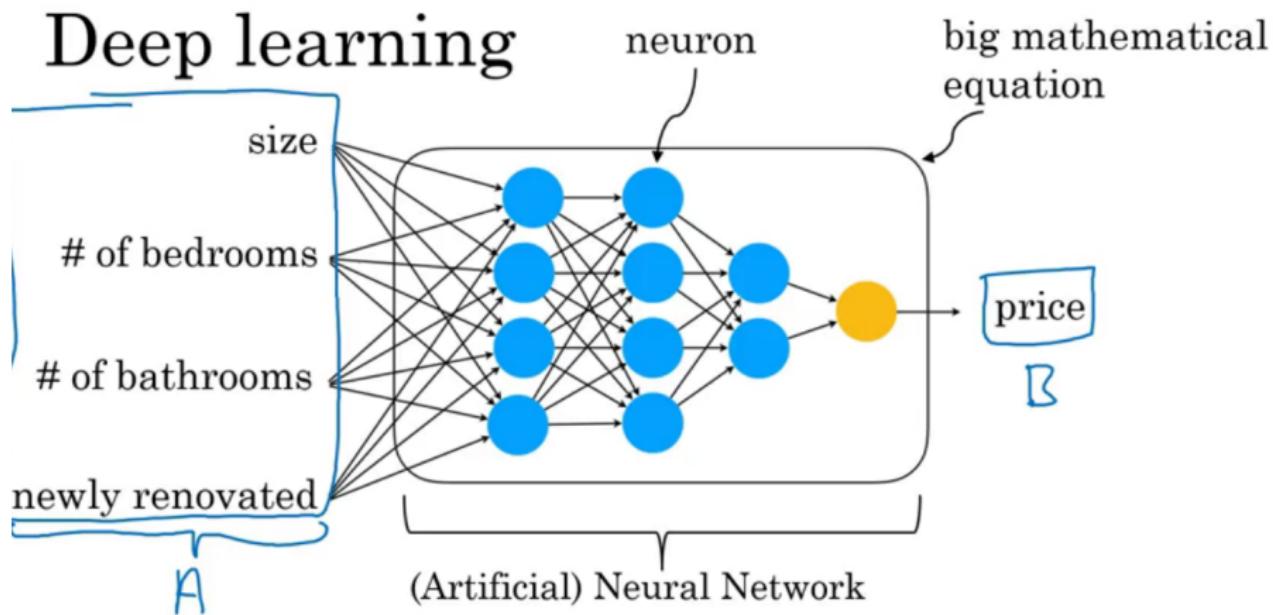
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Figure 6: Home prices (Ng, 2019)

Deep Learning (1/2)





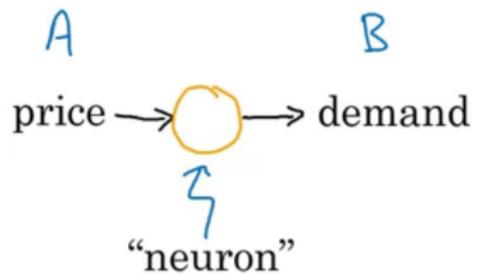
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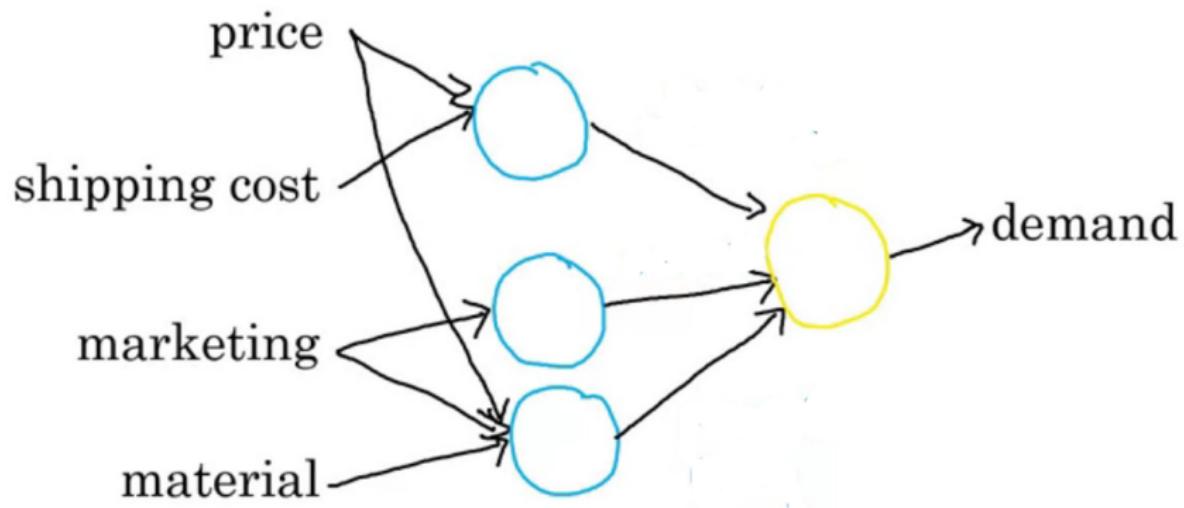
Demand prediction (1/2)



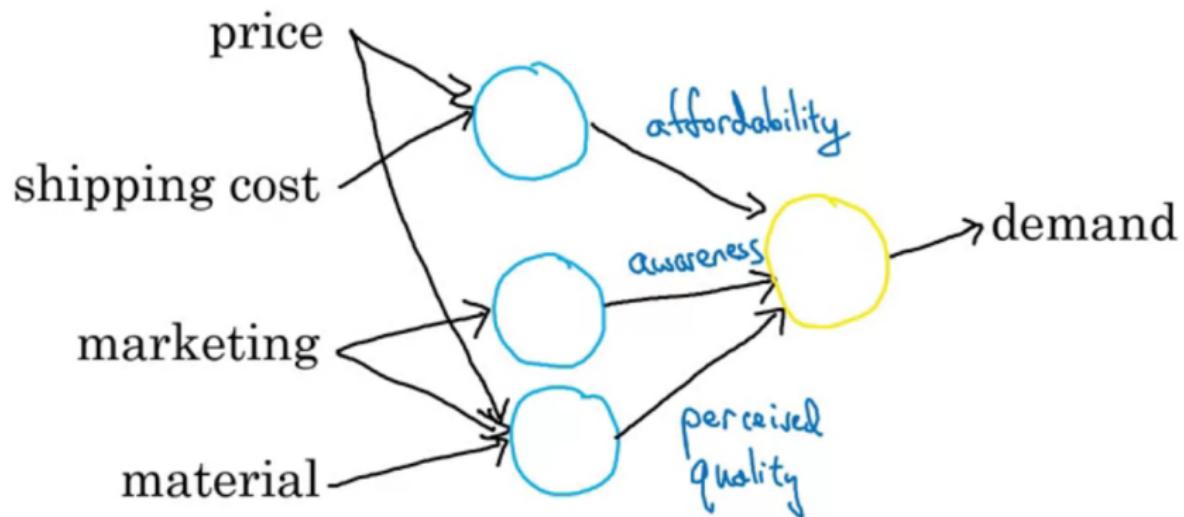
Demand prediction (2/2)



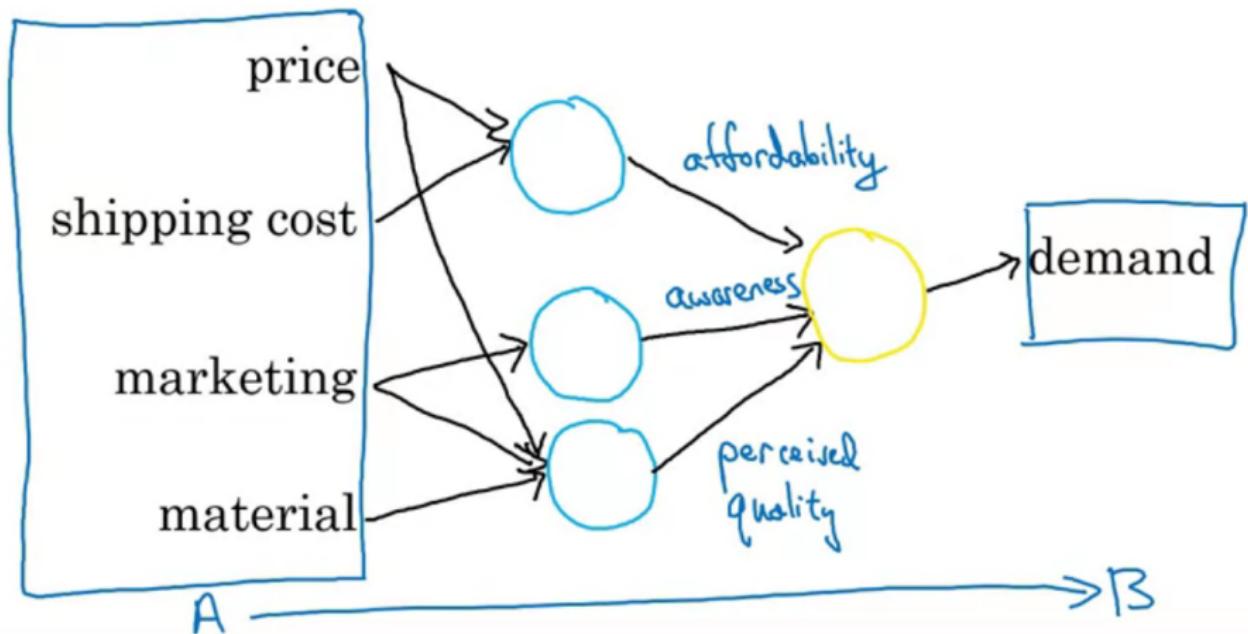
Demand prediction: a little bit more complex (1/4)



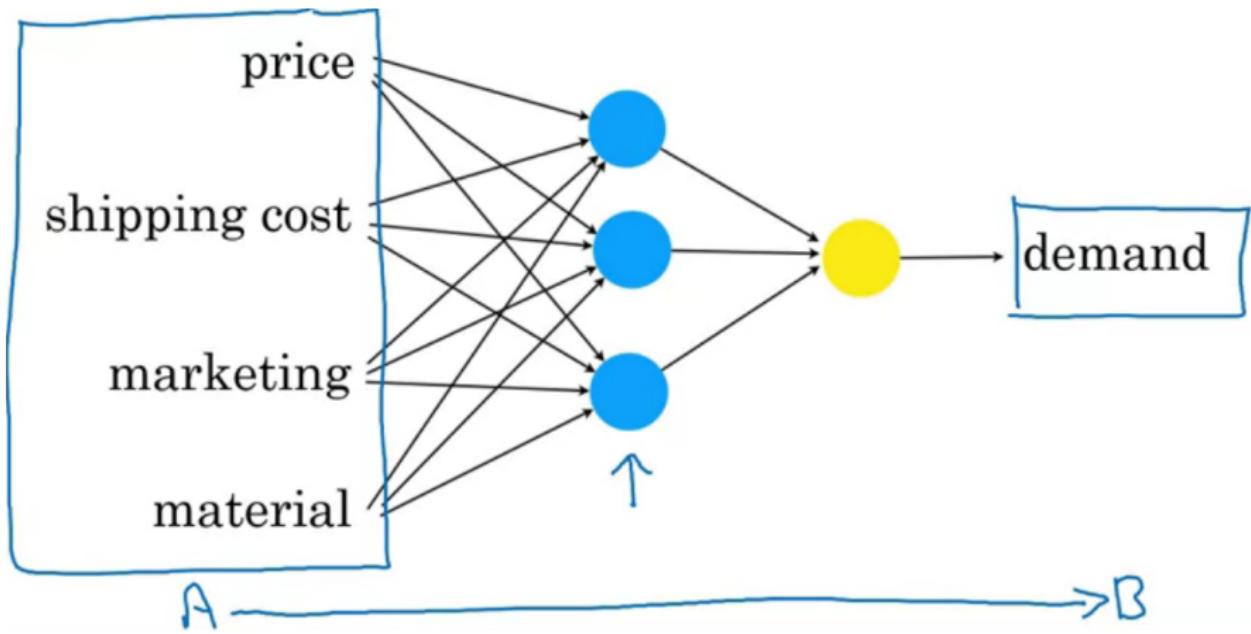
Demand prediction: a little bit more complex (2/4)



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

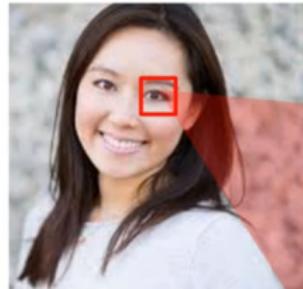


Demand prediction: a little bit more complex (4/4)



NN Application: Face recognition (1/3)

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)

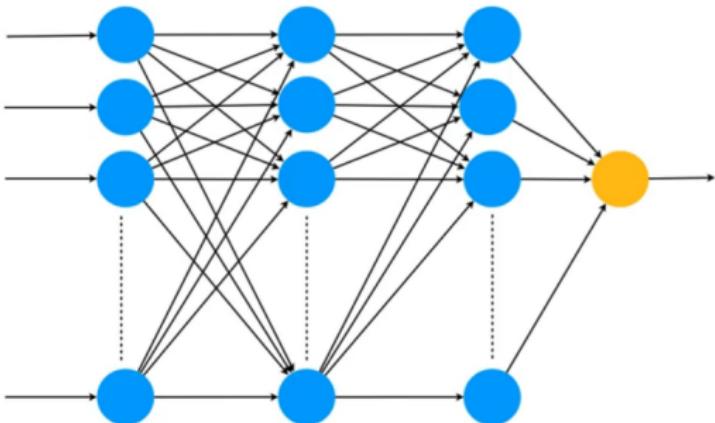
load



1600

1,000,000

3,000,000



NN Application: Face recognition (3/3)

1000

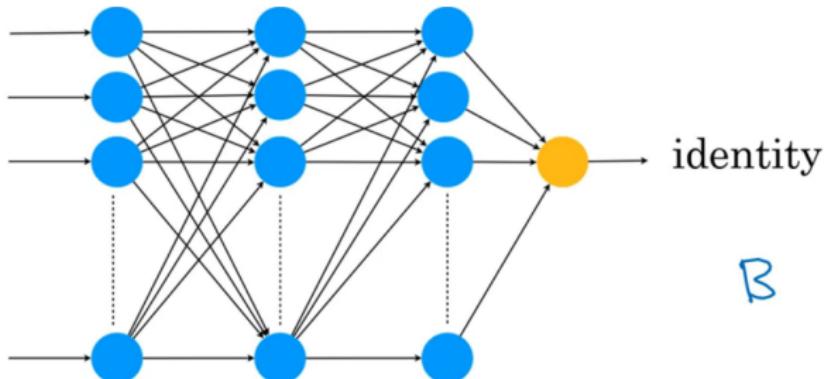


1600

1,000,000

3,000,000

A



B

How Does a Neural Network Learn?

Watch [a Demo](#) by Phiresky (2017).



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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:

→ "Refund request"

Input text → Refund/Shipping/Other

$A \rightarrow B$



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Machine Learning Can Do:

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Input text → Refund/Shipping/Other

$A \rightarrow B$

Machine Learning Cannot Do Elegantly Yet:

→ "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) → **Output (B)**

User email 2-3 paragraph response

Train Data: 1000 examples



What happens if you try?

Input (A) → **Output (B)**

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Train Data: 1000 examples

"My box was damaged" → Thank you for your email.



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Train Data: 1000 examples

"My box was damaged" → Thank you for your email.

"Where do I write a review?" → Thank you for your email.



What happens if you try?

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User email 2-3 paragraph response

Train Data: 1000 examples

"My box was damaged" → Thank you for your email.

"Where do I write a review?" → Thank you for your email.

"What's the return policy" → Thank you for your email.



What happens if you try?

Input (A) → **Output (B)**

User email 2-3 paragraph response

Train Data: 1000 examples

"My box was damaged" → Thank you for your email.

"Where do I write a review?" → Thank you for your email.

"What's the return policy" → Thank you for your email.

"When is my box arriving?" → Thank yes now your....



What makes an ML problem easier

What makes an ML problem easier

- 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

$A \longrightarrow B$
input output



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Self-driving car



Self-driving car

Can do



A → B

Self-driving car

Can do



A → B

Cannot do



stop



hitchhiker



bike turn
left signal

A → B

Self-driving car

Can do



A → B

Cannot do



stop



hitchhiker



bike turn
left signal

A → B

① Data

Self-driving car

Can do



A → B

Cannot do



stop

hitchhiker

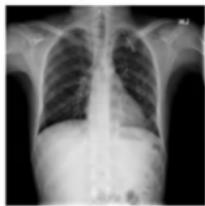
bike turn
left signal

A → B

① Data

② Need high accuracy

X-ray diagnosis



Can do

Cannot do

X-ray diagnosis



Can do

Diagnose pneumonia from
~10,000 labeled images

Cannot do

X-ray diagnosis



Can do

Diagnose pneumonia from
~10,000 labeled images

Cannot do

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

ML tends to work well when:

- ① Learning a "simple" concept

ML tends to work poorly when:



Strengths and weaknesses of machine learning

ML tends to work well when:

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- ② There are lots of data available

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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



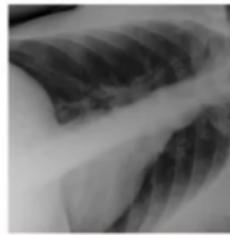
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ML tends to work poorly when:

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



Outline

- 1 Introduction
- 2 Machine Learning
- 3 What is Data?
- 4 Machine Learning vs. Data Science
- 5 Deep Learning
- 6 Non-technical explanation of deep learning
- 7 What Machine Learning Can and Cannot Do
- 8 More examples of what ML can and cannot do
- 9 Survey of major AI application areas



- Image classification/Object recognition



cat

Computer Vision (1/3)

- Image classification/Object recognition



cat

- Face recognition

register



new



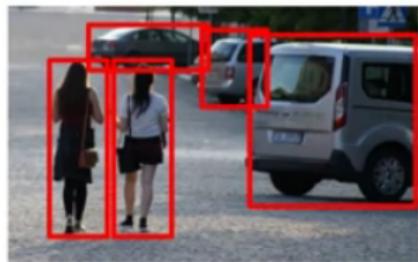
Computer Vision (2/3)

- Object detection



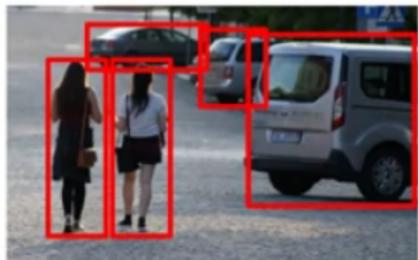
Computer Vision (2/3)

- 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



- Text Classification

Natural Language Processing (1/7)

- Text Classification

Email → Spam/Non-Spam



Natural Language Processing (1/7)

- Text Classification

Email → Spam/Non-Spam
Product description → Product category



Natural Language Processing (1/7)

- Text Classification

Email → Spam/Non-Spam

Product description → Product category

- Sentiment recognition

"The food was good" → 



- Text Classification

Email → Spam/Non-Spam

Product description → Product category

- Sentiment recognition

"The food was good" → 

"Service was horrible" → 

Natural Language Processing (1/7)

- Text Classification

Email → Spam/Non-Spam

Product description → Product category

- Sentiment recognition

"The food was good" → 

"Service was horrible" → 

- 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.”

- **Name entity recognition**

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

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

- **Name entity recognition**

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

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- **Name entity recognition**

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

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

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

- **Machine translation**

"AI adalah listrik baru" \Rightarrow "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)

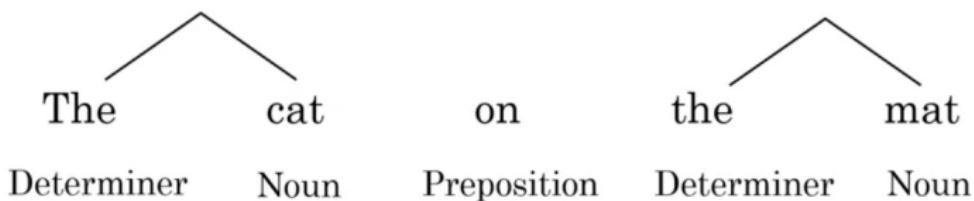
- Others: parsing, part-of-speech tagging

The	cat	on	the	mat
Determiner	Noun	Preposition	Determiner	Noun



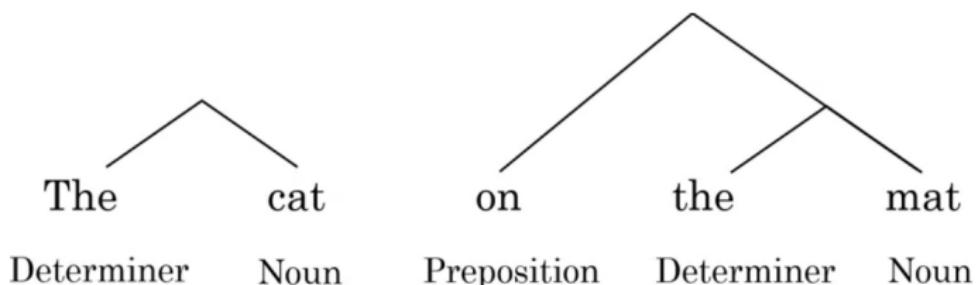
Natural Language Processing (5/7)

- Others: parsing, part-of-speech tagging



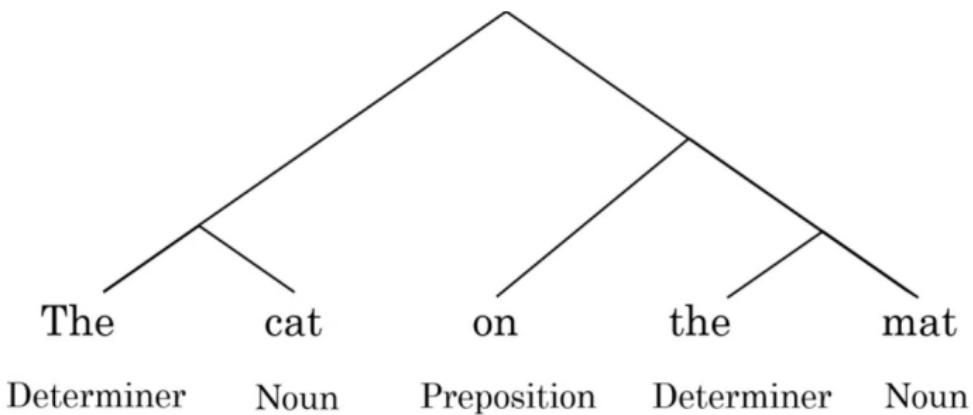
Natural Language Processing (6/7)

- 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)



Amazon
Echo / Alexa



Google
Home



Apple
Siri



Baidu
DuerOS

- Trigger word/wakeword detection
Audio → "Hey device"? (0/1)

Speech (2/2)

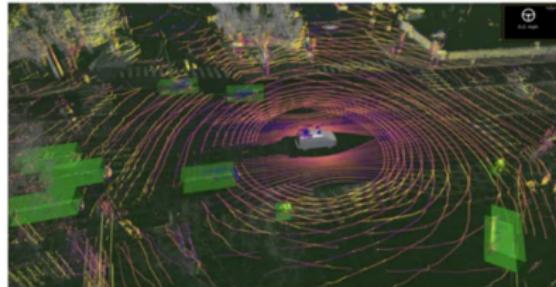
- Speaker ID



- Speaker ID
- Speech synthesis (text-to-speech, TTS)
The quick brown fox jumps over the lazy dog.

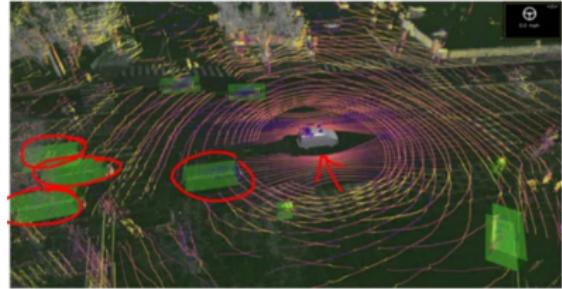
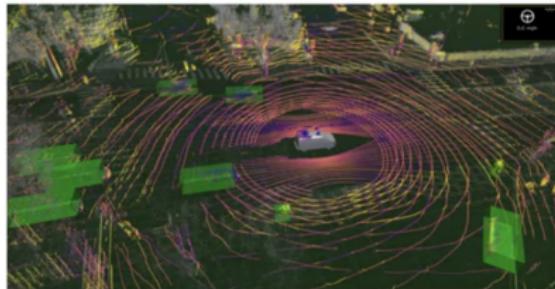
Robotics

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



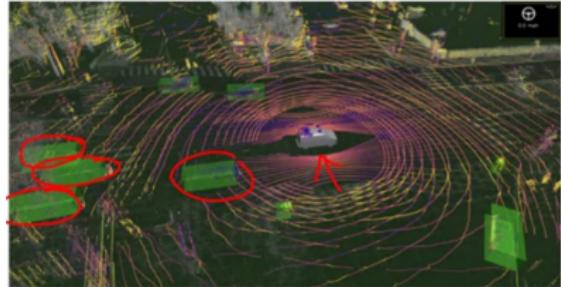
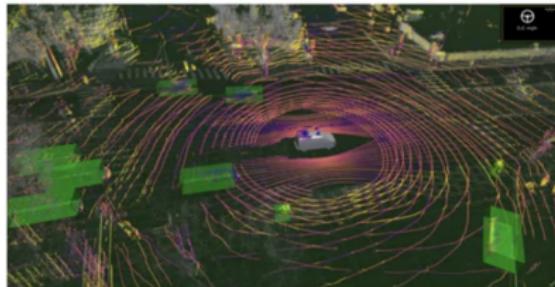
Robotics

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

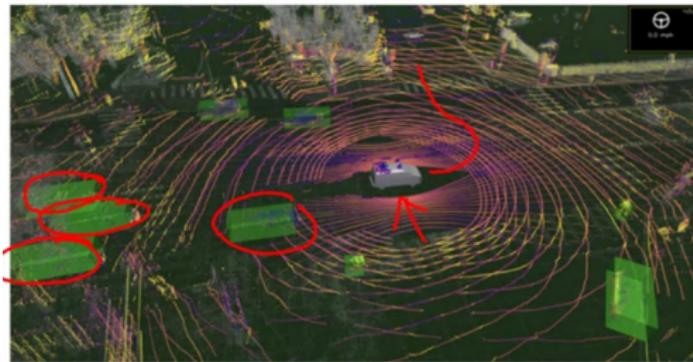


Robotics

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

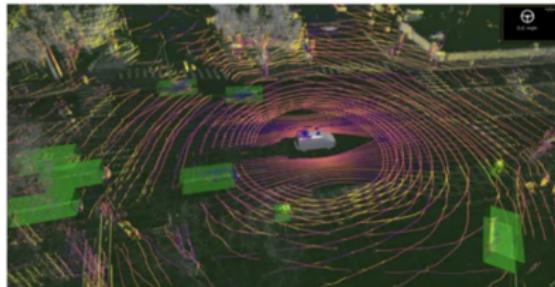


- Motion planning: finding a path for the robot to follow.

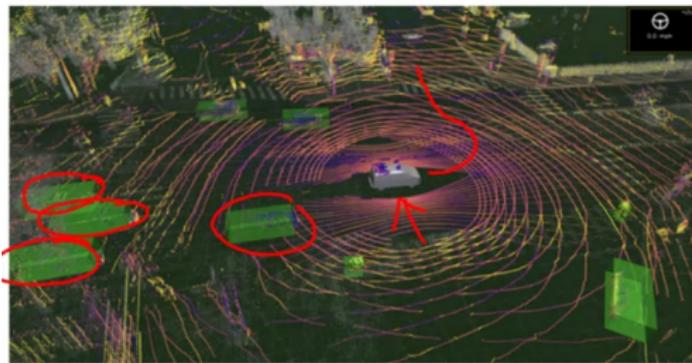


Robotics

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



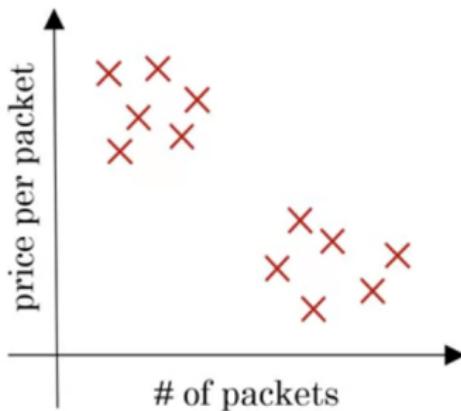
- Motion planning: finding a path for the robot to follow.



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

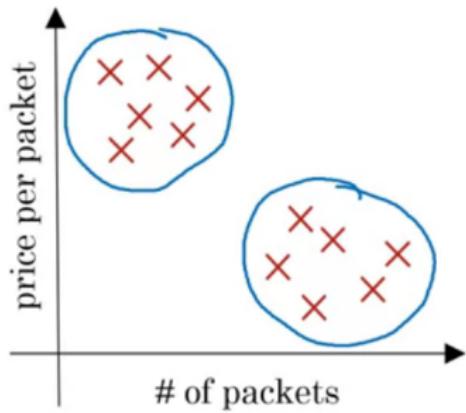
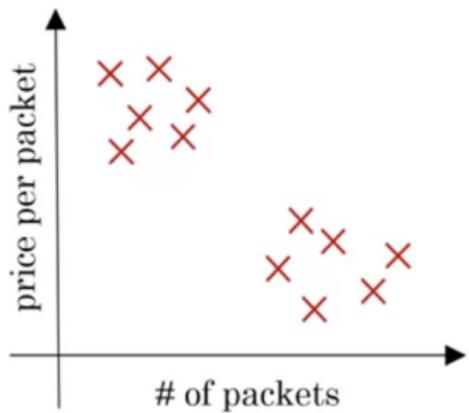
Unsupervised learning (1/2)

Clustering potato chip sales



Unsupervised learning (1/2)

Clustering potato chip sales



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 (2/2)

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

Car detection



100,000 images

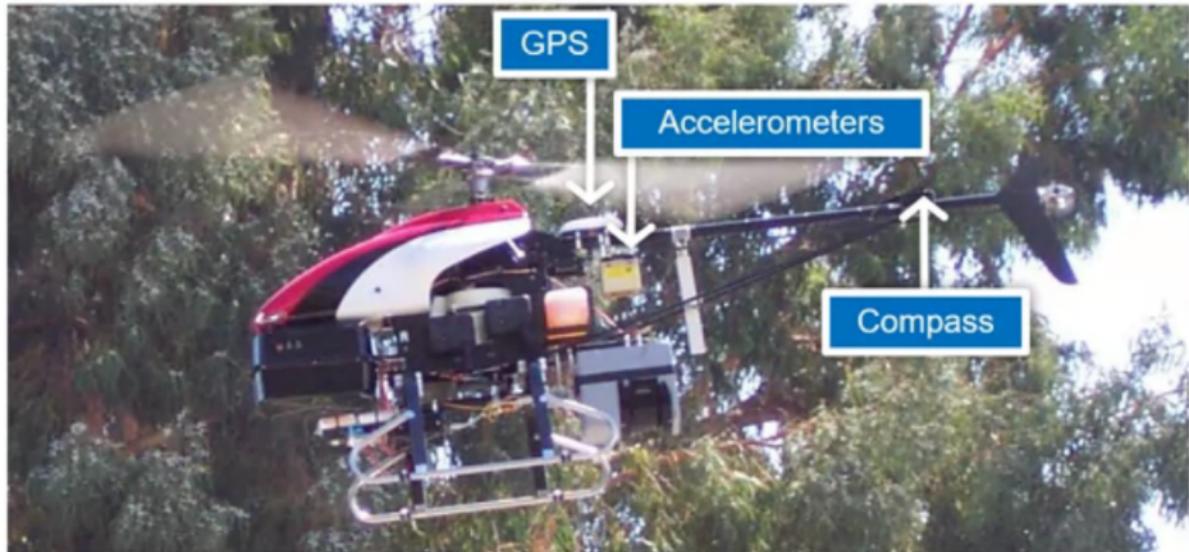
Golf cart detection



100 images

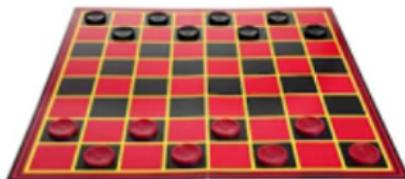
Learn from task A, and use knowledge to help on task B

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)

leonardo da vinci

All Images Books News Videos More Settings Tools

About 154,000,000 results (0.63 seconds)

Leonardo da Vinci - Wikipedia
https://en.wikipedia.org/wiki/Leonardo_da_Vinci ▾
Leonardo di ser Piero da Vinci more commonly Leonardo da Vinci or simply Leonardo, was an Italian polymath of the Renaissance whose areas of interest ...
Known for: Art, science
Movement: High Renaissance
Science and inventions Personal life of Leonardo da ... Portal:Leonardo da Vinci

Leonardo da Vinci - Paintings, Drawings, Quotes, Facts, & Biography
<https://www.leonardoda-vinci.net/> ▾
Leonardo da Vinci was a true genius who graced this world with his presence from April 15, 1452 to May 2, 1519. He is among the most influential artists in ...
10 Facts Bacchus - by Leonardo da Vinci - The Last Supper Masterpieces

Leonardo Da Vinci - The Complete Works - leonardoda-vinci.org
<https://www.leonardoda-vinci.org/> ▾
Leonardo Da Vinci - The complete works, large resolution images, ecard, rating, slideshow and more! One of the largest Leonardo Da Vinci resource on the ...

Leonardo da Vinci - HISTORY
<https://www.history.com/topics/renaissance/leonardo-da-vinci> ▾
Leonardo da Vinci (1452-1519) was a painter, architect, inventor, and student of all things scientific. His natural genius crossed so many disciplines that he...

People also ask

What was Leonardo da Vinci's greatest achievement?



More Images

Leonardo da Vinci

Polymath

Leonardo di ser Piero da Vinci, more commonly Leonardo da Vinci or simply Leonardo, was an Italian polymath of the Renaissance whose areas of interest included invention, drawing, painting, sculpting, ...
[Wikipedia](#)

Born: April 15, 1452, Anchiano, Italy
Died: May 2, 1519, Château du Clos Lucé, Amboise, France
On view: Louvre Museum, Royal Collection Trust, Uffizi Gallery, MORE
Period: High Renaissance, Early renaissance, Renaissance, Italian Renaissance, Florentine painting
Known for: Art, science
Siblings: Giovanni Ser Piero, Guglielmo Ser Piero, MORE

Quotes

View 7+ more

Curiosity is the ultimate sophistication.

Knowledge Graph (2/4)

The screenshot shows a search interface with two main sections. The top section is a search bar with the query "leonardo da vinci". Below it are navigation links for "All", "Images", "Books", "News", "Videos", "More", "Settings", and "Tools". The bottom section is for the query "ada lovelace". It also has "All" selected along with "Images", "Books", "Videos", "News", "More", "Settings", and "Tools". Below these sections, there is a search result for "Ada Lovelace - Wikipedia" with a link to https://en.wikipedia.org/wiki/Ada_Lovelace. The snippet describes Ada Lovelace as an English mathematician and writer, known for her work on Charles Babbage's proposed mechanical computer. It also mentions her resting place at Church of St. Mary Magdalene, her spouse William King-Noel, 1st Earl of Lovelace, and her known fields of Mathematics and Computing. Below this is another snippet for "Ada Lovelace: Founder of Scientific Computing" with a link to <https://www.sdsu.edu/Science/Women/Lovelace.html>. This snippet describes Ada Byron, Countess of Lovelace as the daughter of a brief marriage between the Romantic poet Lord Byron and Anne Isabelle ...

People also ask:

- What is Ada Lovelace famous for?
- What did Ada Lovelace invent and what impact it had?
- When did Ada Lovelace invent the computer?
- What is Ada Lovelace Day?

Ada Lovelace
Mathematician

Augusta Ada King, Countess of Lovelace was an English mathematician and writer, chiefly known for her work on Charles Babbage's proposed mechanical general-purpose computer, the Analytical Engine. [Wikipedia](#)

Born: December 10, 1815, London, United Kingdom
Died: November 27, 1852, Marylebone, United Kingdom
Spouse: William King-Noel, 1st Earl of Lovelace (m. 1835–1852)
Children: Anne Blunt, 15th Baroness Wentworth, MORE
Parents: Lord Byron, Lady Byron
Known for: Mathematics, Computing

People also search for: [View 15+ more](#)

Feedback

Ada Lovelace | Biography & Facts | Britannica.com
<https://www.britannica.com/Biography/Ada-Lovelace>
Jan 3, 2019 - Ada Lovelace, in full Ada King, countess of Lovelace, original name Augusta Ada Byron, Lady Byron, (born December 10, 1815, London, Eng.

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

- Géron, A. (2019). *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems Second Edition*. O'Reilly Media Inc.
- Karras, T., Aila, T., Laine, S., and Lehtinen, J. (2017). Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*.
- Kharkovskyba, O. (2019). A beginner's guide to data science.
<https://towardsdatascience.com/a-beginners-guide-to-data-science-55edd0288973>. Accessed: 2019-11-14.
- Molnar, C. (2019). *Interpretable Machine Learning*.
<https://christophm.github.io/interpretable-ml-book/>.
- Ng, A. Y. (2019). Ai for everyone.
<https://www.coursera.org/learn/ai-for-everyone/home/welcome>. Accessed: 2019-11-10.
- Phiresky (2017). Neural network demo.
<https://phiresky.github.io/neural-network-demo/>. Accessed: 2020-12-16.
- Trask, A. W. (2019). *Grokking Deep Learning*. Manning Publications.



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