

Pengenalan *Artificial Intelligence*

Jalur Peminatan *AI Specialist*

Hendra Bunyamin

Program Studi Teknik Informatika
Fakultas Teknologi Informasi
Universitas Kristen Maranatha

November 21, 2022



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 Jalur Peminatan AI: Becoming AI Specialist



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Introduction

AI value creation
by 2030

\$13
trillion

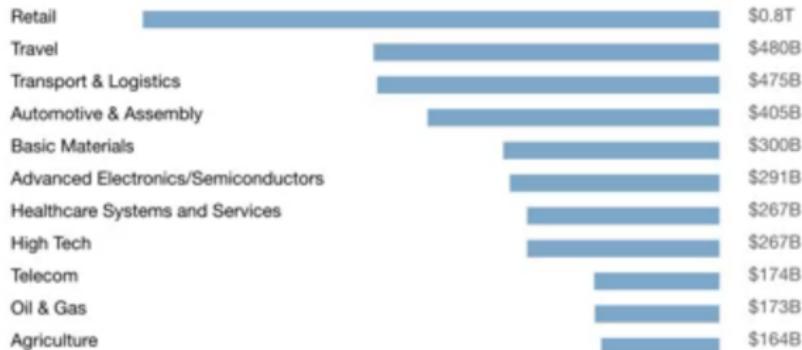


Figure 1: Source: McKinsey Global Institute (Ng, 2019)

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

Demystifying AI

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



Demystifying AI

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

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



Demystifying AI

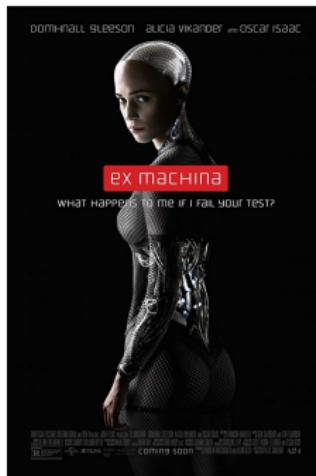
Artificial Intelligence or **AI** can be divided into 2 as follows:

- **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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Machine Learning (1/2)

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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).

Figure 2:



Machine Learning (1/2)

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

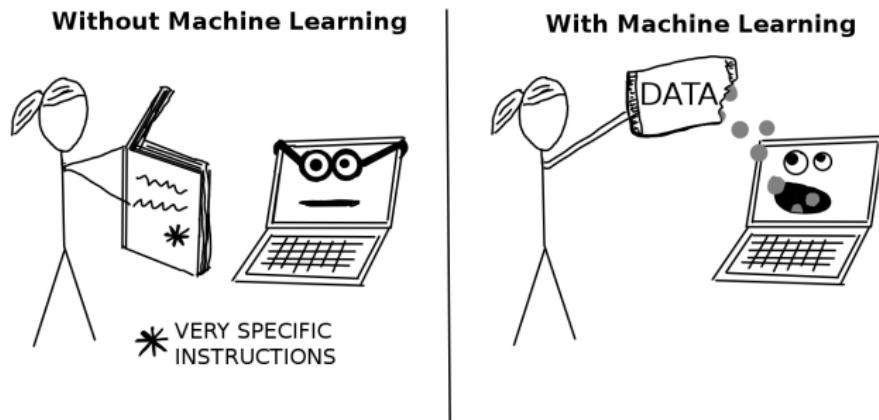


Figure 2: A paradigm shift from "normal programming" to "indirect programming"

Machine Learning (2/2)

The way a machine or computer learns can be categorized into several types (Géron, 2019):

Machine Learning (2/2)

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- Supervised Learning,



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- Supervised Learning,
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- Reinforcement learning



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):



Supervised Learning (2/2)

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

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Supervised Learning (2/2)

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



Supervised Learning (2/2)

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

- Using **pixels** of an image to detect the *presence or absence of a cat*
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- Using someone's **words** to predict whether they're *happy or sad*



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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)

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

Why Now?

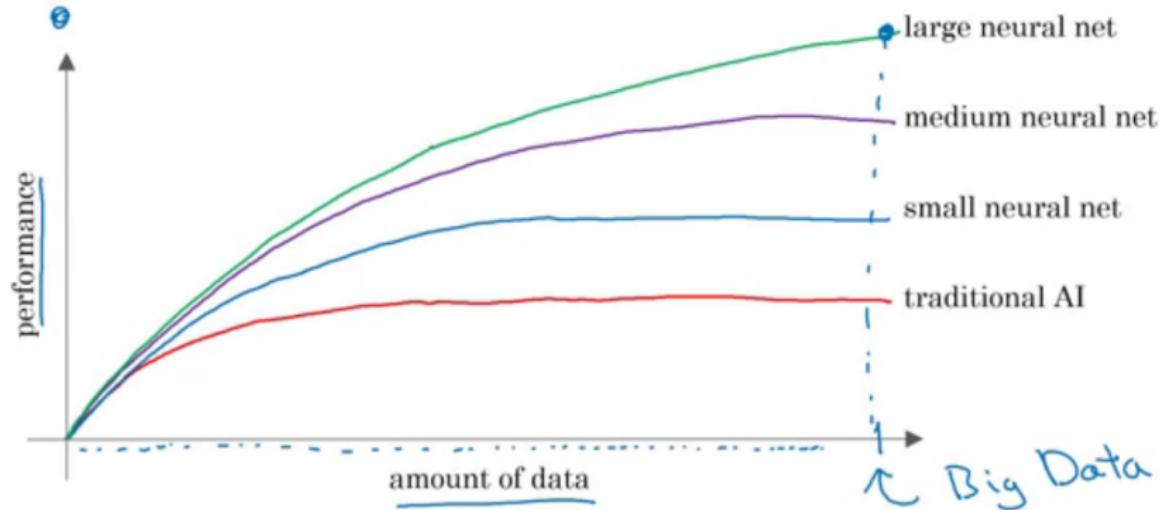


Figure 3: Large neural net + Big Data = High Performance (Ng, 2019)

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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



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

- Manual labeling



cat



not
cat



cat

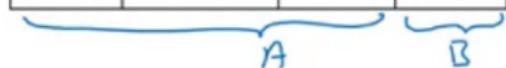


not
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- Download from websites / partnerships

Contoh: [Kaggle](#), [UCI Machine Learning Repo](#)

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
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size of house (square feet)	# of bedrooms	price (1000\$)
523	1	115
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708	unknown	210
1034	3	unknown
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- Multiple types of data
images, audio, text ⇒ **unstructured data**

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AI, Machine Learning, and Data Science

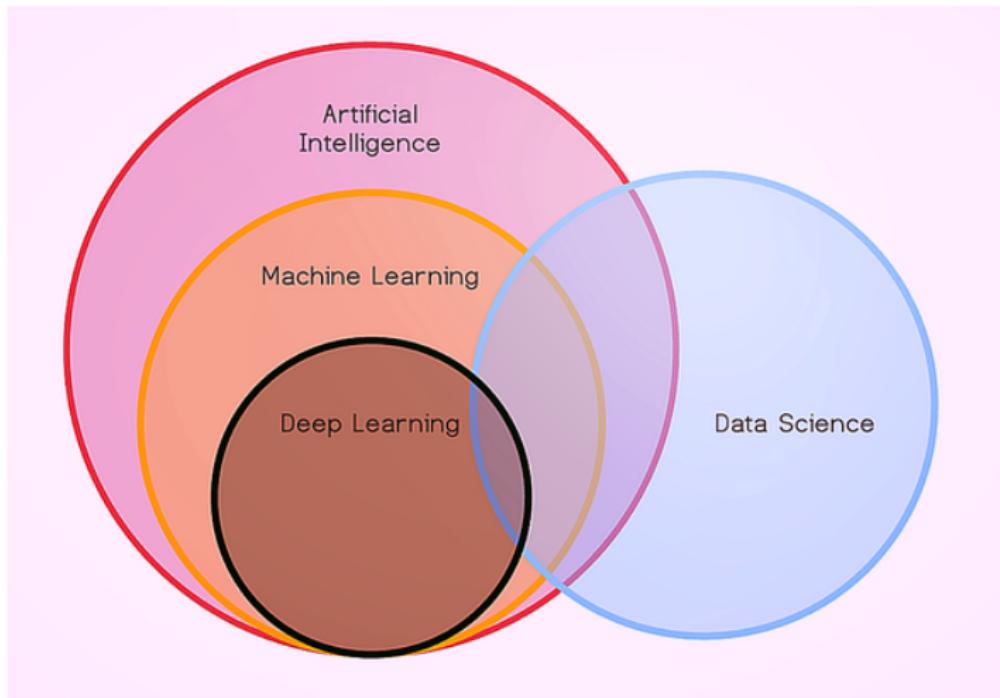


Figure 4: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

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



Figure 5: 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
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Figure 5: 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)

size of house (square feet)	# of bedrooms	# of bathrooms	newly renovated	price (1000\$)
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2545	4	5	Y	440

A  B 

Figure 5: Home prices (Ng, 2019)

- According to **Machine Learning**:

$A \rightarrow B$: 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

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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Dataset: Home Prices

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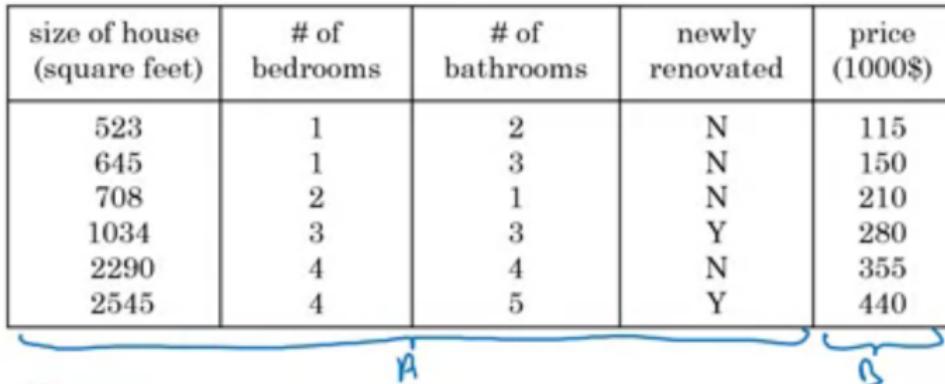
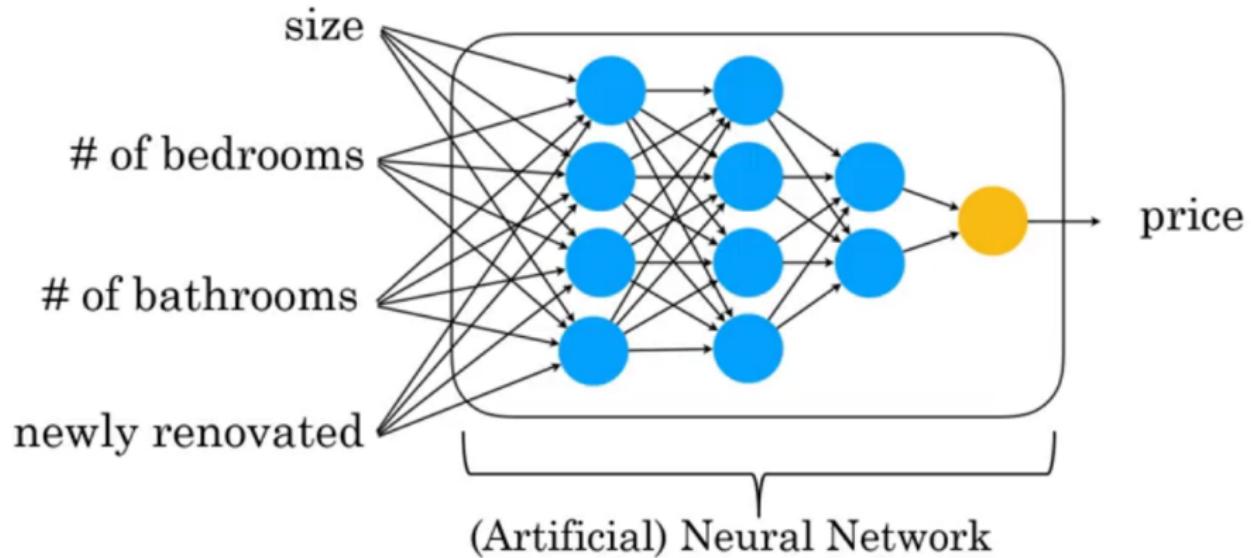


Figure 6: Home prices (Ng, 2019)

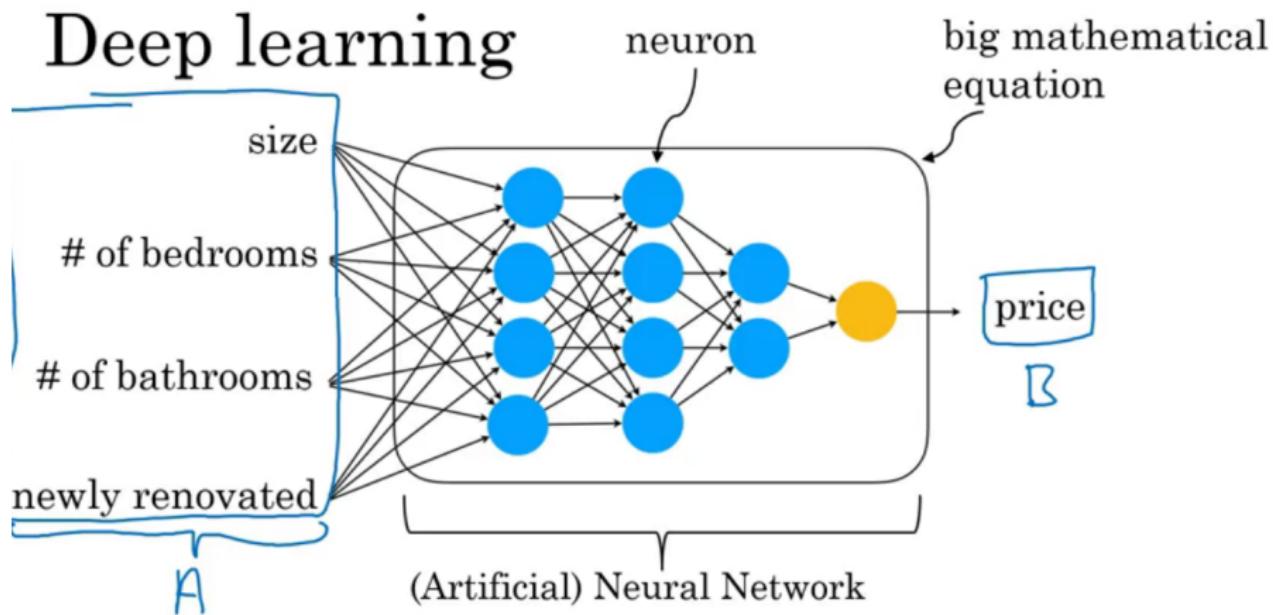
Deep Learning (1/3)



Deep Learning (2/3)



Figure 7: Neuron-neuron di Otak (Ankrom, 2020)



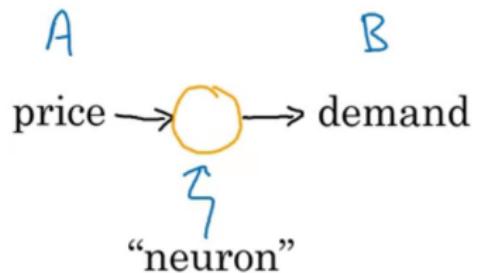
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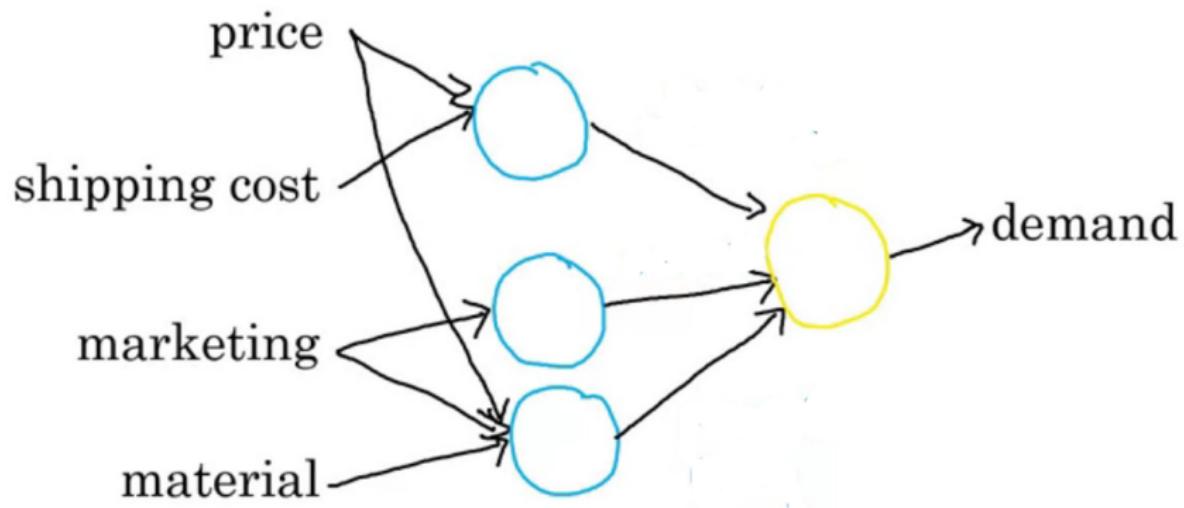
Demand prediction (1/2)



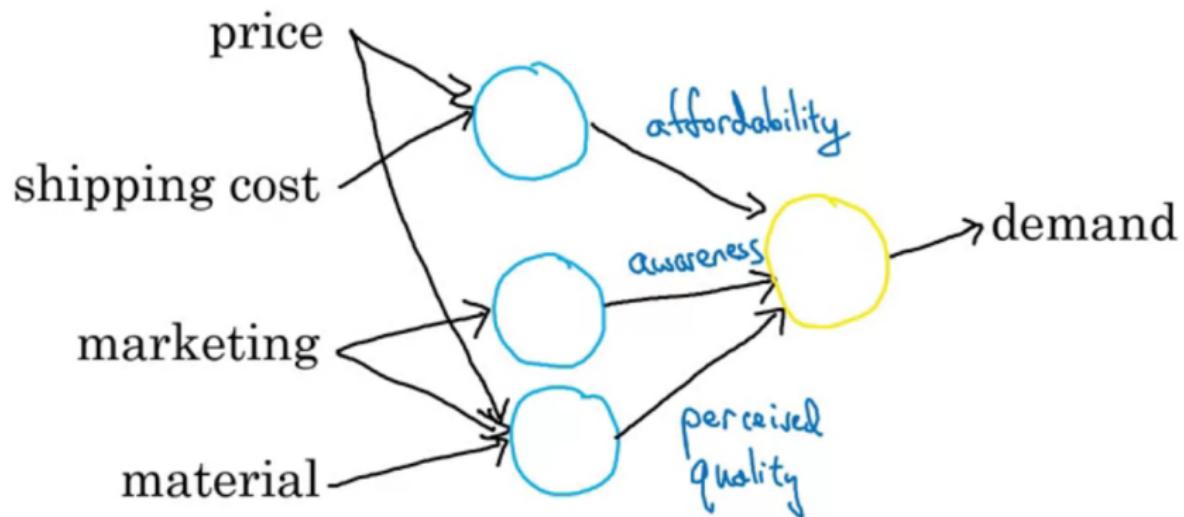
Demand prediction (2/2)



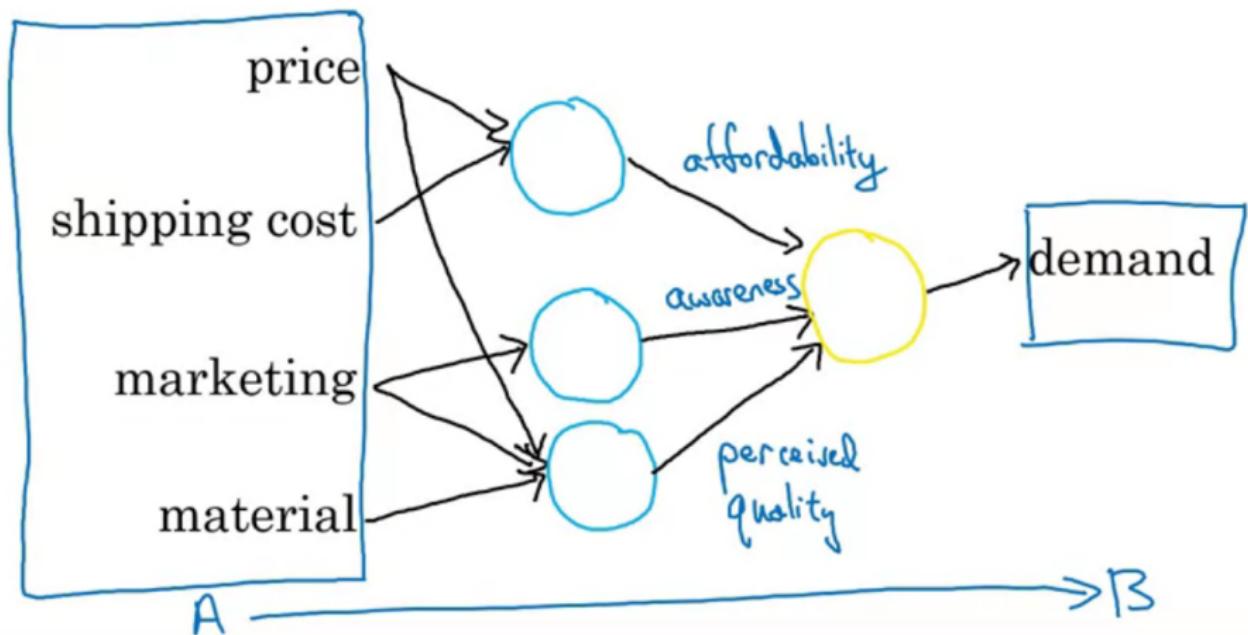
Demand prediction: a little bit more complex (1/4)



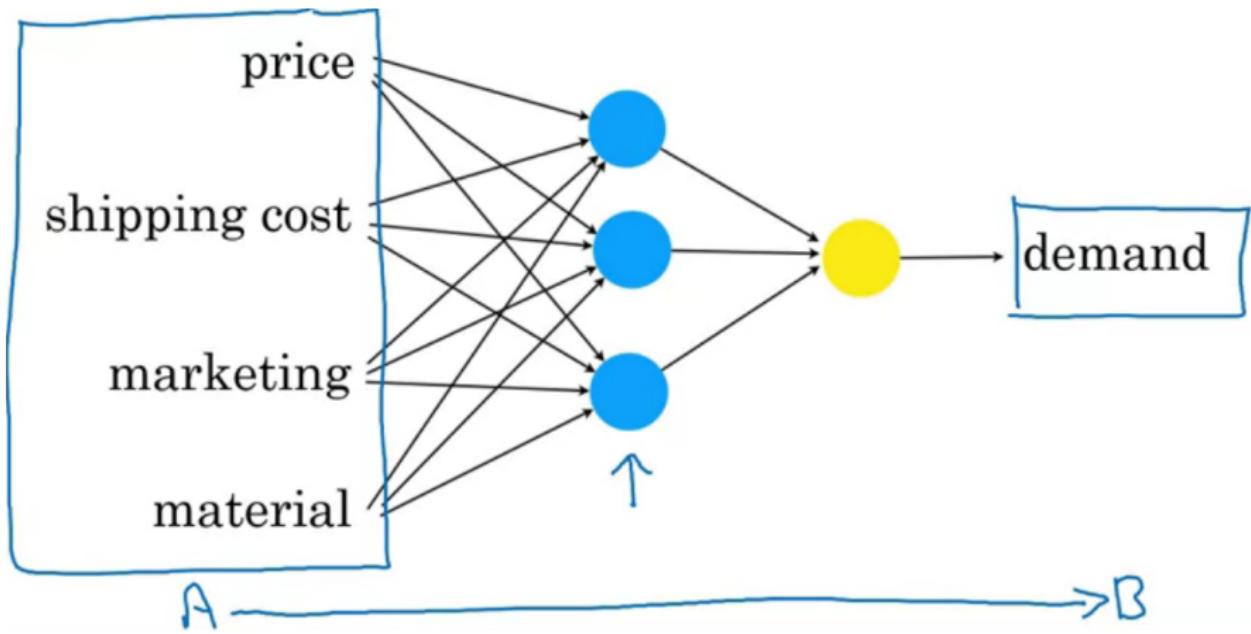
Demand prediction: a little bit more complex (2/4)



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

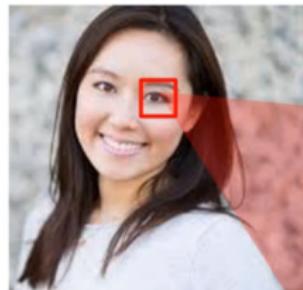


Demand prediction: a little bit more complex (4/4)



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

NN Application: Face recognition (2/3)

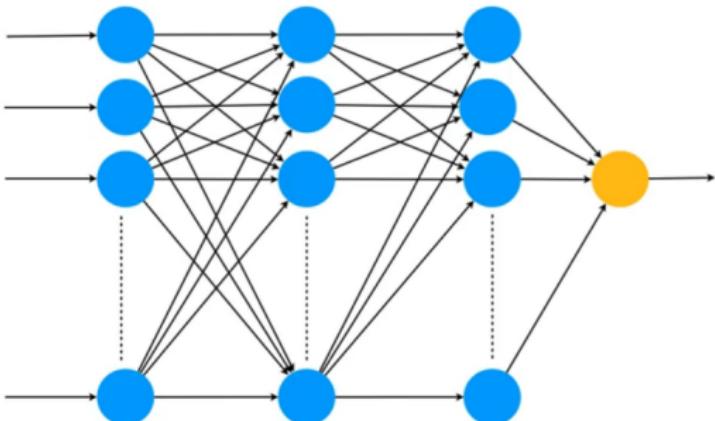


1000

1600

1,000,000

3,000,000



NN Application: Face recognition (3/3)

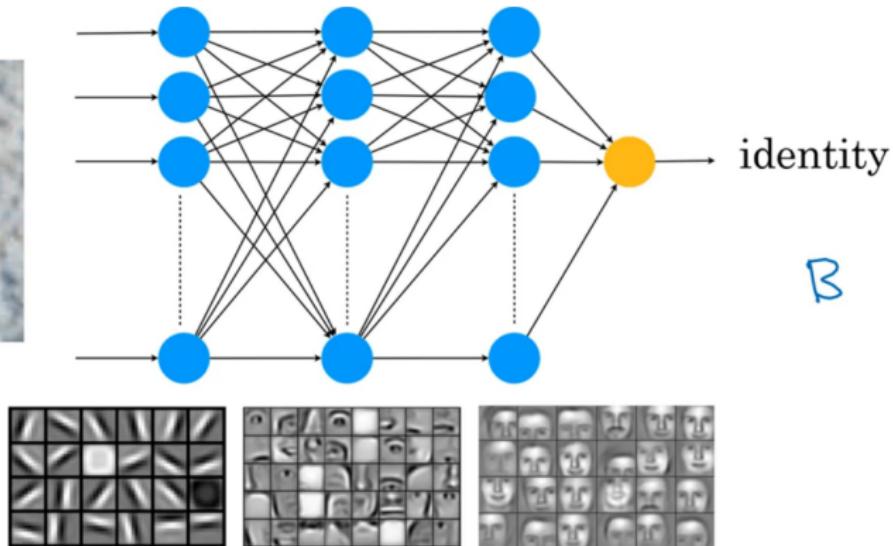


1000

1600

1,000,000

3,000,000



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?



What machine learning today can and cannot do

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

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Machine Learning Can Do:

→ "Refund request"

Input text → Refund/Shipping/Other

$A \rightarrow B$



What machine learning today can and cannot do

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Can I return it?

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)**

User email 2-3 paragraph response

Train Data: 1000 examples

"My box was damaged" → 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 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.



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

$\leq 1 \text{ sec}$

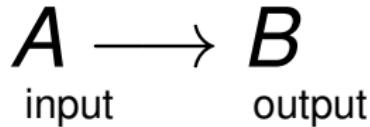


What makes an ML problem easier

- ① Learning a "simple" concept

$\leq 1 \text{ sec}$

- ② Lots of data available



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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:

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

ML tends to work poorly when:



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



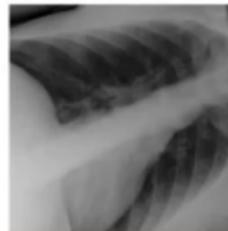
Strengths and weaknesses of machine learning

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



Machine Learning

The way a machine or computer learns can be categorized into several types (Géron, 2019):



Machine Learning

The way a machine or computer learns can be categorized into several types (Géron, 2019):

- Supervised Learning,



Machine Learning

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- Unsupervised Learning.



Machine Learning

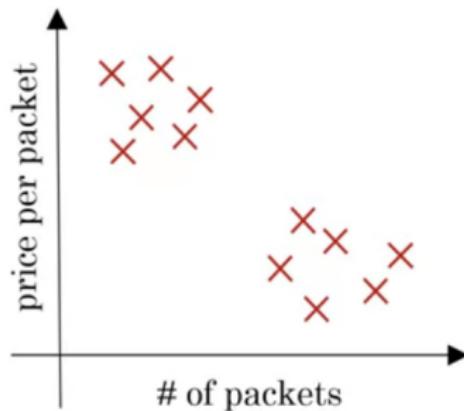
The way a machine or computer learns can be categorized into several types (Géron, 2019):

- Supervised Learning,
- **Unsupervised Learning.**



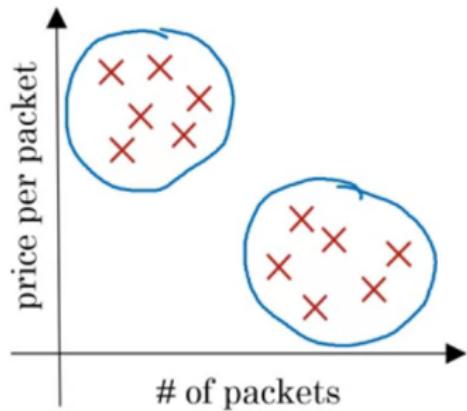
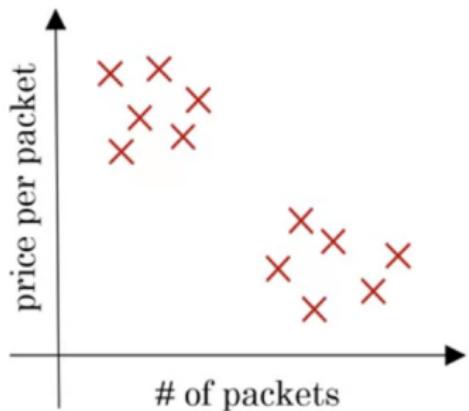
Unsupervised learning (1/2)

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



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 Jalur Peminatan AI: Becoming AI Specialist



- Image classification/Object recognition



cat

Computer Vision (2/7)

- Face verification & face identification

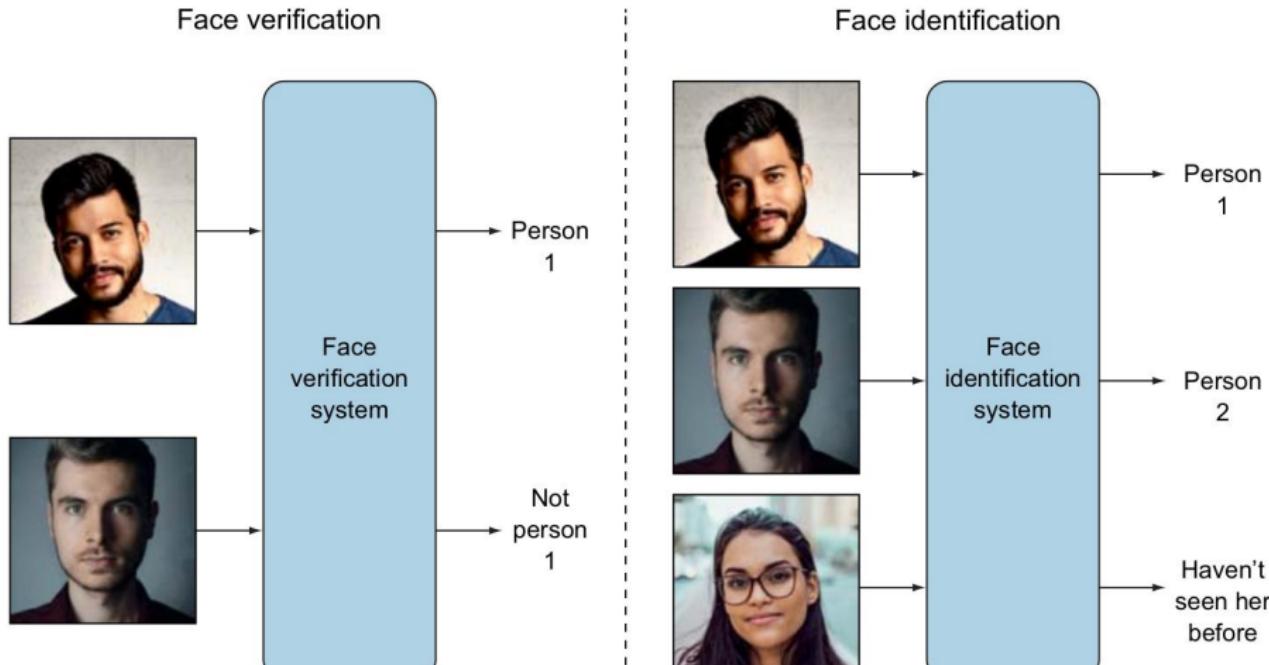


Figure 9: Example of face verification (left) and face recognition (right) (Elgendi, 2020)

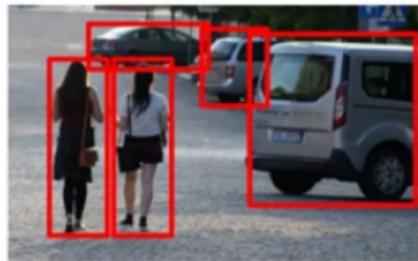
Computer Vision (3/7)

- Object detection



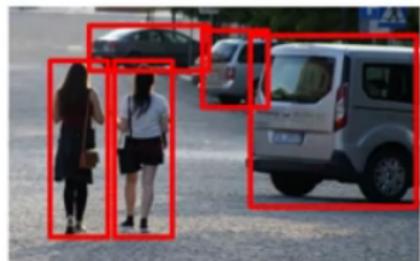
Computer Vision (3/7)

- Object detection



Computer Vision (3/7)

- Object detection



- Image Segmentation



Computer Vision (4/7)

- Image Segmentation



Computer Vision (4/7)

- Image Segmentation



- Tracking



Computer Vision (5/7)

- Membuat gambar baru dari style pelukis ternama.



Figure 10: Style transfer from Van Gogh's The Starry Night onto the original image (Elgendi, 2020)

Computer Vision (6/7)

- Membuat gambar baru dari deskripsi teks

This small blue bird has a short, pointy beak and brown on its wings.



This bird is completely red with black wings and a pointy beak.



Figure 11: StackGAN use a textual description of an object to generate a high-resolution image of the object matching that description (Elgendi, 2020)

Computer Vision (7/7)

- Image recommendation system

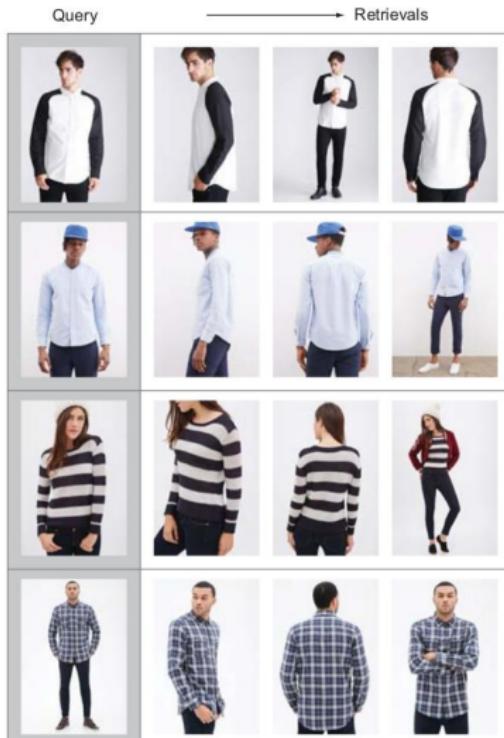


Figure 12: Apparel search (Elgendi, 2020)

Natural Language Processing (1/8)

- Information search atau information retrieval (Kochmar, 2022)

Contoh 1:

Query submitted to the search engine

applications of nlp



Contoh 2:



what temperature does water boil



what temperature does water boil



100°C

Precise answer to a specific question provided by a search engine



Natural Language Processing (2/8)

- Advanced information search: Asking the machine precise questions

A screenshot of a search engine interface. At the top, there is a search bar with the query "what temperature is it in cali". To the right of the search bar are a close button (X) and a search icon. Below the search bar, the query is repeated: "what temperature is it in california". Underneath this, the result is displayed: a weather icon (cloud with sun), the temperature "18°C", and the text "Tue – Los Angeles, CA, USA".

Precise answer to a specific question provided by a search engine



Natural Language Processing (3/8)

The search for factual information on Google returns both the precise answer to the question and the accompanying explanation.

Water / Boiling point

100°C

Precise answer and
accompanying explanation



A liquid at high pressure has a higher boiling point than when that liquid is at atmospheric pressure. For example, water boils at 100 °C (212 °F) at sea level, but at 93.4 °C (200.1 °F) at 1,905 metres (6,250 ft) altitude. For a given pressure, different liquids will boil at different temperatures.

https://en.wikipedia.org/wiki/Boiling_point ::

[Boiling point - Wikipedia](#)



Natural Language Processing (4/8)

- Conversational agents dan intelligent virtual assistants



Natural Language Processing (5/8)

- Text prediction dan language generation

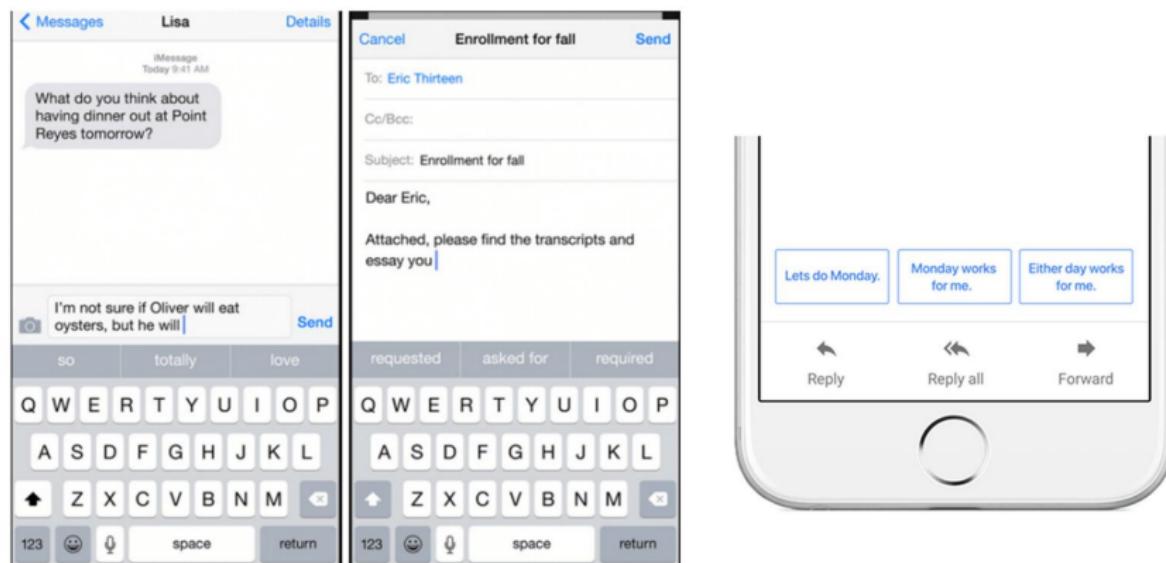


Figure 13: On the right: Google's Smart Reply for emails

- Text Classification

Natural Language Processing (6/8)

- Text Classification
 - Sentiment recognition

- Text Classification
 - Sentiment recognition
- "The food was good" → 

Natural Language Processing (6/8)

- Text Classification
 - Sentiment recognition

"The food was good"



"Service was horrible"



- Text Classification

- Sentiment recognition

"The food was good"



"Service was horrible"



- Spam/Hoax filtering

- Text Classification

- Sentiment recognition

"The food was good"



"Service was horrible"



- Spam/Hoax filtering

- News article classification into: politics, business, sports, and so on.

- **Machine translation**

Contoh 1:

"AI adalah listrik baru" \Rightarrow "AI is new electricity"

Contoh 2:



Figure 14: Phrase translation between English and French

- Spell dan grammar checking

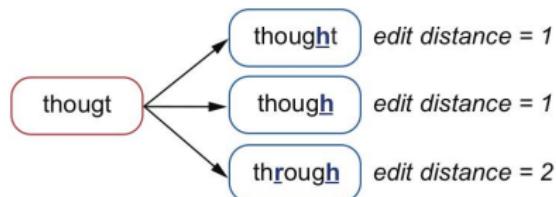


Figure 15: Possible corrections for the misspelling *thoug*

NLP: Speech (1/2)



- Speech recognition (speech-to-text)



Amazon
Echo / Alexa



Google
Home



Apple
Siri



Baidu
DuerOS

NLP: 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)

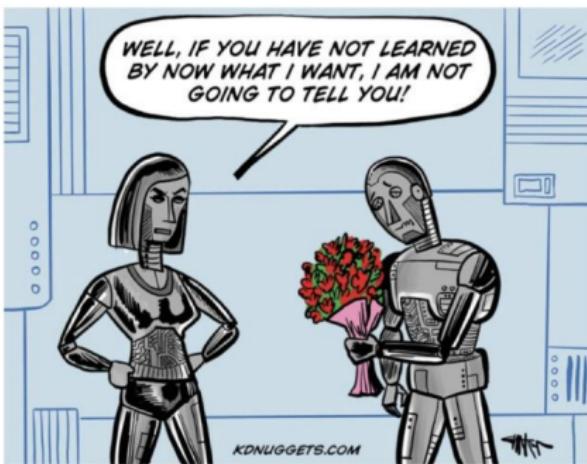
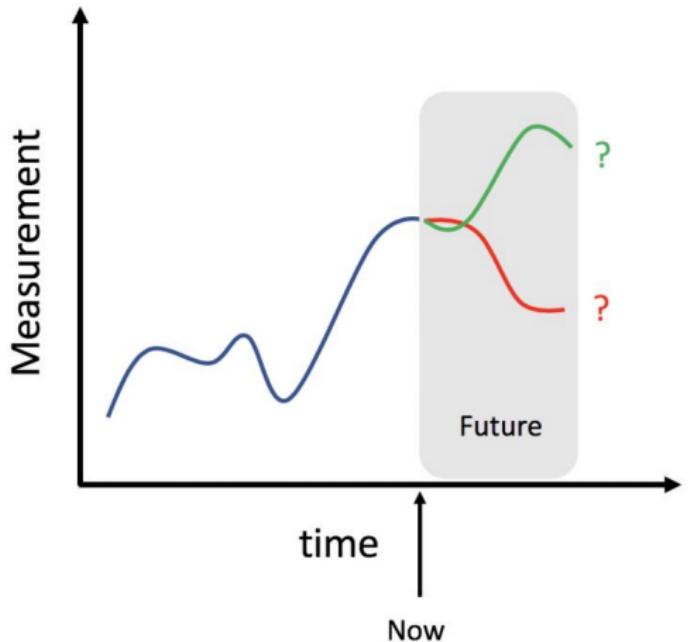
NLP: Speech (2/2)

- Speaker ID



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

Times Series Forecasting (1/3)



Times Series Forecasting (2/3)

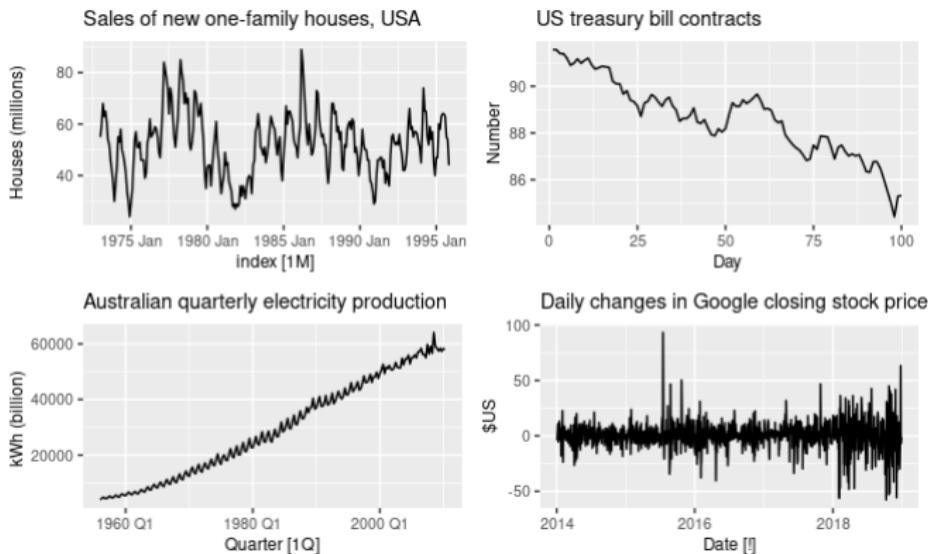
Times Series Forecasting (2/3)

Forecasting has fascinated people for thousands of years, sometimes being considered a *sign of divine inspiration*, and sometimes being seen as a *criminal activity* (Hyndman, 2021).



Times Series Forecasting (2/3)

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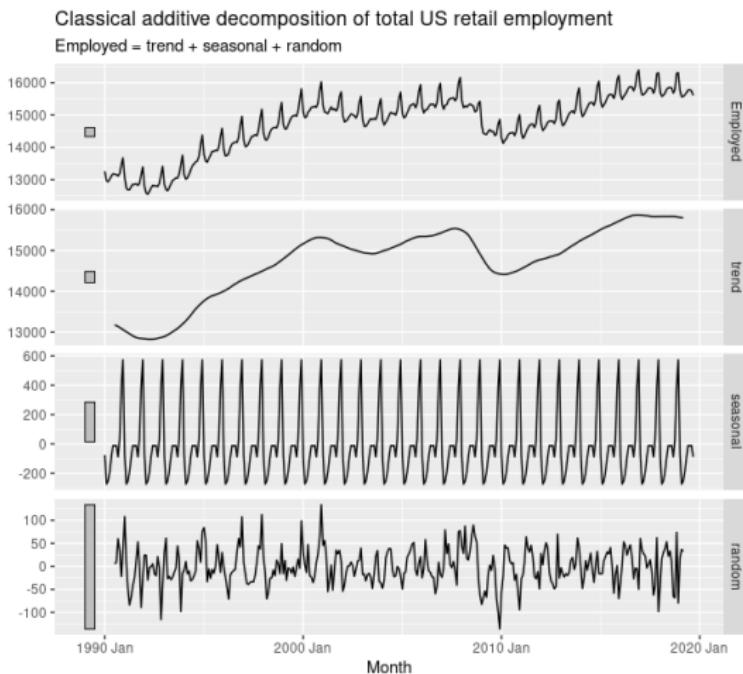
Times Series Forecasting (3/3)

This is an example of a time series which is decomposed by classical decomposition.



Times Series Forecasting (3/3)

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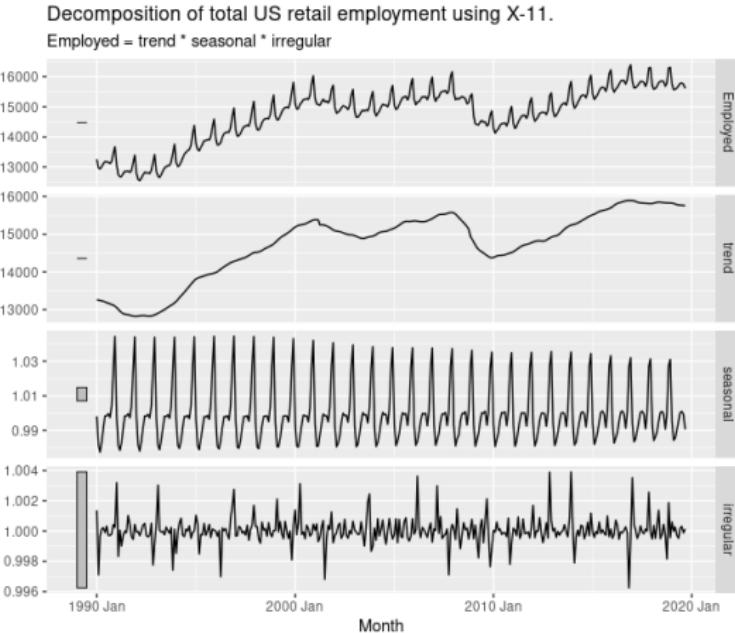
Times Series Forecasting (4/3)

This is an example of a time series which is decomposed by a better decomposition, X-11.



Times Series Forecasting (4/3)

This is an example of a time series which is decomposed by a better decomposition, X-11.



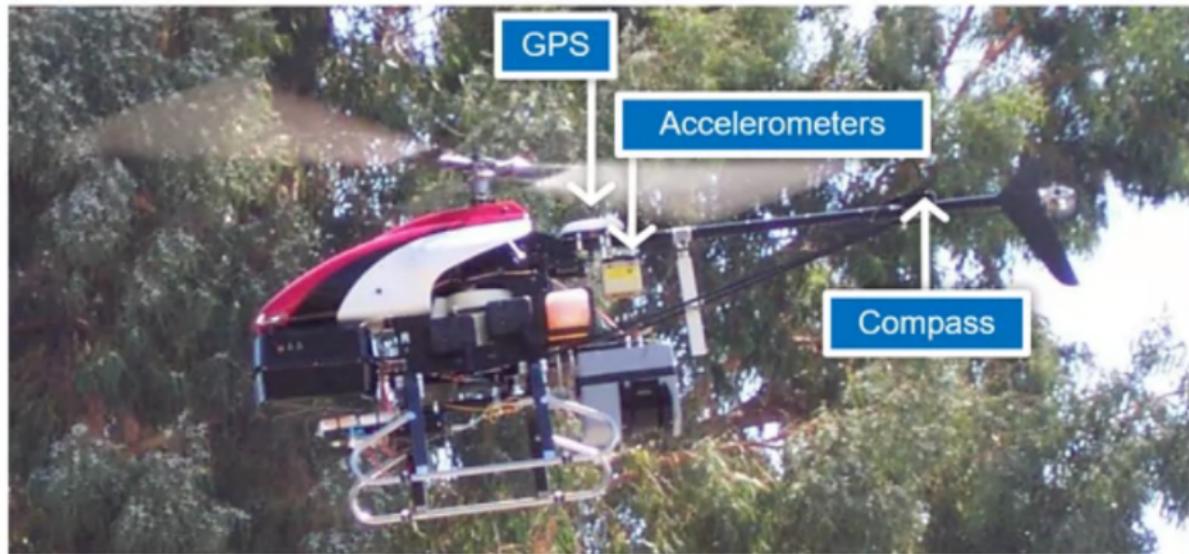
Times Series Forecasting (5/3)



Salah satu algoritma untuk forecasting time series yang populer adalah **Facebook Prophet**.

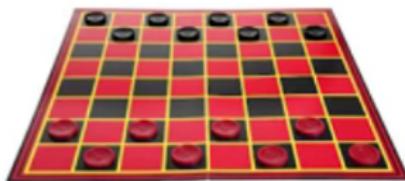


Reinforcement learning (1/3)



Use a "reward" signal to tell the AI when it is doing well or poorly. It automatically learns to maximize its rewards.
(Contoh: **Stanford Autonomous Helicopter**).

Reinforcement learning (2/3)



Use a "reward" signal to tell the AI when it is doing well or poorly. It automatically learns to maximize its rewards. (Contoh: **AlphaGo is beating Humanity**)

Reinforcement learning (3/3)

Dapatkah robot belajar bergerak di alam bebas?

Dengan implementasi yang tepat, *it can be a walk in the park* (Smith et al., 2022).

Link Video is [here](#)



GANs (Generative Adversarial Network) (1/3)

Synthesize new images from scratch (Karras et al., 2017) (**GANs in Action**)



GANs (Generative Adversarial Network) (2/3)

GauGan won a 2019 PopSci Magazine "Best of What's New Award" in the engineering category.

Developed by NVIDIA researchers in 2019, GauGAN is the first AI model that can produce complex images with only a few brushstrokes.

Video Link is [here](#).

Aplikasi yang mirip: [Image-to-Image Demo](#)

GANs (Generative Adversarial Network) (3/3)

- Using AI to generate fashion by utilizing DALL-E.
Video Link is [here](#).
- DALL-E: Introducing Outpainting
Extend creativity and tell a bigger story with DALL-E images of any size.
Video Link is [here](#).



AI Computing Platform

AI Comprehensive Practice	Python Comprehensive Practice	Machine Learning	Natural Language Processing	Deep Learning Open-source Framework MindSpore
AI Products and Application	Deep Learning Open-source Framework MindSpore	AI computing Platform for Atals		
	AI computing Platform for Smart Devices	Enterprise Intelligence Application Platform		
Deep Learning	Deep Neural Network	Activation Function	Optimization Methods	Optimizer
	Deep Learning Implementation Based on TensorFlow	Convolutional Neural Network (CNN)	Convolutional Neural Network (CNN)	Generative Adversarial Network(GAN)
Machine Learning	Machine Learning Classification	Model Construction Procedure	Support Vector Machine (SVM)	Logistic Regression
	Linear Regression	K-Nearest Neighbor (KNN)	Native Bayes	Decision Tree
			Ensemble Learning	Cluster algorithm

Link Video: [here](#)

Huawei HCIA-AI certification : \$200 \$0.



- ① *Computer Vision*
- ② *Natural Language Processing*
- ③ *Time Series Forecasting*
- ④ *Reinforcement Learning*
- ⑤ *AI Computing Platform*

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