AI Now & Future

Jalur Peminatan: AI Specialist

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Fakultas Teknologi Informasi
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Outline

1. Motivasi AI
2. Machine Learning
3. Machine Learning vs. Data Science
4. Deep Learning
5. What Machine Learning Can and Cannot Do
6. Jalur Peminatan AI: Becoming AI Specialist
7. Future of AI: Generative AI

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1. Motivasi AI
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7. Future of AI: Generative AI

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

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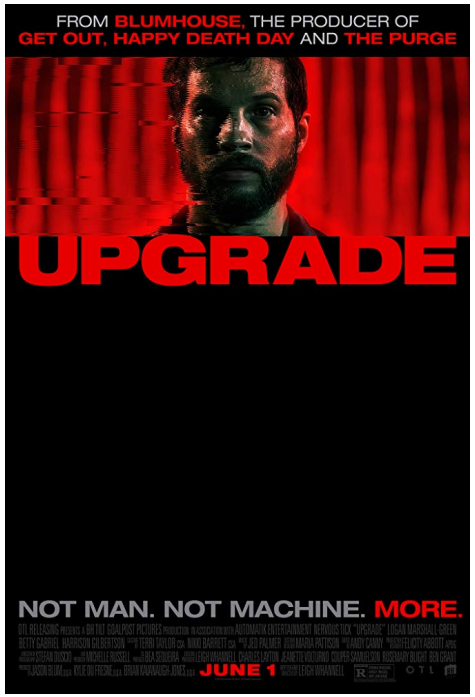
- **ANI** ⇒ *Artificial Narrow Intelligence*.
  Examples: smart speaker, self-driving car, web search, AI in farming and factories.

- **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).

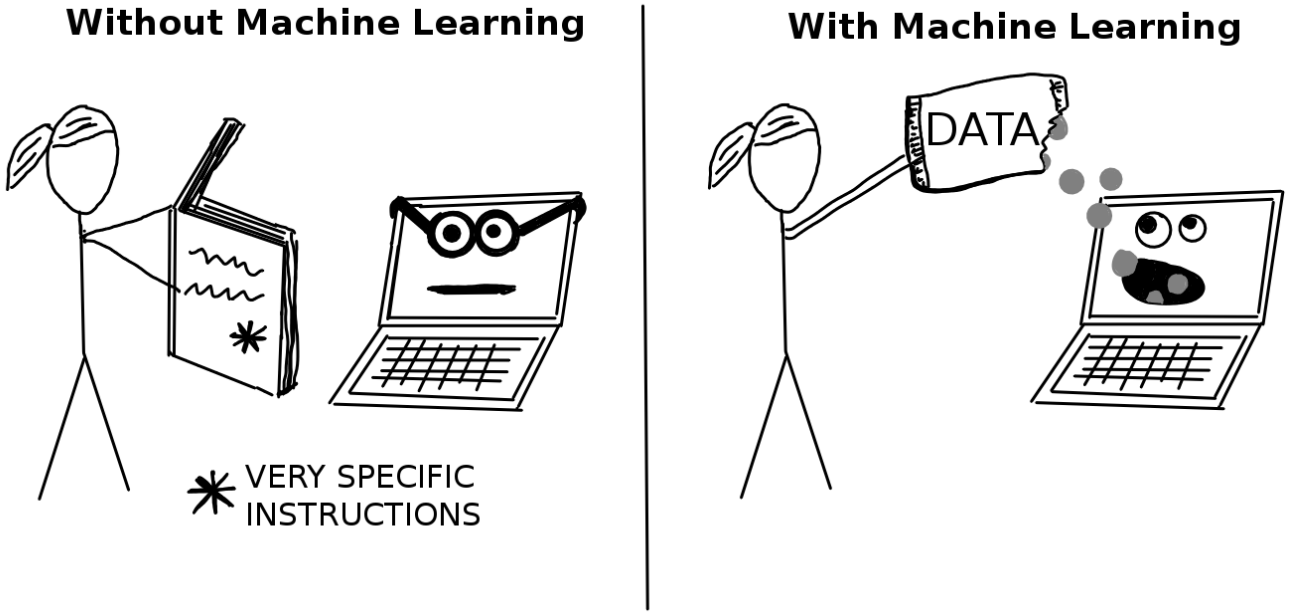

Figure 2: A paradigm shift from "normal programming" to "indirect programming"

Machine Learning (2/2)

The way a machine or computer learns can be categorized into several types (Ng, 2023):

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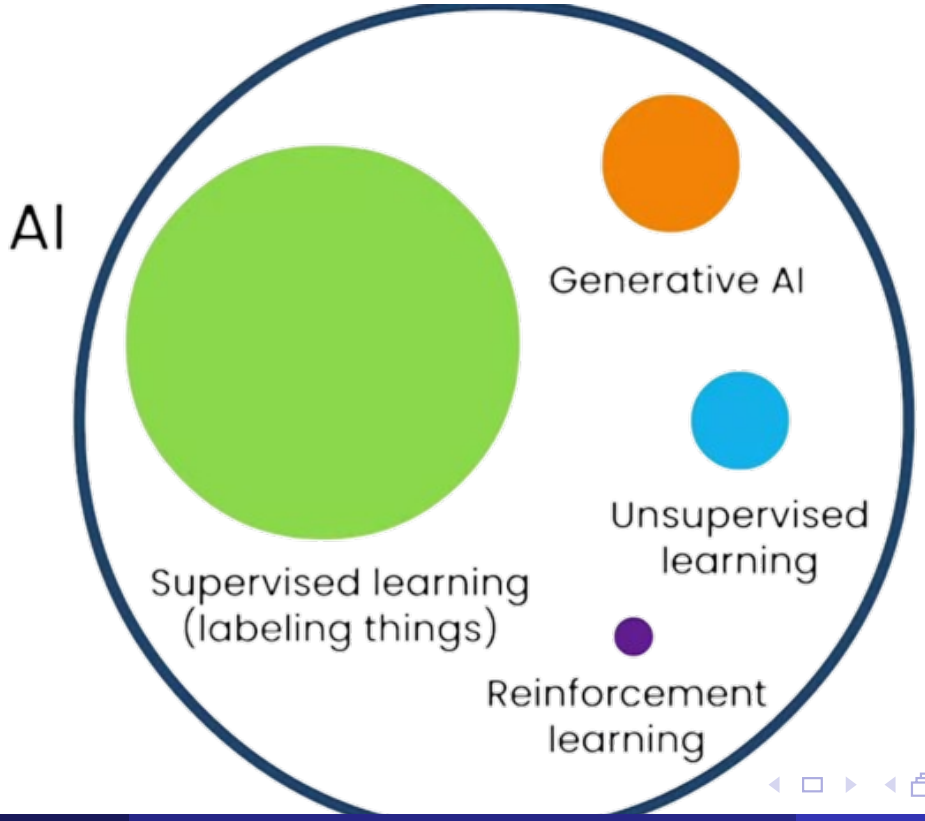

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- **Supervised Learning**,
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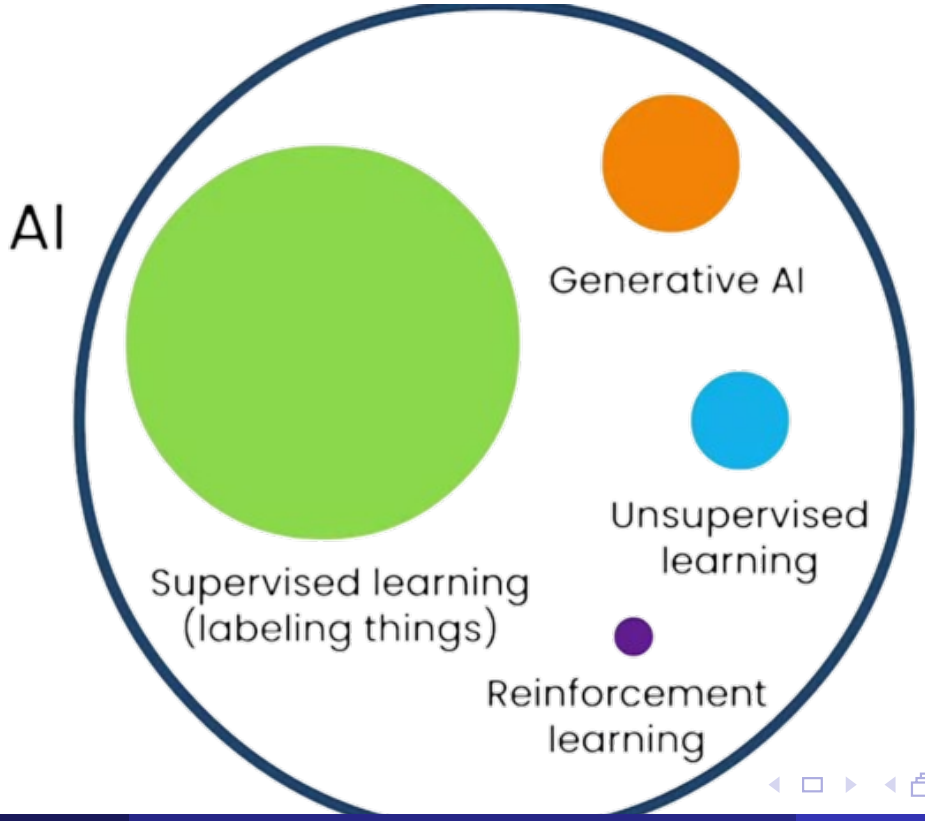

Supervised Learning (1/3)

- 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 (2/3)

Input (A)	Output (B)	Application

Supervised Learning (2/3)

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

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Restaurant reviews	$\longrightarrow$	Sentiment (pos/neg)	**Reputation Monitoring**

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X-ray image	$\longrightarrow$	Diagnosis	**Healthcare**

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

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- Using **news data** to predict tomorrow's stock *price*
- Using a raw **audio file** to predict a *transcript* of the audio.

Why Now?

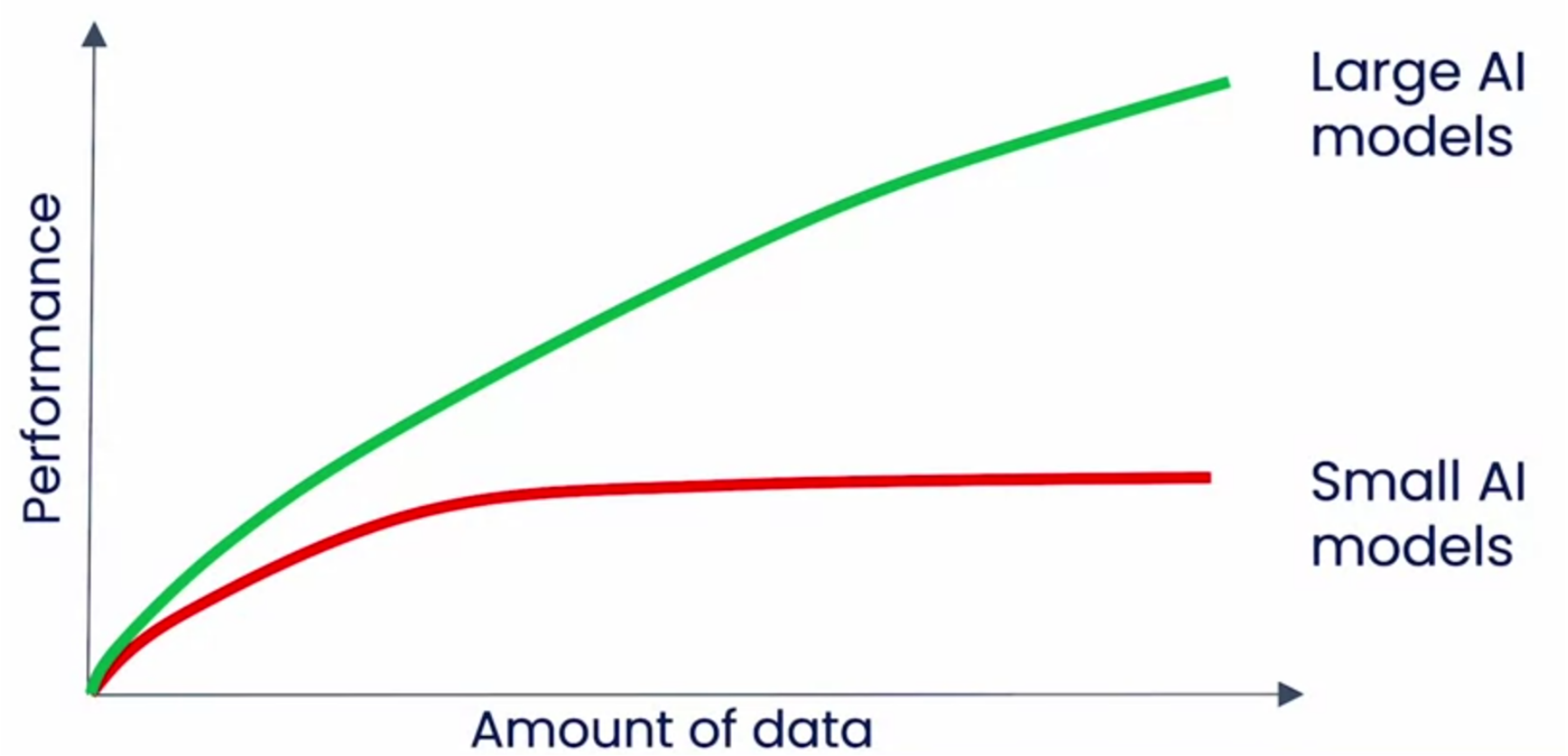

Figure 3: Large neural net + Big Data = High Performance (Ng, 2023)

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 → 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)

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

image	label
	cat
	not cat
	cat
	not cat

A B

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

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- Manual labeling

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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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- 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
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Data is Messy

- Garbage in, garbage out
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- Multiple types of data
  images, *audio*, *text* $\Rightarrow$ **unstructured data**

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AI, Machine Learning, and Data Science

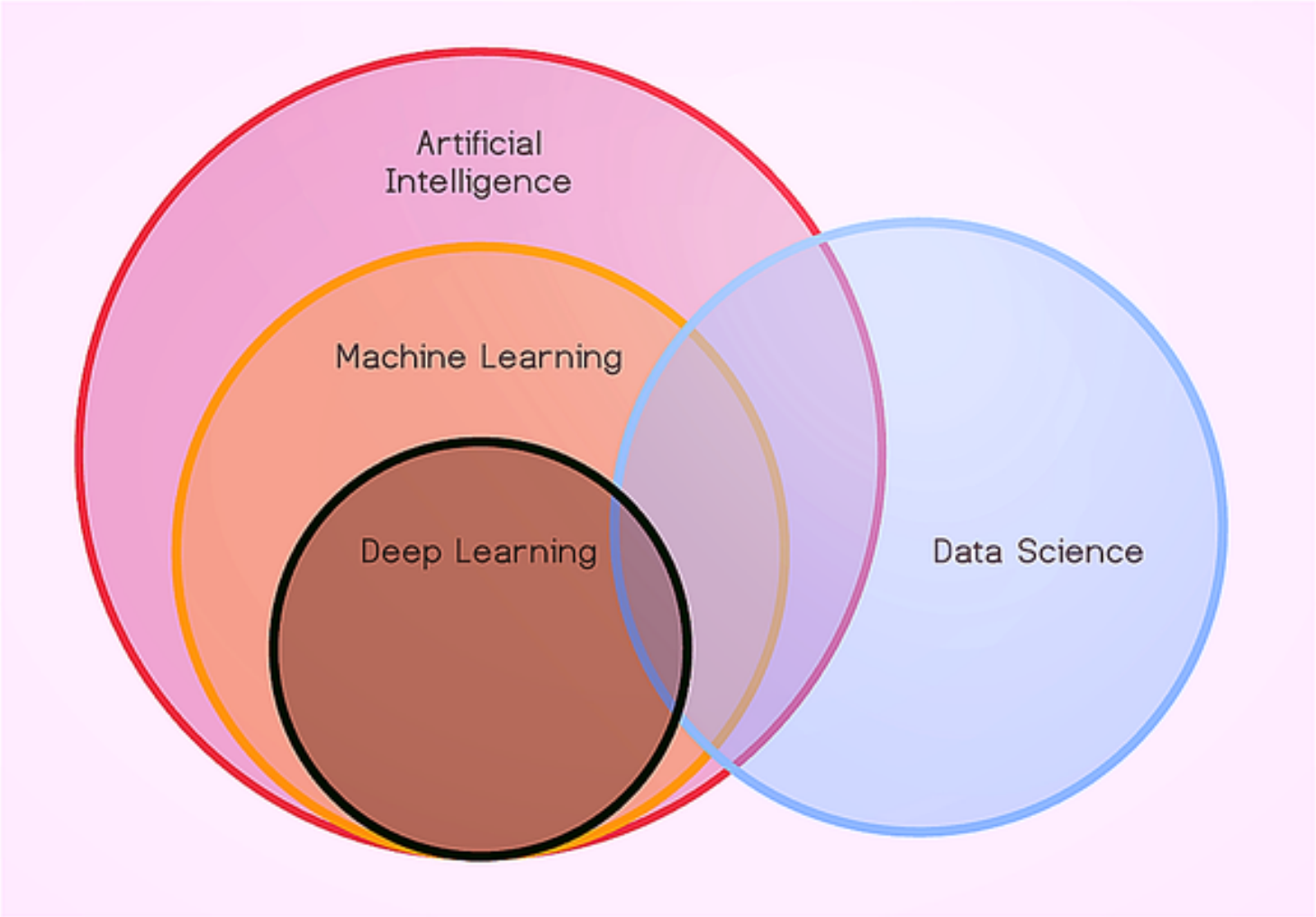

Figure 4: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

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
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A B

Figure 5: Home prices (Ng, 2019)

Machine Learning vs. Data Science (1/2)

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A B

Figure 5: Home prices (Ng, 2019)

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

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A B

Figure 5: 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

"*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.*"	*Science of extracting knowledge and insights from data.*
$\longrightarrow$ **software**	$\longrightarrow$ **slide presentation** or **report**
-Arthur Samuel (1959)	

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Dataset: Home Prices

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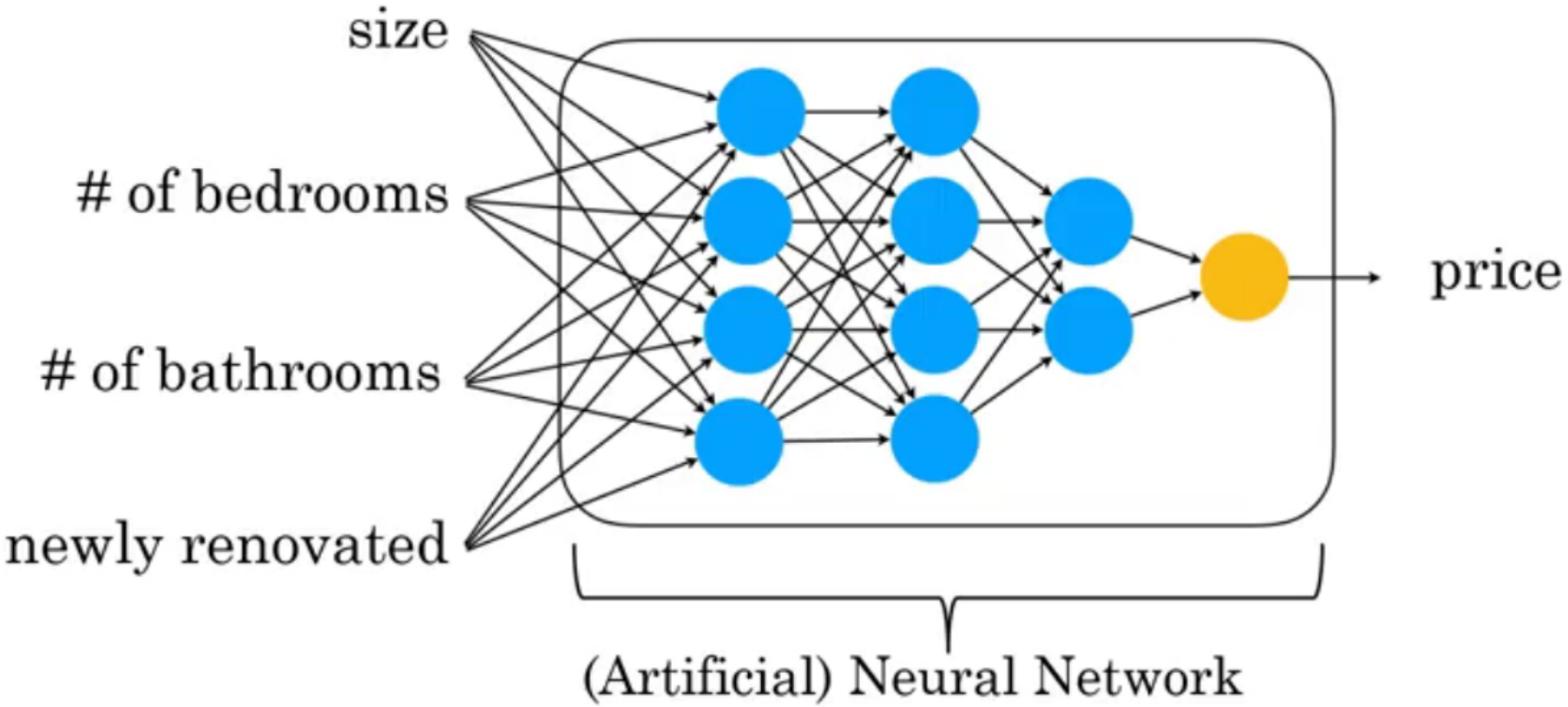
A B

Figure 6: Home prices (Ng, 2019)

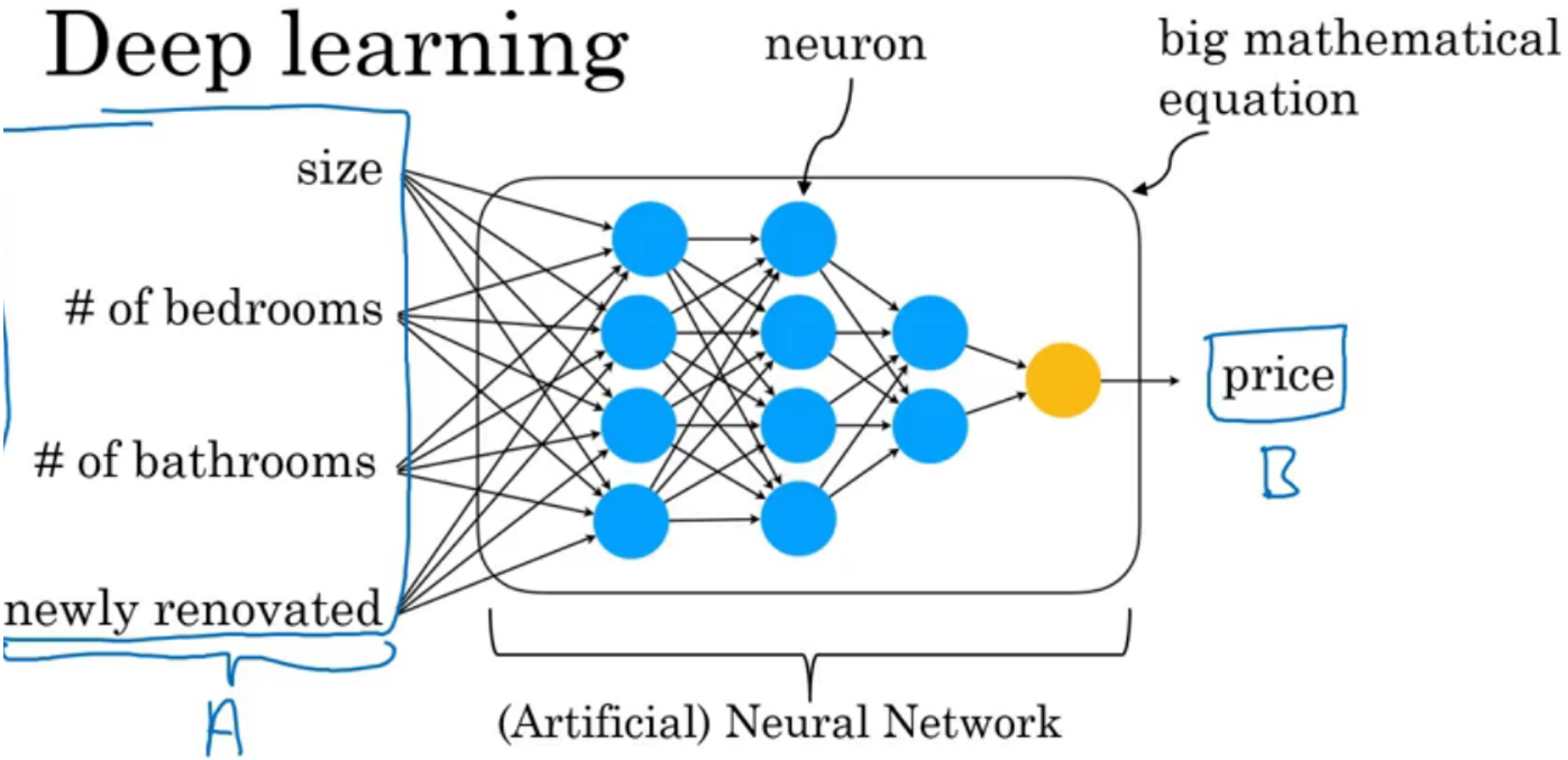
Deep Learning (1/3)



Deep Learning (2/3)

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

Deep Learning (2/3)



Demand prediction (1/2)

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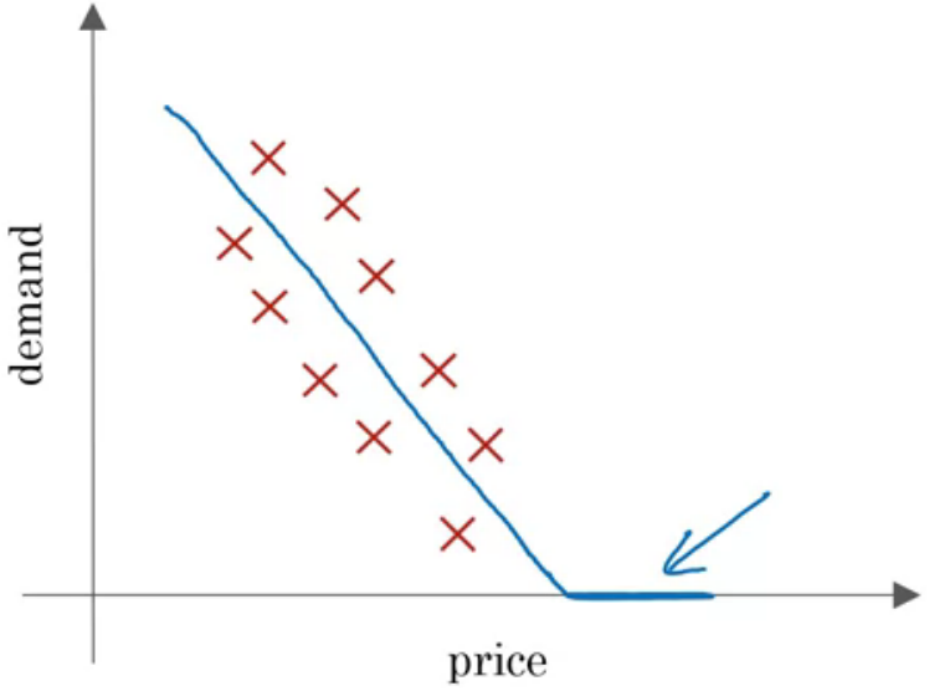
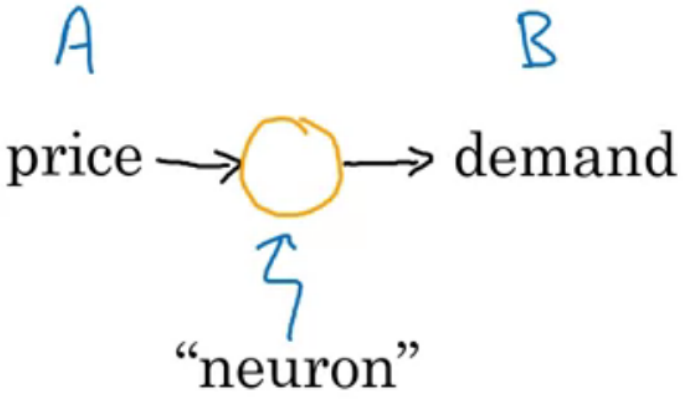
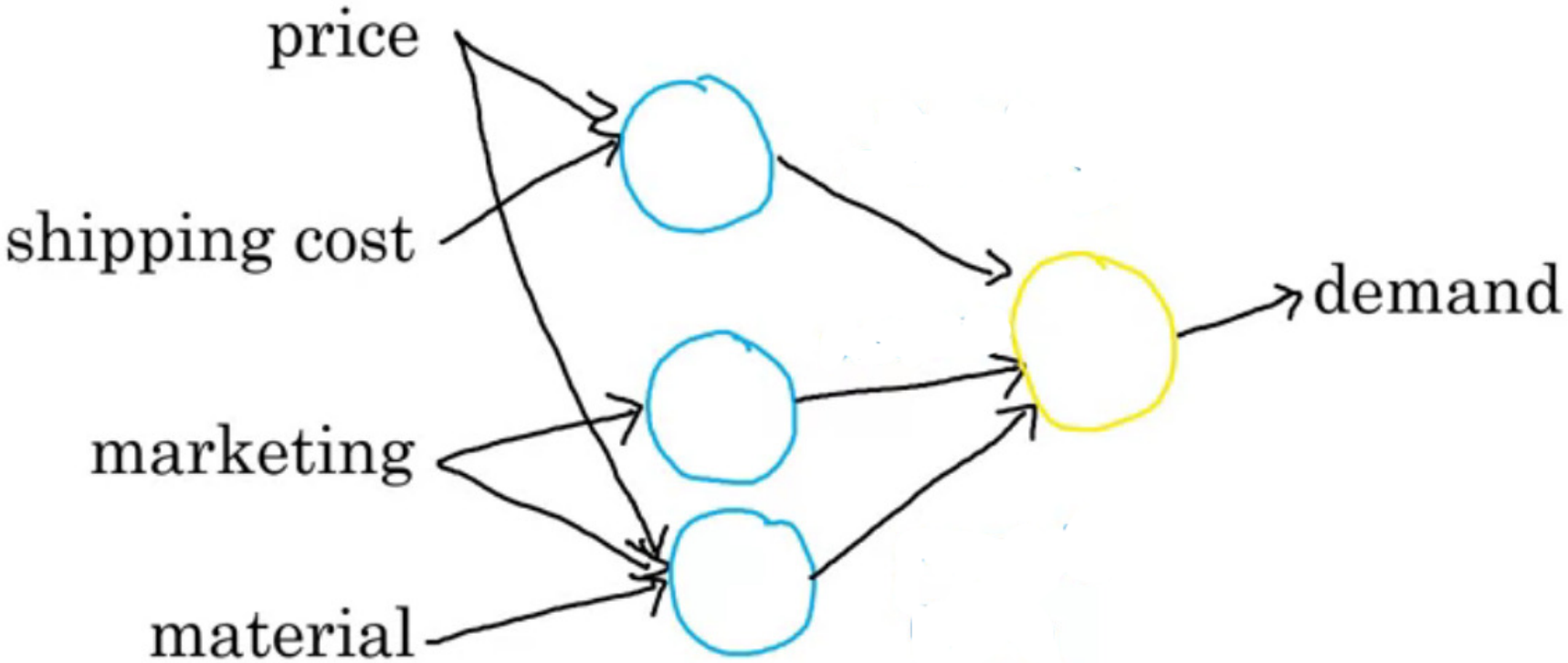
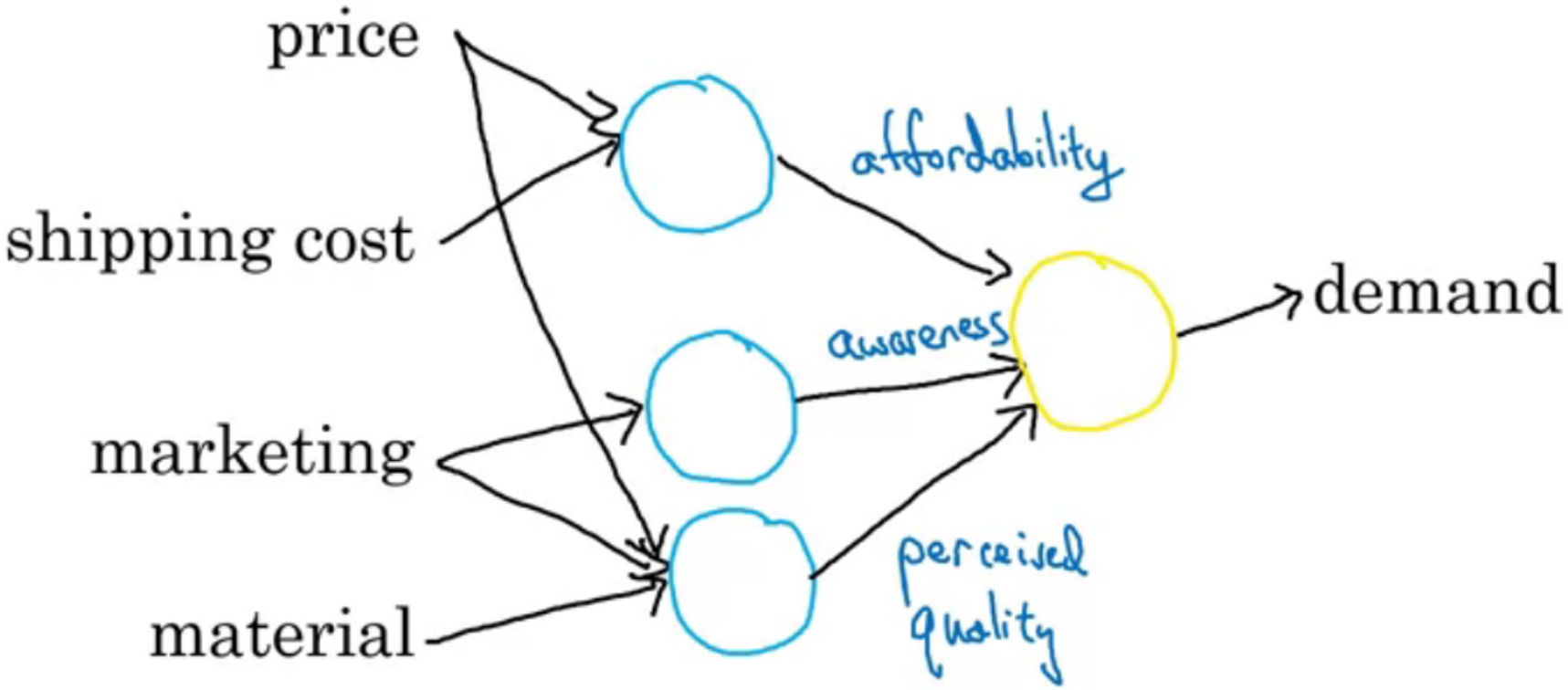




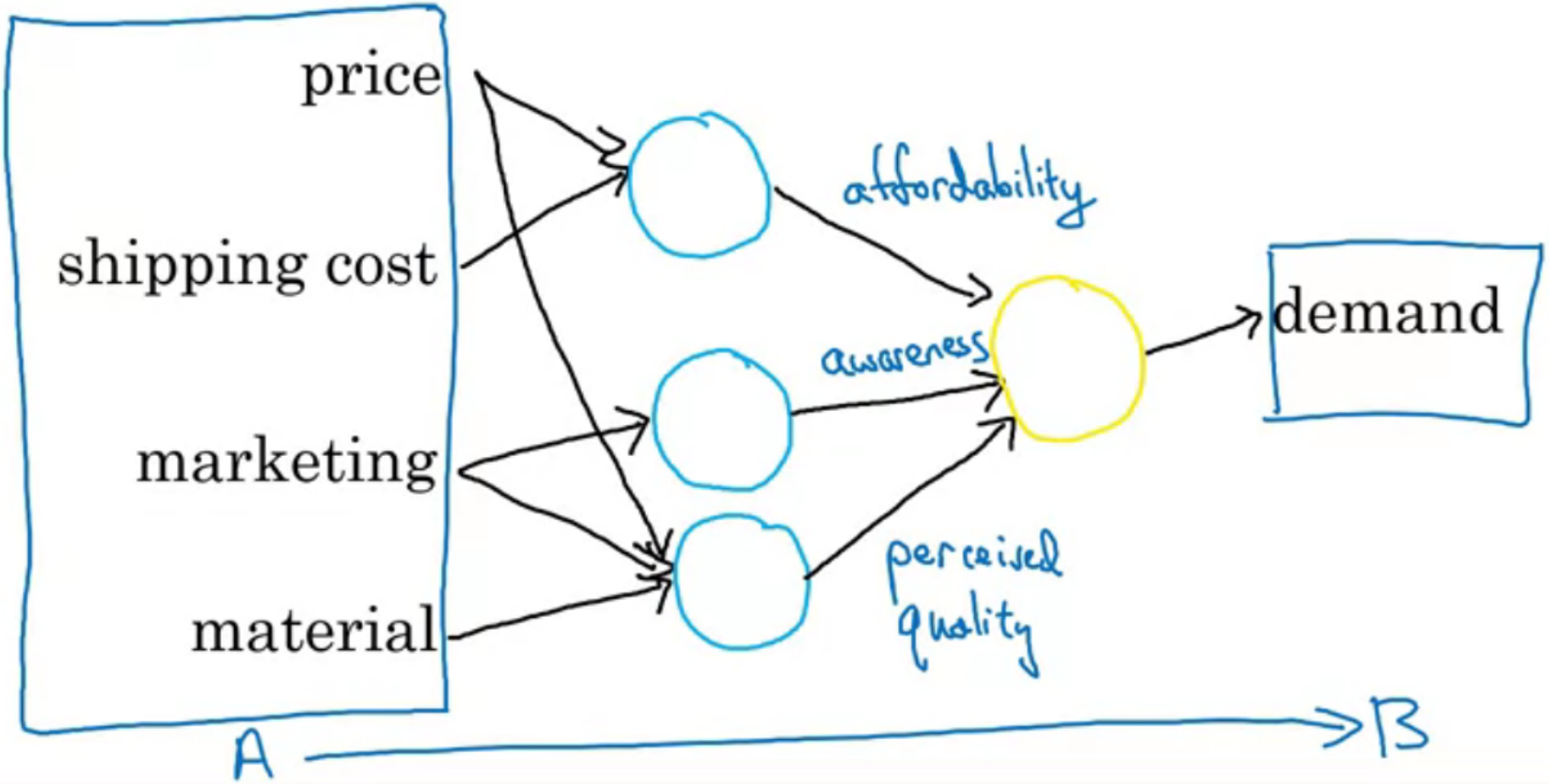
Demand prediction: a little bit more complex (1/4)



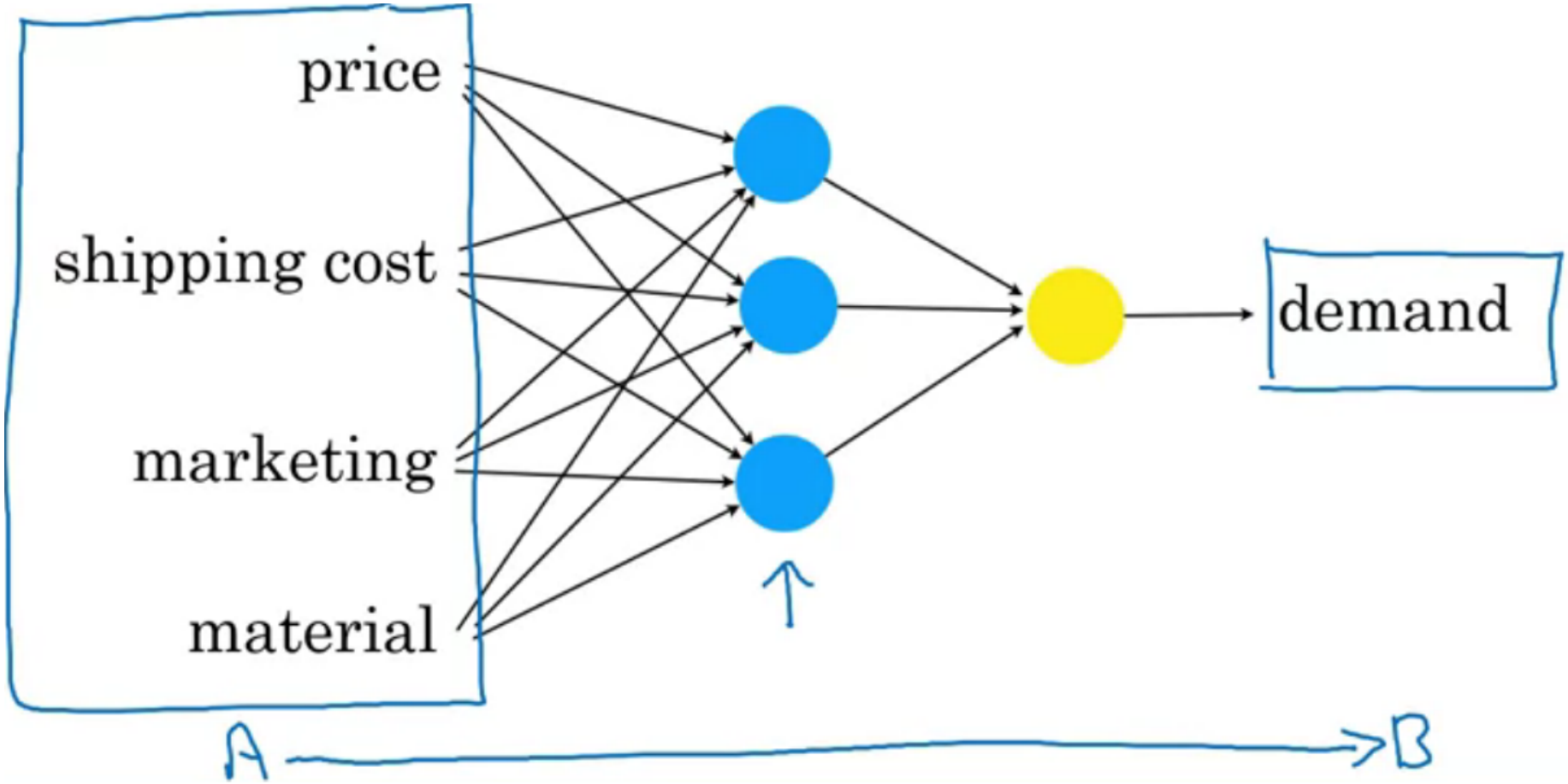
Demand prediction: a little bit more complex (2/4)



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

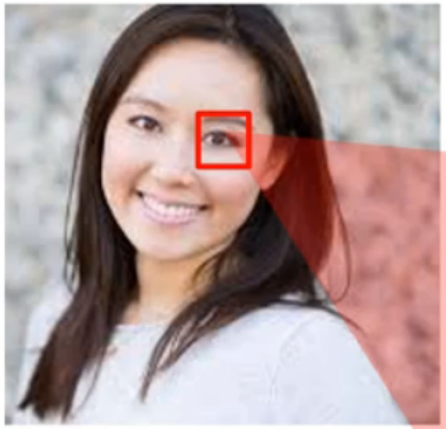


Demand prediction: a little bit more complex (4/4)



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)

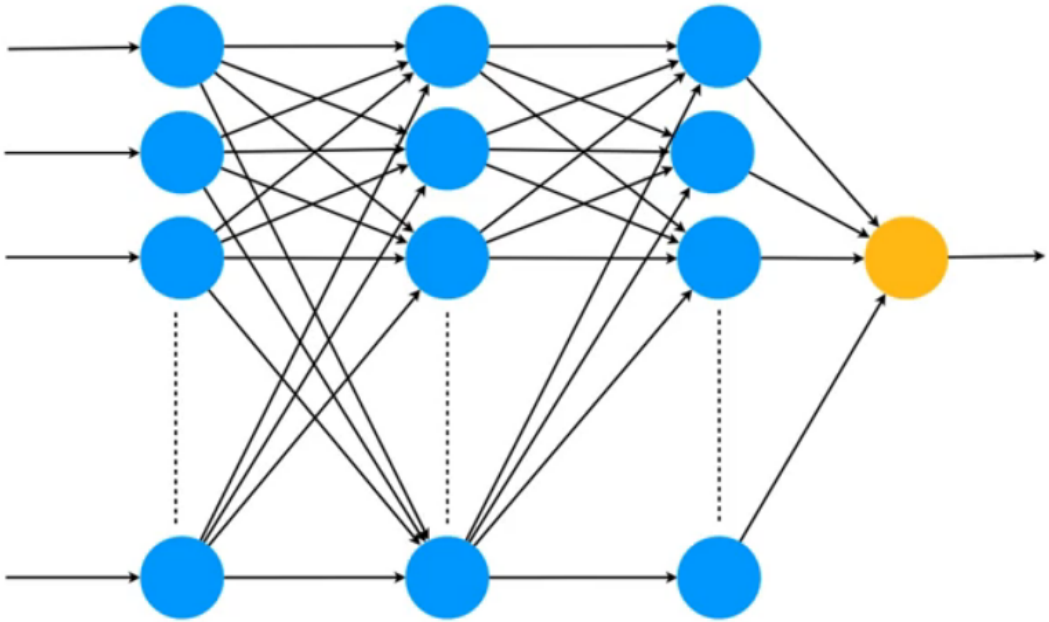
NN Application: Face recognition (2/3)

1000

1000

1,000,000

3,000,000



NN Application: Face recognition (3/3)

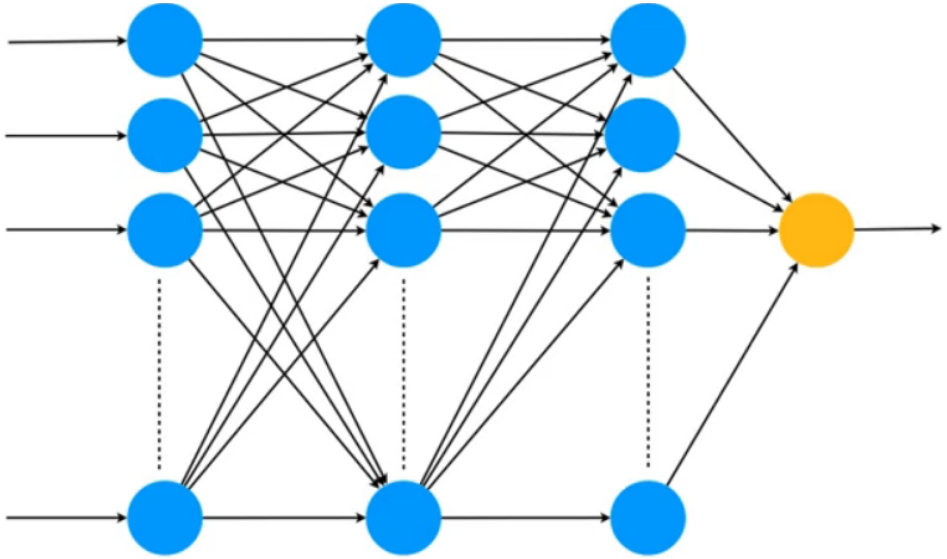
1000

1600

A

1,000,000

3,000,000



B

How Does a Neural Network Learn?

Watch **a Demo** by Phiresky (2017).

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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:

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Can I return it?

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

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?

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

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)**
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 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

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

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

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	**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

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

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ML tends to work poorly when:

1. Learning complex concepts from small amounts of data

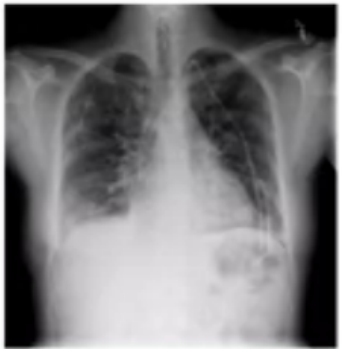
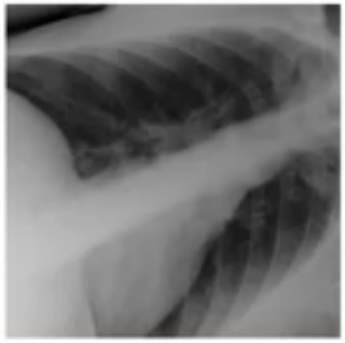
Strengths and weaknesses of machine learning

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

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

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

- Supervised Learning,
- Unsupervised Learning.

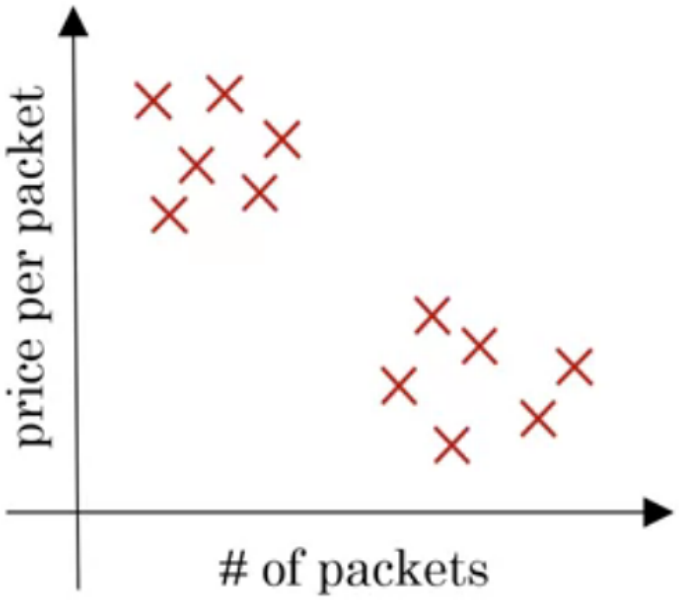
Machine Learning

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

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

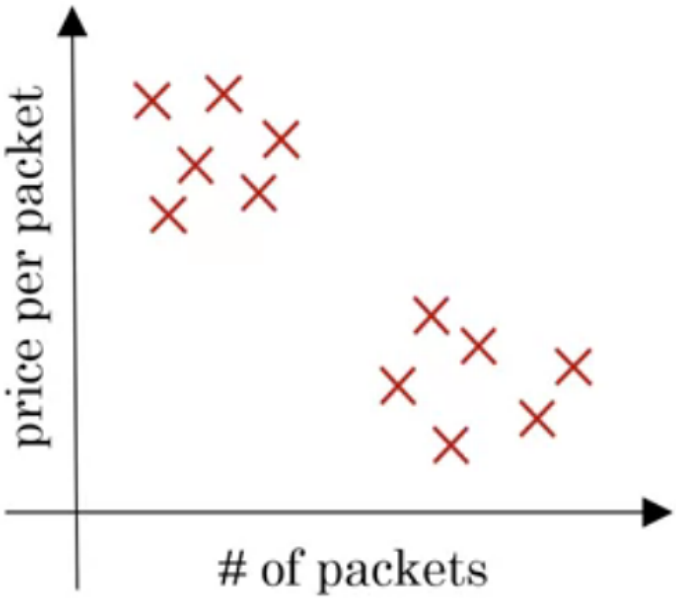
Unsupervised learning (1/2)

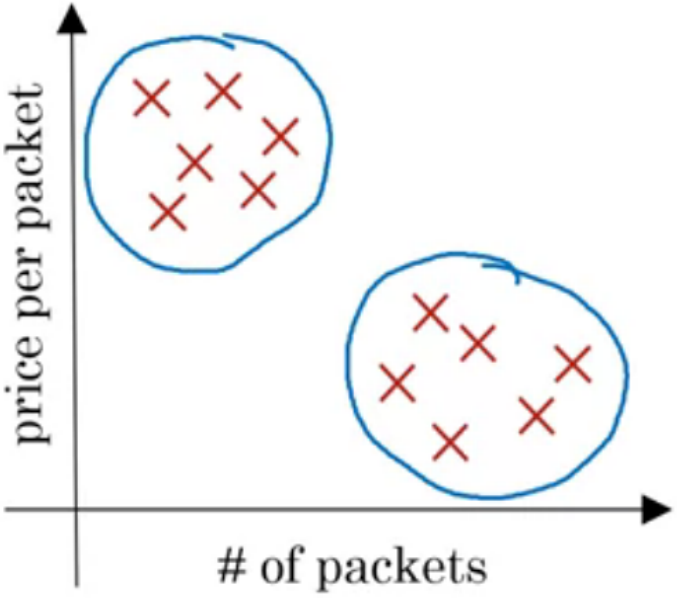
Clustering potato chip sales



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. Motivasi AI
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7. Future of AI: Generative AI

Mata Kuliah-Mata Kuliah Jalur Peminatan *AI Specialist*

1. *Computer Vision*
2. *Natural Language Processing*
3. *AI Computing Platform*

Computer Vision (1/7)

- Image classification/Object recognition

cat

Computer Vision (2/7)

- Face verification & face identification

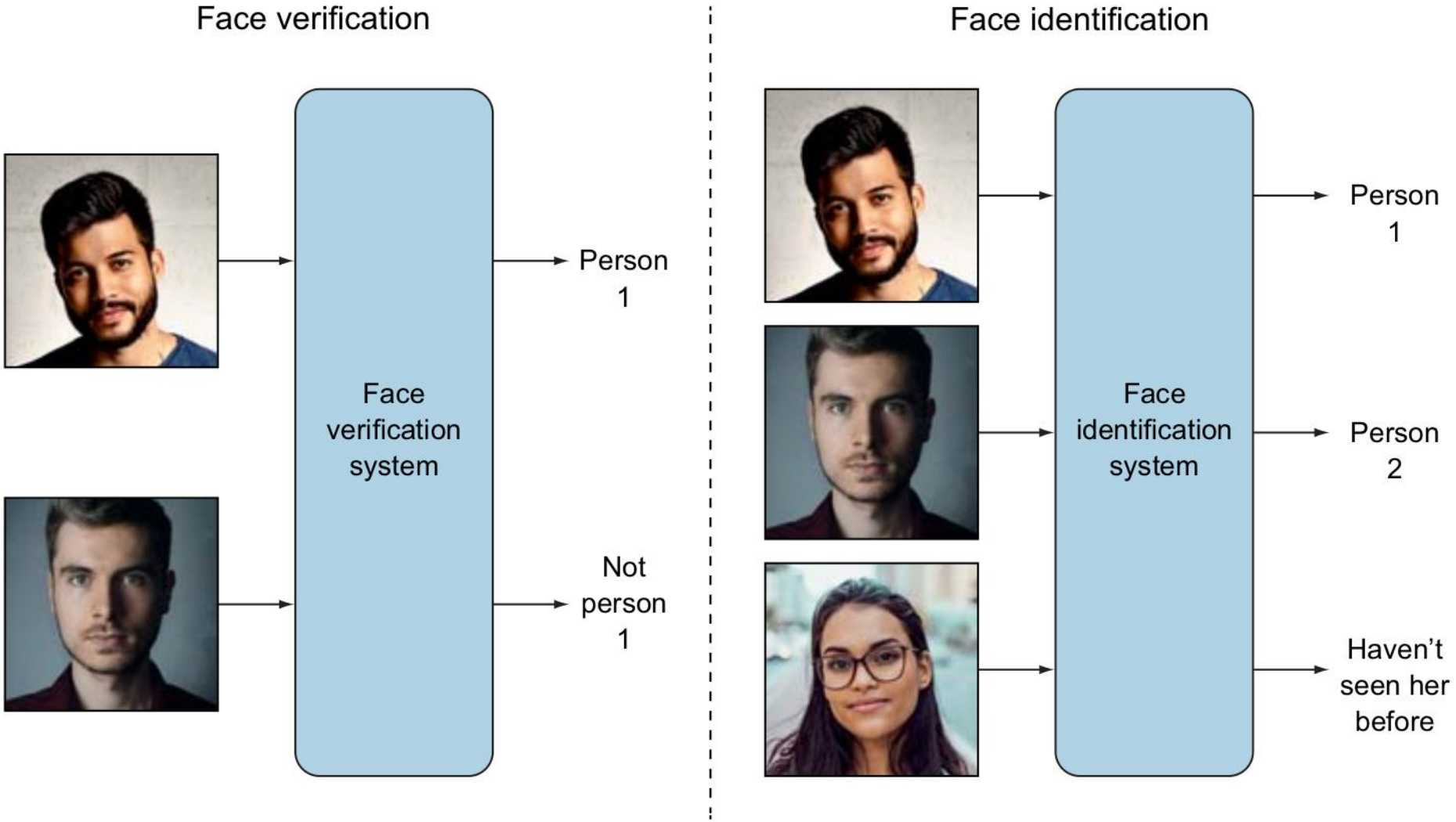


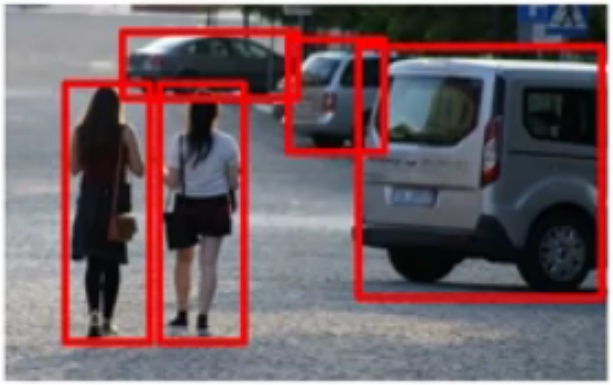
Figure 9: Example of face verification (left) and face recognition (right) (Elgendy, 2020)

Computer Vision (3/7)

- Object detection

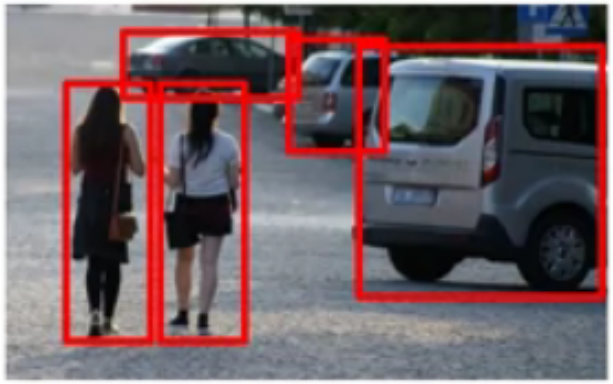
Computer Vision (3/7)

- Object detection



Computer Vision (3/7)

- Object detection



Computer Vision (4/7)

- 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 Goghs The Starry Night onto the original image (Elgendy, 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 (Elgendy, 2020)

Computer Vision (7/7)

- Image recommendation system

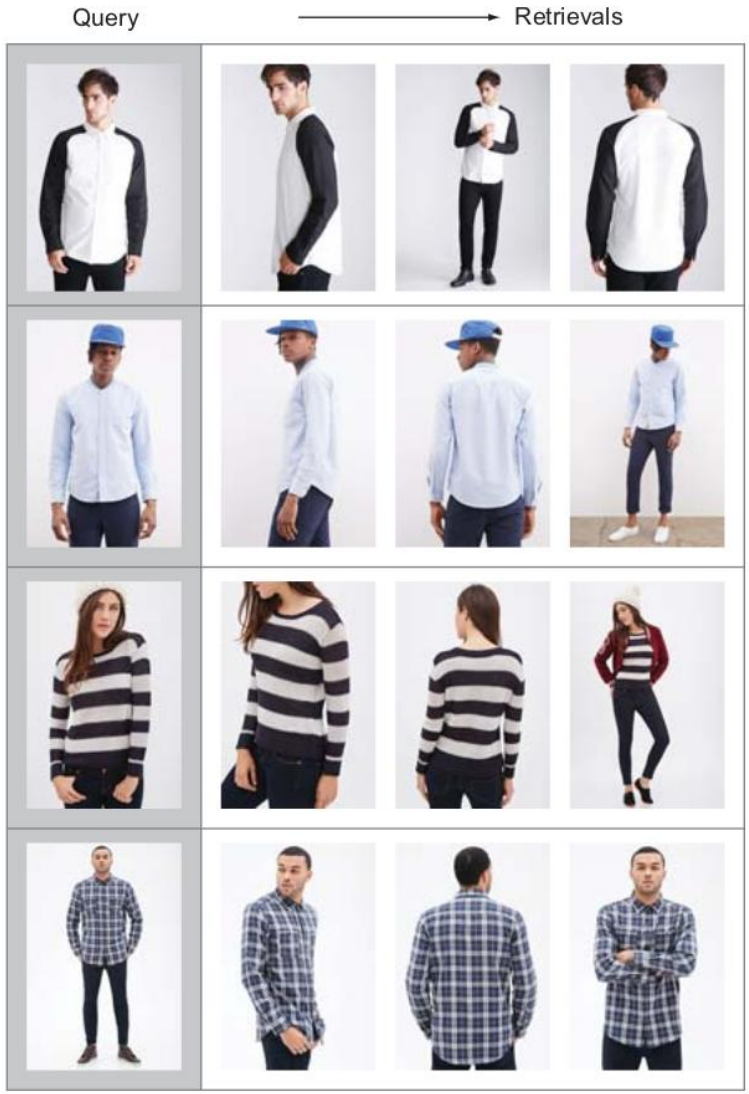
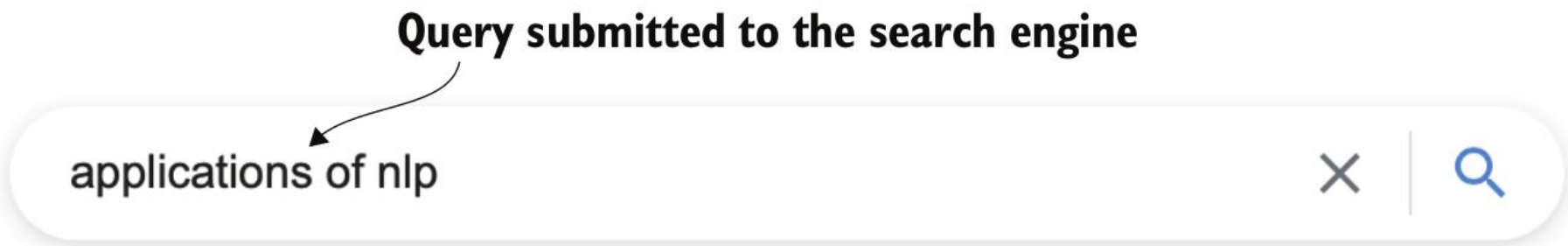


Figure 12: Apparel search (Elgendy, 2020)

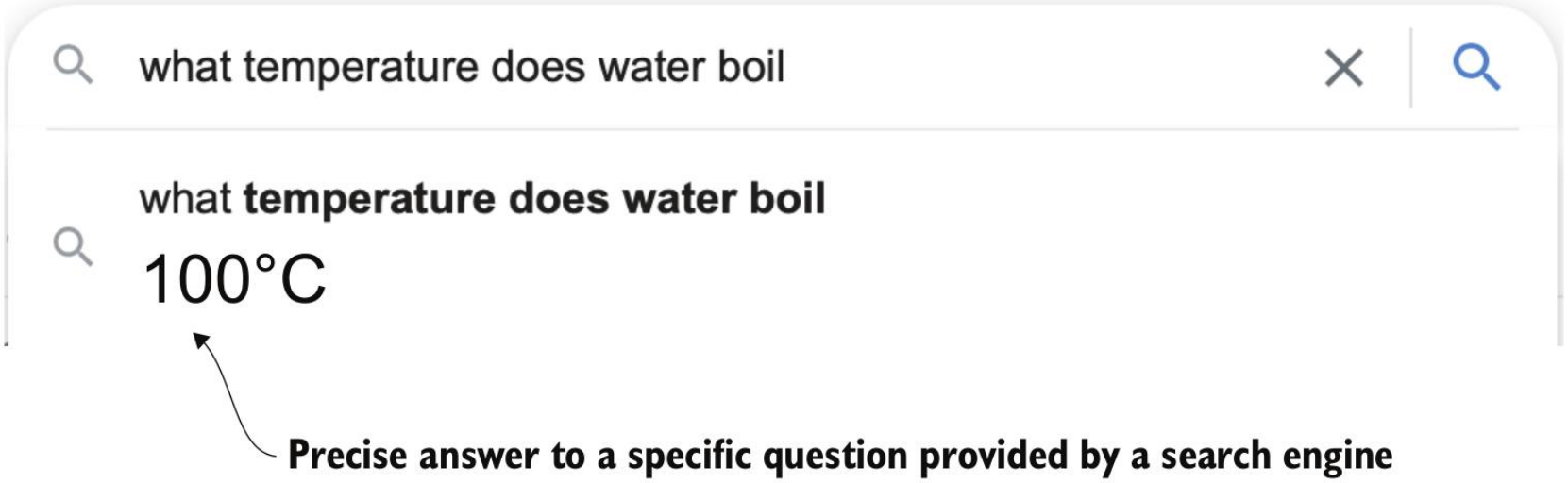
Natural Language Processing (1/8)

- Information search atau information retrieval (Kochmar, 2022)

Contoh 1:

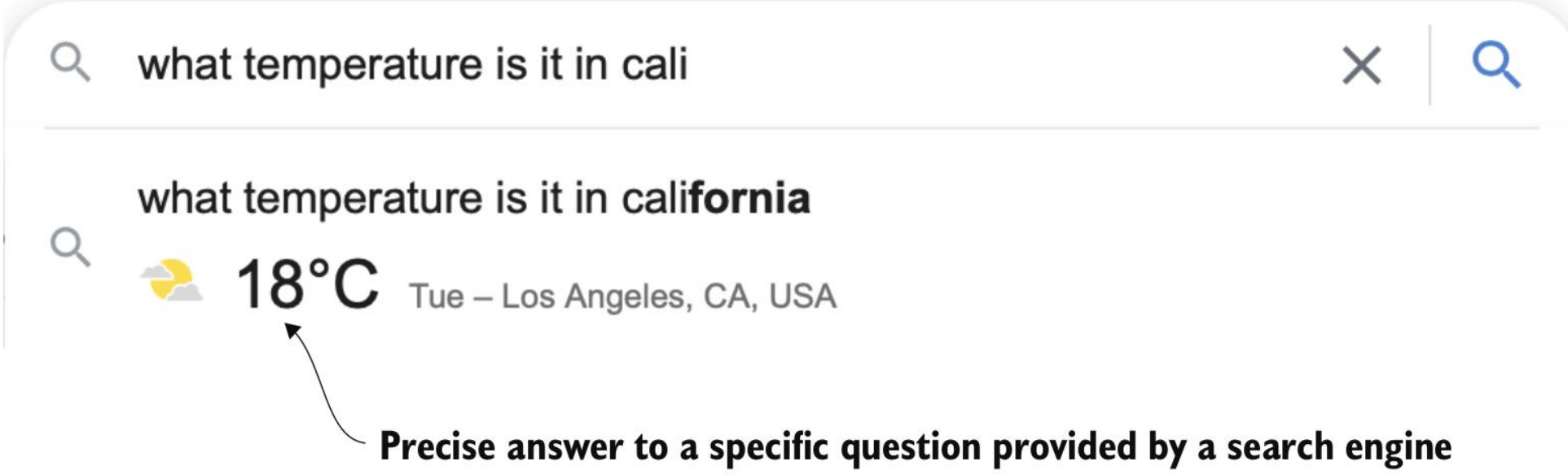


Contoh 2:



Natural Language Processing (2/8)

- Advanced information search: Asking the machine precise questions



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

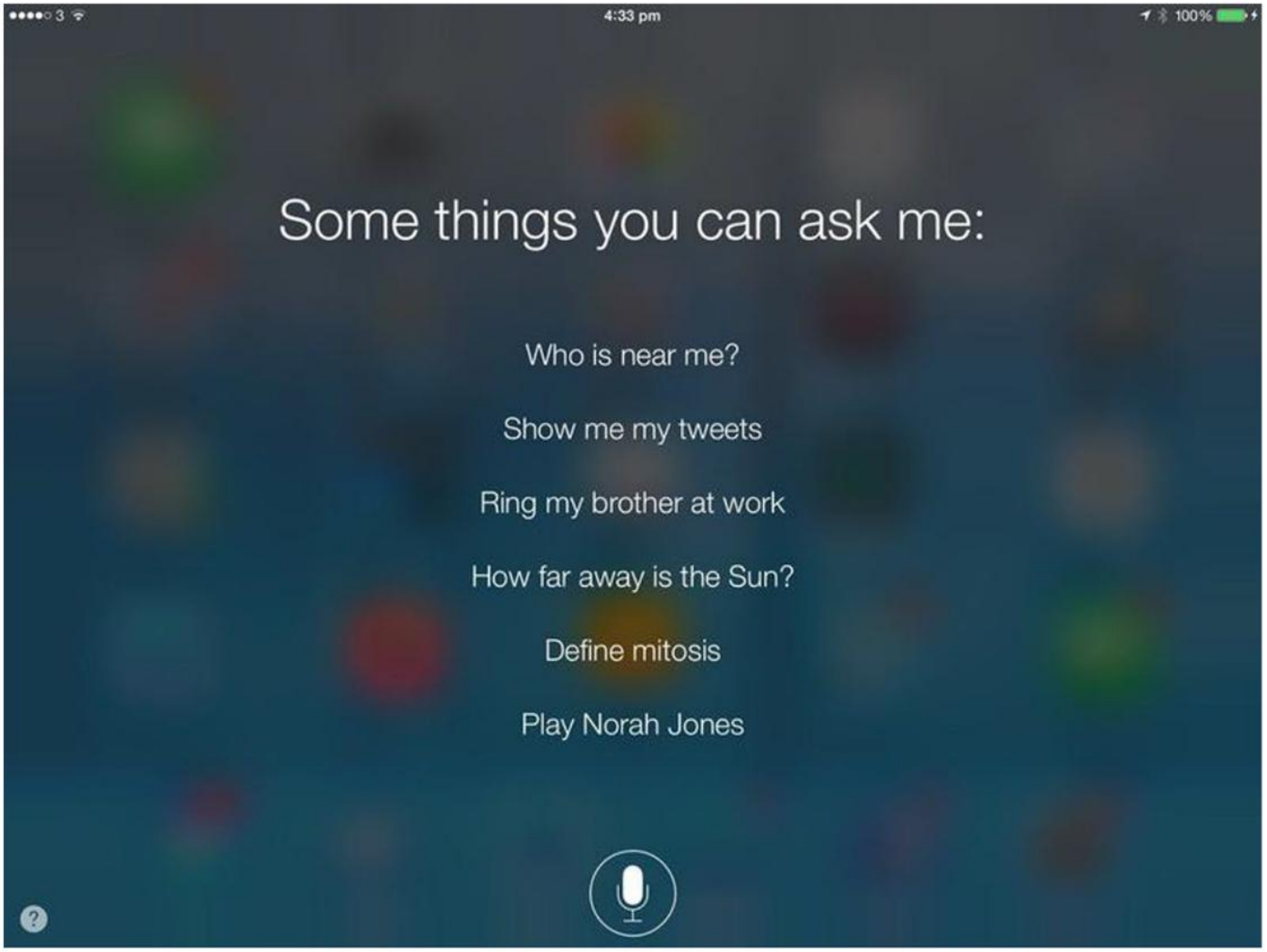
A liquid at high pressure has a higher boiling point than when that liquid is at atmospheric pressure. For example, water boils at 100 °C (212 °F) at sea level, but at 93.4 °C (200.1 °F) at 1,905 metres (6,250 ft) altitude. For a given pressure, different liquids will boil at different temperatures.

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

Boiling point - Wikipedia

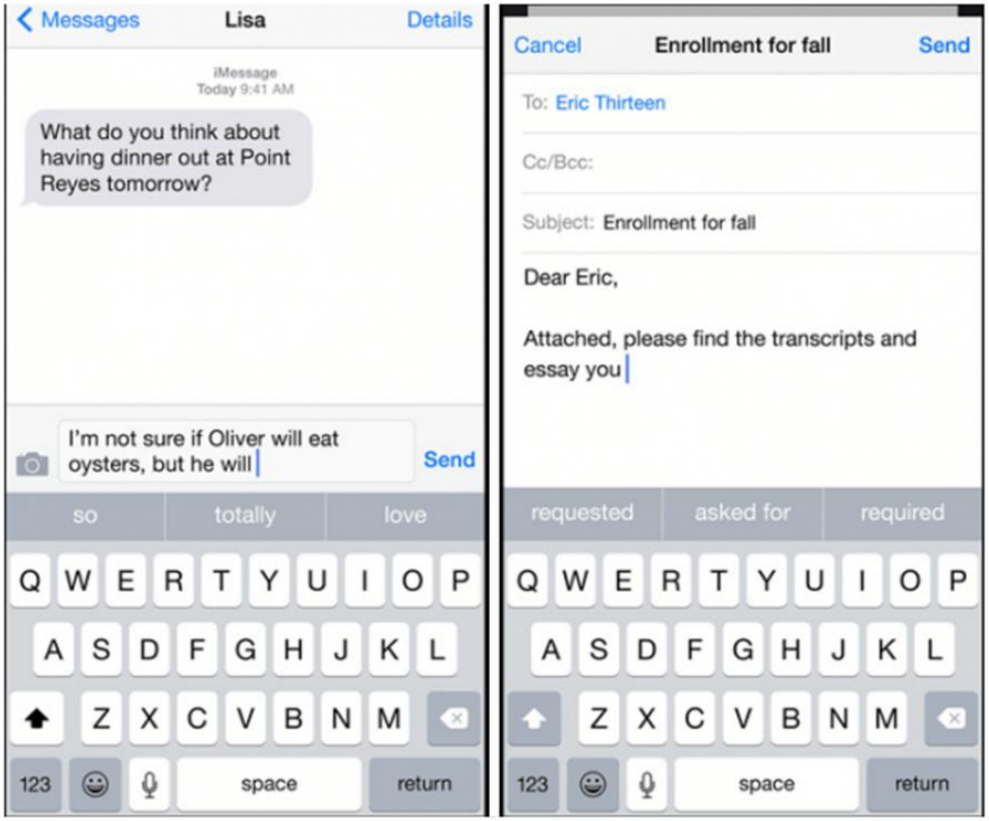
Natural Language Processing (4/8)

- Conversational agents dan intelligent virtual assistants



Natural Language Processing (5/8)

- Text prediction dan language generation



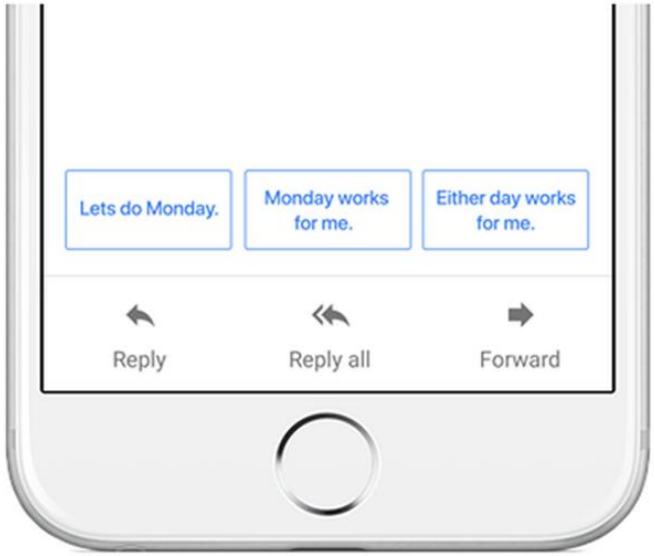


Figure 13: On the right: Google's Smart Reply for emails

Natural Language Processing (6/8)

- Text Classification

Natural Language Processing (6/8)

- Text Classification
  - Sentiment recognition

Natural Language Processing (6/8)

- Text Classification
  - Sentiment recognition

    "The food was good" $\longrightarrow$

Natural Language Processing (6/8)

- Text Classification
  - Sentiment recognition

"The food was good" $\longrightarrow$ ★★★★

"Service was horrible" $\longrightarrow$ ★

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  - Spam/Hoax filtering

Natural Language Processing (6/8)

- Text Classification
  - Sentiment recognition

    "The food was good" $\longrightarrow$ ★★★★

    "Service was horrible" $\longrightarrow$ ★

  - Spam/Hoax filtering
  - News article classification into: politics, business, sports, and so on.

- **Machine translation**
  Contoh 1:
  "AI adalah listrik baru" $\Longrightarrow$ "AI is new electricity"

  Contoh 2:

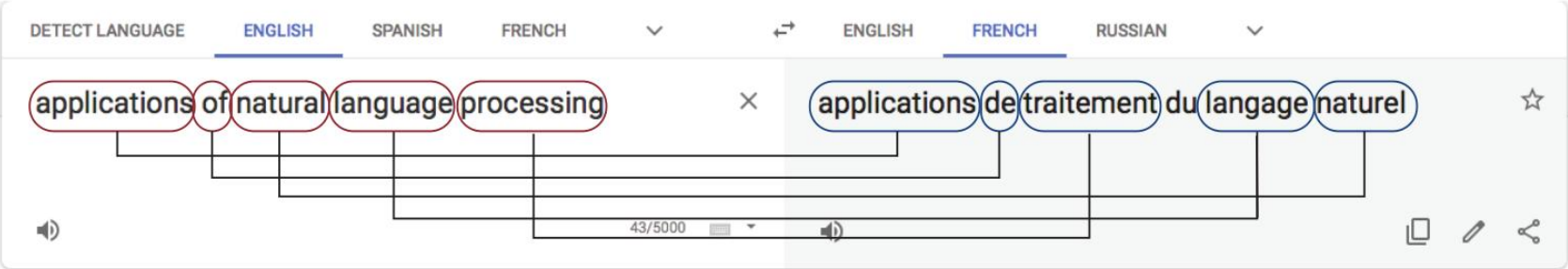


Figure 14: Phrase translation between English and French

Natural Language Processing (8/8)

- **Spell dan grammar checking**

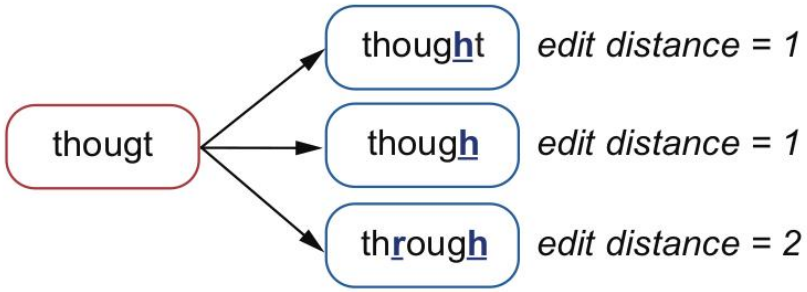


Figure 15: Possible corrections for the misspelling *thougt*

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 $\longrightarrow$ "Hey device"? (0/1)

NLP: Speech (2/2)

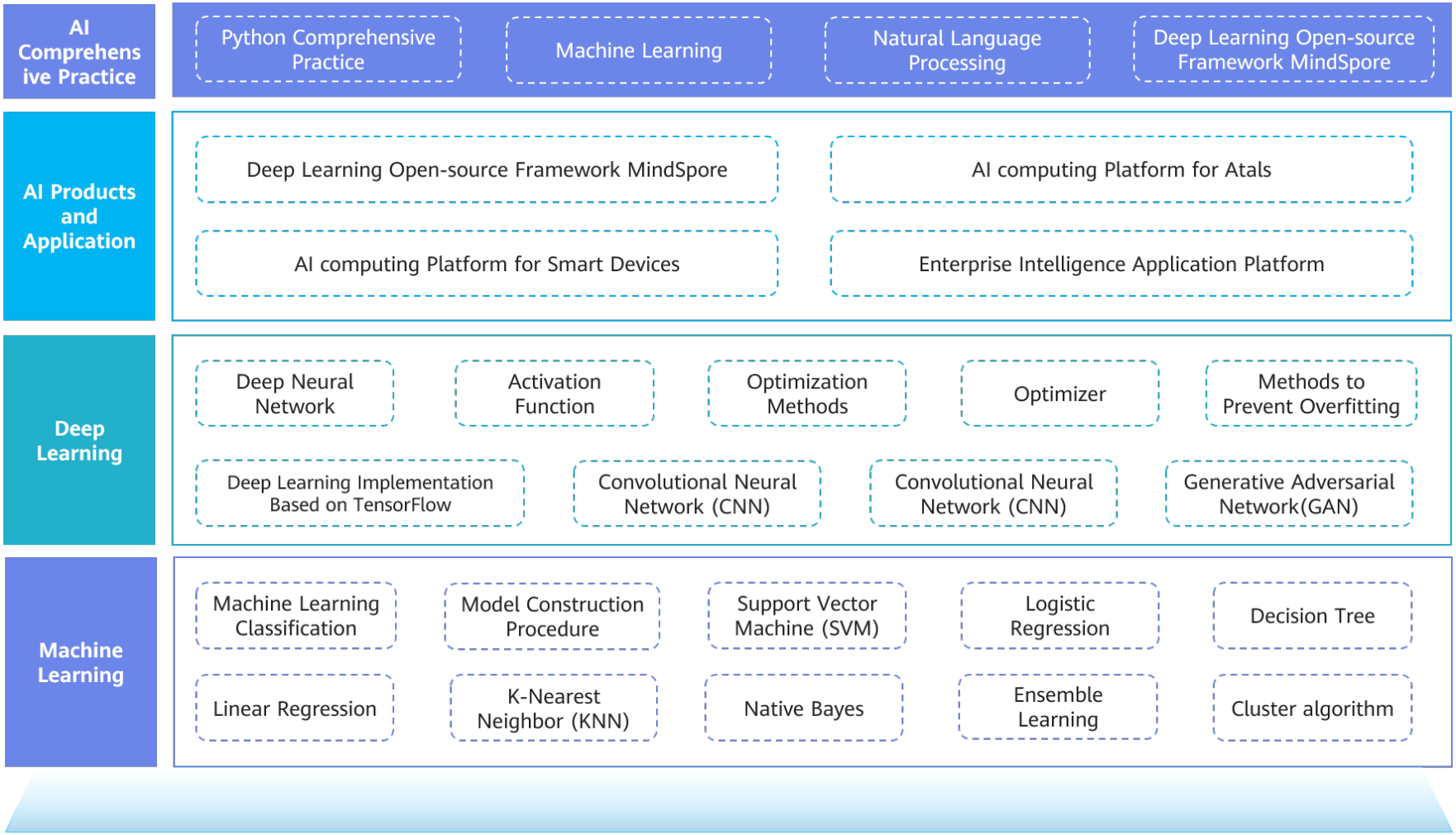
- Speaker ID

NLP: Speech (2/2)

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

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

AI Computing Platform



Link Video: **here**

Huawei HCIA-AI certification : ~~$200~~ **$0**.

Outline

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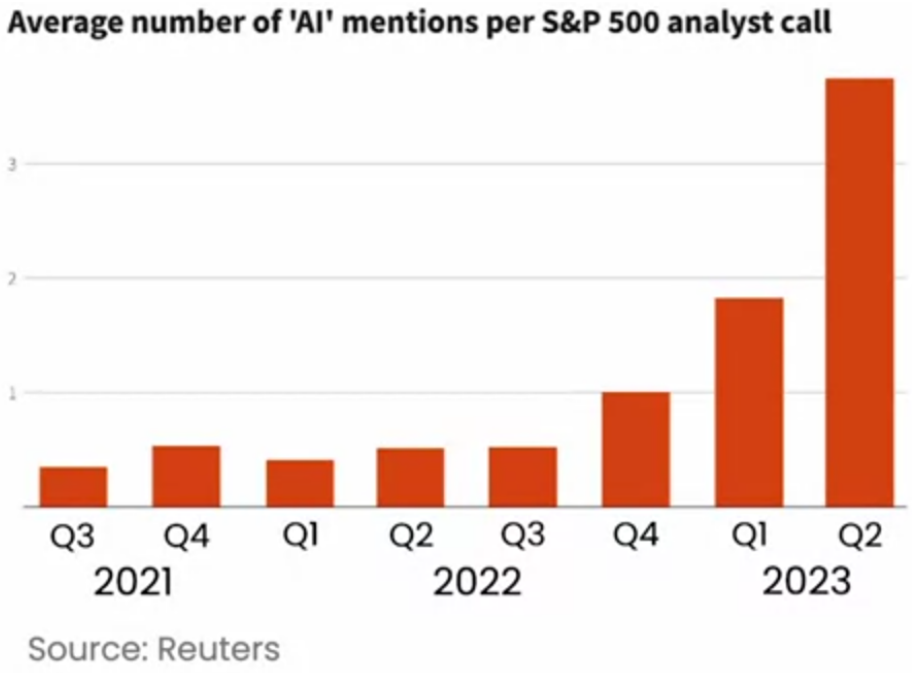
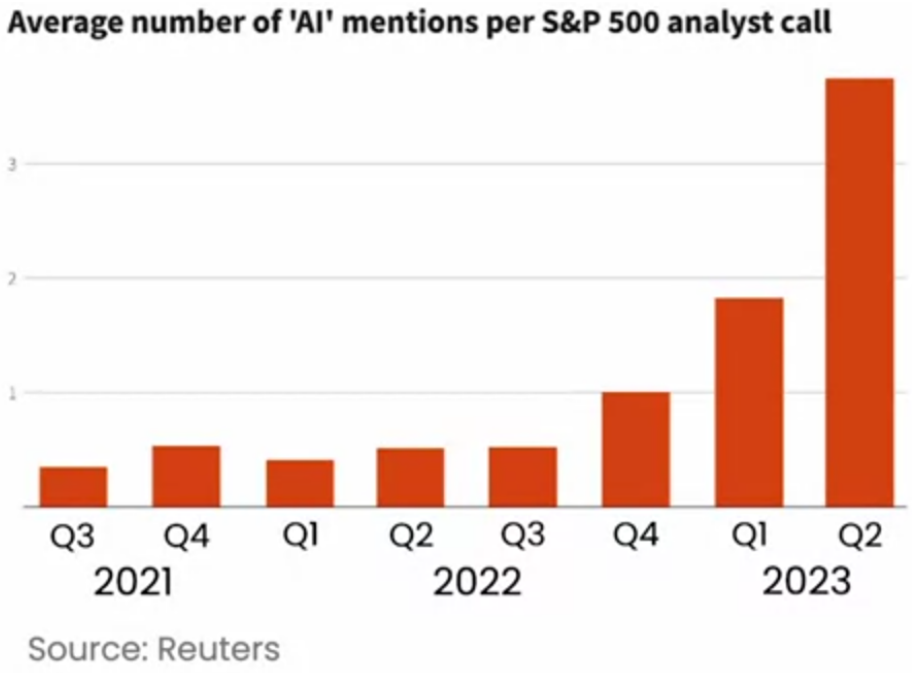
5. What Machine Learning Can and Cannot Do
6. Jalur Peminatan AI: Becoming AI Specialist
7. Future of AI: Generative AI

Kebangkitan Generative AI

Generative AI dapat



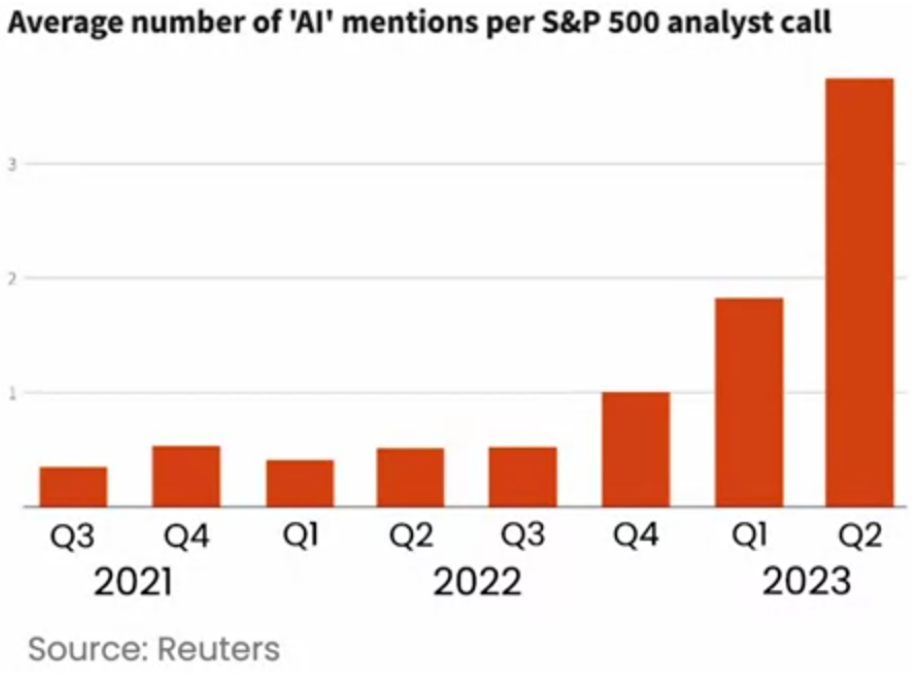
Kebangkitan Generative AI



Generative AI dapat

- Menambah $2,6-$4,4 triliun per tahun ke bidang ekonomi (McKinsey, 2023).

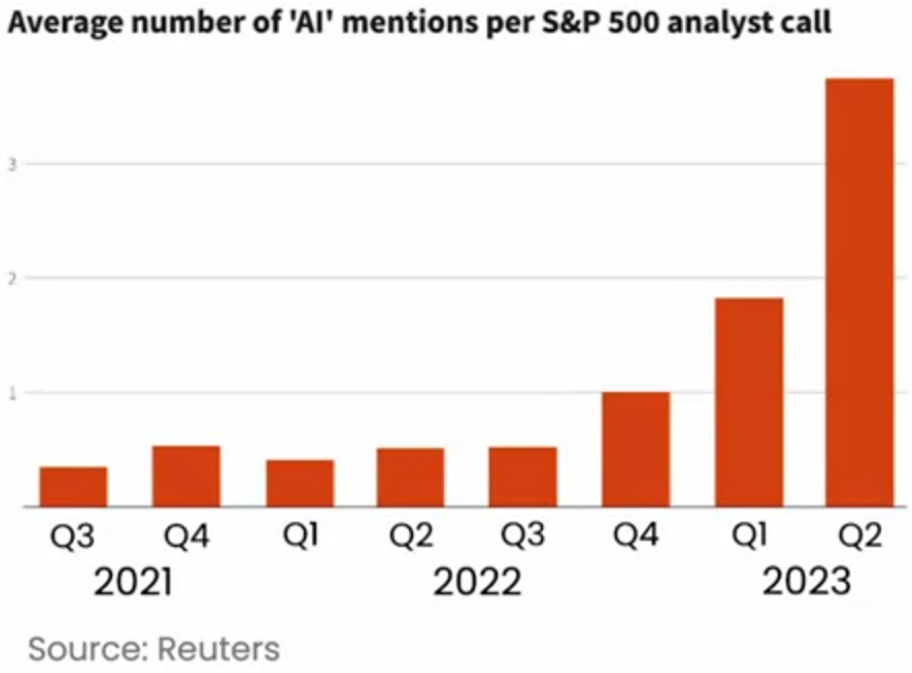
Kebangkitan Generative AI



Generative AI dapat

- Menambah $2,6-$4,4 triliun per tahun ke bidang ekonomi (McKinsey, 2023).
- Meningkatkan global GDP sebesar 7% pada 10 tahun ke depan (Goldman Sachs, 2023).

Kebangkitan Generative AI



Generative AI dapat

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- Meningkatkan global GDP sebesar 7% pada 10 tahun ke depan (Goldman Sachs, 2023).
- Berdampak 10% dari tasks yang dikerjakan harian oleh 80% dari pegawai (Eloundou et al., 2023).

Apakah Generative AI? (1/2)

Sistem Artificial Intelligence yang dapat menghasilkan high quality content, terutama untuk **text**, gambar (**images**), dan suara (**audio**).

Beberapa contoh Generative AI adalah

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- Bard dari Google

Apakah Generative AI? (1/2)

Sistem Artificial Intelligence yang dapat menghasilkan high quality content, terutama untuk **text**, gambar (**images**), dan suara (**audio**).

Beberapa contoh Generative AI adalah

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- Bard dari Google
- Bing Chat dari Microsoft

Apakah Generative AI? (1/2)

Sistem Artificial Intelligence yang dapat menghasilkan high quality content, terutama untuk **text**, gambar (**images**), dan suara (**audio**).

Beberapa contoh Generative AI adalah

- ChatGPT dari OpenAI
- Bard dari Google
- Bing Chat dari Microsoft

Prompt ⇒ pertanyaan yang meng-trigger Generative AI untuk me-respons.

Apakah Generative AI? (2/2)

Generative AI juga merupakan **developer tool** (Ng, 2023).

jupyter

Logout

File Edit View Insert Cell Kernel Help Not Trusted Python 3 (ipykernel)

Run Markdown

```
In [ ]: from langchain.chains import RetrievalQA
        from langchain.chat_models import ChatOpenAI
        from langchain.document_loaders import CSVLoader
        from langchain.vectorstores import DocArrayInMemorySearch
        from IPython.display import display, Markdown

In [ ]: file = 'OutdoorClothingCatalog_1000.csv'
        loader = CSVLoader(file_path=file)

In [ ]: from langchain.indexes import VectorstoreIndexCreator

In [ ]: #pip install docarray

In [ ]: index = VectorstoreIndexCreator(
            vectorstore_cls=DocArrayInMemorySearch
        ).from_loaders([loader])
```

Image, Audio, and Video Generation

A beautiful, pastoral mountain scene. Landscape painting style (**Midjourney**)

Image, Audio, and Video Generation

A beautiful, pastoral mountain scene. Landscape painting style (**Midjourney**)

Image, Audio, and Video Generation

A beautiful, pastoral mountain scene. Landscape painting style (**Midjourney**)

Two cute kittens playing (**DALL-E**)

Image, Audio, and Video Generation

A beautiful, pastoral mountain scene. Landscape painting style (**Midjourney**)

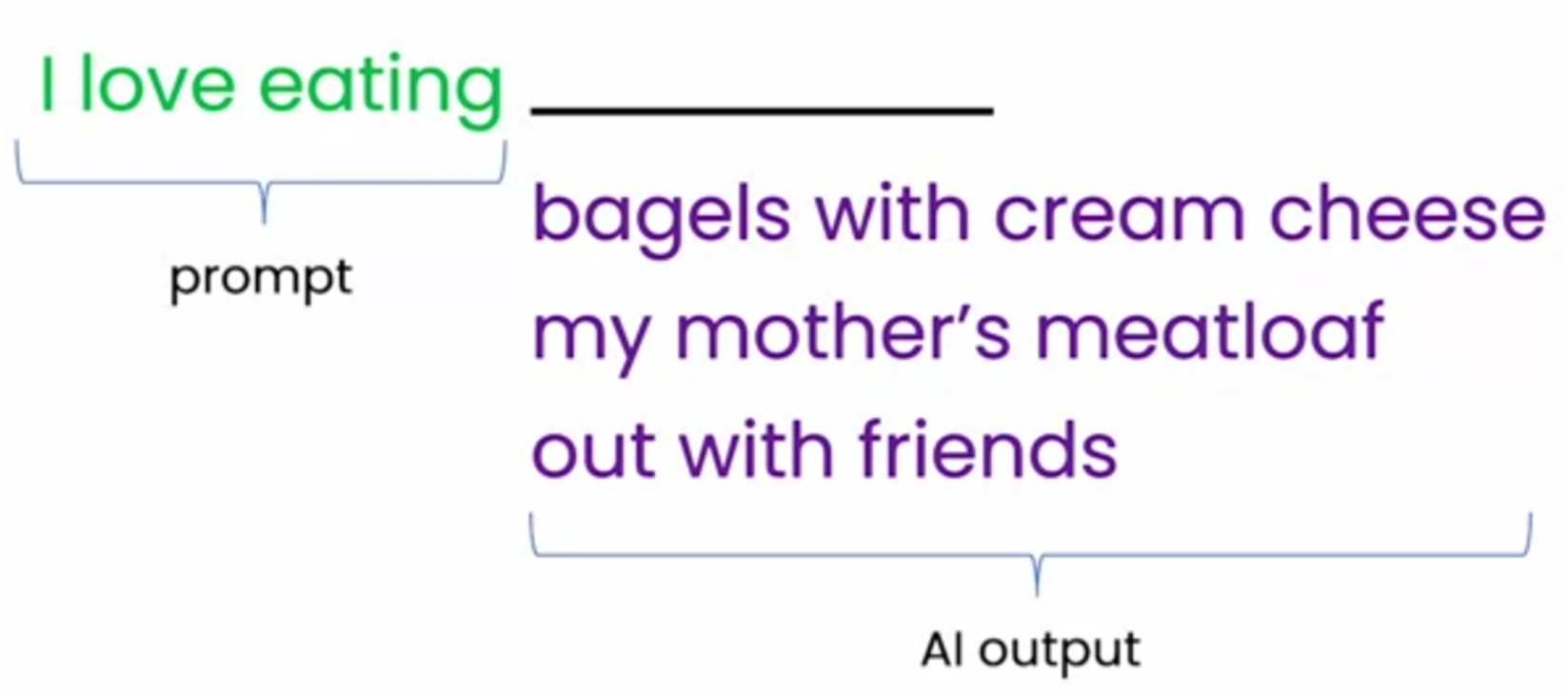
Two cute kittens playing (**DALL-E**)

Menghasilkan Teks dengan Large Language Models (LLMs)

Text generation process (Ng, 2023)

Menghasilkan Teks dengan Large Language Models (LLMs)

Text generation process (Ng, 2023)



Bagaimana LLMs belajar

LLMs dibuat dengan menggunakan supervised learning ($A \rightarrow B$) untuk memprediksi kata berikut secara berulang kali.

Bagaimana LLMs belajar

LLMs dibuat dengan menggunakan supervised learning ($A \rightarrow B$) untuk memprediksi kata berikut secara berulang kali.

My favorite food is a bagel with cream cheese

Input (A)	Output (B)
My favorite food is a	bagel
My favorite food is a bagel	with
My favorite food is a bagel with	cream
My favorite food is a bagel with cream	cheese

Bagaimana LLMs belajar

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My favorite food is a bagel with	cream
My favorite food is a bagel with cream	cheese

Ketika kita melatih sistem AI yang sangat besar pada a lot of data (ratusan miliar kata), kita memperoleh Large Language Model seperti ChatGPT.

Cara Baru Mencari Informasi

Cara Baru Mencari Informasi

What is the capital of South Africa?

South Africa has three capital cities:

1. Pretoria (administrative capital)
2. Cape Town (legislative capital)
3. Bloemfontein (judicial capital)

Cara Baru Mencari Informasi

What is the capital of South Africa?

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2. Cape Town (legislative capital)
3. Bloemfontein (judicial capital)

What does LLM stand for?

LL.M. stands for "Legum Magister" in Latin, which translates to "Master of Laws" in English.

What about in the context of AI?

In the context of AI, LLM refers to "Large Language Model".

Partner Menulis (Ng, 2023)

Partner Menulis (Ng, 2023)

Rewrite this for clarity:

Students all around the world are realizing learning has to happen not just in school but throughout life including after graduation.

Students worldwide understand that learning extends beyond school and continues throughout life.

Partner Menulis (Ng, 2023)

Rewrite this for clarity:

Students all around the world are realizing learning has to happen not just in school but throughout life including after graduation.

Students worldwide understand that learning extends beyond school and continues throughout life.

Write a 300 word story involving trucks for a 3 year old to encourage them to brush their teeth.

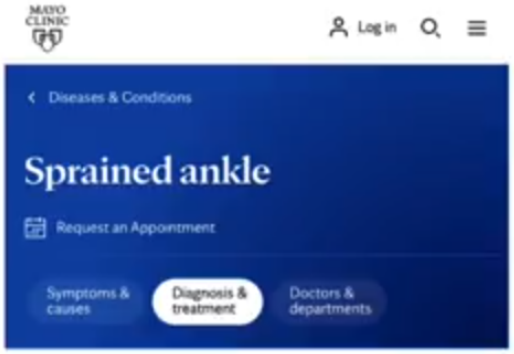
Once upon a time in a town called Toothville, there lived a happy tow truck named Timmy.

One day Timmy noticed that his shiny bumper had a dull spot. Worried, he went to the doctor [...]

Web search atau using an LLM (Ng, 2023)

Web search atau using an LLM (Ng, 2023)

What should I do to treat a sprained ankle?



Diagnosis

During a physical, your doctor will examine your ankle, foot and lower leg. The doctor will touch the skin around the injury to check for points of tenderness and move your foot to check the range of motion and to understand what positions cause discomfort or pain.

If the injury is severe, your doctor may recommend one or more of the following imaging scans to rule out a broken bone or to evaluate in more detail the extent of ligament damage:

Mayo Clinic

PAIN

Recovering from an ankle sprain

June 21, 2021

All it takes is a simple misstep, and suddenly you have a sprained ankle. An ankle sprain is one of the most common musculoskeletal injuries in people of all ages, athletes and couch potatoes alike. The injury occurs when one or more

Harvard Medical School

Web search atau using an LLM (Ng, 2023)

What should I do to treat a sprained ankle?

MAYO CLINIC

Log in

Diseases & Conditions

Sprained ankle

Request an Appointment

Symptoms & causes | Diagnosis & treatment | Doctors & departments

Diagnosis

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Harvard Health Publishing
HARVARD MEDICAL SCHOOL

RECENT BLOG ARTICLES

Produce prescriptions may promote better heart health

1/10

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Harvard Medical School

What should I do to treat a sprained ankle?

I'm not a doctor, but if you believe you have a sprained ankle, the following general steps are often recommended:

- **Rest:** Avoid putting weight on the injured ankle
- **Ice:** Apply ice wrapped in cloth to injured area

[...]

Web search atau using an LLM (Ng, 2023)

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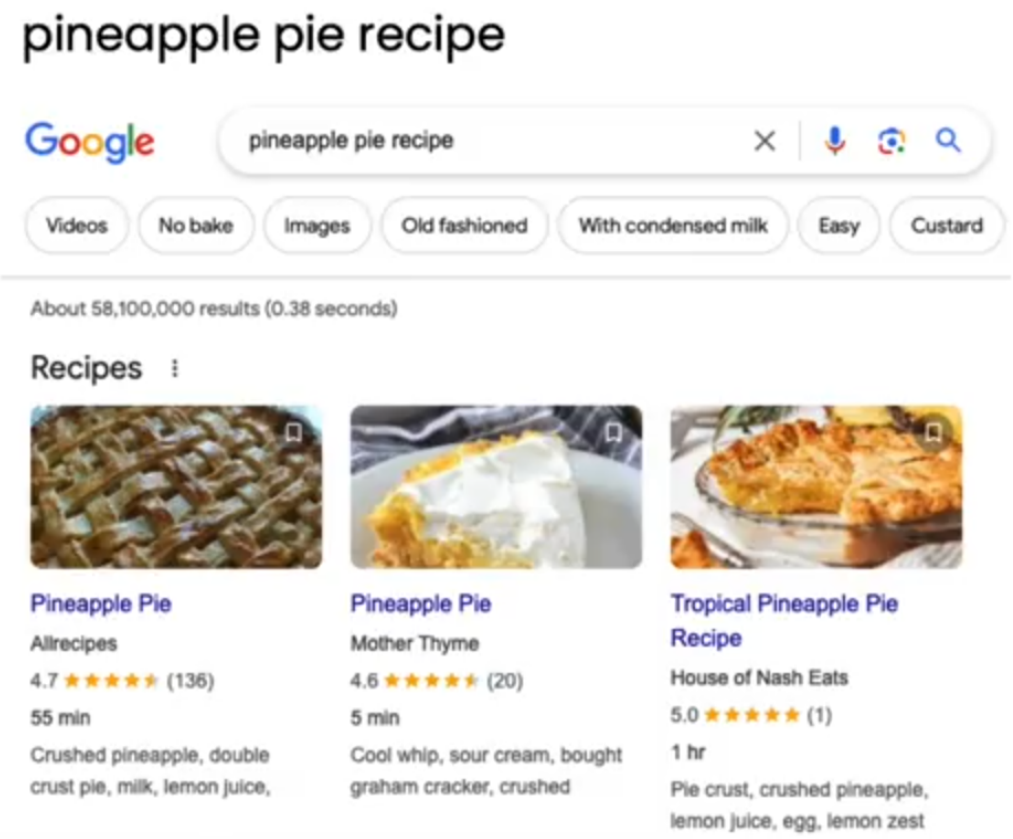

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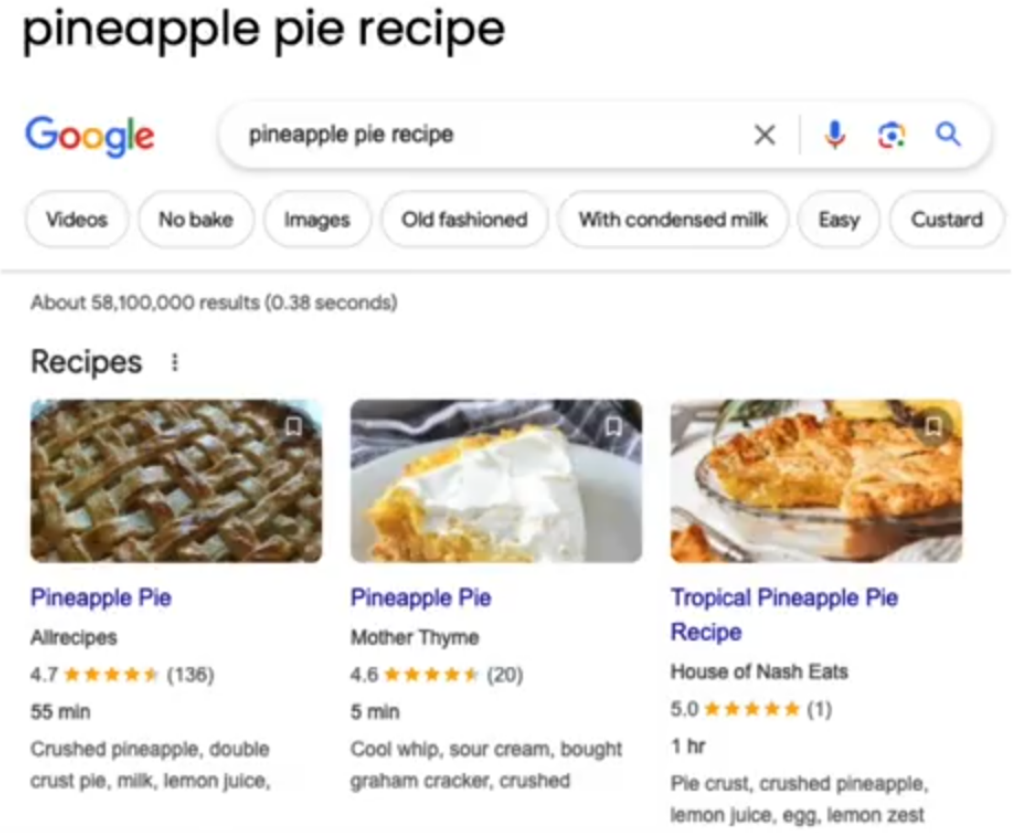

Give me a pineapple pie recipe

Certainly! Here's a simple pineapple pie recipe:

Ingredients:
1 prepared pie crust
2 cups of crushed pineapple (drained)
1 cup of granulated sugar
2 tablespoons cornstarch [...]

Web search atau using an LLM (Ng, 2023)

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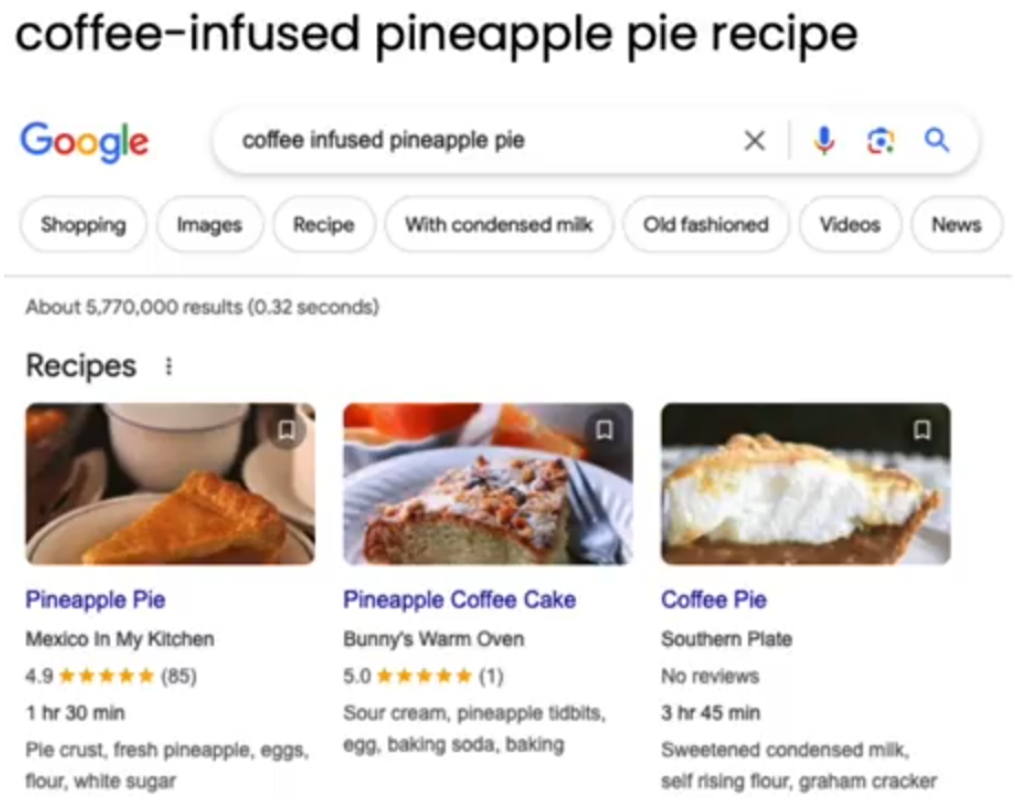

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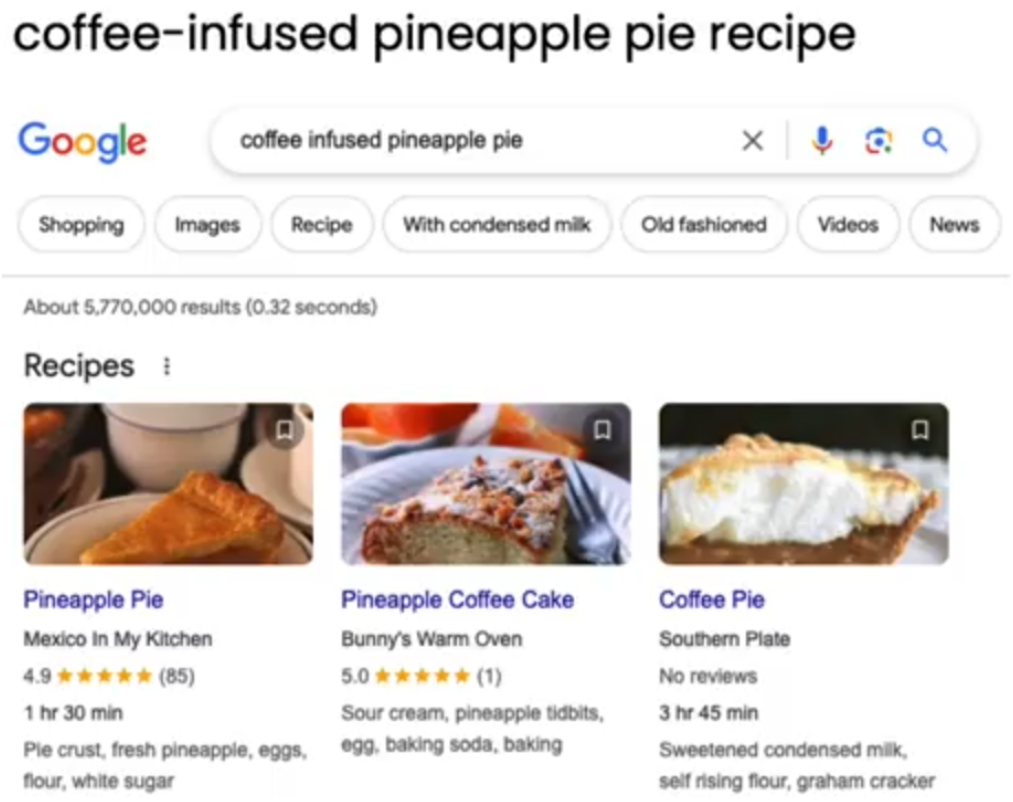

Give me a coffee-infused pineapple pie recipe

Sure! Here's a coffee-infused pineapple pie recipe:

Ingredients:
1 prepared pie crust
2 cups crushed pineapple (drained)
2 tablespoons strong brewed coffee
1 cup granulated sugar [...]

Contoh Tasks yang LLMs dapat Lakukan

Contoh Tasks yang LLMs dapat Lakukan

Writing

Suggest three names for our new analytics platform

Sure, here are three ideas:
1. NexaInsight
2. Quantivue
3. AnalytiSphere

Is there parking for staff?

Yes, employees can park on levels 1 and 2 of the office lot. You can get a sticker at [...].

Contoh Tasks yang LLMs dapat Lakukan

Writing	Reading
Suggest three names for our new analytics platform	*I love my new llama T-shirt! The fabric is so soft.*
Sure, here are three ideas: 1. NexaInsight 2. Quantivue 3. AnalytiSphere	Complaint: NO Department: Apparel
Is there parking for staff?	*I wore my llama T-shirt to a friend's wedding, and now they're mad at me for stealing the show.*
Yes, employees can park on levels 1 and 2 of the office lot. You can get a sticker at [...].	Complaint: YES Department: Apparel

Contoh Tasks yang LLMs dapat Lakukan

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Reading

I love my new llama T-shirt! The fabric is so soft.

Complaint: NO
Department: Apparel

I wore my llama T-shirt to a friend's wedding, and now they're mad at me for stealing the show.

Complaint: YES
Department: Apparel

Chatting

Welcome to BettaBurgers!

I'd like a cheeseburger for delivery!

Awesome. Anything else?

That's it thanks!

Ok, it'll be there in 20 minutes. Enjoy!

Contoh Tasks yang LLMs dapat Lakukan

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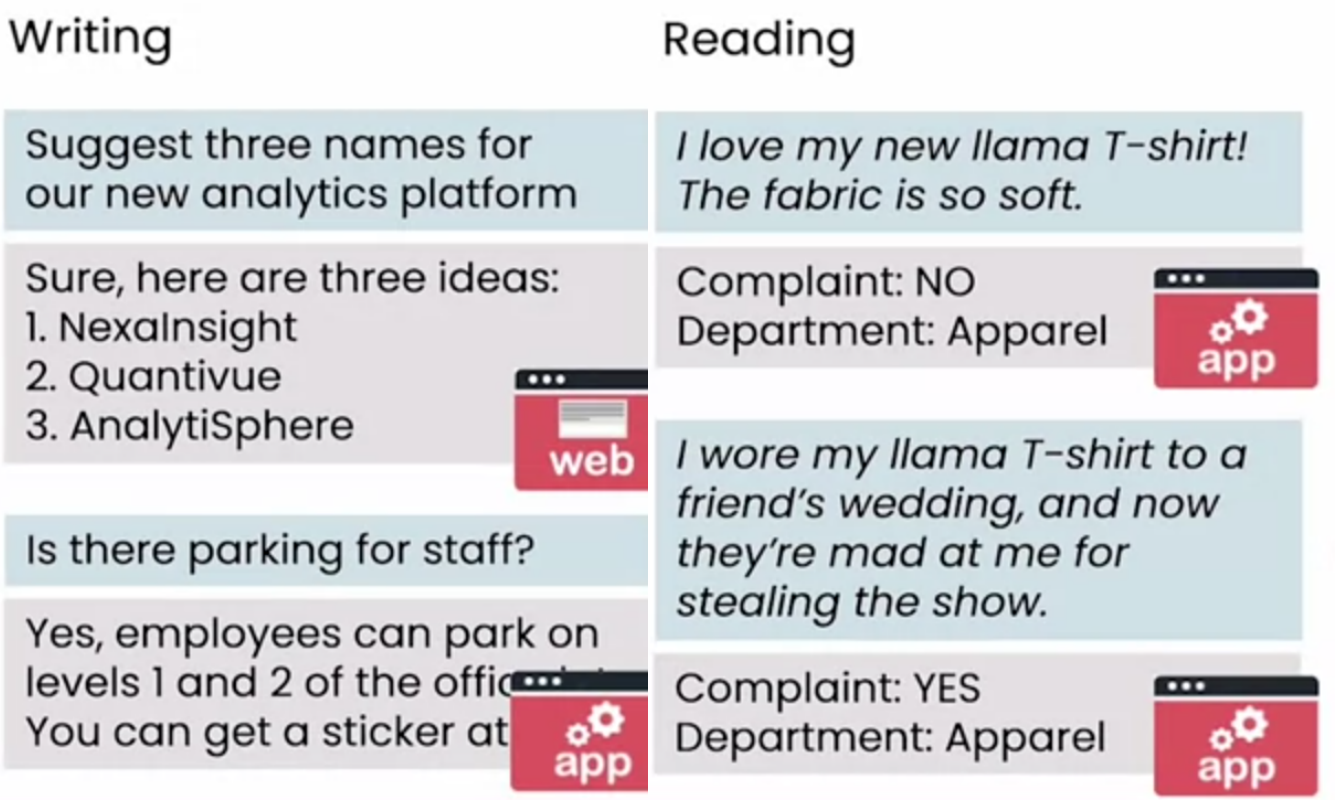

Contoh Tasks yang LLMs dapat Lakukan

Web-based vs. Software application use of LLMs

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Web-based interface applications e.g. ChatGPT, Bard, or Bing Chat

Web-based vs. Software application use of LLMs

Web-based interface applications e.g. ChatGPT, Bard, or Bing Chat

Software-based applications e.g. email routing, document search

Demo: Mencoba Kode Generative AI

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1. Sentiment Analysis dari Restaurant Review.

Demo: Mencoba Kode Generative AI

1. Sentiment Analysis dari Restaurant Review.
2. Sistem Reputation Monitoring.

Writing: Brainstorming product names

Writing: Brainstorming product names

Brainstorm 5 creative names for peanut butter cookies

Sure thing! Here are some ideas:

1. Nutty Nirvana Nibbles
2. ButterBite Bliss
3. Peanut Paddle Pucks
4. ButterNutter Crunchies
5. Nutty Nom-Nom Nuggets

Writing: Developing sales strategy

Writing: Developing sales strategy

Brainstorm five ideas for increasing cookie sales in Q4

1. Limited-time only seasonal flavors.
2. Beautifully packaged gift sets.
3. Buy more, save more deals.
4. Interactive holiday displays
5. Recipe cards

Writing: Memberikan ide riset terbaru

Writing: Memberikan ide riset terbaru

You

Write a novel research topic about computational battery research

ChatGPT

Title: "Optimizing Energy Efficiency in Next-Generation Batteries through Computational Materials Design and Simulation"

Abstract:

As the demand for advanced energy storage solutions continues to grow, there is a pressing need to enhance the performance and efficiency of batteries. This research aims to explore the frontier of computational battery research by employing advanced materials design and simulation techniques to optimize energy efficiency in next-generation battery technologies. The study will focus on leveraging computational models to predict and analyze the electrochemical behaviors of novel materials, with the ultimate goal of designing batteries with improved energy density, cycle life, and safety. By integrating cutting-edge computational tools, this research seeks to accelerate the development of high-performance batteries, addressing the challenges of energy storage for a sustainable and technologically advanced future.

Reading: Proofreading

Reading: Proofreading

Proofread the following text, intended for a website selling children's stuffed toys, for spelling and grammatical errors, and rewrite it with corrections:

Meet this adorable stuffed panda! Made from super snuggle materials and easy to wash in the machine, this toy is the perfect friend for your little one.

Meet this adorable stuffed panda! Made from super snuggly materials that are machine-washable, this toy is the perfect friend for your little one.

Reading: Merangkum Artikel Ilmiah

Reading: Merangkum Artikel Ilmiah

The Turing Trap:

The Promise & Peril of Human-Like Artificial Intelligence

Erik Brynjolfsson

Stanford Digital Economy Lab

http://brynjolfsson.com

Forthcoming in Daedalus, Spring 2022

In 1950, Alan Turing proposed an "imitation game" as the ultimate test of whether a machine was intelligent: could a machine imitate a human so well that it's answers to questions indistinguishable from a human's.[1] Ever since, creating intelligence that matches human intelligence has implicitly or explicitly been the goal of thousands of researchers, engineers and entrepreneurs. The benefits of human-like artificial intelligence (HLAI) include soaring productivity, increased leisure, and perhaps most profoundly, a better understanding of our own minds.

But not all types of AI are human-like – in fact, many of the most powerful systems are very different from humans – and an excessive focus on developing and deploying HLAI can lead us into a trap. As machines become better substitutes for human labor, workers lose economic and political bargaining power and become increasingly dependent on those who control the technology. In contrast, when AI is focused on augmenting humans rather than mimicking them, then humans retain the power to insist on a share of the value created. What's more, augmentation creates new capabilities and new products and services, ultimately generating far more value than merely human-like AI. While both types of AI can be commercially beneficial, there are currently crucial incentives for automation rather than augmentation among technologists, business executives, and policy makers.

E. Brynjolfsson, 2022

Summarize the following paper in 300 words or fewer:

In 1950, Alan Turing proposed an "imitation game" as the ultimate test of whether a machine was Intelligent [...]

Human-like AI offers benefits but risks worker power. Augmenting humans creates more value than imitating them [...]

Reading: Reputation Monitoring

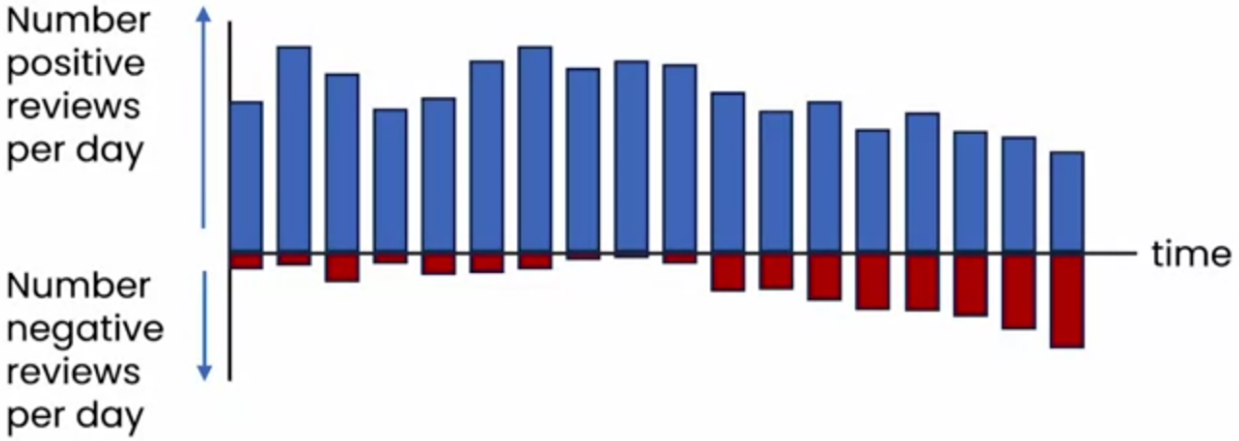
Reading: Reputation Monitoring

Dashboard to track customer sentiment over time

Read the following review and classify it has having either a positive or negative sentiment:

The food was amazing and the servers were so friendly!

Positive



Chatting: ChatBot Khusus

Chatting: ChatBot Khusus

How can I vacation in Paris inexpensively?

Here are some ideas to save money in Paris:
1. Eat at bakeries
2. Take metro, not taxis
3. Visit free attractions [...]

Trip planner

I'm nervous about my big presentation at work...

It's natural to feel nervous. What worries you most?

That I'll forget what to say...

You aren't alone! Here are some tips that may help:

1. Use index cards.
2. Picture a friend in the room to present to [...]

Career coach

What can I make with the following ingredients? Pasta, eggs, lemons, ham

Here's a recipe you can make with those ingredients:

Ham and Lemon Carbonara

Instructions:
1. Cook pasta
2. Whisk eggs, lemon juice and zest in bowl [...]

Recipe ideas

Chatting: IT Service ChatBot

Chatting: IT Service ChatBot

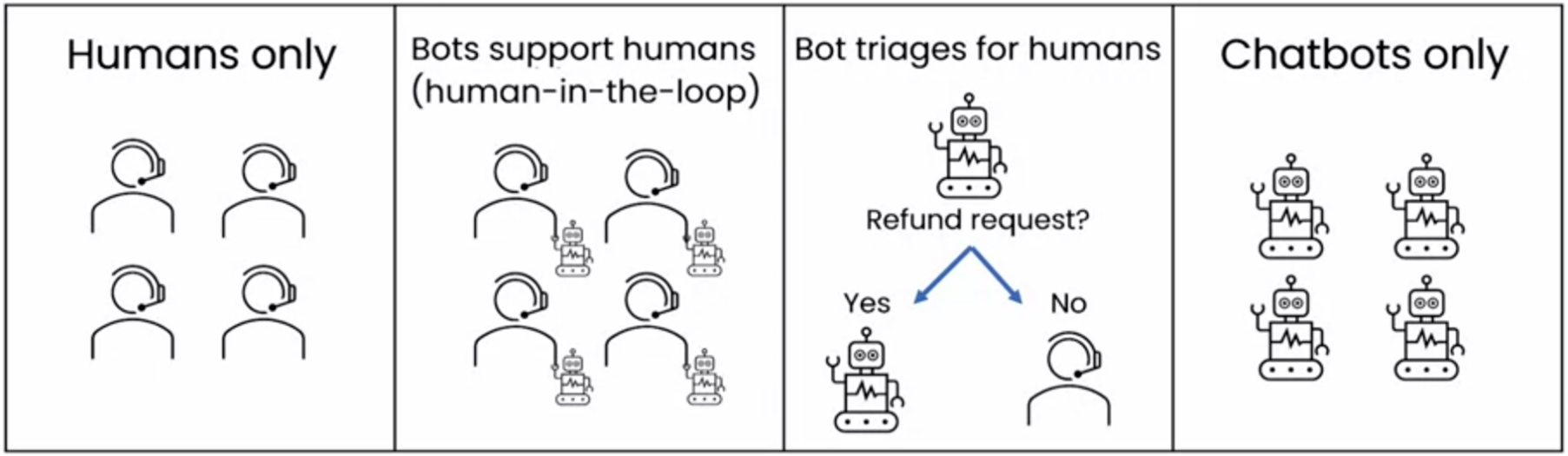
Chatting: The Rise of Chatbots in Customer Service

Chatting: The Rise of Chatbots in Customer Service

Welcome to BettaBurgers!

I'd like a cheeseburger for delivery!

→ Focus on text-based chatbots



Kesimpulan

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7. LLMs dapat diaplikasikan dalam banyak aplikasi, contohnya: writing, reading, chatting, dan masih banyak peluang lainnya.

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