Pengenalan *Artificial Intelligence*

Jalur Peminatan *AI Specialist*

Hendra Bunyamin

Program Studi Teknik Informatika
Fakultas Teknologi Informasi
Universitas Kristen Maranatha

December 10, 2021

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

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

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

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

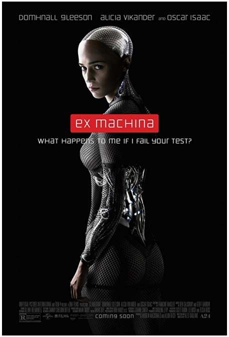
- **ANI** $\Rightarrow$ *Artificial Narrow Intelligence*.
  Examples: smart speaker, self-driving car, web search, AI in farming and factories.

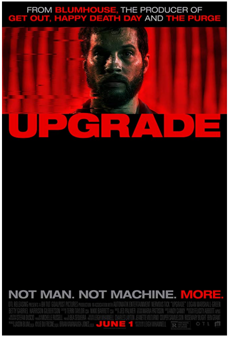
Demystifying AI

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

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

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





Outline

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

AI has many tools

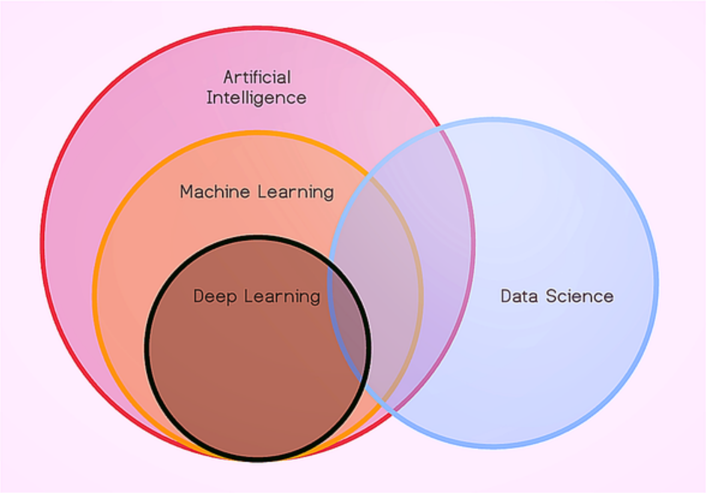


Figure 2: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Machine Learning (1/2)

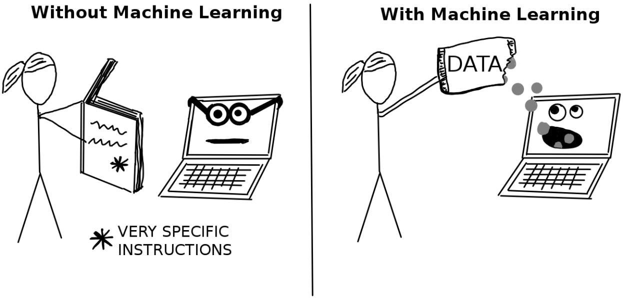
Machine Learning (1/2)

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

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).

- 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).



Machine Learning (2/2)

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

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

- Supervised Learning,

Machine Learning (2/2)

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

- Supervised Learning,
- Unsupervised Learning,

Machine Learning (2/2)

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

- Supervised Learning,
- Unsupervised Learning,
- Semi-supervised Learning, and

Machine Learning (2/2)

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

- Supervised Learning,
- Unsupervised Learning,
- Semi-supervised Learning, and
- Reinforcement learning

Machine Learning (2/2)

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

- **Supervised Learning**,
- Unsupervised Learning,
- Semi-supervised Learning, and
- Reinforcement learning

Supervised Learning (1/2)

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

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

Consider the following examples
(*input A* in **bold** and *output B* in italic) (Trask, 2019):

Supervised Learning (2/2)

Consider the following examples
(*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*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*
- Using **weather sensor data** to predict the *probability of rain*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*
- Using **weather sensor data** to predict the *probability of rain*
- Using **car engine sensors** to predict the optimal tuning *settings*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*
- 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*

Supervised Learning (2/2)

Consider the following examples
(*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*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*
- 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.

Input (A)	**Output (B)**	**Application**

Supervised Learning (2/2)

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

Supervised Learning (2/2)

Input (A)		Output (B)	Application
email	$\longrightarrow$	spam? (0/1)	**spam filtering**
audio	$\longrightarrow$	text transcript	**speech recognition**

Supervised Learning (2/2)

Input (A)		Output (B)	Application
email	$\longrightarrow$	spam? (0/1)	**spam filtering**
audio	$\longrightarrow$	text transcript	**speech recognition**
English	$\longrightarrow$	Indonesia	**machine translation**

Supervised Learning (2/2)

Input (A)		Output (B)	Application
email	$\longrightarrow$	spam? (0/1)	**spam filtering**
audio	$\longrightarrow$	text transcript	**speech recognition**
English	$\longrightarrow$	Indonesia	**machine translation**
ad, user info	$\longrightarrow$	click? (0/1)	**online advertising**

Supervised Learning (2/2)

Input (A)		**Output (B)**	**Application**
email	$\longrightarrow$	spam? (0/1)	**spam filtering**
audio	$\longrightarrow$	text transcript	**speech recognition**
English	$\longrightarrow$	Indonesia	**machine translation**
ad, user info	$\longrightarrow$	click? (0/1)	**online advertising**
image, radar info	$\longrightarrow$	position of other cars	**self-driving car**

Supervised Learning (2/2)

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

Why Now?

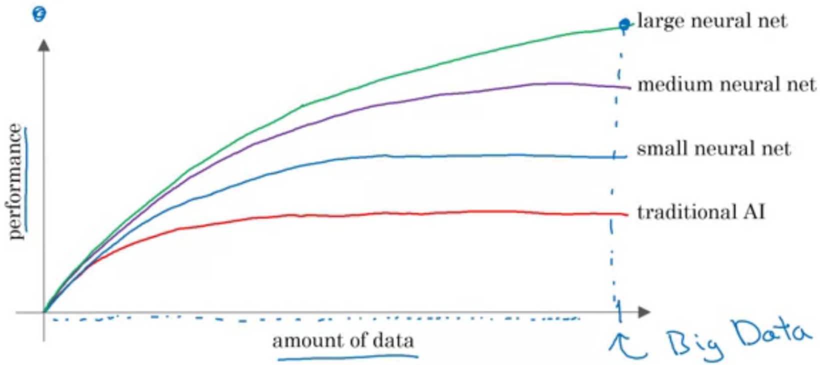


Figure 3: Large neural net + Big Data = High Performance (Ng, 2019)

Outline

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

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

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

A B

$A \longrightarrow B$

Table 1: House prices dataset (Ng, 2019)

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

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

A B

$A \longrightarrow B$

Table 2: House prices dataset (Ng, 2019)

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

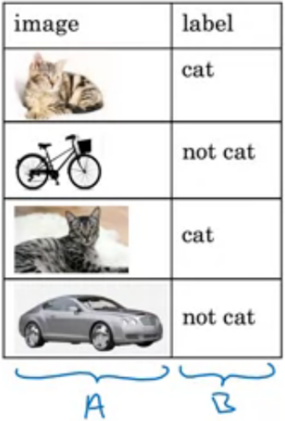


Table 3: Cat images dataset (Ng, 2019)

Acquiring data

Acquiring data

- Manual labeling

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 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

- Download from websites / partnerships

Data is Messy

Data is Messy

- Garbage in, garbage out

Data is Messy

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

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

Data is Messy

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

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

- Multiple types of data
  images, *audio*, *text* $\Rightarrow$ **unstructured 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. Jalur Peminatan AI: Becoming AI Specialist

Machine Learning vs. Data Science (1/2)

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

A

B

Figure 4: Home prices (Ng, 2019)

Machine Learning vs. Data Science (1/2)

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

A B

Figure 4: Home prices (Ng, 2019)

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

Machine Learning vs. Data Science (1/2)

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

A

B

Figure 4: Home prices (Ng, 2019)

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

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

$\longrightarrow$ **software**

-Arthur Samuel (1959)

Data Science

Science of extracting knowledge and insights from data.

$\longrightarrow$ **slide presentation** or **report**

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

AI has many tools

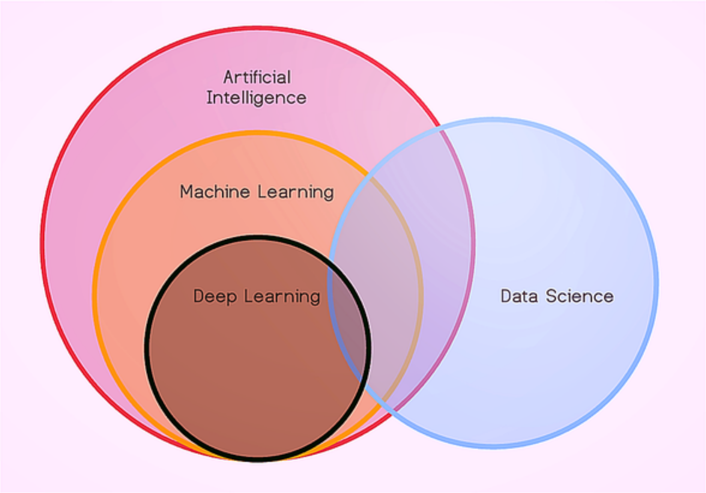


Figure 5: Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Dataset: Home Prices

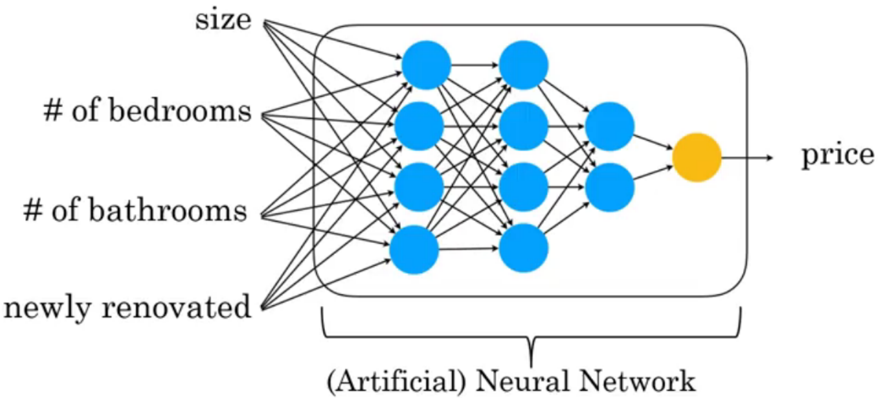
size of house (square feet)	# of bedrooms	# of bathrooms	newly renovated	price (1000$)
523	1	2	N	115
645	1	3	N	150
708	2	1	N	210
1034	3	3	Y	280
2290	4	4	N	355
2545	4	5	Y	440

A

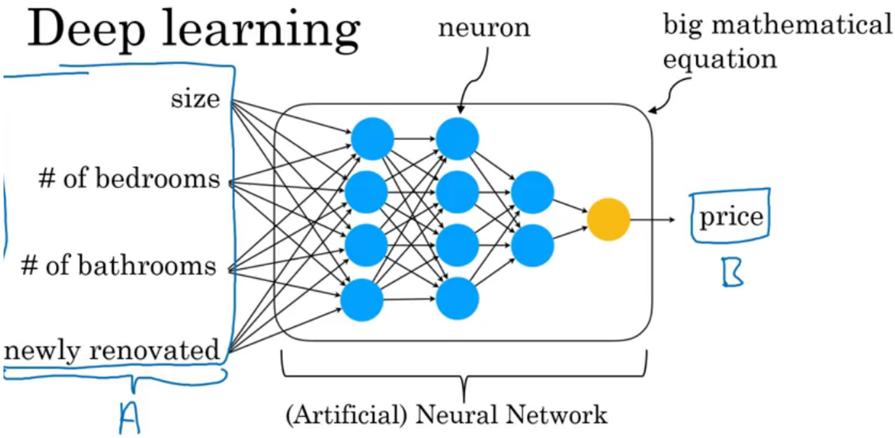
B

Figure 6: Home prices (Ng, 2019)

Deep Learning (1/2)



Deep Learning (2/2)

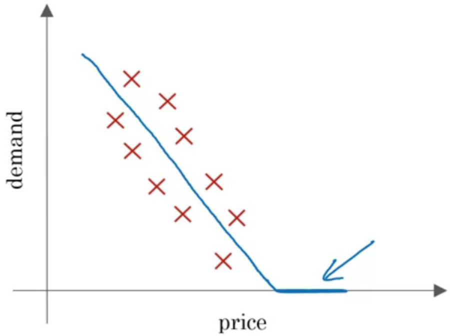


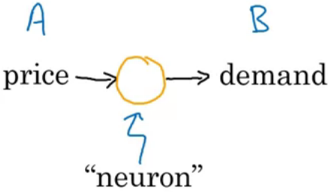
Outline

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

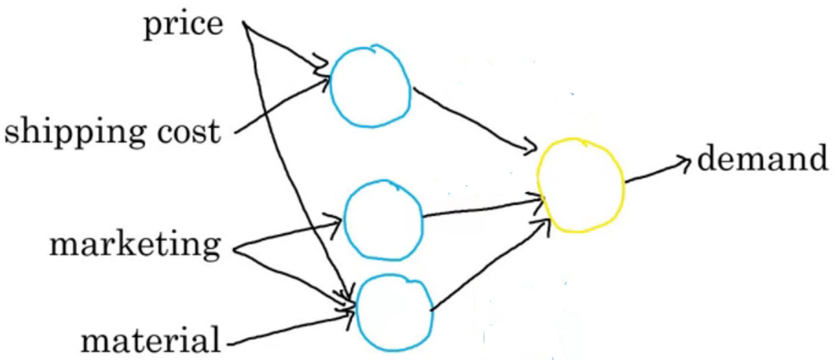
Demand prediction (1/2)

Demand prediction (2/2)

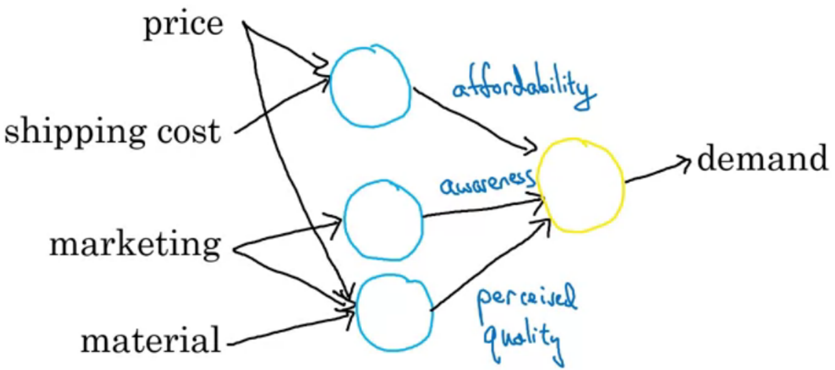




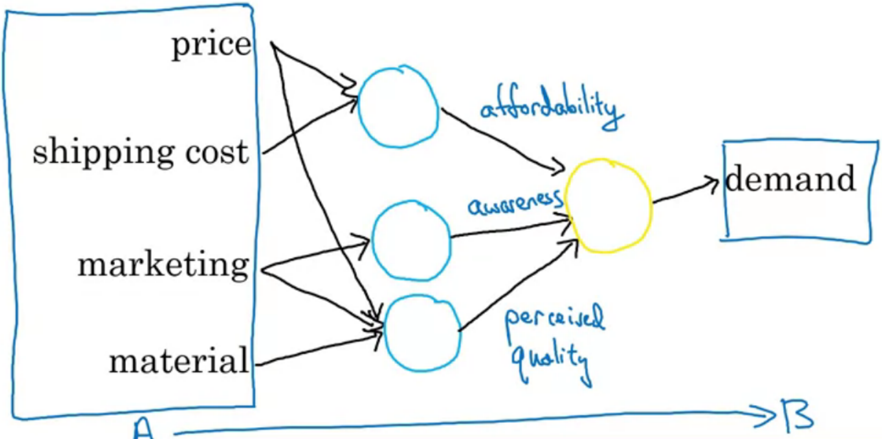
Demand prediction: a little bit more complex (1/4)



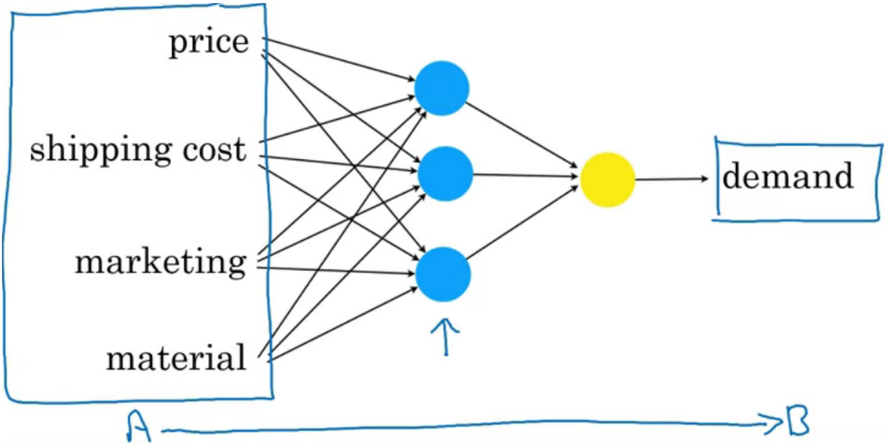
Demand prediction: a little bit more complex (2/4)



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

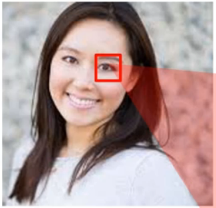


Demand prediction: a little bit more complex (4/4)



NN Application: Face recognition (1/3)

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

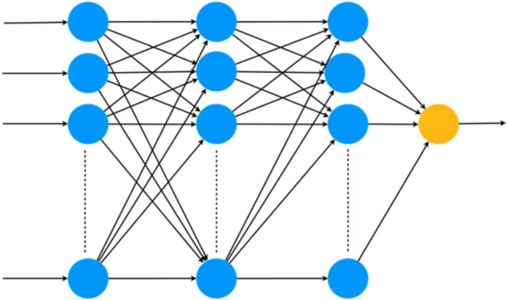


30	32	22	12	10	10	12	33	35	30
12	11	12	234	170	176	13	15	12	12
234	222	220	230	200	222	230	234	56	78
190	220	186	112	110	110	112	180	30	32
49	250	250	250	4	2	254	200	44	6
55	250	250	250	3	1	250	245	25	3
189	195	199	150	110	110	182	190	199	55
200	202	218	222	203	200	200	208	215	222
219	215	220	220	222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

1000

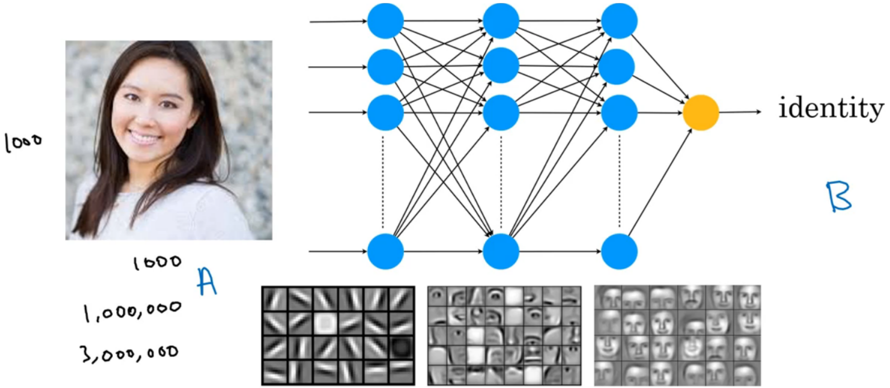


1000

1,000,000

3,000,000

NN Application: Face recognition (3/3)



How Does a Neural Network Learn?

Watch a Demo by Phiresky (2017).

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

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

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

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

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
$A \longrightarrow B$

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

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

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

Self-driving car

Self-driving car

Can do

$A \longrightarrow B$

Self-driving car

Can do

$A \longrightarrow B$

Cannot do

stop

hitchhiker

bike turn
left signal

$A \longrightarrow B$

Self-driving car

Can do

$A \longrightarrow B$

Cannot do

stop

hitchhiker

bike turn left signal

$A \longrightarrow B$

1. Data

Self-driving car

Can do

$A \longrightarrow B$

Cannot do

stop

hitchhiker

bike turn
left signal

$A \longrightarrow B$

1. Data
2. Need high accuracy

X-ray diagnosis

Can do | **Cannot do**

X-ray diagnosis

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

X-ray diagnosis

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

Strengths and weaknesses of machine learning

ML tends to work well when:

ML tends to work poorly when:

Strengths and weaknesses of machine learning

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

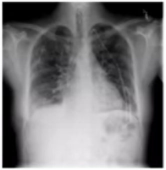
Strengths and weaknesses of machine learning

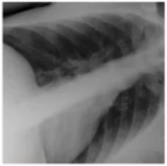
ML tends to work well when:

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





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,

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

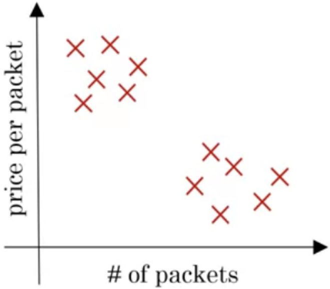
- Supervised Learning,
- Unsupervised Learning.

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

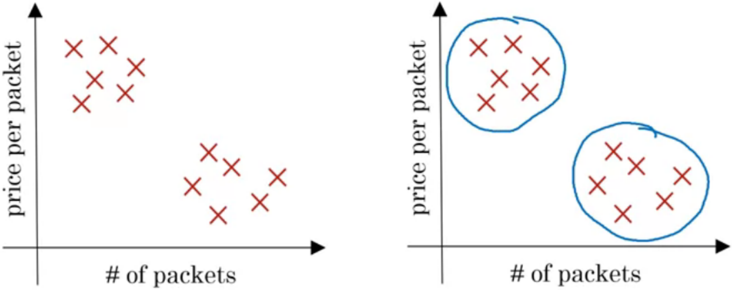
- Supervised Learning,
- **Unsupervised Learning**.

Unsupervised learning (1/2)

Clustering potato chip sales



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

Computer Vision (1/3)

- Image classification/Object recognition

cat

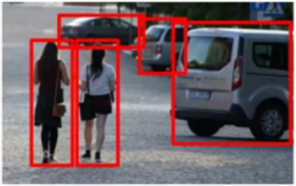
Computer Vision (1/3)

- Image classification/Object recognition

- Face recognition

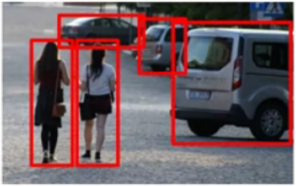
- Object detection

- Object detection



Computer Vision (2/3)

- Object detection


Computer Vision (3/3)

- Image Segmentation

- Image Segmentation

- Image Segmentation


- Tracking

- Text Classification

Natural Language Processing (1/7)

- Text Classification

  Email $\longrightarrow$ Spam/Non-Spam

Natural Language Processing (1/7)

- Text Classification

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

Natural Language Processing (1/7)

- Text Classification

  Email $\longrightarrow$ Spam/Non-Spam

  Product description $\longrightarrow$ Product category

  - Sentiment recognition

    "The food was good" $\longrightarrow$ 

Natural Language Processing (1/7)

- Text Classification

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

  - Sentiment recognition

    "The food was good" $\longrightarrow$ 

    "Service was horrible" $\longrightarrow$ 

Natural Language Processing (1/7)

- Text Classification

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

  - Sentiment recognition

    "The food was good" $\longrightarrow$ 

    "Service was horrible" $\longrightarrow$ 

- Information retrieval
  - E.g., web search

- **Name entity recognition**

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

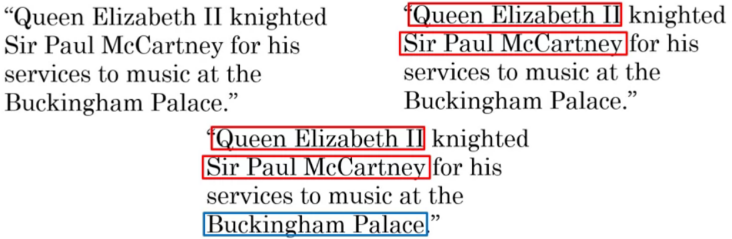
- **Name entity recognition**

"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."

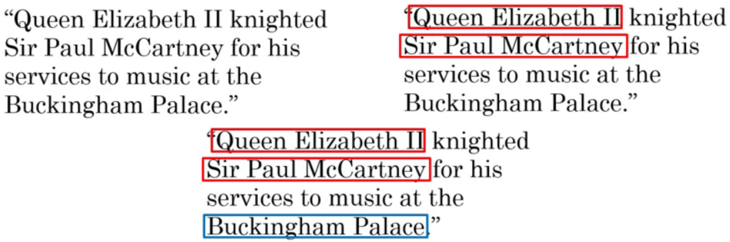
Natural Language Processing (2/7)

- **Name entity recognition**



Natural Language Processing (2/7)

- **Name entity recognition**



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

Natural Language Processing (3/7)

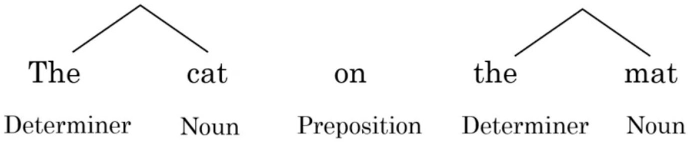
- Others: parsing, part-of-speech tagging

The cat on the mat

- Others: parsing, part-of-speech tagging

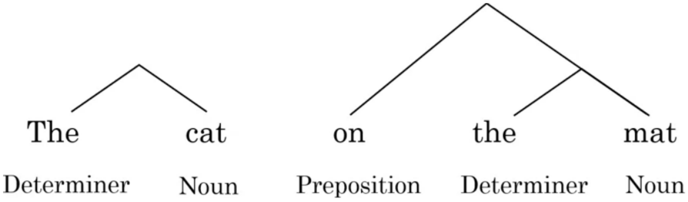
The	cat	on	the	mat
Determiner	Noun	Preposition	Determiner	Noun

- Others: parsing, part-of-speech tagging



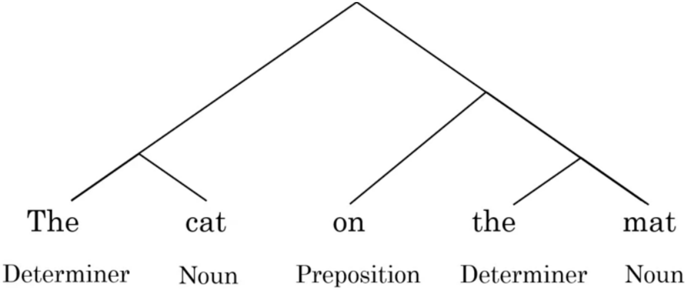
Natural Language Processing (6/7)

- Others: parsing, part-of-speech tagging



Natural Language Processing (7/7)

- Others: parsing, part-of-speech tagging

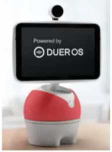


- Speech recognition (speech-to-text)

Amazon
Echo / Alexa

Google
Home

Apple
Siri



Baidu
DuerOS

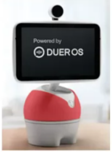
Speech (1/2)

- Speech recognition (speech-to-text)

Amazon
Echo / Alexa

Google
Home

Apple
Siri



Baidu
DuerOS

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

Speech (2/2)

- Speaker ID

Speech (2/2)

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

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

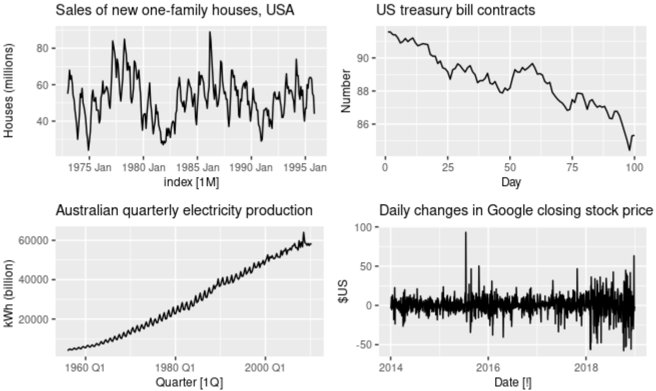
Times Series Forecasting (1/3)

Times Series Forecasting (1/3)

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 (1/3)

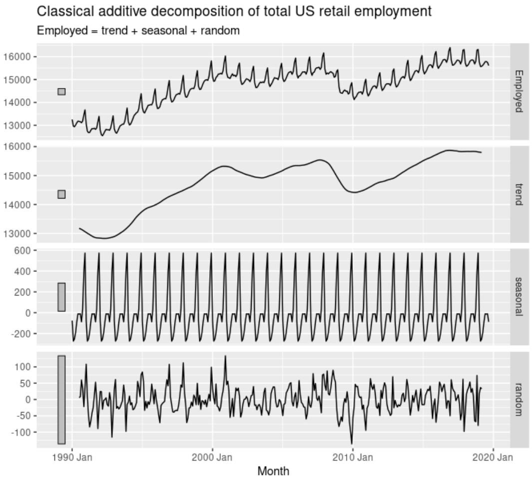
Forecasting has fascinated people for thousands of years, sometimes being considered a *sign of divine inspiration*, and sometimes being seen as *a criminal activity* (Hyndman, 2021).



Times Series Forecasting (2/3)

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

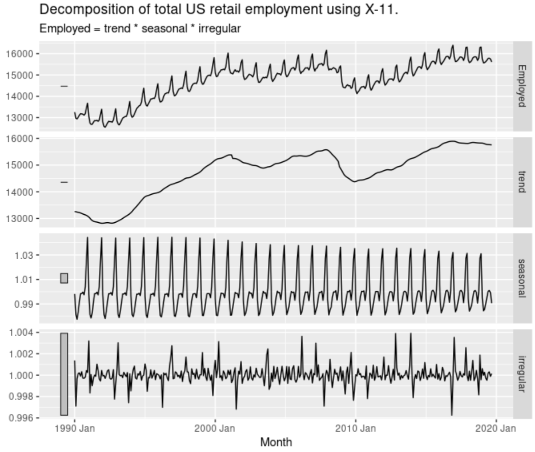
This is an example of a time series which is decomposed by classical decomposition.



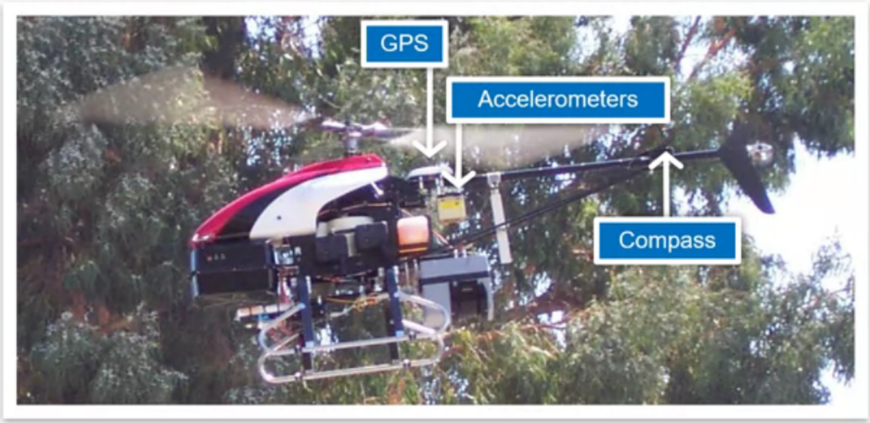
Times Series Forecasting (3/3)

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

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



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.
(Contoh: **Stanford Autonomous Helicopter**).

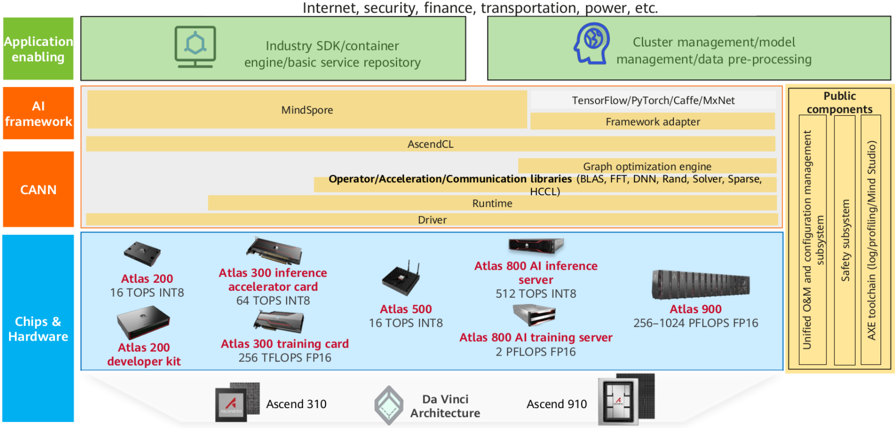
Reinforcement learning (2/2)

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

GANs (Generative Adversarial Network)

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

AI Computing Platform



Link Video: **here**

Mata Kuliah-Mata Kuliah Jalur Peminatan *AI Specialist*

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

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.

Hyndman, R. J. (2021). *Forecasting: Principles and Practice 3rd Edition*. Otexts.

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*.

Kharkovyba, 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.

UNIVERSITAS
KRISTEN
MARANATHA