

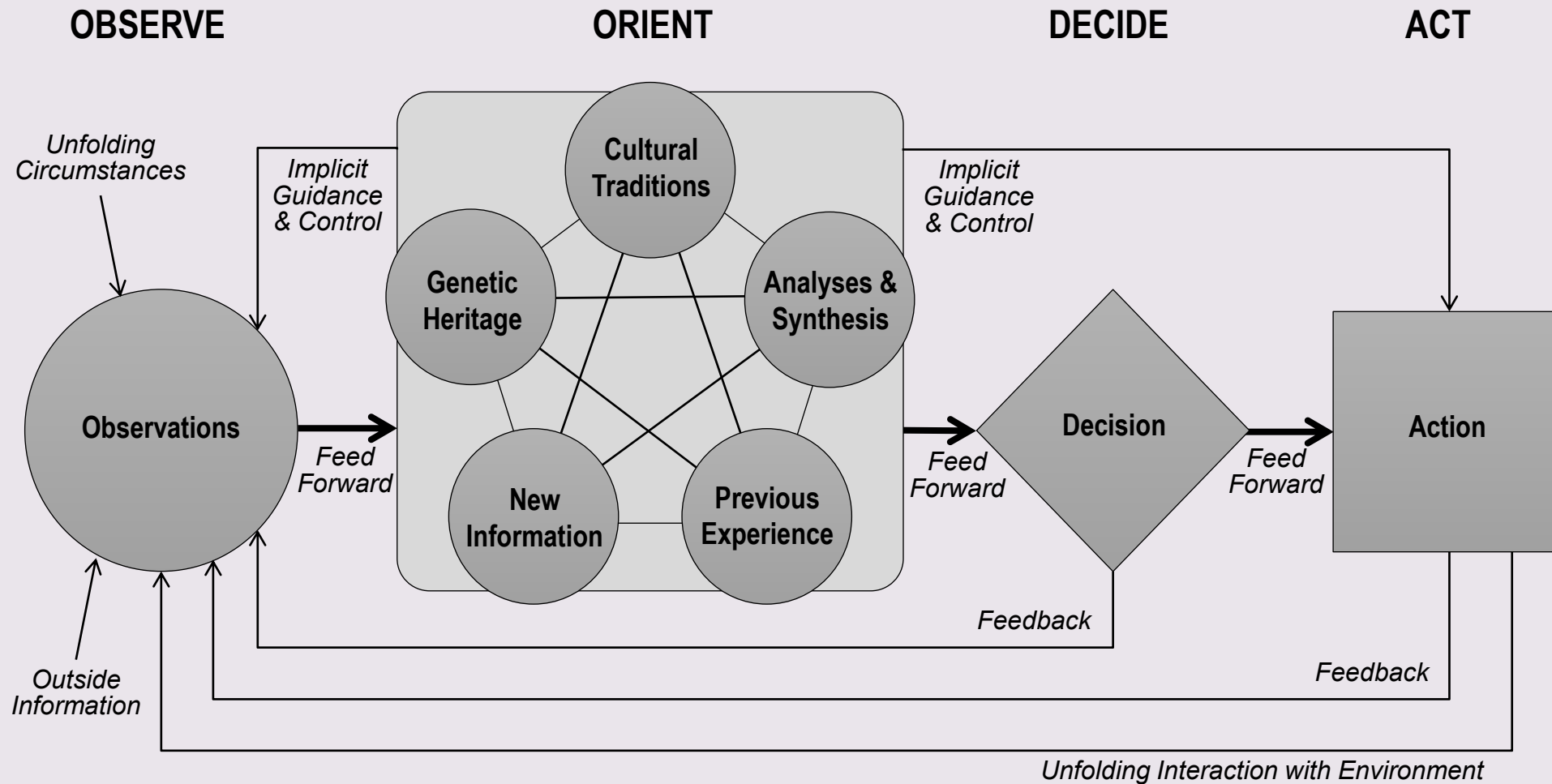
UTIS 2025

ARTIFICIAL INTELLIGENCE IN MACHINING

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FENS, Sabancı University

1st of November 2025

The (Human) OODA Loop

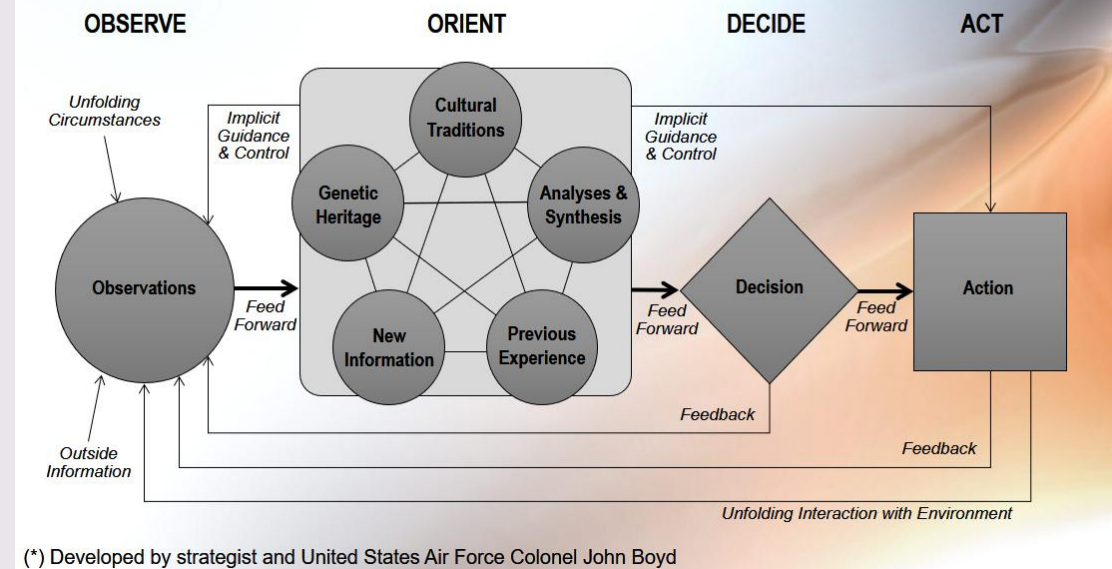


(*) Developed by strategist and United States Air Force Colonel John Boyd

Enabler Technologies of Digitalization

- Internet of Things
- Cloud/Edge Computing
- Blockchain
- Cyber Security
- **Data Analytics / Artificial Intelligence**
- Digital Twins
- Data Driven Manufacturing
- Additive Manufacturing / 3D Printing
- Smart Robotics / Cyber Physical Systems
- Extended Reality: Virtual Reality / Augmented Reality / Mixed Reality

The (Human) OODA Loop (*)



This Tutorial...

Value of Informed Decision

- The Disease Problem
- Classification – OR/1R/DT/RF/ANN

Artificial Intelligence

- Brief History of AI
- Data Mining: Structured Data
- CRISP-DM Framework: Modeling
- Data Mining in Machining

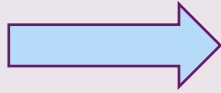
Generative AI

- AI vs. GenAI
- Large Language Models (LLMs for Text Generation)
- Diffusion Models for Image Generation
- GenAI in Machining
- Concluding Remarks

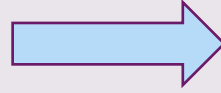
Biography



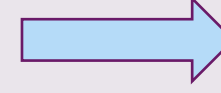
BSc. EE (1995)



MSc. IE (1997)



Ph.D MIE (1997)



FENS IE (2002 -)

Research/Teaching Interests:

- Data Analytics
- Decision Making
- Digital Transformation & Innovation Management

Value of Informed Decision

The Disease Problem

- Suppose that you have a friend who is a doctor.
- A laboratory test is required to determine a disease.
- If they **send** someone who is actually **healthy** for the test, they waste 100 TL (i.e., the **cost** of the test).
- If they **fail to send** someone who is actually **sick** for the test, they pay a **penalty** of 100 TL for the wrong diagnosis.
- If they make this decision by tossing a coin, what would be the cost of wrong decisions for the day?
- For each "actually **healthy**" asking a laboratory test is a **wrong decision (100 TL waste)**.
- For each "actually **sick**" **not** asking a laboratory test is a **wrong decision (100 TL penalty)**.
- Can we minimize the cost of wrong decision by using data? (i.e., **making informed decisions**)

The Disease Problem

#	Disease
1	Healthy
2	Healthy
3	Sick
4	Sick
5	Sick
6	Healthy
7	Sick
8	Healthy
9	Sick
10	Sick
11	Sick
12	Sick
13	Sick
14	Healthy

- Suppose that on that day, 14 people came in for an examination.
Recall:
- A laboratory test is required to determine the illness.
- If they **send** someone who is actually **healthy** for the test, they waste 100 TL (i.e., the cost of the test).
- If they **fail to send** someone who is actually **sick** for the test, they pay a penalty of 100 TL for the wrong diagnosis.
- If they make this decision by tossing a coin, what would be the cost for the day?

The Disease Problem

#	Disease
1	Healthy
2	Healthy
3	Sick
4	Sick
5	Sick
6	Healthy
7	Sick
8	Healthy
9	Sick
10	Sick
11	Sick
12	Sick
13	Sick
14	Healthy

- Suppose that on that day, 14 people came in for an examination.
- **Recall:**
- A laboratory test is required to determine the illness.
- If they **send** someone who is actually **healthy** for the test, they waste 100 TL (i.e., the cost of the test).
- If they **fail to send** someone who is actually **sick** for the test, they pay a penalty of 100 TL for the wrong diagnosis.
- If they make this decision by tossing a coin, what would be the cost for the day?
- **There are 9 sick patients.** Half of the sick patients will make the right decision, and half will make the wrong decision.
- There are **5 healthy** in the group. Half of the healthy patients will make the right decision, and half will make the wrong decision.

TOTAL
450 + 250 = 700 TL!

Creating Value From Data

Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
	Sick
	Sick
	Sick
	Sick

- Suppose that the data suggests that in general population 5 out of 14 is healthy and 9 out of 14 is sick.
- What if we used this data and made informed decisions?

Creating Value From Data

Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
	Sick
	Sick
	Sick
	Sick

- Suppose that the data suggests that in general population **5 out of 14 is healthy** and **9 out of 14 is sick**.
- What if we used this data and made informed decisions?
- If they **send** everyone for the test, they would waste **500 TL** (i.e., the cost of the redundant test for the **5 healthy**).
- If they **don't send** anyone for the test, they would pay a penalty of **900 TL** (for the **9 sick**).
- **Best option is sending everyone for the test!**

Value of Informed Decision

Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
	Sick
	Sick
	Sick
	Sick

- Suppose that the data suggests that in general population 5 out of 14 is healthy and 9 out of 14 is sick.
 - What if we used this data and made informed decisions?
 - If they **send** everyone for the test, they would waste 500 TL (i.e., the cost of the redundant test for the 5 healthy).
 - If they **don't send** anyone for the test, they would pay a penalty of 900 TL (for the 9 sick).
 - **Best option is sending everyone for the test!**
- The cost of w
- NEW TOTAL = 500 TL!**
- Tossing a c
 - Sending everyone
 - The data on the percentage of sick in population saves us:
 $700 \text{ TL} - 500 \text{ TL} = \underline{200 \text{ TL!}}$

Rudimentary Rules – 0R

- Very simple!
- Which ever class is most frequent (i.e., *the mode of the output*) is the prediction for the new test instance.
- So we use 0 input features for classification (thus is referred to as 0R).
- There are 9 Sick & 5 Healthy in the training data.
- So *next instance* is predicted to be as Sick!
- If we use the training data as test:
 - (Training) Accuracy= 9/14
 - (Training) Error=5/14

Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
Healthy	Sick
	Sick
	Sick
	Sick
	Sick

The Disease Problem: Sample Data

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

Rudimentary Rules – 1R

- Basically, it is a **one-level decision tree**.
- It uses only one of the input features (*aka* attribute) for classification.
- Sometimes performs quite well!
- Basic idea:
 - Create a rule for each feature.
 - Classify according to the frequency in training data.
 - Evaluate error rate for each feature.
 - Choose the best feature and the corresponding rule as the classifier.
- Which feature to use? Let's check the data:



The Disease Problem: Sample Data

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

When Age is Young

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

When Age is Middle

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

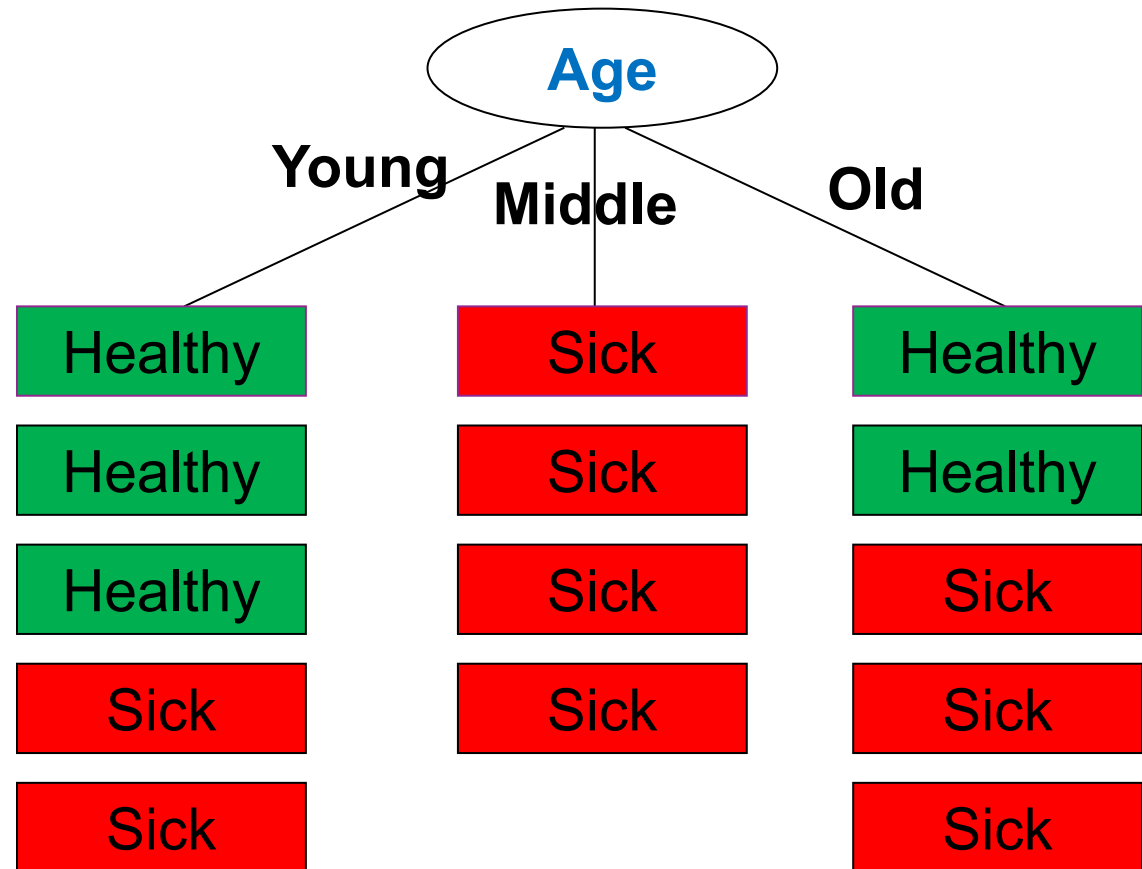
When Age is Old

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

1R: Which Feature to Use?

- If we use **Age**:
- **Rule:** "If Young Then Healthy, otherwise Sick"

(**4 ERRORS**)

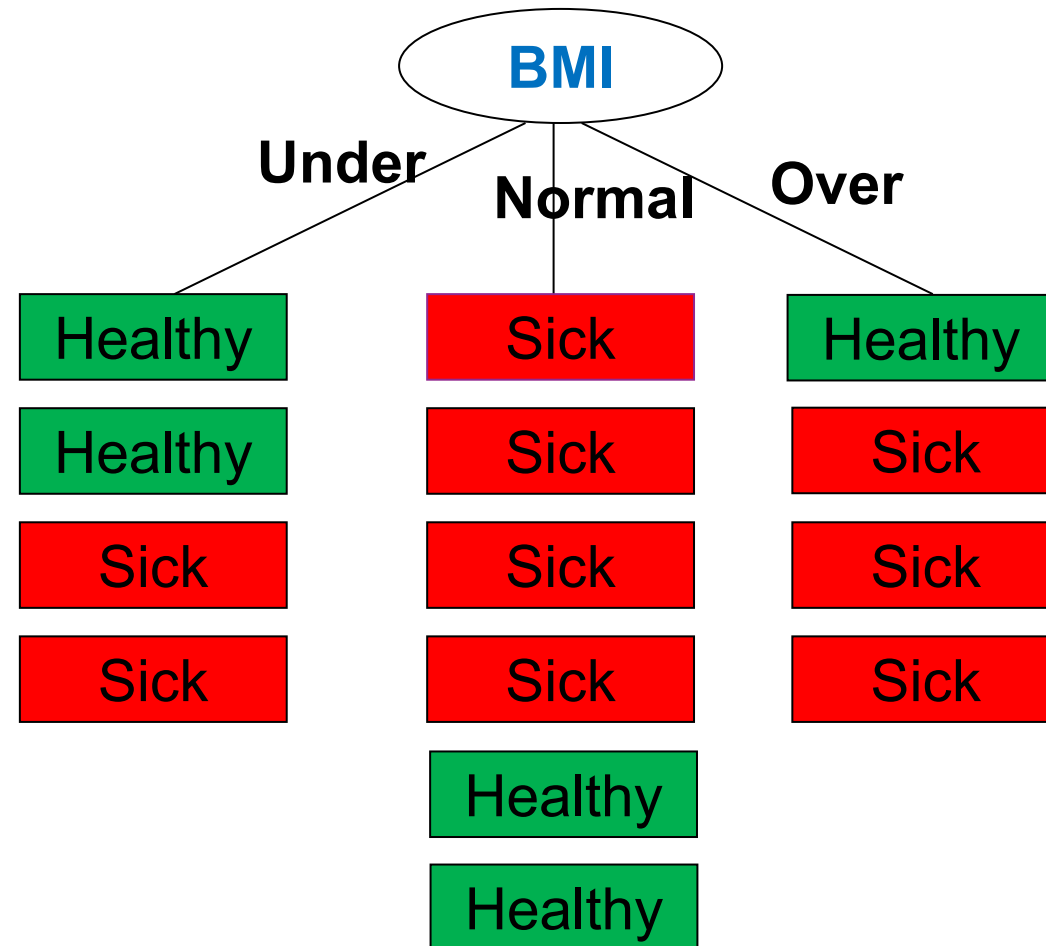


1R: Which Feature to Use?

- If we use **BMI**:

- **Rule:** "If Under Then Healthy/Sick, if Normal or Over Then Sick Healthy, otherwise Sick"

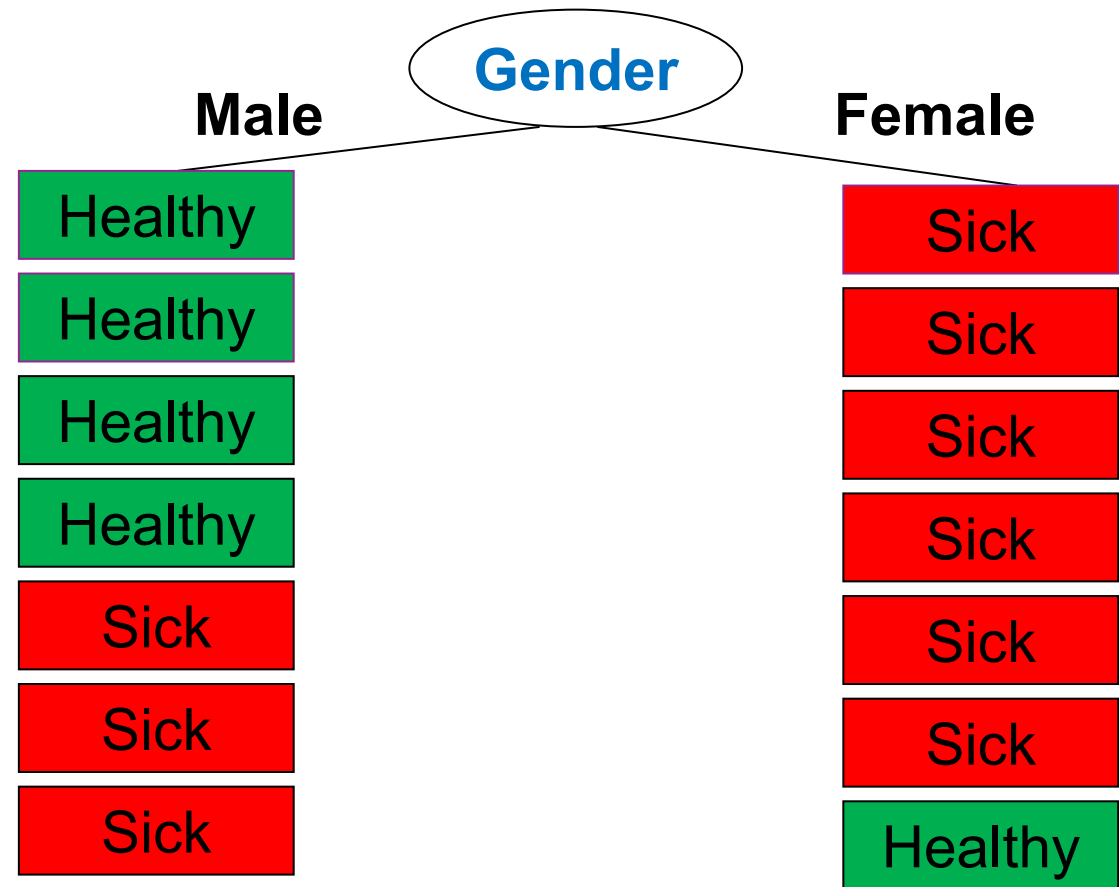
(**5 ERRORS**)



1R: Which Feature to Use?

- If we use Gender:
- Rule: " If Male Then Healthy, if Female Then Sick"

(4 ERRORS)

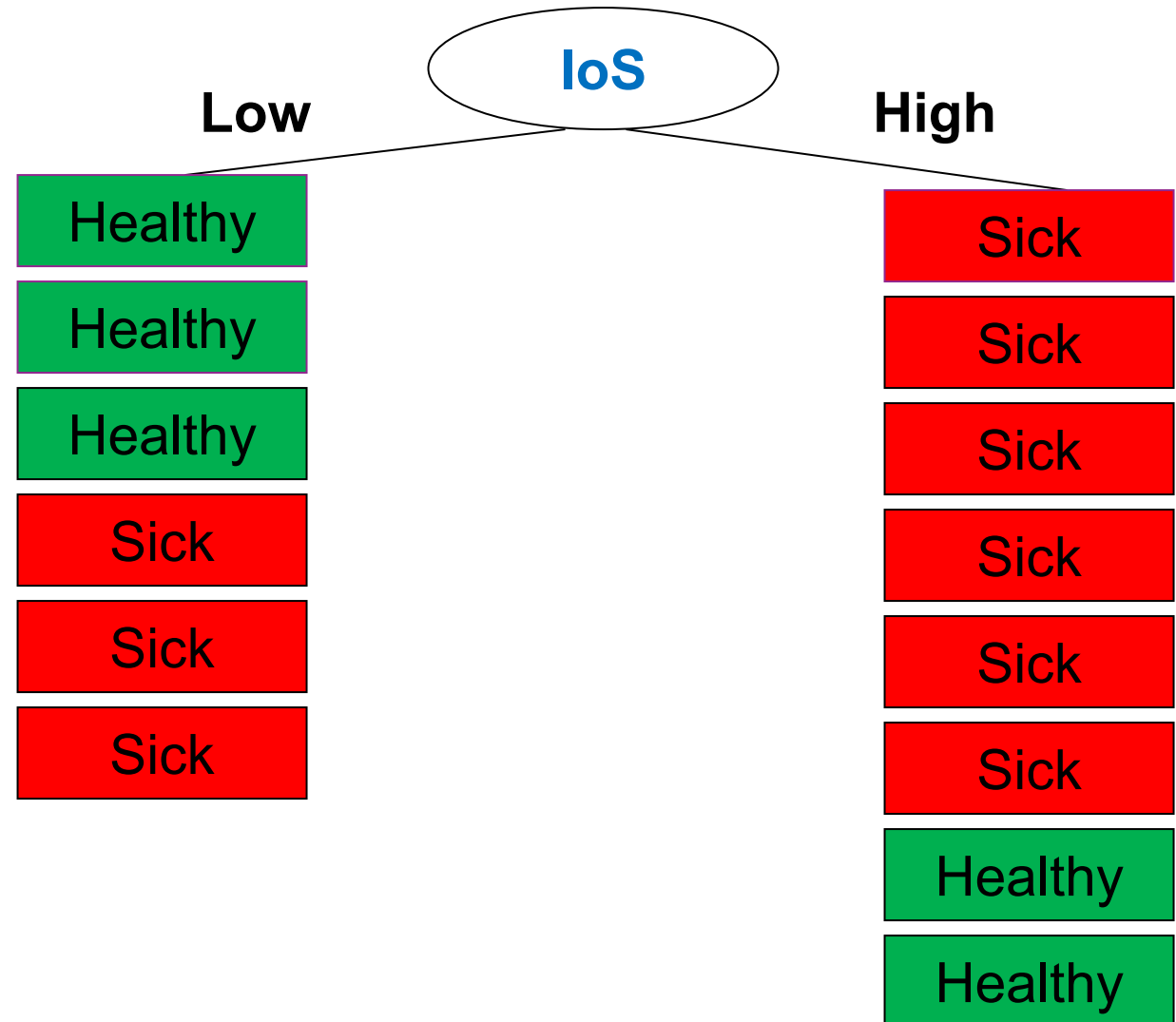


1R: Which Feature to Use?

- If we use **IoS**:

- **Rule:** "If Low Then Healthy/Sick, If High Then Sick"

(**5 ERRORS**)



1 R: Summary of the Analysis

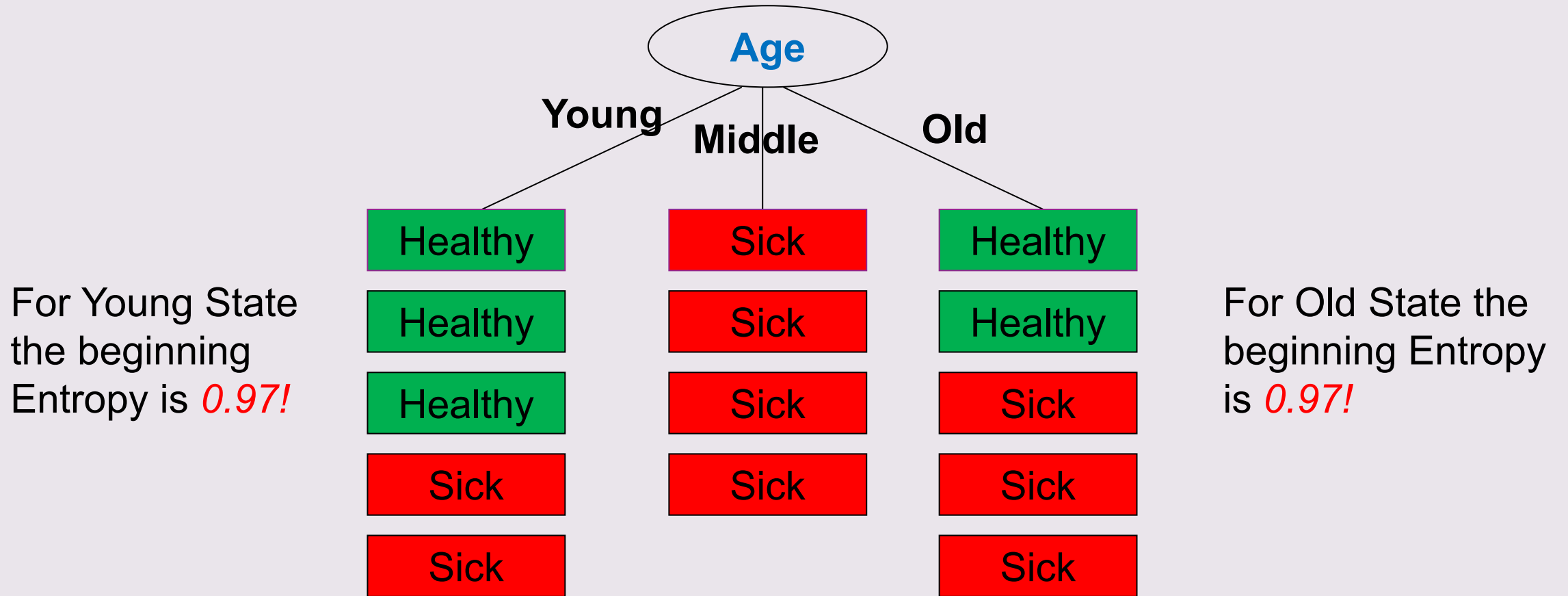
Feature		Rules	Errors	Total
1	Age	Young $\Rightarrow$ Healthy	2/5	4/14
		Middle $\Rightarrow$ Sick	0/4	
		Old $\Rightarrow$ Sick	2/5	
2	BMI	Under $\Rightarrow$ Healthy	2/4	5/14
		Normal $\Rightarrow$ Sick	2/6	
		Over $\Rightarrow$ Healthy	1/4	
3	Gender	Male $\Rightarrow$ Healthy	3/7	4/14
		Female $\Rightarrow$ Sick	1/7	
4	IoS	High $\Rightarrow$ Sick	2/8	5/14
		Low $\Rightarrow$ Healthy	3/6	

The Rule: Check Age. If *young* then no need for lab test, otherwise ask for a test!

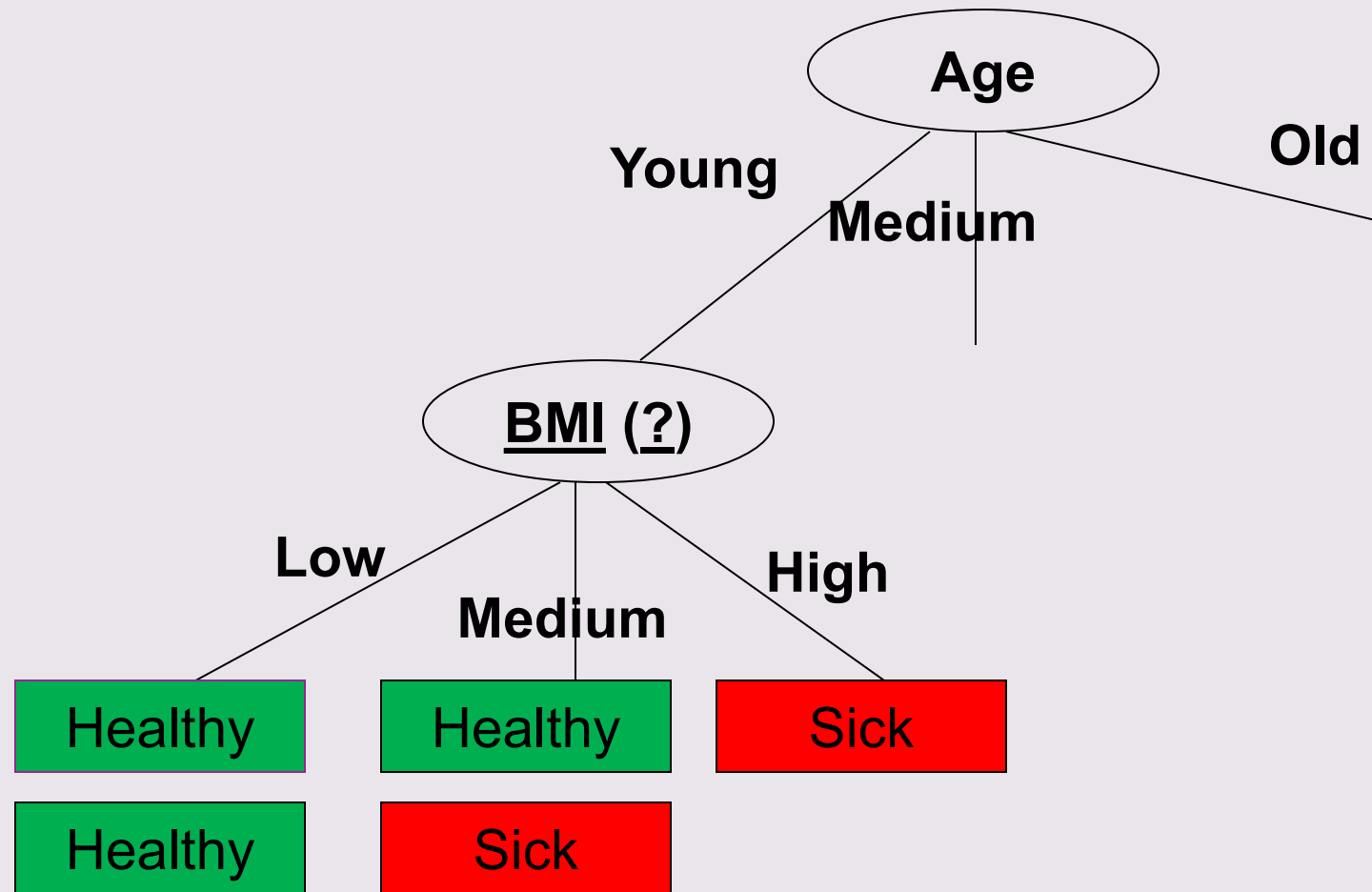
0R vs. 1R : Value of Information

- Recall that 0R training error was = $5/14$.
 - If we use Age training error is $4/14$
 - If we use BMI training error is $5/14$
 - If we use Gender training error is $4/14$
 - If we use loS training error is $5/14$
- NEW TOTAL = 400 TL!
- 1R Rule: "Check Age" → $4/14$
 - 1R Rule: "Check Gender" → $4/14$
- Thus, Age and Gender information yield the value of making 1 less error!

Next? – Second Level?



Next Level: After Young, **BMI** (?)



Entropy



Claude Shannon
1916-2001
American
Mathematician
& Father of
Information Theory

- **Entropy** is a measure of **impurity** in the training data S

$$\text{Entropy}(S) = \sum_{i=1}^c -p_i \log_2 p_i$$

Diagram illustrating the components of the Entropy formula:

- Number of Categories (i.e., Classes)**: Points to the upper limit c of the summation.
- Training Data**: Points to the function $\text{Entropy}(S)$.
- Proportion of the samples from class i in data set S** : Points to the term p_i .

- **$\text{Gain}(S, a)$** is the amount of **expected information gained** about the classification by knowing the value of *feature a* .

$$\text{Gain}(S, a) = \text{Entropy}(S) - \sum_{v \in \text{Values}(a)} \frac{|S_v|}{|S|} \text{Entropy}(S_v)$$
$$S_v = \{s \in S : a(s) = v\}$$

Diagram illustrating the components of the Gain formula:

- All possible values for feature a** : Points to the summation index $v \in \text{Values}(a)$.

Entropy

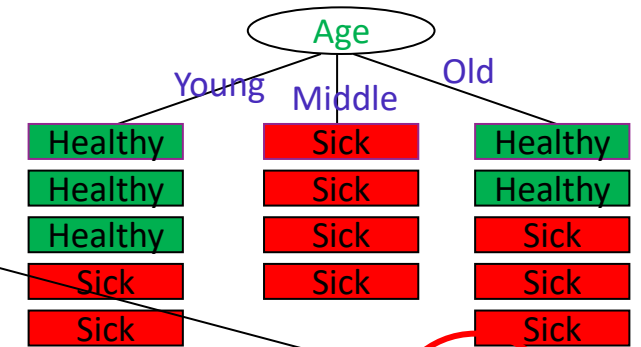


Claude Shannon
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- Beginning Entropy (5 Healthy – 9 Sick)

$$\sum_{i=1}^c -p_i \log_2 p_i = -\frac{5}{14} \log_2 \frac{5}{14} - \frac{9}{14} \log_2 \frac{9}{14} = \underline{0.94}$$

Select! Higher the Gain, better!



- Entropy with Age information

$$= 0.69 \text{ (Information Gain = } 0.94 - 0.69 = \underline{0.25} \text{)}$$

- Entropy with BMI information

$$= 0.92 \text{ (Information Gain = } 0.94 - 0.92 = 0.02 \text{)}$$

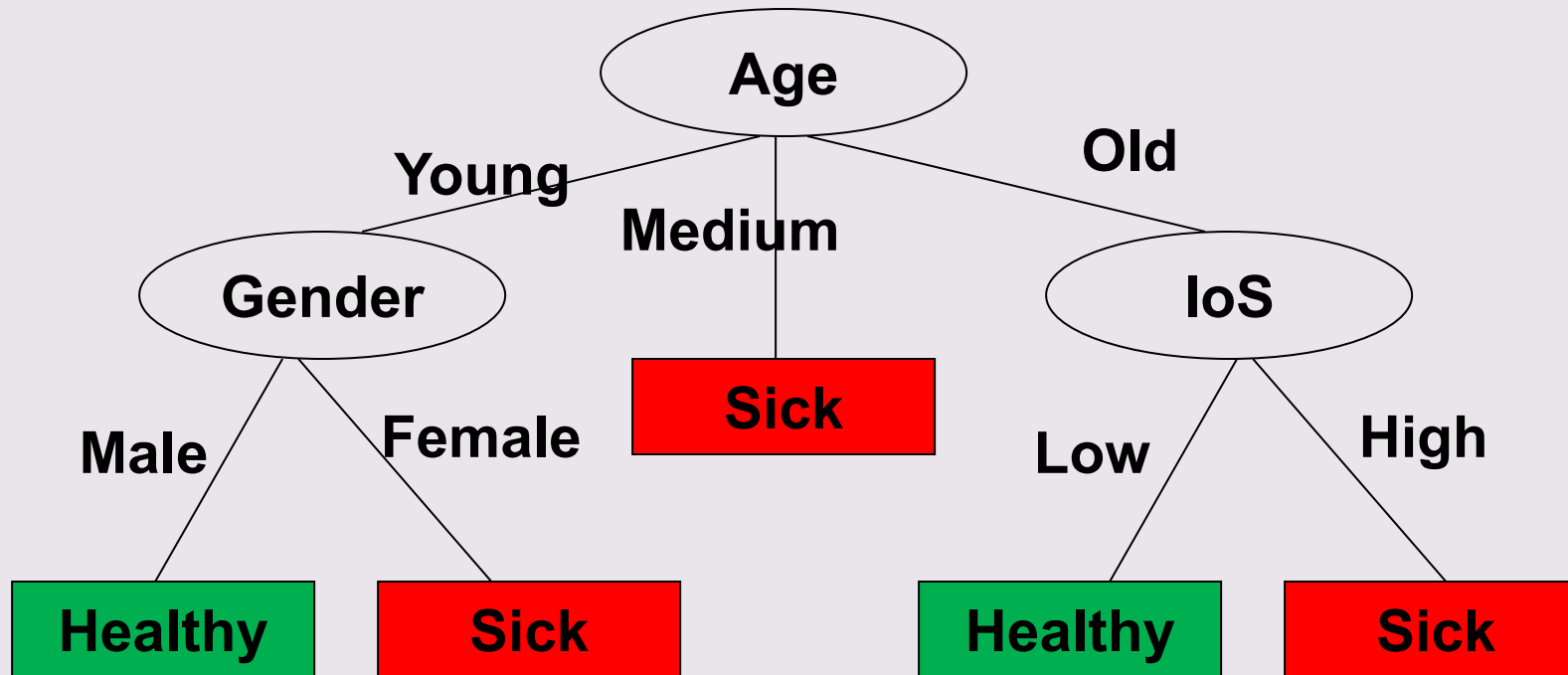
- Entropy with Gender information

$$= 0.79 \text{ (Information Gain = } 0.94 - 0.79 = 0.15 \text{)}$$

- Entropy with loS information

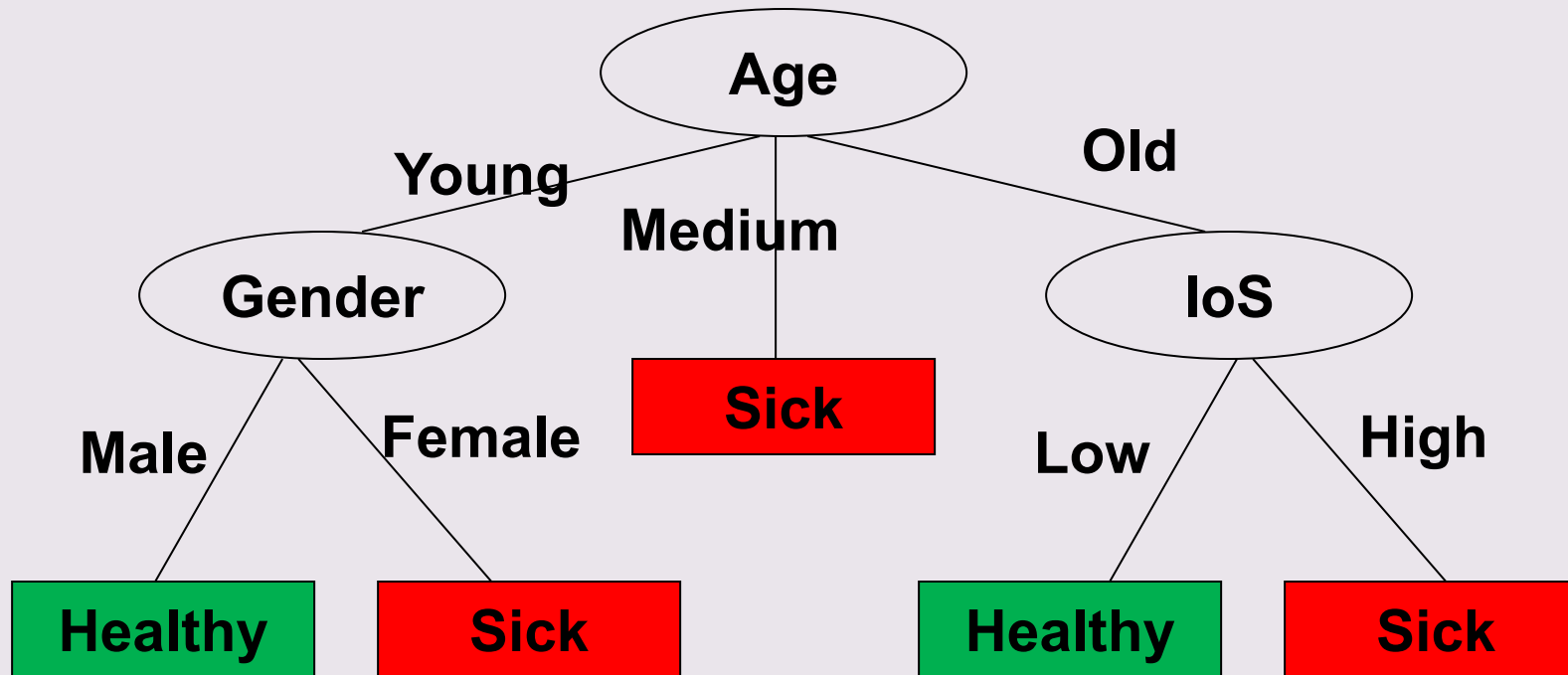
$$= 0.89 \text{ (Information Gain = } 0.94 - 0.89 = 0.05 \text{)}$$

Final Tree



NEW TOTAL = 0 TL!

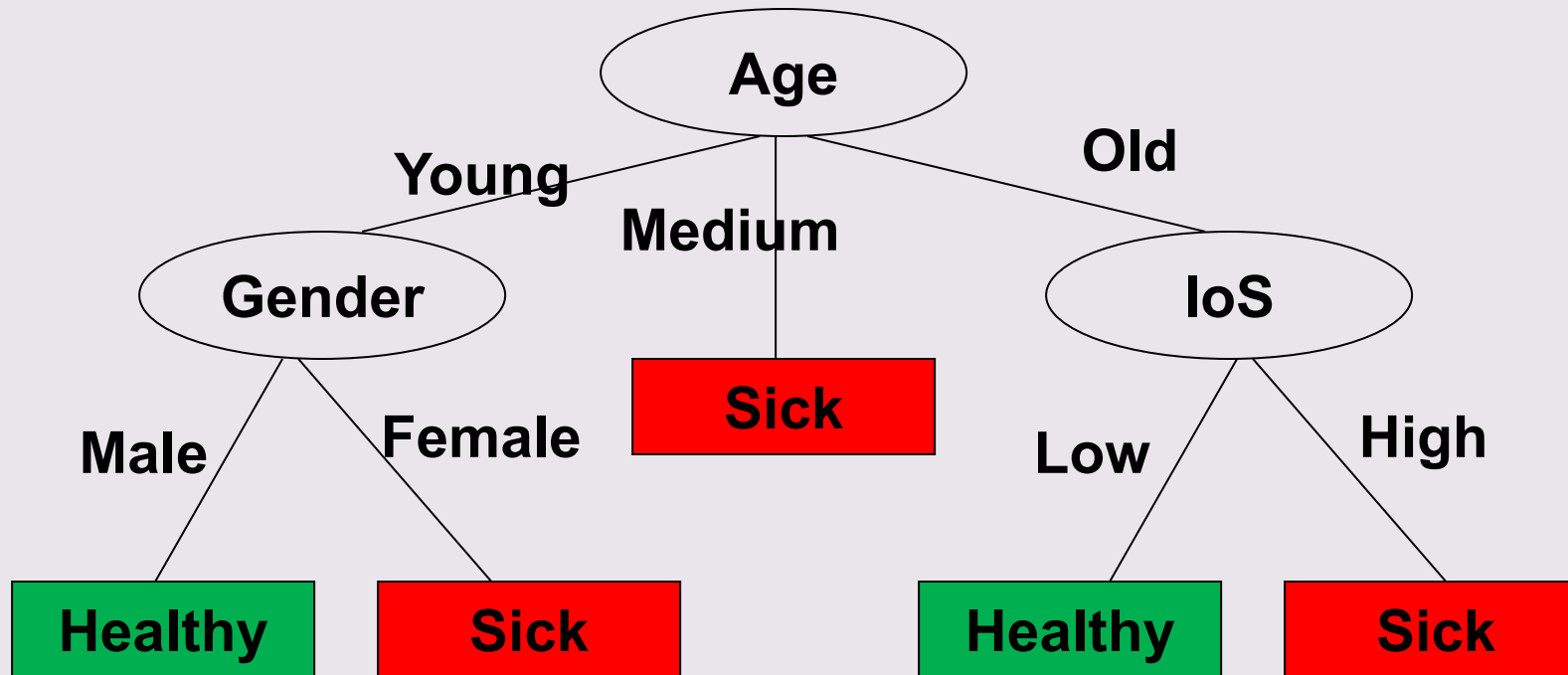
Final Tree – How to Classify?



Consider an old male, who has low BMI and the intensity of symptoms is also low. Healthy or Sick?

How about a middle aged woman, who has low BMI and high intensity of symptoms?

Final Tree – How to Classify?



Consider an old male, who has low BMI and the intensity of symptoms is also low. Healthy or Sick? **Healthy**

How about a middle aged woman, who has low BMI and high intensity of symptoms? **Sick**

Randomization: Random Forest

- You can randomize the training data, the feature subsets or the steps in the algorithm (*or any combination!*).
 - Resample the training **instances** repetitively and generate new trees.
 - Choose a subset of the **features** randomly and generate new trees.
 - Don't pick the best in terms of the Information Gain, but pick one of the best *k*'s (among *a set of promising candidates*) randomly and obtain a *Random Tree*.
- You can repeat the process randomly and obtain different models and you can use voting and obtain a Forest of Random Trees, i.e. *Random Forest*

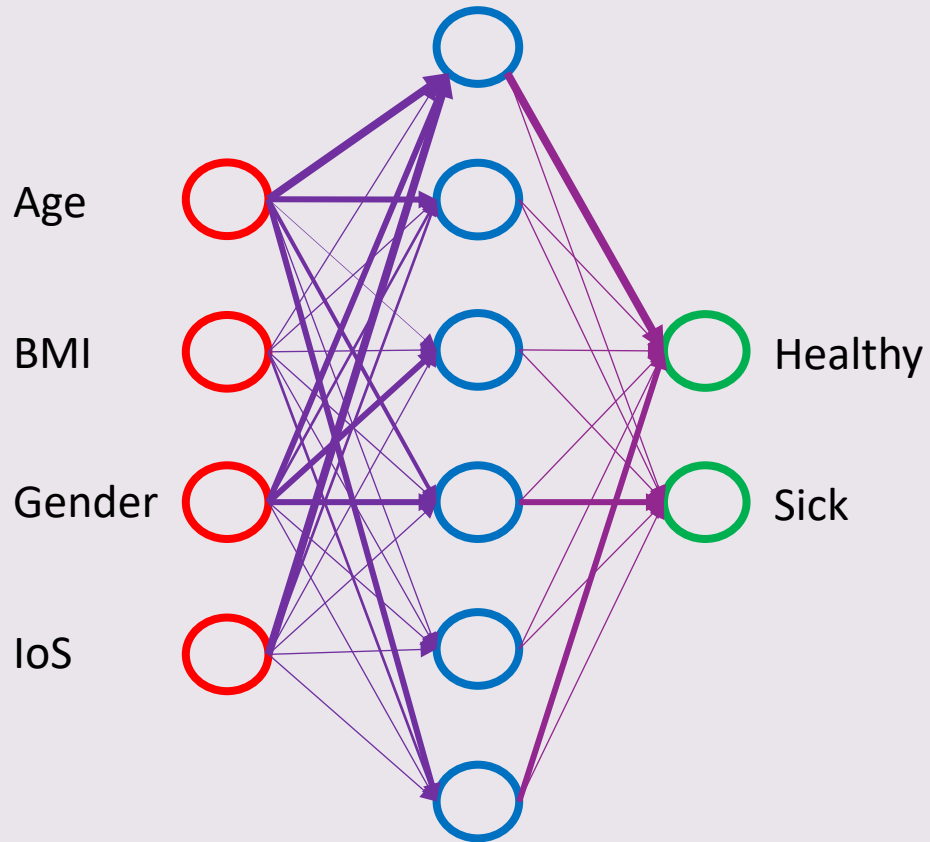
Recall: The Disease Problem

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young	Under	Male	High	Healthy
2	Young	Under	Male	Low	Healthy
3	Middle	Under	Male	High	Sick
4	Old	Medium	Male	High	Sick
5	Old	Over	Female	High	Sick
6	Old	Over	Female	Low	Healthy
7	Middle	Over	Female	Low	Sick
8	Young	Medium	Male	High	Healthy
9	Young	Over	Female	High	Sick
10	Old	Medium	Female	High	Sick
11	Young	Medium	Female	Low	Sick
12	Middle	Medium	Male	Low	Sick
13	Middle	Under	Female	High	Sick
14	Old	Medium	Male	Low	Healthy

The Disease Problem

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
2	Young (1)	Under (1)	Male (1)	Low (1)	Healthy
3	Middle (2)	Under (1)	Male (1)	High (2)	Sick
4	Old (3)	Medium (2)	Male (1)	High (2)	Sick
5	Old (3)	Over (3)	Female (2)	High (2)	Sick
6	Old (3)	Over (3)	Female (2)	Low (1)	Healthy
7	Middle (2)	Over (3)	Female (2)	Low (1)	Sick
8	Young (1)	Medium (2)	Male (1)	High (2)	Healthy
9	Young (1)	Over (3)	Female (2)	High (2)	Sick
10	Old (3)	Medium (2)	Female (2)	High (2)	Sick
11	Young (1)	Medium (2)	Female (2)	Low (1)	Sick
12	Middle (2)	Medium (2)	Male (1)	Low (1)	Sick
13	Middle (2)	Under (1)	Female (2)	High (2)	Sick
14	Old (3)	Medium (2)	Male (1)	Low (1)	Healthy

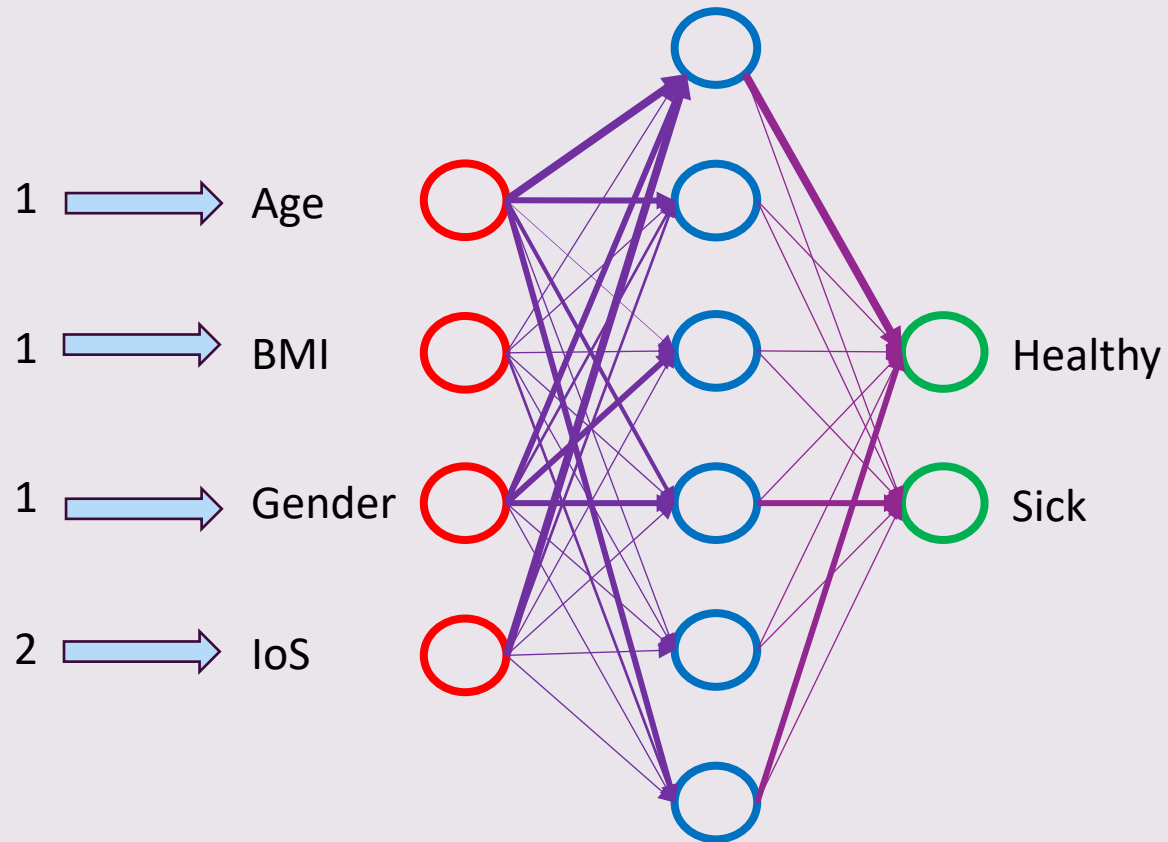
The Disease Problem – ANN Model



- 4 Input Nodes
- 6 Hidden Nodes (No particular reason! 😊)
- 2 Output Nodes
- There are $4 \times 6 + 6 \times 2 = 36$ connections
- 36 weights!
- Also $6 + 2 = 8$ biases.
- Altogether $36 + 8 = 44$ parameters to be optimized!
- LETS ASSUME SOME HOW WE CHOOSE THE PARAMETERS!

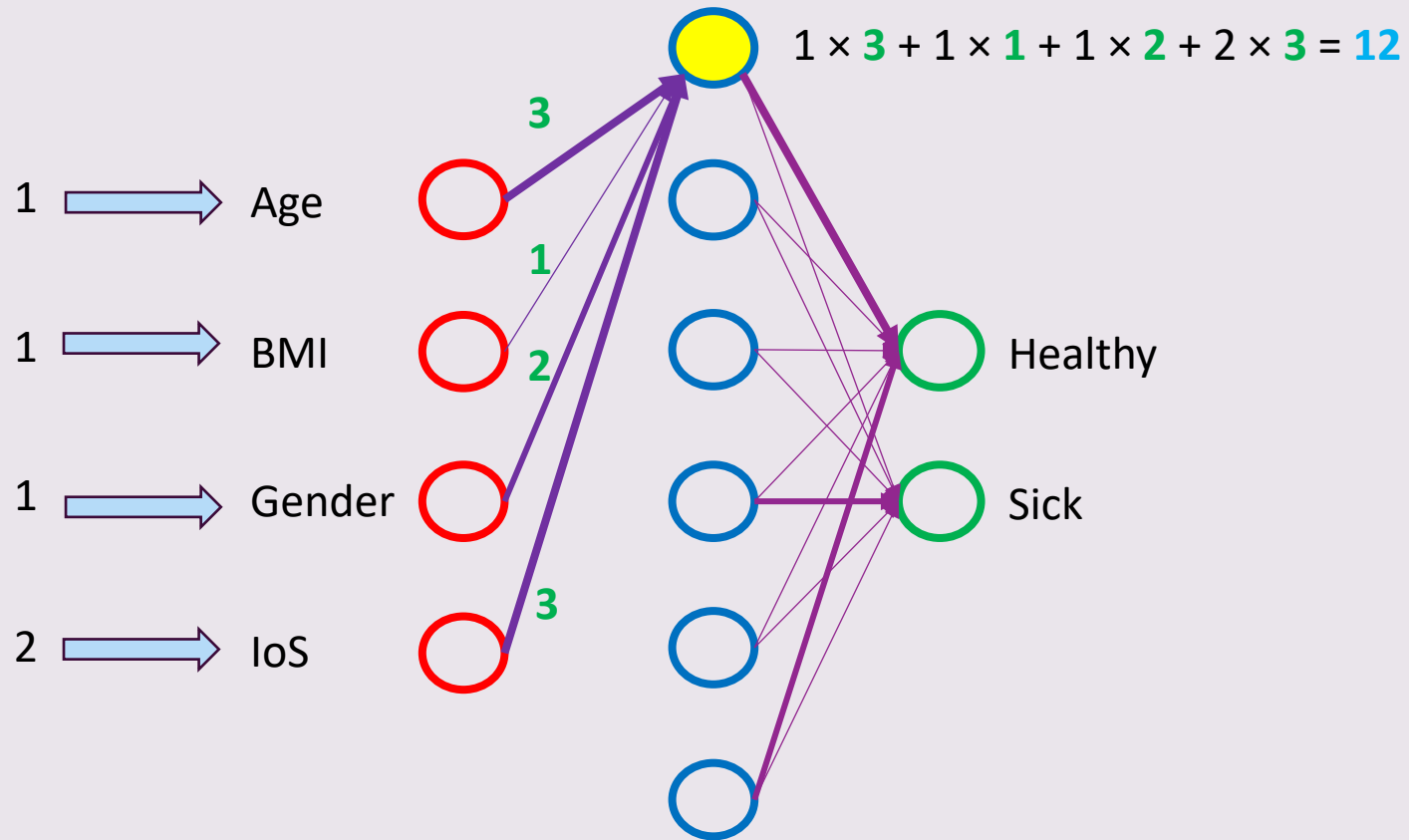
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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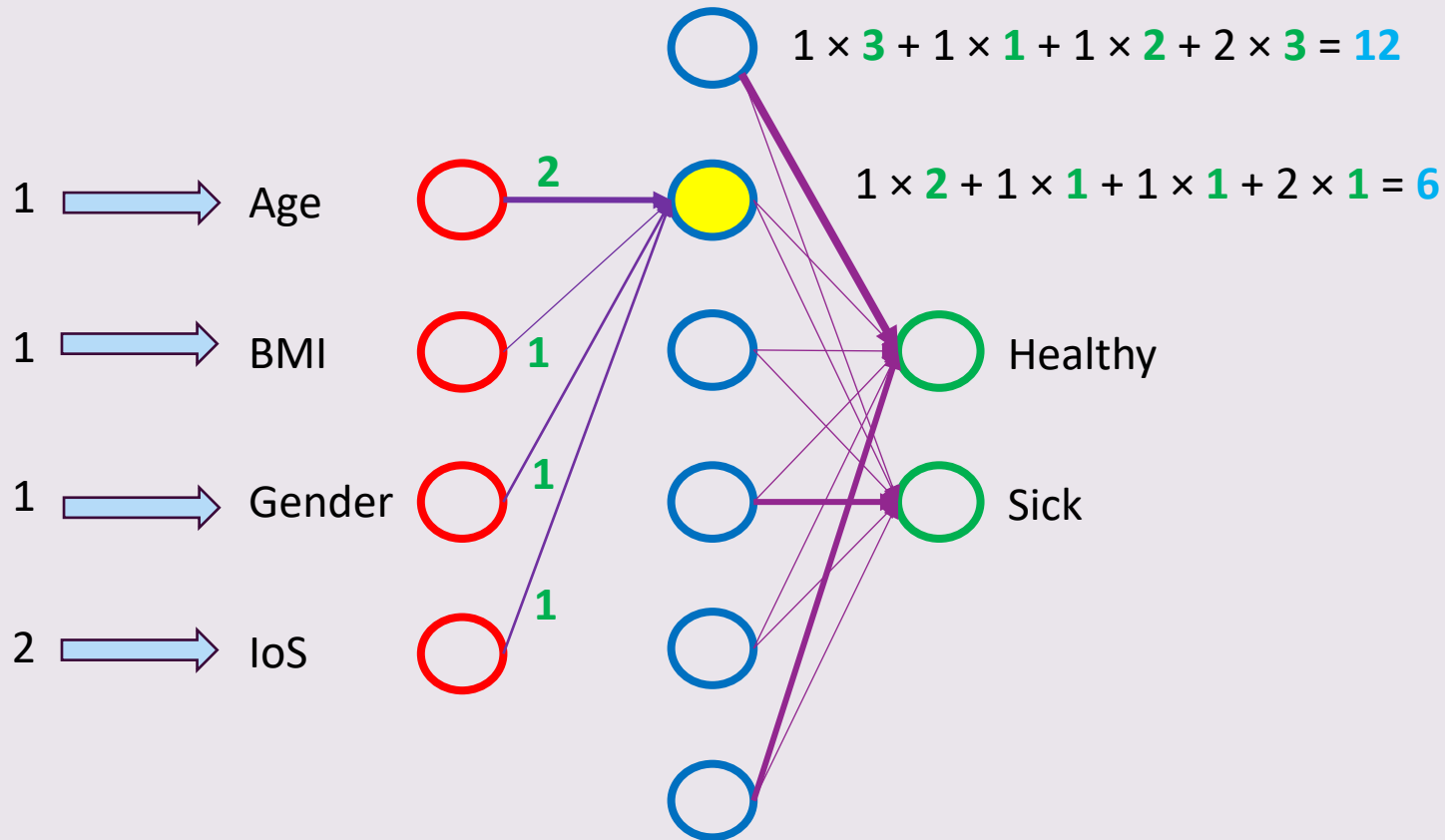
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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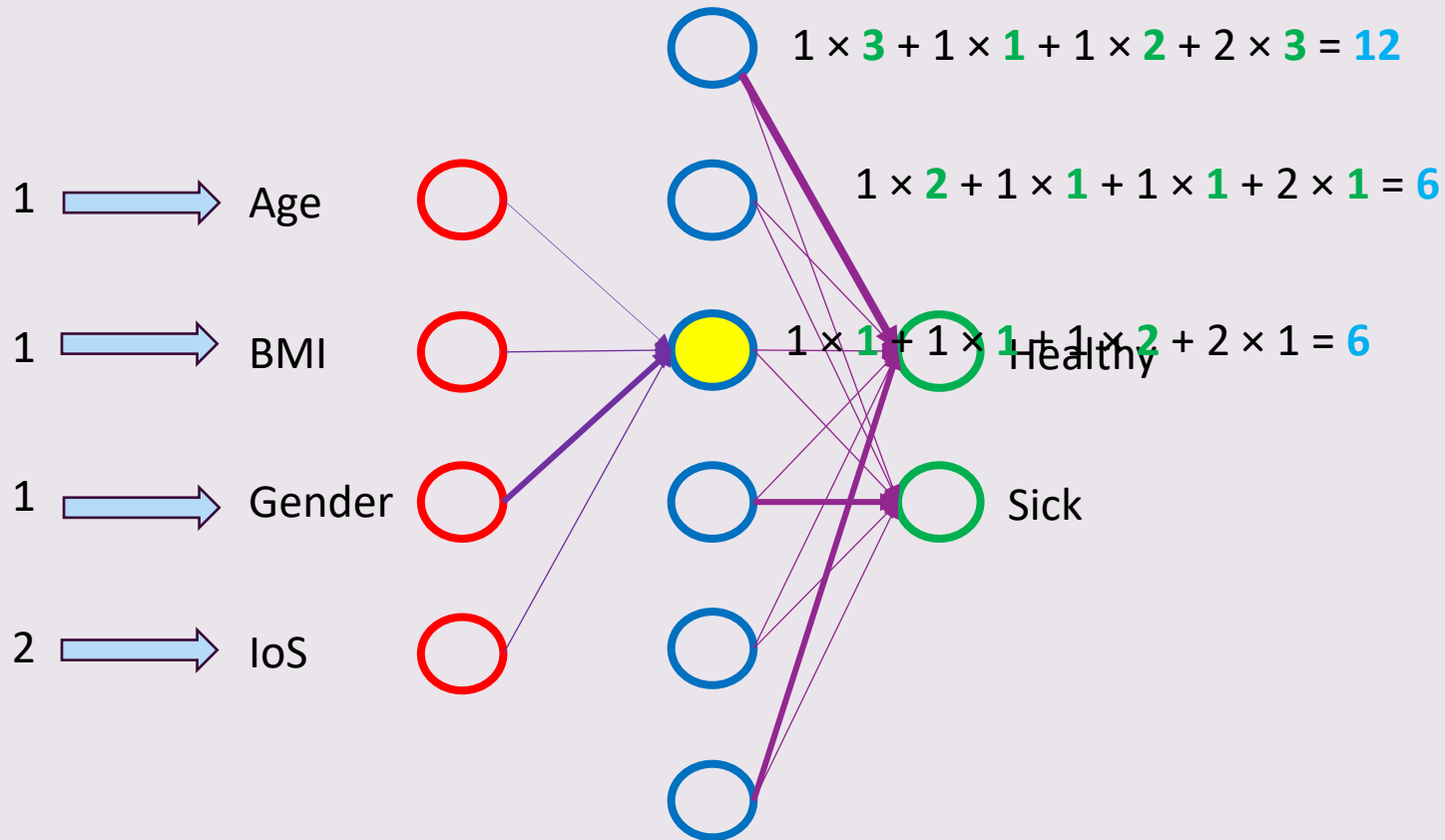
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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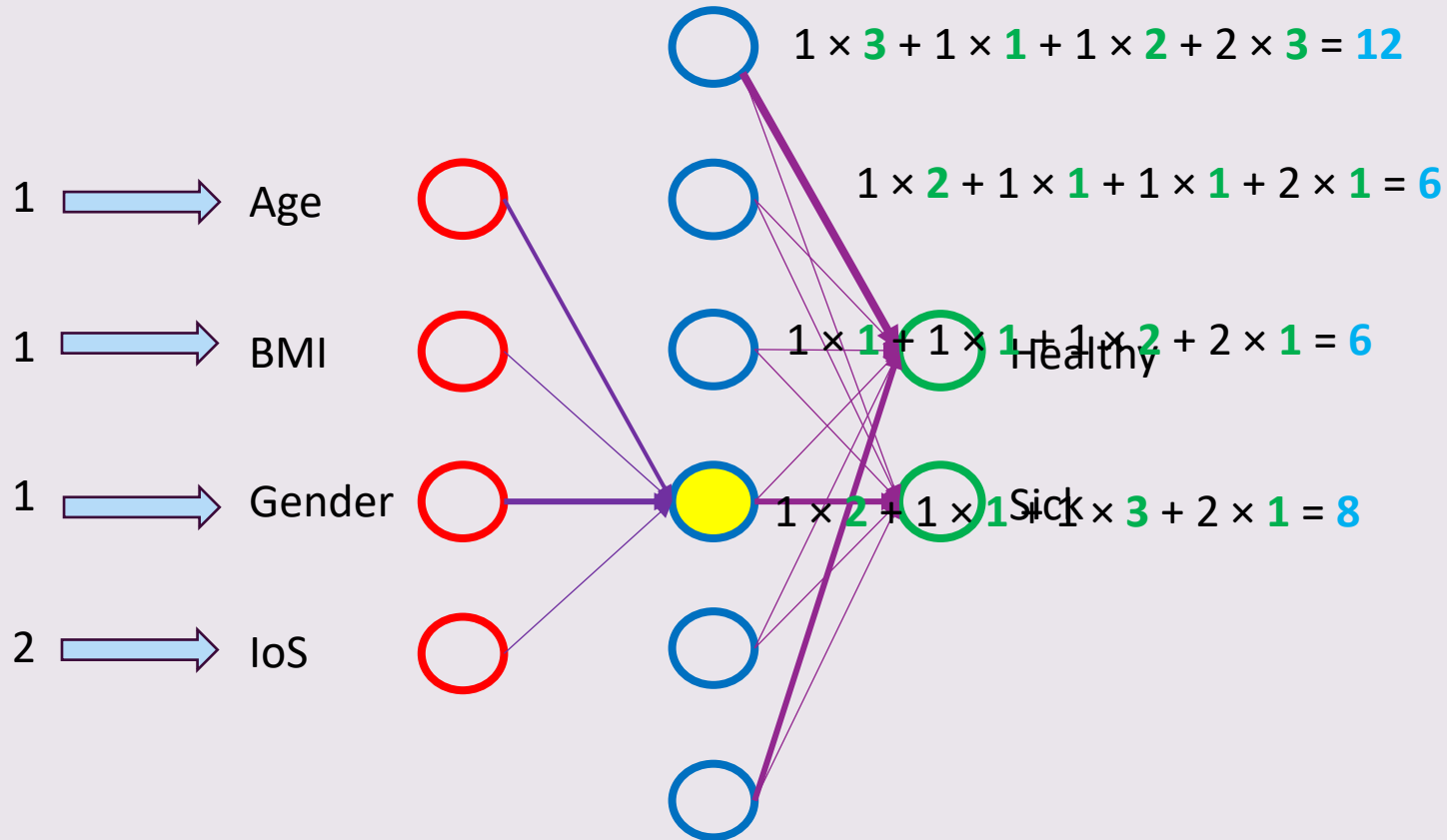
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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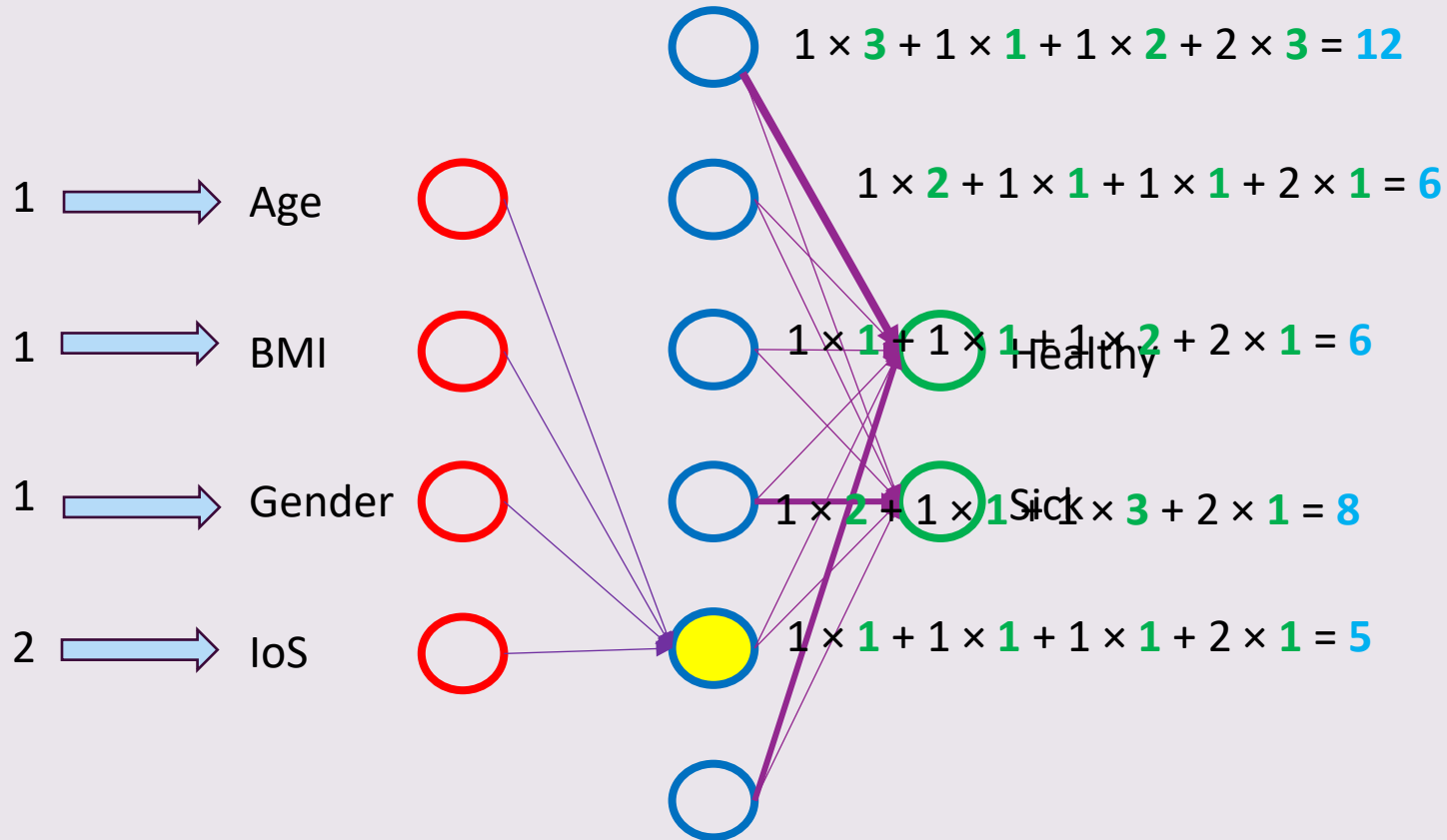
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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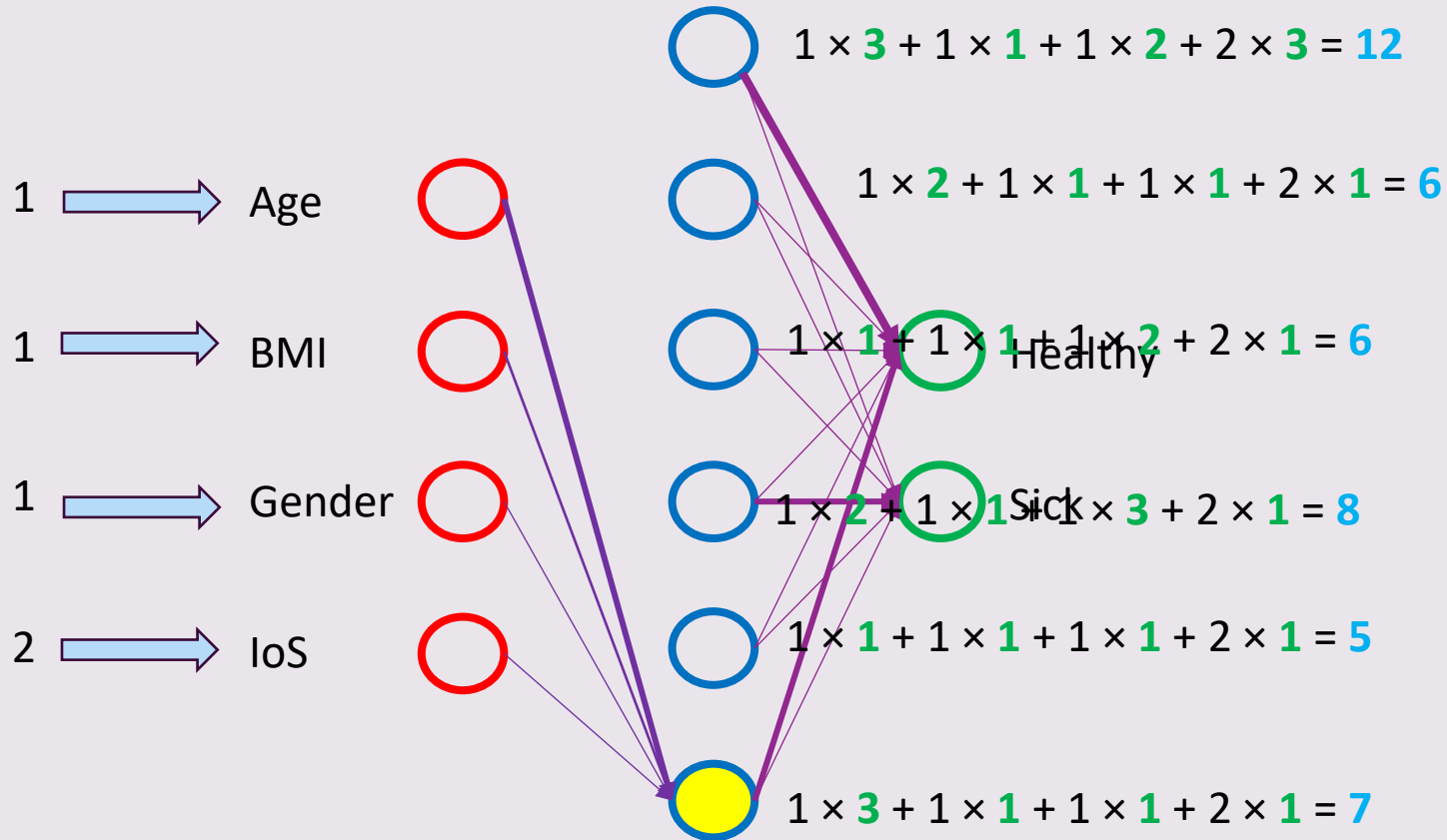
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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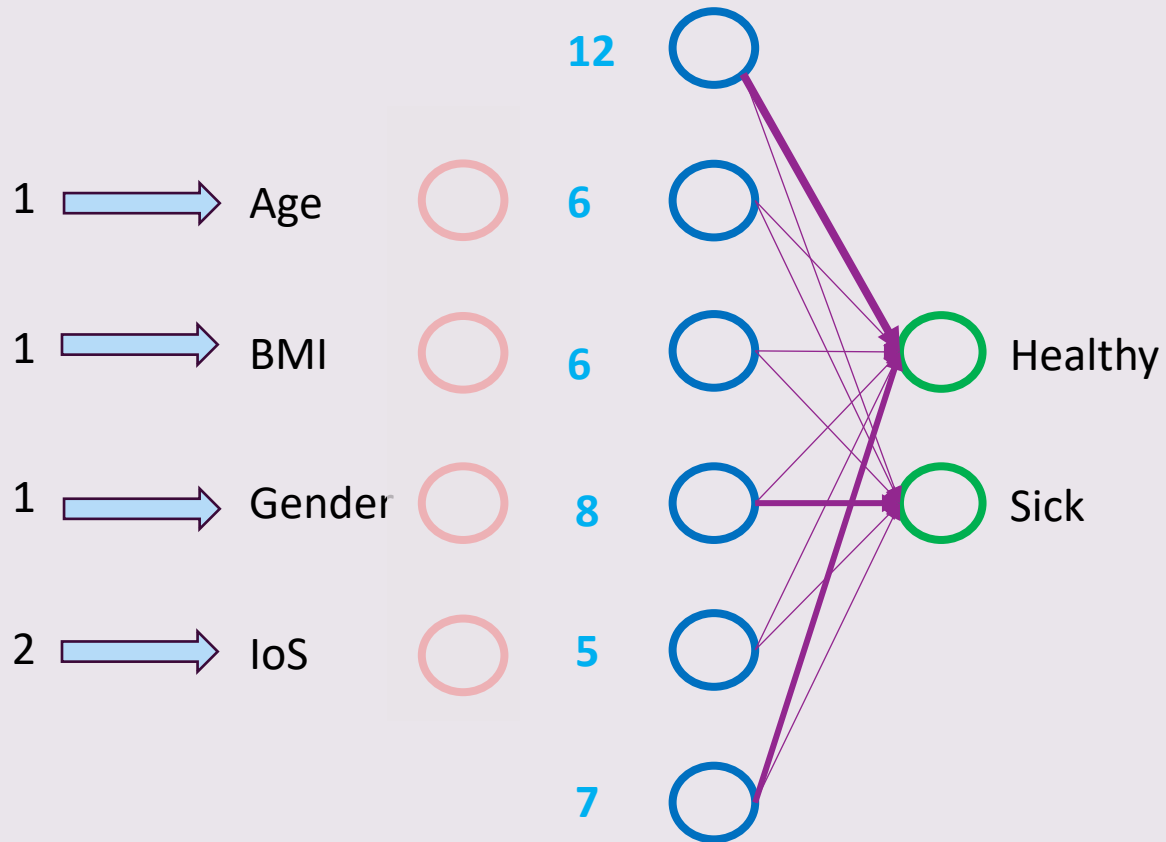
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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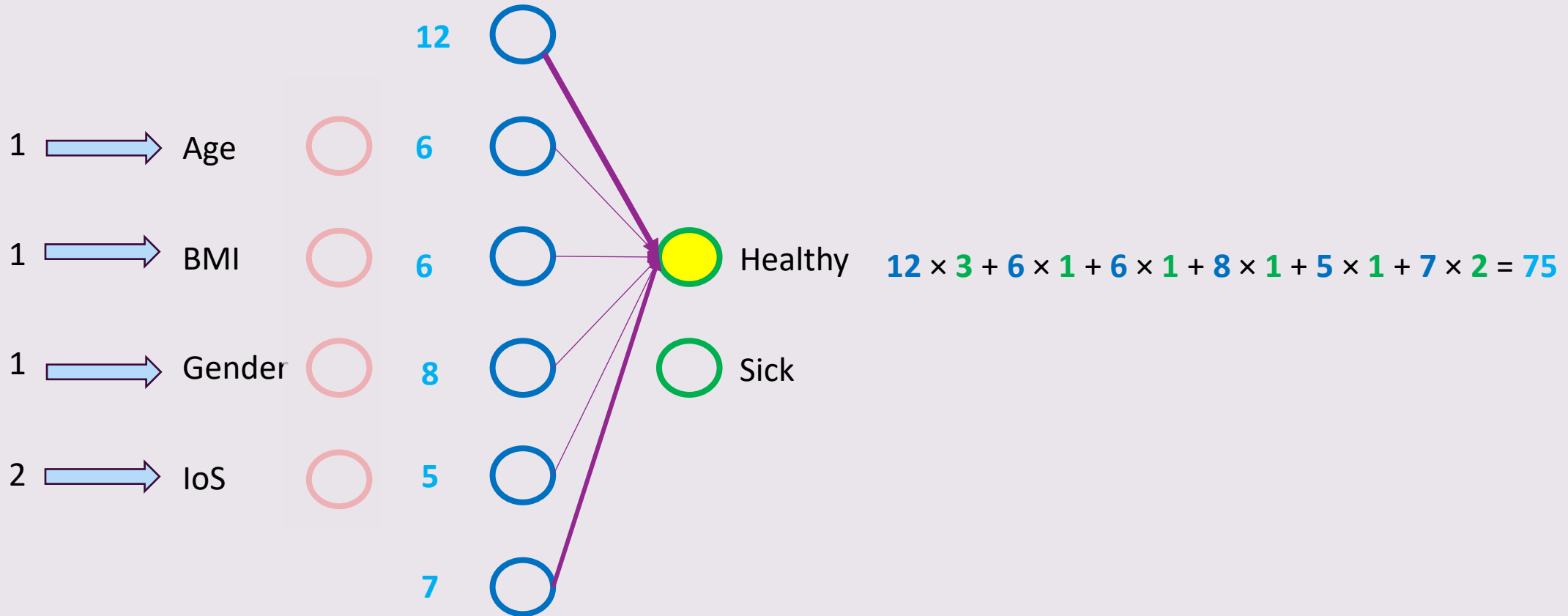
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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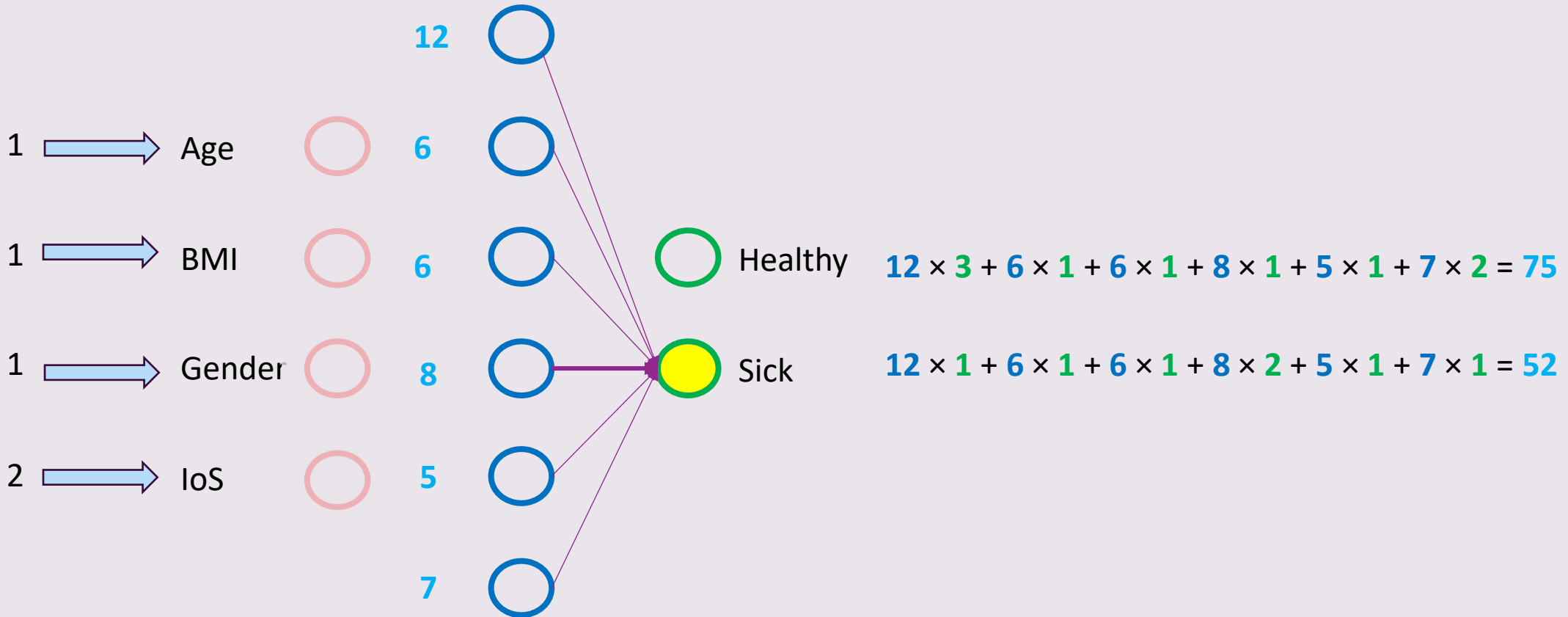
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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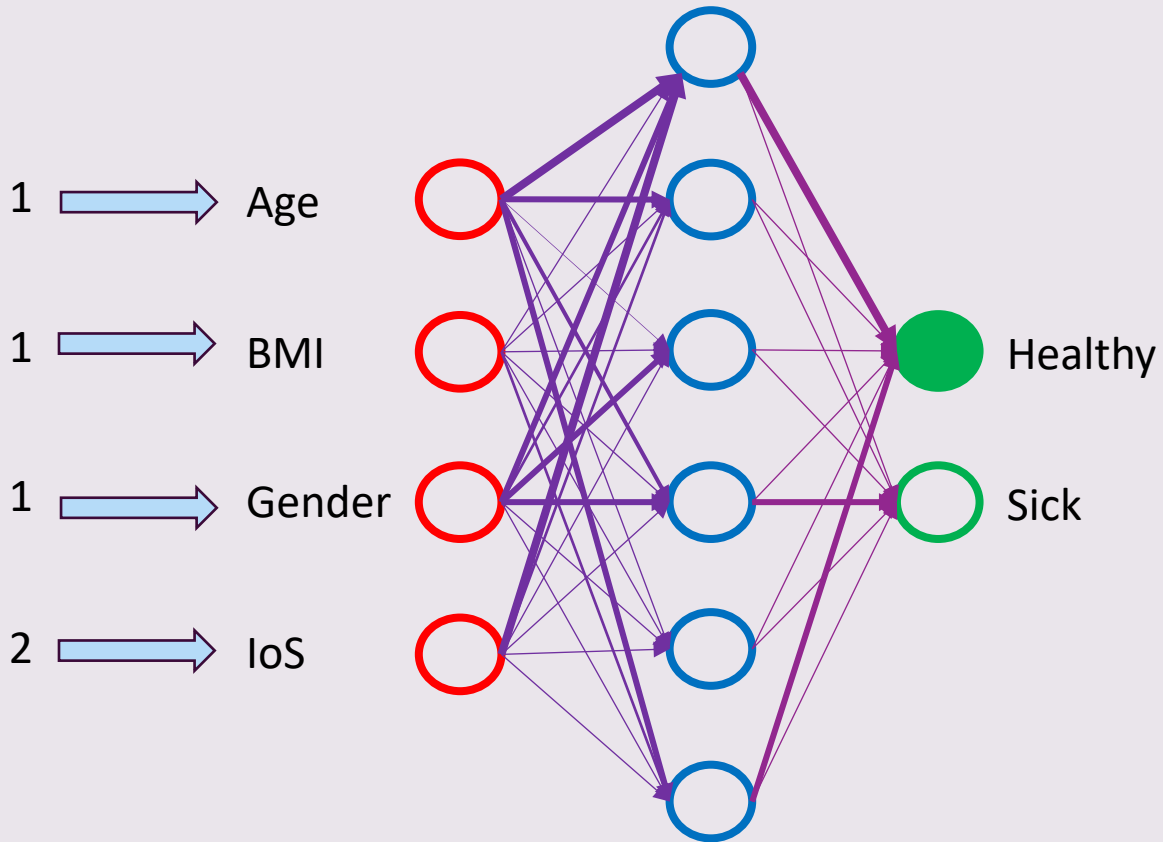
The Disease Problem – ANN Model

1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
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The Disease Problem – ANN Model

1 Young (1) Under (1) Male (1) High (2) Healthy

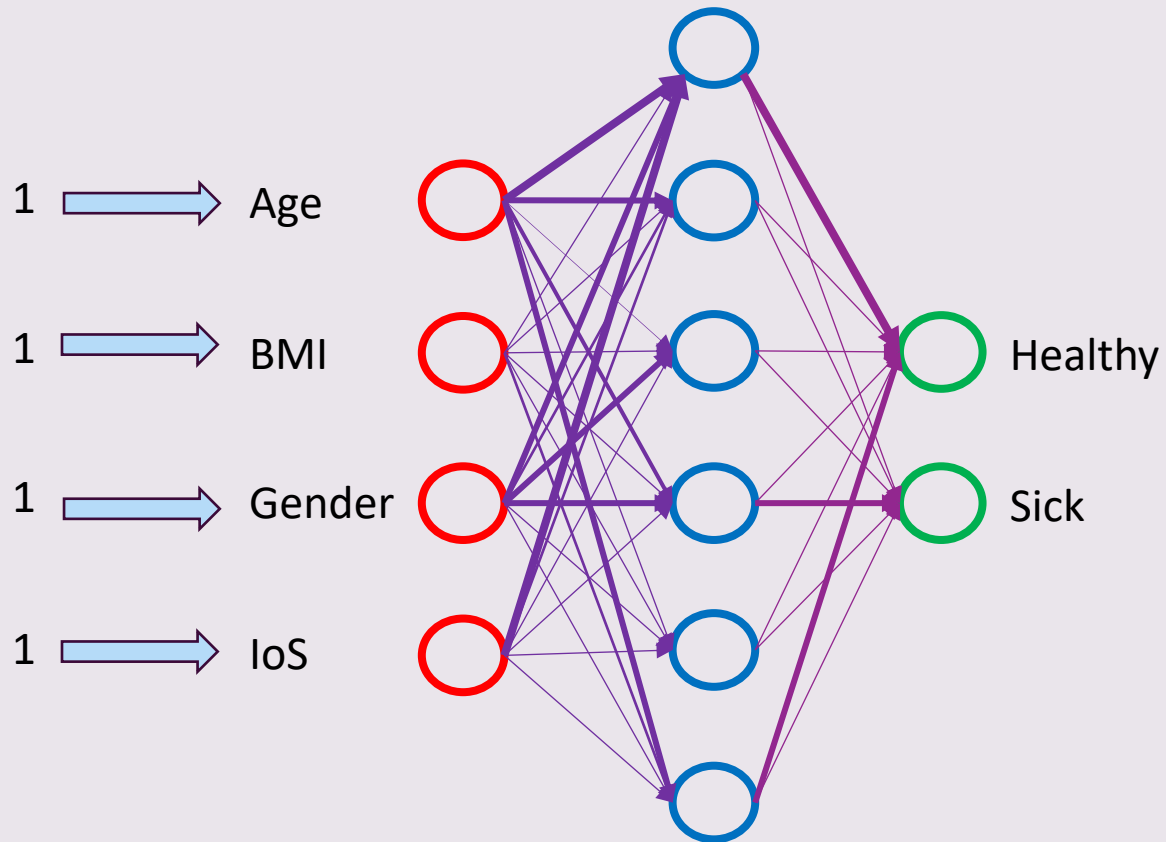


Next:

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
2	Young (1)	Under (1)	Male (1)	Low (1)	Healthy
3	Middle (2)	Under (1)	Male (1)	High (2)	Sick
4	Old (3)	Medium (2)	Male (1)	High (2)	Sick
5	Old (3)	Over (3)	Female (2)	High (2)	Sick
6	Old (3)	Over (3)	Female (2)	Low (1)	Healthy
7	Middle (2)	Over (3)	Female (2)	Low (1)	Sick
8	Young (1)	Medium (2)	Male (1)	High (2)	Healthy
9	Young (1)	Over (3)	Female (2)	High (2)	Sick
10	Old (3)	Medium (2)	Female (2)	High (2)	Sick
11	Young (1)	Medium (2)	Female (2)	Low (1)	Sick
12	Middle (2)	Medium (2)	Male (1)	Low (1)	Sick
13	Middle (2)	Under (1)	Female (2)	High (2)	Sick
14	Old (3)	Medium (2)	Male (1)	Low (1)	Healthy

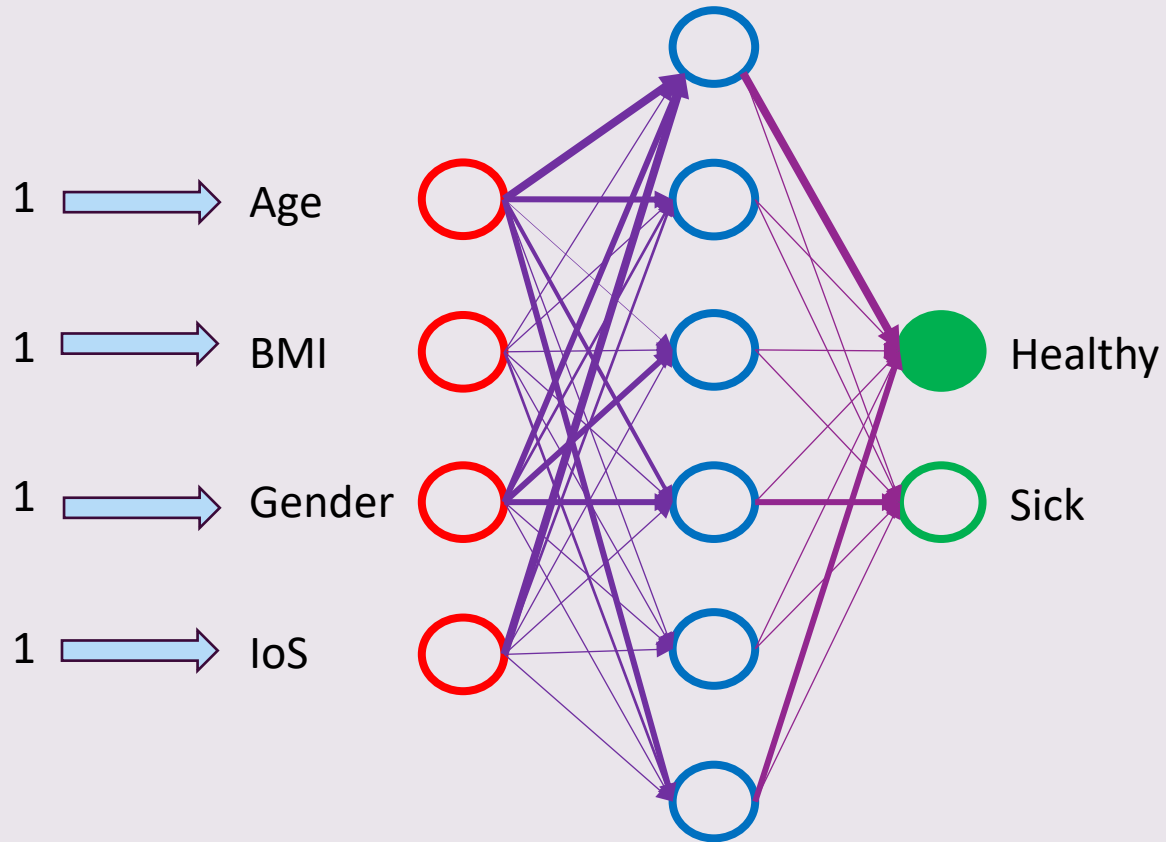
The Disease Problem – ANN Model

2	Young (1)	Under (1)	Male (1)	Low (1)	Healthy
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The Disease Problem – ANN Model

2 Young (1) Under (1) Male (1) Low (1) **Healthy**

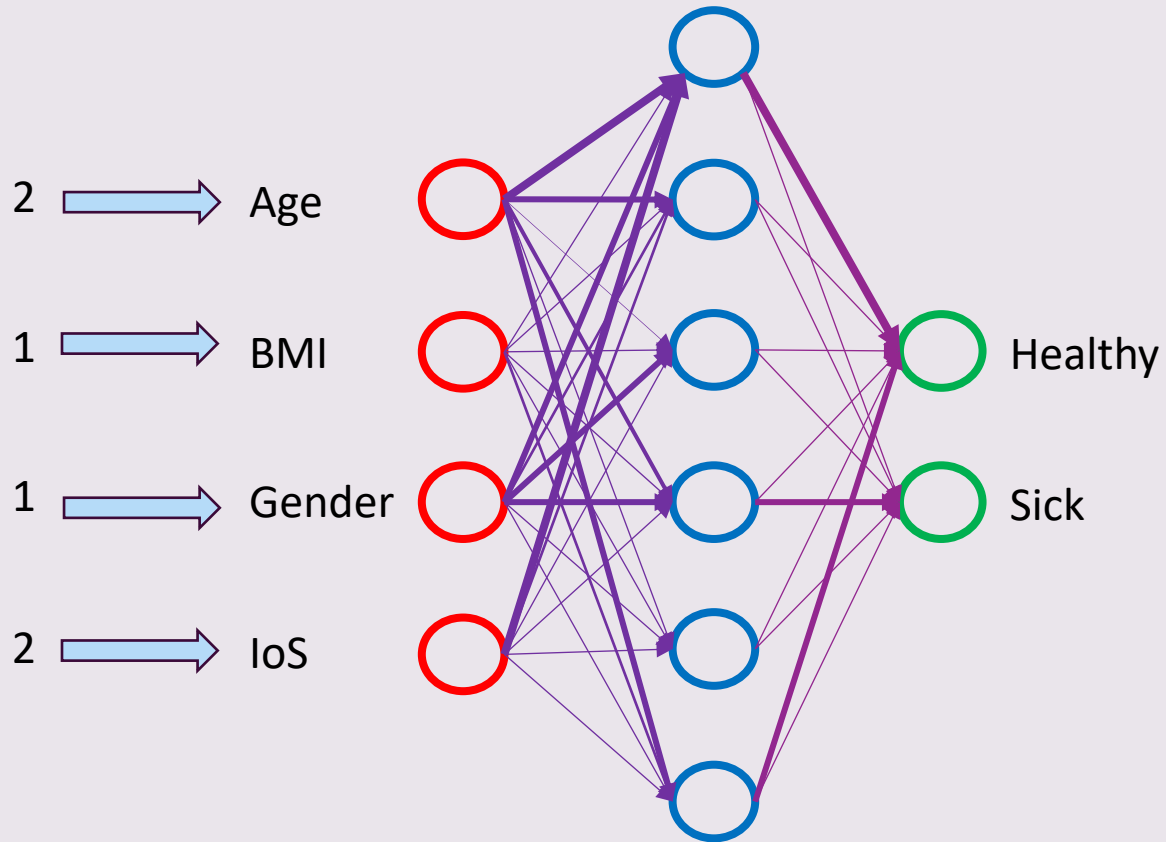


Next:

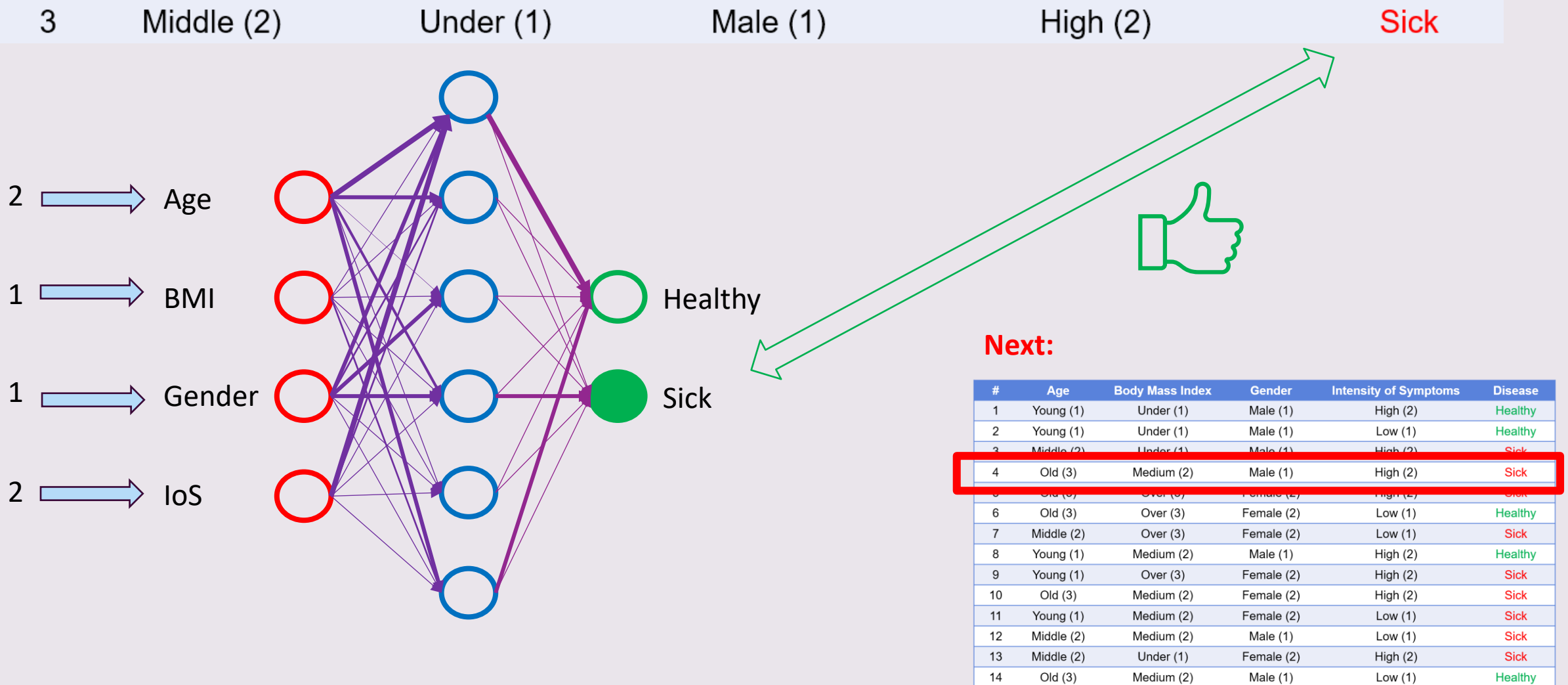
#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
2	Young (1)	Under (1)	Male (1)	Low (1)	Healthy
3	Middle (2)	Under (1)	Male (1)	High (2)	Sick
4	Old (3)	Medium (2)	Male (1)	High (2)	Sick
5	Old (3)	Over (3)	Female (2)	High (2)	Sick
6	Old (3)	Over (3)	Female (2)	Low (1)	Healthy
7	Middle (2)	Over (3)	Female (2)	Low (1)	Sick
8	Young (1)	Medium (2)	Male (1)	High (2)	Healthy
9	Young (1)	Over (3)	Female (2)	High (2)	Sick
10	Old (3)	Medium (2)	Female (2)	High (2)	Sick
11	Young (1)	Medium (2)	Female (2)	Low (1)	Sick
12	Middle (2)	Medium (2)	Male (1)	Low (1)	Sick
13	Middle (2)	Under (1)	Female (2)	High (2)	Sick
14	Old (3)	Medium (2)	Male (1)	Low (1)	Healthy

The Disease Problem – ANN Model

3	Middle (2)	Under (1)	Male (1)	High (2)	Sick
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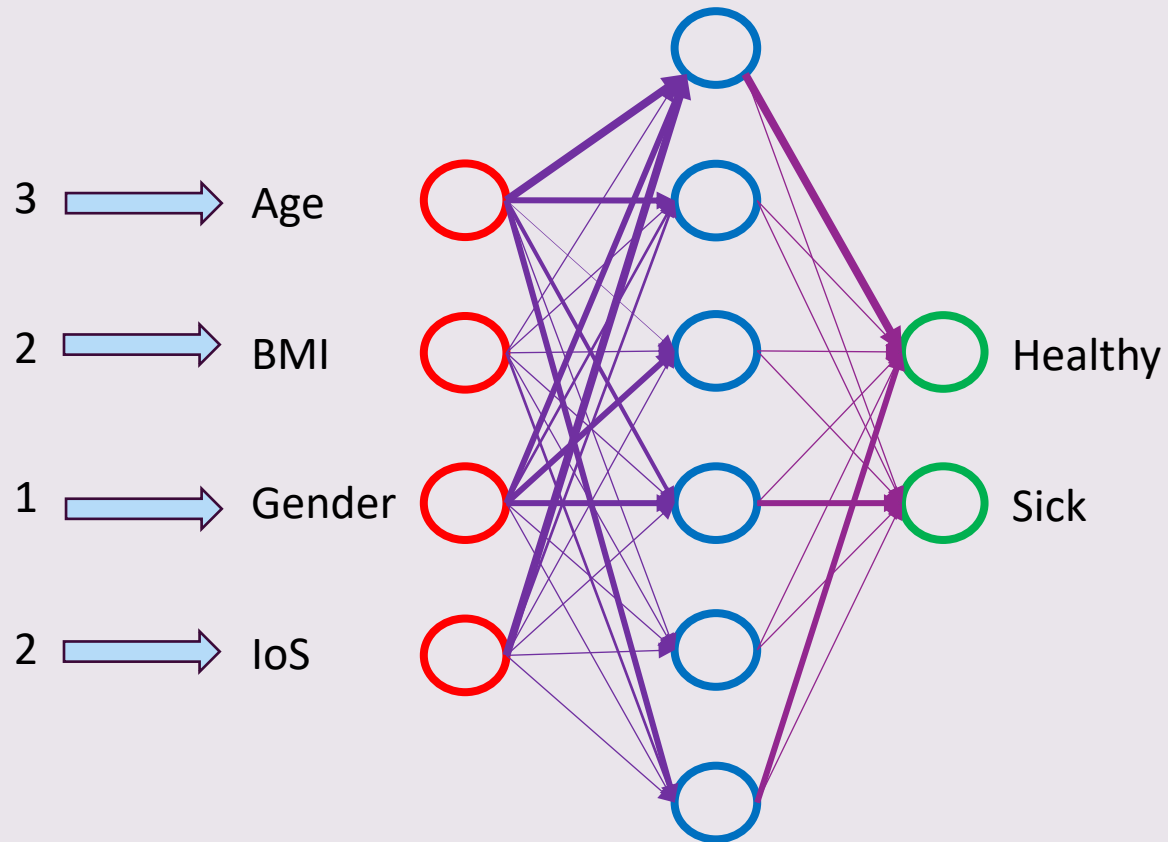


The Disease Problem – ANN Model

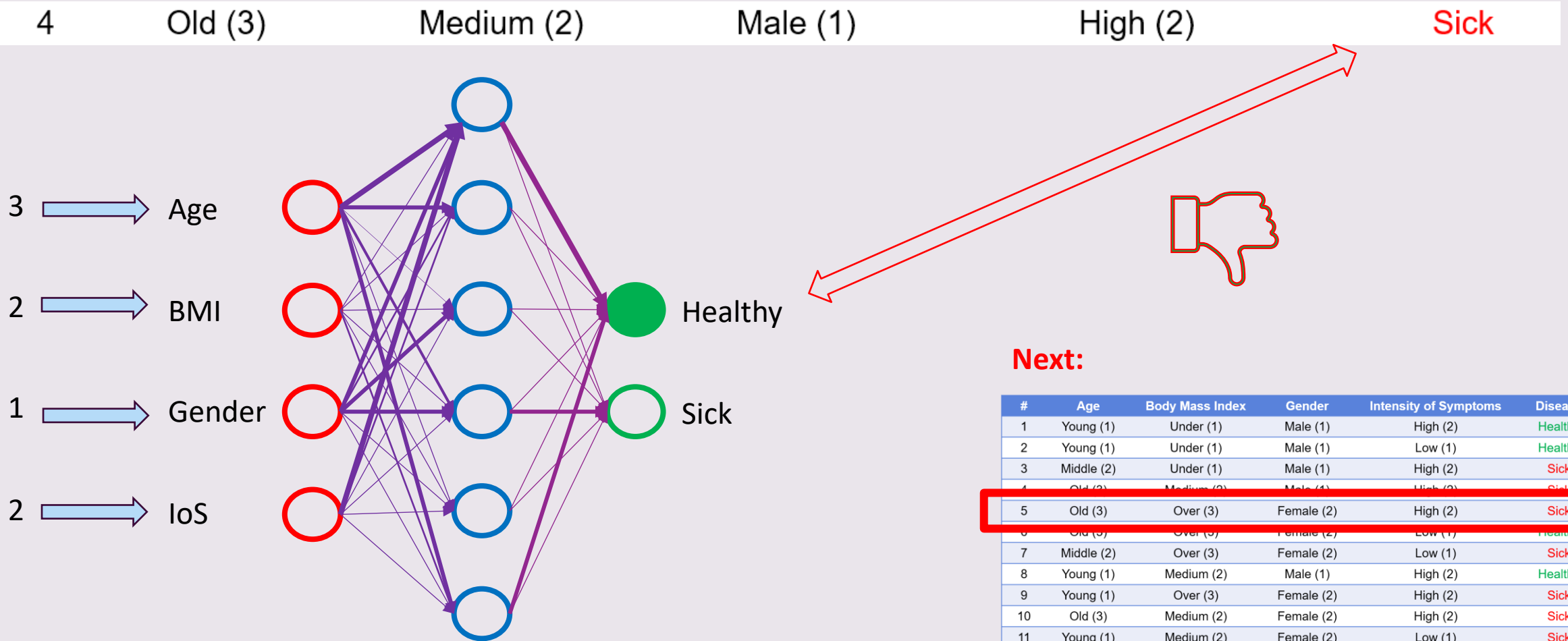


The Disease Problem – ANN Model

4	Old (3)	Medium (2)	Male (1)	High (2)	Sick
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The Disease Problem – ANN Model

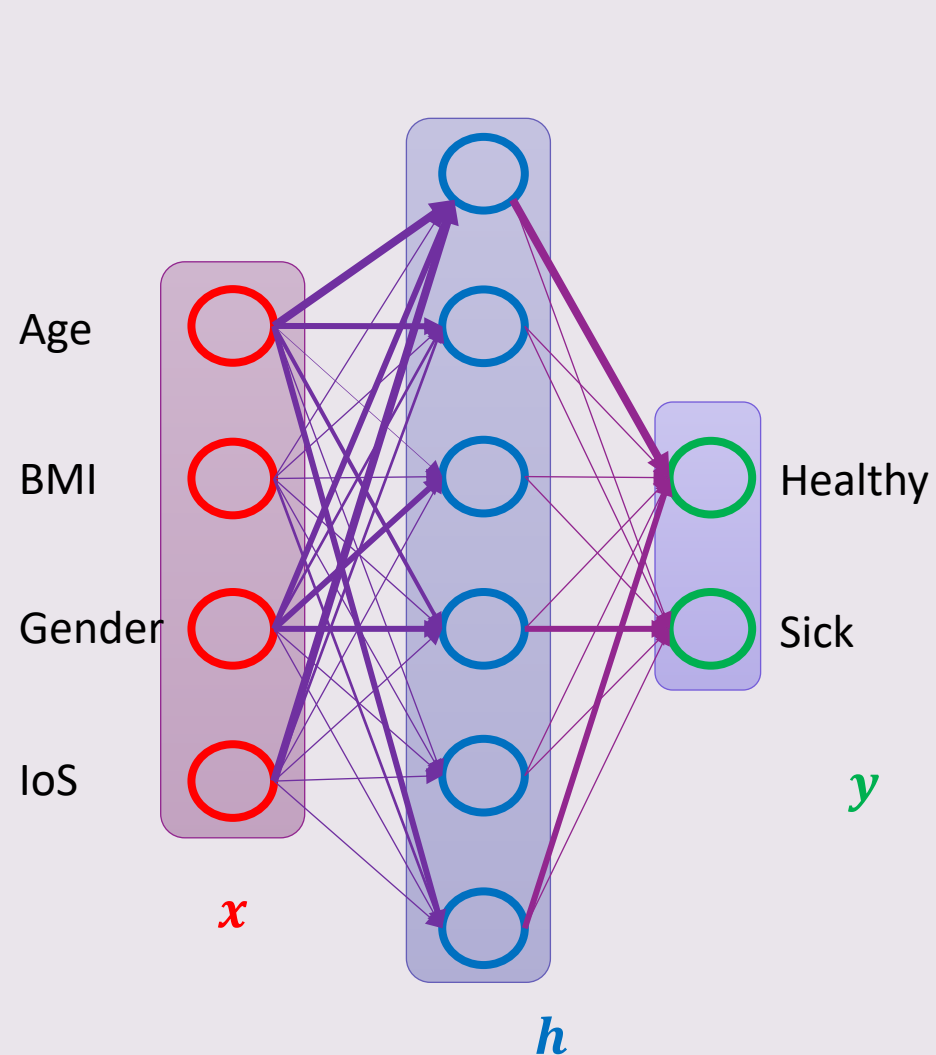


The Disease Problem

#	Age	Body Mass Index	Gender	Intensity of Symptoms	Disease
1	Young (1)	Under (1)	Male (1)	High (2)	Healthy
2	Young (1)	Under (1)	Male (1)	Low (1)	Healthy
3	Middle (2)	Under (1)	Male (1)	High (2)	Sick
4	Old (3)	Medium (2)	Male (1)	High (2)	Sick
5	Old (3)	Over (3)	Female (2)	High (2)	Sick
6	Old (3)	Over (3)	Female (2)	Low (1)	Healthy
7	Middle (2)	Over (3)	Female (2)	Low (1)	Sick
8	Young (1)	Medium (2)	Male (1)	High (2)	Healthy
9	Young (1)	Over (3)	Female (2)	High (2)	Sick
10	Old (3)	Medium (2)	Female (2)	High (2)	Sick
11	Young (1)	Medium (2)	Female (2)	Low (1)	Sick
12	Middle (2)	Medium (2)	Male (1)	Low (1)	Sick
13	Middle (2)	Under (1)	Female (2)	High (2)	Sick
14	Old (3)	Medium (2)	Male (1)	Low (1)	Healthy



Number of Parameters to be Learned



$$h = \sigma(W_1 x + b_1)$$
$$y = \sigma(W_2 h + b_2)$$

Weights

Activation functions

Biases

6 + 2 = 8 neurons (not counting inputs)

$[4 \times 6] + [6 \times 2] = 36$ weights

6 + 2 = 8 biases

44 learnable parameters

Suggested Resources: ANN

3Blue1Brown

But what is a neural network? (19:13 minutes)

- <https://www.youtube.com/watch?v=aircAruvnKk>

◦ *Gradient descent, how neural networks learn (21:00 minutes) – Optional!*

- <https://www.youtube.com/watch?v=aircAruvnKk>

◦ *What is backpropagation really doing? (13:54 minutes)*

- <https://www.youtube.com/watch?v=llg3gGewQ5U>

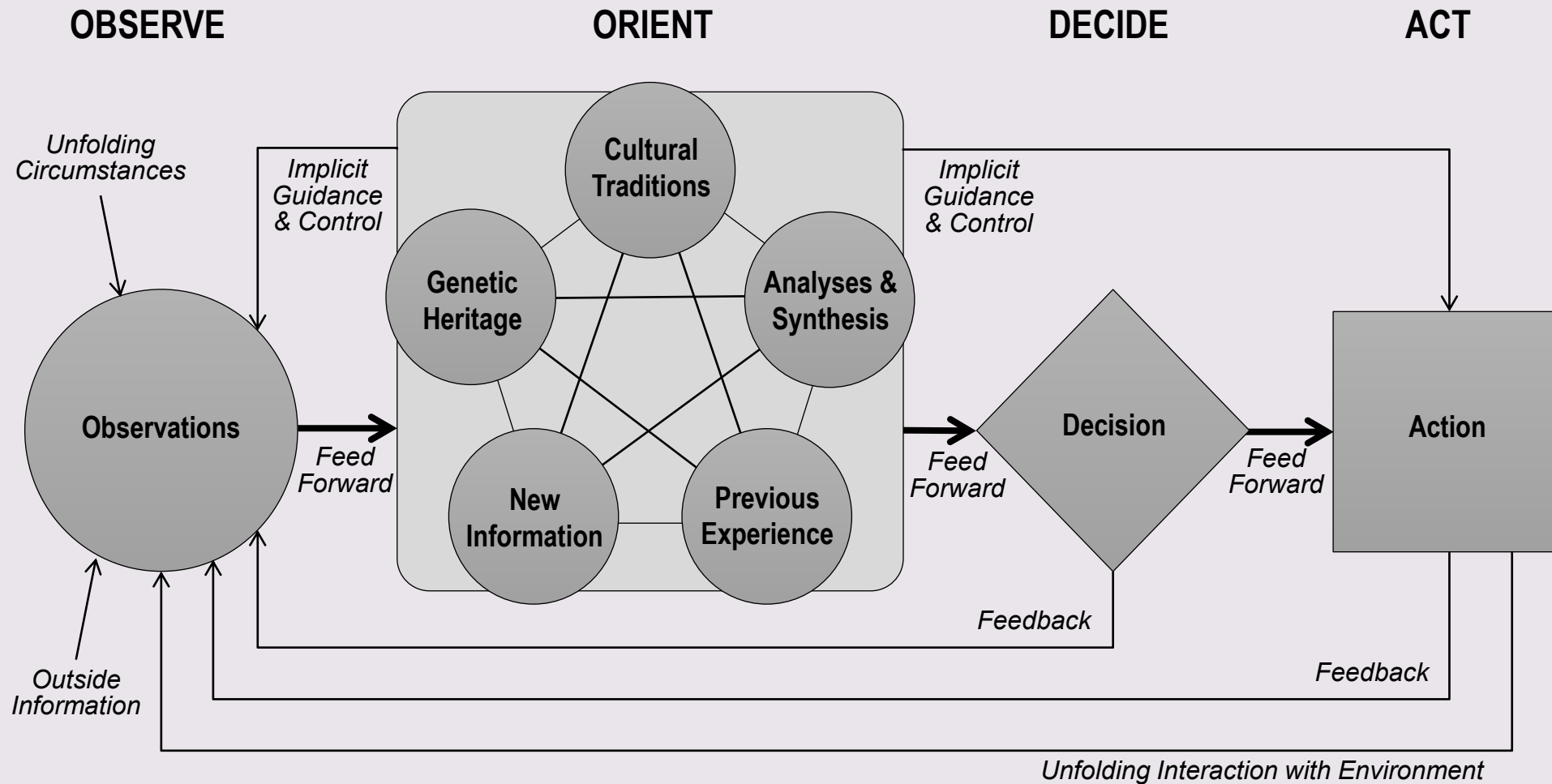
◦ *Backpropagation calculus (10:17 minutes)*

- <https://www.youtube.com/watch?v=tleHLnjs5U8>

Artificial Intelligence



Recall: The (Human) OODA Loop

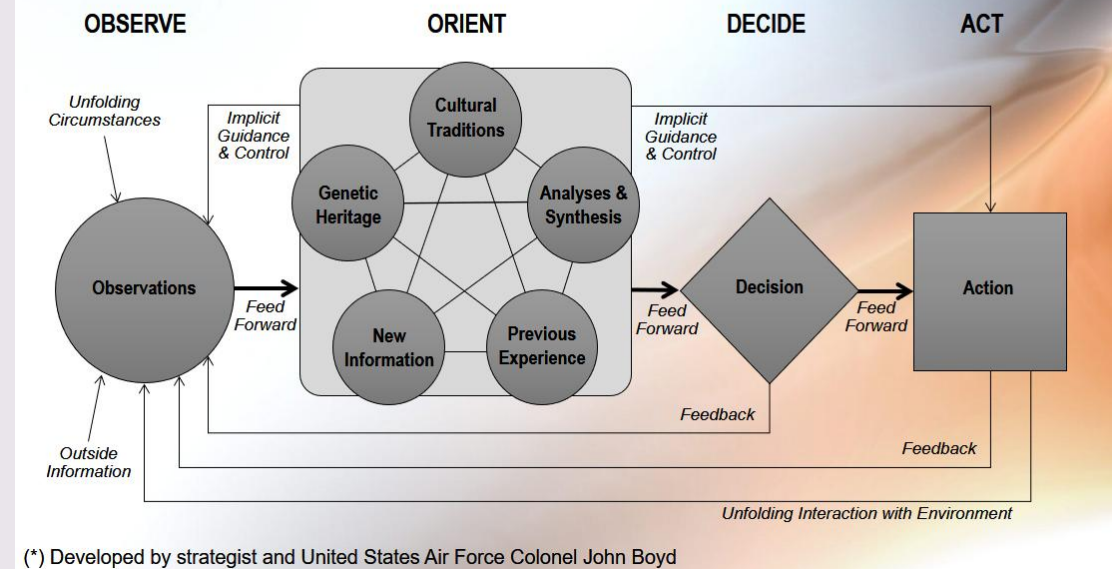


(*) Developed by strategist and United States Air Force Colonel John Boyd

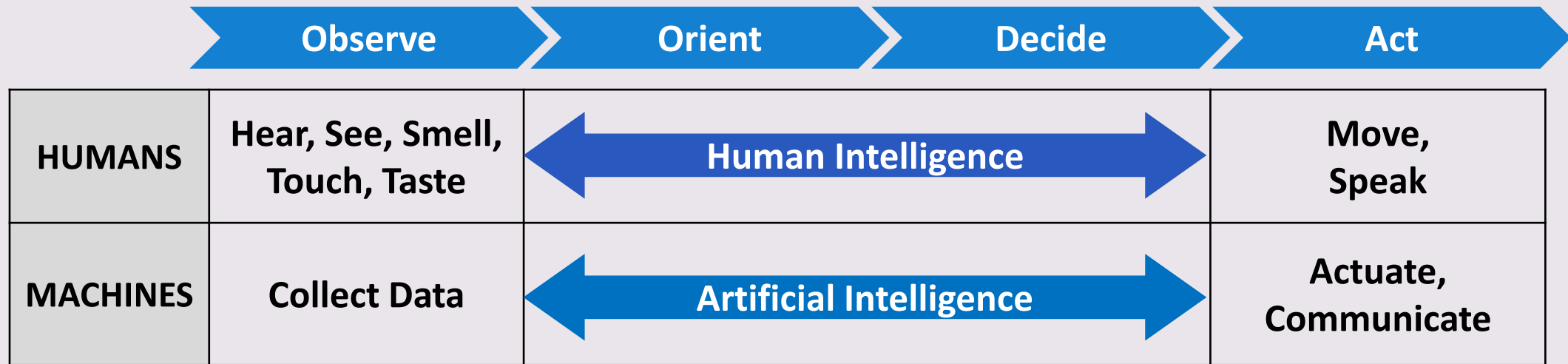
Recall: Enabler Technologies of Digitalization

- Internet of Things
- Cloud/Edge Computing
- Blockchain
- Cyber Security
- **Artificial Intelligence**
- Digital Twins
- Data Driven Manufacturing
- Additive Manufacturing / 3D Printing
- Smart Robotics / Cyber Physical Systems
- Extended Reality: Virtual Reality / Augmented Reality / Mixed Reality

The (Human) OODA Loop (*)



What is Artificial Intelligence?



“Narrow AI”

Computer achieves human or superhuman intelligence on specific tasks or in limited environments

Today

“General AI”

Computer achieves human or superhuman intelligence over the full range of cognitive tasks

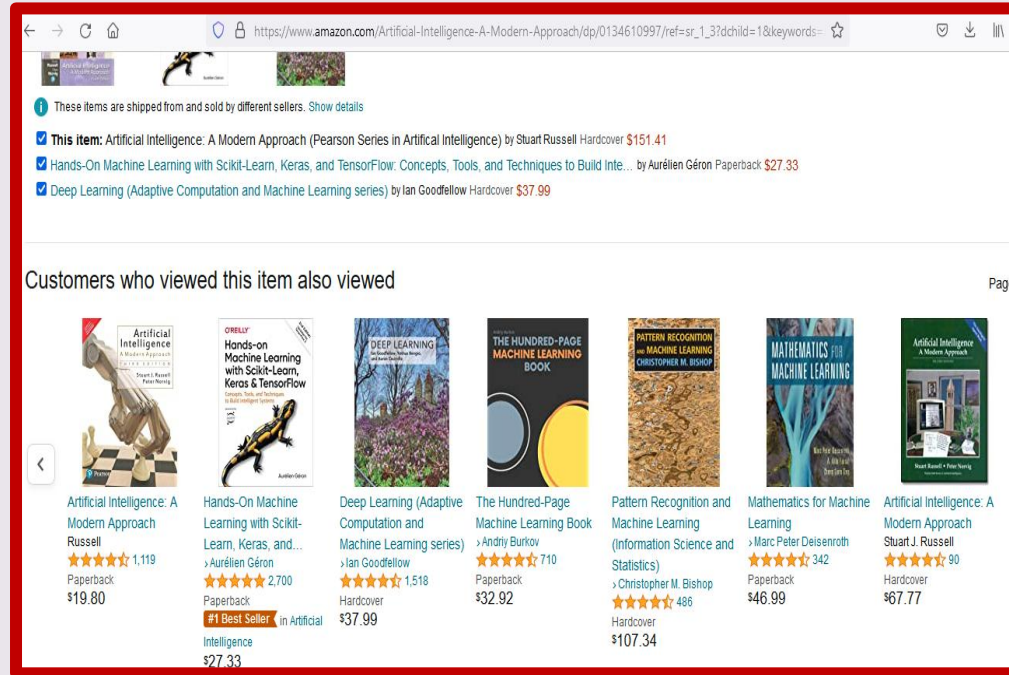
Decades from today?

Artificial Intelligence Everywhere



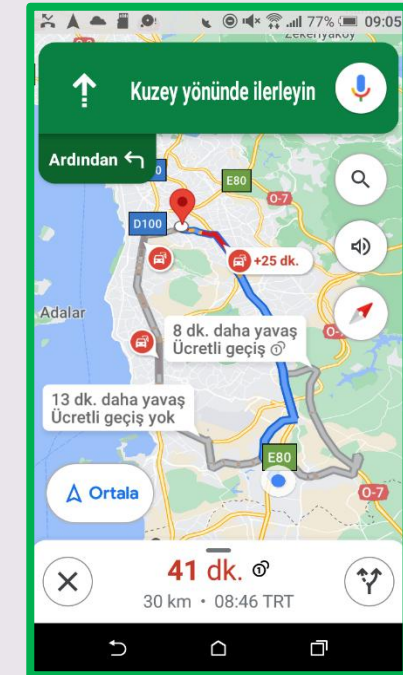
Apple's Siri

Talks with us



Amazon, recommendation system

...And others, e.g., providing financial advice (**Schwab's** Intelligent Portfolio), expert second opinion for cancer patients (**IBM's Watson**)...



Google Maps

Finds the best route for us

Artificial Intelligence

John McCarthy (Stanford) coined the term in Dartmouth Conference (1956) where the aim is stated as:

*"...An attempt will be made to find **how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves.** We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer..." (*)*



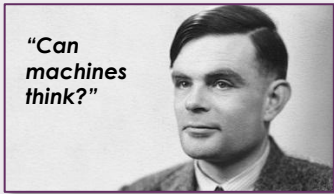
Marvin Minsky - Claude Shannon - Ray Solomonoff - Plus 2 - Dartmouth 1956
photo by courtesy of Minsky family

(*) John McCarthy, Marvin Minsky, Nathan Rochester, and Claude Shannon, "A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence" (1955)

Brief History of Artificial Intelligence

Early AI

1950 – Turing Test



Alan Turing

1956 – Dartmouth Conference



Marvin Minsky – Claude Shannon
Ray Solomonoff – And Others

Machine Learning

1997 – Deep Blue



Garry Kasparov

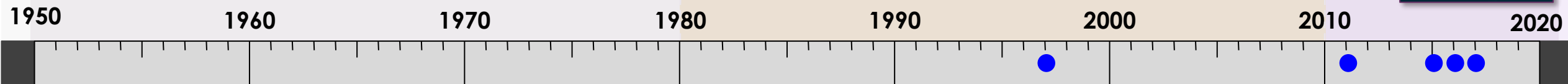
Deep Learning

2016 – AlphaGo



Lee Sedol

2017 – Skin Cancer Detection



1950 – Alan Turing, “Can machines think?”

1956 – John McCarthy coins term Artificial Intelligence

1959 – MIT Artificial Intelligence Project

1979 – Stanford Cart navigates room

1982 – First Expert System DENDRAL

1986 – First self-driving car

1997 – Deep Blue defeats Kasparov

2011 – Watson defeats Jeopardy! champions

2016 – AlphaGo defeats top pro

2015 – Program plays Atari games

2016 – Image recognition

2017 – Libratus defeats top Poker players

2017 – Skin cancer classification

2017 – Speech Recognition

**human or super-human performance*

Recent breakthroughs have begun to fulfill the promise of artificial intelligence (*Third Wave*)

Adapted from 2017 AI Index Report

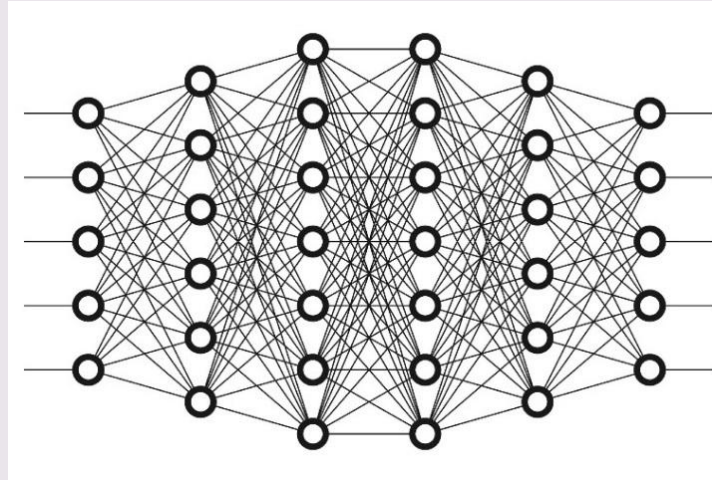
Source: Robert A. Bond’s Presentation which is Adapted from “Preparing for the Future of Artificial Intelligence,” National Science and Technology Council, Oct 2016

Technologies Underlying Recent Progress in AI

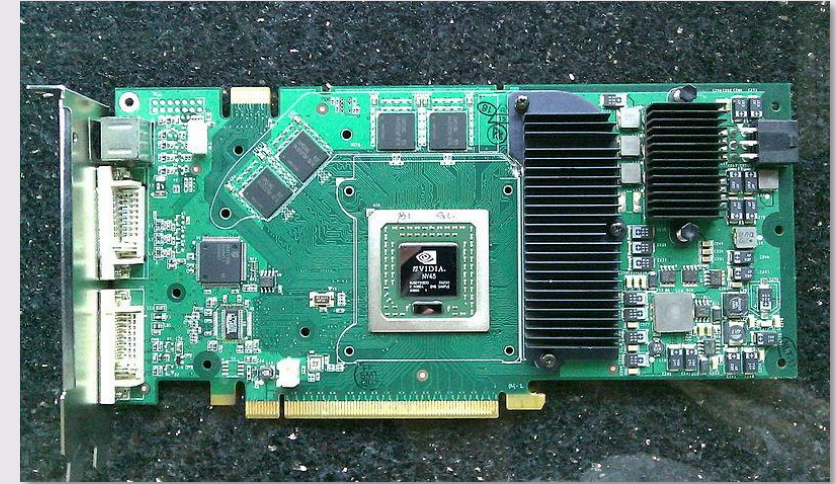
Big Data



Machine Learning Algorithms

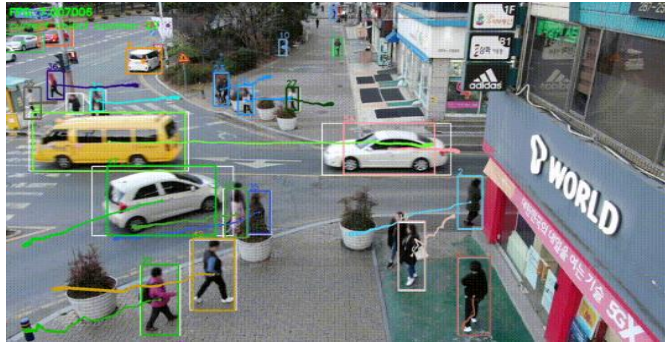


Compute Power

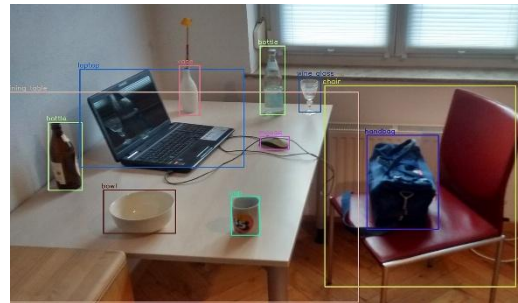


“...deep learning will not only enable us to build more intelligent machines, but will also help us understand human intelligence and the mechanisms of human learning.”

Yann LeCun, Pioneer of Deep Learning



Object movement and tracking

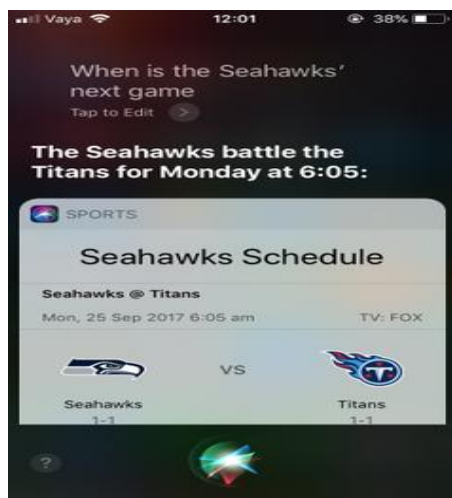


Object recognition and detection.

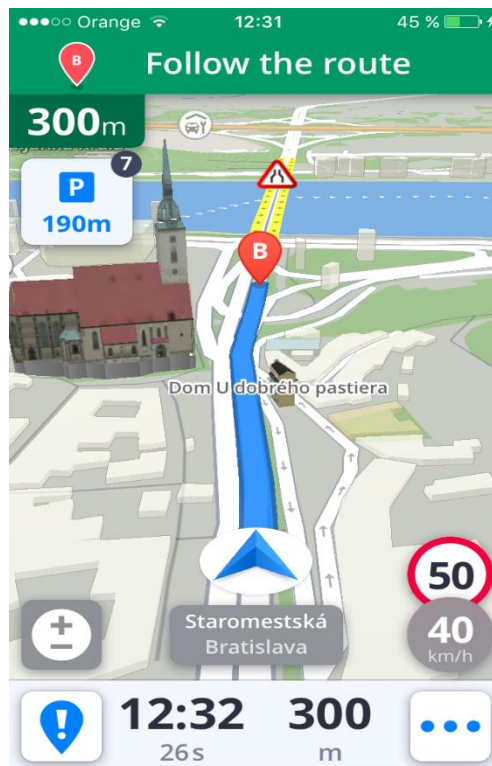
COMPUTER VISION



Speech Recognition



Semantic Understanding



Speech Synthesis

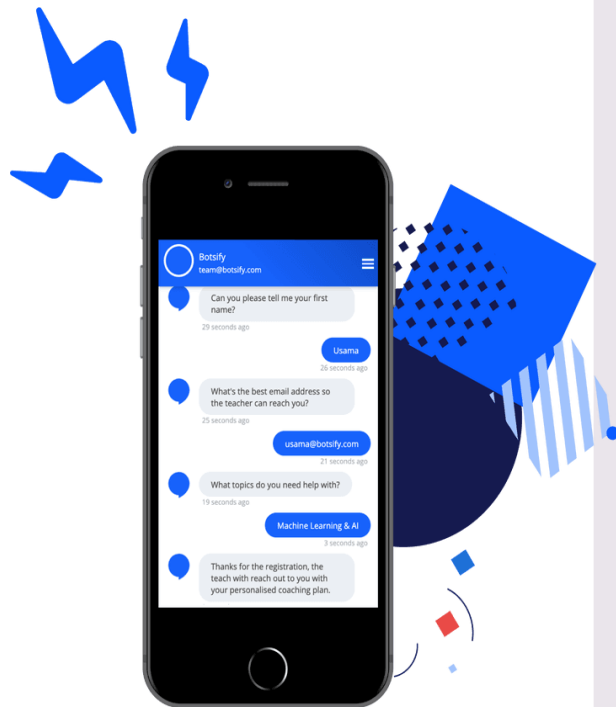
SPEECH PROCESSING



Information Retrieval



Computer Translation



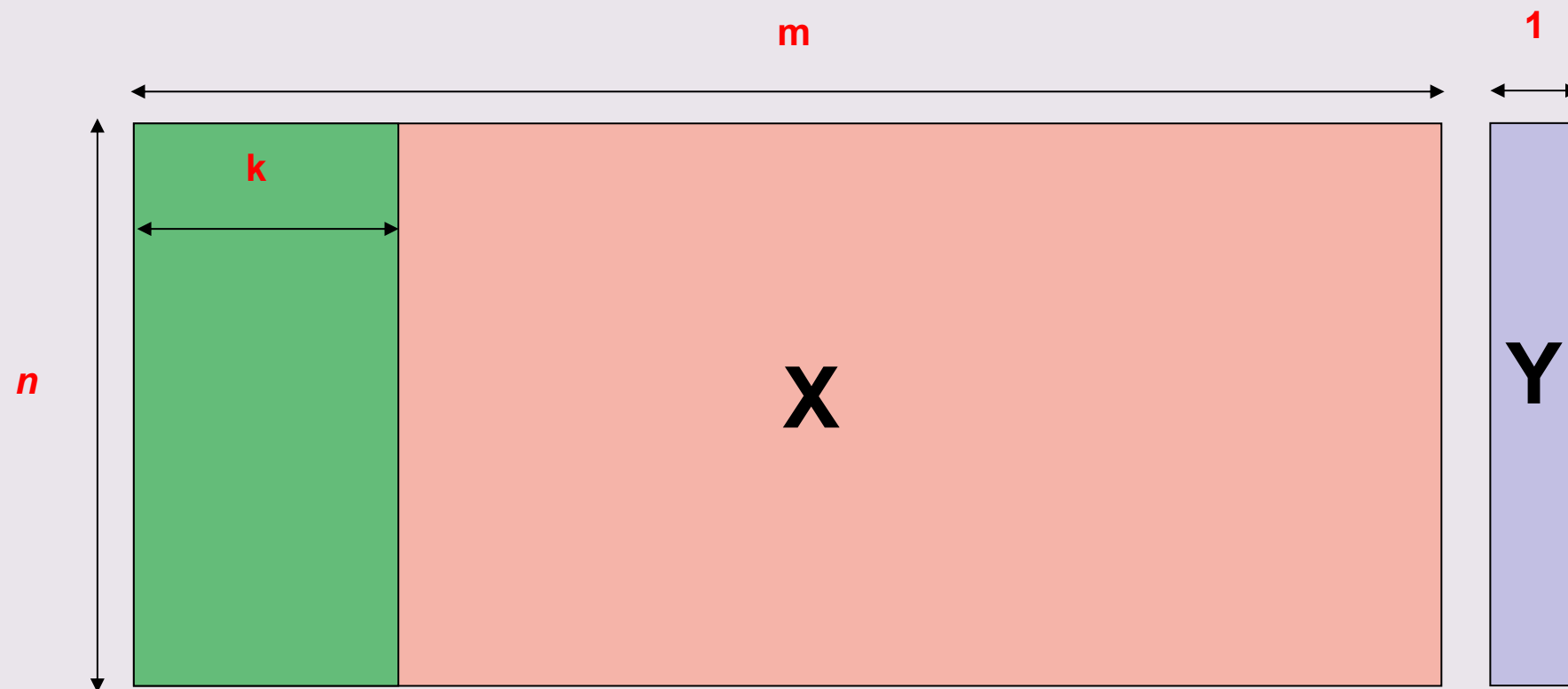
Intelligent Customer Service

NATURAL LANGUAGE PROCESSING

Structured Data

	Status of existing checking account	Duration in month	Credit History	Purpose	Credit Amount	Savings Status	Employment	Instalment Commitment	Personel Status	Other Parties	Residence	Other Property	Age	Other Payment Plans	Housing	Existence of Other Credit	Job	Number of dependents	Own Telephone	Foreing Worker	Class
302	'<0'	6	'critical/other existing credit'	radio/tv	1169	'no known savings'	'>=7'	4	'male single'	none	4	'real estate'	67	none	own	2	skilled	1	yes	yes	good
304	'0<=X<200'	48	'existing paid'	radio/tv	5951	'<100'	'1<=X<4'	2	'female div/depr'	none	2	'real estate'	22	none	own	1	skilled	1	none	yes	bad
305	'no checking'	12	'critical/other existing credit'	education	2096	'<100'	'4<=X<7'	2	'male single'	none	3	'real estate'	49	none	own	1	'unskilled res	2	none	yes	good
306	'<0'	42	'existing paid'	furniture/equipment	7882	'<100'	'4<=X<7'	2	'male single'	guarantor	4	'life insurance'	45	none	'for free'	1	skilled	2	none	yes	good
307	'<0'	24	'delayed previously'	'new car'	4870	'<100'	'1<=X<4'	3	'male single'	none	4	'no known proj	53	none	'for free'	2	skilled	2	none	yes	bad
308	'no checking'	36	'existing paid'	education	9055	'no known savings'	'1<=X<4'	2	'male single'	none	4	'no known proj	35	none	'for free'	1	'unskilled res	2	yes	yes	good
309	'no checking'	24	'existing paid'	furniture/equipment	2835	'500<=X<1000'	'>=7'	3	'male single'	none	4	'life insurance'	53	none	own	1	skilled	1	none	yes	good
310	'0<=X<200'	36	'existing paid'	'used car'	6948	'<100'	'1<=X<4'	2	'male single'	none	2	car	35	none	rent	1	'high qualif/s	1	yes	yes	good
311	'no checking'	12	'existing paid'	radio/tv	3059	'>=1000'	'4<=X<7'	2	'male div/sepr'	none	4	'real estate'	61	none	own	1	'unskilled res	1	none	yes	good
312	'0<=X<200'	30	'critical/other existing credit'	'new car'	5234	'<100'	unemployed	4	'male mar/wid'	none	2	car	28	none	own	2	'high qualif/s	1	none	yes	bad
313	'0<=X<200'	12	'existing paid'	'new car'	1295	'<100'	'<1'	3	'female div/depr'	none	1	car	25	none	rent	1	skilled	1	none	yes	bad
314	'<0'	48	'existing paid'	business	4308	'<100'	'<1'	3	'female div/depr'	none	4	'life insurance'	24	none	rent	1	skilled	1	none	yes	bad
315	'0<=X<200'	12	'existing paid'	radio/tv	1567	'<100'	'1<=X<4'	1	'female div/depr'	none	1	car	22	none	own	1	skilled	1	yes	yes	good
316	'<0'	24	'critical/other existing credit'	'new car'	1199	'<100'	'>=7'	4	'male single'	none	4	car	60	none	own	2	'unskilled res	1	none	yes	bad
317	'<0'	15	'existing paid'	'new car'	1403	'<100'	'1<=X<4'	2	'female div/depr'	none	4	car	28	none	rent	1	skilled	1	none	yes	good
318	'<0'	24	'existing paid'	radio/tv	1282	'100<=X<500'	'1<=X<4'	4	'female div/depr'	none	2	car	32	none	own	1	'unskilled res	1	none	yes	bad
319	'no checking'	24	'critical/other existing credit'	radio/tv	2424	'no known savings'	'>=7'	4	'male single'	none	4	'life insurance'	53	none	own	2	skilled	1	none	yes	good
320	'<0'	30	'no credits/all paid'	business	8072	'no known savings'	'<1'	2	'male single'	none	3	car	25	bank	own	3	skilled	1	none	yes	good
321	'0<=X<200'	24	'existing paid'	'used car'	12579	'<100'	'>=7'	4	'female div/depr'	none	2	'no known proj	44	none	'for free'	1	'high qualif/s	1	yes	yes	bad
322	'no checking'	24	'existing paid'	radio/tv	3430	'500<=X<1000'	'>=7'	3	'male single'	none	2	car	31	none	own	1	skilled	2	yes	yes	good
323	'no checking'	9	'critical/other existing credit'	'new car'	2134	'<100'	'1<=X<4'	4	'male single'	none	4	car	48	none	own	3	skilled	1	yes	yes	good
324	'<0'	6	'existing paid'	radio/tv	2647	'500<=X<1000'	'1<=X<4'	2	'male single'	none	3	'real estate'	44	none	rent	1	skilled	2	none	yes	good
325	'<0'	10	'critical/other existing credit'	'new car'	2241	'<100'	'<1'	1	'male single'	none	3	'real estate'	48	none	rent	2	'unskilled res	2	none	no	good
326	'0<=X<200'	12	'critical/other existing credit'	'used car'	1804	'100<=X<500'	'<1'	3	'male single'	none	4	'life insurance'	44	none	own	1	skilled	1	none	yes	good
327	'no checking'	10	'critical/other existing credit'	furniture/equipment	2069	'no known savings'	'1<=X<4'	2	'male mar/wid'	none	1	car	26	none	own	2	skilled	1	none	no	good
328	'<0'	6	'existing paid'	furniture/equipment	1374	'<100'	'1<=X<4'	1	'male single'	none	2	'real estate'	36	bank	own	1	'unskilled res	1	yes	yes	good
329	'no checking'	6	'no credits/all paid'	radio/tv	426	'<100'	'>=7'	4	'male mar/wid'	none	4	car	39	none	own	1	'unskilled res	1	none	yes	good
330	'>=200'	12	'all paid'	radio/tv	409	'>=1000'	'1<=X<4'	3	'female div/depr'	none	3	'real estate'	42	none	rent	2	skilled	1	none	yes	good
331	'0<=X<200'	7	'existing paid'	radio/tv	2415	'<100'	'1<=X<4'	3	'male single'	guarantor	2	'real estate'	34	none	own	1	skilled	1	none	yes	good
332	'<0'	60	'delayed previously'	business	6836	'<100'	'>=7'	3	'male single'	none	4	'no known proj	63	none	own	2	skilled	1	yes	yes	bad
333	'0<=X<200'	18	'existing paid'	business	1913	'>=1000'	'<1'	3	'male mar/wid'	none	3	'real estate'	36	bank	own	1	skilled	1	yes	yes	good
334	'<0'	24	'existing paid'	furniture/equipment	4020	'<100'	'1<=X<4'	2	'male single'	none	2	car	27	stores	own	1	skilled	1	none	yes	good
335	'0<=X<200'	18	'existing paid'	'new car'	5866	'100<=X<500'	'1<=X<4'	2	'male single'	none	2	car	30	none	own	2	skilled	1	yes	yes	good
336	'no checking'	12	'critical/other existing credit'	business	1264	'no known savings'	'>=7'	4	'male single'	none	4	'no known proj	57	none	rent	1	'unskilled res	1	none	yes	good
337	'>=200'	12	'existing paid'	furniture/equipment	1474	'<100'	'<1'	4	'female div/depr'	none	1	'life insurance'	33	bank	own	1	'high qualif/s	1	yes	yes	good
338	'0<=X<200'	45	'critical/other existing credit'	radio/tv	4746	'<100'	'<1'	4	'male single'	none	2	'life insurance'	25	none	own	2	'unskilled res	1	none	yes	bad
339	'no checking'	48	'critical/other existing credit'	education	6110	'<100'	'1<=X<4'	1	'male single'	none	3	'no known proj	31	bank	'for free'	1	skilled	1	yes	yes	good

Structured Data



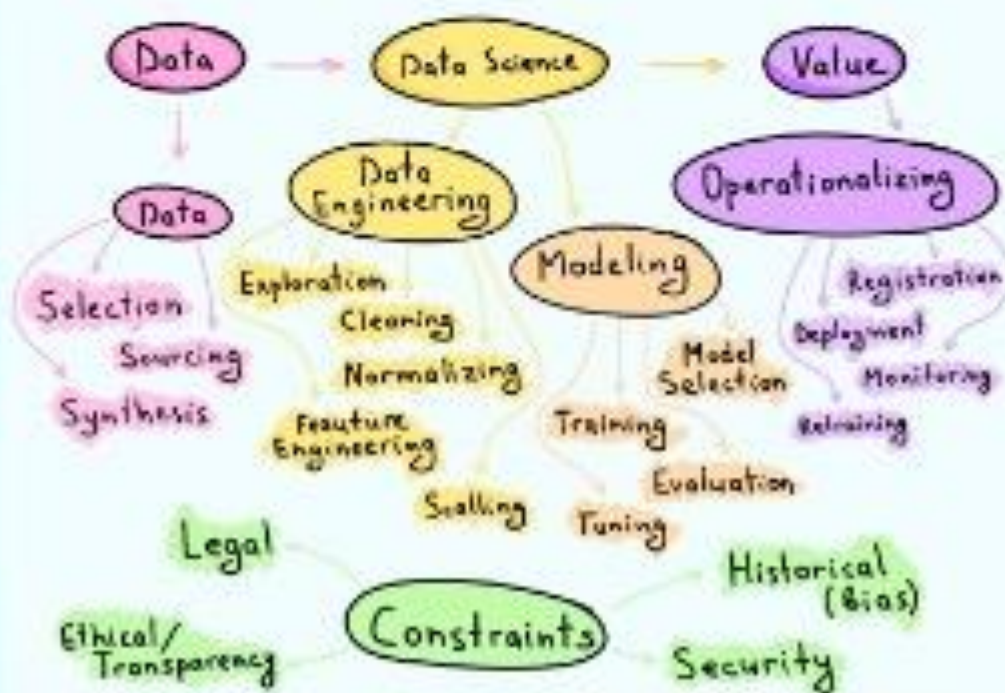
Data Mining

- According to Fayyad *et al.* (1996) data mining is a stage of the Knowledge Discovery in Databases (KDD) process.
- According to the Cross Industry Standard Process for Data Mining (CRISP-DM) data mining is the *whole* process.
- This difference between KDD and CRISP-DM leads to some confusion in use of proper terminology.
- **Mining is extracting useful minerals from the surface of earth.**
- **Data Mining** is basically extracting the patterns (i.e., information that is useful) hidden inside the data; *giving meaning to data*. Generally speaking, the term is reserved for **Structured Data**.
- **Both Descriptive Analytics and Predictive Analytics is used in the process.** The machines (i.e., computers) use **Machine Learning (ML) Algorithms** for this purpose.

WHAT COMPANIES THINK A.I. LOOKS LIKE



WHAT IT ACTUALLY IS



Data Mining Process

Knowledge Discovery in Databases (KDD)

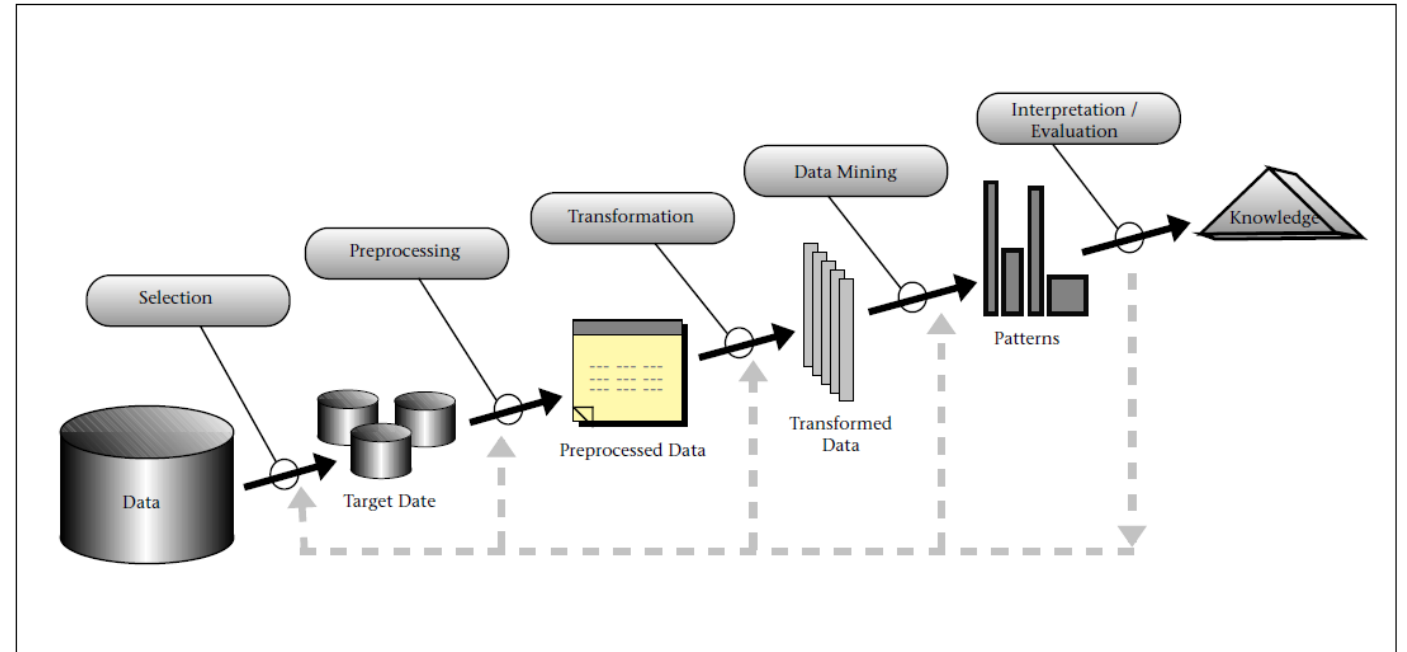


Figure 1. An Overview of the Steps That Compose the KDD Process.

Data Mining Process

Cross Industry Standard Process for Data Mining (CRISP-DM)

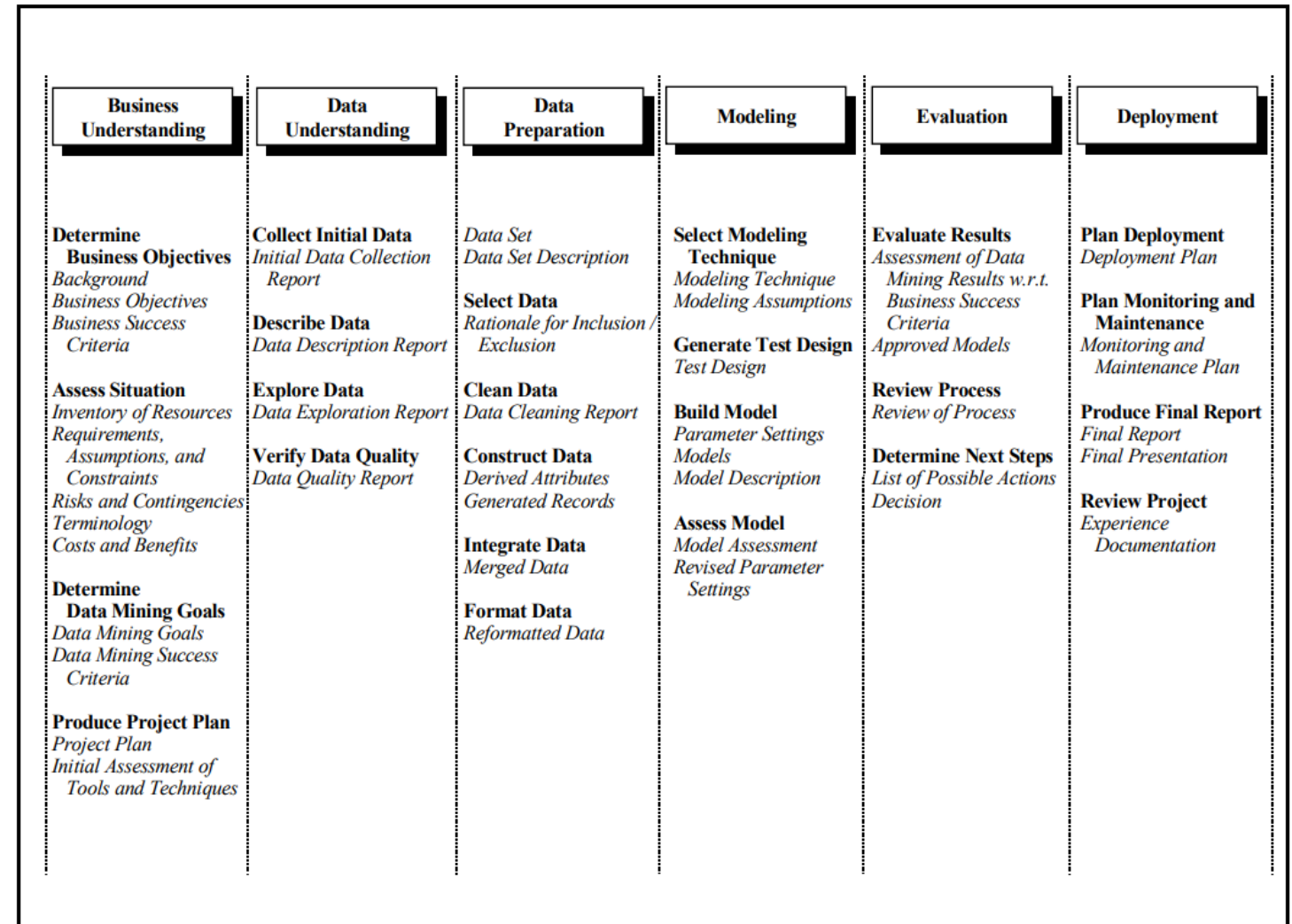


Figure 3: Overview of the CRISP-DM tasks and their outputs.

Data Mining Process

Cross Industry Standard Process for Data Mining (CRISP-DM)

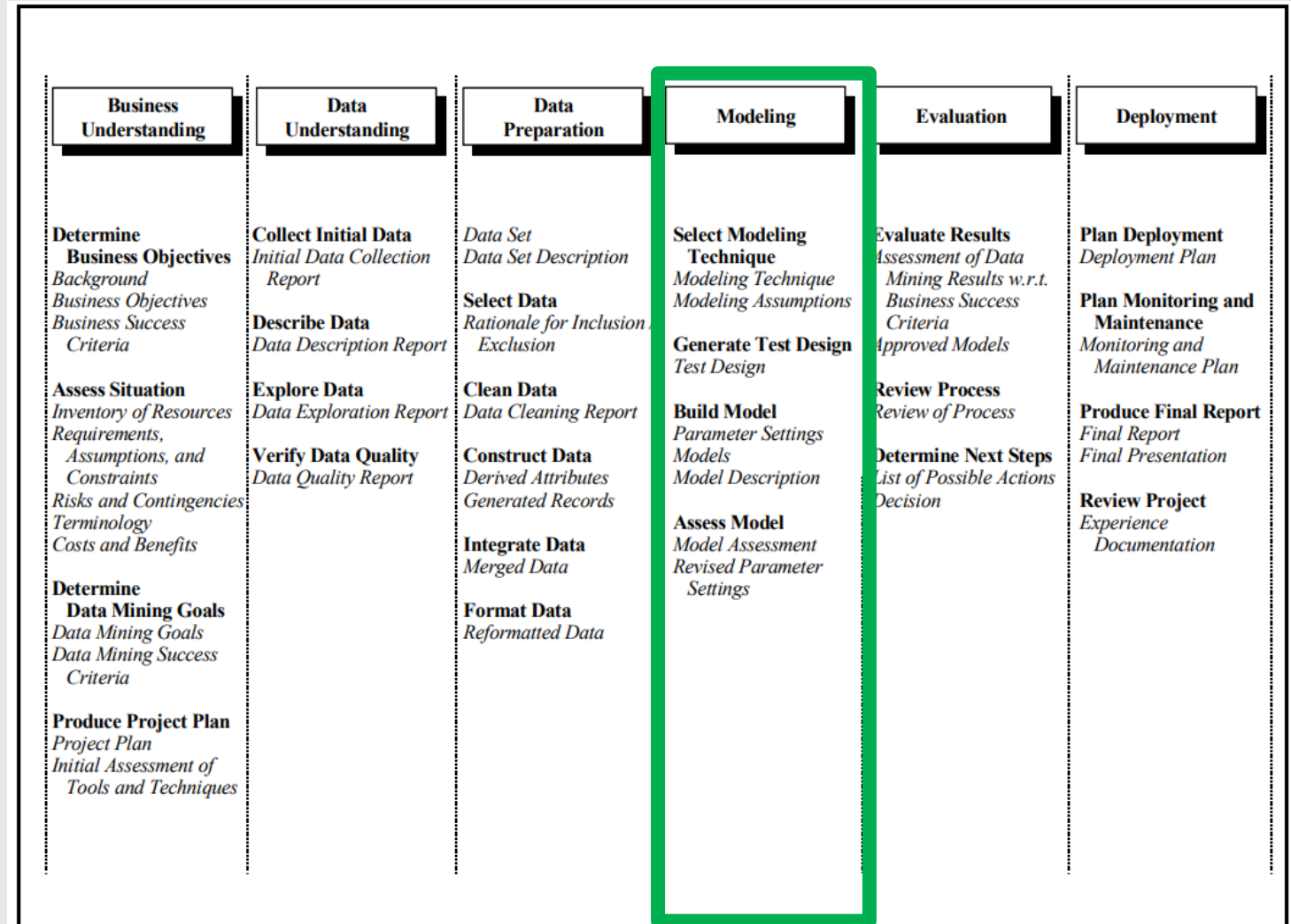
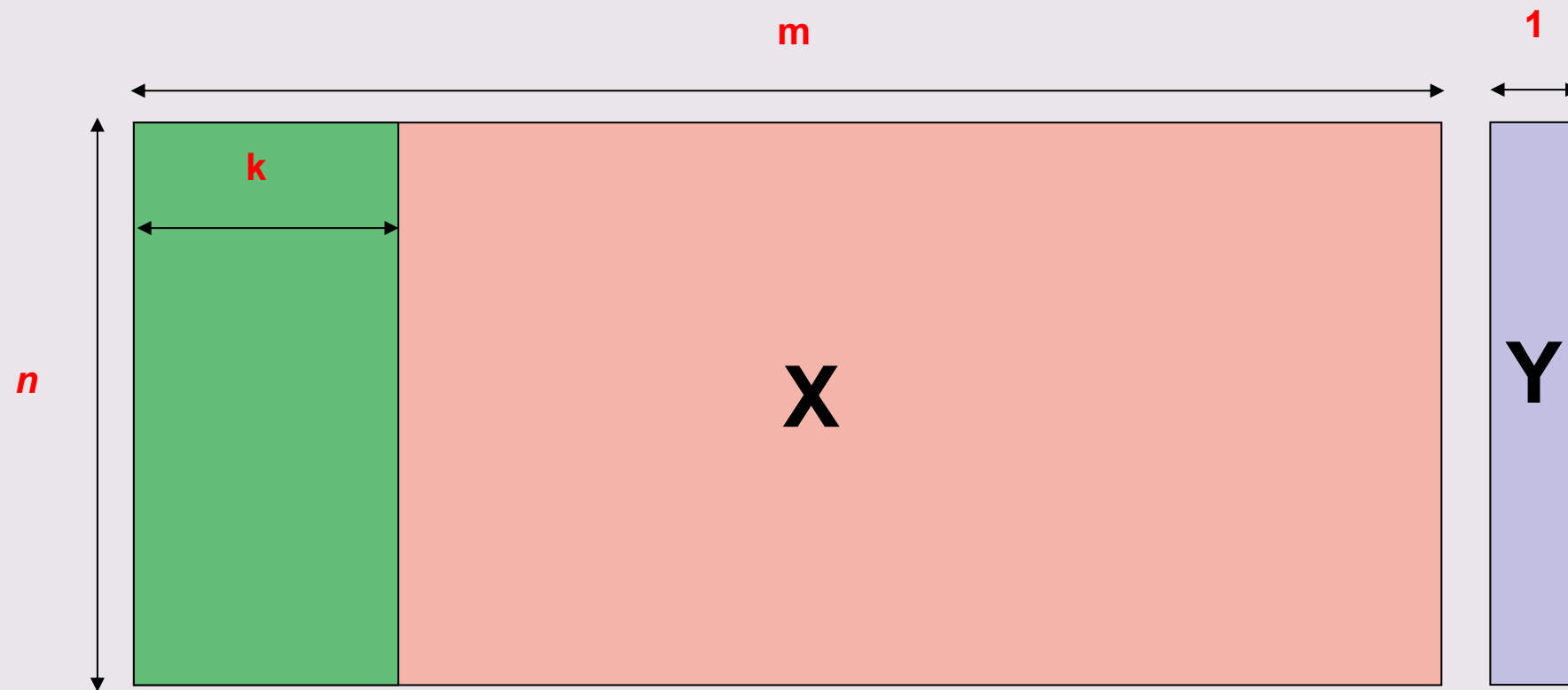
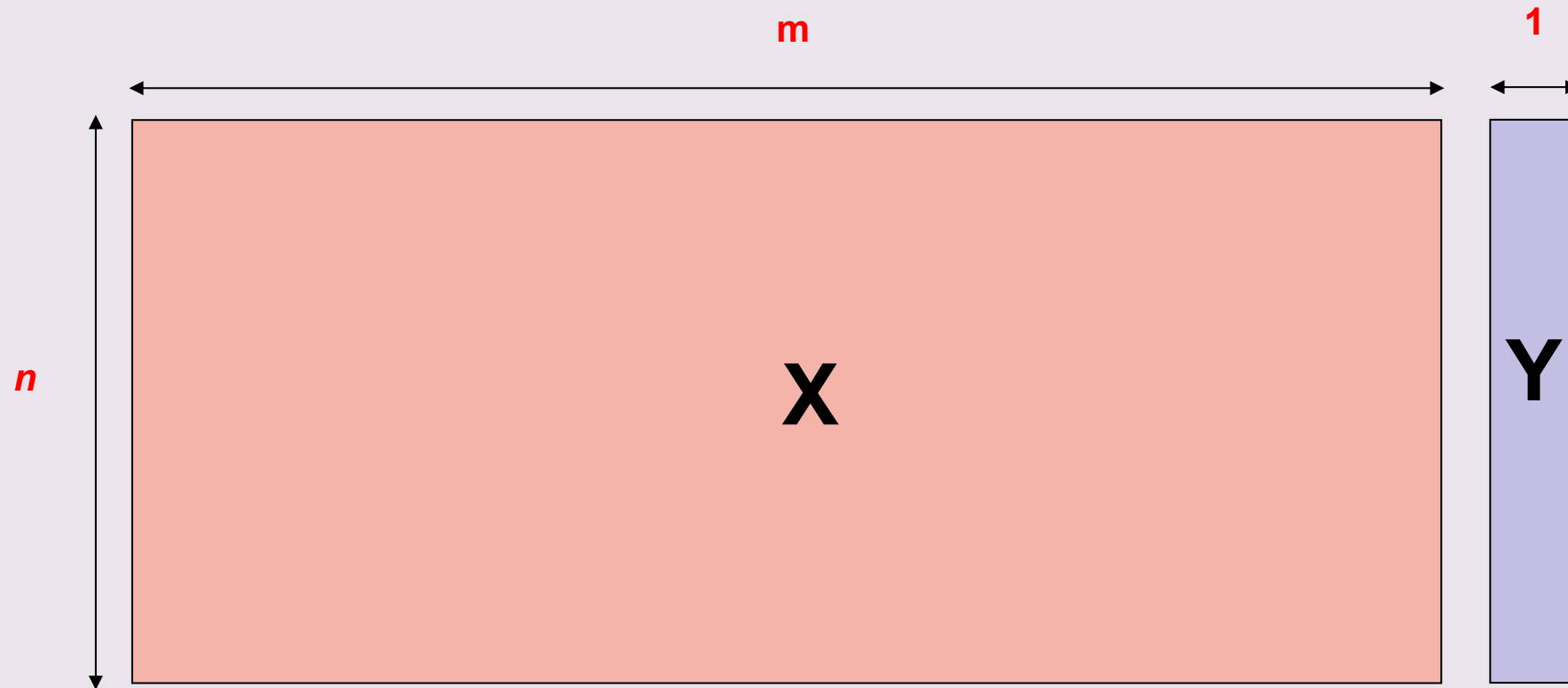


Figure 3: Overview of the CRISP-DM tasks and their outputs.

Data

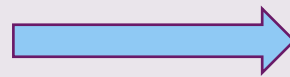


Supervised Learning

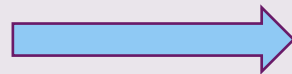


Types of Scales

- Scale is defined as a set of numbers, amounts, etc. used to measure or compare the level of something (*Cambridge Dictionary*)
- There is a hierarchy based on the information level provided by the type of the scale. From the simplest to the most informative:
 - *Nominal Scale*
 - *Ordinal Scale*
 - *Interval Scale*
 - *Ratio Scale*



Categorical Data



Numerical Data

Supervised Learning

- **Data Set:** Both the input features and the output(s) are available.
- The question that is addressed is "For which values of input features, we obtain a particular output value?", so that we can infer/deduce for an unseen case and/or future (i.e., *population*).
- The goal is to determine the hidden relationships between the input features and the outputs.
- Supervised Learning has a central role in the context of *Predictive Analytics*.
- Output(s) might be numerical data (in this case we refer to the problem as **Regression**) or categorical, i.e., *nominal* or *ordinal* (in this case we refer to the problem as **Classification**)

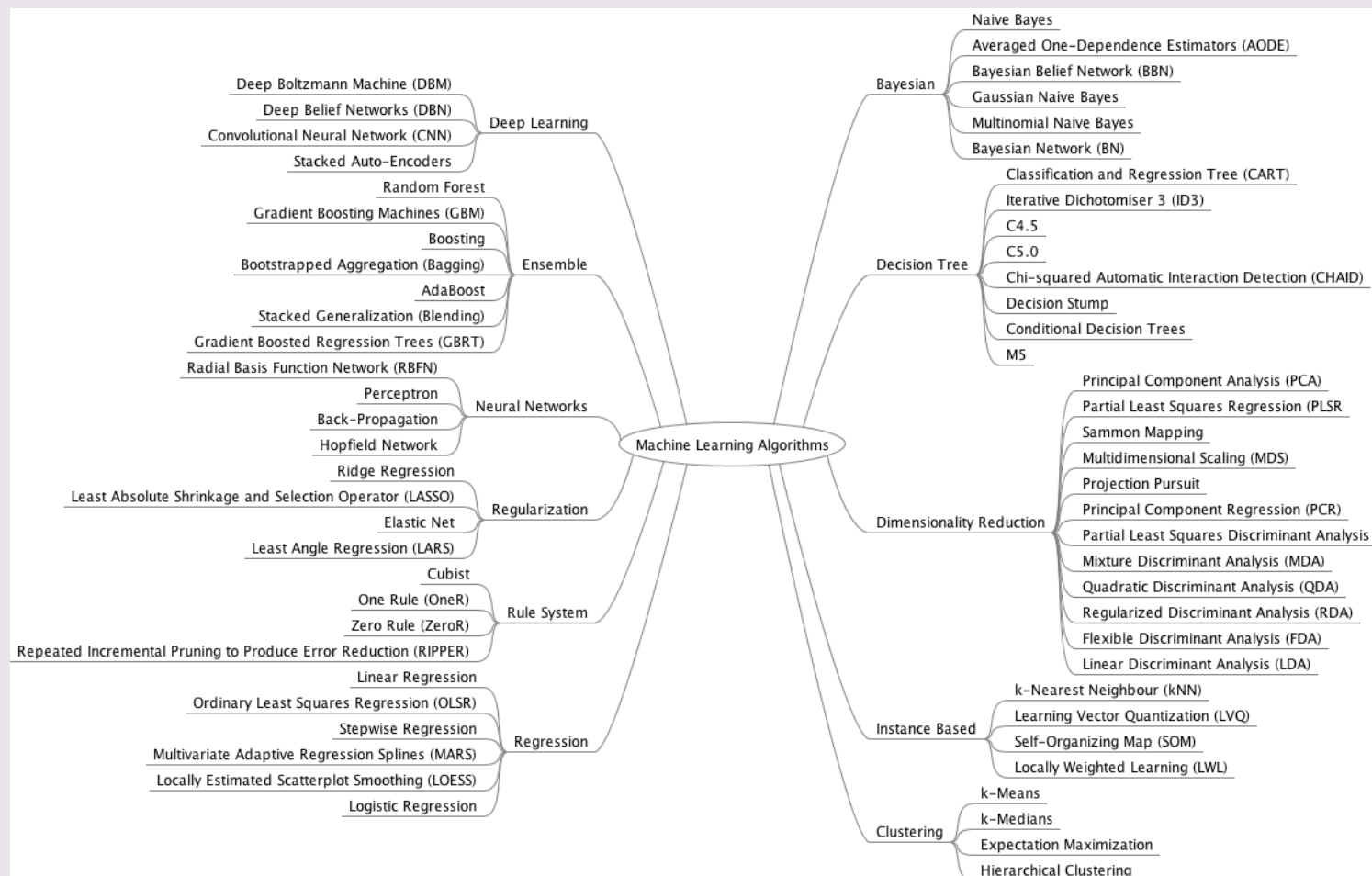
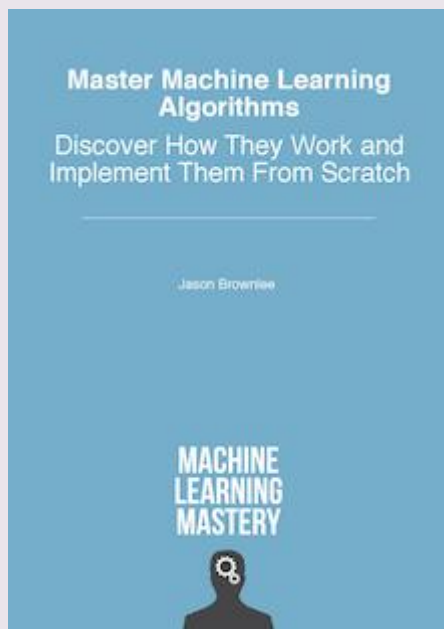
Supervised Learning – Toolbox

- **Classification Algorithms:**

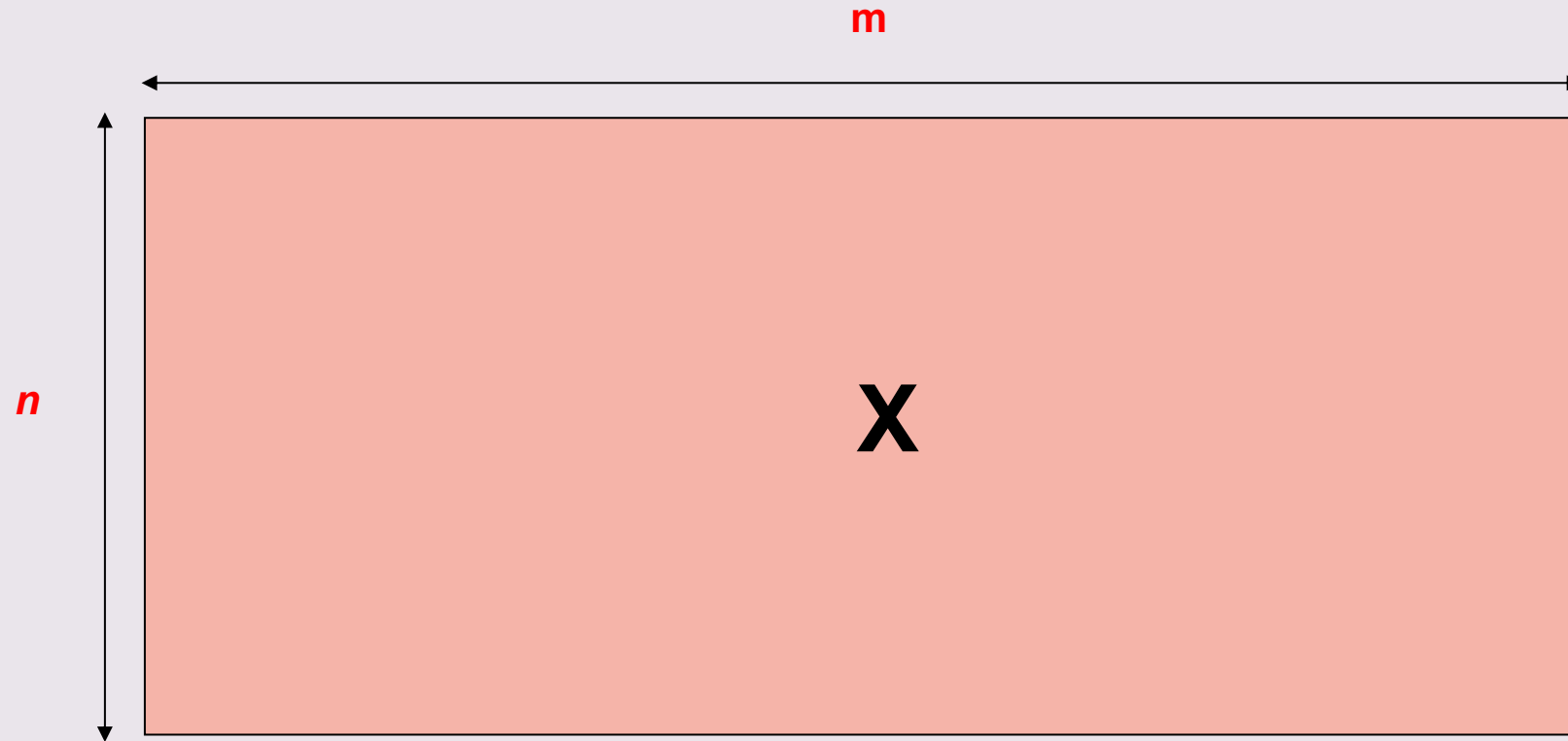
- Rudimentary Rules – e.g.: 0R, 1R,...,etc.
- Statistical Modeling – e.g.: Naïve Bayes
- Divide and Conquer – e.g.: Decision Trees
- Instance Based Learning – e.g.: kNN, K*, LWL, vb.
- Logistic Regression
- Support Vector Machines
- Ensemble Learning – e.g.: Boosting (AdaBoost, XGBoost,...,etc.) , Bagging, Randomization (e.g.: Random Trees, Random Forest,..., etc.), Stacking
- Artificial Neural Networks – MLP, CNN, LSTM, GANs,..., etc.
- ...

Machine Learning Algorithms

- A mind map of ML algorithms created by Jason Brownlee (2013)



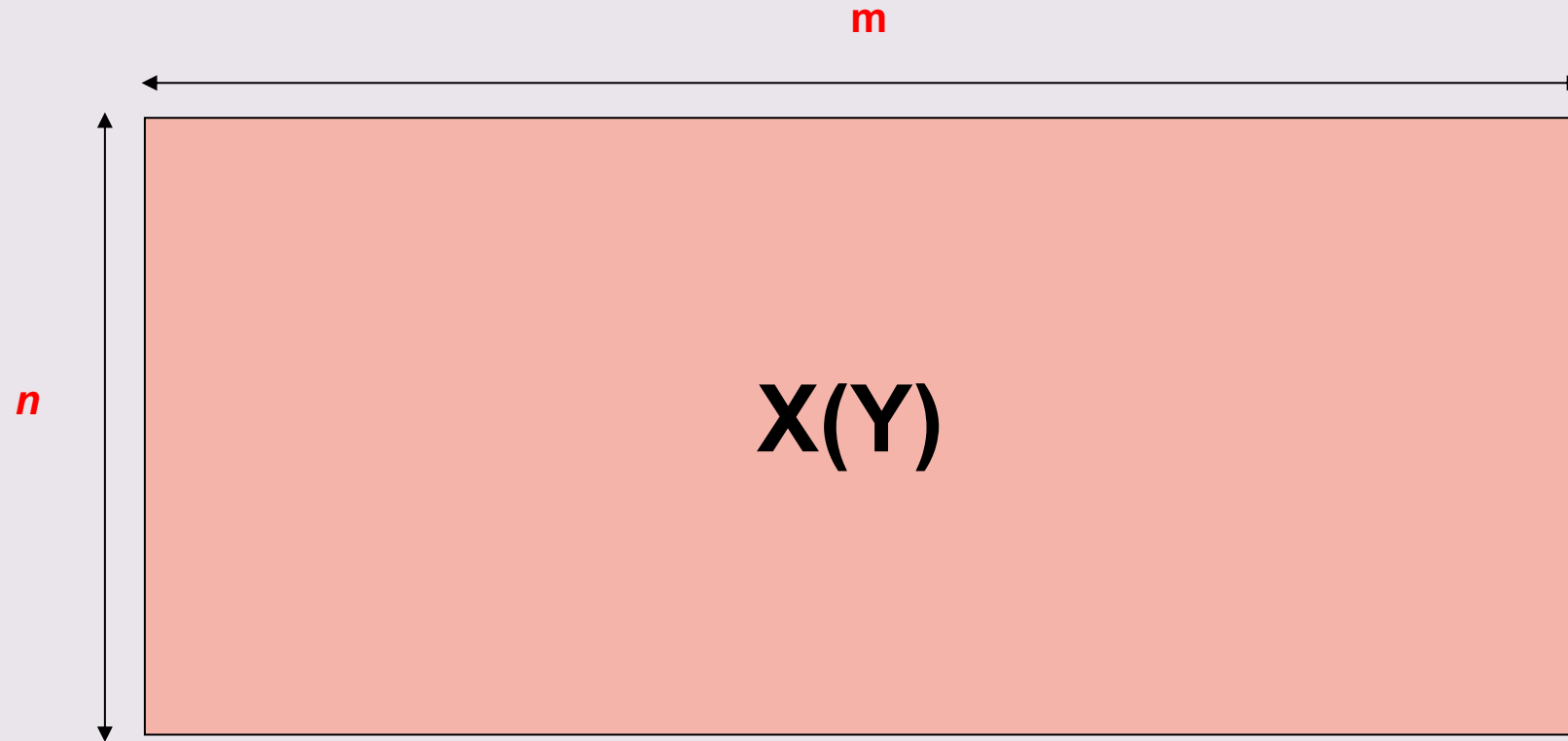
Unsupervised Learning



Unsupervised Learning

- **Data Set:** Only the input features are available (i.e., No Labels/Outputs).
- The question we are addressing is "Are there natural groupings within the data?". It is part of the **Descriptive Analytics** in this aspect.
- However, it is also possible to use these groups as labels, and start predicting for the population these labels based on the available input feature vector of the newcomers.
- That is to say, after establishing the natural groupings (i.e., clusters, segments, profiles, etc.) it is also possible to address "This new one, which natural group does it belong to?"
- In that case, we incorporate unsupervised learning to a **Predictive Analytics** process.
- Depending on how one defines "natural" the objective function changes thus the optimization formulation and the resulting solution algorithm changes. Thus we have **K-Means, K-Medians, E-M, DBSCAN, FCM** etc.

Association Rules



Association Rules

- It is useful to mine the patterns in datasets where there is no input/output differentiation among the features.
- The receipts in a grocery is a typical example of this type of transactional datasets.
- There are rules such as "Whoever bought Bread and Butter also bought Milk"

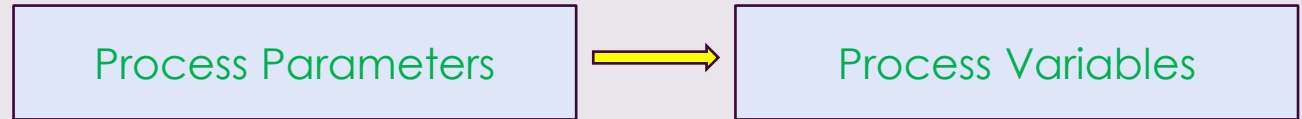


- That's why it is usually referred to as the *Market Basket Analysis*

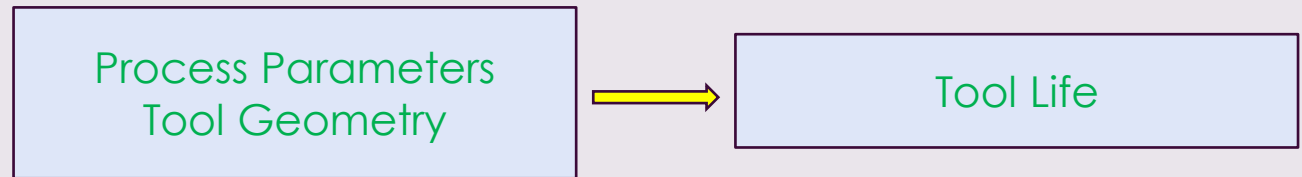


Data Mining in Machining

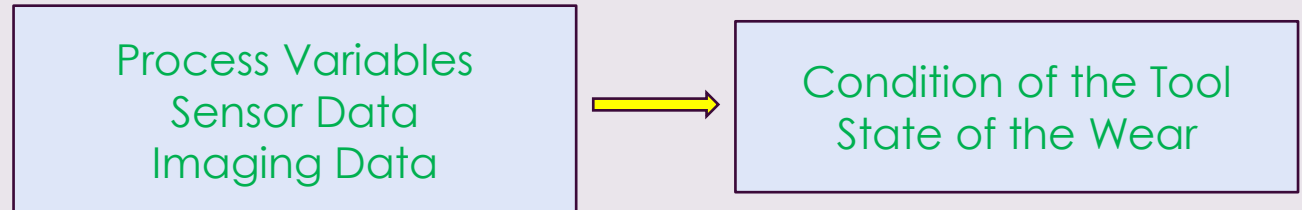
- **Process Characteristics Prediction:**



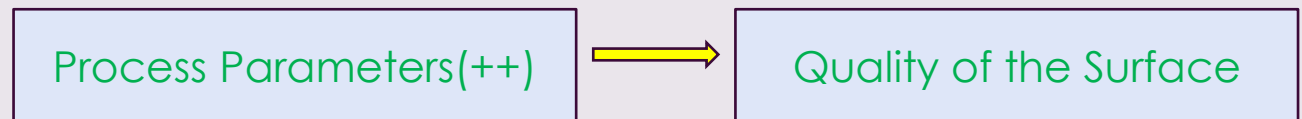
- **Tool Wear Prediction:**



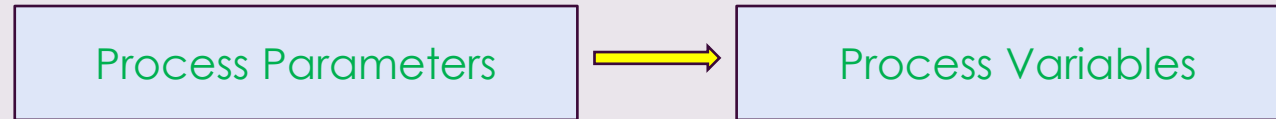
- **Process/Tool Condition Monitoring:**



- **Product Quality Prediction:**

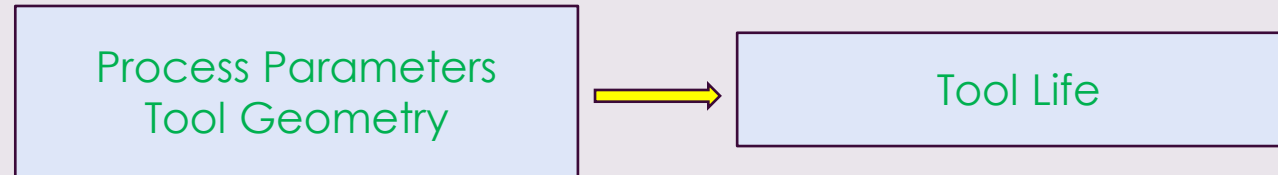


Process Characteristics Prediction



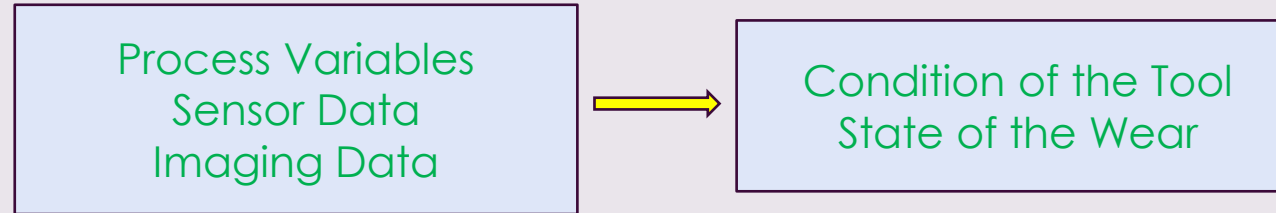
- **Input Features:** Process parameters such as cutting speed, depth of cut and feed value most widely used inputs.
- **Target Variables:** Cutting and Grinding forces are the predominant target variables (i.e., outputs) available in the literature. Thus, regression problem.
- Milling is the most studied machining process.
- Some other inputs include tool geometry, tool type, coating, nose radius of indexable inserts, voltage, acoustic emissions (depending on the availability of the data).
- Some other target variables include temperature and chatter.
- ANN, SVR, RF, KNN, ANFIS and Regression Analysis are the most preferred learning algorithms.

Tool Wear Prediction



- **Input Features:** (i) Process parameters such as cutting speed, depth of cut (ii) Tool geometry such as tool diameter, dresser width are most widely used inputs.
- **Target Variables:** Tool life, wear characteristics are common outputs in the literature.
- Turning and Milling are the most studied machining process.
- Some other inputs include tool geometry, tool type, coating, nose radius of indexable inserts, voltage, acoustic emissions (depending on the availability of the data).
- Some other target variables include wear marks, crater wear.
- ANFIS, ANN, SVR and RF dominates as the preferred algorithms.

Process/Tool Condition Monitoring



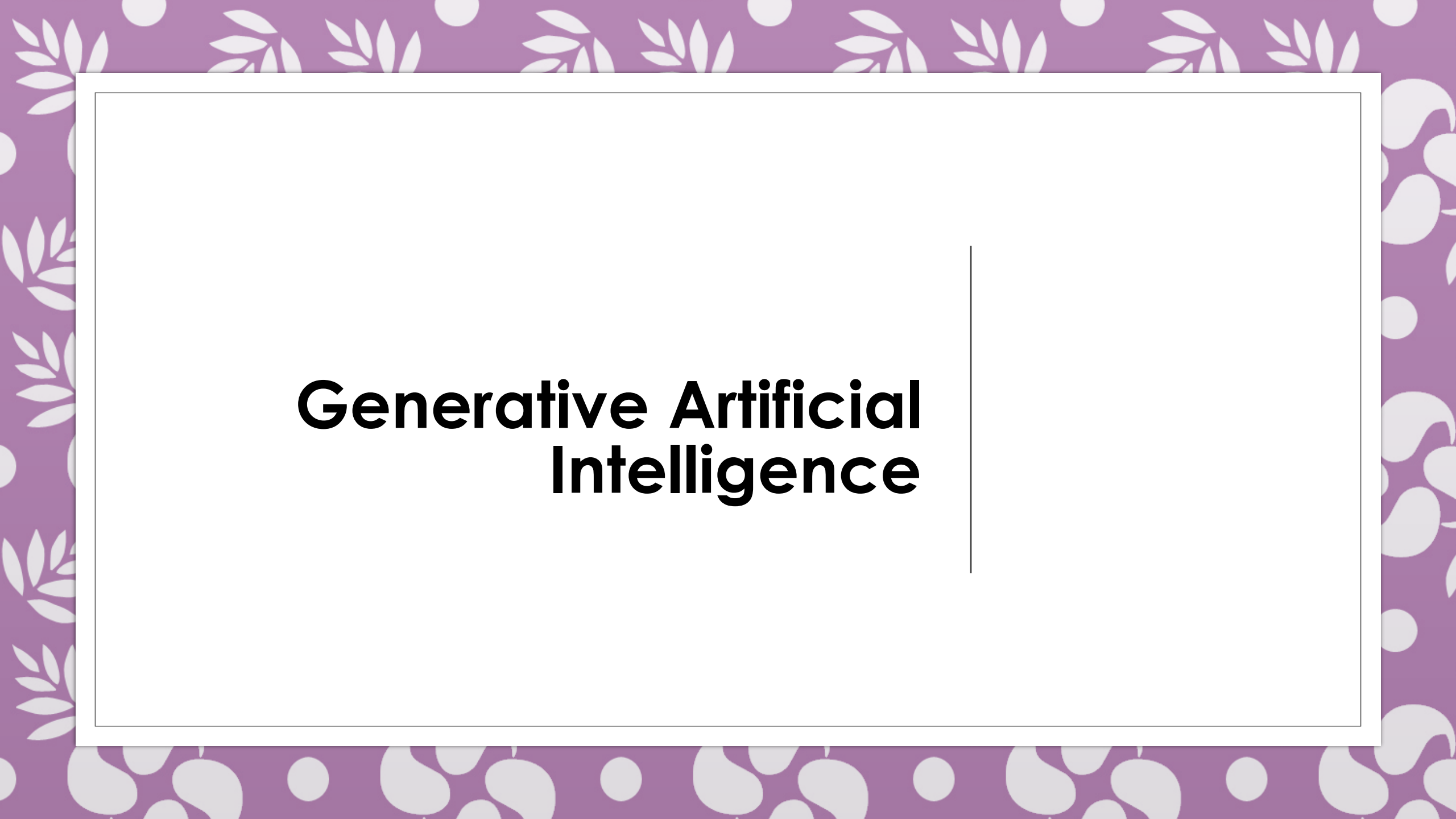
- **Input Features:** (i) Process variables such as Cutting Forces (ii) Acoustic Emission (iii) Image Processing are most frequently used inputs.
- **Target Variables:** State of the wear, condition of the tool.
- Milling, Grinding and Turning are the most studied machining process.
- Some other inputs include spindle load, spindle current, and vibrations. Image processing is particularly helpful used in grinding operations.
- ANN is the most preferred algorithm. SVR and RF are also preferred for Process/Tool Condition Monitoring problems.

Product Quality Prediction

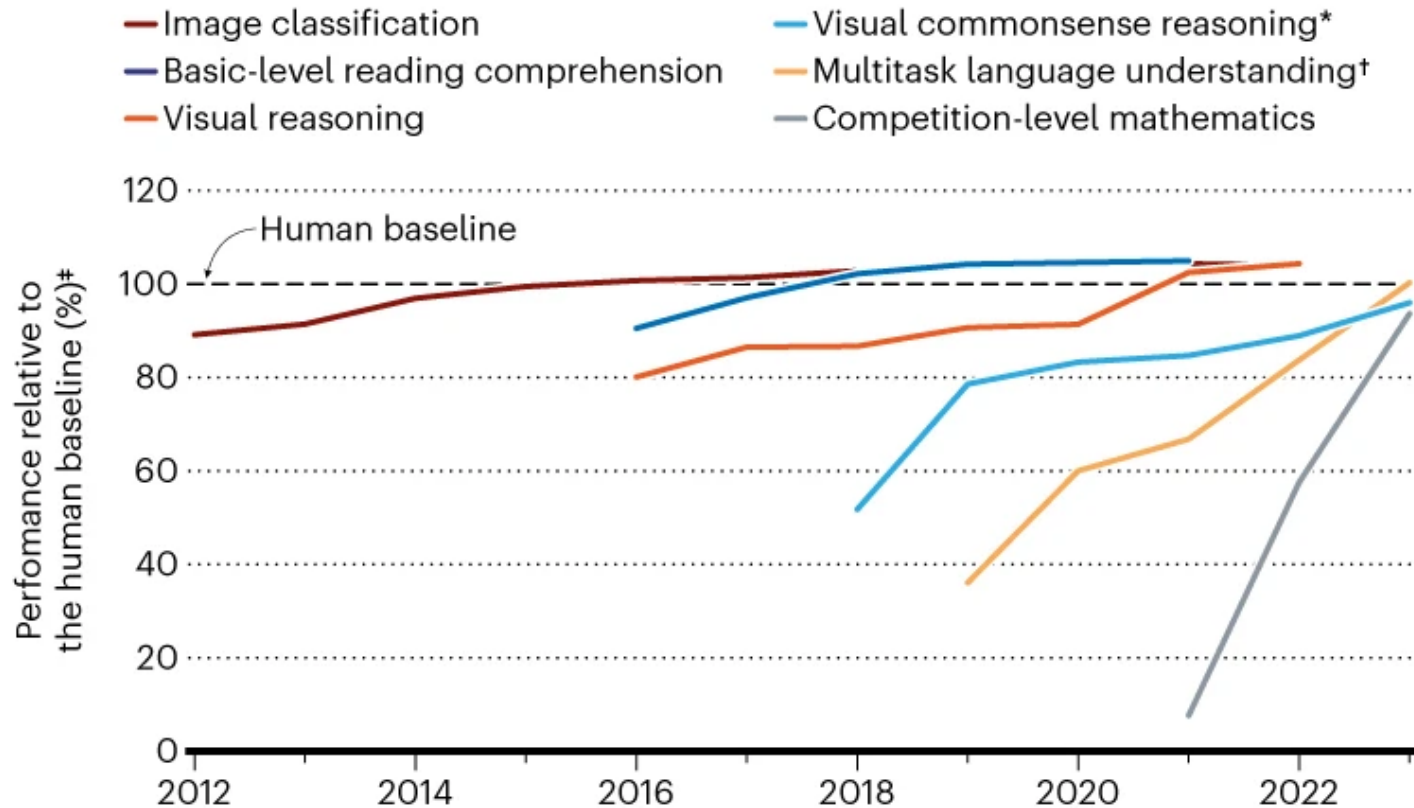


- **Input Features:** Process parameters (cutting speed, depth of cut and feed value) is the predominant inputs.
- **Target Variables:** Roughness and residual stresses are the most common target variables.
- Turning and Milling are the most studied machining process.
- Some other inputs include temperature, tool wear, acoustic emissions (particularly in grinding process), vibration, and power. (++) In some models process variables, e.g. forces and quality measures such as roughness are used for predicting other quality measures
- Some other target variables include fatigue, flatness, micro hardness and roundness.
- ANNs are the most frequently preferred learning algorithm followed by SVR, and RF.

Generative Artificial Intelligence



In the past several years, some AI systems have surpassed human performance on certain benchmark tests, and others have made rapid progress.



*Requires an AI system to answer questions about an image and provide a rationale for why its answers are true.

†Tests an AI model's knowledge and problem-solving ability with regard to 57 subjects, including broader topics such as mathematics and history, and narrower areas such as law and ethics.

*Data indicate the best performance of an AI model that year.

©nature

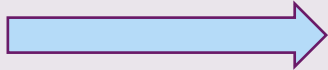
SPEEDY ADVANCES

What is Generative AI (GenAI)

- Artificial Intelligence systems that can produce high quality content, specifically **text**, **images** and **audio**.

What is Generative AI (GenAI)

PROMPTS!



- Artificial Intelligence systems that can produce high quality content, specifically **text**, **images** and **audio**.



Hi, I'm DeepSeek.

How can I help you today?

Can you generate three greetings for the beginning of a short course on generative AI?

DeepThink (R1)

Search



Certainly! Here are three greetings you can use to kick off a short course on generative AI:

1. Warm and Welcoming:

"Hello everyone, and welcome to this exciting journey into the world of generative AI! Whether you're here to explore, learn, or innovate, I'm thrilled to have you join us. Over the next few sessions, we'll dive into the fascinating tools and techniques that power creativity in machines—and hopefully inspire some of your own. Let's get started!"

2. Inspirational and Forward-Looking:

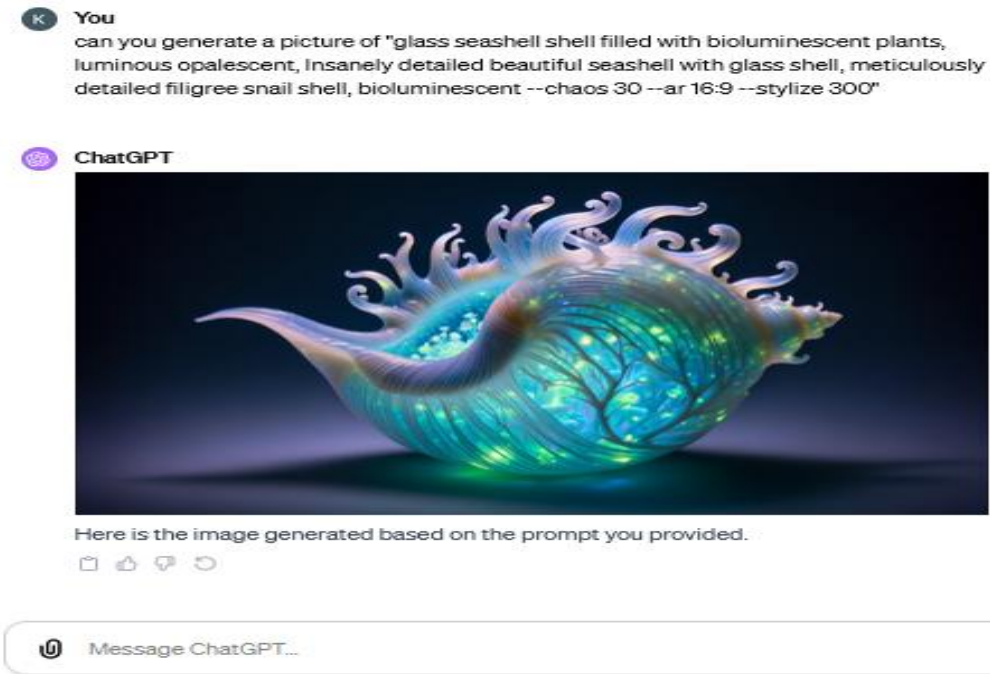
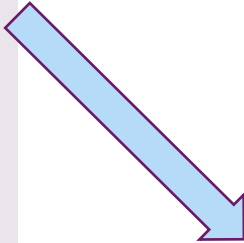
"Good [morning/afternoon], and welcome to our short course on generative AI! This is a field that's r

DeepSeek

What is Generative AI (GenAI)

- Artificial Intelligence systems that can produce high quality content, specifically **text**, **images** and **audio**.

PROMPTS!



OpenAI's Dall-E 3 (ChatGpt)

What is Generative AI (GenAI)

- Artificial Intelligence systems that can produce high quality content, specifically **text**, **images** and **audio**.



ChatGPT

I did a [quick search](#) for more information and here's what I found.

There are several popular audio tools based on generative AI that cater to different needs, from voice generation to music creation. Here's a summary of some of the most talked-about tools:

1. **ElevenLabs** - This platform is known for creating human-sounding voices quickly and offers a user-friendly interface. It's suitable for anyone needing a clear voiceover and offers a free tier with subscription options starting from \$5/month [\[1\]](#).
2. **Descript** - A comprehensive content creation tool that offers features like filler-word removal, voice cloning, and video editing. It's a strong option for professional podcasters, video content creators, and audio editors. Descript provides a free tier, with paid subscriptions starting at \$12/month [\[2\]](#).
3. **Murf.ai** - Specializing in text-to-speech, Murf is great for voiceovers for YouTube videos, audio ads, e-learning content, and presentations. It has a free tier with restrictions, and paid subscriptions begin at \$29/month [\[3\]](#).
4. **Krisp** - Rather than generating voices, Krisp improves the clarity of human voice files, making it useful for call centers, remote businesses, or content creators. It has a free individual tier and business subscriptions starting at \$8/month [\[4\]](#).
5. **Lovo** - Offers a complete range of AI voice generator features, including text-to-speech and voice cloning. While it has a 14-day free trial, subscriptions start from \$19/month, making it best suited for professionals with a higher budget [\[5\]](#).

PROMPTS!
Text-to-Speech

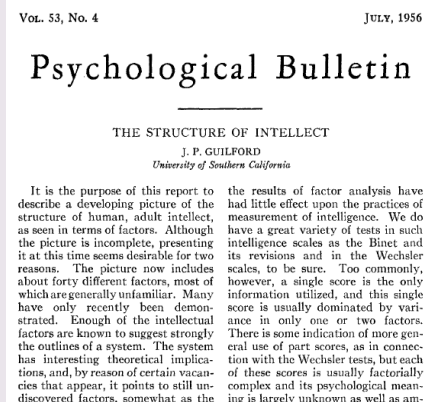
Person Centric Approach



Joy Paul Guilford

1897 – 1987

American Psychologist



(1956)

- **Convergent thinking** is a problem solving technique involving the bringing together different ideas from different participants or fields **to determine a single best solution** to a lucidly defined problem
- The focus for this thinking strategy is **speed, logic and accuracy** and on identifying the known, reapplying techniques, and amassing stored information.
- Convergent thinking is also linked to **knowledge** as it involves manipulating existing knowledge by means of standard procedures
- **Most IQ tests measure convergent thinking.**
- Convergent thinking is often used **in conjunction** with divergent thinking.

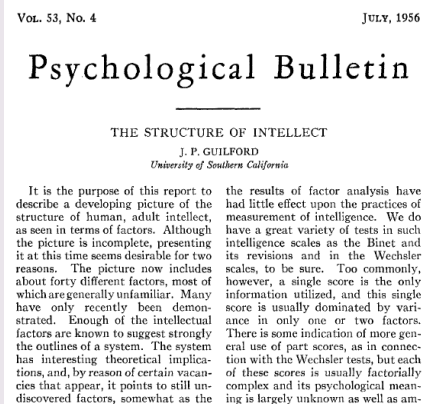
Free Flow with DT and conclude with CT!

Person Centric Approach



Joy Paul Guilford
1897 – 1987

American Psychologist



(1956)

- **Divergent thinking ability**, defined as the ability to generate multiple possible solutions to a problem in terms of fluency, flexibility, originality, and elaboration.
- When people are generating ideas, they need to keep **four qualities** in mind. Depending on the task at hand, not all of the qualities will be used, or a few may be used more than the others.
- **Fluency** is the ability to generate a lot of options. (*Quantity*)
- **Flexibility** is the ability to find options in as many different categories as possible. (*Variety*)
- **Originality** is the ability to think of unique and novel ideas.
- **Elaboration** is the ability to expand upon an option in order to make it more interesting and richer

Classical AI vs. Generative AI (1)

Aspect	Classical AI	Generative AI (GenAI)
<i>Thinking Style</i>	Convergent Thinking : Focuses on finding a single, optimal solution to a specific problem.	Divergent Thinking : Emphasizes generating multiple, creative, and original solutions.
<i>Primary Goal</i>	Solve specific, well-defined problems (e.g., prediction, classification, optimization).	Create novel, open-ended content (e.g., text, images, music, code).
<i>Output Type</i>	Structured and measurable (e.g., numbers, probabilities, categories).	Unstructured and creative (e.g., stories, artwork, melodies).
Fluency (Divergent Thinking)	Low : Produces limited outputs tied to a specific task (e.g., one prediction).	High : Can generate numerous outputs for a single prompt (e.g., many story variations).
Flexibility (Divergent Thinking)	Limited : Works within predefined tasks (e.g., demand forecasting, churn prediction).	High : Adapts to diverse tasks across domains (e.g., writing, drawing, composing).
Originality (Divergent Thinking)	Low : Outputs are based on patterns in data, not novel creations (e.g., a churn probability).	High : Produces unique, previously unseen content (e.g., a new poem or painting).

Classical AI vs. Generative AI (2)

Aspect	Classical AI	Generative AI (GenAI)
Elaboration (Divergent Thinking)	Minimal: Outputs are concise and task-focused (e.g., a single forecast).	High: Can expand simple ideas into detailed outputs (e.g., a short prompt into a novel).
Example Tasks	- Demand forecasting - Predictive maintenance - Customer churn prediction	- Writing a story - Generating an image - Composing music
Training Approach	Task-specific: Trained on targeted datasets for defined problems.	General-purpose: Trained on vast, diverse datasets for broad creativity.
User Interaction	Predictable: Users expect specific, task-related outputs.	Open-ended: Users can request diverse, unexpected, creative results.
Error Tolerance & Adaptability	Low Tolerance: Struggles with ambiguous or undefined tasks; requires clear data and goals.	High Tolerance: Can handle vague or novel requests, improvising with creative outputs.
Example Analogy	A gardener planting a specific type of flower, like roses, based on learning from experience to grow them perfectly.	A gardener creating a wild, colorful garden, mixing all kinds of flowers, shapes, and patterns to invent a unique, vibrant landscape.

Generative Pre-trained Transformer (GPT)

From Wikipedia:

- **Generative pre-trained transformers (GPT)** are a type of **large language model (LLM)** and a prominent framework for generative artificial intelligence. They are artificial neural networks that are used in natural language processing tasks.
- ChatGPT, Microsoft Copilot, Google Bard etc. are all LLMs based on ANN.
- They are **merely predicting the next token (you can consider it as word)** that is most likely possible to follow the previous ones.
- Not much different than Autocomplete. 😊

How LLMs Work?

LLMs are built by using supervised learning ($A \rightarrow B$) to repeatedly predict the next word.

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

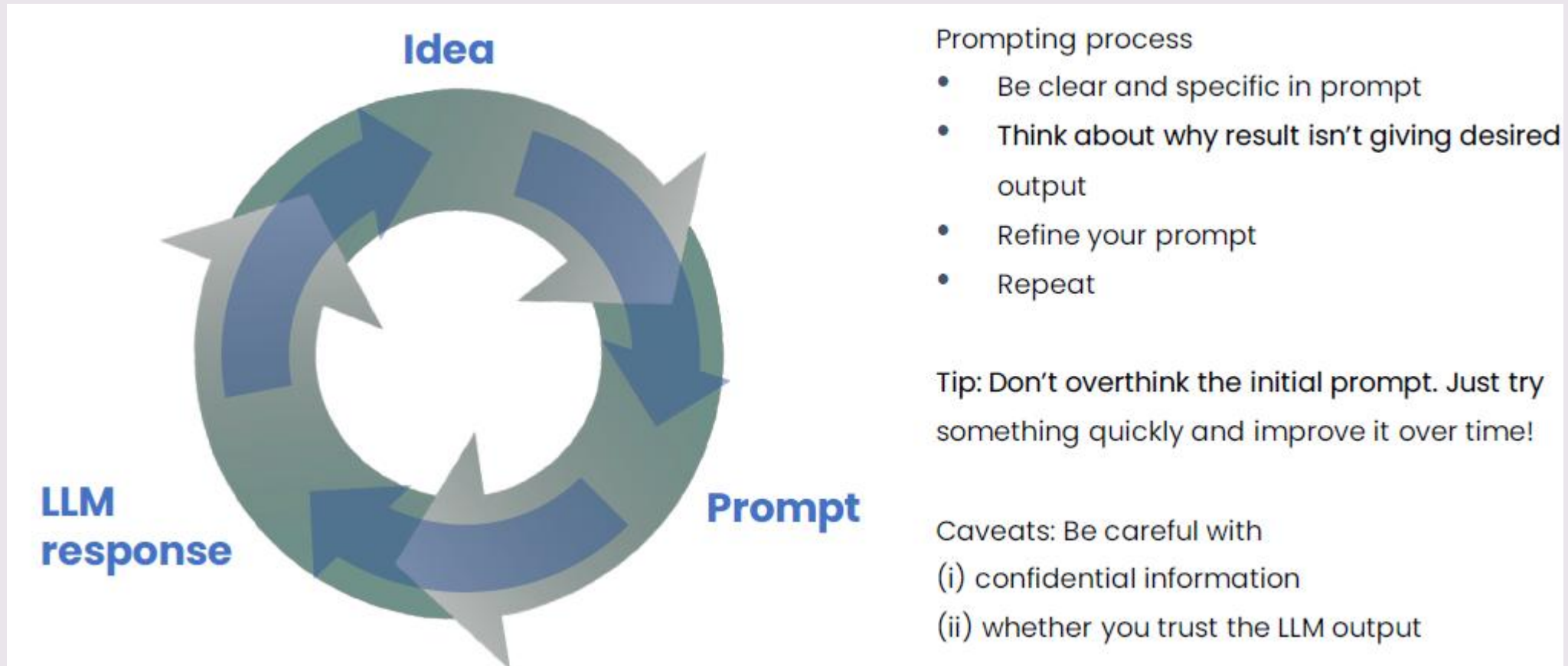
When we train a very large AI system on a lot of data (hundreds of billions of words), we get a Large Language Model like ChatGPT.

Self Supervised Learning!

GenAI Use Cases – TEXT (LLM)

- ***Writing Assistant***
 - *Paraphrase* – Make it more understandable, rule-compliant, and in the correct language.
 - *Translate* - Translate in almost any language!
 - *Content Generator* – Creating content, e.g., first drafts on topics you're not very familiar with.
 - *Copywriter* - A writer, especially one who creates striking, attention-grabbing text.
 - *Coder* – Developing starting code or debugging in a language you're not very skilled in.
- ***Reading Assistant:***
 - *Interpreter* – Making complex texts understandable in a simpler way and language.
 - *Summarize* – Summarizing long texts and listing the main points.
 - *Criticize* – Criticizing your content, texts, or the structure in your mind, brainstorming partner.

Recommendation on Prompting – Iterations!





USE AI TO LEARN ANYTHING FASTER

1. EXPLAIN LIKE I'M 5

Description:

Break down tough ideas so even a kid could get it. Perfect for when you're totally lost on a topic.

**Prompt Template:**

"Explain [insert concept or topic] as if you were talking to a 5-year-old child. Use simple language and everyday examples."

2. EXAMPLES AND ANALOGIES

Description:

Get real-world examples that make abstract ideas click.

**Prompt Template:**

"Explain [insert concept or topic] using three different real-world examples or analogies that would be easy for a beginner to understand."

3. MOTIVATION

Description:

Get tips to keep yourself motivated about learning, even when it gets tough.

**Prompt Template:**

"I'm struggling to stay motivated while learning [insert subject or skill]. Provide me with 5 practical strategies to boost my motivation and maintain consistency in my studies."

4. ROLE-PLAY

Description:

Act out scenarios to practice what you've learned.

**Prompt Template:**

"Let's role-play a scenario where I'm [insert role] and you're [insert another role]. We'll practice [insert skill or situation]. Begin the scenario, and I'll respond accordingly."

5. STUDY PLAN

Description:

Map out your learning journey from start to finish. Great for tackling big subjects without getting overwhelmed.

**Prompt Template:**

"Create a detailed study plan for learning [insert subject or skill] over the course of [insert time frame]. Include specific goals, resources, and milestones."

6. QUIZ

Description:

Create some practice questions to see if you've really got the hang of things.

**Prompt Template:**

"Generate a 10-question quiz on [insert topic], including a mix of multiple-choice, true/false, and short-answer questions. Provide answers and brief explanations for each question."

7. MINDMAP

Description:

Sketch out your thoughts to see how everything connects. Really helpful when you're trying to wrap your head around a big topic.

**Prompt Template:**

"Create a detailed mind map for the topic [insert topic]. Include main branches, sub-branches, and key concepts or ideas for each."

8. EXPERT ROUNDTABLE

Description:

Simulate a discussion between people who really know their stuff. Great for getting different views on tricky topics.

**Prompt Template:**

"Simulate a roundtable discussion with me and three experts in [insert field] discussing [insert topic or question]. Present their different viewpoints and any potential areas of agreement or disagreement."

9. MENTAL ASSOCIATIONS

Description:

Come up with clever memory tricks to help stuff stick in your brain. Useful for remembering lists, facts, or tricky concepts.

**Prompt Template:**

"Help me create mental associations or mnemonic devices to remember key information about [insert topic or concept]."

10. IMPROVE WHAT YOU HAVE

Description:

Get feedback and suggestions to make your work even better. Great for polishing up something you've already created.

**Prompt Template:**

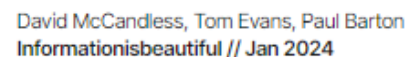
"Here's something I've [written/created/produced]: [insert your work]. Please provide specific suggestions to improve it, focusing on [aspect you want to improve, e.g., clarity, structure, persuasiveness]. Explain why each change would make it better."

ranked by capabilities, sized by billion parameters used for training

anthropic chinese google meta microsoft mistral openAI other

🔍 search...

show only: all



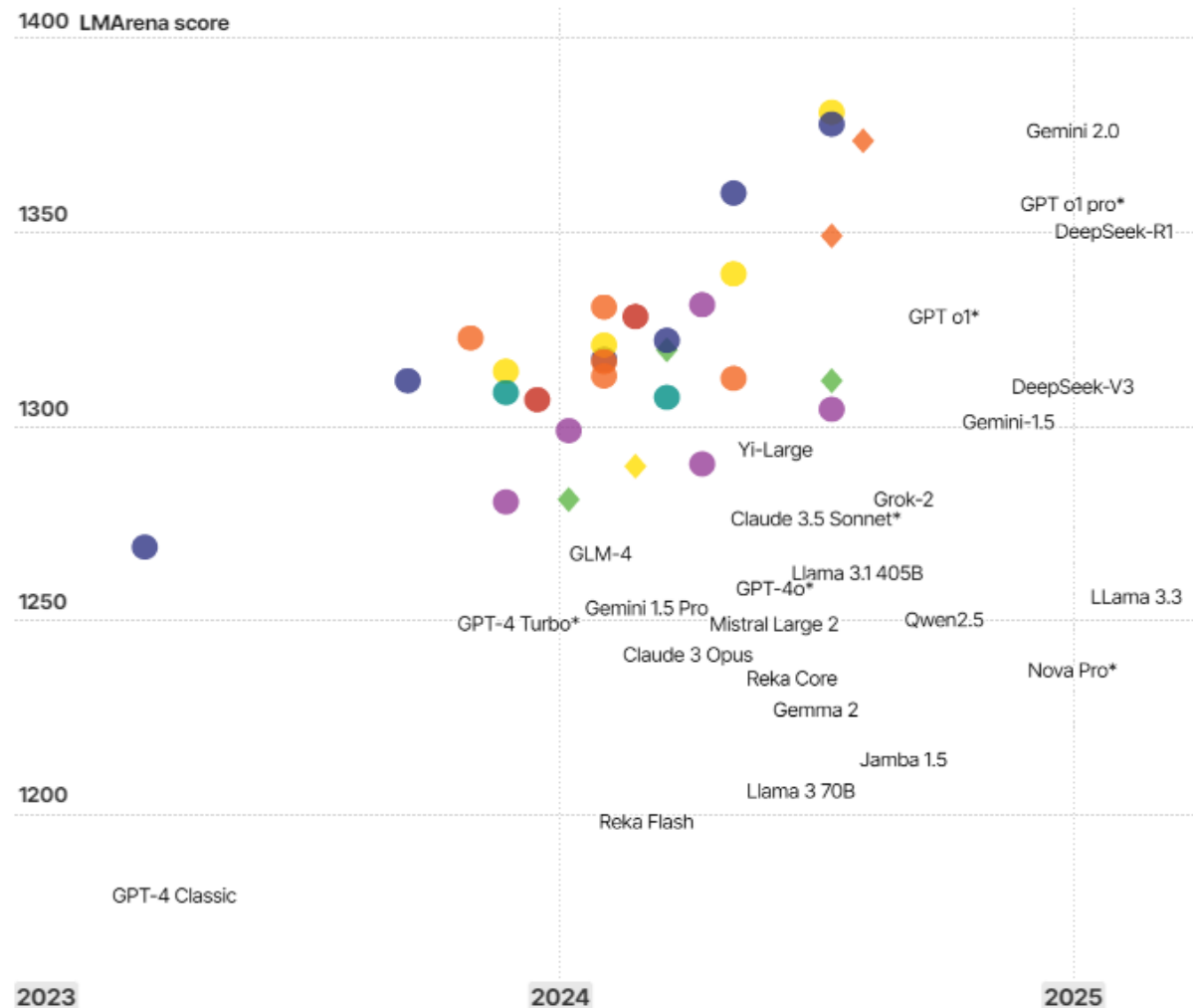
MMLU = benchmark for measuring LLM capabilities
* = parameters undisclosed // source: LifeArchitect // data

Source: : <https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-language-models-llms-like-chatgpt/>

Major LLMs ranked by LMArena Score*

AI Benchmarking community with over 1m user votes

anthropic chinese google meta mistral openAI other



David McCandless, Tom Evans, Paul Barton

Informationisbeautiful // Jan 2024

LMArena = an open platform for crowdsourced AI
benchmarking with over 1m user votes

Source: : <https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-language-models-llms-like-chatgpt/>

and this is a single cluster
in a single floor



Tools to Improve Performance

Building Generative AI is a highly empirical (experimental) process – we repeatedly find and fix mistakes.

- Prompting
- Retrieval augmented generation (RAG)
 - Give LLM access to external data sources
- Fine-tune models
 - Adapt LLM to your task
- Pretrain models
 - Train LLM from scratch

How do chat systems learn to follow instructions? (1)

1. Generative pre-training

Pretraining

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

2. Supervised fine-tuning

Fine-tuning

Help me brainstorm some fun museums to visit in Bogotá.

Sure, here are some suggestions:
[...]

Input (A)	Output (B)
Help me brainstorm some fun museums to visit in Bogotá.	Sure,
Help me brainstorm some fun museums to visit in Bogotá. Sure,	here
Help me brainstorm some fun museums to visit in Bogotá. Sure, here	are
Help me brainstorm some fun museums to visit in Bogotá. Sure, here are	some
Help me brainstorm some fun museums to visit in Bogotá. Sure, here are some	suggestions:
...	...

How do chat systems learn to follow instructions? (1)

3. Reinforcement learning from human feedback (RLHF)

Helpful, Honest, Harmless

Step 1: Train an answer quality (reward) model

Prompt:
Advise me on how to apply for a job.

Input (A)

Response

Output (B)

Score
(reward)

I'm happy to help! Here are some steps to follow [...]

5

Just try your best!

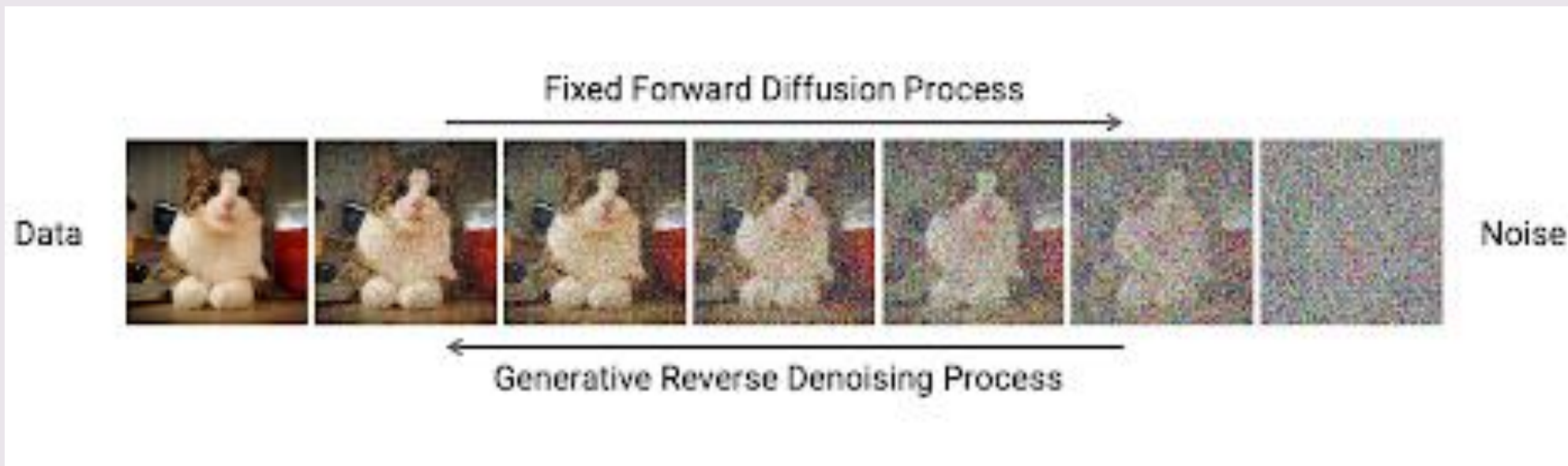
3

It's hopeless – why bother?

1

Step 2: Have LLM generate a lot of answers. Further train it to generate more responses that get high scores.

Diffusion Models



Diffusion Models – Image Generation



Image 1



Image 2

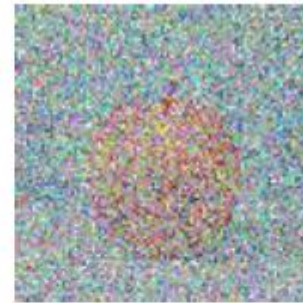


Image 3

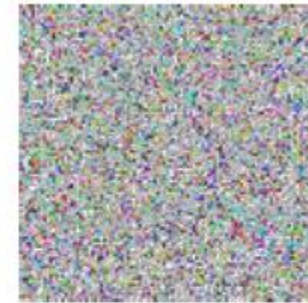


Image 4

Input (A)

Noisy
image



Output (B)

Slightly
less noisy
image

Input (A)	Output (B)
Image 2	Image 1
Image 3	Image 2
Image 4	Image 3

Diffusion Models – Image Generation

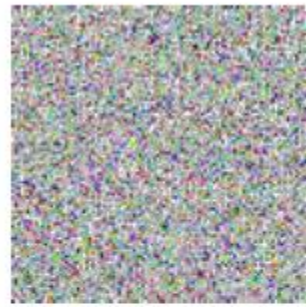


Image 1

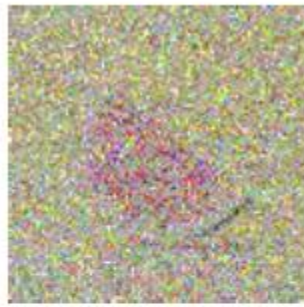


Image 2



Image 3



Image 4

Typically ~100 steps for diffusion model

Diffusion Models – Image Generation

Adding text



Image 1,
"red apple"



Image 2

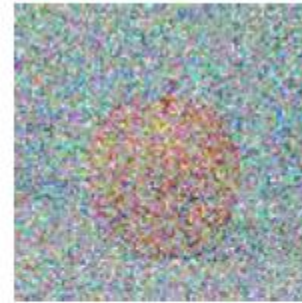


Image 3

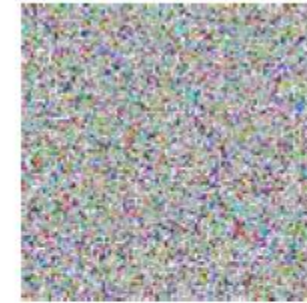


Image 4

Input (A)
Noisy image
and caption



Output (B)
Slightly
less noisy
image

Input (A)	Output (B)
Image 2, "red apple"	Image 1
Image 3, "red apple"	Image 2
Image 4, "red apple"	Image 3

THE VISITORS

- **VEO 3**
(Google DeepMind)

By Hashem Al-Ghaili



“...This mini project was completed in 8 hours, from start to finish, by one person...” (Veo 3, ElevenLabs, Suno, ChatGPT is used in the process)

IKEA ADVERTISEMENT

- *VEO 3*
(Google DeepMind)

By Min Choi



Source: <https://x.com/minchoi/status/1947141905910771855>

- **VEO 3**
(Google DeepMind)

By Min Choi

Source: <https://x.com/minchoi/status/1947141905910771855>

IKEA ADVERTISEMENT - PROMPT

metadata: prompt_name: "IKEA Empty Room Assembly" base_style: "cinematic, photorealistic, 4K" aspect_ratio: "16:9" room_description: "An empty, large, sunlit Scandinavian room with white walls and light wood floors." camera_setup: "A single, fixed, wide-angle shot. The camera does not move for the entire 8-second duration." assembled_elements_list: "A sealed IKEA box" assembled_elements: "yellow IKEA throw blankets" - "lamps" - "wardrobe" - "sofa" - "art" - "rug" - "curtains" - "potted plants" negative_prompts: ["no people", "no text overlays", "no distracting music"] timeline: - sequence: 1 timestamp: "00:00-00:01" action: "In the center of the otherwise empty room, a sealed IKEA box sits on the floor and begins to tremble gently." audio: "Low, subtle rumbling sound. The echo of a large, empty room." - sequence

2 timestamp: "00:01-00:02" action: "The box seams burst open with a puff of cardboard dust." audio: "A sharp 'POP' sound, followed by tearing cardboard." - sequence: 3 timestamp: "00:02-00:06" action: "Hyper-lapse: From the fixed wide perspective, furniture pieces fly out of the box and assemble themselves, creating all the elements' list." audio: "A fast-paced ASMR soundscape of furniture pieces snapping into place." timestamp: "00:06-00:08" action: "The final piece—the yellow throw blanket—gracefully lands on the newly formed bed. The room is now perfectly furnished and serene. All motion ceases." audio: "All chaotic sounds stop. A single, soft 'fwoomp' as the blanket lands. The sound of a furnished, quiet room."

ALMOST 0 BUDGET!

Tilly Norwood

- *Disrupting Hollywood ?!?*

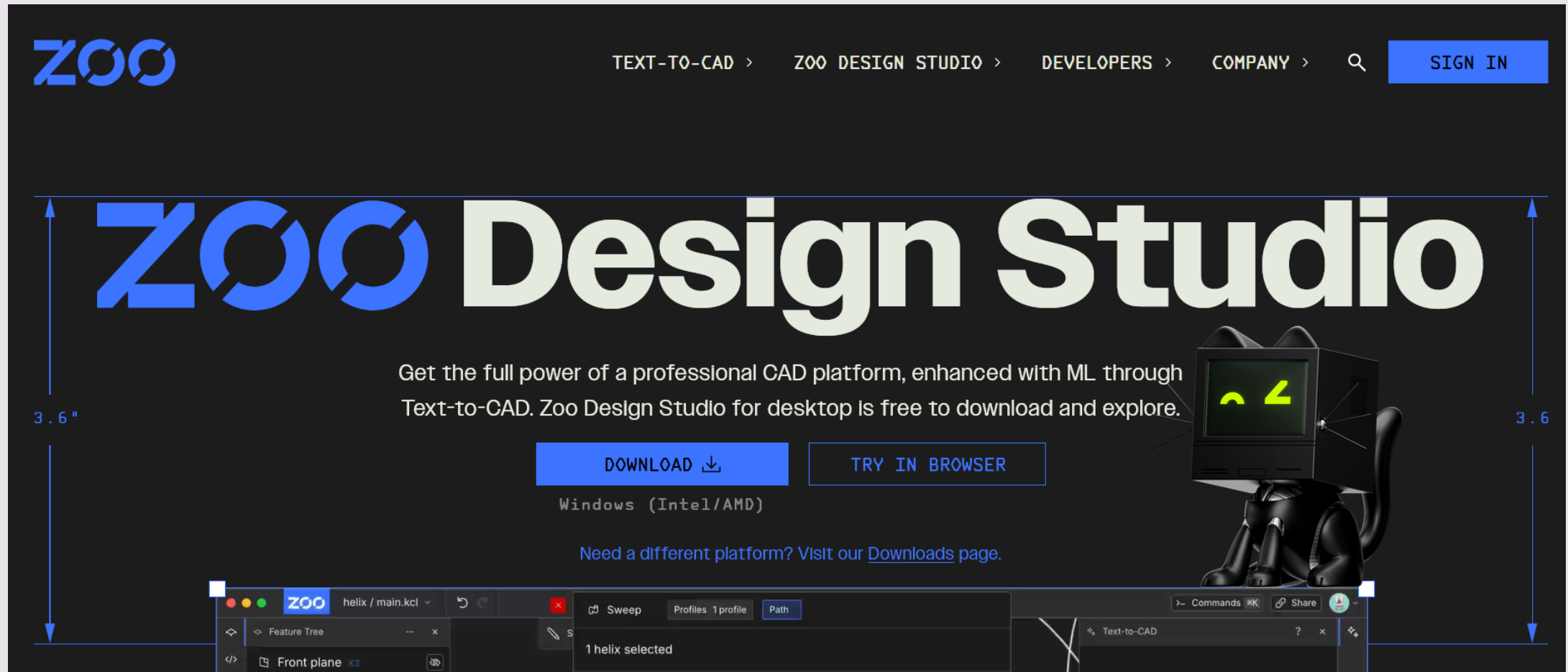


Source: https://www.youtube.com/watch?v=6s59Ao_wvk4

GEN-AI in Machining

- GEN-AI in 3D Modeling: Given the text, image and voice generate the code corresponding the CAD model.

GEN-AI in Machining: Text2CAD



CAM Assist (CloudNC)

- CAM Assist is an AI-driven plugin for popular CAD/CAM software like Autodesk Fusion and Mastercam.
- Launched by CloudNC (backed by Autodesk and Lockheed Martin), it's designed for 3-axis and now 3+2 axis CNC milling, addressing ~2/3 of the global machining market.
 - a. Ingest your setup: Upload a 3D model, and it pulls from your tool library (ensuring compatibility with holders and materials).
 - b. Simulate trillions of options: It evaluates endless strategy combinations, optimizing for cycle time, tool wear, and robustness—far beyond manual trial-and-error.
 - c. Output G-Code: Delivers ready-to-run toolpaths, feeds, and speeds, with monthly updates adding new capabilities like better handling of complex geometries.

CAM Assist in MSP Manufacturing

- ***CAM Assist***

By CloudNC



Source: <https://www.youtube.com/watch?v=8&xV7vM:5E>

AslanX: Generative Design

- Purpose of Generative Design is automatically conduct **design exploration** under the constraints defined by the designers.
- AI can explore the design space, evaluate tens of thousands of design alternatives in real time and inspires new designs.
- Drastically reduces the required time and cost of the process
- Namwoo Kang – KAIST & NarniaLabs (AslanX)
- Topology Optimization, Parametric Design & Deep Generative Models are all subsets of Generative Design.
- *What is the goal?* **Single best solution (Design Optimization) or generating alternatives (Generative Design)?**
- Junior Engineers can perform as senior engineers.

Generative Design with AslanX

- *AslanX*

By Narnia Labs



Source: [Johnny Goode, MSP Manufacturing](#)

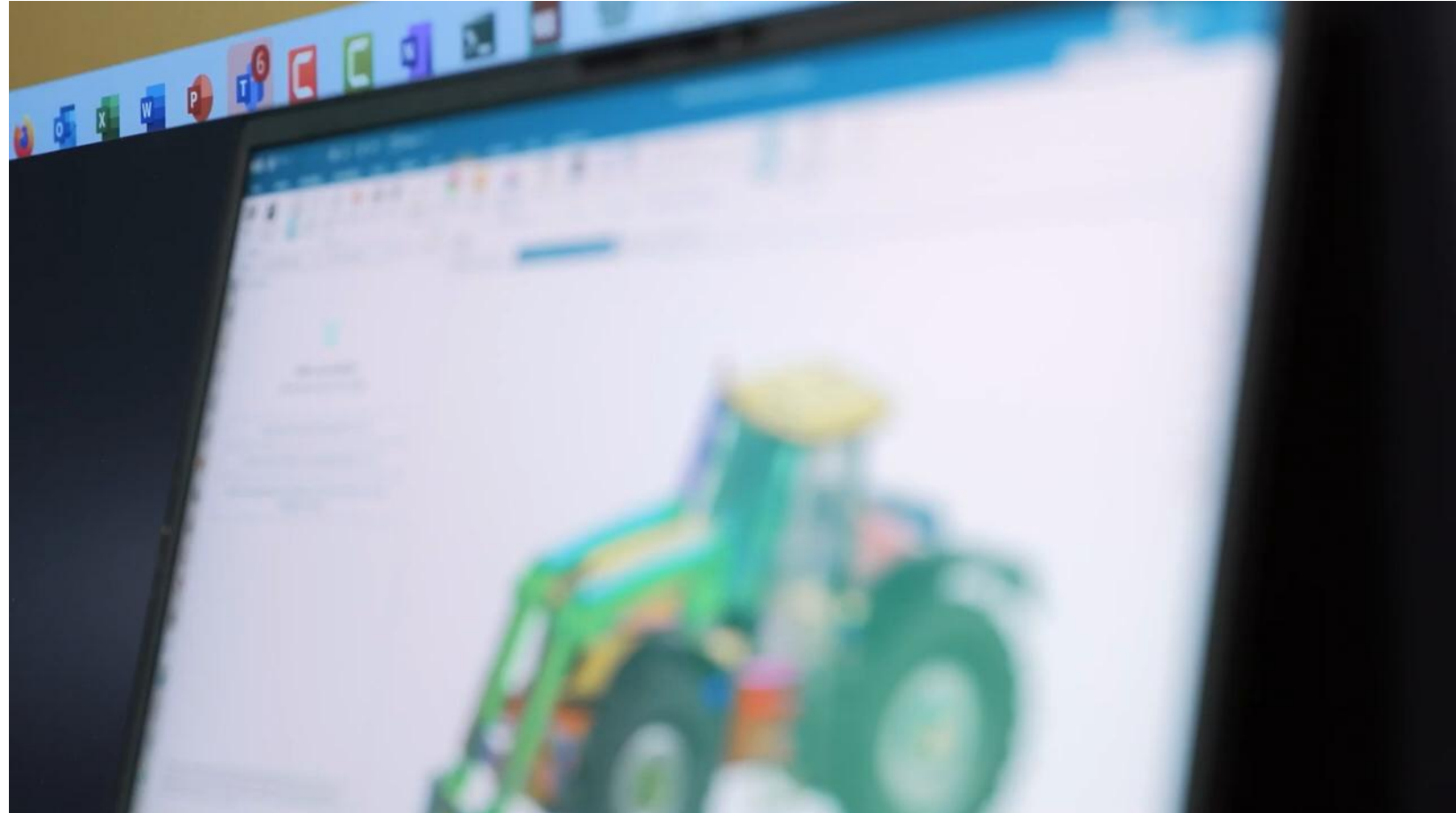
Industrial Foundational Model (Siemens)

- Developed by Siemens in corporation with Microsoft, is a generative model that is fine tuned for industrial context. The data that is used for training includes 3D CAD data, 2D Drawings, bills of materials, process simulations, toolpaths for CNC programming, sensor logs, engineering standards, tolerances, quality inspection datasets, technical specifications etc. (+150 Petabytes)
- **In CNC Programming:** Suggest cutting strategies, tools, and toolpaths while enabling direct interaction through an intuitive user interface. It can identify machining features, recommend strategies, and justify decisions, automating key aspects of CAM programming to save valuable time and reduce skill dependencies.
- **In Manufacturing Planning:** From Engineering BOM where the focus is to design intent, functionality, modularity to Manufacturing BOM where the focus is production, cost, efficiency, in minutes.
- **In Simulation and Validation:** AI can validate assembly processes in 3D on the fly without needing to duplicate data. It can check feasibility, highlight potential issues, and suggest process improvements well before production begins.

IFM – Speaking the Language of Engineers

- ***Industrial Foundation Model (IFM)***

***By Siemens (In
corporation with
Microsoft)***



Source: <https://www.youtube.com/watch?v=ipY1IC-WsI>



Changing the Fundamental Nature of Engineering

- Volatile / Uncertain / Complex / Ambiguous
- A new mindset for the new normal
- Operations Management *to* Supply Chain Management
- Supply Chain Management *to* Ecosystem
 - Productivity/Efficiency **and** Agility
 - Intelligence **and** Creativity
 - Single Best Solution **and** Many Alternatives
 - Intensification **and** Diversification
 - Order **and** Chaos
 - Focus **and** Leisure
 - Guard **and** Unguard
 - Learn **and** Unlearn
 - ...



Changing the Fundamental Nature of Engineering

Execution	Exploration
Comfort Zone	Uncharted Territories
Known Unknowns	Unknown Unknowns
Plan + Execute	Fail, Fail Fast (DT) Build – Measure - Learn (LS)
Waterfall Project Planning	Agile Project Planning
Business Excellence	Discovery / Learning
Find the right answer (Best).	Generate a lot of alternative solutions (Robust)
Focus / Intensification / Exploitation	Diversification / Exploration
Full Commitment	Critical Thinking / Doubt
Model & Data Driven Decisions	Intuition Disciplined with Data

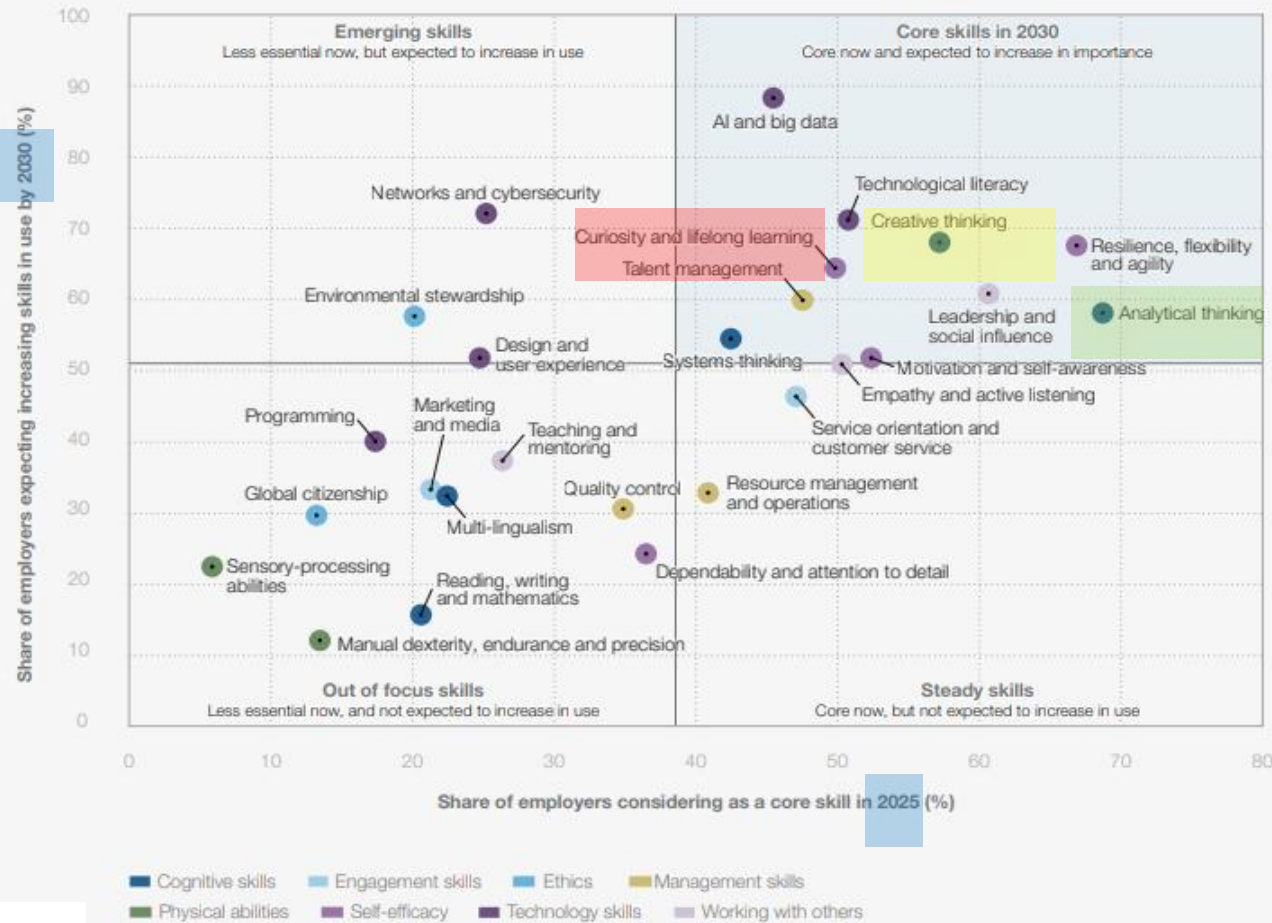


FUTURE OF JOBS – WEF (2018 / 2020 / 2023 / 2025)

FIGURE 3.6

Core skills in 2030

Share of employers considering skills to be a core skill in 2025 and share of employers expecting skills to increase in importance by 2030.

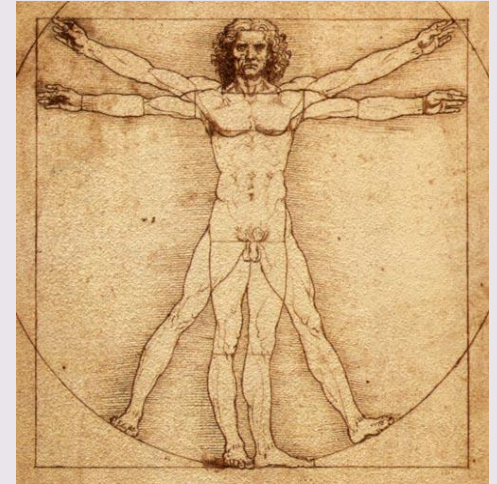


Future of Jobs Report 2025



Changing the Fundamental Nature of Engineering

- **The future demands** individuals who are not confined by narrow expertise but are driven by *curiosity, humility, empathy* and a *relentless passion for lifelong learning & doing!* (i.e., *Learning Personas!*).
- By embracing knowledge across diverse fields and engaging in *collaboration*—whether with others **or** GenAI tools—individuals can harness the power of *crosspollination* to spark innovative solutions to global challenges.
- Leaders must cultivate environments that encourage this *interdisciplinary perspective*, empowering societies to thrive in an era of relentless change.



Suggested Resources: LLM

Basics of LLMs (3Blue1Brown) (Total 2 Hours):

- Video 1: [Large Language Models explained briefly](#)
- Video 2: [Transformers \(how LLMs work\) explained visually | DL5](#)
- Video 3: [Attention in transformers, step-by-step | DL6](#)
- Video 4: [How might LLMs store facts | DL7](#)

Fundamentals of LLM :

- Vector Databases – Embedding (1 Hour): [Vector Databases: from Embeddings to Applications - DeepLearning.AI](#)
- How Transformers LLM works (1.5 Hours): [How Transformer LLMs Work - DeepLearning.AI](#)
- Pretraining LLMs (1.5 Hours): [Pretraining LLMs - DeepLearning.AI](#)

Improving LLM :

- Reinforcement Learning (1.5 Hours): [Reinforcement Learning from Human Feedback - DeepLearning.AI](#)
- Finetuning LLMs (1.5 Hour) : [Finetuning Large Language Models - DeepLearning.AI](#)
- Building RAG (1.5 Hour): [Building and Evaluating Advanced RAG Applications - DeepLearning.AI](#)

Reasoning in LLMs:

- Reasoning with O1 (1 Hour): [Reasoning with o1 - DeepLearning.AI](#)