Specialist Programme on Artificial Intelligence for IT & ITES Industry

From Human Intelligence to Artificial Intelligence

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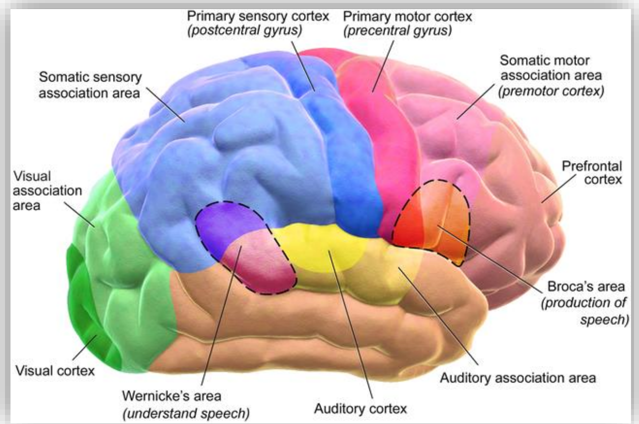
Singapore e-Government Leadership Centre
National University of Singapore

Inspire Lead Transform

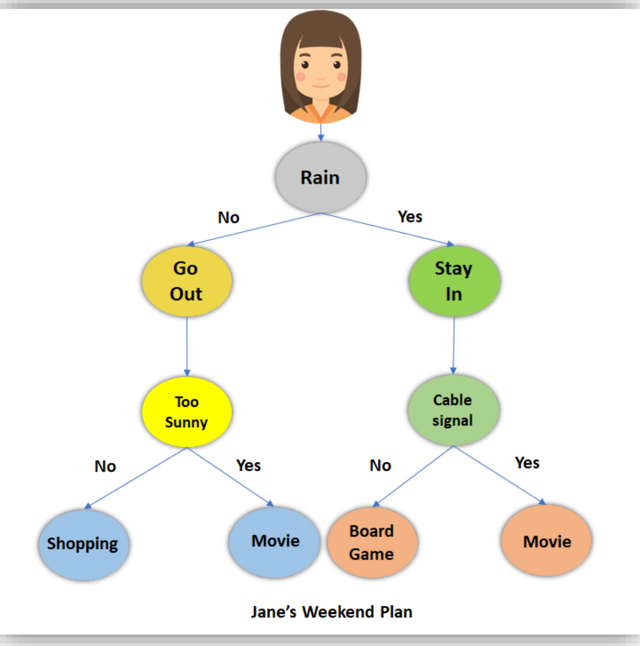
Human Intelligence vs. Artificial Intelligence



Thinking vs Acting (acting = behaviour)

Human vs Rational (rationality = doing the right thing)

Systems that think like humans (cognitive science)	Systems that think rationally (logic/laws of thought)
Systems that act like humans (c.f. Turing test)	Systems that act rationally (agents)



Source https://slideplayer.com/slide/4644026/15/images/20/Systems+that+think+like+humans+%28cognitive+science%29.jpg

An hopefully intelligent lifelong learning human

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- GU Zhan 顾瞻 (Sam) lectures Master of Technology programme in the areas of data science, machine intelligence, and soft computing. Prior to joining ISS, he was in New Zealand running start-up, delivering artificial intelligence training programs. Sam had also spent many years in financial and engineering sector wearing versatile hats: data scientist, project manager, consultant, system manager and software engineer.
- He devotes himself into pedagogy, and is very passionate in inspiring next generation of artificial intelligence lovers and leaders.

Agenda

1.1 Human Intelligence/Cognition

Memory; Learning; Reasoning

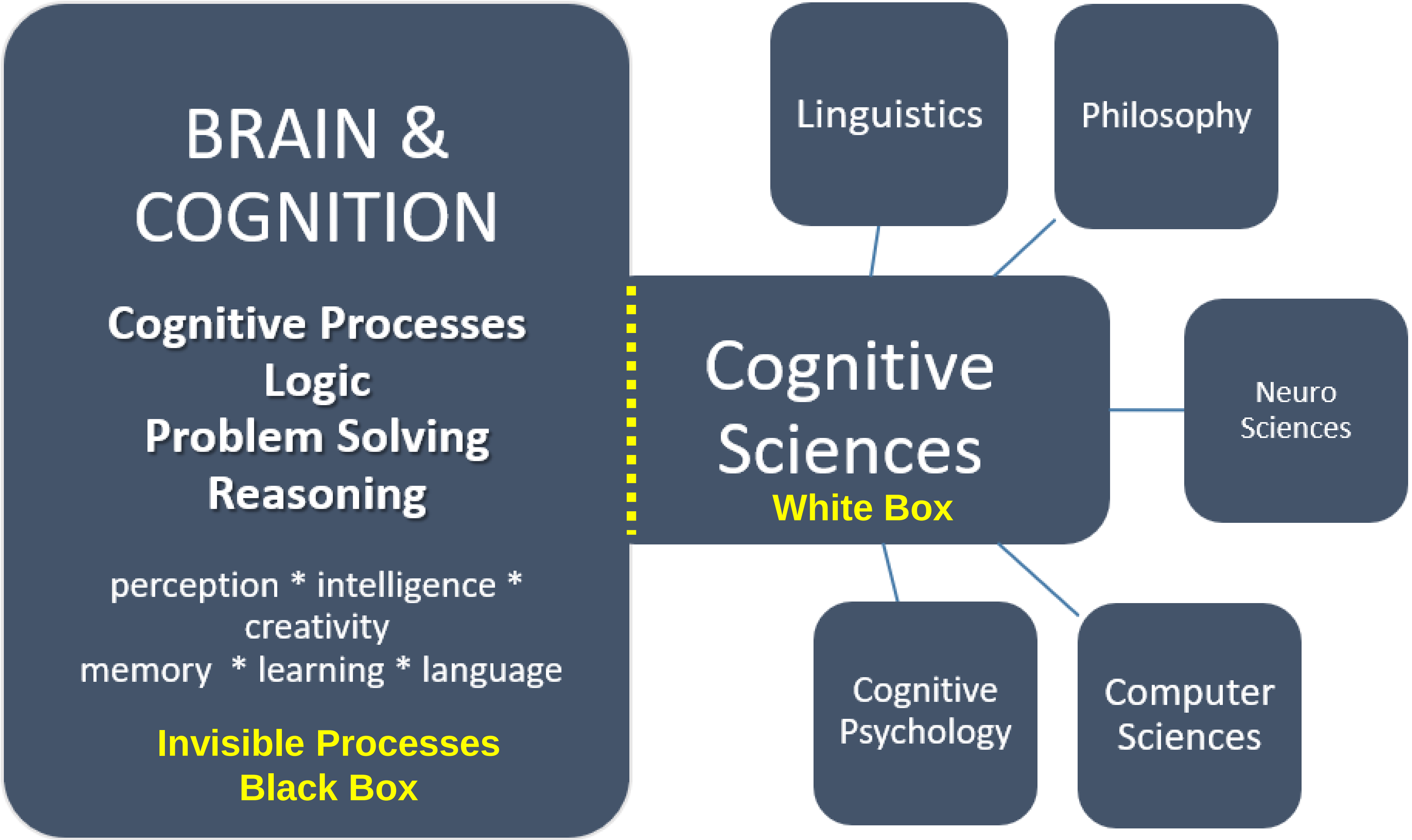
1.2 A “Model” View of Intelligence

1.3 Artificial Intelligence/Cognition

Goals; Roots; Sub Fields

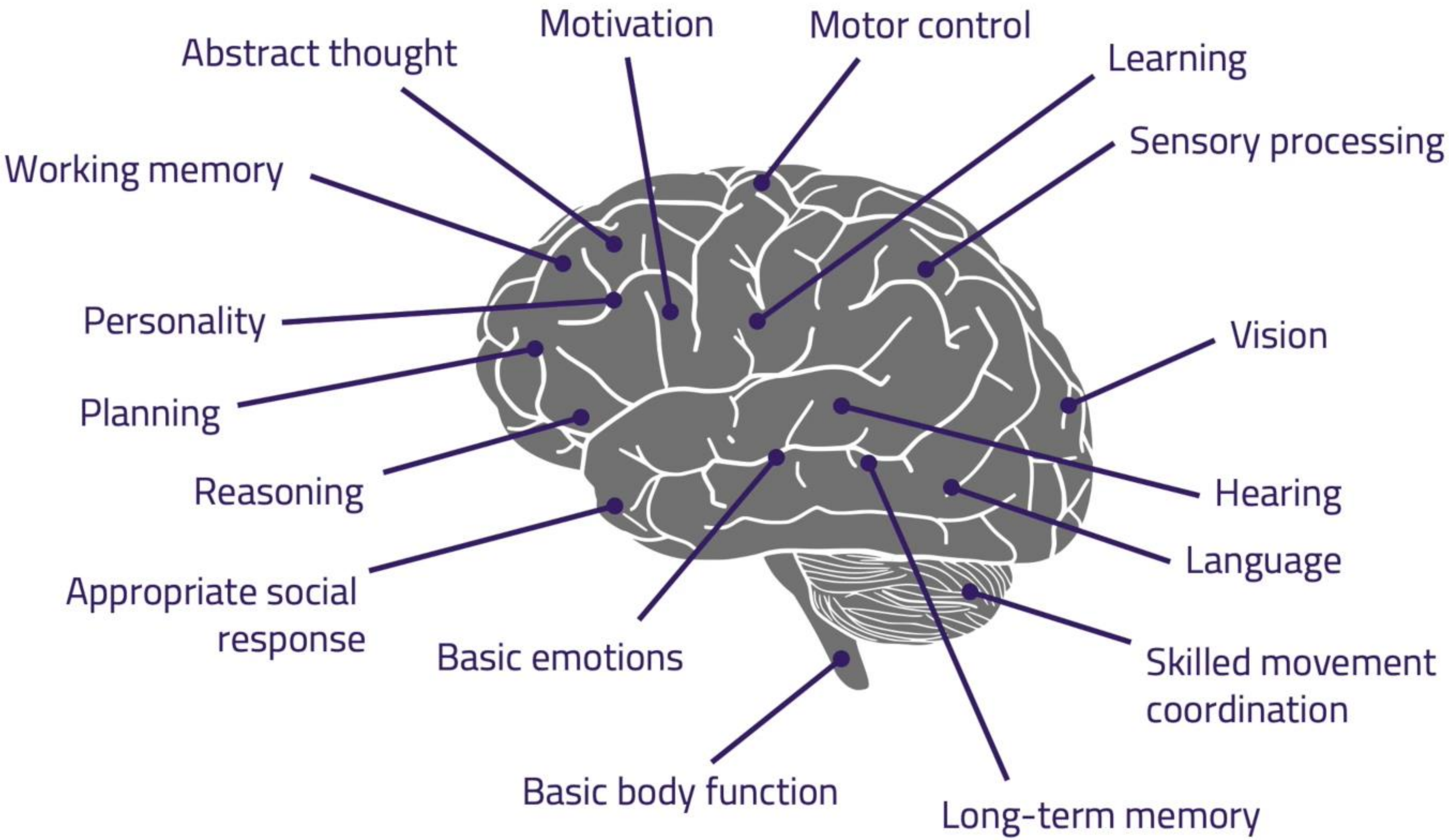
1.4 Intelligent Minimum Viable Product (MVP) Show Cases

Human Intelligence/Cognition



Source https://medium.com/womeninai/human-cognition-and-artificial-intelligence-a-plea-for-science-21a2388f6e7e

Human Capabilities



Source https://youtu.be/JlcGfwb6CDE

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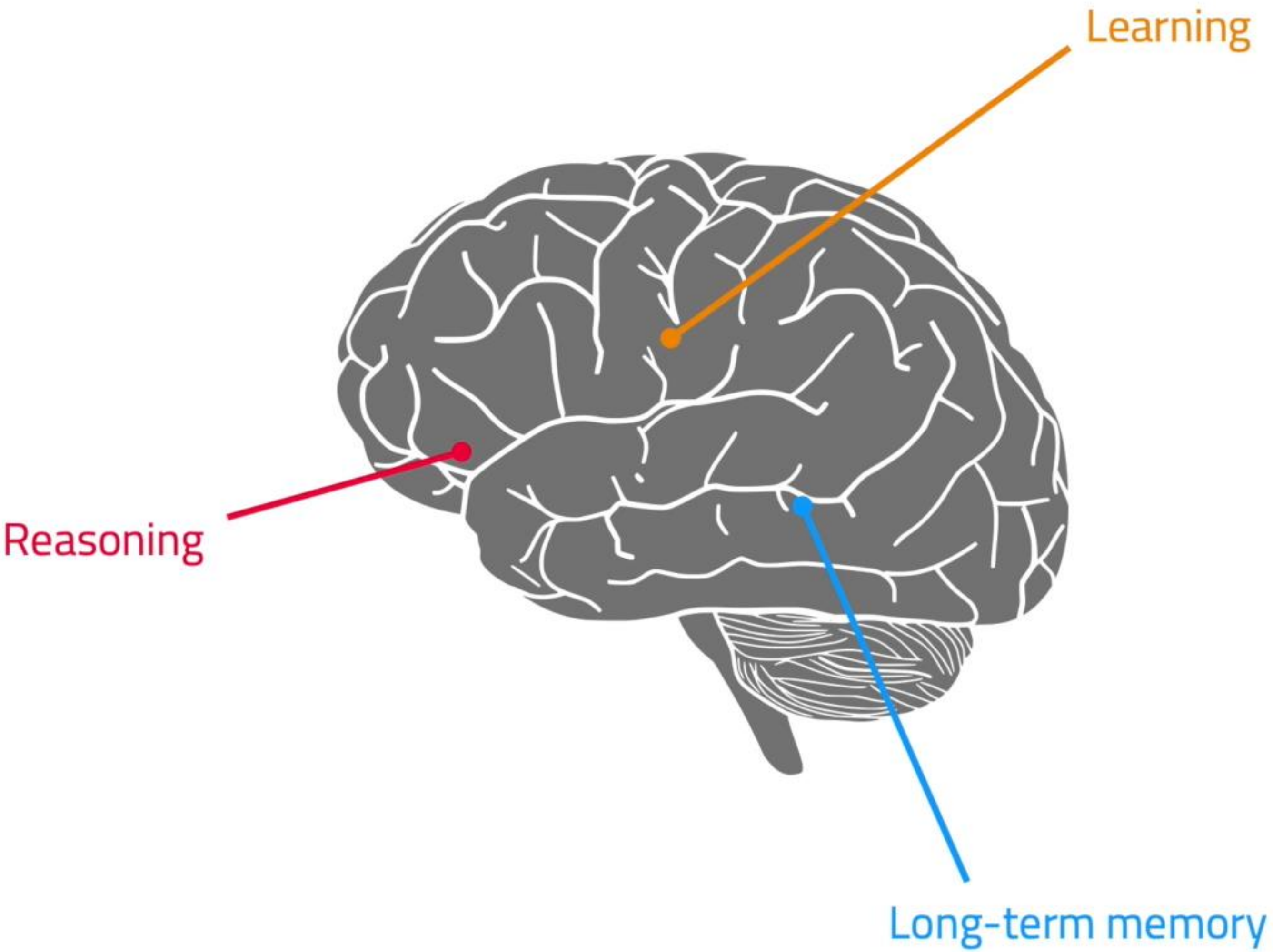
Human Capabilities



Source https://youtu.be/JlcGfwb6CDE

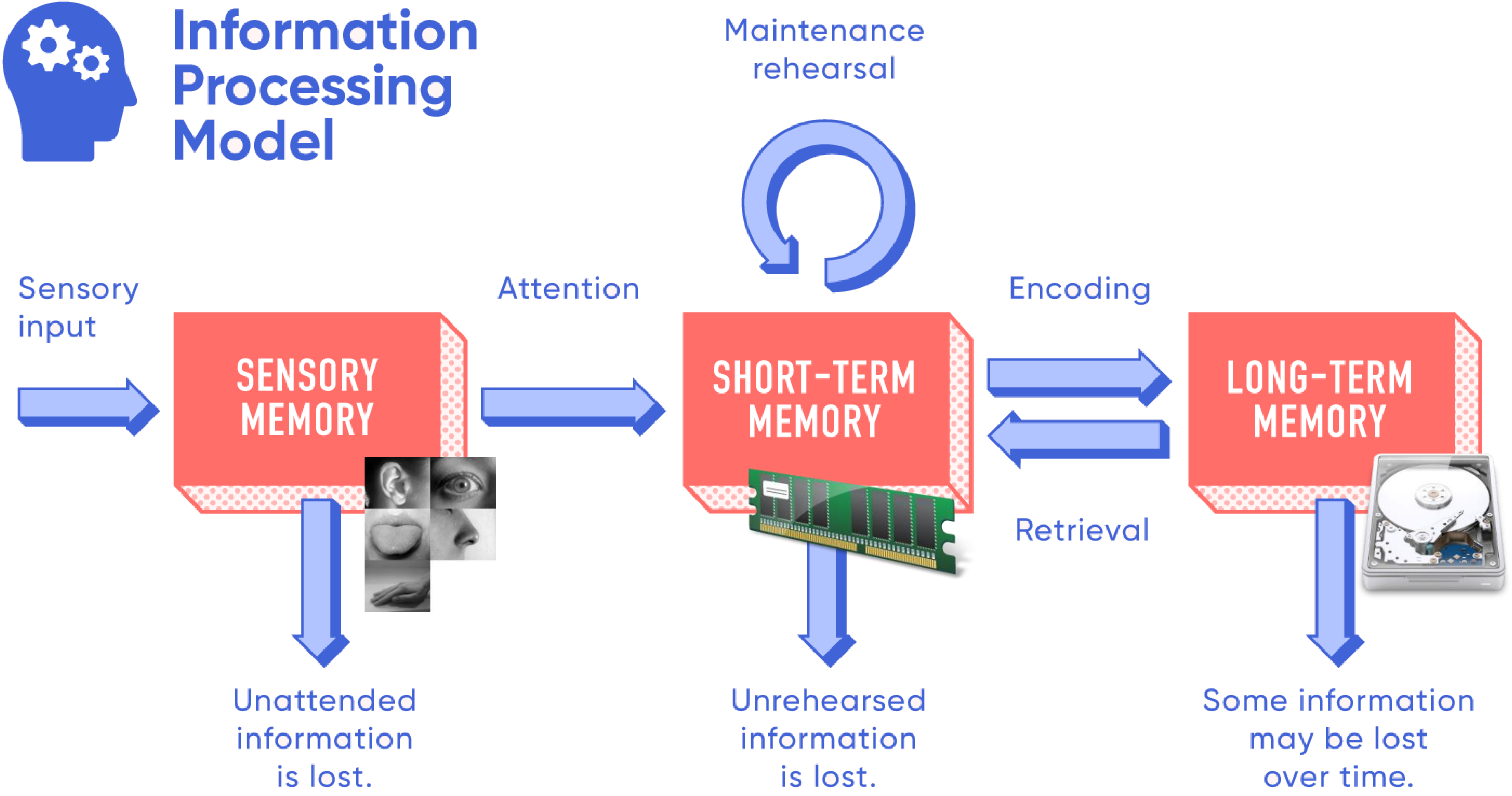
Human Long-term Memory

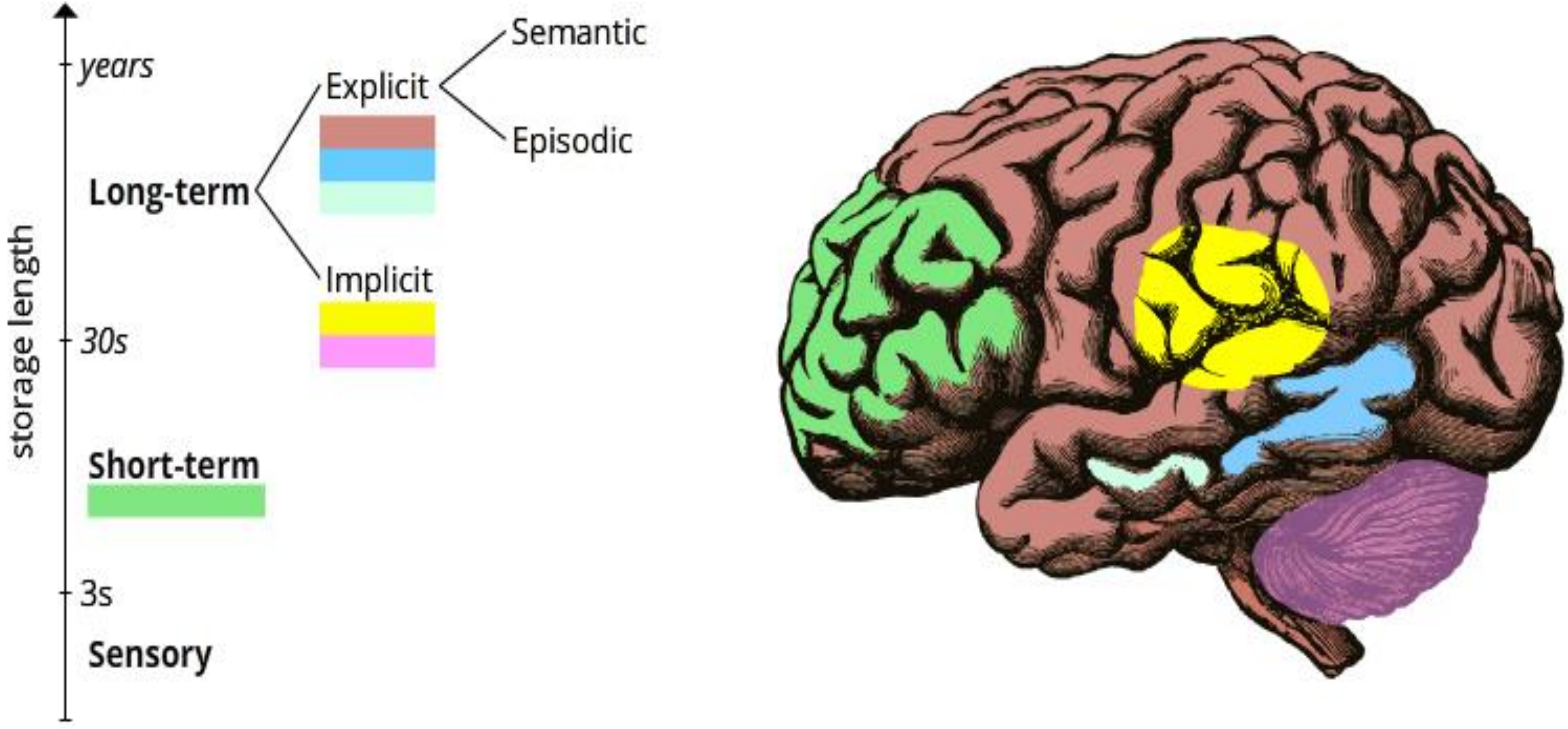
to **store** knowledge data

Human Working/Sensory Memory

to **store** raw/sensory/interim data

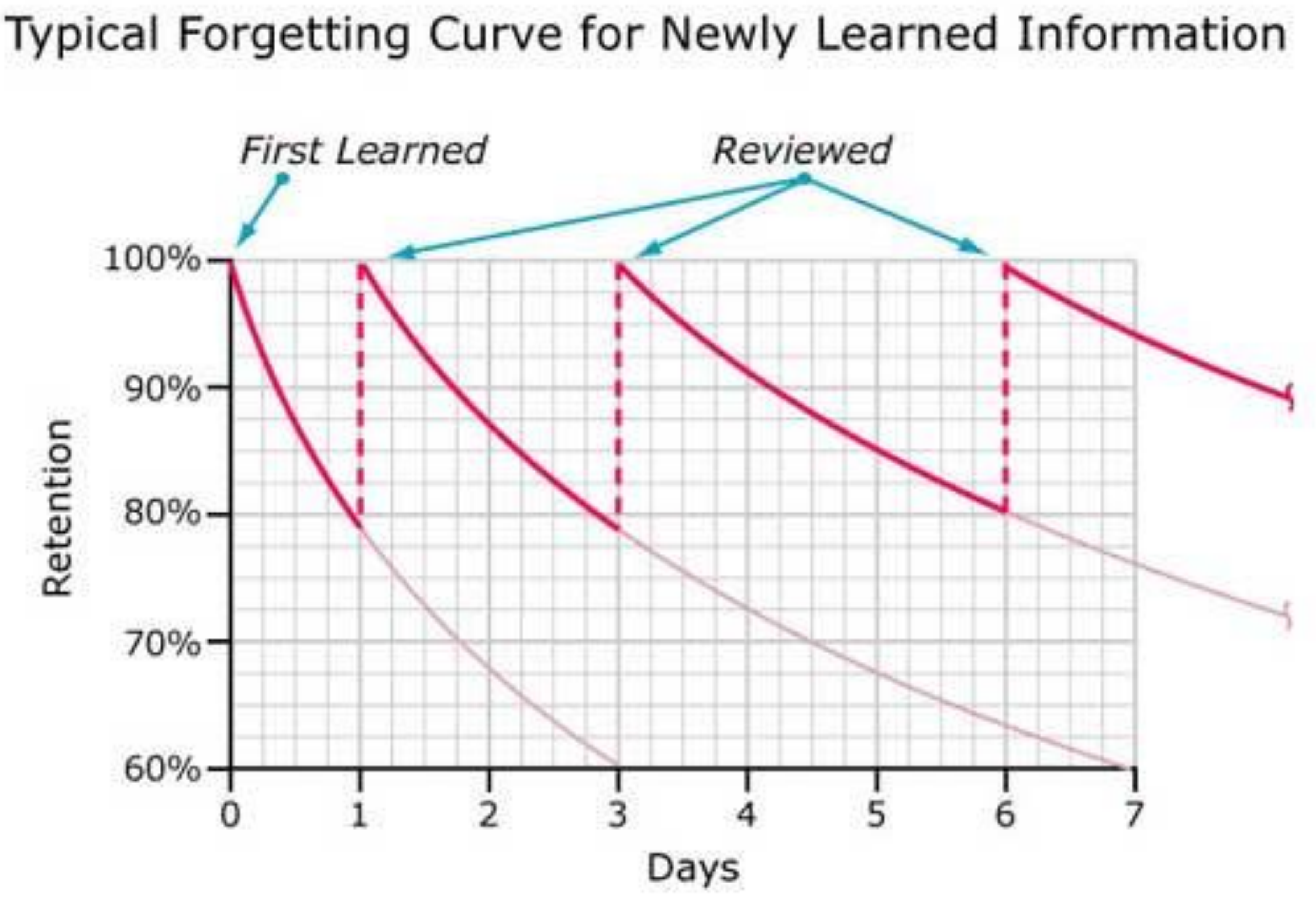
Information Processing Model

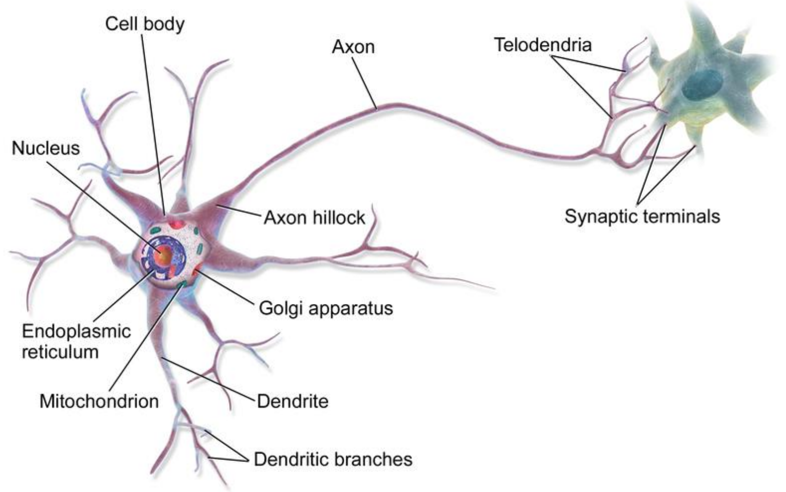


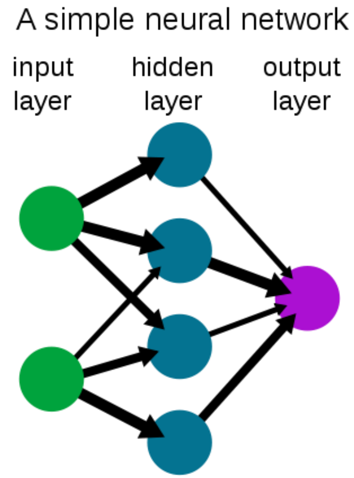

storage length
years
30s
3s
Long-term
Explicit
Semantic
Episodic
Implicit
Short-term
Sensory

Memorizing requires repetition;

Memorizing enables Learning.

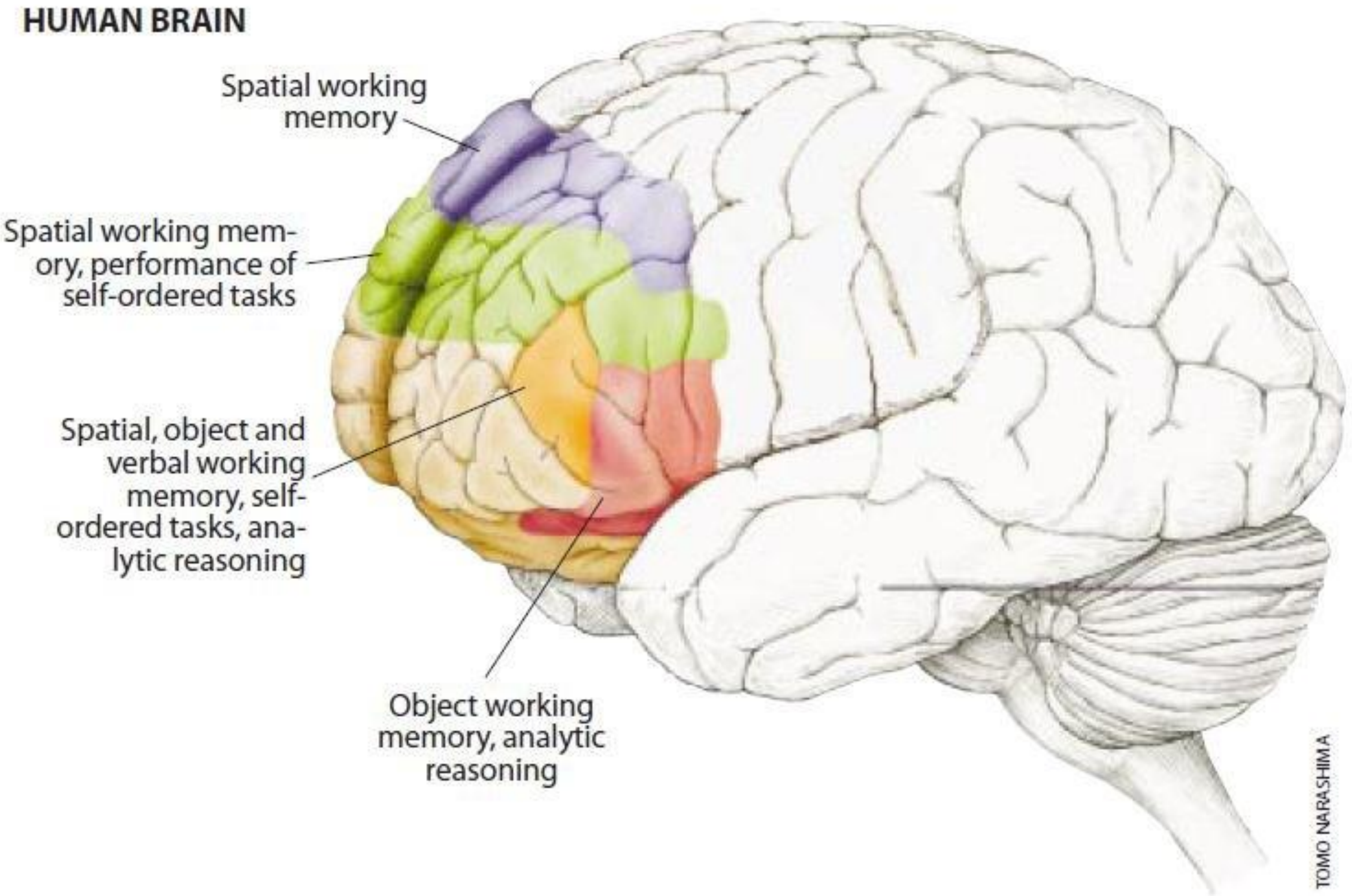


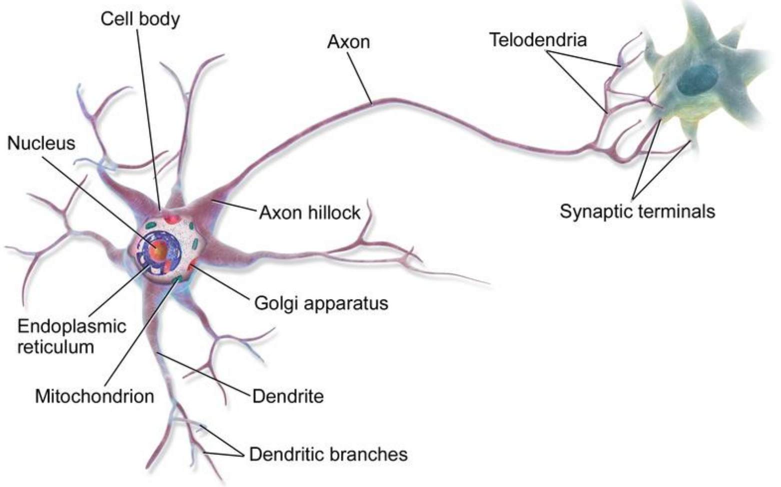




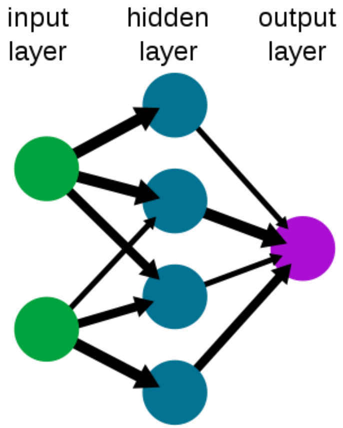
Source https://teachlikeachampion.com/blog/using-now-retrieval-practice-update-alex-laney/

Memorized/Learnt knowledge/data are represented as black box storage in brain.





A simple neural network



Source https://www.researchgate.net/figure/Prefrontal-Cortex-Deeply-Relevant-to-Working-Memory-Beardsley-1997_fig5_327269915

Human Learning

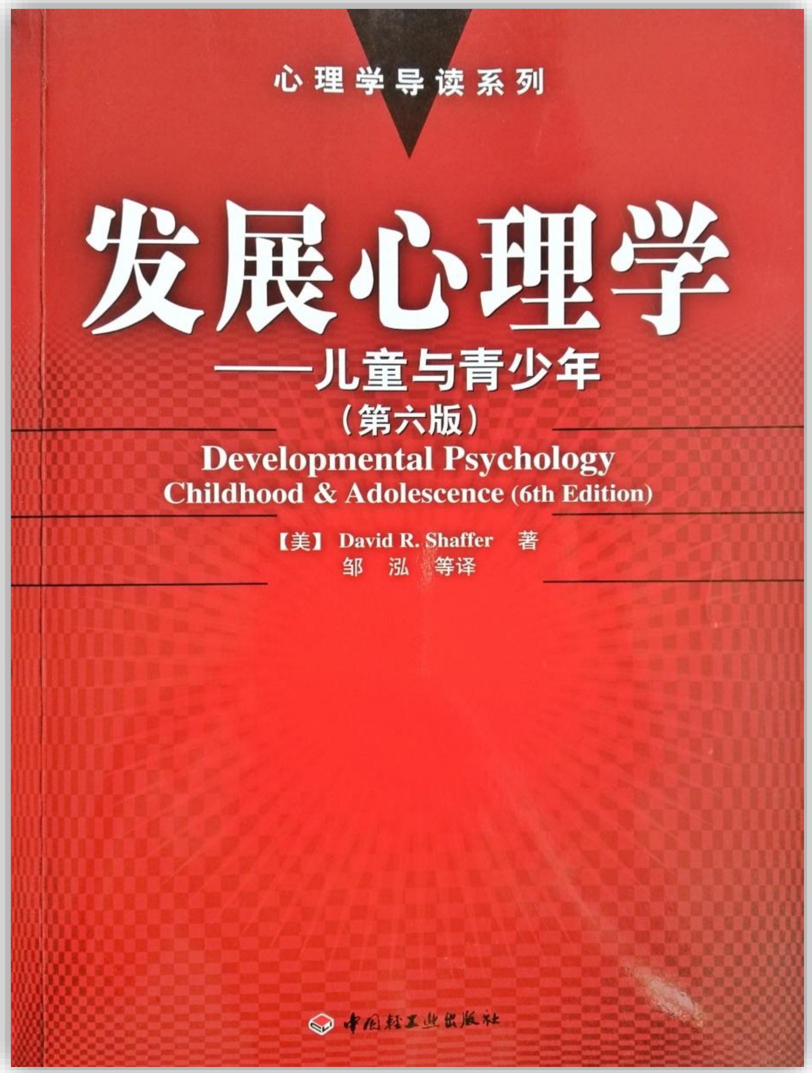
to **<u>generate new</u>** knowledge

Model:
Learn

Model:
Recognize

Common Forms of Learning

1. **Habituation**
   - AI: Unsupervised Learning
   - AI: Anomaly Detection
2. **Classical conditioning**
   - AI: Association (between stimuli or events)
3. **Operant conditioning**
   - AI: Reinforcement Learning
   - AI: Supervised/Semi-Supervised Learning
4. **Observational learning**
   - AI: Imitation Learning
   - AI: Unsupervised/Semi-Supervised Learning



Common Forms of Learning

1. Habituation

- Unsupervised Learning; Anomaly Detection

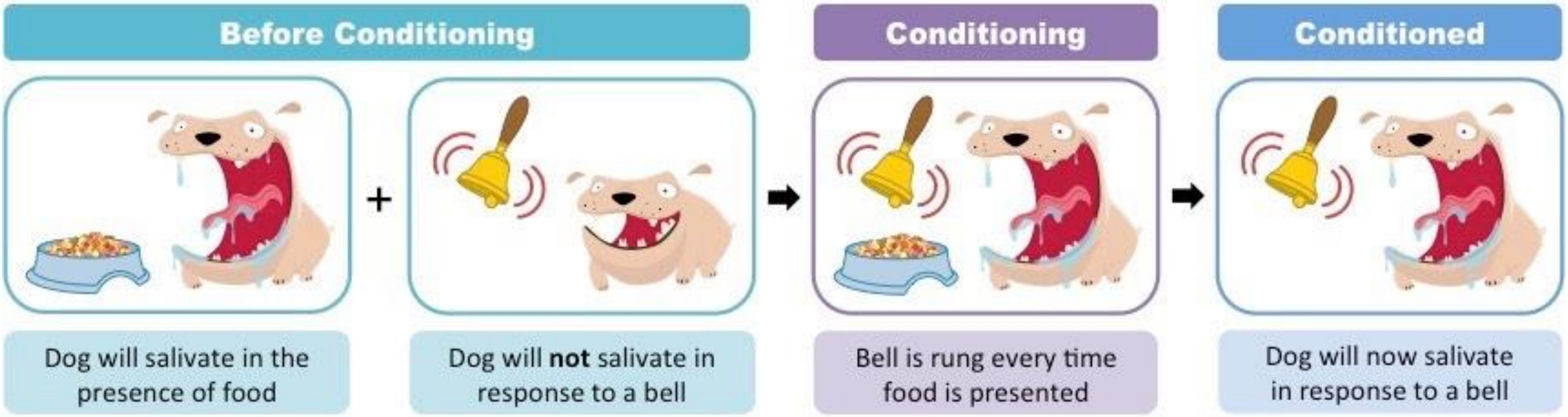
Crows present in corn field | Introduction of scarecrow | Prolonged exposure to scarecrow

Source https://ib.bioninja.com.au/options/option-a-neurobiology-and/a4-innate-and-learned-behav/habituation.html

Common Forms of Learning

2. Classical (Reflex) conditioning

- Association (between stimuli or events)

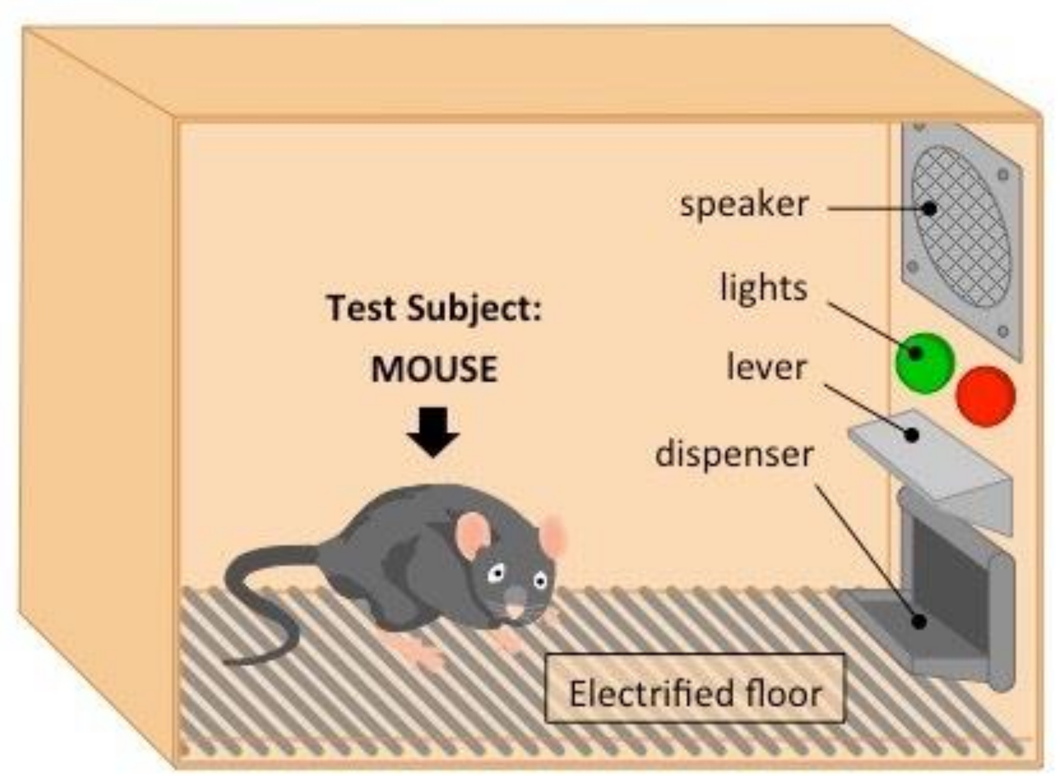


Source https://ib.bioninja.com.au/options/option-a-neurobiology-and/a4-innate-and-learned-behav/conditioning.html

Common Forms of Learning

3. Operant conditioning

- Reinforcement Learning; Supervised/Semi-Supervised Learning



	Something **given** to the mouse	Something **taken** from the mouse
Increases likelihood of repeated behavior	**POSITIVE REINFORCEMENT** Mouse given food when lever pressed (after green light)	**NEGATIVE REINFORCEMENT** Loud noise stopped when lever pressed
Decreases likelihood of repeated behavior	**POSITIVE PUNISHMENT** Mouse is shocked when lever pressed (after red light)	**NEGATIVE PUNISHMENT** Not applicable in this scenario

Source https://ib.bioninja.com.au/options/option-a-neurobiology-and/a4-innate-and-learned-behav/conditioning.html

Common Forms of Learning

3. Operant conditioning

Reinforcement Learning
https://deepmind.com/blog/alphago-zero-learning-scratch/
https://telescopeuser.wordpress.com/

DiDi: A Reinforcement Learning Agent

Reinforcement Learning in Daily Life

[Author: DiDi & GU Zhan (Sam)]

[Tags: MTech IS, AI, Reinforcement learning, Agent, Markov decision process]

Common Forms of Learning

4. Observational learning

- Imitation Learning; Unsupervised/Semi-Supervised Learning

Source https://courses.lumenlearning.com/wsu-sandbox/chapter/observational-learning-modeling/

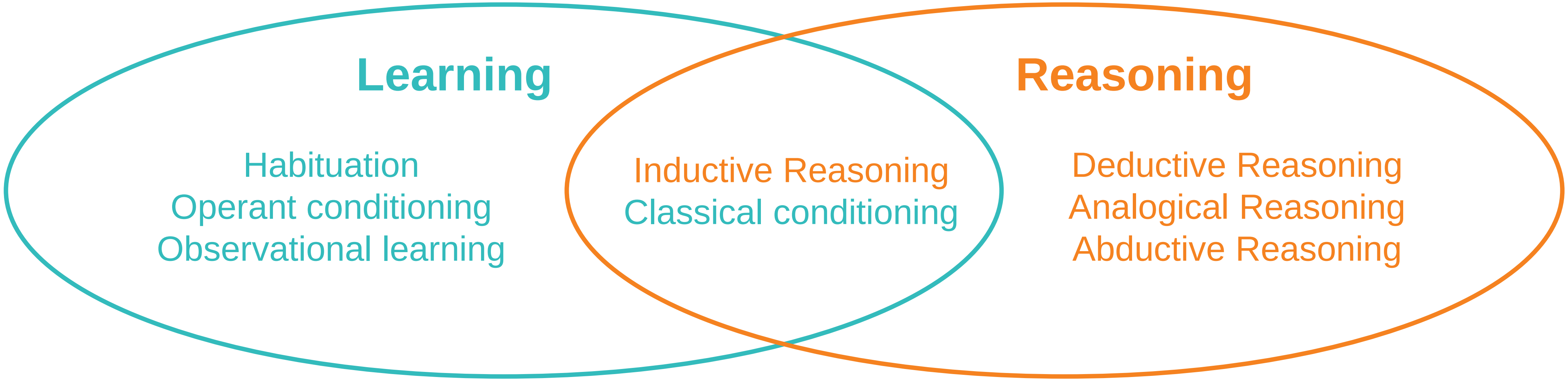
Human Reasoning

to **<u>use existing</u>** knowledge

Model:
Reason/Think

Common Forms of Reasoning

1. **Deductive Reasoning** (Formal logic; Aristotle's syllogism)
2. **Inductive Reasoning** (Statistical learning / recognition)
3. **Analogical Reasoning** (Case based reasoning)
4. **Abductive Reasoning** (Hypothesis ~ Evidence; Probability)



Common Forms of Reasoning

1. Deductive Reasoning

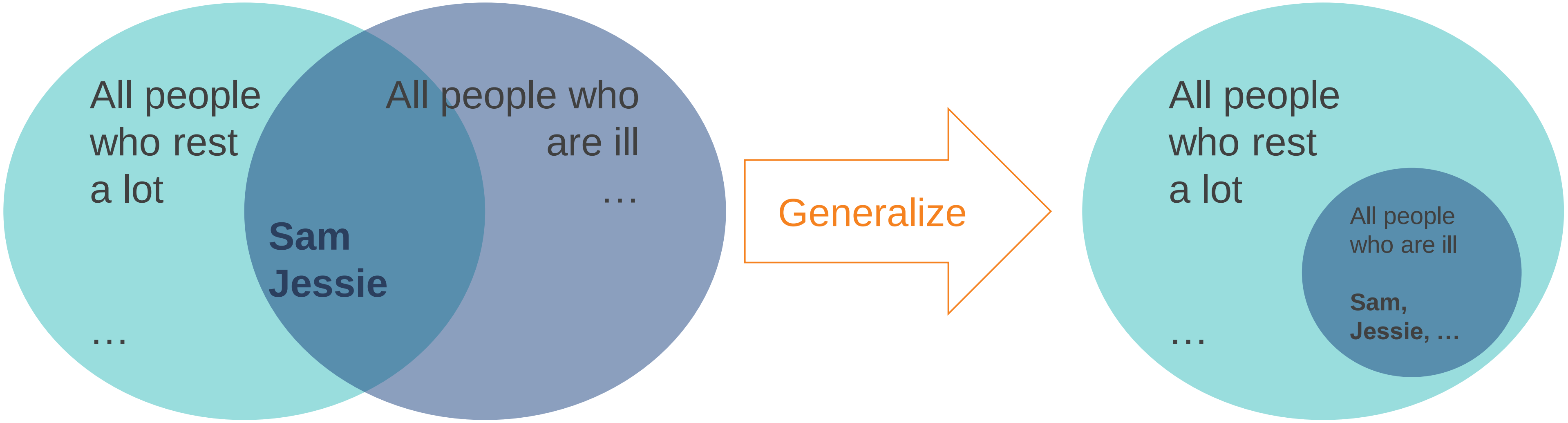
- **Knowledge/Rule** : **All people** who are **ill**, they rest a lot.
- **Individual 1** : **Sam** is **ill**, therefore he rest a lot.
- **Individual 2** : **Jessie** is **ill**, therefore she rest a lot.
- **Individual …**

☺ **Reasoning Rationality: Universal → Individual**

Common Forms of Reasoning

2. Inductive Reasoning

- **Individual 1** : When **Sam** is **ill**, he rests a lot.
- **Individual 2** : When **Jessie** is **ill**, she rests a lot.
- **Generalised Rule** : **All people** who are **ill**, they rest a lot.

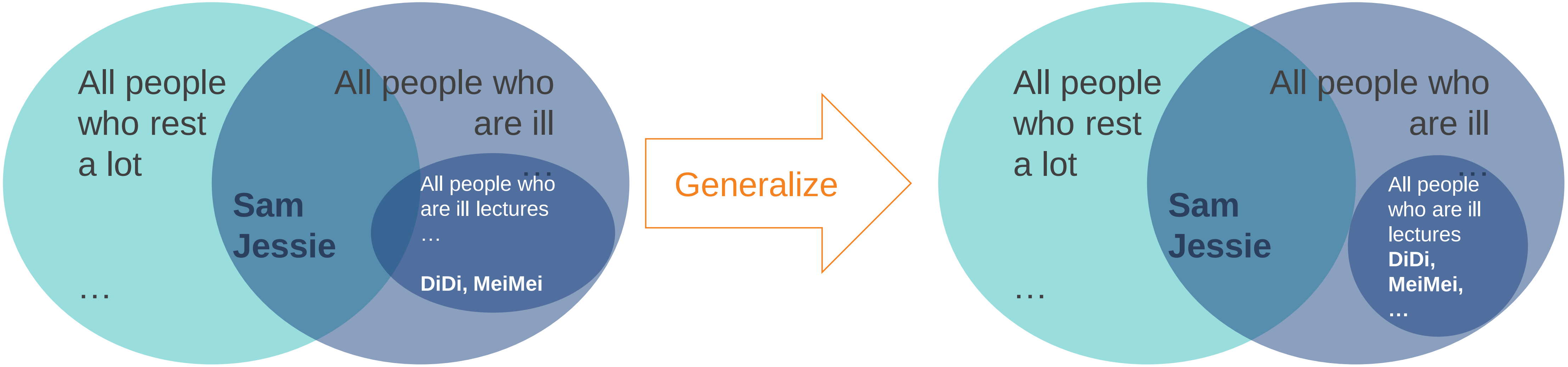


☺ **Reasoning Rationality: Individual → Universal (Machine Learning)**

Common Forms of Reasoning

2. Inductive Reasoning

- **Individual 1** : When **DiDi** is **ill** AND he is **lecturer**, he doesn't rest a lot.
- **Individual 2** : When **MeiMei** is **ill** AND she is **lecturer**, she doesn't rest a lot.
- **Generalised Rule** : **All people** who are **ill lecturers**, they don't rest a lot.



☺ Reasoning Rationality: Individual → Universal (Machine Learning)

Common Forms of Reasoning

3. Analogical Reasoning

- **Known case** : **Sam** is ill with his symptoms: fever, flame, cough, and rash.
- **Inferred case** : **Jessie** is ill too, therefore she **would** have **same** symptoms as **Sam**: fever, flame, cough, and rash.

Sam is ill.
Observed symptoms:
Fever
Flame
Cough
Rash

Assume similarity →

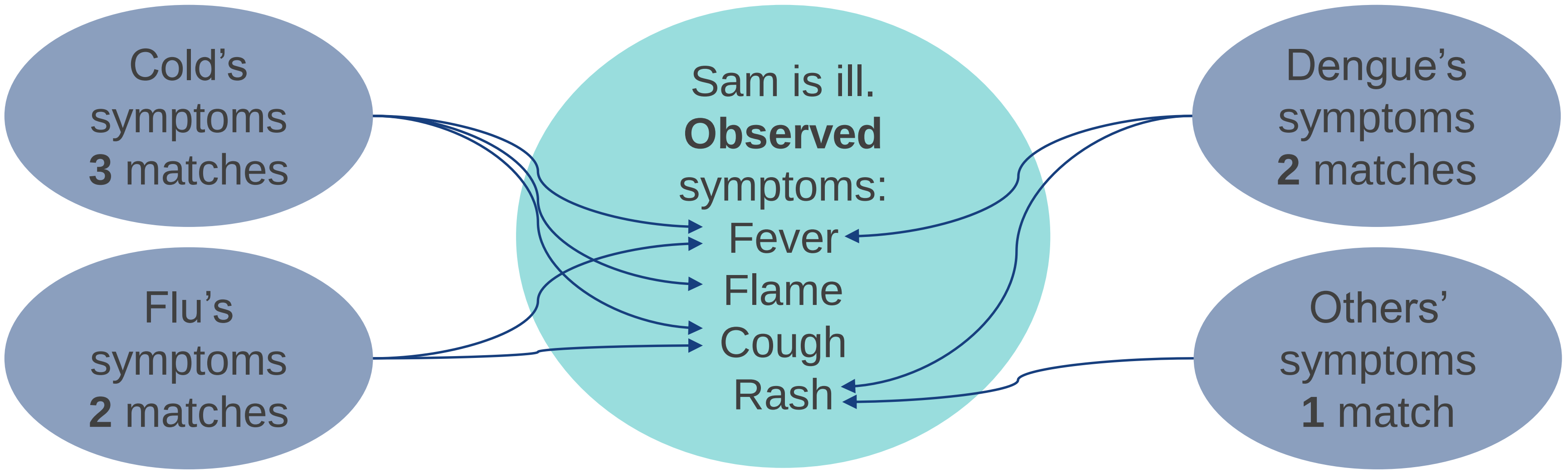
Jessie is ill.
Inferred symptoms:
Fever
Flame
Cough
Rash

☺ Reasoning Rationality: Known case → Inferred case

Common Forms of Reasoning

4. Abductive Reasoning

- **Known observations** : **Sam** is ill with his symptoms: fever, flame, cough, and rash.
- **Inferred root cause** : **Cold? Flu? Dengue? Others?**



☺ **Reasoning Rationality: Observations → Causes likelihood**

Common Forms of Reasoning

Others Types: Fuzzy Reasoning

Long Hair Group ←	Hair length ≥ 10 cm	
	Hair length < 10 cm	→ Short Hair Group
Long Hair Group ←	Hair length is long	
	Hair length is short	→ Short Hair Group

What if the hair length is both long and short → Which Group?

Source https://www.google.com/search?q=nicolas+cage&rlz=1C1GCEU_enSG820SG820&source=lnms&tbm=isch&sa=X&ved=0ahUKEwiOt7bhkqTjAhVcknAKHTSZBHgQ_AUIECgB&biw=1920&bih=896

Common Forms of Reasoning

Aliens

Not aliens

Which one is alien?

A B C D E

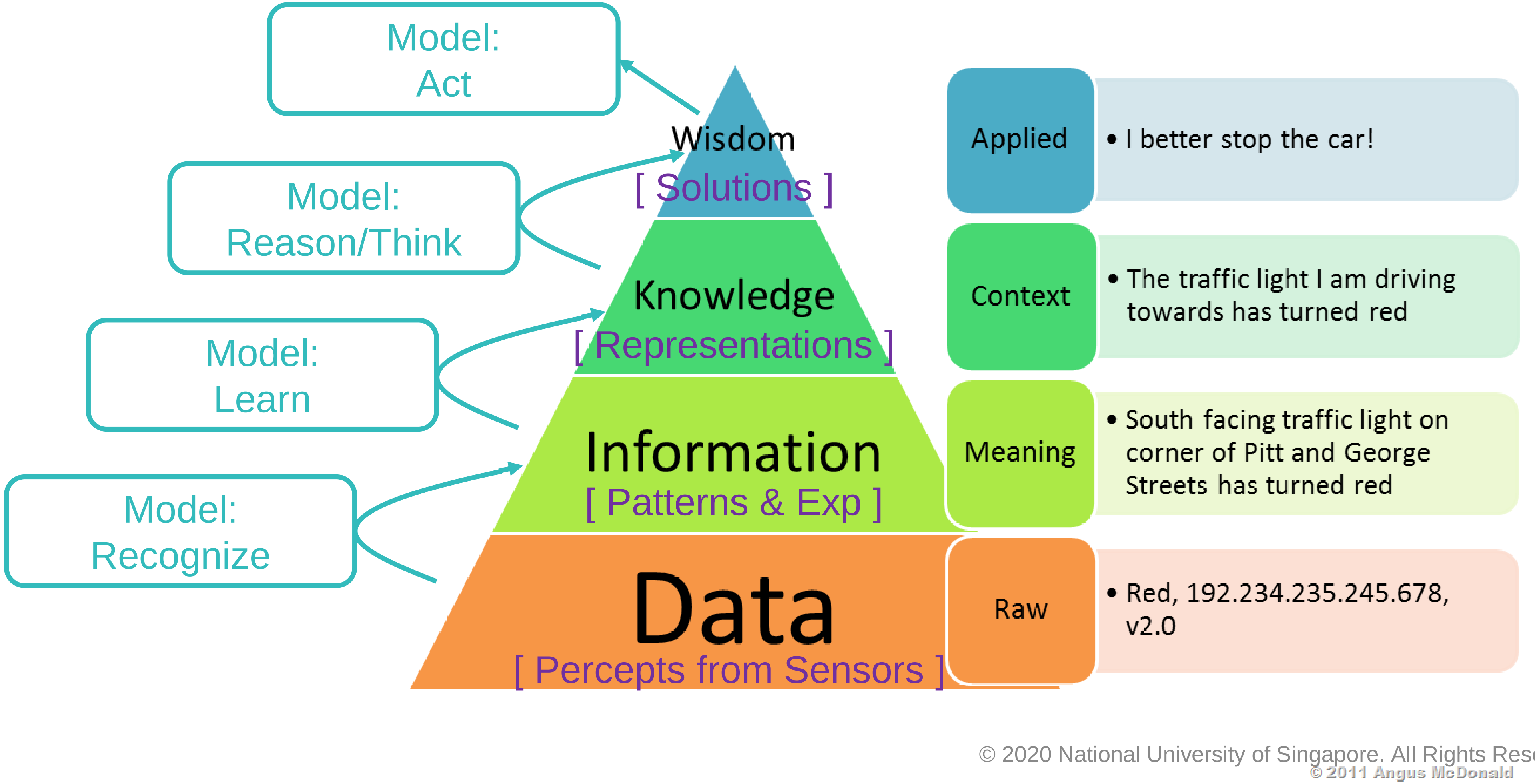
Revisit Cognition – One Definition:

Cognition is "the mental action or process of **acquiring knowledge and understanding** through **thought** **(recognition, learning, computation, reasoning & thinking)**, **experience** **(information & data)**, and the **senses** **(perceptions & sensors)**". It encompasses many aspects of **intellectual functions** and processes such as attention, the formation of knowledge, memory and working memory, judgment and evaluation, reasoning and "computation", problem solving and decision making, comprehension and production of language.

Cognitive processes **use existing knowledge** **(computation, reasoning & thinking)** and **generate new knowledge** **(learning supported by pattern recognition using experience/information from data/perceptions/sensors).**

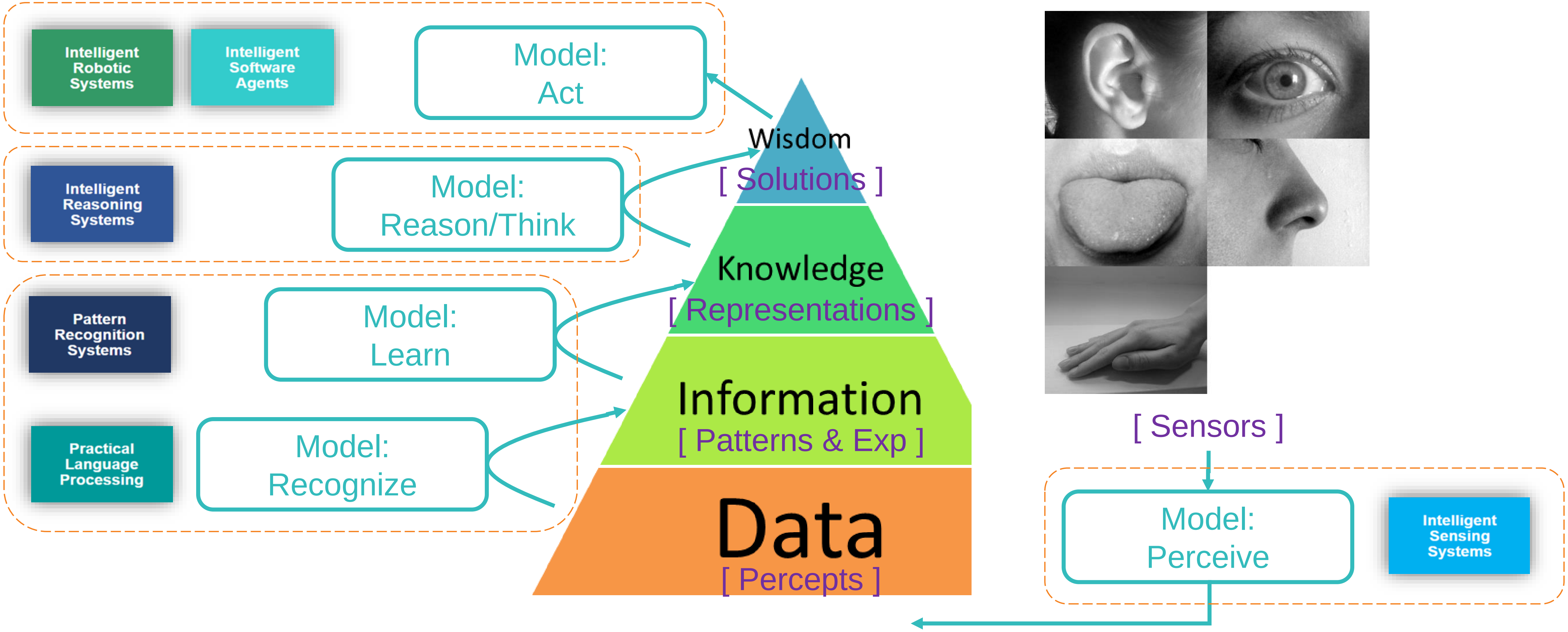
Cognitive Processes/Functions/Models

- Use **existing** knowledge through: Reasoning/Thinking
- Generate **new** knowledge through: Learning/Recognition



Cognitive Processes/Functions/Models

Functions/Models: Perceive; Think; Act; Recognize



Intelligent Reasoning Systems	Pattern Recognition Systems	Intelligent Sensing Systems	Intelligent Software Agents	Practical Language Processing	Intelligent Robotic Systems
NICF - Machine Reasoning (SF) **4 Days**	NICF - Problem Solving using Pattern Recognition (SF) **5 Days**	NICF - Vision Systems (SF) **5 Days**	NICF- RPA and IPA - Strategy and Management (SF) **2 Days**	NICF - Text Analytics (SF) **3 Days**	NICF - Robotic Systems (SF) **5 Days**
NICF - Reasoning Systems (SF) **5 Days**	NICF - Intelligent Sensing and Sense Making (SF) **4 Days**	NICF - Spatial Reasoning from Sensor Data (SF) **3 Days**	NICF- Software Robots - Best Practices (SF) **2 Days**	NICF - New Media and Sentiment Mining (SF) **4 Days**	Autonomous Robots & Vehicles* **5 Days**
NICF - Cognitive Systems (SF) **3 Days**	NICF - Pattern Recognition and Machine Learning Systems (SF) **5 Days**	NICF-Real Time Audio-Visual Sensing and Sense Making (SF) **4 Days**	NICF- Intelligent Process Automation (SF) **3 Days**	NICF - Text Processing using Machine Learning(SF) **5 Days**	Human-Robot System Engineering* **4 Days**
			NICF- Self-Learning Systems (SF) **4 Days**	NICF-Conversational UIs (SF)* **4 Days**	
Practice Module (10 man days)	Practice Module (10 man days)	Practice Module (10 man days)	Practice Module (10 man days)	Practice Module (10 man days)	Practice Module (10 man days)
Graduate Certificate in Intelligent Reasoning Systems	**Graduate Certificate in Pattern Recognition Systems**	**Graduate Certificate in Intelligent Sensing Systems**	**Graduate Certificate in Intelligent Software Agents**	**Graduate Certificate in Practical Language Processing**	**Graduate Certificate in Intelligent Robotic Systems**

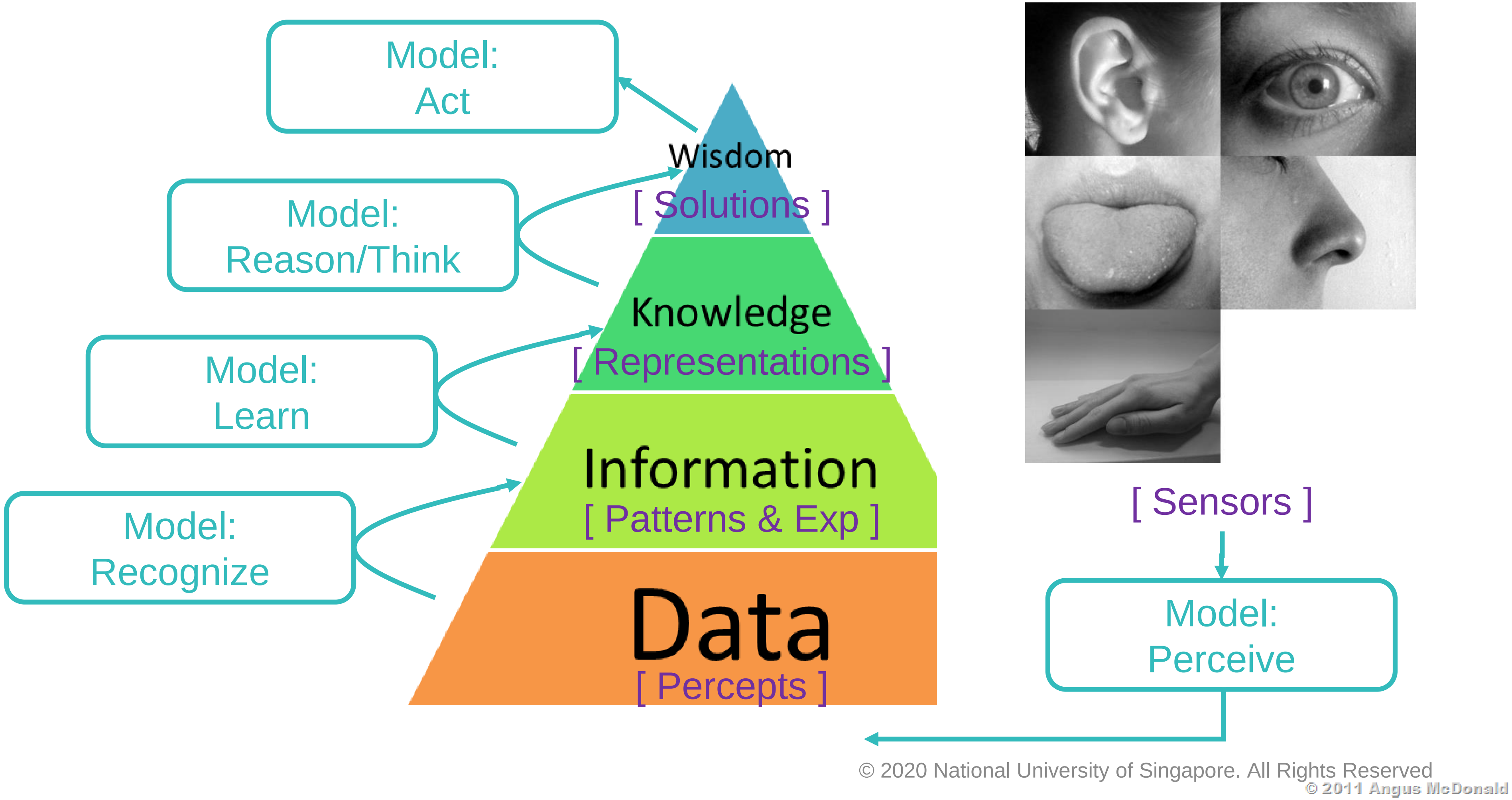
Artificial Intelligence Intelligent Systems

https://www.iss.nus.edu.sg/stackable-certificate-programmes/Intelligent-systems

https://www.iss.nus.edu.sg/executive-education/discipline/detail/artificial-intelligence

What’s a “model”?

What's a "model"?



What's a <u>conceptual</u> model?

A ***model*** is a piece of **organized & represented *knowledge*** (our understanding of the *world/domain*), which can **be (re)used** to **generate/predict** outcome results based on input observations. Technically, it's a ***function*** (white or black box), which **maps** input(s) to output(s)

What's a physical model?

A *model* could be considered just as a tangible text file stored in computer/server, e.g. model.txt

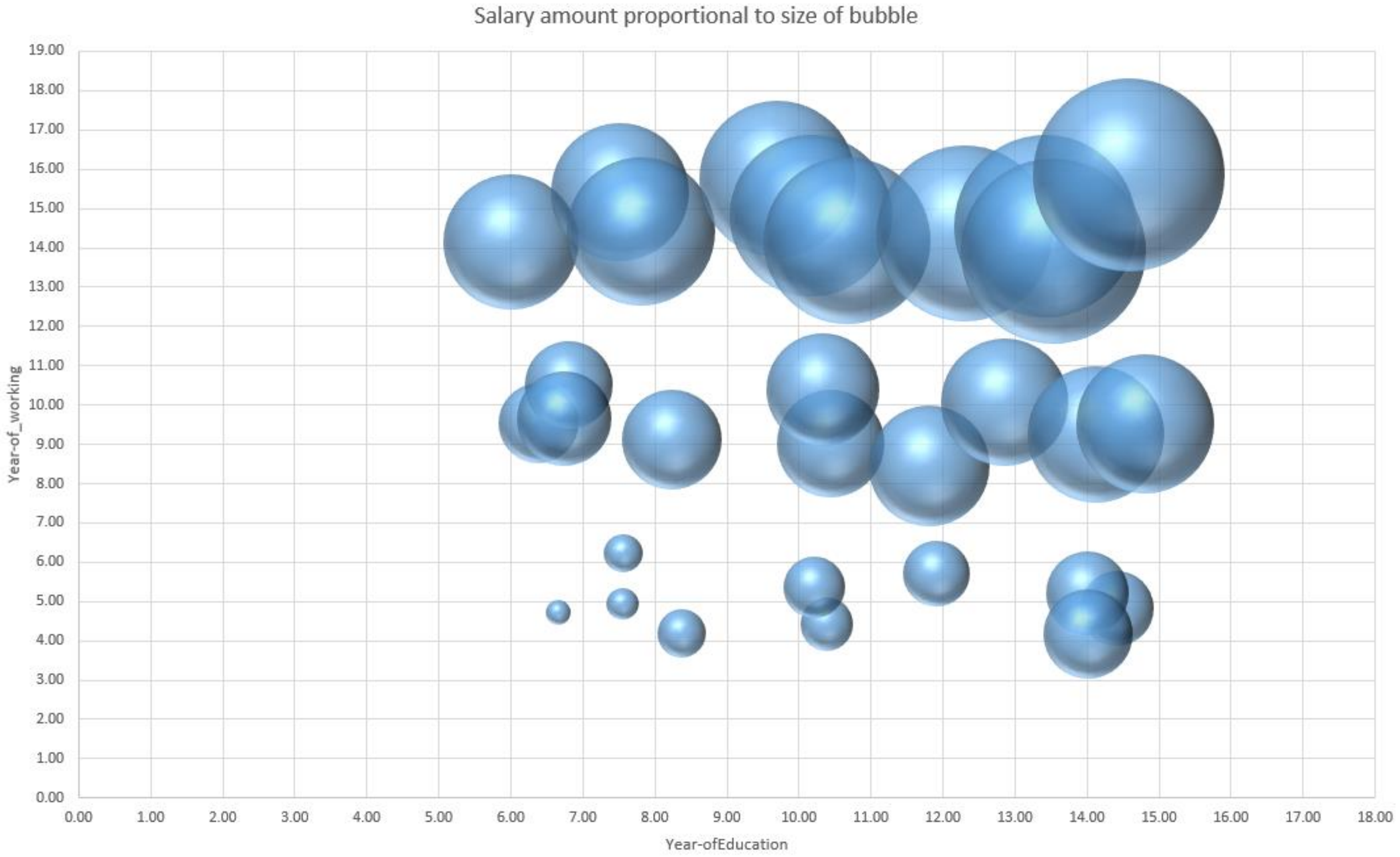
model.txt - Notepad

File Edit Format View Help

```
Output  : Salary
Input 1 : Year-of-Education
Input 2 : Year-of-Working

Formula : Output  = a x Input 1 + b x Input 2 + c
          (Salary)    (Year-of-Education) (Year-of-Working)

Formula parameters/coefficients       : a = 520
Formula parameters/coefficients       : b = 798
Formula parameters/coefficients       : c = -5007
```

Salary.xlsx

sn	Year-of-Education	Year-of-Working	Salary
1	6.65	4.72	$1,817
2	7.55	4.94	$2,305
3	7.56	6.22	$2,832
4	8.37	4.19	$3,502
5	10.39	4.42	$3,890
6	10.22	5.35	$4,568
7	11.91	5.70	$4,884
8	14.41	4.82	$5,478
9	14.00	5.20	$6,181
10	14.01	4.18	$6,597
11	6.38	9.54	$5,860
12	6.81	10.52	$6,519
13	6.74	9.66	$7,018
14	8.23	9.12	$7,405
15	10.44	9.01	$7,945
16	10.33	10.40	$8,384
17	11.80	8.45	$8,954
18	12.85	10.06	$9,482
19	14.12	9.25	$10,102
20	14.81	9.52	$10,339
21	6.00	14.16	$10,067
22	7.51	15.43	$10,301
23	7.80	14.42	$11,056
24	9.69	15.76	$11,652
25	10.17	14.81	$12,078
26	10.66	14.17	$12,463
27	12.30	14.38	$13,144
28	13.42	14.55	$13,561
29	13.53	13.93	$13,851
30	14.57	15.86	$14,344



Salary v02.xlsx - Excel

File | Home | Insert | Page Layout | Formulas | Data | Review | View | Team | Enterprise Connect | Tell me what you want to do... | Sign in | Share

AZ92

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.984375561
R Square	0.968995246
Adjusted R Square	0.966698597
Standard Error	667.5580743
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	376041022.2	188020511.1	421.9170953	4.30806E-21
Residual	27	12032112.13	445633.7825		
Total	29	388073134.3			

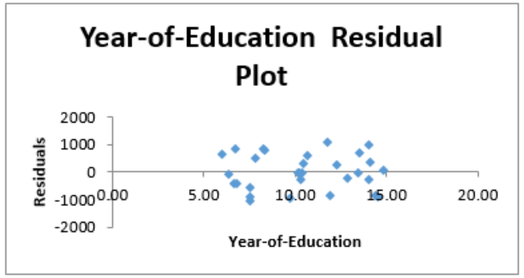
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-5007.776515	551.1804093	-9.085548816	1.06587E-09	-6138.705299	-3876.847731	-6138.705299	-3876.847731
Year-of-Education	520.7382643	42.89431991	12.14002846	1.90221E-12	432.7263898	608.7501389	432.7263898	608.7501389
Year-of-Working	798.286873	30.15824157	26.46994093	7.53819E-21	736.4072726	860.1664733	736.4072726	860.1664733

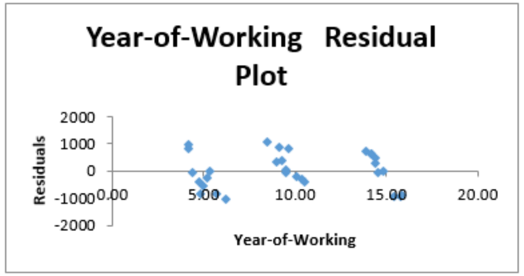
RESIDUAL OUTPUT

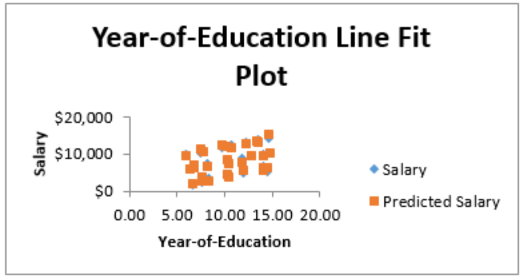
Observation	*Predicted Salary*	*Residuals*	*Standard Residuals*
1	2227.378049	-410.3780489	-0.63710672
2	2865.1592	-560.1591999	-0.869640059
3	3897.843043	-1065.843043	-1.654707816
4	2696.024781	805.9752188	1.251266313
5	3934.190757	-44.19075715	-0.06860559
6	4582.710338	-14.71033805	-0.022837613
7	5745.008025	-861.0080251	-1.336704047
8	6348.358938	-870.3589379	-1.351221221
9	6439.491245	-258.4912447	-0.401304382
10	5626.422479	970.5775209	1.506809301
11	5932.578944	-72.57894434	-0.112677891
12	6933.034306	-414.0343056	-0.642783012
13	6208.28567	809.7143298	1.257071236
14	6555.942708	849.057292	1.318150686
15	7624.171392	320.8286079	0.498082348

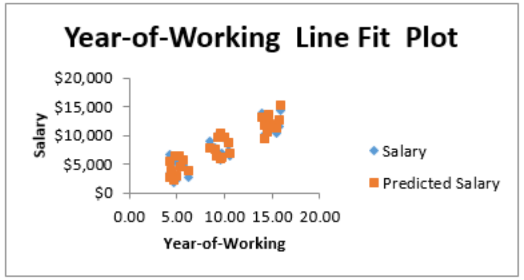
PROBABILITY OUTPUT

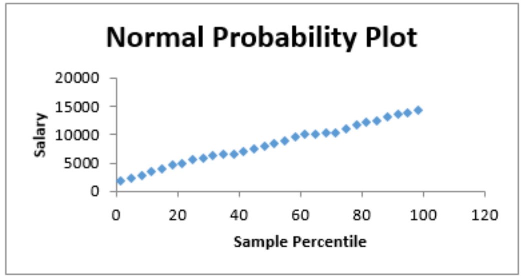
Percentile	*Salary*
1.666666667	1817
5	2305
8.333333333	2832
11.66666667	3502
15	3890
18.33333333	4568
21.66666667	4884
25	5478
28.33333333	5860
31.66666667	6181
35	6519
38.33333333	6597
41.66666667	7018
45	7405
48.33333333	7945









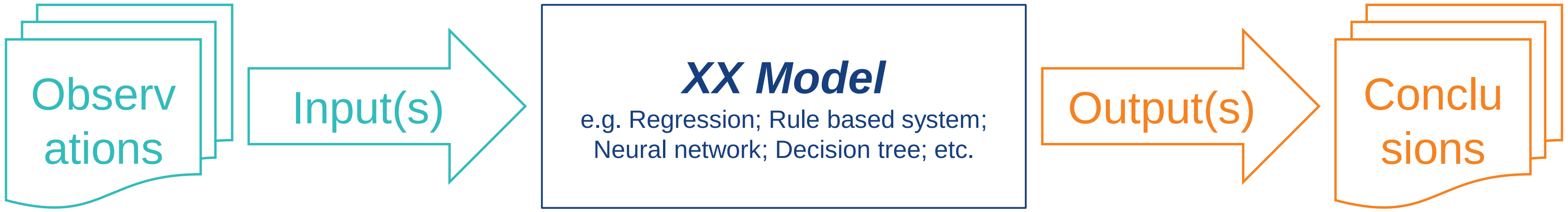


data | regression

Ready

What are differences between models?

Different ***(machine learning) model*** *(applied mathematical algorithm, which is capable of minimizing an objective function's value)*, e.g. Regression; Neural network; Decision tree, etc., **extracts**, **organizes** and **represents** ***knowledge*** in **different** ways: **different** (mathematical) forms.



Artificial Intelligence/Cognition

Artificial Intelligence: (philosophy, cognitive science, psychology, mathematics, economics, computer science, software engineering, mechanical engineering…)

The approximation and augmentation to Human Intelligence

Artificial Intelligence

- Goals
- Roots
- Sub Fields

ARTIFICIAL INTELLIGENCE

Goals

"Artificial Intelligence (AI) is the part of computer science concerned with designing intelligent computer systems, that is, systems that exhibit characteristics we associate with intelligence in human behaviour – understanding language, learning, reasoning, solving problems, and so on."

(Barr & Feigenbaum, 1981)

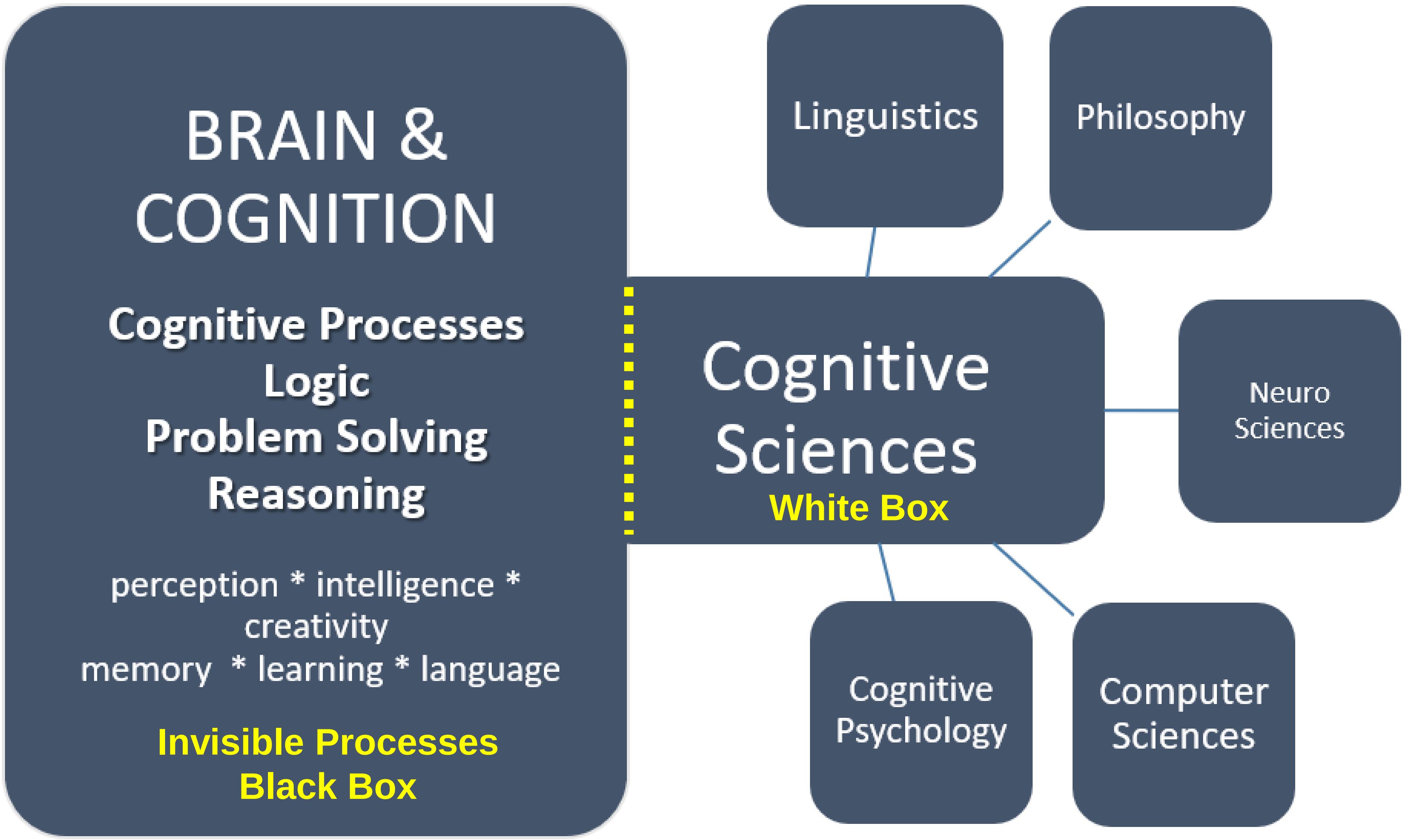
- **Scientific Goal:** To determine which **ideas/frameworks** about knowledge representation, learning, reasoning, (ir)rationality, and so on, explain various sorts of real/augmented intelligence.

- **Engineering Goal:** To solve valuable real world problems using **AI techniques (tools, codes and libraries)** such as knowledge representation, learning, rule systems, search, model/function approximation, and so on.

Roots

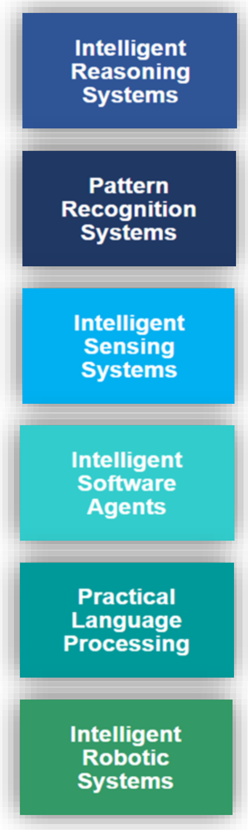
Rooted from older disciplines, particularly:

- **Philosophy**, e.g. Syllogism, Deductive Reasoning
- **Logic/Mathematics**, e.g. First-order logic, Knowledge Graph
- **Computation**, e.g. Calculation, Turing Machine
- **Psychology/Cognitive Science**, e.g. Mind Operations, Language, Knowledge Representation, Learning
- **Biology/Neuroscience**, e.g. Neural Network, Function Approximation
- **Evolution**, e.g. Natural Selection, Genetic Programming



Source https://medium.com/womeninai/human-cognition-and-artificial-intelligence-a-plea-for-science-21a2388f6e7e

ARTIFICIAL INTELLIGENCE
Sub Fields



Major AI Sub-fields, with a variety of techniques:

- **Neural Networks**, e.g. brain modelling, time series prediction, classification
- **Evolutionary Computation**, e.g. genetic algorithms, genetic programming
- **Vision**, e.g. object recognition, image understanding
- **Robotics**, e.g. dynamic control, autonomous exploration
- **Expert Systems**, e.g. decision support systems, teaching systems
- **Speech Processing**, e.g. speech recognition and production
- **Natural Language Processing**, e.g. machine translation
- **Planning**, e.g. search, scheduling, game playing
- **Machine Learning**, e.g. decision tree learning, version space learning

Demystify Machine Reasoning

Machine Learning

Machine Perception

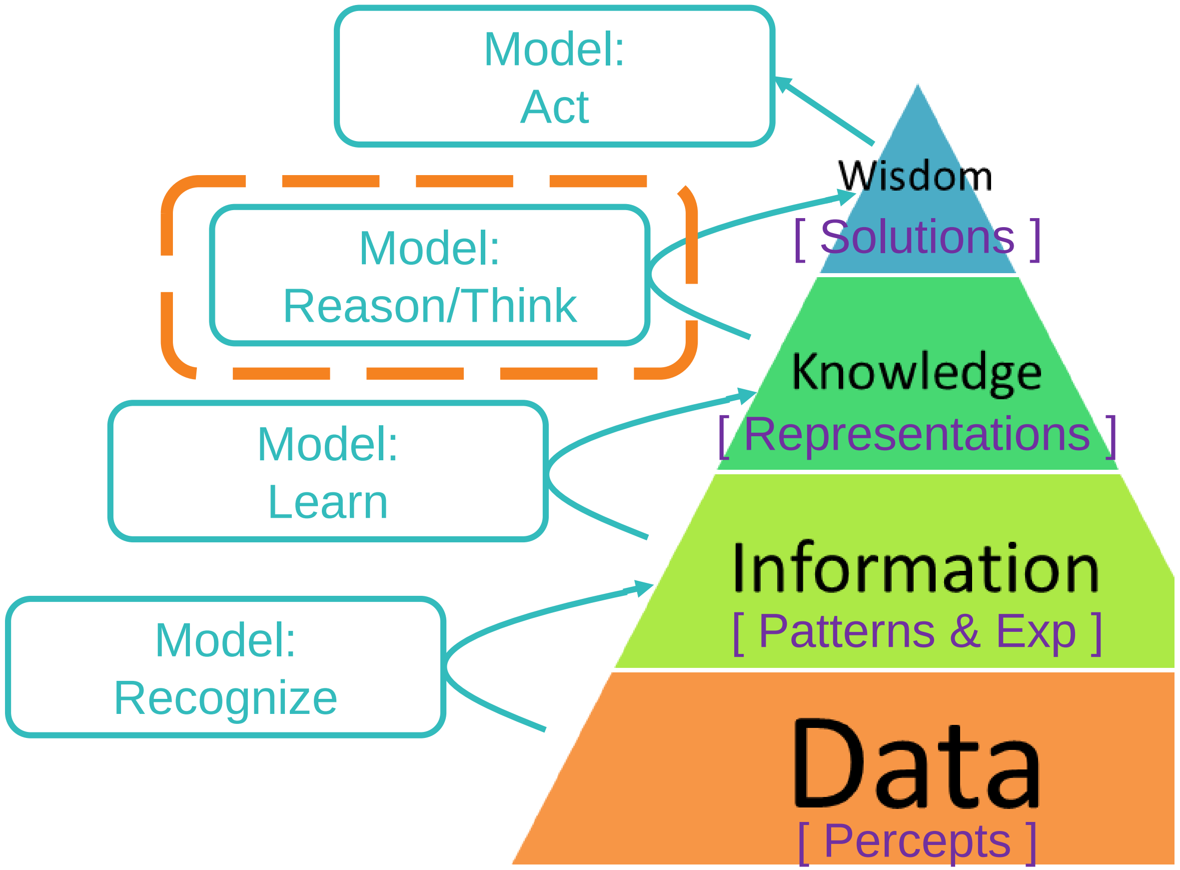
Machine Action

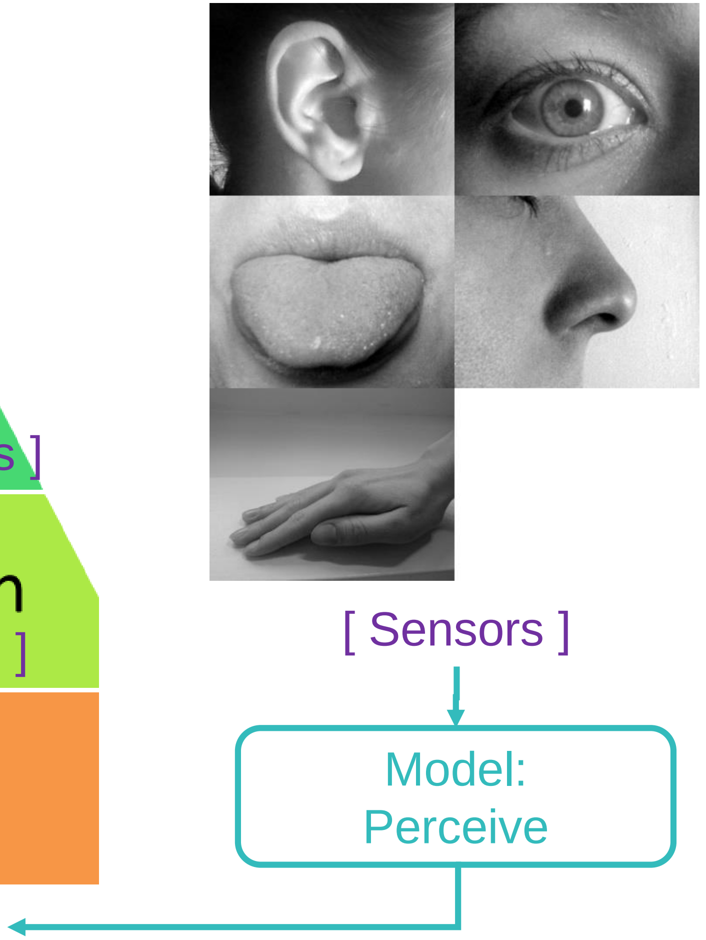
Model: Reason/Think
Model: Learn
Model: Perceive
Model: Act

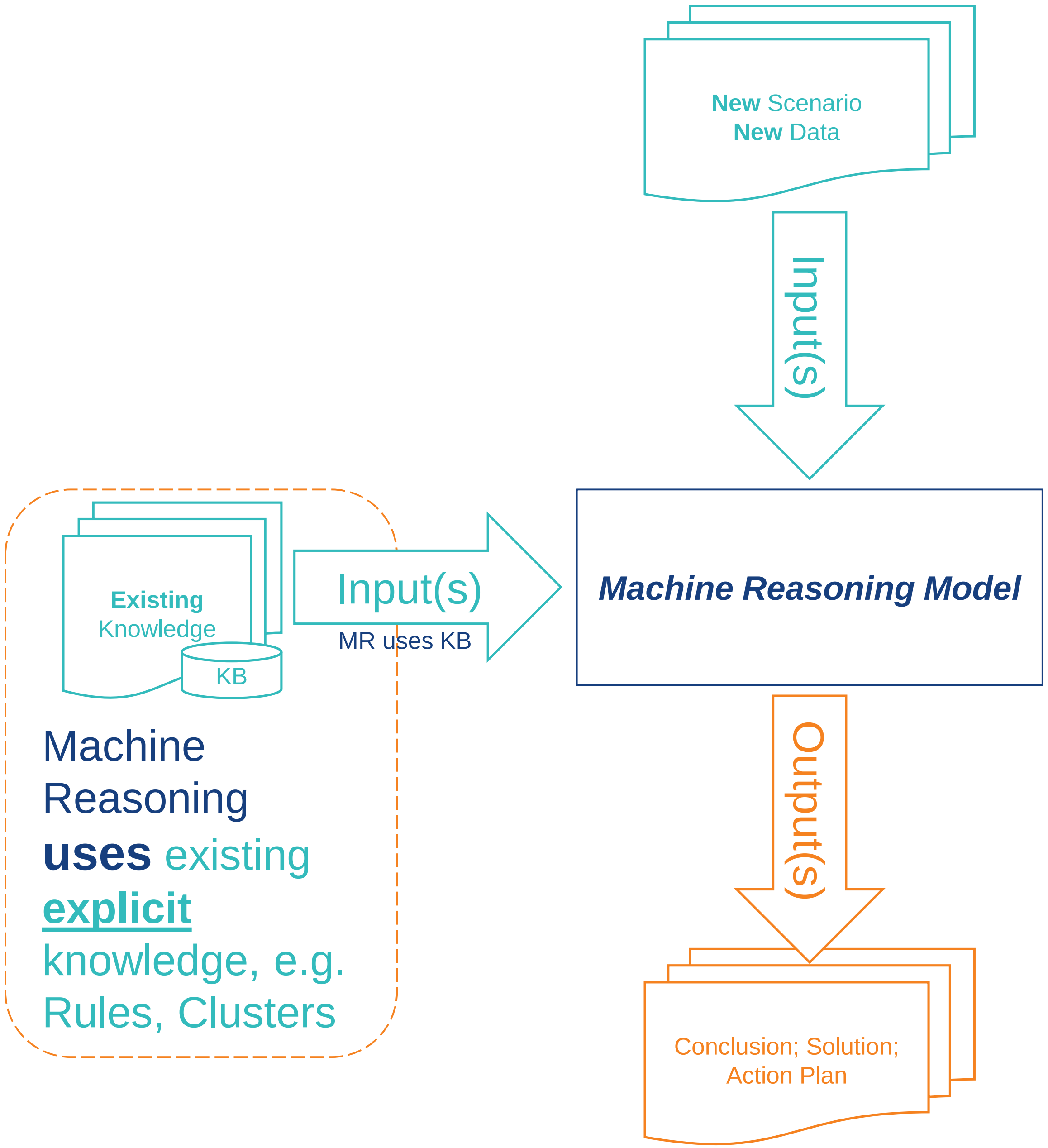
A “model” view of “reasoning/thinking”

Model: Reason/Think

What’s a (reasoning/thinking) “model”?





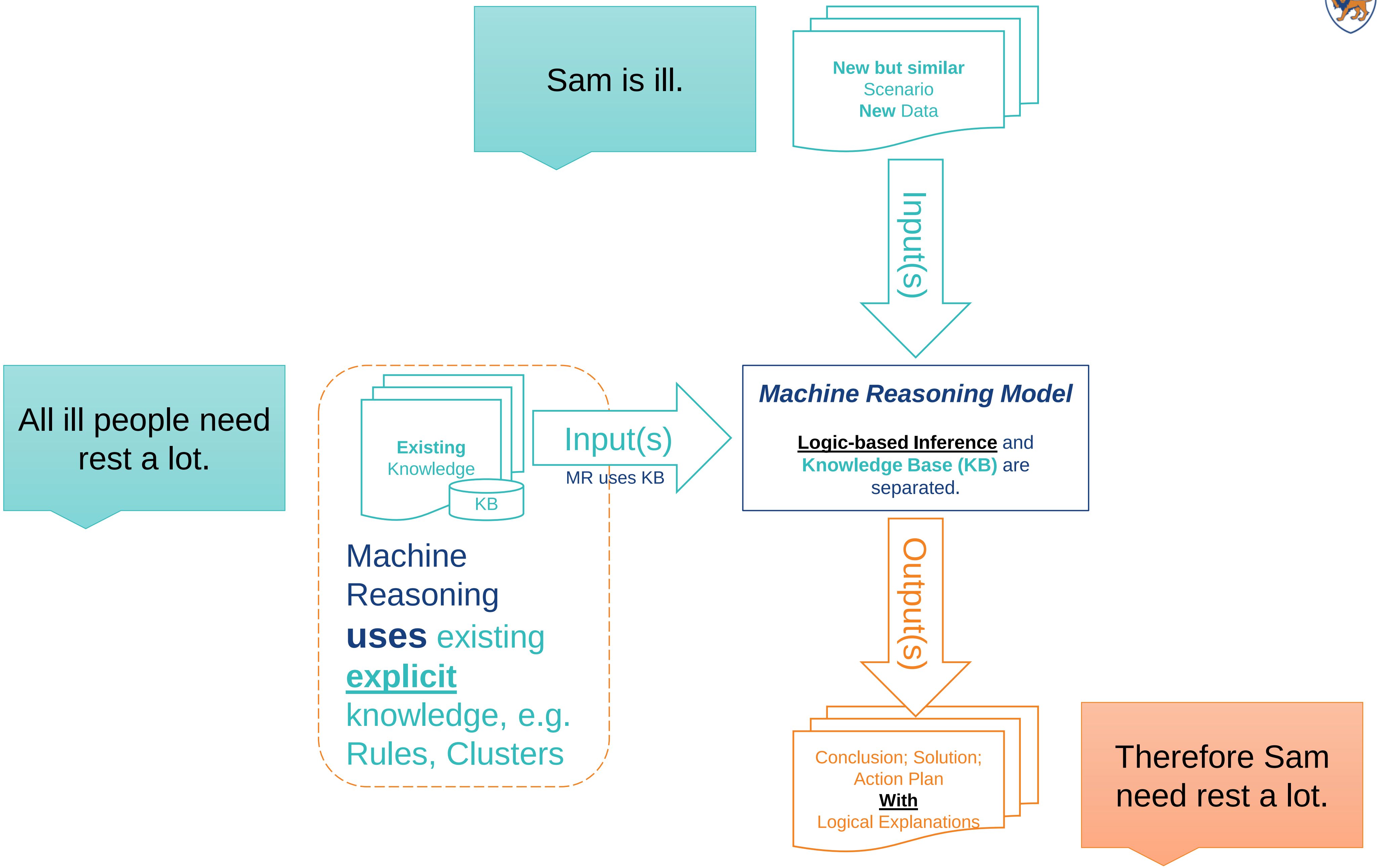

New Scenario
New Data
Input(s)
Existing
Knowledge
KB
Input(s)
MR uses KB
Machine Reasoning Model
Output(s)
Conclusion; Solution;
Action Plan
Machine Reasoning **uses** existing **explicit** knowledge, e.g. Rules, Clusters

EXAMPLE OF MACHINE REASONING (LOGICAL INFERENCE)

Deductive Reasoning

- **Knowledge/Rule** : **All ill people** need rest a lot.
- **Individual 1** : **Sam** is **ill**, therefore he need rest a lot.
- **Individual 2** : **Jessie** is **ill**, therefore she need rest a lot.
- **Individual …**

☺ **Reasoning Rationality: Universal → Individual**


Sam is ill.
New but similar
Scenario
New Data
Input(s)
All ill people need rest a lot.
Existing
Knowledge
KB
Input(s)
MR uses KB
Machine Reasoning Model
Logic-based Inference and Knowledge Base (KB) are separated.
Machine Reasoning uses existing explicit knowledge, e.g. Rules, Clusters
Output(s)
Conclusion; Solution;
Action Plan
With
Logical Explanations
Therefore Sam need rest a lot.

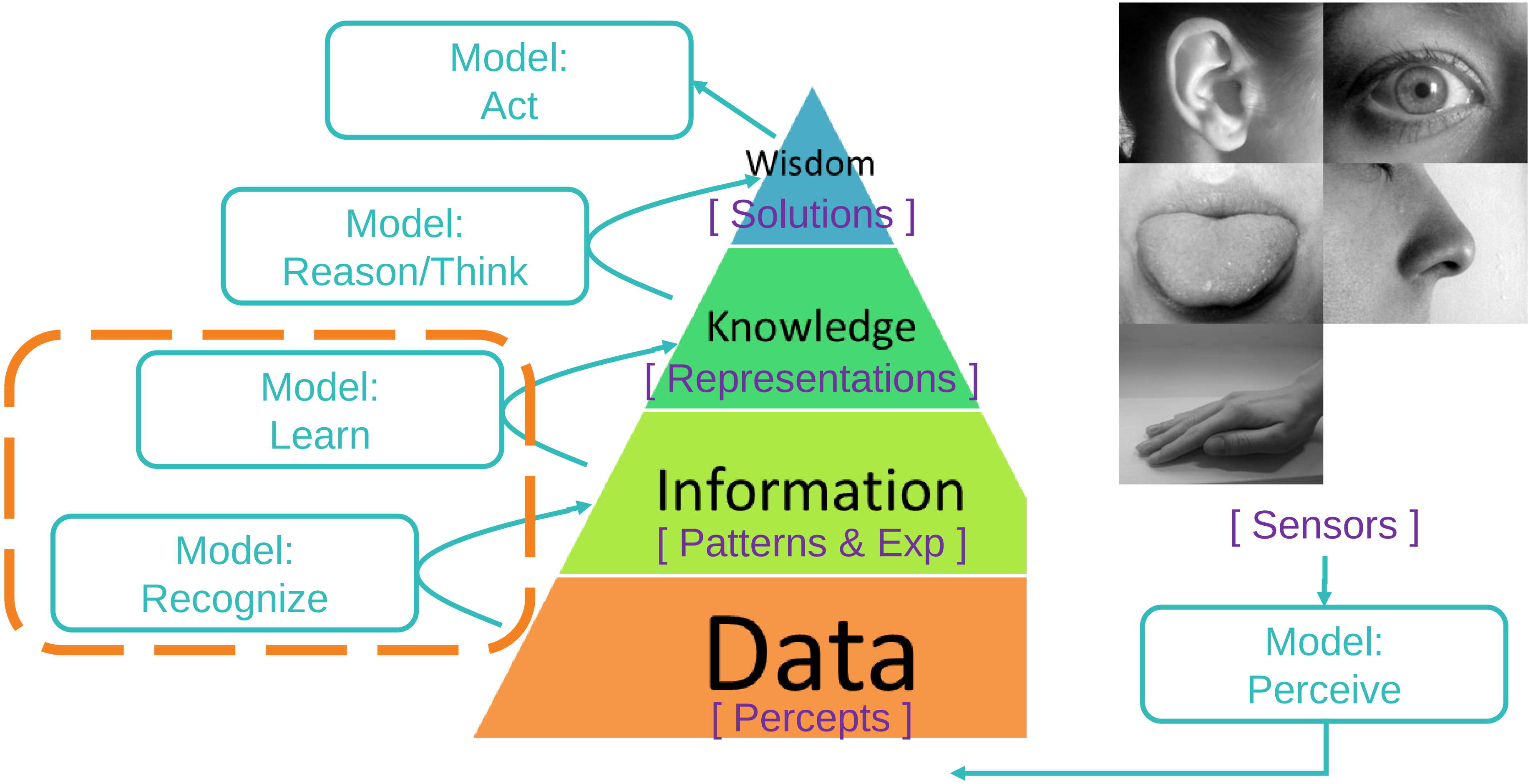
A “model” view of “learning/recognition”

Model: Recognize

Model: Learn

- knowledge-discovery-based (white box) machine learning model
- function-approximation-based (black box) machine learning model

What’s a (knowledge-discovery-based machine learning) “model”?



Past Experiences
Historical Data
Without
Target/Labels

Input(s)

Machine Learning Model
Type 1: knowledge discovery by unsupervised algorithm, e.g. k-means

Output(s)

Generated New Knowledge
KB

Machine Learning **generates** new **explicit/implicit** knowledge, e.g. clusters

Past Experiences
Historical Data
With
Target/Labels

Input(s)

Machine Learning Model
Type 2: knowledge discovery by supervised algorithm, e.g. decision tree

Output(s)

Generated New Knowledge
KB

Machine Learning **generates** new **explicit** knowledge, e.g. Rules

Past Experiences
Historical Data
Without
Target/Labels

Input(s)

Machine Learning Model
Type 1: knowledge discovery by unsupervised algorithm, e.g. k-means

Output(s)

Generated New Knowledge

KB

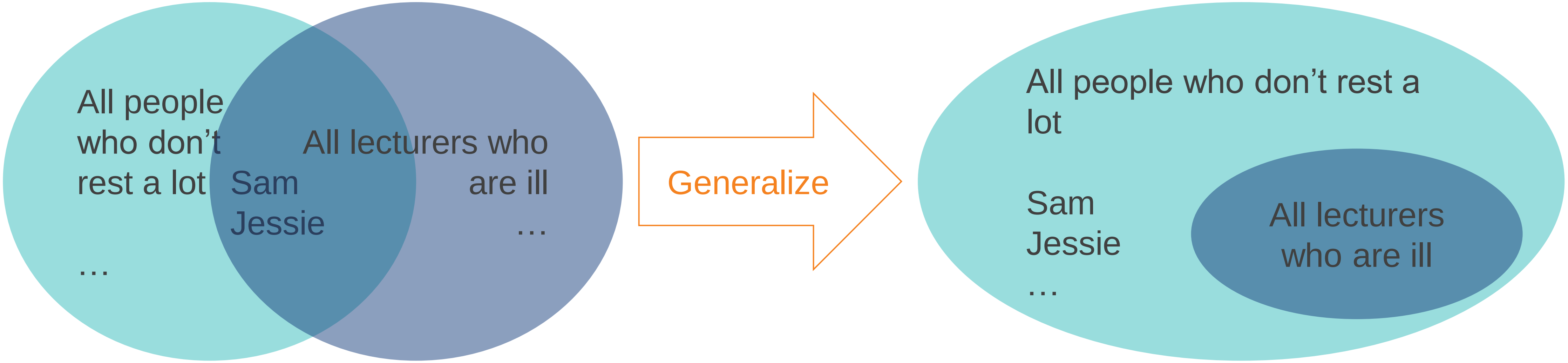
Machine Learning **generates** new **explicit/implicit** knowledge, e.g. clusters

EXAMPLE OF MACHINE LEARNING

Inductive Reasoning

- **Individual 1** : When **lecturer Sam** is **ill**, he doesn't rest a lot.
- **Individual 2** : When **lecturer Jessie** is **ill**, she doesn't rest a lot.
- **Generalised Rule** : **All lecturers** who are **ill**, they don't rest a lot.

Targets: No-Rest



☺ **Reasoning Rationality: Individual → Universal** (Machine Learning)

Past Experiences **Historical** Data <u>**Without**</u> Target/Labels

Input(s)

Machine Learning Model

Type 1: knowledge discovery by <u>unsupervised</u> algorithm, e.g. k-means

Output(s)

Generated New Knowledge

KB

Machine Learning **generates** new <u>**explicit/implicit**</u> knowledge, e.g. clusters

When lecturer Sam is ill, he doesn't rest a lot. Target Label: No-Rest

When lecturer Jessie is ill, she doesn't rest a lot. Target Label: No-Rest

Past Experiences **Historical** Data <u>**With**</u> Target/Labels

Input(s)

Machine Learning Model

Type 2: knowledge discovery by <u>supervised</u> algorithm, e.g. decision tree

Output(s)

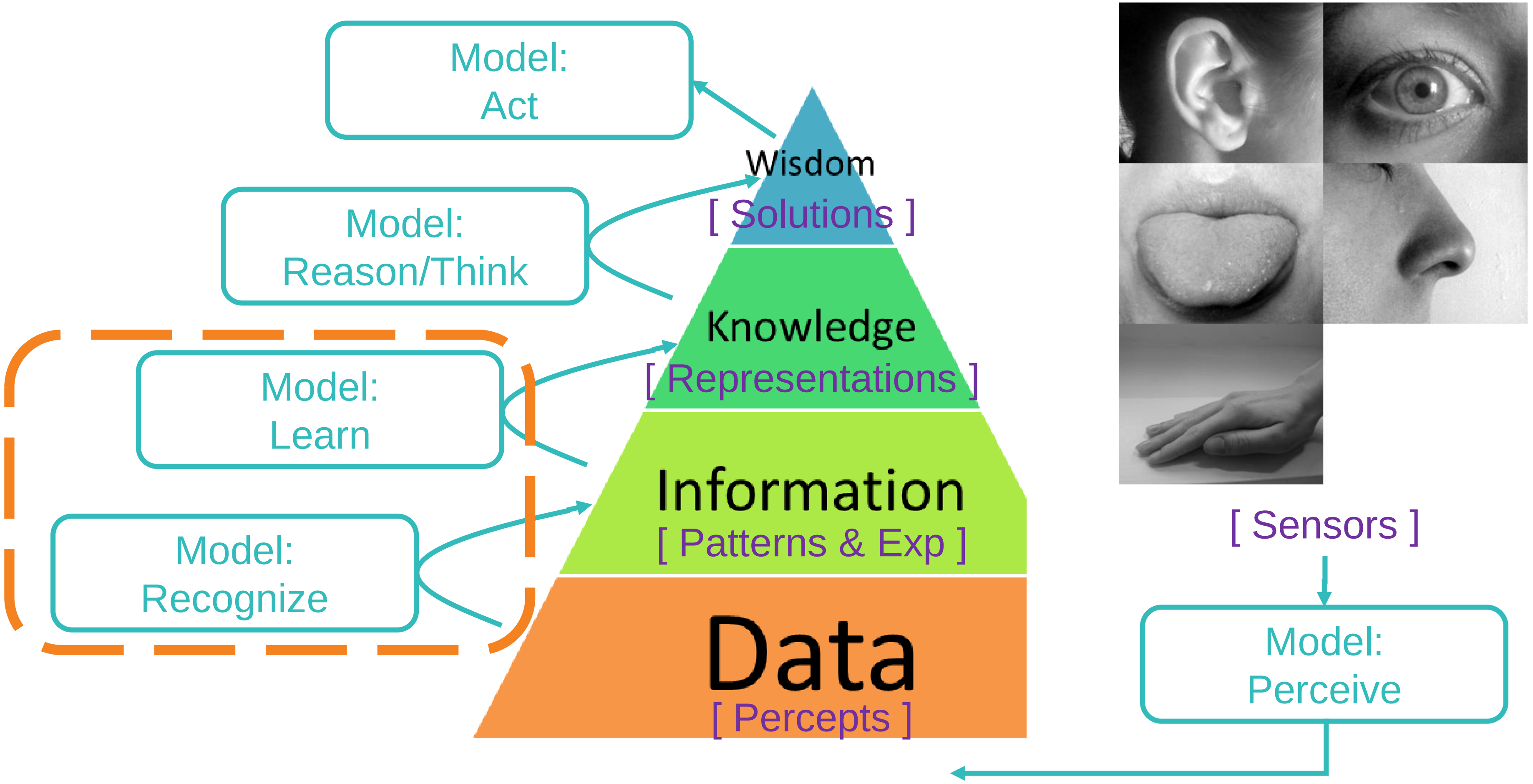
Generated New Knowledge

KB

Machine Learning **generates** new <u>**explicit**</u> knowledge, e.g. Rules

All lecturers who are ill, they don't rest a lot.

What’s a (function-approximation-based machine-learning) “model”?



Past Experiences
Historical Data
With
Target/Labels

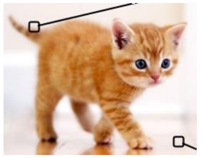
Input(s)

Machine Learning Model
Type 2: knowledge discovery by <u>supervised</u> algorithm, e.g. decision tree

Output(s)

Generated New Knowledge
KB

KB/Rules/Conditions:
WHEN:



Eye = round forward
Ear = triangular
Tail = long & hairy
Limb = paws

THEN: cat
ELSE: not cat

Machine Learning **generates** new **<u>explicit</u>** knowledge, e.g. Rules

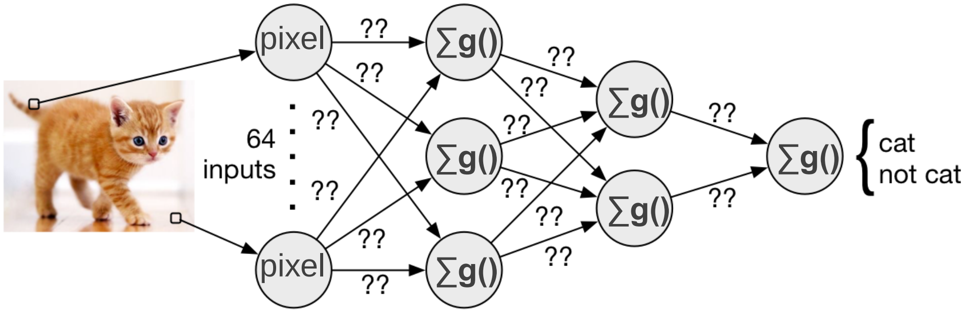
Past Experiences
Historical Data
With
Target/Labels

Input(s)

Machine Learning Model
Type 3: function approximation (input-output mapping) by <u>supervised</u> algorithm, e.g. neural network; deep learning

Output(s)

Generated New Knowledge
KB
F()



Machine Learning **generates** new **<u>implicit</u>** knowledge, e.g. functions F()

Is this model a white box or black box?

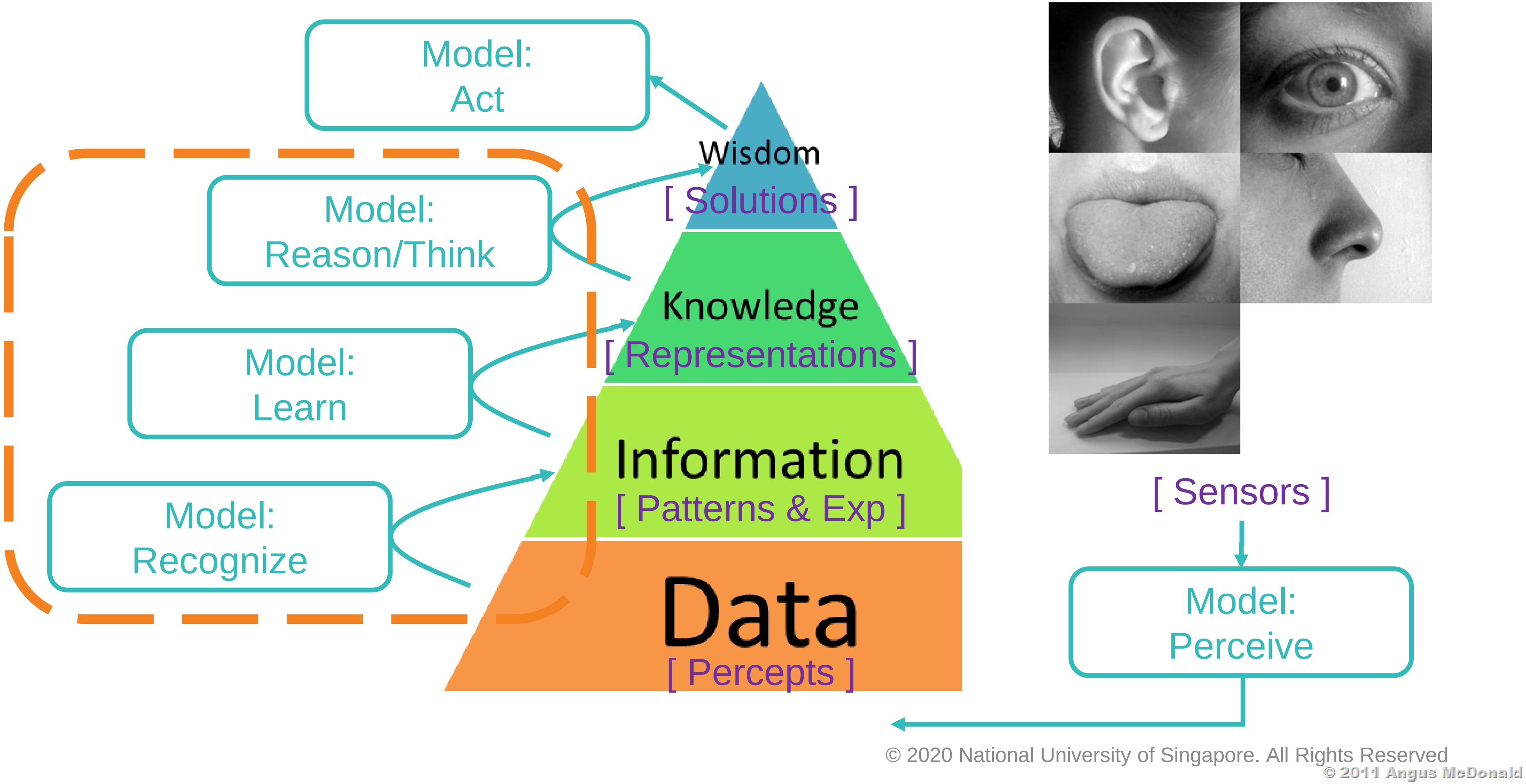
- knowledge-discovery-based (white box)
- function-approximation-based (black box)

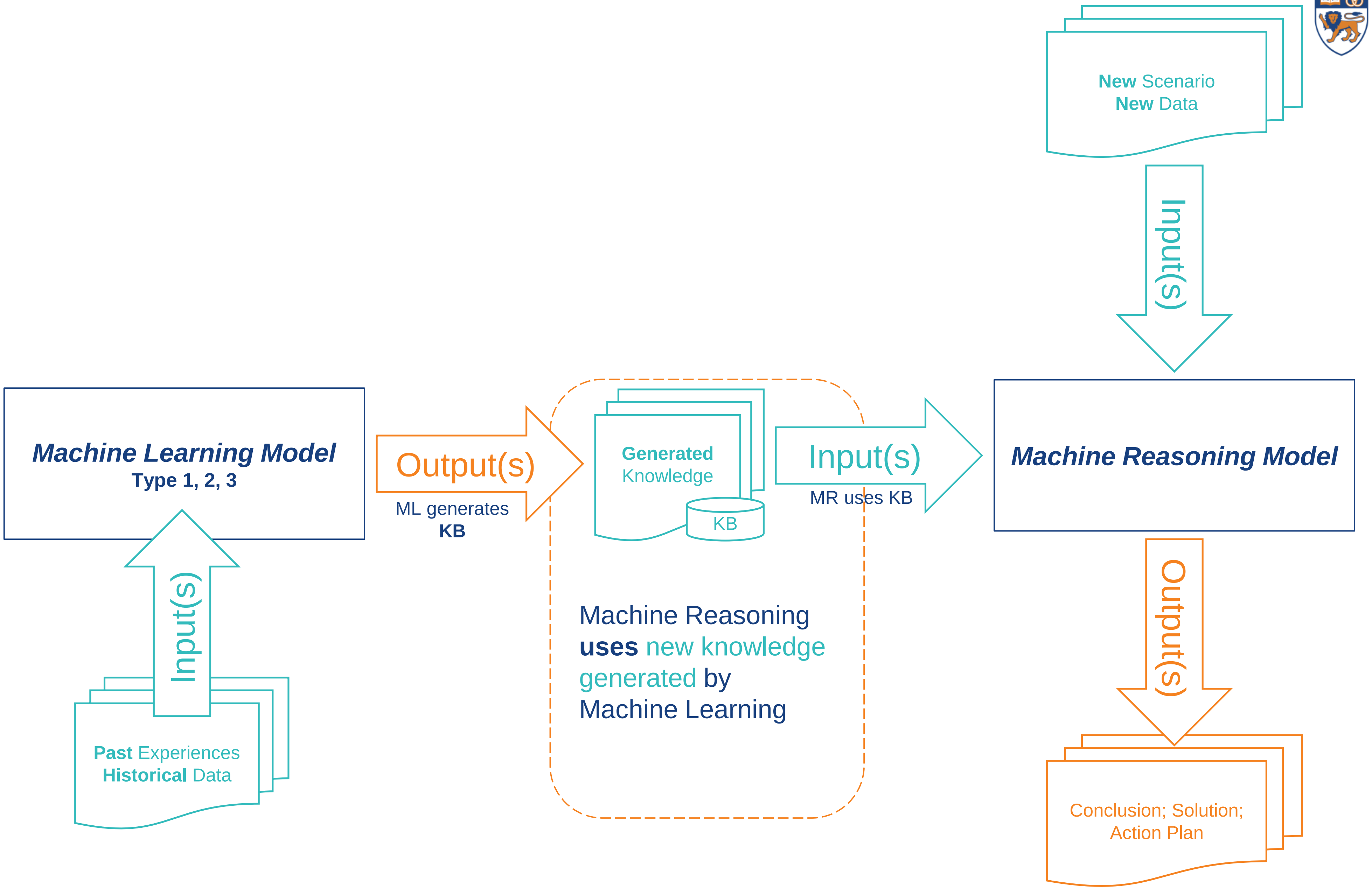
model.txt - Notepad

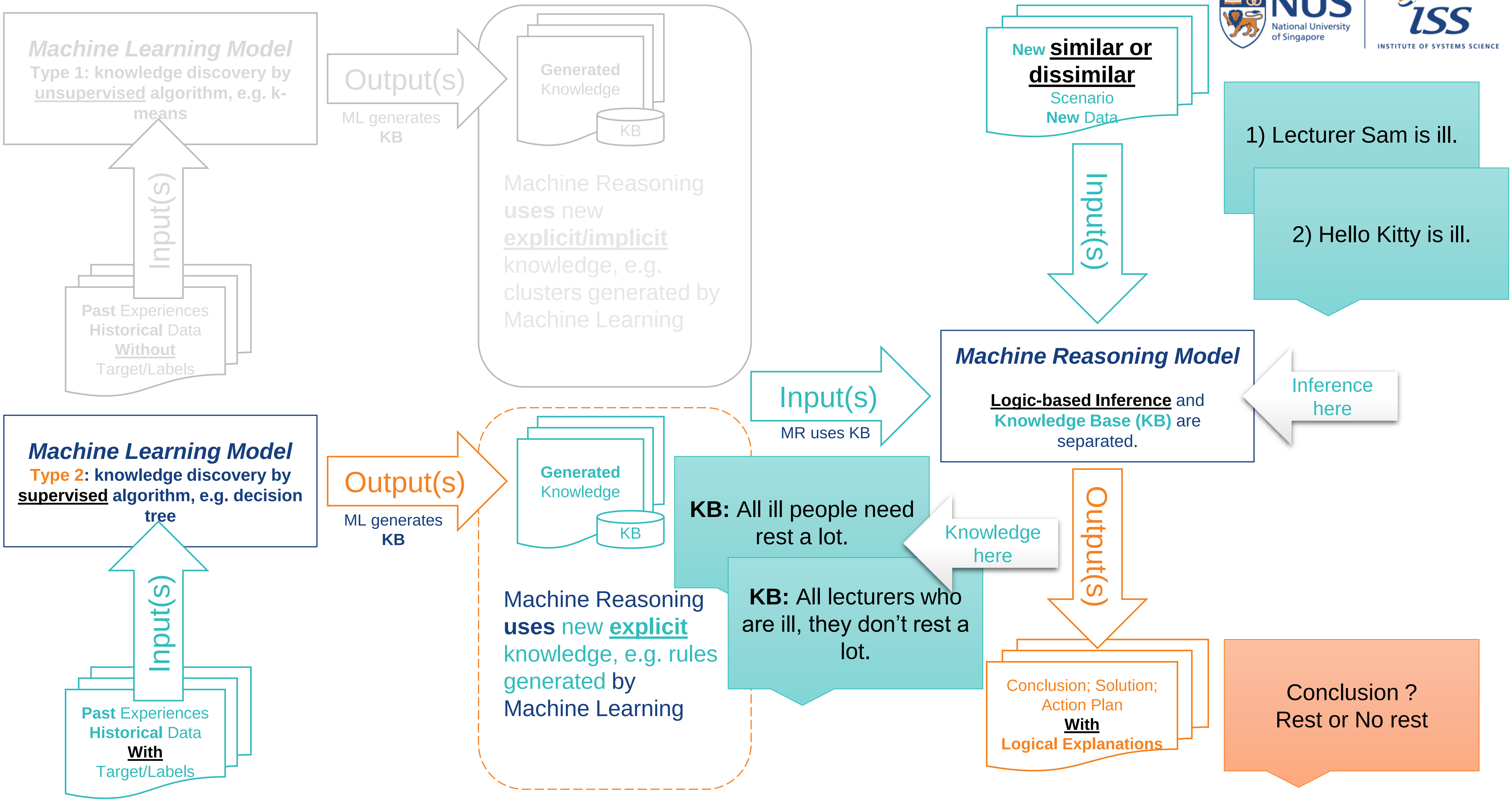
File Edit Format View Help

```
Output  : Salary
Input 1 : Year-of-Education
Input 2 : Year-of-Working

Formula : Output = a x Input 1 + b x Input 2 + c
          (Salary)    (Year-of-Education) (Year-of-Working)

Formula parameters/coefficients      : a = 520
Formula parameters/coefficients      : b = 798
Formula parameters/coefficients      : c = -5007
```

What's a (learning + reasoning) "model"?




New Scenario
New Data
Input(s)
Machine Learning Model
Type 1, 2, 3
Input(s)
Past Experiences
Historical Data
Output(s)
ML generates
KB
Generated
Knowledge
KB
Input(s)
MR uses KB
Machine Reasoning Model
Machine Reasoning
uses new knowledge
generated by
Machine Learning
Output(s)
Conclusion; Solution;
Action Plan


Machine Learning Model
Type 1: knowledge discovery by unsupervised algorithm, e.g. k-means
Output(s)
ML generates KB
Generated Knowledge
KB
Machine Reasoning uses new explicit/implicit knowledge, e.g. clusters generated by Machine Learning
Input(s)
Past Experiences Historical Data Without Target/Labels
New similar or dissimilar Scenario New Data
1) Lecturer Sam is ill.
2) Hello Kitty is ill.
Input(s)
Input(s)
MR uses KB
Machine Reasoning Model
Logic-based Inference and Knowledge Base (KB) are separated.
Inference here
Machine Learning Model
Type 2: knowledge discovery by supervised algorithm, e.g. decision tree
Output(s)
ML generates KB
Generated Knowledge
KB
KB: All ill people need rest a lot.
Knowledge here
KB: All lecturers who are ill, they don't rest a lot.
Output(s)
Machine Reasoning uses new explicit knowledge, e.g. rules generated by Machine Learning
Input(s)
Past Experiences Historical Data With Target/Labels
Conclusion; Solution; Action Plan With Logical Explanations
Conclusion ? Rest or No rest

Machine Learning Model
Type 1: knowledge discovery by unsupervised algorithm, e.g. k-means

Input(s)

Past Experiences
Historical Data
Without
Target/Labels

Output(s)
ML generates KB

Generated Knowledge
KB

Machine Reasoning uses new explicit/implicit knowledge, e.g. clusters generated by Machine Learning

Machine Learning Model
Type 2: knowledge discovery by supervised algorithm, e.g. decision tree

Input(s)

Past Experiences
Historical Data
With
Target/Labels

Output(s)
ML generates KB

Generated Knowledge
KB

Machine Reasoning uses new explicit knowledge, e.g. rules generated by Machine Learning

New similar or dissimilar Scenario
New Data

Input(s)

Input(s)
MR uses KB

Machine Reasoning Model

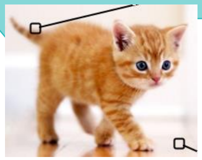
Logic-based Inference and Knowledge Base (KB) are separated.

Inference here

KB (Cat):
Eye = round forward
Ear = triangular
Tail = long & hairy
Limb = paws

THEN: cat

ELSE: not cat

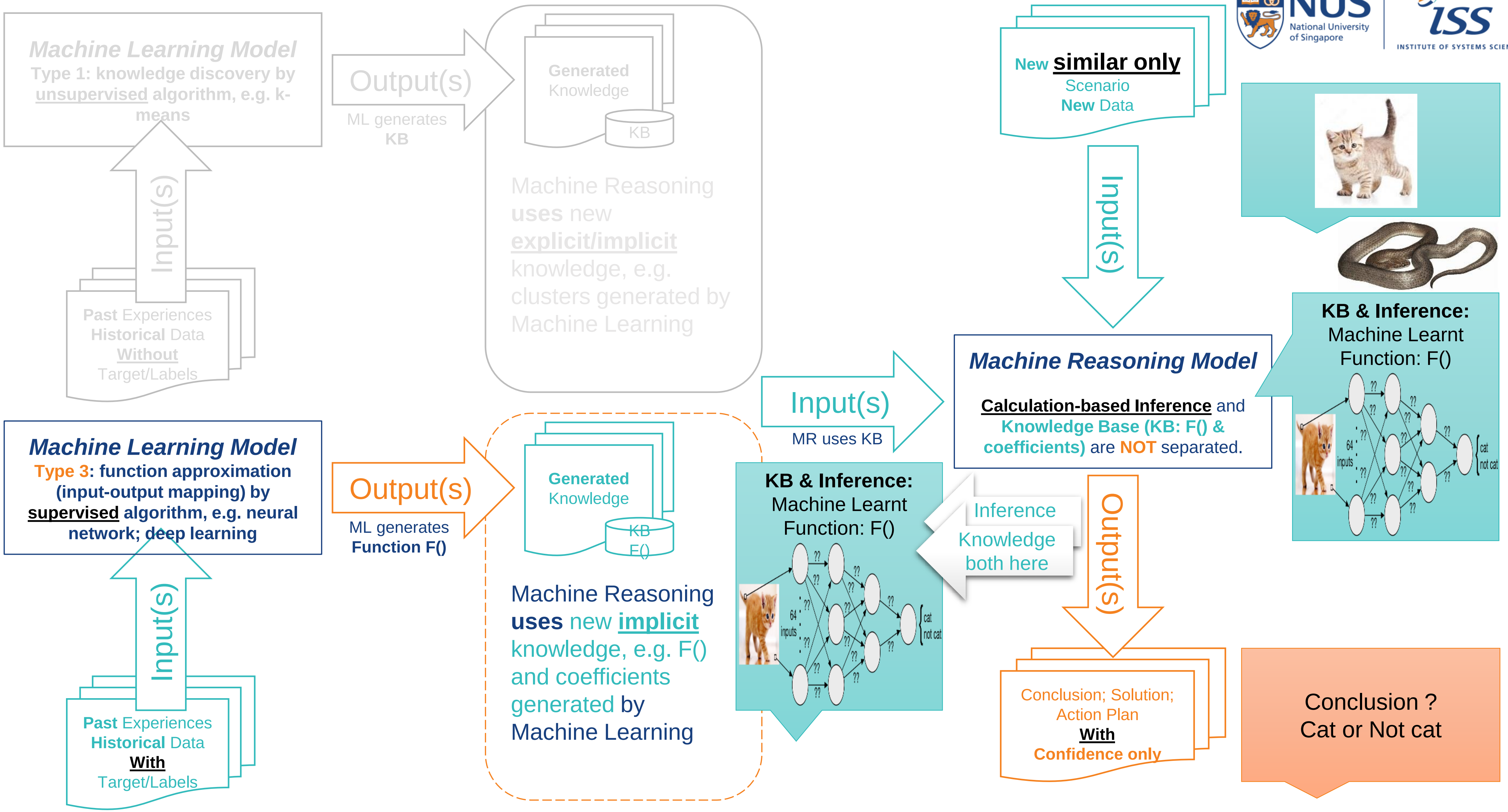


Knowledge here

Output(s)

Conclusion; Solution; Action Plan
With
Logical Explanations

Conclusion ?
Cat or Not cat


Machine Learning Model
Type 1: knowledge discovery by unsupervised algorithm, e.g. k-means
Output(s)
ML generates KB
Generated Knowledge
KB
Machine Reasoning uses new explicit/implicit knowledge, e.g. clusters generated by Machine Learning
Input(s)
Past Experiences
Historical Data
Without
Target/Labels
Machine Learning Model
Type 3: function approximation (input-output mapping) by supervised algorithm, e.g. neural network; deep learning
Output(s)
ML generates Function F()
Generated Knowledge
KB F()
Machine Reasoning uses new implicit knowledge, e.g. F() and coefficients generated by Machine Learning
Input(s)
Past Experiences
Historical Data
With
Target/Labels
New similar only Scenario New Data
Input(s)
Input(s)
MR uses KB
Machine Reasoning Model
Calculation-based Inference and Knowledge Base (KB: F() & coefficients) are NOT separated.
KB & Inference: Machine Learnt Function: F()
Inference
Knowledge both here
KB & Inference: Machine Learnt Function: F()
Output(s)
Conclusion; Solution; Action Plan With Confidence only
Conclusion ? Cat or Not cat

What does a Strong AI look like?

An AI who can answer **the Ultimate Question of Life, the Universe, and Everything!**

What's the answer to the ultimate question of life, the universe and everything?

question

AI Model

Artificial General Intelligence (AGI)

answer

?

Source https://en.wikipedia.org/wiki/The_Hitchhiker%27s_Guide_to_the_Galaxy

Explainable AI and Counterfactuals

Published on January 6, 2019

Dr. Finn Macleod | Follow
Director, Beautiful Data

20 2 4

Explainable AI is a *legal* requirement in modern business. The EU GDPR clearly states the right to challenge algorithmic decisions that have been made without human intervention. More importantly the EU GDPR requires the data controller to prevent algorithmic bias arising from the basis of race, gender, religion or other sensitive data.

> **"In any case, such processing should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision"**

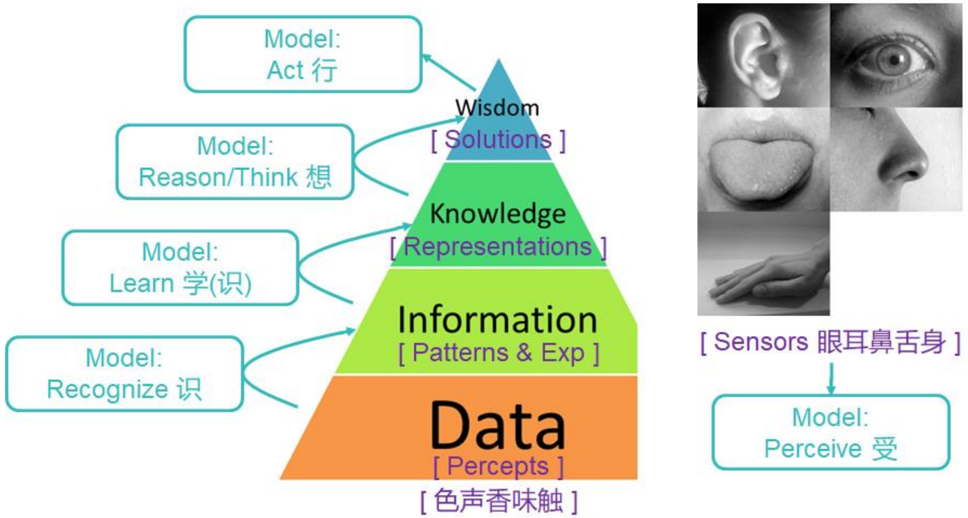
Explainability - Extracts from recital 71, GDPR

Source: https://www.linkedin.com/pulse/explainable-ai-counterfactuals-dr-finn-macleod

A “model” view of “perceiving”

[skipped – use your analogical reasoning]

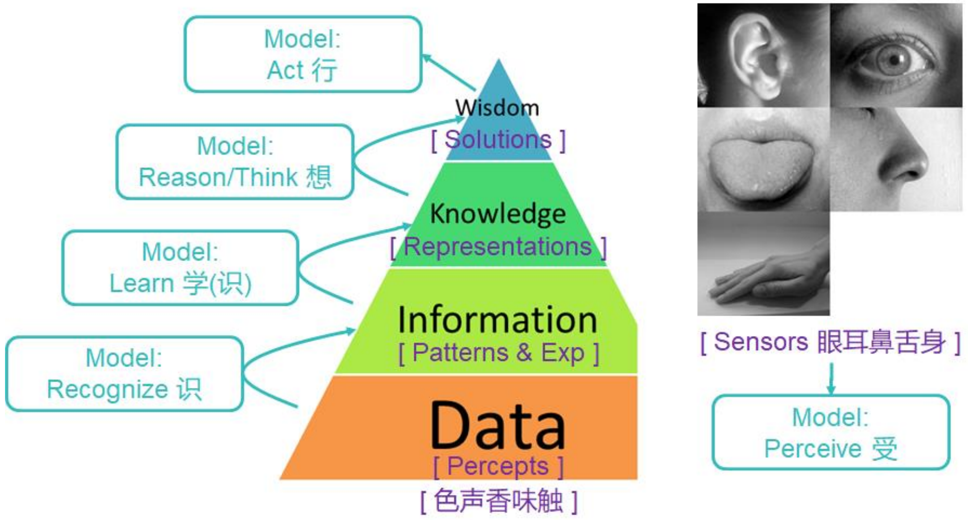
Model:
Perceive



A “model” view of “acting”

[skipped – use your analogical reasoning]

Model:
Act



Intelligent Minimum Viable Product (MVP) Show Cases

Intelligent Systems MVPs

Systems are deployed in areas of:

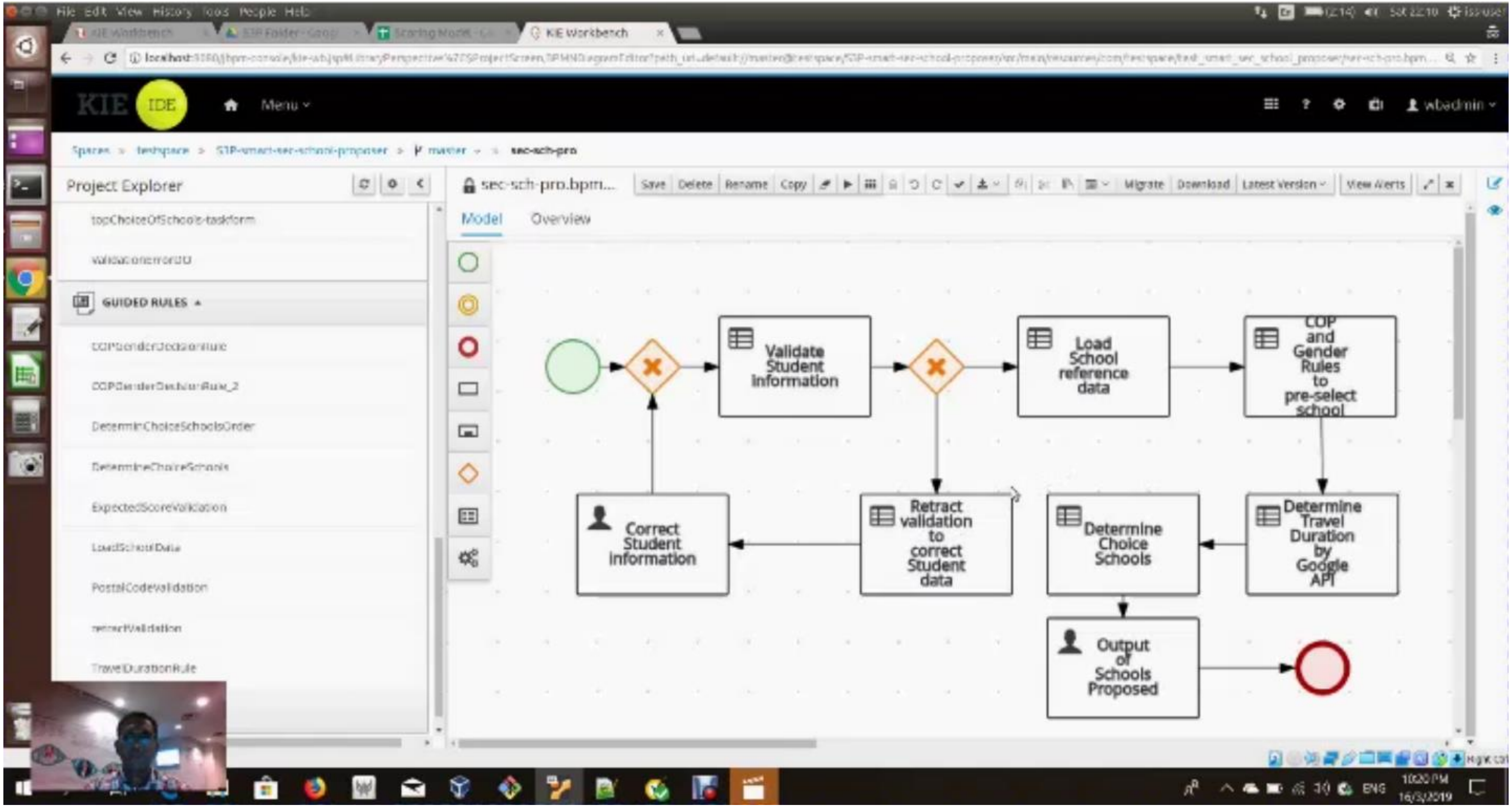
- Decision Support
- Recommendation
- Resource/Operation Optimization
- Virtual Assistant

Want to choose a decent school, but hate to do research/groundwork?

Empower you to piggy back on those diligent (kiasu) parents, with:

Intelligent School Proposer

[Education] Secondary School Proposer



Source https://github.com/IRS-MR/IRS-MR-2019-01-19-IS1PT-GRP-aiVoyagers-S3P-smart-sec-school-proposer

Hate to get up early to escort your schooling child in early morning?

Empower your and your kid to luxurily sleep more, with:

Intelligent School Shuttle

[Education] School Shuttle Scheduler

Intelligent Rapid Shuttle

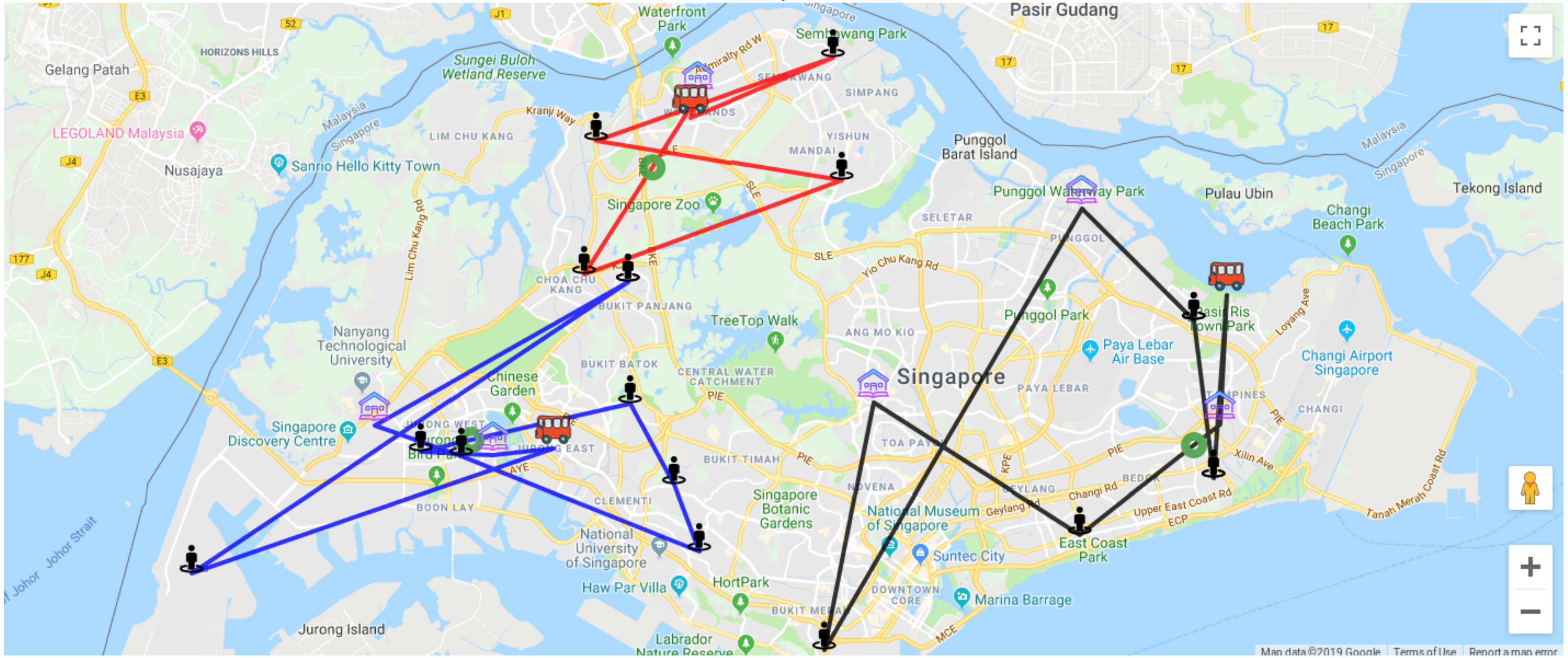
AI powered Shuttle Service -The fastest way to reach School at an affordable price

DataSet 1(8 Students, 3 Schools, 2 Vehicles)
DataSet 2(18 Students, 5 Schools, 3 Vehicles)
DataSet 3(23 Students, 8 Schools, 3 Vehicles)
DataSet 4(Same as Dataset3 + 1 Vehicle)

Show on Map

Find Best Route for the Students | Score : 0hard/-3381soft

Mouse over or Click Student, School or Vehicle for information



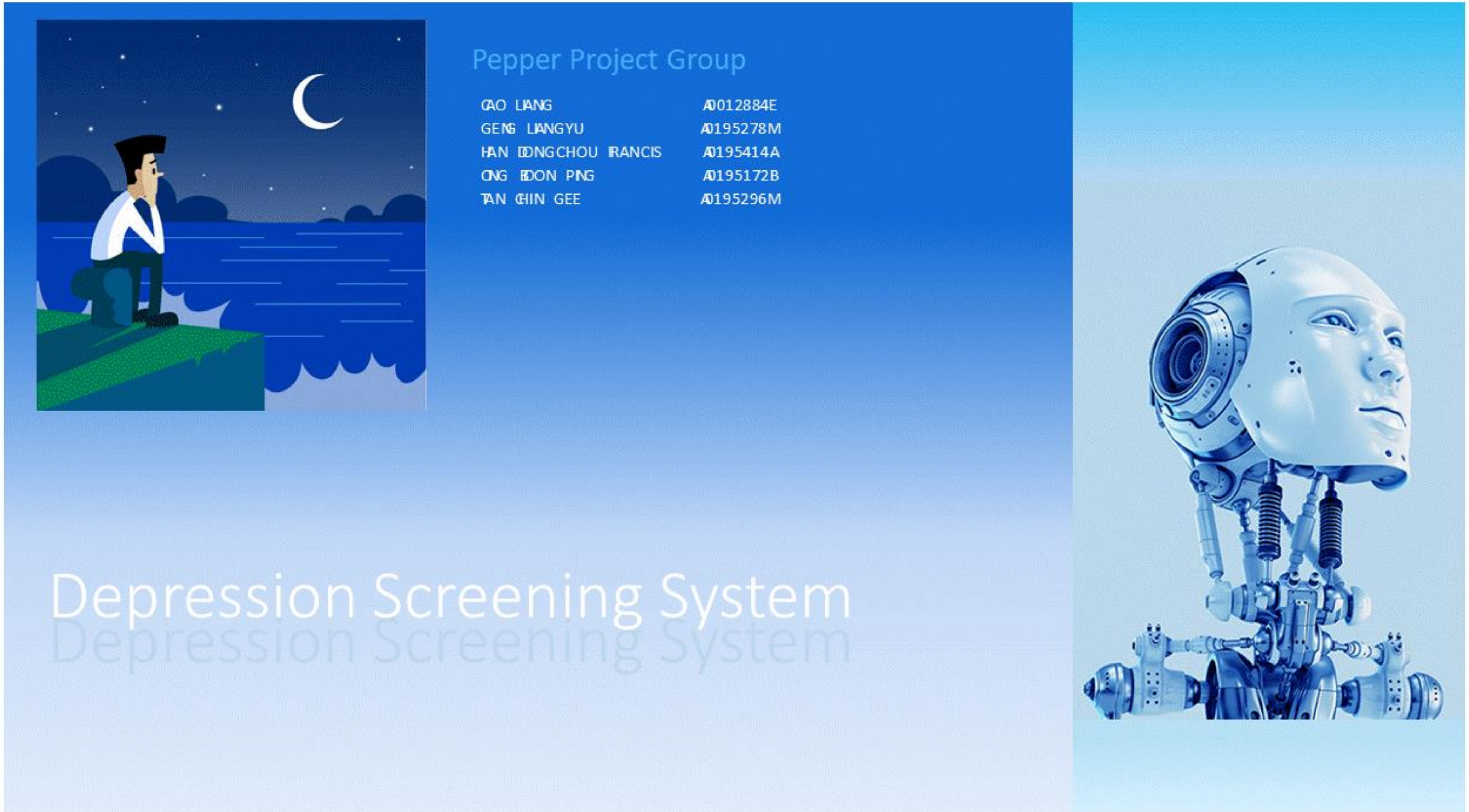
Source https://github.com/IRS-RS/IRS-RS-2019-03-09-IS1PT-GRP-aiVoyagers-irs-Intelligent-Rapid-Shuttle

Suspect of depression by overwhelming daily stresses, but shy to consult a doctor?

Empower you to conduct professional assessment DIY, with:

Depression Screener

[Health] Depression Screener



Source https://github.com/IRS-MR/IRS-MR-2019-01-19-IS1PT-GRP-Pepper-DepressionScreeningSystem

Want to consult a depression specialist, but worried about shy personality, Chinese speaking only, and other concerns... Which doctor to see?

Empower you to meet a doctor suitable to your needs, with:

Patient-Doctor Matcher

[Health] Patient-Doctor Matcher

Source https://github.com/IRS-RS/IRS-RS-2019-03-09-IS1PT-GRP-Pepper-PatientMatchingSystem

Get a new job in semiconductor quality assurance, but lack of localized knowledge within the organization?

Empower you to diagnose and assign defective integrated circuits to right engineering teams for further investigation, with:

Integrated Circuits Lot Disposition Recommender

[Manufacturing] Integrated Circuits Lot Disposition Recommender

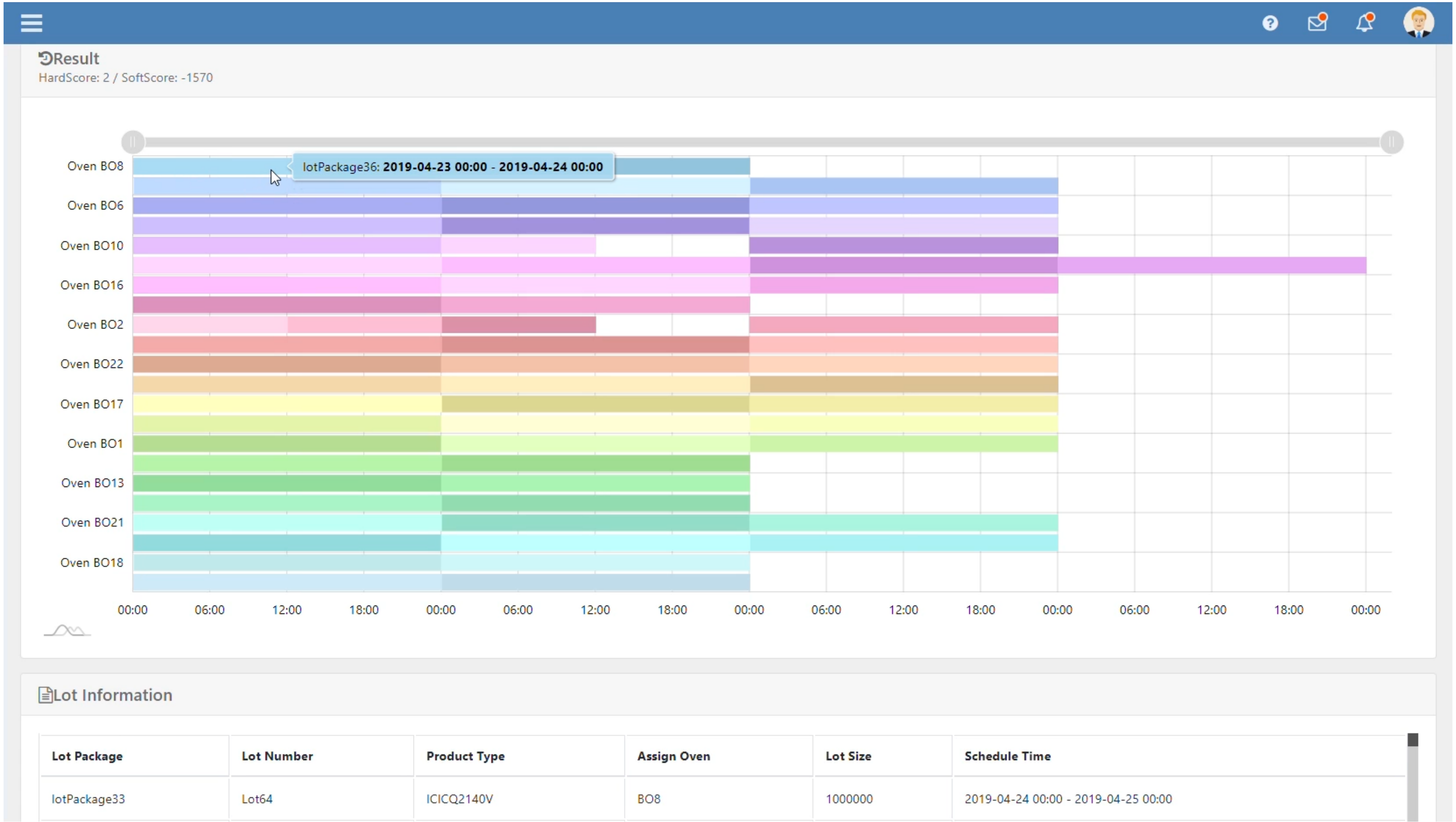
Source https://github.com/IRS-MR/IRS-MR-2019-01-19-IS1PT-GRP-HEX-LOH_Disposition_Decision-Making_Process_System

Just created a perfect plan to bake the integrated circuits in industry ovens, but one oven broke down unexpected just now… Re-plan?!

Empower you to optimally schedule and (re)plan integrated circuit batches/lots to available ovens, in real time, with:

Integrated Circuits Lot-Oven Scheduling and Dispatch Optimizer

[Manufacturing] Integrated Circuits Lot-Oven Scheduling and Dispatch Optimizer



Source https://github.com/IRS-RS/IRS-RS-2019-03-09-IS01PT-GRP-Hex-Sdot_Scheduling_and_Dispatch_Optimization_Tool

[Health] Clinical Decision Support

BUILDING A CLINICAL DECISION ENGINE PLATFORM WITH RED HAT DECISION MANAGER

redhat

RTInsights.com
Accelerate Your Business with Real-Time Insights

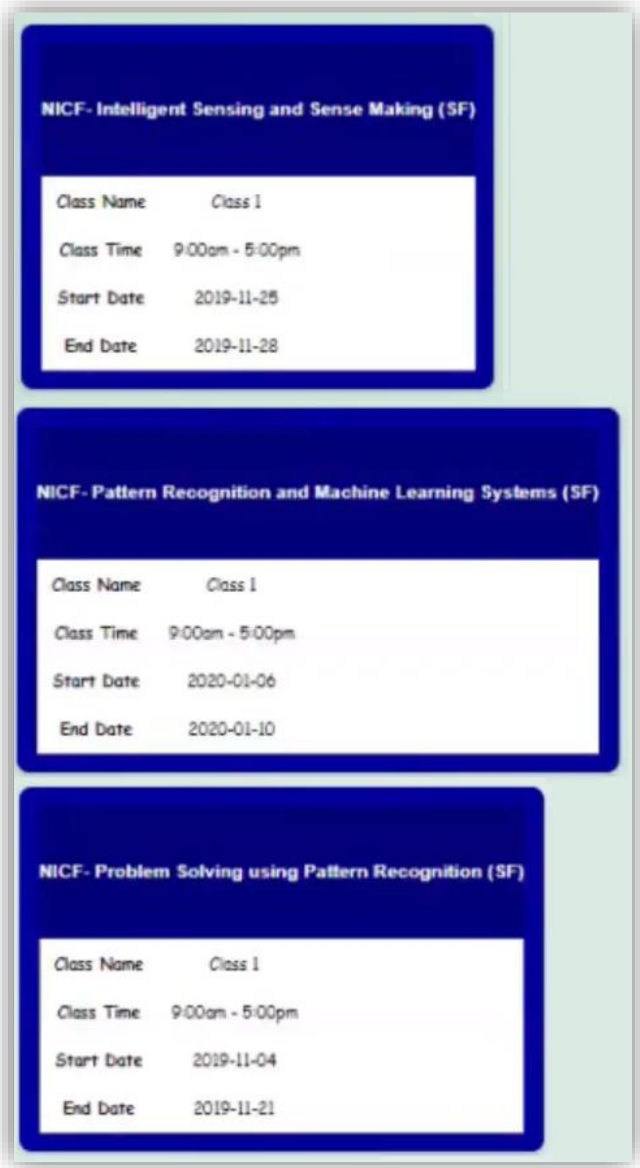
Northwell Health℠

Source https://www.redhat.com/en/resources/building-a-clinical-decision-engine-rtinsights-article

[Health] Meal Planner for Diabetics

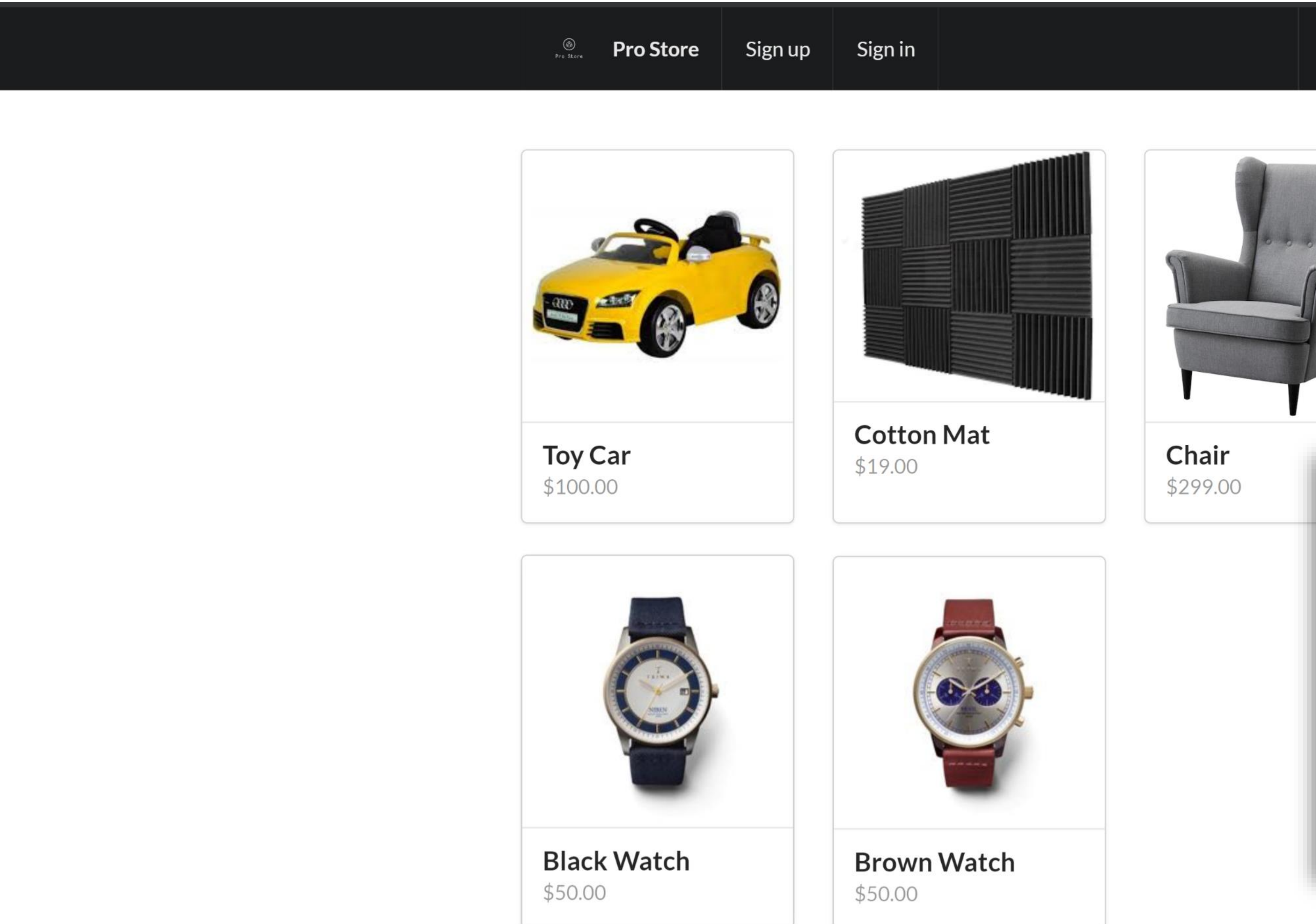
Source https://github.com/IRS-RS/IRS-MRS-2019-07-01-IS01FT-GRP9-Meal-Planner-for-Diabetics

[Education] ISS Course Recommender



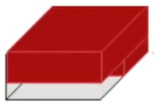
Source https://github.com/IRS-RS/IRS-MRS-2019-07-01-IS01FT-GRP1-ISS-COURSE-RECOMMENDER-SYSTEM

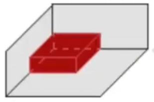
[E-Commerce] Shipping and Packing Optimizer



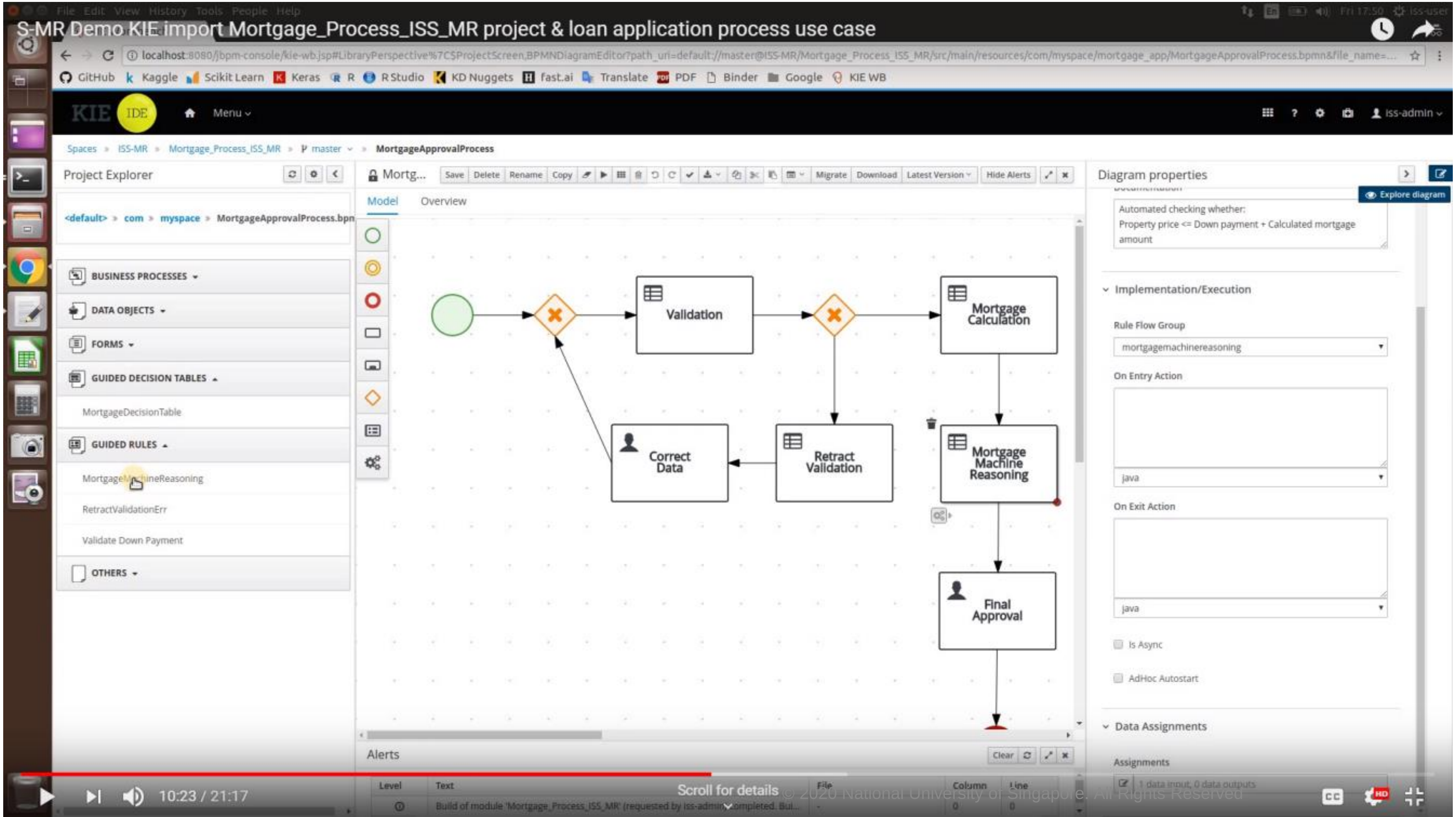
Delivery Name	Delivery Time (Days)	Shipping Cost	Select
SF	2 to 3	$35.5	
UPS	3 to 5	$77.4	
DHL	2	$72.75	
FedEX	4	$72.6	

Note Your package will be packed in the following manner to minimize shipping cost!

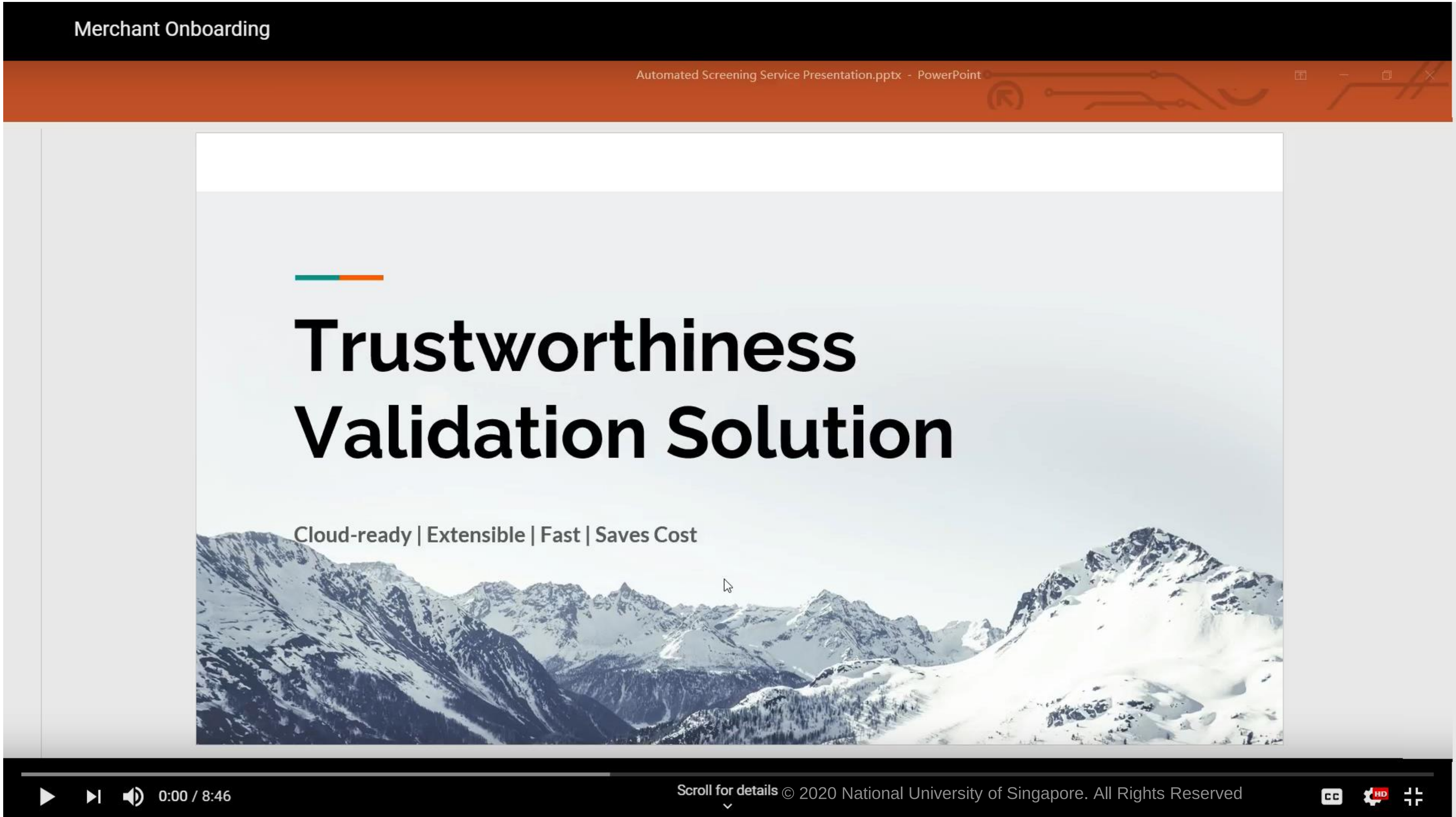

30x15x30 Final Packing


15x5x15 Toy Car

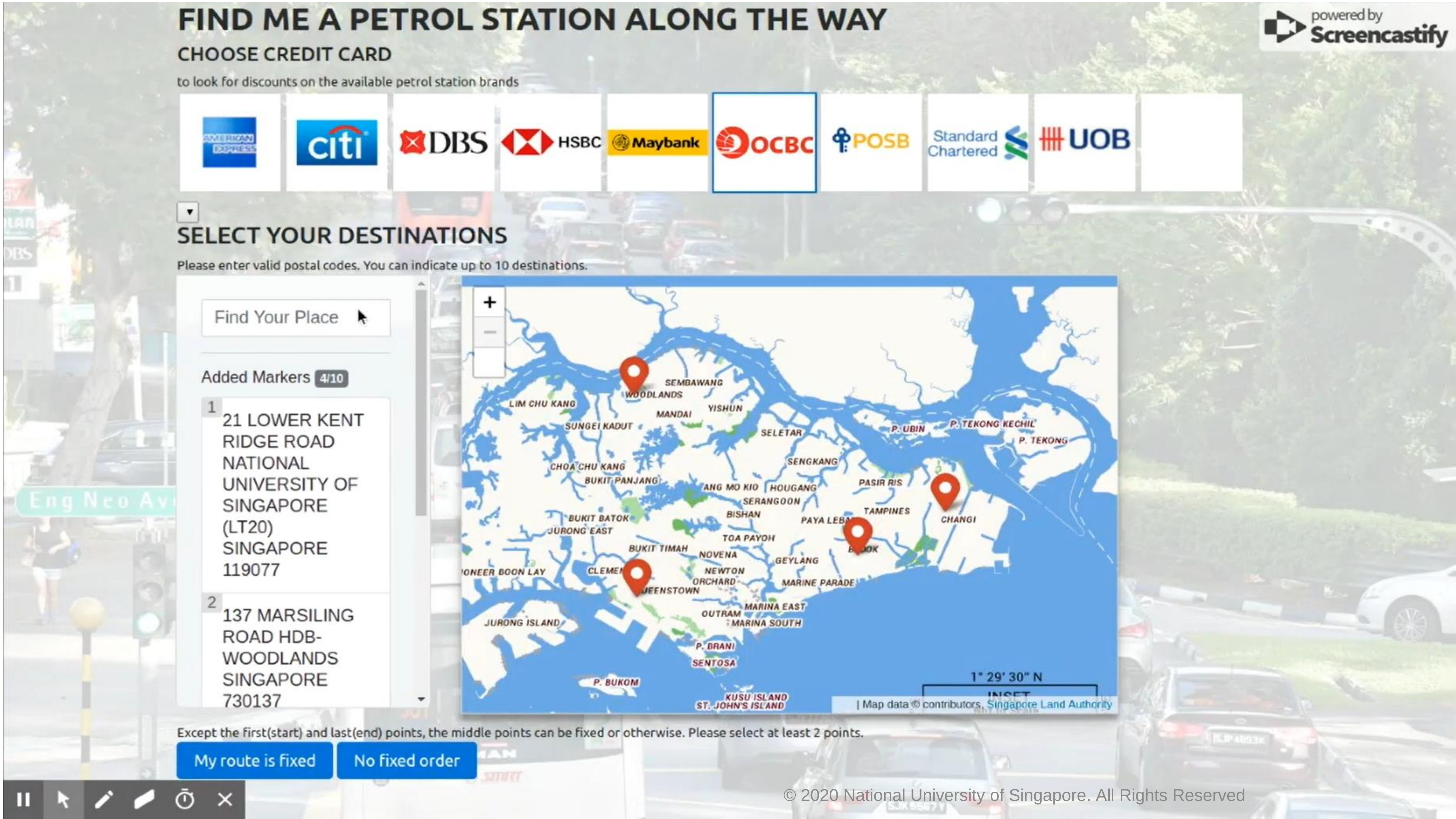
[FinTech] Mortgage Automation



[FinTech] Merchant On-boarding



[FinTech] Co-branded Petrol Credit Card



Workshop / Homework

Reading 1

The Rise and Fall of Thinking Machines

Gary A. Taubes

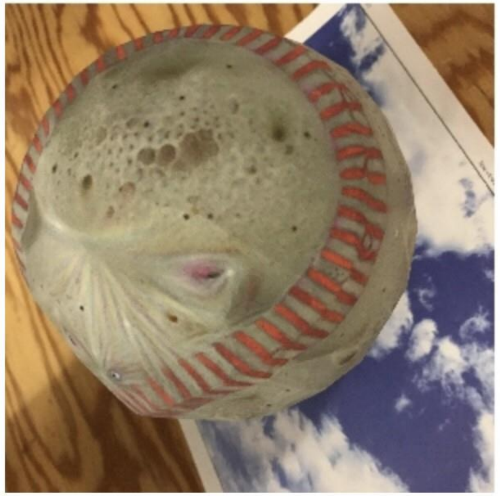
https://www.inc.com/magazine/19950915/2622.html

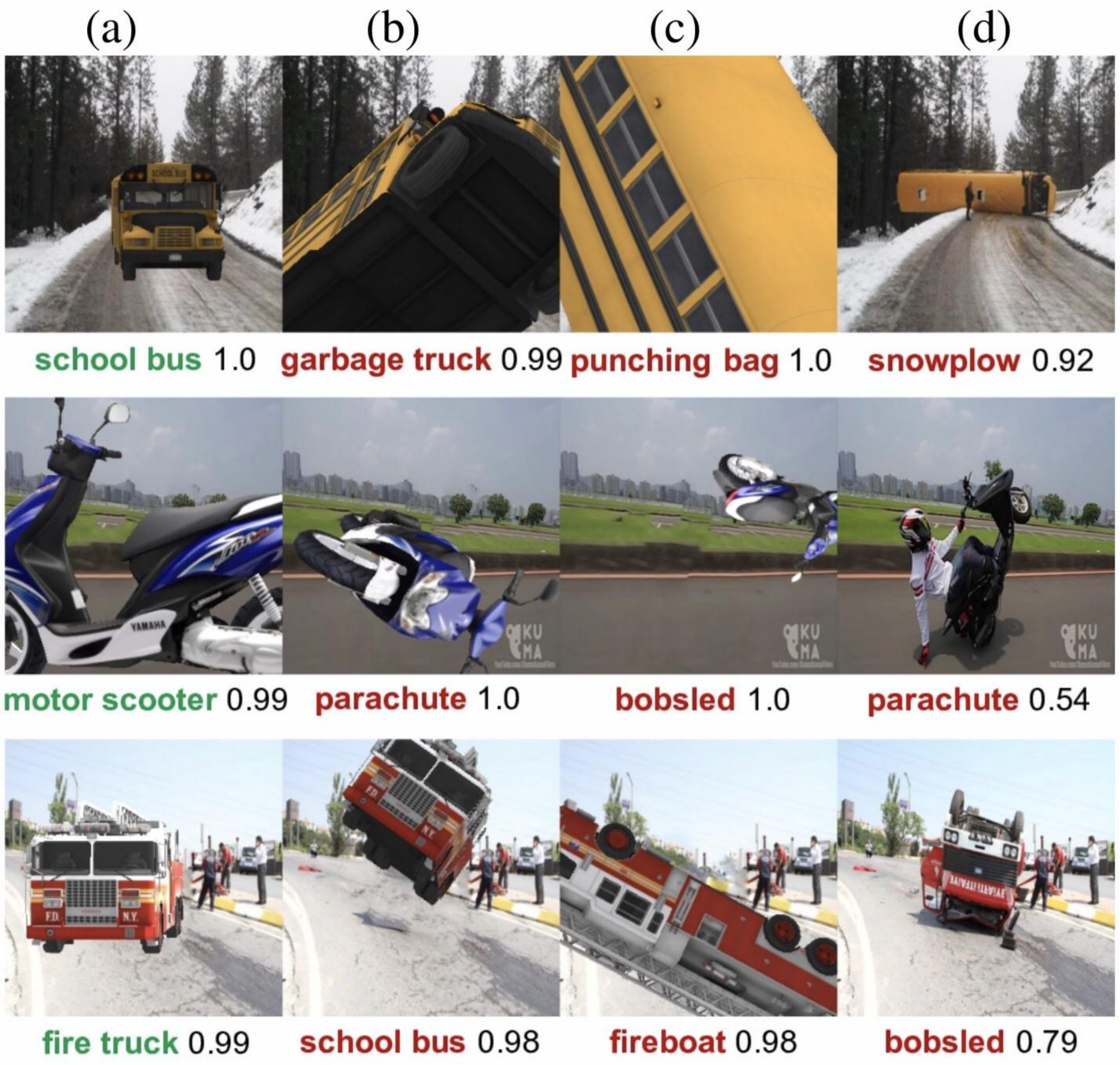
Reading 2

The Deepest Problem with Deep Learning

Gary Marcus

https://medium.com/@GaryMarcus/the-deepest-problem-with-deep-learning-91c5991f5695





Reading 3

How Your Mind Can Amaze and Betray You

- We used to think that the human brain was a lot like a computer: using logic to figure out complicated problems. It turns out, it's a lot more complex and, well, weird than that. This video discusses thinking & communication, solving problems, creating problems, and a few ideas about what our brains are doing up there.

Source https://courses.lumenlearning.com/wsu-sandbox/chapter/video-cognition-how-your-mind-can-amaze-and-betray-you/

MORE INTELLIGENT SYSTEMS MVPS / HOMEWORK

- **Explore Intelligent Systems MVP created by past learners**

https://github.com/IRS-PM	Hybrid Systems
https://github.com/IRS-CGS	Chat-bots
https://github.com/IRS-RS	Resource Optimization
https://github.com/IRS-MR	Decision Support

End of Lecture Notes

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