



DATA SCIENCE & MACHINE LEARNING WORKSHOP

Week 4 - Intro to Machine Learning

GOOGLE GEMINI X ALGOSOC TALK ON AI

WE WILL HAVE SOME EXTERNAL SPEAKERS THAT WILL BE DELIVERING AN ENGAGING WORKSHOP FOR STUDENTS ON HOW TO LEVERAGE GEMINI, GOOGLE'S AI TOOL, TO PRACTICALLY AND ETHICALLY ENHANCE—NOT REPLACE—THEIR ACADEMIC STUDIES.

THERE WILL BE 2 SLOTS:

1:30PM - 3:30PM

2:40PM - 5:00PM.

YOU ARE FREE TO ATTEND EITHER ONE - THEY WILL BE THE SAME TALK.

**LIMITED AVAILABILITY!!!
SCAN THE QR CODE TO SECURE YOUR SPOT!!!**



**LOCATION - Y3-G34
DATE - 20TH NOV 2025**

AGENDA

Week 4 topic:

- Do we need modelling and machine learning
- Types of Machine learning (supervised, unsupervised, reinforced)
- Intro to Supervised (Types of Supervised)
- Uncertainties
- Training vs. testing data
- Modelling example

Full agenda this semester:

<https://bit.ly/DataScienceAlgosoc>

Repository:

<https://github.com/AlgoSoc/Data-Science>

WHEN DO WE NEED MODELLING

The term machine learning has been thrown around so much, seems like we need to build a **machine learning predictive model** for everything now.

But do we actually need to?

Consider this case:

- Can we train a machine learning predictive model to predict celsius temperature given farrenheit? Yes
 - Should we? No
- Say your company has a promo set up, customers above 60 years old are entitled to discounts, can we make a predictor for it? Yes
 - Should we? No
- Given text data with **information we can't really associate manually**, can we make a sentiment classifier? Yes
 - Should we? Yes

WHEN DO WE NEED MODELLING

We should use machine learning when:

- The problem seems unsolveable (intrinsically hard)
- The problem is big (we can extract information but would just be too tedious)
- Information to make a decision are hard to be interpreted

We should **NOT** use machine learning when:

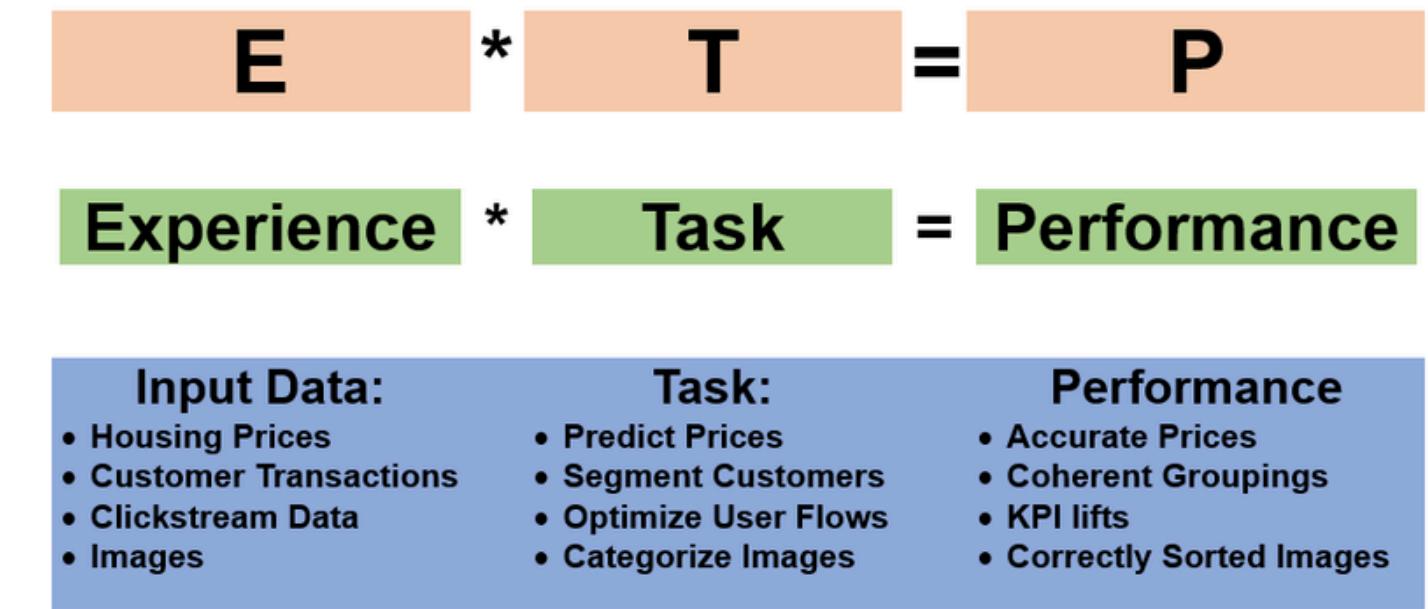
- The problem is straightforward
- We have limited resources
- Supporting information for decision can be determined easily (e.g., setting age threshold for discount)

Keep in mind, when using machine learning, we introduce **uncertainties**

WHAT IS MACHINE LEARNING

What is Machine Learning?

- Arthur Samuel (1959): Machine learning is the field of study that gives computers the ability to learn **without being explicitly programmed**.
- Tom Mitchell (1998): A computer programme is said to learn from **experience** E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.
- Kevin Murphy (2012): The goal of machine learning is to develop methods that can automatically detect patterns in **data**, and then to use the uncovered patterns to **predict** future data or other outcomes of interest.
- Oxford Languages Dictionary: the use and development of computer systems that are able to **learn and adapt without following explicit instructions**, by using algorithms and statistical models to analyse and draw inferences from patterns in **data**.



<https://www.linkedin.com/pulse/what-machine-learning-ml-mohammad-mehrabani-2qgie>

*taken from Leandro Minku's Lecture on Machine Learning

TYPES OF MACHINE LEARNING

Three Types of Machine Learning

Supervised Learning

Has outcome information (“labels”)

Finds patterns that relate to those outcomes

Uses patterns to predict outcomes not yet known

Unsupervised Learning

No outcome information available

Analyzes or identifies groups without labels or human instruction

Offers insights into characteristics that define groups

Reinforcement Learning

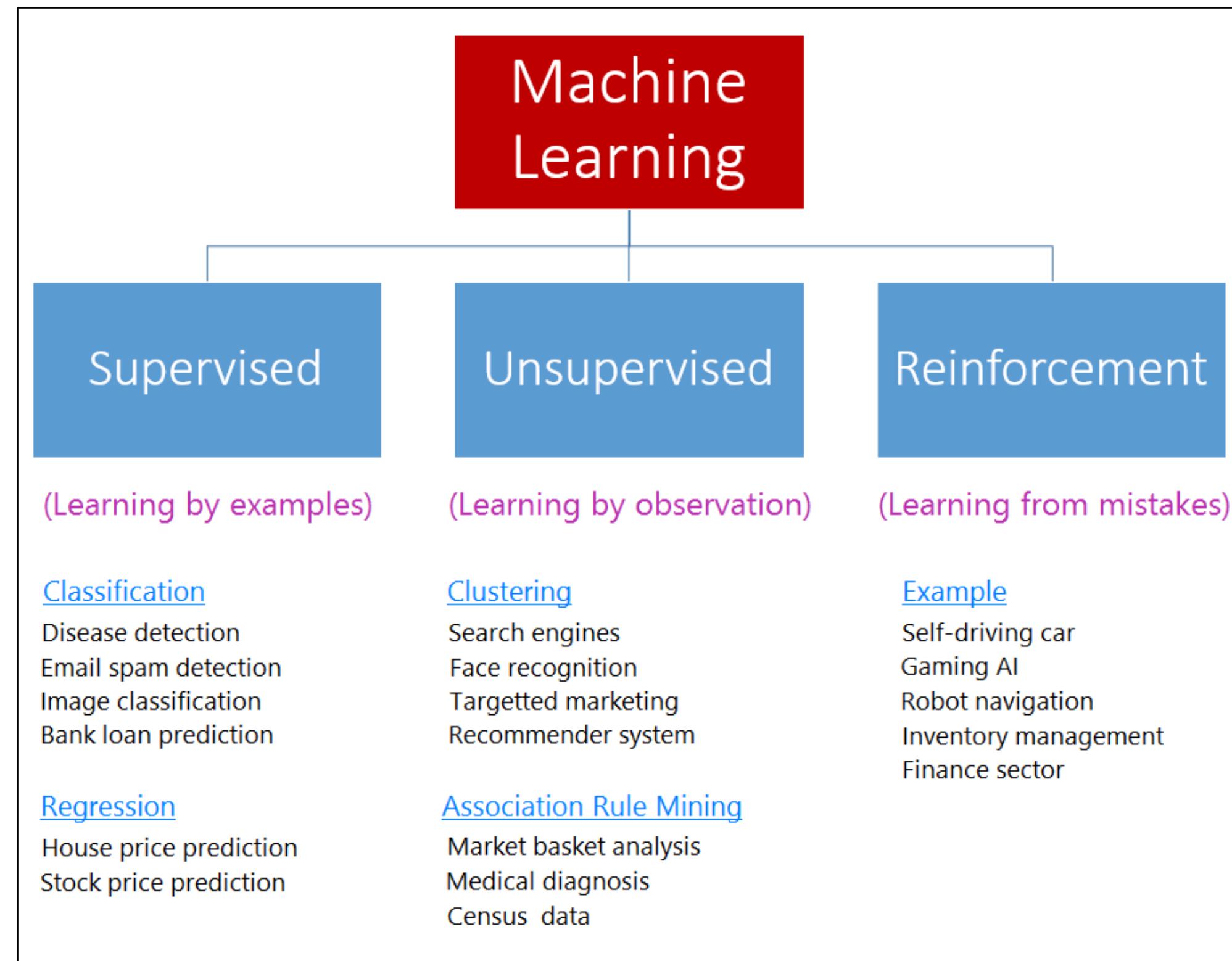
Makes decisions based on trial and error

Decision-making algorithm is constantly refined based on “rewards”

Excels in complex situations

 Pecan

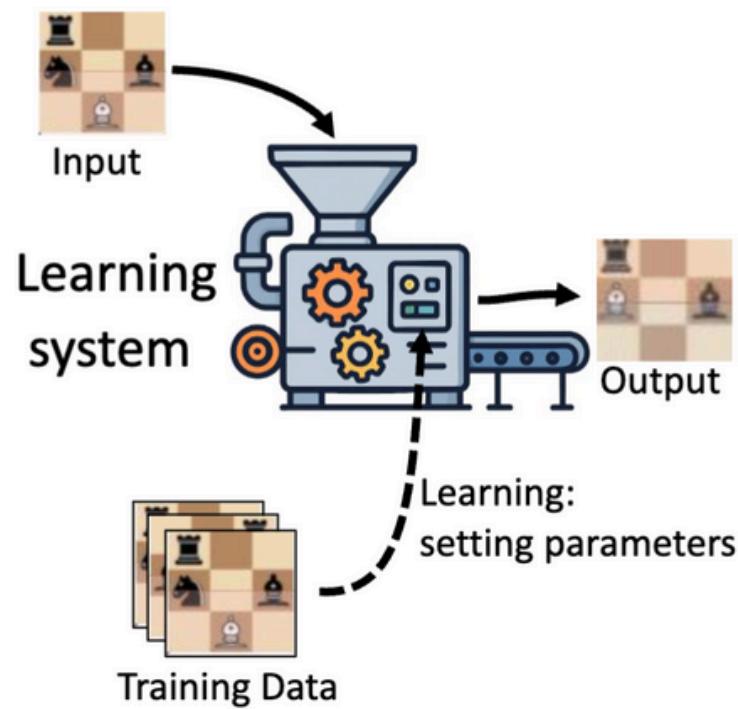
TYPES OF MACHINE LEARNING



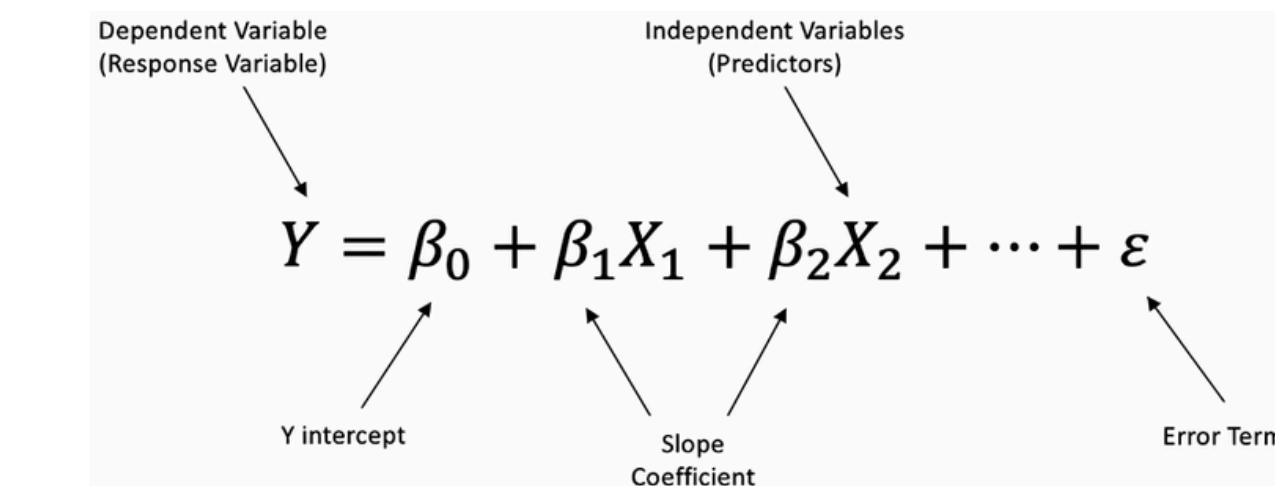
SUPERVISED LEARNING

In supervised learning we are concerned in letting our machine to learn from our example of inputs (X) and (desired) output (y)

Most of the time, it means we want the computer to **learn** the parameters (settings) of our model. By letting the machine learn the appropriate parameters, we are performing supervised learning



Taken from Alexander Krull's lecture on Neural Computation



A diagram showing the linear regression equation $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \varepsilon$. The equation is centered. Above it, "Dependent Variable (Response Variable)" and "Independent Variables (Predictors)" are labeled with arrows pointing to the Y term and the X_i terms respectively. Below the equation, "Y intercept" and "Slope Coefficient" are labeled with arrows pointing to the β_0 term and the $\beta_i X_i$ terms. An arrow labeled "Error Term" points to the ε term at the end of the equation.

Image Source: https://www.researchgate.net/figure/Linear-regression-equation_fig1_373123252

If our model is a linear function, we would usually want to let the computer learn what are the appropriate **y-intercept and slope coefficient**

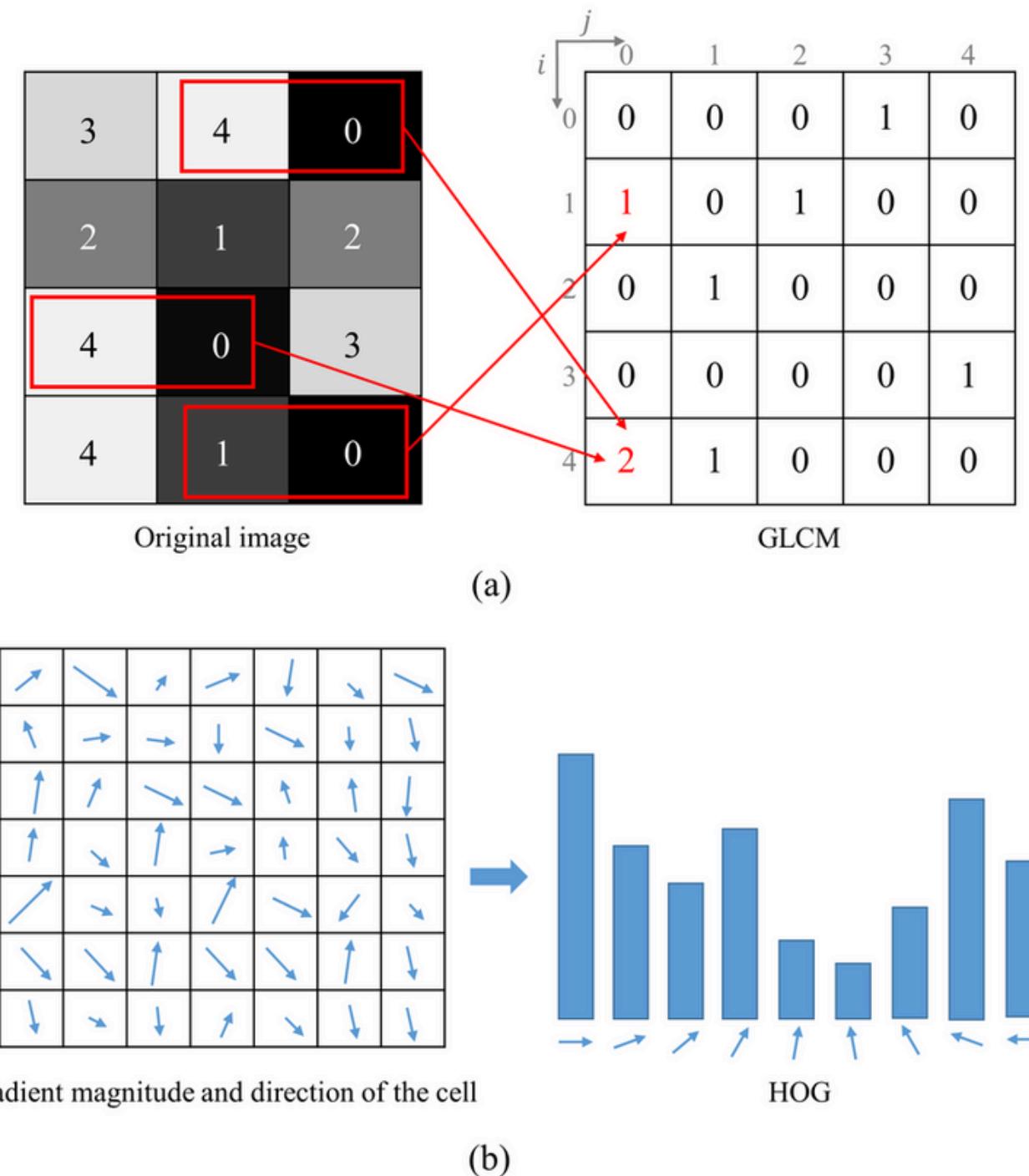
While ε is the **underlying uncertainty**

SUPERVISED LEARNING

Task	Task Description	Input (X) Type	Output (y) Type
Regression	Based on the given information, predict a numeric value	Numeric data, categorical data	Numeric values
Classification	Based on the given information, discriminate between two classes of information that the model has known of	Numeric and categorical data	categorical values

What about image and textual data?

SUPERVISED LEARNING



https://www.researchgate.net/figure/Feature-extraction-methods-in-image-processing-GLCM-and-HOG-a-An-example-of_fig1_337940559

Word	TF		IDF	TF*IDF	
	A	B		A	B
The	1/7	1/7	$\log(2/2) = 0$	0	0
Car	1/7	0	$\log(2/1) = 0.3$	0.043	0
Truck	0	1/7	$\log(2/1) = 0.3$	0	0.043
Is	1/7	1/7	$\log(2/2) = 0$	0	0
Driven	1/7	1/7	$\log(2/2) = 0$	0	0
On	1/7	1/7	$\log(2/2) = 0$	0	0
The	1/7	1/7	$\log(2/2) = 0$	0	0
Road	1/7	0	$\log(2/1) = 0.3$	0.043	0
Highway	0	1/7	$\log(2/1) = 0.3$	0	0.043

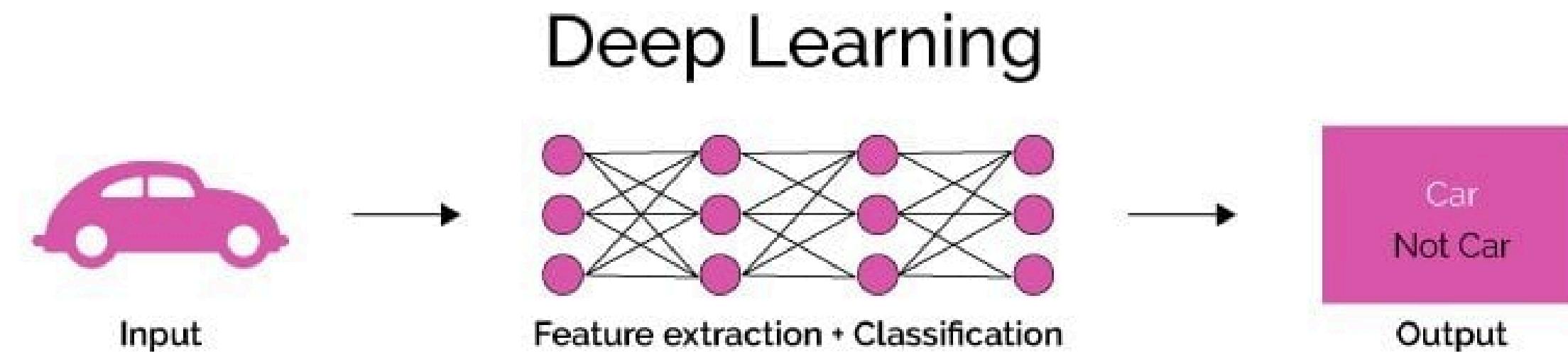
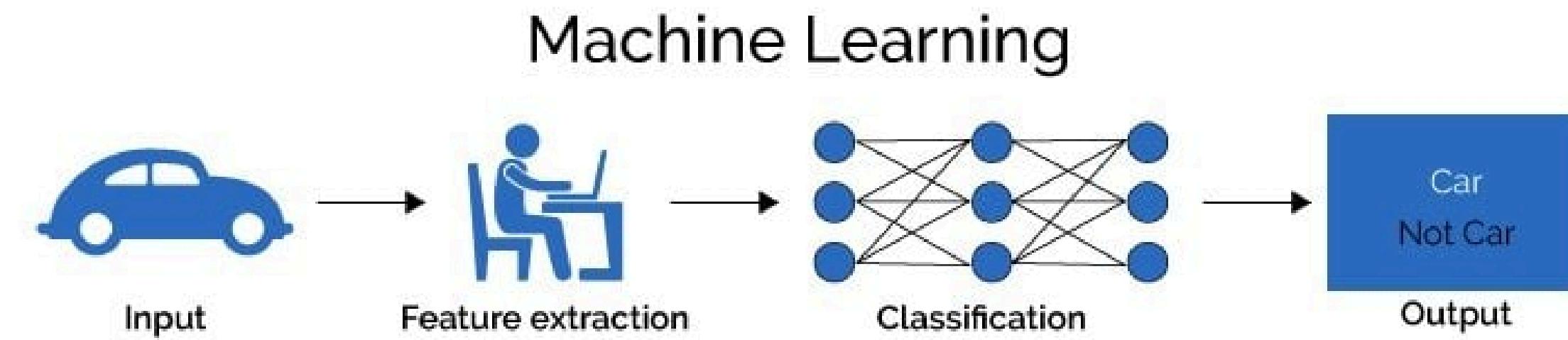
https://www.researchgate.net/figure/Feature-extraction-methods-in-image-processing-GLCM-and-HOG-a-An-example-of_fig1_337940559

Images are essentially matrix, and we can extract numerical feature such as **Histogram of Oriented Gradients** to become numerical inputs for our model

Texts can be represented numerically using features such as **TF-IDF**. These can then become input for our models.

SUPERVISED LEARNING

Calculating Histogram of Oriented Gradients, and TF-IDF can be tedious and more often not representative of the data itself. To solve this, we can use deep learning where (most of the time) we can use the unstructured data in its original form

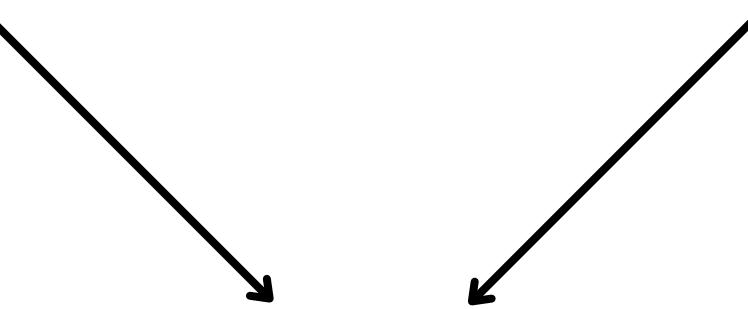


UNCERTAINTY

To measure how well our model is doing, we can quantify the performance of our models.

$f(X)$: Model
prediction

y : Ground
truth



Performance
metric
calculation



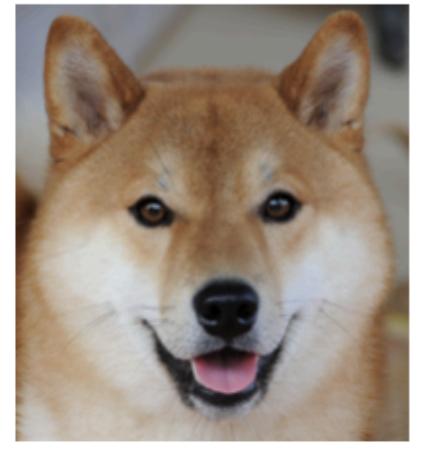
Performance
metric result

UNCERTAINTY

Actual

For classification:

Predicted

		CAT	NOT CAT
CAT	CAT		
	NOT CAT		

UNCERTAINTY

For classification:

		Real Label	
		Positive	Negative
Predicted Label	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

Precision = $\frac{\sum \text{TP}}{\sum \text{TP} + \text{FP}}$

Recall = $\frac{\sum \text{TP}}{\sum \text{TP} + \text{FN}}$

Accuracy = $\frac{\sum \text{TP} + \text{TN}}{\sum \text{TP} + \text{FP} + \text{FN} + \text{TN}}$

$$\begin{aligned}\text{F1 Score} &= \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \\ &= \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\end{aligned}$$

https://www.researchgate.net/figure/Calculation-of-Precision-Recall-and-Accuracy-in-the-confusion-matrix_fig3_336402347

UNCERTAINTY

For regression:

Mean squared error

$$\text{MSE} = \frac{1}{n} \sum_{t=1}^n e_t^2$$

Root mean squared error

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2}$$

Mean absolute error

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |e_t|$$

Mean absolute percentage error

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{e_t}{y_t} \right|$$

We would define the error e as:

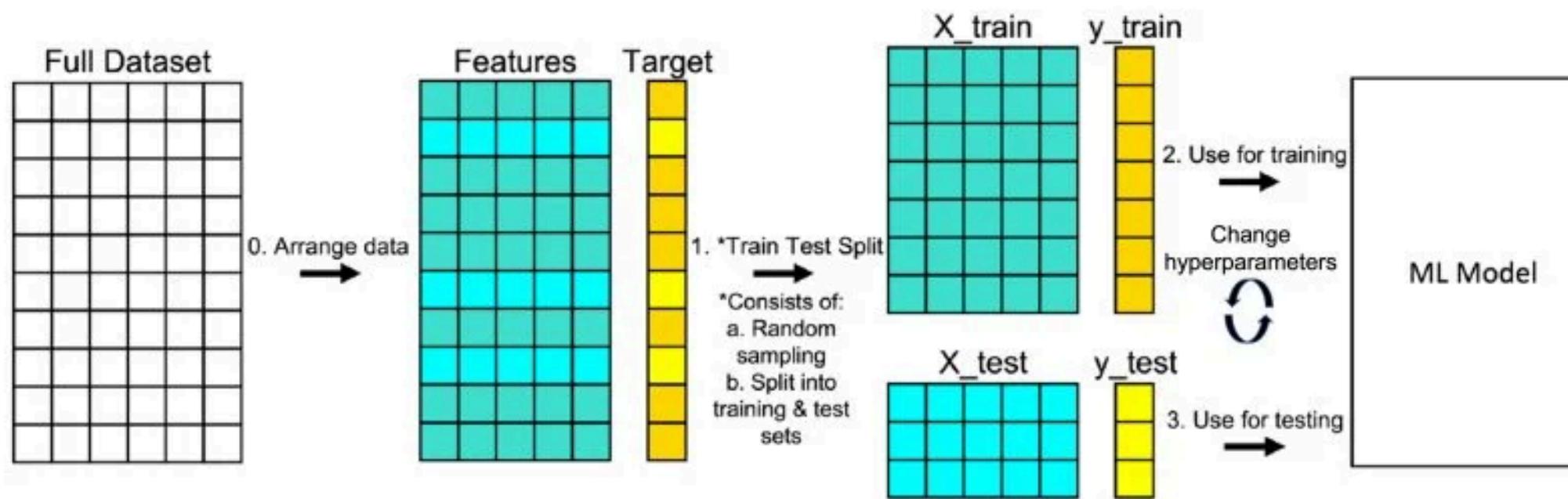
$$e = (f(x) - y)$$

where:

- $f(x)$: model prediction
- y : true value

TRAIN AND TEST

We want to measure the model's performance on **unseen data (i.e., data not used on training)**



<https://builtin.com/data-science/train-test-split>

The uncertainty measurement usually would be evaluated against the model's performance with the test data, **NOT** the training data

Recommended further read on:

- Model selection (cross validation)
- Validation set in deep learning

HANDS ON

Link

<https://bit.ly/AlgosocWk4>

Colab