

Essence of Machine Learning (and Deep Learning)

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hoamle.github.io

Examples

- <https://www.youtube.com/watch?v=BmkA1ZsG2P4>
- <http://www.r2d3.us/visual-intro-to-machine-learning-part-1/>

Machine Learning is about ...

... a computer program (machine) learns to do a task (problem) from experience (data)

- *learning* \triangleq improved *performance* with more experience

- Tom Mitchell



predictive modelling with sample data



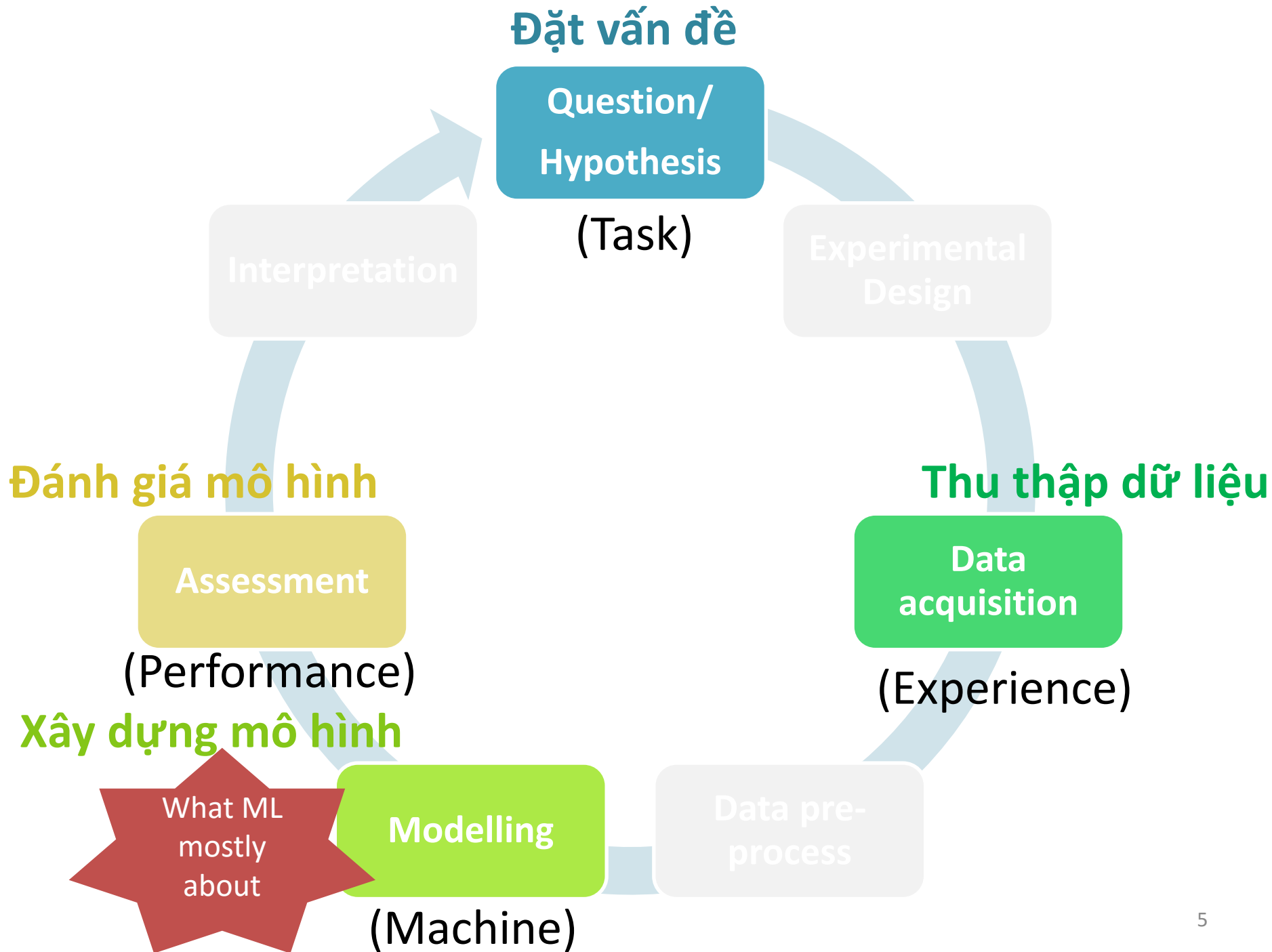
"heuristics" & statistical modelling

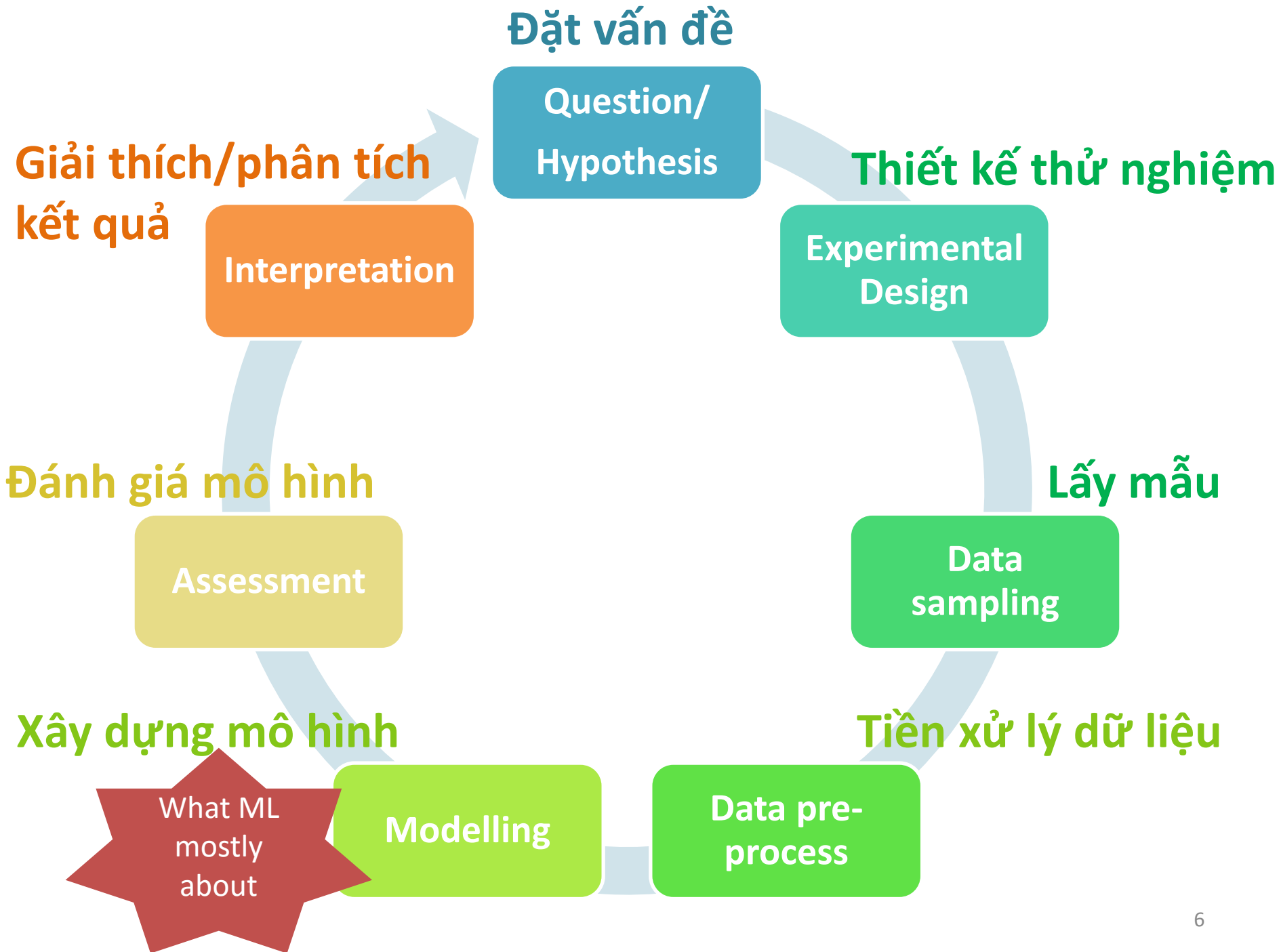
note 1: "heuristic" as in "intuitive, but not (yet!) rigorously proven by mathematical tools at some extend"

note 2: predictive modelling can also be in the form of rule-based systems, models in physics, etc

BUILD
A MACHINE LEARNING SOLUTION

the Pipeline





Đặt vấn đề

Question/
Hypothesis

Q.a. **What are** there in an **arbitrary photo**?

Q.b. **What is** there in an **arbitrary photo**?

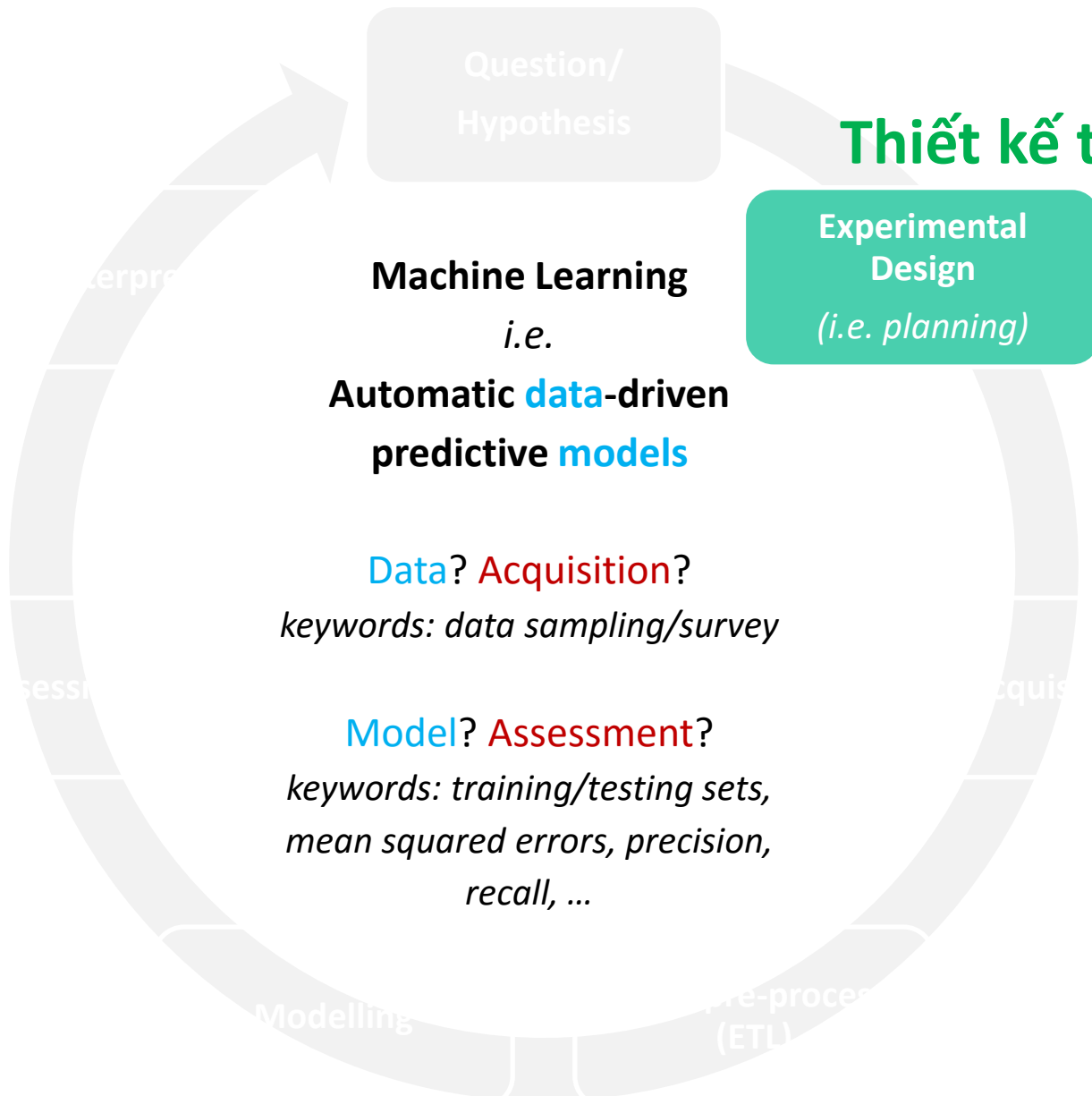
Q.c. **Is there** any puppy an **arbitrary photo**?



cat
flower
dog
jet
ground
grass
...

Other questions:

- **Where** are the puppies in a photo?
- **How confident** can I assure that there is a cat a photo?
- **For what reasons** can I know that there is a cat in a photo?



Question/
Hypothesis

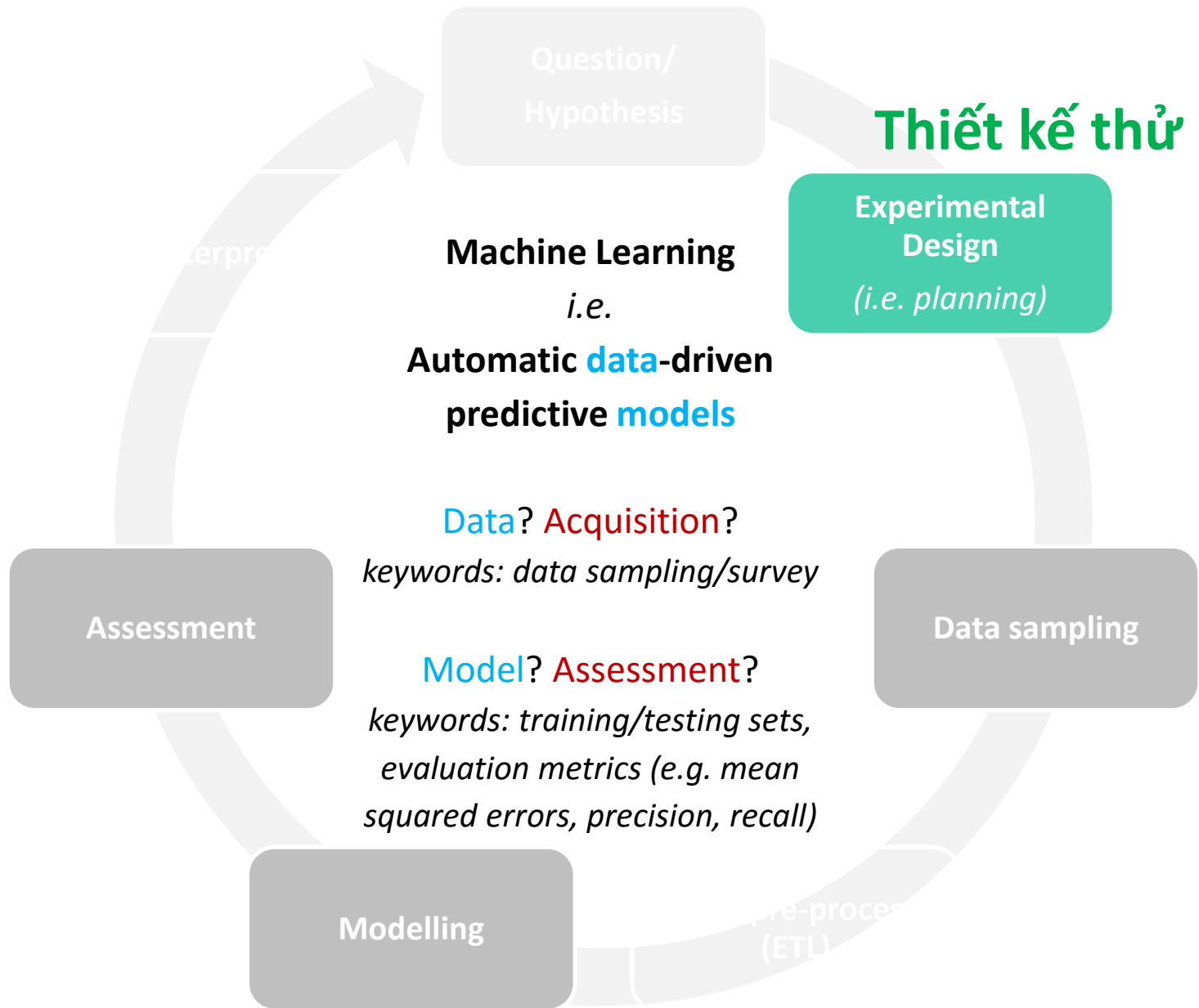
Thiết kế thử nghiệm

Experimental
Design
(i.e. planning)

Machine Learning
i.e.
**Automatic data-driven
predictive models**

Data? Acquisition?
keywords: data sampling/survey

Model? Assessment?
*keywords: training/testing sets,
mean squared errors, precision,
recall, ...*



Thiết kế thử nghiệm

Experimental Design
(i.e. planning)

Machine Learning
i.e.

Automatic data-driven
predictive models

Data? Acquisition?

keywords: data sampling/survey

Model? Assessment?

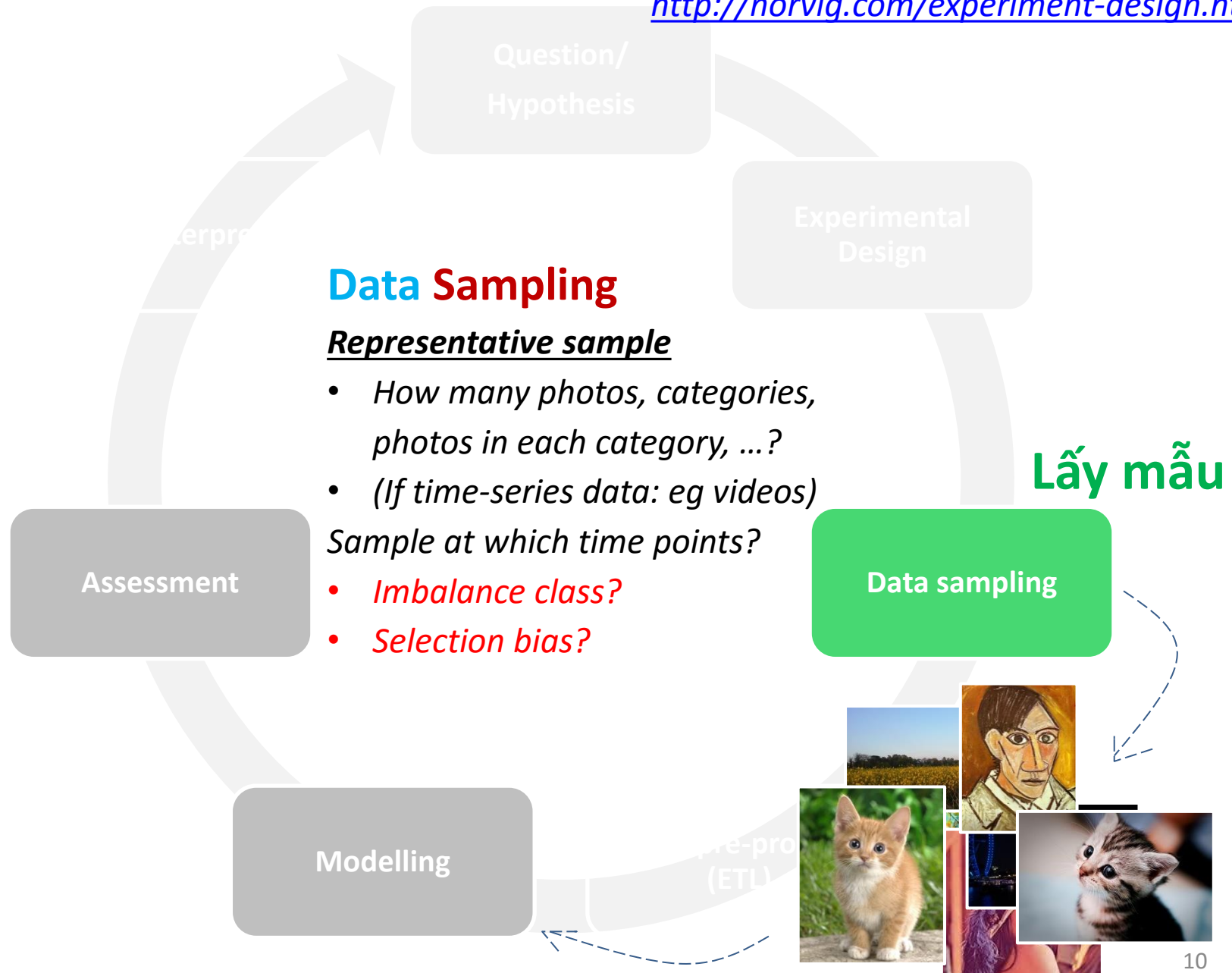
keywords: training/testing sets,
evaluation metrics (e.g. mean squared errors, precision, recall)

Assessment

Data sampling

Modelling

pre-process
(ETL)



Data Sampling

Representative sample

- How many photos, categories, photos in each category, ...?
- (If time-series data: eg videos)

Sample at which time points?

- *Imbalance class?*
- *Selection bias?*

Which metrics to use depend on which problem
http://scikit-learn.org/stable/modules/model_evaluation.html

Đánh giá mô hình

Assessment

Model Assessment

Evaluation metrics

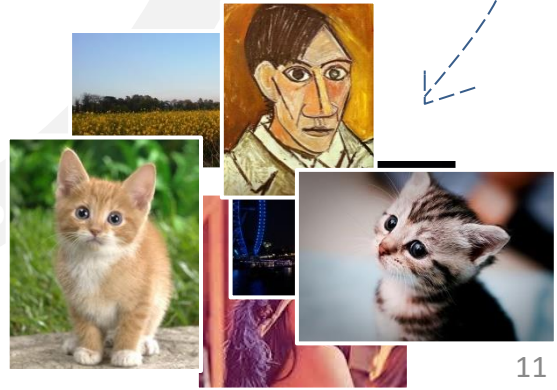
- Accuracy
 - Precision, Recall
 - Area Under Curve (AUC)
 - Mean squared errors (MSE)
 - ...
- (If hypothesis testing problem)
- t-statistic, z-statistic, χ^2 -statistic, ...

Modelling

Experimental Design

Data sampling

cat
flower
dog
jet
ground
grass



If training/testing set split is well designed with sufficient examples, we might not need to repeat many experiments.

Đánh giá mô hình

Assessment

- cat
- flower
- dog
- jet
- ground
- grass

Modelling

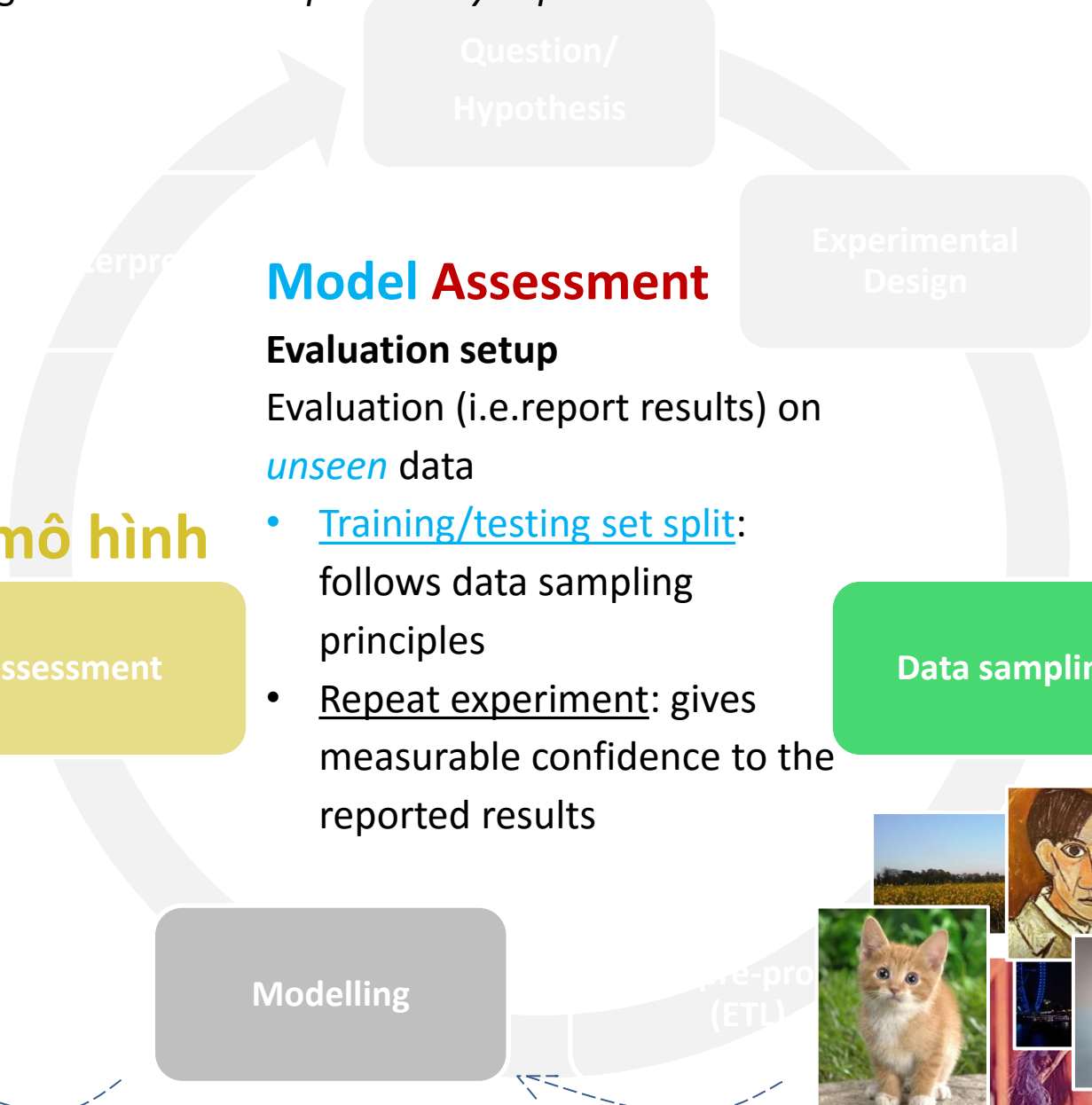
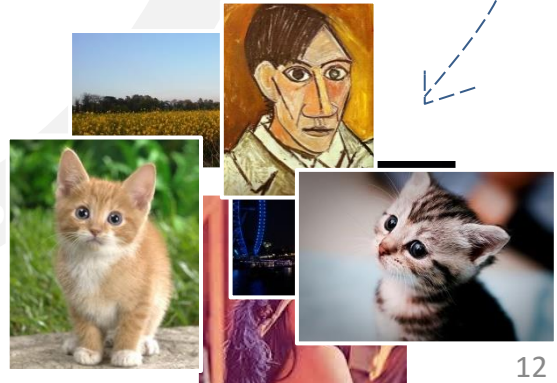
Model Assessment

Evaluation setup

Evaluation (i.e. report results) on *unseen* data

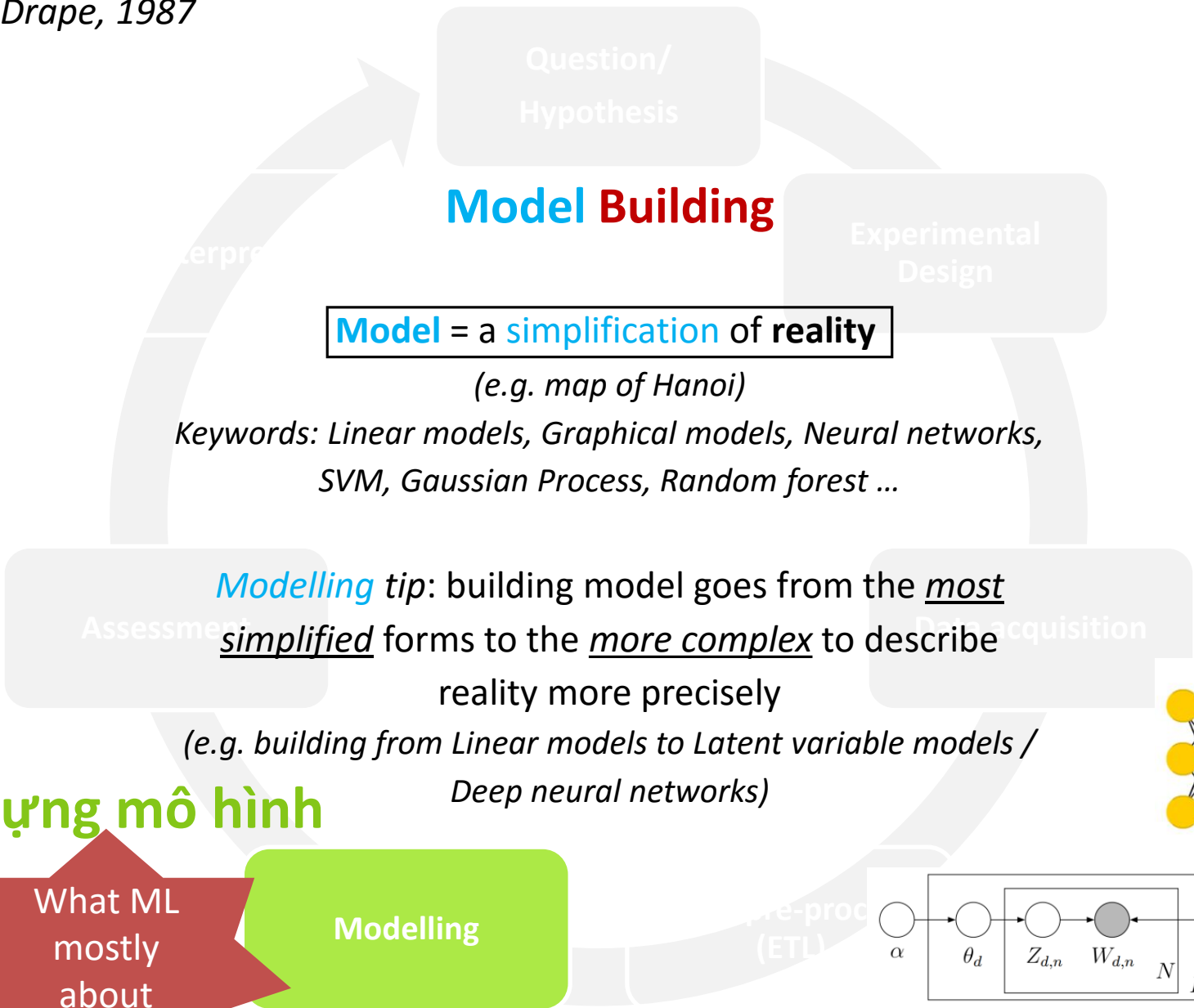
- Training/testing set split: follows data sampling principles
- Repeat experiment: gives measurable confidence to the reported results

Data sampling



“All models are wrong, but some are useful.”

- Box and Drape, 1987



Model = a simplification of reality

(e.g. map of Hanoi)

Keywords: Linear models, Graphical models, Neural networks, SVM, Gaussian Process, Random forest ...

Modelling tip: building model goes from the most simplified forms to the more complex to describe

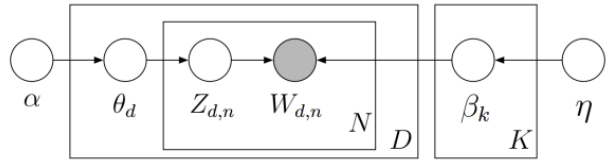
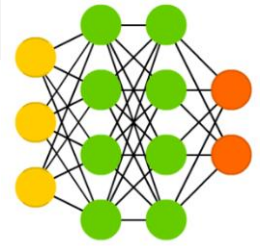
reality more precisely

(e.g. building from Linear models to Latent variable models / Deep neural networks)

Xây dựng mô hình

What ML mostly about

Modelling



Raw data → Post-processed data



Assessment

- *Data ETL: extract, transform, load*
- *Data standardisation / normalisation*
- *Data imputation (if missing values)*

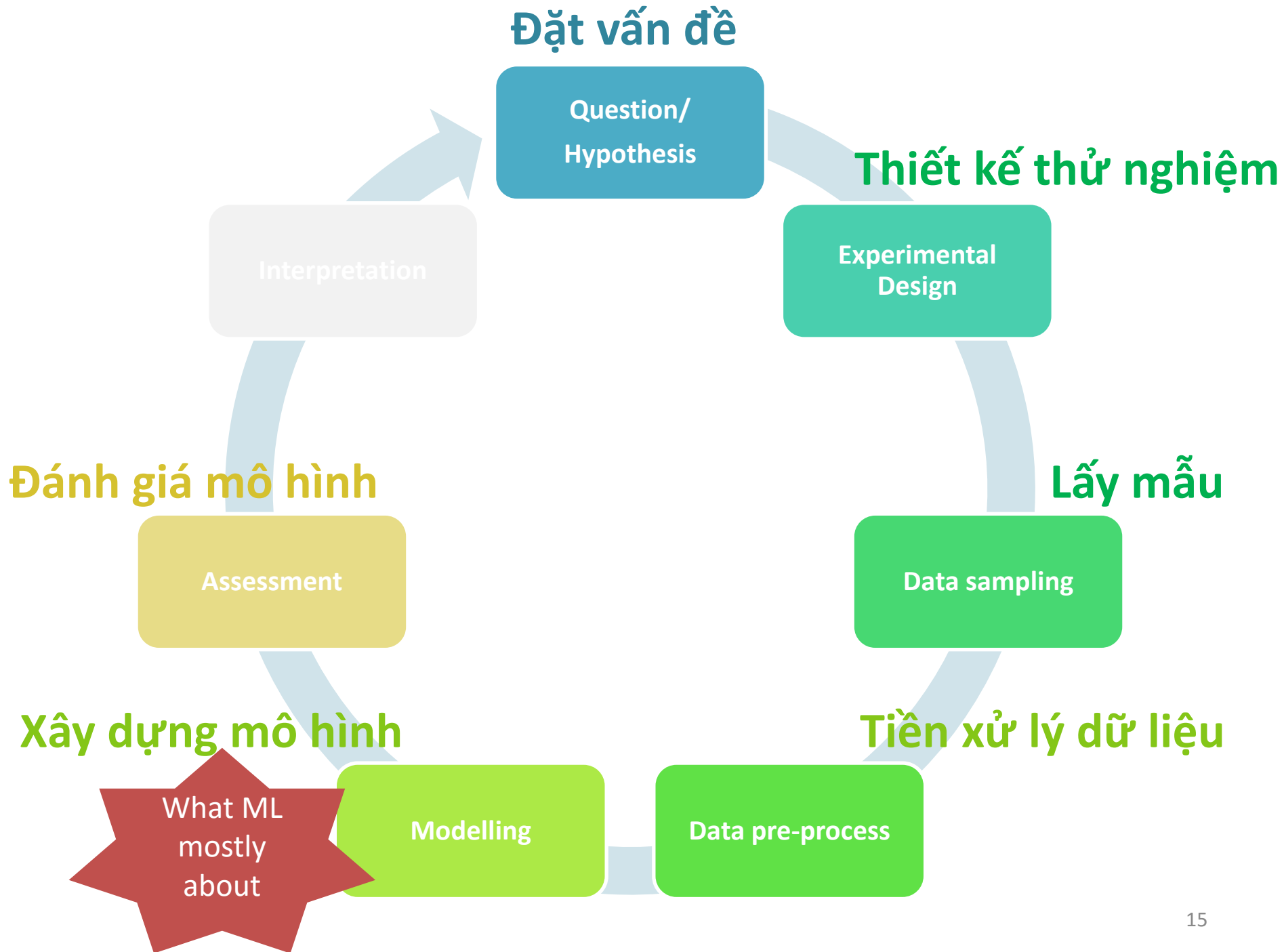
-0.34	-0.46	-0.87
1.47	-0.24	2.21
-1.05	0.02	-1.74
0.09	-0.58	1.02
1.63	-0.53	0.06
1.11	-0.63	-0.93
-0.34	-0.46	-0.87
1.47	-0.24	2.21
-1.05	0.02	-1.74
0.09	-0.58	1.02
1.63	-0.53	0.06
1.11	-0.63	-0.93
0.09	-0.58	1.02
1.63	-0.53	0.06
1.11	-0.63	-0.93
.....

Feature extraction

Tiền xử lý dữ liệu

Modelling

Data pre-process



Vấn đề, câu hỏi mới

Giải thích/phân tích
kết quả

Interpretation

NEW Question/
Hypothesis

Thiết kế thử nghiệm

Experimental
Design

Đánh giá mô hình

Assessment

Lấy mẫu

Data sampling

Xây dựng mô hình

Tiền xử lý dữ liệu

What ML
mostly
about

Modelling

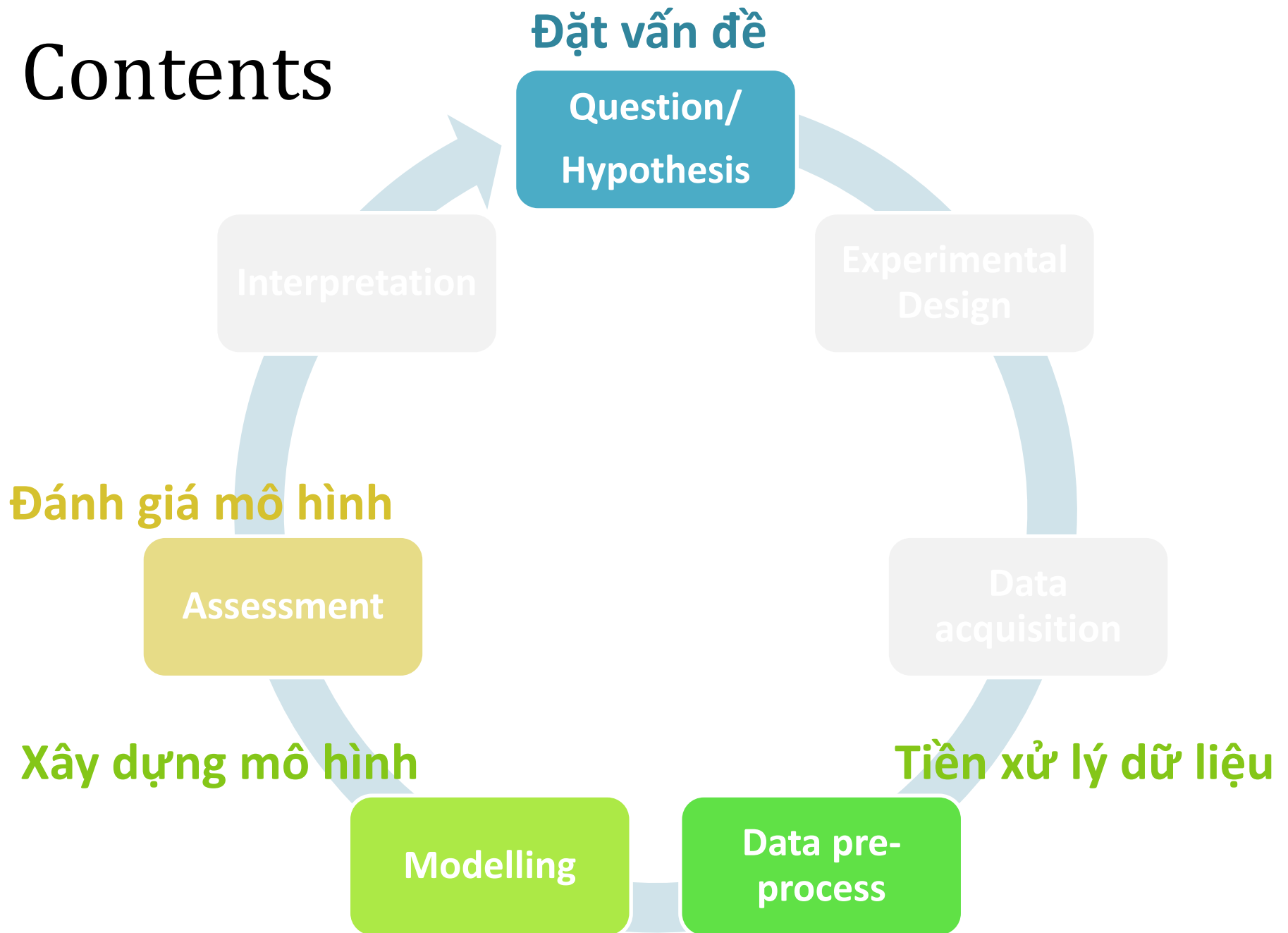
Data pre-process

PRINCIPLES OF MODELLING

Statistical reasoning (*)

() A machine learning algorithm does not necessarily have a probabilistic interpretation, or developed from a statistical framework. Nevertheless, statistical reasoning provides a rigorous mathematical tool for estimation and inference to make optimal decision (e.g. prediction, action) under **uncertainty**, which is one of the ultimate objectives in ML.*

Contents



ML problem: Classification

Question

Is there any cat in an arbitrary photo?

Experience: dataset of {image, label} pairs $\mathcal{D} = \{x_n, y_n\}_{n=1}^N$

Modelling

predict \hat{y}_n – *cat existence* – given arbitrary x_n



Image

x_n
 $\mathbb{N}^{400 \times 600 \times 3}$

Cat?
Not cat?

Prediction

\hat{y}_n
{True, False}

(single-class)

**binary
classification
problem**

**supervised
learning**

Assessment

$$\text{Accuracy} = \frac{1}{N} \sum_n \mathbb{I}(\hat{y}_n = y_n)$$

Precision, Recall, F1-score

Area Under Curve (AUC)

...

Example models:

Logistic regression (linear model)

Neural Net with sigmoid output (nonlinear model)

ML problem: Classification

Question

What is there in an arbitrary photo?

Experience: dataset of {image, label} pairs $\mathcal{D} = \{x_n, y_n\}_{n=1}^N$

Modelling

predict \hat{y}_n – *object identity* – given arbitrary x_n



Image

x_n
 $\mathbb{N}^{400 \times 600 \times 3}$



cat
flower
dog
jet
ground
grass

Prediction

\hat{y}_n
{1,2,3,4,5,6}

(multi-class)

**categorical
classification
problem**

**supervised
learning**

Assessment

$$\text{Accuracy} = \frac{1}{N} \sum_n \mathbb{I}(\hat{y}_n = y_n)$$

Precision, Recall, F1-score

Area Under Curve (AUC)

...

Example models:

Softmax classification (linear model)

Neural Net with softmax output (nonlinear model)

ML problem: Regression

Question

How much is the price of a house given ...

Experience: dataset of {(area, location, #rooms), price} pairs $\mathcal{D} = \{x_n, y_n\}_{n=1}^N$

Modelling

predict \hat{y}_n – *house price* – given arbitrary x_n

Area	100m ²
Location	24.7°N 183.0°E
#Rooms	3

→ \$150,000

Features/Predictors

$$x_n \\ \mathbb{R} \times \mathbb{R}^2 \times \mathbb{N}$$

Prediction

$$\hat{y}_n \\ \mathbb{R}$$

regression
problem

supervised
learning

Assessment

$$\text{squared_errors} = \frac{1}{N} \sum_n (\hat{y}_n - y_n)^2$$

Example models/algorithms:

Linear regression (linear model)

Neural Net with linear output (nonlinear model)

Curve fitting algorithm

ML problem: Clustering

Question

What is the “topic” that a news article is talking about?

Experience: dataset of article content *only* $\mathcal{D} = \{x_n\}_{n=1}^N$

Modelling

predict z_n – “topic” (cluster) identity – given arbitrary x_n

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here, two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 125 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 850 genes are plenty to do the job—but that anything short of 100 wouldn't be enough. Although the numbers don't match precisely, these products are “are not all that far apart,” especially in comparison to the 75,000 genes in the human genome, notes Sten Andersson of Uppsala University in Sweden, who arrived at the 850 number. But coming up with a consensus answer may be more than just a genetic number, particularly as more and more genomes are completely mapped and sequenced. “It may be a way of organizing any newly sequenced genome,” exclaims Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Computing an

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12. Stripping down, Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Article (text)

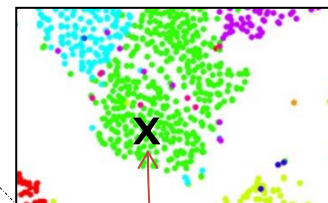
x_n
 $N=1500$



Prediction

z_n
 $\{1, 2, \dots, 10\}$

unsupervised learning



x_n
 $z_n = \text{green}$

Assessment

$$\text{mean_distance_to_clusters} = \frac{1}{N} \sum_n (x_n - \mu_{z_n})^2$$

Example models/algorithms:

k-means algorithm

Generative models: Mixture models, Topic models

Note: “topic” = group/cluster in this context, and is not pre-defined
We will meet the term “topic” again when visiting Topic models

A ML problem can also be:

- both **supervised** and **unsupervised** (*semi-supervised*)
- combination of **regression** and **classification** sub-problems *e.g. image localisation*

Classification: C classes

Input: Image

Output: Class label

Evaluation metric: Accuracy



→ CAT

Localization:

Input: Image

Output: Box in the image (x, y, w, h)

Evaluation metric: Intersection over Union



→ (x, y, w, h)

**Classification
+ Localization**



CAT

PRINCIPLES OF MODELLING

1. **Model structure** - constructs relationships (*stochastic and/or deterministic*) between model elements: data, parameters, and hyper-parameters.

Keywords: graphical model

2. **Learning principle** - defines a framework to estimate unknown parameters (and unobserved i.e. hidden/latent variables)

Keywords: Maximum Likelihood criterion, Bayesian inference, ++ others

3. **Regularisation**

Keywords: over-fitting, Bayesian inference, ++ others

Relevant keywords: L2-regularisation (Ridge), L1-regularisation (LASSO)

- ⇒ **ALGORITHM** - implements 1 + 2 + 3 to train the model

Keywords: (stochastic) gradient descent, Expectation-Maximisation (EM), Variational Inference (VI), sampling-based inference methods

4. **Model selection**

Keywords: cross-validation

Before we get going...

“Mathematics is the art of giving the
same name to different things .”

-Henri Poincaré.

“The purpose of computation is insight, not numbers.”

-Richard Hamming

$$p(\mathbf{w} | \alpha, \beta) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \int \left(\prod_{i=1}^k \theta_i^{\alpha_i - 1} \right) \left(\prod_{n=1}^N \sum_{i=1}^k \prod_{j=1}^V (\theta_i \beta_{ij})^{w_n^j} \right) d\theta,$$
$$p(D | \alpha, \beta) = \prod_{d=1}^M \int p(\theta_d | \alpha) \left(\prod_{n=1}^{I \times d} \sum_{z_{dn}} p(z_{dn} | \theta_d) p(w_{dn} | z_{dn}, \beta) \right) d\theta_d.$$