Essence of Machine Learning (and Deep Learning)

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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

$\Uparrow$

predictive modelling with **sample data**

$\Uparrow$

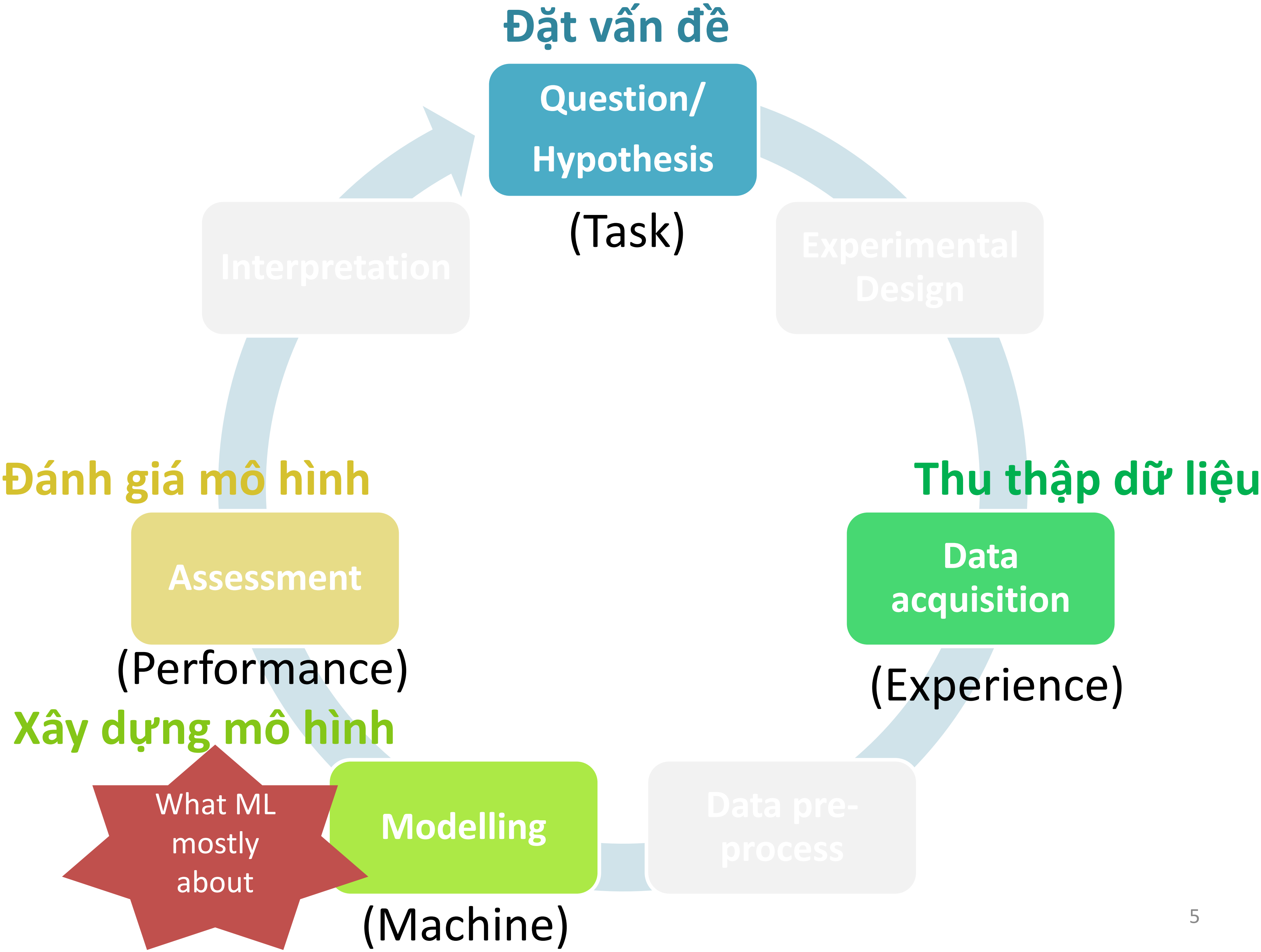
$\boxed{\text{"heurestics" \& statistical modelling}}$

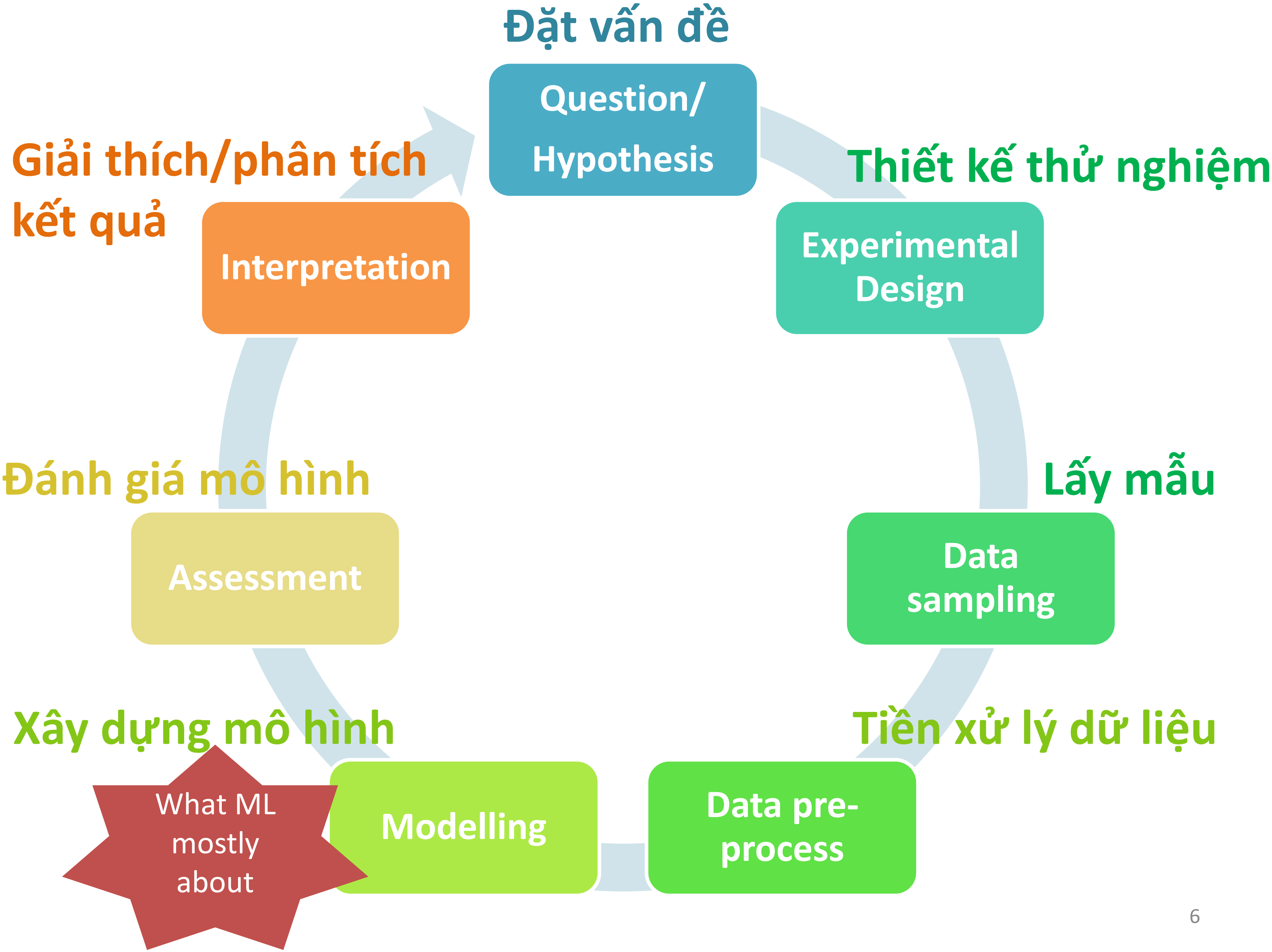
note 1: “heurestic” as in “intuitive, but not (yet!) rigorously proven by mathematical tools at some extend”

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
(Task)
Experimental
Design
Thu thập dữ liệu
Data
acquisition
(Experience)
Data pre-
process
Modelling
(Machine)
What ML
mostly
about
Xây dựng mô hình
Assessment
(Performance)
Đánh giá mô hình
Interpretation



Đặt vấn đề
Question/ Hypothesis
Thiết kế thử nghiệm
Experimental Design
Lấy mẫu
Data sampling
Tiền xử lý dữ liệu
Data pre-process
Xây dựng mô hình
Modelling
What ML mostly about
Đánh giá mô hình
Assessment
Giải thích/phân tích kết quả
Interpretation

Đặt vấn đề

Question/
Hypothesis

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

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

Q.c. Is there any puppy an **abitrary 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?*

Thiết kế thử nghiệm

Experimental Design

(i.e. planning)

Machine Learning

i.e.

Automatic data-driven predictive models

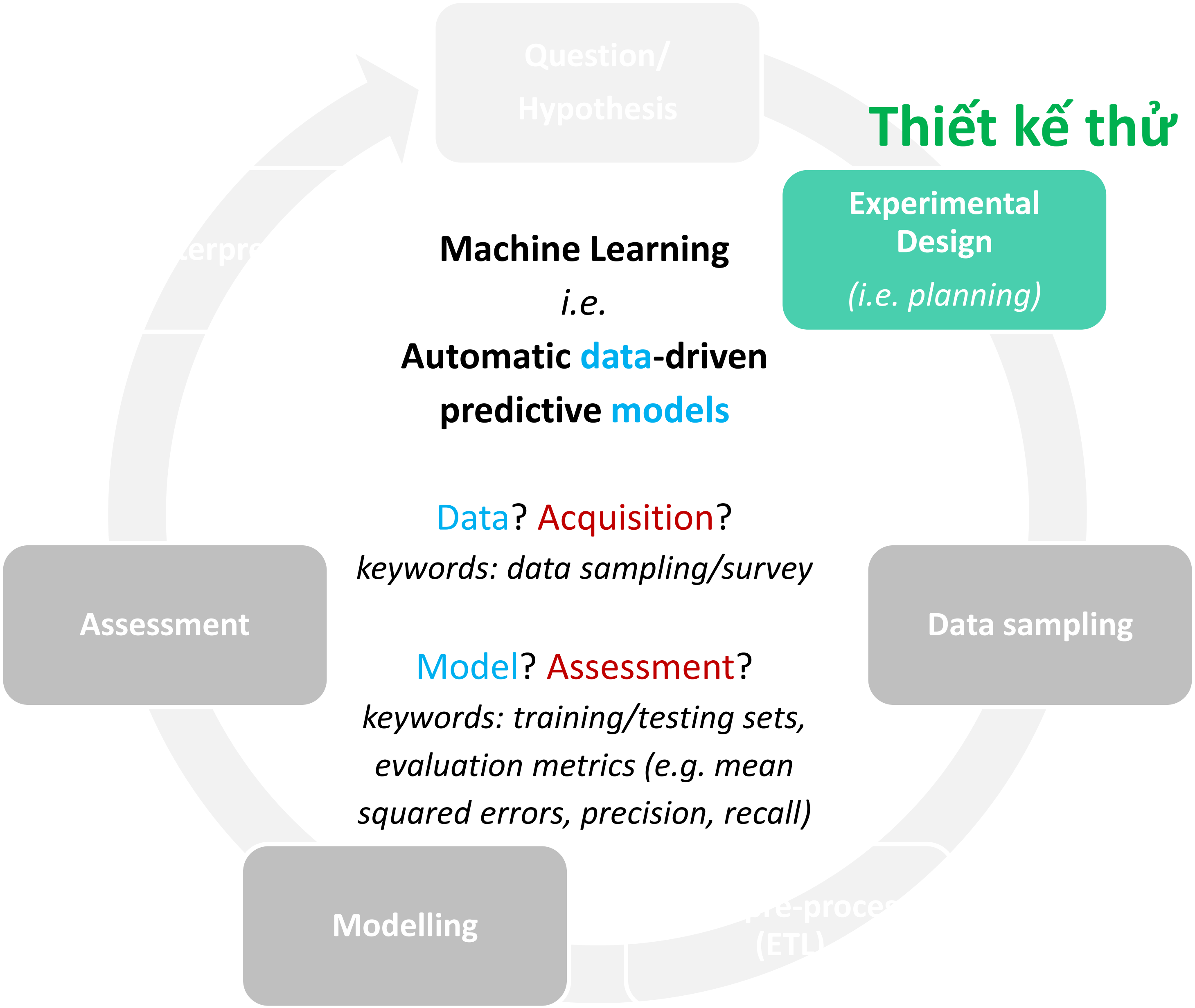
Data? Acquisition?

keywords: data sampling/survey

Model? Assessment?

keywords: training/testing sets, mean squared errors, precision, recall, …

Thiết kế thử nghiệm



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)

Avoid as many sampling biases as possible
http://norvig.com/experiment-design.html

Question/
Hypothesis

Experimental
Design

Data Sampling

Representative sample

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

Sample at which time points?

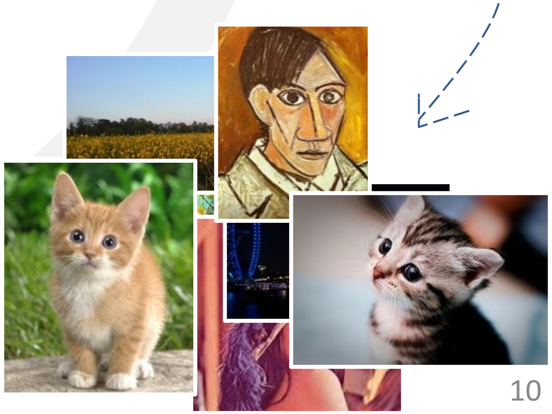
- *Imbalance class?*
- *Selection bias?*

Lấy mẫu

Assessment

Data sampling

Modelling



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

Question/ Hypothesis

Experimental Design

Model Assessment

Evaluation metrics

- *Accuracy*
- *Precision, Recall*
- *Area Under Curve (AUC)*
- *Mean squared errors (MSE)*
- …

(If hypothesis testing problem)

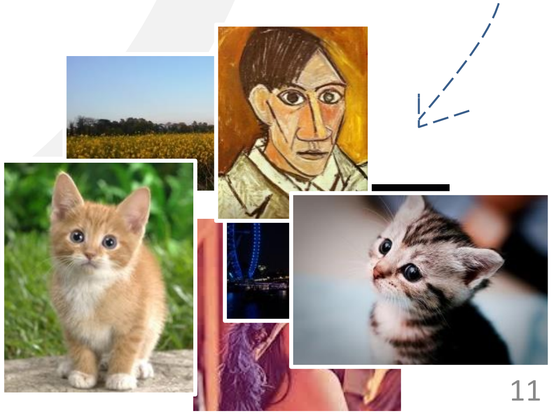
- *t-statistic, z-statistic, χ^2-statistic, …*

Đánh giá mô hình

Assessment

Data sampling

Modelling



```
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.

Question/ Hypothesis

Experimental Design

Model Assessment

Evaluation setup

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

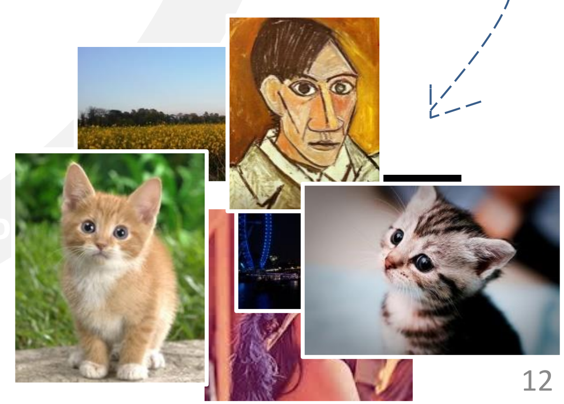
- Training/testing set split: follows data sampling principles
- Repeat experiment: gives measurable confidence to the reported results

Đánh giá mô hình

Assessment

Data sampling

Modelling



```
cat
flower
dog
jet
ground
grass
```

"All models are wrong, but some are useful."
- Box and Drape, 1987

Model Building

Model = a simplification of **reality**

(e.g. map of Hanoi)

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

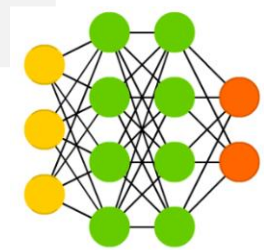
Modelling tip: building model goes from the ***most simplified*** forms to the ***more complex*** to describe reality more precisely

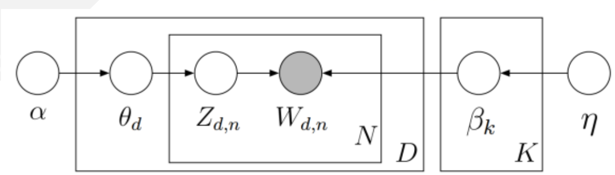
(e.g. building from Linear models to Latent variable models / Deep neural networks)

Xây dựng mô hình

What ML mostly about

Modelling





Graphics:
- http://www.asimovinstitute.org/neural-network-zoo/
- LDA (Blei's KDD 2011 tutorial)

Raw data → Post-processed data

- *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
 ....  ....  ....
```

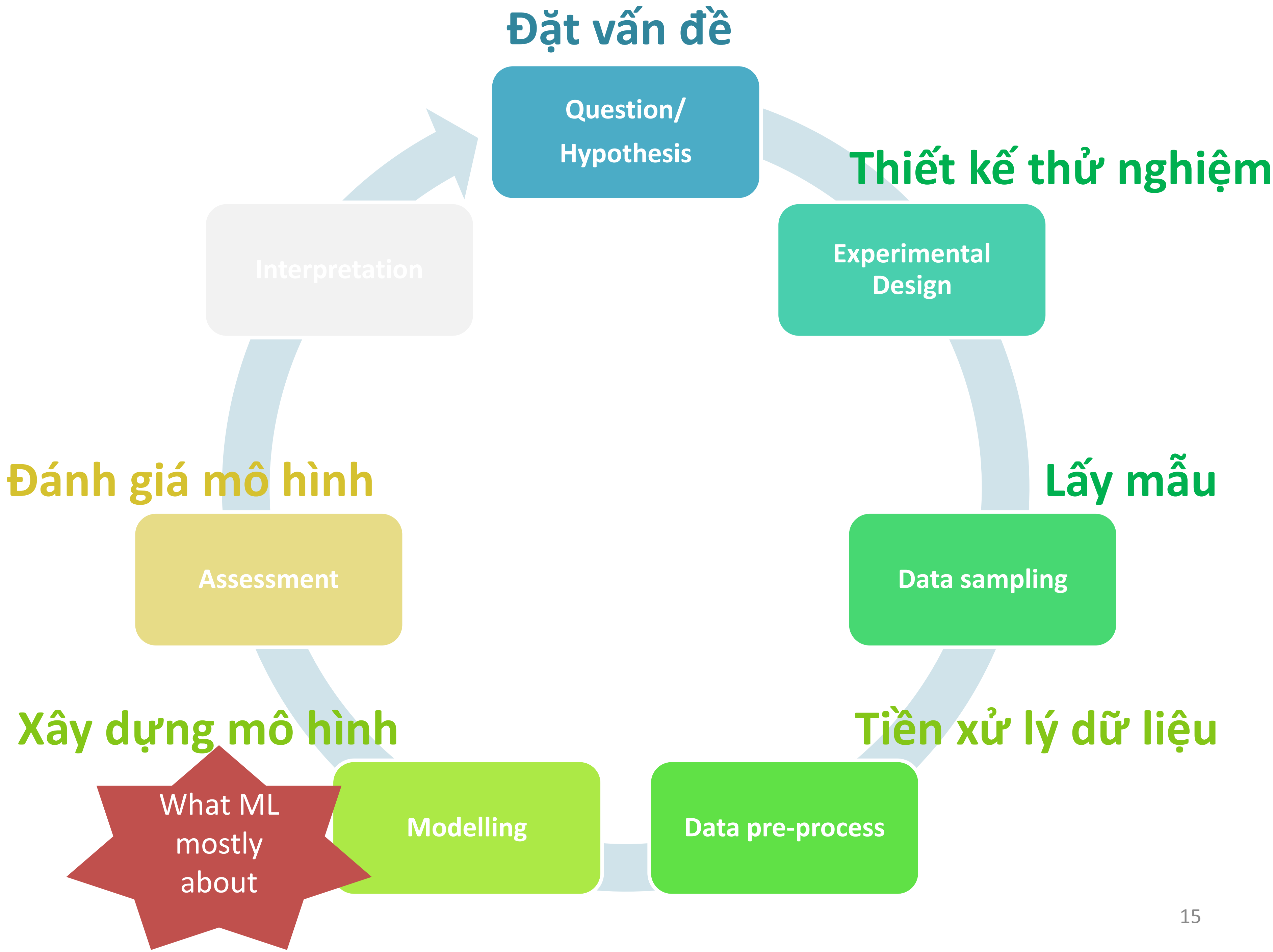
Feature extraction

Foreshadowing: the core idea of ***Deep Learning*** is to incorporate *feature extraction* stage into a model, for which how the features are extracted is also *learnt from the data*.

Tiền xử lý dữ liệu

Modelling

Data pre-process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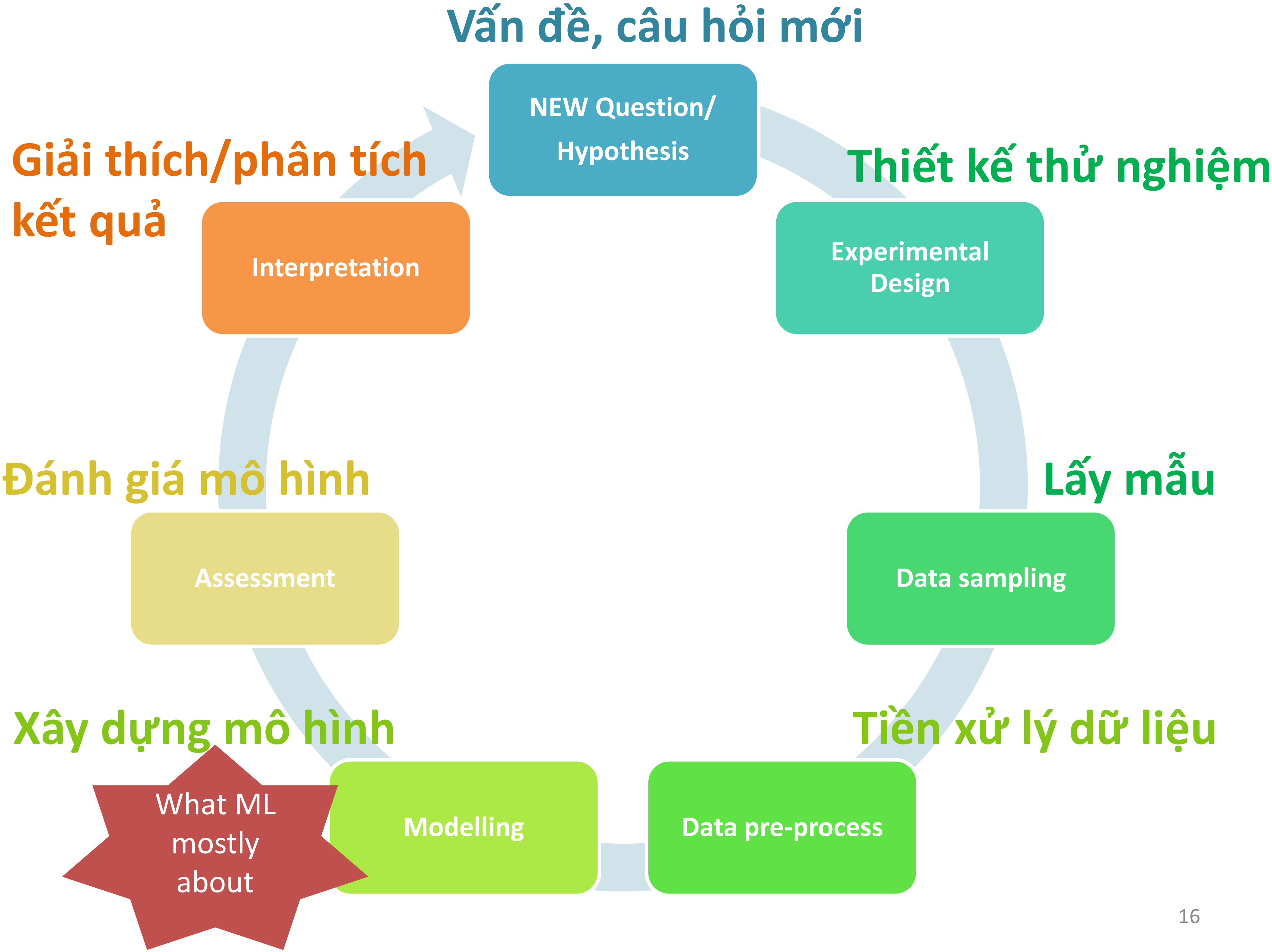
Vấn đề, câu hỏi mới
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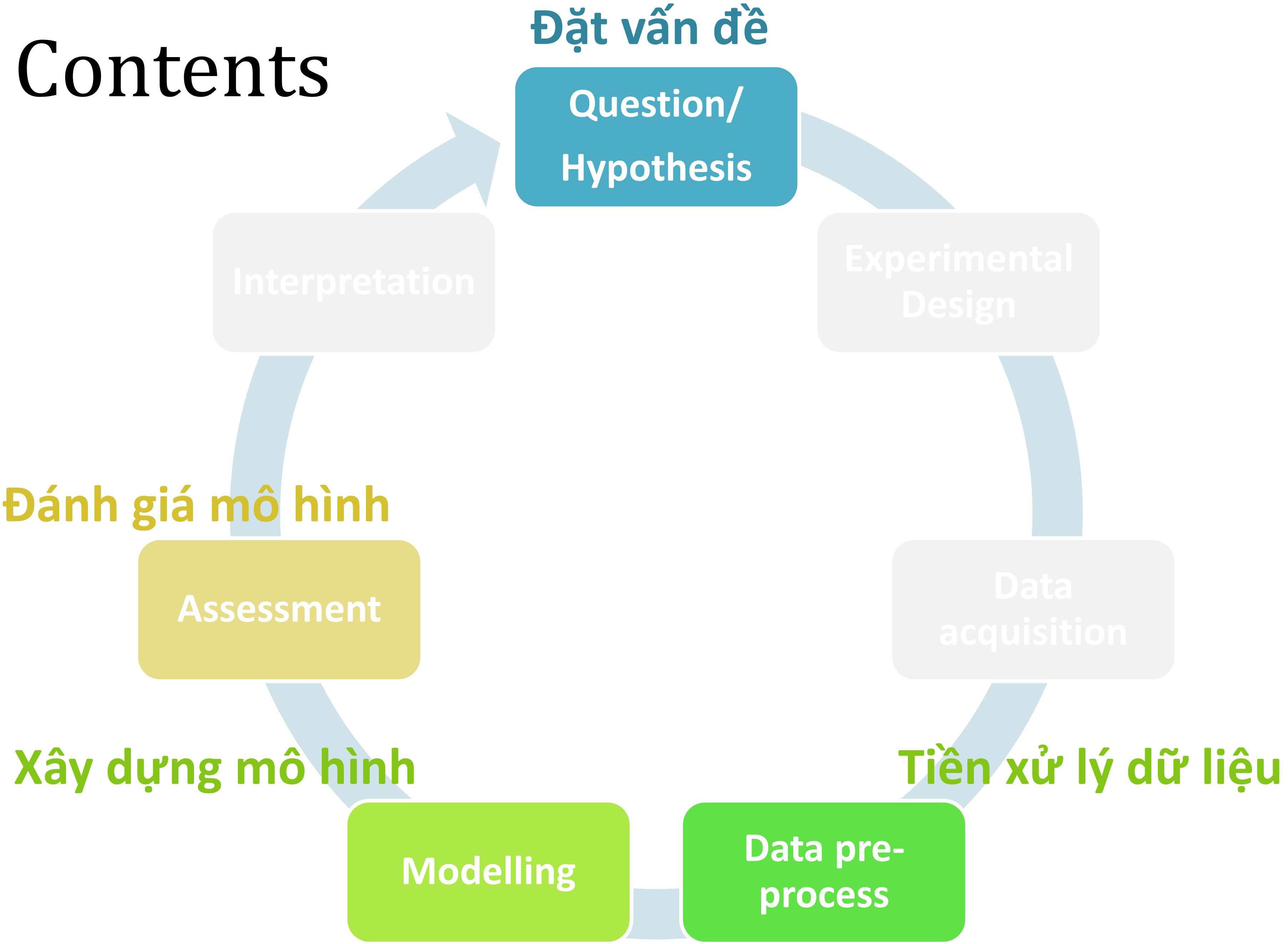
PRINCIPLES OF MODELLING

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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ML problem: Classification

Question

Is there any cat in an abitrary photo?

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

supervised learning

Modelling

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

Cat?
Not cat?

Image

x_n

$\mathbb{N}^{400\times600\times3}$

Prediction

$\hat{y}_n$

$\{\text{True}, \text{False}\}$

(single-class)

binary classification problem

Assessment

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 abitrary 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

cat
flower
dog
jet
ground
grass

Image

x_n
$\mathbb{N}^{400\times600\times3}$

Prediction

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

supervised learning

(multi-class)

categorical classification problem

Assessment

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^{0}N 183.0^{0}E
#Rooms	3

$150,000

supervised learning

Features/Predictors

x_n

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

Prediction

$\hat{y}_n$

$\mathbb{R}$

regression problem

Assessment 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

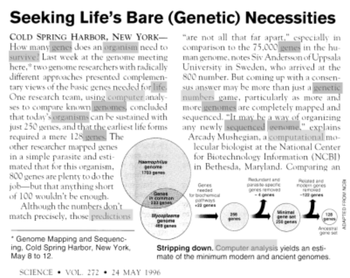
ML problem: Clustering

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 $\boxed{z_n}$ – *"topic" (cluster) identity – given arbitrary* x_n

unsupervised learning



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 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

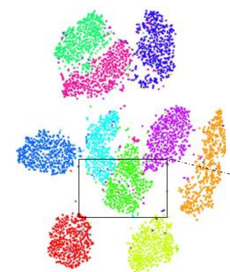
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Article (text)

x_n

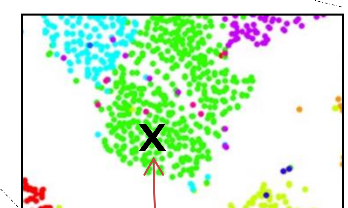
$\mathbb{N}^{1500}$



Prediction

z_n

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



x_n

z_n = **green**

Graphics:

- David Blei, KDD 2011
- https://lvdmaaten.github.io/tsne/examples/mnist_tsne.jpg

Assessment

$$\text{mean\_distance\_to\_clusters} = \frac{1}{N}\sum_n \left(x_n - \mu_{z_n}\right)^2$$

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

Example models/algorithms:
k-means algorithm
Generative models: Mixture models, 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

$$p(\mathbf{w} \mid \alpha, \beta) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \int \left(\prod_{i=1}^{k} \theta_i^{\alpha_i - 1} \right) \left(\prod_{n=1}^{N} \sum_{i=1}^{k} \prod_{j=1}^{V} (\theta_i \beta_{ij})^{w_n^j} \right) d\theta,$$

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d \mid \alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(w_{dn} \mid z_{dn}, \beta) \right) d\theta_d.$$