Introduction to Data Science

(Khoa học dữ liệu)

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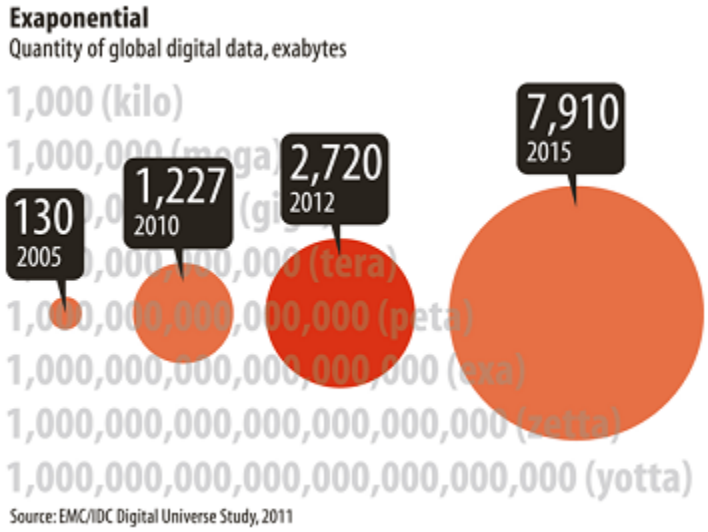
Contents of the course

- Introduction to Data Science
- Data crawling and processing
- Data cleaning and integration
- Exploratory data analysis
- **Machine Learning**
- Big data analysis
- Visualization
- Text analysis
- Image and video analysis
- Graph analysis
- Recommender system

Why Machine Learning?

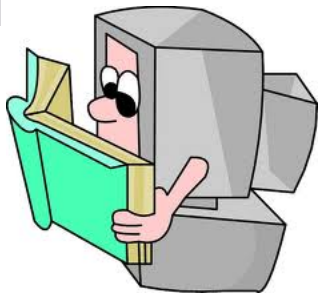
- ML: data mining, inference, prediction
- ML provides an efficient way to make intelligent systems/services.
- ML provides vital methods and a foundation for Big Data.

Each day:
230M tweets,
2.7B comments to FB,
86400 hours of video
to YouTube



What is Machine Learning?

- Machine Learning (ML) is an active discipline of Artificial Intelligence.
- ML seeks to answer the question: [Mitchell, 2006]
  - *How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?*
- Some other views on ML:
  - Build systems that automatically improve their performance [Simon, 1983].
  - Program computers to optimize a performance objective at some task, based on data and past experience [Alpaydin, 2010]

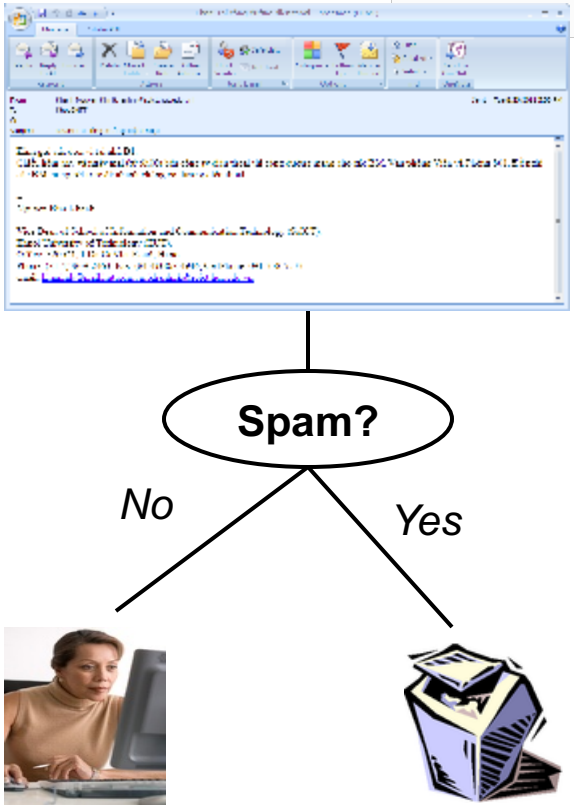


A learning machine

- We say that a machine *learns* if the system reliably improves its performance **P** at task **T**, following experience **E**.
- A *learning problem* can be described as a triple (**P, T, E**).
- ML is close to and intersects with many areas.
  - Computer Science,
  - Statistics, Probability,
  - Optimization,
  - Psychology, Neuroscience,
  - Computer Vision,
  - Economics, Biology, Bioinformatics, …

Some real examples (1)

- Spam filtering for emails
  - **T**: filter/predict the emails that are spam.
  - **P**: the accuracy of prediction, that is the percentage of emails that are correctly classified into normal/spam.
  - **E**: set of old emails, each with a label of spam/normal.



Some real examples (2)

- Image tagging
  - **T**: give some words that describe the meaning of a picture.
  - **P**: ?
  - **E**: set of pictures, each has been labelled with a set of words.

FISH WATER OCEAN
TREE CORAL

PEOPLE MARKET PATTERN
TEXTILE DISPLAY

BIRDS NEST TREE
BRANCH LEAVES

What does a machine learn?

- A mapping (function):

$$f : x \mapsto y$$

  - x: observations (data), past experience
  - y: prediction, new knowledge, new experience,…

- Regression (hồi quy): if y is real
- Classification (phân loại): if y belongs to a discrete set

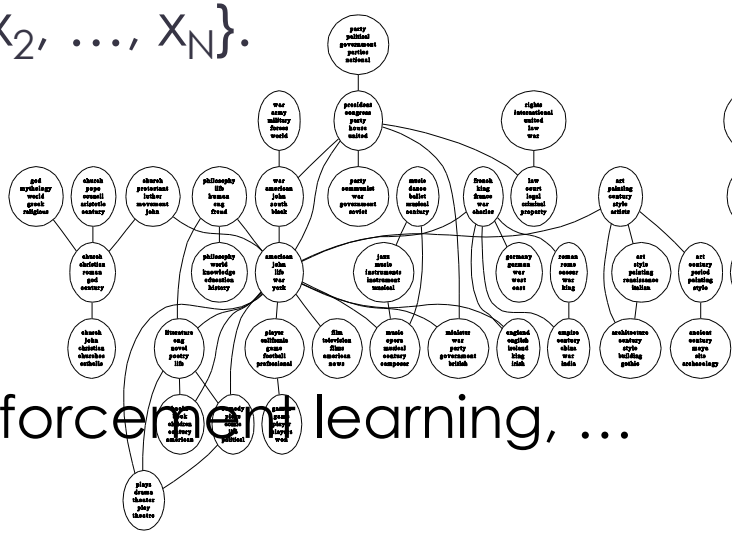
Where does a machine learn from?

- Learn from a set of training observations (**training set**, tập học, tập huấn luyện) { $\{x_1, x_2, \ldots, x_N\}$; $\{y_1, y_2, \ldots, y_M\}$ }
  - x_i is an observation of x in the past.
  - y_j is an observation of y in the past. Y_j is often called ***label*** or ***response***
- After learning:
  - We obtain a function (model, new knowledge, or new experience)
  - We can use that model/function to do *prediction* or *inference* for future observations, e.g.,

$$y = f(x)$$

Two basic learning problems

- **Supervised learning** (học có giám sát): learn a function $y = f(x)$ from a given training set $\{\{x_1, x_2, \ldots, x_N\}; \{y_1, y_2, \ldots, y_N\}\}$ so that $y_i \cong f(x_i)$ for every i.
  - *Classification* (categorization, **phân loại**): if y only belongs to a discrete set, for example {spam, normal}
  - *Regression* (**hồi quy**): if y is a real number
- **Unsupervised learning** (học không giám sát): learn a function $y = f(x)$ from a given training set $\{x_1, x_2, \ldots, x_N\}$.
  - y can be a data cluster
  - y can be a hidden structure
  - y can be a trend



- Other: semi-supervised learning, reinforcement learning, …

Supervised learning: classification

- ***Multiclass*** *classification (phân loại nhiều lớp):* when the output y is one of the pre-defined labels $\{c_1, c_2, \ldots, c_L\}$
  (mỗi đầu ra chỉ thuộc 1 lớp, mỗi quan sát x chỉ có 1 nhãn)
  - Spam filtering: y in {spam, normal}
  - Financial risk estimation: y in {high, normal, no}
  - Discovery of network attacks: ?

- ***Multilabel*** *classification (phân loại đa nhãn):* when the output y is a subset of labels
  (mỗi đầu ra là một tập nhỏ các lớp;
  mỗi quan sát x có thể có nhiều nhãn)
  - Image tagging: y = {birds, nest, tree}
  - sentiment analysis

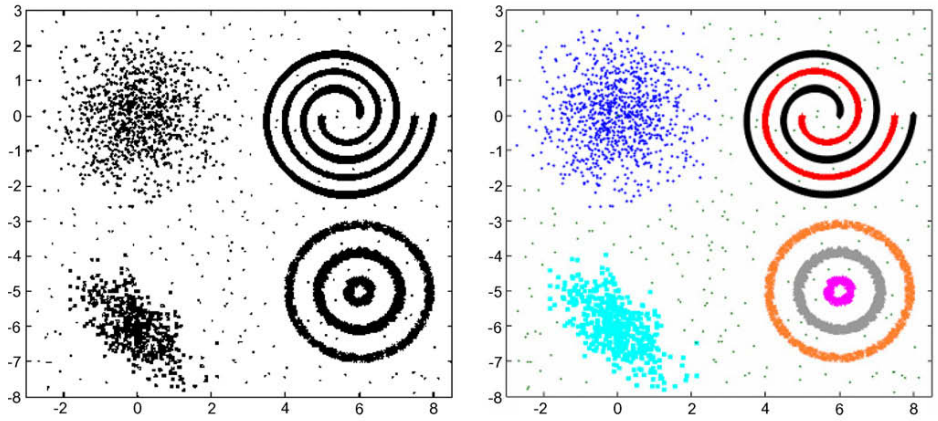
BIRDS NEST TREE

Supervised learning: Regression

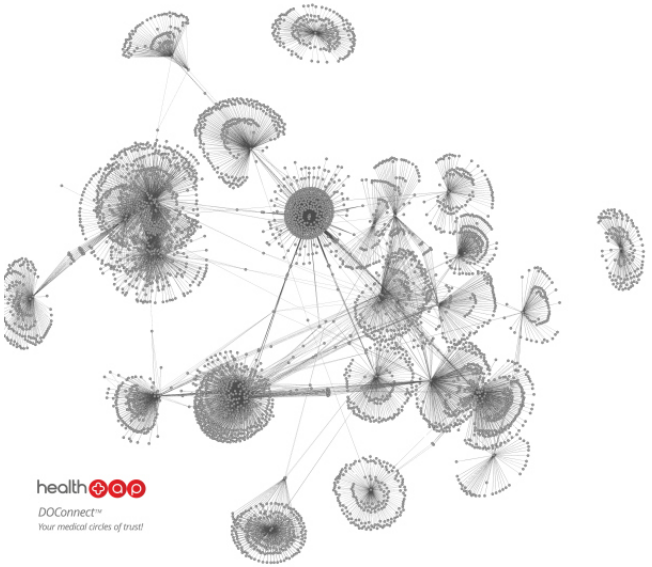
- Prediction of stock indices

Unsupervised learning: examples (1)

- Clustering data into clusters
  - Discover the data groups/clusters

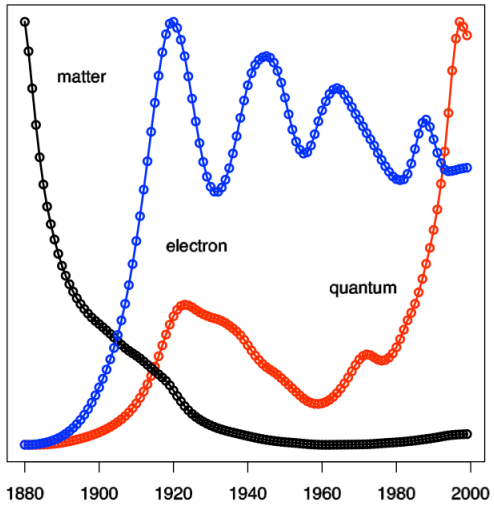


- Community detection
  - Detect communities in online social networks



Unsupervised learning: examples (2)

- Trends detection
  - Discover the trends, demands, future needs of online users



Design a learning system (1)

- Some key issues should be carefully considered when designing a learning system.
- Select a training set:
  - The training set plays the key role in the effectiveness of the system.
  - Do the observations have any label?
  - The training observations should characterize the whole data space →good for future predictions.
- Determine the type of the function to be learned
  - F: $X \rightarrow \{0,1\}$
  - F: $X \rightarrow$ set of labels/tags
  - F: $X \rightarrow R$

Design a learning system (2)

- Select a representation for the function: (model)
  - Linear?
  - Polynomial?
  - A set of rules?
  - A decision tree? …
- Select a good algorithm to approximate the function:
  - Ordinary least square? Ridge regression?
  - Random forest?
  - Back-propagation?

ML: some issues (1)

- **Learning algorithm**
  - Under what conditions the chosen algorithm will (asymtotically) converge?
  - For a given application/domain and a given objective function, what algorithm performs best?
- *No-free-lunch theorem* [Wolpert and Macready, 1997]: if an algorithm performs well on a certain class of problems then it necessarily pays for that with degraded performance on the set of all remaining problems.
  - *No algorithm can beat another on all domains.*
    (không có thuật toán nào luôn hiệu quả nhất trên mọi miền ứng dụng)

ML: some issues (2)

- **Training data**
  - *How many observations* are enough for learning?
  - Whether or not does the *size of the training set* affect performance of an ML system?
  - What is the effect of the *disrupted* or *noisy* observations?

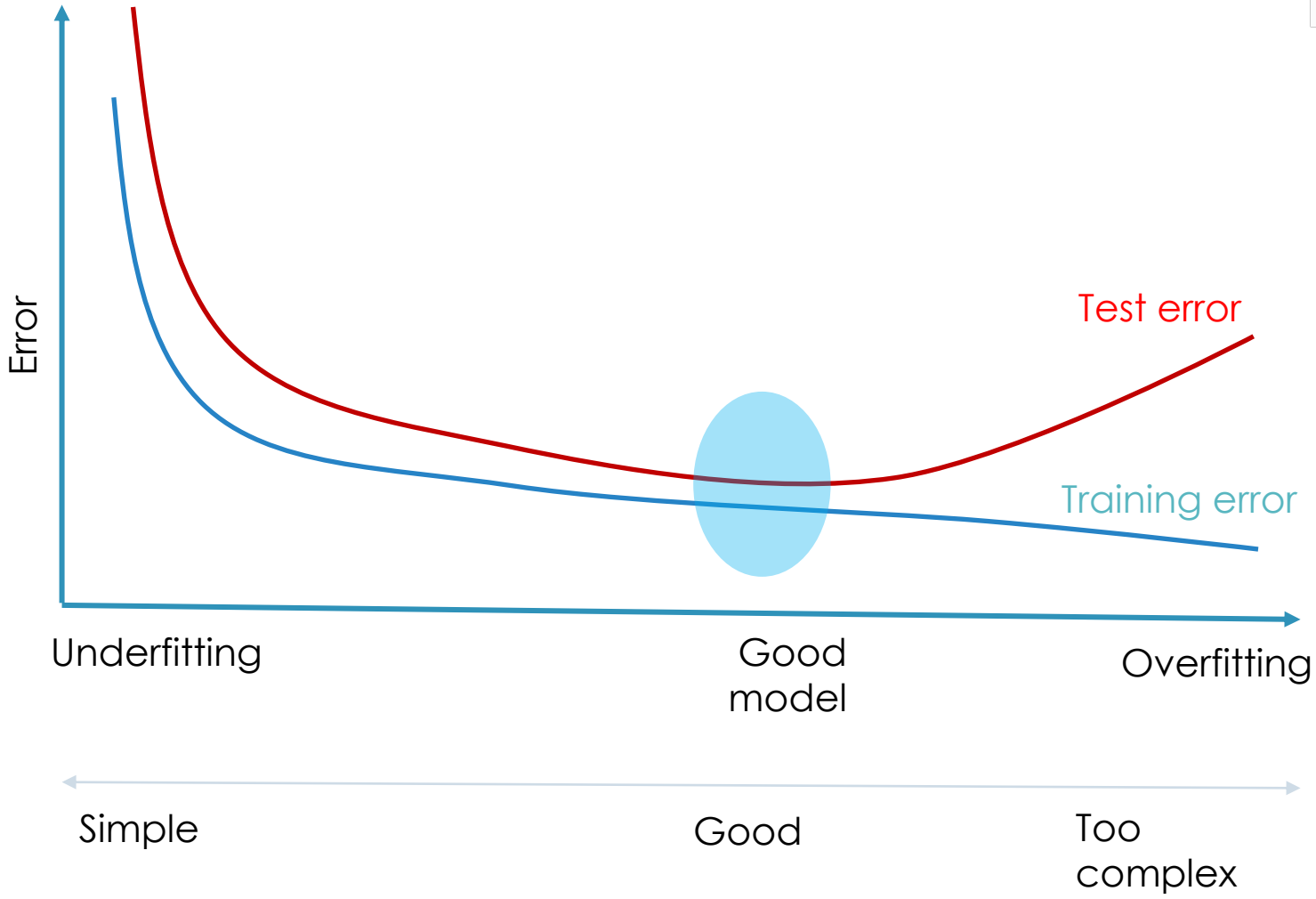
ML: some issues (3)

- **Learnability**:
  - The goodness/limit of the learning algorithm?
  - What is the generalization (**tổng quát hoá**) of the system?
    - Predict well new observations, not only the training data.
    - Avoid overfitting.

Overfitting (quá khớp, quá khít)

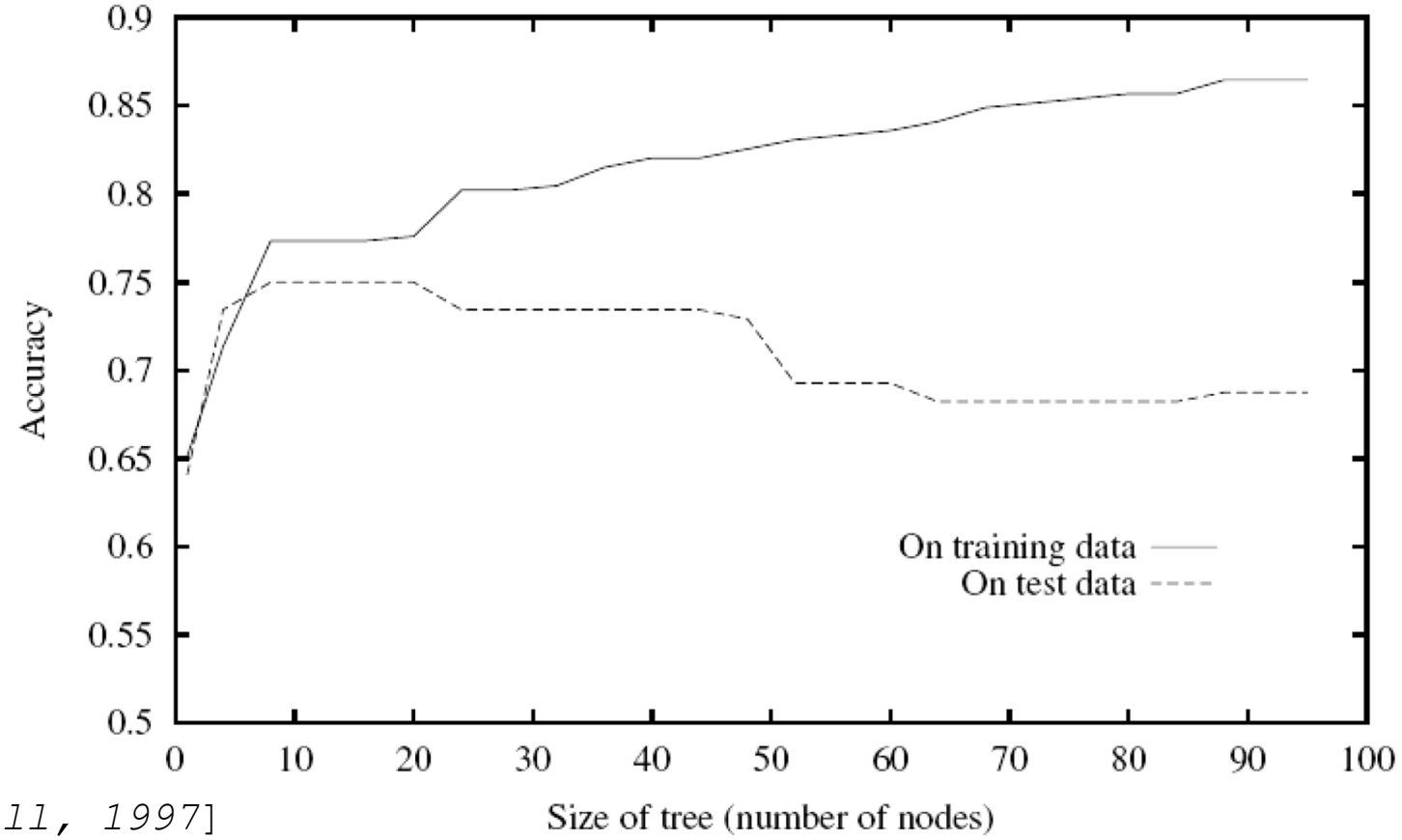
- Function h is called *overfitting* if there exists another function g such that:
  - g might be worse than h for the training data, but
  - g is better than h for future data.
- A learning algorithm is said to overfit relative to another one if it is *more accurate in fitting* known data, but *less accurate in predicting* unseen data.
- Overfitting is caused by many factors:
  - The function/model is too complex or have too much parameters.
  - Noises or errors are present in the training data.
  - The training size is too small, not characterizing the whole space.

Overfitting



Overfitting: example

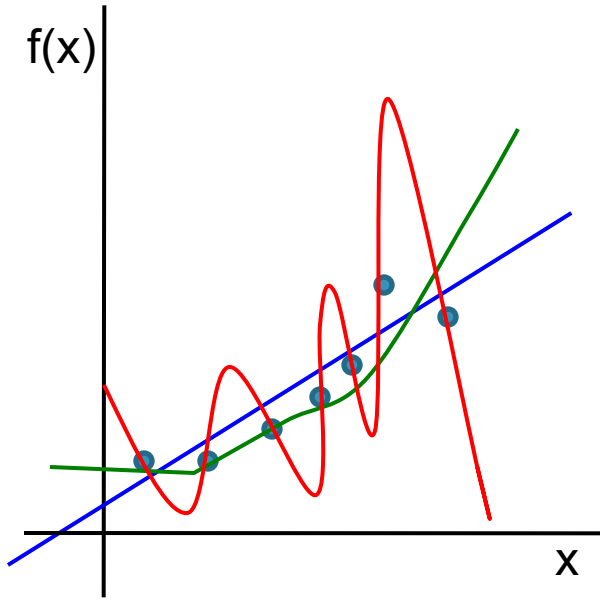
- Increasing the size of a decision tree can degrade prediction on unseen data, even though increasing the accuracy for the training data.



[*Mitchell, 1997*]

Overfitting: Regularization

- Among many functions, which one can generalize best from the given training data?
  - *Generalization is the main target of ML.*
  - Predict well with unseen data.
- **Regularization:** a popular choice
  - Restrict the function space



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