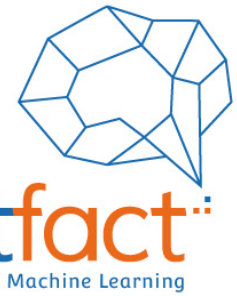
Approches prédictives dans le digital

Online and Unsupervised Learning

Sébastien Loustau, CEO

Chaire DAMI, le 28 Mars 2017



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Machine learning

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Machine learning

$$x \longrightarrow \boxed{\text{nature}} \longrightarrow y$$

- **prédire** la réponse y à partir de x,

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Machine learning

$$x \longrightarrow \boxed{\text{nature}} \longrightarrow y$$

- **prédire** la réponse y à partir de x,
- **comprendre** le lien entre x et y.

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$$x \longrightarrow \boxed{\text{algorithm}} \longrightarrow \widehat{y}$$

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Statistical Learning vs Online Learning

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Real time ML : un enjeu de taille

DATA

stockage massif
et couteux

analyses
off-line

décision tardive

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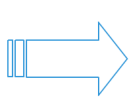
Real time ML : un enjeu de taille

analyses
on-line



décision
temps réel

stockage
allégé

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Supervised learning

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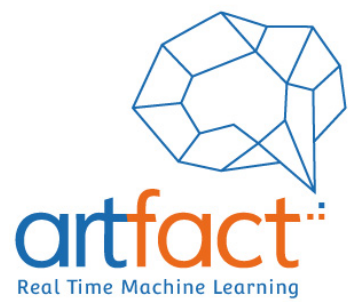
Today : unsupervised learning



Today : unsupervised learning

$$\boxed{\text{nature}} \longrightarrow x$$

- décrire les observations x,

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Real Time Machine Learning

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- grouper les observations x.

Today : unsupervised learning

$$\boxed{\text{nature}} \longrightarrow x$$

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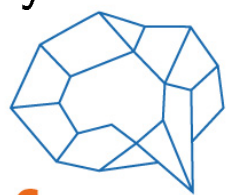
Vanilla algorithms and recent hot topics

PCA, k-means, gaussian mixtures, change points or more recently words embeddings, community detection, generative models (GAN)...



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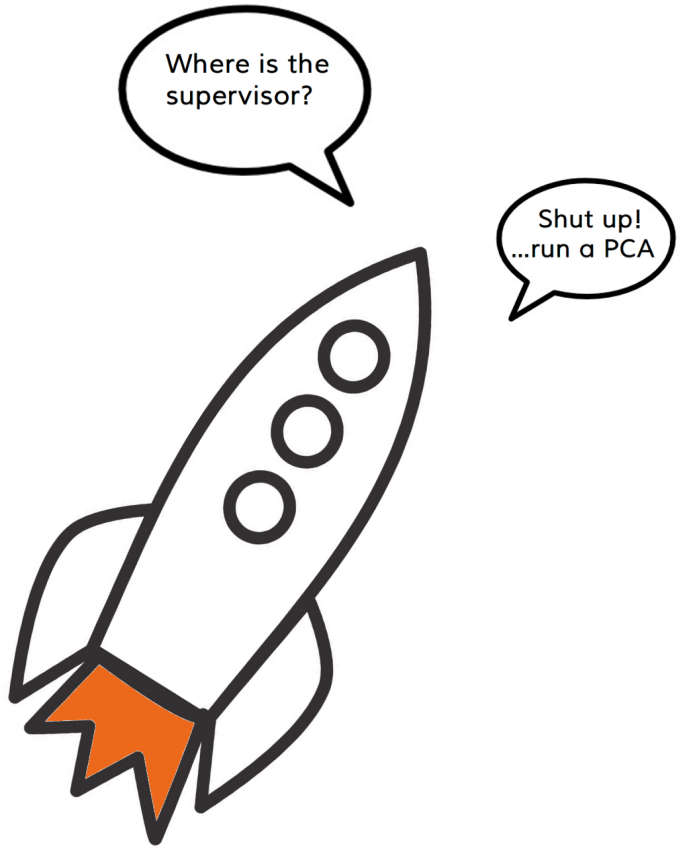
Qu'est-ce que ça change ?



UNSUPERVISED LEARNING

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Supervised routine

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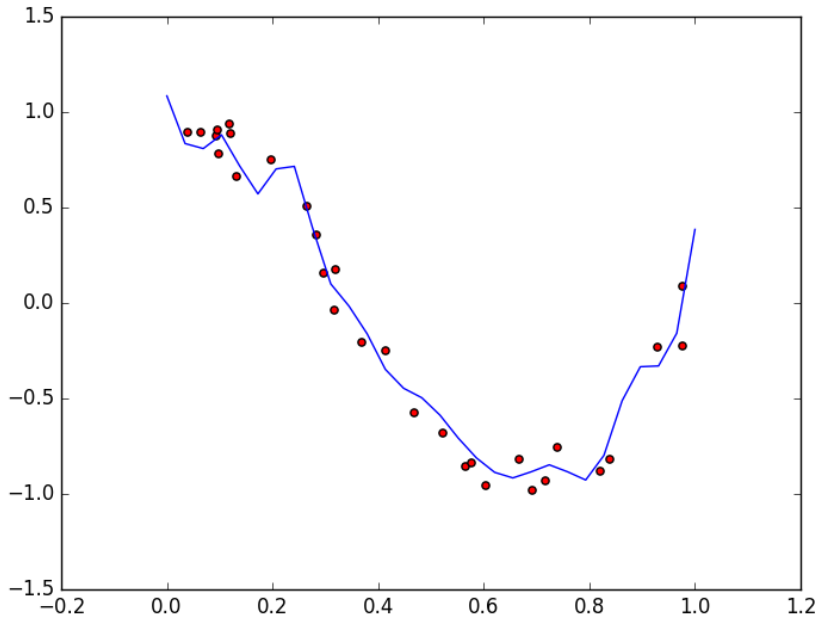

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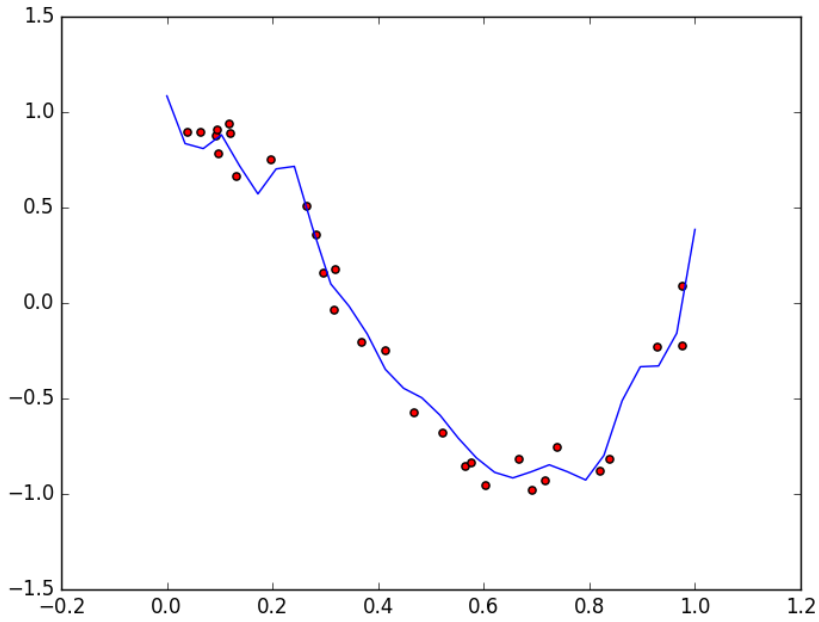

- Solution : Training set + test set, Leave-One-Out, V-fold Cross validation.

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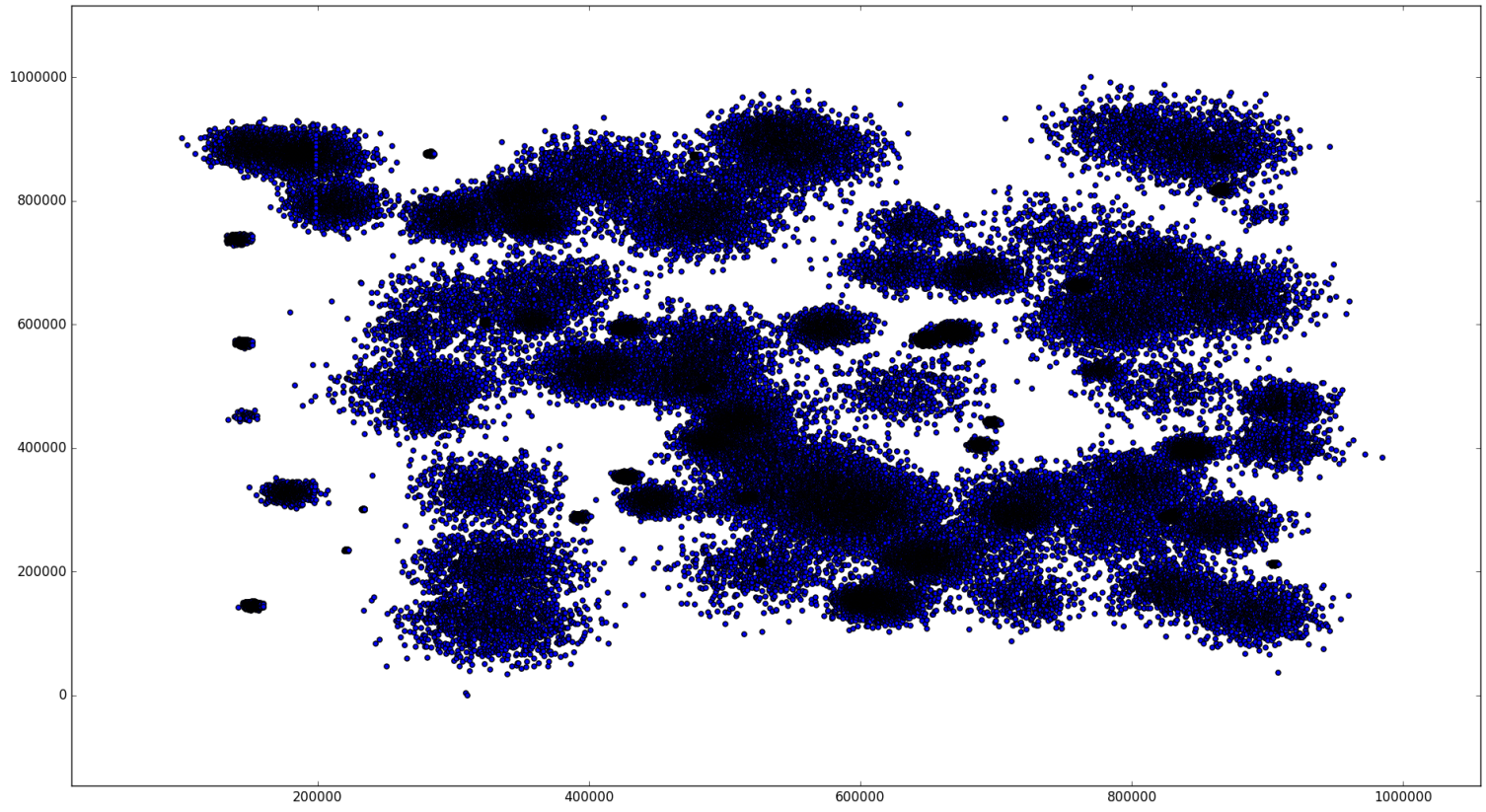
Unsupervised : science or art ?



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Unsupervised : the hype

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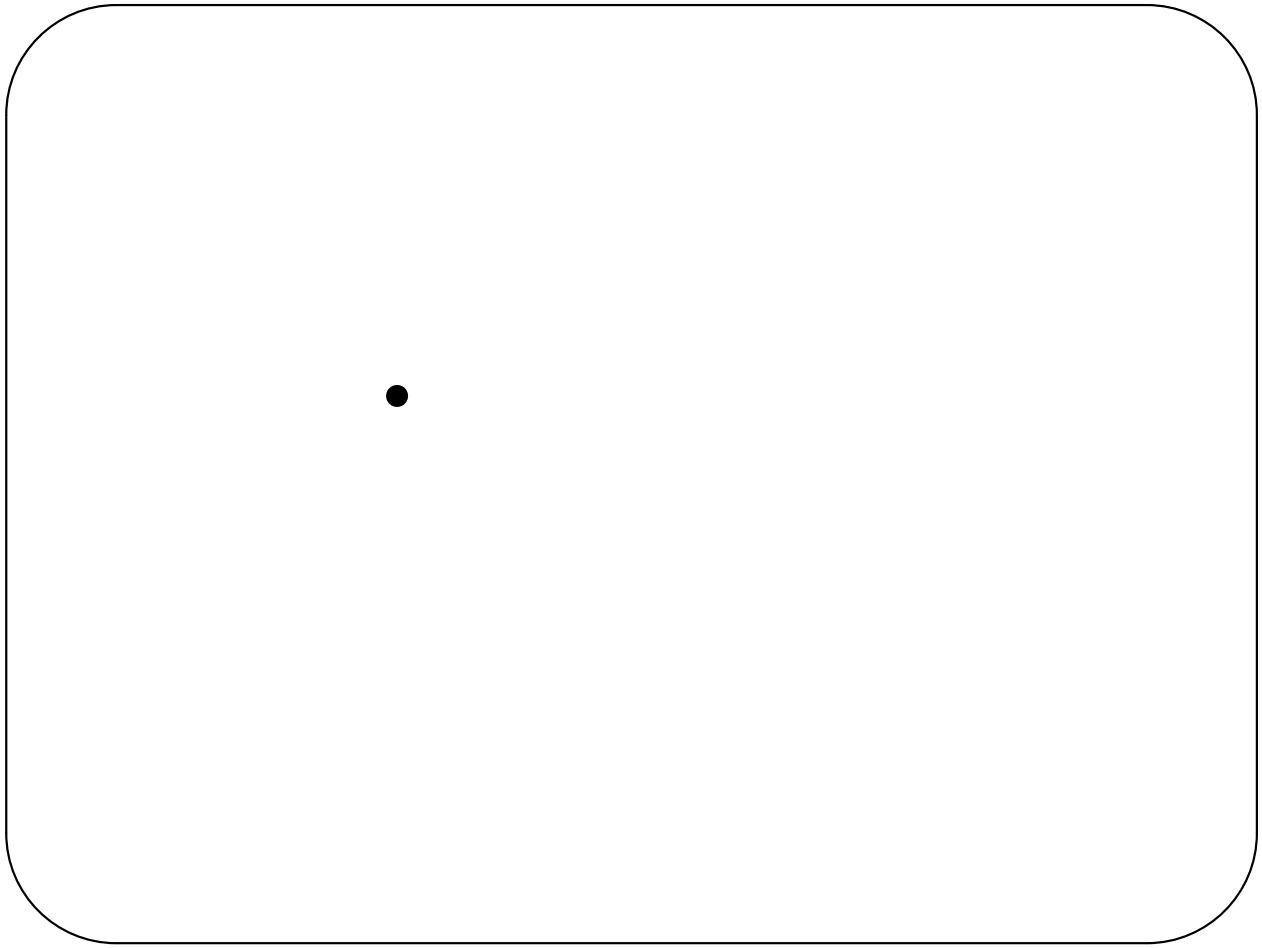

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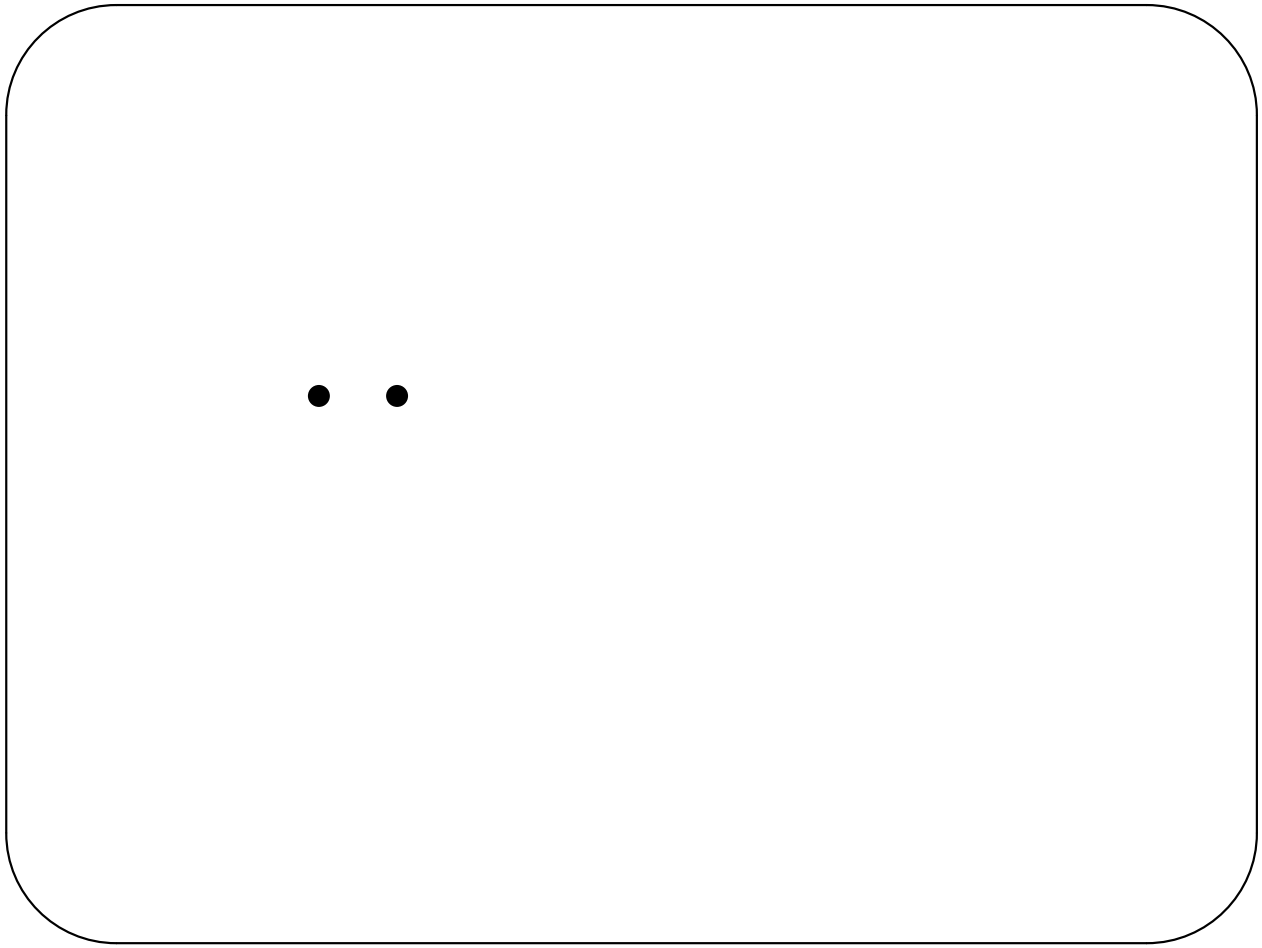

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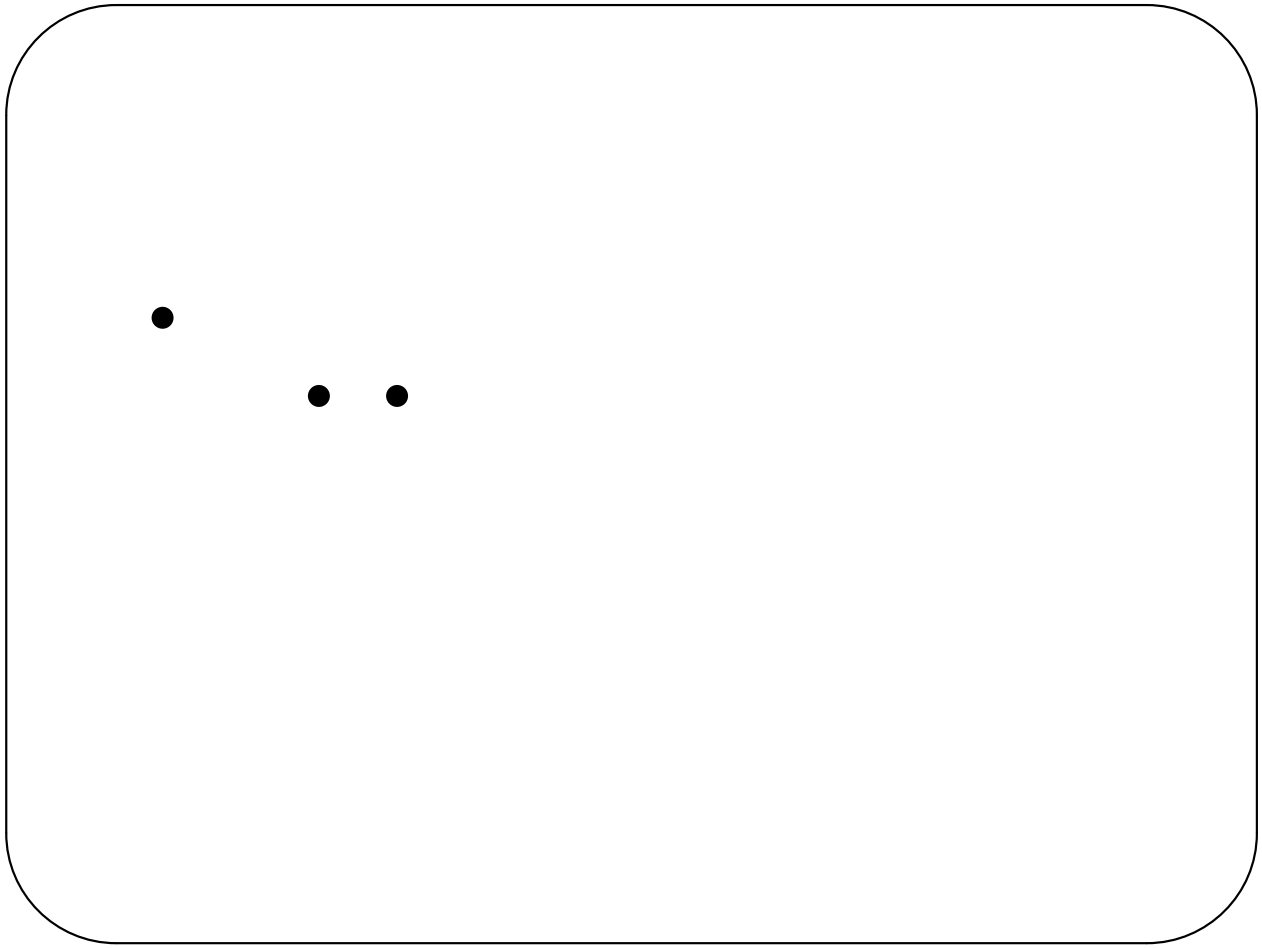

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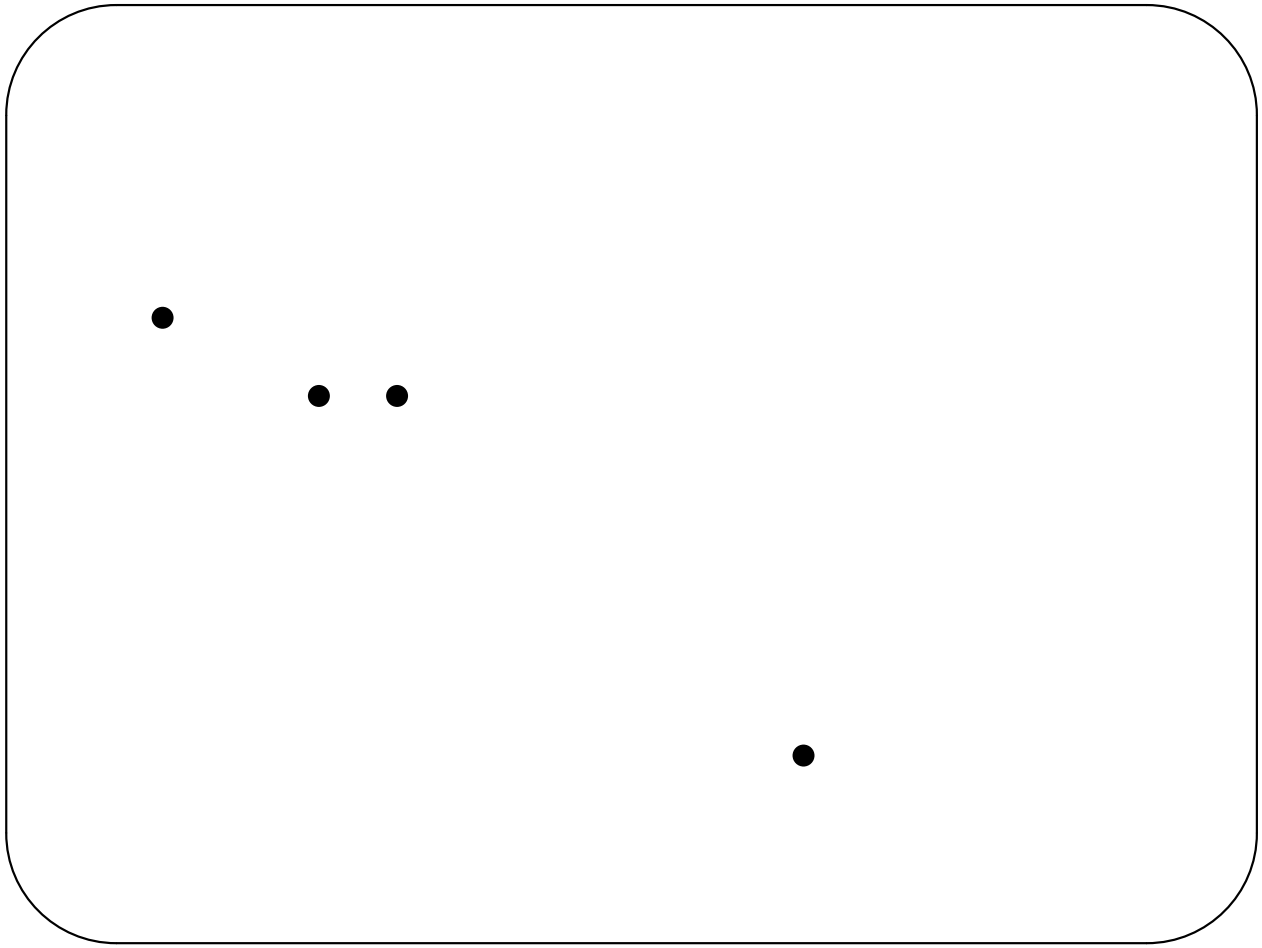

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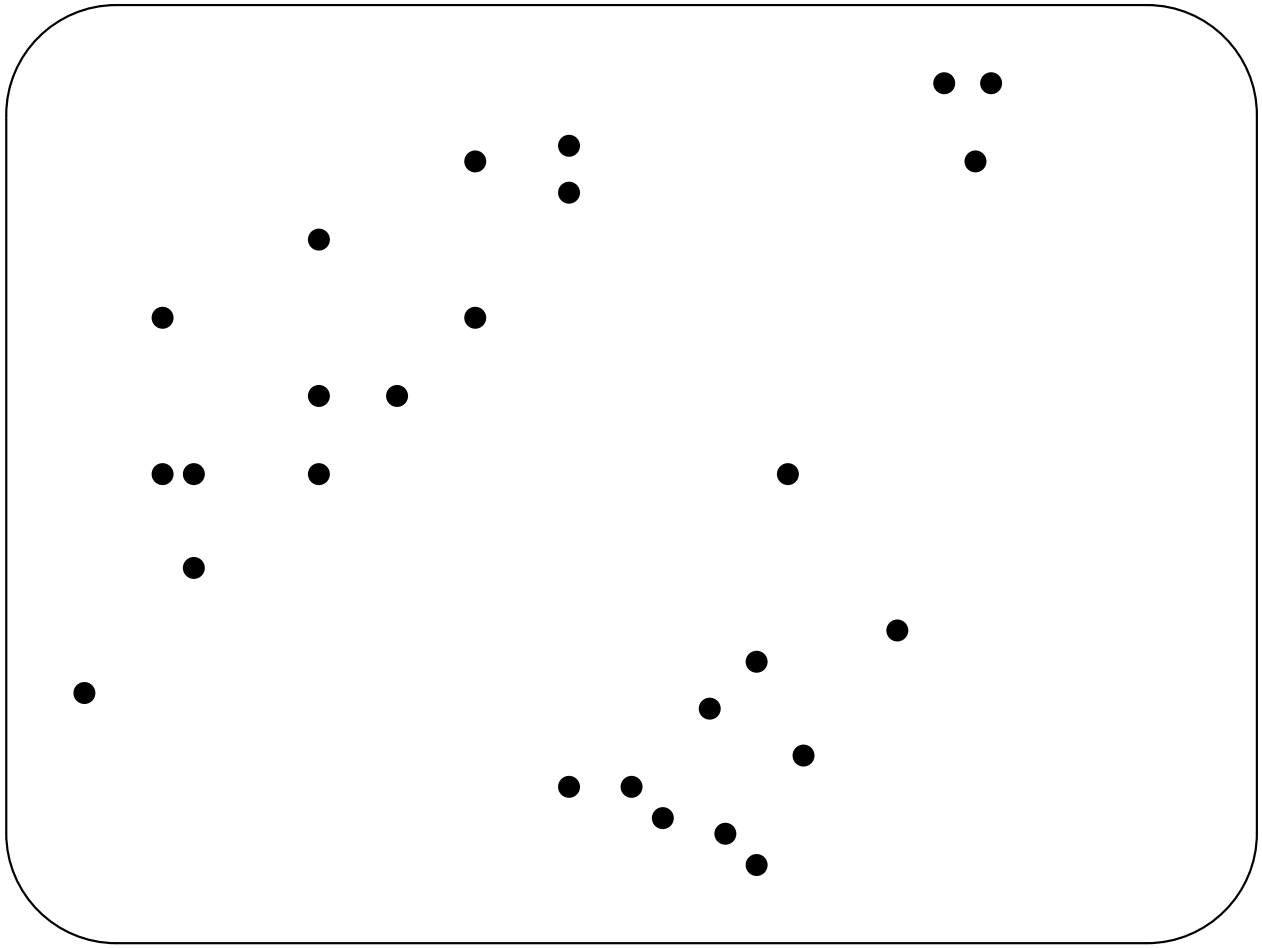

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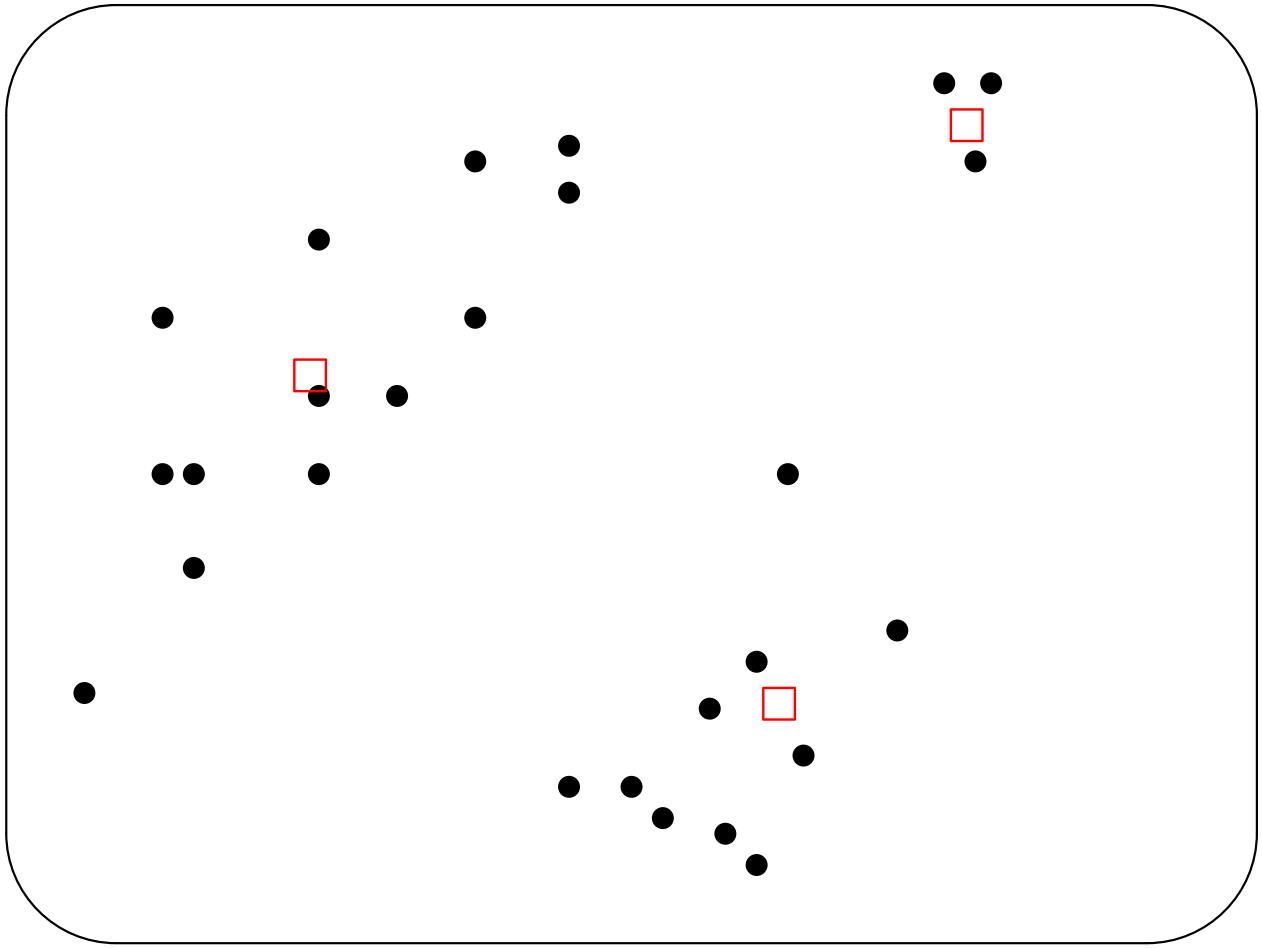

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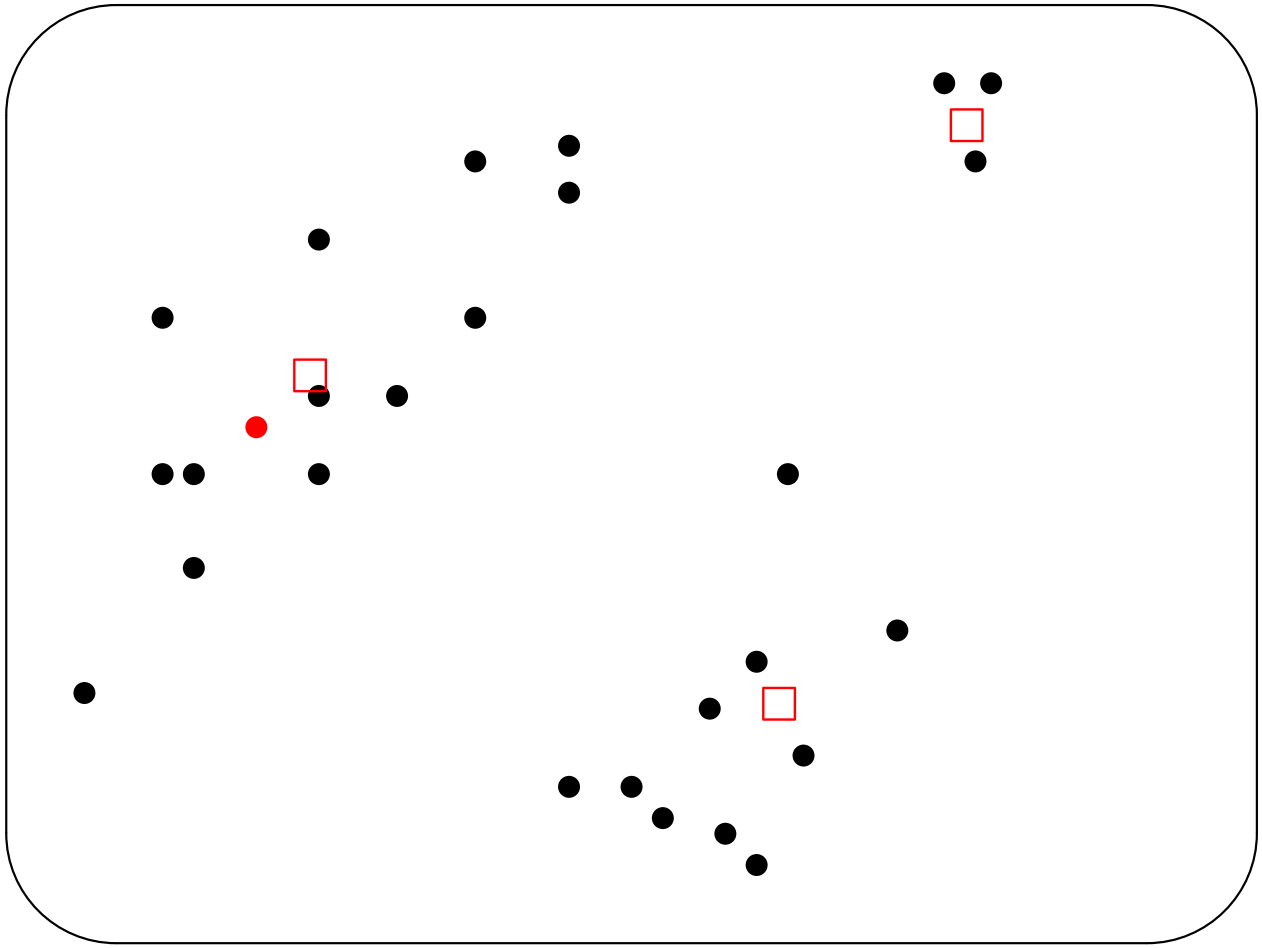

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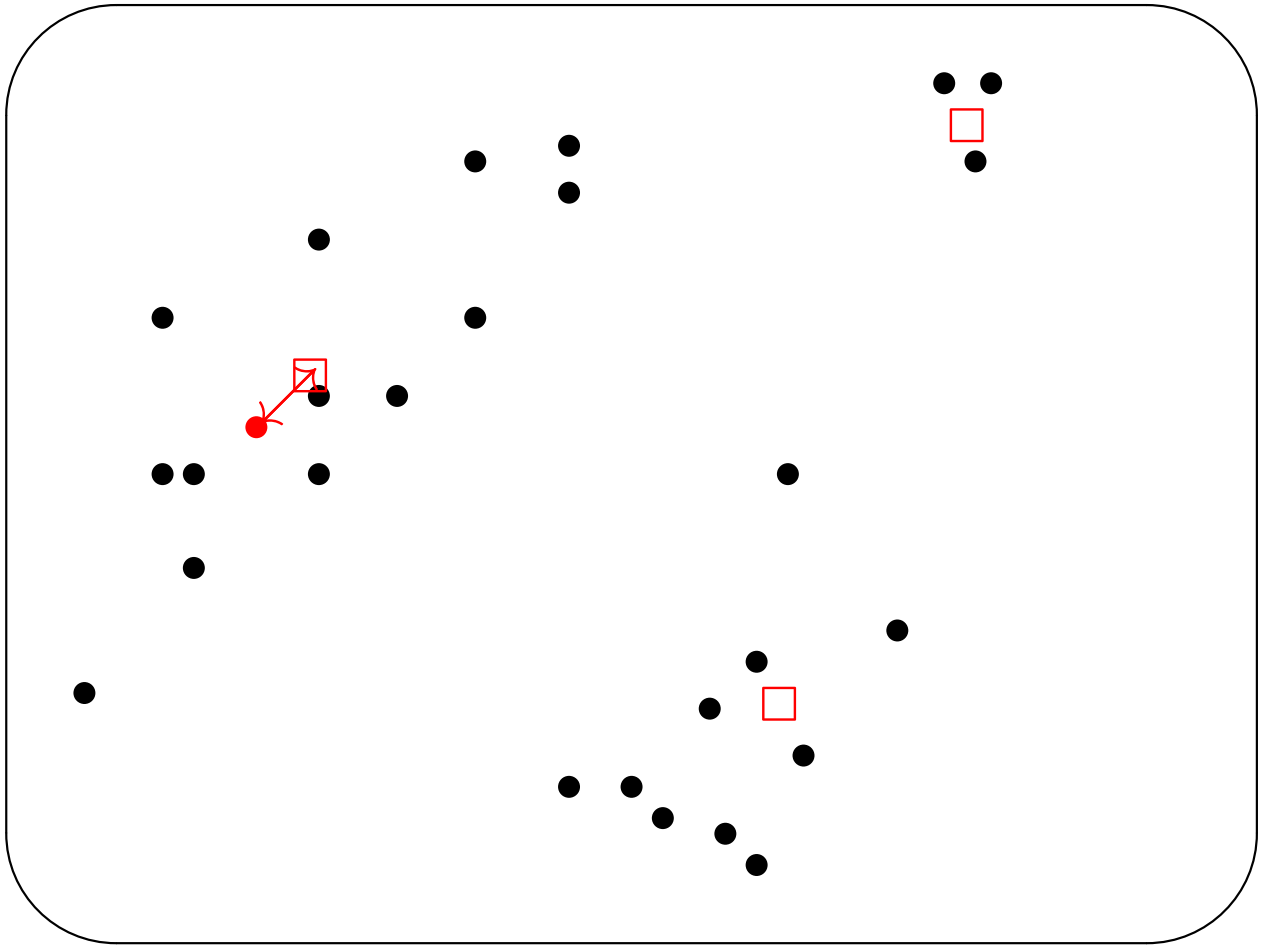

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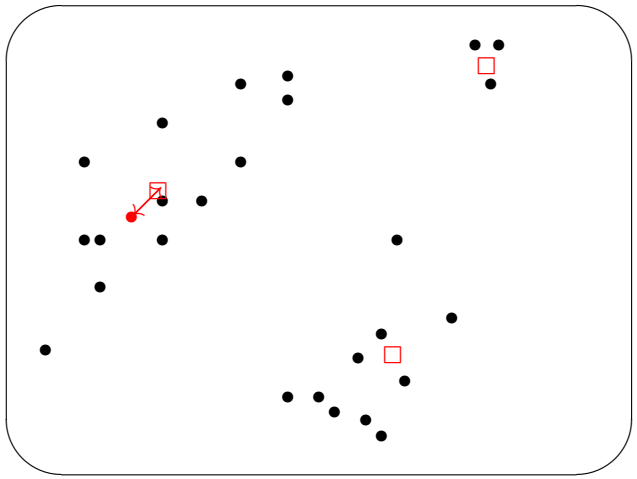

- Principle : clustering as prediction !

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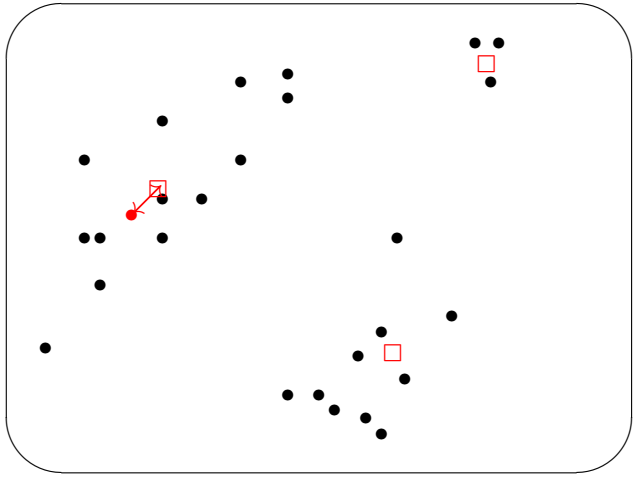

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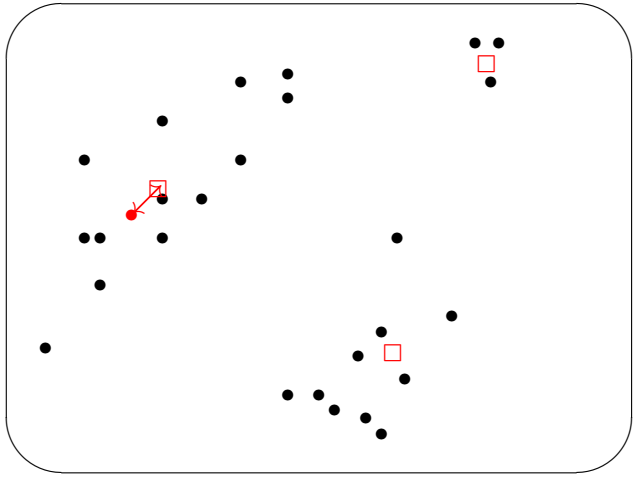

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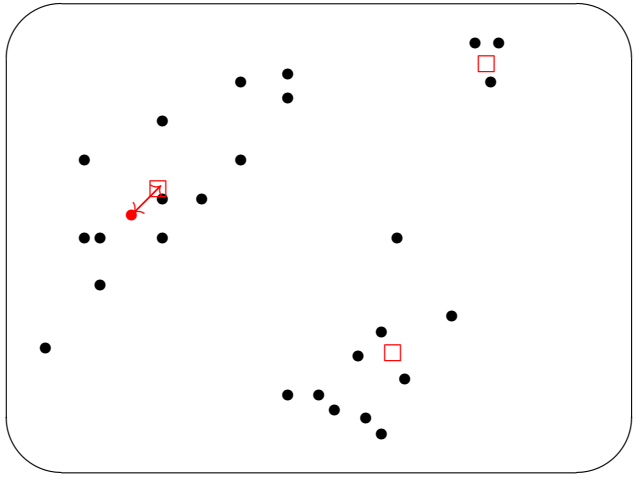

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$$\sum_{t=1}^{T} \ell(\hat{\mathbf{c}}_t, x_t) - \inf_{\mathbf{c} \in \mathbb{R}^{dp}} \left\{ \sum_{t=1}^{T} \ell(\mathbf{c}, x_t) + \lambda |\mathbf{c}|_0 \right\},$$

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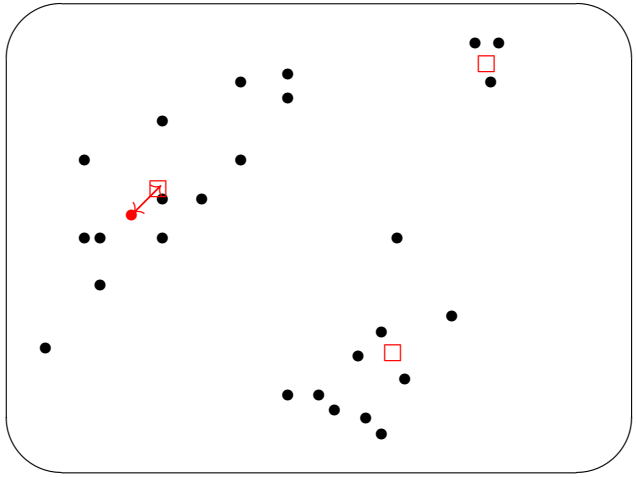

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where $|\mathbf{c}|_0 = \text{card}\{j = 1, \ldots, p : c_j \neq 0_{\mathbb{R}^d}\}$ and

$$\ell(\mathbf{c}, x) = \min_{j=1,\ldots,p} \|c_j - x\|_2^2.$$

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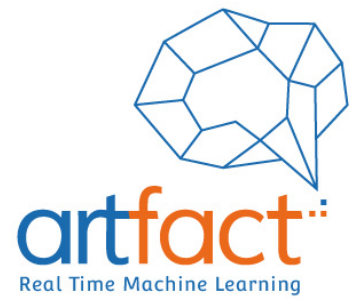
Business case

- **Client** : éditeur de logiciel dans le commerce conversationnel



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L'existant

- Absence de stockage

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- Absence d'architecture Big Data

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- Réglage manuel des règles de ciblage

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Proof of concept (POC) : périmètre

- 11 sites
- 20M pvues/mois
- 160k events/heure

Proof of concept (POC) : objectifs

- Automatiser le ciblage
- Simplifier l'administration et la mise à jour
- Améliorer les performances

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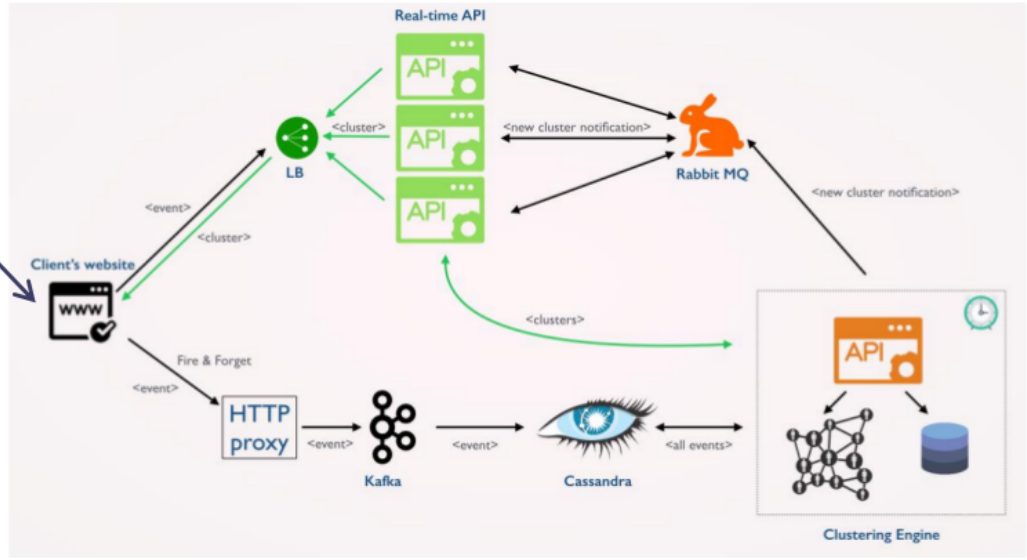
Industrialisation : architecture

Site e-commerce:
Source des données



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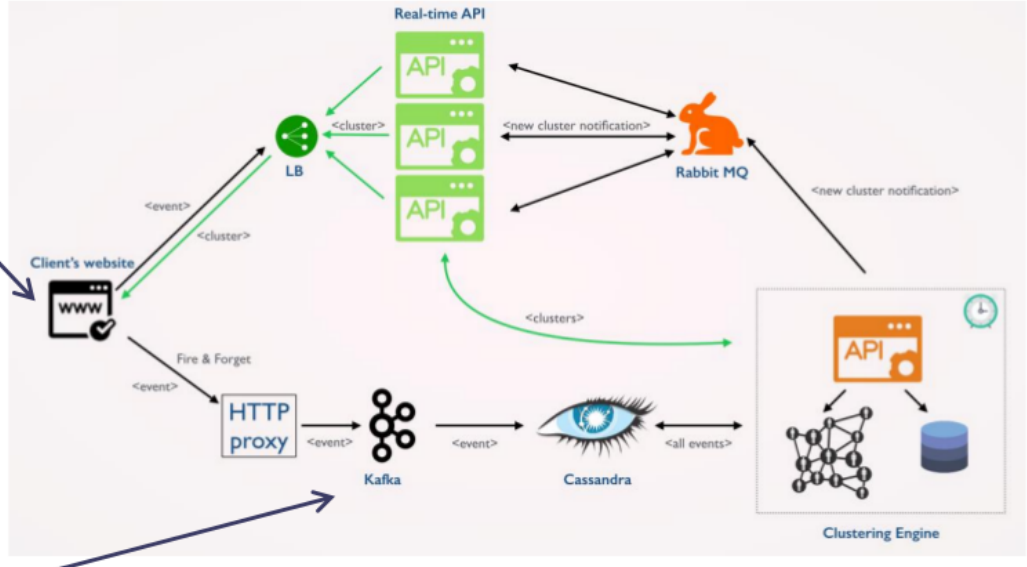

Collecte des events

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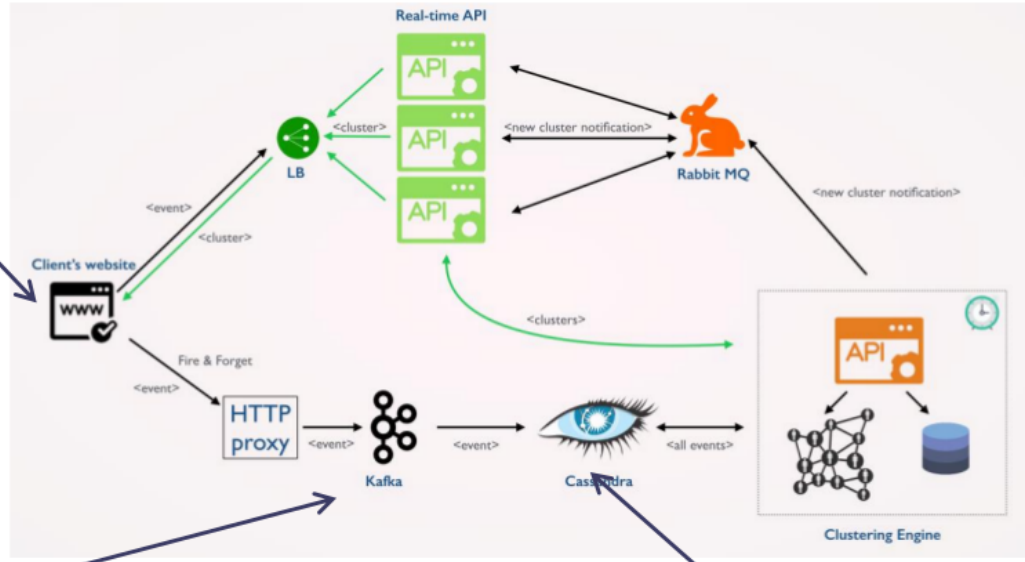

Collecte des events

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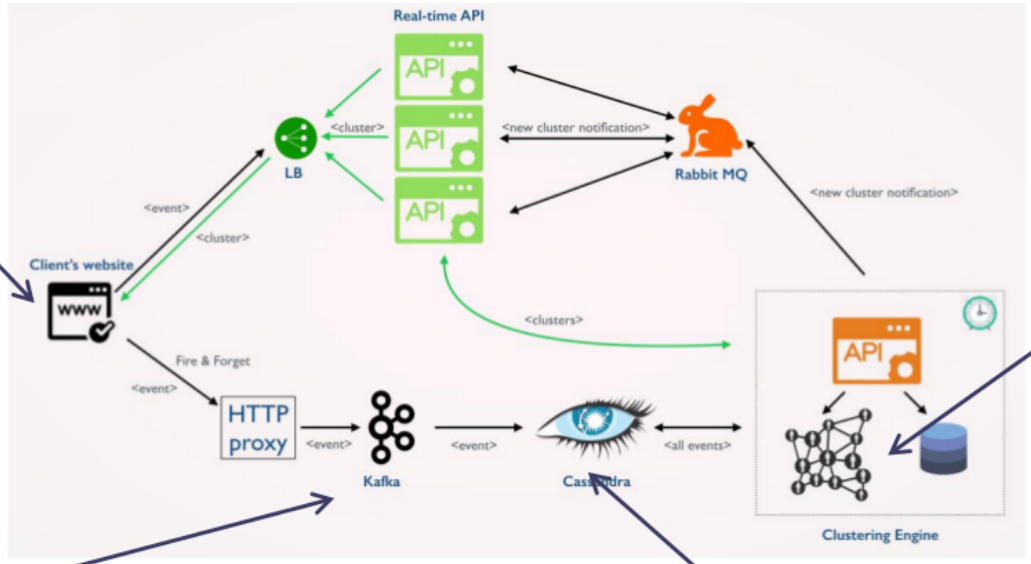

Algorithme

Collecte des events

Stockage des events

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Industrialisation : architecture

Stockage des résultats du clustering
> Probabilité d'achat, d'ajout au panier etc.

rce:
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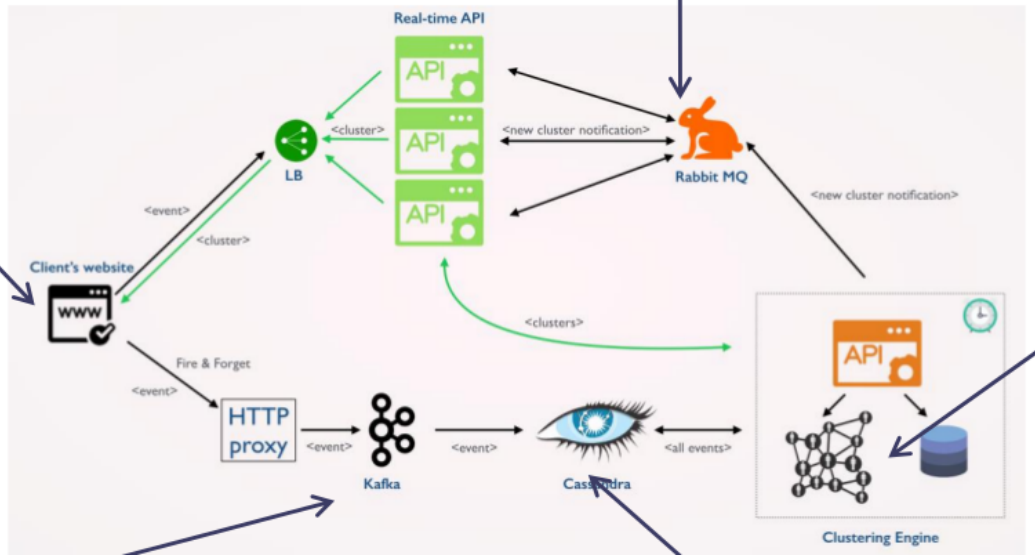

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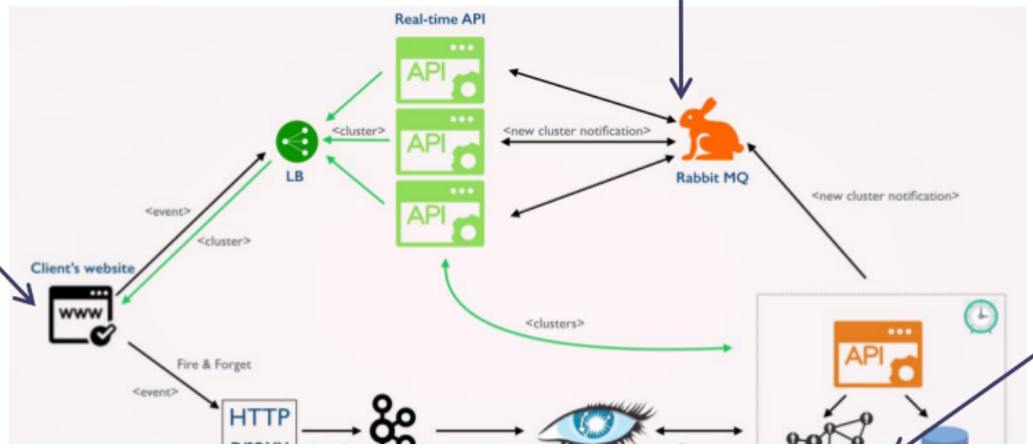

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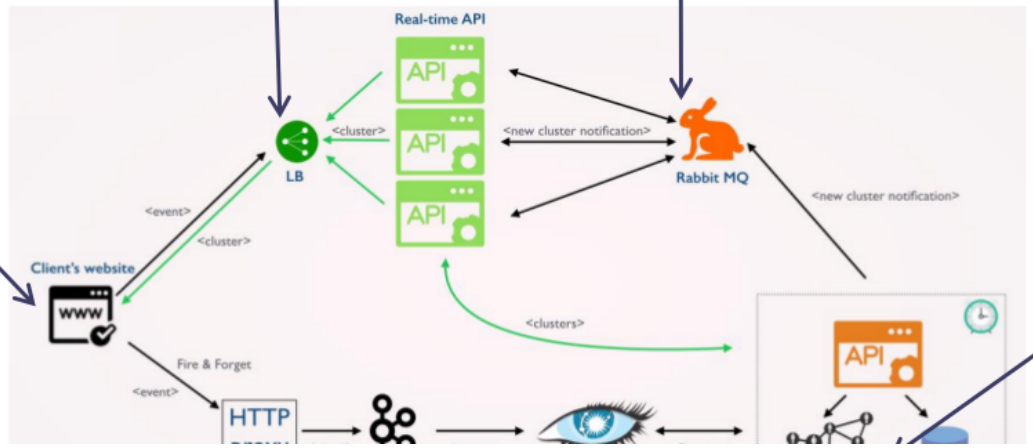

Algorithme

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Graph clustering

- Proposer l'analyse précédente sur un graphe

Graph clustering

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- Nouveaux challenges

Graph clustering

- Proposer l'analyse précédente sur un graphe
- Nouveaux challenges
- Have a look !

Ingrédients

- Théorie des graphes
- Optimisation par Monte Carlo Markov Chain (MCMC)
- Calculs parallèles

Qu'est-ce qu'un graphe ?

Définition (Wikipédia) :

> *Un graphe est un ensemble de points nommés nœuds (parfois sommets ou cellules) reliés par des traits (segments) ou flèches nommées arêtes (ou liens ou arcs). L'ensemble des arêtes entre nœuds forme une figure similaire à un réseau.*

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Keyp point : **relational structure**.

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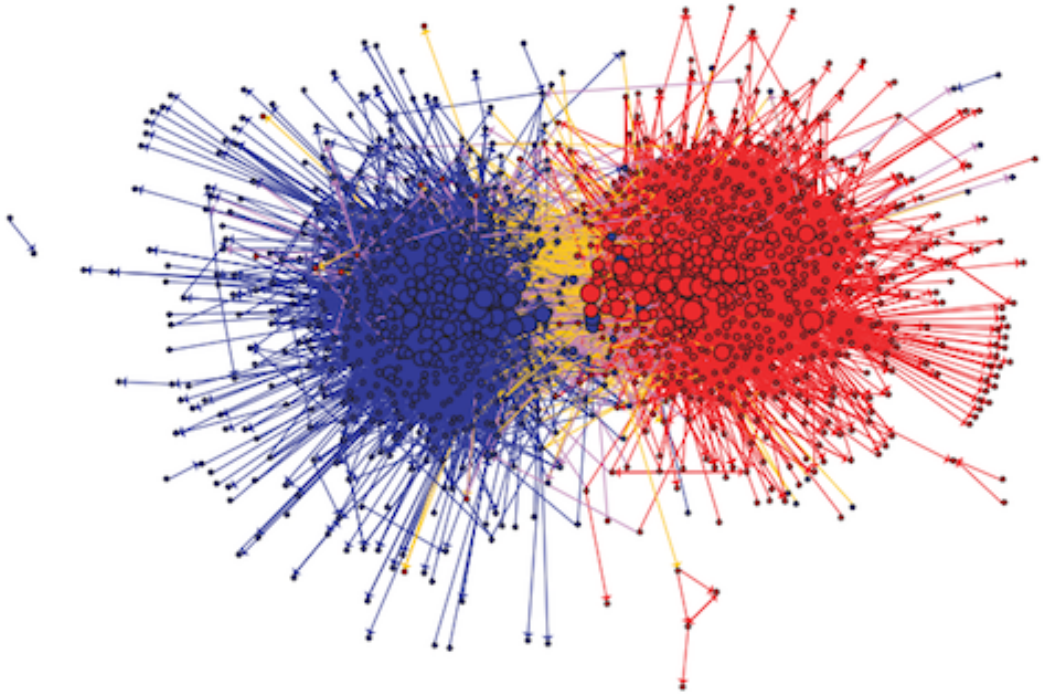
Illustrations : political blog



Network of U.S. political blogs by Adamic and Glance (2004)

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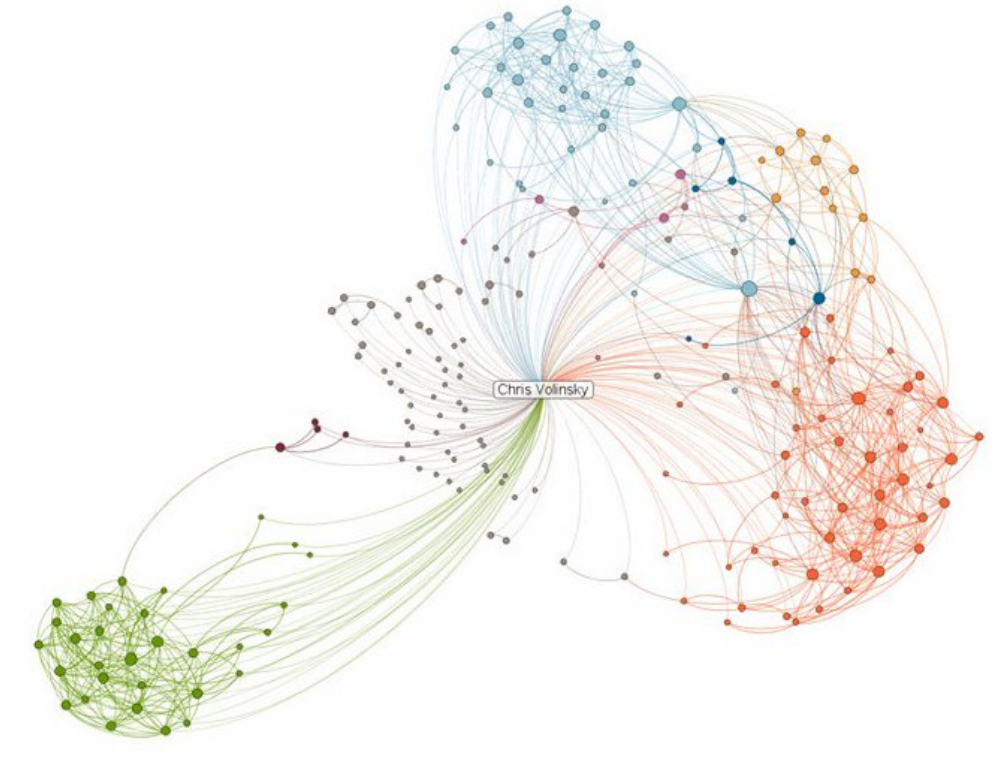
Illustrations : LinkedIn community



LinkedIn community of Chris Volinski (2011, Columbia University), see www.socilab.com

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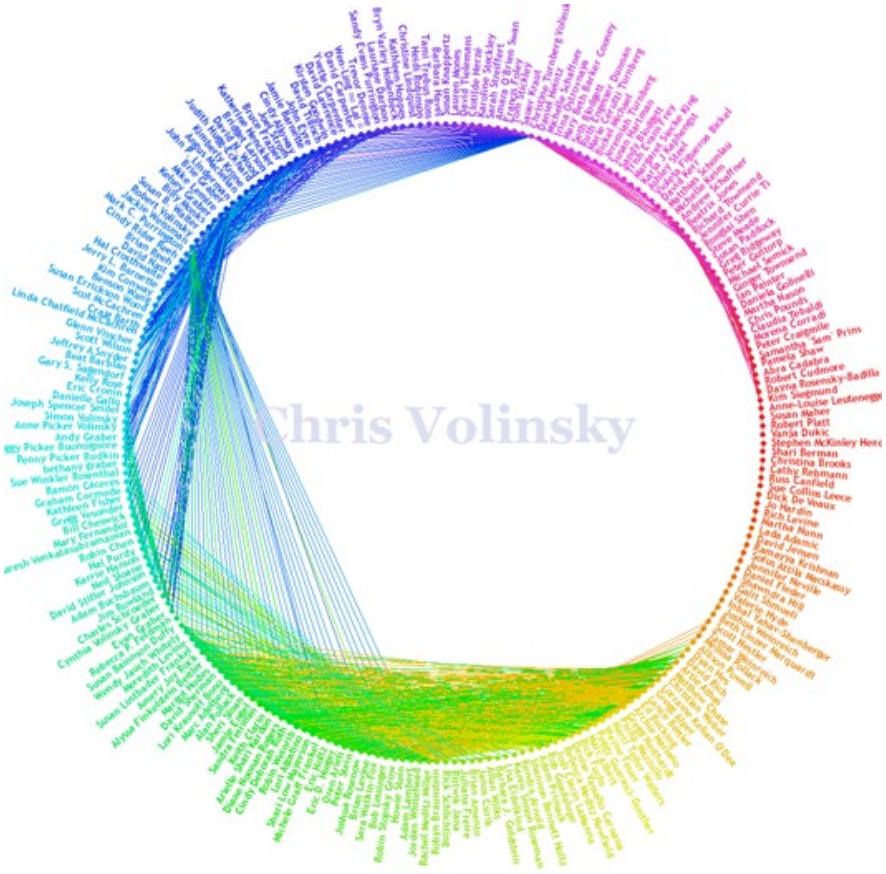
Illustrations : Facebook friends



Facebook of Chris Volinski (2011, Columbia University)

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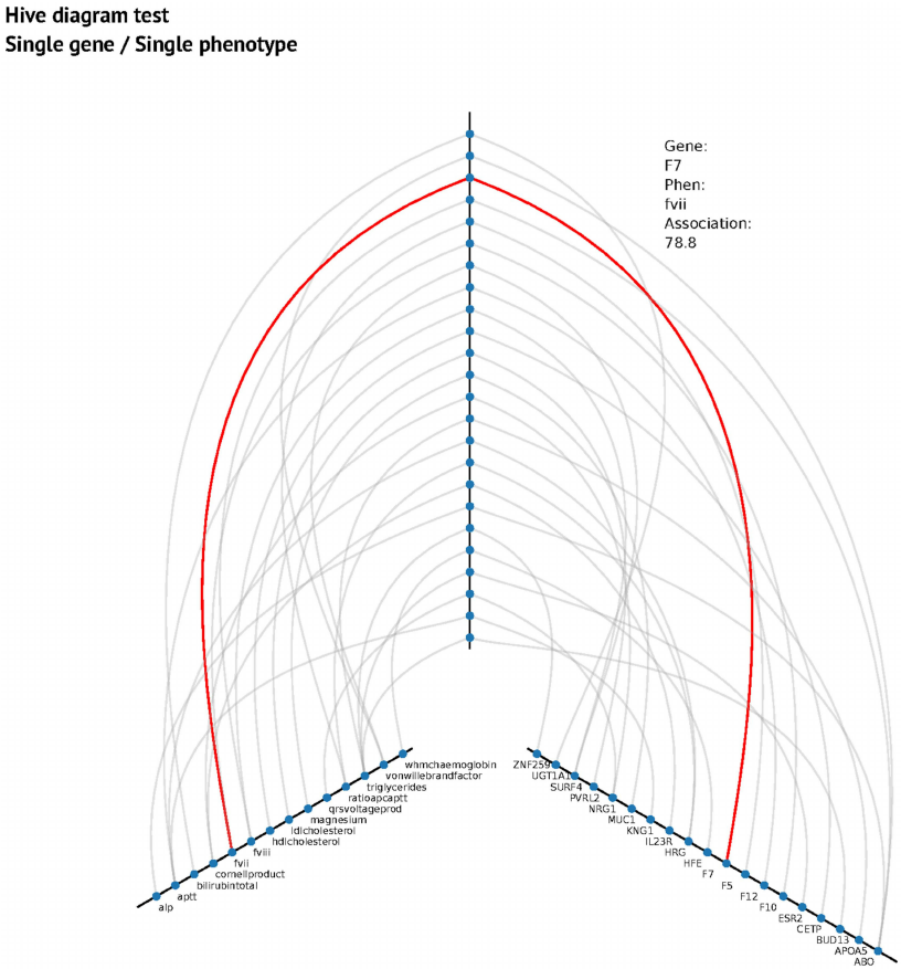
Illustrations : Gene/phenotype interactions



Canonical Correlation Analysis for Gene-Based Pleiotropy Discovery (Plos Computational Biology, 2016)

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Formalisme mathématique

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Definition

Pour un graphe $G = (E, V)$, le degré d'un nœud $v \in V$ est le nombre d'arêtes dans E partant de v.

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Propriétés élémentaires

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A **sparse graph** is a graph (E, V) such that $|E|$ is of order $|V|$.

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A graph G with N vertices satisfies the **small-world property** if in expectation, 2 randomly chosen vertices i and j have distances proportional to $\log N$.

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Détection de communautés (ou graph clustering)

- Partition des nœuds qui vérifie : beaucoup d'arêtes à l'intérieur des groupes, peu d'arêtes entre les groupes.

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$$L = D - A,$$

où A est la matrice d'adjacence et D la matrice des degrés.

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- Optimisation d'un critère appelé la modularité :

$$\mathcal{M}_G(\mathbf{c}) = \frac{1}{2m} \sum_{(i,j)} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta_{\mathbf{c}}(i,j).$$

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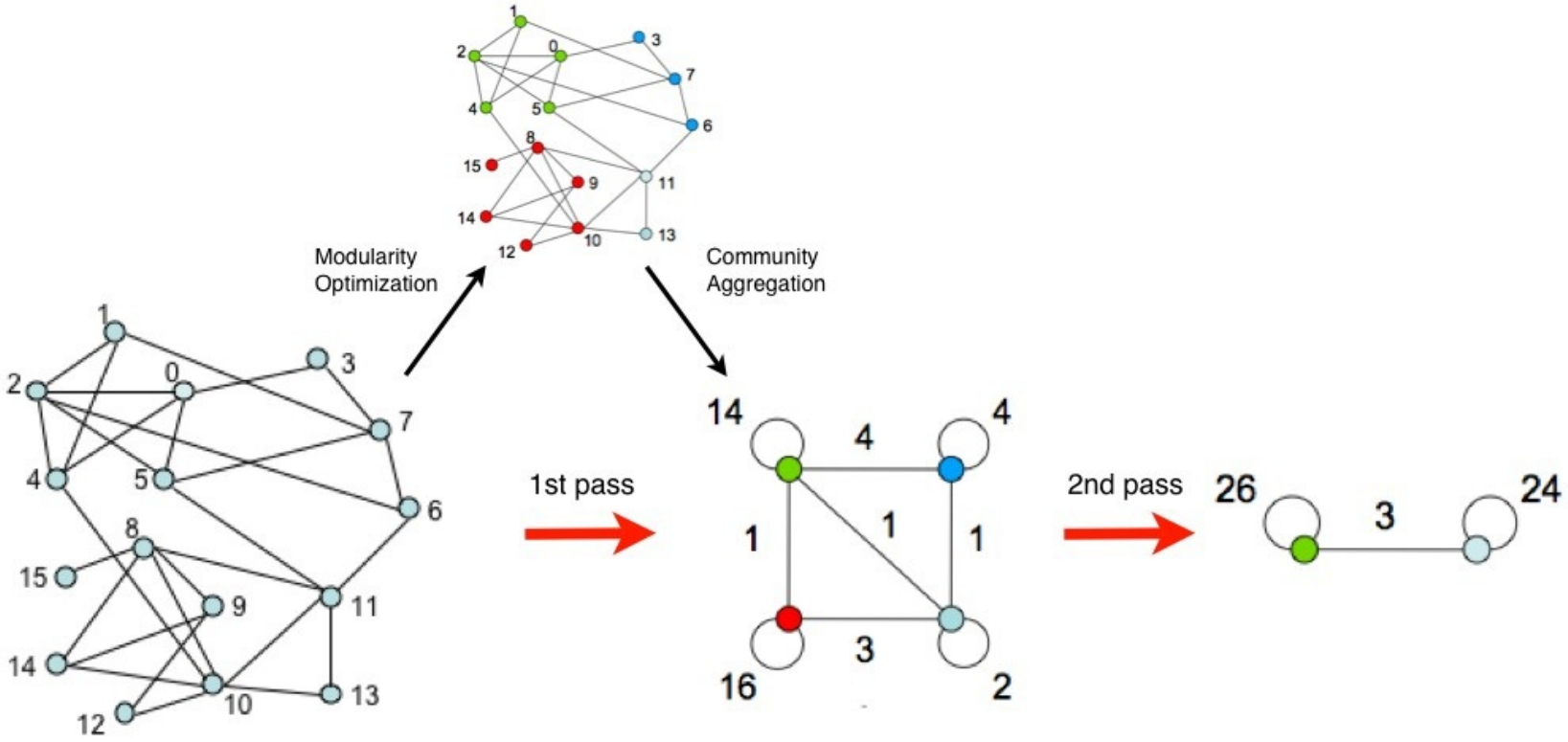
Algorithme glouton



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Algorithme MCMC

- Select at random a neighborhood C' of the current coloration C
- Accept the proposal with standard Metropolis accept/reject ratio

Algorithm 1 MH for Community Detection

1: Initialization $\lambda > 0$, $C^{(0)}$.
2: For $k = 1, \ldots, N$:
3: Draw $C' \sim p(\cdot|C^{(k-1)})$ where $p(\cdot|C^{(k-1)}) \in \mathcal{P}(\mathcal{N}^{C^{(k-1)}})$ is the proposal distribution over $\mathcal{N}^{C^{(k-1)}}$, a neighborhood of $C^{(k-1)}$.
4: Update $C^{(k)} = C'$ with acceptance ratio :

$$\rho = 1 \wedge \left(r_{C^{(k-1)} \to C'} \frac{\exp\left(\lambda Q^{C'}\right)}{\exp\left(\lambda Q^{C^{(k-1)}}\right)} \right), \text{ where } r_{C \to C'} := p(C^{(k-1)}|C')/p(C'|C^{(k-1)}).$$

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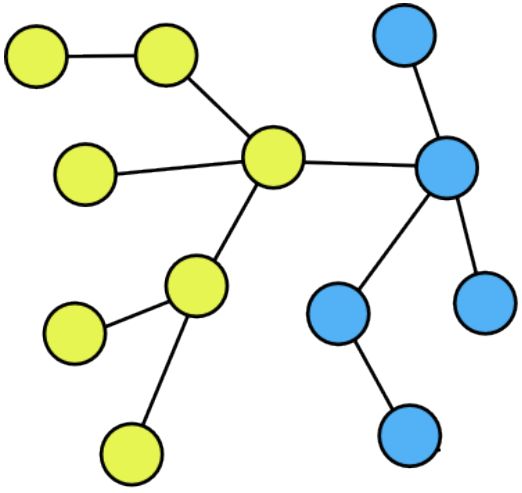
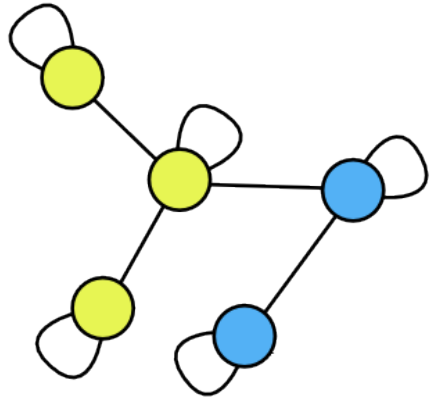
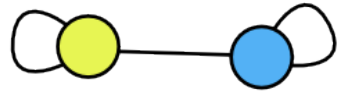
Algorithme final



L = 0



L = 1



L = 2

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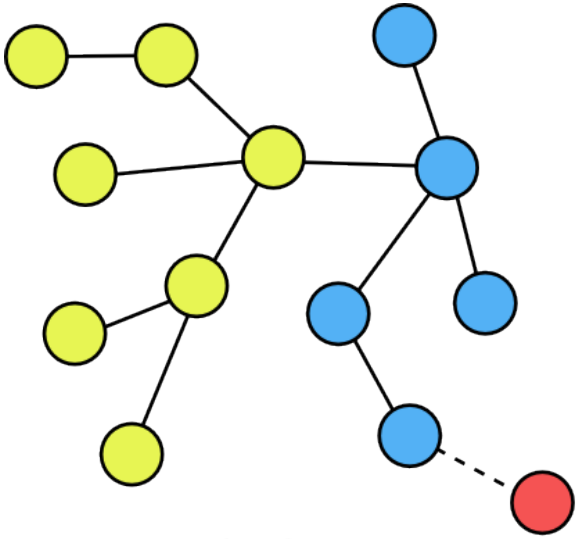
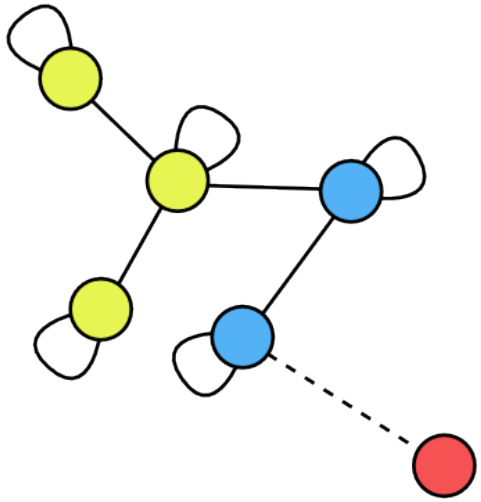
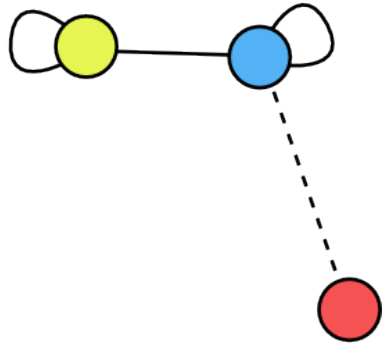
Algorithme final



L = 0



L = 1



L = 2

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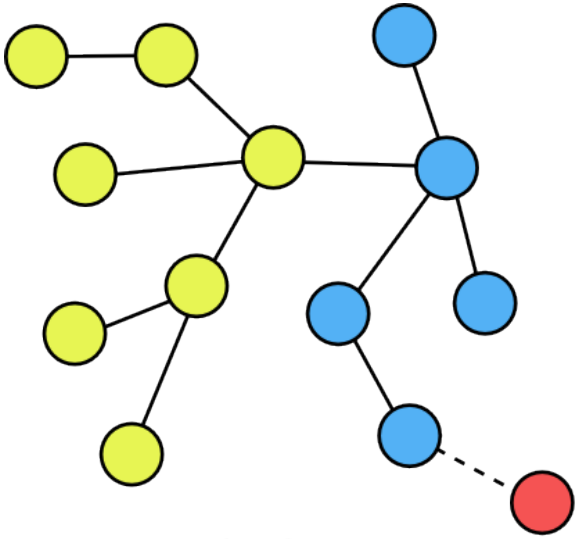
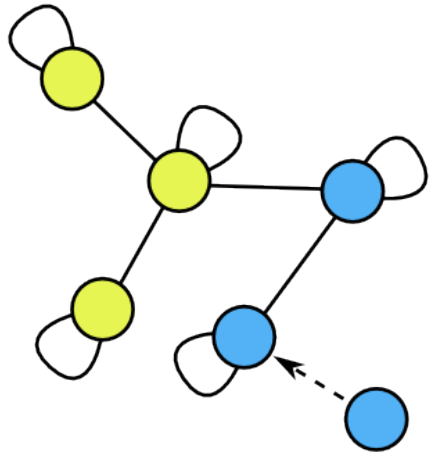
Algorithme final



L = 0



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Business case : appel à volontaire

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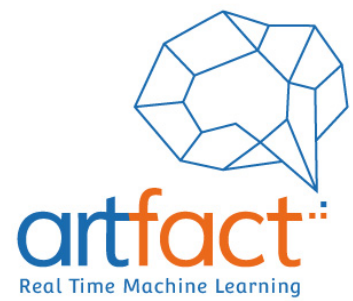

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