Unsupervised and Online Learning

Twitter API usecase

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Machine learning

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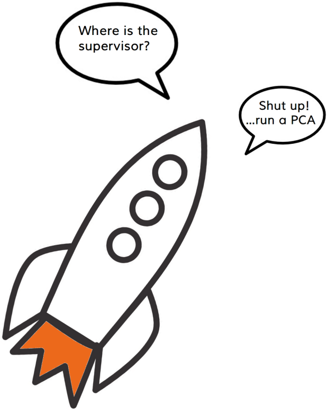
Algorithms

PCA, k-means, spectral k-means, hierarchical clustering, Gaussian mixtures, Principal curves analysis, word2vect...

Qu'est-ce que ça change ?



UNSUPERVISED LEARNING

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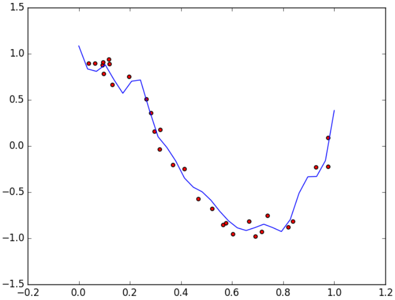

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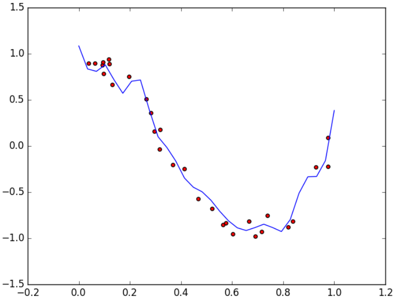
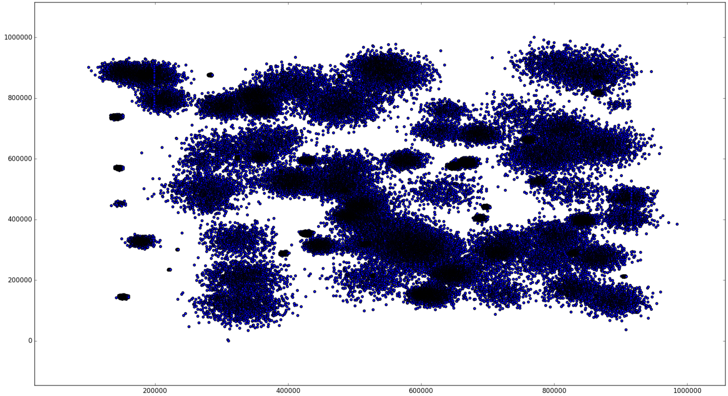


- Solution : Training set + test set, Leave-One-Out, V-fold Cross validation.

Unsupervised : science or art ?



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Data arrives sequentially. At each time t, we want to make a decision based on past observations. **No assumption over the data mechanism**.

Game with expert advices

$$y = \begin{matrix} 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{matrix}$$

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Keep or Kill + Majority vote algorithm

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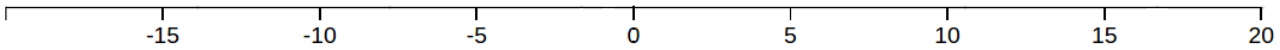
We end up with $k \leq C \log N$!

General case



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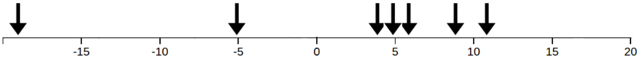

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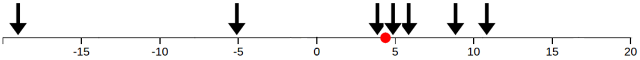

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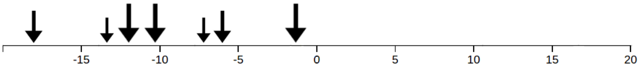

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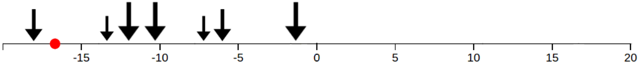

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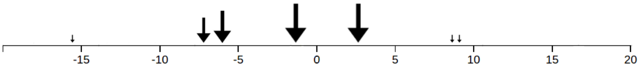

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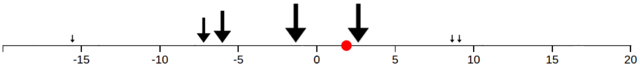

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Popular loss functions include $\ell(\hat{y}, y) = (\hat{y} - y)^2$, $|\hat{y} - y|$, $(1 - \hat{y}y)_+$.

General result

In the general case, we want to control the "regret" :

$$\sum_{t=1}^{T} (\hat{y}_t - y_t)^2 - \sum_{t=1}^{T} (y_t^\star - y_t)^2,$$

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Cesa-Bianci & Lugosi, 2006

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where :

$$\hat{y}_t = \sum_{k=1}^{N} \frac{e^{-\lambda \sum_{u=1}^{t-1} \ell(p_{k,u}, y_u)}}{W_{t-1}} p_{k,t}, \ \forall t = 1, \dots, T.$$

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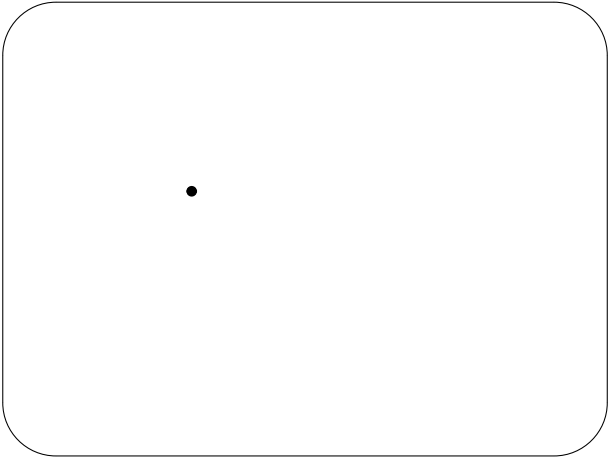

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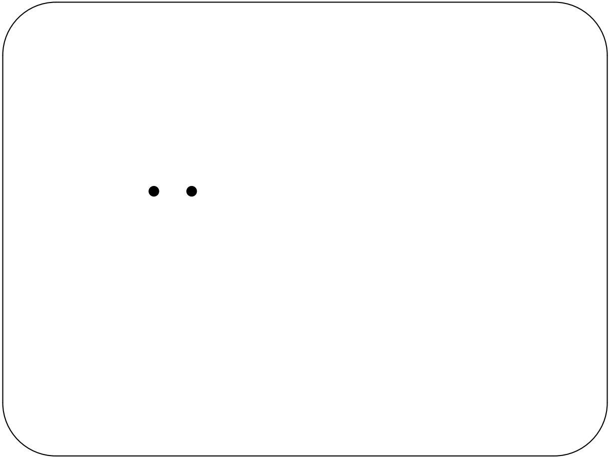

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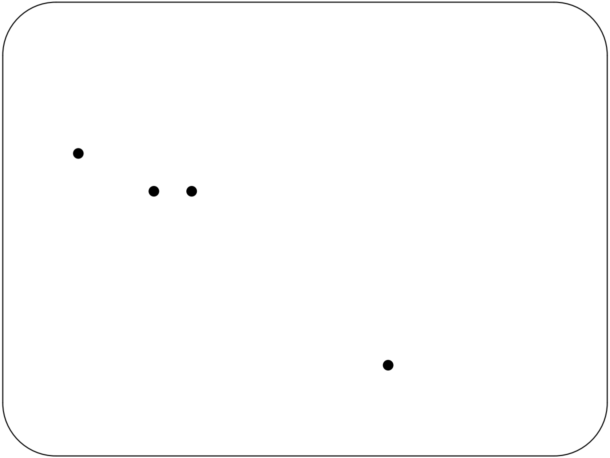

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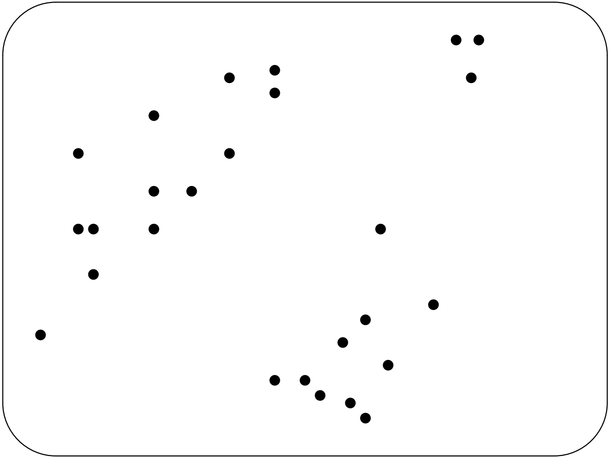

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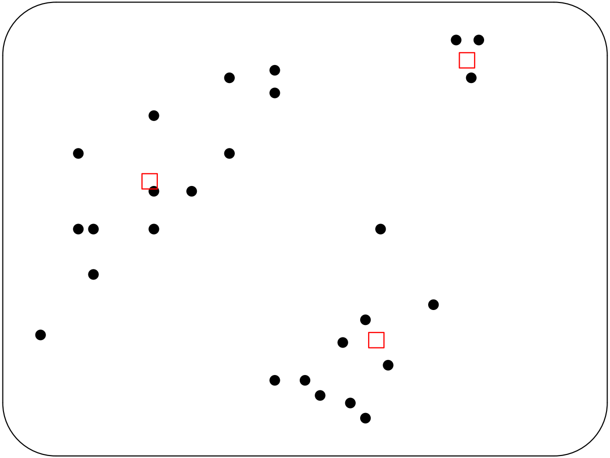

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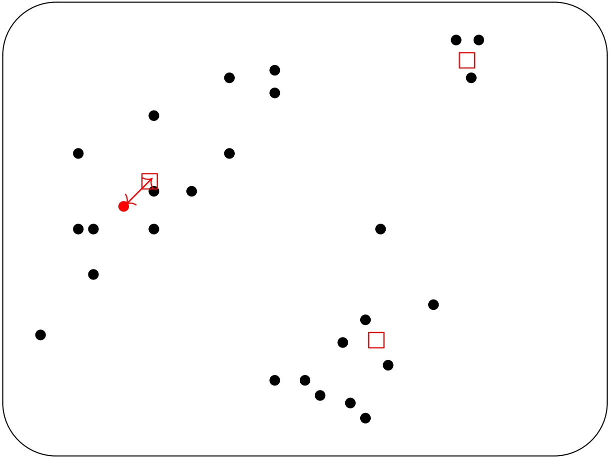

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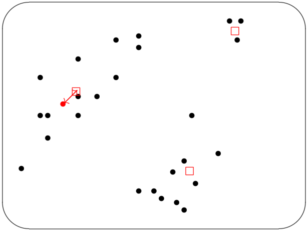

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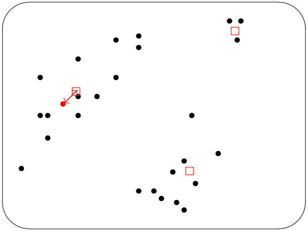

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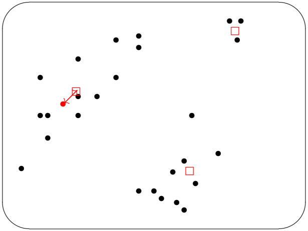

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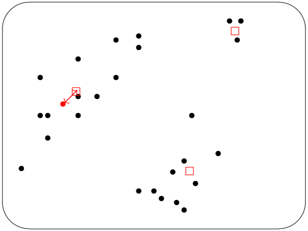

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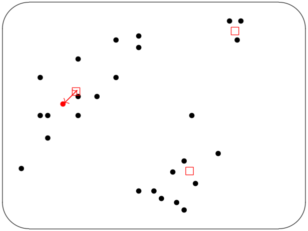

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Meaning ? Sentiment ? From words to vectors ?

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- Gigantic dimension !

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- Compute the **coocurence matrix**:

	I	love	dancing	swimming	NLP	and
I	2	2	1	1	1	0
love	2	2	1	1	1	1
dancing	1	1	1	1	0	1
swimming	1	1	1	1	0	1
NLP	1	1	0	0	0	1
and	0	1	1	1	0	1

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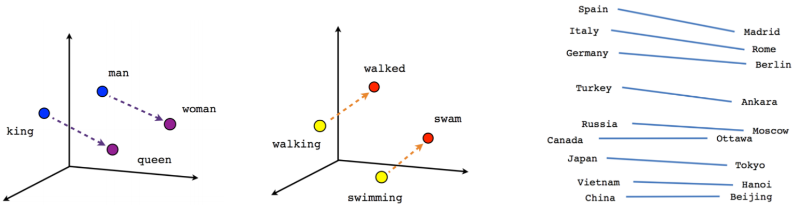
where

$$p(o|c) = \frac{\exp\left(\langle u_{\mathrm{o}}, v_{\mathrm{c}} \rangle\right)}{\sum_{w=1}^{W} \exp\left(\langle u_{\mathrm{w}}, v_{\mathrm{c}} \rangle\right)}.$$

- Optimization with Online Stochastic Gradient Descent.

Word2vect : linear relationships



Male-Female Verb tense Country-Capital