Une école de l'IMT

Lecture 4 - Text classification

SD-TSIA214

Chloé Clavel

Reminder

NLP tasks

2 kind of tasks:

- **Classify documents by themes, opinions etc...**
  - Supervised learning
    - Ex : SVM (support vector machines), Naive Bayesian
  - Unsupervised learning
    - Ex: Clustering
- **Detect particular expressions**
  - Ex: Named Entities
    - o

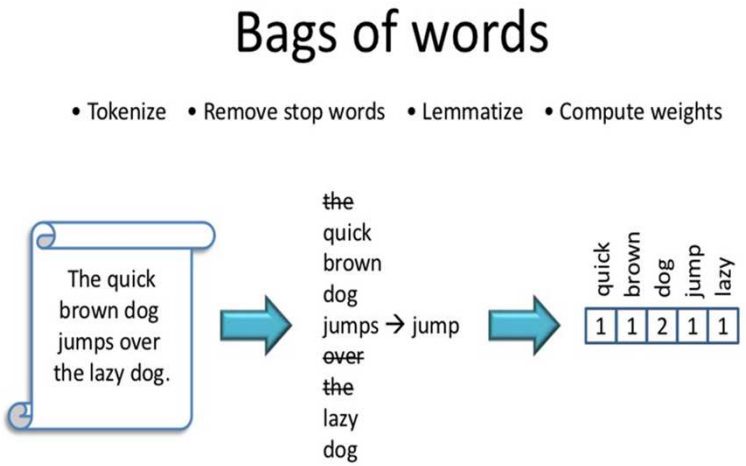
From http://www.tal.univ-paris3.fr/plurital/travaux-2009-2010/bao-2009-2010/MarjorieSeizou-AxelCourt/webservices.html

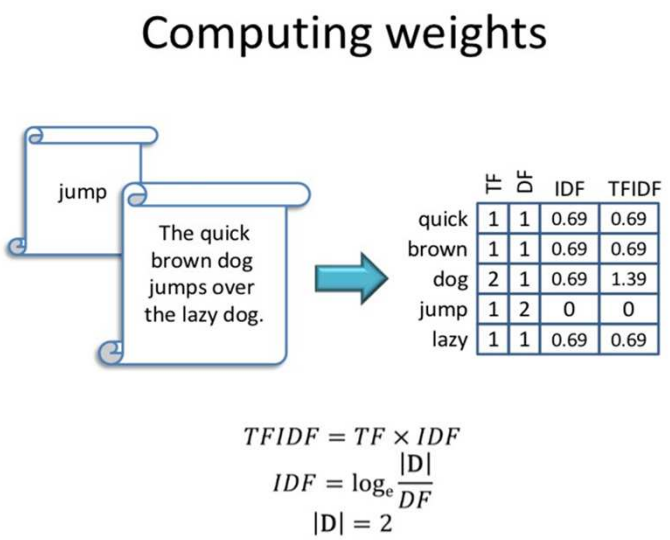
Reminder

- **Learning the classes**

|’T’|’h’|’i’|’s’|’ ‘|’m’|’o’|’v’|’i’|’e’|’ ‘|’i’|’s’|’ ‘|’r’|’e’|’a’|’l’|’l’|’y’|’ ‘|’g’|’o’|’o’|’d’|’.’|

Reminder : Convert documents into a matrix





Sparse vs. Dense representations (word2vec)

Objective of the lecture

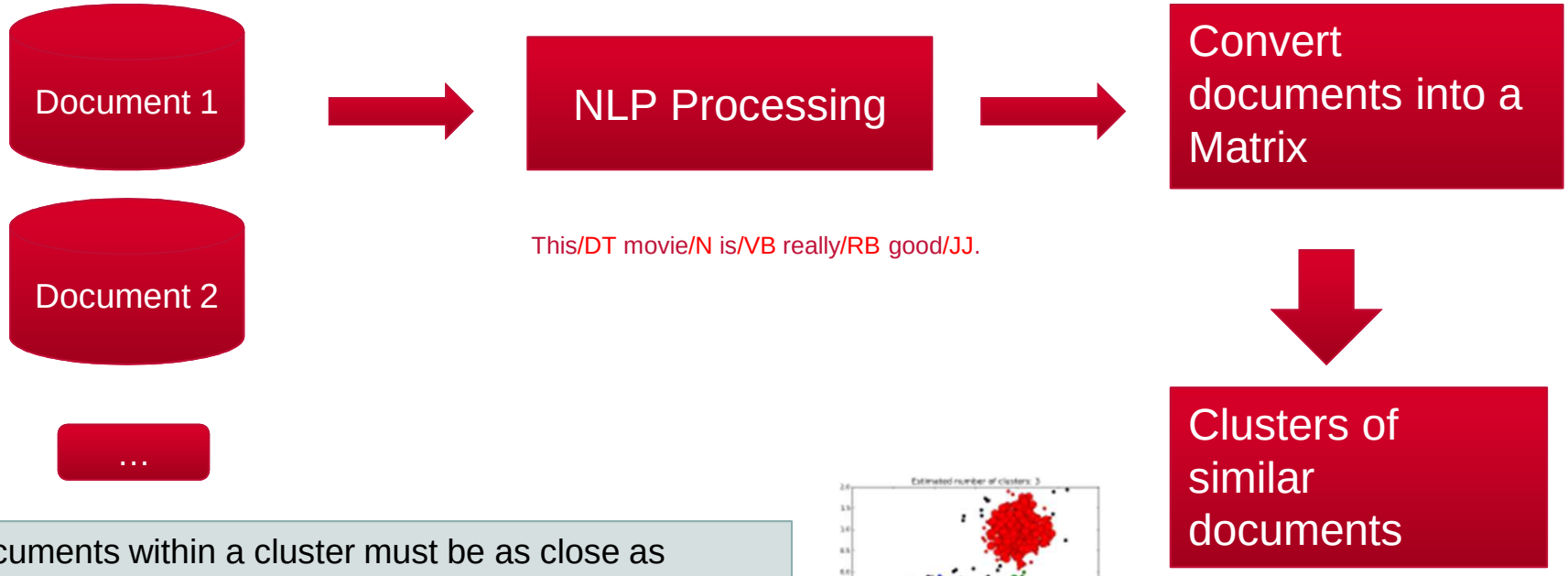
- **Get familiar with:**
  - Text Clustering
  - Supervised text classification

Clustering

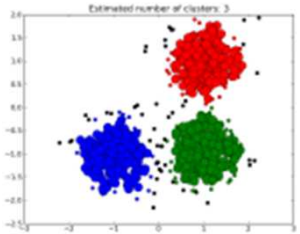
Unsupervised learning

Text clustering

Unsupervised learning : no labelling based on human expertise



Documents within a cluster must be as close as possible
Documents in different clusters should be the least similar possible



Text clustering

Unsupervised learning : no labelling based on human expertise

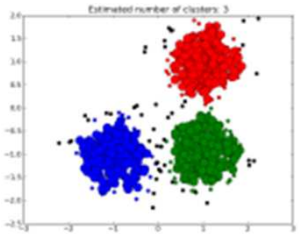
- **Principles:**
  - Methods for grouping similar textual documents
  - Problem of partitioning documents
  - Require the definition of criteria to evaluate the quality of the partitionning

Documents within a cluster must be as close as possible
Documents in different clusters should be the least similar possible

Text clustering

Unsupervised learning : no labelling based on human expertise

- **The cluster membership is determined by :**
  - the distribution of the data
  - the make-up of the data



In this figure, it is visually clear that there are three distinct clusters of points

=> Clustering methods are algorithms that find such clusters in an unsupervised fashion

Clustering vs. classification

- **Classification is a form of supervised learning**
  - The goal is to replicate a categorical distinction that a human supervisor imposes on the data
- **Clustering is a form of unsupervised learning**
  - We have no teacher (human labeller) to guide the clustering

Text clustering

- **The different types of clustering methods**
  - Hierarchical Clustering:creates a hiearchy of clusters
    - Graphs, Trees
  - Non hierarchical methods/Flat clustering:creates a flat set of clusters without any explicit structure that would relate clusters to each other
    - k-means, ISODATA,

But not all the clustering methods are relevant for TEXT clustering

ex: hierarchical-agglomerative clustering

Key input to clustering algorithms

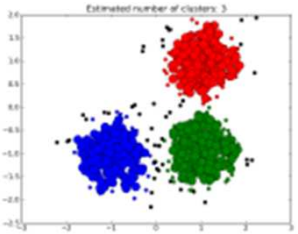
- **distance / similarity measure**
  - Will influence clustering outputs
    - Different distance measures give rise to different clustering
    - => make up your vector space model and your distance according to your clustering task:
      - Topic similarity for topic clustering
      - Language similarity for language clustering

EXAMPLE : when computing topic similarity, stop words can be safely ignored but not for language similarity

« the » and « la » are useful for langague similarity

Key input to clustering algorithms

- **distance / similarity measure**
  - Will influence clustering outputs
    - Different distance measures give rise to different clustering
    - => make up your distance according to your clustering task:
      - Topic similarity for topic clustering
      - Language similarity for language clustering
  - Some distances :
    - Euclidean distance

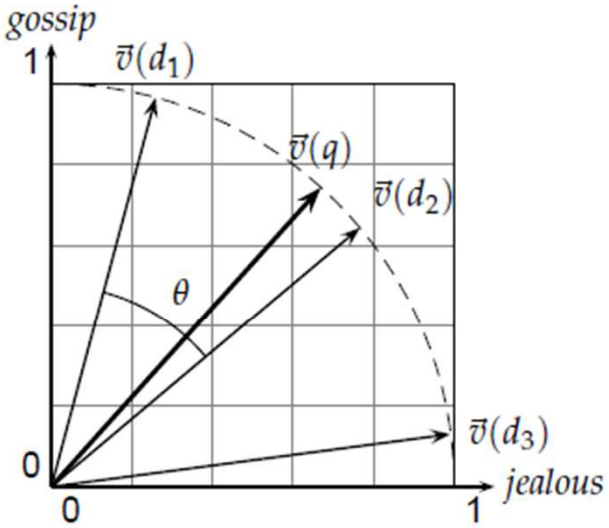


In this figure, the euclidean distance in the 2d-plane suggests three different clusters

    - Distance / similarity cosine
    - Distance from Jaccard

Key input to clustering algorithms

- **Cosine similarity**



$$\text{sim}(d_1, d_2) = \frac{\vec{V}(d_1) \cdot \vec{V}(d_2)}{|\vec{V}(d_1)||\vec{V}(d_2)|},$$

▶ Figure 6.10 Cosine similarity illustrated. $\text{sim}(d_1, d_2) = \cos\theta$.

Key input to clustering algorithms

- **Distance based on Jaccard index**

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

$$J_\delta(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}$$

Focus on flat clustering

- **Problem statement**
  - Inputs
    - a set of N documents D = {D1,…, DN}
    - A desired number of clusters K
    - An objective function that evaluates the quality of the clustering
  - Outputs
    - An assignment function f: D -> {1,…,K} that minimizes/maximizes the objective function
  - NB : the algo has also to identify the best K

Focus on k-means

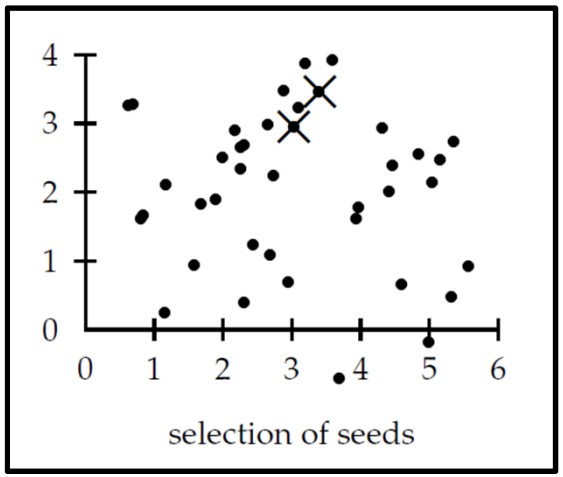
General principle

- Distance measure :
  - euclidean distance
- Objective function to minimize
  - Intra-cluster inertial : average squared Euclidean distance of documents from their cluster centers μ_k

$$\sum_{k \in \{1,\ldots,K\}} \sum_{i \in \mathcal{C}_k} \|x_i - \mu_k\|_2^2$$

Focus on k-means

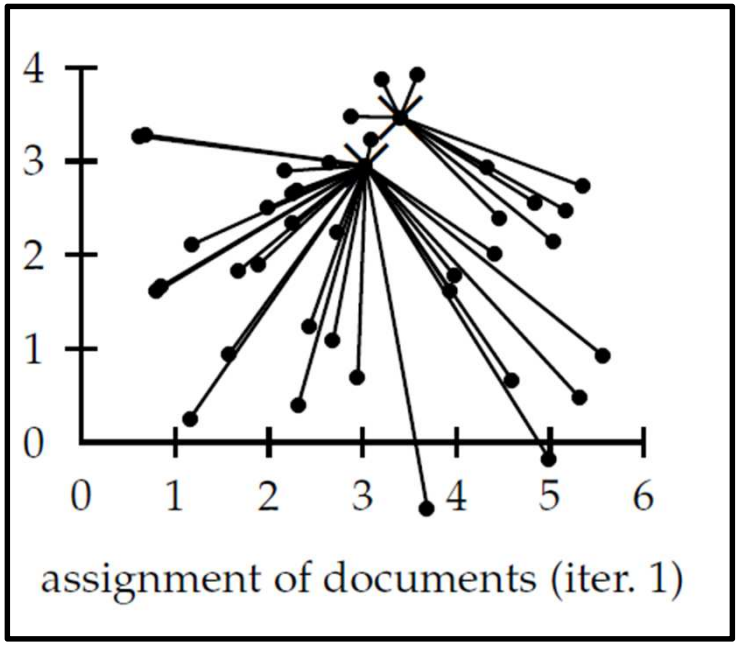
- **ALGO**
  - INPUT: D set of N documents = points of a multi-dimensional space, provided with a distance d.
  - Initialization:
    - Select randomly K documents in D
      - to define the K initial cluster centers = the *seeds*



From IR book

Focus on k-means

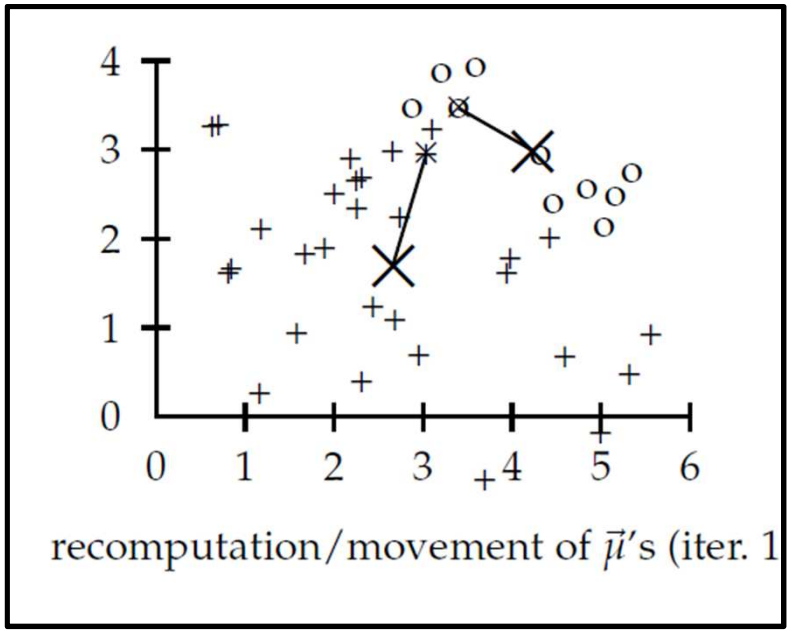
- i^{th} Iteration
  - Assign the N documents to the cluster with the closest cluster center (assignment function f_i: D -> {1,…,K})



Focus on k-means

- i^{th} Iteration
  - Calculation of the centroid of each cluster as the barycenter of the current members of the cluster:

$$\mu_k = \frac{1}{|\mathcal{C}_k|} \sum_{i \in \mathcal{C}_k} x_i, \quad \forall k \in \{1, \ldots, K\}$$



Focus on k-means

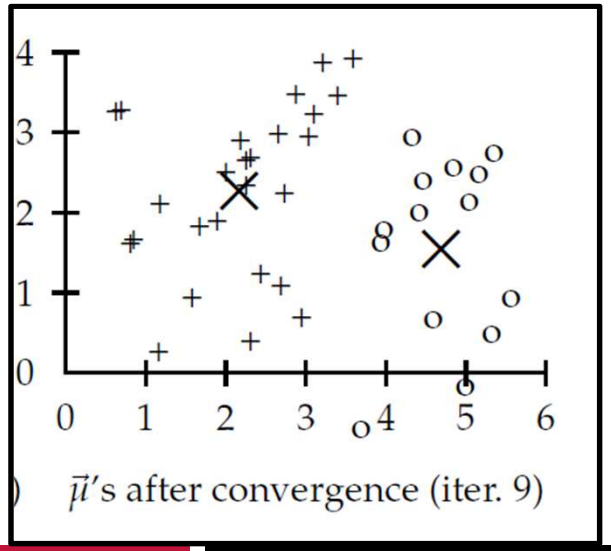
– calculation of intra-class inertia

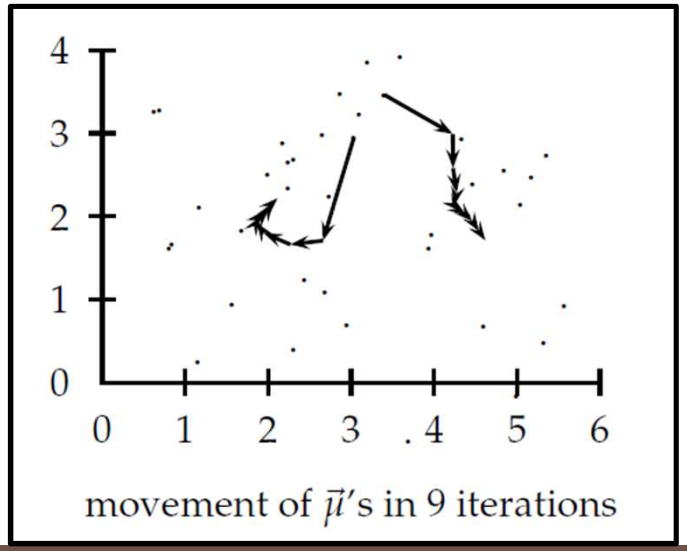
$$\sum_{k\in\{1,\dots,K\}} \sum_{i\in\mathcal{C}_k} \|x_i - \mu_k\|_2^2$$

– i-> i+1

Focus on k-means

- Termination options
  - Stop after a fixed number of iterations
  - Stop when the assignment function or centroids do not change between iterations
  - Stop when inertia falls below a threshold
  - Stop when inertia converges (the decrease of inertia falls below a small threshold)





Focus on flat clustering

Mix of Multinomial Laws

General principle :

- Looking for a description of classes / clusters by:
  - By their probability density:
- we know :
  - the shapes of probability densities (ex: mixture of multinomial laws)
- we look for :
  - the parameters of the densities (ex: parameters of the gaussians)
  - … that maximize a criterion of grouping documents according to these classes

Flat clustering

- **Mix of Multinomial Laws**
  - initialization:
    - consider a set of K clusters and initialize the parameters of the law associated with each cluster
    - Assign each document to a cluster based on the probability of the document to belong to a class (most likely class) -> initial partitioning
  - iteration:
    - Recalculate model parameters based on current partitioning clusters
    - Redistribute documents in clusters from this new template.

Text classification

Rule-based and supervised learning

EXAMPLE : Is this e-mail spam?

Good Day,
My name is Dr William Monroe, a staff in the Private Clients Section of a well-known bank, here in London, England. One of our accounts, with holding balance of £15,000,000 has been dormant and last operated three years ago. From my investigations, the owner of the said account, John Shumejda died on the 4th of January 2002 in a plane crash.

I have decided to find a reliable foreign partner to deal with. I therefore propose to do business with you, standing in as the next of kin of these funds from the deceased. This transaction is totally free of risk and troubles as the fund is legitimate and does not originate from drug, money laundry or terrorism. On your interest, let me hear from you URGENTLY.

Best Regards,

Dr William Monroe Financial Analysis and Remittance Manager

Classification Tasks - example

- Is this e-mail spam?
- Positive or negative review?
- What is the topic of this article?
- Predict hashtags for a tweet
- Age/gender identification
- Language identification
- Sentiment analysis

Types of Classification Tasks

- Binary classification (true, false)
- Multi-class classification (politics, sports, gossip)
- Multi-label classification (#party #FRIDAY #fail)
- Clustering (labels unknown)

Classification Methods

- **By hand**
  - E.g. Yahoo in the old days
    - ✔ Very accurate and consistent assuming experts
    - ✘ Super slow, expensive, does not scale
- **Rule-based**
  - E.g. Advanced search criteria (”site:ox.ac.uk”)
    - ✔ Accuracy high if rule is suitable
    - ✘ Need to manually build and maintain rule-based system.
- **Machine learning**
    - ✔ Scales well, can be very accurate, automatic
    - ✘ Requires classified training data. Sometimes a lot!

Rule-based methods

- **Objectif :**
  - décrire l'information à extraire pour un métier, un domaine spécifique ou une thématique en modélisant l'information sous forme de lexiques/ontologies et patrons/règles linguistiques/grammaires/automates.

« manque de qualité de service » ➡ Concept **INSATISFACTION**

« il n'y a vraiment pas eu de contact », …

Rule-based methods

- **Modélisation sémantique :**
  - Utilisation de lexiques et de règles
  - Règles qui répertorient toutes les formulations possibles d'une même information
    - langage d'expressions régulières
      - Appel de lemmes : ex. *« avoir »*
      - Appel de catégories grammaticales : « *#PREP_DE* » « *#NEG* »
      - Appel de lexiques prédéfinis: « *~services-lex* »

« manque de qualité de service » ➡ Concept **INSATISFACTION**

« il n'y a vraiment pas eu de contact », …

*(manque|~negation-patt|(il/#NEG/y/avoir/~negation-patt))/(#PREP_DE)?/ (conseil|contact|~services-lex)**

* Exemple : syntaxe de l'outil TEMIS et exemple d'utilisation à EDF pour des analyses des opinions des clients

Rule-based methods using regular expressions

- **Syntaxe courante (Unix, perl, etc.)**

Expression	Langage accepté
`r*`	0 ou plusieurs `r`
`r+`	1 ou plusieurs `r`
`r?`	0 ou 1 `r`
`[abc]`	`a` ou `b` ou `c`
`[a-z]`	N'importe quel caractère dans l'intervalle `a...z`
`.`	N'importe quel caractère sauf `\n`
`[^s]`	N'importe quel caractère sauf ceux de `s`
`r{m,n}`	Entre `m` et `n` occurences de `r`
`r1 r2`	La concaténation de `r1` et `r2`

Expression	Langage accepté
`r1 | r2`	`r1` ou `r2`
`(r)`	`r`
`^r`	`r` en début de ligne
`r$`	`r` en fin de ligne
`"s"`	Le string `s`
`\c`	Le caractère `c`
`r1 / r2`	`r1` quand il est suivi de `r2`

- `[a-zA-z]` Une lettre.
- `[0-9]` Un chiffre.
- `a[^A-Za-z]b` Un `a`, suivi d'un caractère non alphabétique, suivi d'un `b`.
- `^Monsieur` `Monsieur` en début de ligne.
- `[a-zA-Z]([a-zA-Z]|[0-9])*` Un identifiant Pascal. ...

Tiré de http://www.ulb.ac.be/di/ssd/ggeeraer/lg/extexpreg_print.pdf

Rule-based methods using regular expressions - Practice

- **Donnez l'expression régulière acceptant l'ensemble des phrases «correctes» selon les critères suivants :**
  - Le premier mot de la phrase a une majuscule ;
  - la phrase se termine par un point ;
  - la phrase est composée d'un ou plusieurs mots (caractères a...z et A...Z), séparés par un espace ;

Test des regexp :
http://www.regexplanet.com/advanced/java/index.html
https://regex101.com/

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```
^[A-Z][A-Za-z]*(\ [A-Za-z]+)*\.$
```

Sites pour vérifier les expressions régulières: regexplanet.com

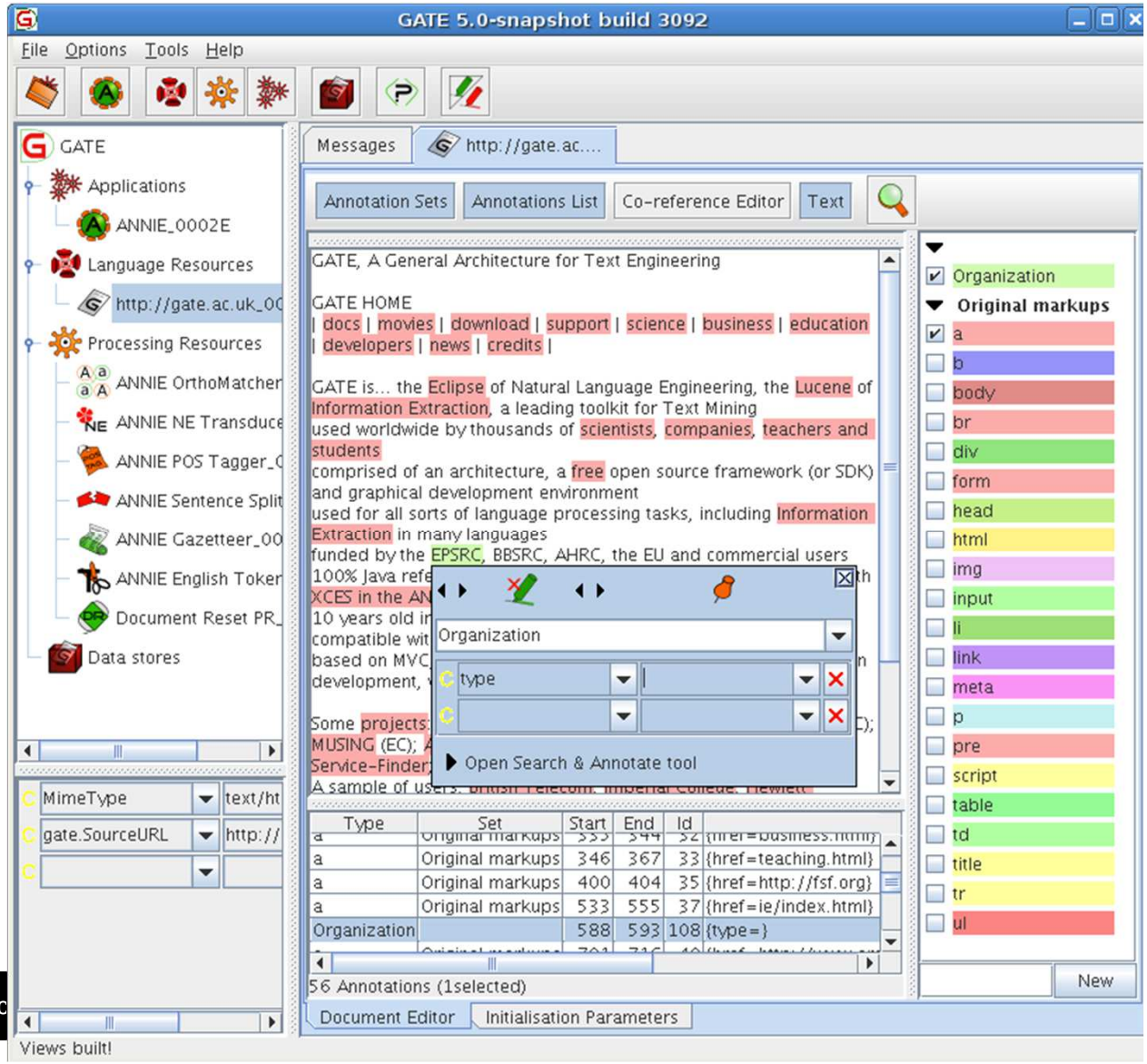
Tiré de http://www.ulb.ac.be/di/ssd/ggeeraer/lg/extexpreg_print.pdf

Tools

- Unitex : http://www-igm.univ-mlv.fr/~unitex/
- Les grammaires de NLTK
- Gate

GATE

- General Architecture for Text Engineering,
- Suite Java pour l'extraction d'info et le NLP,
- Utilisé à l'échelle internationale avec des mises à jour continues,
- Intégration facile des différents outils et formats: divers taggers etc.



GATE

Fonctionnalités:

- **Système d'extraction d'information (ANNIE)**
- **Annotation à base de règles: JAPE**
- **Ontologies**
- **Machine Learning**

Dictionnaires externes (Gazetteer)

Permet une conception d'un système hybride: à base de règles + Machine Learning

- **Interface pour l'annotation manuelle**
- **Possibilité d'intégrer GATE à Hadoop :**

Hadoop-GATE https://github.com/wpm/Hadoop-GATE

GATE

- **Différents exemples de projets de recherche avec GATE**
  - Environnement web permettant d'effectuer les tâches d'annotation manuelle (crowdsourcing) (Bontcheva et al., 2014)
  - Interface permettant d'interroger des ontologies (Damljanovic, 2010)
  - Classification de textes en sentiments:
    - GATE+SVM (Funk, 2008)
    - À base de règles JAPE

GATE : JAPE Grammars

- **Voir le tutoriel : https://gate.ac.uk/sale/thaker-jape-tutorial/GATE%20JAPE%20manual.pdf**
- **Exemple :**
  - Texte : *AC Milan player David Beckham is going to comment on his future with LA Galaxy, who are eager to keep him in USA.*
  - Règle : If mention of the word “player” followed by a name of a person Then the person = a player.

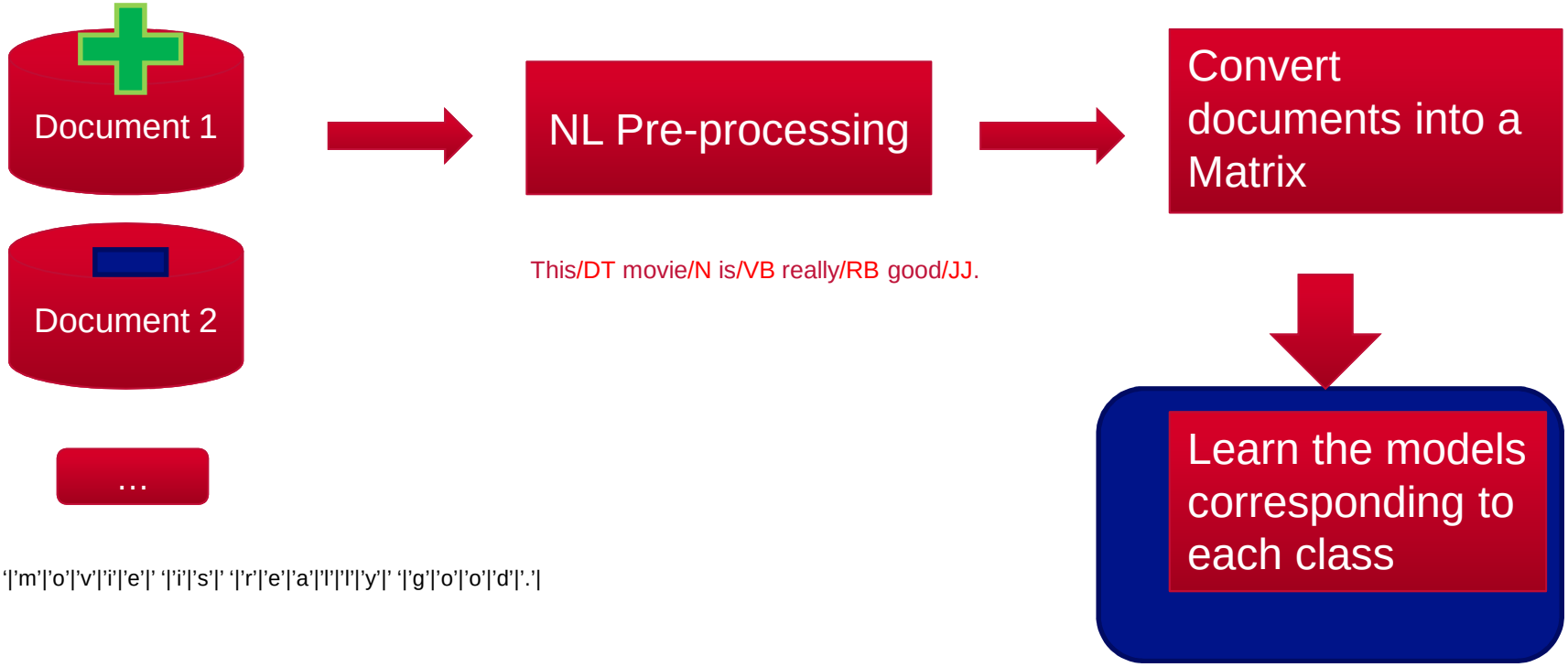
```
Phase:nestedpatternphase
Input: Lookup Token
//note that we are using Lookup and Token both
inside our rules.
Options: control = brill
Rule: playerid
(
 {Token.string == "player"}
)
:temp
(
{Lookup.majorType == Person}
|
(
 {Token.kind==word, Token.category==NNP,
Token.orth==upperInitial}
 {Token.kind==word, Token.category==NNP,
Token.orth==upperInitial}
)
)
```

Supervised machine learning

- **Phase 1 – learning**
  - Training corpus = set of documents annotated
    Annotation : each document is assigned to a class :
  - Goal : Learn from this corpus the specific features of each class
- **Phase 2 – classification**
  - Using the learned features, the system is able to assign a class to a new document

Phase 1 – learning

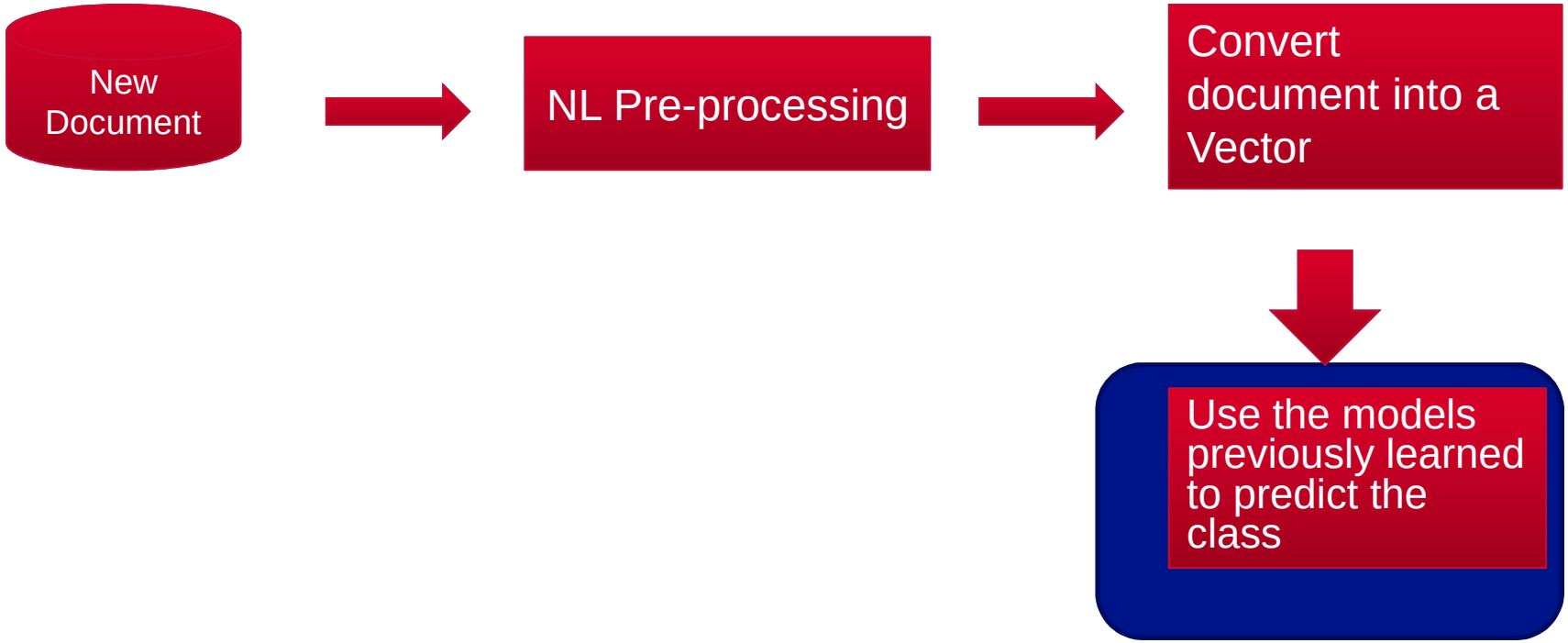
- **Learning the classes**



|’T’|’h’|’i’|’s’|’ ‘|’m’|’o’|’v’|’i’|’e’|’ ‘|’i’|’s’|’ ‘|’r’|’e’|’a’|’l’|’l’|’y’|’ ‘|’g’|’o’|’o’|’d’|’.’|

Phase 2 – classification

- **Predict the class of a new document**

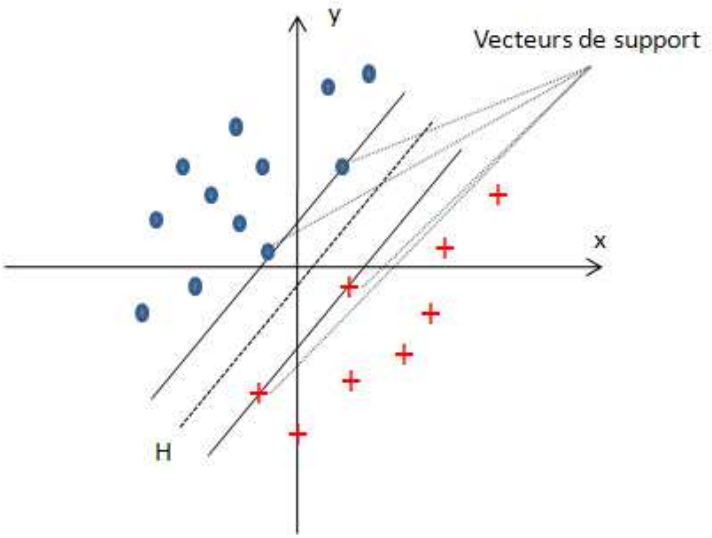


Generative vs. Discriminative Models

- **Generative (joint) models P(c, d)**
  - Model the distribution of individual classes and place probabilities over both observed data and hidden variables (such as labels)
  - E.g. hidden Markov models, Naïve Bayes,
- **Discriminative (conditional) models P(c|d)**
  - Learn boundaries between classes. Take data as given and put probability over the hidden structure given the data.
  - E.g. logistic regression, maximum entropy models, conditional random fields, support-vector machines, ...

Reminder – Support Vector Machines

- **SVM – Support Vector Machines [Vapnik, 1995]**
  - Main idea



- Split the training data into 2 sets while maximizing the distance to the separating hyperplan
- Support vectors : the closest points to the hyperplan
- Margin : minimal distance between the hyperplan and the training samples
- => learning = maximize the margin
- Decision : position of the new point relative to the hyperplan

Reminder – Support Vector Machines

- **SVM – Support Vector Machines [Vapnik, 1995]**
  - Usually
    - Use a transformation (a kernel) to move to a space with more dimensions to ensure that the problem can be linearly solved
    - Examples:
      - Linear : $k(x,y) = \exp(\frac{-\|x-y\|^2}{2\sigma^2})$
      - Gaussian $k(x,y) = x.y$
      - Polynomial $K(x,y) = (1+x.y)^d$

Naive Bayes Classifier

Classification Principle

- Choose the class c maximizing $P(c \mid o)$
  - Given an observation $o = document$

$$\hat{c} = \arg\max_{c} P(c \mid o)$$

  - Bayes rule + the fact that $P(o)$ is independent from the class =>

$$\hat{c} = \arg\max_{c} P(c \mid o) = \arg\max_{c} \frac{P(o \mid c)P(c)}{P(o)} = \arg\max_{c} P(o \mid c)P(c)$$

Naive Bayes Classifier

$$\hat{c} = \arg\max_{c} P(c \mid o) = \arg\max_{c} \frac{P(o \mid c)P(c)}{P(o)} = \arg\max_{c} P(o \mid c)P(c)$$

- Naive : assumptions of strong independance between the features
  - $o = doc$ and $(m_1, \ldots, m_N)$ the words of document o
  - $P(o|c) = P(m_1, \ldots, m_N|c) = \prod_{i=1}^{N} P(m_i|c)$ -> use the log

$$\hat{c} = \arg\max_{c \in \mathbb{R}} [log(P(c)) + \sum_{i=1}^{N} log(P(m_i/c))]$$

Naive Bayes Classifier

$$\hat{c} = \arg\max_{c \in \mathbb{R}} [log(P(c)) + \sum_{i=1}^{N} log(P(m_i/c))]$$

- Training on the labelled database
  - Estimating $P(c)$ and $P(m_i|c)$
    - $P(c) = \frac{documents\ in\ class\ C}{total\ number\ of\ documents}$
    - $P(m_i|c) = frequency\ of\ the\ word\ m_i\ in\ class\ c$

TP Sentiment analysis avec NB

TRAINMULTINOMIALNB($\mathbb{C}, \mathbb{D}$)
1 $V \leftarrow$ EXTRACTVOCABULARY($\mathbb{D}$)
2 $N \leftarrow$ COUNTDOCS($\mathbb{D}$)
3 **for each** $c \in \mathbb{C}$
4 **do** $N_c \leftarrow$ COUNTDOCSINCLASS($\mathbb{D}, c$)
5 $prior[c] \leftarrow N_c/N$
6 $text_c \leftarrow$ CONCATENATETEXTOFALLDOCSINCLASS($\mathbb{D}, c$)
7 **for each** $t \in V$
8 **do** $T_{ct} \leftarrow$ COUNTTOKENSOFTERM($text_c, t$)
9 **for each** $t \in V$
10 **do** $condprob[t][c] \leftarrow \frac{T_{ct}+1}{\sum_{t'}(T_{ct'}+1)}$
11 **return** $V, prior, condprob$

APPLYMULTINOMIALNB($\mathbb{C}, V, prior, condprob, d$)
1 $W \leftarrow$ EXTRACTTOKENSFROMDOC(V, d)
2 **for each** $c \in \mathbb{C}$
3 **do** $score[c] \leftarrow \log prior[c]$
4 **for each** $t \in W$
5 **do** $score[c] \mathrel{+}= \log condprob[t][c]$
6 **return** $\arg\max_{c \in \mathbb{C}} score[c]$

▶ Figure 13.2 Naive Bayes algorithm (multinomial model): Training and testing.

$P(m_i|c) =$ $frequency\ of$ $the\ word\ t$ $in\ class\ c$
+ Laplace smoothing

Question

- **Is Naïve Bayes a generative or a discriminative model?**
  - Na¨ıve Bayes is a generative model!
  - P(c|d) = P(d|c)P(c) P(d) P(c|d)P(d) = P(d|c)P(c) = P(d, c)
  - While we use a conditional probability P(c|d) for classification, we model the joint probability of c and d
  - This means it is trivial to invert the process and generate new text given a class label.

Logistic regression

- **If we only want to classify text, we do not need the full power of a generative model, but a discriminative model is sufficient.**
- **We only want to learn P(c|d).**
- **A general framework for this is logistic regression.**
  - logistic because it uses a logistic function regression combines a feature vector (d) with weights (β) to compute an answer

Logistic regression

- **Binary case:**

$$P(\text{true}|d) = \frac{1}{1 + exp(\beta_0 + \sum_i \beta_i X_i)}$$

$$P(\text{false}|d) = \frac{exp(\beta_0 + \sum_i \beta_i X_i)}{1 + exp(\beta_0 + \sum_i \beta_i X_i)}$$

- **Multinomial case:** $P(c|d) = \frac{exp(\beta_{c,0} + \sum_i \beta_{c,i} X_i)}{\sum_{c'} exp(\beta_{c',0} + \sum_i \beta_{c',i} X_i)}$

$$P(c|d) = \frac{exp(z_c)}{\sum_{c'} exp(z_{c'})}$$ Softmax function

  - where X are the features contained in d (for example tf-idf of word2vec).

Logistic regression

- Given this model formulation,
  - we want to learn parameters (the weights β) that maximise the conditional likelihood of the data according to the model P(c/d).
- Due to the softmax function
  - we not only construct a classifier, **but learn probability distributions over classes.**
- There are many ways to chose weights :
  - Perceptron : Find misclassified examples and move weights in the direction of their correct class
  - Margin-Based Methods such as Support Vector Machines : can be used for learning weights
  - **Logistic Regression : Directly maximize the conditional log-likelihood via gradient descent**

Logistic regression

- **Directly maximize the conditional log-likelihood**

$$\log P(c|d,\beta) = \log \prod_{c,d\in(C,D)} P(c_n|d_n,\beta)$$

$$= \sum_{c,d\in(C,D)} \log P(c_n|d_n,\beta)$$

$$\log P(c_n|d_n,\beta) = \sum_{c,d\in(C,D)} \log \frac{exp(\sum_i \beta_{c,i} X_i)}{\sum_{c'} exp(\sum_i \beta_{c',i} X_i)}$$

- **via gradient descent**
  - Derivative with respect to β is concave

Evaluation scores

- **In the task of correct assignment to class c**
  - R = Recall : (number of system's correct assignments to class c) / (number of documents labelled c)
    - A system that tends to infrequently assign class c (high system *silence* for class c) will have a low recall

Evaluation scores

- **In the task of correct assignment to class c**
  - P = Precision : (number of system's correct assignments to class c) / (number of system's assignments to class c)
    - A system that tends to allocate class c too frequently (system *noise* is high for class c) will have precision

Evaluation scores

- **In the task of correct assignment to class c**
  - F-score : harmonic mean between recall and precision
    = 2×(P ×R) / (P +R)

Hybrid methods

- **Hand-crafted features based on linguistic features to support classification**
  - Example 1 : In the term-document matrix
    - The terms are replaced by concepts in the term / document matrix « j'aimerais » => attentes du client L. Kuznick, A-L. Guènet, A. Peradotto, and C. Clavel. L'apport des concepts métiers pour la classification des questions ouvertes d'enquête. In Actes de TALN, Montréal, 2010.
  - Example 2 : linguistic and syntactic patterns are used as inputs of supervised machine learning
    - Barrière, V., Clavel, C., Essid, E., Opinion Dynamics Modeling for Movie Review Transcripts Classification with Hidden Conditional Random Fields, Interspeech 2017

Semi-supervised learning

- **When using big unlabelled data but labelled data are missing**
  - Example
    - Train word2vec on the unlabelled data
    - Supervised learning on the labelled part
      - Johnson, R., & Zhang, T. (2015). Semi-supervised convolutional neural networks for text categorization via region embedding. In *Advances in neural information processing systems*

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