Similarités sémantiques et spatialité : méthodes d'autocorrelation spatiale appliquées au texte

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La spatialité

Autocorrélation Globale

Autocorrélation Locale

Clustering



Introduction

Dans ce travail, les unités étudiées sont les **tokens** d'un corpus. Deux aspects sont mis en relation :

- Les similarités sémantiques entre tokens, obtenues via des sources externes.
- La spatialité des tokens, c'est-à-dire leur position les uns par rapport aux autres.

De ces deux ingrédients, nous pourrons obtenir :

- Un indice d'autocorrélation globale des tokens d'un corpus.
- Un indice d'autocorrélation locale pour chacun des tokens.
- Un **clustering** des tokens.

GitHub: https://github.com/sliunil/SemSim_AutoCor



Les similarités sémantiques

Les similarités sémantiques

En anglais, il existe une distinction entre *semantic similarity* et *semantic relatedness* :

- La semantic similarity désigne le fait que deux mots possèdent une relation de type hyponymie-hyperonymie (p.ex : chien et animal)
- La semantic relatedness est plus large, désignant des relations de n'importe quel type, comme
 l'holonymie-méronimie (p.ex : chien et truffe), l'antonymie (p.ex : mort et vivant) ou même une relation de type « fait partie du même univers » (p.ex : voiture et route).

Dans ce travail, lorsque nous parlons de **similarités sémantiques**, il s'agit donc plutôt de la deuxième définition :

Deux mots sont proches sémantiquement s'il existe une forte

relation, de n'importe quel type, entre (l'un de) leur(s) signifié(s).

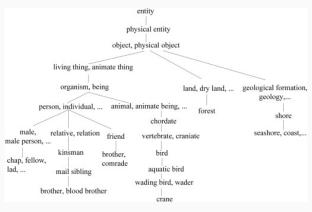
Les mesures de similarités sémantiques

Dans la pratique, il existe plusieurs manières d'obtenir une **mesure de similarité sémantique** entre deux termes. Dans ce travail, ces mesures vont être extraites via deux types d'objet :

- En utilisant l'ontologie WordNet.
- En utilisant un plongement lexical (Word Embedding) pré-entrainé sur un très grand corpus.

WordNet

WordNet [Fellbaum, 1998] est une ontolgie entre différents synsets (ensembles de mots représentant un concept). Plusieurs relations (antonymie, holonymie-meronymie, etc.) sont représentées dans cette ontologie, mais la plus complète est celle d'hyponymie-hyperonymie.



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Il existe de nombreuses similarités basées sur WordNet.

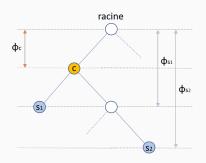
La similarité de Wu-Palmer

[Wu and Palmer, 1994] entre deux synsets s_1 et s_2 :

$$s_{s_1 s_2}^{wup} = \max_{c \in S(s_1, s_2)} \left(\frac{2\phi_c}{\phi_{s_1} + \phi_{s_2}} \right)$$

 $S(s_1, s_2)$ est l'ensemble des synsets hyperonymes à s_1 et s_2 .

 ϕ_s est la **profondeur** du synset s, c'est-à-dire la longueur du chemin le reliant à la racine.



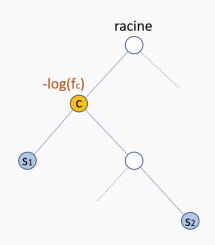
La similarité de Resnik

[Resnik, 1995] entre deux synsets s_1 et s_2 :

$$s_{s_1s_2}^{res} = \max_{c \in S(s_1, s_2)} (-\log(f_c))$$

 $S(s_1, s_2)$ est l'ensemble des synsets hyperonymes à s_1 et s_2 .

 f_c est la **probabilité d'utilisation** du synset c (estimée depuis un corpus donné)





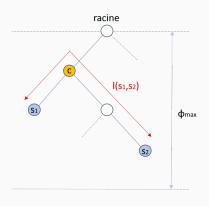
La similarité de Leacock-Chodorow

[Leacock and Chodorow, 1998] entre deux synsets s_1 et s_2 :

$$s_{s_1s_2}^{lec} = -\log\left(\frac{I(s_1, s_2)}{2\phi_{\mathsf{max}}}\right)$$

 $l(s_1, s_2)$ est la **longueur du chemin** reliant s_1 à s_2 .

 ϕ_{max} est la **profondeur maximale** de WordNet.



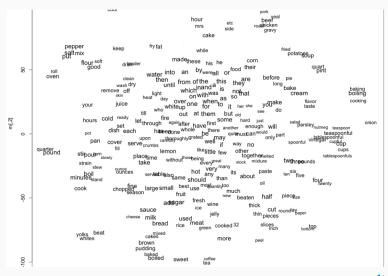
Il existe cependant des **difficultés** à utiliser les similarités WordNet afin de calculer une **similarité entre deux tokens** d'un corpus donné :

- Sans désambiguïsation, il n'est pas possible de savoir à quels synsets ces tokens appartiennent.
- WordNet contient plusieurs racines, pour les noms, verbes, adjectifs et adverbes. Il est difficile de calculer une similarité en passant d'un arbre à un autre.

Les méthodes de **plongement lexical** sont nombreuses : Word2Vec [Mikolov et al., 2013], GloVe [Pennington et al., 2014], FastText [Bojanowski et al., 2017], etc. mais elles partagent toutes le même principe :

- On utilise un grand corpus pour transformer chaque type en un vecteur de dimension r.
- Ces vecteurs sont calculés depuis le corpus pour que les types possédant un contexte similaire (i.e. une fenêtre de taille ±t tokens) donnent des vecteurs proches dans l'espace.
- La similarité sémantique entre deux types peut ensuite être obtenue grâce à la similarité du cosinus entre leurs deux vecteurs :

$$s_{kl}^{\mathsf{we}} = \mathsf{cos}(\mathbf{\textit{v}}_k, \mathbf{\textit{v}}_l) = \frac{\mathbf{\textit{v}}_k^{ op} \mathbf{\textit{v}}_l}{\|\mathbf{\textit{v}}_k\| \|\mathbf{\textit{v}}_l\|}$$



Source: https://www.adityathakker.com/introduction-to-word2vec-how-it-works/

Ici, nous allons utiliser:

- La méthode Word2Vec
- appliquée sur Wikipedia (anglais)
- avec une fenêtre de ±5 tokens
- qui donneront des vecteurs à 300 dimensions.

Ces vecteurs pré-entraînés (dans plusieurs langues) se trouvent sur https://wikipedia2vec.github.io/wikipedia2vec/

Les similarités obtenues via des plongements lexicaux présentent également des **désavantages** :

- Il y a un unique vecteur par type, représentant donc une moyenne de tous les sens possibles.
- Ces vecteurs représentent les sens trouvés dans le corpus utilisé pour l'entraînement et peuvent être différents dans le texte étudié.
- Plus gênant pour nos méthodes, ces méthodes utilisent la spatialité pour construire les similarités sémantiques.

Transformation d'une similarité en dissimilarité

Dans la suite, nous avons généralement besoin d'une dissimilarité plutôt qu'une similarité. Il existe plusieurs transformations possibles, par exemple :

$$d_{ij}^{\text{minus_log}} = \begin{cases} -\log(s_{ij}) & \text{si } s_{kl} > 0, \forall k, l \\ -\log(s_{ij} - \min_{kl} s_{kl} + \epsilon) & \text{sinon} \end{cases}$$
$$d_{ij}^{\text{max_minus}} = \max_{kl} s_{kl} - s_{ij}$$

Dans la pratique, la transformation **minus_log** semble donner des résultats plus convaincants, nous n'allons donc utiliser que cette dernière.

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Les similarités sémantiques : pour résumé

L'étude portera sur 3 similarités sémantiques issues de WordNet pour calculer la similarité entre deux tokens i et j :

- La similarité de Wu-Palmer : s_{ii}^{wup}
- La similarité de Resnik : s_{ij}^{res}
- La similarité de Leacock-Chodorow : s_{ij}^{lec}

Pour ces similarités, le sens le plus fréquemment utilisé définira les synsets de i et j et elles ne seront appliquées qu'à des tokens d'une même catégorie (nom, verbe, adjectif, adverbe). De plus, on aura :

La similarité issue de Word2Vec sur Wikipedia : s_{ij}^{we}

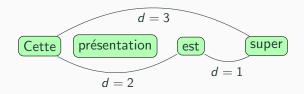
où cette similarité sera obtenue en fonction du type de i et du type de j.

Les similarités seront transformées en dissimilarités avec minus_log.

La spatialité

La spatialité

La spatialité des tokens est plus facile à définir, il s'agit leur position dans le texte, vu comme un espace unidimensionnel.



lci, on prefera définir la spatialité via une **relation de voisinage** c'est-à-dire via une **matrix d'adjacence** A de taille $n_{\text{token}} \times n_{\text{token}}$:

$$A = \left(\begin{array}{cccc} 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{array}\right)$$

La spatialité

Il est cependant possible de définir ce voisinage avec **une fenêtre de taille** r, permettant de représenter plus fidèlement notre manière de lire. Il y a cependant deux choix possibles : Un **voisinage uniforme** :

Un voisinage gaussien:

$$a_{i:} = \begin{pmatrix} \dots & 0.004 & 0.054 & 0.242 & 0.399 & 0.242 & 0.054 & 0.004 & \dots \end{pmatrix}$$



La matrice d'échange

Dans notre formalisme, nous aurons besoin d'une matrice d'échange $E = (e_{ij})$. Les composantes e_{ij} représentent les liens de voisinage entre les tokens i et j et cette dernière doit vérifier :

- $e_{ij} \geq 0$
- $e_{ij} = e_{ji}$
- $e_{i\bullet} = f_i$

où f_i sont les poids des tokens (généralement uniforme).

Des méthodes particulières (utilisant le Laplacien d'un graphe et un algorithme de Metropolis-Hastings) permettent d'**obtenir E à partir de A**, tout en respectant les poids des tokens f_i .

La spatialité : pour résumé

La **spatialité** des tokens sera définie via une **relation de voisinage** contenue dans une **matrice d'échange** $E = (e_{ij})$ symétrique, où e_{ij} représente le lien entre les tokens i et j, et $e_{i\bullet} = f_i$ le poids du token i.

Un entier $r \ge 1$ va définir la largeur de voisinage que l'on considère.

Il y a deux choix sur la distribution des liens dans le voisinage :

- Une distribution **uniforme** sur une fenêtre de $\pm r$: $\textbf{\textit{E}}_r^{\text{unif}}$
- Une distribution **normale** de « diffusion » $r : E_r^{\text{norm}}$

Les méthodes

Nous avons défini deux objets sur les tokens :

- Une matrice de dissimilarité entre tokens D = (d_{ij}), quantifiant à quel point ces derniers sont sémantiquement éloignés.
- Une matrice d'échange entre tokens $E = (e_{ij})$, définissant leurs relations spatiales.

Ces deux ingrédients vont nous permettre d'obtenir :

- Une mesure d'autocorrelation globale [Bavaud et al., 2015], quantifiant en moyenne sur un corpus donné à quel point les tokens voisins sont similaires sémantiquement.
- Une mesure d'autocorrelation locale, quantifiant pour chaque token d'un corpus donné à quel point celui-ci est similaire sémantiquement à son voisinage.
- Un clustering des tokens [Ceré and Bavaud, 2017], qui permet de regrouper les tokens proches sémantiquement ET spatialement.

Autocorrélation Globale

L'autocorrélation globale

Sur un corpus donné, on peut définir l'inertie globale des tokens (de poids f_i) avec :

$$\Delta := \frac{1}{2} \sum_{ij} f_i f_j \mathbf{d}_{ij}$$

cette dernière quantifie l'éloignement sémantique moyen entre tous les tokens.

De manière similaire, on peut définir l'inertie locale avec :

$$\Delta_{\mathsf{loc}} := rac{1}{2} \sum_{ij} e_{ij} oldsymbol{d}_{ij}$$

cette fois-ci, il s'agit de l'éloignement sémantique moyen entre tokens voisins.

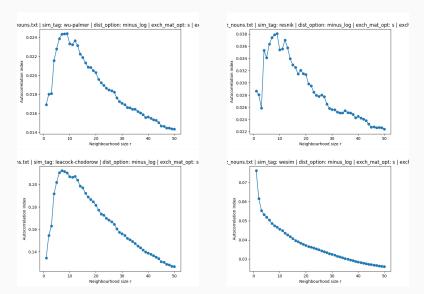
On peut alors définir un indice d'autocorrelation globale avec :

$$\delta := \frac{\Delta - \Delta_{\mathsf{loc}}}{\Delta}$$

qui peut prendre des valeurs entre -1 et 1.

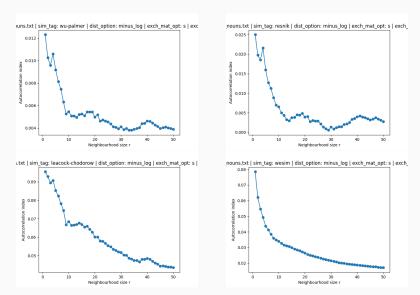
L'autocorrélation globale : résultats

The Wonderful Wizard of Oz (L. Frank Baum) - nouns, $\boldsymbol{E}_r^{\text{unif}}$:



L'autocorrélation globale : résultats

Animal Farm (G. Orwell) - nouns, E_r^{unif} :



Autocorrélation Locale

L'autocorrélation locale

On peut également définir un **indice d'autocorrélation locale pour chaque token** *i* avec :

$$\delta_i = \frac{\sum_k w_{ik} \mathbf{b}_{ki}}{\Delta}$$

où:

- W = (w_{ij}) est une matrice de transition de la chaîne de Markov issue de E, i.e. W := Diag(f)⁻¹E.
- $B = (b_{ij})$ est la matrice des produits scalaires, issue de de D, i.e. $B := -\frac{1}{2}HDH^{\top}$ avec $H := I_n I_n f^{\top}$.

Cet indice mesure donc **la similarité sémantique moyenne entre** *i* **et ses voisins**.

On peut montrer que l'autocorrélation globale est la moyenne (pondérée) des autocorrélations locales :

$$\delta = \sum_{i} f_{i} \delta_{i}$$



L'autocorrélation locale : résultats

The Wonderful Wizard of Oz (L. Frank Baum), \mathbf{S}^{we} , $\mathbf{E}_{100}^{\text{unif}}$:

chapter ildorothy lived midst great kansa prairie uncle henry wa farmer aunt em wa farmer wife house wa small lumber build had be carried wagon many mile were wall floor roof made room room contained justy looking cooking stove cupboard dish table chair bed uncle henry aunt em had big bed corner dorothy little bed corner wa garret at all cellar small hole dug ground called cyclone cellar family go case great whirlwind arose mighty enough crush building path wa reached trap door middle floor ladder led down small dark hole dorothy stood doorway looked around see nothing great gray prairie side not tree house broke broad sweep flat country reached edge sky direction sun had baked plowed land gray mass little crack running even grass wa not green sun had burned top long blade were same gray color be seen everywhere once house had been painted sun blistered paint rain washed away now house wa a dull gray everything else aunt em came there live wa young pretty wife sun wind had changed too had taken sparkle eye left sober gray had taken red cheek lip were gray also wa thin gaunt never smiled now dorothy wa orphan first came aunt em had been so startled child laughter scream press hand heart dorothy merry voice reached ear still looked little girl wonder find anything laugh uncle henry never laughed worked hard morning night did not know joy wa wa gray also long beard rough boot looked stern solemn rarely spoke wa toto made dorothy laugh saved growing a gray other surroundings toto wa not gray wa little black dog long silky hair small black eve twinkled merrily side funny wee nose toto played day long dorothy played loyed dearly to day however were not playing uncle henry sat door step looked anxiously sky wa even graver usual dorothy stood door toto arm looked sky too aunt em wa washing dish far north heard low wail wind uncle henry dorothy see long grass bowed wave coming storm there now came sharp whistling air south turned eve way saw ripple grass coming direction also suddenly uncle henry stood cyclone coming called wife go look stock then ran shed cow horse were kept aunt em dropped work came door glance told danger close hand quick dorothy screamed run cellar toto jumped dorothy arm hid bed girl started get aunt em badly frightened threw trap door floor climbed ladder small dark hole dorothy caught toto last started follow aunt wa half way room came great shrick wind house shook so hard lost footing sat suddenly floor strange thing then happened house whirled around time rose slowly air dorothy felt were going balloon north south wind met house stood made exact center cyclone middle cyclone air is generally still great pressure wind side house raised higher higher wa very top cyclone there remained wa carried mile mile away a easily carry feather wa very dark wind howled horribly dorothy found wa riding quite easily first few whirl around other time house tipped badly felt were being rocked gently baby cradle toto did not like ran room now here now there barking loudly dorothy sat quite still floor waited see happen once toto got too open tran door fell first little girl thought had lost soon saw ear sticking hole strong pressure air wa keeping not fall creet hole caught toto our dragged room again afterward closing trap door more accident happen hour hour passed slowly dorothy got fright felt quite lonely wind shrieked so loudly all nearly became deaf first had wondered be dashed piece house fell again hour passed nothing terrible happened stopped worrying resolved wait calmly see future bring last crawled swaying floor bed lay toto followed lay spite swaying house wailing wind dorothy soon closed eye fell fast asleep chapter wa awakened shock so sudden severe dorothy had not been lying soft bed have been hurt wa ar made catch breath wonder had happened toto out cold little nose face whined dismally dorothy sat noticed house wa not moving wa dark bright sunshine came in window flooding little nosm sprang bed toto heel ran opened door little girl gave cry amazement looked eve growing bigger bigger wonderful sight saw exclone had set house very gently exclone midst country marvelous beauty were lovely patch green sward all about stately tree bearing rich luscious fruit bank gorgeous flower were hand bird rare brilliant plumage sang fluttered tree bash little way off wa small brook rushing snarkling along green bank murmuring voice very grateful little girl had lived so long dry gray prairie stood looking eagerly strange beautiful sight noticed coming group queerest people had ever seen were not a big grown folk had always been used were very small fact seemed about a tall dorothy wa well grown child age were so far look to many year older were men woman were oddly dressed wore round hat rose small point foot head little bell brim sweetly moved hat men were blue little woman hat wa white wore white gown hung plaif shoulder were sprinkled little star glistened sun diamond men were dressed blue same shade hat wore well polished boot deep roll blue top men dorothy thought were about a old uncle henry had beard little woman wa doubtless much older face wa covered wrinkle hair wa nearly white walked rather stiffly people drew house dorothy wa standing doorway paused whispered afraid come farther little old woman walked dorothy made low bow said sweet voice are welcome most noble sorceress land munchkins are so grateful having killed wicked witch east setting people free bondage dorothy listened speech wonder little woman possibly mean calling sorceress saying had killed wicked witch east dorothy wa innocent harmless little girl had been carried evolune many mile home had never killed anything life little woman evidently expected answer so dorothy said besitation are very kind be mistake have not killed anything house did anyway replied little old woman laugh is same thing see continued pointing corner house are toe still sticking block wood dorothy looked gave little cry fright there indeed just corner great beam house rested foot were sticking shod silver shoe pointed toe dear cried dorothy classing hand together dismay house have fallen ever do is nothing be done said little woman calmly wa asked dorothy wa wicked witch east said answered little woman ha held munchkins bondage many year making slave night day now are all set free are grateful favour are munchkins enquired dorothy are people live land east wicked witch ruled are munchkin asked dorothy am friend live land north saw witch east wa dead munchkins sent swift messenger came once am witch north cried dorothy are real witch indeed answered little woman am good witch people love am not a powerful wicked witch wa ruled here have set people free thought witch were wicked said girl wa half frightened facing real witch is great mistake were only witch land or live north south are good witch know is true am be mistaken dwelt east west were indeed wicked witch now have killed is wicked witch land or one life west said dorothy moment thought aunt em ha told witch were all dead year year ago is aunt em inquired little old woman is aunt life kansa came witch north seemed think time head bowed ever ground then looked said do not know kansa is have never heard country mentioned before tell is civilized country replied dorothy then account civilized country believe are witch left wizard sorceress magician see land oz ha never been civilized are cut rest world therefore still have witch wizard are wizard asked dorothy oz is great wizard answered witch sinking voice whisper is more powerful rest together life city emerald dorothy wa going ask question just then munchkins had been standing silently by gave loud shout pointed corner house wicked witch had been lying is asked little old woman looked began laugh

Clustering

Clustering des tokens

Il est également possible d'utiliser ces deux ingrédients pour obtenir un **clustering flou des tokens** d'un corpus.

Posons p le nombre de groupes. Le résultat d'un clustering flou sur les n tokens peut être donnée par une **matrice d'appartenance** $Z = (z_{ig})$, de taille $(n \times p)$, qui vérifie :

- $z_{ig} \geq 0$
- $z_{i\bullet}=1$

La quantité z_{ig} nous donnera donc l'appartenance (en pourcent) du token i au groupe g.

Clustering: l'inertie intra-groupe

Plusieurs quantités peuvent être calculée à partir d'une matrice d'appartenance Z.

L'inertie intra-groupe $\Delta_W[Z]$, définie par

$$\Delta_W[Z] := \sum_g \rho_g \Delta_g$$

où:

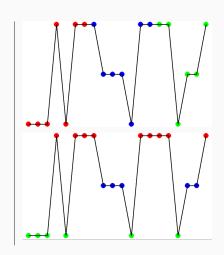
- $\rho_g := \sum_i f_i z_{ig}$ est le **poids du groupe** g.
- $\Delta_g := \sum_{ij} rac{f_i z_{ig}}{
 ho_g} rac{f_j z_{jg}}{
 ho_g} d_{ij}$ est l'inertie du groupe g

Clustering: l'inertie intra-groupe

Cette quantité mesure donc la variation sémantique des tokens à l'intérieur des groupes :

 $\Delta_W[{m Z}]$ élevé

 $\Delta_W[\mathbf{Z}]$ faible





Clustering : la modularité généralisée

La modularité généralisée $C^{\kappa}[Z]$, définie par

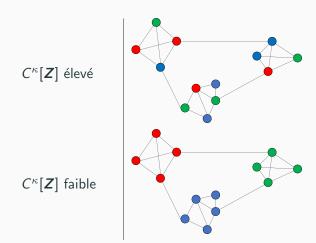
$$C^{\kappa}[\mathbf{Z}] := \sum_{\mathbf{g}} \frac{
ho_{\mathbf{g}}^2 - e(\mathbf{g}, \mathbf{g})}{
ho_{\mathbf{g}}^{\kappa}}$$

où:

- $\rho_g := \sum_i f_i z_{ig}$ est le **poids du groupe** g.
- e(g,g) := ∑_{ij} e_{ij} z_{ig} z_{jg} est la moyenne pondérée du nombres de liens (de voisinage) dans le groupe g.
- $\kappa \in [0,1]$ un **paramètre libre**, permettant de passer d'un objectif de modularité ($\kappa=0$) à un objectif de N-cut ($\kappa=1$)

Clustering: l'inertie intra-groupe

Cette quantité mesure donc la quantité des liens (de voisinage) entre les groupes :



Clustering: l'inertie intra-groupe

Finalement, on peut aussi définir l'information mutuelle $K[\mathbf{Z}]$ par :

$$K[\boldsymbol{Z}] = \sum_{ig} f_i z_{ig} \frac{z_{ig}}{\rho_g}$$

Cette quantité mesure la dépendance entre les groupes et les tokens, i.e. :

- K[Z] sera élevé si chaque token appartient à un groupe bien défini (solution dure).
- K[Z] sera faible si chaque token appartient en partie à chaque groupe (solution floue).

Clustering: la fonctionnelle

Le but sera de chercher un clustering Z qui minimise l'énergie libre F[Z], définie comme :

$$F[Z] = \beta \Delta_{W}[Z] + \frac{\alpha}{2} C^{\kappa}[Z] + K[Z]$$

où $\alpha>$ 0, $\beta>$ 0 et $\kappa\in[0,1]$ sont des paramètres libres.

- Augmenter α relativement à β favorisera l'émergence de groupes spatialement continus, i.e. de longues suites de tokens.
- Augmenter β relativement à α favorisera l'émergence de groupes homogènes, sémantiquement parlant.
- Baisser α ET β favorisera l'émergence de groupes flous.
- κ fait passer l' **objectif spatial** d'un critère de modularité (=0) à un critère du N-cut (=1).

Un algorithme itératif permet de trouver la solution Z qui minimise cette fonctionnelle.

Il est difficile de se rendre compte si les groupes de tokens trouvés correspondent à quelque chose, surtout qu'il y a **beaucoup d'hyperparamètres** :

- Choix de la similarité sémantique.
- Choix du voisinage : $\mathbf{E}_r^{\text{unif}}$ ou $\mathbf{E}_r^{\text{norm}}$, définir r.
- Choix du nombre de groupes p.
- Choix des hyperparamètres de la fonctionnelle : α , β et κ .

Pour essayer de voir si ce clustering est capable de regrouper des passages sémantiquement proches, nous avons créer une technique d'évaluation originale.

Quatre livres, parlant de sujets à priori bien différents, ont été sélectionnés sur le projet Gutenberg. Il s'agit de :

- Sidelights on relativity, livre de vulgarisation de physique de Albert Einstein,
- Metamorphosis, roman de Franz Kafka.
- On the Duty of Civil Disobedience, essai politique de Henry David Thoreau.
- Lectures On Landscape, recueil de cours académiques sur la peinture de paysage de John Ruskin.

A partir de ces livres, 4 corpus ont été créés en mélangeant les différents livres :

- Mix_word1, où chaque token est tiré aléatoirement d'un des livres.
- Mix_word3, où chaque séquence de 3 token est tirée aléatoirement d'un des livres.
- Mix_sent1, où chaque phrase est tirée aléatoirement d'un des livres.
- Mix_sent10, où chaque séquence de 10 phrases est tirée aléatoirement d'un des livres.

Chaque phrase doit comporter 5 tokens minimum et les corpus sont construits afin d'avoir des nombres relativement égaux de tokens issus de chaque livre.

On va effectuer un **recherche sur grille** pour les hyperparamètres et mesurer à chaque fois l'adéquation entre les groupes obtenus et les vrais groupes grâce à l'indice d'**information mutuelle normalisé (NMI)**. Les paramètres posés/explorés sont :

- La similarité sémantique issue du word embedding : \boldsymbol{S}^{we}
- La matrice d'échange gaussienne : $\boldsymbol{E}_r^{\mathrm{norm}}$
- Le facteur de diffusion de la matrice d'échange : $r \in \{3, 5, 10, 15\}.$
- Le nombre de groupes sera posé à p = 4.
- Le paramètre $\alpha \in \{0.1, 1, 2, 5, 10, 50, 100\}.$
- Le paramètre $\beta \in \{0.1, 1, 5, 10, 50, 100, 300\}.$
- Le paramètre $\kappa \in \{0, \frac{1}{3}, \frac{2}{3}, 1\}$.

Dataset	Best parameters	NMI	NMI - LDA	
Mix_word1	$r = 3, \alpha = 2, \beta = 100, \kappa = 0$	0.05	0.0026	
Mix_word3	$r = 3, \alpha = 2, \beta = 10, \kappa = 1/3$	0.06	0.0029	
Mix_sent1	$r = 15, \alpha = 2, \beta = 10, \kappa = 1/3$	0.16	0.0025	
Mix_sent10	$r = 15, \alpha = 2, \beta = 10, \kappa = 1/3$	0.35	0.0025	

Gauche: meilleurs résultats. Droite: Mix_sent1

rphosis gregor samsa woke troubled found transformed bed horrible inaugural stated holdin ofessorship direct practical chiefly natural history having course past year laid foundational eleart sufficiently invite enter real work accordingly propose following term give practical leading ementary study branch natural history form kind center lay lifted head little see brown slightly ivided arch stiff sidelight relativity ether theory relativity address delivered may university leyden do ome idea ponderable is derived abstraction everyday physicist set idea existence kind outset short ate position landscape painting animal painting hold higher branch landscape painting is thou ssionate representation physical condition appointed human bedding wa hardl dy slide imitates record visible thing are dangerous beneficial display human method deali given rise theory action property light have led undulatory animal painting investigates law eater le nobility character organic comparative anatomy examines greater le development organ nction animal painting is bring notice minor unthought condition power physiology is ascertain mode life is therefore he struck awkwardness apparent uselessness collection textile same spread table sams wa travelling salesman there hung picture had recently cut illustrated magaz used gilded sketching day several head bird became vital matter interest know use bony process head ng great found appeared absurd wa certainly unanswerable communication motion push heating bustion mean is true even everyday experience is sense action play very impe ed fur hat fur boa sat raising heavy fur muff covered whole lower arm gregor then turned loo dow dull drop rain be heard hitting made feel quite have have just lands tion wa theory gravitation first assigned cause gravity interpreting action proceeding s gory is probably greatest stride ever made effort causal nexus natural sleep little bit longer forget wa mething wa unable do wa used sleeping present state get however hard threw always rolled back nding army is only arm standing vet theory evoked lively sense discomfort seemed be conflict inciple springing rest be reciprocal action only not immediate action here are landscape turn atest vesuvius government is only mode people have chosen execute is equally liable





Gauche: meilleurs résultats. Droite: Mix_sent10

nosis gregor samsa woke troubled found transformed bed horrible lay lifted head little se rown slightly domed divided arch stiff bedding wa hardly able cover seemed ready slide many tifully thin compared size rest waved about helplessly proper human room little too lay peace miliar collection textile sample lay spread table samsa wa travelling salesman there hung picture ha ecently cut illustrated magazine housed gilded showed lady fitted fur hat fur boa sat raising heavy fu nuff covered whole lower arm gregor then turned look window dull drop rain be heard hitting made eel quite sleep little bit longer forget wa something wa unable do wa used sleeping present state go naugural stated holding professorship direct practical chiefly natural history having course past ital matter interest know use bony process head asking great found appeared absurd wa certain answerable have have just landscape painting ren sobedience heartily accept government is best governs like see acted more rapidly carried finall nount also government is best governs not men are prepared be kind government government is be ost government are government are objection have been brought standing are many deserve also at ast be brought standing standing army is only arm standing government is only mode people have hosen execute is equally liable be abused perverted people act witness present mexican work omparatively few individual using standing government people not have consented american is recei deavoring transmit unimpaired instant losing ha not vitality force single living single man bend is ort wooden gun people is not le necessary people have complicated machinery hear satisfy idea overnment government show thus successfully men be imposed even impose own government never jurthered alacrity got character inherent american people ha done ha been have done somew government had not sometimes got government is men fain succeed letting one ha been is most governed are most let alone trade were not made never manage bounce obstacle legislator are ontinually putting were judge men wholly effect action not partly deserve be classed punished person out obstruction speak practically call ask not once better let man make known kind government nand be step obtaining after practical reason power is once hand majority are long period rule is ot are most likely be seems fairest are physically government majority rule case not be based even

netamorphosis gregor samsa woke troubled found transformed bed horrible lay lifted head little see rown slightly domed divided arch stiff bedding wa hardly able cover seemed ready slide many itifully thin compared size rest waved about helplessly proper human room little too lay peaceful amiliar collection textile sample lay spread table samsa wa travelling salesman there hung picture ha ecently cut illustrated magazine boused gilded showed lady fitted fur hat fur boa sat raising heavy fi auff covered whole lower arm gregor then turned look window dull drop rain be heard hitting mad eel quite sleep little bit longer forget wa something wa unable do wa used sleeping present state g fience heartily accept government is best governs like see acted more rapidly carried final mount also government is best governs not men are prepared be kind government government is b nost government are government are objection have been brought standing are many deserve also last be brought standing standing army is only arm standing government is only mode people have chosen execute is equally liable be abused perverted people act witness present mexican work omparatively few individual using standing government people not have consented american is recei endeavoring transmit unimpaired instant losing ha not vitality force single living single man bend i ort wooden gun people is not le necessary people have complicated machinery hear satisfy idea government government show thus successfully men be imposed even impose own government never furthered alacrity got character inherent american people ha done ha been have done somewhat government had not sometimes got government is men fain succeed letting one ha been is most overned are most let alone trade were not made never manage bounce obstacle legislator are continually nutting were judge men wholly effect action not partly deserve be classed nunished person put obstruction speak practically call ask not once better let man make known kind government command be step obtaining after practical reason power is once hand majority are long period rule not are most likely be seems fairest are physically government majority rule case not be based even far men understand sidelight relativity ether theory relativity address delivered may university leyder



Appartenance moyenne par type (top10), Mix_sent1

Groupe	1	Groupe	2	Groupe 3		Groupe	4
ask	0.95	street	0.97	differential	0.99	is	0.96
forgive	0.95	hat	0.97	inertial	0.98	consists	0.90
postpone	0.95	hung	0.96	homogeneous	0.98	are	0.72
consented	0.95	headboard	0.96	variability	0.98	constitutes	0.61
suffer	0.94	slid	0.96	euclidean	0.98	represents	0.48
decide	0.94	boa	0.96	comparative	0.98	conforms	0.39
believed	0.94	buried	0.96	scalar	0.98	governs	0.30
accuse	0.94	muff	0.96	continuum	0.98	exists	0.21
expect	0.94	gilded	0.96	computation	0.97	enjoys	0.14
actually	0.94	sat	0.96	finite	0.97	commonly	0.14

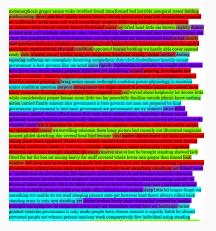
Classification semi-supervisée : résultats préliminaires

Dataset	NMI - 5%	NMI - 10%	NMI - 20%
	0.06	0.06	0.06
Mix_word1	$r = 10, \alpha = 5$	$r = 15, \alpha = 0.1$	$r = 3, \alpha = 10$
	$\beta=100, \kappa=0$	$\beta=300, \kappa=1$	$\beta=300, \kappa=1$
	0.09	0.10	0.14
Mix_word3	$r=3,\alpha=2$	$r=3, \alpha=5$	$r=3, \alpha=5$
	$\beta=10,\kappa=1/3$	$\beta=50,\kappa=2/3$	$\beta=50, \kappa=1/3$
	0.29	0.40	0.54
Mix_sent1	$r=3, \alpha=5$	$r=5, \alpha=5$	$r=3, \alpha=5$
	$eta=10,\kappa=0$	$eta=10, \kappa=0$	$eta=10, \kappa=0$
	0.77	0.90	0.95
Mix_sent10	$r=15, \alpha=5$	$r = 10, \alpha = 2$	r=15, lpha=2
	$\beta=10, \kappa=0$	$\beta = 10, \kappa = 2/3$	$\beta=5, \kappa=1$

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Classification semi-supervisée : résultats préliminaires

Gauche: meilleurs résultats 10%. Droite: Mix_sent1







Classification semi-supervisée : résultats préliminaires

Gauche: meilleurs résultats 10%. Droite: Mix_sent10

tamorphosis gregor samsa woke troubled found transformed bed horrible lay lifted head little see rown slightly domed divided arch stiff bedding wa hardly able cover seemed ready slide man pitifully thin compared size rest waved about helplessly proper human room little too lay peaceful amiliar collection textile sample lay spread table samsa wa travelling salesman there hung picture had ecently cut illustrated magazine housed gilded showed lady fitted fur hat fur boa sat raising heavy fu ouff covered whole lower arm gregor then turned look window dull drop rain be heard hitting maeel quite sleep little bit longer forget wa something wa unable do wa used sleeping press heartily accept government is best governs like see acted more rapidly carried final nount also government is best governs not men are prepared be kind government government is bes nost government are government are objection have been brought standing are many deserve also a ast be brought standing standing army is only arm standing government is only mode people have iosen execute is equally liable be abused perverted people act witness present mexican work omparatively few individual using standing government people not have consented american is recen deavoring transmit unimpaired instant losing ha not vitality force single living single man bend is ort wooden gun people is not le necessary people have complicated machinery hear satisfy idea overnment government show thus successfully men be imposed even impose own government never furthered alacrity got character inherent american people ha done ha been have done somewhat government had not sometimes got government is men fain succeed letting one ha been is most overned are most let alone trade were not made never manage bounce obstacle legislator are ntinually putting were judge men wholly effect action not partly deserve be classed punished person out obstruction speak practically call ask not once better let man make known kind government nmand be step obtaining after practical reason power is once hand majority are long period rule ar men understand sidelight relativity ether theory relativity address delivered may university

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Conclusion

En conclusion:

- L'indice d'autocorrélation globale peut servir d'indicateur global sur un corpus donné.
- L'indice d'autocorrélation locale permet de repérer la redondance sémantique des tokens.
- Le clustering fonctionne bien pour découper le texte en parties grossières (p.ex. paragraphes) parlant d'un thème similaire.

Pistes d'amélioration :

- Arriver à construire des similarités WordNet entre tokens de différentes catégories (noms, verbes, adjectifs et adverbes).
- Voir si la notion de *perplexité* peut s'appliquer au clustering.
- Affiner la validation du clustering : textes plus variés, touver le state-of-the-art, intervalles de confiance du NMI.

Conclusion

Merci pour votre attention!

(et désolé pour la longueur)

Des questions?

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