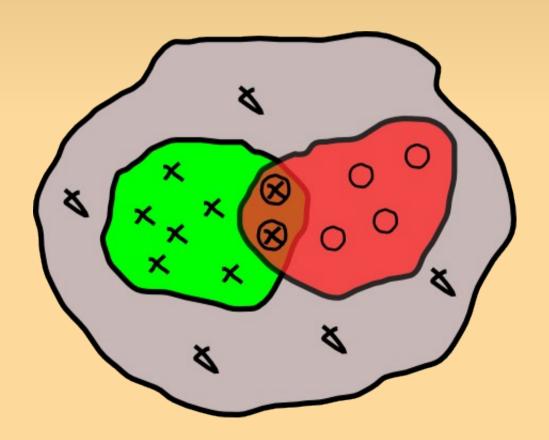
Quelques techniques d'extraction sémantique

Adrian Dimulescu Telecom ParisTech 30 mars 2009

Qu'est-ce que le sens?

Le sens est le contexte



Plan

- Latent semantic analysis
- Complexité de Kolmogorov
- Distance informationnelle
- Quelques exemples

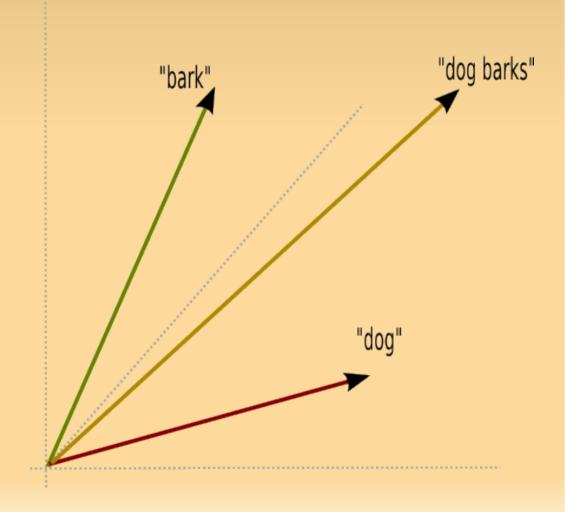
Latent Semantic Analysis

- Matrice éparse énorme: terms x documents
- Normalisation: log(cell)/entropie

		40 millions							documents		
Γ		0	0	0	0	1	0/		2	2	0
o	demograph	0	0	0	0	0			<	0	0
O	democrat	0	2	0	0	0	7	_		0	0
o	demolish	0	0	0	0	0				0	0
o	demon	0	0	0	3	0				0	0
o	demonstr	0	0	0	0	0	\int	>		0	0
O	denmark	1	0	0	0	0	\setminus			1	1
		0	0	0	0	0		_		0	0

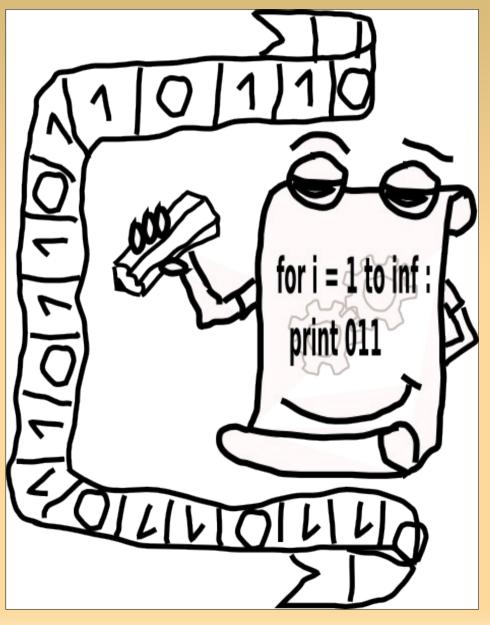
Latent Semantic Analysis

- Tout mot/concept est un vecteur
- Tout prédicat/phrase est un vecteur
- Tout document est un vecteur



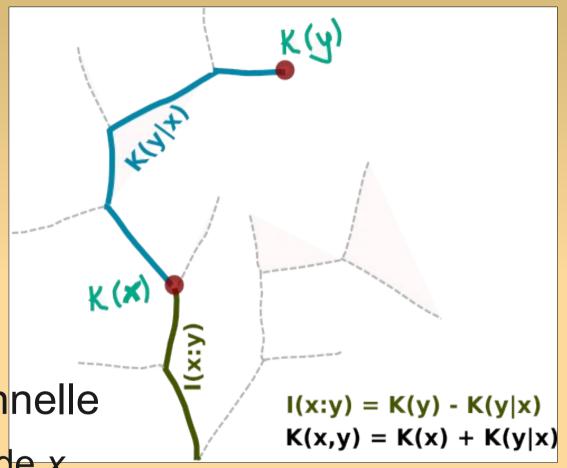
LSA

- SVD : réduction de dimensionalité
 - "compression": approx 300 colonnes
- Mesure de similarité: cosinus des vecteurs
- Inconvenients
 - Non-incrémental
 - Passe mal à l'échelle
- Random indexing
 - Évite la grande matrice éparse du début



- Absolue
- Non-calculable
 - Mais approximable:
 Gzip, bzip2 etc.

- Complexité conditionnelle
 - K(x|y) la complexité de x
 si l'on a déjà y en entrée (≤ K(x))
 - $I(x:y) \approx I(y:x)$

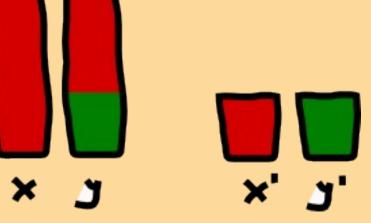


Information distance

- $E(x,y) = \max \{K(x|y), K(y|x)\}$
 - Le program qui transforme x en y et l'inverse
 - The largest transformation program "includes" the

smallest (almost)

- Absolue, minorise tout
- Normalization
 - Quelle paire est plus similaire en couleur ?
 - d(x,y) = K(y|x) / K(y)



Normalized compression distance

- Etant donne le compresseur C (ex. Bzip2)
 - Comme C(y|x) = C(x,y) C(x), si C(y) > C(x)

$$NCD(x,y) = \frac{C(xy) - C(x)}{C(y)}$$

- On peut donc calculer des distances entre fichiers, génomes, romans, pièces musicales, en comprimant les objets séparément et ensemble
- Algorithmes de clustérisation sans paramètres

Le compresseur doit être normal

- Un compresseur C est normal si :
 - Idempotence: C(xx) = C(x)
 - Monotonicité: C(xy) >= C(x)
 - Symmetrie: C(xy) = C(yx)
 - Distributivité: C(xy)+C(z) <= C(xz)+C(yz)
- Alors seulement la distance NCD est une metrique de similarité:
 - D(x,y) = 0 iff x = y; D(x,y) = D(y,x), et
 - $D(x,y) \le D(x,z) + D(z,y)$ (triangle ineq)
 - Et contrainte de densité: $\sum_{i=1}^{\infty} 2^{-d(x_i,y_i)} K(x_i) \leq 1$

Pourquoi ces formules?

- De toute façon quand on veut approximer K on est en état de pèche
 - On ne sait pas si on approxime bien ou pas
- La compression peut donner des résultats intéressants
 - mais uniquement si le compresseur est (quasi)normal
- Chercher donc des compresseurs normaux

Normalized Google Distance

- Google comme compresseur
 - Pourquoi Google comprime : le code dérivé des probabilités G(x) = -log p(x) est minimal. Si hits(y) < hits(x):

$$NGD(x,y) = \frac{G(xy) - G(x)}{G(y)}$$

$$NGD(x, y) = \frac{\log hits(y) - \log hits(xy)}{\log N - \log hits(x)}$$

Google JSON API

http://ajax.googleapis.com/ajax/services/search/web?v=1.0&q=horse&rsz=small

```
{"responseData": {"results":[{"GsearchResultClass":"GwebSearch","unescapedUrl":"
http://en.wikipedia.org/wiki/Horse",
"url": "http://en.wikipedia.org/wiki/Horse",
"visibleUrl": "en.wikipedia.org", e: Your Guide to Equine Health
Care", "titleNoFormatting": "The Horse: Your Guide to Equine Health
Care", "content": "\u003cb\u003eHorse\u003c/b\u003e health news and veterinarian-
approved equine health care information from TheHorse.com. Learn more about basic
care, injuries, diseases, lameness, \u003cb\u003e...\u003c/b\u003e"}],
"cursor":{"pages":[{"start":"0","label":1},{"start":"4","label":2},
{"start": "8", "label": 3}, {"start": "12", "label": 4}, {"start": "16", "label": 5},
{"start":"20","label":6},{"start":"24","label":7},
{"start": "28", "label":8}], "estimatedResultCount": "27700000", "curren
tPageIndex":0, "moreResultsUrl": "http://www.google.com/search?
oe\u003dutf8\u0026ie\u003dutf8\u0026source\u003duds\u0026start\u003d0\u0026hl\u003d
fr\u0026g\u003dhorse"}}, "responseDetails": null, "responseStatus": 200}
```

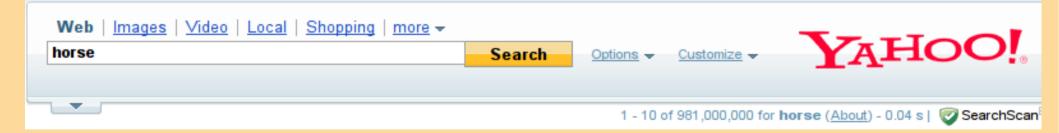


Yahoo BOSS API

http://boss.yahooapis.com/ysearch/web/v1/horse?appid=...&format=xml (or json)

```
<ysearchresponse responsecode="200">
<nextpage>
/ysearch/web/v1/horse?count=10&appid=...&format=xml&start=10
</nextpage>
<resultset_web count="10" start="0"

totalhits="32651389" deephits="981000000">
```



Exemple: street - building

```
log(f('street')) = log2(134,000,000) = 26.9976577597819; g = f/N = 0.0067; G = log(1/g) = 7.22162318909168
```

```
log(f('building')) = log2(74,400,000) = 26.1487992855448; g = f/N = 0.00372; G = log(1/g) = 8.07048166332878
```

log(f("street" "building"")) = log2(76,700,000) = 26.1927232419397; g = f/N = 0.003835; G = log(1.6,000) = 8.02655770693388

(26.9976577597819 - 26.1927232419397) / (34.2192809488736 - 26.1487992855448)

NGD('street', 'building') = 0.0997381013204846

Exemple: street - slap

```
log(f('street')) = log2(134,000,000) = 26.9976577597819; g = f/N = 0.0067; G = log(1/g) = 7.22162318909168
```

```
log(f('slap')) = log2(3,700,000) = 21.8190938400658; g = f/N = 0.000185; G = log(1/g) = 12.4001871088079
```

log(f("street" "slap"")) = log2(258,000) = 17.9770115400853; g = f/N = 1.29e-05; G = log(1/g) = 16.2422694087883

(26.9976577597819 - 17.9770115400853) / (34.2192809488736 - 21.8190938400658)

NGD('street', 'slap') = 0.727460492373477

Indexation de Wikipedia

- Lucene : outil Java d'indexation
 - Snowball English stemmer; wikipedia tokenizer
- Indexation
 - par paragraph (petite fenêtre de coccurence)
 - NGD à l'origine se fait sur Google par page
 - en.wikipedia : 18GB text
 - 8M pages
 - 40M paragraphs

Indexation de Wikipedia

- 7 millions terms
 - 7k avec freq > 10.000 (ex: kindergarten, basket)
 - 31k avec freq > 1000 (ex: radiocarbon, kryptonit)
 - 92k freq > 200 (ex: hölder, ipsilater, jolanda)
- Counting hits a posteriori is slow for lots of documents
- Solution: matrice de coocurrence pendant le parsing
 - Matrice de coocurrence doit rentrer en RAM
 - Optimisation : symmetrique, zero diag

Carte sémantique

- Calculer toutes les distances entre tous les mots (10.000)
- Pour chaque mot récupérer les voisins les plus proches
 - Mémoire sémantique: on peut retrouver les "voisins" d'un concept
- Difficile sur un vrai moteur de recherche public
 - Mais faisable sur son petit home-grown search engine

Exemples

- HUNT: prey, witch, deer, fish, hound, wild, predat, treasur, herd, trap, wildlif, dog, bounti, hike, lodg,
- LEADERSHIP:rite, resign, organiz, faction, skill, caucus, leader, membership, apostol, cabinet, coalit
- FRANCE: french, département, commune, pari, région, belgium, itali, comté, germani, inse, arrondiss
- CHILDREN:marri, husband, marriag, coupl, older, alon, spous, togeth, someon, household, individu
- BABY:pregnant, cry, gonna,infant, wanna, child, ain't, mama, sweet, tonight, doll, daddy, goodby, mother

Exemples (2)

- ROAD: junction, highway, terminus, intersect, rout, traffic, lane, motorway, bypass, parkway,
- STREET:avenu, downtown, boulevard, wall, corner, intersect, manhattan, neighborhood, coron, shop
- MONSTER: creatur, dungeon, beast, alien, horror, unleash, evil, summon, dragon, demon, loch.
- SEVENTH :eighth, sixth, ninth, fifth, tenth, eleventh, twelfth.
- TERRY:ron, bobbi, jimmi, ted, larri, jeff, ken
- VICEROY:granada, marquess, napl, peru, spaniard, río

Mais... (words without meaning)

- WHICH (freq: 2M): there, been, had, into, also, alon, some, most, them, but, onli, howev
- BAD (200k): faith, isn't, realli, doesn't, sure, can't, agre, someon, thing, obvious,
- GOOD (500k): think, don't, i'm, thing, realli, look, faith, seem, sure, veri, i'v, isn't, know, say, get
 - Mais la fréquence n'est pas tout: PERFORM (lui aussi 500k):concert, theatr, stage, audienc, orchestra, solo, ensembl, soloist, sing, tour, repertoir, festiv, theater, singer, danc, grammi, musician

LSA vs. NGD: Cosinus vs. K(x|y)

Ex (session Octave):

```
$ x = 50 * rand(1,300) - 25

$ y = 1 + x

$ x * y' / (norm(x) * norm(y))

0.99753

$ y = x .^ 2

$ x * y' / (norm(x) * norm(y))

0.097678
```

 (une transformation mathématiquement simple peut mener à des différences structurales importantes)

Bibliographie

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