Word-embeddings

Corpus de textos

Wikipedia
The Free Encyclopedia

Word-embeddings

Latent Semantic Análisis

Ejemplo

Human-computer interaction

- c1:**Human** machine interface for ABC computer applications.
- c2:A survey of user opinion of computer **system** response time.
- c3: The EPS user interface management **system**.
- c4: System and **human system** engineering testing of EPS.
- c5: Relation of user perceived response time to error measurement.

Graphs theory

- m1: The generation of random, binary, ordered **trees**.
- m2: The intersection **graph** of paths in **trees**.
- m3: **Graph** minors IV: Widths of **trees** and well-quasi-ordering.
- m4: **Graph** minors: A survey.

Deerwester et al. 1990

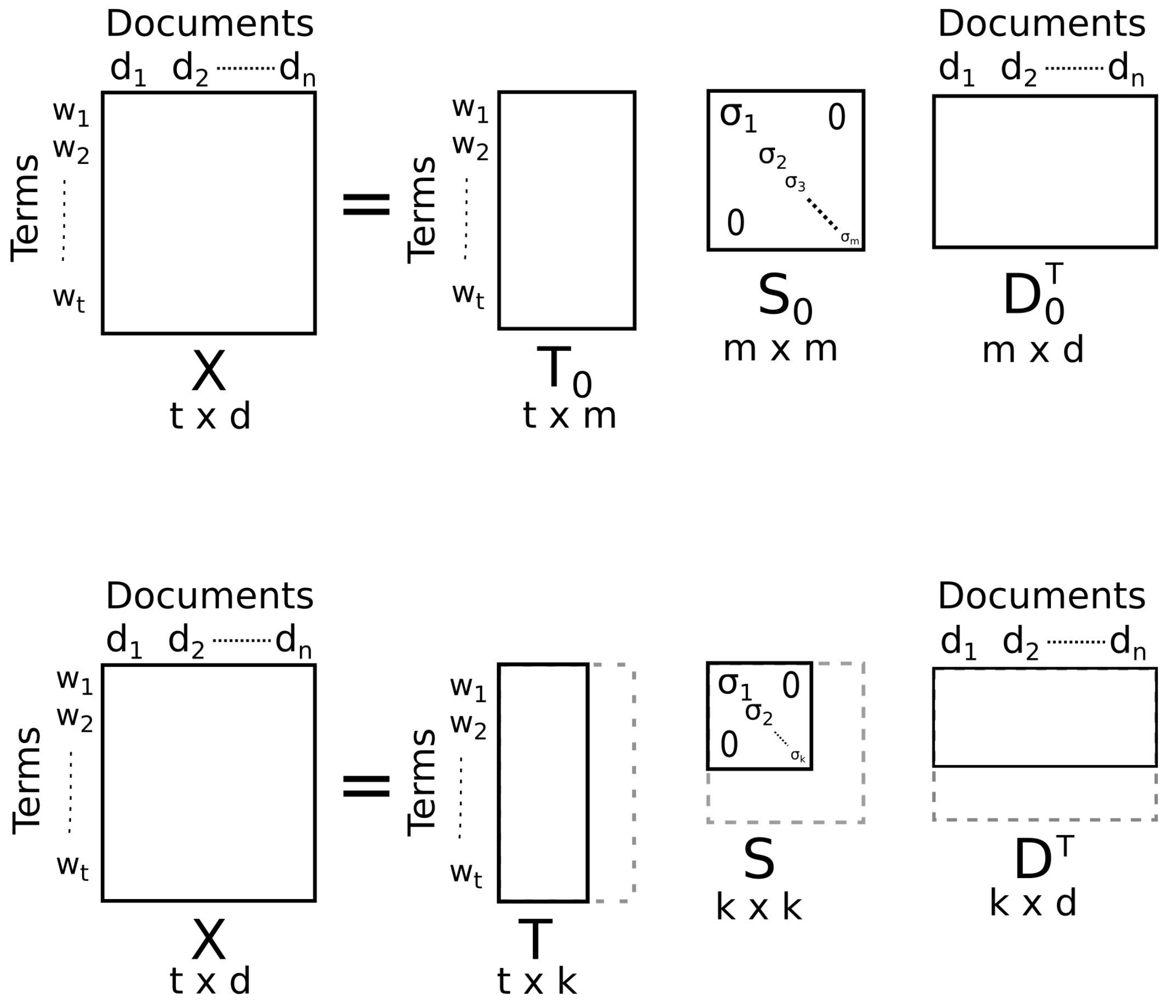
Term-Documents Matrix

X =

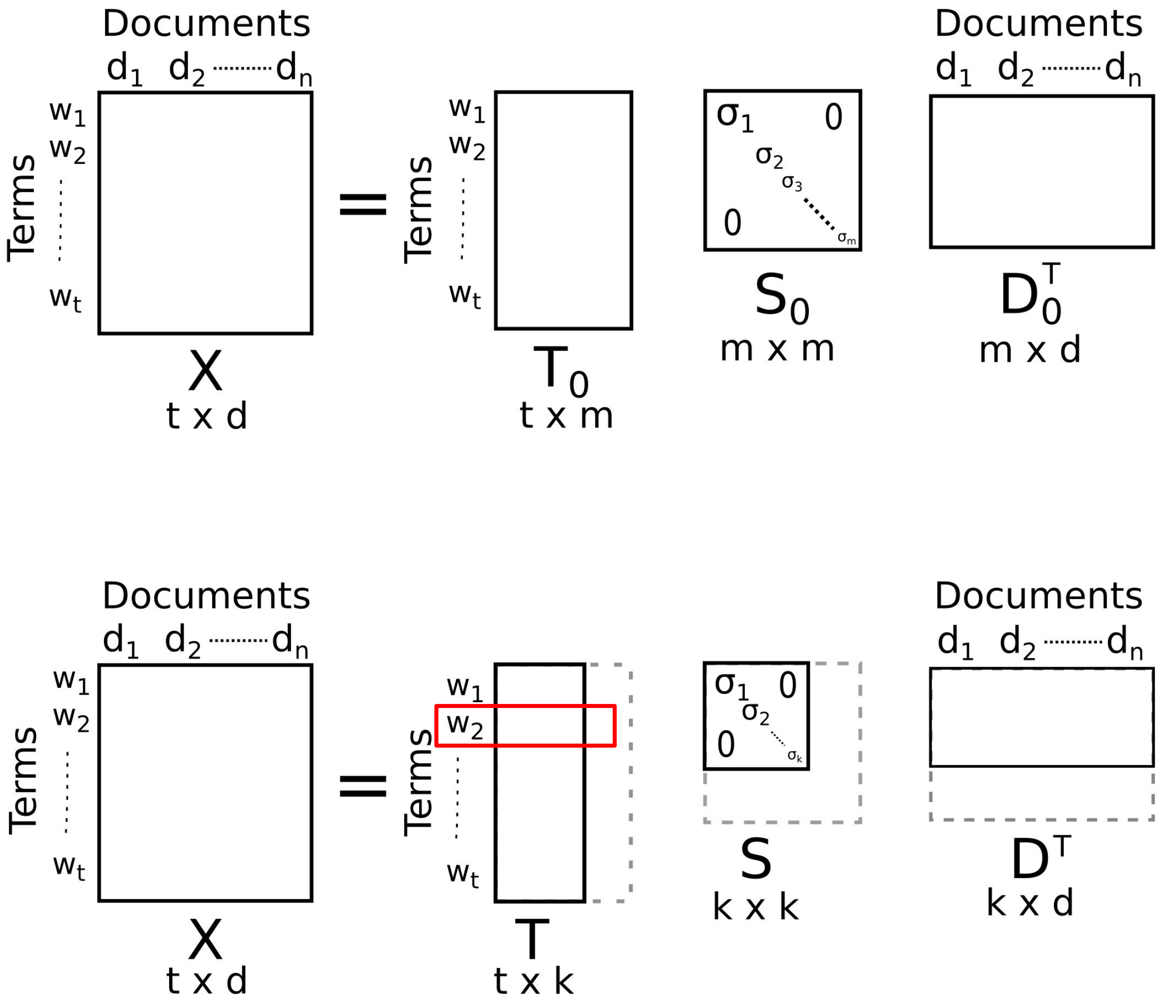
	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

Introduction to Latent Semantic, Landauer et al. (1998)

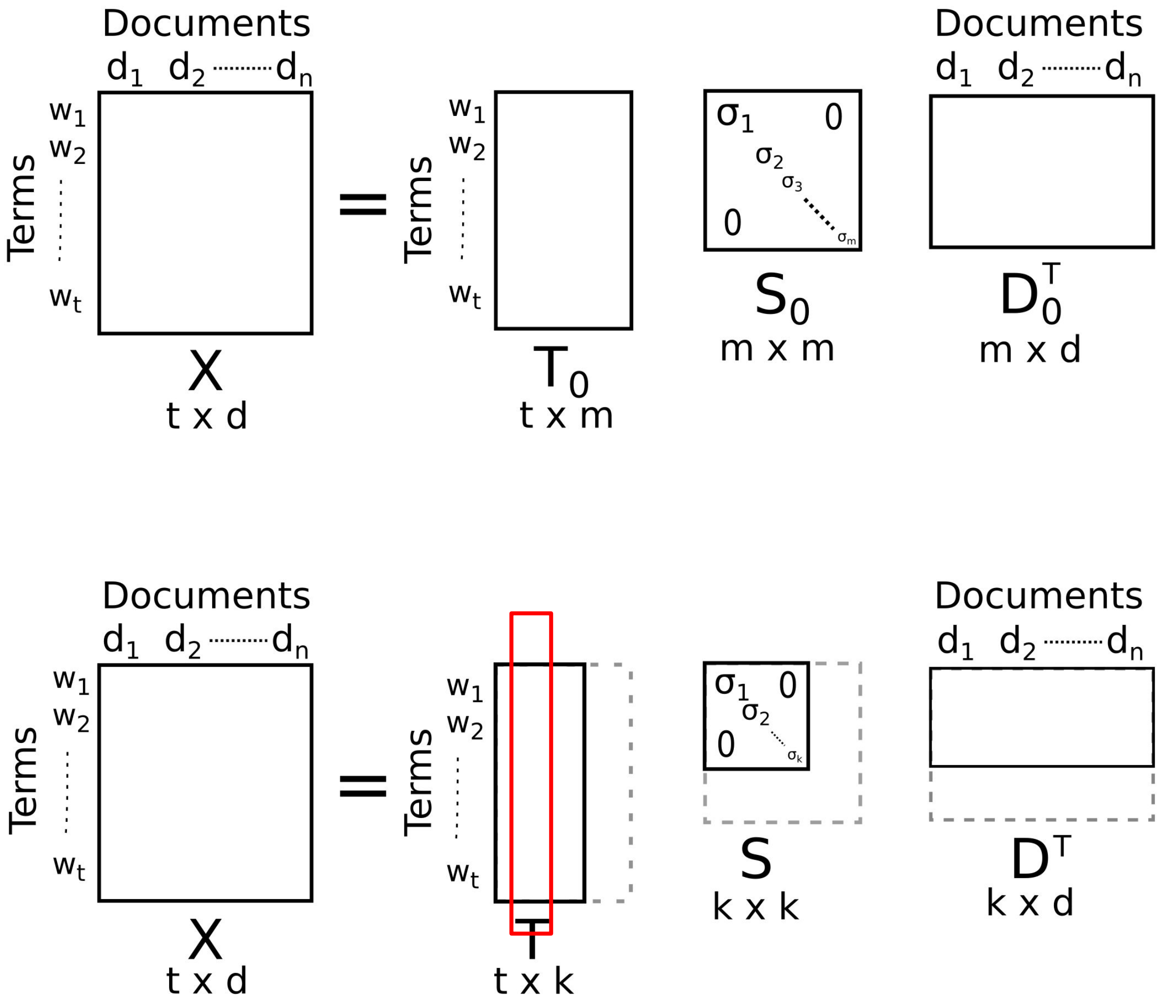
SVD


Documents
d_1 d_2 d_n
Terms
w_1
w_2
w_t
=
σ_1 0
σ_2
σ_3
0 σ_m
X
t x d
T_0
t x m
S_0
m x m
D_0^T
m x d
Documents
d_1 d_2 d_n
Terms
w_1
w_2
w_t
=
σ_1 0
σ_2
0 σ_k
X
t x d
T
t x k
S
k x k
D^T
k x d

SVD


Documents
d_1 d_2 d_n
Terms
w_1 w_2 w_t
X
t x d
=
T_0
t x m
σ_1 σ_2 σ_3 σ_m 0 0
S_0
m x m
D_0^T
m x d
X
t x d
T
t x k
σ_1 σ_2 σ_k 0 0
S
k x k
D^T
k x d

SVD

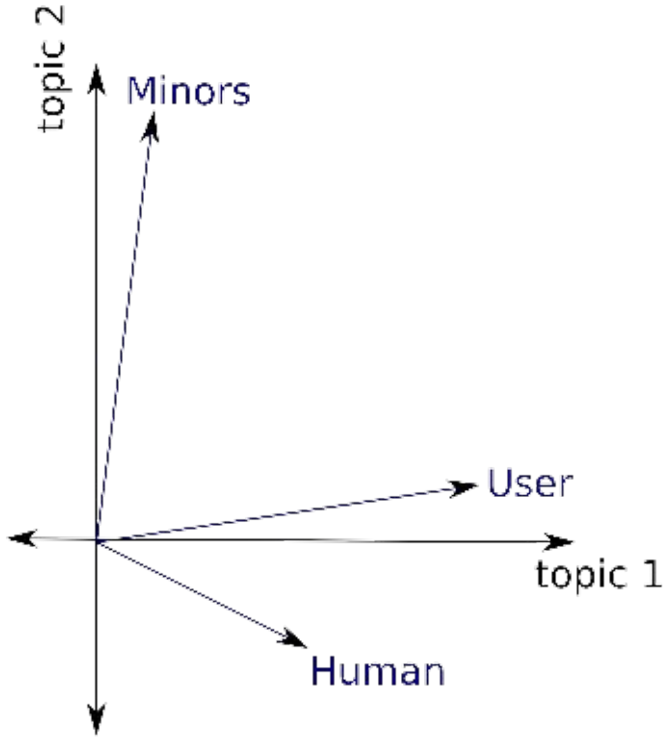


Documents
d1 d2 dn
Terms
w1 w2 wt
X
t x d
=
T0
t x m
σ1 σ2 σ3 σm 0 0
S0
m x m
D0T
m x d
X
t x d
T
t x k
σ1 σ2 σk 0 0
S
k x k
DT
k x d

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	**0**	**1**	**1**	**0**	**1**	**0**	**0**	**0**	**0**
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	**1**
trees	0	0	0	0	0	1	1	1	**0**
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

$$
= \quad
\begin{array}{r}
\\ \\ \\ \text{user} \\ \\ \\ \\ \\ \\ \\ \\ \\
\end{array}
\overset{W}{\begin{array}{rr}
0.22 & -0.11 \\
0.20 & -0.07 \\
0.24 & 0.04 \\
0.40 & 0.06 \\
0.64 & -0.17 \\
0.27 & 0.11 \\
0.27 & 0.11 \\
0.30 & -0.14 \\
0.21 & 0.27 \\
0.01 & 0.49 \\
0.04 & 0.62 \\
0.03 & 0.45
\end{array}}
\quad
\overset{S}{\begin{array}{rr}
3.34 & 0.00 \\
0.00 & 2.54
\end{array}}
\quad
\overset{C}{\begin{array}{rrrrrrrrr}
0.20 & 0.60 & 0.46 & 0.54 & 0.28 & 0.00 & 0.02 & 0.02 & 0.08 \\
-0.06 & 0.17 & -0.13 & 0.53 & -0.23 & 0.11 & 0.19 & 0.44 & 0.62
\end{array}}
$$

$$
\begin{array}{ccc}
 & W & \\
\text{Human} \rightarrow & \boxed{0.22 \quad -0.11} & \\
 & 0.20 \quad -0.07 & \\
 & 0.24 \quad 0.04 & \\
\text{User} \rightarrow & \boxed{0.40 \quad 0.06} & \\
 & 0.64 \quad -0.17 & \\
 & 0.27 \quad 0.11 & \\
 & 0.27 \quad 0.11 & \\
 & 0.30 \quad -0.14 & \\
 & 0.21 \quad 0.27 & \\
 & 0.01 \quad 0.49 & \\
 & 0.04 \quad 0.62 & \\
\text{Minors} \rightarrow & \boxed{0.03 \quad 0.45} &
\end{array}
\qquad
\begin{array}{c}
S \\
\begin{matrix} 3.34 & 0.00 \\ 0.00 & 2.54 \end{matrix}
\end{array}
\qquad
\begin{array}{c}
C \\
\begin{matrix} 0.20 & 0.60 & 0.46 & 0.54 & 0.28 & 0.00 & 0.02 & 0.02 & 0.08 \\ -0.06 & 0.17 & -0.13 & 0.53 & -0.23 & 0.11 & 0.19 & 0.44 & 0.62 \end{matrix}
\end{array}
$$



W

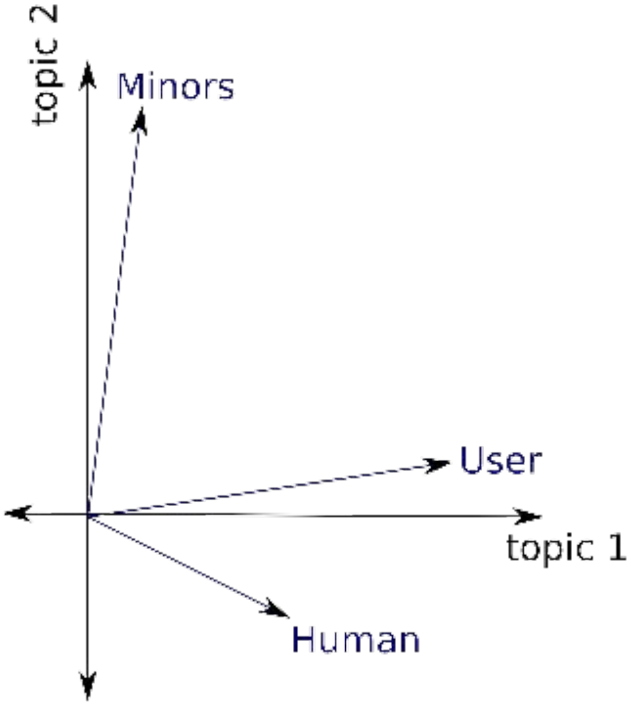
Human →	0.22	-0.11
	0.20	-0.07
	0.24	0.04
User →	0.40	0.06
	0.64	-0.17
	0.27	0.11
	0.27	0.11
	0.30	-0.14
	0.21	0.27
	0.01	0.49
	0.04	0.62
Minors →	0.03	0.45

S

3.34	0.00
0.00	2.54

C

0.20	0.60	0.46	0.54	0.28	0.00	0.02	0.02	0.08
-0.06	0.17	-0.13	0.53	-0.23	0.11	0.19	0.44	0.62

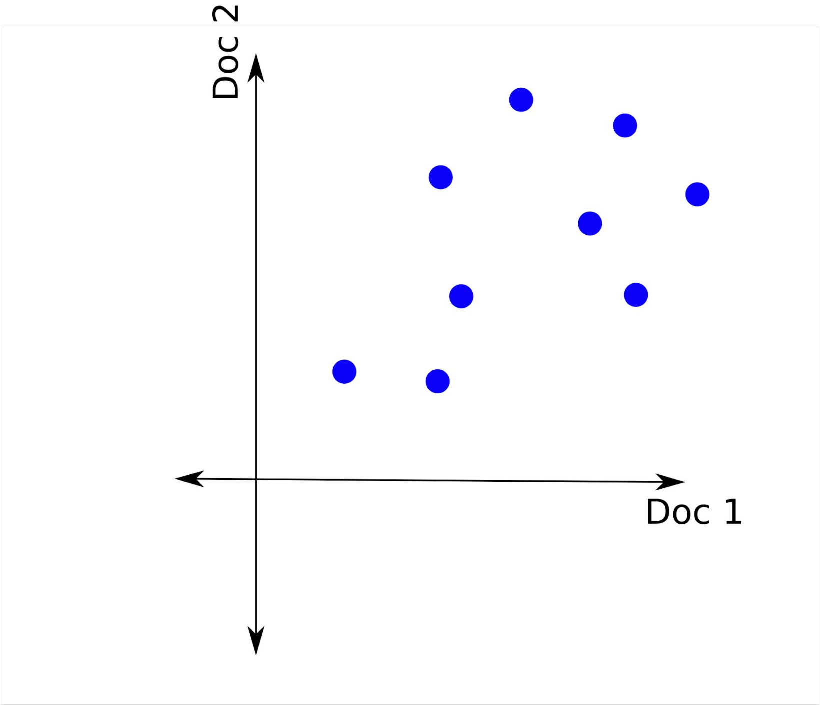


Cosine similarity

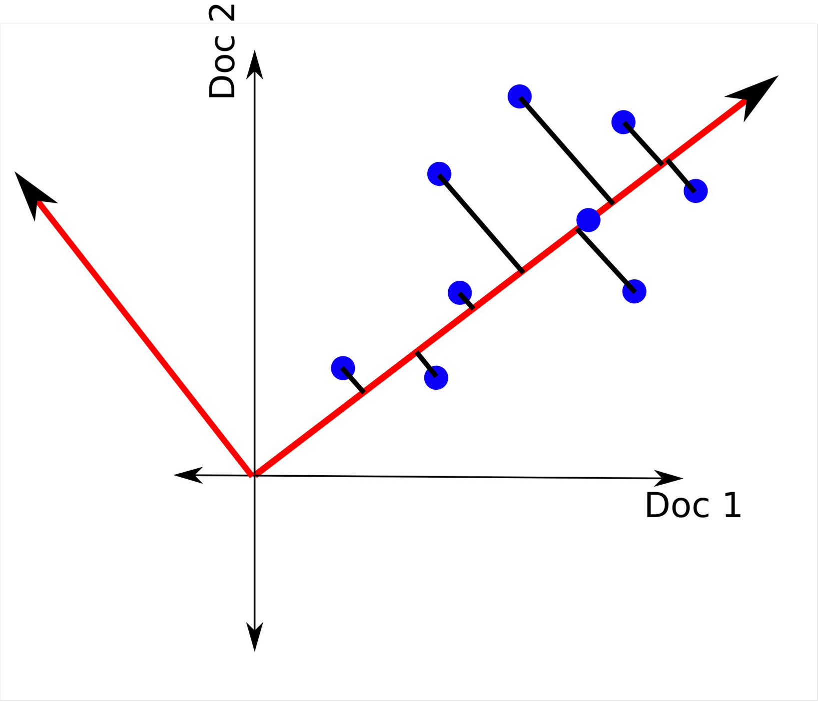
$$cossim(\bar{v}_1, \bar{v}_2) = \cos(angle) = \frac{\bar{v}_1 . \bar{v}_2}{|\bar{v}_1| . |\bar{v}_2|}$$

$$cossim(\bar{v}_1, \bar{v}_2) \in [-1, 1]$$

Más sobre SVD



Más sobre SVD



Antes de usar el SVD se puede aplicar una transformación

TF-IDF

$$\text{tf-idf}\,(t,d) = \text{tf}\,(t,d).\,\text{idf}\,(t)$$

$$\text{idf}\,(t) = \log \frac{1+|D|}{1+|\{d{:}t\in d\}|} + 1$$

Log-Entropy

$$\text{LogEnt}\,(t,d) = \log(\text{tf}\,(t,d)+1).\,W_g$$

$$W_g = 1 + \frac{\sum_d P(t,d)\log(P(t,d))}{\log(|D|+1)}$$

con $$P(t,d) = \frac{\text{tf}\,(t,d)}{\sum_d \text{tf}\,(t,d)}$$

Un LSA alternativo:

Term-context matrix

	choripan	vino	chimichurri	uva	pera	...	kiwi
choripan	1	54	23	5	2	...	1
vino	54	5	17	21	3	...	4
chimichurri	23	17	0	1	1	...	0
uva	5	21	1	3	20	...	19
pera	2	3	1	20	12	...	11
...	...	...	...	...	...	...	...
kiwi	1	4	0	19	11	...	21

LSA tips:

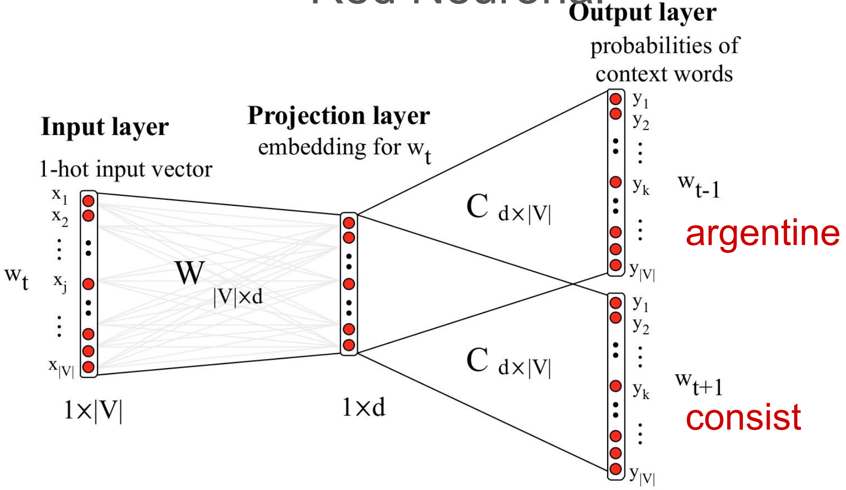
- Un número estándar de dimensiones es k=300 (ambiente científico)
- El k óptimo depende del número de tópicos distintos existente en los textos y de la tarea a realizar.
- Muchas veces sirve tirar la primer dimensión o hasta las primeras 50
- La similaridad coseno entre palabras no es absoluta. Cuanto mayor sea k, las palabras van a estar más distantes entre sí (menor similaridad)

Word2Vec (Skip-gram)

Choripan. The Argentine *choripán* consists of a sausage made out of beef and pork, hot off the grill, split down the middle, and served on a roll. The *chorizo* may be used whole or cut in half lengthwise, in which case it is called a *mariposa* (butterfly). It is customary to add sauces on the bread, most likely *chimichurri*.

WIKIPEDIA
The Free Encyclopedia

Red Neuronal



Objective function

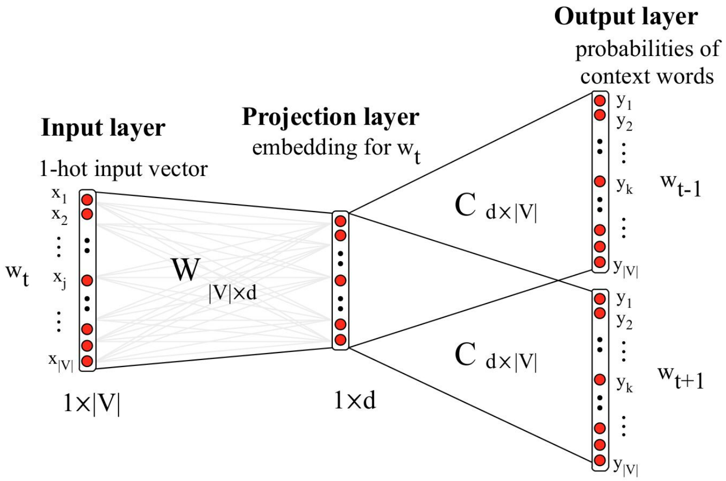
$$
\begin{aligned}
O &= \sum_{-c\leq j\leq c, j\neq 0} \log p(w_{t+j}|w_t)) \\
&= \log p(argentine|choripan) + \log p(consist|choripan)
\end{aligned}
$$

Soft-max function

argentine

$$p(w_k|w_j) = \frac{exp(c_k \cdot v_j)}{\sum_{i\in|V|} exp(c_i \cdot v_j)}$$

choripan



argentina

$$p(w_k|w_j) = \frac{exp(\boxed{c_k} \cdot \boxed{v_j})}{\sum_{i\in|V|} exp(c_i \cdot \boxed{v_j})}$$

choripan

		1	2	...	k-1	k
costanera	v_1	0.22	0.51	...	0.12	0.11
vino	v_2	0.20	0.47	...	0.30	0.47
chimichurri	v_3	0.24	0.34	...	0.21	0.24
...	...	0.40	0.26	...	0.40	0.16
choripan	v_j	0.64	0.17	...	0.14	0.37
...	...	...	...	...	...	...
kiwi	$v_{\|V\|}$	0.17	0.11	...	0.27	0.31

target embeddings

	costanera		argentina		kiwi
	c_1	...	c_k	...	$c_{\|V\|}$
1	0.41	...	0.13	...	0.21
2	0.76	...	0.33	...	0.43
3	0.52	...	0.93	...	0.34
4	0.33	...	0.30	...	0.54
..	...	...	...	...	...
k-1	0.22	...	0.42	...	0.34
k	0.25	...	0.18	...	0.57

context embeddings

choripan

argentina

$$p(w_k|w_j) = \frac{exp(c_k \cdot v_j)}{\sum_{i \in |V|} exp(c_i \cdot v_j)}$$

Es imposible de calcular!

Negative sampling

Sampleo *k* palabras (w_i) de la distribución p(w)

$$\log p(w_k|w_j) \approx \log \sigma(c_k . v_j) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim p(w)} [\log \sigma(-w_i . v_j)]$$

con $\sigma(x) = \frac{1}{e^{-x}+1} = \frac{e^x}{1+e^x}$

$$x \gg 1 \Longrightarrow \sigma(x) \approx 1$$
$$x \ll -1 \Longrightarrow \sigma(x) \approx 0$$

Con 5 Negative samples (k=3)

Ej: {el, gorro, cafetera}

$$\log p(w_k|w_j) \approx \log \sigma(c_k . v_j) + \log \sigma(-w_1 . v_j) + \log \sigma(-w_2 . v_j) + \log \sigma(-w_3 . v_j)$$

Función objetivo a maximizar

$$O = \sum_{k=1}^{|V|} \sum_{j=1}^{|V|} \#(w_k, w_j) \left[\log(\bar{c}_k . \bar{v}_j) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim p(w)} [\log \sigma(-\bar{w}_i . \bar{v}_j)] \right]$$

con $\sigma(x) = \frac{1}{e^{-x}+1} = \frac{e^x}{1+e^x}$

La solución óptima cumple:

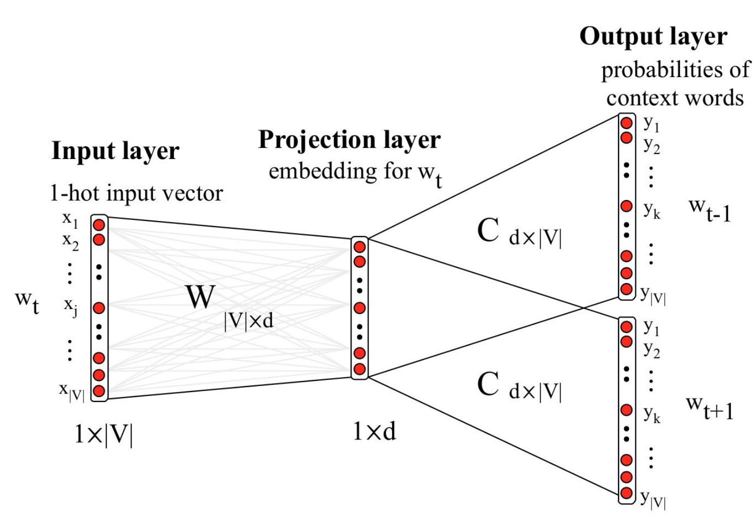
$$\bar{c}_k . \bar{v}_j = PMI(w_k, w_j) - \log(k)$$

El Skip-gram factoriza el PMI en 2 matrices

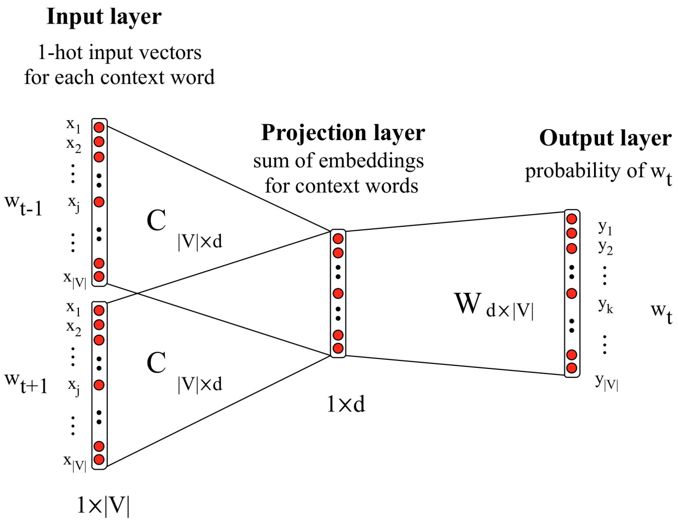
$$C.V = X^{PMI} - \log(k)$$

Word2vec

Skip-gram

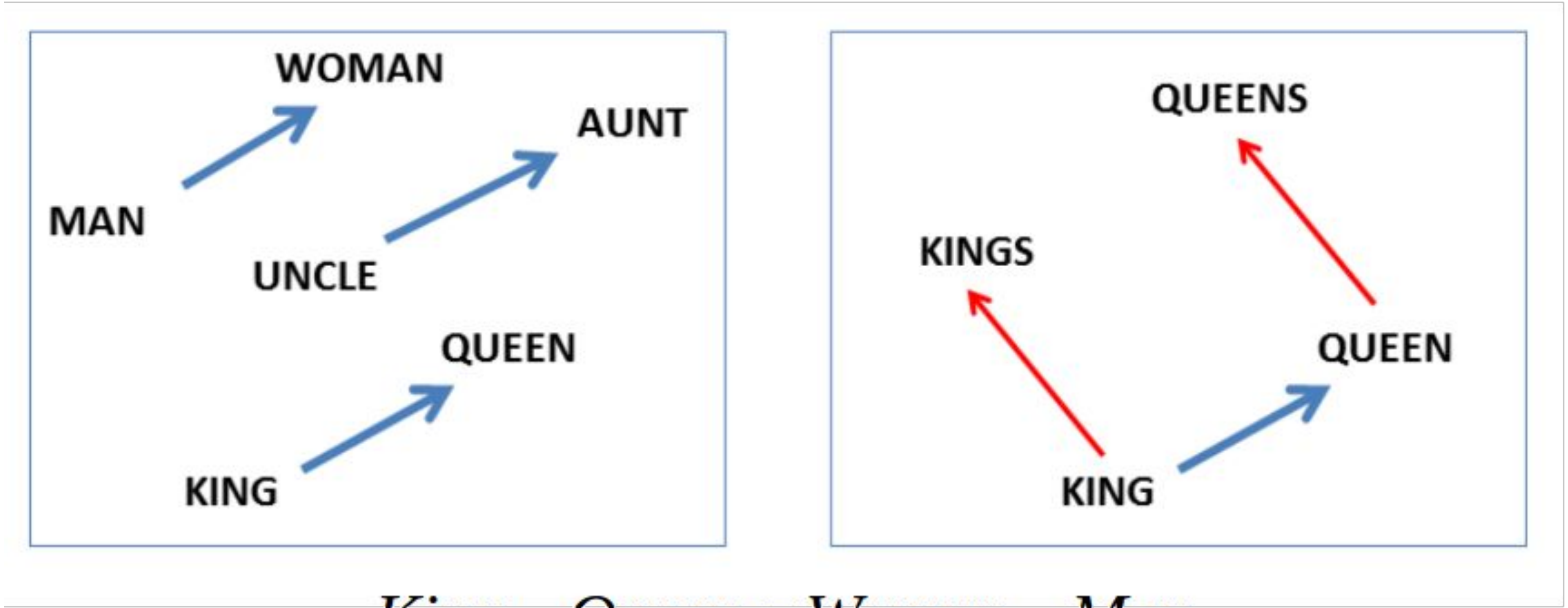


CBOW



Mikolov et al. (2013) Distributed Representations of Words and Phrases and their Compositionality
Jurafsky & Martin (2015) Speech and Language Processing. 2nd edition

Word analogy task



$$King - Queen \approx Woman - Man$$

$$King \approx Woman - Man + Queen$$

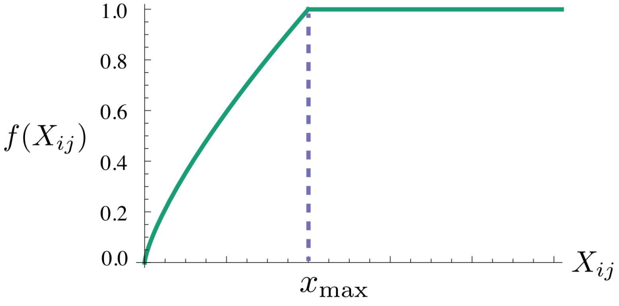
Linguistic Regularities in Continuous Space Word Representations Mikolov et al. (2013)

Más modelos:
Global Vectors for Word Representation (GLOVE)

Loss function

bias

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$$



$$f(x) = \begin{cases} (x/x_{\max})^\alpha & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases}$$

Pennington, Socher and Manning (2014) GloVe: Global Vectors for Word Representation

LSA

Edad: 29 años

The Force: 14700 citas

VS

Word2vec

Edad: 6 años

The Force: 15700 citas

Evaluación de word-embeddings: TOEFL test

Encontrar el sinónimo entre 4 opciones

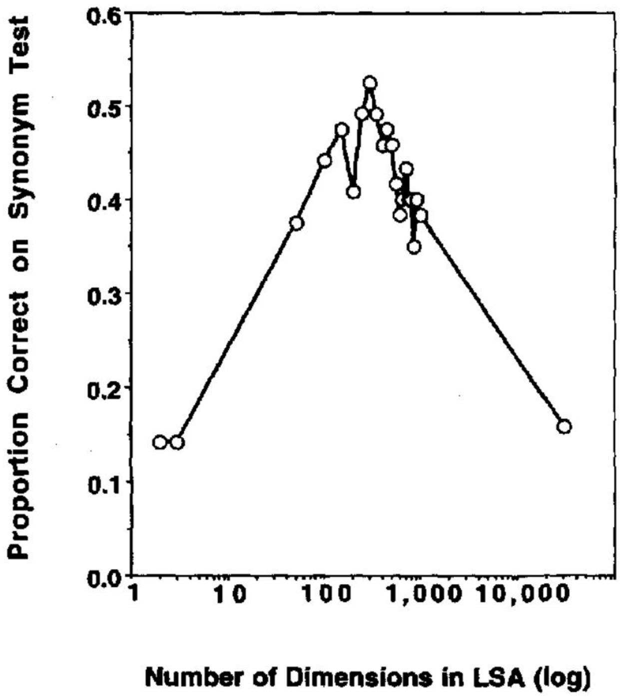
	Palabra	Opcion 1	Opcion 2	Opcion 3	Opcion 4
Pregunta 1	hue	color	scent	contrast	glare
Pregunta 2	hind	rear	curved	muscular	hairy
...	...	...	...	...	...
Pregunta 80	make	earn	print	trade	borrow

Busco el más cercano.

Métrica:
porcentaje de acierto

Landauer and dumais (1997) A Solution to Plato's Problem: The Latent Semantic Analysis Theory of acquisition, Induction, and Representation of Knowledge

Evaluación de word-embeddings: TOEFL test



Landauer and dumais (1997) A Solution to Plato's Problem: The Latent Semantic Analysis Theory of acquisition, Induction, and Representation of Knowledge

Evaluación de word-embeddings: similaridad

WordSimilarity-353 Test

Word 1	Word 2	Human
tiger	tiger	10
fuck	sex	9.44
Maradona	football	8.62
book	paper	7.46
...	...	...
professor	cucumber	0.31
king	cabbage	0.23

embedding1
1
0.52
0.42
0.45
...
0.002
0.001

embedding2
1
0.40
0.35
0.25
...
0.015
0.003

Quiero ver que embedding captura mejor las similaridades puntuadas por humanos

➢ Correlación

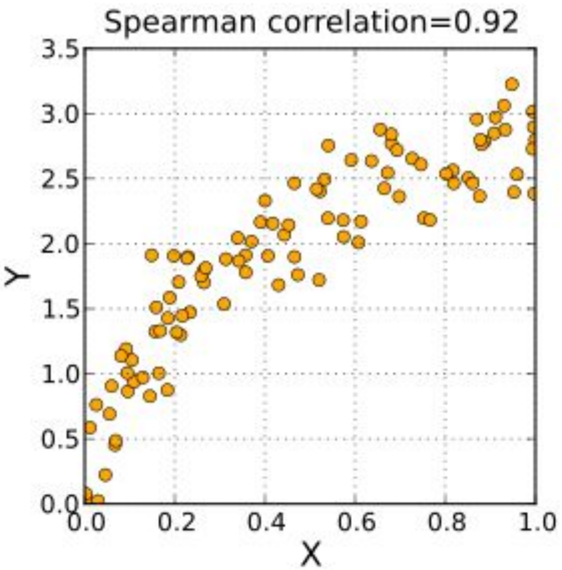
http://www.cs.technion.ac.il/~gabr/resources/data/wordsim353/wordsim353.html

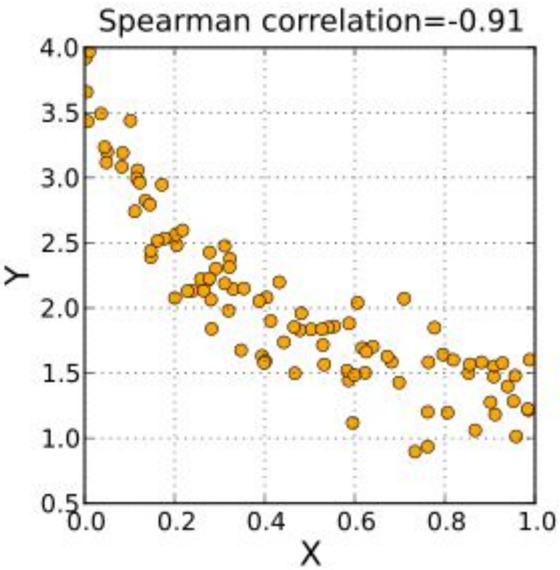
Spearman correlation

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}.$$

$$d_i = \mathrm{rg}(X_i) - \mathrm{rg}(Y_i)$$

ranking





Wikipedia mayo 2018

WordSimilarity-353 Test Collection

Human	embedding1	embedding2
10	1	1
9.44	0.52	0.40
8.62	0.42	0.35
7.46	0.45	0.25
...	...	...
0.31	0.002	0.015
0.23	0.001	0.003

Comparo correlaciones

	embedding1	embedding2
Spearman Correlation	0.82	0.74

http://www.cs.technion.ac.il/~gabr/resources/data/wordsim353/wordsim353.html

Categorization Test

53 categorías de 10 palabras cada una (patel 1997)

Performance: Silhouette Coefficient

Distancia promedio al cluster más cercano

Distancia promedio al cluster propio

$$S_i = \frac{b_i - a_i}{\max(a_i, b_i)}$$

Altszyler et al. (2017) The interpretation of dream meaning: Resolving ambiguity using Latent Semantic Analysis in a small corpus of text
Patel, M., Bullinaria, J. A., & Levy, J. P. (1997). Extracting semantic representations from large text corpora.

- Probablemente no exista una técnica de word-embeddings que sea universalmente mejor en todas las tareas

- Para una tarea particular (x ej. sentiment analysis), lo óptimo es seleccionar el embedding que mejor realice esa tarea

LSA

Edad: 28 años

The Force: 13000 citas

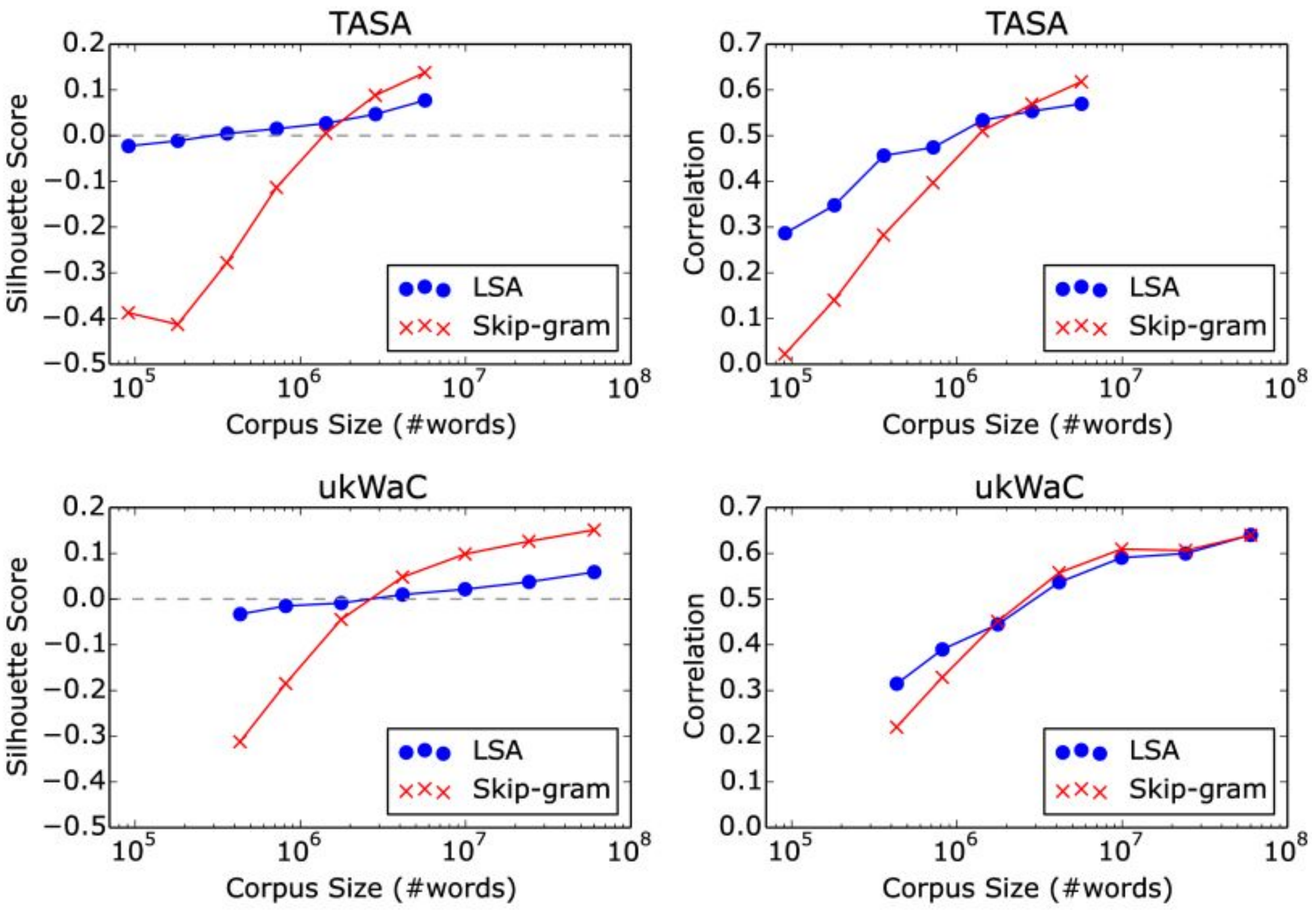
VS

Word2vec

Edad: 5 años

The Force: 8000 citas

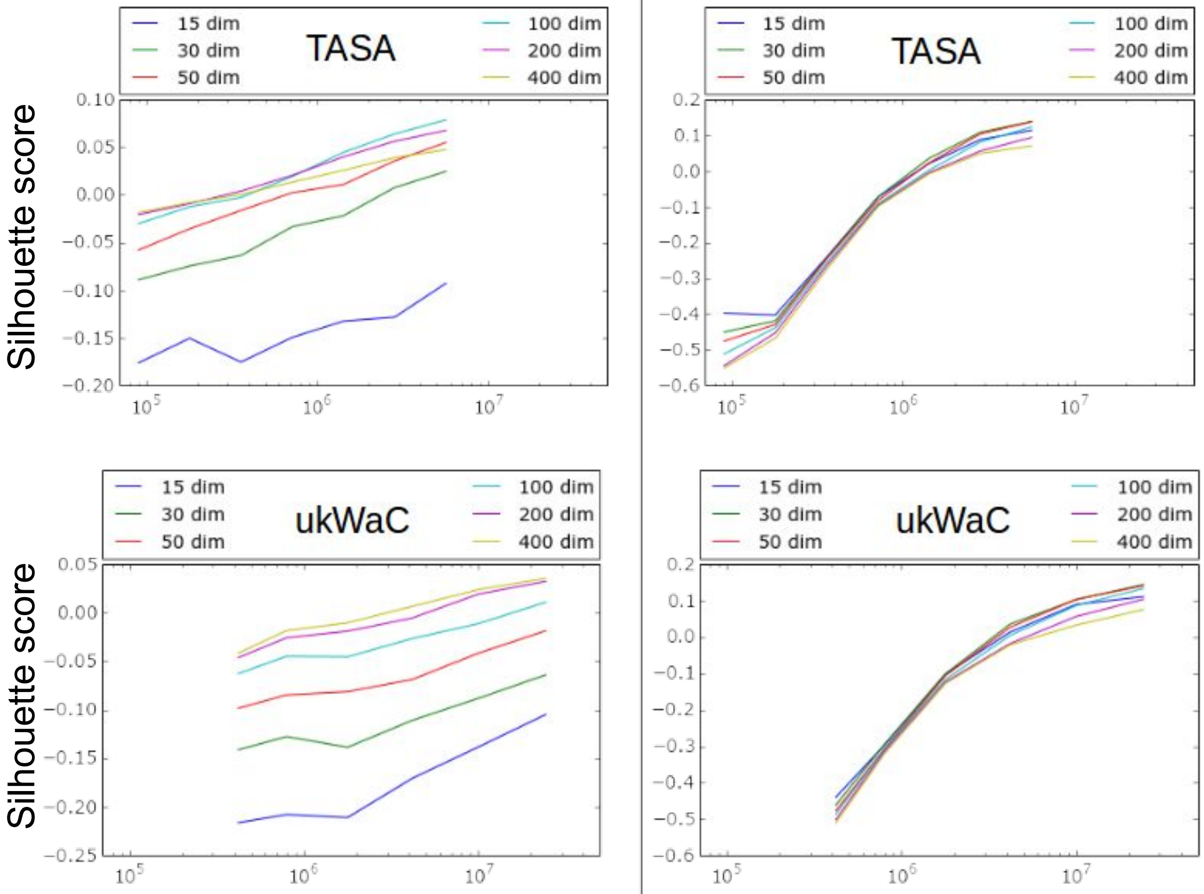
Baroni et al. (2016) Don’t count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors



Altszyler et al. (2017) The interpretation of dream meaning: Resolving ambiguity using Latent Semantic Analysis in a small corpus of text

LSA

Word2vec



Pre-trained word-embeddings

- Word2vec en google news, 100B words words, (https://code.google.com/archive/p/word2vec/)
- Glove (https://nlp.stanford.edu/projects/glove/):
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Fastext (https://fasttext.cc):
  - crawl-300d-2M.vec.zip: 2 million word vectors trained on Common Crawl (600B tokens).
  - en wikipedia en distintos idiomas (incluido **español**)
    https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md

Ejemplo de uso 1

Embeddings como features

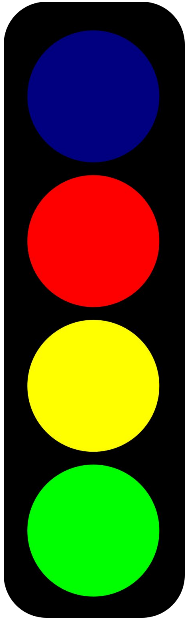
Competencia: CLPsych 2017 shared task

Competencia: CLPsych 2017 shared task

@Author - 06 Sep 2015, 15:56

Re: psychosis

I've had a difficult day. I got very close to self harming, but my best mates keep me safe. Now I'm at home seeing GoT.



- **Crisis:** El autor está en riesgo. Los moderadores deben atender este mensaje urgentemente
- **Rojo**: los moderadores deben atender este mensaje cuanto antes
- **Amarillo:** Los moderadores deben atender este mensaje en algún momento
- **Verde:** No requiere atención de un moderador

Dataset

	crisis	red	amber	green	total
train	40	137	296	715	1188
test	42	48	94	216	400
extra	-	-	-	-	156375

Embeddings as features

	crisis	red	amber	green	total
train	40	137	296	715	1188
test	42	48	94	216	400
extra	-	-	-	-	156375

→ Set de entrenamiento de un embedding

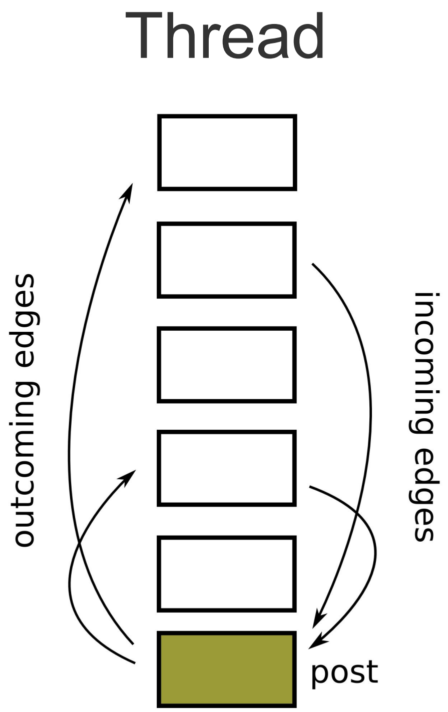
I've had a difficult day. I got very close to self harming, but my best mates keep me safe. Now I'm at home seeing GoT.

embedding →

I've → (0.4,0.9,...0.3)
had → (0.5,0.8,...0.5)
… → (…)
GoT → (0.1,0.9,...0.1)

mean → (0.1,0.3,...0.4)

Embeddings as features



- Mean embedding incoming posts
- Mean embedding outcoming posts

Embeddings as features

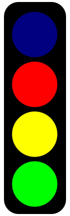
I've had a difficult day. I got very close to self harming, but my best mates keep me safe. Now I'm at home seeing GoT.

embedding

I've	→ (0.4,0.9,...0.3)
had	→ (0.5,0.8,...0.5)
…	→ (…)
GoT	→ (0.1,0.9,...0.1)

Deep Neural Network

prediction

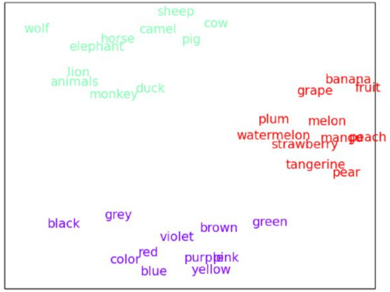


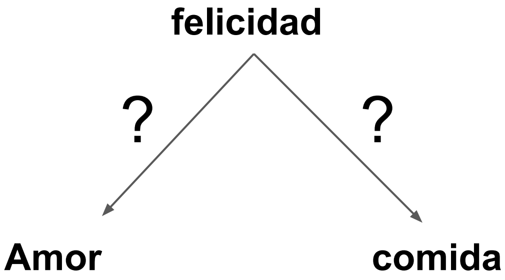
Ejemplo de uso 2

Embeddings como método para investigar un corpus

Estudio de asociaciones de palabras
Inspeccionando el dataset

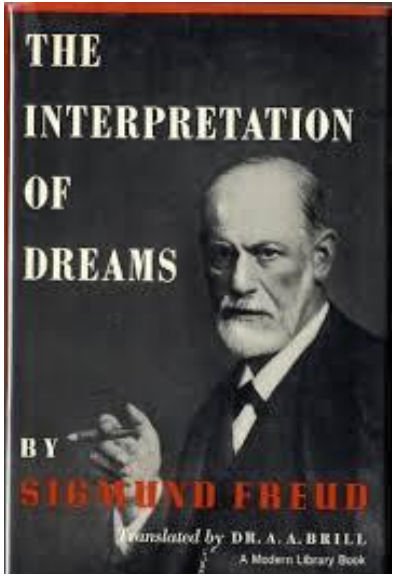
WIKIPEDIA
The Free Encyclopedia





Los sueños como ventana a la mente

Más de 20.000 reportes de sueños



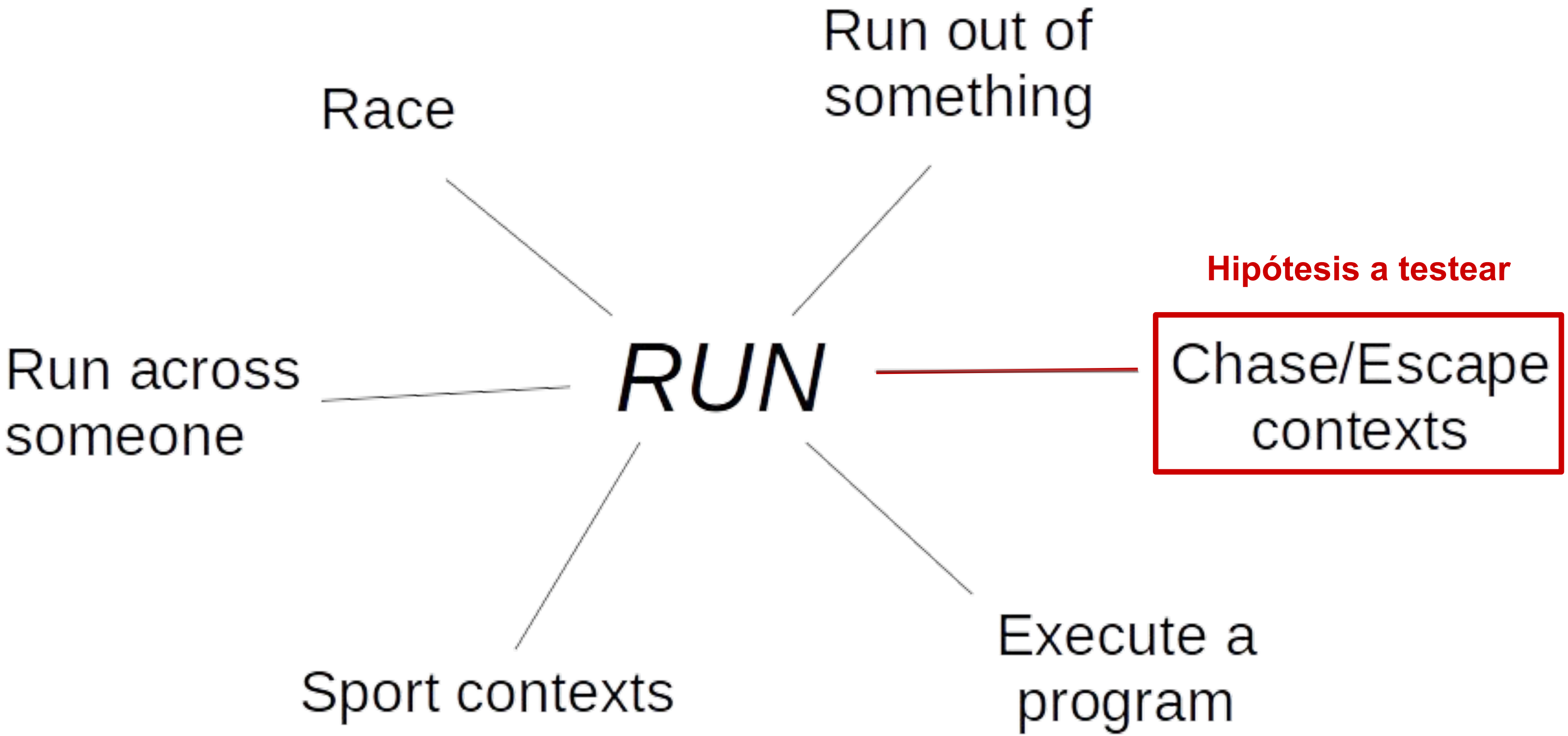
La interpretación de los sueños, Freud 1899

Schneider, A., & Domhoff, G. W. (2016). The Quantitative Study of Dreams.

Teoría de la simulación de amenazas

Antti Revonsuo (2000) The reinterpretation of dreams: An evolutionary hypothesis of function of dreaming

De que corremos en los sueños?



De que corremos en los sueños?

Palabras más cercanas a “run”

Rank	LSA Dreams	Word2vec Dreams	LSA TASA	Word2vec TASA	LSA UkWaC	Word2vec UkWaC
1st	running	chase	drive	running	running	running
2nd	escape	running	ride	runs	dash	runs
3rd	catch	scream	running	ran	jumping	marathon
4th	chase	chasing	stay	go	jump	bash
5th	chasing	escape	go	operate	yell	start
6th	follow	runs	haul	organise	workouts	rlogin
7th	ran	chases	walk	compete	kick	runners
8th	sight	grab	jump	start	jogging	starts
9th	coming	screaming	throw	break	workout	jump
10th	runs	nazi	staying	install	stretch	loaded
11th	dangerous	hide	get	operated	tiring	weekend
12th	guards	chased	carry	gone	fun	vms
13th	robbers	yells	move	move	fast	startx
14th	hide	safety	stop	set	repetitions	marathons
15th	toward	wolf	cut	managed	throw	mkdir

Ejemplo de uso 3

Embeddings como métrica de similaridad semántica externa

Competencia: CLPsych 2017 shared task

Word-embeddings como métrica de similaridad semántica

depression

0.01 0.1 0.15 0.1 0.3

@Author - 06 Sep 2015, 15:56

Re: psychosis

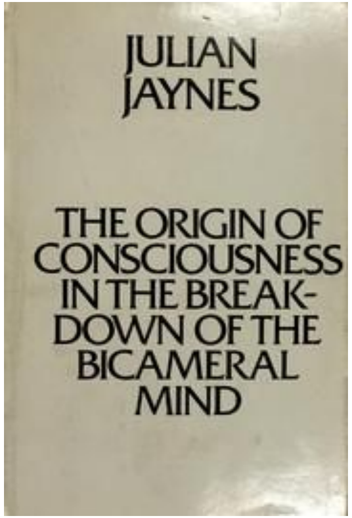
I've had a rough day. I got very close to self **harming**. Took myself to **hospital** to talk to **mental health** team to calm down. Now I'm at my best mates to keep safe tonight.

- ➢ Cercanía promedio = 0.05
- ➢ Fracción de palabras cercanas= 4/35

Usamos muchas palabras
depression - fear - anxiety - mental_health - hopelessness - suicide - antidepressant

Palabras cercanas a depression:
Bipolar_disorder, depression_anxiety, mental_illness, psychosis, alcoholism, depressive, suicidal_thoughts, schizophrenia, anxiety_disorders, psychological_distress, manic_depression, anxiety_disorder, mental_disorders, Depression, major_depressive_disorder, postpartum_depression, obsessive_compulsive_disorder, mood_disorders, insomnia, depressive_symptoms, psychiatric_disorders, bulimia, loneliness, PTSD, migraines, antidepressants, dementia

La historia de la introspección



Hipótesis: cambios en la introspección a través del tiempo

La historia de la introspección

Introspección

0.12

Hipnotismo de un flagelo dulce, tan dulce. cuero, piel y metal carmín y charol. Cuando el cuerpo no espera lo que llaman amor. Cada lágrima de hambre el mas puro néctar nada mas dulce que el deseo en cadenas. Mas se pide y se vive canción animal

Libro 1

Introspección

0.09

Ella tambien se canso de este sol viene a mojarse los pies a la luna Ella tambien se canso de este sol viene a mojarse los pies a la luna Cuando se cansa de tanto querer ella es tan clara que ya no es ninguna

Libro 2

...

Introspección

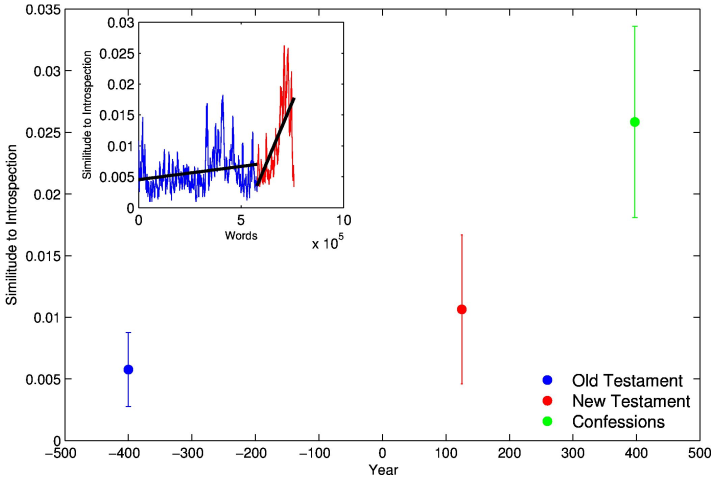
0.17

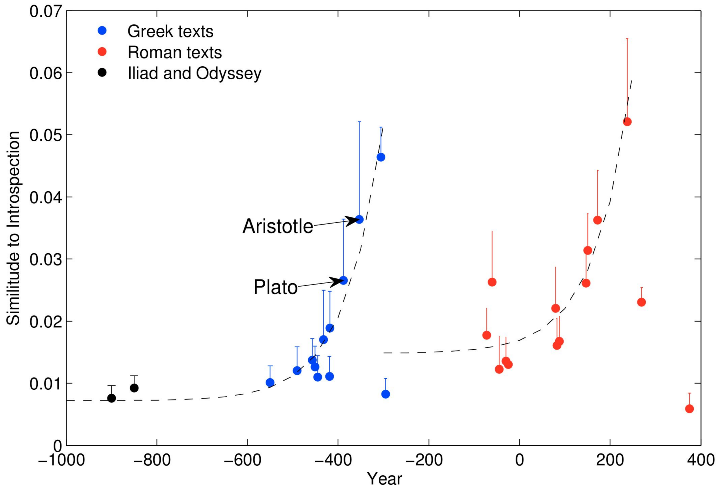
Me veras volar por la ciudad de la furia, donde nadie sabe de mi y yo soy parte de todos. Nada cambiara con un aviso de curvas, en sus caras veo el temor ya no hay fabulas en la ciudad de la furia

Libro N

Primeras 20 palabras:
Soul_searching, introspective, navel_gazing, contemplation, catharsis, contemplative, self_pity, rumination, self_indulgence, reflection, discernment, enlightenment, recrimination, repentance, self_congratulation, meditation, cynicism, reminiscence, humility, self_loathing

La historia de la introspección



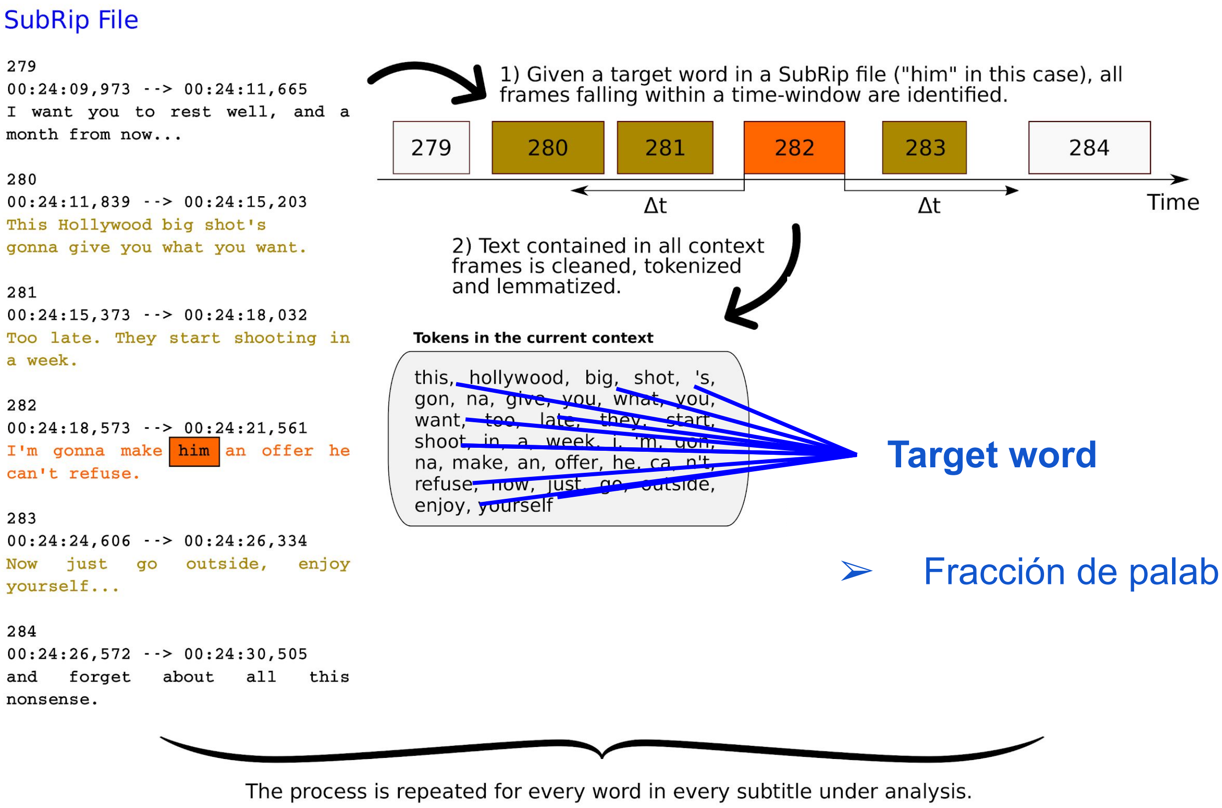


"A quantitative philology of introspection." Diuk, Carlos G., D. Fernandez Slezak, I. Raskovsky, M. Sigman, and G. A. Cecchi. (2012).

Observatorio de Hollywood

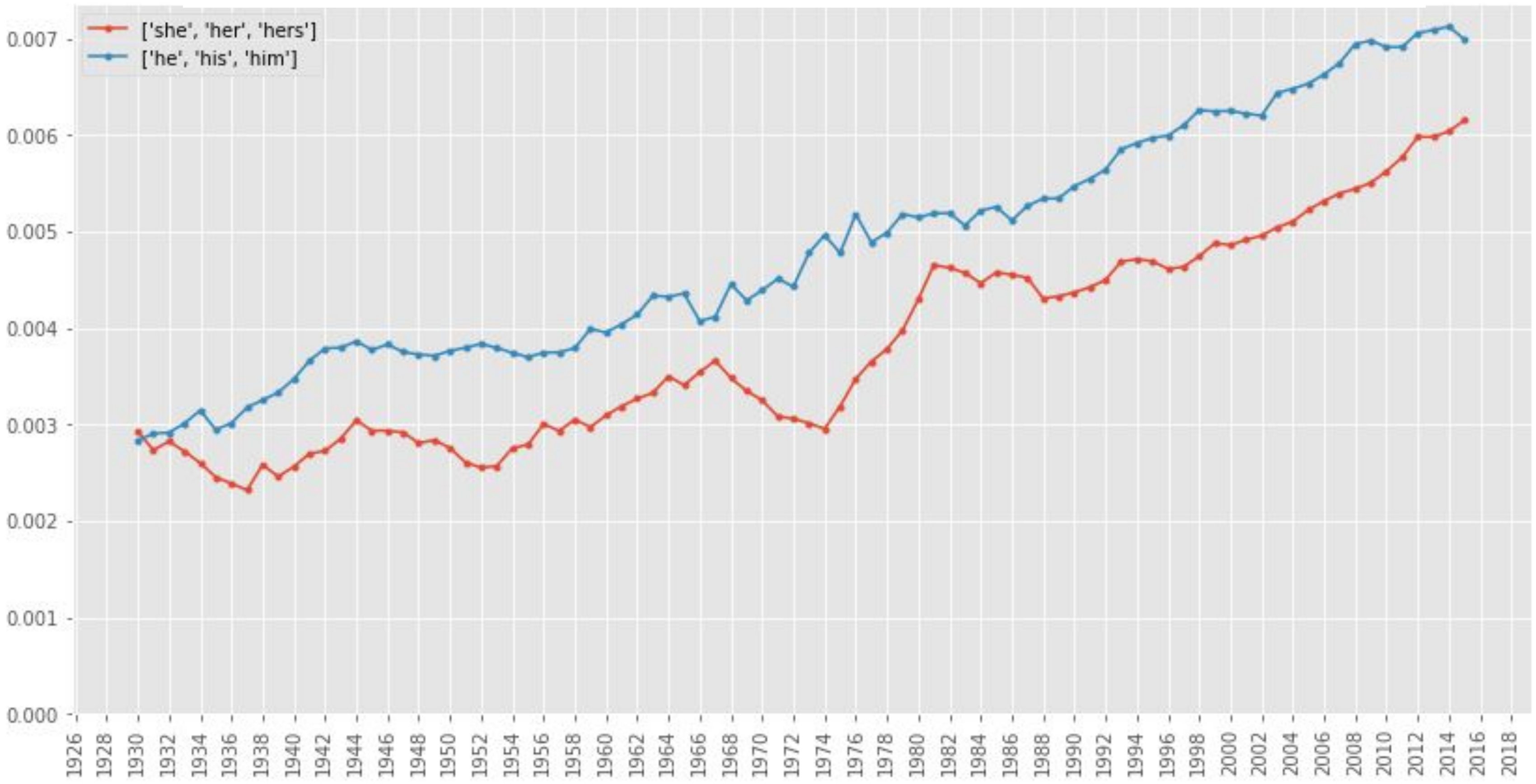
¿Qué ves cuando me ves?

Gálvez H. R., Tiffemberg V. and Altszyler E. (2018) Half a century of stereotyping associations between gender and intellectual ability in films



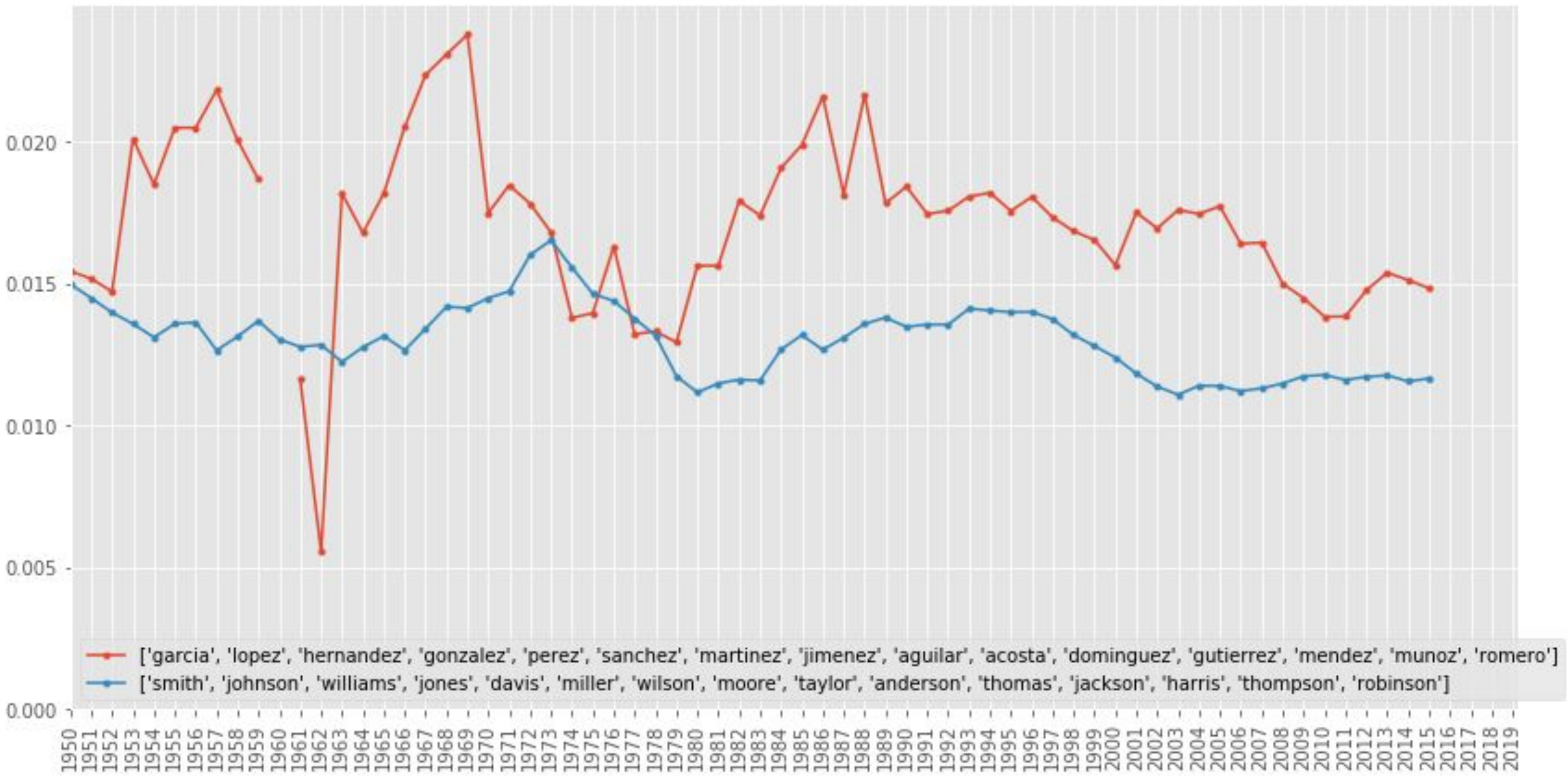
➢ Fracción de palabras cercanas = 0.20

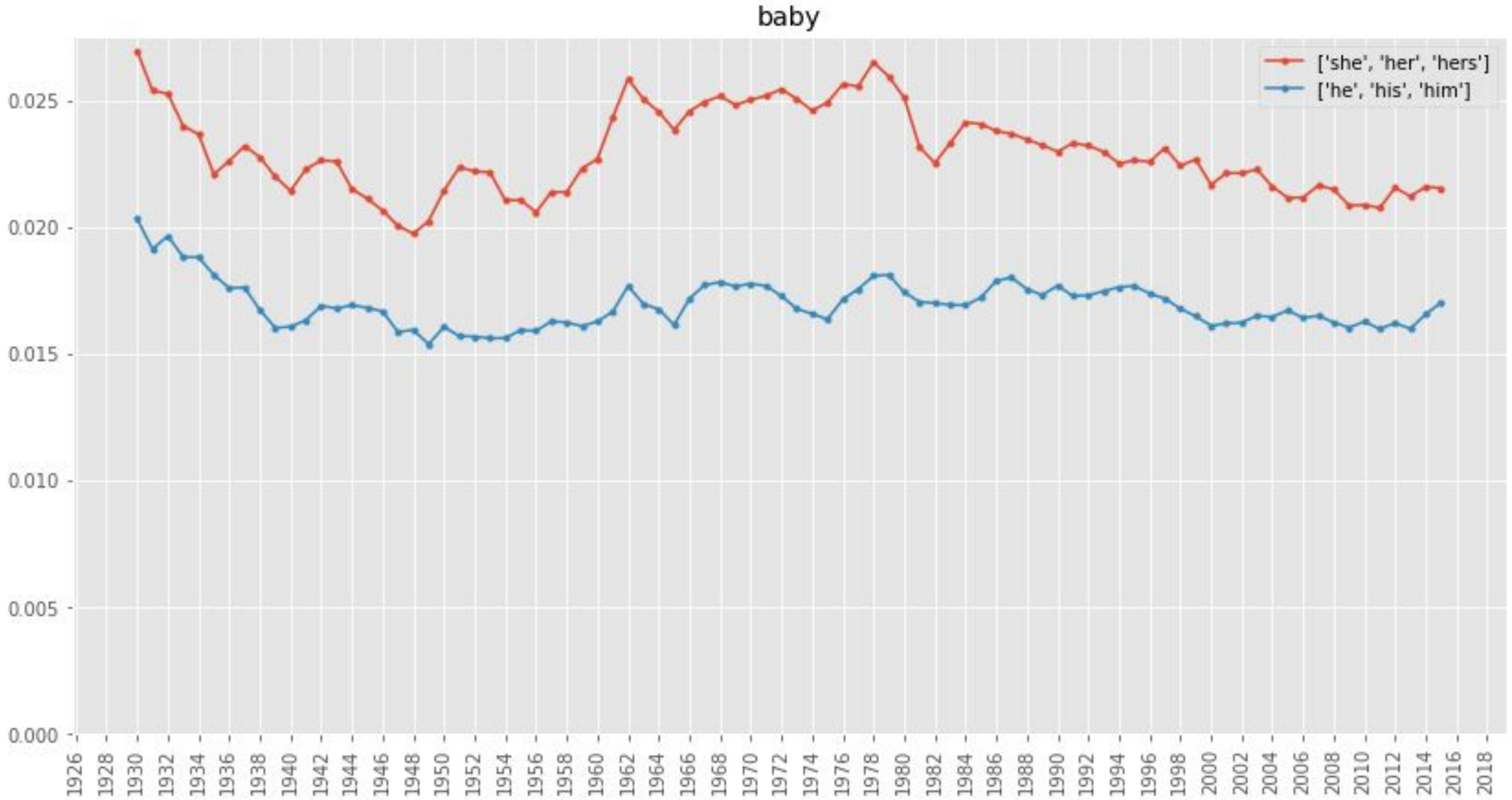
Asociación con **technology**



¿Quien es Smith y quién es García?

Asociación con **robbers**




baby
['she', 'her', 'hers']
['he', 'his', 'him']
0.025
0.020
0.015
0.010
0.005
0.000
1926
1928
1930
1932
1934
1936
1938
1940
1942
1944
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2012
2014
2016
2018

Palabras más cercanas a “baby” según Word2vec

Newborn, babies, infant, newborn_baby, toddler, child, triplets, Baby, newborns, unborn_baby, twins, tot, quadruplets, newborn_babies, infants, mother, grandchild, daughter, kitten, pregnant, mommy, Babies, birth, firstborn, Newborn, fetus, puppy, puppies, mom, toddlers, mama, pups, womb, girl, unborn_child, birthing, crib, pup, kittens, pregnancy, daddy, Caesarean_section, stillborn, **boy**, premature_babies, Jayden, expectant_mothers, mothers, twin_daughters, pacifier, diaper_bag, mommies, expectant_parents, stroller, piglet, preschooler, diaper, **son**, caesarean_section, Ava, baby_sitter, expectant_mother, daughter_Ava, breastfeeding, babysitter, momma, stork, cuddles, Infant, children, cesarean_section, diapers, bassinet, Mommy, grandmother, tots, octuplets, childbirth, preemies, cub, piglets, granddaughter, mothering, nappy, Suri_Cruise, surrogate_mother, breast_feeding, Mom, born_prematurely, maternity_ward, Caesarean, cuddle, pram, chick, mum, Toddler, tummy, sextuplets, midwife, giraffe

baby

0.43 0.28

woman man

¡Siempre chequear el significado de las palabras que uso!

FIN