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Coding School

DATA SCIENCE

MÓDULO 4

Embeddings

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1. **Introducción a redes neuronales**

2. **Embedding y Word2Vec**

3. **Ejemplos de aplicaciones**

Redes Neuronales

Redes Neuronales

Input

Hidden

Output

"Las **redes neuronales** son un modelo computacional. La información de entrada atraviesa la red neuronal (donde se somete a diversas operaciones) produciendo unos valores de salida." (wikipedia)
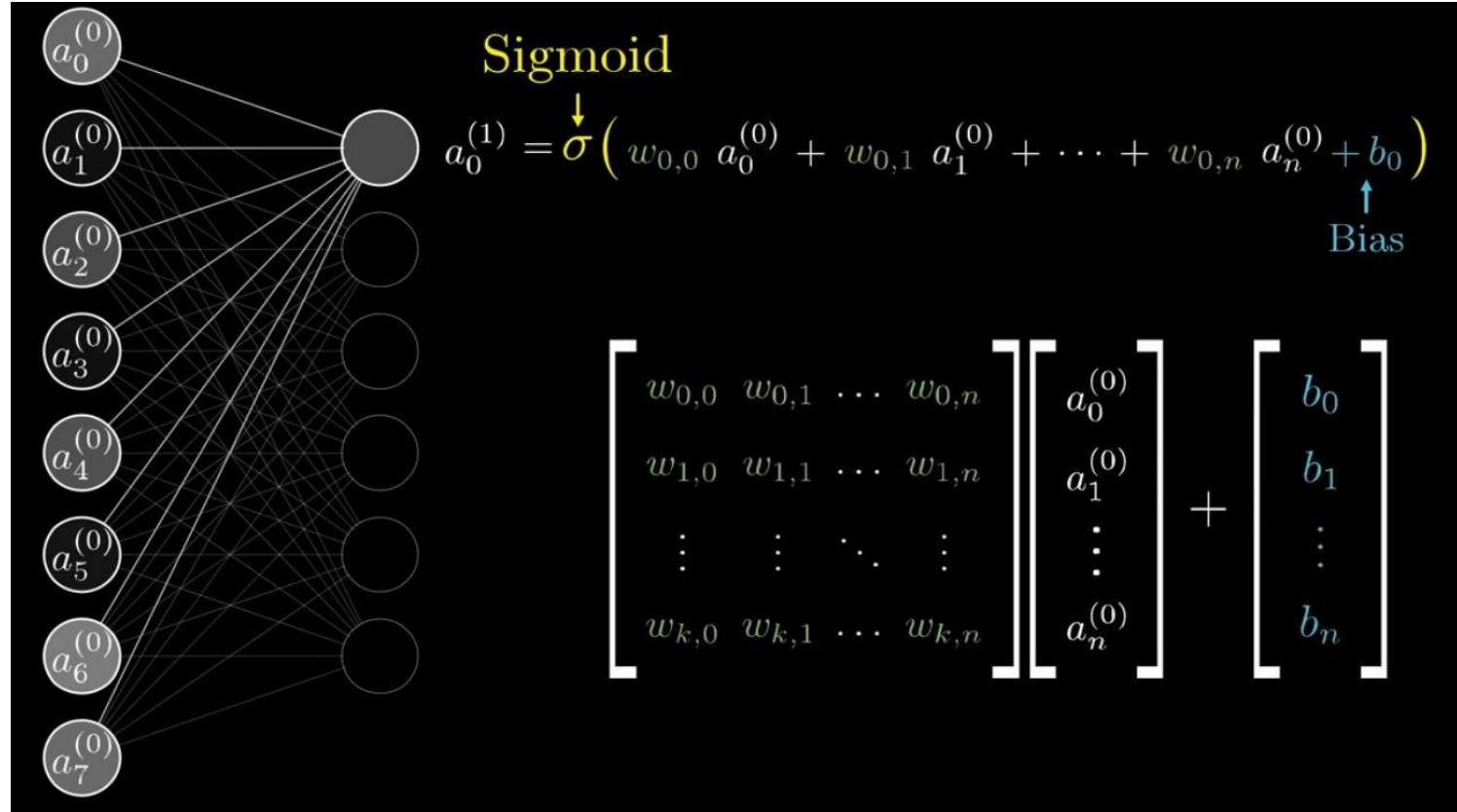
Redes Neuronales

Sigmoid

$$a_0^{(1)} = \sigma \left(w_{0,0}\, a_0^{(0)} + w_{0,1}\, a_1^{(0)} + \cdots + w_{0,n}\, a_n^{(0)} + b_0 \right)$$

Bias

$$\begin{bmatrix} w_{0,0} & w_{0,1} & \cdots & w_{0,n} \\ w_{1,0} & w_{1,1} & \cdots & w_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,0} & w_{k,1} & \cdots & w_{k,n} \end{bmatrix} \begin{bmatrix} a_0^{(0)} \\ a_1^{(0)} \\ \vdots \\ a_n^{(0)} \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix}$$

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Función de activación:

Sigmoid

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

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Sigmoid

$$a_0^{(1)} = \sigma\left(w_{0,0}\, a_0^{(0)} + w_{0,1}\, a_1^{(0)} + \cdots + w_{0,n}\, a_n^{(0)} + b_0 \right)$$

Bias

$$
\begin{bmatrix}
w_{0,0} & w_{0,1} & \cdots & w_{0,n} \\
w_{1,0} & w_{1,1} & \cdots & w_{1,n} \\
\vdots & \vdots & \ddots & \vdots \\
w_{k,0} & w_{k,1} & \cdots & w_{k,n}
\end{bmatrix}
\begin{bmatrix}
a_0^{(0)} \\
a_1^{(0)} \\
\vdots \\
a_n^{(0)}
\end{bmatrix}
+
\begin{bmatrix}
b_0 \\
b_1 \\
\vdots \\
b_n
\end{bmatrix}
$$

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Ejemplo: mnist

Redes Neuronales

Redes Neuronales

Redes Neuronales

Back Propagation

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Back Propagation

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Back Propagation

$$\text{Cost} \longrightarrow C_0(\dots) = (a^{(L)} - y)^2$$

$$z^{(L)} = w^{(L)} a^{(L-1)} + b^{(L)}$$

$$a^{(L)} = \sigma(z^{(L)})$$

Desired output

La función de costo determina mi error a partir del valor predicho y el valor real.

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Back Propagation

Para saber cuánto tengo que cambiar los valores, hago:

$$\frac{\partial C_0}{\partial w^{(L)}} = \frac{\partial z^{(L)}}{\partial w^{(L)}} \frac{\partial a^{(L)}}{\partial z^{(L)}} \frac{\partial C0}{\partial a^{(L)}} = a^{(L-1)} \sigma'(z^{(L)}) 2(a^{(L)} - y)$$

Como variaciones de w modifican el costo C.

Luego

$$\frac{\partial C}{\partial w^{(L)}} = \frac{1}{n} \sum_{k=0}^{n-1} \frac{\partial C_k}{\partial w^{(L)}}$$

Average of all training examples

Equivalente para el bias

figura obtenida de 3BLUE1BROWN

Redes Neuronales

Back Propagation

Finalmente, para actualizar los valores de w hago:

$$w_i^+ = w_i - \eta * \frac{\partial C}{\partial w_i}$$

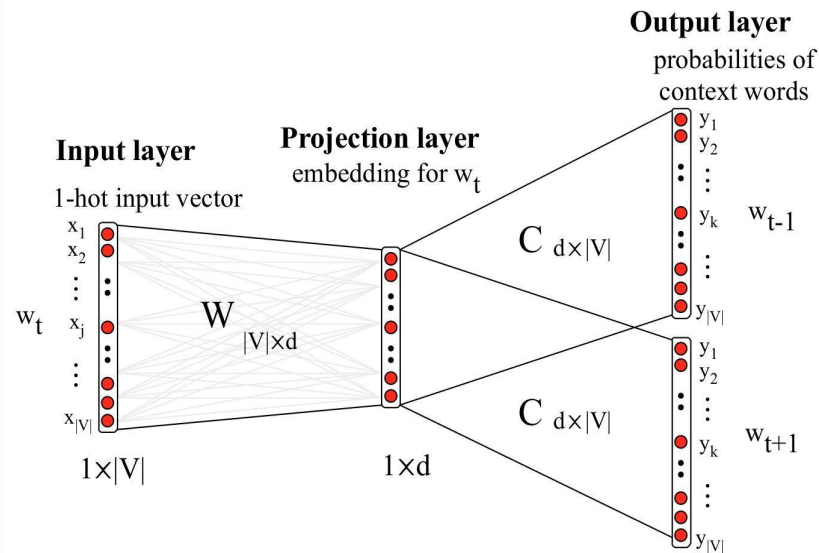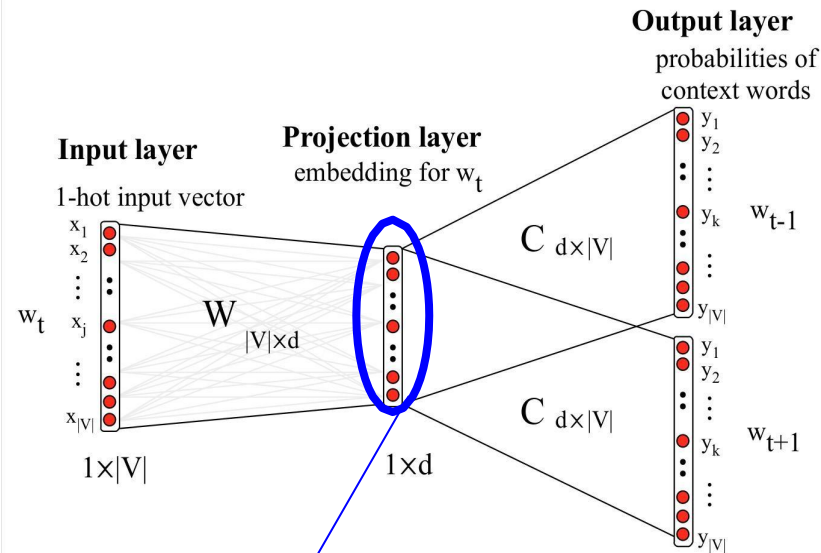donde eta es el "learning rate"

Word2Vec

Word2Vec

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

Output layer
probabilities of context words

Input layer
1-hot input vector

Projection layer
embedding for w_t

x_1
x_2
$\vdots$
w_t x_j
$\vdots$
$x_{|V|}$

W
$|V| \times d$

$1 \times |V|$

$1 \times d$

$C\ d \times |V|$

$C\ d \times |V|$

y_1
y_2
$\vdots$
y_k w_{t-1}
$\vdots$
$y_{|V|}$

y_1
y_2
$\vdots$
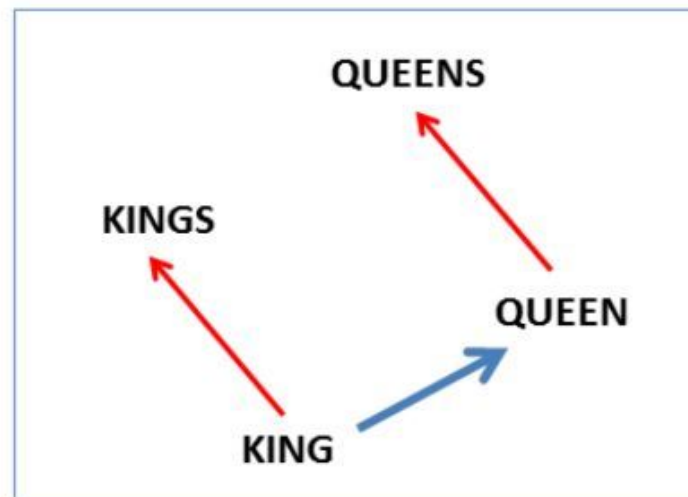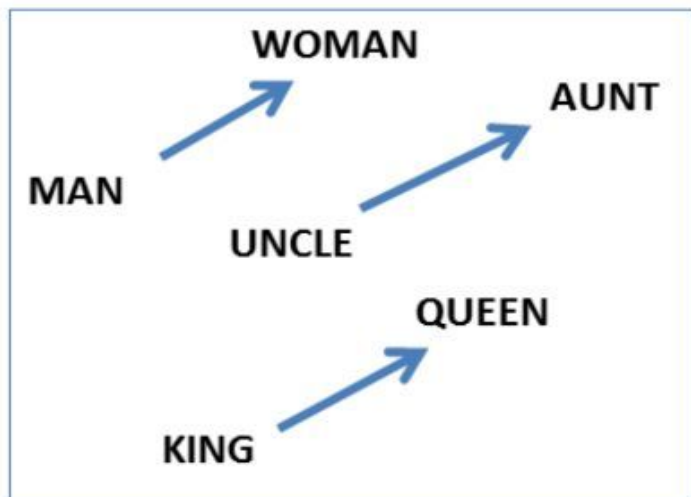y_k w_{t+1}
$\vdots$
$y_{|V|}$

Word2Vec

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*.

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1-hot input vector

x_1
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$\vdots$
w_t x_j
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$x_{|V|}$

W
$|V| \times d$

$C_{d \times |V|}$

y_1
y_2
$\vdots$
y_k w_{t-1}
$\vdots$
$y_{|V|}$

$C_{d \times |V|}$

y_1
y_2
$\vdots$
y_k w_{t+1}
$\vdots$
$y_{|V|}$

$1 \times |V|$

$1 \times d$

Me quedo con esto:
Representación vectorial de dimensión d
de un término

Word2Vec

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

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

Visualización t-sne
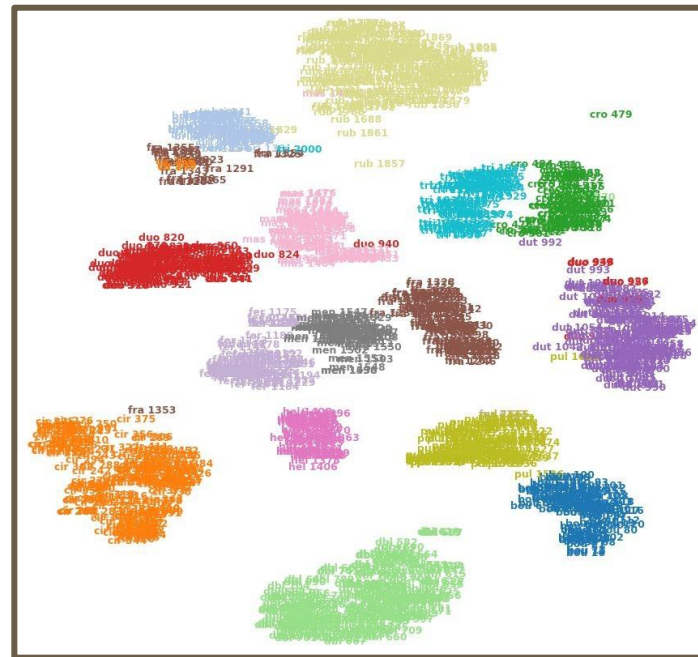
T-SNE: T-distributed Stochastic Neighbor Embedding

¿Qué es?

Técnica de reducción dimensional.

¿Cómo funciona?

Busca preservar la estructura
local de los datos (no tanto la global
como MDS).

T-SNE: T-distributed Stochastic Neighbor Embedding

Pasos:

1. Convertir las similitudes entre puntos en probabilidad de elegir un punto como vecino de otro.
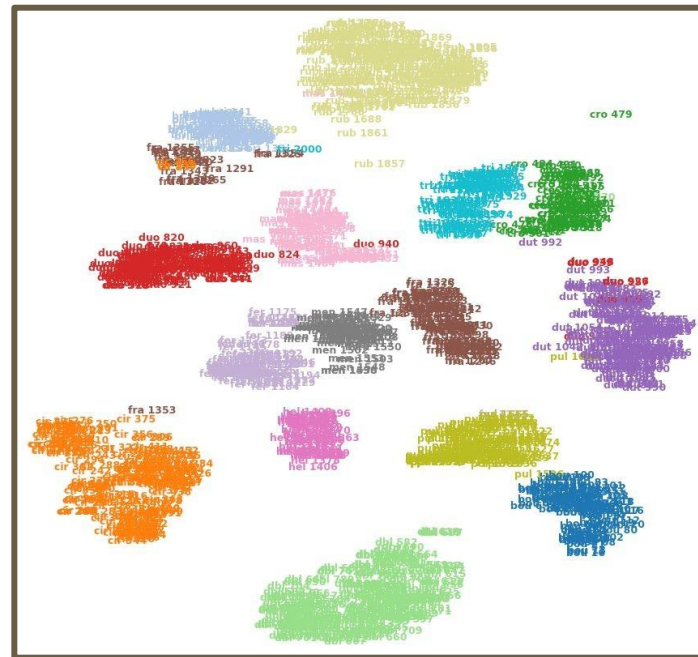
$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2 / 2\sigma_i^2)},$$

2. Proyectar los puntos en la dimensión baja.

3. Convertir similitudes en probabilidades

$$q_{ij} = \frac{(1 + \|\mathbf{y}_i - \mathbf{y}_j\|^2)^{-1}}{\sum_{k \neq l} (1 + \|\mathbf{y}_k - \mathbf{y}_l\|^2)^{-1}}$$

4. Minimizar (mediante descenso de gradiente)

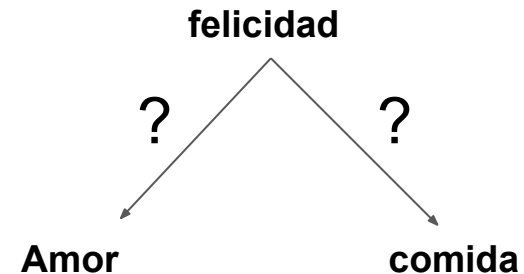$$Costo = \sum_i KL(P_i \| Q_i) = \sum_i \sum_j p_{j|i} \log\left(\frac{p_{j|i}}{q_{j|i}}\right)$$

Ejemplos

Ejemplo 1: ¿qué son los sueños?

Estudio de asociaciones de palabras inspeccionando el dataset

WIKIPEDIA
The Free Encyclopedia

felicidad

?   ?

Amor   comida

Ejemplo 1: ¿qué son los sueños?

Los sueños como ventana a la mente

Más de 20.000 reportes de sueños

Schneider, A., & Domhoff, G. W. (2016). The Quantitative Study of Dreams.
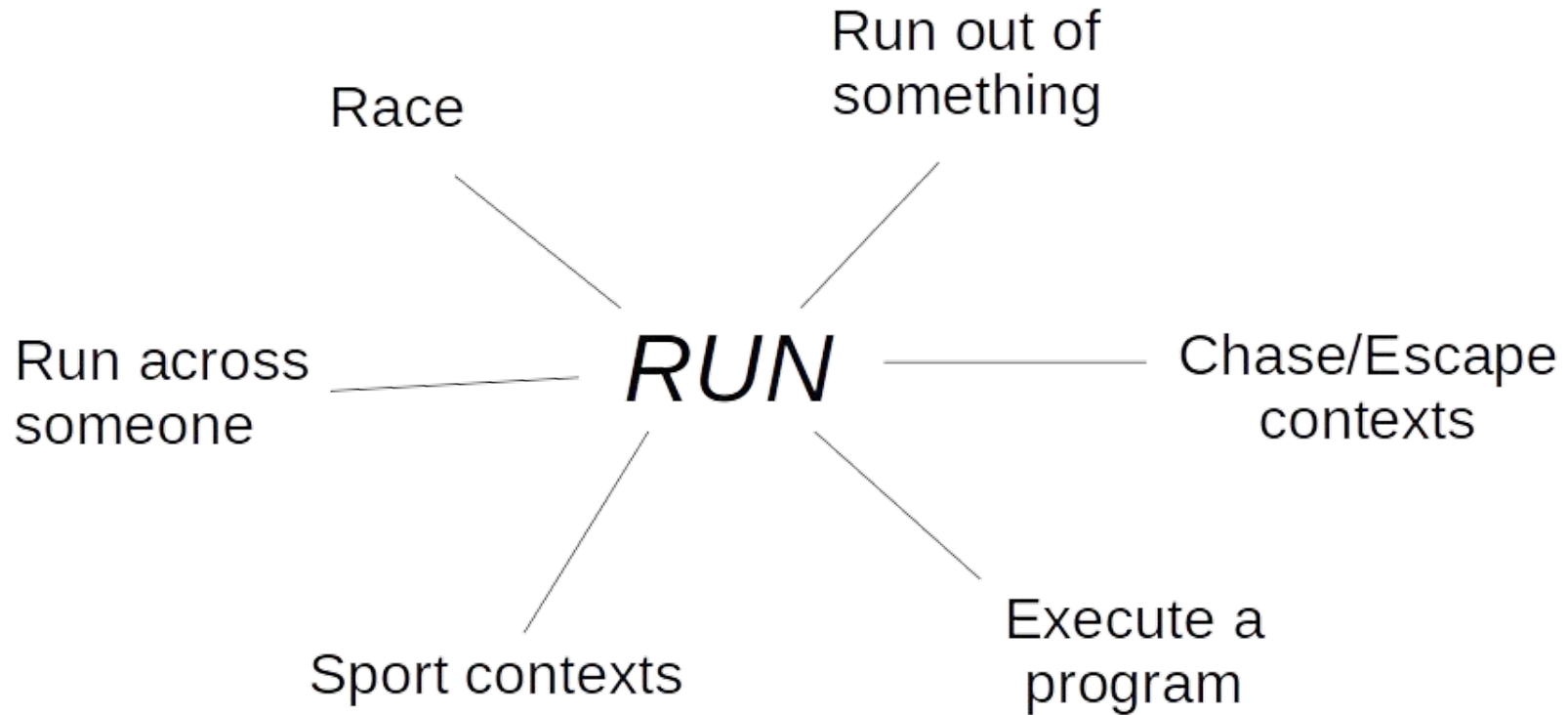
Ejemplo 1: ¿qué son los sueños?

Teoría de la simulación de amenazas

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

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¿De qué corremos en los sueños?

Race

Run out of something

Run across someone

RUN

Chase/Escape contexts

Sport contexts

Execute a program

Ejemplo 1: ¿qué son los sueños?

¿De qué corremos en los sueños? Palabras 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 2: similaridad semántica

@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.
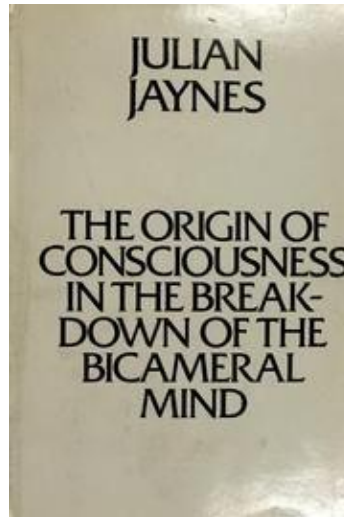
Ejemplo 2: similaridad semántica

depression

@Author - 06 Sep 2015, 15:56

0.01 **0.1 0.15**   **0.3**

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
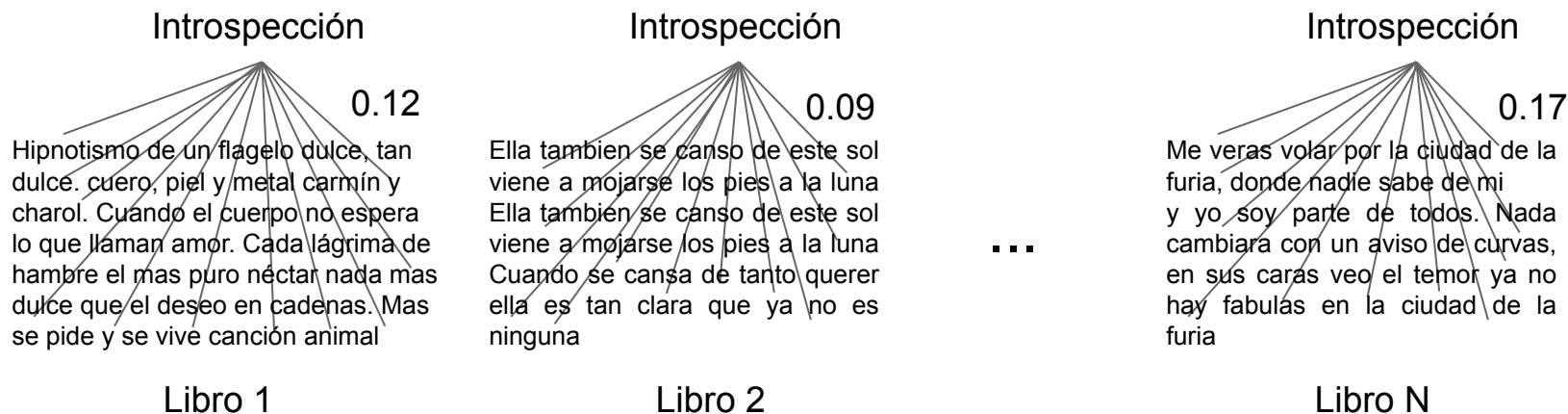
Palabras cercanas a depression:

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

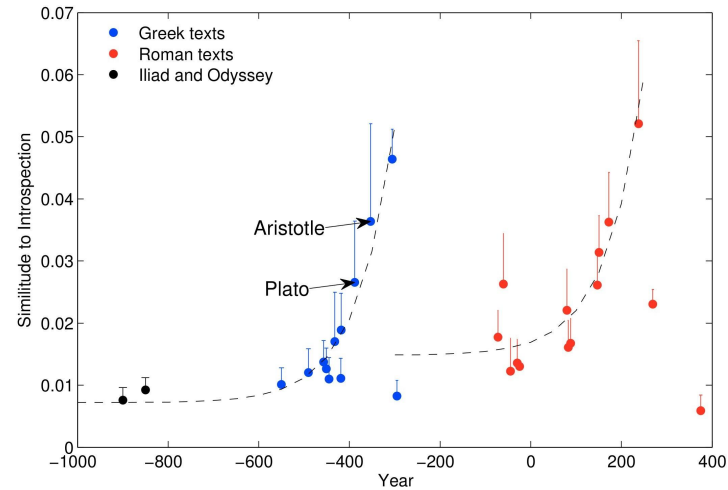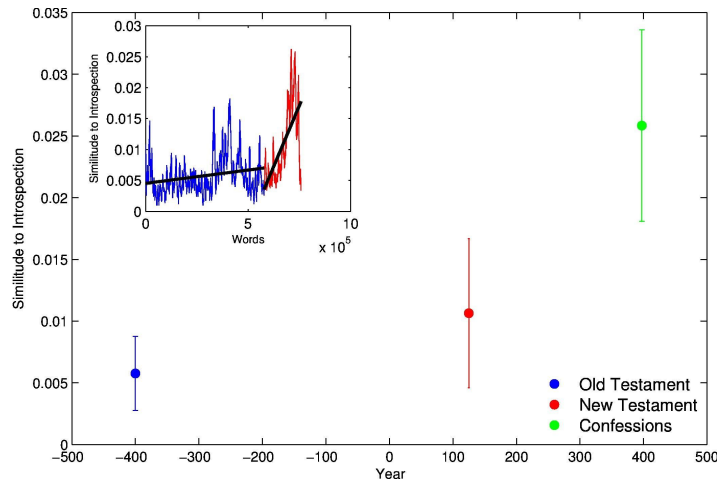**Hipótesis:** cambios en la introspección a través del tiempo

Ejemplo 2: similaridad semántica

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 también 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

SubRip File

```
279
00:24:09,973 --> 00:24:11,665
I want you to rest well, and a
month from now...

280
00:24:11,839 --> 00:24:15,203
This Hollywood big shot's
gonna give you what you want.

281
00:24:15,373 --> 00:24:18,032
Too late. They start shooting in
a week.

282
00:24:18,573 --> 00:24:21,561
I'm gonna make him an offer he
can't refuse.

283
00:24:24,606 --> 00:24:26,334
Now just go outside, enjoy
yourself...

284
00:24:26,572 --> 00:24:30,505
and forget about all this
nonsense.
```
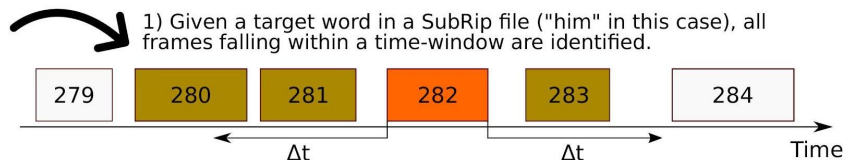
1) Given a target word in a SubRip file ("him" in this case), all frames falling within a time-window are identified.

| 279 | 280 | 281 | 282 | 283 | 284 |

Δt Δt Time

2) Text contained in all context frames is cleaned, tokenized and lemmatized.

Tokens in the current context

this, hollywood, big, shot, 's, gon, na, give, you, what, you, want, too, late, they, start, shoot, in, a, week, i, 'm, gon, na, make, an, offer, he, ca, n't, refuse, now, just, go, outside, enjoy, yourself
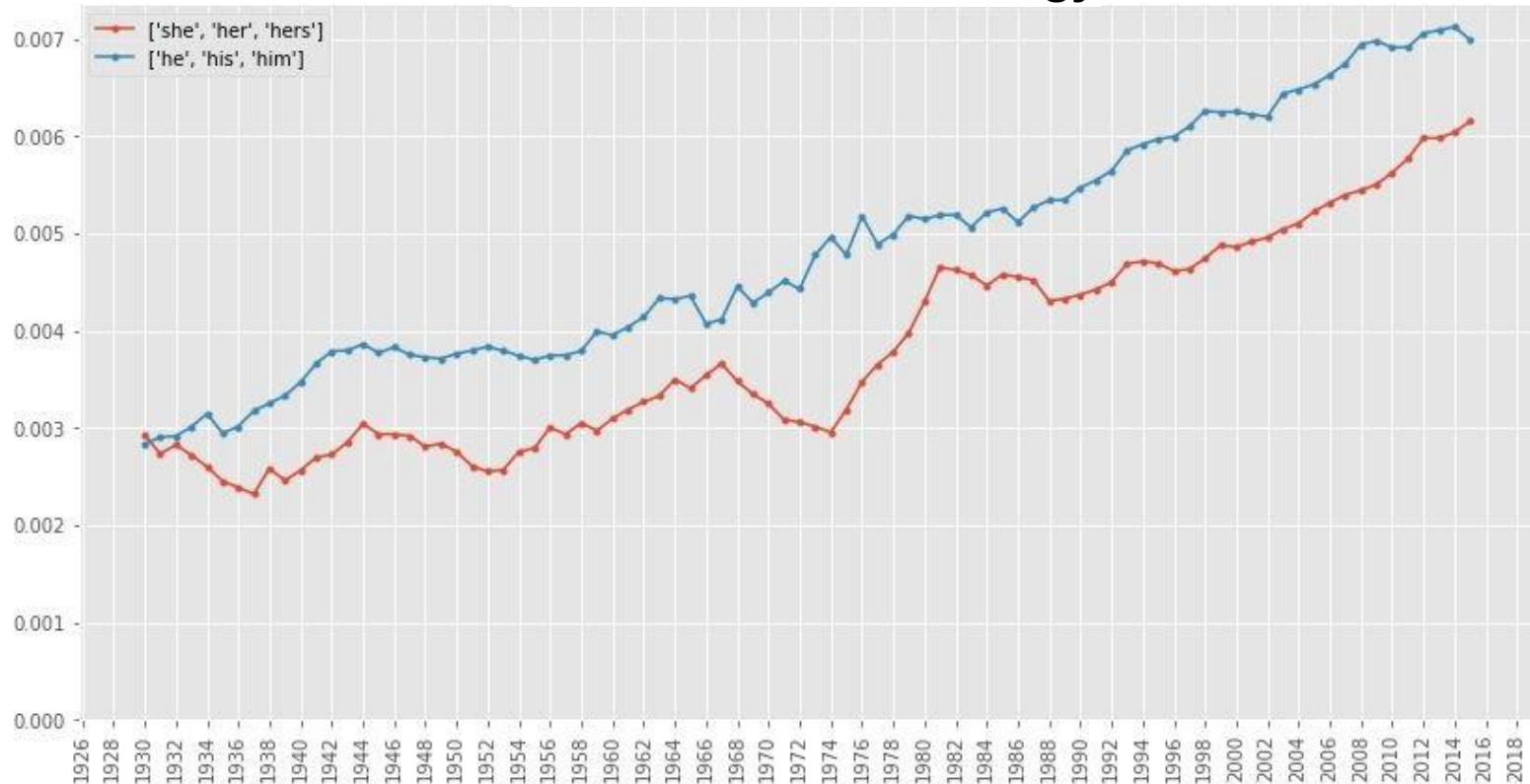
Target word

➤ Fracción de palabras cercanas = 0.20

The process is repeated for every word in every subtitle under analysis.

Gálvez H. R., Tiffemberg V. and Altszyler E. (2018) Half a century of stereotyping associations between gender and intellectual ability in films
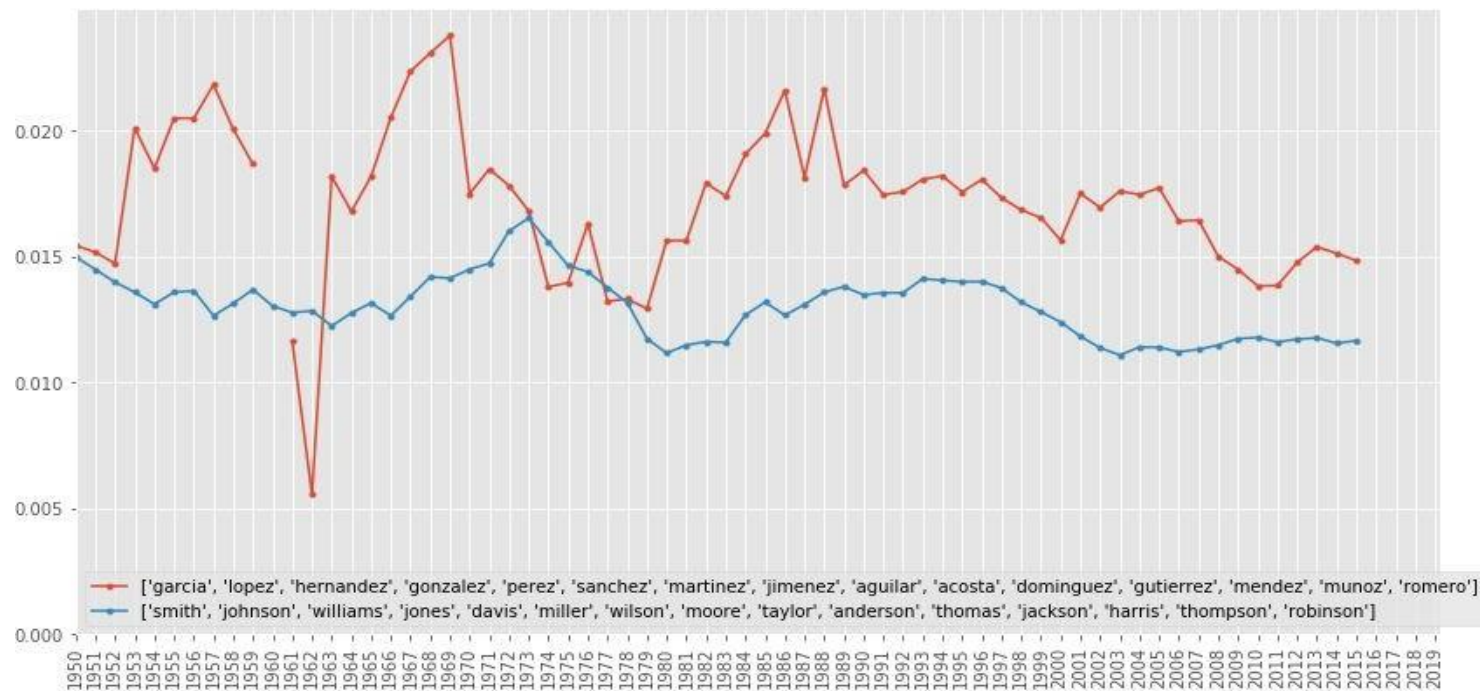
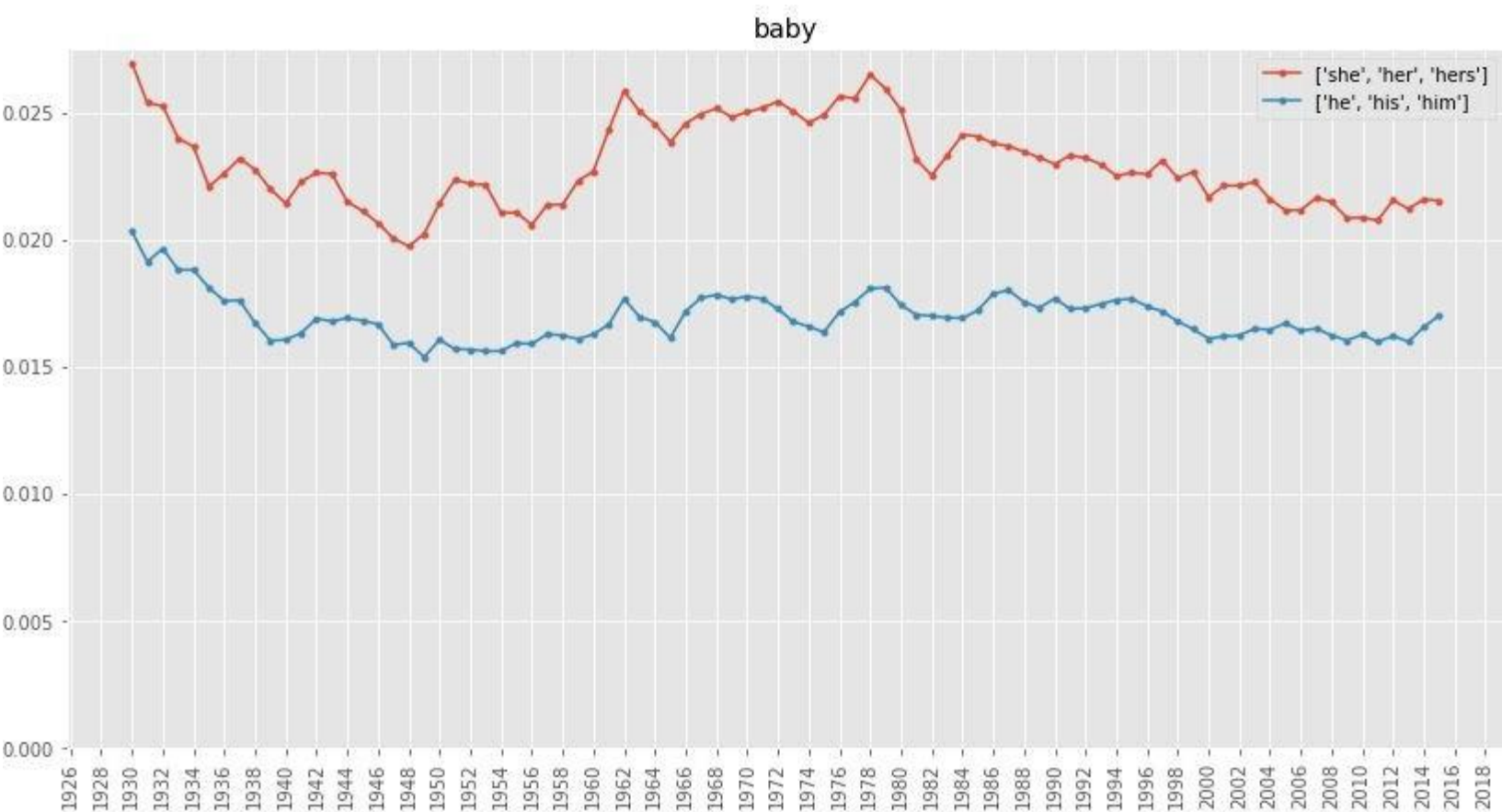# Ejemplo 2: similaridad semántica

Asociación con **technology**

¿Quién es Smith y quién es García?

Asociación con **robbers**

['garcia', 'lopez', 'hernandez', 'gonzalez', 'perez', 'sanchez', 'martinez', 'jimenez', 'aguilar', 'acosta', 'dominguez', 'gutierrez', 'mendez', 'munoz', 'romero']
['smith', 'johnson', 'williams', 'jones', 'davis', 'miller', 'wilson', 'moore', 'taylor', 'anderson', 'thomas', 'jackson', 'harris', 'thompson', 'robinson']

Ejemplo 2: similaridad semántica

baby

Legend: ['she', 'her', 'hers'] (red), ['he', 'his', 'him'] (blue)

Ejemplo 2: similaridad semántica
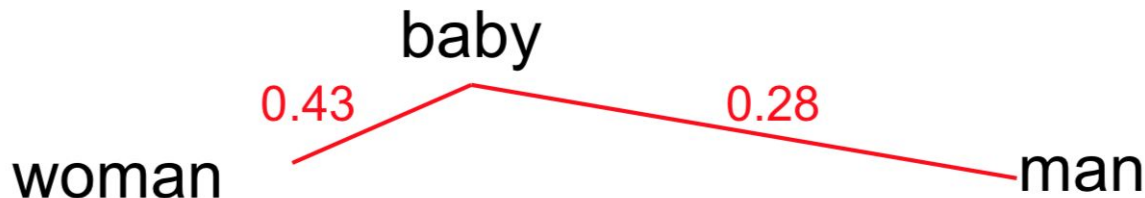
Palabras más cercanas a "baby" según Word2vec

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

woman   0.43   0.28   man

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

¡Siempre chequear el significado de las palabras que uso!

baby

woman — 0.43 — baby — 0.28 — man