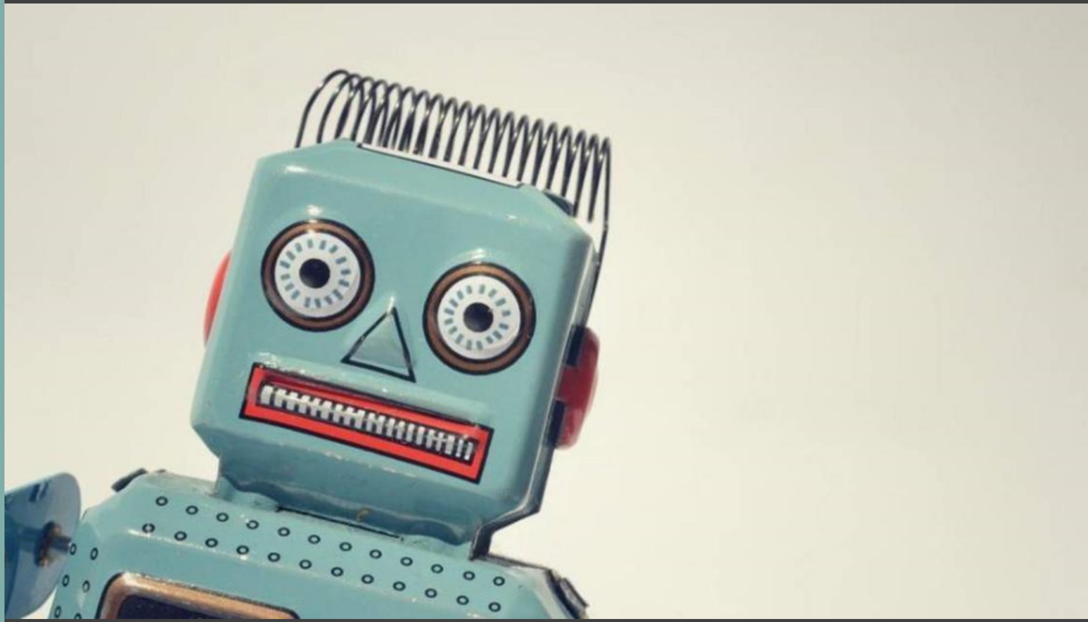
Natural Language Processing for Linguistics & Social Sciences

What? How? and Why?



Ana Valdivia, PhD

UNIVERSIDAD DE GRANADA

| *PyData Salamanca, 21 de Marzo de 2019*

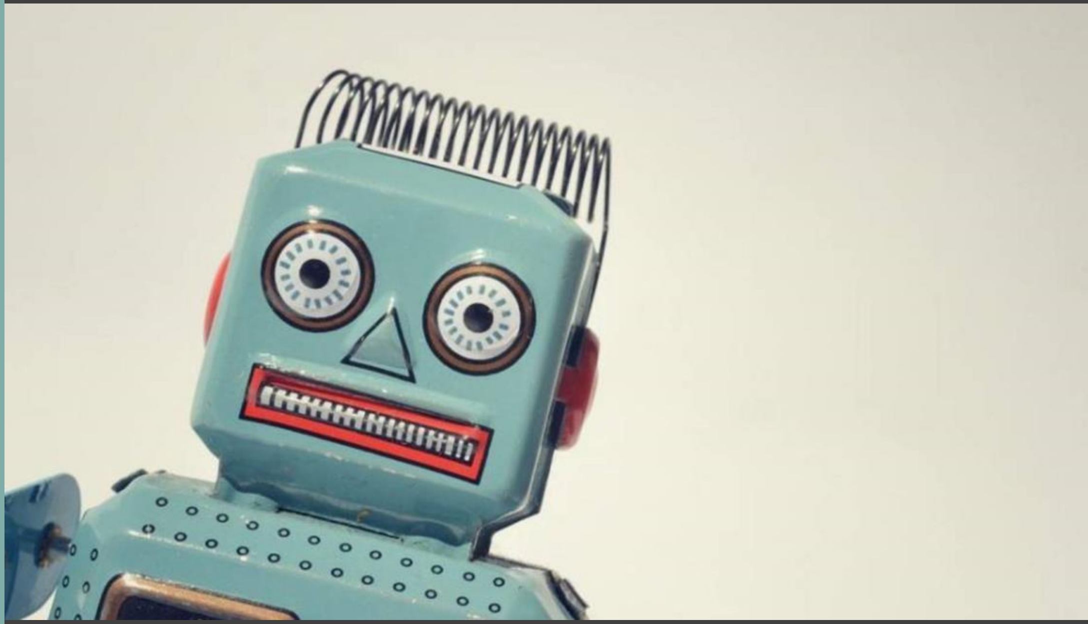
ABOUT ME

Ana Valdivia
Major in **Mathematics** (UPC)
PhD in **Computer Sciences** (UGR)

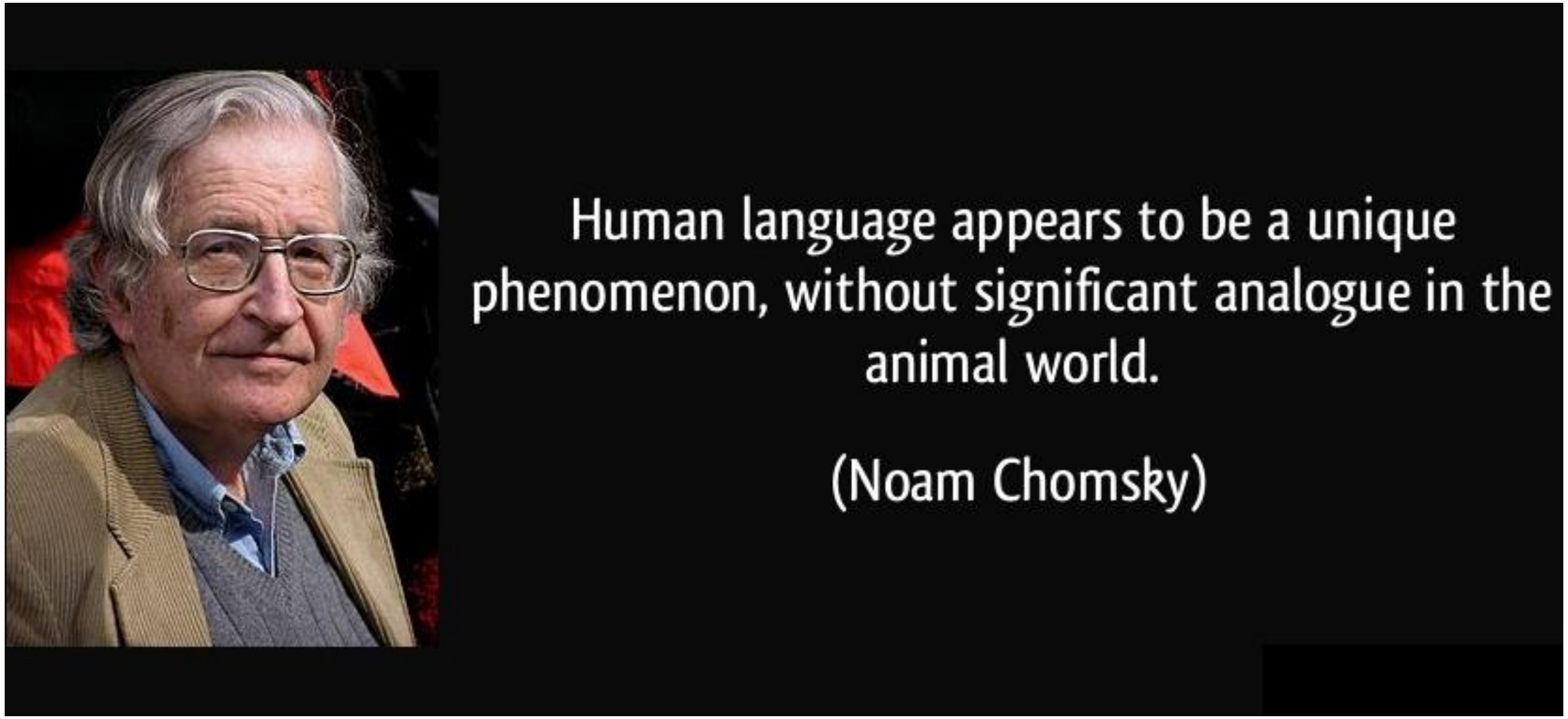
valdilab.wordpress.com

@ana_valdi

Natural Language Processing



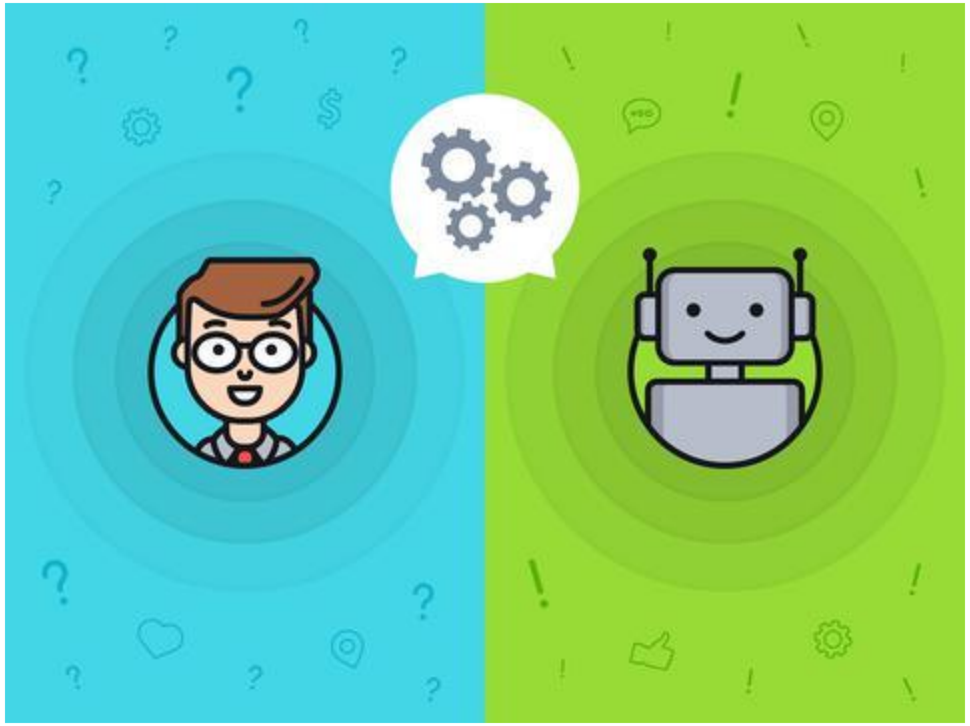
Human Language



Natural Language Processing (NLP)

N
L
P

Natural Language Processing (*NLP*) is a sub-field of ***Artificial Intelligence*** that is focused on enabling computers to "understand", process and generate human languages, to get computers closer to a human-level understanding of language.



N
L
P

Natural Language Processing (NLP)

Natural Language Processing (*NLP*) is a sub-field of *Artificial Intelligence* that is focused on enabling computers to "understand", process and generate human languages, to get computers closer to a human-level understanding of language.

Tasks:

- github.com/Kyubyong/nlp_tasks
- nlp.lsi.upc.edu/freeling

LOW

- Part of Speech Tagging
- Named Entity Recognition
- Spam Detection

MEDIUM

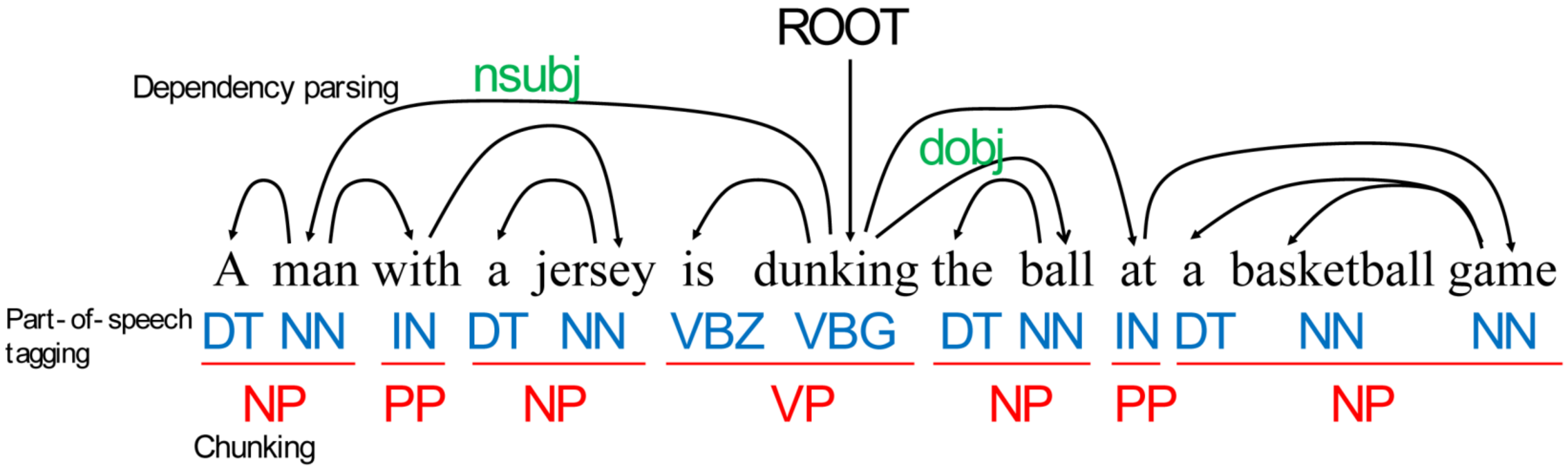
- Syntactic Parsing
- Word Sense Disambiguation
- Sentiment Analysis
- Topic Modeling

HIGH

- Machine Translation
- Text Generation
- Automatic Summarization
- Question Answering

N
L
P

LOW: Part of Speech Tagging



N
L
P

LOW: Part of Speech Tagging

- **Stemming** algorithms work by cutting off the end or the beginning of the word, taking into account a list of common prefixes and suffixes that can be found in an inflected word. This indiscriminate cutting can be successful in some occasions, but not always, and that is why we affirm that this approach presents some limitations. Below we illustrate the method with examples in both English and Spanish.

Form	Suffix	Stem
studies	-es	studi
studying	-ing	study
niñas	-as	niñ
niñez	-ez	niñ

- **Lemmatization**, on the other hand, takes into consideration the morphological analysis of the words. To do so, it is necessary to have detailed dictionaries which the algorithm can look through to link the form back to its lemma. Again, you can see how it works with the same example words.

Form	Morphological information	Lemma
studies	Third person, singular number, present tense of the verb study	study
studying	Gerund of the verb study	study
niñas	Feminine gender, plural number of the noun niño	niño
niñez	Singular number of the noun niñez	niñez

N
L
P

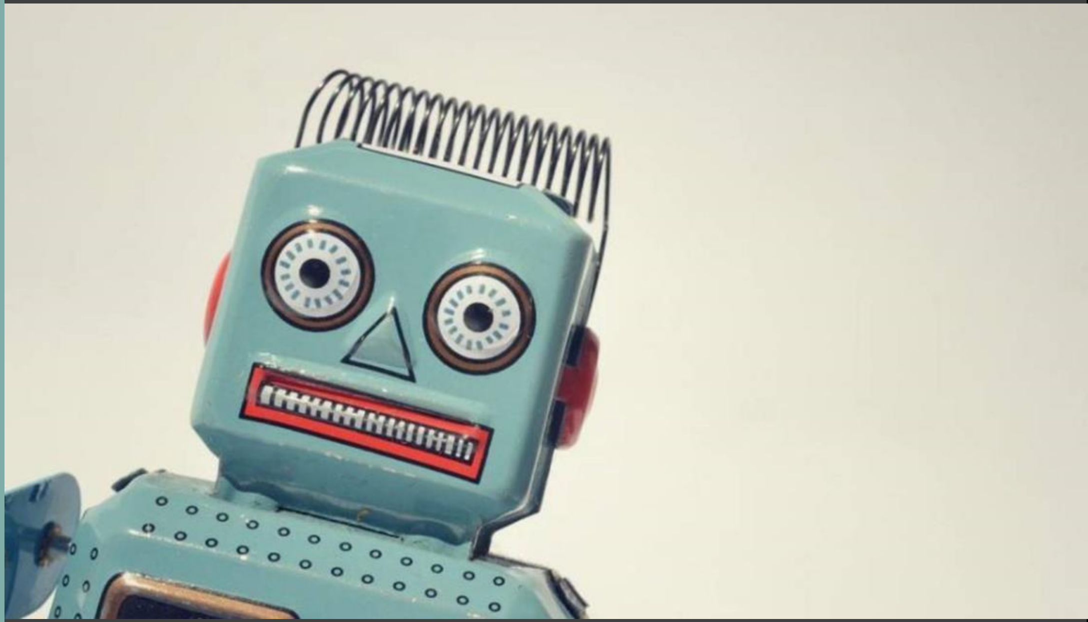
MEDIUM: Sentiment Analysis

HIGH: Text Generation

We've trained a large-scale unsupervised language model which generates coherent paragraphs of text, achieves state of the art performance on many language modeling benchmarks, and performs rudimentary reading comprehension, machine translation, question answering, and summarization —

openai.com

Word Embeddings



How to transform a word into a number?

How to transform a *word* into a *number*?

one-hot encoding

```
dog = [ 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 ]

cat = [ 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ]
```

How to transform a *word* into a *number*?

tf*idf

```
dog = [ 2.4 39.1 99.3 23.2 233.3 1.0]

cat = [ 22.1 56.3 98.2 0.5 443.2 7.0]
```

$$\underbrace{\text{TF-IDF}_{(n,d)}}_{\text{Peso de un término (n) en un documento (d)}} = \underbrace{\text{TF}_{(n,d)}}_{\text{Frecuencia de aparición de un término (n) en un documento (d)}} \times \underbrace{\text{IDF}_{(n)}}_{\text{Factor IDF de un término (n)}}$$

How to transform a *word* into a *number*?

Lack of information:

How a model will know that these two words are related/similar?

```
airplane = [ 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 ]
flight   = [ 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ]
```

How to transform a *word* into a *number*?

word embeddings

Word embedding is the collective name for a set of language modeling and feature learning techniques in NLP where words or phrases from the vocabulary are mapped to vectors of real numbers.

CONTEXT.

- “What time is your **airplane** scheduled?”
- “The pilot marked the cruise speed on our **airplane**'s flight.”
- “The engine of an **airplane** uses the propulsion force to take off.”
- “Many passengers are afraid to fly, even though the **airplane** is the safest mode of transportation.”

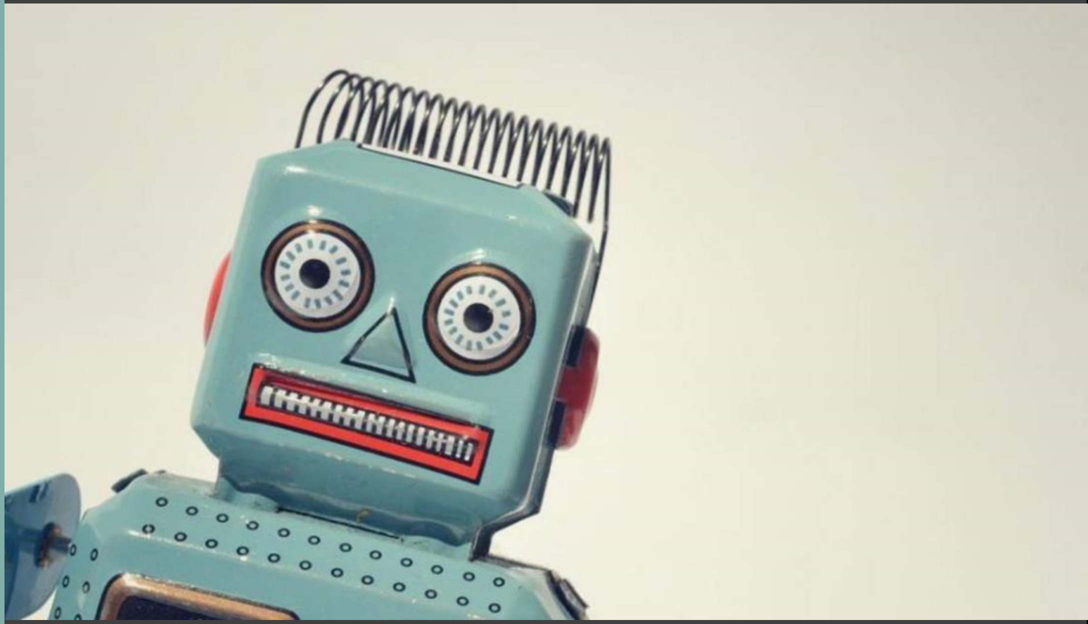
- **Airplane** is related with **scheduled, cruise speed, pilot, fligh, take off, passengers**, etc.

How to transform a *word* into a *number*?

word embeddings

- Matrix representations: LDA, GloVe
- Neural networks: **word2vec**, ELMo

word2vec



How to transform a *word* into a *number*?

word2vec (Mikolov et. al. 2013)

- Two **neural networks** with two **layers**:
  - *input*: one-hot vectors.
  - *hidden* layer: lineal.
  - *output*: softmax function.

- **CBOW** (Conditional Bag of Words): given the **context** $\{w_{t\text{-}C} \dots, w_{t\text{-}1}, w_{t+1}, \dots, w_{t+C}\}$, to predict the **word** w_t.

- **Skip-gram**: given the **word** w_t to predict the **context** $\{w_{t\text{-}C} \dots, w_{t\text{-}1}, w_{t+1}, \dots, w_{t+C}\}$.

- **Weights** of the hidden layer are the embeddings representations.

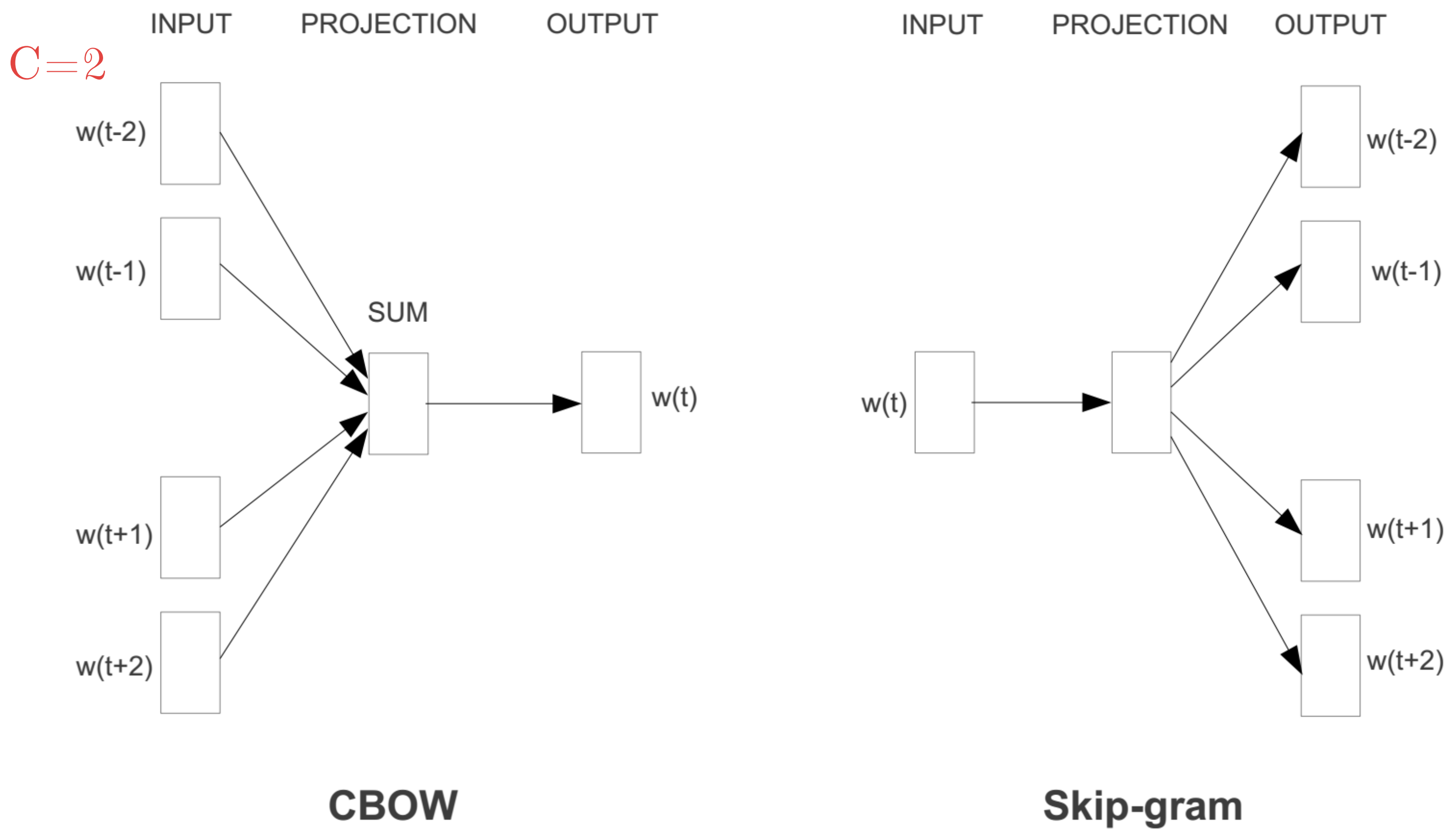
- Its performance depends on the size of the corpus (the bigger, the better).

How to transform a *word* into a *number*?

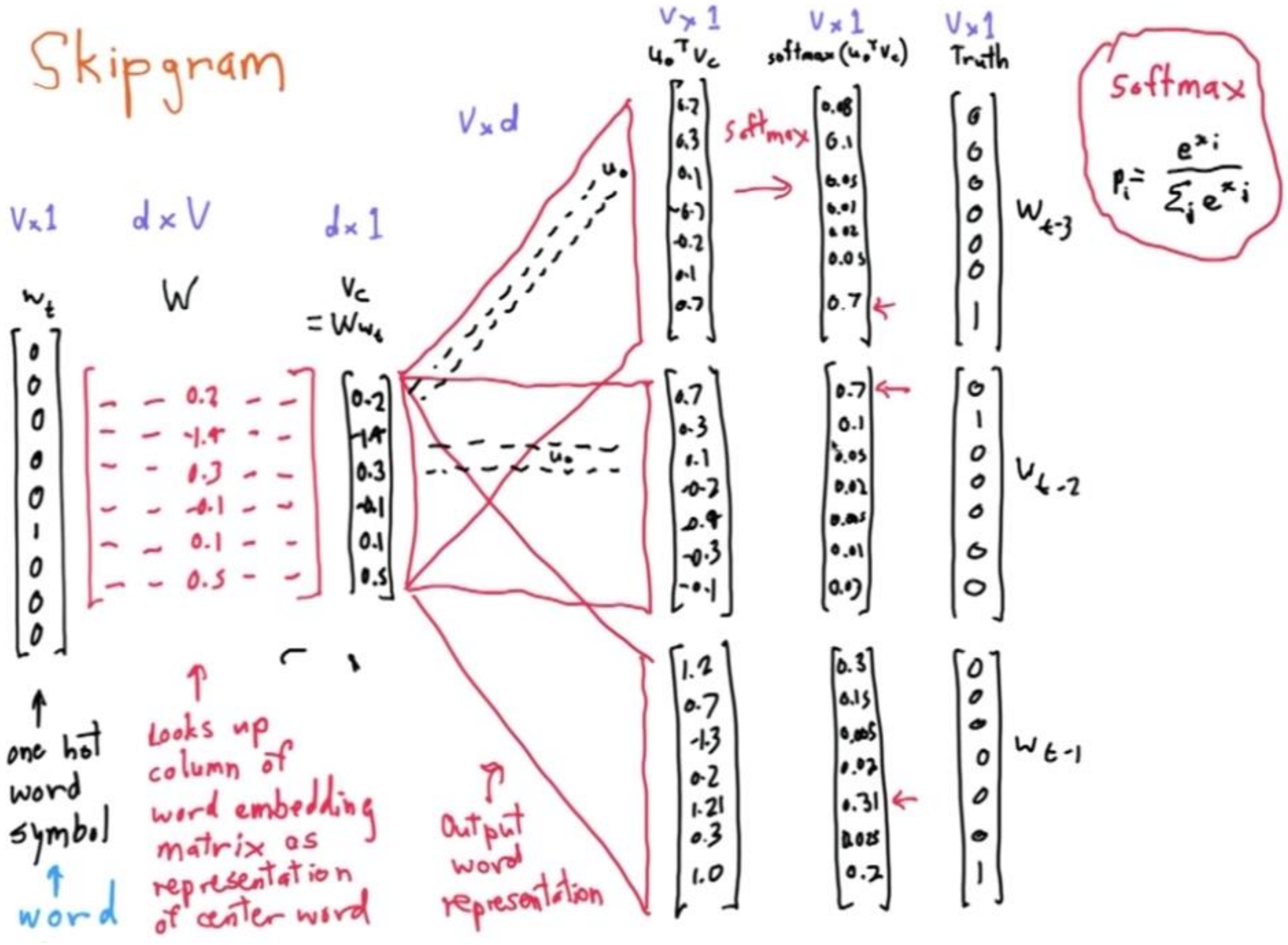
word2vec (Mikolov et. al. 2013)

How to transform a *word* into a *number*?

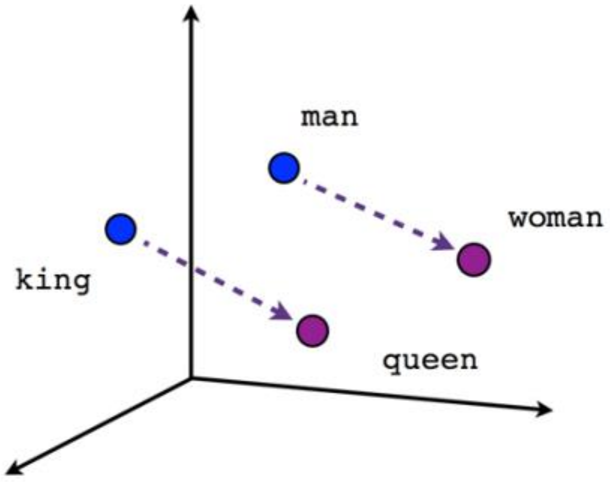
word2vec (Mikolov et. al. 2013)



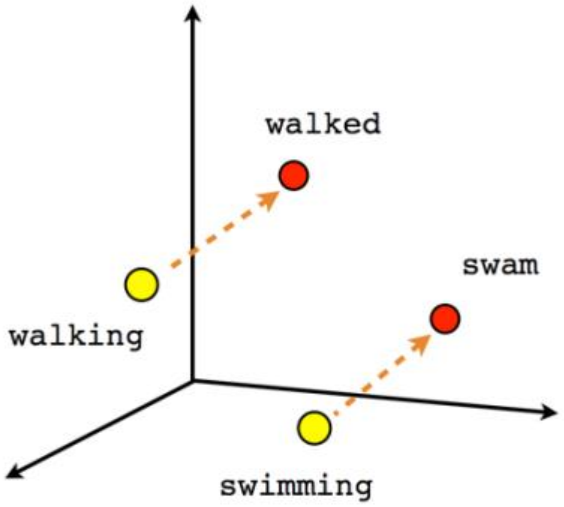
How to transform a *word* into a *number*?



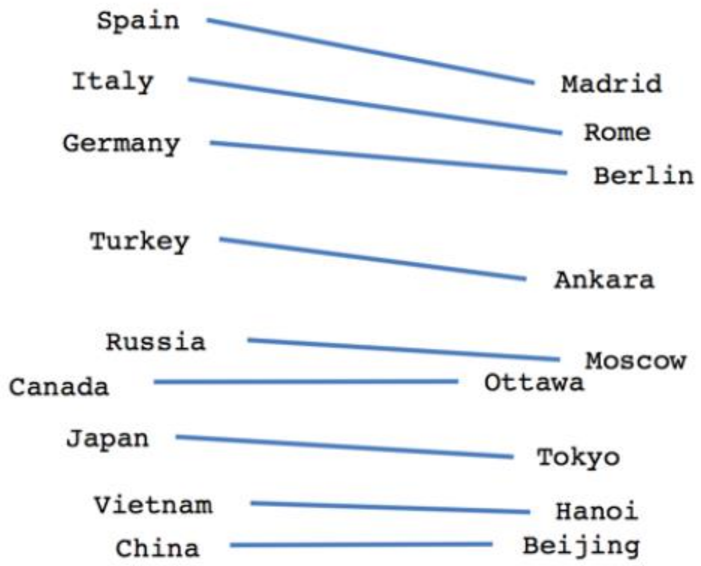
word2vec



Male-Female

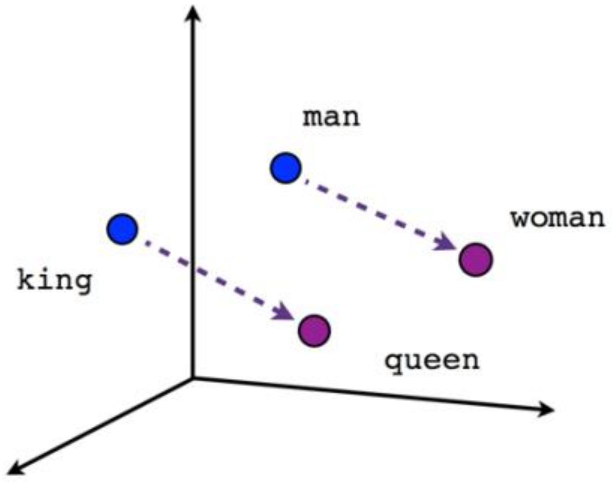


Verb tense

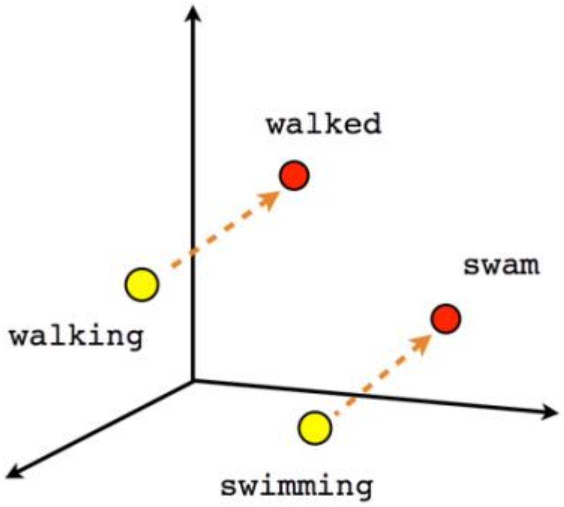


Country-Capital

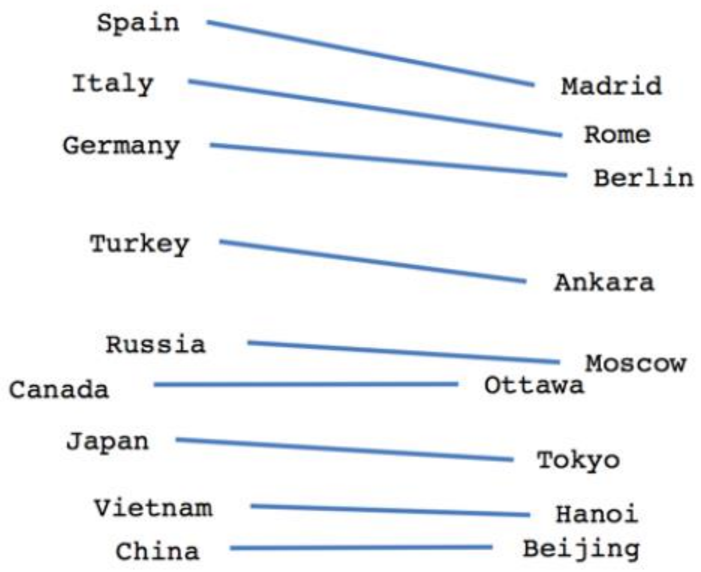
word2vec



Male-Female

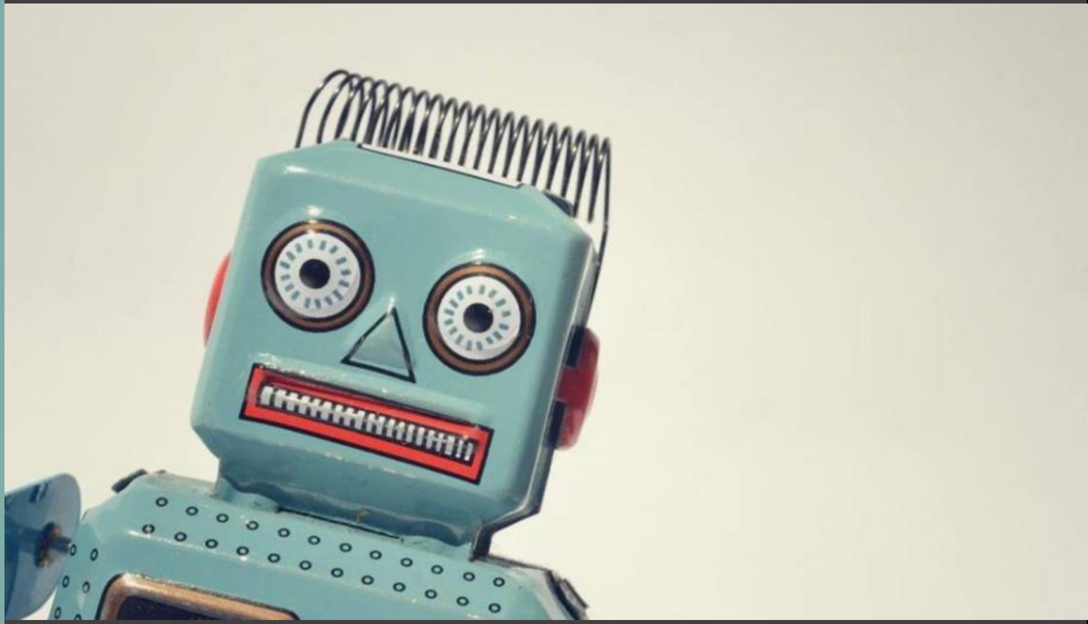


Verb tense

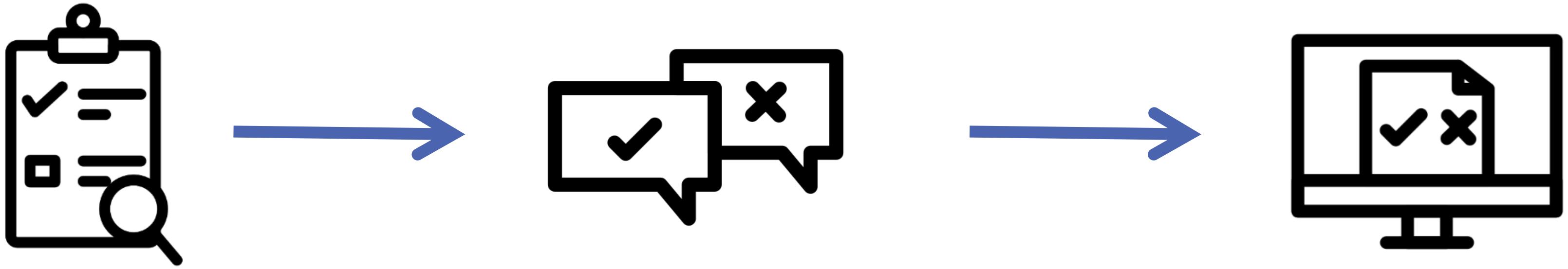


Country-Capital

Applications



How cultural monuments analyze people's opinion?



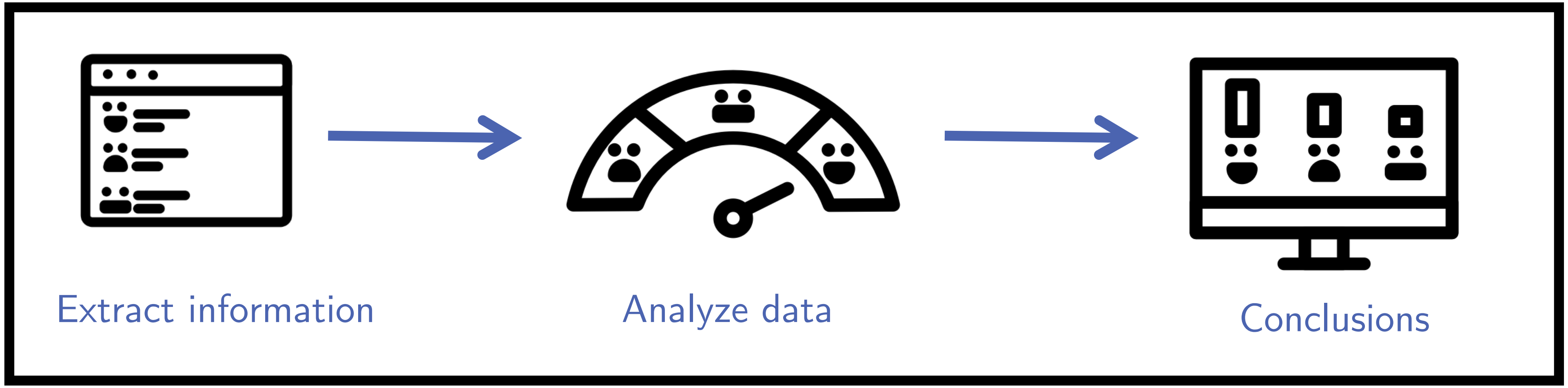
Survey design → Visitants interview → Conclusions

Survey's drawbacks

- What happens if we don't ask key questions?
- What happens if people don't want to answer questions?
- ...

PhD Thesis

How cultural monuments **may** analyze people's opinion?



tripadvisor

Web 2.0 and social networks

Machine and Deep Learning
Sentiment Analysis

PhD Thesis

1. Relation between Users and SAMs?

Users

SAMs

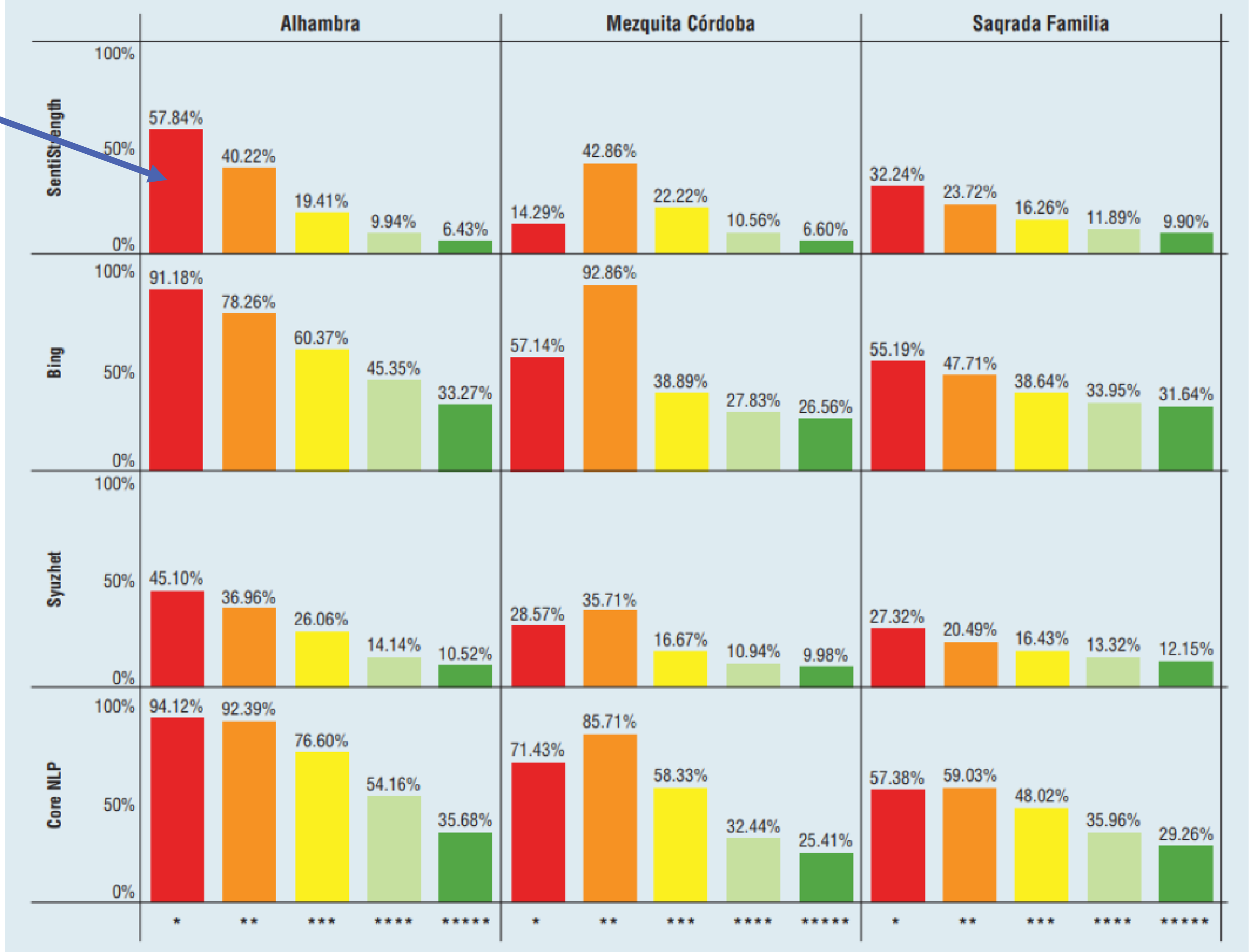
How related are their polarities?

P
h
D

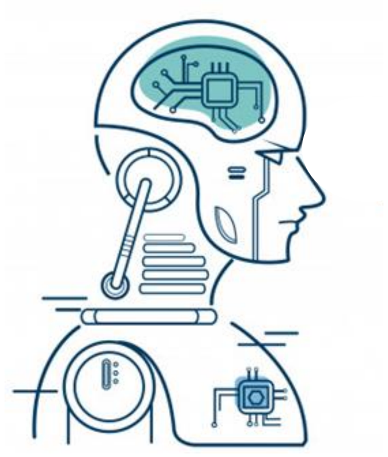
T
h
e
s
i
s

The problem of inconsistencies

SentiStrength detects as negative a 57.84 % of all reviews with one Bubble (*).



2. Neutrality



Are neutral polarities a key for a better classification performance?

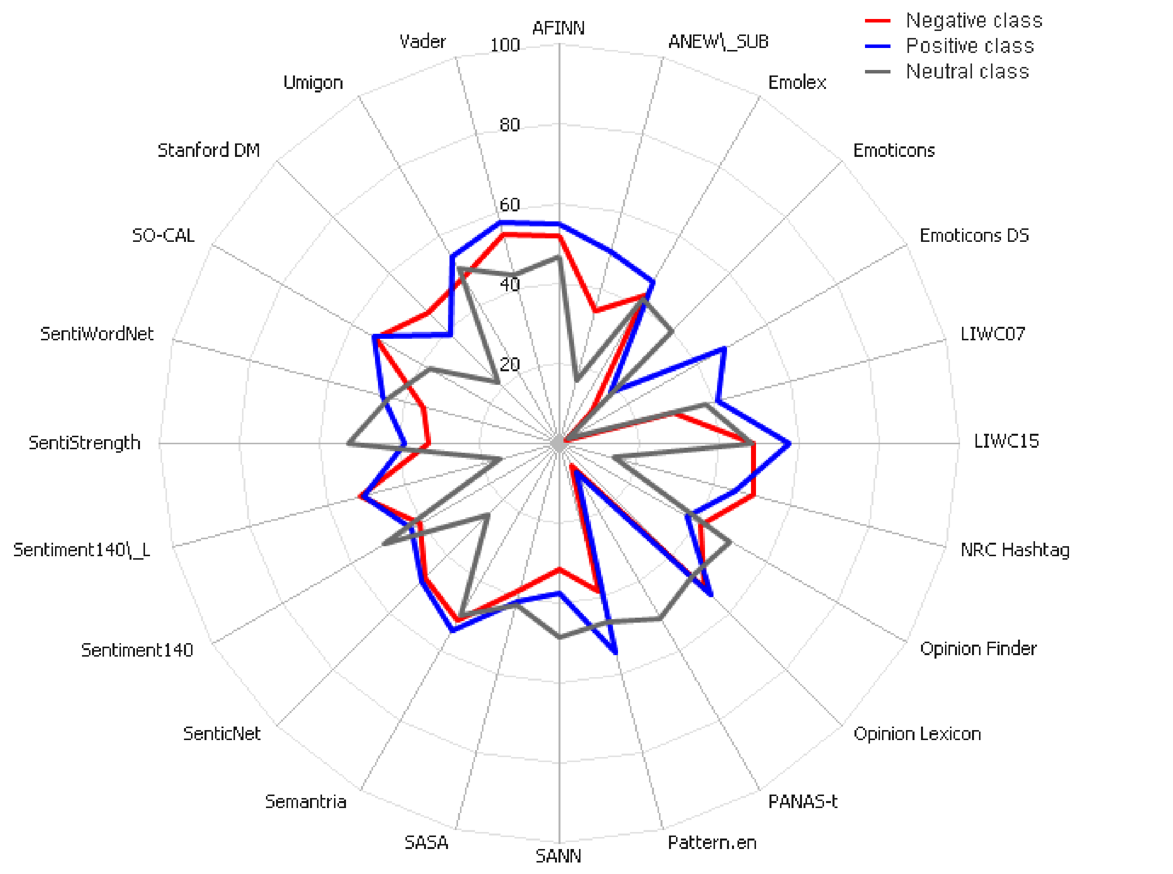


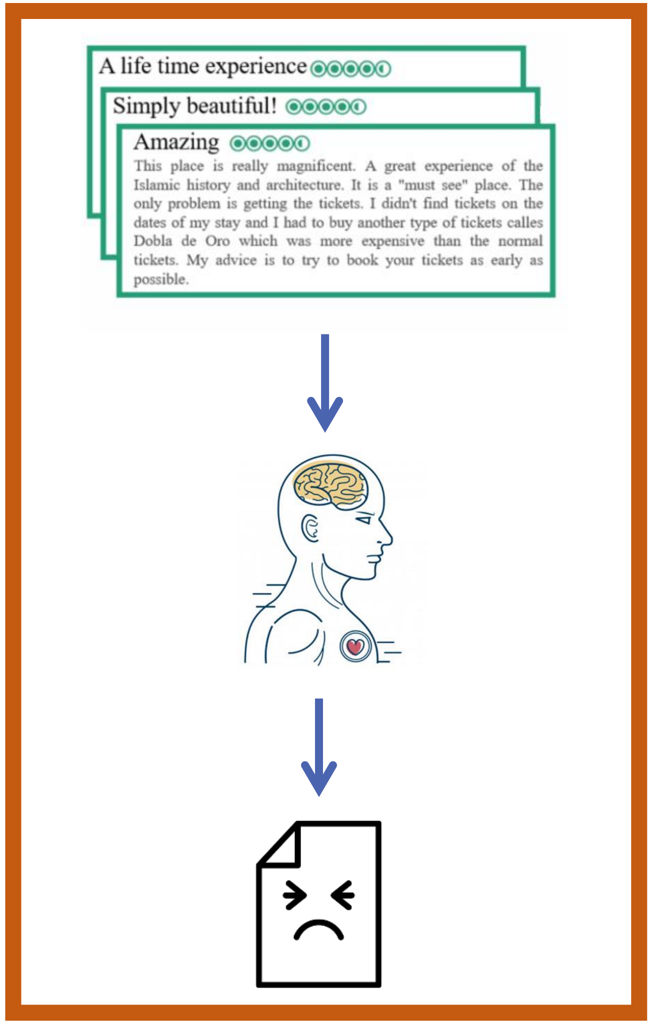
Figure 2 Average *F*1 score for each class. This figure presents the average *F*1 of positive and negative class and as we can see, methods use to achieve better prediction performance on positive messages.

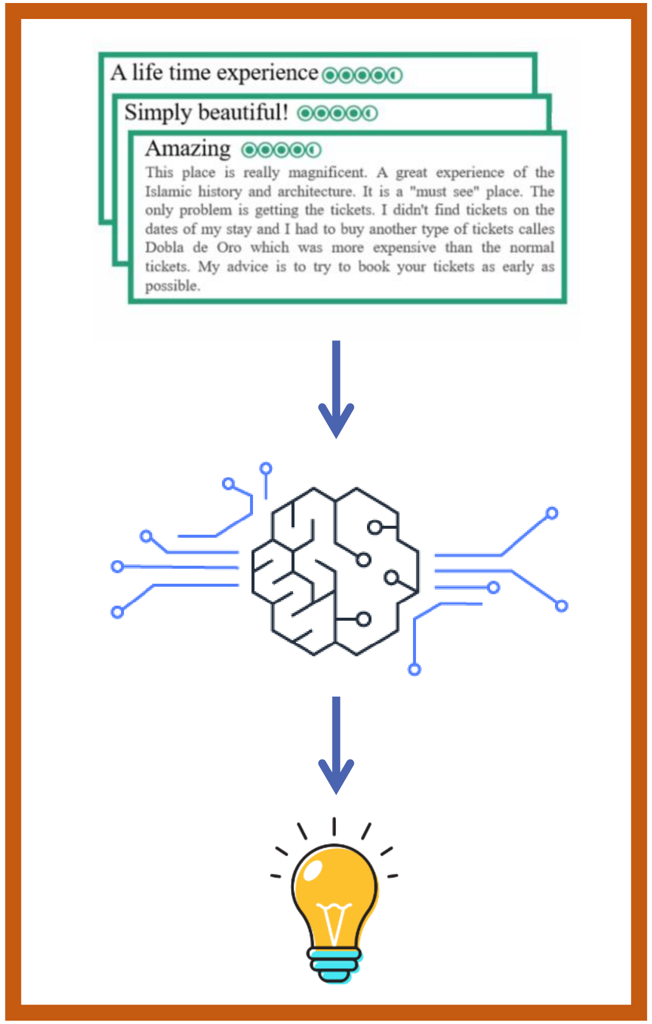
Ribeiro, F. N., Araújo, M., Gonçalves, P., Gonçalves, M. A., & Benevenuto, F. (2016). **Sentibench-a benchmark comparison of state-of-the-practice sentiment analysis methods.** *EPJ Data Science*, *5*(1), 1-29.

Neutrality detection

Corpus (500 reviews per Corpus)	AllAgree	AtLeastOneAgree
Amazon	3	404
ClintonTrump	9	433
Food	0	422
Cinema	3	377
Movies	0	357
RW	0	441
Ted	0	388
TA-Sagrada Familia	0	348
TA-Alhambra	0	369

3. How to represent thousand reviews?





Can Machine Learning techniques help humans to understand thousand reviews?

PhD Thesis

Results

Monument	Cluster Label	Cluster Content
Alhambra	BDA	staff, staff member, local staff, hotel staff, map staff, ground staff, male staff
Alhambra	GG	tickets, individual tickets, garden tickets, access tickets, internet tickets
Alhambra	BFD	gardens, garden, generalife gardens, gardens water features, garden ticket, beauty of the gardens, general life gardens, main garden, generalife garden
Mezquita	BJB	ceiling, floors, marble ceiling, walls, vaulted ceiling, marble floor, roof
Mezquita	EG	guard, security guard, security guard berating
Mezquita	GG	audio guide, audio guide available, audio guides, map audio guide, auto lingual guide, audio guide facility
Sagrada Familia	GI	lift, lift up amp, lift amp lift ride 65m, lift elevator, tower lift, lift down, towers lift up, lift down wait, lift service
Sagrada Familia	BAI	ticket online, tickets on-line online tickets, tickets online, entrance tickets online, online ticket, entrance ticket online, prepurchased online tickets, book your ticket online
Sagrada Familia	BFJ	shop, souvenir shop, gauds shop, bookshop, citys souvenir shops

Examples of aspects grouped into clusters, with $k = 200$.

PhD Thesis

Results

Aspect	Rule	Cov	Sup	Conf	WRAcc
staff	{ BDA = 1 } ⟶ { negative }	0.03	< 0.01	0.28	< 0.01
guard	{ BDG = 1 } ⟶ { negative }	< 0.01	< 0.01	0.38	< 0.01
cashier	{ HH = 1 } ⟶ { negative }	< 0.01	< 0.01	0.27	< 0.01
queue	{ BDI = 1 } ⟶ { negative }	< 0.01	< 0.01	0.15	< 0.01
staff, price	{ BDA = 1, BGI = 1 } ⟶ { negative }	< 0.01	< 0.01	0.48	< 0.01

Most relevant rules of the Alhambra monument.

Aspect	Rule	Cov	Sup	Conf	WRAcc
mosque	{ BHF = 1 } ⟶ { negative }	0.18	< 0.01	0.02	0
garden	{ BHB = 1 } ⟶ { negative }	0.06	< 0.01	0.03	< 0.01
architecture	{ BEJ = 1 } ⟶ { negative }	0.17	< 0.01	0.02	0
place	{ DJ = 1 } ⟶ { negative }	0.06	< 0.01	0.03	0
arches	{ BIC = 1 } ⟶ { negative }	0.07	< 0.01	0.02	0

Most relevant rules of the Mezquita monument.

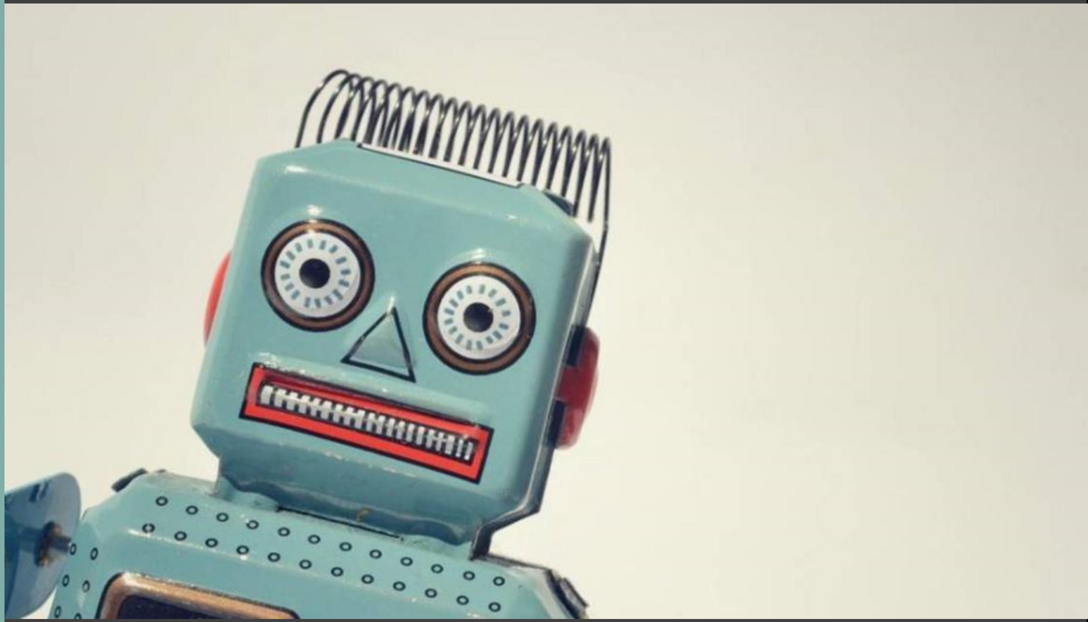
PhD Thesis

Results

Aspect	Rule	Cov	Sup	Conf	WRAcc
ceiling	{ CJ = 1 } $\longrightarrow$ { negative }	< 0.01	< 0.01	0.1	< 0.01
natural	{ HG = 1 } $\longrightarrow$ { negative }	0.04	< 0.01	0.07	< 0.01
entry	{ CI = 1 } $\longrightarrow$ { negative }	0.01	< 0.01	0.07	< 0.01
queue	{ BCD = 1 } $\longrightarrow$ { negative }	< 0.01	< 0.01	0.05	0
sagrada familia	{ BEJ = 1 } $\longrightarrow$ { negative }	0.01	< 0.01	0.07	< 0.01

Most relevant rules of the Sagrada Familia monument.

Bias of word2vec



Bias of word2vec

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{king}} - \overrightarrow{\text{queen}}$$

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}.$$

Bias of word2vec

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukbasi[1], Kai-Wei Chang[2], James Zou[2], Venkatesh Saligrama[1,2], Adam Kalai[2]
[1]Boston University, 8 Saint Mary's Street, Boston, MA
[2]Microsoft Research New England, 1 Memorial Drive, Cambridge, MA
tolgab@bu.edu, kw@kwchang.net, jamesyzou@gmail.com, srv@bu.edu, adam.kalai@microsoft.com

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Bias of word2vec

Semantics derived automatically from language corpora contain human-like biases

Aylin Caliskan,[1]* Joanna J. Bryson,[1,2]* Arvind Narayanan[1]*

Table 1. Summary of Word-Embedding Association Tests. We replicated eight well-known IAT findings using word embeddings (rows 1 to 3 and 6 to 10); we also help explain prejudiced human behavior concerning hiring in the same way (rows 4 and 5). Each result compares two sets of words from target concepts about which we are attempting to learn with two sets of attribute words. In each case, the first target is found compatible with the first attribute, and the second target with the second attribute. Throughout, we use word lists from the studies we seek to replicate. N, number of subjects; N_T, number of target words; N_A, number of attribute words. We report the effect sizes (d) and P values (P, rounded up) to emphasize that the statistical and substantive significance of both sets of results is uniformly high; we do not imply that our numbers are directly comparable with those of human studies. For the online IATs (rows 6, 7, and 10), P values were not reported but are known to be below the significance threshold of 10^{-2}. Rows 1 to 8 are discussed in the text; for completeness, this table also includes the two other IATs for which we were able to find suitable word lists (rows 9 and 10). We found similar results with word2vec, another algorithm for creating word embeddings, trained on a different corpus, Google News (see the supplementary materials).

Target words	Attribute words	Original finding				Our finding			
		Ref.	N	d	P	N_T	N_A	d	P
Flowers vs. insects	Pleasant vs. unpleasant	*(5)*	32	1.35	10^{-8}	25 × 2	25 × 2	1.50	10^{-7}
Instruments vs. weapons	Pleasant vs. unpleasant	*(5)*	32	1.66	10^{-10}	25 × 2	25 × 2	1.53	10^{-7}
European-American vs. African-American names	Pleasant vs. unpleasant	*(5)*	26	1.17	10^{-5}	32 × 2	25 × 2	1.41	10^{-8}
European-American vs. African-American names	Pleasant vs. unpleasant from (5)	*(7)*	Not applicable			16 × 2	25 × 2	1.50	10^{-4}
European-American vs. African-American names	Pleasant vs. unpleasant from (9)	*(7)*	Not applicable			16 × 2	8 × 2	1.28	10^{-3}
Male vs. female names	Career vs. family	*(9)*	39k	0.72	$<10^{-2}$	8 × 2	8 × 2	1.81	10^{-3}
Math vs. arts	Male vs. female terms	*(9)*	28k	0.82	$<10^{-2}$	8 × 2	8 × 2	1.06	.018
Science vs. arts	Male vs. female terms	*(10)*	91	1.47	10^{-24}	8 × 2	8 × 2	1.24	10^{-2}
Mental vs. physical disease	Temporary vs. permanent	*(23)*	135	1.01	10^{-3}	6 × 2	7 × 2	1.38	10^{-2}
Young vs. old people's names	Pleasant vs. unpleasant	*(9)*	43k	1.42	$<10^{-2}$	8 × 2	8 × 2	1.21	10^{-2}

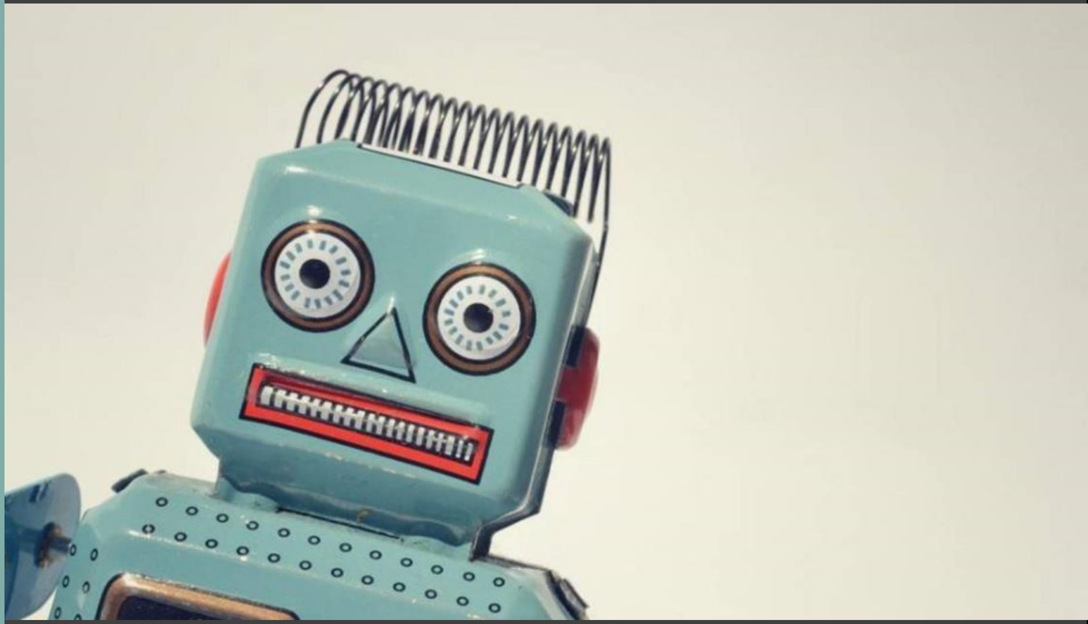
Bias of word2vec

The Real Reason Voice Assistants Are Female (and Why it Matters)

PCMag Follow
Jan 29, 2018 · 3 min read

It's critical that we challenge stereotypical gender roles in our personal assistants. Our interactions with AI teach and train it, but we are also shaped by these experiences. It's why parents are concerned about unintentionally raising rude children when Alexa does not require a "please" or "thank you" to carry out a task.

NLP for Social Good



NLP for Social Good

SCIENTIFIC REPORTS

MENU

Article | OPEN | Published: 09 May 2018

Identifying Suicide Ideation and Suicidal Attempts in a Psychiatric Clinical Research Database using Natural Language Processing

Andrea C. Fernandes, Rina Dutta, Sumithra Velupillai, Jyoti Sanyal, Robert Stewart & David Chandran

Scientific Reports **8**, Article number: 7426 (2018) | Download Citation

N
L
P

f
o
r

S
o
c
i
a
l

G
o
o
d

Automatic Detection of Incoherent Speech for Diagnosing Schizophrenia

Dan Iter[1], Jong H. Yoon[2], and Dan Jurafsky[1]

[1]Department of Computer Science
[2]Department of Psychiatry and Behavioral Sciences
Stanford University
{daniter, jhyoon1, jurafsky}@stanford.edu

N
L
P

f
o
r

S
o
c
i
a
l

G
o
o
d

Automatic Detection of Incoherent Speech for Diagnosing Schizophrenia

Dan Iter[1], Jong H. Yoon[2], and Dan Jurafsky[1]

[1]Department of Computer Science
[2]Department of Psychiatry and Behavioral Sciences
Stanford University
{daniter, jhyoon1, jurafsky}@stanford.edu

Featured Prediction Competition

Toxic Comment Classification Challenge

Identify and classify toxic online comments

$35,000
Prize Money

Jigsaw/Conversation AI · 4,551 teams · a year ago

Overview Data Kernels Discussion Leaderboard Rules **Join Competition**

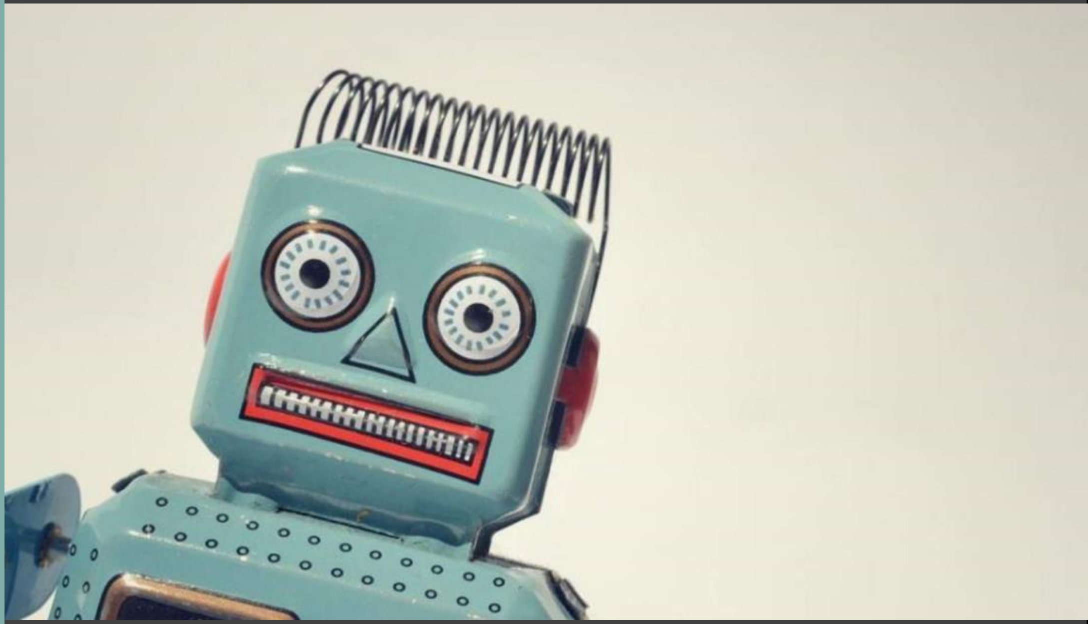
Overview

Description
Evaluation
Timeline
Prizes

Discussing things you care about can be difficult. The threat of abuse and harassment online means that many people stop expressing themselves and give up on seeking different opinions. Platforms struggle to effectively facilitate conversations, leading many communities to limit or completely shut down user comments.

The Conversation AI team, a research initiative founded by Jigsaw and Google (both a part of Alphabet) are working on tools to help improve online conversation. One area of focus is the study of negative online behaviors, like toxic comments (i.e. comments that are rude, disrespectful or otherwise likely to make someone leave a discussion). So far they've built a range of

Thanks!



B I L B I O G R A P H Y

- Mikolov, Tomas, et al. "**Distributed representations of words and phrases and their compositionality**." Advances in neural information processing systems. 2013.

- Rong, Xin. "**word2vec parameter learning explained**." *arXiv preprint arXiv:1411.2738* (2014).

- Bolukbasi, Tolga, et al. "**Man is to computer programmer as woman is to homemaker? debiasing word embeddings**." Advances in neural information processing systems. 2016.

- Caliskan, Aylin, Joanna J. Bryson, and Arvind Narayanan. "**Semantics derived automatically from language corpora contain human-like biases**." Science 356.6334 (2017): 183-186.

- https://github.com/genimarca/caepia2018_tutorial_nlp_sa/blob/master/2018_caepia_tutorial_nlp.pdf