Human Biases in Multilingual Models

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Details of this Presentation Available in

The (Undesired) Attenuation of Human Biases by Multilinguality

Cristina España-Bonet, Alberto Barrón-Cedeño

Abstract

Some human preferences are universal. The odor of vanilla is perceived as pleasant all around the world. We expect neural models trained on human texts to exhibit these kind of preferences, i.e. biases, but we show that this is not always the case. We explore 16 static and contextual embedding models in 9 languages and, when possible, compare them under similar training conditions. We introduce and release CA-WEAT, multilingual cultural aware tests to quantify biases, and compare them to previous English-centric tests. Our experiments confirm that monolingual static embeddings do exhibit human biases, but values differ across languages, being far from universal. Biases are less evident in contextual models, to the point that the original human association might be reversed. Multilinguality proves to be another variable that attenuates and even reverses the effect of the bias, specially in contextual multilingual models. In order to explain this variance among models and languages, we examine the effect of asymmetries in the training corpus, departures from isomorphism in multilingual embedding spaces and discrepancies in the testing measures between languages.

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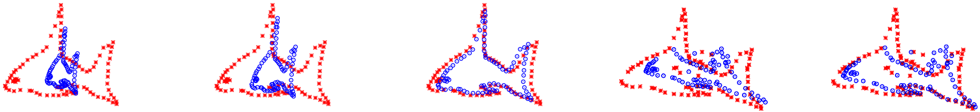
Year: 2022

Motivation

What does Multilinguality Involve in Machine Learning Models?

Most multilingual models just use a
combination of monolingual corpora for training.

Are we distorting semantics?



[https://en.wikipedia.org/wiki/Point-set_registration]

Motivation

What does Multilinguality Involve in Machine Learning Models?

Most multilingual models just use a
combination of monolingual corpora for training.

Are we distorting semantics?

- We need something that is language and cultural independent
- We chose non-social (human) biases for this

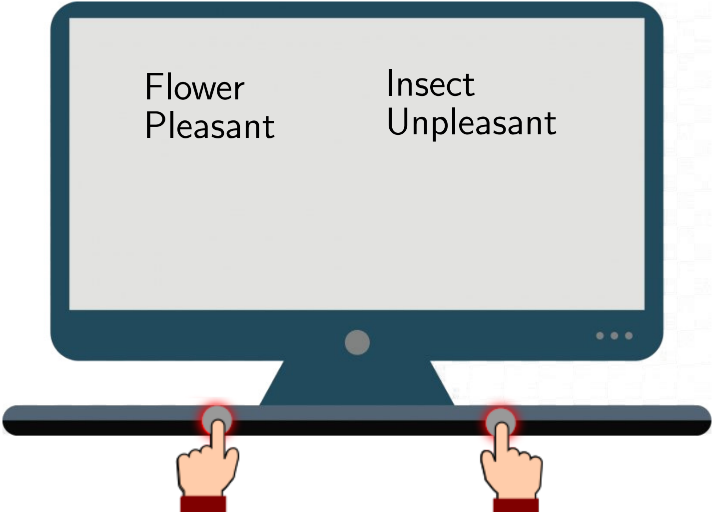
Outline

IAT: Implicit Association Tests

Non-Social Human Biases

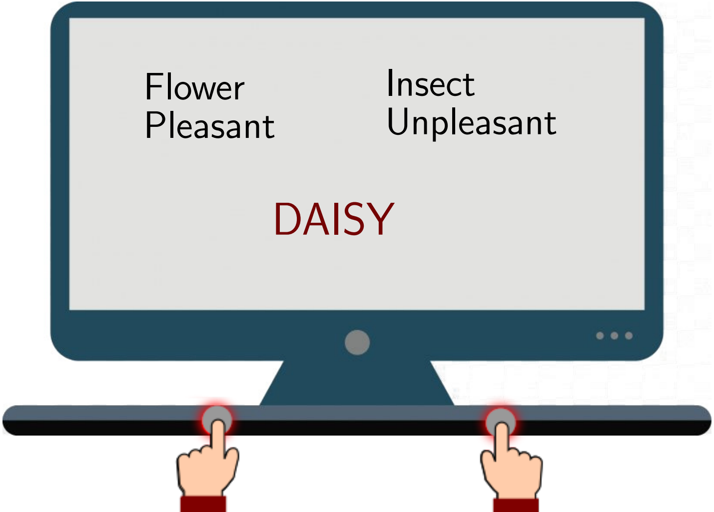
IAT: Implicit Association Tests

Non-Social Human Biases



IAT: Implicit Association Tests

Non-Social Human Biases



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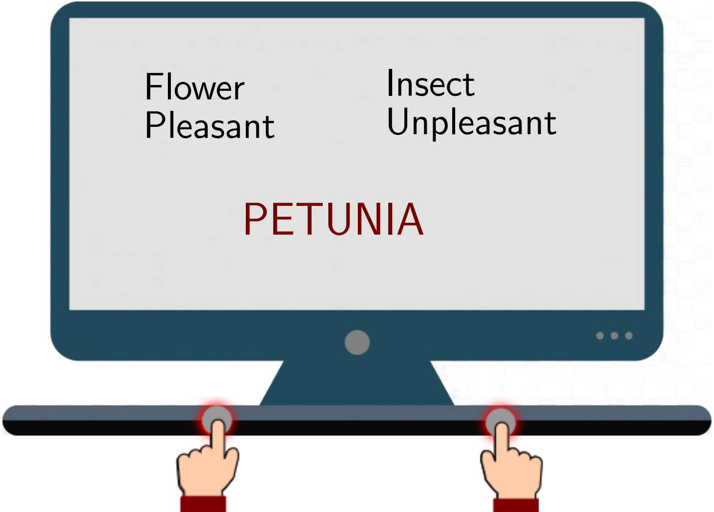

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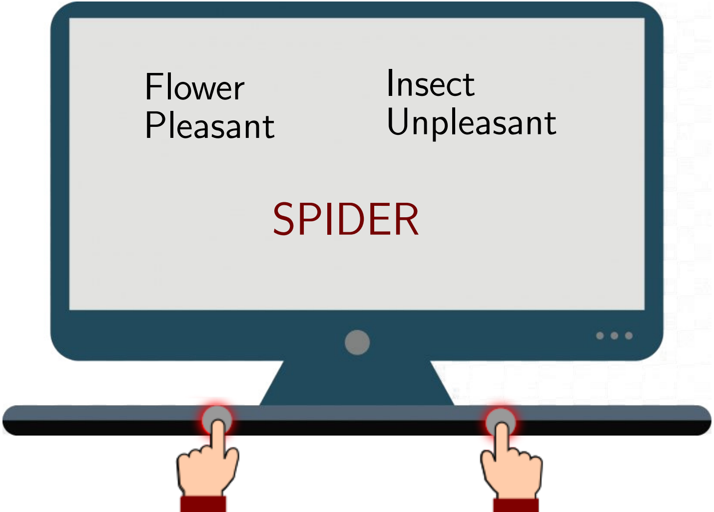

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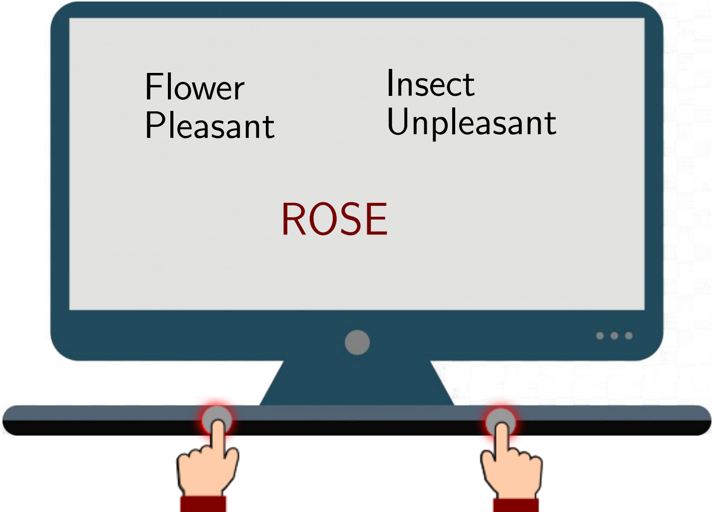

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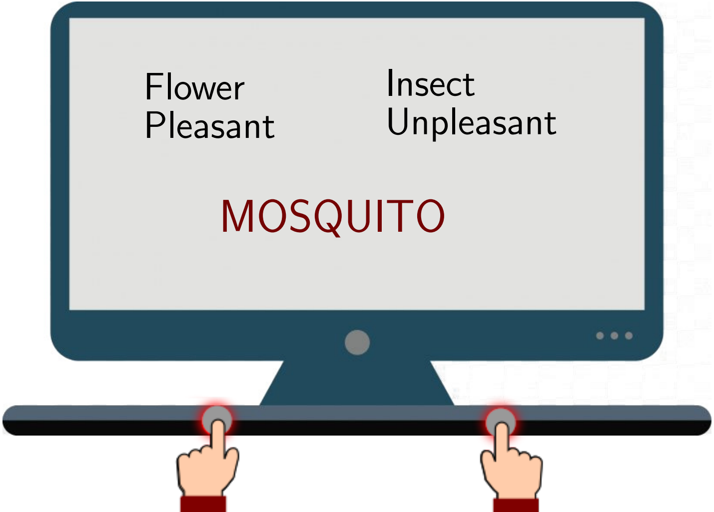

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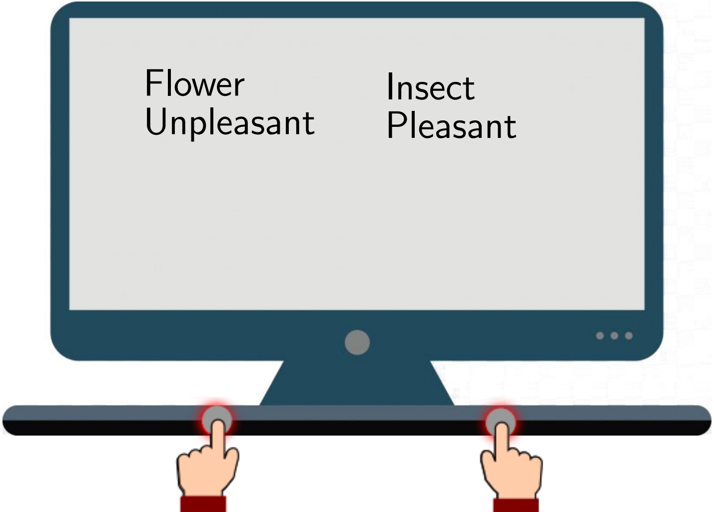

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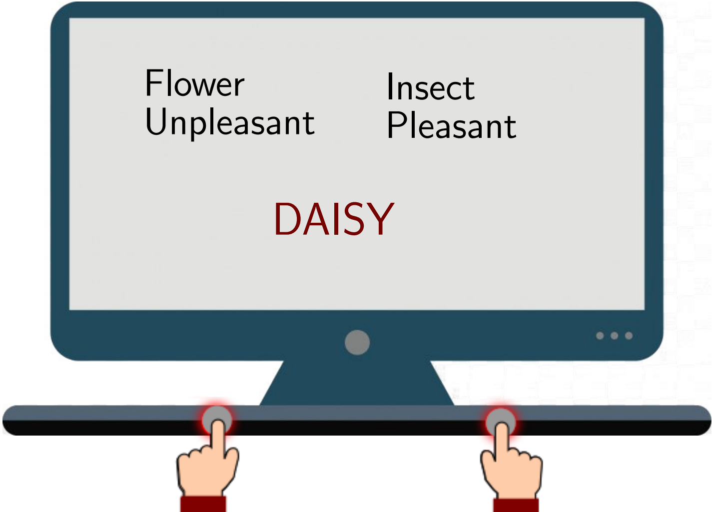

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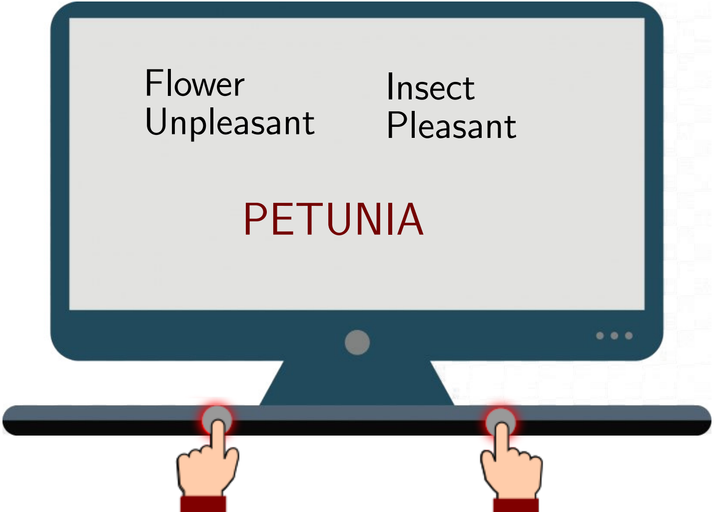

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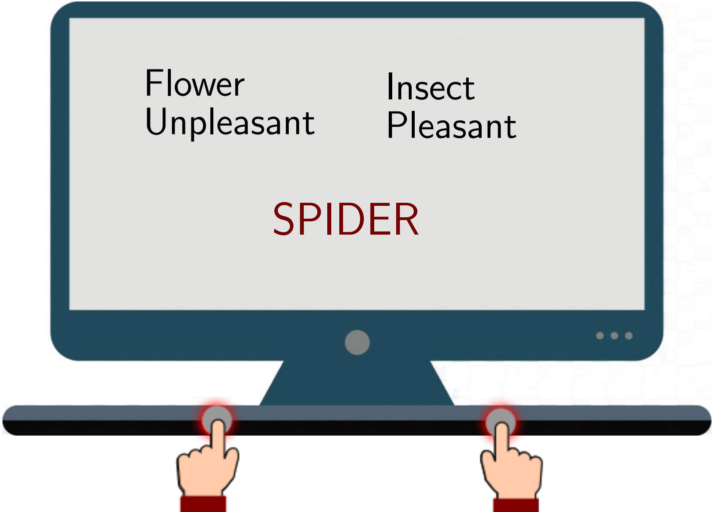

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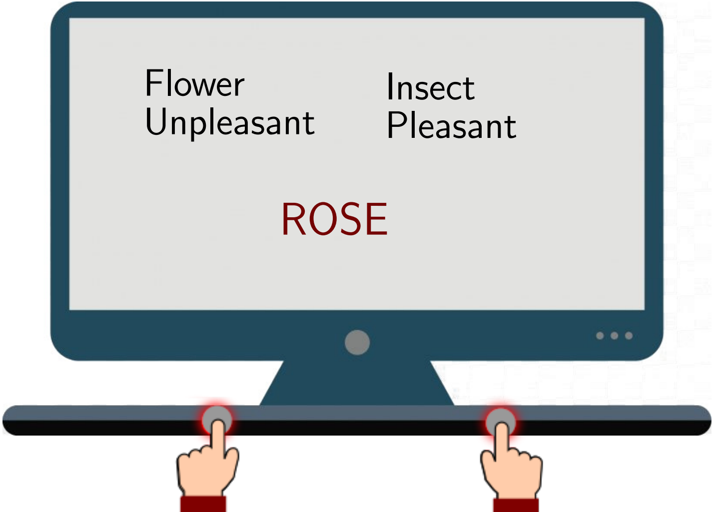

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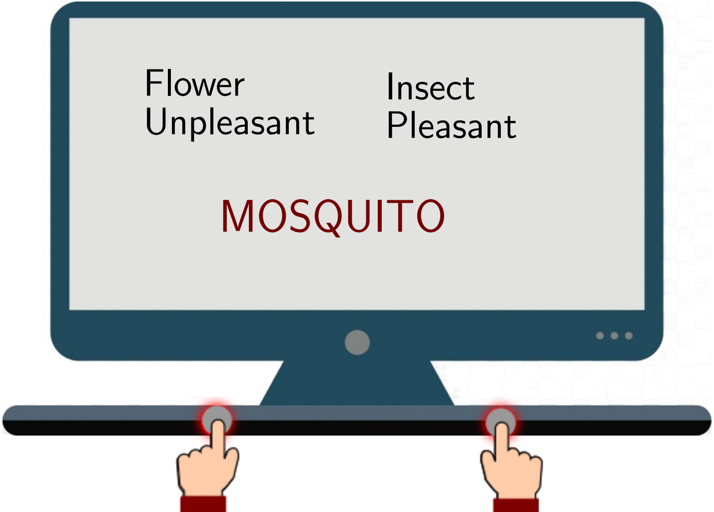

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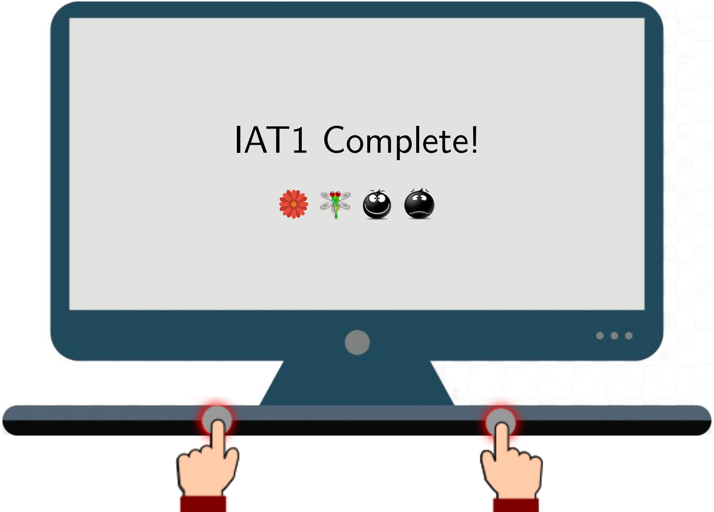
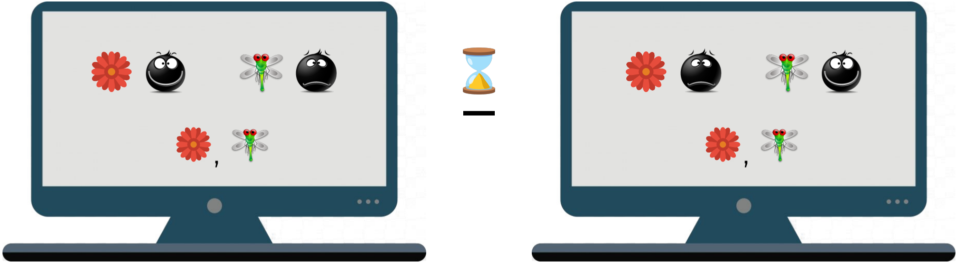


IAT1: difference in response time

(flowers & insects)

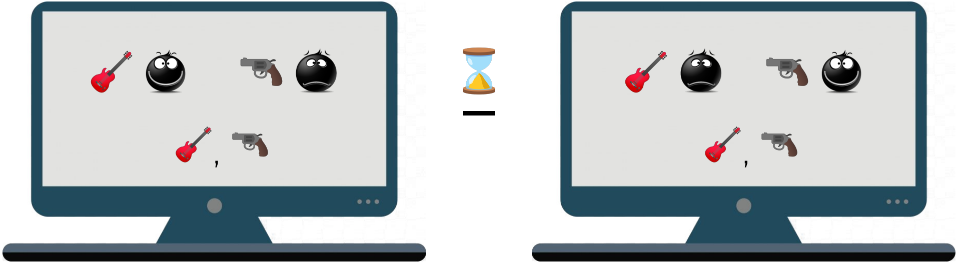


IAT: Implicit Association Tests

Non-Social Human Biases

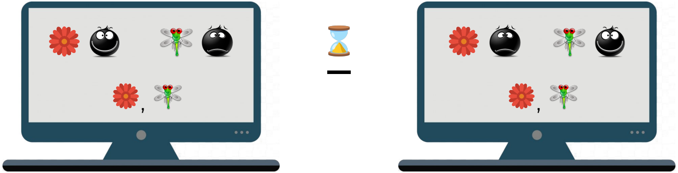
IAT2: difference in response time

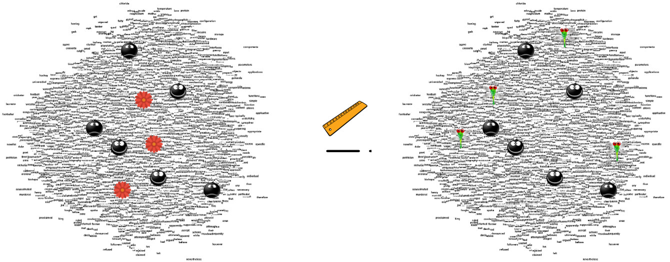
(musical instruments & weapons)



WEAT: Association Tests in Word Embeddings

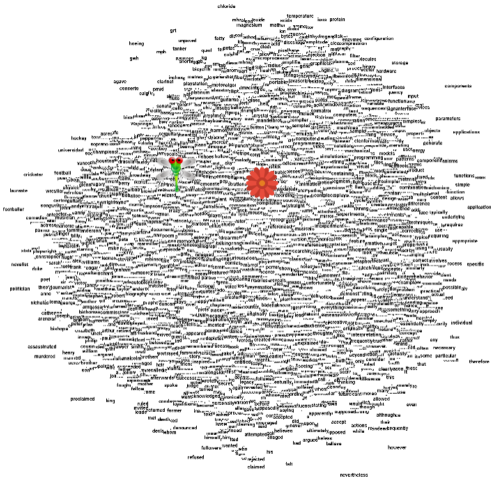
WEAT, Intuition





WEAT: Association Tests in Word Embeddings

Intuition, in our Embedding Space we can Measure Distances



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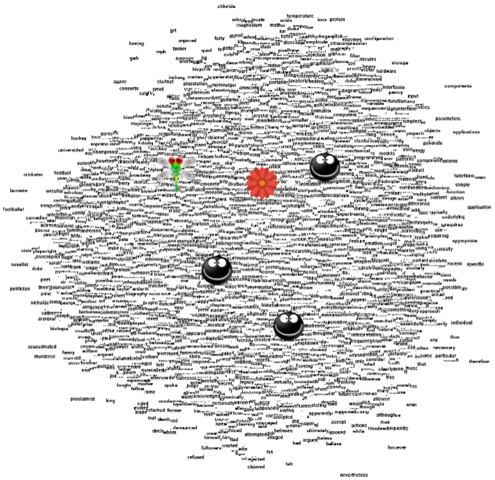

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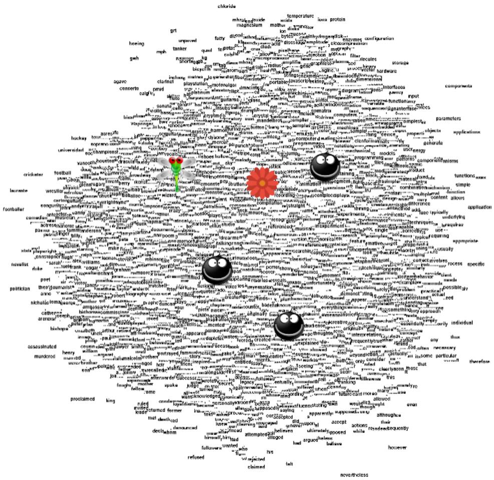

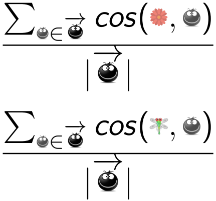

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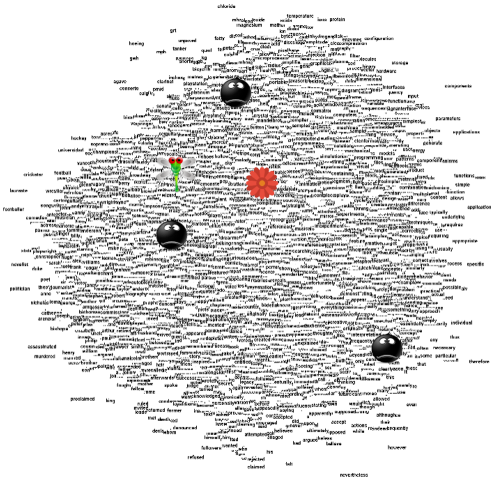

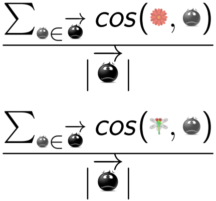

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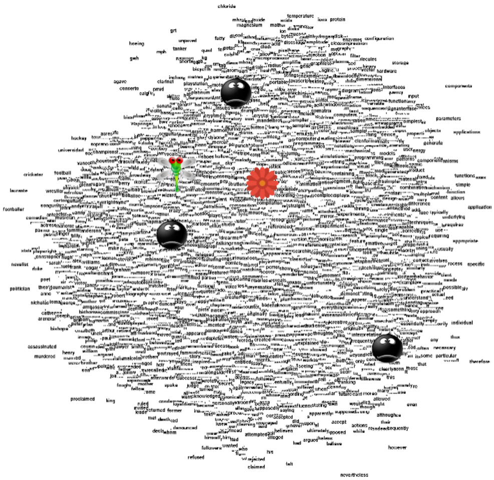

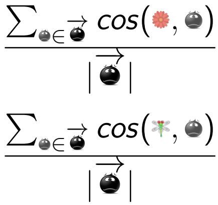

$$assoc(t, A) = \frac{\sum_{a \in A} cos(\mathbf{t}, \mathbf{a})}{|A|}$$

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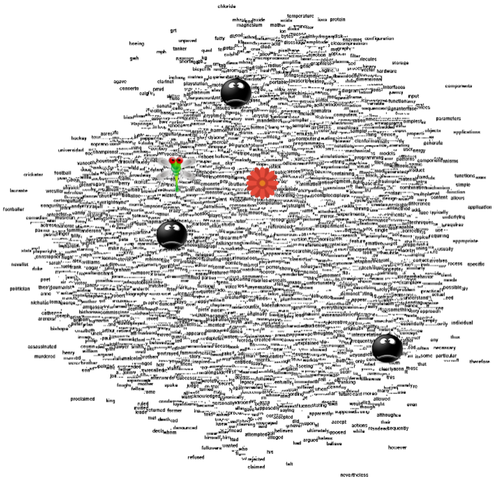
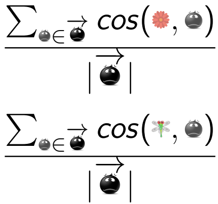




$$assoc(t, A) = \frac{\sum_{a \in A} cos(\mathbf{t}, \mathbf{a})}{|A|}$$

$$\Delta_{assoc}(t, A, B) = assoc(t, A) - assoc(t, B)$$

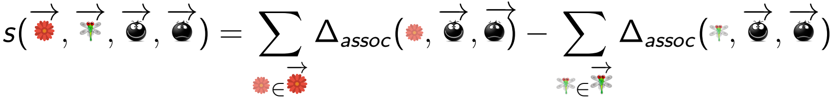
What do we Measure?

The difference in association for a term:

$$\Delta_{assoc}(t, A, B) = assoc(t, A) - assoc(t, B)$$

The statistic:

$$s(X, Y, A, B) = \sum_{x \in X} \Delta_{assoc}(x, A, B) - \sum_{y \in Y} \Delta_{assoc}(y, A, B)$$



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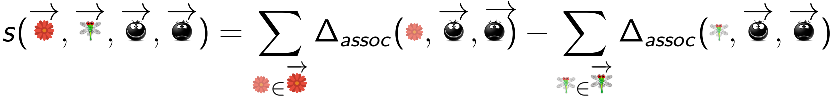

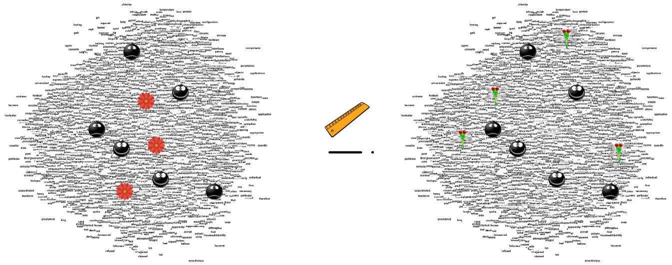

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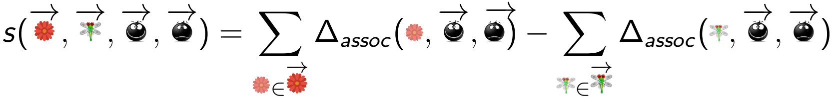
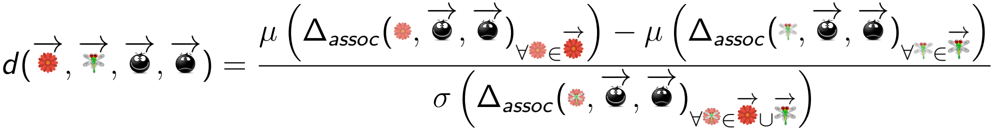


The size effect:



WEAT: Association Tests in Word Embeddings

Do Word Embeddings Reflect Implicit Human Associations?

[Caliskan et al., Nature, 2017]

Semantics derived automatically from language corpora contain human-like biases:

- morally neutral as toward insects or flowers, —our non-social—
- problematic as toward race or gender,
- veridical, reflecting the status quo distribution of gender with respect to careers or first names.

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For multilinguality we need universals $\Rightarrow$ non-social only

Outline

Multilinguality and Cultural-Aware WEAT

WEAT1 and WEAT2 Original Lists

WEAT1 target items	
Flowers	aster, clover, hyacinth, marigold, poppy, azalea, crocus, iris, orchid, rose, bluebell, daffodil, lilac, pansy, tulip, buttercup, daisy, lily, peony, violet, carnation, gladiola, magnolia, petunia, zinnia
Insects	ant, caterpillar, flea, locust, spider, bedbug, centipede, fly, maggot, tarantula, bee, cockroach, gnat, mosquito, termite, beetle, cricket, hornet, moth, wasp, blackfly, dragonfly, horsefly, roach, weevil
WEAT2 target items	
Instruments	bagpipe, cello, guitar, lute, trombone, banjo, clarinet, harmonica, mandolin, trumpet, bassoon, drum, harp, oboe, tuba, bell, fiddle, harpsichord, piano, viola, bongo, flute, horn, saxophone, violin
Weapons	arrow, club, gun, missile, spear, axe, dagger, harpoon, pistol, sword, blade, dynamite, hatchet, rifle, tank, bomb, firearm, knife, shotgun, teargas, cannon, grenade, mace, slingshot, whip
WEAT1 and WEAT2 attributes	
Pleasant	caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest, lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation
Unpleasant	abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred, pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison

Original and X-WEAT Lists

Original version (WEAT1, WEAT2)

[Battig and Montague, 1969; Bellezza et al., 1986; Greenwald et al., 1998]

- Collected from college students in Eastern US
- Frequent terms
- Non-ambiguous terms

Multilinguality and Cultural-Aware WEAT

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[Battig and Montague, 1969; Bellezza et al., 1986; Greenwald et al., 1998]

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- Non-ambiguous terms

Multilingual version (X-WEAT)

[Lauscher and Glavaš, 2019; Lauscher et al., 2020]

- Literal translation
- Arabic, Croatian, German, Italian, Russian, Spanish and Turkish

Multilinguality and Cultural-Aware WEAT

Features and Issues with WEAT and X-WEAT (the safe version :-))

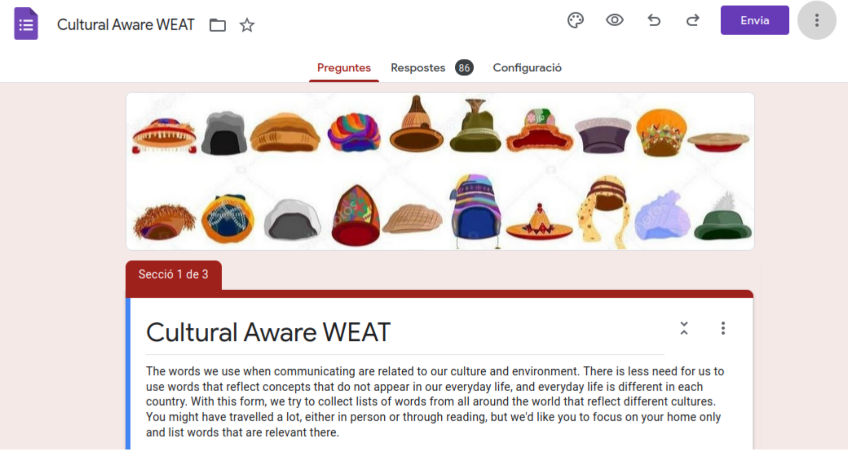
- WEAT: American English, represents the culture of the (Eastern) US
- X-WEAT: Multilingual, but represents the culture of the (Eastern) US!

  —and this applies to all NLP using translation—

  - duplicates? (violin, fiddle → violín)
  - frequent terms? (gnat → jején)
  - non-ambiguous terms? (blade → hoja)
- CA-WEAT: Multilingual and culturaly aware

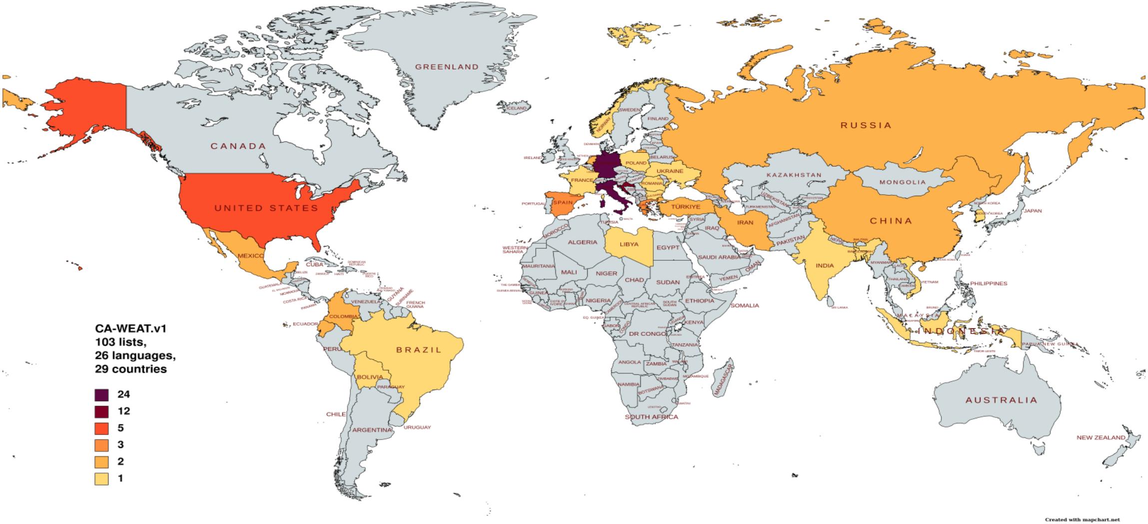
Multilinguality and Cultural-Aware WEAT

CA-WEAT



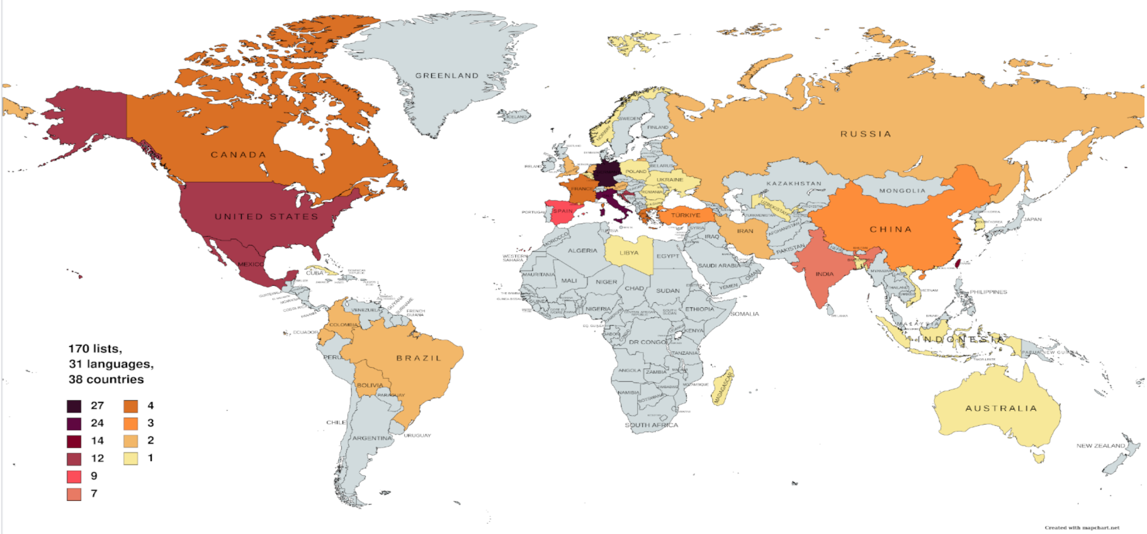
Multilinguality and Cultural-Aware WEAT

CA-WEATs per Country (not the best Distribution!)



Multilinguality and Cultural-Aware WEAT

A few more Today!



Multilinguality and Cultural-Aware WEAT

Monolingual (English) lists

	apple, pear, grape, strawberry, blackberry, blueberry, raspberry, plum, apricot, orange, tangerine, clementine, lemon, lime, watermelon, pepper, squash, pumpkin, tomato, banana, pineapple, fig, date, mango, papaya
	apple, banana, orange, grape, cherry, strawberry, raspberry, blueberry, tangerine, mango, peach, nectarine, pineapple, plum, mandarin, kiwi, papaya, blackberry, blackcurrant, redcurrant, apricot, raisin, gooseberry, pear, melon
	apple, orange, banana, kiwi, grape, lemon, cherry, pear, strawberry, blueberry, raspberry, blackberry, avocado, lime, mango, peach, plum, apricot, nectarine, pineapple, papaya, watermelon, lychee, longan, durian

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Multilinguality and Cultural-Aware WEAT

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UK English	apple, banana, orange, grape, cherry, strawberry, raspberry, blueberry, tangerine, mango, peach, nectarine, pineapple, plum, mandarin, kiwi, papaya, blackberry, blackcurrant, redcurrant, apricot, raisin, gooseberry, pear, melon
AU English	apple, orange, banana, kiwi, grape, lemon, cherry, pear, strawberry, blueberry, raspberry, blackberry, avocado, lime, mango, peach, plum, apricot, nectarine, pineapple, papaya, watermelon, lychee, longan, durian

Multilinguality and Cultural-Aware WEAT

Multilingual Lists. Disclaimer: my Translation...

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BR Portuguese	apple, banana, guava, pineapple, apricot, pear, watermelon, orange, lemon, cherry, tangerine, kiwi, pequi, açaí, cashew, hog plum, soursop, strawberry, raspberry, blackberry, plum, peach, passion fruit, lychee, jabuticaba
	maçã, banana, goiaba, abacaxi, damasco, pêra, melancia, laranja, limão, cereja, mexerica, kiwi, pequi, açaí, caju, cajá, graviola, morango, framboesa, amora, ameixa, pêssego, maracujá, lichia, jabuticaba
Traditional Chinese	banana, apple, pineapple, guava, orange, grape, peach, cherry, blueberry, Java apple, papaya, lychee, strawberry, tomato, cantaloupe, tangerine, lemon, lime, raspberry, Japanese banana, sugarcane, watermelon, durian, sugar apple, coconut
	香蕉, 蘋果, 鳳梨, 芭樂, 柳丁, 葡萄, 水蜜桃, 櫻桃, 藍莓, 蓮霧, 木瓜, 荔枝, 草莓, 番茄, 哈密瓜, 橘子, 檸檬, 萊姆, 覆盆莓, 芭蕉, 甘蔗, 西瓜, 榴蓮, 釋迦, 椰子

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Multilinguality and Cultural-Aware WEAT

(Cross-lingual) Cultural Biases in NLP

- Disclaimer: 1 list is just an example, 100 lists start saying something
- But CA-WEATs seem different to X-WEAT!
- Multilingual models trained on an asymmetric distribution of data
  - Most of it US English
  - Yes, also chatGPT :-)
- "Write an article about agriculture"

Outline

Experiments

Embedding Models & Languages

- Pre-trained fastText word embeddings

  WP WPali CCWP

- Comparable word embeddings with a subset of CC-100

  CCe CCeVMuns CCeVMsup CCe2langs CCe9langs

- Word embeddings extracted from contextual models at different layers

  BERT mBERT XLM XGLM

Embedding Models & Languages

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  WP WPali CCWP

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- Word embeddings extracted from contextual models at different layers

  BERT mBERT XLM XGLM

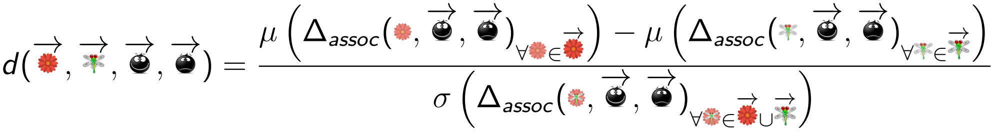
- Languages

  Arabic (ar), Catalan (ca), Croatian (hr), English (en), German (de), Italian (it), Russian (ru), Spanish (es) and Turkish (tr)

Experiments

What we Report here (More in the Paper!)

- Size effect



Sawilowsky's scale: very small (d<0.01), small (<0.20), medium (<0.50), large (<0.80), very large (<1.20), and huge (<2.00)

  - CA-WEAT: median and 95% CI with order statistics
  - WEAT, CA-WEAT, X-WEAT: 5,000 bootstraps (median and 95% CI)

Experiments

What we Report here (More in the Paper!)

- Size effect

$$d(\vec{\text{🌼}}, \vec{\text{🦟}}, \vec{\text{😀}}, \vec{\text{☹}}) = \frac{\mu\left(\Delta_{assoc}(\text{🌼}, \vec{\text{😀}}, \vec{\text{☹}})_{\forall \text{🌼} \in \vec{\text{🌼}}}\right) - \mu\left(\Delta_{assoc}(\text{🦟}, \vec{\text{😀}}, \vec{\text{☹}})_{\forall \text{🦟} \in \vec{\text{🦟}}}\right)}{\sigma\left(\Delta_{assoc}(\text{🌼🦟}, \vec{\text{😀}}, \vec{\text{☹}})_{\forall \text{🌼🦟} \in \vec{\text{🌼}} \cup \vec{\text{🦟}}}\right)}$$

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  - CA-WEAT: median and 95% CI with order statistics
  - WEAT, CA-WEAT, X-WEAT: 5,000 bootstraps (median and 95% CI)

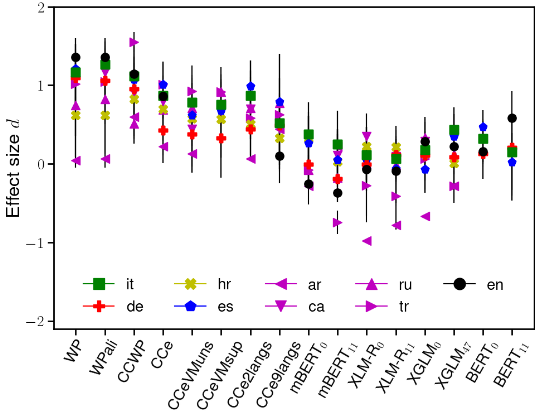
- IAT1 (🌼 🦟); IAT2 (🎸 🔫) is equivalent

Experiments

Do our embeddings show (human) biases?
All embedding models? All languages?

Experiments

Wide Overview (WEAT, CA-WEAT)

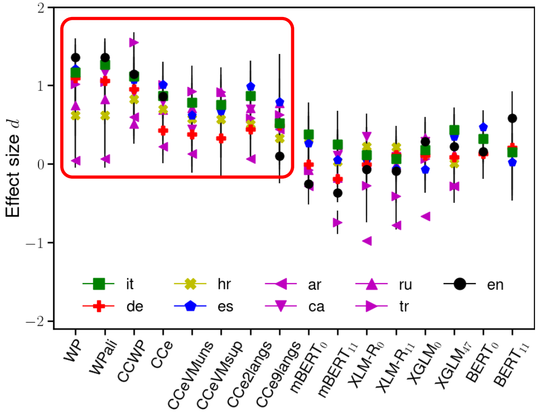


Experiments

Wide Overview (WEAT, CA-WEAT)

Word embeddings:

- All WE models have $d > 0$



Experiments

Wide Overview (WEAT, CA-WEAT)

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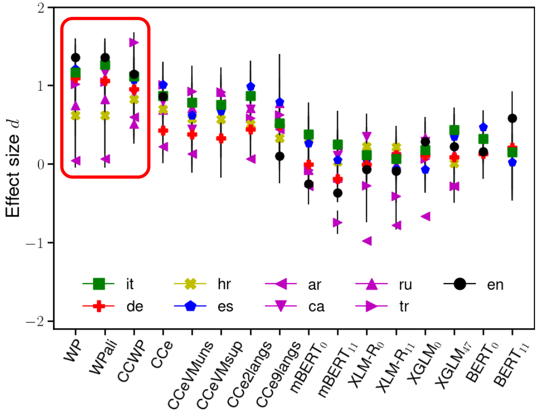
- Pre-trained models have higher σ across languages



Experiments

Wide Overview (WEAT, CA-WEAT)

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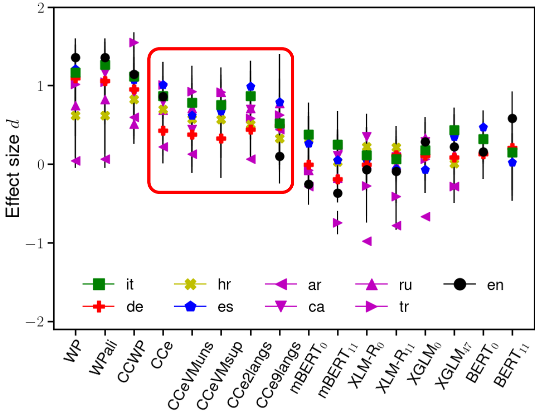
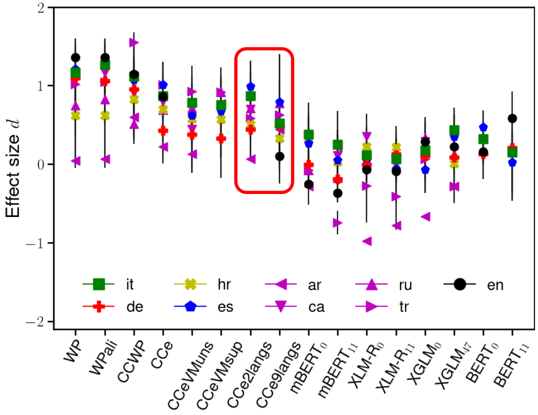


Experiments

Wide Overview (WEAT, CA-WEAT)

Word embeddings:

- All WE models have $d > 0$
- Pre-trained models have higher σ across languages
- Equivalent projection methods
- Multilinguality attenuates

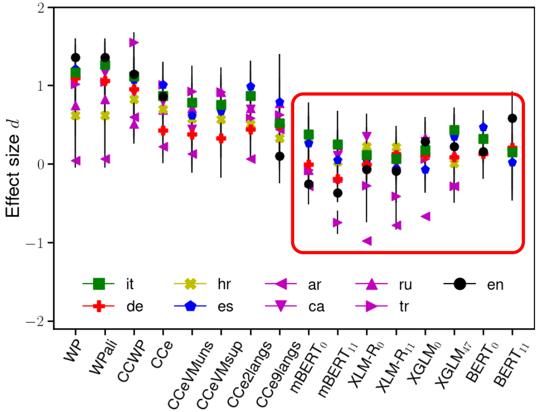


Experiments

Wide Overview (WEAT, CA-WEAT)

Contextual embeddings:

- d compatible with no bias

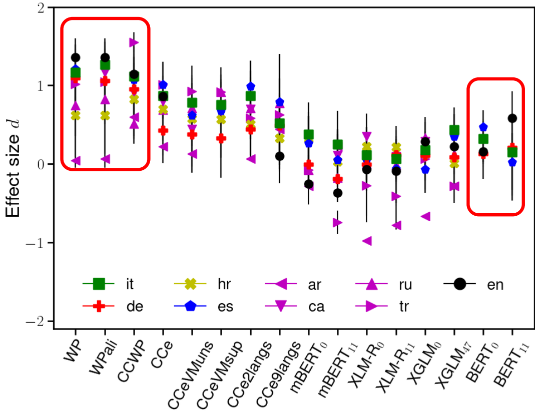


Experiments

Wide Overview (WEAT, CA-WEAT)

Contextual embeddings:

- *d* compatible with no bias
- Effect of contextualisation

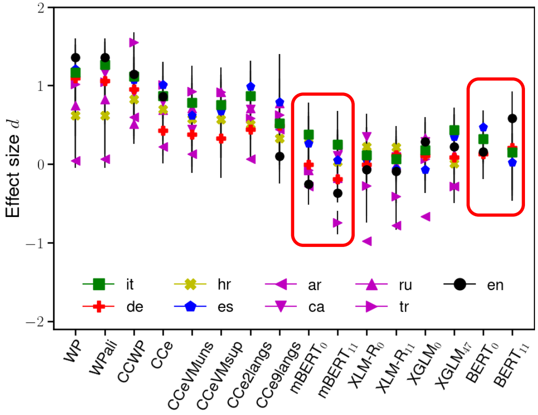


Experiments

Wide Overview (WEAT, CA-WEAT)

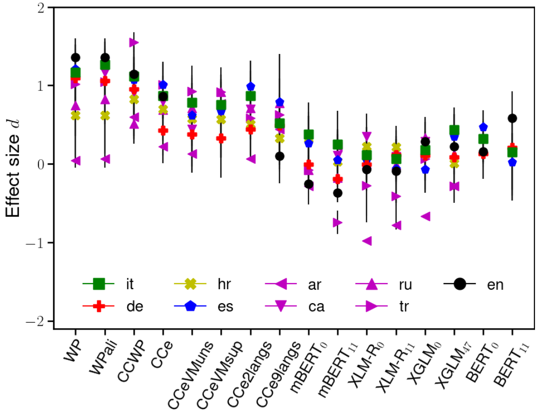
Contextual embeddings:

- *d* compatible with no bias
- Effect of contextualisation
- But multilinguality attenuates further



Experiments

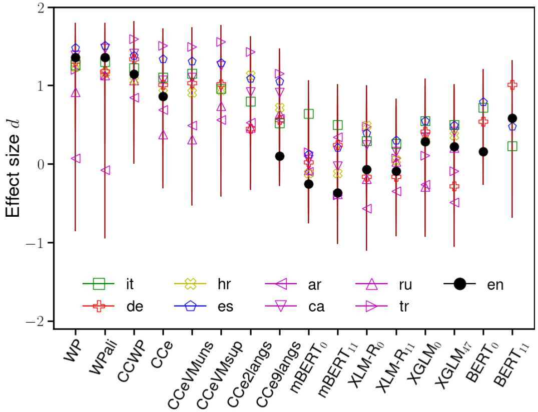
Wide Overview (CA-WEAT vs X-WEAT)



Experiments

Wide Overview (CA-WEAT vs X-WEAT)

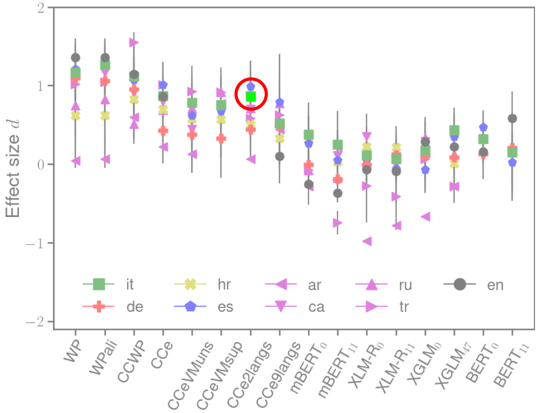
- X-WEAT shows similar trends as CA-WEAT
- But! With a higher dispersion across languages
- No universal *d*



Experiments

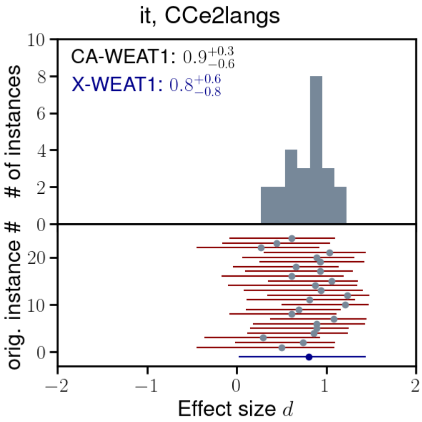
Wide Overview (CA-WEAT vs X-WEAT)

Let's focus!



Experiments

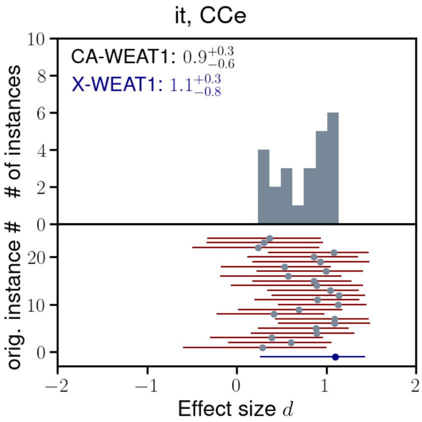
WEAT vs X-WEAT vs CA-WEAT



- Lists show a high dispersion (bootstrapped and averaged)
- X-WEAT lies within CA-WEAT (close languages)

Experiments

WEAT vs X-WEAT vs CA-WEAT



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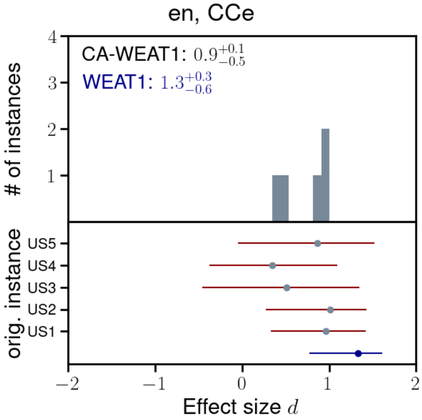
- Distributions non-normal (yet!)

Experiments

WEAT vs X-WEAT vs CA-WEAT



- Lists show a high dispersion (bootstrapped and averaged)
- X-WEAT lies within CA-WEAT (close languages)
- Distributions non-normal (yet!)
- English interesting for further study

Experiments

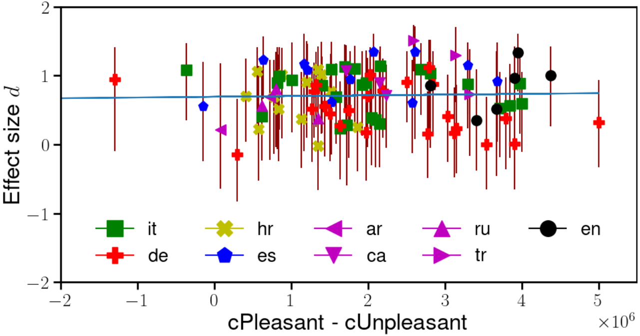
Why is d non-universal?

Is it data differences? Is it forcing multiliguality?
Is it the dispersion?

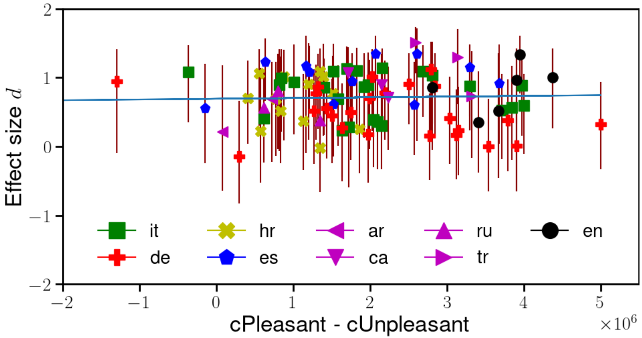
Experiments

Why is d non-universal?

- Asymmetries in term frequencies are not a reason (Pleasant vs Unpleasant terms in CCe)
  $\rho = 0.0$; explains 0% of the variance



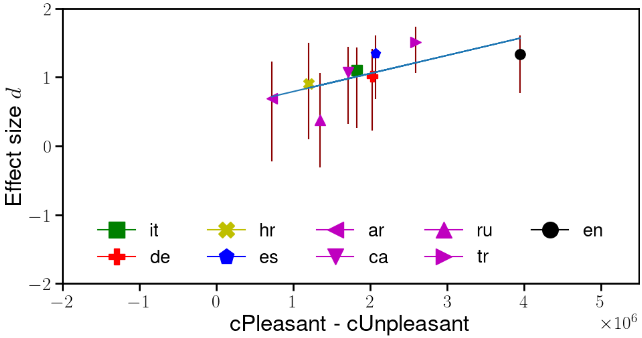
WEAT1+X-WEAT1+CA-WEAT1: no relation



Experiments

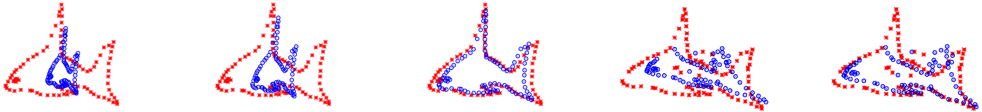
Comparison with Previous Work

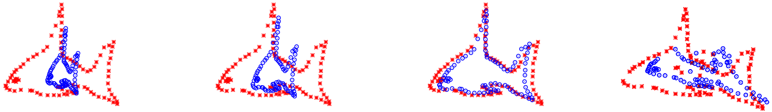
X-WEAT1: Simpson's paradox?



Experiments

Isomorphism





- Measures: Gromov-Hausdorff (GH) distance and Eigenvector similarity (EV)
- Isomorphism between a language (sub-)space and the English (sub-)space
- For contextual models we consider the vocab from CCe

Experiments

Isomorphism between a Language (sub-)Space and the English (sub-)Space

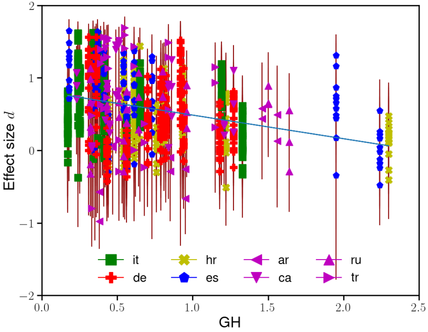
	ar		ca		de		es		hr		it		ru		tr	
	EV	GH	EV	GH	EV	GH	EV	GH	EV	GH	EV	GH	EV	GH	EV	GH
WP	106	0.47	12	0.49	12	0.31	10	0.18	42	0.54	21	0.24	16	0.43	49	0.39
WPali	143	0.55	22	0.51	22	0.36	16	0.37	46	0.61	19	0.34	30	0.32	36	0.44
CCWP	15	0.40	85	0.42	42	0.92	23	0.41	51	0.65	41	0.37	32	0.64	28	0.55
CCe	55	0.62	253	0.23	26	0.79	166	0.54	91	0.61	223	0.25	8	0.56	25	0.43
CCeVMuns	229	1.56	229	1.27	27	0.82	167	1.95	69	0.93	220	1.19	27	0.96	36	0.84
CCeVMsup	36	0.56	231	0.86	32	0.70	87	0.73	27	0.61	123	0.65	25	0.80	11	0.41
CCe2langs	93	0.53	8	0.43	19	0.94	72	0.35	33	0.81	51	0.41	39	0.51	64	0.61
CCe9langs	475	1.46	23	0.84	171	1.27	21	0.61	53	1.22	51	0.41	403	1.50	149	1.15
mBERT_0	154	0.85	133	0.33	95	0.56	99	0.56	270	0.44	131	0.17	161	0.54	589	0.51
XLM-R_0	54	0.38	74	0.45	59	0.43	150	0.44	58	0.54	113	0.56	111	0.32	277	0.33
XGLM_0	67	0.95	88	1.21	144	1.18	135	2.24	*2584	*2.30	130	1.33	85	1.64	475	0.68

- No clear distinction between WE and CE wrt. isomorphism distances
- Language and embedding model effects are also mixed

Experiments

Why is *d* non-universal?

- (Lack of) ismorphism between (sub-)spaces is not a reason either!
  $\rho = -0.3$; explains 10% of the variance



Outline

Conclusions

Wrapping up

- Using (literal) translation in NLP does not in general preserve culture
- We therefore create CA-WEAT (in contrast to X-WEAT) to analyse desirable biases in embeddings across languages

Conclusions

Wrapping up

- Using (literal) translation in NLP does not in general preserve culture
- We therefore create CA-WEAT (in contrast to X-WEAT) to analyse desirable biases in embeddings across languages

- Monolingual and bilingual WE reproduce non-social human biases
- We do not observe a universal value even in the comparable setting
- Contextualisation and multiliguality attenuate biases, why?

Conclusions

Wrapping up

- Using (literal) translation in NLP does not in general preserve culture
- We therefore create CA-WEAT (in contrast to X-WEAT) to analyse desirable biases in embeddings across languages

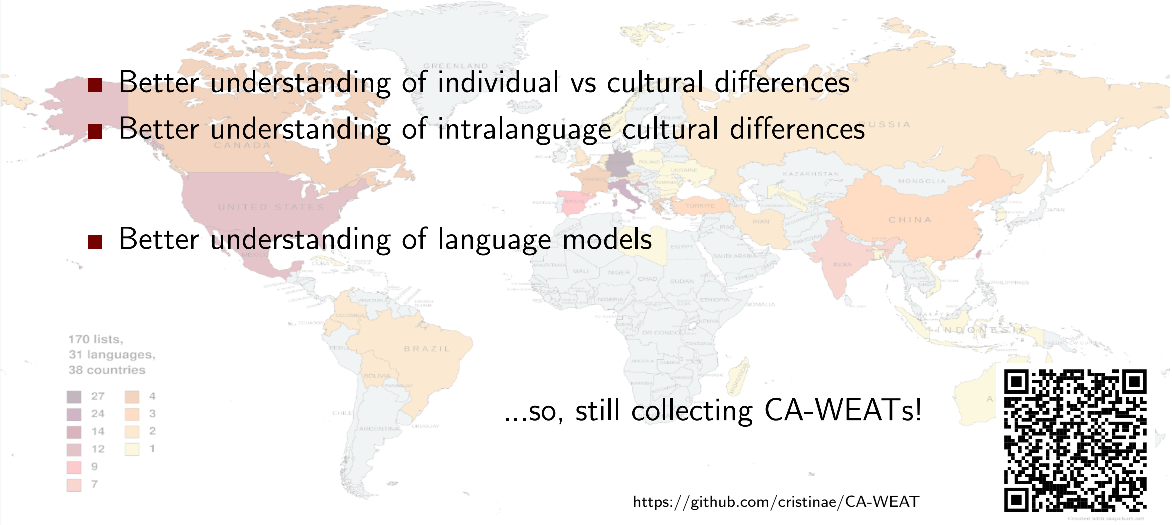
- Monolingual and bilingual WE reproduce non-social human biases
- We do not observe a universal value even in the comparable setting
- Contextualisation and multiliguality attenuate biases, why?

- Due to the large variablility (models & languages) we want...

Conclusions

Future Work

- Better understanding of individual vs cultural differences
- Better understanding of intralanguage cultural differences
- Better understanding of language models



...so, still collecting CA-WEATs!

https://github.com/cristinae/CA-WEAT

That’s All Folks!

Thanks! And...

A Reviewer's Comment

There is a huge variability.

Shouldn't one use more (WEAT) tests?

How do we find more tests?!

We want universality...

The Perception of Odor Pleasantness is Shared Across Cultures

[Arshamian et al., Current Biology, 2022]

- Culture plays a minimal role in the perception of odor pleasantness
- Individuals within cultures vary as to which odors they find pleasant
- Human olfactory perception is strongly constrained by universal principles

Extra Slides

The Perception of Odor Pleasantness is Shared Across Cultures