CS378: Natural Language Processing

Lecture 8: Bias in Embeddings, Multilingual Embeddings

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Announcements

- Assignment 2 due in one week
- Bias in embeddings response due next Tuesday (submit on Canvas)
- Nanyun Peng talk Friday; 11am 6.302

Recap

Playing around with embeddings

- See Instapoll

Using Word Embeddings

- Approach 1: learn embeddings as parameters from your data
  - Often works pretty well
- Approach 2: initialize using GloVe, keep fixed
  - Faster because no need to update these parameters
- Approach 3: initialize using GloVe, fine-tune
  - Works best for some tasks

Beyond Word Embeddings

fastText: Sub-word Embeddings

- Same as SGNS, but break words down into n-grams with n = 3 to 6

  where:
  3-grams: <wh, whe, her, ere, re>
  4-grams: <whe, wher, here, ere>,
  5-grams: <wher, where, here>,
  6-grams: <where, where>

- Replace $w \cdot c$ in skip-gram computation with $\left(\sum_{g \in \mathrm{ngrams}} w_g \cdot c\right)$

Bojanowski et al. (2017)

Preview: Subword Tokenization

- Words are a difficult unit to work with, word vocabularies get very large
- Character-level models don't work well
- Compromise solution: use thousands of "word pieces" (which may be full words but may also be parts of words)

Input: _the **_eco tax** _port i co _in _Po nt - de - Bu is …

- Rare words (ecotax, portico, Pont-de-Buis) all get broken up into smaller units we can embed

Sennrich et al. (2016)

Preview: Subword Tokenization

(a)	**Original:**	furiously	(b)	**Original:**	tricycles
	BPE:	_fur | iously		**BPE:**	_t | ric | y | cles
	Unigram LM:	_fur | ious | ly		**Unigram LM:**	_tri | cycle | s
(c)	**Original:**	Completely preposterous suggestions			
	BPE:	_Comple | t | ely | _prep | ost | erous | _suggest | ions			
	Unigram LM:	_Complete | ly | _pre | post | er | ous | _suggestion | s			

- Byte-pair encoding (BPE) produces less linguistically plausible units than another technique based on a unigram language model

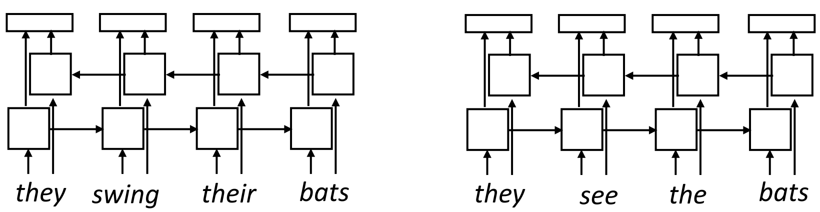
Bostrom and Durrett (2020)

Sentence Embeddings

- What if we want embedding representations for whole sentences?
- Skip-*thought* vectors (Kiros et al., 2015), similar to skip-gram generalized to a sentence level (more later)
- Is there a way we can compose vectors to make sentence representations? Summing?
- Will return to this in a few weeks as we move on to syntax and semantics

Preview: Context-dependent Embeddings

- How to handle different word senses? One vector for *bats*



- ELMo: train a neural language model to predict the next word given previous words in the sentence, use its internal representations as word vectors
- *Context-sensitive* word embeddings: depend on rest of the sentence
- *Huge* improvements across nearly all NLP tasks over GloVe

Peters et al. (2018)

Bias in Word Embeddings

What can go wrong with word embeddings?

- What's wrong with learning a word's "meaning" from its usage? Maybe some words are used in ways we don't want to replicate?
- What data are we learning from?
- What are we going to learn from this data?

Bias Exercise

Answer the following in <=3 sentences each.

Consider learning word embeddings from a **corpus of news articles.**

1. Think about a similarity association a model might learn that you believe constitutes **bias.** For this association, list (a) what the word pair is; (b) why you think this is present in the data (e.g., give an example of how it could appear in a news story)

2. Embeddings are often used at the input layer of a neural network. Can you think of a task for which this biased association might lead to bias in the system?

Now consider learning word embeddings from a **corpus of social media data comments (think about reddit + Twitter).**

3. Do you think you're likely to see the bad association from above? Why or why not?

4. Come up with a new biased similarity association; list (a) what the word pair is; (b) why you think this is present in social media data

What do we mean by bias?

- Compare distance (using cosine similarity) of many occupations to the vectors for *he* and *she*

$$\cos(u,v) = \frac{u \cdot v}{\|u\|\|v\|}$$

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

- These regularities are not restricted to gendered pronouns. *receptionist* is closer to *softball* than *football*
- This work focuses on binary gender stereotypes, but it can be extended

Bolukbasi et al. (2016)

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Bolukbasi et al. (2016)

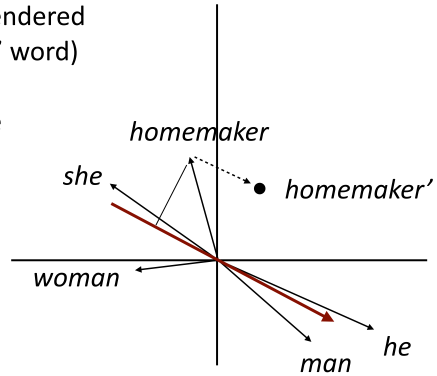
Racial Analogies	
black → homeless	caucasian → servicemen
caucasian → hillbilly	asian → suburban
asian → laborer	black → landowner
Religious Analogies	
jew → greedy	muslim → powerless
christian → familial	muslim → warzone
muslim → uneducated	christian → intellectually

Manzini et al. (2019)

- Nearest neighbor of (b - a + c)

Debiasing

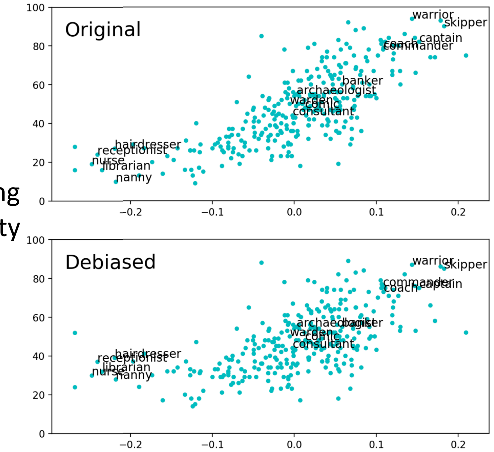
- Identify gender subspace with gendered words (avg “male” - avg “female” word)
- Project words onto this subspace
- Subtract those projections from the original word



Bolukbasi et al. (2016)

Hardness of Debiasing

- Not that effective…and the male and female words are still clustered together
- Bias pervades the word embedding space and isn’t just a local property of a few words



Gonen and Goldberg (2019)

Toxicity

- “Toxic degeneration”: neural models that generate toxic stuff

- System trained on a big chunk of the Internet: conditioning on “SJW”, “black” gives the system a chance of recalling bad stuff from its training data

https://toxicdegeneration.allenai.org/

Multilingual Word Embeddings

Recall: Training Embeddings

- Input: a large corpus of text in some language (English)
- Output: embedding for each word
- What if we have *multiple corpora* of text in *different languages*?
- Learning embeddings on each language individually: these embeddings aren't expected to have any relation

Multilingual Embeddings

- Input: corpora in many languages. Output: embeddings where similar words *in different languages* have similar embeddings

I have an apple
47 24 18 427

J' ai des oranges
47 24 89 1981

ID: 24
ai have

ID: 47
I Je J'

- multiCluster: use bilingual dictionaries to form clusters of words that are translations of one another, replace corpora with cluster IDs, train "monolingual" embeddings over all these corpora
- Works okay but not all that well

Ammar et al. (2016)

Aligning existing embeddings

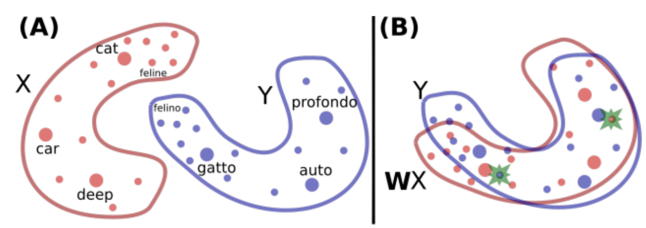
- What if you already have embeddings in two languages and you just want to align them?
- Given: dictionary of pairs (x_i, z_i), where *x* are word embeddings in a source lang (English) and *z* are word embeddings in a target lang (French)
- Learn a matrix *W* to minimize the following:

$$\min_W \sum_{i=1}^{n} \|Wx_i - z_i\|^2$$

(Looks like a loss function! Can learn with SGD on the pairs)

Mikolov et al. (2013)

Aligning existing embeddings



- Rotation learns to align these word embedding spaces! Does this cartoon match reality?

Conneau et al. (2017)

Aligning existing embeddings

Table 2: Accuracy of the word translation methods using the WMT11 datasets. The Edit Distance uses morphological structure of words to find the translation. The Word Co-occurrence technique based on counts uses similarity of contexts in which words appear, which is related to our proposed technique that uses continuous representations of words and a Translation Matrix between two languages.

Translation	**Edit Distance**		**Word Co-occurrence**		**Translation Matrix**		**ED + TM**		**Coverage**
	P@1	P@5	P@1	P@5	P@1	P@5	P@1	P@5	
En → Sp	13%	24%	19%	30%	33%	51%	43%	60%	92.9%
Sp → En	18%	27%	20%	30%	35%	52%	44%	62%	92.9%
En → Cz	5%	9%	9%	17%	27%	47%	29%	50%	90.5%
Cz → En	7%	11%	11%	20%	23%	42%	25%	45%	90.5%

Mikolov et al. (2013)