Lecture Notes for

Neural Networks and Machine Learning

A Practical Example of Ethically Aware NLP

Logistics and Agenda

- Logistics
    - Post about your preferred lecture discussion or paper summary if you haven't yet!
- Last Time:
    - Ethical Guidelines
    - Case Studies
- Agenda
    - Paper Presentation:
        - Data (dis)contents
    - NLP Review
    - Extended Example

Paper Presentation


Data and its (dis)contents: A survey of dataset development and use in machine learning research

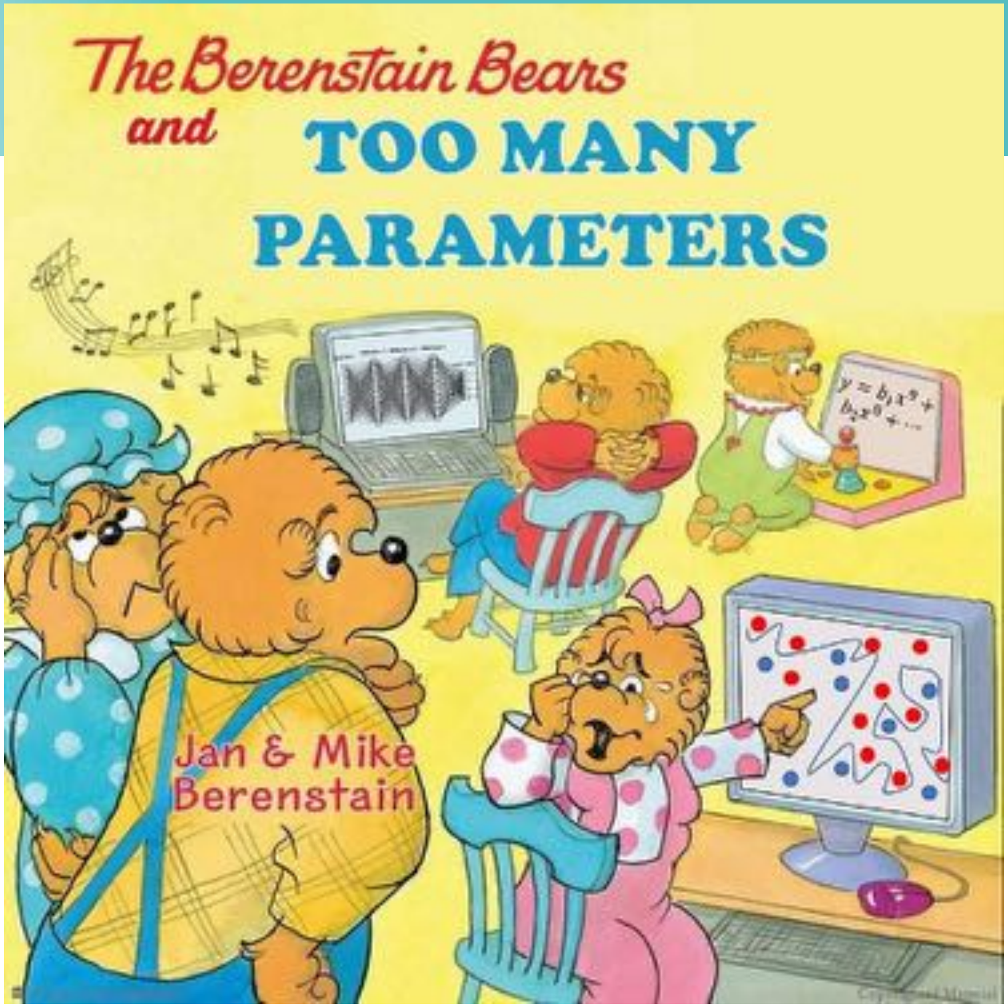
Abstract

1 Introduction

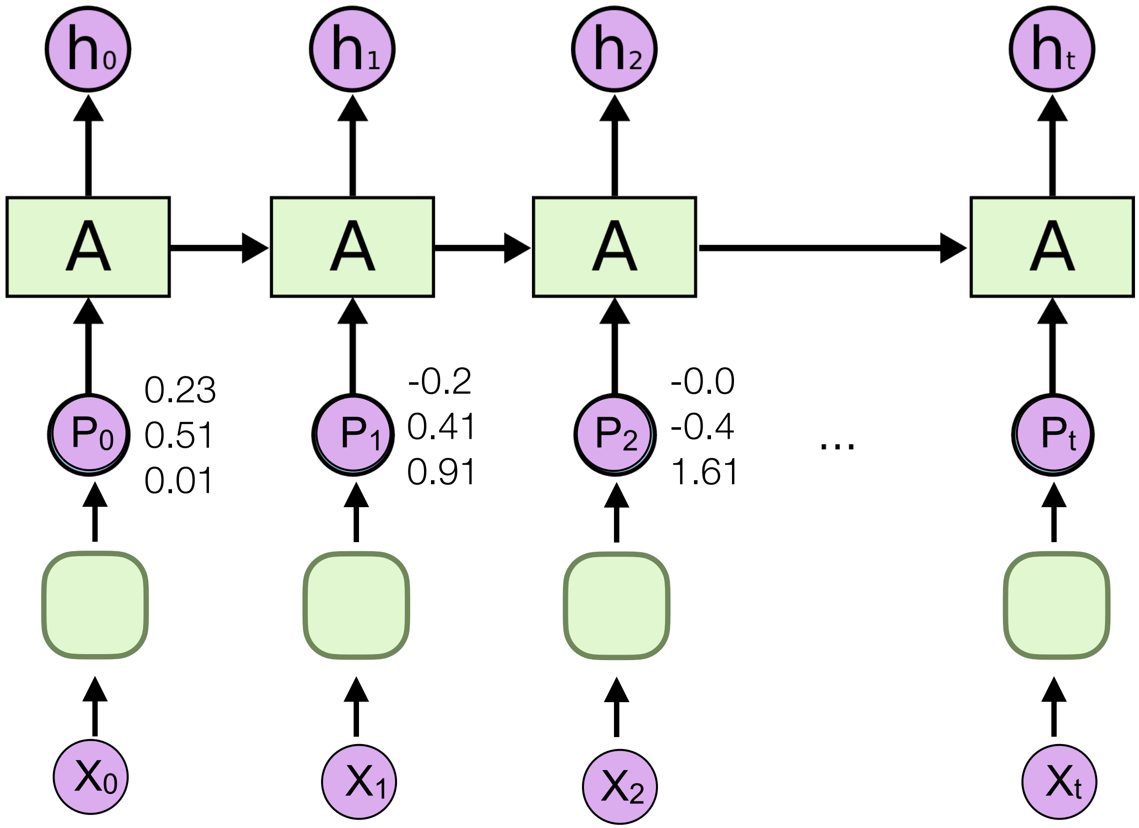
https://arxiv.org/pdf/2012.05345.pdf

NeurIPS 2020 Workshop: ML Retrospectives, Surveys & Meta-analyses (ML-RSA), Virtual.

NLP Embeddings Review



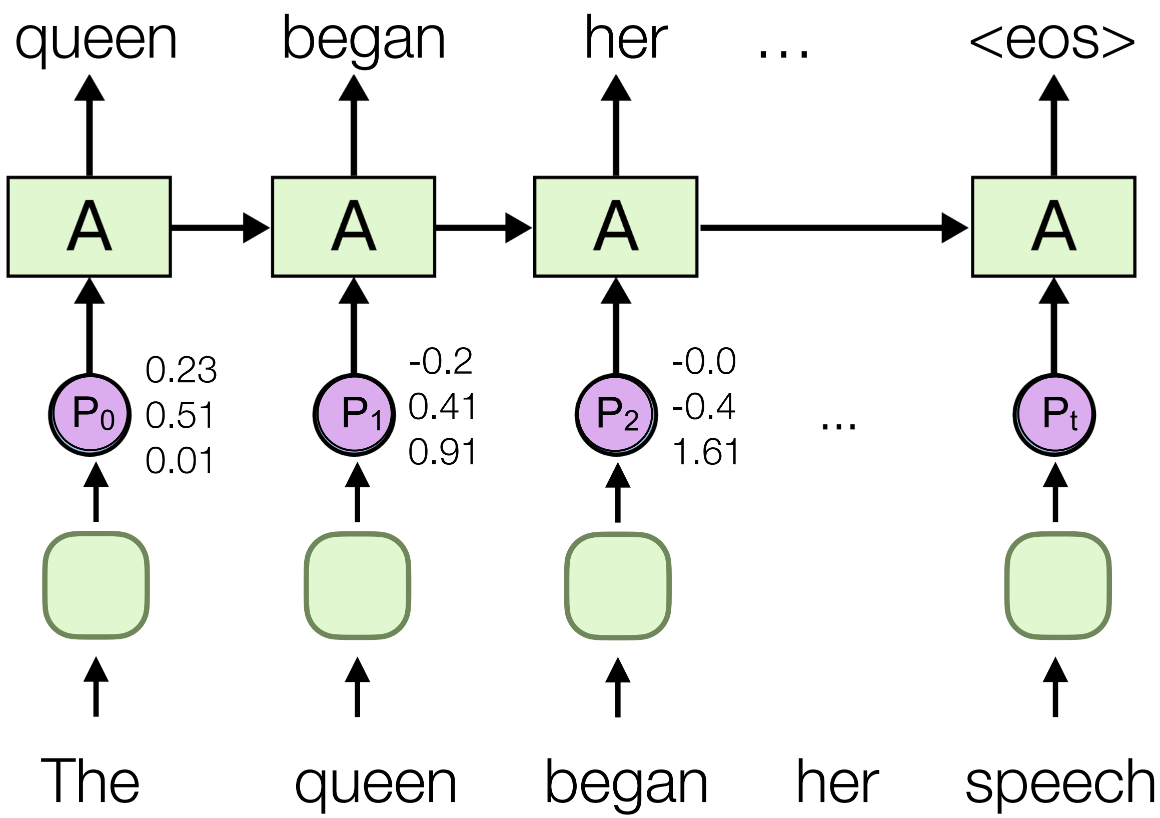
Word Embeddings (like Wide/Deep)



int:	3	1	17
one hot:	0 0 1 0 0 0 0	1 0 0 0 0 0 0	0 0 0 0 0 0 0

Word Embeddings: Training

- many training options exist
  - a popular option, next word prediction



Word Embeddings

GloVe

Global Vectors for Word Representation

Highlights

1. Nearest neighbors

The Euclidean distance (or cosine similarity) between two word vectors provides an effective method for measuring the linguistic or semantic similarity of the corresponding words. Sometimes, the nearest neighbors according to this metric reveal rare but relevant words that lie outside an average human's vocabulary. For example, here are the closest words to the target word *frog*:

0. *frog*
1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus

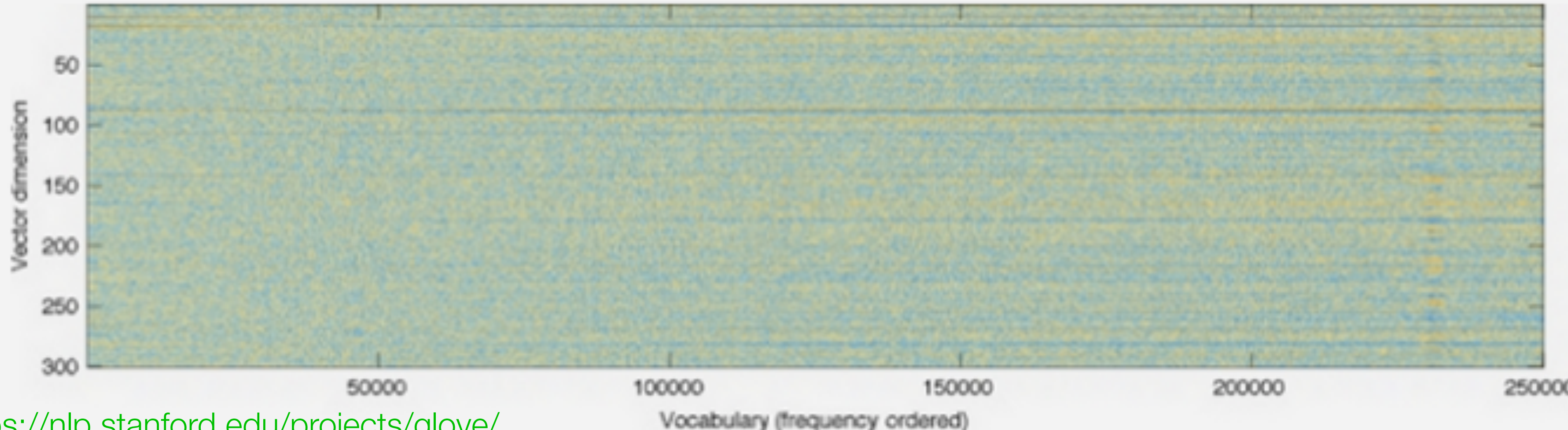
3. litoria

4. leptodactylidae

5. rana

7. eleutherodactylus

GloVe produces word vectors with a marked banded structure that is evident upon visualization:

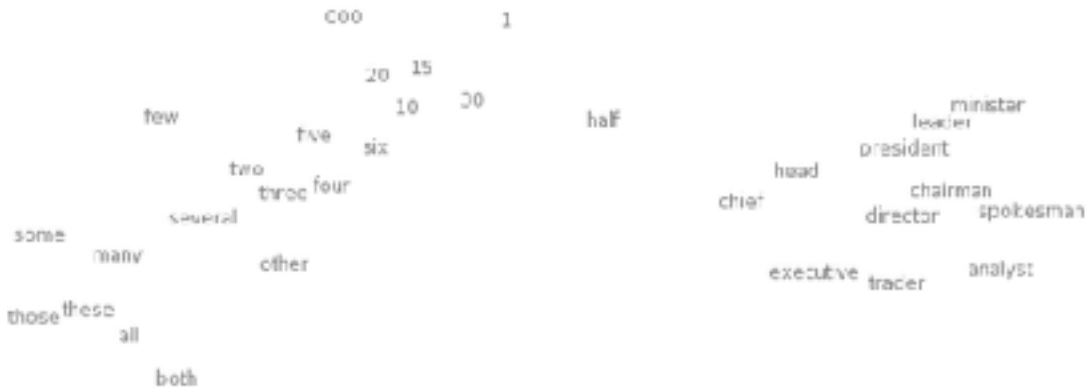


https://nlp.stanford.edu/projects/glove/

Word Embeddings: proximity

GloVe

Global Vectors for Word Representation



t-SNE visualizations of word embeddings. Left: Number Region; Right: Jobs Region. From Turian *et al.* (2010), see complete image.

FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAYISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
HUNGARY	PARVATI	GEFORCE	SILVERY	SLASHED	GBIT/S
SWITZERLAND	GRACE	CAPCOM	YELLOWISH	RIPPED	AMPERES

What words have embeddings closest to a given word? From Collobert *et al.* (2011)

The **chairman** called the **meeting** to order.

The **director** called the **conference** to order.

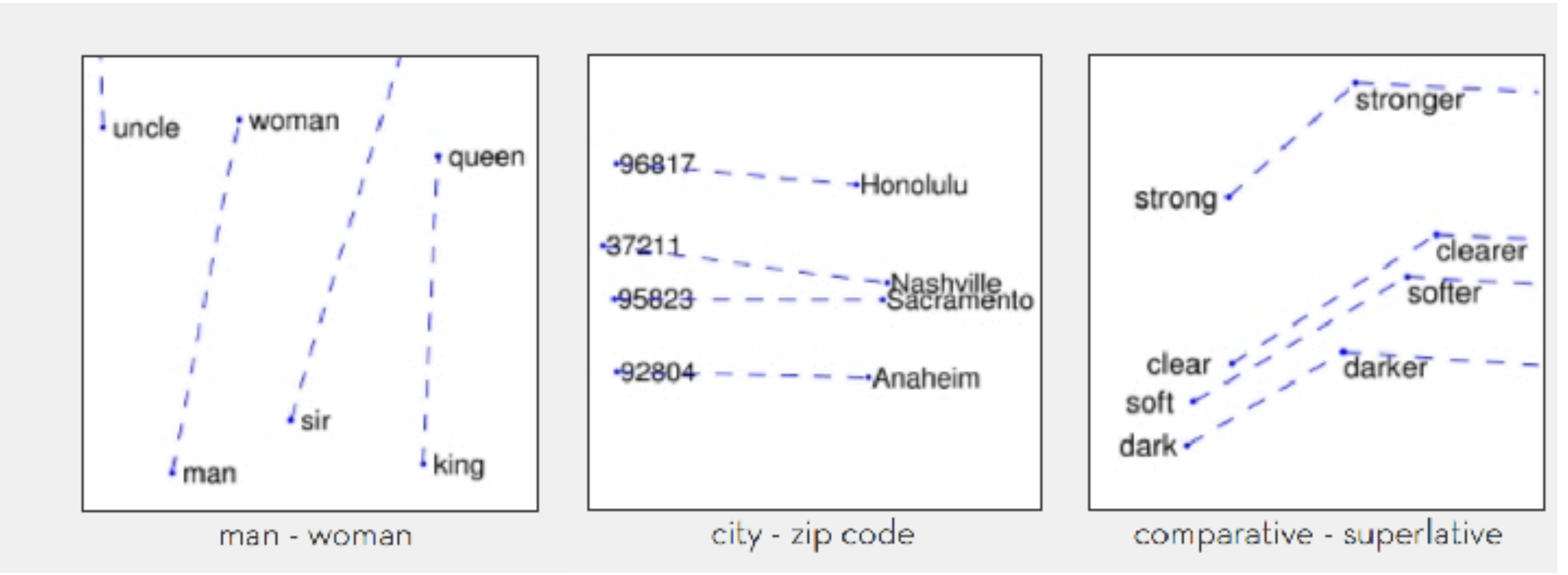
The **chief** called the **council** to order.

http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/

Word Embeddings: Analogy

GloVe

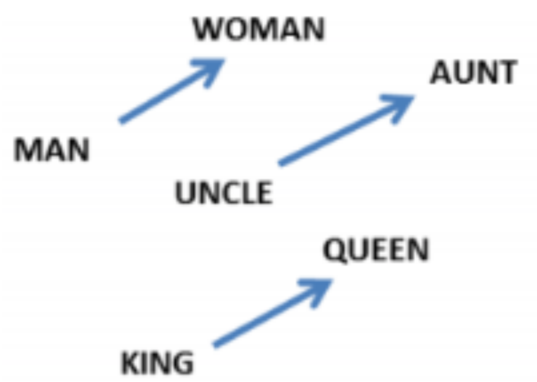
Global Vectors for Word Representation



each vector difference **might** encode analogy

https://nlp.stanford.edu/projects/glove/ http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/

Word Embeddings: Analogy?



From Mikolov *et al.* (2013a)

$$W(\text{``woman''}) - W(\text{``man''}) \simeq W(\text{``aunt''}) - W(\text{``uncle''})$$

$$W(\text{``woman''}) - W(\text{``man''}) \simeq W(\text{``queen''}) - W(\text{``king''})$$

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

Trained on New York Times

😳

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

Bolukbasi et al., NeurIPs 2016
https://arxiv.org/pdf/1607.06520.pdf

https://nlp.stanford.edu/projects/glove/

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

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One Possible Solution

Step 1: Identify gender subspace. Inputs: word sets W, defining sets $D_1, D_2, \ldots, D_n \subset W$ as well as embedding $\{\vec{w} \in \mathbb{R}^d\}_{w \in W}$ and integer parameter $k \geq 1$. Let

$$\mu_i := \sum_{w \in D_i} \vec{w}/|D_i|$$

be the means of the defining sets. Let the bias subspace B be the first k rows of SVD($\mathbf{C}$) where

$$\mathbf{C} := \sum_{i=1}^{n} \sum_{w \in D_i} (\vec{w} - \mu_i)^T (\vec{w} - \mu_i)/|D_i|.$$

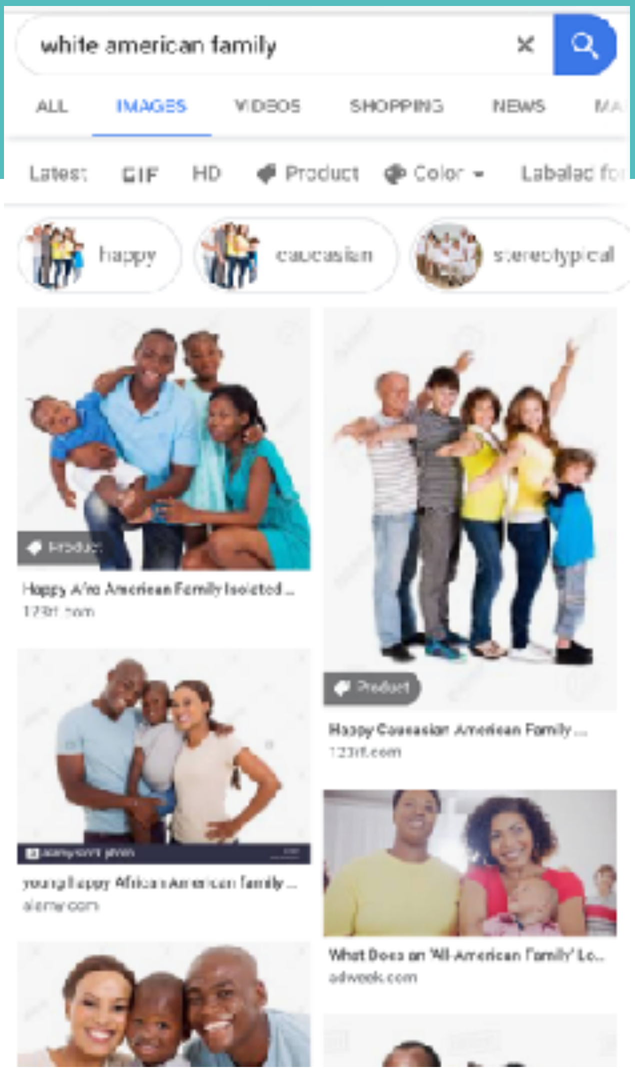
Step 2a: Hard de-biasing (neutralize and equalize). Additional inputs: words to neutralize $N \subseteq W$, family of equality sets $\mathcal{E} = \{E_1, E_2, \ldots, E_m\}$ where each $E_i \subseteq W$. For each word $w \in N$, let $\vec{w}$ be re-embedded to

$$\vec{w} := (\vec{w} - \vec{w}_B)/\|\vec{w} - \vec{w}_B\|.$$

For each set $E \in \mathcal{E}$, let

$$\begin{aligned} \mu &:= \sum_{w \in E} w/|E| \\ \nu &:= \mu - \mu_B \\ \text{For each } w \in E, \quad \vec{w} &:= \nu + \sqrt{1 - \|\nu\|^2}\, \frac{\vec{w}_B - \mu_B}{\|\vec{w}_B - \mu_B\|} \end{aligned}$$

Practical Example in NLP



ConceptNet

en cooking dinner

An English term in ConceptNet 5.7

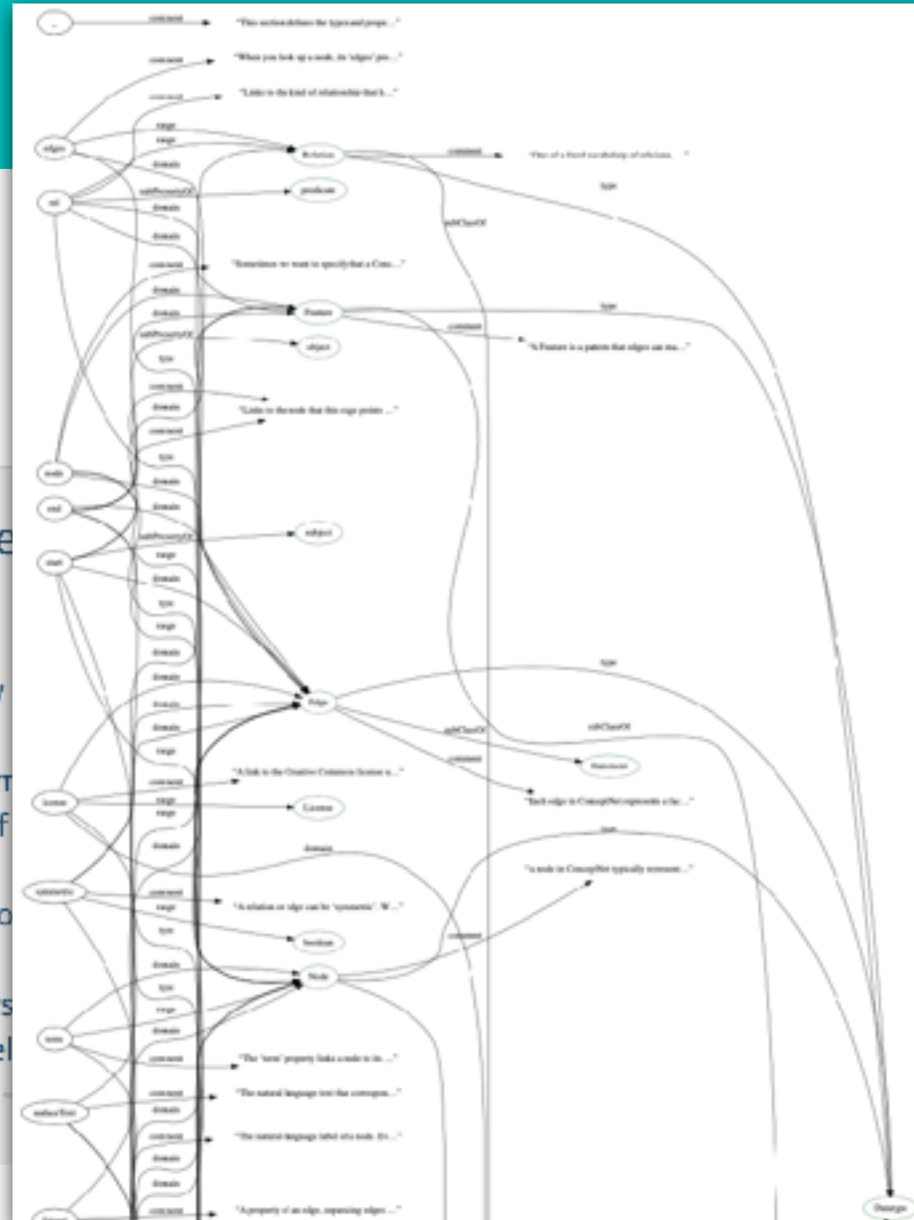
Source: Open Mind Common Sense contributors
View this term in the API

cooking dinner is a subevent of...

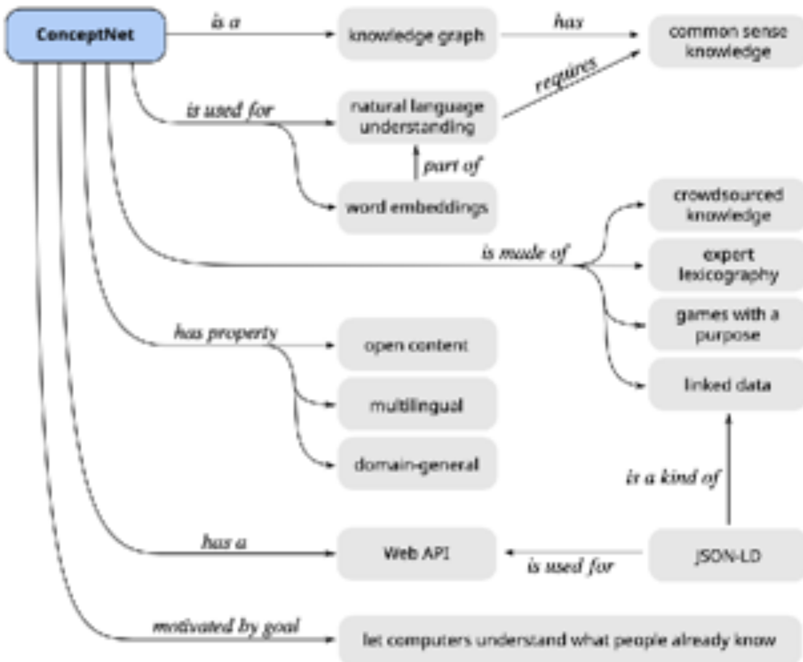
- en boiling water →
- en it burns →
- en preheat the oven →
- en taste the food →
- en boil salt water →
- en boil water →
- en brown the hamburger →
- en chop a vegetable →
- en defrost →
- en a fire →
- en the fire alarm might go off →

cooking dinne for...

- en feeding a family
- en TO EAT →
- en entertaining com
- en feeding yourself
- en anyone →
- en avoiding fast foo
- en being a cook →
- en caring for others
- en cheering yoursel
- en creative people
- en eating →



ConceptNet Numberbatch



- Create with a Knowledge Graph (from multiple sources with relations like *UsedFor*, *PartOf*, *etc*.)
- Based on this KG, perturb existing embeddings (like GloVe) to optimize:

$$\Psi(Q) = \sum_{i=1}^{n} \left[\underbrace{\alpha_i \|q_i - \hat{q}_i\|^2}_{\text{(keep similar to original)}} + \underbrace{\sum_{(i,j)\in E} \beta_{ij} \|q_i - q_j\|^2}_{\text{(make similar according to other knowledge)}} \right]$$

new embed

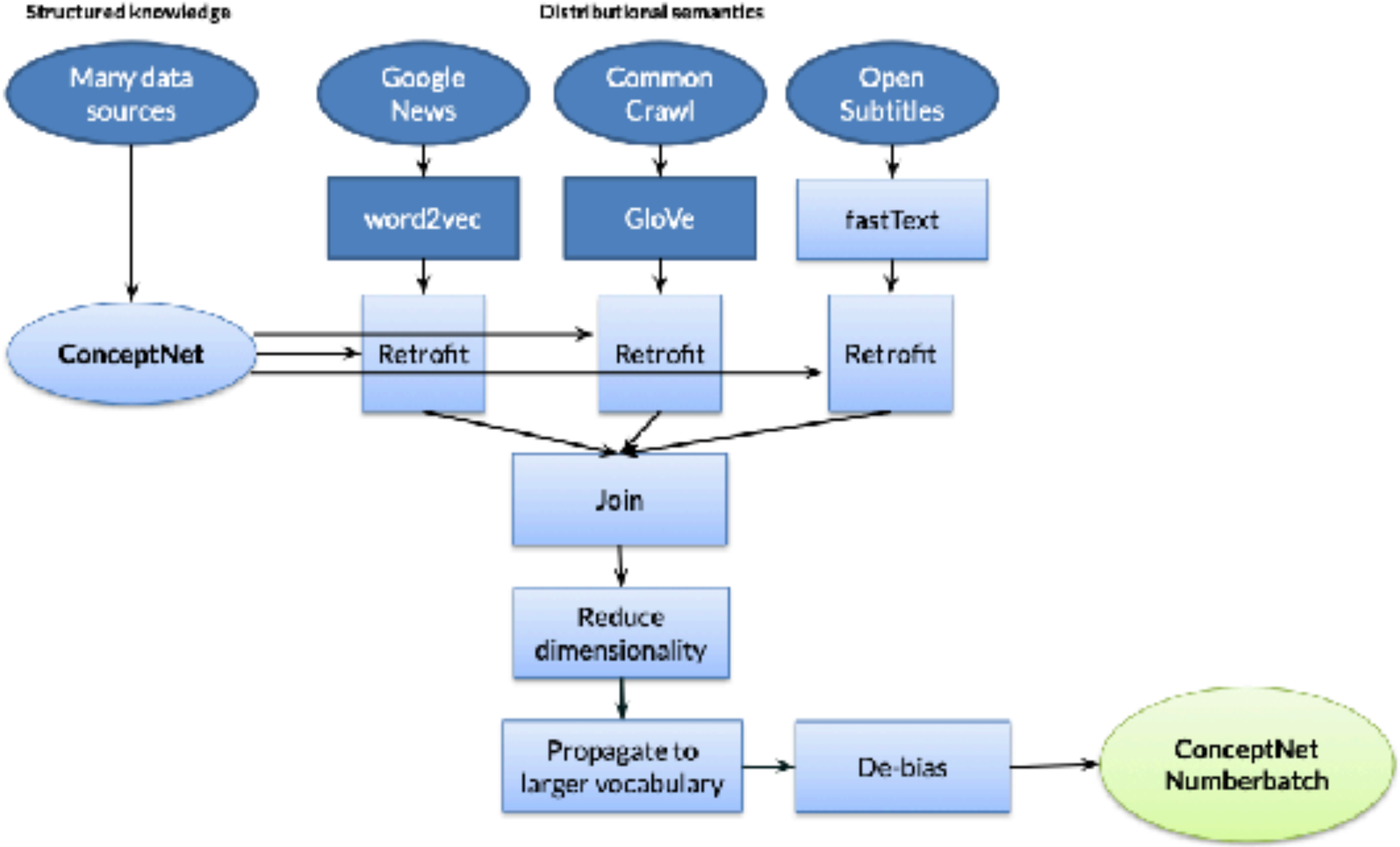
old embed

neighbors from KG

- Easy to optimize the objective by averaging neighbors in the ConceptNet KG
- Multiple embeddings achieved by merging through “retrofitting” which projects onto a shared matrix space (with SVD)

ConceptNet 5.5: An Open Multilingual Graph of General Knowledge, Speer et al., 2017

Building ConceptNet Numberbatch



LUMINOSO

Aside: Transparency in Research

ConceptNet is all you need

Our full classifier used the linear combination of 5 types of input features shown above. This point is labeled **ABCDE** on the graph to the right. The other points are ablated versions of the classifier, trained on subsets of the five sources.

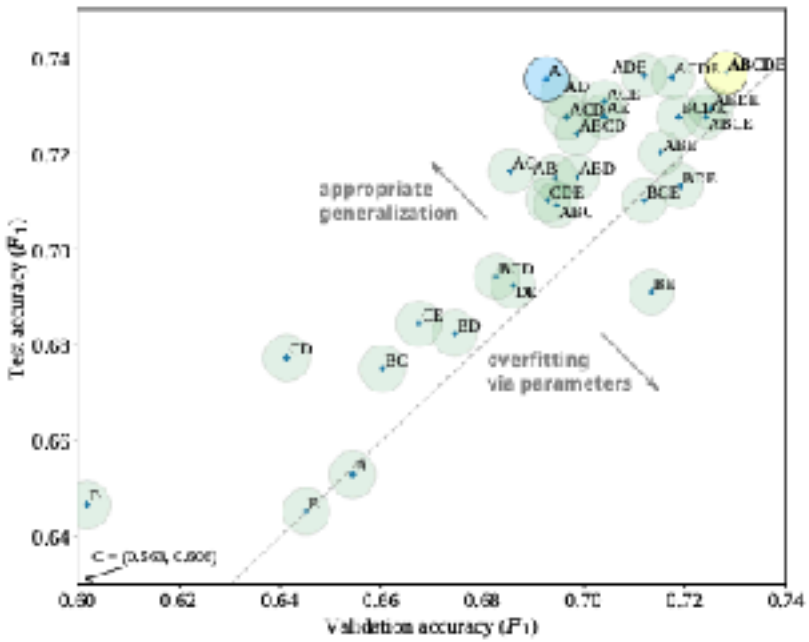
We found that the single feature of ConceptNet similarity (**A**) performed just as well on the test data as the full classifier, despite its lower validation accuracy.

This one-feature classifier could be more simply described as a heuristic over cosine similarities of ConceptNet embeddings:

$$\mathrm{sim}(term_1, att) - \mathrm{sim}(term_2, att) > 0.0961$$

It seems that the test data contained distinctions that can already be found by comparing ConceptNet embeddings, and that more complex features may have simply provided an opportunity to overfit to the validation set by parameter selection.

Results for all subsets of sources



This graph shows the validation and test accuracy of classifiers trained on subsets of the five sources of features. Ellipses indicate standard error of the mean, assuming that the data is sampled from a larger set.

https://blog.conceptnet.io/2018/06/naacl2018-poster.pdf

ConceptNet Numberbatch

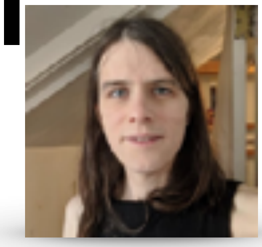
As a kid, I used to hold marble racing tournaments in my room, rolling marbles simultaneously down plastic towers of tracks and funnels. I went so far as to set up a bracket of 64 marbles to find the fastest marble. I kind of thought that running marble tournaments was peculiar to me and my childhood, but now I've found out that marble racing videos on YouTube are a big thing! Some of them even have overlays as if they're major sporting events.

In the end, there's nothing special about the fastest marble compared to most other marbles. It's just lucky. If one ran the tournament again, the marble champion might lose in the first round. But the one thing you could conclude about the fastest marble is that it was no *worse* than the other marbles. A bad marble (say, a misshapen one, or a plastic bead) would never luck out enough to win.

In our paper, we tested 30 alternate versions of the classifier, including the one that was roughly equivalent to this very simple system. We were impressed by the fact that it performed as well as our real entry. And this could be because of the inherent power of ConceptNet Numberbatch, or it could be because it's the lucky marble.

-Robyn Speer
http://blog.conceptnet.io

How to Make a Racist AI without Really Trying



Robyn Speer, 2017
http://blog.conceptnet.io/posts/2017/how-to-make-a-racist-ai-without-really-trying/

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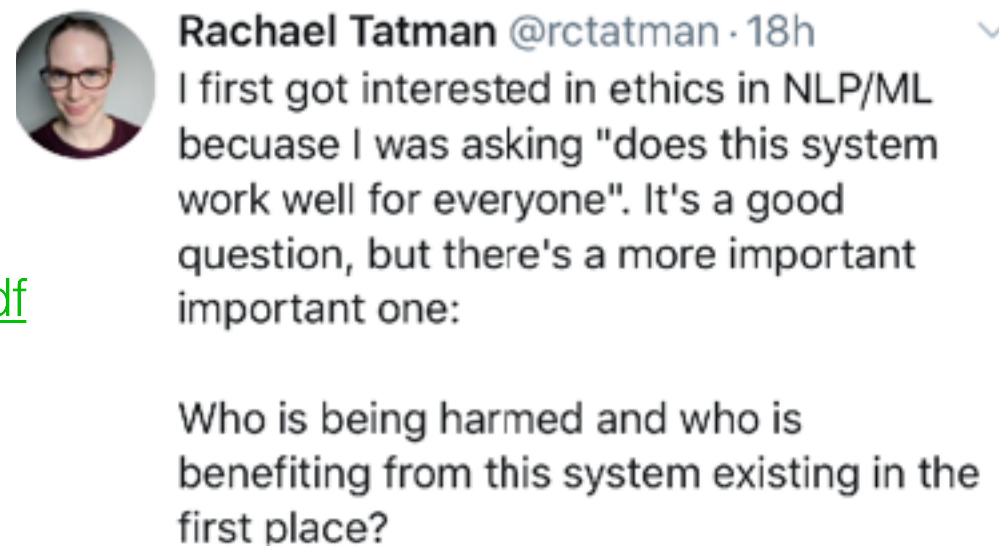
Speer et al., AAAI 2017
https://arxiv.org/pdf/1612.03975.pdf



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Next Time:
CNN Visualization

Reading: Chollet Article