Mathematical structures for word embeddings

Siddharth Bhat

IIIT Hyderabad

October 23th, 2021

■ Map words to mathematical objects.

- Map words to mathematical objects.
- $lue{}$ Semantic ideas on words \simeq mathematical operations on these objects.

- Map words to mathematical objects.
- \blacksquare Semantic ideas on words \simeq mathematical operations on these objects.
- Most common: *vector embeddings* (word2vec)

- Map words to mathematical objects.
- \blacksquare Semantic ideas on words \simeq mathematical operations on these objects.
- Most common: *vector embeddings* (word2vec)

 $\textcolor{red}{\blacksquare} \hspace{0.1cm} \texttt{king} - \texttt{man} + \texttt{woman} = \texttt{queen}. \hspace{0.1cm} \texttt{[Analogy]}$

- king man + woman = queen. [Analogy]
- $\quad \blacksquare \ \, \mathsf{nope!} \ \, \mathit{normalize}(\mathtt{king}-\mathtt{man}+\mathtt{woman}) = \mathit{queen}$
- word2vec"vectors" are always normalized!

- king man + woman = queen. [Analogy]
- \blacksquare nope! normalize(king man + woman) = queen
- word2vec"vectors" are always normalized!
- Cannot add, substract, scale them. So in what sense is the embedding "vectorial"?

- \blacksquare king man + woman = queen. [Analogy]
- nope! normalize(king man + woman) = queen
- word2vec"vectors" are always normalized!
- Cannot add, substract, scale them. So in what sense is the embedding "vectorial"?
- In the sense that we have "vectors" elements of the space $[-1,1]^N$ with a normalization condition $(\sum_i x_i^2 = 1)$.

- king man + woman = queen. [Analogy]
- \blacksquare nope! normalize(king man + woman) = queen
- word2vec"vectors" are always normalized!
- Cannot add, substract, scale them. So in what sense is the embedding "vectorial"?
- In the sense that we have "vectors" elements of the space $[-1,1]^N$ with a normalization condition $(\sum_i x_i^2 = 1)$.
- Can we ascribe a different meaning to these "vectors"?

Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.

- Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.
- A mathematical analogy: The *meaning* of an expression $\forall x \in \mathbb{Z}, x \leq 2$ is the *set* of possible values where the meaning holds true: $(-\infty, 2] = \{x \in \mathbb{Z} : x \leq 2\}$.

- Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.
- A mathematical analogy: The *meaning* of an expression $\forall x \in \mathbb{Z}, x \leq 2$ is the *set* of possible values where the meaning holds true: $(-\infty, 2] = \{x \in \mathbb{Z} : x \leq 2\}$.
- Meaning ≃ subsets. Is word2vecsubsets?

- Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.
- A mathematical analogy: The *meaning* of an expression $\forall x \in \mathbb{Z}, x \leq 2$ is the *set* of possible values where the meaning holds true: $(-\infty, 2] = \{x \in \mathbb{Z} : x \leq 2\}$.
- Meaning ≃ subsets. Is word2vecsubsets? Yes, fuzzy sets.

- Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.
- A mathematical analogy: The *meaning* of an expression $\forall x \in \mathbb{Z}, x \leq 2$ is the *set* of possible values where the meaning holds true: $(-\infty, 2] = \{x \in \mathbb{Z} : x \leq 2\}$.
- Meaning ≃ subsets. Is word2vecsubsets? Yes, fuzzy sets.
- Set: binary membership. $(1 \in \{1, 2\} = T, 3 \notin \{1, 2\} = F)$.

- Montague semantics: The meaning of a word is the set of possible worlds where the meaning holds true.
- A mathematical analogy: The *meaning* of an expression $\forall x \in \mathbb{Z}, x \leq 2$ is the *set* of possible values where the meaning holds true: $(-\infty, 2] = \{x \in \mathbb{Z} : x \leq 2\}$.
- Meaning ≃ subsets. Is word2vecsubsets? Yes, fuzzy sets.
- Set: binary membership. $(1 \in \{1, 2\} = T, 3 \notin \{1, 2\} = F)$.
- Fuzzy set: probabilistic membership. $(1 \in_{fuz} F = 0.1, 2 \in_{fuz} F = 0.5)$.

Given the set of vectors, normalize the components of the vector across all vectors.

- Given the set of vectors, normalize the components of the vector across all vectors.
- fuzembed_{word}[i] \equiv vecembed_{word}[i] $/ \sum_{w \in CORPUS} vecembed_w[i]$.

- Given the set of vectors, normalize the components of the vector across all vectors.
- fuzembed_{word}[i] \equiv vecembed_{word}[i] $/ \sum_{w \in CORPUS} vecembed_w[i]$.
- Fuzzy set embedding from word2vecembeddings.

- Given the set of vectors, normalize the components of the vector across all vectors.
- fuzembed_{word}[i] \equiv vecembed_{word}[i] $/ \sum_{w \in CORPUS} vecembed_w[i]$.
- Fuzzy set embedding from word2vecembeddings.
- Use fuzzy set operations for NLP tasks.

What does this buy us anyway?

Take-aways

Pat II: What's a geometer to do?

From vectors to subspaces

A research agenda, and carrying the baton forward

Conclusion

- word2vec is performant but poorly understood.
- We extract fuzzy set embeddings from word2vec, appeasing Montague!
- We ponder on the geometry of word2vec, and indicate potential extensions.
- TL;DR: Mathematical modelling (fuzzy sets, grassmanians) is useful to extend empirical results (word2vec)!