

Natural language is
unreasonably simple, unreasonably often
Adding up word embeddings works far too well, why is
that?

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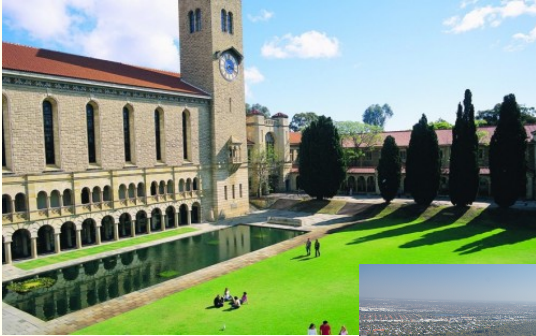


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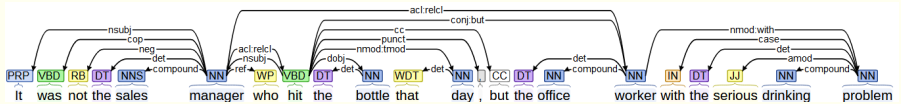
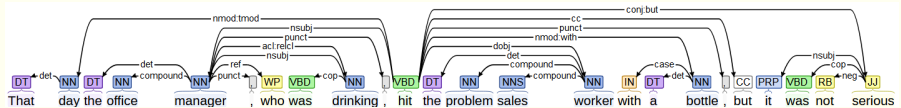
Australia, really it is quiet far away



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We like to think language is very complicated



This is what we do, and complicated models make us feel good and publish well.

and sometimes language is

This movie is a truly excellent example of the quality of cinematography this century; bring back the good old days of real cinema!

You shouldn't miss this,
that would be the worst mistake.

It's not that it is was bad,
but it wasn't what I hoped for.

And so we need the complicated models.

but sometimes language isn't

- ▶ The girl stands on the tennis court.
- ▶ **Not:** The tennis court stands on the girl.

but sometimes language isn't

- ▶ The girl stands on the tennis court.
- ▶ Not: The tennis court stands on the girl.

How do we know?

World Knowledge: girl is an agent, that can take actions
OR

Language Modelling: the trigram tennis court stands
never occurs in the Google Books corpus.

And so simple methods work

and often it looks like it is complicated
but isn't

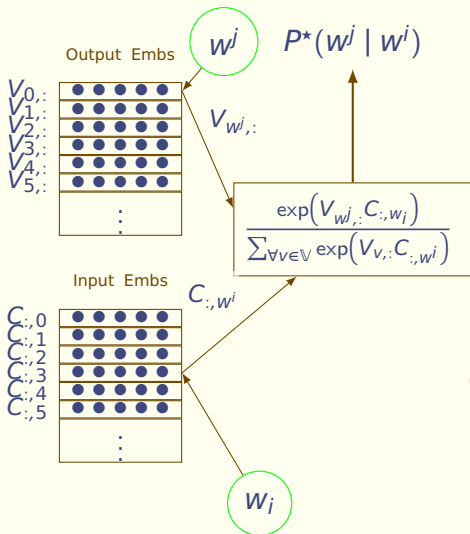
color modifier head color
dark greenish blue
basic modifier meta modifier

color modifier head color
(red) (from noun)
ruddy coral
meta modifier

color modifier head color
dark bluish green
basic modifier meta modifier

and so using complicated methods leads to
worse performance.

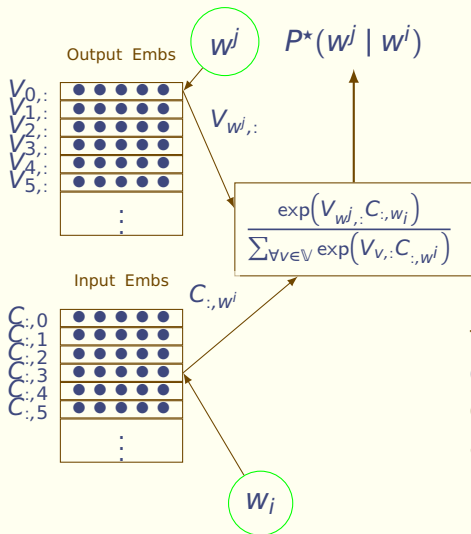
SkipGram is the most well known of recent word embedding methods



$$\begin{aligned} P^*(w^j | w^i) &= \text{smax}(V C_{:,w^i})_{w^j} \\ &= \frac{\exp(V_{w^j,:} C_{:,w^i})}{\sum_{\forall k \in \mathbb{V}} \exp(V_{k,:} C_{:,w^i})} \end{aligned}$$

Maximise $P^*(w^j | w^i)$ for combinations of words w^j , w^i that actually co-occur.

SkipGram is the most well known of recent word embedding methods



$P^*(w^j | w^i)$ is maximised when $V_{w^j,:} C_{:,w^i}$ is maximized.

i.e. when the dot-product of the input embeddings and the output embeddings of collocated words approaches 1

SkipGram is a iterative algorithm for weighted collocation matrix factorization.

V is a $300 \times |\mathbb{V}|$ input embeddings matrix
 C is a $|\mathbb{V}| \times 300$ output embeddings matrix
 X is a $|\mathbb{V}| \times |\mathbb{V}|$ collocation count matrix
 f is some monotonic weighting function.
(Levy, Goldberg, and Dagan 2015)

$$\begin{aligned} \text{Loss} &\propto -X \odot \exp(VC) \\ &\propto VC - \log X \\ &\propto VC - f(X) \end{aligned}$$

Loss is minimized
when $VC \approx f(X)$

When trying to factorize very large matrices numerical linear algebraicians often use iterative methods.

So SkipGrams are a
dimensionality reduction algorithm,
that tries remember collocated words

- ▶ PCA is a dimensionality reduction algorithm, that tries to remember the most variant factors
- ▶ Compressing knowledge of collocated words into a dense vector, gives us Firth's Criterion.

Matrix product with onehot vector is indexed slicing

Consider the onehot representation of some word w ,
as $\tilde{e}_w = [0, \dots, \underbrace{1}_{\text{wth position}}, 0, \dots, 0]$

It's word embedding is given by $C_{:,w} = C^T e_w$

Sum of word embeddings is the same as
matrix product with bag of words

Concatenation followed by matrix product
is the same as
matrix product followed by addition

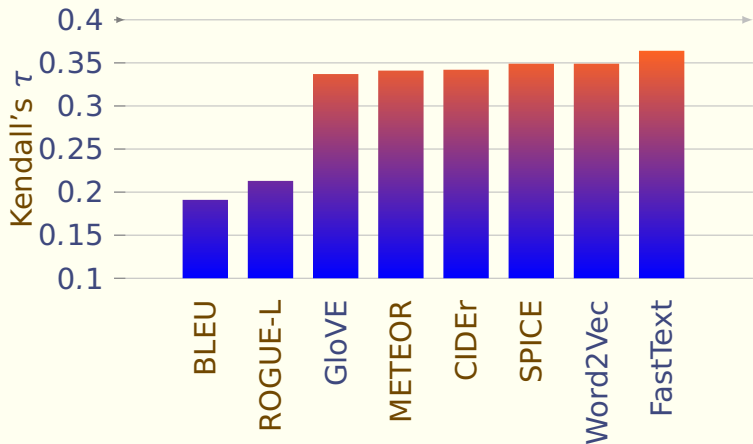
Bag of words information is not lost in sums of word embeddings

- ▶ A bag of words captures all unigram information in a sentence/document etc

We can reliably recover all words from a sum of word embeddings

Consider machine captioning evaluation

Correlation with human ranking in the COMPOSITE captioning evaluation dataset. Aditya et al. 2017



*Forthcoming publication Naeha Sharif, Lyndon White, Mohammed Bennamoun and Syed Afaq Ali Shah.

What is going on? How can a unigram method
be beating everything?

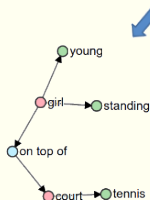
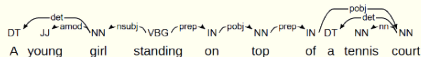
Captioning quality can be assessed on
fluency and on **adequacy**

All captions in COMPOSITE are **fluent**

- ▶ We are really good at language modelling now.
- ▶ In theory our RNN language models can capture all needed state
- ▶ COMPOSITE captions are a mix of human generated and state-of-the-art machine generated.

Trying to capture fluency in your captioning metric is thus not important

The proper way to look at adequacy is to build a semantic graph, and apply reasoning to it



This is what SPICE does .

Anderson et al. 2016

But you could use AMR etc

Banarescu et al. 2013.

To get to a form that reasoning can be applied on.

This semantic graph must be derived from the **right words** in the **right order**

Semantic graph comes from syntactic graph

- ▶ The syntactic graph comes from the word order and word content.
- ▶ In theory, different words in different orders could give the same semantic graph
- ▶ and the same words in a different order could give a different semantic graph.

Due to ambiguity in possible word order
semantic meaning should not be derivable
from averaged lexical meaning representation

- ▶ Well written sentences are short: 14-17 words
- ▶ They don't have complicated clauses and negations.
- ▶ Words are used in consistent phrases:
 - ▶ The girl stands on the tennis court
 - ▶ Not: The tennis court stands on the girl
- ▶ Good captions are such good sentences.

But in-practice, it probably is

Some might say the problems we are assessing on are not sufficiently difficult

The problems are exactly as difficult as they are.

- real world problems on real data.