

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

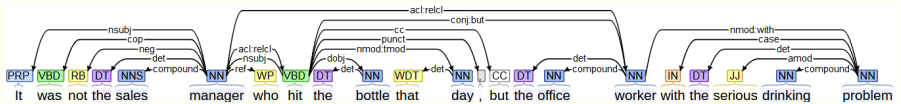
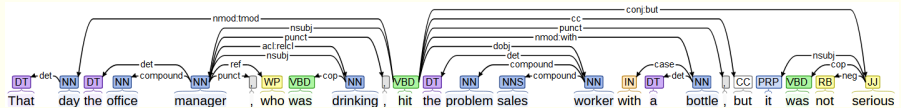
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THE UNIVERSITY OF  
**WESTERN  
AUSTRALIA**

# 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; for  
goodness sake, 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

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)  
rudd y      coral  
meta modifier

color modifier      head color  
dark      bluish      green  
basic modifier      meta modifier

and so using complicated methods leads to  
worse performance.

Two (overlapping) types of problems

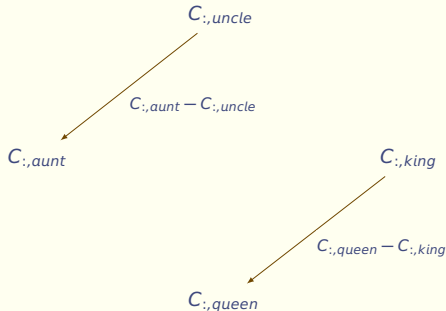
Natural Language  
Generation

Natural Language  
Understanding

We're interested in the latter



# Word Embeddings are important in modern NLP



Gladkova, Drozd, and Matsuoka (2016),

“Analogy-based detection of morphological and semantic relations with word embeddings: what works and what doesn’t.”

40 subcategories of knowledge.

Analogy Algebra: is a **sufficient** condition for good separability with consistency

# Word Embeddings capture lexical (word level) semantics

Firth's Criterion:

You shall know a word by the company it keep.

The Distributional Hypothesis:

Words that occur in similar **contexts**, have similar **meanings**.

they are a very effective dense representation  
of words

You can just add up word embeddings and  
uses it as a representation

Cířka and Bojar (2018), “Are BLEU and Meaning  
Representation in Opposition?”

*“On classification tasks, our [LSTM encoder-decoder] models  
are outperformed even by GloVe-BOW, except for the NLI  
tasks. . . ”*

Conneau et al. (2018), “What you can cram into a single  
\$&!#\* vector: Probing sentence embeddings for linguistic  
properties”

*“Our first striking result is the good overall performance of  
Bag-of-Vectors, confirming early insights that aggregated  
word embeddings capture surprising amounts of sentence  
information. . . ”*

# Some reasons why lexical semantics is capturing what looks like sentence semantics.

Conneau et al. (2018), “What you can cram into a single \$&!#\* vector: Probing sentence embeddings for linguistic properties”

- ▶ Most words have same temporal tense as sentence.
- ▶ Nouns and adjectives both tend to mark quantities of same things.
- ▶ The presence of some words (Why, Where, etc) strongly hints at the structure of the sentence

Redundant encoding of information in the words

# Content is king

Considering further [Conneau et al. 2018](#)

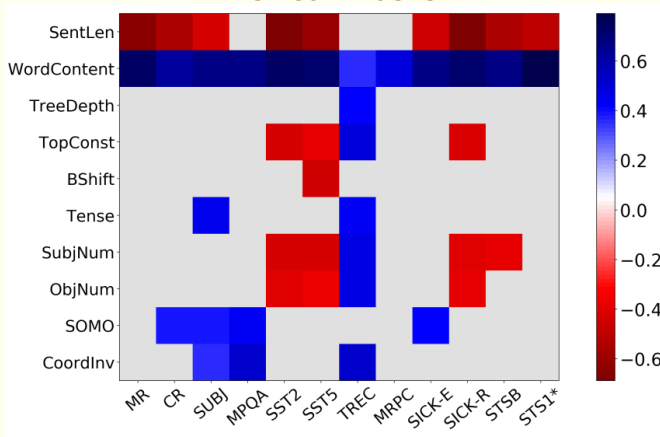
- ▶ They looked at  $3 \times 8 + 5$  models
- ▶ 10 probing tasks were used to evaluate the models.
- ▶ Of the [baseline](#) models SOWE was often the best.
- ▶ It was rarely better than the best performing sophisticated model
- ▶ Except on Word Content

The words people use are the most important part of what they are saying

# Content is king

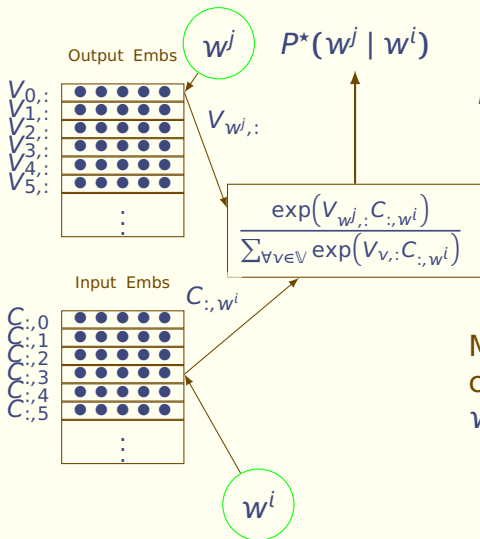
Considering further [Conneau et al. 2018](#)

When the probing task results are correlated against 12 downstream tasks.



The words people use are the most important part of what they are saying

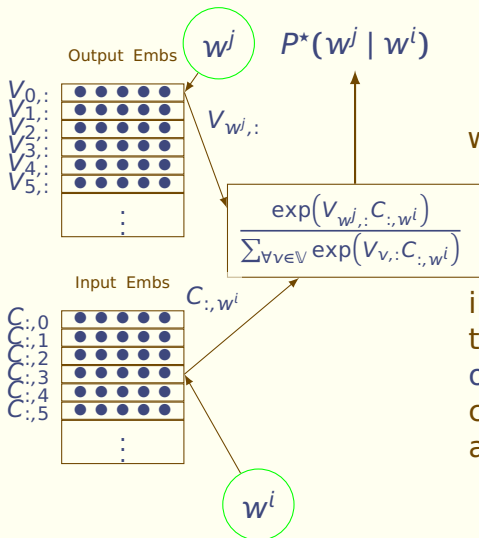
# SkipGram is the most well known of recent word embedding methods



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

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 an iterative algorithm for weighted collocation matrix factorization.

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

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

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

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

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

- ▶ Contrast: PCA is a dimensionality reduction algorithm, that tries to remember the most variant factors
- ▶ Contrast: t-SNE is a dimensionality reduction algorithm, that tries to preserve similarity as distance
- ▶ Compressing knowledge of collocated words into a dense vector, gives us Firth's Criterion.

Sums of embeddings actually link to intersection of collocation probabilities

$$P^*(w^j | w^i) = \frac{\exp(V_{w^j, :} C_{:, w^i})}{\sum_{\forall k \in \mathbb{V}} \exp(V_{k, :} C_{:, w^i})}$$

$$C_{:, a} \propto \log P(\mathbb{V} | a)$$

$$C_{:, b} \propto \log P(\mathbb{V} | b)$$

$$\begin{aligned} \therefore C_{:, a} + C_{:, b} &\propto \log P(\mathbb{V} | a) + \log P(\mathbb{V} | b) \\ &= \log P(\mathbb{V} | a) \cdot P(\mathbb{V} | b) \\ &\propto \log P(\mathbb{V} | b \cap a) \end{aligned}$$

Mikolov et al. (2013), “Distributed representations of words and phrases and their compositionality”

## Matrix product with onehot vector is indexed slicing

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

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

A bag of words can be represented as a vector of the counts of each word in the vocabulary.

For a sequence of words:  $(w^1, w^2, \dots)$

The bag of words can be given by

$$\tilde{x} = \sum_{\forall i} \tilde{e}_{w^i}.$$

The sum of word embeddings for the same sequence is:

$$\sum_{\forall i} C_{:, w^i} = C^T \sum_{\forall i} \tilde{e}_{w^i}$$

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

$$\begin{bmatrix} U & V \end{bmatrix} \begin{bmatrix} \tilde{a} \\ \tilde{b} \end{bmatrix} = U\tilde{a} + V\tilde{b}$$

Thus

$$\begin{aligned} C(\tilde{a} + \tilde{b}) &= C\tilde{a} + C\tilde{b} \\ &= \begin{bmatrix} C & C \end{bmatrix} \begin{bmatrix} \tilde{a} \\ \tilde{b} \end{bmatrix} \end{aligned}$$

A summed input is the same as a  
concatenated input  
with blockwise weight tying.

We are now going to take a very short break



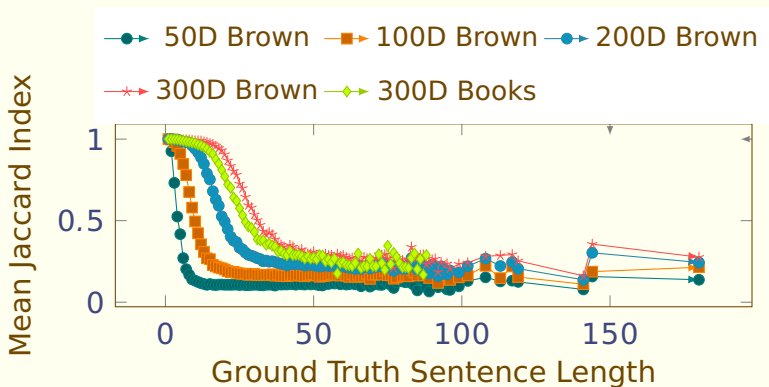
# Bag of words information is not lost in sums of word embeddings

- ▶ A bag of words captures all unigram information in a sentence/document etc
- ▶ A greedy method can (mostly) recover the BOW from a SOWE
  - White et al. (2016), “Generating Bags of Words from the Sums of their Word Embeddings”
    1. Greedily add nearest word to remaining the SOWE to bag
    2. Check each word in bag and swap it for a better one
    3. Repeat until no change.
- ▶ Thus, SOWE captures similar **most** unigram information.

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



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



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

# Sentence embeddings space should partition readily according to paraphrases

- ▶ Paraphrases are defined by bidirectional entailment.
- ▶ This is an equivalence relation
- ▶ It thus gives rise to a partition of natural language space.

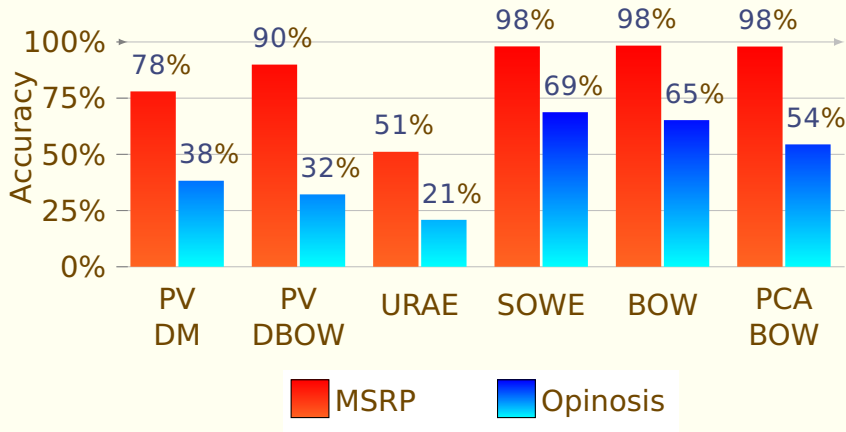
# What does it mean to partition readily?

There are many ways one could define the quality of a space, on its ability to be partitioned according to another linked space's partitions.

Convex	No twists, bulges, holes, jumps etc.
Seperable	Should not overlap, should be separate
Concentrated	small area

Notice: these are the same criteria needed linear SVM to work well.

## When assessing ability to match partitions using a linear SVM classification task



Knowing word content is really useful

# What is going on here?

## PV-DM / PV-DBOW

Le and Mikolov (2014), “Distributed Representations of Sentences and Documents”

*“It shows that the paragraph vectors, when evaluated correctly, do not work better than bag-of-words (bag-of-ngrams being even better)”*

– Tomas Mikolov (23/11/17) w.r.t Mesnil et al. 2014

## URAE

Socher et al. (2011), “Dynamic Pooling and Unfolding Recursive Autoencoders for Paraphrase Detection”

Only 200D so not entirely fair.

Based on binary constituency parse structure

Deep, compressing each layer, 2 inputs to one output.

# What is going on here?

BOW

Bag of Words

Several thousand dimensions

1000D spaces tend to be very separable

No synonym capacity

PCA BOW

Principle Component Analysis Hotelling 1933

Drop down to 300D to match others

PCA is inferior to GloVe as a dimensionality reduction technique, for semantic preservation.

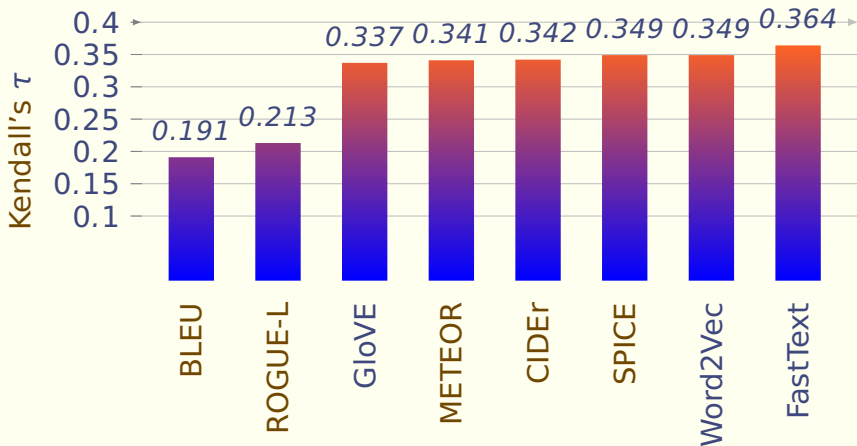
# Consider machine captioning evaluation

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

- ▶ For each image, there are 5 captions.
- ▶ A mix of human generated
- ▶ and machine generated.
- ▶ this is an evaluation of evaluation metrics

Task is to rate the captions in the same order as the human rankers.

## Look what wins



\*Forthcoming publication Naeha Sharif, Lyndon White, Mohammed Bennisamoun, Wei Liu, and Syed Afaq Ali Shah.

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

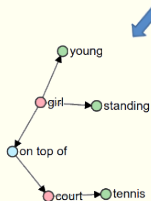
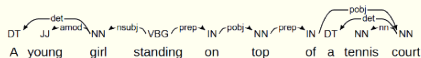


## All captions in COMPOSITE are **fluent**

- ▶ 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)

You could use AMR (Banarescu et al. 2013), or ERS (Bender et al. 2015).

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**

# The proper way to assess adequacy is a semantic 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.

Semantic graph comes from syntactic 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

# Word order is more predictable than you may think

- ▶ Consider some sentence; can you rearrange the words and punctuation and make new sentence
- ▶ Is it grammatical?
- ▶ Is it a paraphrase?
- ▶ Is it likely (or sensible) based on world knowledge?
- ▶ Was it following some standard transform, like just swapping to proper nouns?

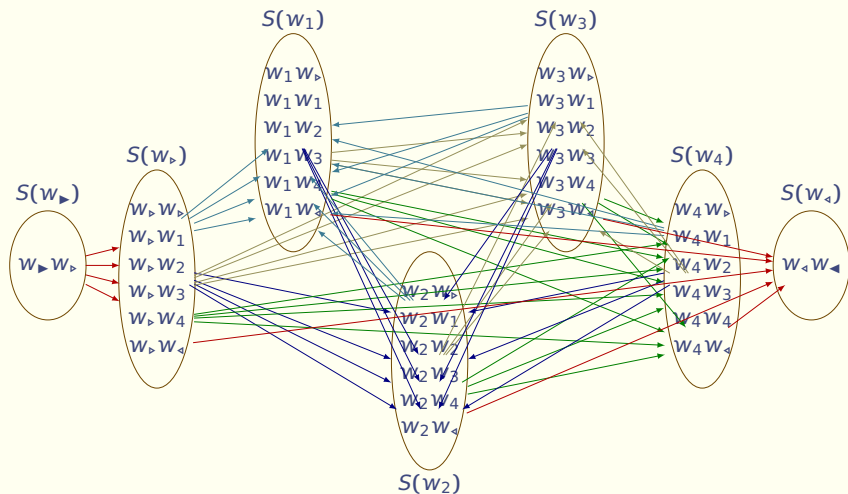
# You can recover most probable sentence order from bag of words

White et al. (2016), “Modelling Sentence Generation from  
Sum of Word Embedding Vectors as a Mixed Integer  
Programming Problem”

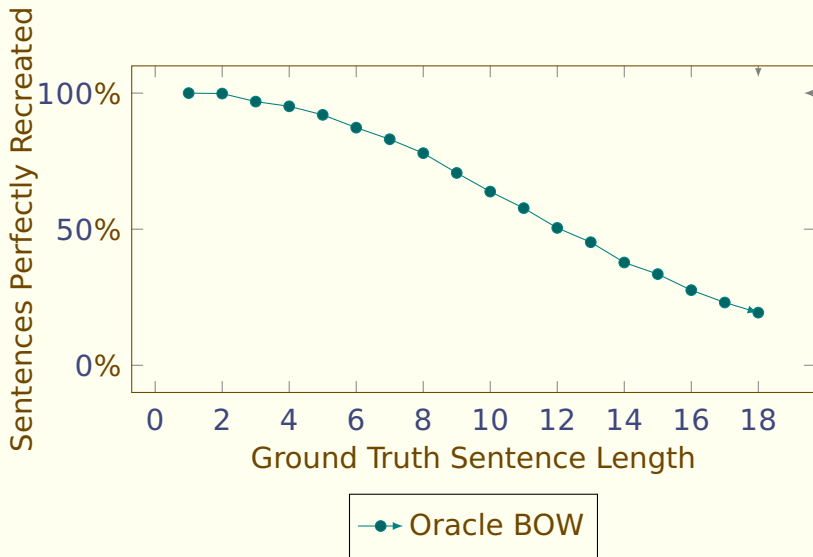
- ▶ Using a **language model** you can evaluate the probability of any given order for a bag of words.
- ▶ With an appropriate **optimization/search** technique you can find the most likely order
- ▶ This particular work was a simple **trigram language model**

Not a great way to generate sentences,  
though

For trigram language models, word ordering is a variation of travelling salesman

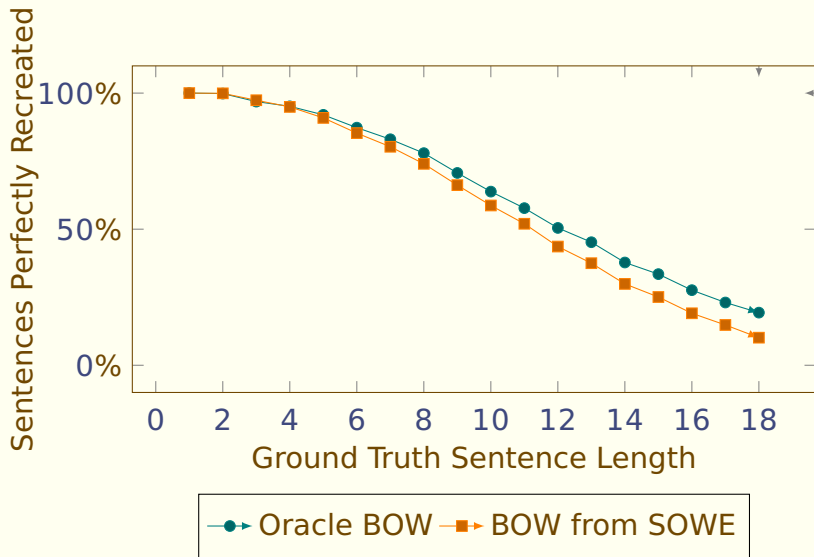


# How well can word order be recovered?

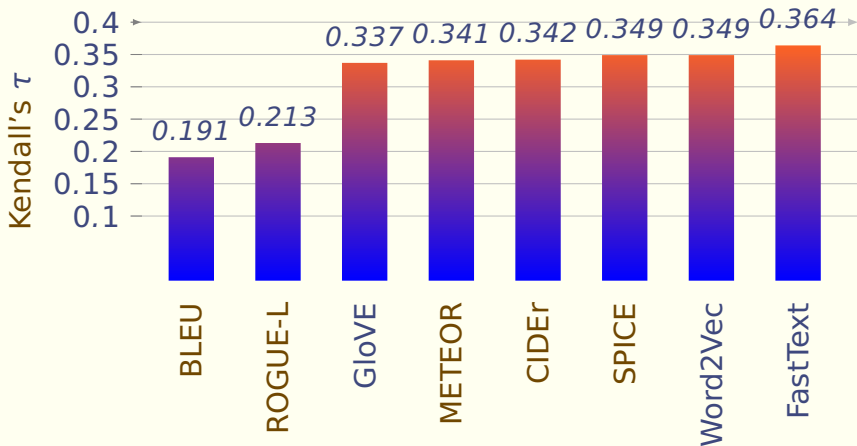




# How well can word order be recovered?



## Look what wins



\*Forthcoming publication Naeha Sharif, Lyndon White, Mohammed Bennisamoun, Wei Liu, and Syed Afaq Ali Shah.

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

## Why it wins is now clear

- ▶ A caption being close in SOWE space to reference, means
  - ▶ Same word content
  - ▶ One of only a small number of possible orders
- ▶ Language models are really effective
  - ▶ If a language model based system has the right words, it will be creating them in the right order.
  - ▶ Even the very basic language model I showed could do that.

We only need to access adequacy, if fluency is always high.

# Colors look like a complex subdomain

- ▶ A lot of structure
- ▶ A lot of words used in different ways
  - ▶ noun-adjective dual identity
  - ▶ arbitrary nouns being used as color words
  - ▶ modifiers, meta-modifiers
  - ▶ Order matters for identity

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

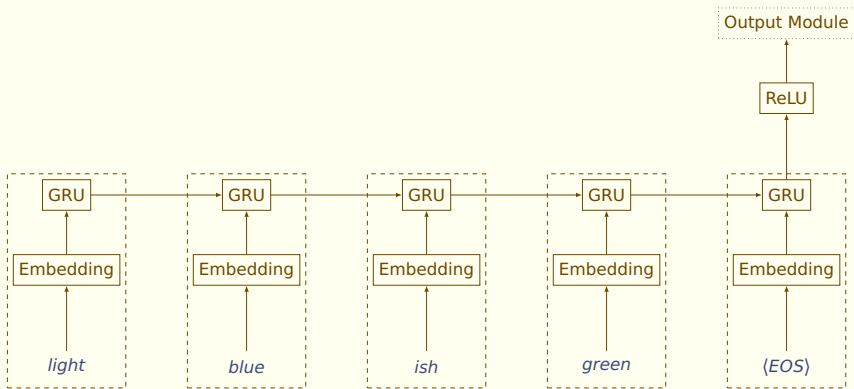
color modifier      head color  
dark      greenish      blue  
basic modifier      meta modifier

color modifier      head color  
(red)      (from noun)  
rudd y      coral  
meta modifier

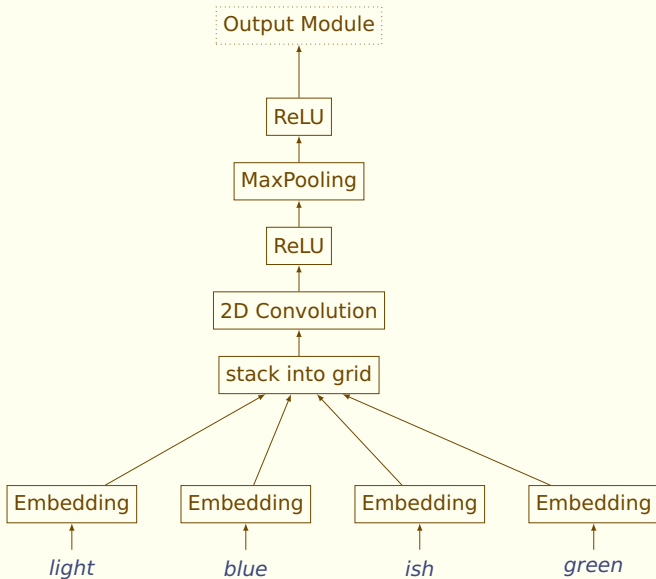
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and so using complicated methods leads to  
worse performance.

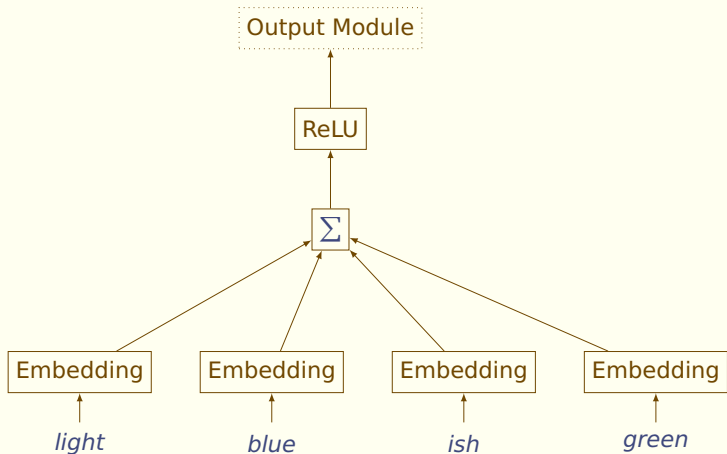
# RNN input module



# CNN input module

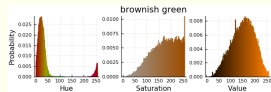
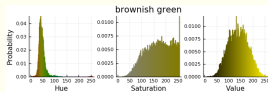
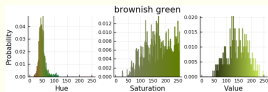
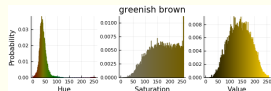
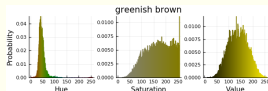
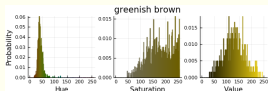
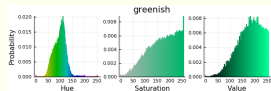
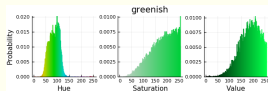
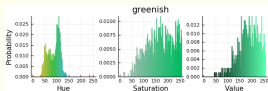
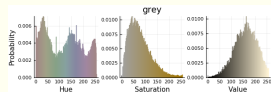
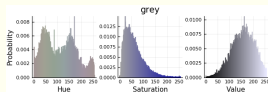
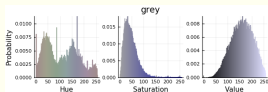


# SOWE input module





# Some example outputs from the model

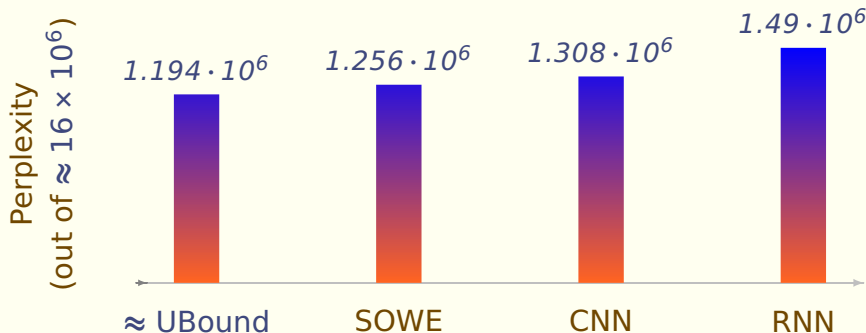


Training Data

SOWE

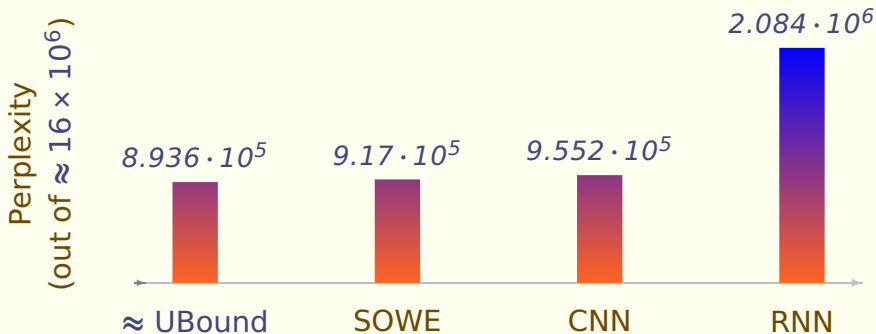
RNN

# Full Distribution Estimation



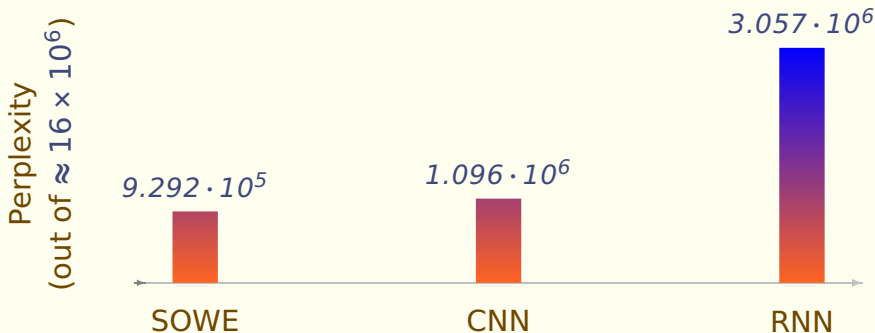
Lower perplexity is better

# Order Distribution Estimation



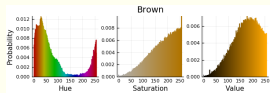
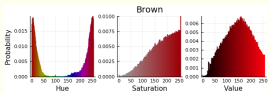
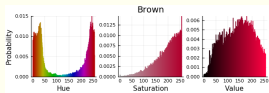
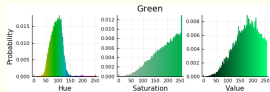
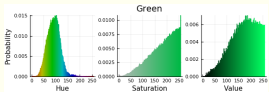
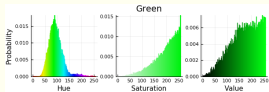
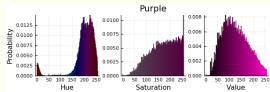
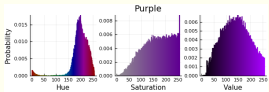
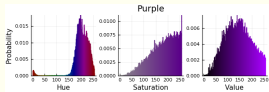
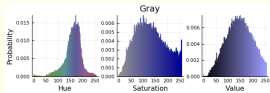
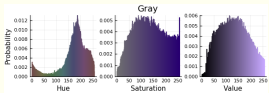
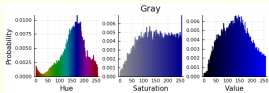
Lower perplexity is better

# Unseen Combinations of Terms Dist Est



Lower perplexity is better

## OOV model outputs



# SOWE

# CNN

## RNN

## 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.
- ▶ They are being constantly affirmed:
  - ▶ if you are doing anything like [text classification](#) SOWE is all you need.
  - ▶ [Arora, Liang, and Ma \(2017\)](#), “A simple but tough-to-beat baseline for sentence embeddings”

# We need **adversarial** examples to advance the field

- ▶ People use words to communicate – they are trying to be clear.
- ▶ Adversarial examples are easy enough to create, but rare in-practice.
- ▶ Handling them can cause problems that overall decrease performance.

but do not forget the **non-adversarial majority**

# Maybe we are not really doing natural language understanding

- ▶ Often NLP is an engineering discipline
- ▶ and Computational Linguistics is maybe a scientific one
- ▶ NLP: what can linguistics do for you
- ▶ CL: what can you do for linguistics

As engineers doing something useful is what matters.

but practically we are certainly doing something useful