# IN5550: Neural Methods in Natural Language Processing
## Sub-lecture 5.6
## *Contextualized embeddings*

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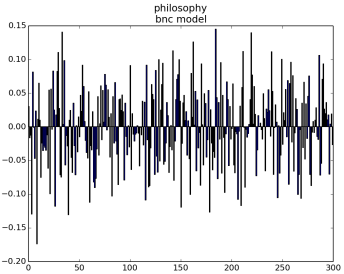

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# Brief Recap

## Word embeddings

- Distributional models are based on distributions of word co-occurrences in large training corpora;
- they represent lexical meanings as dense vectors (embeddings);
- the representations are also distributed: meaning is expressed via values of multiple vector entries;
- particular vector entries (features) are not directly related to any particular semantic 'properties', and thus not directly interpretable;
- words occurring in similar contexts have similar vectors.

Important: each word is associated with exactly one dense vector.
Hence, such models are sometimes called 'static embeddings'.



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# Problems of static word embeddings

**Meaning is meaningful only in context**

English sentences with the word 'bank' in two different senses:

1. '*She was enjoying her walk down the quiet country lane towards the river bank.*' (**sense 0**)
2. '*The bank obtained its customer payment or reimbursement and released the goods to the customer.*' (**sense 1**)

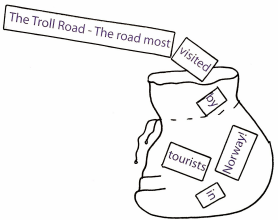
Even most perfect 'static' embeddings will always yield the same vector for 'bank' . But in fact the meaning is different!

What can be done?

# Problems of static word embeddings

One can represent 'bank' as the average embedding of all the context words [Schütze, 1998].
But:

1. Context words themselves can be ambiguous.
2. Their contextual senses will be lost.
3. In this 'bag of embeddings', word order information is also entirely lost.




So, what to do?

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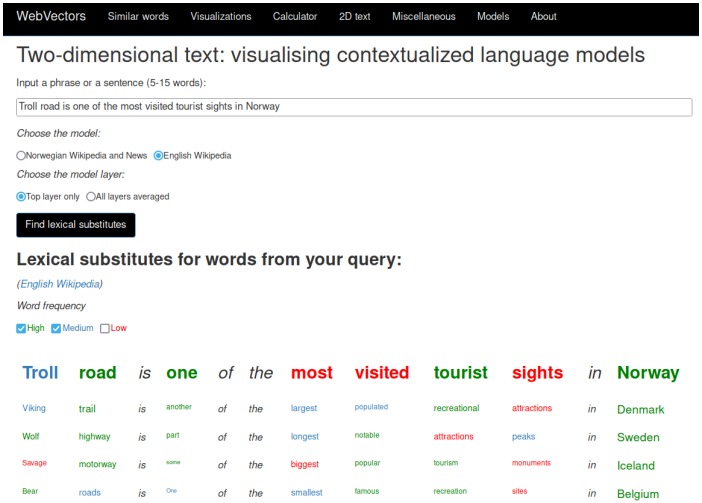

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# Solution: contextualized embeddings

- Idea: at inference time, assign each word a vector which is a function of the whole input phrase! [Melamud et al., 2016, McCann et al., 2017]
- Now our word representations are context-dependent: one and the same word has different vectors in different contexts.
- Token embeddings VS type embeddings.
- As an input, our model takes not an isolated word, but a phrase, sentence or text.

# Solution: contextualized embeddings

http://vectors.nlpl.eu/explore/embeddings/en/contextual/



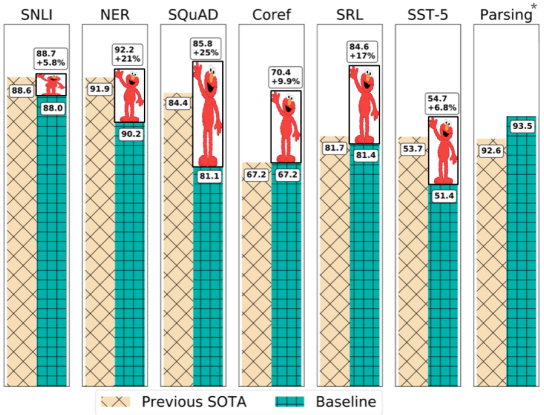
# Solution: contextualized embeddings

## More complex is more expressive

- There is no one-to-one correspondence between a word and its embedding any more.
- Word vectors are not fixed: they are learned functions of the internal states of a deep neural network.
- The architecture itself is no more a simple lookup table:
- it is a full-fledged language model.

# Solution: contextualized embeddings

- 2018: ELMo (Embeddings from Language MOdels) conquered almost all NLP tasks
  [Peters et al., 2018]




*Kitaev and Klein, ACL 2018 (see also Joshi et al., ACL 2018)

- 2019: BERT (Bidirectional Encoder Representations from Transformer) did the same
  [Devlin et al., 2019]

# Solution: contextualized embeddings

**Both architectures used deep neural networks for language modeling**

- ELMo employed bidirectional LSTMs.
- BERT employed transformers with self-attention (next week).
- Many other Sesame street characters made it into NLP since then!

**Deep Neural Networks Are Our Friends**

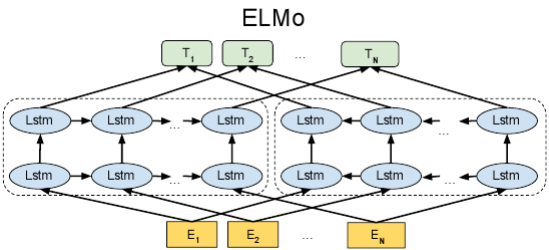


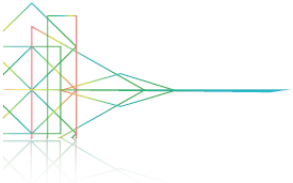
Wang Ling Google DeepMind

# We need to talk about ELMo

## Embeddings from Language MOdels

- Contextualized ELMo models are trained on raw text, optimizing for the language modeling task (next word prediction).
- Two BiLSTM layers over one layer of a character-based convolutional network (CNN).
- Takes sequences of characters as an input.
  - ...actually, they are UTF-8 code units (bytes), not characters *per se*.
- LSTM output states for each word are the ELMo embeddings.





# Method

ELMo represents a word $t_k$ as a linear combination of corresponding hidden layers (inc. its embedding)

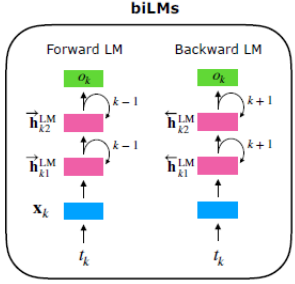
ELMo is a task specific representation. A down-stream task learns weighting parameters

$$\mathbf{ELMo}_k^{\text{task}} = \gamma^{\text{task}} \times \sum \left\{ s_2^{\text{task}} \times \mathbf{h}_{k2}^{\text{LM}},\ s_1^{\text{task}} \times \mathbf{h}_{k1}^{\text{LM}},\ s_0^{\text{task}} \times \mathbf{h}_{k0}^{\text{LM}} \right.$$

$$\left. ([\mathbf{x}_k ; \mathbf{x}_k]) \right.$$

Concatenate hidden layers

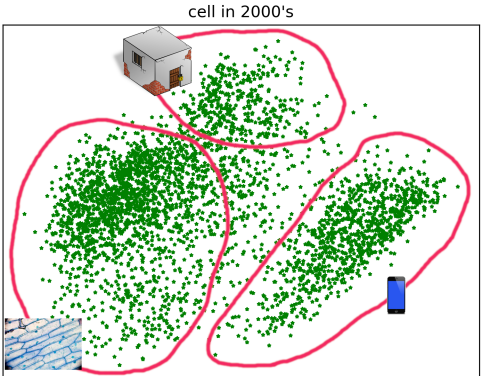
$$[\overrightarrow{\mathbf{h}}_{kj}^{\text{LM}} ; \overleftarrow{\mathbf{h}}_{kj}^{\text{LM}}]$$




Unlike usual word embeddings, ELMo is assigned to every *token* instead of a *type*

[Peters et al., 2018]

# Representing word senses




- 2-dimensional PCA projections of ELMo embeddings for each occurrence of *'cell'* in the Corpus of Historical American English (2000-2010).
- Left clusters: biological and prison senses.
- Large cluster to the right: 'mobile phone' sense.

NB: each dot represents an embedding of *'cell'* in a particular sentence.

# We need to talk about ELMo

Norwegian ELMo in word sense disambiguation (PCA projection of '*rett*' embeddings):



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# Using contextualized embeddings

## How one uses contextualized embeddings?

1. As 'feature extractors': pre-trained contextualized representations are fed to the target task (e.g., document classification)
   - conceptually, the same workflow as with 'static' word embeddings
2. Fine-tuning: the whole model undergoes additional training on the target task data
   - Potentially more powerful, but computationally expensive. More on that later in the course.

| Conditions | | | Guidelines |
|---|---|---|---|
| Pretrain | Adapt. | Task | |
| Any | ❄ | Any | Add many task parameters |
| Any | 🔥 | Any | Add minimal task parameters<br>⚠ Hyper-parameters |
| Any | Any | Seq. / clas. | ❄ and 🔥 have similar performance |
| ELMo | Any | Sent. pair | use ❄ |
| BERT | Any | Sent. pair | use 🔥 |

Table 1: This paper's guidelines for using feature extraction (❄) and fine-tuning (🔥) with ELMo and BERT. Seq.: sequence labeling. Clas.: classification. Sent. pair: sentence pair tasks.

Recommendations from [Peters et al., 2019]

# References I


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