Contemporary Natural Language Processing reflected in Language Modeling

Andrey Kutuzov

HSE

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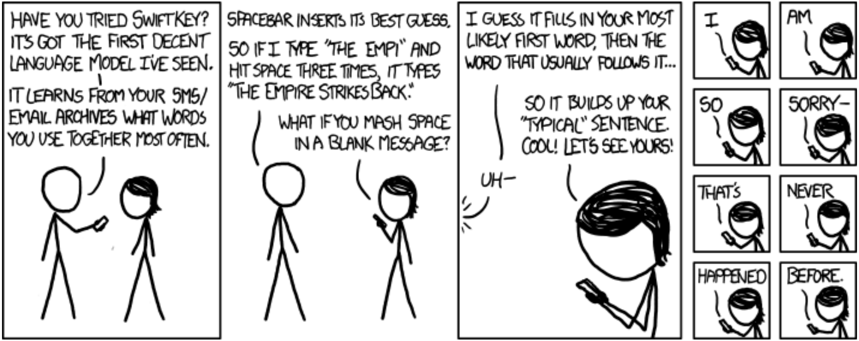
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IT LEARNS FROM YOUR SMS/EMAIL ARCHIVES WHAT WORDS YOU USE TOGETHER MOST OFTEN.
SPACEBAR INSERTS ITS BEST GUESS. SO IF I TYPE "THE EMPI" AND HIT SPACE THREE TIMES, IT TYPES "THE EMPIRE STRIKES BACK."
WHAT IF YOU MASH SPACE IN A BLANK MESSAGE?
I GUESS IT FILLS IN YOUR MOST LIKELY FIRST WORD, THEN THE WORD THAT USUALLY FOLLOWS IT...
SO IT BUILDS UP YOUR "TYPICAL" SENTENCE. COOL! LET'S SEE YOURS!
UH–
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(XKCD)

Contents

Language modeling task definition

Modeling linguistic sequences

- Task 1: to assign probabilities to natural language sequences:
  - 'What is the probability of *lazy dog*?'
  - 'What is the probability of *The quick brown fox jumps over the lazy dog*?'
  - 'What is the probability of *green colorless ideas sleep furiously*?'
- Task 2: to assign a probability for the likelihood of a word a to follow a word sequence S of length n:
  - 'What is the probability of seeing *jumps* after *The quick brown fox*?'
- These two tasks are mathematically equivalent.

$$P(w_{1:n}) = P(w_1)P(w_2|w_1)P(w_3|w_{1:2})P(w_4|w_{1:3})...P(w_n|w_{1:n-1}) \quad (1)$$

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Markov assumption

- Multiplying hundreds or thousands of probabilities can be cumbersome.
- Hence, the Markov assumption a.k.a. Markov property:
  - **future is independent of the past given the present**.
- In LM context: we can look at only the last k words.
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- Language modeling is widely used in NLP applications (machine translation, chat-bots, summarization...).
- LMs are measured by perplexity (how surprised is the model by test word sequences, the lower the better).
- For a test corpus of n word tokens:

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Extract probabilities from corpus counts!

1. Take a large enough corpus;
2. count all sequences;
3. use maximum likelihood estimate for each word m:
   $\hat{P}\left((w_{i+1} = m) \,|\, w_{i-k:i}\right) = \frac{\#(w_{i-k:i+1})}{\#(w_{i-k:i})}$
4. where $\#$ are corpus counts.
5. Et voila! You have probabilities for all seen words given previous sequences:
   $\hat{P}\left((w_4 = jumps) \,|\, [the, quick, brown, fox]\right) = 0.5$
6. .. because your corpus had 2 occurrences of '*the quick brown fox*', and in one case it was followed by '*jumps*', while in another by '*barks*'.

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- Sequence not seen in the training data? $\hat{P} = 0$
- There are ways to deal with unseen events...
  - but they are tricky...
  - ...and do not scale well to larger n-grams.
- Unseen events become more frequent as one increases k;
- number of possible word combinations is $|V|^k$;
- for the vocabulary of 10 000 words and 5-grams: 10000^5.
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- Representation power not shared between similar words
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- concatenate learned embeddings of the previous k words;
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- ...with hidden layers and non-linearities;
- cross-entropy loss, the next words as the gold predictions.
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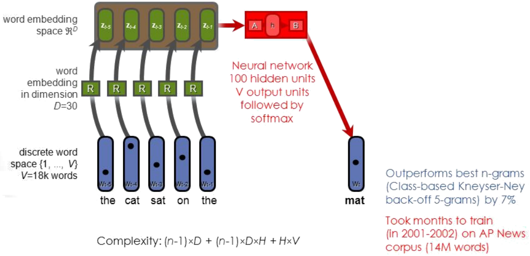

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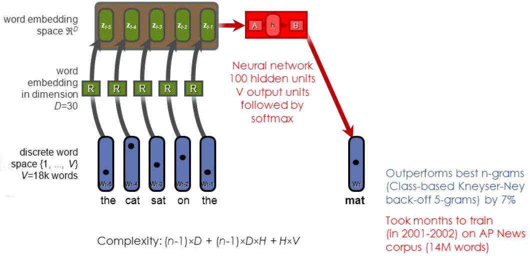

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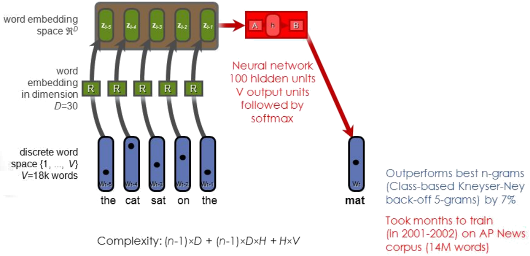

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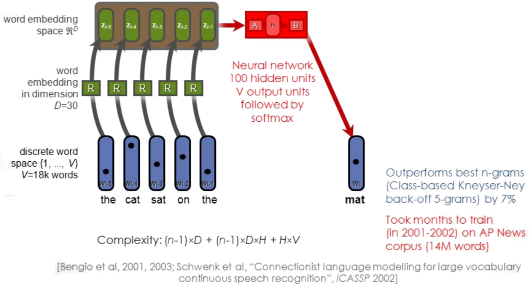

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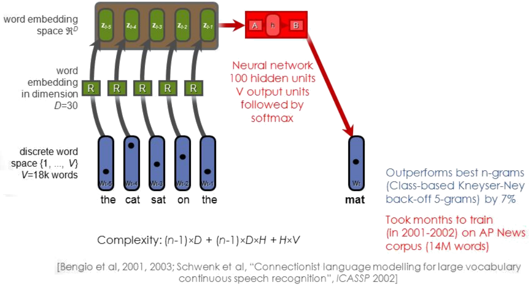

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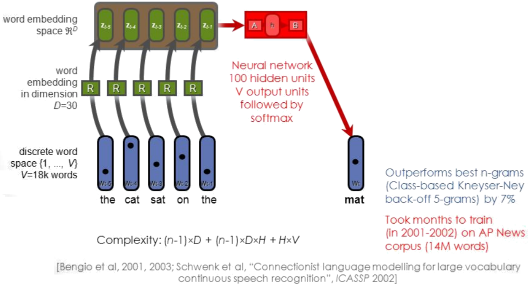

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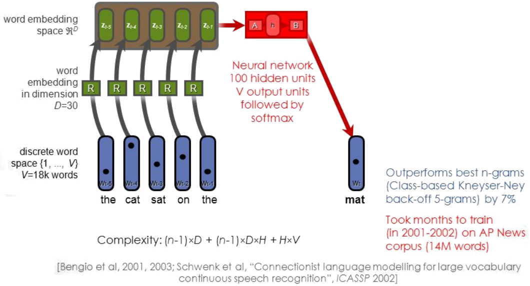

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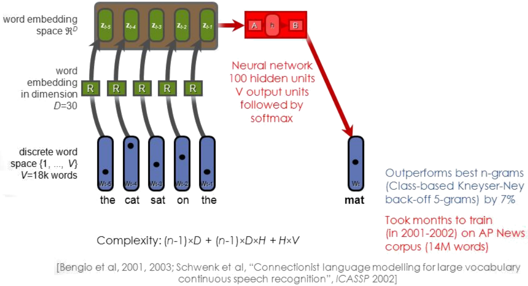

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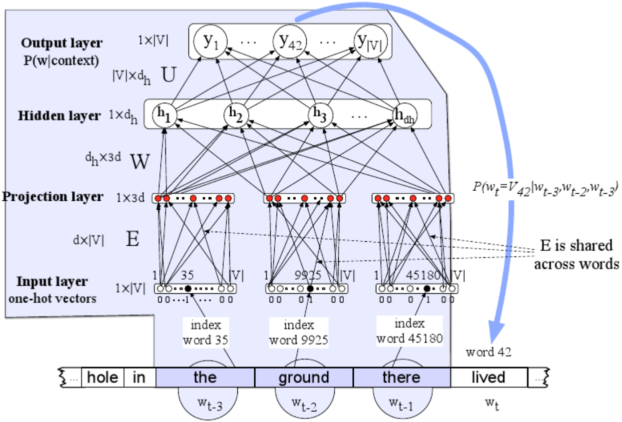

Feed-forward neural LM moving through a text

(from Jurafsky and Martin, 2018)

Modern neural LMs are mostly recurrent (gated RNNs like LSTM or GRU).

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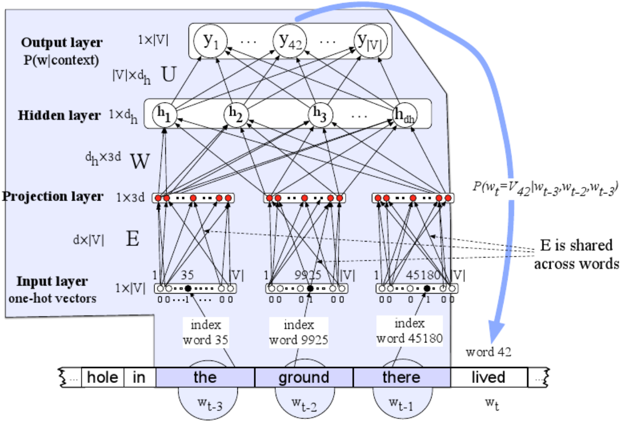

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- Scales well: higher k leads to linear increase in the parameters number...
- ...in traditional LMs it was polynomial.
- Words in different positions share statistical strength.
- Generalizations to unseen data: similar words get similar representations in the embedding and the output layers:
  - '*fox eats*': seen 1000 times; '*dog eats*': seen 1000 times; '*wolf eats*': seen 0 times; $\hat{P}([wolf, eats]) \gg 0$, because '*wolf*' is similar to '*fox*' and '*dog*'.
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  - '*fox eats*': seen 1000 times; '*dog eats*': seen 1000 times; '*wolf eats*': seen 0 times; $\hat{P}([wolf, eats]) \gg 0$, because '*wolf*' is similar to '*fox*' and '*dog*'.
- Can easily add more hidden layers.

Neural language modeling

Shortcomings

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- Increasing the output $|V|$ can significantly slow down the network (already slower than traditional models).
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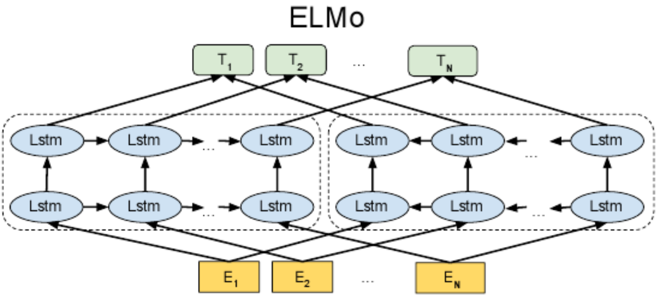
Language models can provide contextualized word embeddings, with different representations in different contexts.

- Embeddings from Language MOdels (ELMo) use LSTMs [Peters et al., 2018]
- Bidirectional Encoder Representations from Transformer (BERT) use bidirectional transformers [Devlin et al., 2018]



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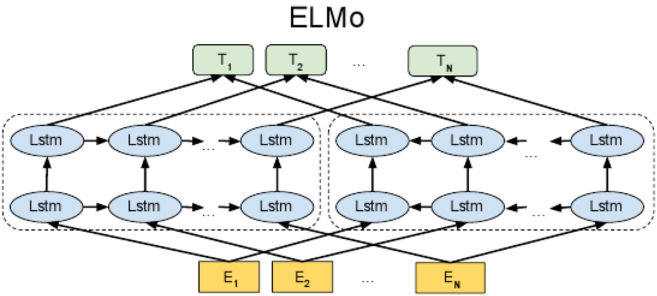

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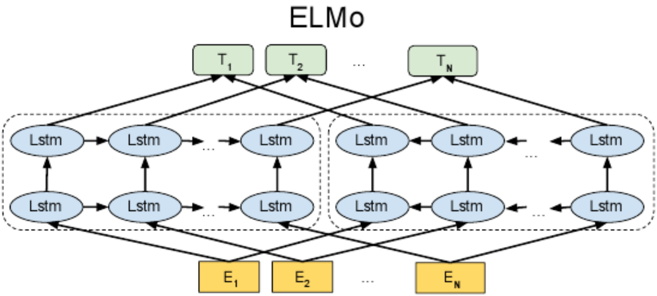

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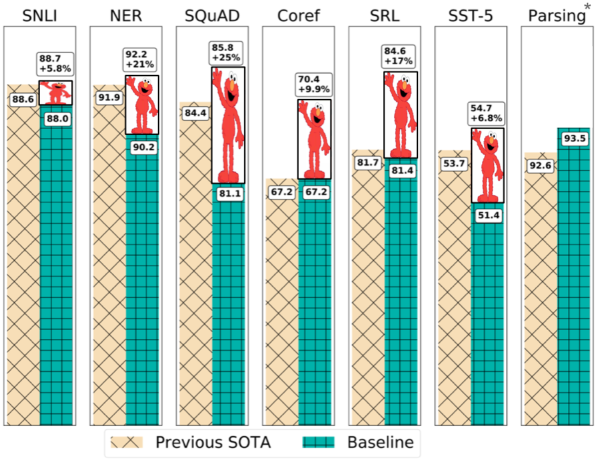
ELMo seem to improve any NLP task you apply them for:



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

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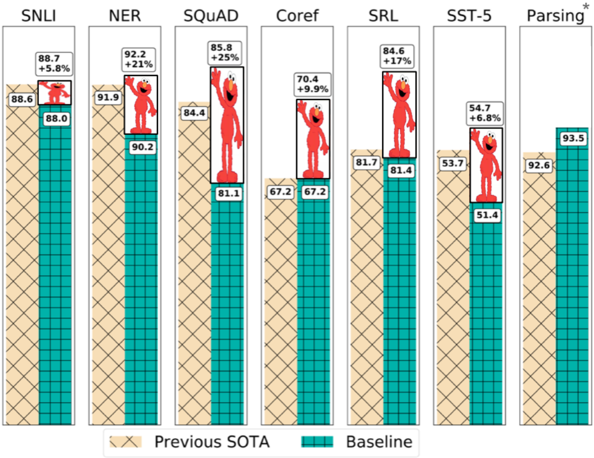

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Modes of usage

1. 'as is': contextualized representations are fed into the overarching architecture like the old-school 'static' embeddings;
2. the whole model is fine-tuned on target task data.

Layers of ELMo reflect language tiers

- word embedding layer: morphology;
- the first LSTM layer: syntax;
- the second LSTM layer: semantics (including word senses).

More info

- https://allennlp.org/elmo
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