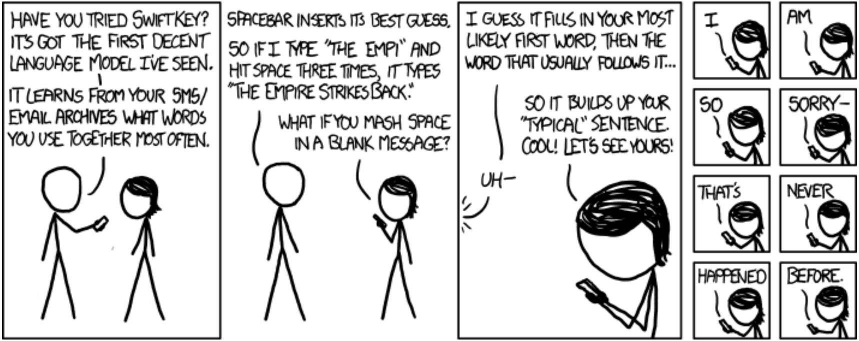
Contemporary Natural Language Processing reflected in Language Modeling

Andrey Kutuzov

UTMN

3-4 July 2019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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-
I
AM
SO
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THAT'S
NEVER
HAPPENED
BEFORE.

(XKCD)

Outline

- 15:45 - 17:15 : 1st part
- 17:15 - 17:30 : break
- 17:30 - 19:00 : 2nd part

What we will cover

1. 'Toy' language models:
   - Random LM
   - Frequency-based LM
2. Markov trigram LMs
3. LMs based on recurrent neural networks (RNNs):
   - Long short-term memory (LSTM)
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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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- Multiplying hundreds or thousands of probabilities can be cumbersome.
- Hence, the Markov assumption a.k.a. Markov property:
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- In LM context: we can look at only the last k words.
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- LMs are evaluated by perplexity (how surprised is the model by test word sequences, the lower the better).
- For a test corpus of n word tokens:

$$probs = \sum_{i=1}^{n} \log_2 LM(w_i | w_{1:i-1})$$
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- Always predict a random word from V.
- Uniform probability for all words: $\frac{1}{|V|}$

Frequency-based LM

- Extract frequency vocabulary V from the training corpus of size n.
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Take context into account: Markov n-gram models

1. Take a large enough corpus;
2. count all word sequences of length k;
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, for example:
   $\hat{P}\left((w_4 = jumps) \,|\, [the, quick, brown, fox]\right) = 0.6$
6. .. because your corpus had 10 occurrences of '*the quick brown fox*', and in 6 cases it was followed by '*jumps*', while in another 4 cases by '*barks*'.

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Many shortcomings

- 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.
- Number of parameters raises polynomially when increasing $|V|$ and exponentially when increasing k.
- Model size quickly goes insane.

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Lack of generalization power

Words are discrete features:

- Representation power not shared between similar words
- we saw '*fox eats*' and '*dog eats*' 1000 times each
- we never saw '*wolf eats*'
- the probability of '*wolf eats*' will still be 0.

However, Markov models still work surprisingly well.

Let's experiment a bit with the code.

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Question:

why using frequencies does not result in better perplexity?

Answer:

Because of Zipf law

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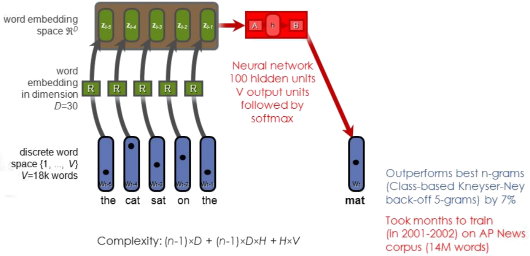
- concatenate learned embeddings of the previous k words;
- this concatenation is fed into a feed-forward neural network...
- ...with hidden layers and non-linearities;
- cross-entropy loss, the next words as the gold predictions.
- Output probability distribution over possible next words across the whole vocabulary V (using softmax and the second embedding matrix).
- Input and output vocabularies can be different.



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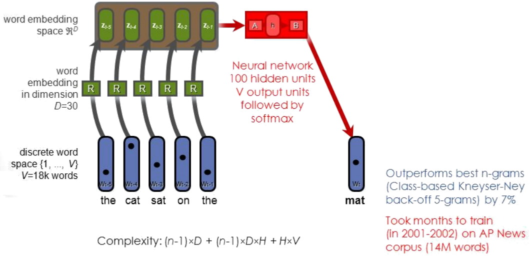

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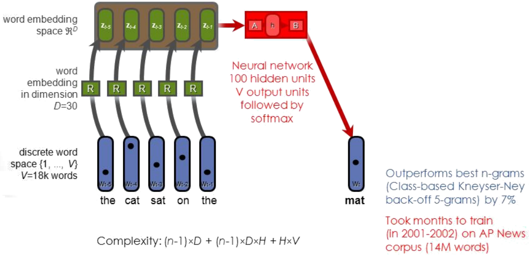

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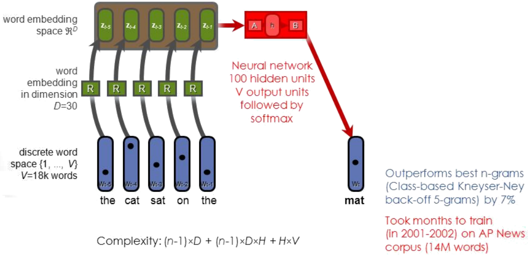

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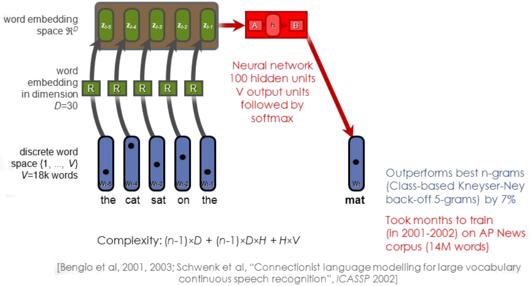

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- Neural LM model proposed in [Bengio et al., 2003]:
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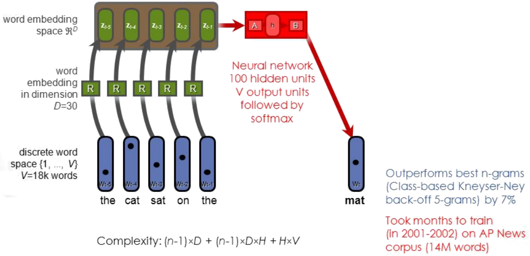

[Bengio et al, 2001, 2003; Schwenk et al, "Connectionist language modelling for large vocabulary continuous speech recognition", ICASSP 2002]

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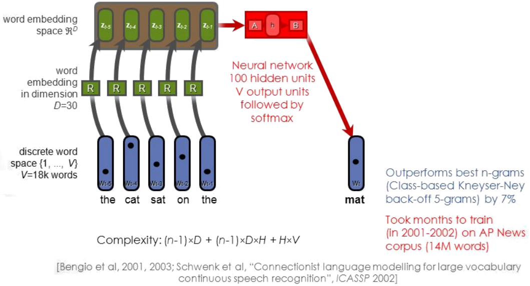

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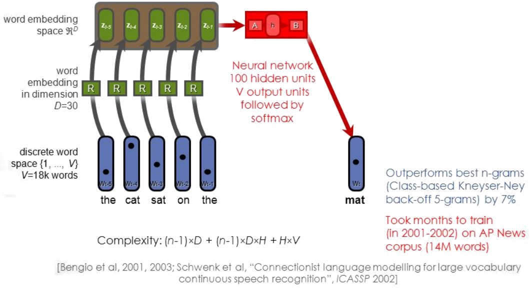

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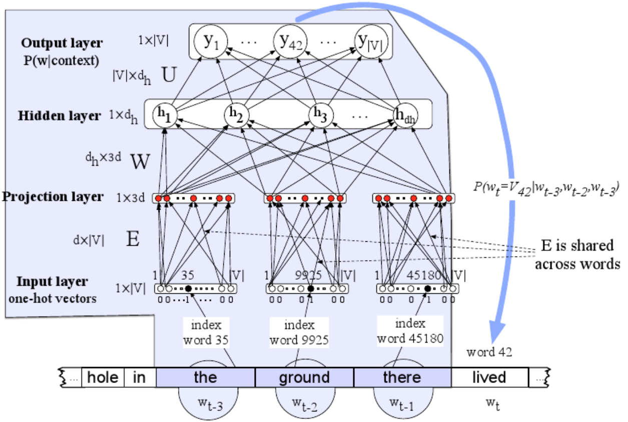

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(from Jurafsky and Martin, 2018)

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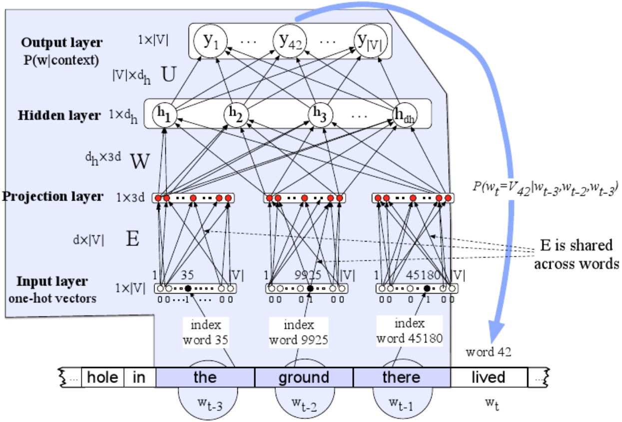

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- ...in traditional LMs it was exponential.
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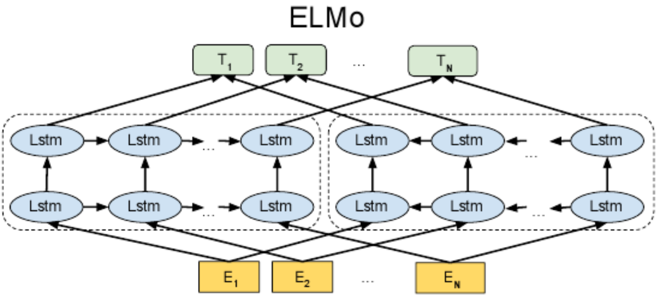

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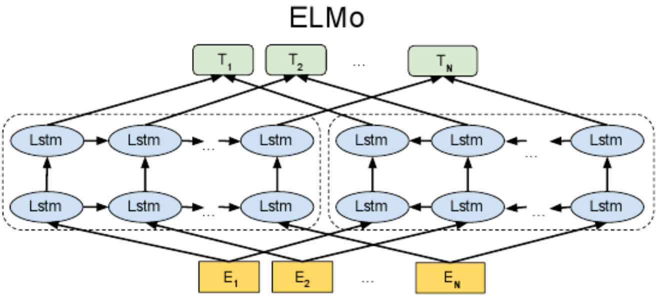

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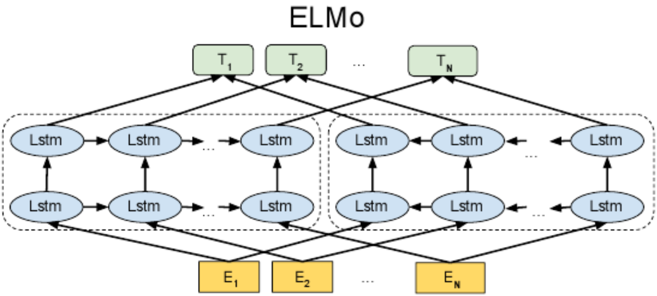

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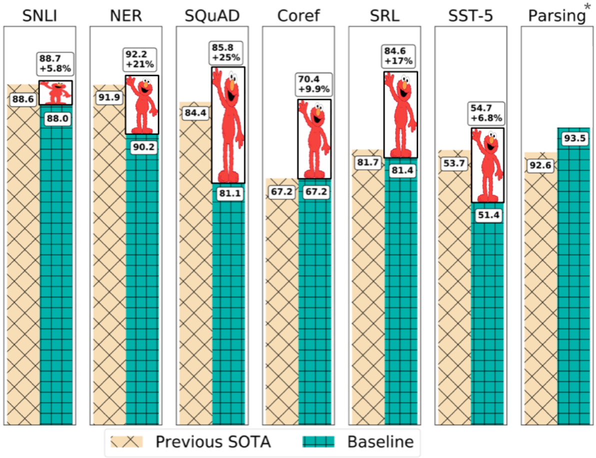

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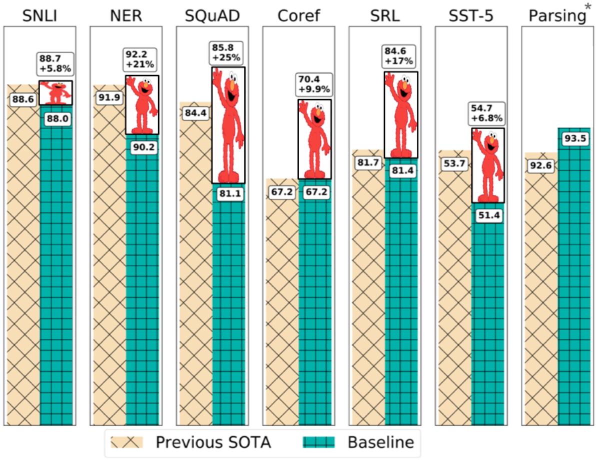

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