IN5550: Neural Methods in Natural Language Processing
Sub-lecture 4.4
Deep learning and language models

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2. Neural LM and word embeddings
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New way: neural language modeling



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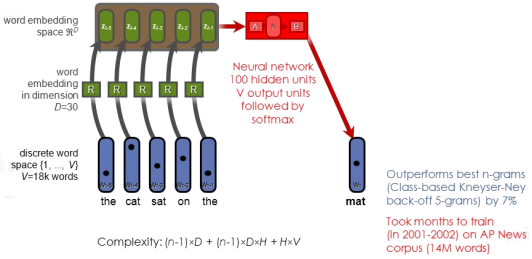
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- Output probability distribution over possible next words across the vocabulary V (using softmax and the second embedding matrix).

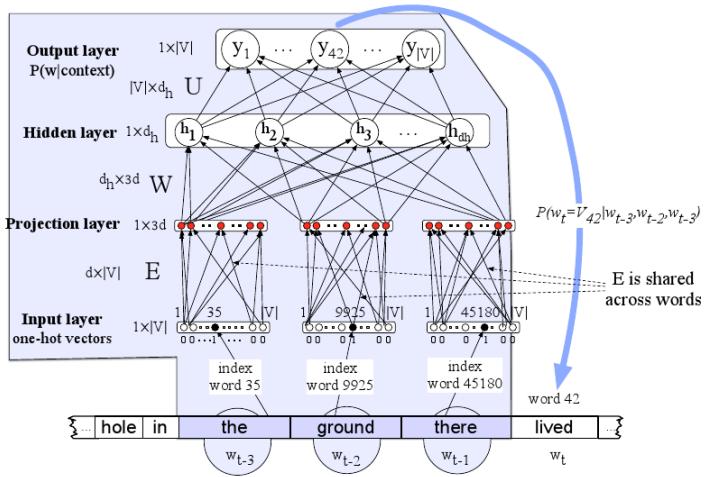
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- Input and output vocabularies can be different.



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

New way: neural language modeling



Feedforward neural LM moving through a text

(from Jurafsky and Martin, 2019)

New way: neural language modeling



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- This online demo uses transformer-based GPT-2 [Radford et al., 2019] for language generation:
  - `https://talktotransformer.com/`
- More on that in the next lectures.

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Benefits

- Outperforms traditional LMs as measured by perplexity.

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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*'.

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- There are ways to deal with this (more next week).

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Neural LM and word embeddings



What about word embeddings? Let's recall:

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Neural LM and word embeddings



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How come that we can get good word embeddings without any manual supervision? Will see next week!

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Next group session: February 15



- Working with word embeddings

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Next week lecture trailer



- Obligatory 1 results

Next week lecture trailer

- Obligatory 1 results

Distributional hypothesis and distributed word embeddings

- Distributional hypothesis: '*Meaning is context*'
- Word2vec revolution.
- Training word embeddings on large text corpora.

References I

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