ELEC-E5510 Speech Recognition

Recurrent Neural Networks in Language Modeling

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Department of Signal Processing and Acoustics

Introduction

Why not just n-grams?

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- High order n-grams are rare
- Using large n-grams is inefficient
- Google's English n-grams: 24 GB, up to 5-grams (that appear at least 40 times)

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Neural LM, input words

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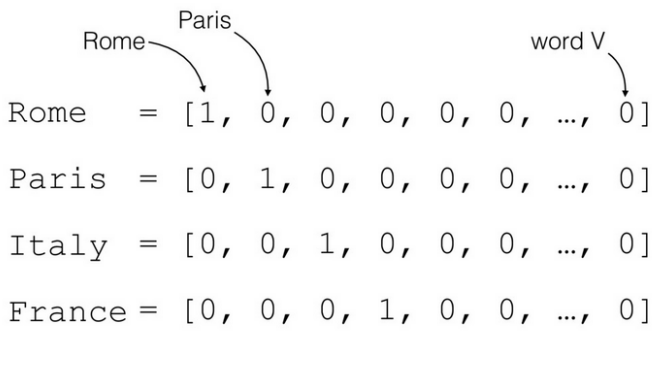

Picture by Marco Bonzanini

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- Don't forget to submit the answers in MyCourse!

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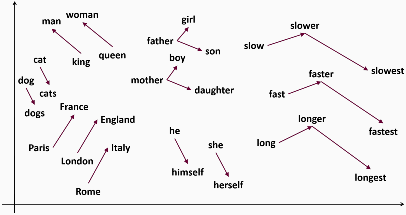

Picture by Samy Zafrany

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- Using a few thousand units could cover a large vocabulary

Neural LM, long context

Using context with NNLM

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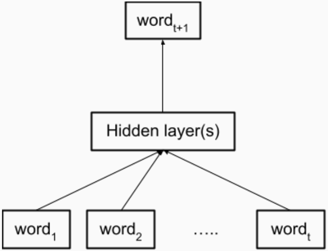

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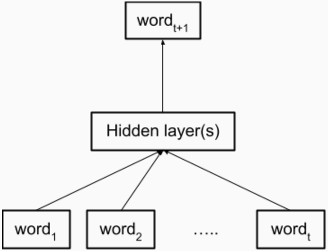

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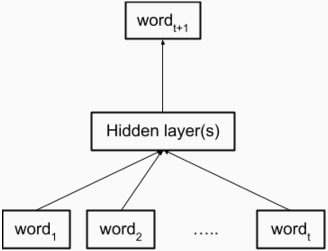

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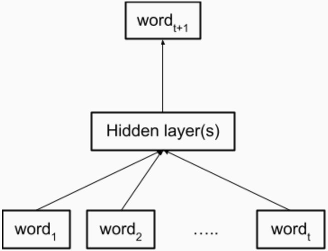

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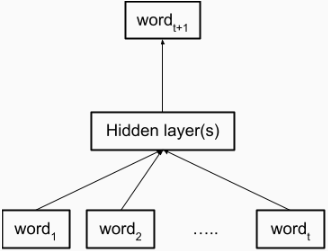

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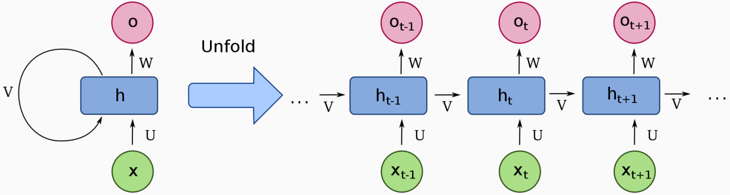

Picture by Wikipedia

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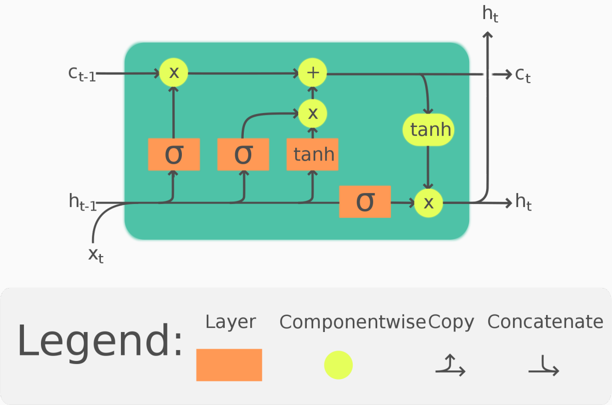

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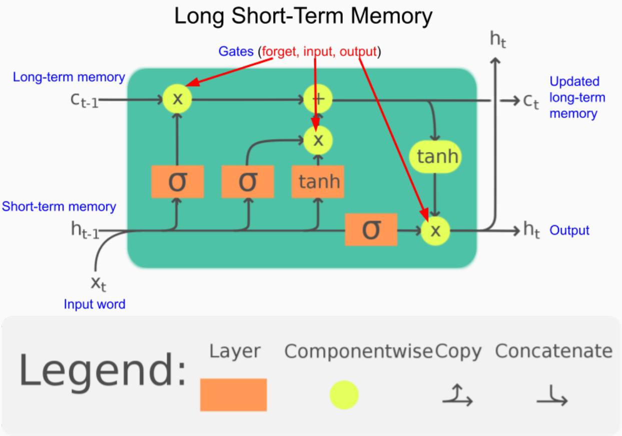

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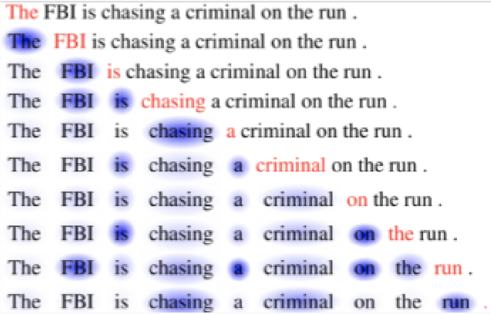

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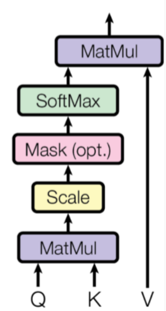

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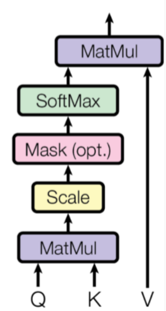

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Note: this it the dot-product attention variant. There are several other ways to compute the scores (for more see Attention-Tutorial)

Efficient NNLM Training

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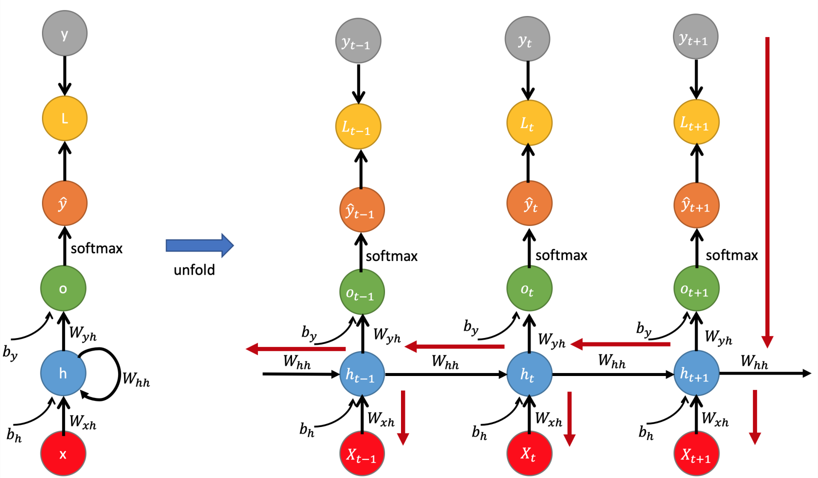

Picture by Mustafa Murat Arat

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- We can exploit this to reduce the required number of computations!

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Using NNLM in ASR

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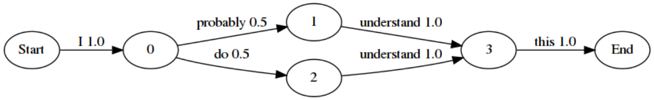

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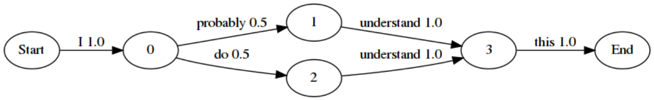

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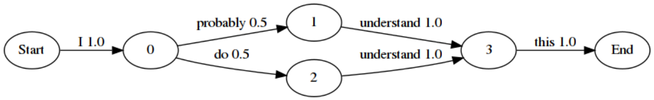

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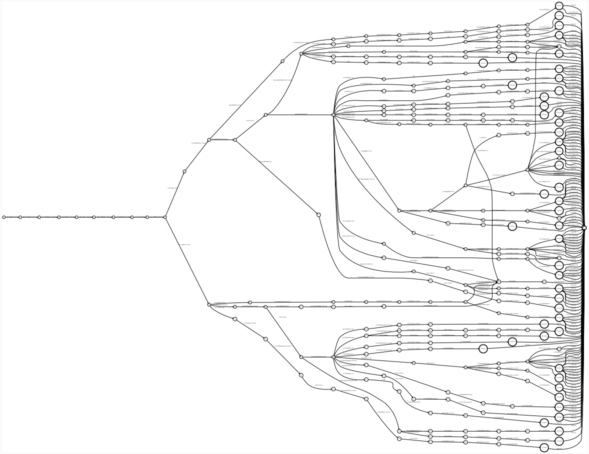

Summary

The main topics briefly explained in this presentation:

1. NNLM
2. Recurrent models
3. Attention
4. Techniques to make the training efficient