Deep Generative Language Models

DGM4NLP

Miguel Rios
University of Amsterdam

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Outline

Recap Generative Models of Word Representation

Discriminative embedding models
word2vec

In the event of a chemical spill, most children know they should **evacuate** *as advised by people in charge.*

Place words in $\mathbb{R}^d$ as to answer questions like

"Have I seen this word in this context?"

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Place words in $\mathbb{R}^d$ as to answer questions like

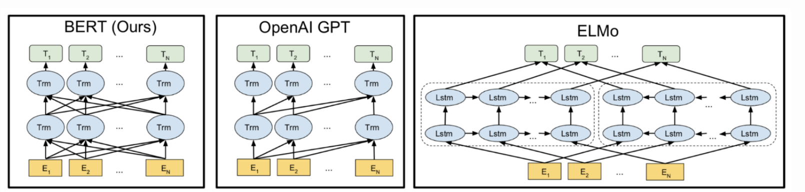
"Have I seen this word in this context?"

Fit a binary classifier

- positive examples
- negative examples

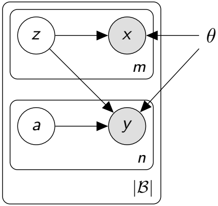
Recap Generative Models of Word Representation

- The models processes a sentence and outputs a word representation:



Recap Generative Models of Word Representation

quickly evacuate the area / deje el lugar rápidamente



[redacted]

X

Z

A

Z_a

Y

[redacted]

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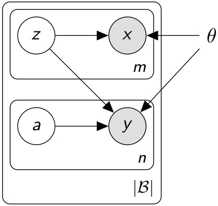

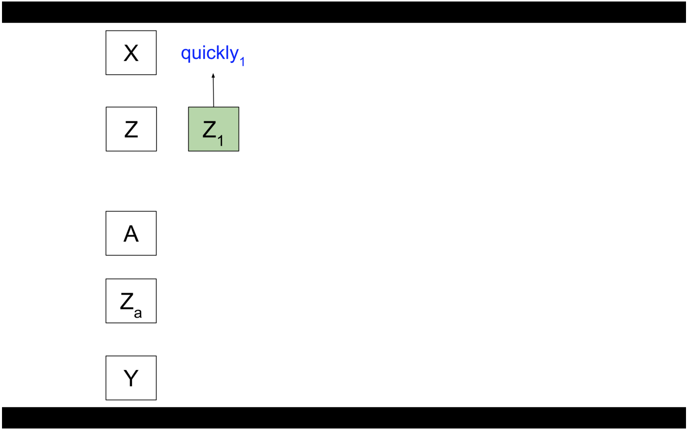

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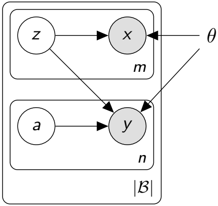

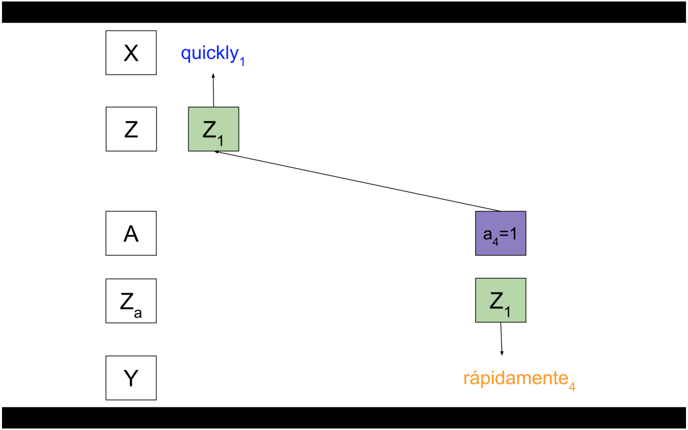

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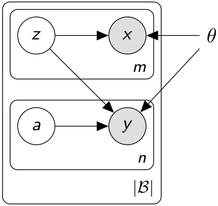

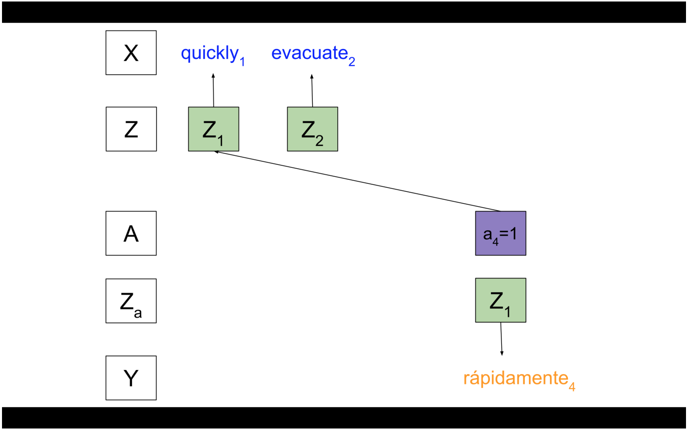

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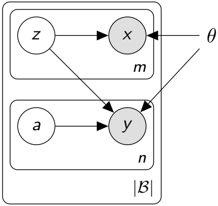

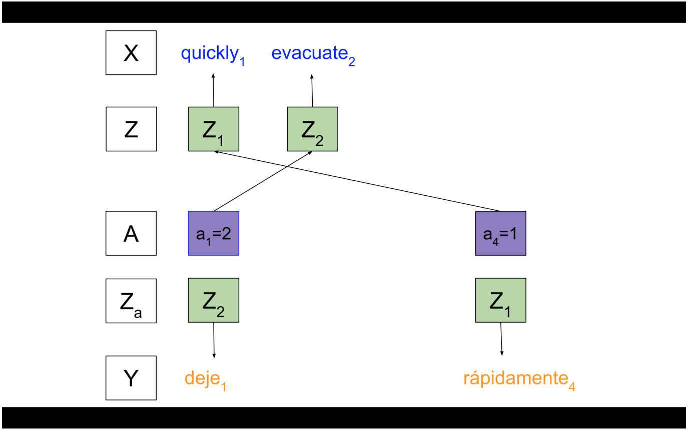

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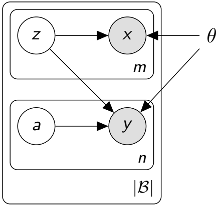

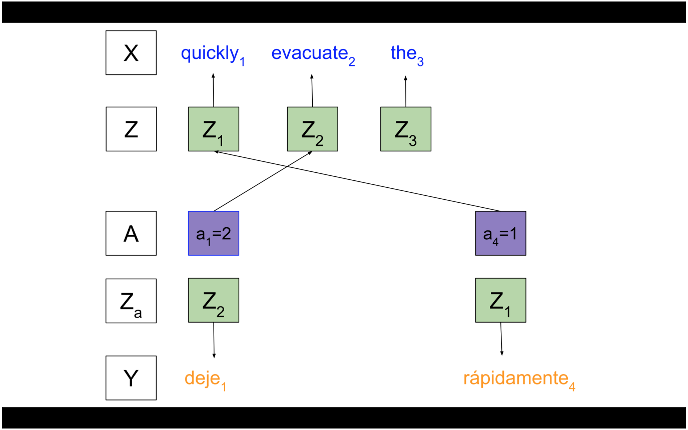

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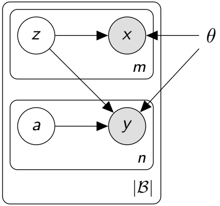

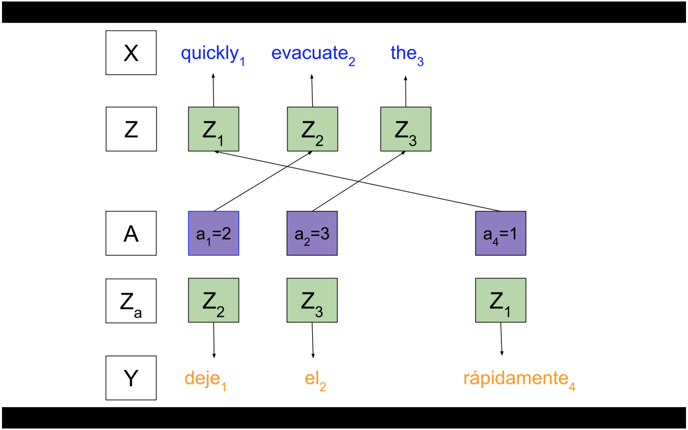

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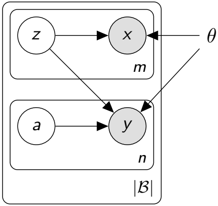

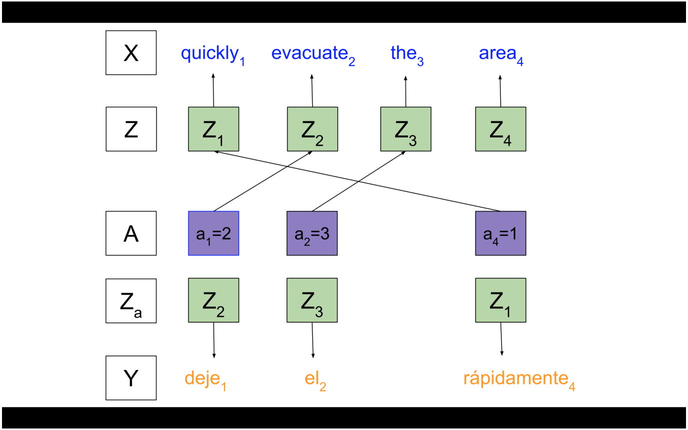

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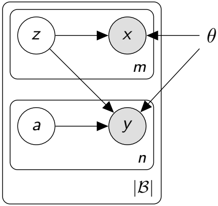

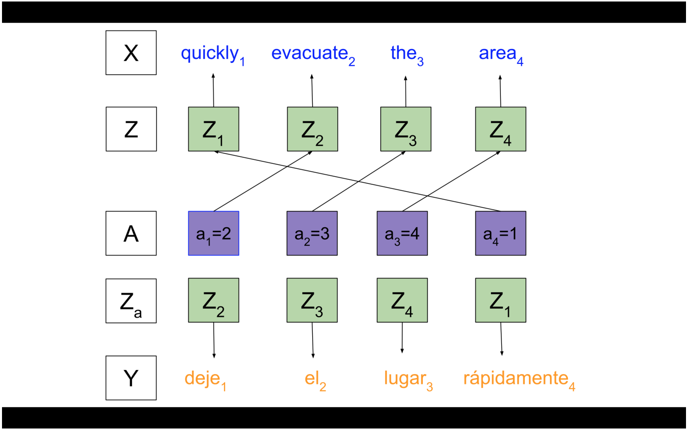

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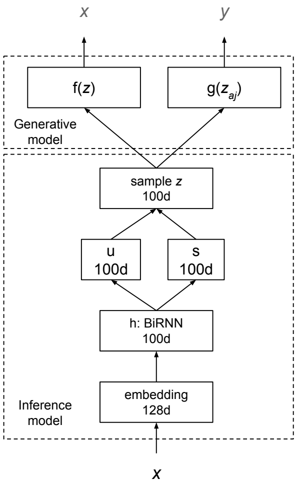

Introduction

- you know nothing, jon x

Introduction

- you know nothing, jon x
- ground control to major x

Introduction

- you know nothing, jon x
- ground control to major x
- the x

Introduction

- the quick brown x

Introduction

- the quick brown x
- the quick brown fox x

Introduction

- the quick brown x
- the quick brown fox x
- the quick brown fox jumps x

Introduction

- the quick brown x
- the quick brown fox x
- the quick brown fox jumps x
- the quick brown fox jumps over x

Introduction

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- the quick brown fox x
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- the quick brown fox jumps over x
- the quick brown fox jumps over the x

Introduction

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- the quick brown fox jumps over the x
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Introduction

- the quick brown x
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- the quick brown fox jumps over the lazy dog

Definition

- Language models give us the probability of a sentence;

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- At a time step, they assign a probability to the next word.

Applications

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Applications

- Very useful on different tasks:
- Speech recognition;
- Spelling correction;
- Machine translation;
- LMs are useful in almost any tasks that deals with generating language.

Language Models

- N-gram based LMs;

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- Log-linear LMs;

Language Models

- N-gram based LMs;
- Log-linear LMs;
- Neural LMs.

N-gram LM

- x is a sequence of words

N-gram LM

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- $x = x_1, x_2, x_3, x_4, x_5$
  $=$ you, know, nothing, jon, snow

N-gram LM

- To compute the probability of a sentence

$$p(x) = p\left(x_1, x_2, \ldots, x_n\right) \tag{1}$$

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- We limit the history with a Markov order:
$p(x_i | x_1, \ldots, x_{i-1}) \simeq p(x_i | x_{i-4}, x_{i-3}, x_{i-2}, x_{i-1})$

N-gram LM

- Chain rule:

$$p(x) = \prod_i p\left(x_i | x_1, \ldots, x_{i-1}\right) \quad (3)$$

N-gram LM

- We make a Markov assumption of conditional independence:

$$p\left(x_i \middle| x_1, \ldots, x_{i-1}\right) \simeq p\left(x_i \middle| x_{i-1}\right) \tag{4}$$

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- Laplace smoothing:

$$p_{\mathrm{add1}}\left(x_i|x_{i-1}\right) = \frac{\text{count}\left(x_{i-1},x_i\right)+1}{\text{count}\left(x_{i-1}\right)+V} \tag{6}$$

Log-linear LM

- $$p(y|x) = \frac{\exp \boldsymbol{w} \cdot \phi(x, y)}{\sum_{y' \in V_y} \exp w \cdot \phi\left(x, y'\right)} \tag{7}$$

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- w are the model parameters.

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- we need to find useful features

Feed-forward NLM

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  2. a probability function over word sequences is expressed in terms of these vectors;
  3. we jointly learn the feature vectors and the parameters of the probability function.

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- The cat is walking in the bedroom.
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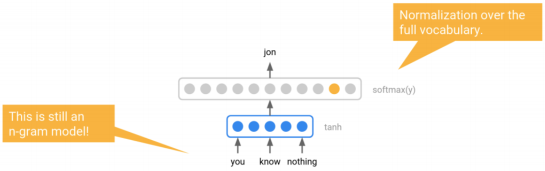
- Take-away message:
  The presence of only one sentence in the training data will increase the probability of a combinatorial number of neighbours in sentence space.

Feed-forward NLM

- FF-LM



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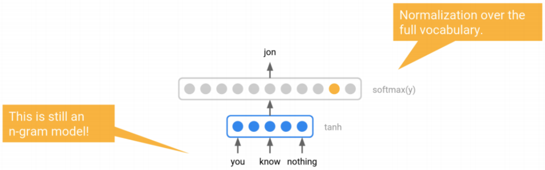

- $\boldsymbol{E}_{\text{you}}, \boldsymbol{E}_{\text{know}}, \boldsymbol{E}_{\text{nothing}} \in \mathbb{R}^{100}$

$$\begin{aligned} \boldsymbol{x} &= [\boldsymbol{E}_{\text{you}}; \boldsymbol{E}_{\text{know}}; \boldsymbol{E}_{\text{nothing}}] \in \mathbb{R}^{300} \\ \boldsymbol{y} &= \boldsymbol{W}_3 \tanh(\boldsymbol{W}_1 \boldsymbol{x} + \boldsymbol{b}_1) + \boldsymbol{W}_2 \boldsymbol{x} + \boldsymbol{b}_2 \end{aligned} \tag{8}$$

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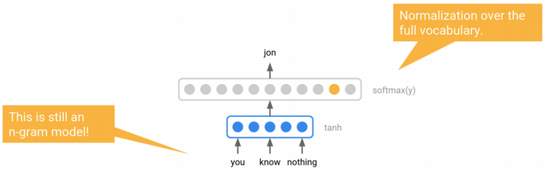

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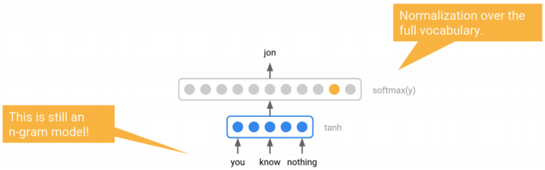

- The non-linear activation functions perform feature combinations that a linear model cannot do;

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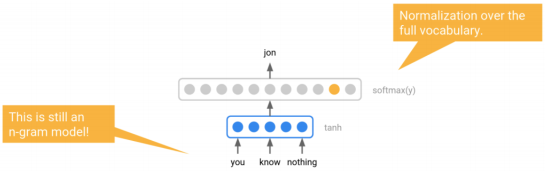

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- End-to-end training on next word prediction.

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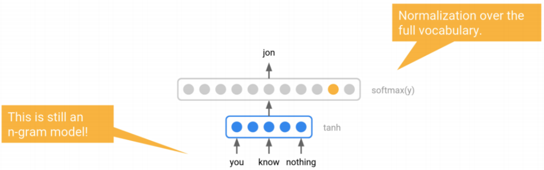

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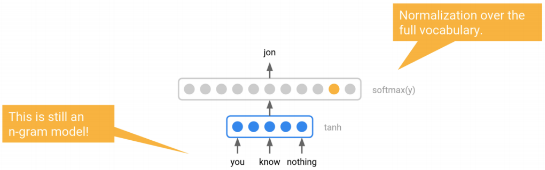

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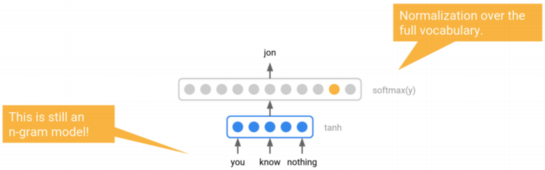

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- Recurrent neural networks have unlimited history

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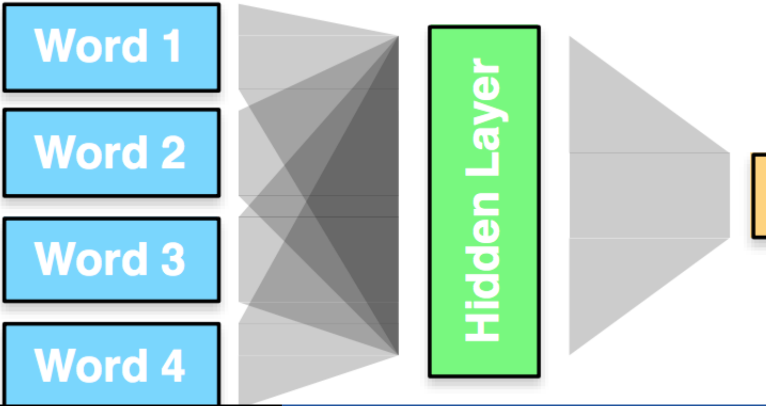

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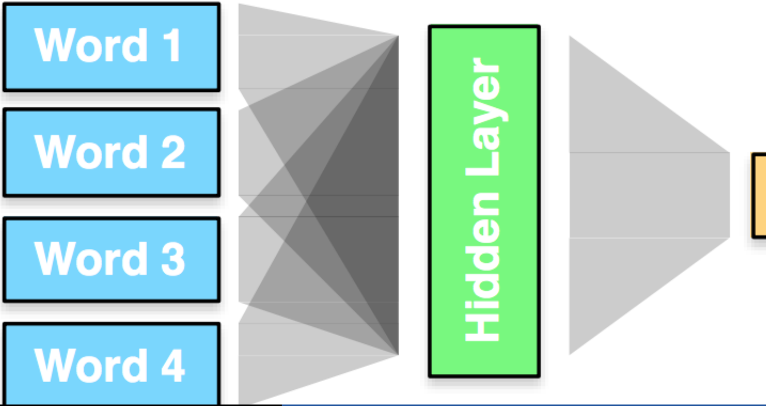

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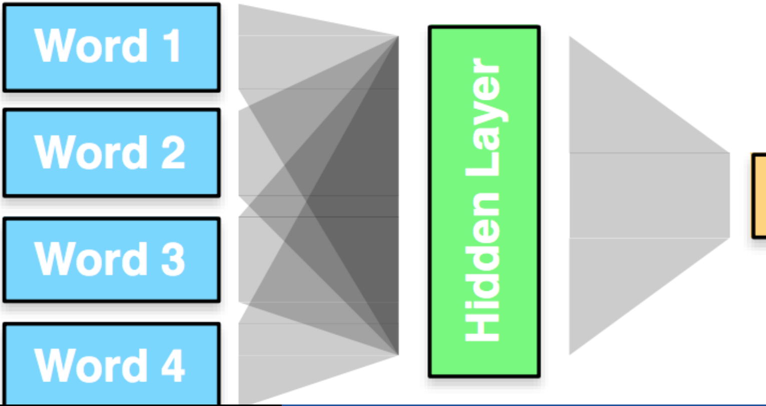
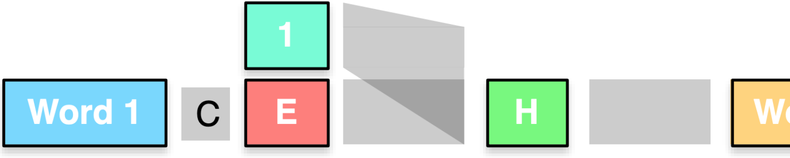


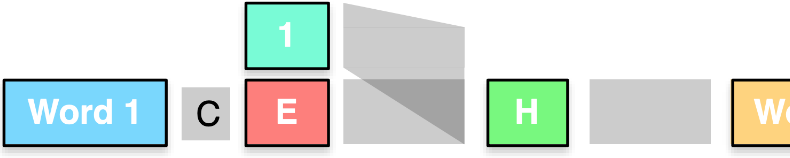
RNN NLM

- RNN-LM



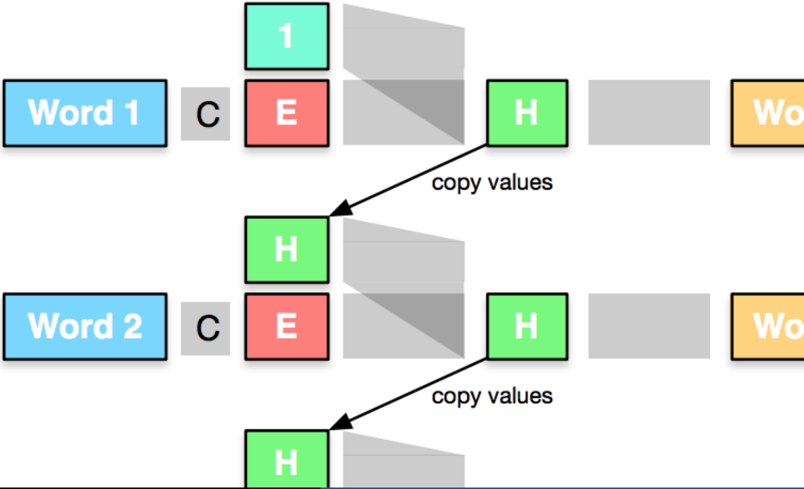
RNN NLM

- RNN-LM



- Start: predict second word from first

RNN NLM



Outline

1. Language Modelling
2. Variational Auto-encoder for Sentences
   - Model

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References I