Distributed representations and RNNs

Computational Semantics 2021

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Plan

- Part 1: Distributed representations (25 min)
- Part 2: Language modeling (20 min)
- Part 3: Break (15min)
- Part 4: PyTorch example: Part-of-Speech tagging (45 min)

The great switcheroo

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- But count vectors have several problems:
  - Sparsity:
    - few degrees of similarity
    - language have a Zipfian-distribution
  - Post-processing necessary:
    - Weighting: TF-IDF, PPMI, ...
    - Dimensionality reduction: SVD

Distributed representations

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- We train a binary classifier on a task T: does w_a occur in the context of w_b?
- The thing we care about is the *embeddings*
- That is, can we use the embeddings to predict other things than the context (for example word similarity)

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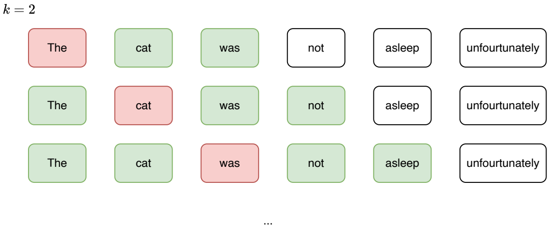
- Like with count vectors we must define what a context *is*, which we do with a *hyperparameter* k (aka. window size)
- In this setup we have a center word w_c and some context words w_o (outside words)

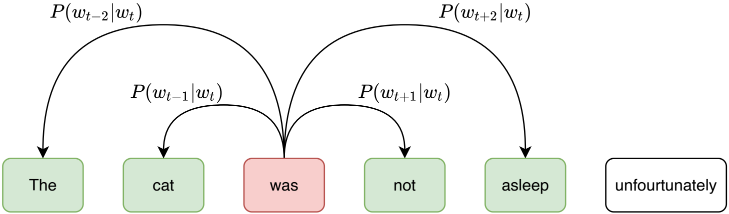


Word2Vec

- We'll consider two methods, SkipGram and Continuous Bag-of-words (CBOW)
- aka. Word2Vec

Skip-Gram Model

- We select a center word t and predict the context words



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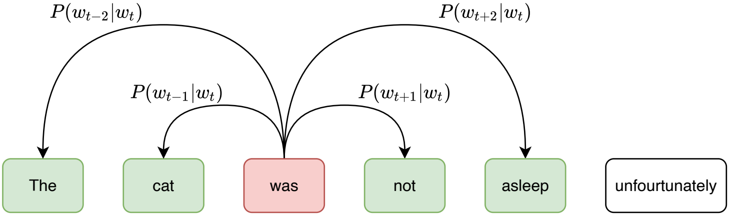
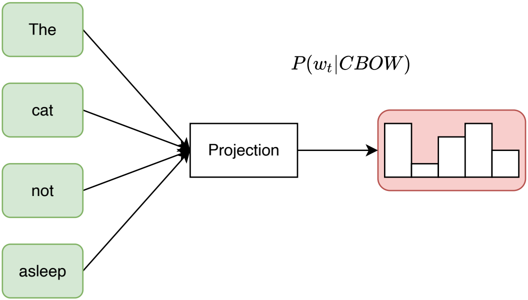


Predicting the context words

$$P(w_{t-1}|w_t) = \frac{exp(w_{t-1}^T w_t)}{\sum_{w \in V} exp(w^T w_t)}$$

CBOW Model

- Based on a "bag of words", predict the center word



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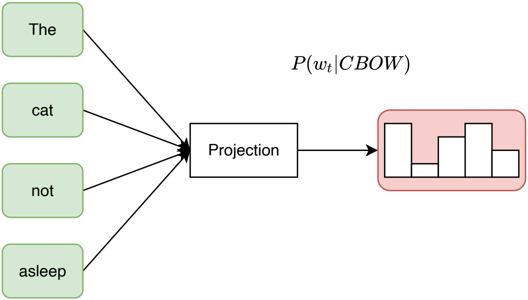

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A neural network for Word2Vec

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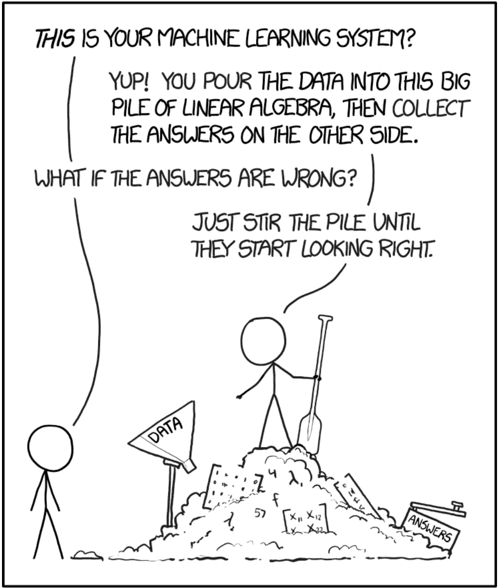
- In both methods, the setup is simple:
  - Perform non-linear transformations with weight matrices
  - Calculate the probability of the target word
  - Calculate loss with Negative Log Likelihood
  - Adjust the weight matrices with gradient descent such that the accuracy goes up (that is, minimize the negative log likelihood)

What is a weight matrix?

$$W^{n,d} = \begin{bmatrix} x_0^0 & \dots & x_n^0 \\ & \vdots & \\ x_0^d & \dots & x_n^k \end{bmatrix}$$

- takes an input of size n, and produces and output of size d

Machine learning expert visualization (https://xkcd.com/1838/)



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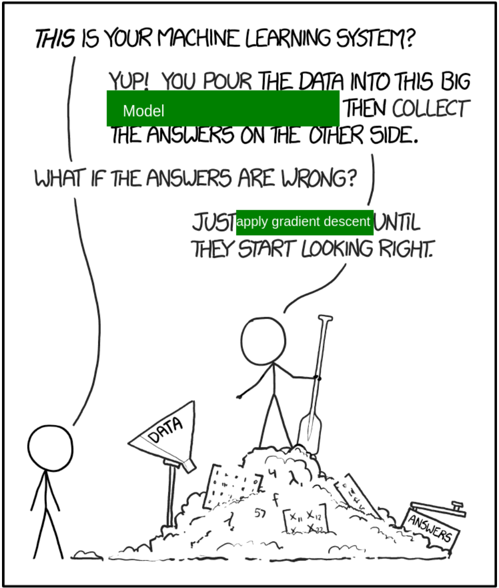
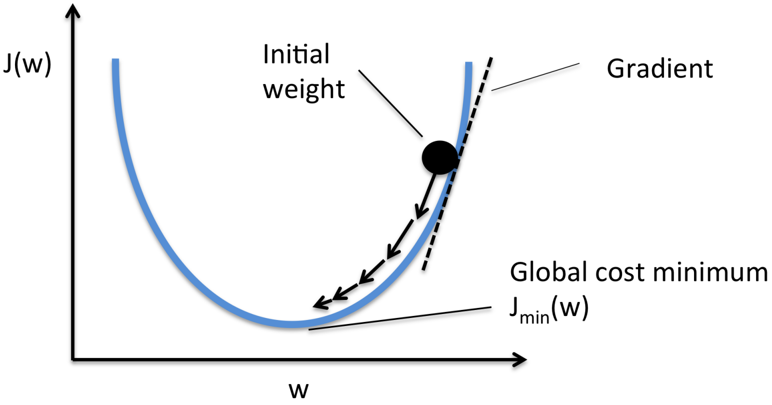
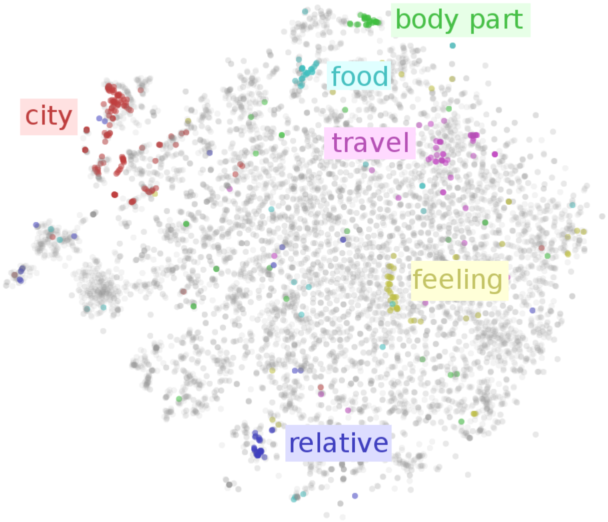


A quick look at Stochastic Gradient Descent



Semantic Space



The big WOW: Bilingual Dictionary Induction

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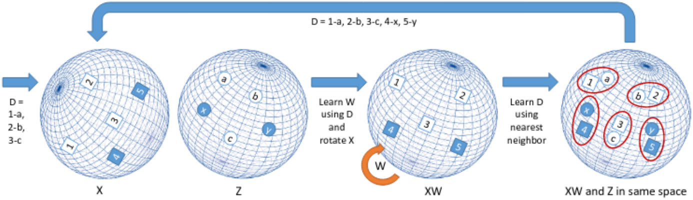

Figure 1: A general schema of the proposed self-learning framework. Previous works learn a mapping W based on the seed dictionary D, which is then used to learn the full dictionary. In our proposal we use the new dictionary to learn a new mapping, iterating until convergence.

Bilingual Dictionary Induction

- "Learning bilingual word embeddings with (almost) no bilingual data" (Artexe, et. al (2017))
- We formalize our objective as the euclidean distance between the items in our seed dictionary:

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	English-Italian			English-German			English-Finnish		
	5,000	**25**	**num.**	**5,000**	**25**	**num.**	**5,000**	**25**	**num.**
Mikolov et al. (2013a)	34.93	0.00	0.00	35.00	0.00	0.07	25.91	0.00	0.00
Xing et al. (2015)	36.87	0.00	0.13	41.27	0.07	0.53	28.23	0.07	0.56
Zhang et al. (2016)	36.73	0.07	0.27	40.80	0.13	0.87	28.16	0.14	0.42
Artetxe et al. (2016)	39.27	0.07	0.40	**41.87**	0.13	0.73	**30.62**	0.21	0.77
Our method	**39.67**	**37.27**	**39.40**	40.87	**39.60**	**40.27**	28.72	**28.16**	**26.47**

Table 1: Accuracy (%) on bilingual lexicon induction for different seed dictionaries

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- Predict which word from a vocabulary that comes next given a piece of text
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- assign probability (and consequently a representation) to a sequence of symbols

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- Translation
- Actually, as it turn out: 99% (*handwavy number*) of NLP benefit from language modeling (Nikolai will tell you more about this in the next lecture)

HOW!? OH GOD HOW!? Part 1

Let us consider some history (oh god, no...)

- First statistical (language) models were based on n-grams and co-occurrence
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- Neural Networks use RNNs to process sequences, which can model an arbitrarily long contexts
  - Not really, RNNs still have trouble with long dependencies
- Words are represented as distributed *vectors*
- which allows a model to compute *similarities* which helps with rare words (and frequent words for that matter)

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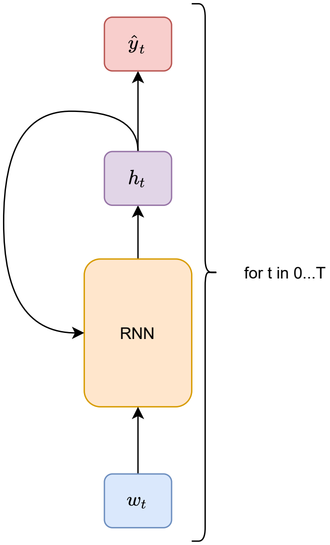
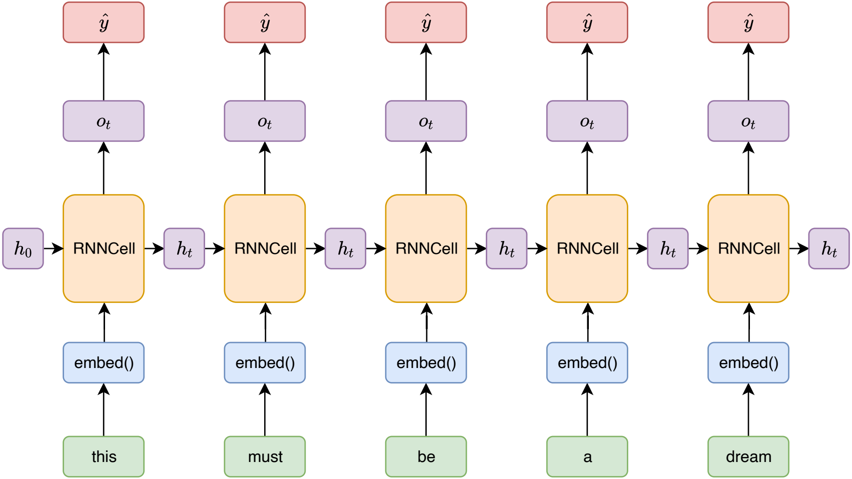
- Continue until you've reached the end of the sentence

RNN



RNN un-rolled



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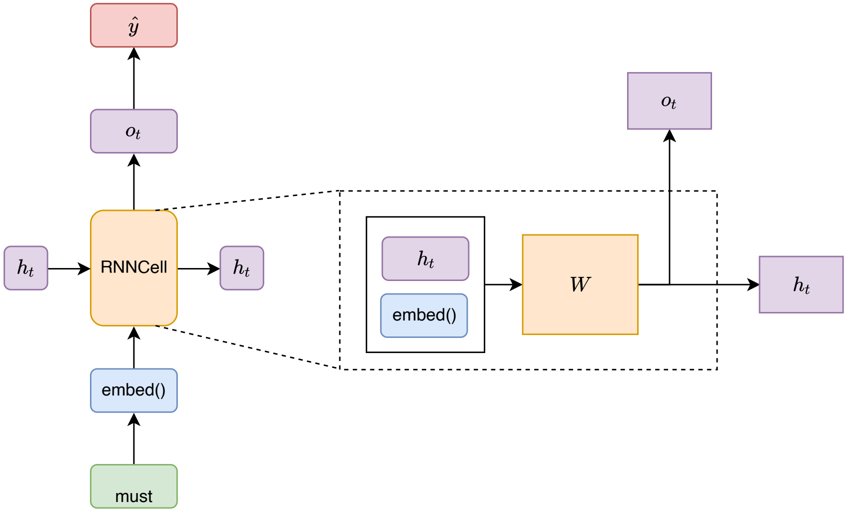
  $\rightarrow$ It's a summary because this is the accumulated hidden state from the entire input sequence

The RNN Cell



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  $\rightarrow h_t W + b$ where $W \in \mathbb{R}^{d(h_t),|V|}$

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- The target word is predicted by $\hat{y}' = softmax(\hat{y})$
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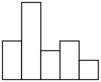

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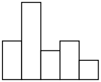

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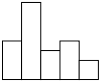

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- Then we calculate the Negative Log Likelihood loss :) and stir the pile (with gradient descent)

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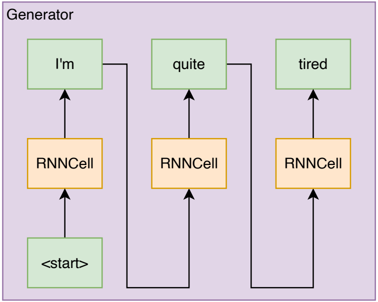
  - Plug the word representations obtained into another model (parsing/QA-model/...)

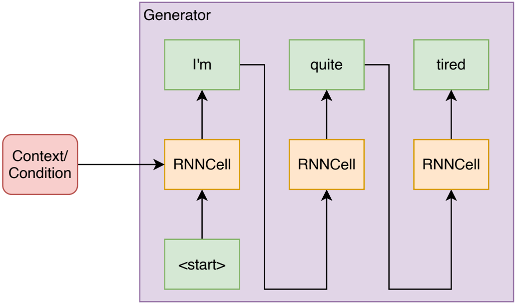
Natural Language Generation (NLG)

- We can use language models to *generate* language



Conditioned Natural Language Generation (NLG)

- But generating based on nothing will most likely just give us nonsense...
- Language usually happens in some *context*, or as an response to *something*



Machine translation (MT)

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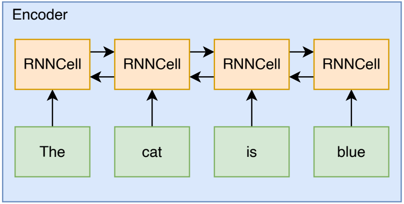

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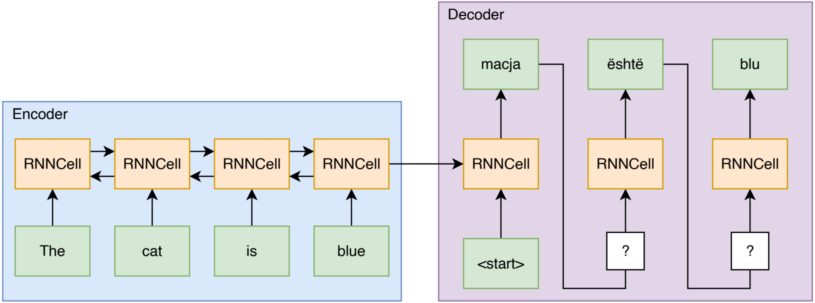

Next up...

Questions?

A short look at the attention mechanism

- When using NLG or MT, the contextual information (etc...) are encoded only in the initial hidden state h_t
- This information will easily be forgotten after some time-steps
- We can use *attention* to alleviate this problem by looking back at the context at *every time-step*

Attention