Natural Language Processing

Neural Networks and Neural LMs

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Readings

- Neutral networks chapters in J&M 3:
  - https://web.stanford.edu/~jurafsky/slp3/7.pdf
  - https://web.stanford.edu/~jurafsky/slp3/8.pdf
  - https://web.stanford.edu/~jurafsky/slp3/9.pdf

- Hundreds of blog posts and tutorials

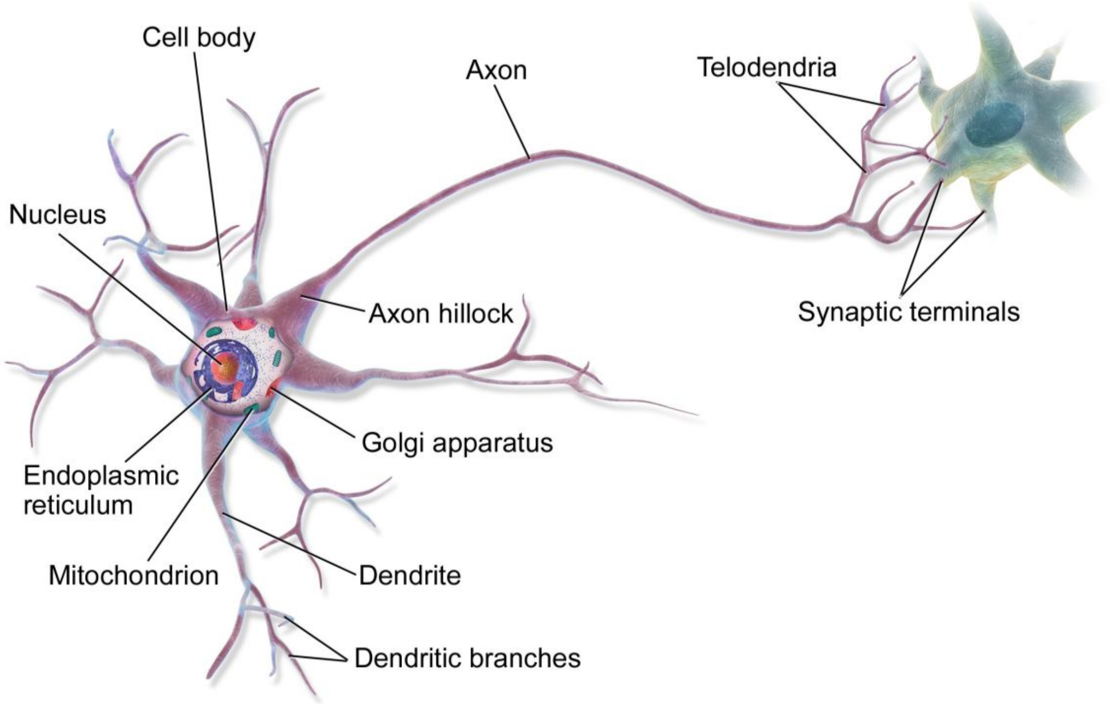
- The Annotated Transformer
  https://nlp.seas.harvard.edu/2018/04/03/attention.html

We'll discuss 2 kinds of embeddings

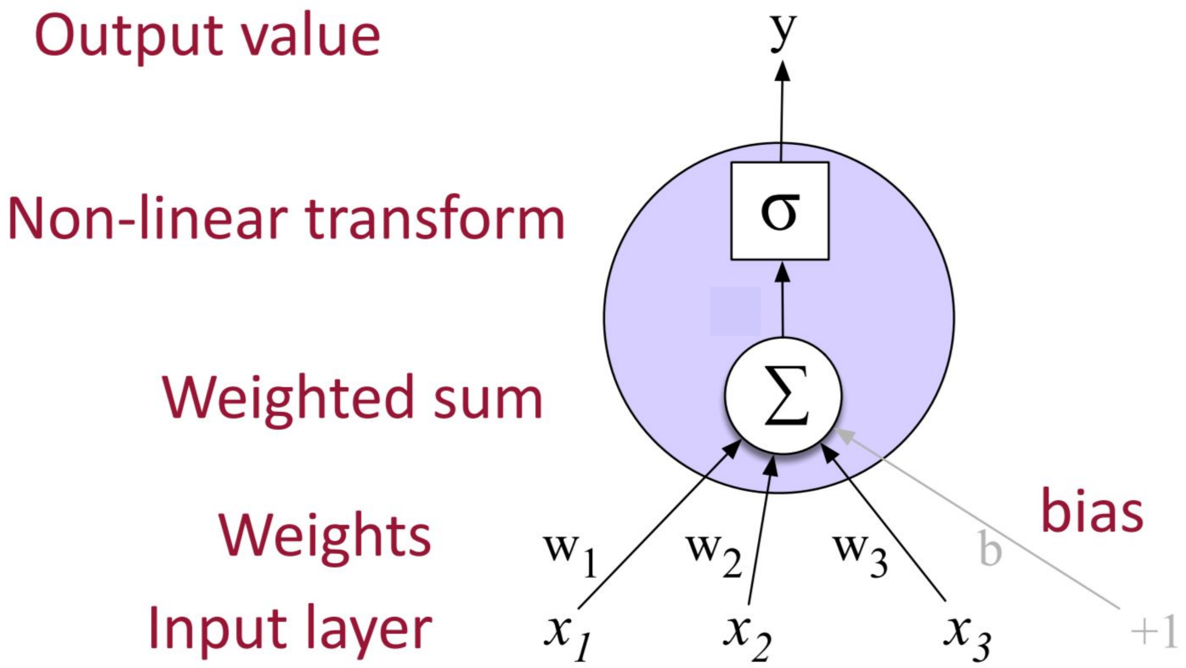
- **tf-idf**
  - Information Retrieval workhorse!
  - A common baseline model
  - Sparse vectors
  - Words are represented by (a simple function of) the counts of nearby words

- **Word2vec**
  - Dense vectors
  - Representation is created by training a classifier to predict whether a word is likely to appear nearby
  - https://fasttext.cc/docs/en/crawl-vectors.html
  - Later we'll discuss extensions called contextual embeddings

This is in your brain



Neural Network Unit (this is not in your brain)



Neural unit

- Take weighted sum of inputs, plus a bias

$$z = b + \sum_i w_i x_i$$

$$z = w \cdot x + b$$

- Instead of just using z, we'll apply a nonlinear activation function f:

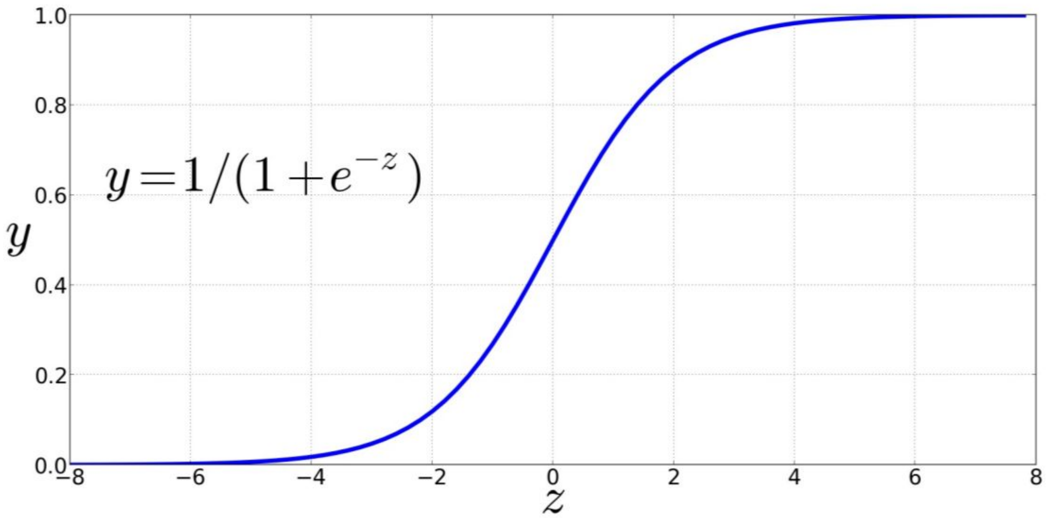
$$y = a = f(z)$$

Non-Linear Activation Functions

- We've already seen the sigmoid for logistic regression:

Sigmoid

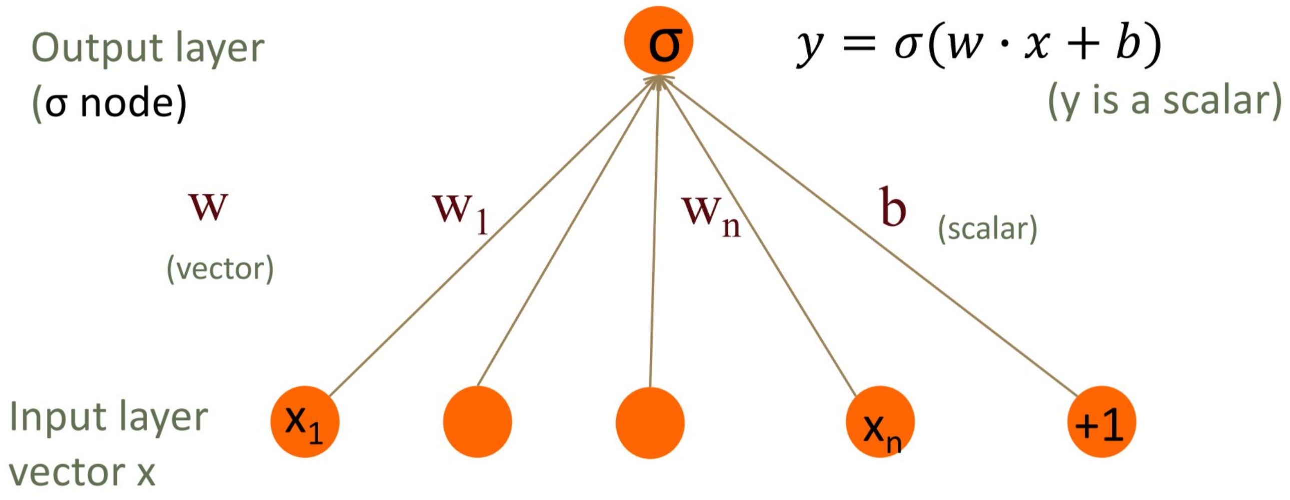
$$y = \sigma(z) = \frac{1}{1+e^{-z}}$$



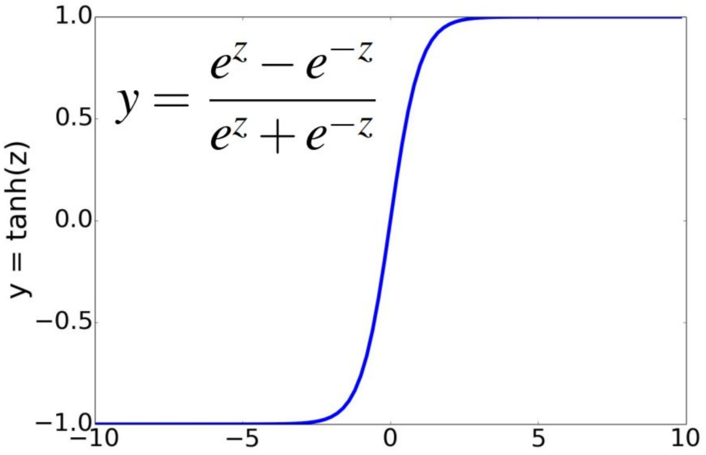
Final function the unit is computing

$$y = \sigma(w \cdot x + b) = \frac{1}{1 + \exp(-(w \cdot x + b))}$$

Binary Logistic Regression as a 1-layer network

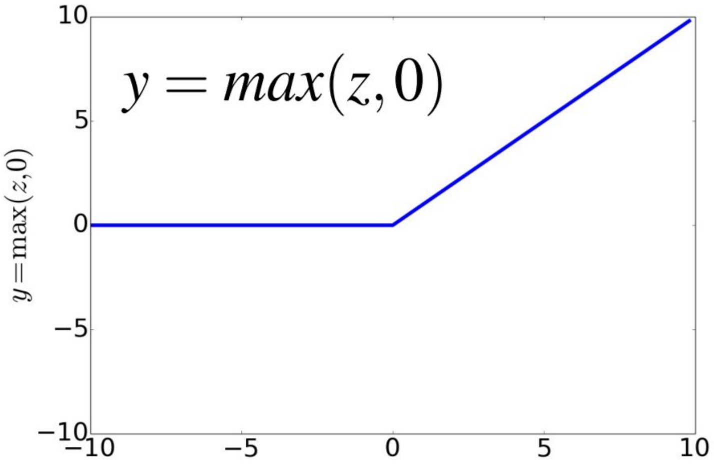


Non-Linear Activation Functions besides sigmoid



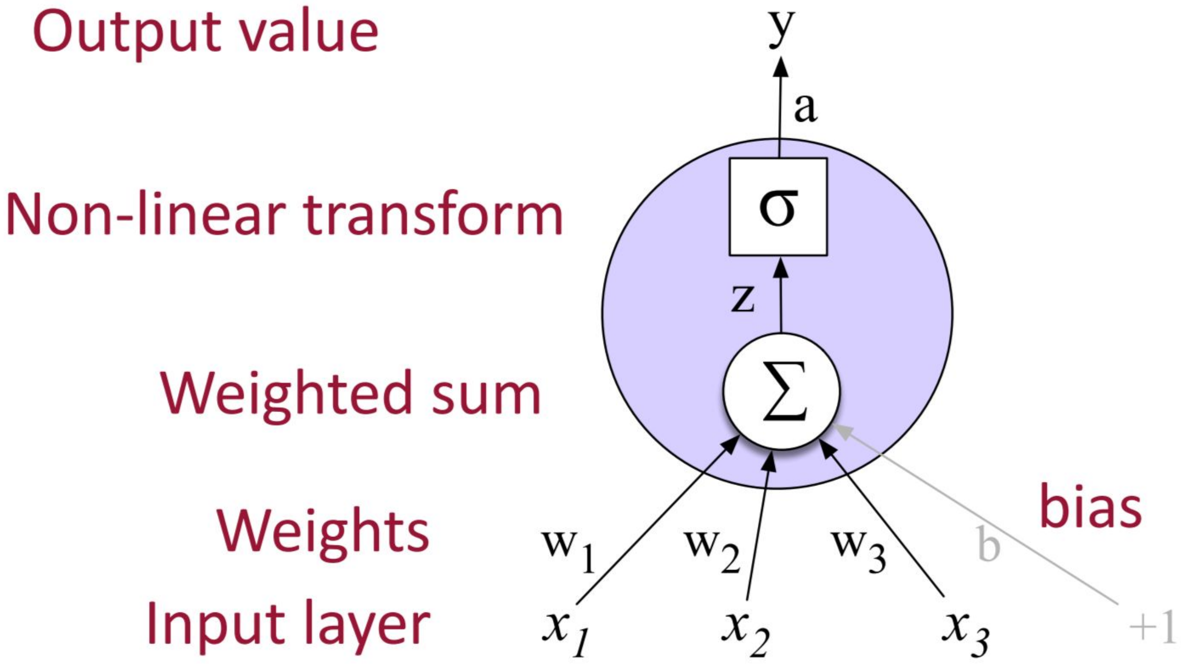
tanh

Most Common:



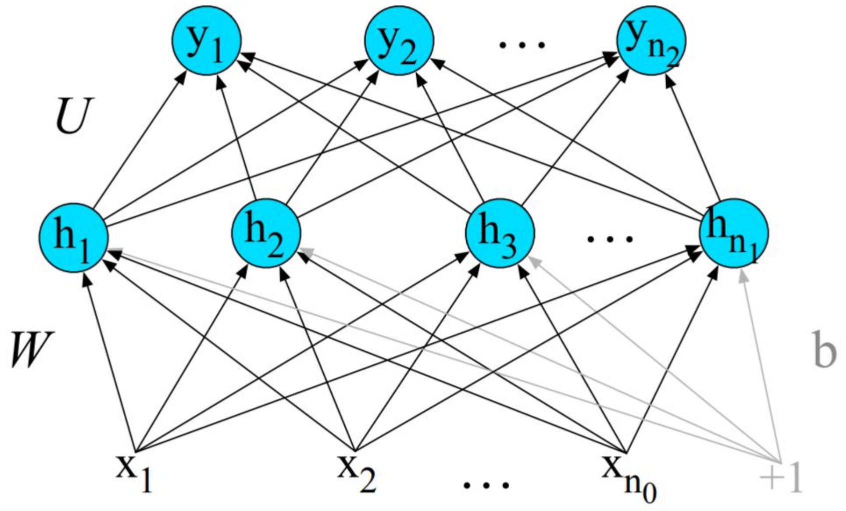
ReLU
Rectified Linear Unit

Final unit again

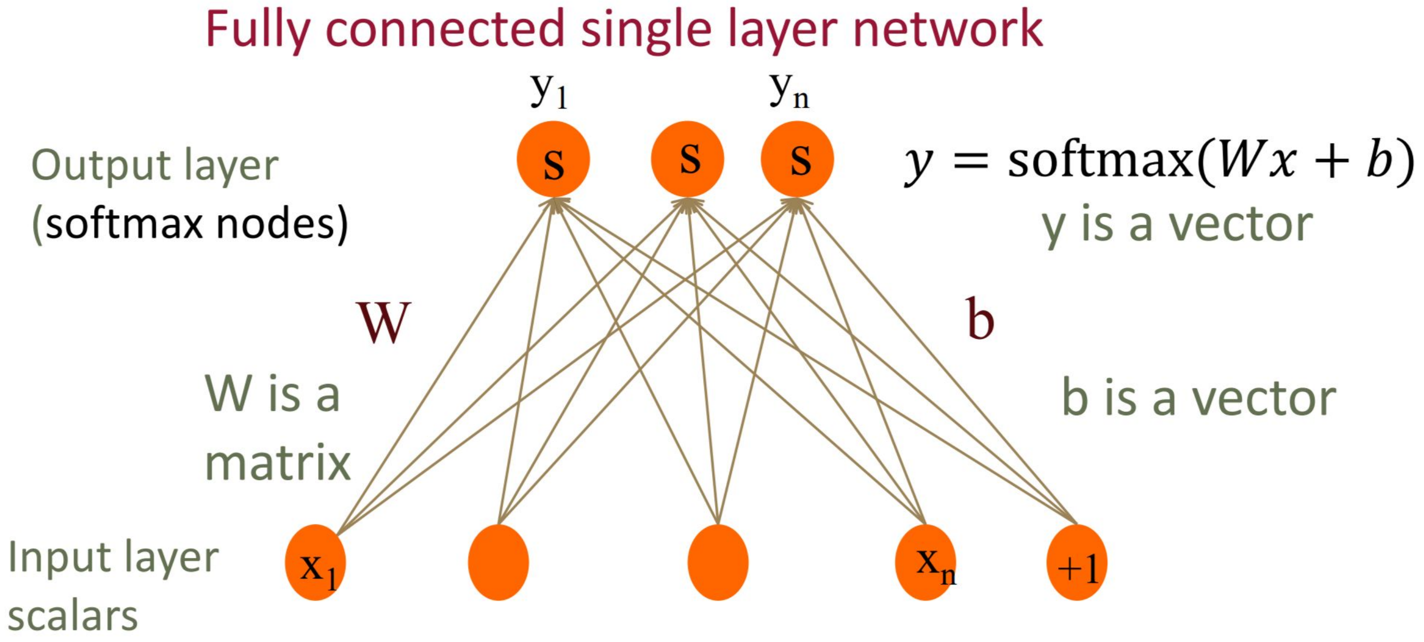


Feedforward Neural Networks

- Can also be called **multi-layer perceptrons (or MLPs)** for historical reasons
    - (we don't count the input layer in counting layers!)



Multinomial Logistic Regression as a 1-layer Network



softmax: a generalization of sigmoid

- For a vector z of dimensionality k, the softmax is:

$$\text{softmax}(z) = \left[\frac{\exp(z_1)}{\sum_{i=1}^{k}\exp(z_i)}, \frac{\exp(z_2)}{\sum_{i=1}^{k}\exp(z_i)}, \ldots, \frac{\exp(z_k)}{\sum_{i=1}^{k}\exp(z_i)}\right]$$

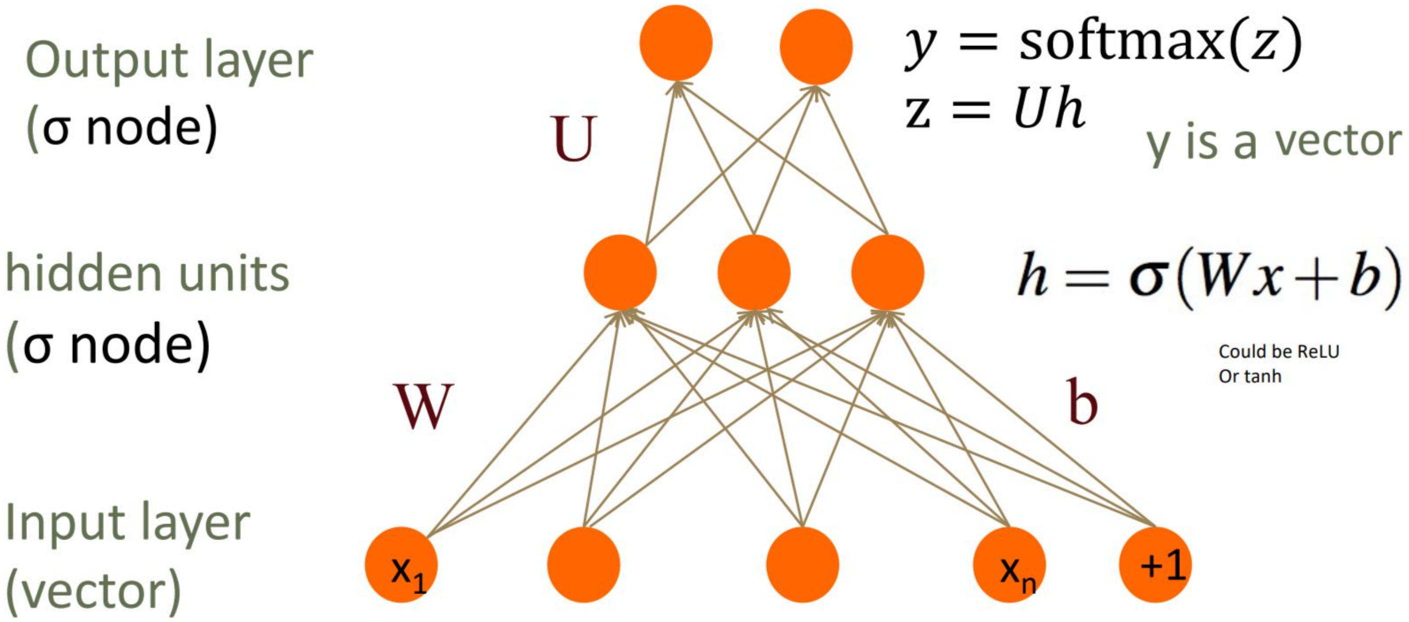
$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{k}\exp(z_j)} \quad 1 \leq i \leq k$$

Example:

$$z = [0.6, 1.1, -1.5, 1.2, 3.2, -1.1]$$

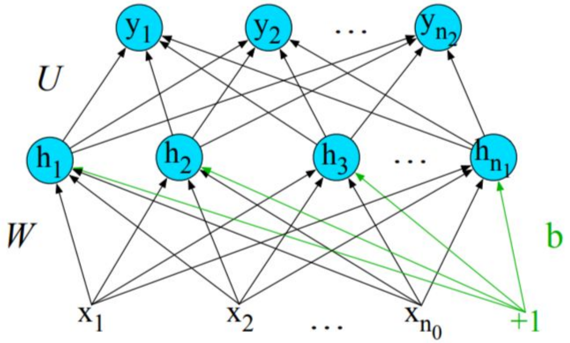
$$\text{softmax}(z) = [0.055, 0.090, 0.006, 0.099, 0.74, 0.010]$$

Two-Layer Network with softmax output

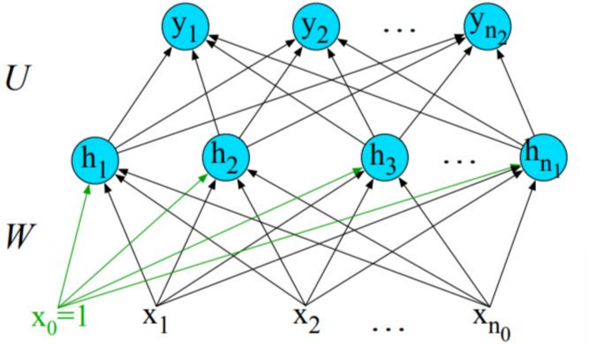


Replacing the bias unit

Instead of:



We'll do this:

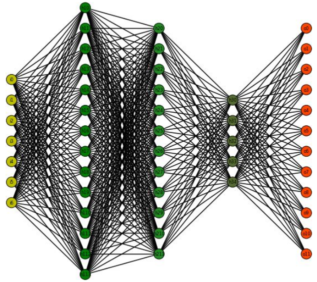


Learning the weights

- Cross-entropy loss
- Backpropagation algorithm

Algorithm 1 Backpropagation Algorithm

procedure TRAIN
  $X \leftarrow$ Training Data Set of size mxn
  $y \leftarrow$ Labels for records in X
  $w \leftarrow$ The weights for respective layers
  $l \leftarrow$ The number of layers in the neural network, 1...L
  $D_{ij}^{(l)} \leftarrow$ The error for all l,i,j
  $t_{ij}^{(l)} \leftarrow 0$. For all l,i,j
  For $i = 1$ to m
    $a^l \leftarrow feedforward(x^{(i)}, w)$
    $d^l \leftarrow a(L) - y(i)$
    $t_{ij}^{(l)} \leftarrow t_{ij}^{(l)} + a_j^{(l)} \cdot t_i^{l+1}$
  if $j \neq 0$ **then**
    $D_{ij}^{(l)} \leftarrow \frac{1}{m} t_{ij}^{(l)} + \lambda w_{ij}^{(l)}$
  else
    $D_{ij}^{(l)} \leftarrow \frac{1}{m} t_{ij}^{(l)}$
    where $\frac{\partial}{\partial w_{ij}^{(l)}} J(w) = D_{ij}^{(l)}$



Applying neural networks to NLP tasks

Use cases for feedforward networks

- Word representations
- Text classification
- Language modeling

State of the art systems use more powerful neural architectures (we will learn transformers architectures on Friday), but simpler models are useful to consider!

Distributed representations

Word Vectors

WORD	d1	d2	d3	d4	d5	...	d50
summer	0.12	0.21	0.07	0.25	0.33	...	0.51
spring	0.19	0.57	0.99	0.30	0.02	...	0.73
fall	0.53	0.77	0.43	0.20	0.29	...	0.85
light	0.00	0.68	0.84	0.45	0.11	...	0.03
clear	0.27	0.50	0.21	0.56	0.25	...	0.32
blizzard	0.15	0.05	0.64	0.17	0.99	...	0.23

Sparse versus dense vectors

tf-idf (or PMI) vectors are

- long (length |V|= 20,000 to 50,000)
- sparse (most elements are zero)

Alternative: learn vectors which are

- short (length 50-1000)
- dense (most elements are non-zero)

Sparse versus dense vectors

Why dense vectors?

- Short vectors may be easier to use as **features** in machine learning (fewer weights to tune)
- Dense vectors may **generalize** better than explicit counts
- Dense vectors may do better at capturing synonymy:
  - car and automobile are synonyms; but are distinct dimensions
  - a word with car as a neighbor and a word with automobile as a neighbor should be similar, but aren't
- **In practice, they work better**

Common methods for getting short dense vectors

- In count-based models - Singular Value Decomposition (SVD)
  - A special case of this is called LSA – Latent Semantic Analysis

- “Neural Language Model”-inspired models
  - The weight matrix in the input layer is often used as “word embeddings”
  - Compute one embeddings for each word (word types)

- Alternative to these "static embeddings":
  - Contextual Embeddings (ELMo, BERT)
  - Compute distinct embeddings for a word in its context
  - Separate embeddings for each token of a word

Simple static embeddings you can download!

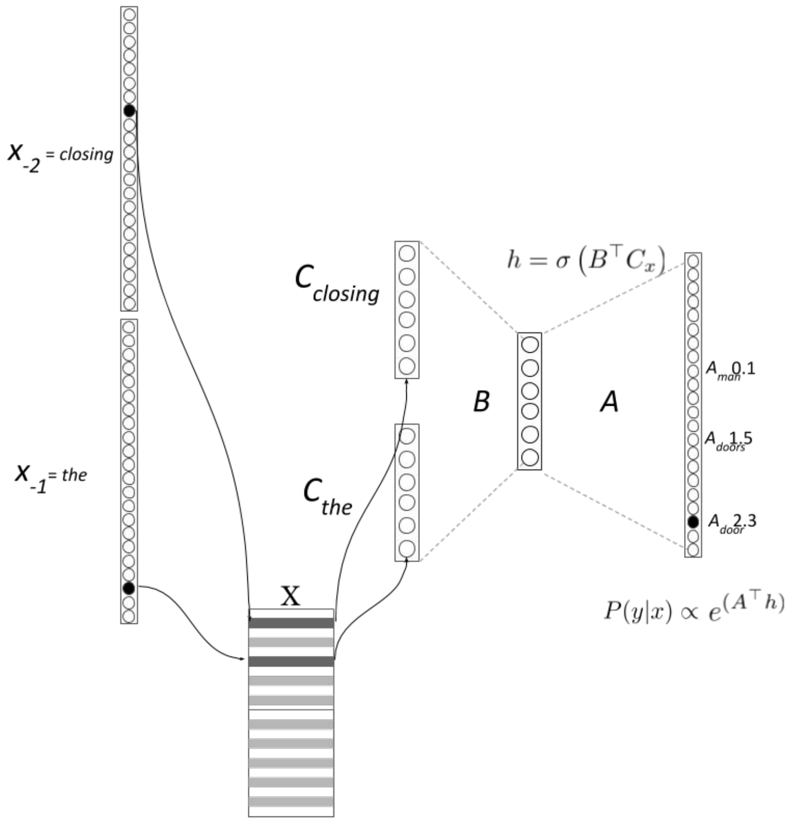
word2vec (Mikolov et al)

https://code.google.com/archive/p/word2vec/

GloVe (Pennington, Socher, Manning)

http://nlp.stanford.edu/projects/glove/

“One hot” vectors and dense word vectors (embeddings)

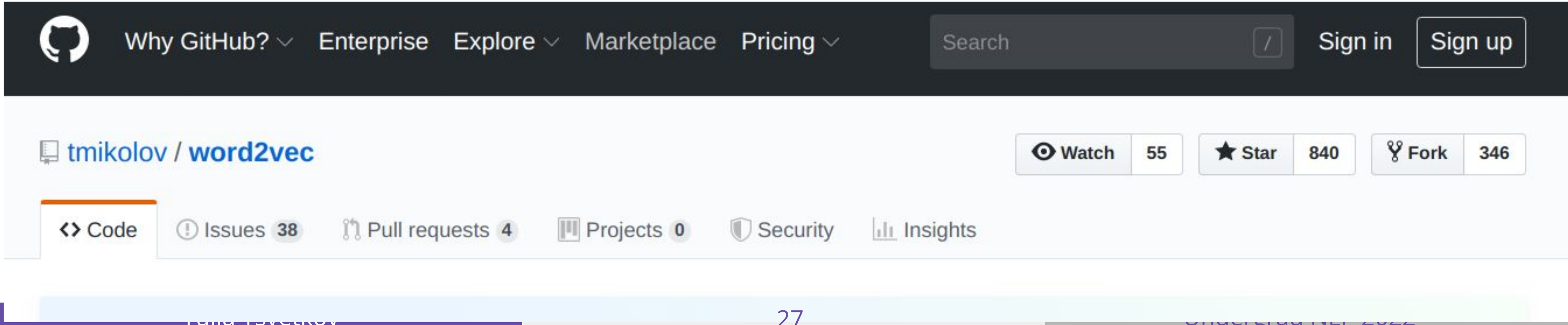


Low-dimensional word representations

- Learning representations by back-propagating errors
  - Rumelhart, Hinton & Williams, 1986
- A neural probabilistic language model
  - Bengio et al., 2003
- Natural Language Processing (almost) from scratch
  - Collobert & Weston, 2008
- Word representations: A simple and general method for semi-supervised learning
  - Turian et al., 2010
- Distributed Representations of Words and Phrases and their Compositionality
  - Word2Vec; Mikolov et al., 2013

word2vec

- Popular embedding method
- Very fast to train
- Code available on the web
- Idea: predict rather than count



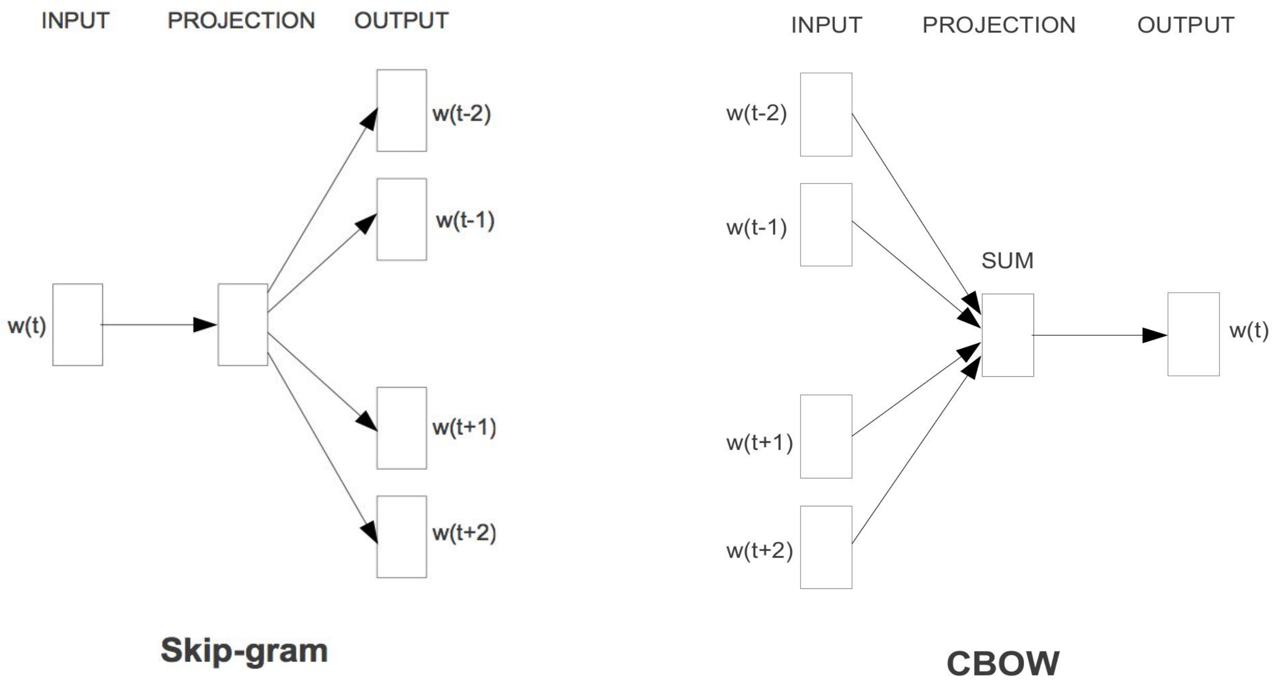
word2vec

- Instead of counting how often each word w occurs near "apricot"
  - Train a classifier on a binary **prediction** task:
    - Is w likely to show up near "apricot"?

- We don’t actually care about this task
  - But we'll take the learned classifier weights as the word embeddings

- Big idea: **self-supervision**:
  - A word c that occurs near apricot in the corpus cats as the gold "correct
  - answer" for supervised learning
  - No need for human labels
  - Bengio et al. (2003); Collobert et al. (2011)

word2Vec

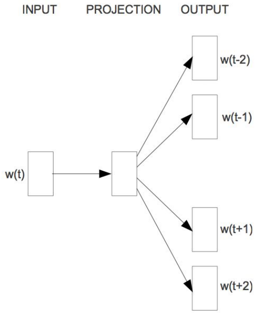


- [Mikolov et al.' 13]

Skip-gram Prediction

- Predict vs Count

the cat sat on the mat



Skip-gram

Skip-gram Prediction

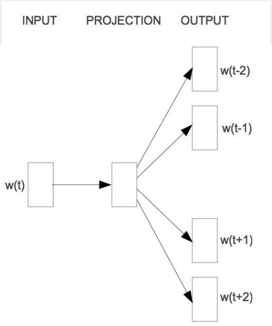
- Predict vs Count

<u>the</u> cat sat on the mat

w_t = the → **CLASSIFIER** →

w_{t-2} = <start$_{-2}$>
w_{t-1} = <start$_{-1}$>
w_{t+1} = cat
w_{t+2} = sat

context size = 2



Skip-gram

Skip-gram Prediction

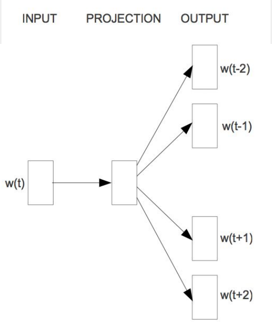
- Predict vs Count

the cat sat on the mat

w_t = cat → CLASSIFIER →

w_{t-2} = <start$_{-1}$>
w_{t-1} = the
w_{t+1} = sat
w_{t+2} = on

context size = 2



Skip-gram

Skip-gram Prediction

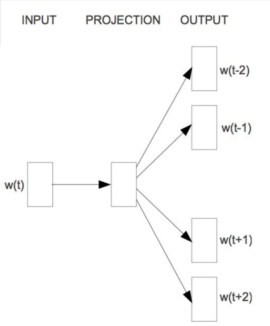
- Predict vs Count

the cat sat on the mat

w_t = sat → CLASSIFIER →

w_{t-2} = the
w_{t-1} = cat
w_{t+1} = on
w_{t+2} = the

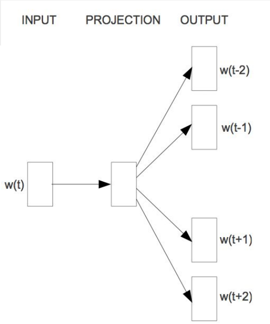
context size = 2



Skip-gram

Skip-gram Prediction

- Predict vs Count



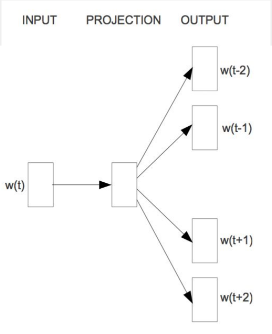
Skip-gram

the $\boxed{\text{cat sat }\underline{\text{on}}\text{ the mat}}$

w_t = on → **CLASSIFIER** → w_{t-2} = cat, w_{t-1} = sat, w_{t+1} = the, w_{t+2} = mat

context size = 2

Skip-gram Prediction



Skip-gram

- Predict vs Count

the cat sat on <u>the</u> mat

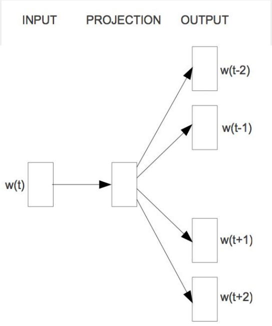
w_t = the → **CLASSIFIER** →

w_{t-2} = sat
w_{t-1} = on
w_{t+1} = mat
w_{t+2} = <end$_{+1}$>

context size = 2

Skip-gram Prediction

- Predict vs Count



Skip-gram

the cat sat on the mat

w_t = mat → **CLASSIFIER** →

w_{t-2} = on
w_{t-1} = the
w_{t+1} = <end$_{+1}$>
w_{t+2} = <end$_{+2}$>

context size = 2

Skip-gram Prediction

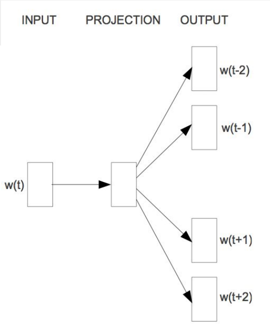
- Predict vs Count

w_t = the → **CLASSIFIER** →

w_{t-2} = sat
w_{t-1} = on
w_{t+1} = mat
w_{t+2} = <end$_{+1}$>

w_t = the → **CLASSIFIER** →

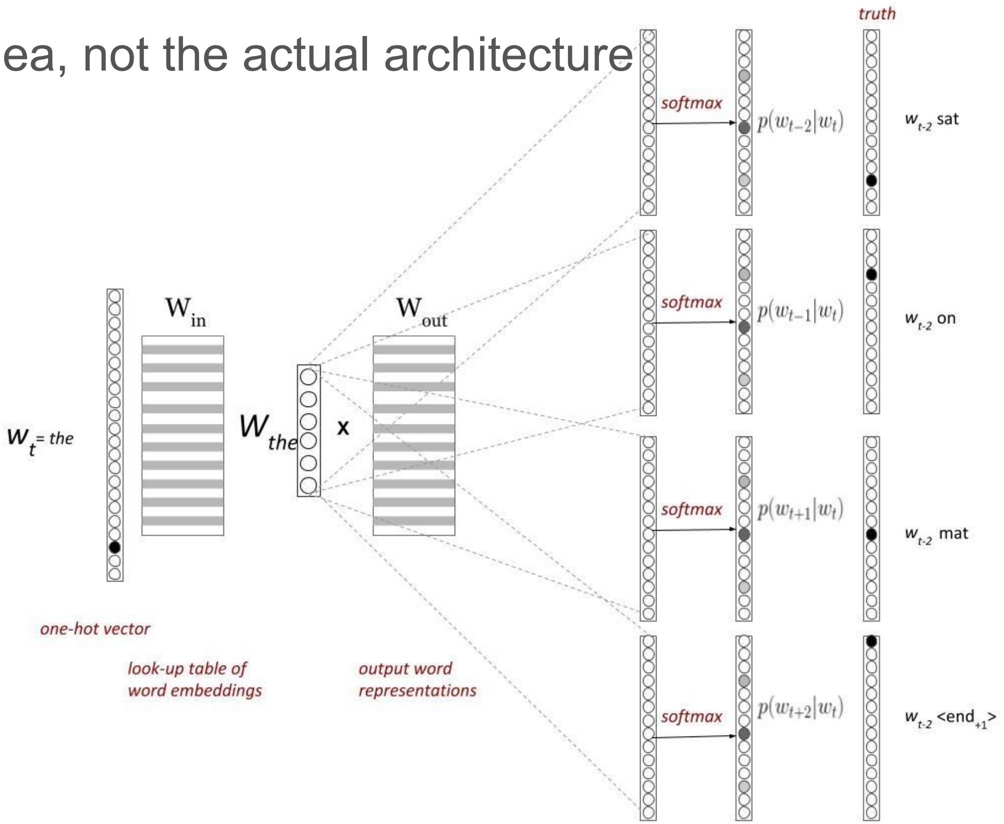
w_{t-2} = <start$_{-2}$>
w_{t-1} = <start$_{-1}$>
w_{t+1} = cat
w_{t+2} = sat

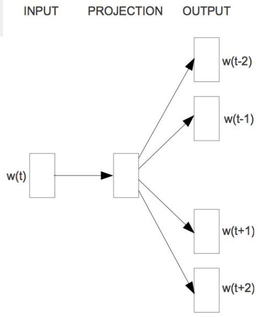


Skip-gram

Skip-gram Prediction

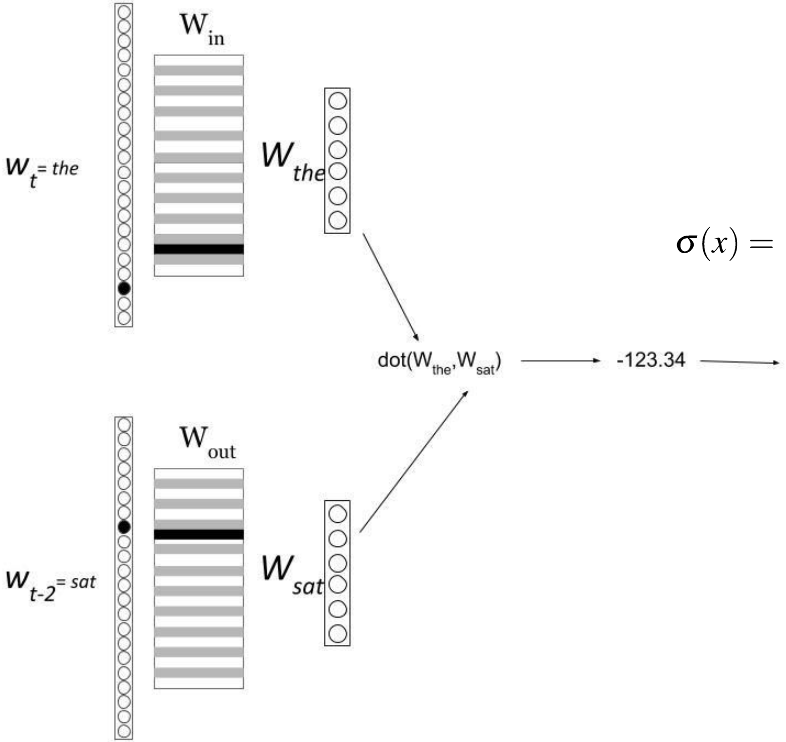
- Conceptual idea, not the actual architecture



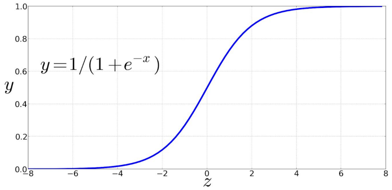


Skip-gram

How to compute p(+|t,c)?



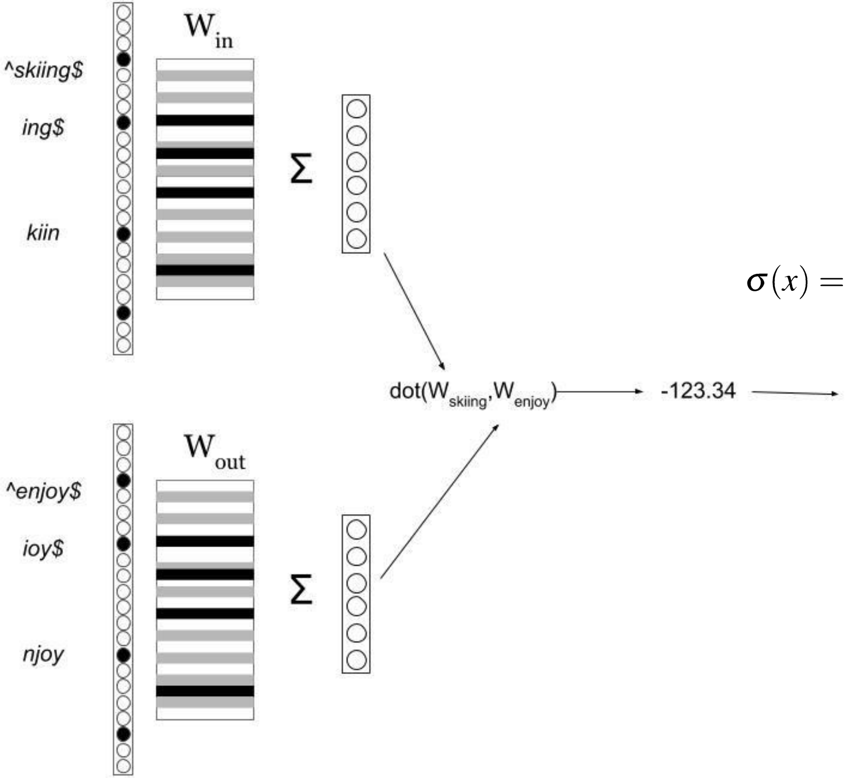
$$\sigma(x) = \frac{1}{1+e^{-x}}$$



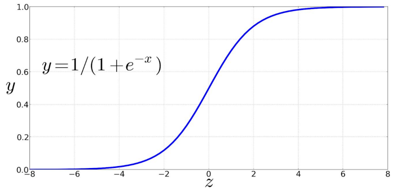
Approach: predict if candidate word c is a “neighbor”

1. Treat the target word *t* and a neighboring context word *c* as **positive examples**
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

FastText



$$\sigma(x) = \frac{1}{1+e^{-x}}$$



SGNS

Given a tuple (t,c) = target, context

- (cat, sat)
- (cat, aardvark)

Return probability that c is a real context word:

$$P(+|t,c) = \frac{1}{1+e^{-t\cdot c}}$$

$$\begin{aligned} P(-|t,c) &= 1 - P(+|t,c) \\ &= \frac{e^{-t\cdot c}}{1+e^{-t\cdot c}} \end{aligned}$$

Learning the classifier

- Iterative process
  - We'll start with 0 or random weights
  - Then adjust the word weights to
    - make the positive pairs more likely
    - and the negative pairs less likely
  - over the entire training set:

$$\sum_{(t,c)\in +} logP(+|t,c) + \sum_{(t,c)\in -} logP(-|t,c)$$

- Train using gradient descent

BERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html

Properties of Embeddings

The kinds of neighbors depend on window size

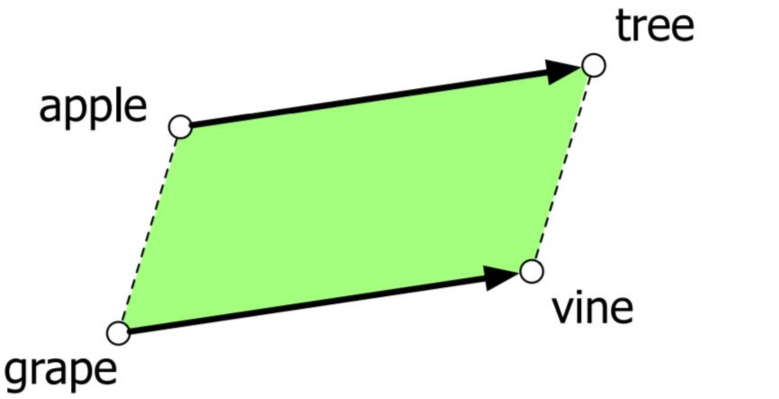
- Small windows (C= +/- 2) : nearest words are syntactically similar words in same taxonomy
  - Hogwarts nearest neighbors are other fictional schools
  - Sunnydale, Evernight, Blandings
- Large windows (C= +/- 5) : nearest words are related
  - Hogwarts nearest neighbors are Harry Potter world:
  - Dumbledore, half-blood, Malfoy

Analogical relations

The classic parallelogram model of analogical reasoning (Rumelhart and Abrahamson 1973)

To solve: "apple is to tree as grape is to ________"

Add $\overrightarrow{\text{tree}} - \overrightarrow{\text{apple}}$ to $\overrightarrow{\text{grape}}$ to get $\overrightarrow{\textbf{vine}}$



Analogical relations via parallelogram

The parallelogram method can solve analogies with both sparse and dense embeddings (Turney and Littman 2005, Mikolov et al. 2013b)

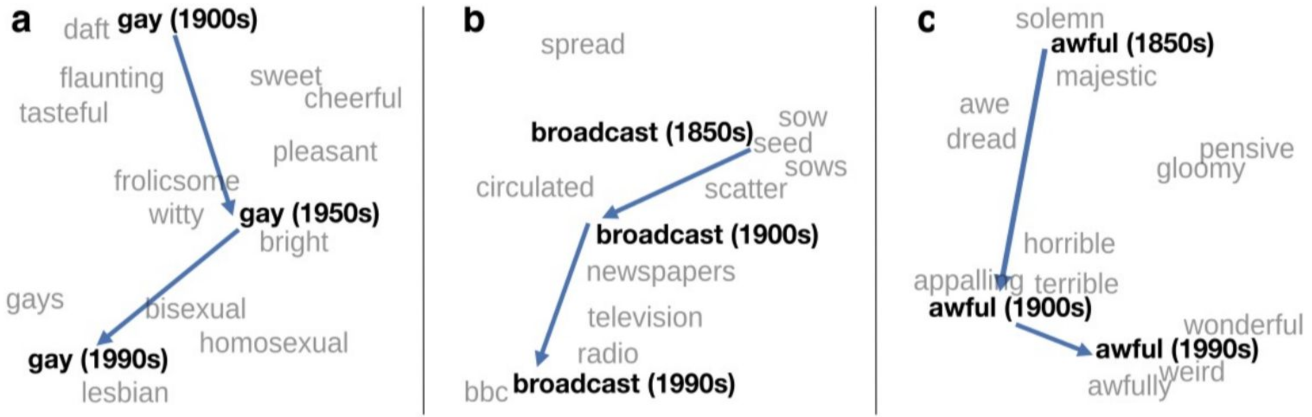
$$\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{woman}} \text{ is close to } \overrightarrow{\text{queen}}$$

$$\overrightarrow{\text{Paris}} - \overrightarrow{\text{France}} + \overrightarrow{\text{Italy}} \text{ is close to } \overrightarrow{\text{Rome}}$$

Embeddings as a window onto historical semantics

Train embeddings on different decades of historical text to see meanings shift

~30 million books, 1850-1990, Google Books data



William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change. Proceedings of ACL.

Embeddings reflect cultural bias!

- Ask “Paris : France :: Tokyo : x”
  - x = Japan
- Ask “father : doctor :: mother : x”
  - x = nurse
- Ask “man : computer programmer :: woman : x”
  - x = homemaker

Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." In NeurIPS, pp. 4349-4357. 2016

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring

Use cases for feedforward networks

- Word representations
- Text classification
- Language modeling

State of the art systems use more powerful neural architectures (we will learn transformers architectures on Monday), but simple models are useful to consider!

Neural LMs

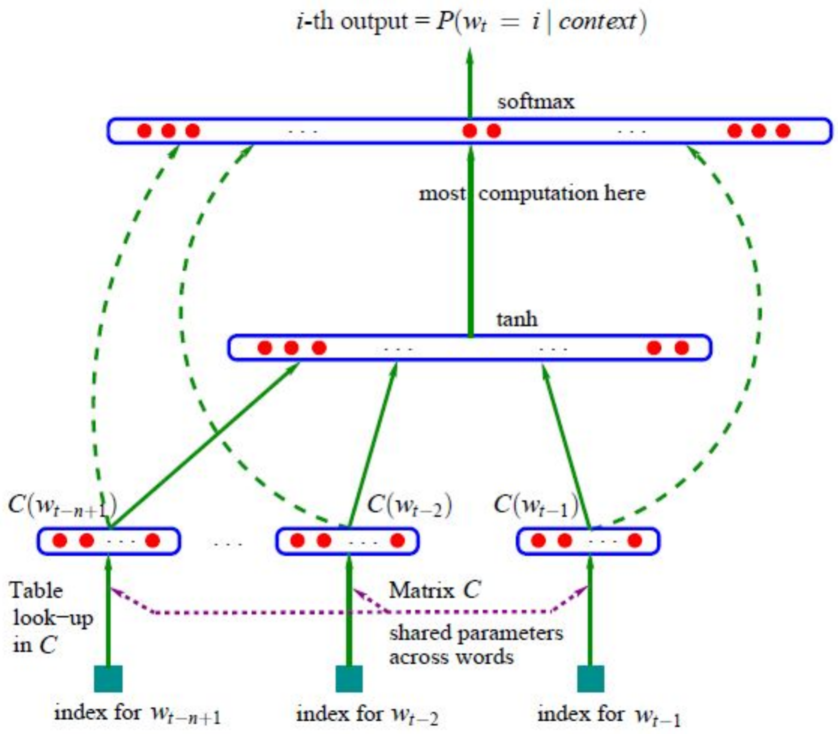


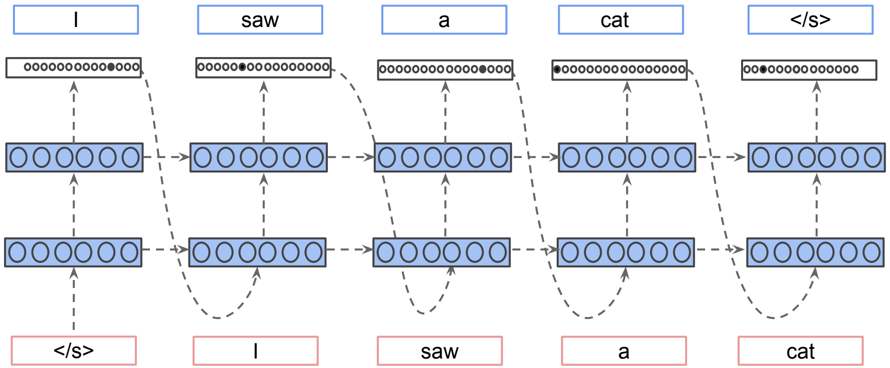
Image: (Bengio et al, 03)

Neural LMs

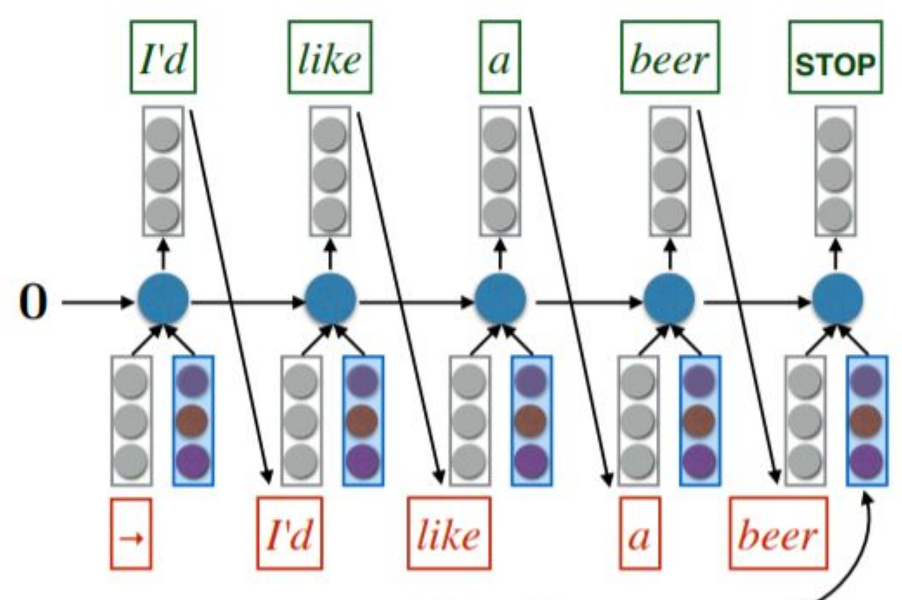
	n	c	h	m	direct	mix	train.	valid.	test.
MLP1	5		50	60	yes	no	182	284	268
MLP2	5		50	60	yes	yes		275	257
MLP3	5		0	60	yes	no	201	327	310
MLP4	5		0	60	yes	yes		286	272
MLP5	5		50	30	yes	no	209	296	279
MLP6	5		50	30	yes	yes		273	259
MLP7	3		50	30	yes	no	210	309	293
MLP8	3		50	30	yes	yes		284	270
MLP9	5		100	30	no	no	175	280	276
MLP10	5		100	30	no	yes		265	**252**
Kneser-Ney back-off	3							334	323
Kneser-Ney back-off	4							332	321
Kneser-Ney back-off	5							332	321

(Bengio et al, 03)

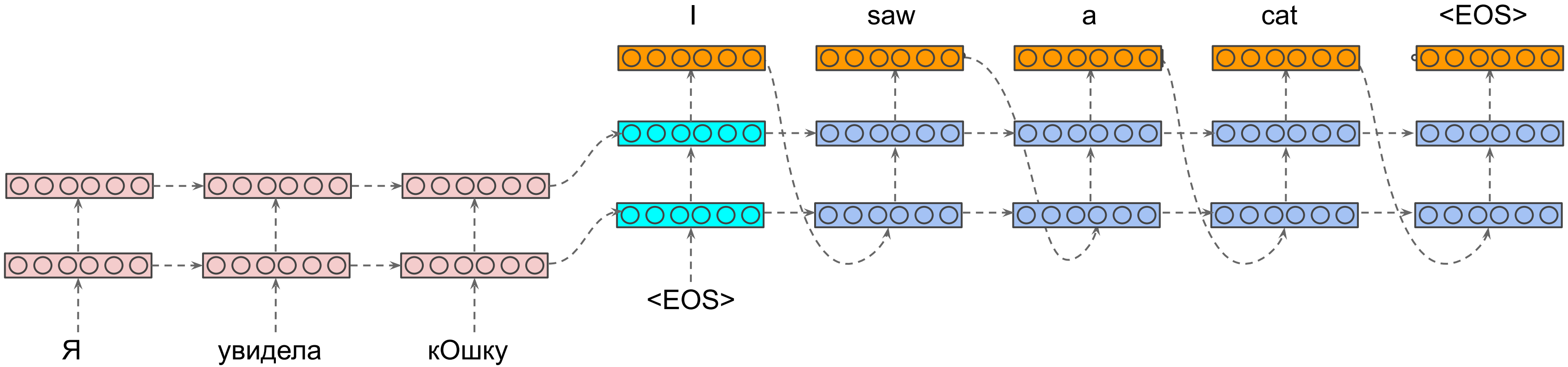
Recurrent LMs



Recurrent LMs

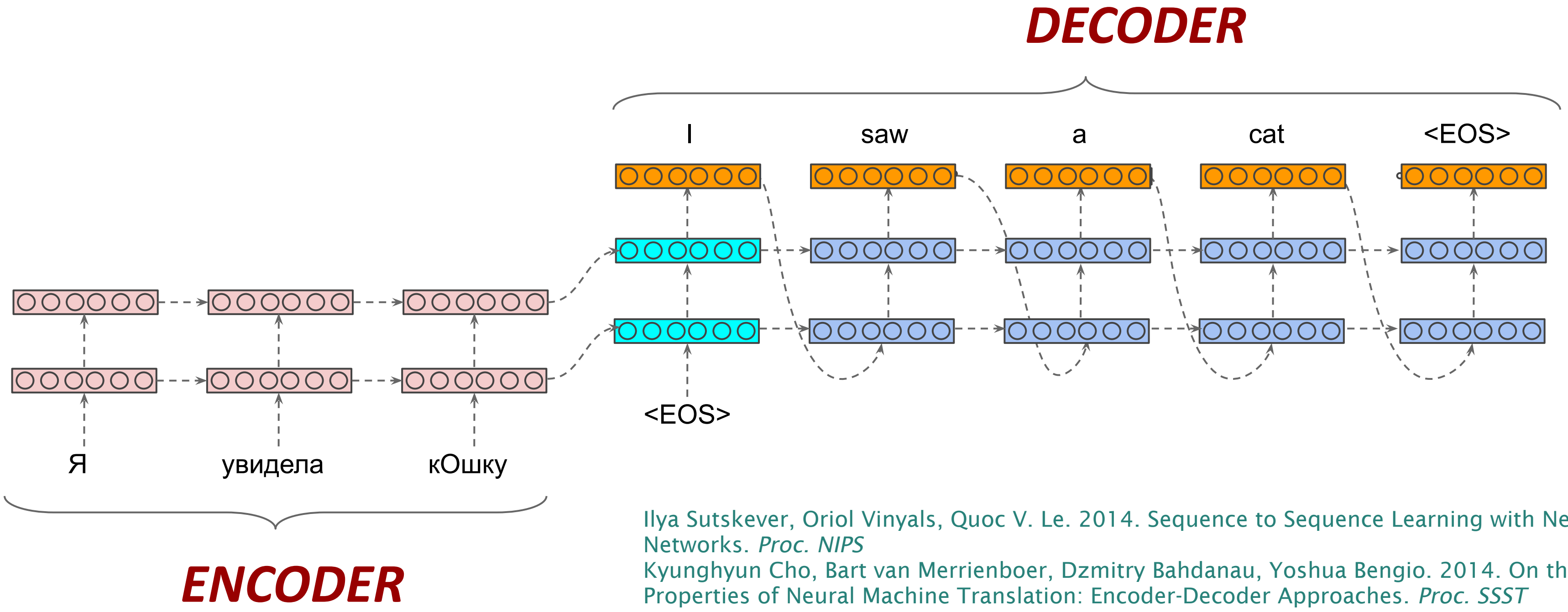


Sequence-to-Sequence Models



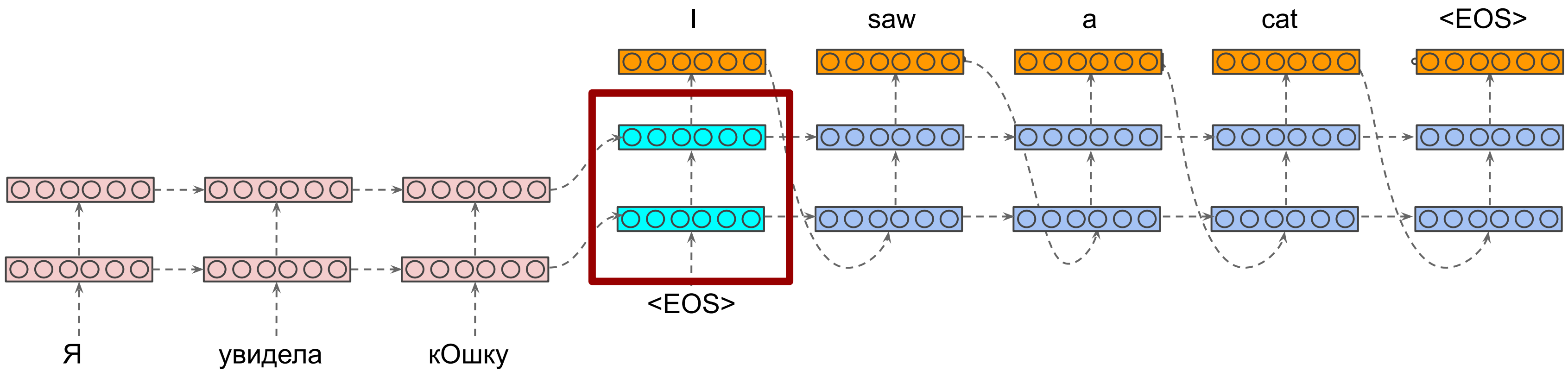
Ilya Sutskever, Oriol Vinyals, Quoc V. Le. 2014. Sequence to Sequence Learning with Neural Networks. Proc. NIPS

Sequence-to-Sequence Models for Neural Machine Translation



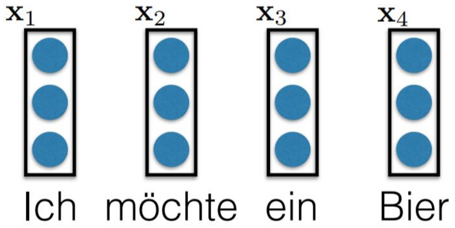
Ilya Sutskever, Oriol Vinyals, Quoc V. Le. 2014. Sequence to Sequence Learning with Neural Networks. *Proc. NIPS*
Kyunghyun Cho, Bart van Merrienboer, Dzmitry Bahdanau, Yoshua Bengio. 2014. On the Properties of Neural Machine Translation: Encoder-Decoder Approaches. *Proc. SSST*

Sequence-to-Sequence Models for NMT

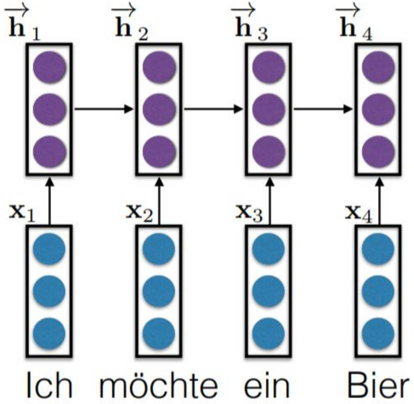


sentence representation

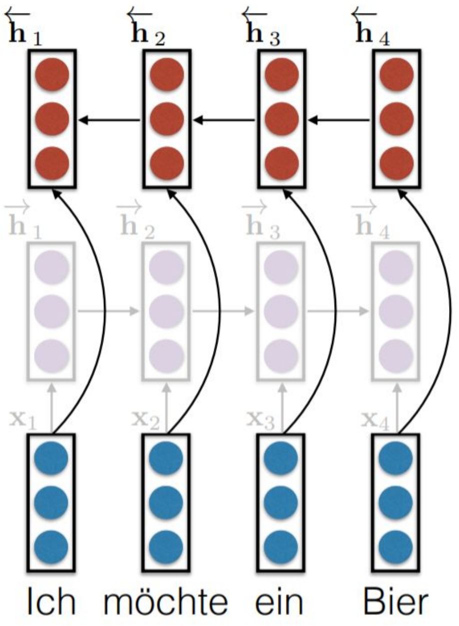
Encoder: Bidirectional RNN



Encoder: Bidirectional RNN

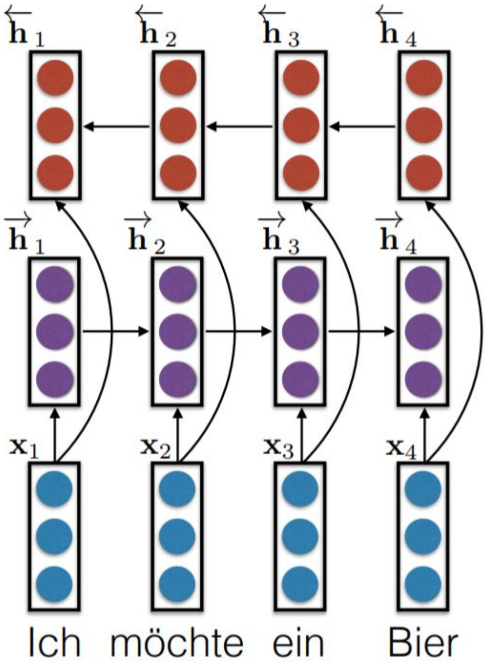


Encoder: Bidirectional RNN

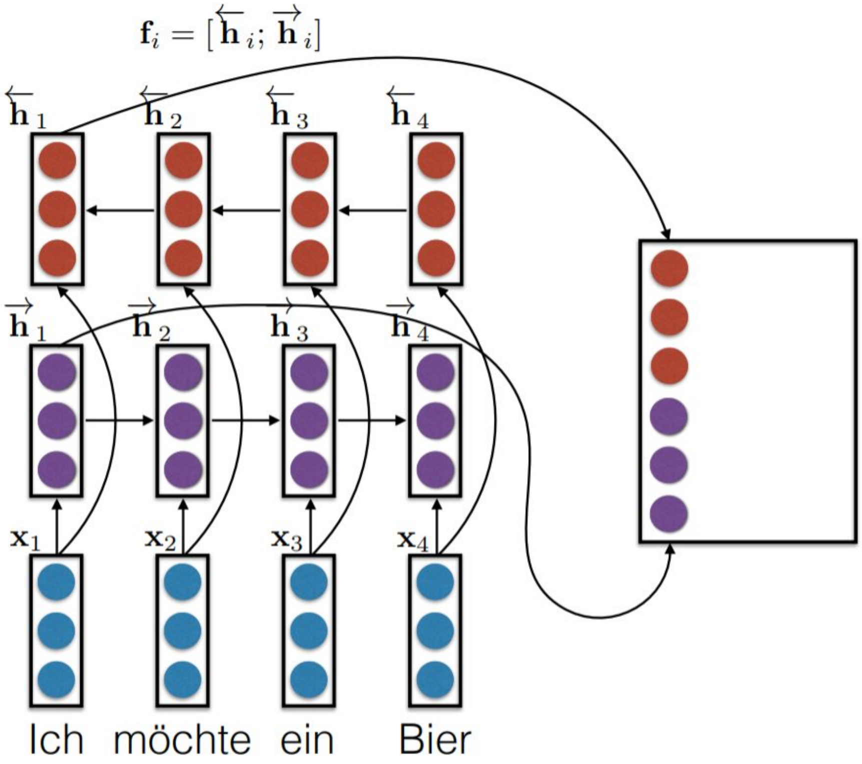


Encoder: Bidirectional RNN

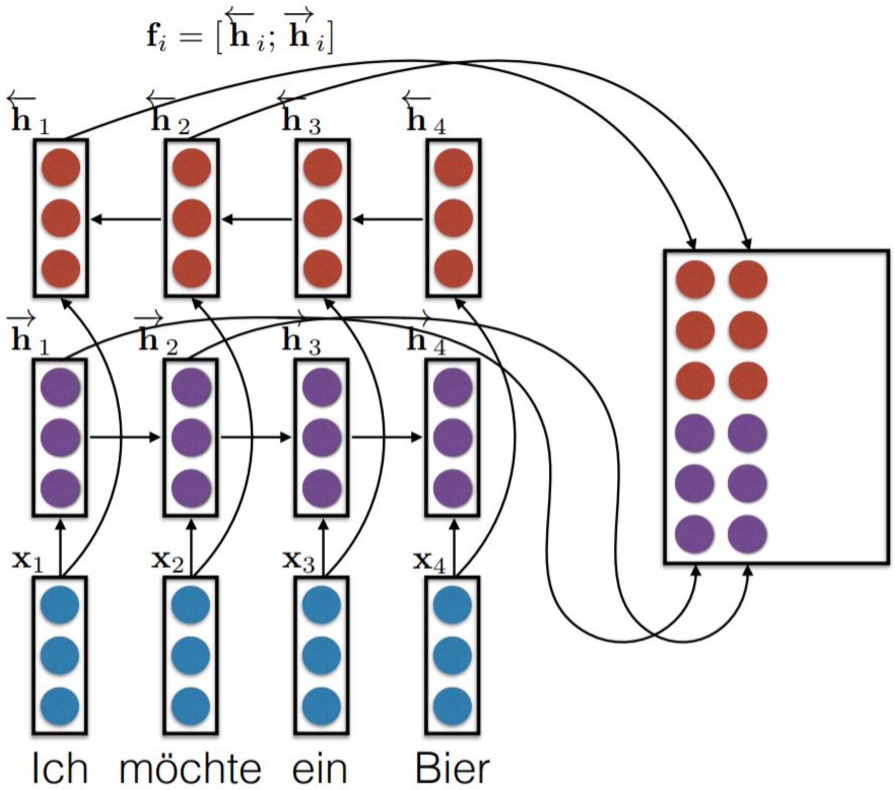
$$\mathbf{f}_i = [\overleftarrow{\mathbf{h}}_i; \overrightarrow{\mathbf{h}}_i]$$



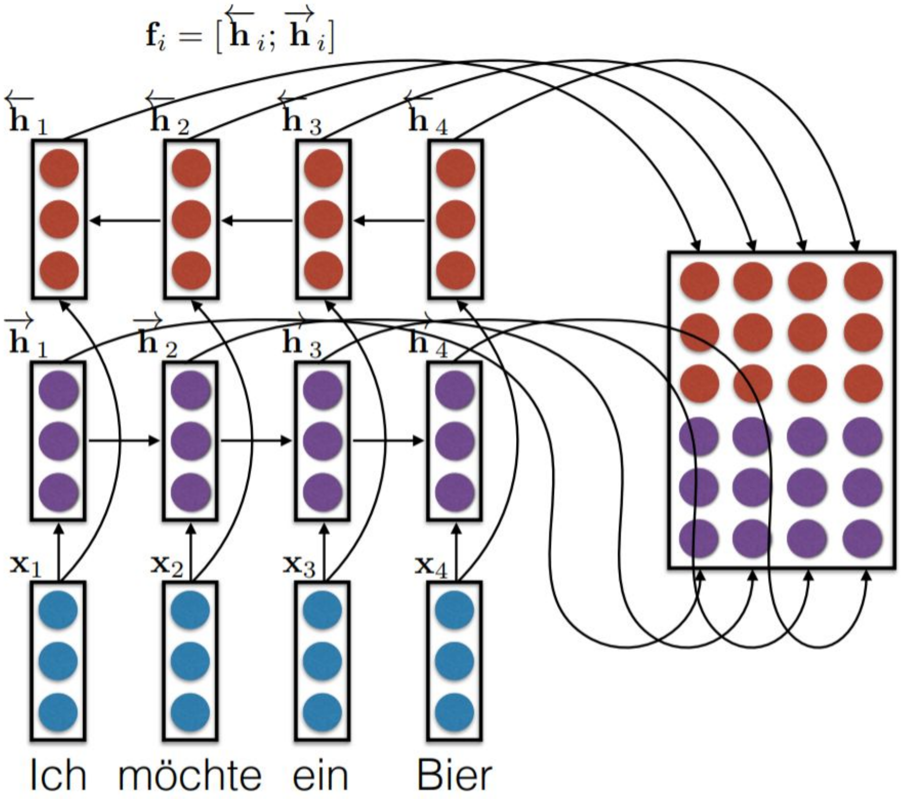
Encoder: Bidirectional RNN



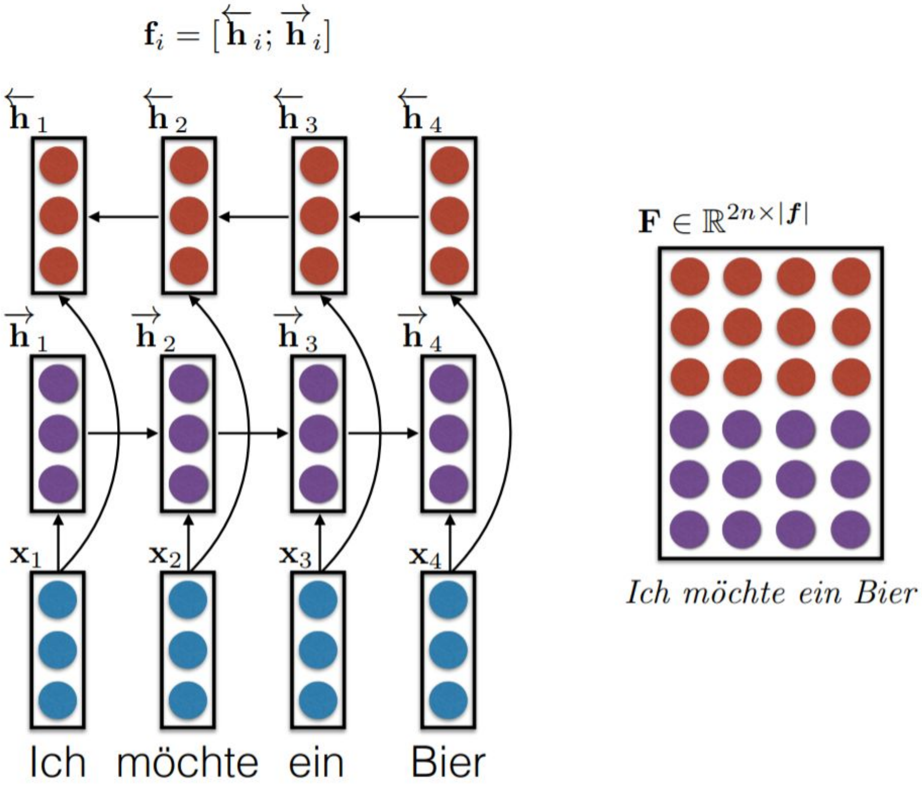
Encoder: Bidirectional RNN



Encoder: Bidirectional RNN

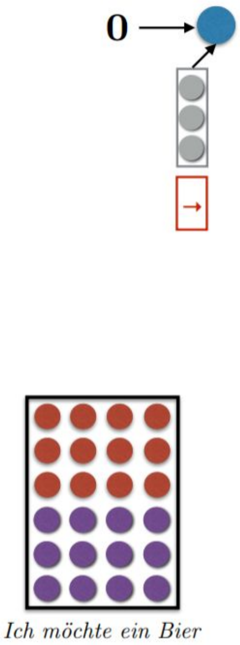


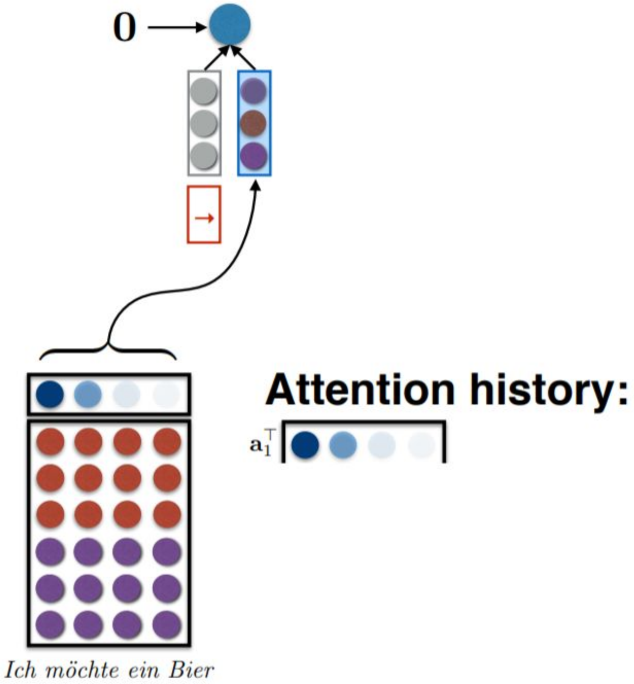
Matrix Sentence Encoding

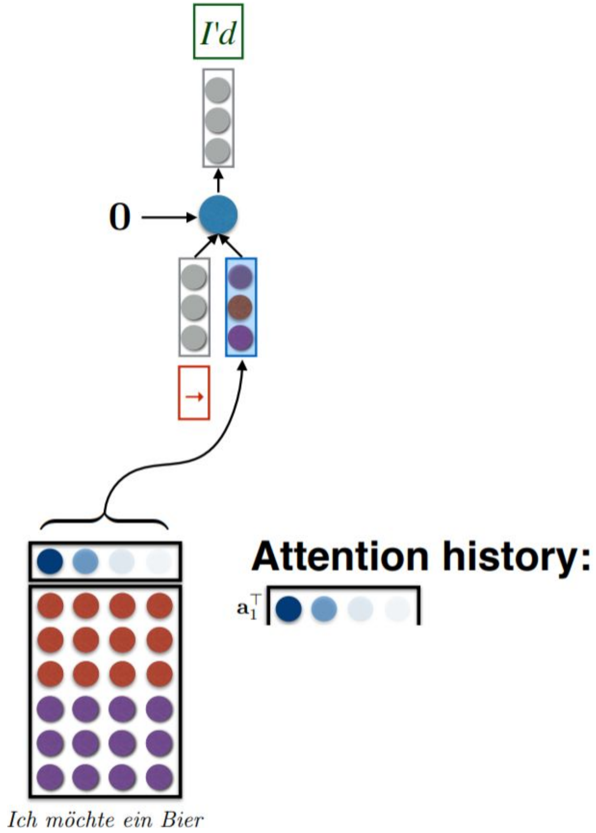


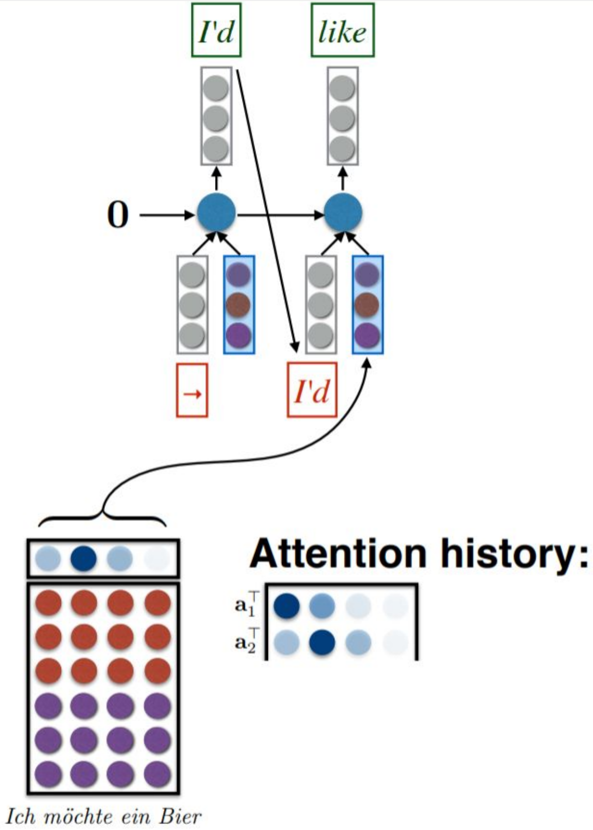
- matrix-encoded sentence

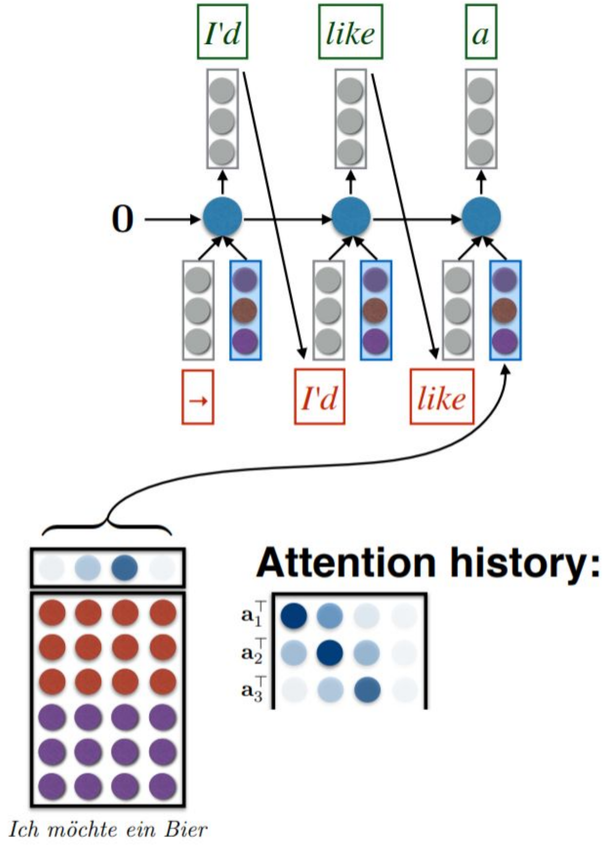
Decoder: RNN + Attention

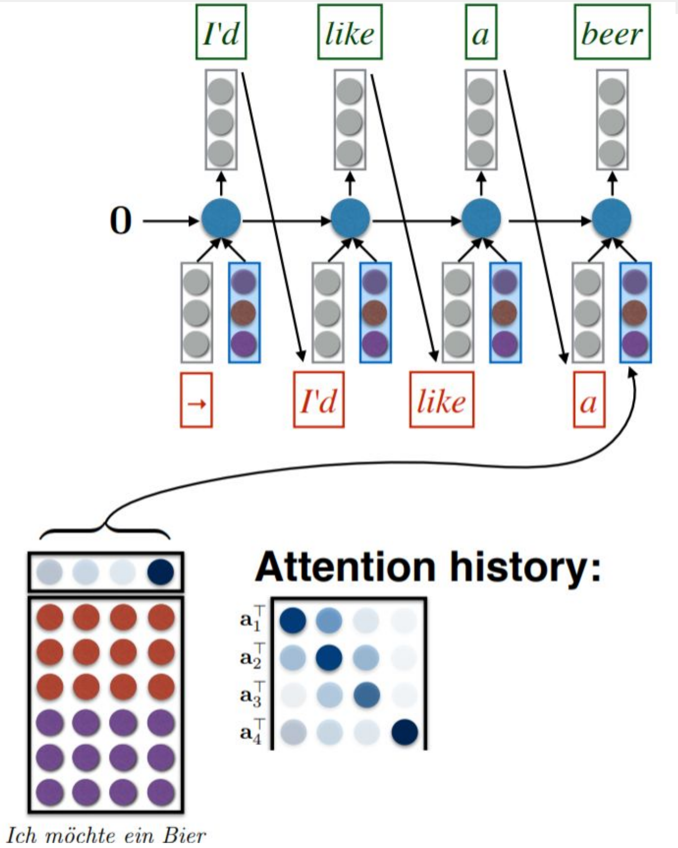


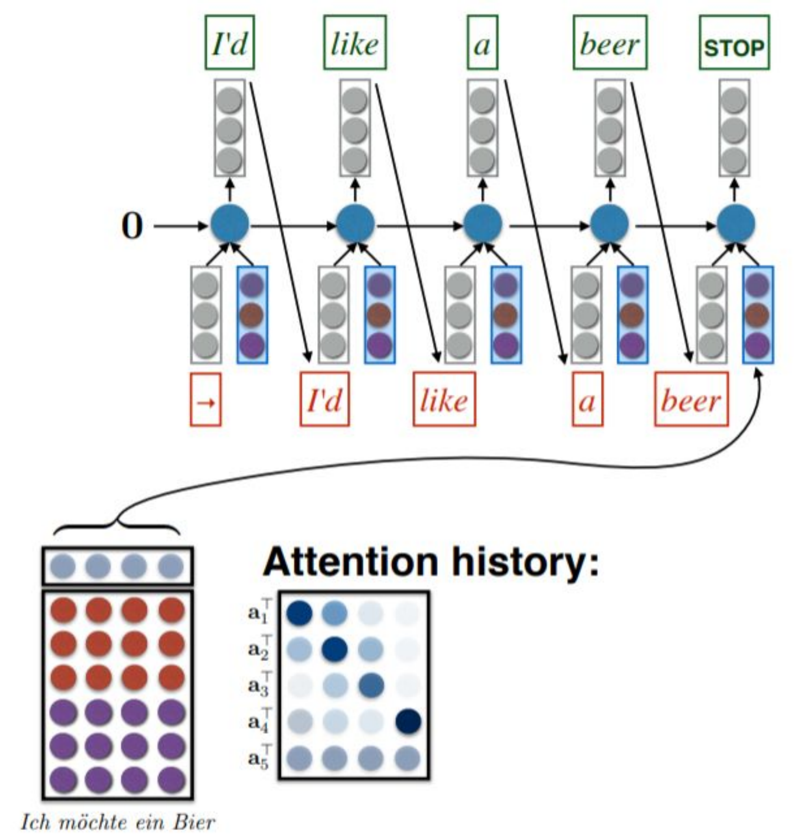

0
Attention history:
$a_1^\top$
Ich möchte ein Bier


I'd
0
→
Attention history:
$\mathbf{a}_1^\top$
Ich möchte ein Bier


I'd
like
0
→
I'd
Ich möchte ein Bier
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$


I'd
like
a
0
→
I'd
like
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
Ich möchte ein Bier


I'd
like
a
beer
0
→
I'd
like
a
Attention history:
$a_1^\top$
$a_2^\top$
$a_3^\top$
$a_4^\top$
Ich möchte ein Bier


I'd
like
a
beer
STOP
0
→
I'd
like
a
beer
Attention history:
$\mathbf{a}_1^\top$
$\mathbf{a}_2^\top$
$\mathbf{a}_3^\top$
$\mathbf{a}_4^\top$
$\mathbf{a}_5^\top$
Ich möchte ein Bier