10707
Deep Learning

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Language Modeling

Natural Language Processing

- Natural language processing is concerned with tasks involving language data
  - ➢ we will focus on text data NLP

- Much like for computer vision, we can design neural networks specifically adapted to the processing of text data
  - ➢ main issue: text data is inherently high dimensional

Natural Language Processing

- Typical preprocessing steps of text data
  - Form vocabulary of words that maps words to a unique ID
  - Different criteria can be used to select which words are part of the vocabulary
  - Pick most frequent words and ignore uninformative words from a user-defined short list (ex.: “ the ”, “ a ”, etc.)
  - All words not in the vocabulary will be mapped to a special “out-of-vocabulary’
- Typical vocabulary sizes will vary between 100,000 and 1,000,000

Vocabulary

- Example:

Word	w
"the"	1
"and"	2
"dog"	3
"."	4
"OOV"	5

"the"
"cat"
"and"
"the"
"dog"
"play"
"."

1
5
2
1
3
5
4

- We will note word IDs with the symbol w
  - ➢ we can think of w as a categorical feature for the original word
  - ➢ we will sometimes refer to w as a word, for simplicity

One-Hot Encoding

- From its word ID, we get a basic representation of a word through the one-hot encoding of the ID

  - the one-hot vector of an ID is a vector filled with 0s, except for a 1 at the position associated with the ID
  - For vocabulary size D=10, the one-hot vector of word ID w=4 is:

$$e(w) = [\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ ]$$

  - A one-hot encoding makes no assumption about word similarity
  - This is a natural representation to start with, though a poor one

One-Hot Encoding

- The major problem with the one-hot representation is that it is very high-dimensional
  - the dimensionality of e(w) is the size of the vocabulary
  - a typical vocabulary size is ≈100,000
  - a window of 10 words would correspond to an input vector of at least 1,000,000 units!
- This has 2 consequences:
  - vulnerability to overfitting (millions of inputs means millions of parameters to train)
  - computationally expensive

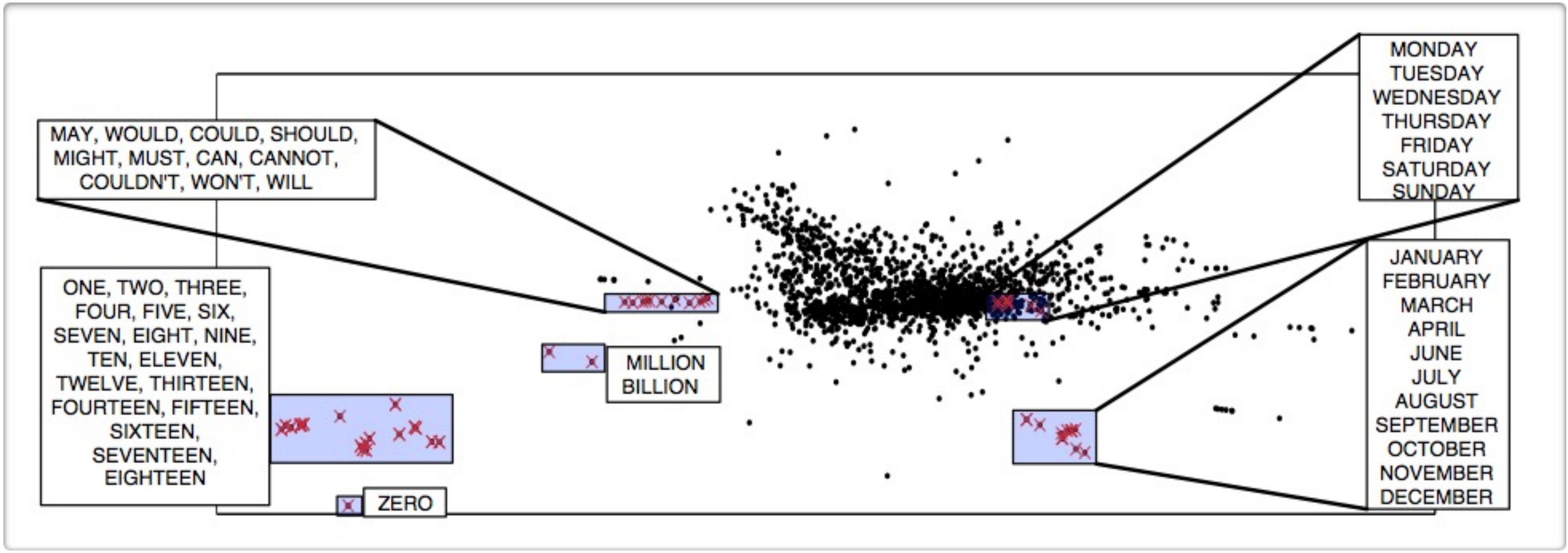
Continuous Representation of Words

- Each word w is associated with a real-valued vector C(w)

Word	w	$C(w)$
"the"	1	[0.6762, -0.9607, 0.3626, -0.2410, 0.6636]
"a"	2	[0.6859, -0.9266, 0.3777, -0.2140, 0.6711]
"have"	3	[0.1656, -0.1530, 0.0310, -0.3321, -0.1342]
"be"	4	[0.1760, -0.1340, 0.0702, -0.2981, -0.1111]
"cat"	5	[0.5896, 0.9137, 0.0452, 0.7603, -0.6541]
"dog"	6	[0.5965, 0.9143, 0.0899, 0.7702, -0.6392]
"car"	7	[-0.0069, 0.7995, 0.6433, 0.2898, 0.6359]
...	...	...

Continuous Representation of Words

- We would like the distance ||C(w)-C(w')|| to reflect meaningful similarities between words



(from Blitzer et al. 2004)

Continuous Representation of Words

- Learn a continuous representation of words
  - we could then use these representations as input to a neural network
- We learn these representations by gradient descent
  - we don't only update the neural network parameters
  - we also update each representation C(w) in the input x with a gradient step:

$$C(w) \Longleftarrow C(w) - \alpha \nabla_{C(w)} l$$

where *l* is the loss function optimized by the neural network

Continuous Representation of Words

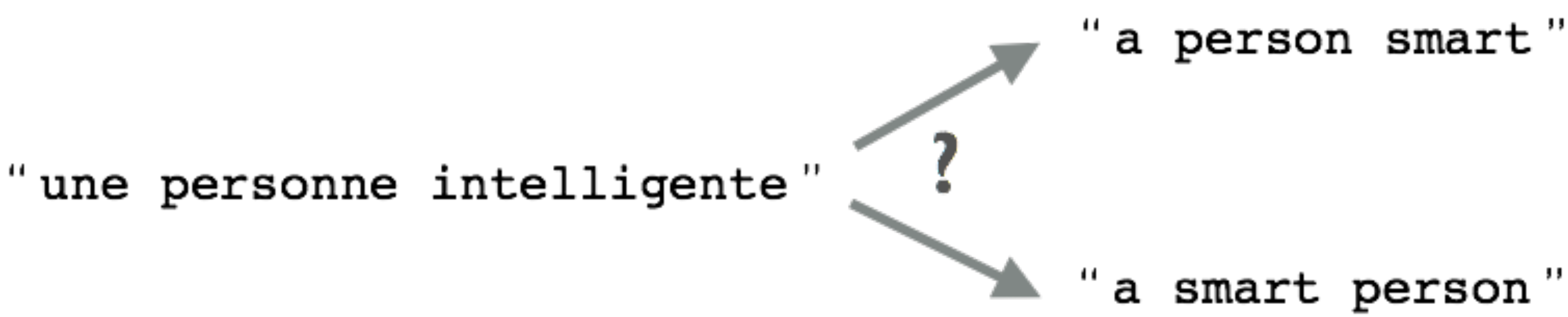
- Let C be a matrix whose rows are the representations C(w)
  - obtaining C(w) corresponds to the multiplication $e(w)^T C$
  - view differently, we are projecting e(w) onto the columns of C
  - this is a continuous transformation, through which we can propagate gradients

- In practice, we implement C(w) with a lookup table, not with a multiplication

Language Modeling

$$p(w_1, \ldots ,w_T)$$

- language modeling is the task of learning a language model that assigns high probabilities to well formed sentences
- plays a crucial role in speech recognition and machine translation systems



Language Modeling

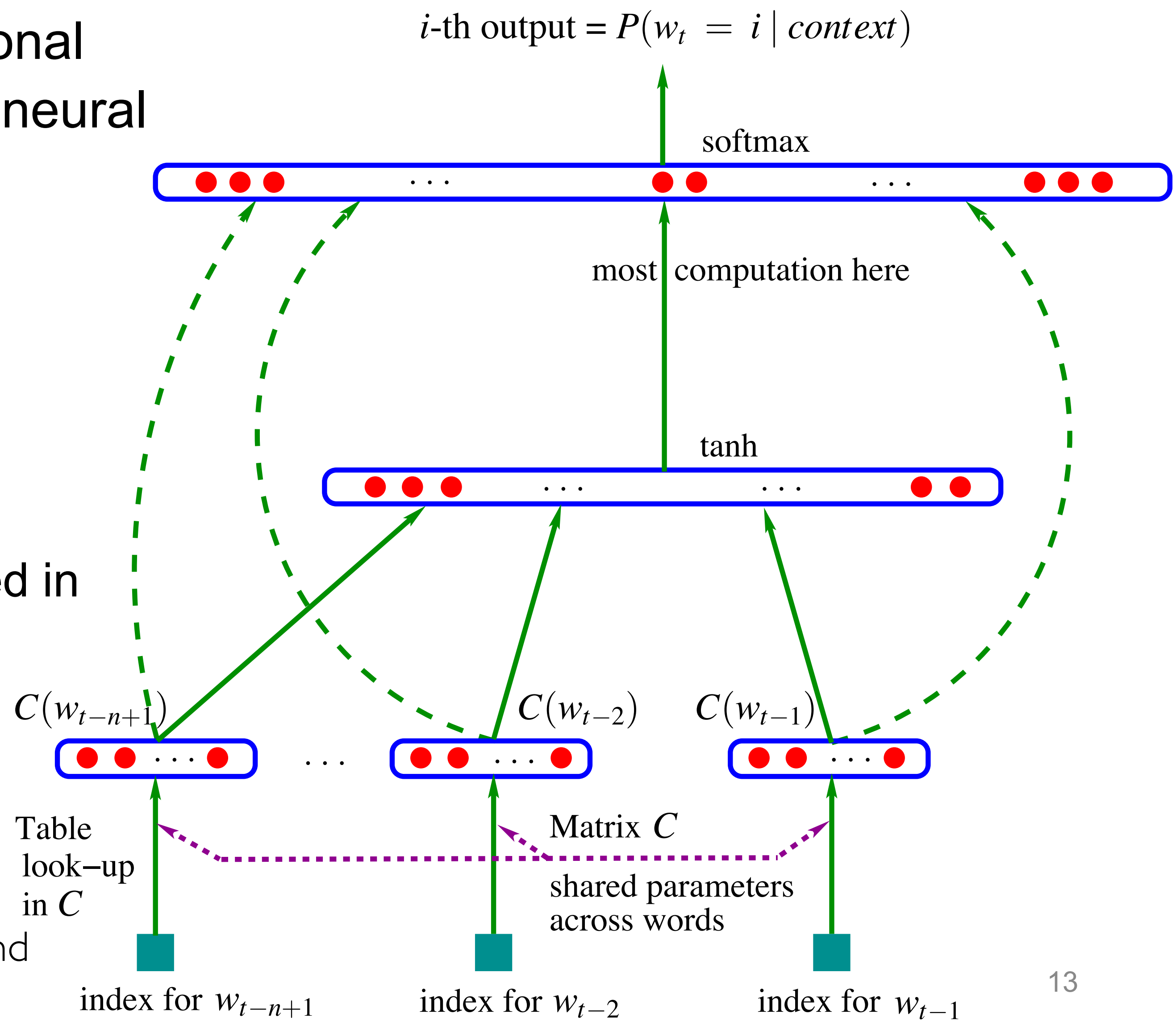
$$p(w_1, \ldots, w_T) = \prod_{t=1}^{T} \boldsymbol{p(w_t \mid w_{t-(n-1)}, \ldots, w_{t-1})}$$

- the t[th] word was generated based only on the n−1 previous words
- we will refer to $w_{t-(n-1)}, \ldots, w_{t-1}$ as the context

Neural Language Model

- Model the conditional distributions with a neural network:

➢ learn word representations to allow transfer to n-grams not observed in training corpus



Bengio, Ducharme, Vincent and Jauvin, 2003

Neural Language Model

- Can potentially generalize to contexts not seen in training set

  - Example: *P(“ eating ” | “ the ”, “ cat ”, “ is ”)*

  - Imagine 4-gram [“ the ”, “ cat ”, “ is ”, “ eating ”] is not in training corpus, but [“ the ”, “ dog ”, “ is ”, “ eating ”] is

  - If the word representations of “ cat ” and “ dog ” are similar, then the neural network will be able to generalize to the case of “ cat ”

Neural Language Model

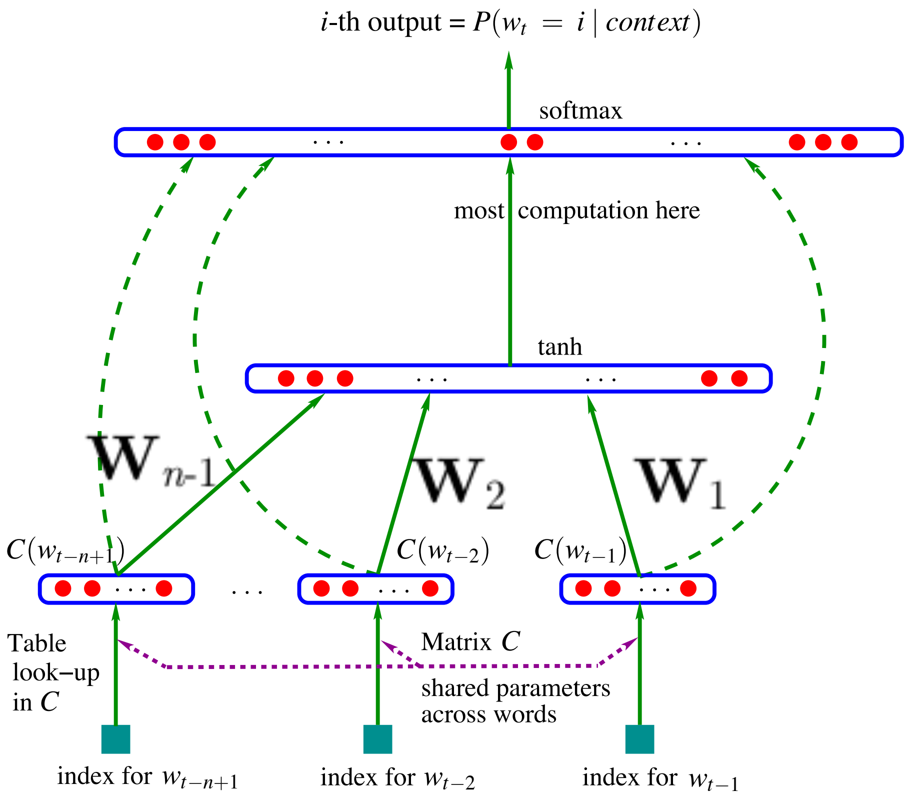
- We know how to propagate gradients in such a network

$$\nabla_{\mathbf{a}(\mathbf{x})} l$$

- ➢ let's note the submatrix connecting w_{t-i} and the hidden layer as $\boldsymbol{W_i}$

- The gradient wrt $C(w)$ for any w is

$$\nabla_{C(w)} l = \sum_{i=1}^{n-1} 1_{(w_{t-i}=w)} \, \mathbf{W}_i^\top \, \nabla_{\mathbf{a}(\mathbf{x})} l$$



Performance Evaluation

- In language modeling, a common evaluation metric is the perplexity
  - it is simply the exponential of the average negative log-likelihood
- Evaluation on Brown Corpus
  - n-gram model (Kneser-Ney smoothing): 321
  - neural network language model: 276
  - neural network + n-gram: 252

How About Generating Sentences!

Input

Output

A man skiing down the snow covered mountain with a dark sky in the background.

How About Generating Sentences!

Input

Output

A man skiing down the snow covered mountain with a dark sky in the background.

We want to model:

$$p(w_1, w_2, ..., w_n) =$$

$$p(w_1)p(w_2|w_1)p(w_3|w_1, w_2)...p(w_n|w_1, w_2, ..., w_{n-1})$$

Caption Generation with NLM

LZ

a car is parked in
the middle of nowhere .

a wooden table and chairs
arranged in a room .

there is a cat sitting on a shelf .

a ferry boat on a marina
with a group of people .

a little boy with a bunch
of friends on the street .

Caption Generation with NLM

the two birds are trying to be seen in the water .
(can't count)

a giraffe is standing next to a fence in a field .
(hallucination)

a parked car while driving down the road .
(contradiction)

Caption Generation with NLM

the two birds are trying to be seen in the water . (can't count)

a giraffe is standing next to a fence in a field . (hallucination)

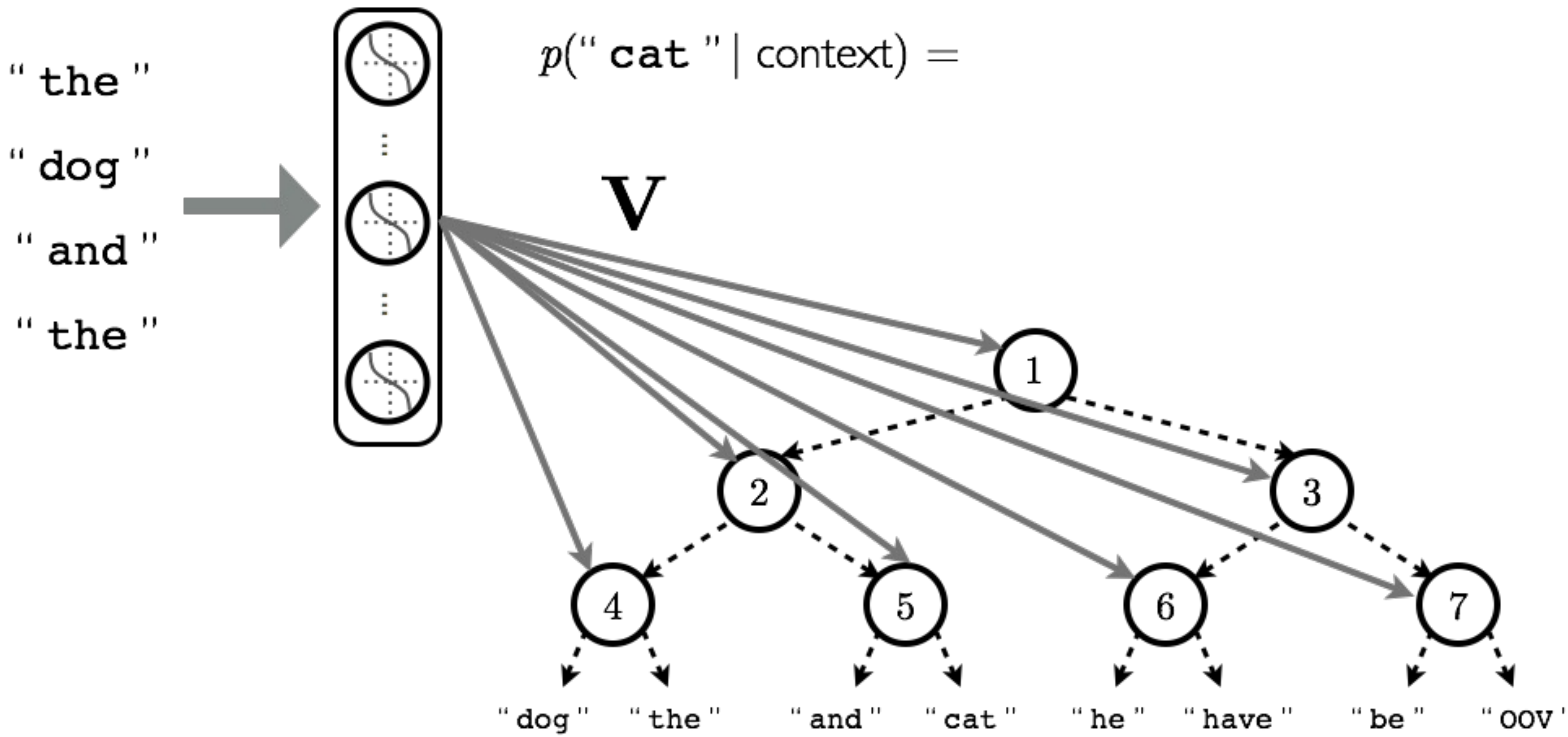
a parked car while driving down the road . (contradiction)

the handlebars are trying to ride a bike rack . (nonsensical)

a woman and a bottle of wine in a garden . (gender)

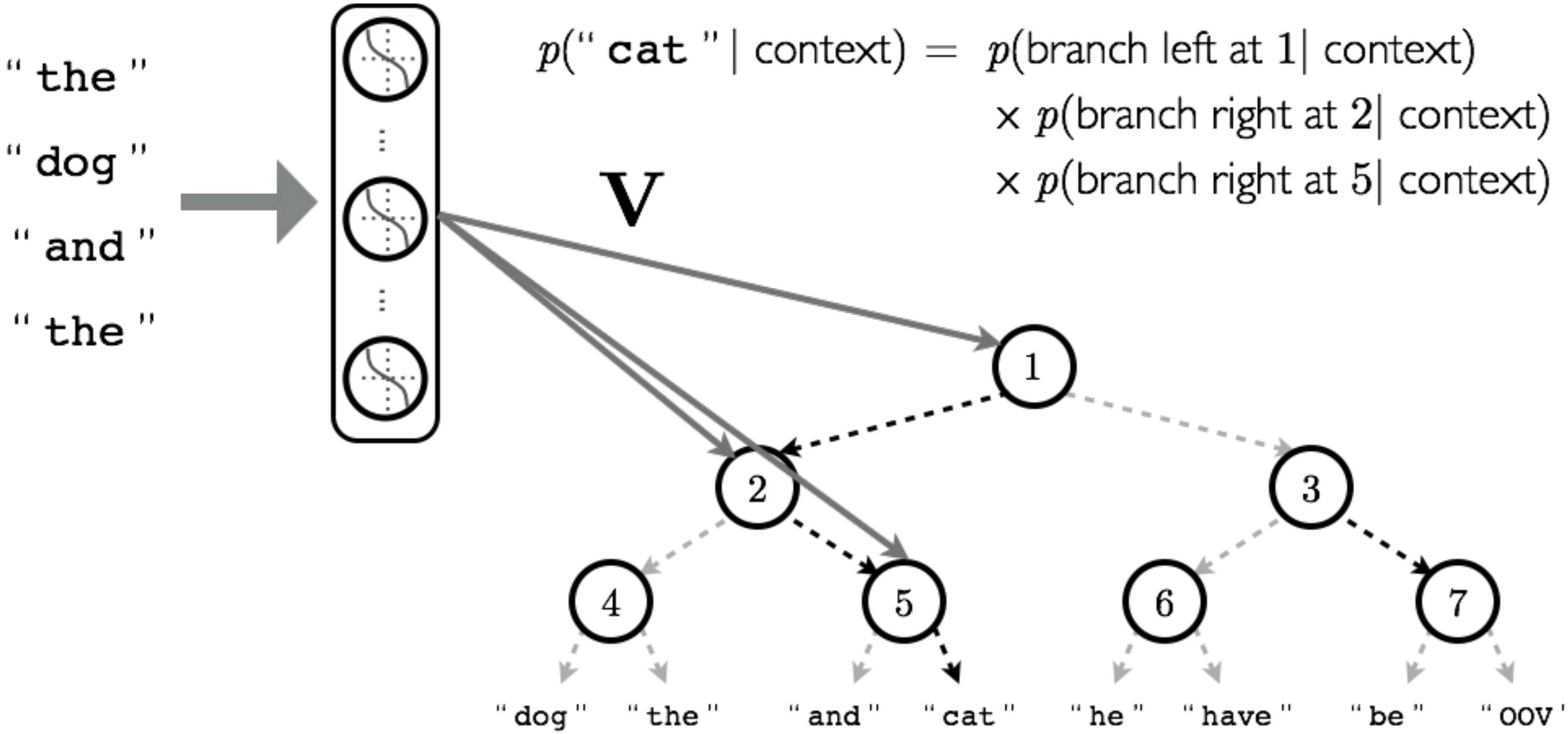
Hierarchical Output Layer

- Example: [“ the ”, “ dog ”, “ and ”, “ the ”, “ cat ”]



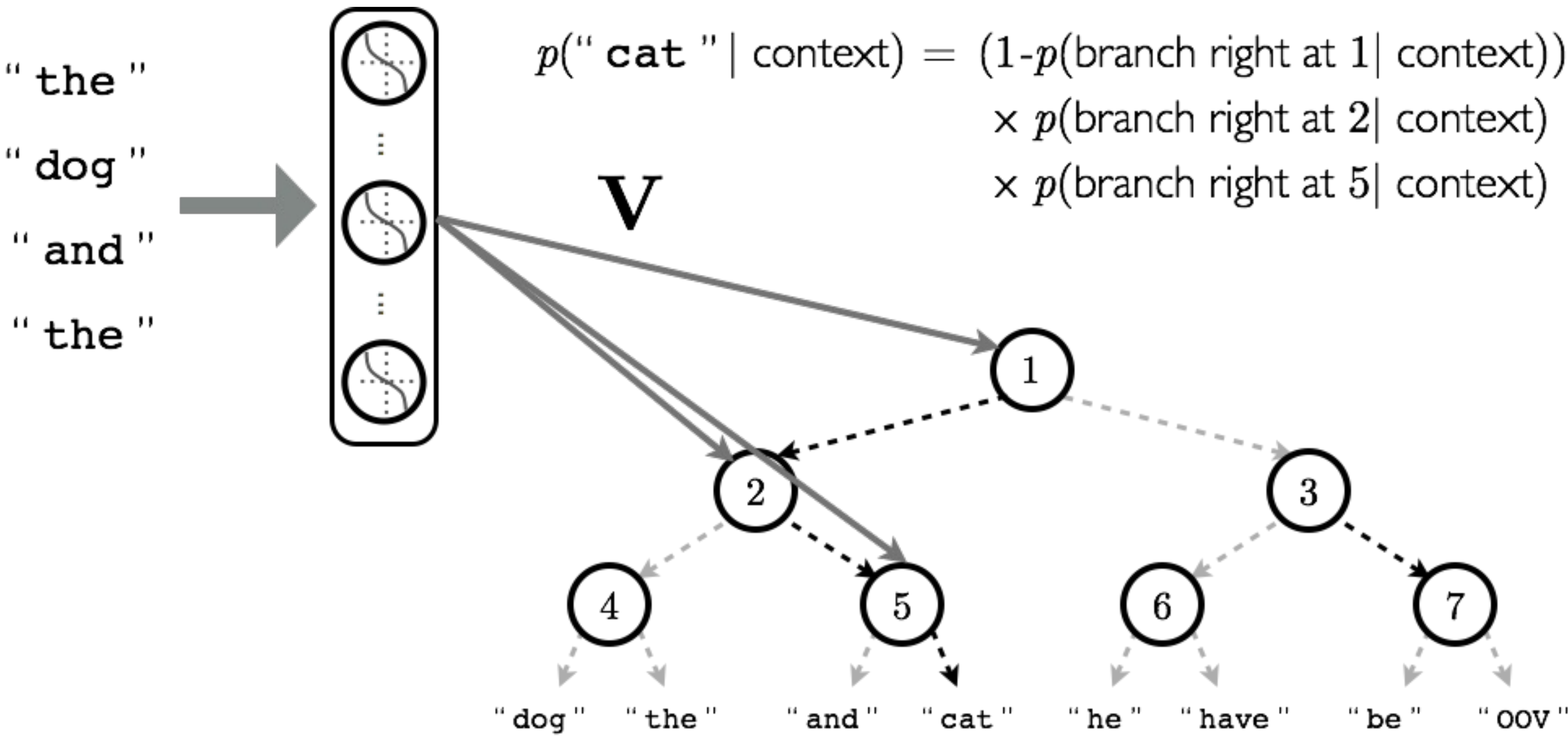
Hierarchical Output Layer

- Example: [" the ", " dog ", " and ", " the ", " cat "]



Hierarchical Output Layer

- Example: [" the ", " dog ", " and ", " the ", " cat "]

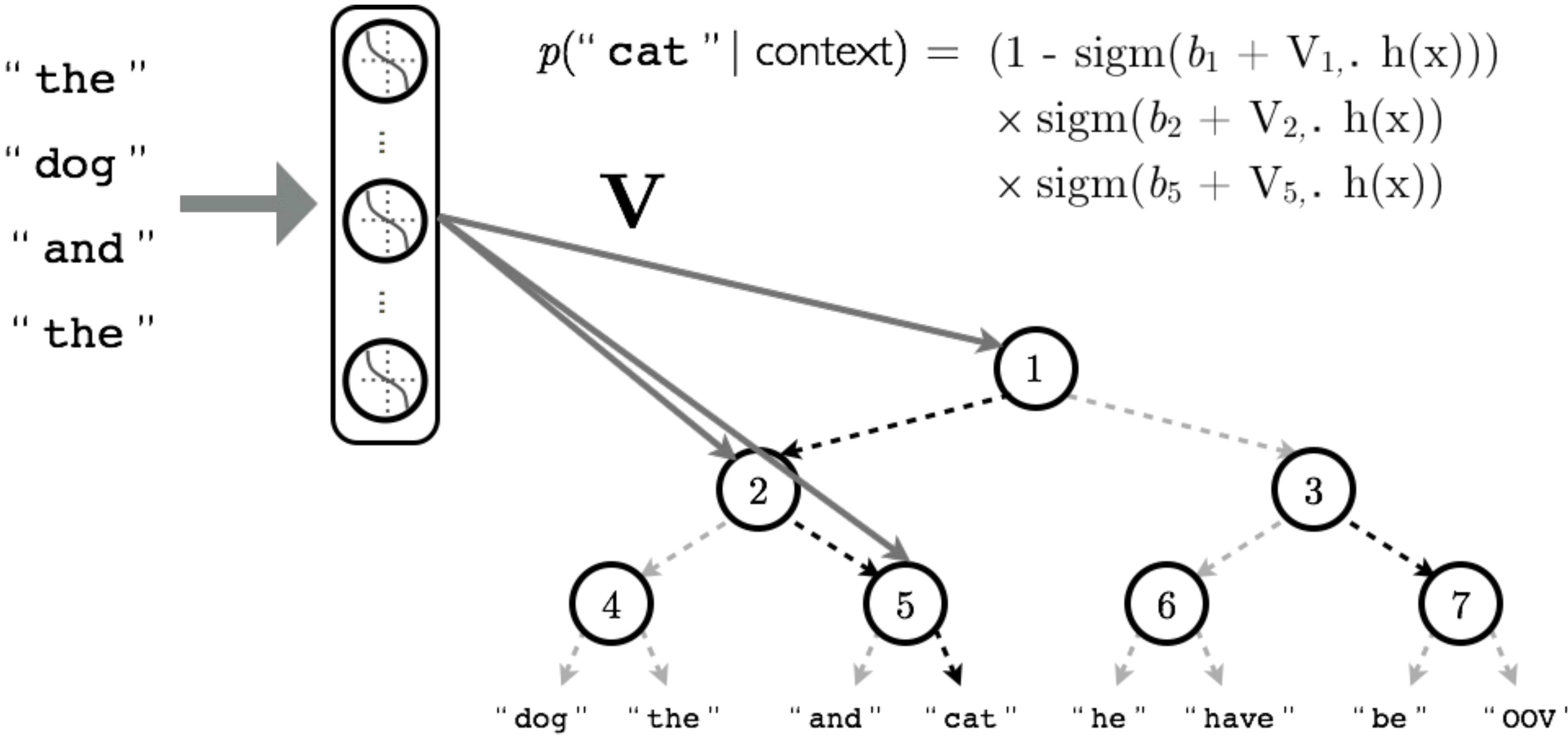


$$
\begin{aligned}
p(\text{" }\mathtt{cat}\text{ "} \mid \text{context}) = {} & (1\text{-}p(\text{branch right at } 1 \mid \text{context})) \\
& \times p(\text{branch right at } 2 \mid \text{context}) \\
& \times p(\text{branch right at } 5 \mid \text{context})
\end{aligned}
$$

Hierarchical Output Layer

- Example: [“ the ”, “ dog ”, “ and ”, “ the ”, “ cat ”]

$$p(\text{“}\mathbf{cat}\text{”} \mid \text{context}) = (1 - \mathrm{sigm}(b_1 + V_{1,\cdot}\ h(x))) \times \mathrm{sigm}(b_2 + V_{2,\cdot}\ h(x)) \times \mathrm{sigm}(b_5 + V_{5,\cdot}\ h(x))$$



Hierarchical Output Layer

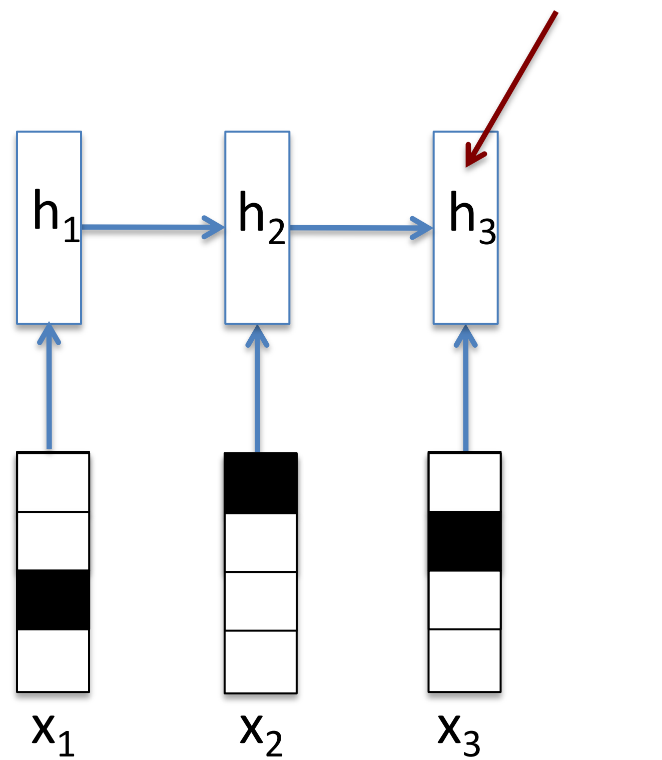
- How to define the word hierarchy?

  - can use a randomly generated tree
  - can use existing linguistic resources, such as WordNet
  - can learn the hierarchy using a recursive partitioning strategy

    A Scalable Hierarchical Distributed Language Model Mnih and Hinton, 2008

    They report a speedup of 100x, without performance decrease

Encoding Sentences via Recurrent Neural Network



1-of-K encoding of words

Recurrent Neural Network

Recurrent Neural Network

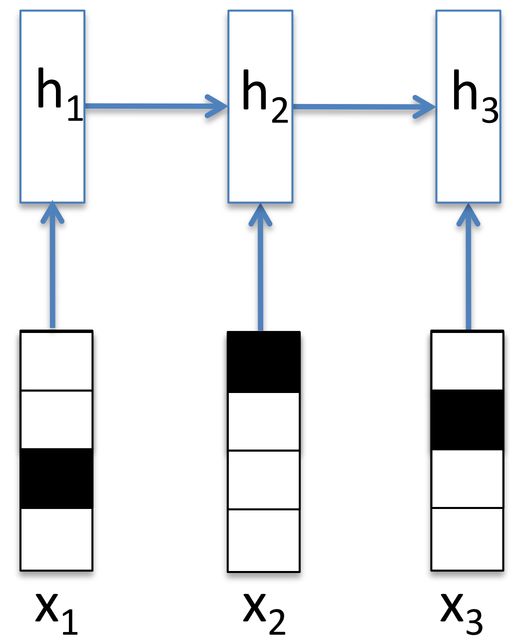
- Replace

Input at time step t

$$\mathbf{h_t} = \phi(\mathbf{U}\mathbf{h_{t-1}} + \mathbf{W}\mathbf{x_t} + \mathbf{b})$$

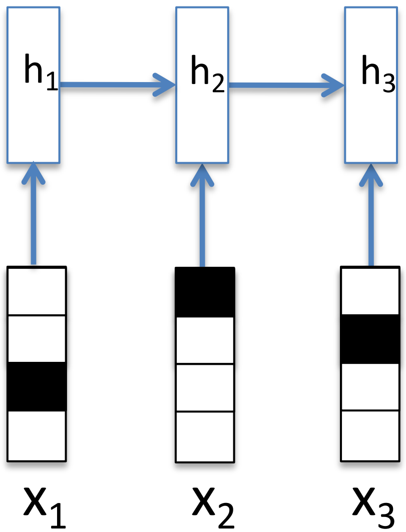
Nonlinearity

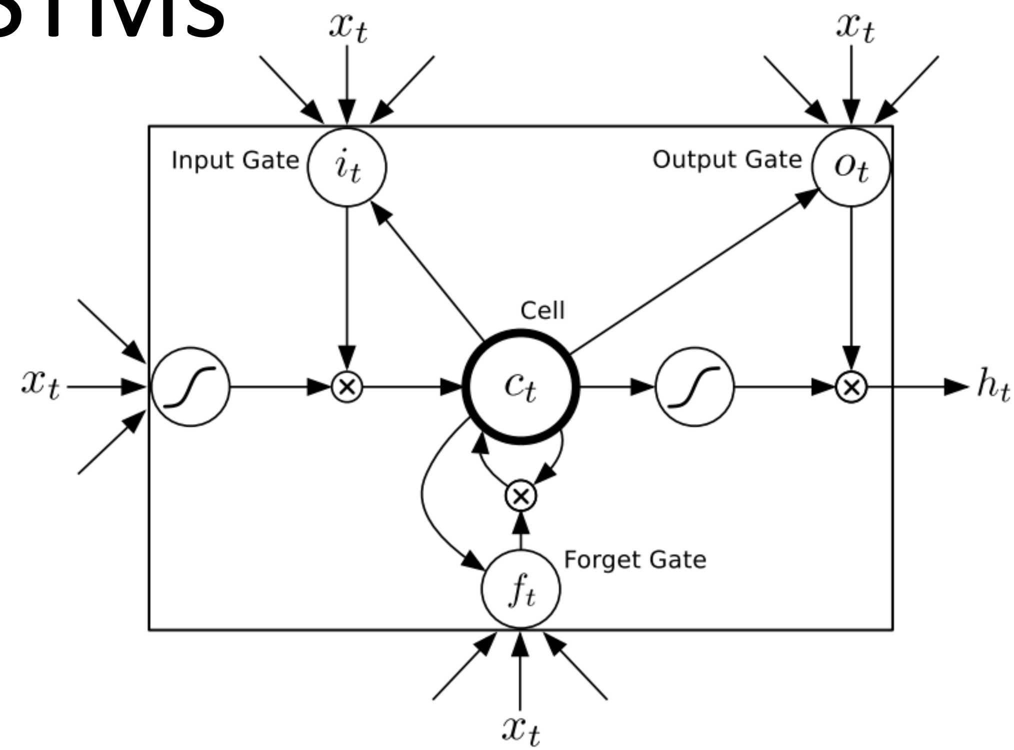
Hidden State at previous time step



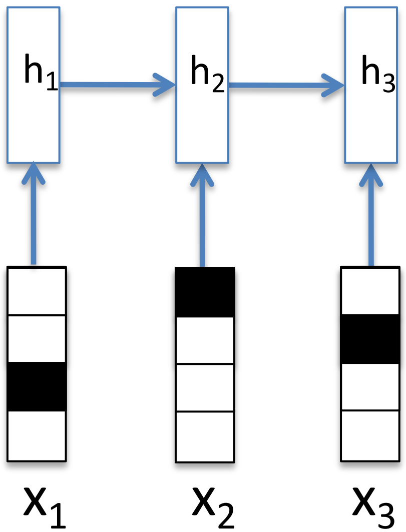
- Can be viewed as a deep neural network with tied weights.

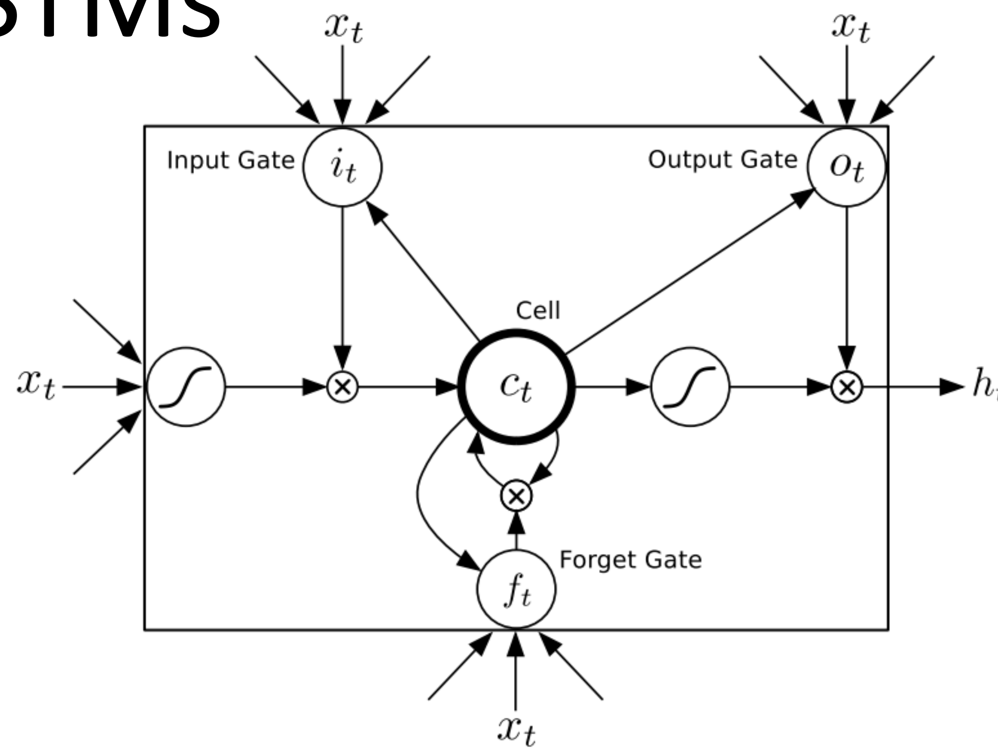
LSTMs


h1
h2
h3
x1
x2
x3


x_t
Input Gate
i_t
Output Gate
o_t
Cell
c_t
h_t
Forget Gate
f_t

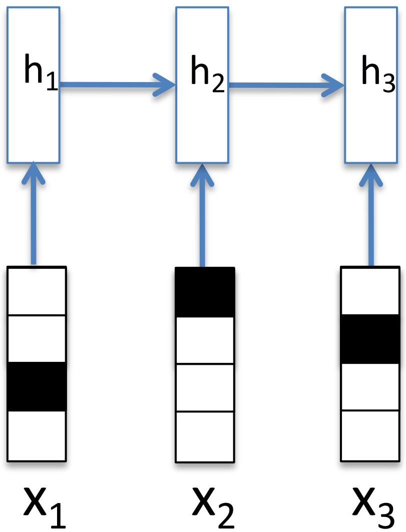
LSTMs

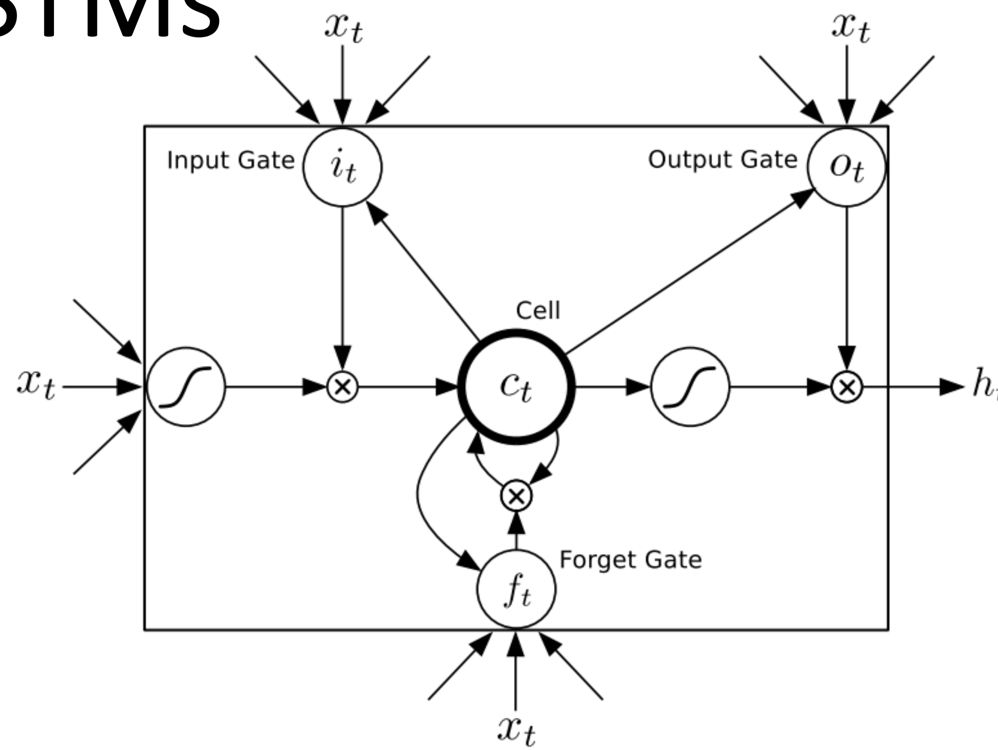




$$\mathbf{i}_t = \sigma\left(W_{xi}\mathbf{x}_t + W_{hi}\mathbf{h}_{t-1} + W_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i\right),$$

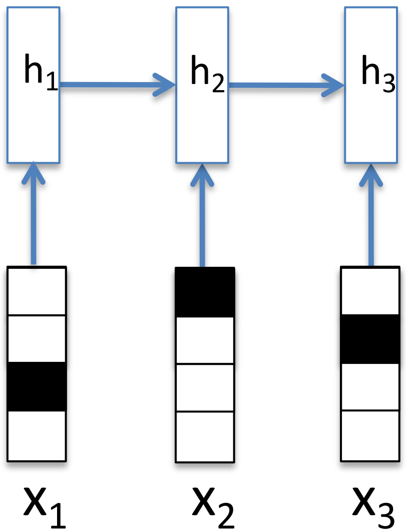
LSTMs

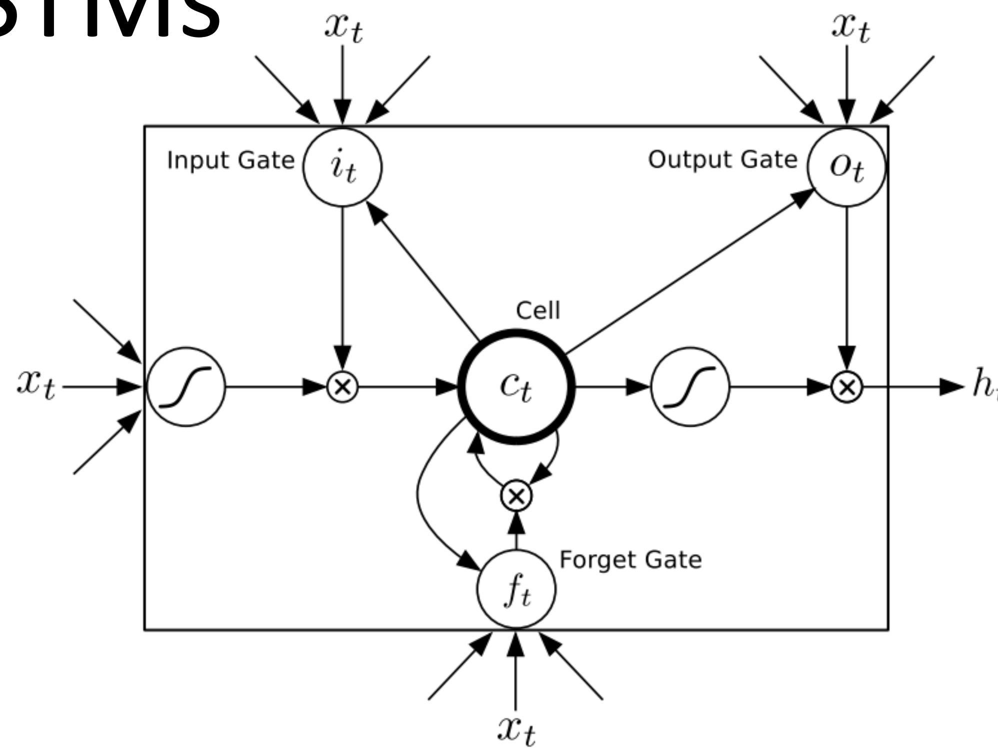




$$
\begin{aligned}
\mathbf{i}_t &= \sigma\left(W_{xi}\mathbf{x}_t + W_{hi}\mathbf{h}_{t-1} + W_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i\right), \\
\mathbf{f}_t &= \sigma\left(W_{xf}\mathbf{x}_t + W_{hf}\mathbf{h}_{t-1} + W_{cf}\mathbf{c}_{t-1} + \mathbf{b}_f\right),
\end{aligned}
$$

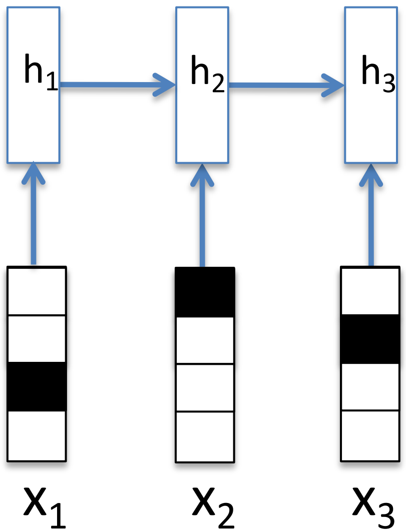
LSTMs

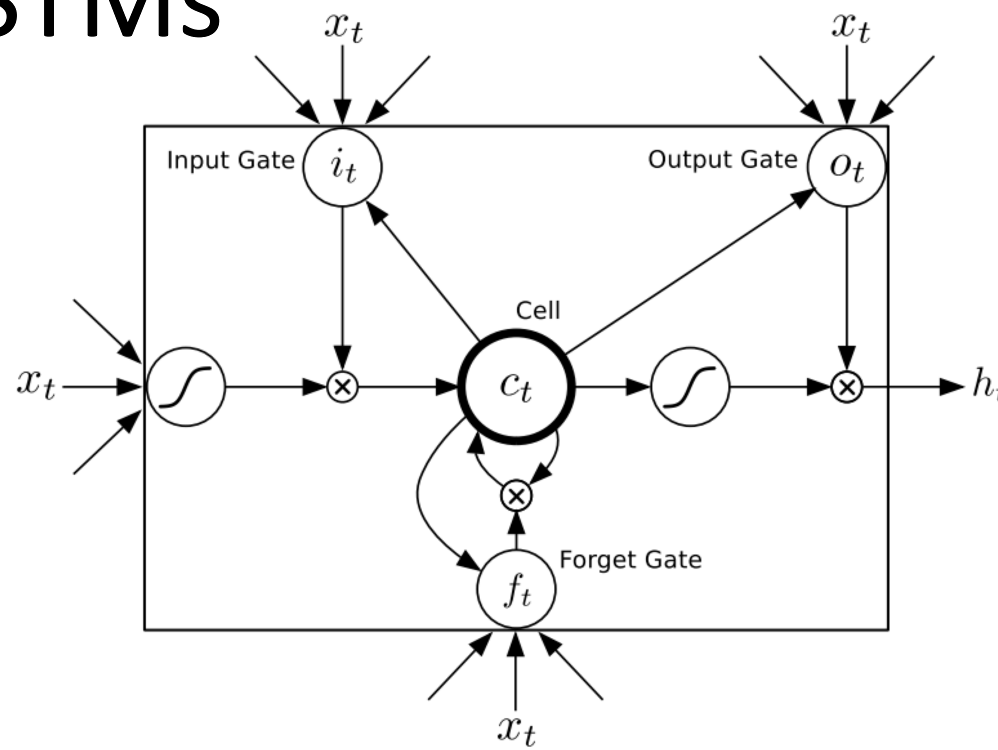




$$
\begin{aligned}
\mathbf{i}_t &= \sigma\left(W_{xi}\mathbf{x}_t + W_{hi}\mathbf{h}_{t-1} + W_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i\right), \\
\mathbf{f}_t &= \sigma\left(W_{xf}\mathbf{x}_t + W_{hf}\mathbf{h}_{t-1} + W_{cf}\mathbf{c}_{t-1} + \mathbf{b}_f\right), \\
\mathbf{c}_t &= \mathbf{f}_t\mathbf{c}_{t-1} + \mathbf{i}_t \tanh\left(W_{xc}\mathbf{x}_t + W_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c\right),
\end{aligned}
$$

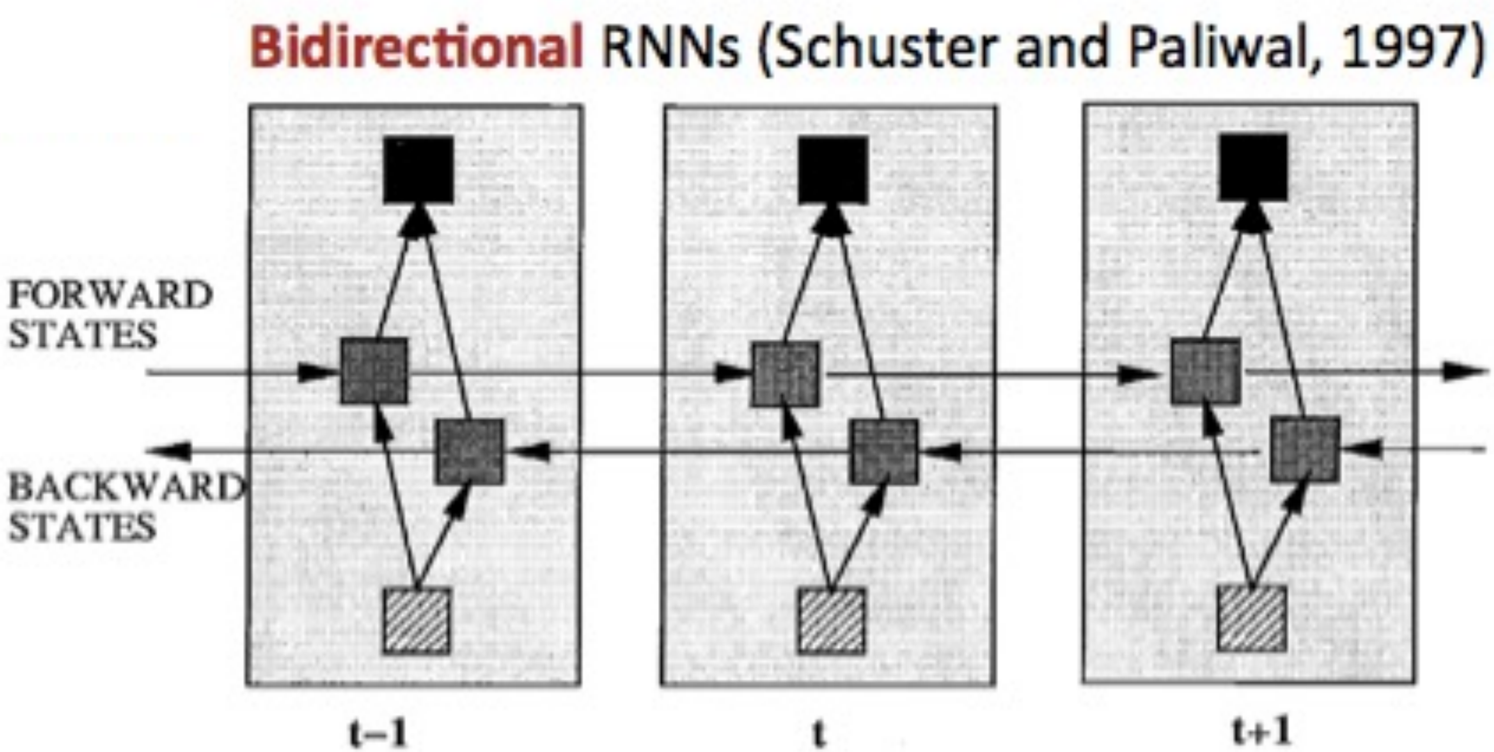
LSTMs





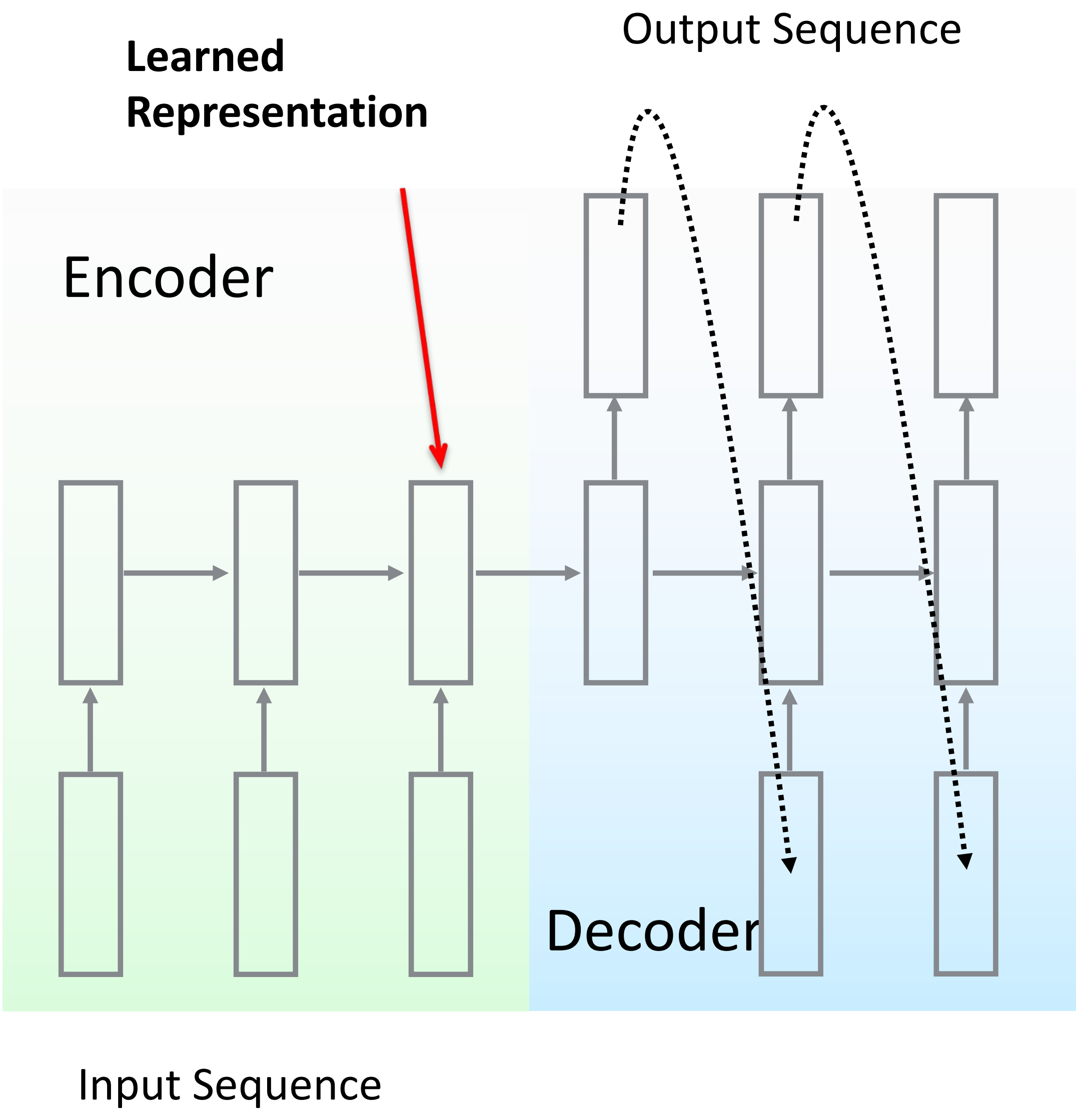
$$
\begin{aligned}
\mathbf{i}_t &= \sigma\left(W_{xi}\mathbf{x}_t + W_{hi}\mathbf{h}_{t-1} + W_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i\right), \\
\mathbf{f}_t &= \sigma\left(W_{xf}\mathbf{x}_t + W_{hf}\mathbf{h}_{t-1} + W_{cf}\mathbf{c}_{t-1} + \mathbf{b}_f\right), \\
\mathbf{c}_t &= \mathbf{f}_t\mathbf{c}_{t-1} + \mathbf{i}_t \tanh\left(W_{xc}\mathbf{x}_t + W_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c\right), \\
\mathbf{o}_t &= \sigma\left(W_{xo}\mathbf{x}_t + W_{ho}\mathbf{h}_{t-1} + W_{co}\mathbf{c}_t + \mathbf{b}_o\right), \\
\mathbf{h}_t &= \mathbf{o}_t \tanh(\mathbf{c}_t).
\end{aligned}
$$

Bidirectional RNNs



- Heavily used in language modeling.

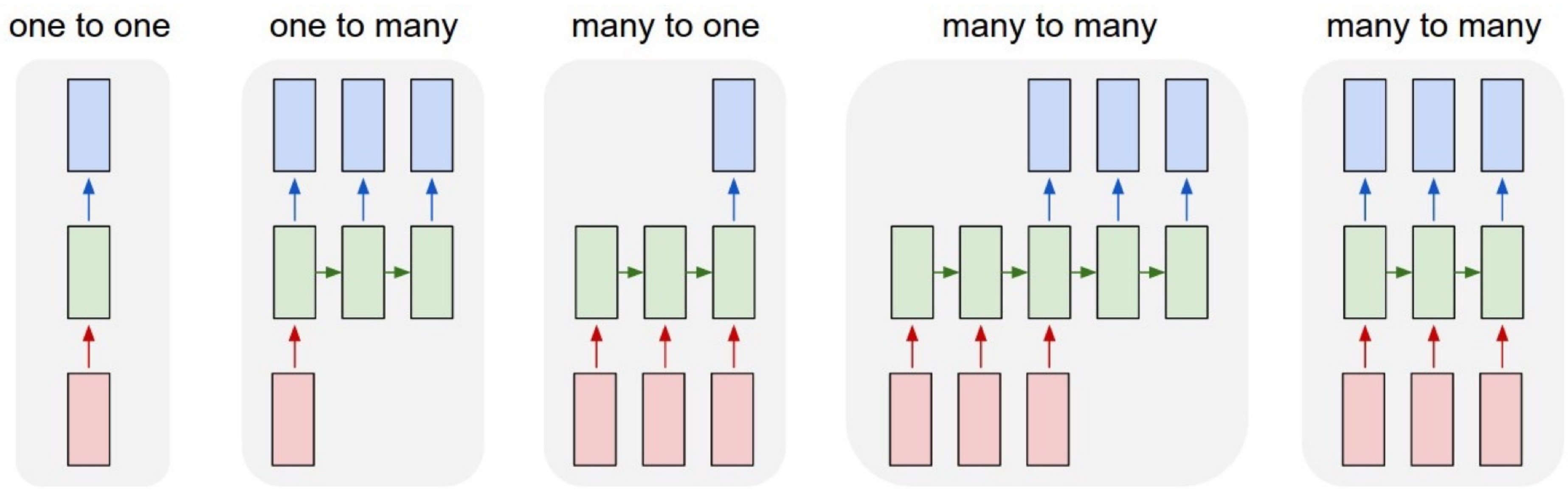
Sequence to Sequence Learning



- RNN Encoder-Decoders for Machine Translation (Sutskever et al. 2014; Cho et al. 2014; Kalchbrenner et al. 2013, Srivastava et.al., 2015)

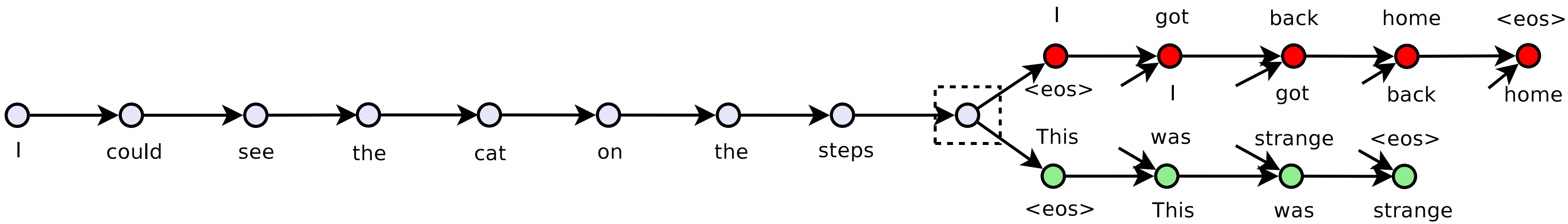
Sequence to Sequence Models

- Natural language processing is concerned with tasks involving language data



Andrej Karpathy. The Unreasonable Effectiveness of Recurrent Neural Networks

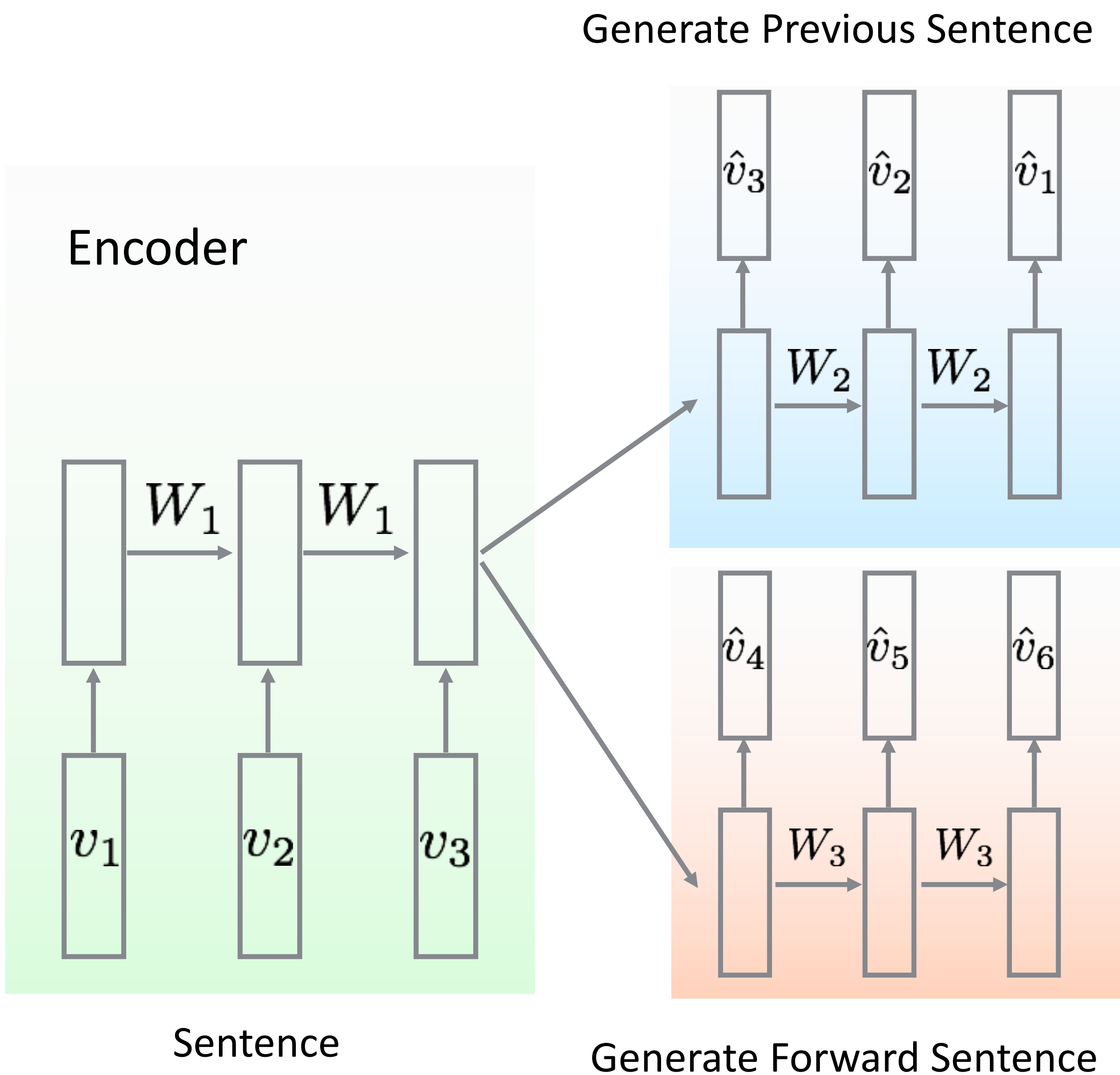
Skip-Thought Model



- Given a tuple (s_{i-1}, s_i, s_{i+1}) of contiguous sentences:
  - the sentence s_i is encoded using LSTM.
  - the sentence s_i attempts to reconstruct the previous sentence and next sentence s_{i+1}.

- The input is the sentence triplet:
  - I got back home.
  - I could see the cat on the steps.
  - This was strange.

Skip-Thought Model



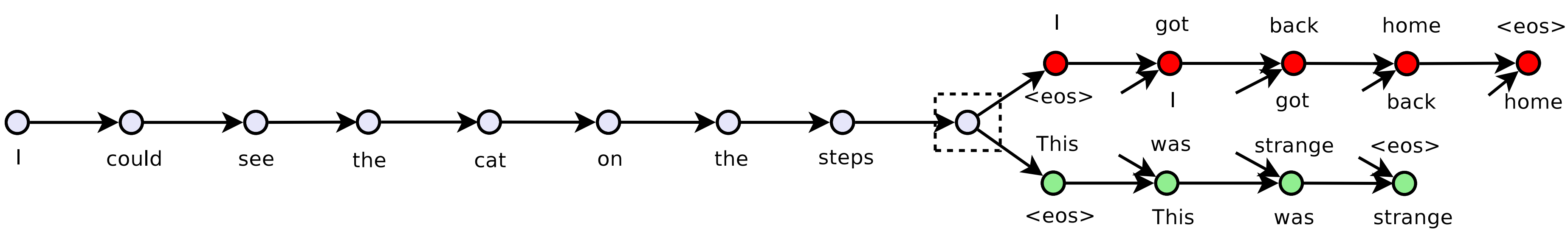
Learning Objective

- We are given a tuple (s_{i-1}, s_i, s_{i+1}) of contiguous sentences.

- Objective: The sum of the log-probabilities for the next and previous sentences conditioned on the encoder representation:

representation of encoder

$$\sum_t \underbrace{\log P(w_{i+1}^t | w_{i+1}^{<t}, \mathbf{h}_i)}_{\text{Forward sentence}} + \sum_t \underbrace{\log P(w_{i-1}^t | w_{i-1}^{<t}, \mathbf{h}_i)}_{\text{Previous sentence}}$$



Book 11K corpus

# of books	# of sentences	# of words	# of unique words
11,038	74,004,228	984,846,357	1,316,420

- Query sentence along with its nearest neighbor from 500K sentences using cosine similarity:
  - He ran his hand inside his coat, double-checking that the unopened letter was still there.
  - He slipped his hand between his coat and his shirt, where the folded copies lay in a brown envelope.

Semantic Relatedness

- SemEval 2014 Task 1: semantic relatedness SICK dataset: Given two sentences, produce a score of how semantically related these sentences are based on human generated scores (1 to 5).

- The dataset comes with a predefined split of 4500 training pairs, 500 development pairs and 4927 testing pairs.

- Using skip-thought vectors for each sentence, we simply train a linear regression to predict semantic relatedness.
  - For pair of sentences, we compute component-wise features between pairs (e.g. $|u-v|$).

Semantic Relatedness

	Method	r	ρ	MSE
SemEval 2014 sub-missions	Illinois-LH [18]	0.7993	0.7538	0.3692
	UNAL-NLP [19]	0.8070	0.7489	0.3550
	Meaning Factory [20]	0.8268	0.7721	0.3224
	ECNU [21]	0.8414	–	–
Results reported by Tai et.al.	Mean vectors [22]	0.7577	0.6738	0.4557
	DT-RNN [23]	0.7923	0.7319	0.3822
	SDT-RNN [23]	0.7900	0.7304	0.3848
	LSTM [22]	0.8528	0.7911	0.2831
	Bidirectional LSTM [22]	0.8567	0.7966	0.2736
	Dependency Tree-LSTM [22]	**0.8676**	**0.8083**	**0.2532**
Ours	uni-skip	0.8477	0.7780	0.2872
	bi-skip	0.8405	0.7696	0.2995
	combine-skip	0.8584	0.7916	0.2687
	combine-skip+COCO	0.8655	0.7995	0.2561

- Our models outperform all previous systems from the SemEval 2014 competition. This is remarkable, given the simplicity of our approach and the lack of feature engineering.

Semantic Relatedness

Sentence 1	Sentence 2	GT	pred
A little girl is looking at a woman in costume	A young girl is looking at a woman in costume	4.7	4.5
A little girl is looking at a woman in costume	The little girl is looking at a man in costume	3.8	4.0
A little girl is looking at a woman in costume	A little girl in costume looks like a woman	2.9	3.5
A sea turtle is hunting for fish	A sea turtle is hunting for food	4.5	4.5
A sea turtle is not hunting for fish	A sea turtle is hunting for fish	3.4	3.8
A man is driving a car	The car is being driven by a man	5	4.9
There is no man driving the car	A man is driving a car	3.6	3.5
A large duck is flying over a rocky stream	A duck, which is large, is flying over a rocky stream	4.8	4.9
A large duck is flying over a rocky stream	A large stream is full of rocks, ducks and flies	2.7	3.1
A person is performing acrobatics on a motorcycle	A person is performing tricks on a motorcycle	4.3	4.4
A person is performing tricks on a motorcycle	The performer is tricking a person on a motorcycle	2.6	4.4
Someone is pouring ingredients into a pot	Someone is adding ingredients to a pot	4.4	4.0
Nobody is pouring ingredients into a pot	Someone is pouring ingredients into a pot	3.5	4.2
Someone is pouring ingredients into a pot	A man is removing vegetables from a pot	2.4	3.6

- Example predictions from the SICK test set. GT is the ground truth relatedness, scored between 1 and 5.
- The last few results: slight changes in sentences result in large changes in relatedness that we are unable to score correctly.

Paraphrase Detection

- Microsoft Research Paraphrase Corpus: For two sentences one must predict whether or not they are paraphrases.

	Method	Acc	F1
Recursive Auto-encoders	feats [24]	73.2	
	RAE+DP [24]	72.6	
	RAE+feats [24]	74.2	
	RAE+DP+feats [24]	76.8	83.6
Best published results	FHS [25]	75.0	82.7
	PE [26]	76.1	82.7
	WDDP [27]	75.6	83.0
	MTMETRICS [28]	**77.4**	**84.1**
Ours	uni-skip	73.0	81.9
	bi-skip	71.2	81.2
	combine-skip	73.0	82.0
	combine-skip + feats	75.8	83.0

The training set contains 4076 sentence pairs (2753 are positive)

The test set contains 1725 pairs (1147 are positive).

Classification Benchmarks

- 5 datasets: movie review sentiment (MR), customer product reviews (CR), subjectivity/objectivity classification (SUBJ), opinion polarity (MPQA) and question-type classification (TREC).

	Method	MR	CR	SUBJ	MPQA	TREC
Bag-of-words	NB-SVM [41]	79.4	81.8	93.2	86.3	
	MNB [41]	79.0	80.0	93.6	86.3	
	cBoW [6]	77.2	79.9	91.3	86.4	87.3
Super-vised	GrConv [6]	76.3	81.3	89.5	84.5	88.4
	RNN [6]	77.2	82.3	93.7	90.1	90.2
	BRNN [6]	82.3	82.6	94.2	90.3	91.0
	CNN [4]	81.5	85.0	93.4	89.6	**93.6**
	AdaSent [6]	**83.1**	**86.3**	**95.5**	**93.3**	92.4
	Paragraph-vector [7]	74.8	78.1	90.5	74.2	91.8
Ours	uni-skip	75.5	79.3	92.1	86.9	91.4
	bi-skip	73.9	77.9	92.5	83.3	89.4
	combine-skip	76.5	80.1	93.6	87.1	92.2
	combine-skip + NB	80.4	81.3	93.6	87.5	

Midterm Review

- Polynomial curve fitting – generalization, overfitting

- Loss functions for regression

$$\mathbb{E}[L] = \int\int \left(t - y(\mathbf{x})\right)^2 p(\mathbf{x}, t)\,\mathrm{d}\mathbf{x}\,\mathrm{d}t.$$

- Generalization / Overfitting

- Statistical Decision Theory

Midterm Review

- Bernoulli, Multinomial random variables (mean, variances)
- Multivariate Gaussian distribution (form, mean, covariance)
- Maximum likelihood estimation for these distributions.
- Linear basis function models / maximum likelihood and least squares:

$$
\begin{aligned}
\ln p(\mathbf{t}|\mathbf{X}, \mathbf{w}, \beta) &= \sum_{i=1}^{N} \ln \mathcal{N}(t_n|\mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_n), \beta) \\
&= -\frac{\beta}{2}\sum_{n=1}^{N}\left(t_n - \mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_n)\right)^2 + \frac{N}{2}\ln\beta - \frac{N}{2}\ln(2\pi).
\end{aligned}
$$

$$
\mathbf{w}_{\mathrm{ML}} = \left(\mathbf{\Phi}^{\mathrm{T}}\mathbf{\Phi}\right)^{-1}\mathbf{\Phi}^{\mathrm{T}}\mathbf{t}
$$

Midterm Review

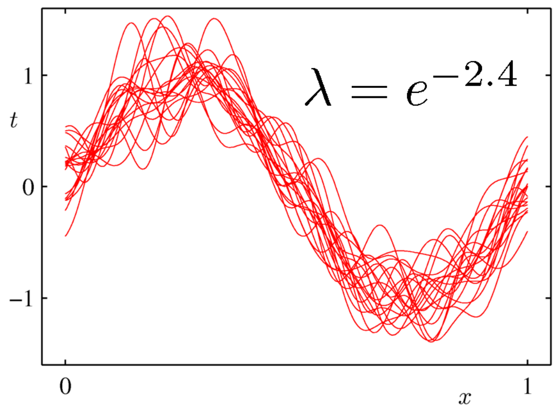
Ridge regression

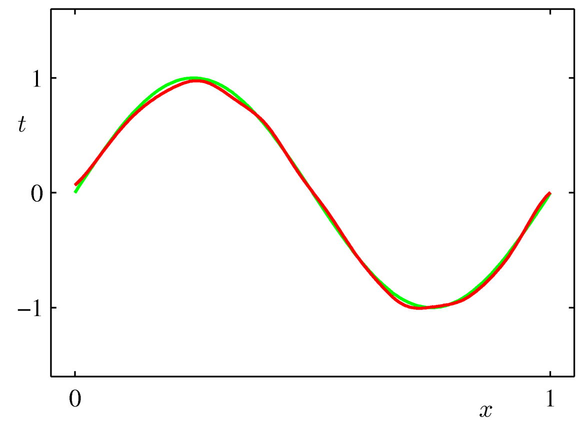
- Regularized least squares:

$$\frac{1}{2}\sum_{n=1}^{N}\{t_n - \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}_n)\}^2 + \frac{\lambda}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} \qquad \mathbf{w} = \left(\lambda\mathbf{I} + \boldsymbol{\Phi}^{\mathrm{T}}\boldsymbol{\Phi}\right)^{-1}\boldsymbol{\Phi}^{\mathrm{T}}\mathbf{t}.$$

- Bias-variance decomposition.

High variance



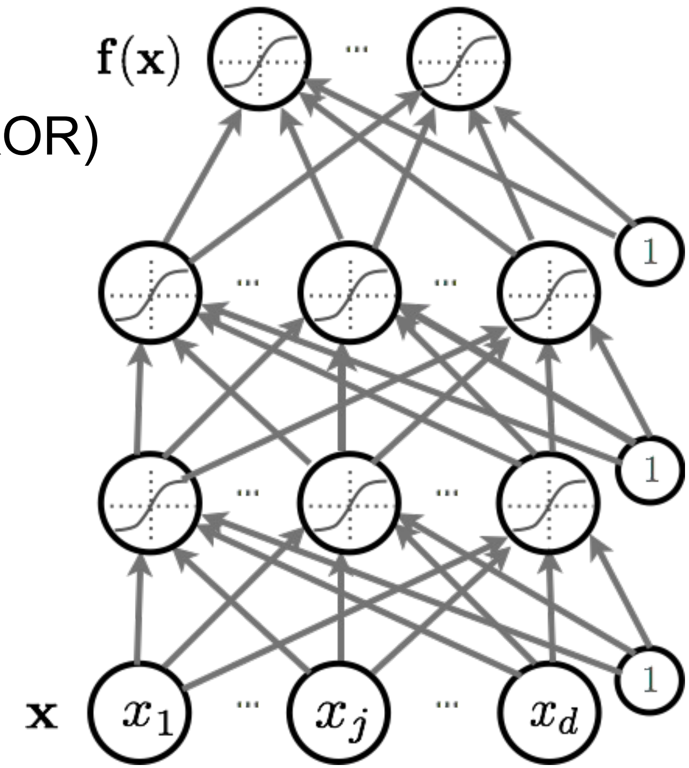


Low bias

- Gradient Descend, SGD, Parameter Update Rules

Neural Networks

- How neural networks predict f(x) given an input x:
  - Forward propagation
  - Types of units
  - Capacity of neural networks (AND, OR, XOR)
- How to train neural nets:
  - Loss function
  - Backpropagation with gradient descent
- More recent techniques:
  - Dropout
  - Batch normalization
  - Unsupervised Pre-training



Neural Networks

- SGD Training, cross entropy loss, ReLU activations
- Classification with neural networks
- Regularization, Dropout, Batchnorm
- Forward Propagation and Backprop (computing derivatives)

Conv Nets

- Convolutional networks leverage these ideas
  - Local connectivity
  - Parameter sharing
  - Convolution
  - Pooling / subsampling hidden units
  - Understanding Receptive Fields

- Local contrast normalization, rectification

Graphical Models

- Directed and Undirected Graphs
  - Definition
  - Factorization Properties
  - Markov Blanket / Conditional Independence Properties
  - Gaussian Examples / Chain Graphs

RBMs

- Restricted Boltzmann Machines
  - Probably distribution, energy definition
  - Factorization Properties, Conditional probabilities
  - Maximum likelihood estimation (positive and negative phases)
  - Gradients estimation / derivation
  - Contrastive Divergence (CD) learning, Gibbs sampling

Deep Belief Networks / Autoencoders

- DBNs, definition
  - Probably distribution, energy definition
  - Factorization Properties, Conditional probabilities
  - Greedy pretraining algorithm
  - Gradients estimation / derivation
  - Variational bound derivation
  - Autoencoders (variations, denoising, contrastive learning)

Language Modelling

- Neural Language Models
- RNNs, LSTMs definitions
- Sequence to Sequence