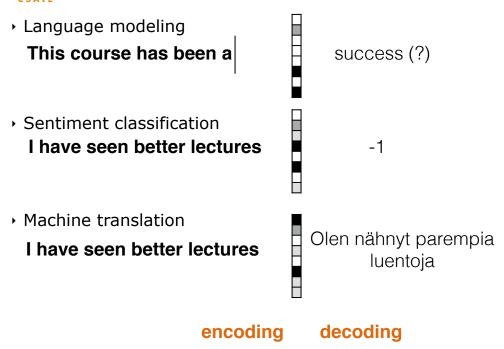
Modeling with Machine Learning: RNN (part 2)

Outline (part 2)

- Modeling sequences: language models
 - Markov models
 - as neural networks
 - hidden state, Recurrent Neural Networks (RNNs)
- Example: decoding images into sentences

Recall: learning to encode/decode



Markov Models

 Next word in a sentence depends on previous symbols already written (history = one, two, or more words)

The lecture leaves me bumfuzzled

 Similar, next character in a word depends on previous characters already written

bumfuzzled

 We can model such kth order dependences between symbols with Markov Models

Markov Language Models

- ullet Let $w \in V$ denote the set of possible words/symbols that includes
 - an UNK symbol for any unknown word (out of vocabulary)
 - <beg> symbol for specifying the start of a sentence
 - <end> symbol for specifying the end of the sentence

beg> The lecture leaves me UNK <end>

 $w_0 \quad w_1 \quad w_2 \quad w_3 \quad w_4 \quad w_5 \quad w_6$

 In a first order Markov model (bigram model), the next symbol only depends on the previous one

A first order Markov model

 Each symbol (except <beg>) in the sequence is predicted using the same conditional probability table until an <end> symbol is seen

		w_i						
		ML	course	is	UNK	<end></end>		
w_{i-1}	<beg></beg>	0.7	0.1	0.1	0.1	0.0		
	ML	0.1	0.5	0.2	0.1	0.1		
	course	0.0	0.0	0.7	0.1	0.2		
	is	0.1	0.3	0.0	0.6	0.0		
	UNK	0.1	0.2	0.2	0.3	0.2		

Sampling from a Markov model

 w_i

course is UNK <end>

0.0 0.1 0.2 0.0

		141	ocaroc	10	OIVIX	
20.	<beg></beg>	0.7	0.1	0.1	0.1	
	ML	0.1	0.5	0.2	0.1	
w_{i-1}	course	0.0	0.0	0.7	0.1	
	is	0.1	0.3	0.0	0.6	
	UNK	0.1	0.2	0.2	0.3	

М

Maximum likelihood estimation

The goal is to maximize the probability that the model can generate all the observed sentences (corpus S)

$$s \in S, \ s = \{w_1^s, w_2^s, \dots, w_{|s|}^s\}$$

Maximum likelihood estimation

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 The ML estimate is obtained as normalized counts of successive word occurrences (matching statistics)

Feature based Markov Model

 We can also represent the Markov model as a feedforward neural network (very extendable)

Feature based Markov Model

 We can also represent the Markov model as a feedforward neural network (very extendable)

Temporal/sequence problems

Language modeling: what comes next?

This course has been a tremendous ...

tremendous
$$\begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix}$$
a
$$\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

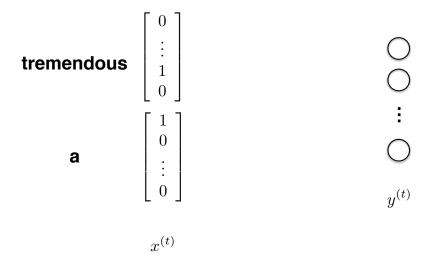
Temporal/sequence problems

• A trigram language model

tremendous $\begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix}$ a $\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$

Temporal/sequence problems

→ A trigram language model



CSAIL

RNNs for sequences

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RNNs for sequences

Language modeling: what comes next?

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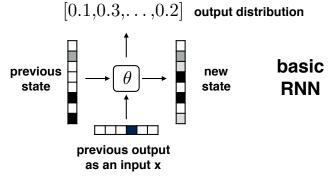
tremendous
$$\begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix}$$
?

$$s_t = \tanh(W^{s,s}s_{t-1} + W^{s,x}x_t)$$
 state $p_t = \operatorname{softmax}(W^os_t)$ output distribution



Decoding, RNNs

 Our RNN now also produces an output (e.g., a word) as well as update its state

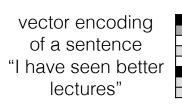


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Decoding (into a sentence)

 Our RNN now needs to also produce an output (e.g., a word) as well as update its state

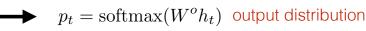




Decoding, LSTM

 $[0.1,0.3,\dots,0.2] \quad \text{output distribution}$ previous state $\theta \mapsto \theta \mapsto \theta$ state $\theta \mapsto \theta$ previous output as an input x

$$\begin{split} f_t &= \operatorname{sigmoid}(W^{f,h}h_{t-1} + W^{f,x}x_t) \quad \text{forget gate} \\ i_t &= \operatorname{sigmoid}(W^{i,h}h_{t-1} + W^{i,x}x_t) \quad \text{input gate} \\ o_t &= \operatorname{sigmoid}(W^{o,h}h_{t-1} + W^{o,x}x_t) \quad \text{output gate} \\ c_t &= f_t \odot c_{t-1} + i_t \odot \tanh(W^{c,h}h_{t-1} + W^{c,x}x_t) \quad \text{memore} \\ h_t &= o_t \odot \tanh(c_t) \quad \text{visible state} \end{split}$$

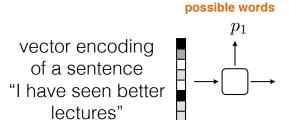




Decoding (into a sentence)

 Our RNN now needs to also produce an output (e.g., a word) as well as update its state

distribution over the





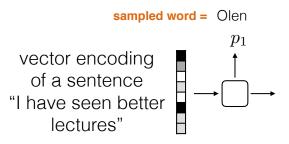
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 Our RNN now needs to also produce an output (e.g., a word) as well as update its state



Decoding (into a sentence)

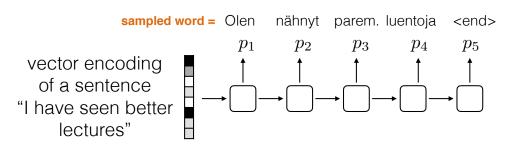
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Decoding (into a sentence)

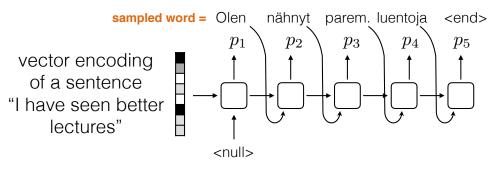
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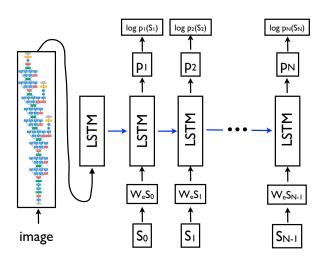
Decoding (into a sentence)

- Our RNN now needs to also produce an output (e.g., a word) as well as update its state
- The output is fed in as an input (to gauge what's left)





Mapping images to text



Key things

- Markov models for sequences
 - how to formulate, estimate, sample sequences from
- → RNNs for generating (decoding) sequences
 - relation to Markov models
 - evolving hidden state
 - sampling from
- Decoding vectors into sequences



Examples











hting over the puck.



Describes with minor errors











