Recurrent Neural Networks

CS 6956: Deep Learning for NLP

THE UNIVERSITY OF UTAH

Overview

1. Modeling sequences
2. Recurrent neural networks: An abstraction
3. Usage patterns for RNNs
4. BiDirectional RNNs
5. A concrete example: The Elman RNN
6. The vanishing gradient problem
7. Long short-term memory units

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Sequences abound in NLP

S a l t   L a k e   C i t y

Words are sequences of characters

Sequences abound in NLP

S a l t L a k e C i t y

John lives in Salt Lake City

Sentences are sequences of words

Sequences abound in NLP

S a l t   L a k e   C i t y

John   lives   in   Salt   Lake   City

John lives in Salt Lake City.   He enjoys hiking with his dog.   His cat hates hiking.

Paragraphs are sequences of sentences

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And so on… inputs are naturally sequences at different levels

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Outputs can also be sequences

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Part-of-speech tags form a sequence

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Noun Verb Preposition Noun Noun Noun

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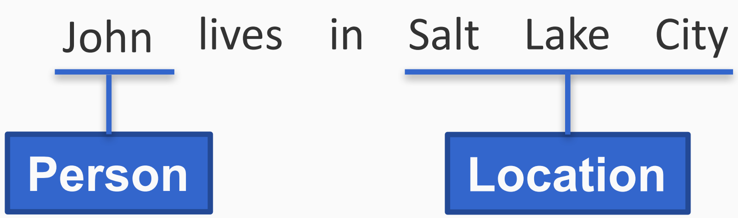

Even things that don't look like a sequence can be made to look like one

Example: Named entity tags

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B-PER O O B-LOC I-LOC I-LOC

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Noun   Verb   Preposition   Noun   Noun   Noun

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And we can get very creative with such encodings

Example: We can encode parse trees as a sequence of decisions needed to construct the tree

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Natural question: How do we model sequential inputs and outputs?

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Natural question: How do we model sequential inputs and outputs?

More concretely, we need a mechanism that allows us to

1. Capture sequential dependencies between inputs
2. Model uncertainty over sequential outputs

And we can get very creative with such encodings

Example: We can encode parse trees as a sequence of decisions needed to construct the tree

Modeling sequences: The problem

Suppose we want to build a language model that computes the probability of sentences

We can write the probability as

$$P(x_1, x_2, x_3, \cdots, x_n) = \prod_i P(x_i \mid x_1, x_2 \cdots, x_{i-1})$$

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$$P(\text{bright}|\text{It was a})\times$$ ← Probability of a word following "It was a"

$$P(\text{cold}|\text{It was a bright})\times$$

$$P(\text{day}|\text{It was a bright cold}) \times \cdots$$

A history-based model

$$P(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} P(x_i | x_1, x_2, \cdots, x_{i-1})$$

- Each token is dependent on all the tokens that came before it
  - Simple conditioning
  - Each $P(x_i \mid \ldots)$ is a multinomial probability distribution over the tokens

- What is the problem here?

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- What is the problem here?
  - How many parameters do we have?
    - Grows with the size of the sequence!

The traditional solution: Lose the history

Make a modeling assumption

Example: The first order Markov model assumes that

$$P\ (\ x_i \mid x_1, x_2, \cdots, x_{i-1}\ ) = P(x_i \mid x_{i-1})$$

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This allows us to simplify

$$P(x_1, x_2, x_3, \cdots, x_n) = \prod_i P(x_i \mid x_1, x_2 \cdots, x_{i-1})$$

These dependencies are ignored

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If there are K tokens/states, how many parameters do we need? $O(K^2)$

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- Can we represent arbitrarily long sequences as fixed sized vectors?
  - Perhaps to provide features for subsequent classification
- Answer: Recurrent neural networks (RNNs)