

# Recurrent Neural Networks



# 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

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John lives in Salt Lake City

Sentences are sequences of words

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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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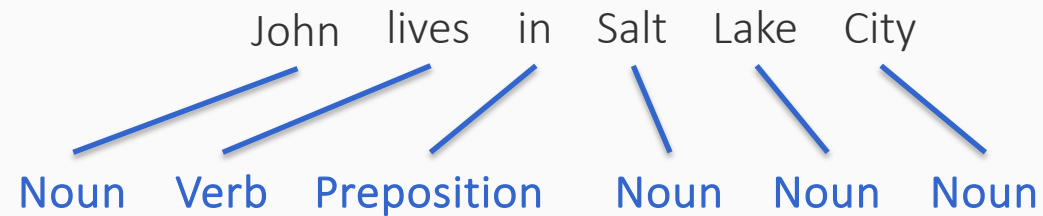
Part-of-speech tags form a sequence

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Noun   Verb   Preposition   Noun   Noun   Noun



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

Example: Named entity tags

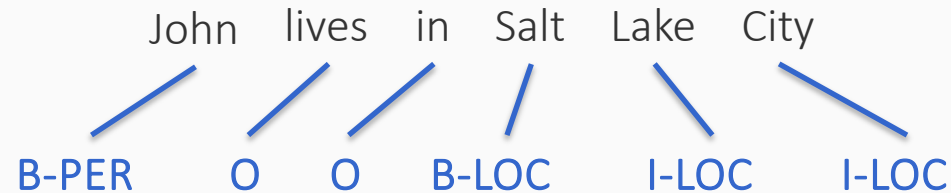
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And we can get very creative with such encodings

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

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



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

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

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

# A history-based model

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

Each token is dependent on all the tokens that came before it

- Simple conditioning
- Each  $P(x_i | \dots)$  is a multinomial probability distribution over the tokens

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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

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These dependencies are ignored

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

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If there are  $K$  tokens/states, how many parameters do we need?

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

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- Answer: Recurrent neural networks (RNNs)