Lecture 2: Sequence Modeling with Neural Networks

Examples of Sequences

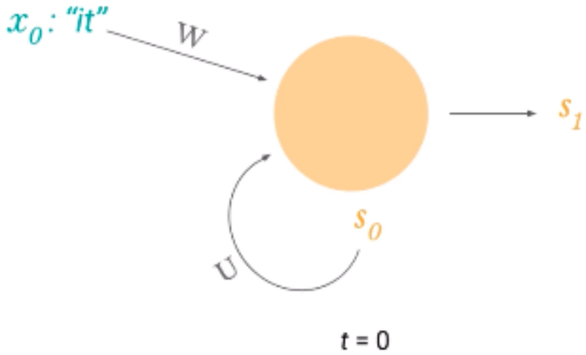
- Sentences: "This morning I took a dog for a walk"
- Medical signals: consist of many measurements
- Waveforms: many measurements
- QAS and Machine translation are sequence modelling taks

Example: Sequence Modeling Problem

- Predict the next word in a sentence
- "Given these words, what comes next?"
- Has variable length input and output
- Can we use a fixed window?
  - Use previous 2 words, one-hot encode them
  - But we can't predict long-term dependencies (e.g. need information from beginning of sentence)
- Can we use the entire sequence as a set of counts? ("bag of words" method)
  - Count of each word appearing (fixed length vector)
  - But we lose temporal sequence information
- Can we use a really large fixed window?
  - Use previous 7 words
  - However, there's no parameter sharing (words' position parameters are not being shared)
- We need the following things:
  - Dealing with variable-length sequences
  - Maintain sequence order
  - Keep track of long-term dependencies
  - Share parameters across sequence
- Solution: RNNs

The Recurrent Neural Network

- Structure is similar, but each unit "remembers" its old state

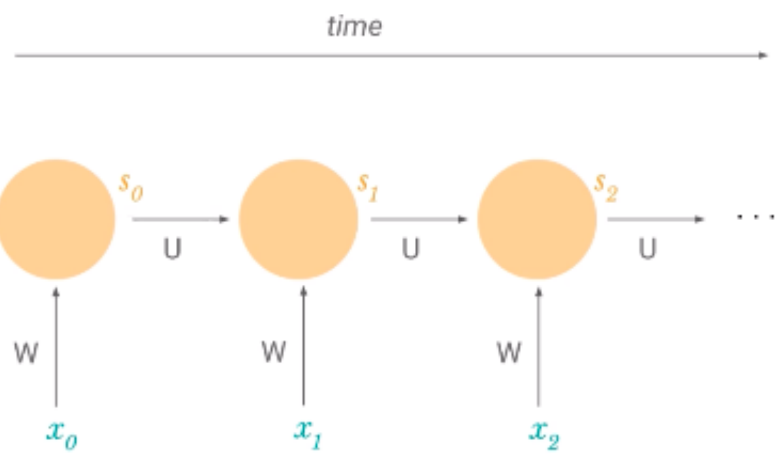


x_0 : vector representing first word
s_0 : cell state at $t = 0$ (some initialization)
s_1 : cell state at $t = 1$

$s_1 = tanh(Wx_0 + Us_0)$

$W,\ U$: weight matrices

- Hidden unit is activated as $\tanh\left(Wx_0 + Us_0\right)$
- Subscript = time step (s_0 is initial state, s_1 new state at $t = 1$)
- W and U don't change across time steps
  - Helps us deal with parameter sharing and variable length sequences



- s_n can have info from previous time steps
  - Each cell state is function of previous cell state

Training RNNs

- Backpropagation with a time component
- Since we have an input at each timestep, we have a loss at each time step
  - $\mathcal{L}_t = J_t(\Theta)$
- Total loss: $J(\Theta) = \sum_t J_t(\Theta)$
- Total gradients: $\frac{\partial J}{\partial P} = \sum_t \frac{\partial J_t}{\partial P}$
- To get gradient over time: $\frac{\partial J_2}{\partial W} = \sum_{k=0}^{t} \left(\frac{\partial J_t}{\partial y_t} \frac{\partial y_t}{\partial s_t} \frac{\partial s_t}{\partial s_k} \frac{\partial s_k}{\partial W} \right)$

Issues With Training RNNs

Vanishing Gradient

- As the gap between timesteps get bigger, the product needed to find J gets longer
  - We get smaller gradients from further back time-steps
  - Parameters become biased to capture short-term dependencies
- Solution: Use ReLU or similar
- Solution: Initialize W to I_n, and biases to zeroes
- Solution: Use a more complex cell
  - Use a LSTM/GRU/etc. cell (is a complex unit with gates)

Solution: LSTM Cells

- Forget irrelevant parts of previous state
- Selectively update cell state values
- Output certain parts of cell state

Why LSTMs?

1. Forget gate allows info to pass unchanged
2. Cell state is separate from output
3. s_j depends on s_{j-1} using addition, meaning no long products

Possible Tasks

- Music generation
- Machine translation
  - 2 RNNs