

Tools & Models for Data Science

Deep Neural Networks (3): RNN

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- Rx counts and costs
- Genome sequences
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- Clinical trial descriptions
- Books (Sherlock Holmes, War and Peace, Shakespeare)
- Wikipedia newsgroups

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Data Representation

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 - Books (Sherlock Holmes, War and Peace, Shakespeare)
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- How have we represented the text data?
 - Bag of words
- ? What are the limitations of this representation?

Issues with Data Representation

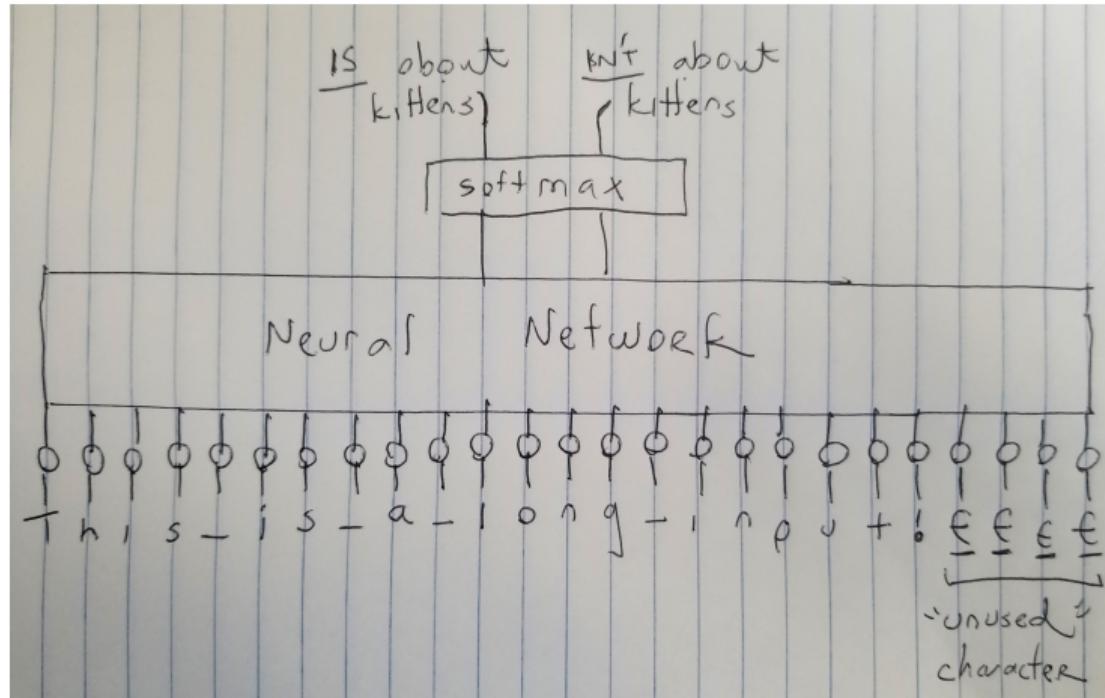
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- How have we represented the text data?
 - Bag of words
- What are the limitations of this representation?
 - Lose the order/context

Consider our Simple Feed-Forward Networks

- They don't easily handle sequences
- What if I want to classify text docs?
 - And I don't want to do the bag-of-words thing
 - After all: bag-of-words loses word order
 - ? What are my options?

Standard Idea

- Use FF network with enough input units (e.g. 20,000 words)
 - To handle any document in training/testing
 - Pad unused tokens with a special character



Issues with Standard idea

- High model complexity
 - Max n input tokens
 - Size m first hidden layer
 - Means $n \times m$ weights to learn

$$10^4 \times 10^5 = 10^9 = 1\text{B weights}$$

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- High model complexity
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 - What if max tokens is 100K, average is 1000?
 - We are spending effort learning a network that is too big
 - Not much training data for right-most inputs
- ? What other issues are there?

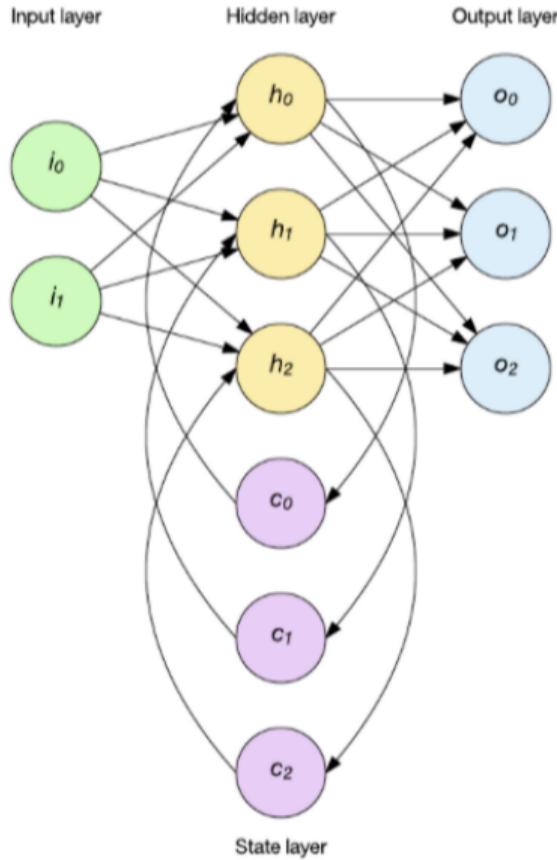
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 - What if max tokens is 100K, average is 1000?
 - We are spending effort learning a network that is too big
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- ? What other issues are there?
 - We can't handle bigger lengths
 - We have to use all the inputs
 - Words positions are considered equivalent

Words Position Issues

- Position i treated as different from position j
 - Not always the case!
 - If we see “kitten” at pos 34 or pos 1034, it is perhaps the same
 - We want to recognize pattern “kitten” regardless of position
 - Or consider swapping the order of 2 paragraphs on Wikipedia. No one would notice!

So Idea Is To Allow Recursive Links

- Results in an RNN
- Classic RNN is Elman Network
- The output from the hidden layer is pushed to the output AND copied to the state layer
- Input from context neurons is fed in with the input data
- There are NO weights from the neurons output to the states
- There ARE weights from the states to the neuron inputs



- Have a set of context nodes (the "state layer") ("c" neurons in previous slide)
- They read value of the hidden layer
 - Non-trainable (e.g. values are not transformed)
 - Value simply remembered for one time tick
- To process t ticks of data:

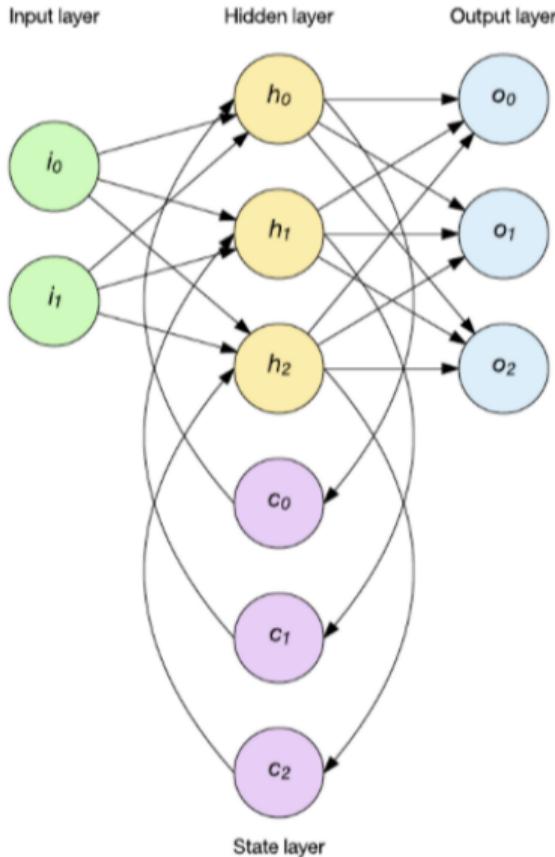
```
init state layer to zeros
for i = 1 to t
    read input  $x_i$ 
     $x_i$  along with state layer used to update hidden layer
    if ( $i == t$ ) // for sequence-to-sequence, omit "if clause"
        hidden layer used to produce output
    hidden layer copied to state layer
end for
```

Sequence-to-Sequence?

- Input is a sequence
- Output is a sequence
- Output is generated at each time tick
- Lengths do not have to be identical
- Examples
 - Machine translation
 - Creating captions for video
 - Questions and answers

Elman Network in Practice

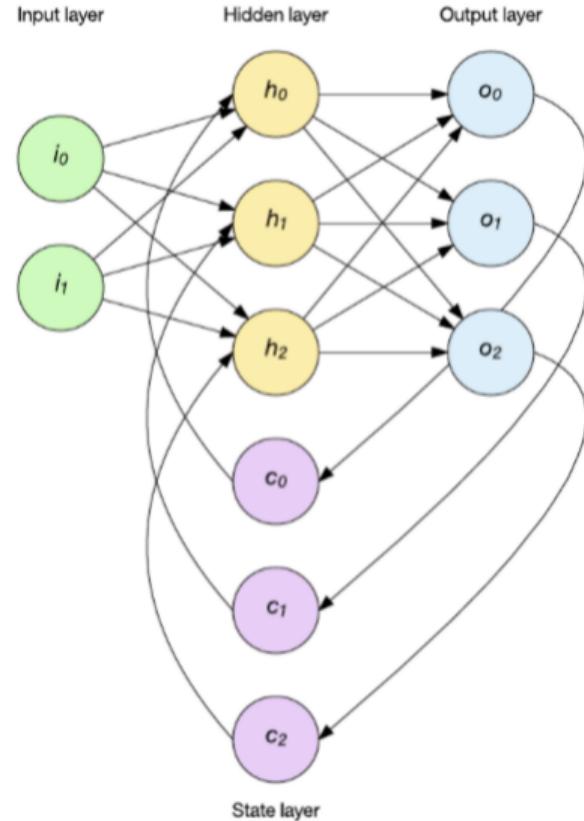
- Concatenate x_i and the state values
- Perform the matrix multiplication to get the inputs to the next layer
- At the top, use only the hidden layer to produce the output



- We can have many hidden layers
- That is, a “deep net”
- In this case
 - Last hidden layer output copied to state
 - State used as input to first hidden layer...
 - In next time tick

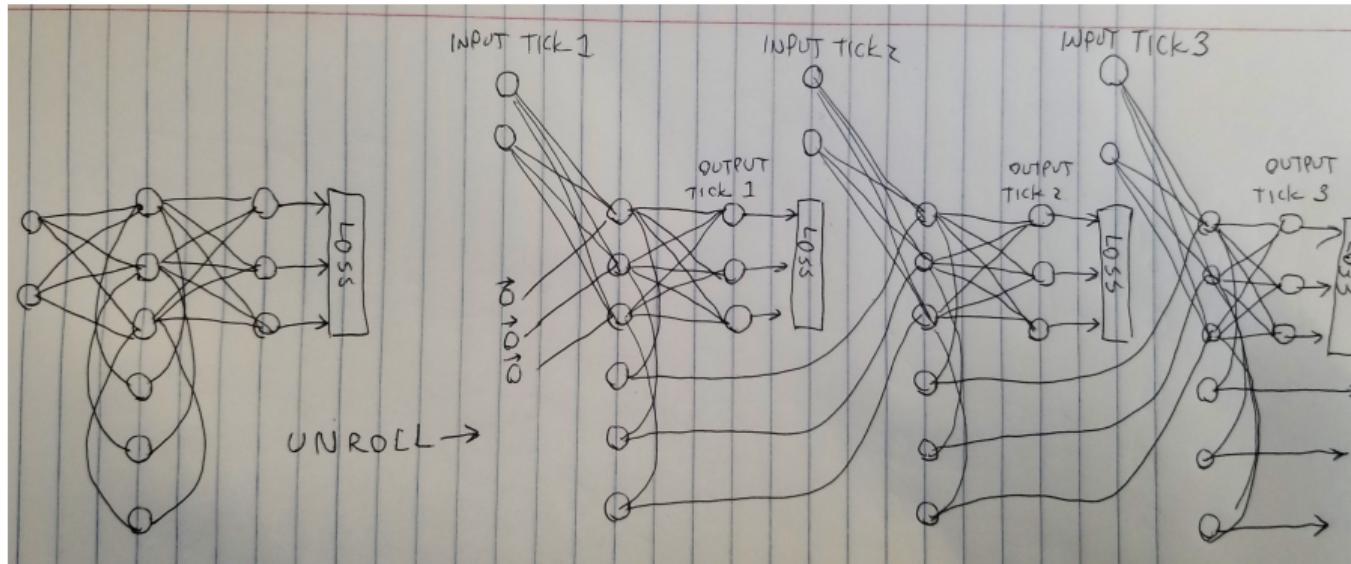
Jordan Network

- Similar, but copy output values, not hidden values
- Can be used for sequence-to-sequence
- Must be producing output at each tick



- Classic algorithm is back-propagation through time
- That is, view RNN as compact representation for a complex graph
- Unroll the complex graph
- And then use back-propagation on that
 - Key difference from classic back-propagation:
 - Weights are constrained to repeat

Example: Unrolling an Elman Network



- Example of unrolling a network for three time ticks
- Note distance backpropogated error from last time tick must travel
 - Goes through output neurons at time tick 3
 - Through hidden neurons time tick 3
 - Through hidden neurons time tick 2
 - Through hidden neurons time tick 1

Training Difficulty: Vanishing Gradient

- Errors fall off exponentially as backpropogated thru layers
 - Problem is that derivative of loss wrt activation function often $<< 1$
 - Repeatedly multiplying causes backpropogated errors to tend to zero
 - Happens with deep, feed-forward nets, too
 - But unrolled RNNs are often especially deep

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 - Happens with deep, feed-forward nets, too
 - But unrolled RNNs are often especially deep
- Means that in a deep net...
 - ...backprop does not affect weights in first (leftmost) few layers

Training Difficulty: Vanishing Gradient

- Especially a problem if there is just one output at end of unrolled RNN
- Like in a pure classification task
 - Means that you will learn to classify
 - ...using only the last few time-tick's worth of data
 - Because early data can't interact with backpropogated error

Other Issues with RNNs

- Very expensive to train
- Still expensive to use

- Long Short Term Memory networks

- Special RNN designed to deal with vanishing gradient problem
- In LSTM, long term memory is not pushed through activation functions
- So we don't have vanishing gradients
- Will discuss next time!

Questions?