Introduction to Neural Networks

ECEN 678

Dr. Mahmoud Nabil Mahmoud
mnmahmoud@ncat.edu

North Carolina A & T State University

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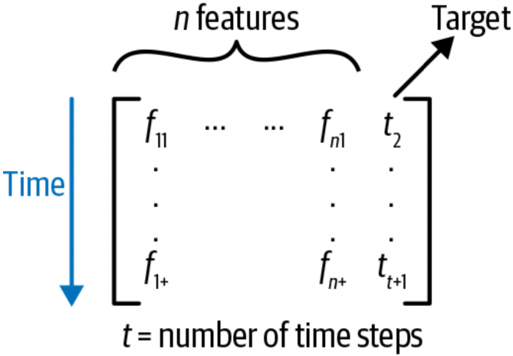
Outline

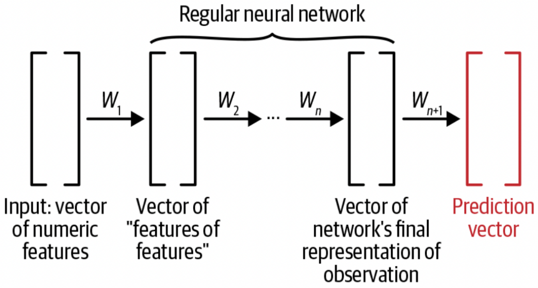
Introduction

- Recurrent neural networks are designed to handle data that appears in sequences
- Instead of each observation being a vector with, say, features, it is now a two-dimensional array of dimension features by time steps.



Why this kind of data is different?

- Suppose an application of converting your speech into text (i.e., automatic captioning system)
- The previous matrix can encode the set of signal features at time window t, and the target is the spoken word
- Regular Neural Network shown below will give bad performance if each target is predicted in isolation. **Why?**



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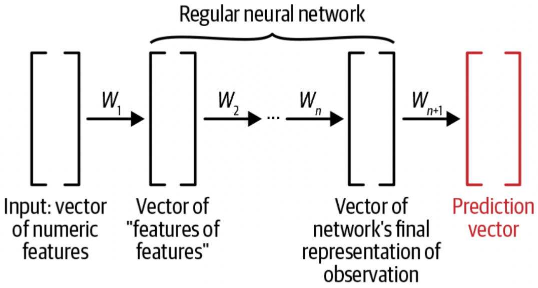

Because the temporal dependency is ignored.

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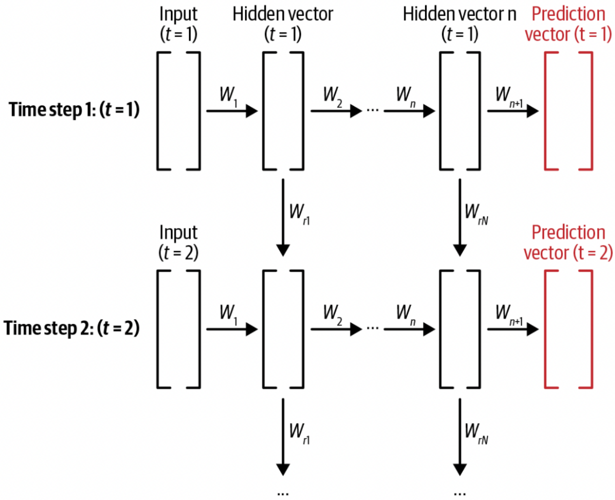
- In the second time step, $t = 2$, we would pass the features of this time along with a learned representation from the previous time step feature to make to make predictions for $t = 2$.
- In the third time step, we would pass through the features from $t = 3$ as well as the representations that now incorporate the information from $t = 1$ and , $t = 2$ and use this information to make predictions for $t = 3$.

Outline

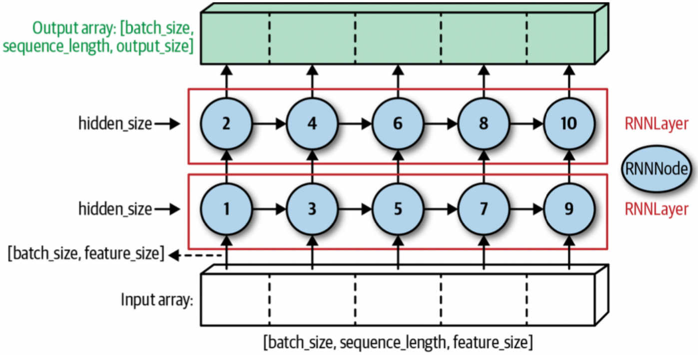
RNN Architecture



RNN Input Data Shape

- RNNs deal with data in which each input sample is two-dimensional matrix, with shape `(sequence_length, num_features)`
- Since it is always more efficient computationally to pass data forward in batches, the input size will be 3d matrix of shape `(batch_size,sequence_length, num_features)`
- Output is also 3d matrix with shape `(batch_size,sequence_length, output_size)`

RNN Architecture And Order



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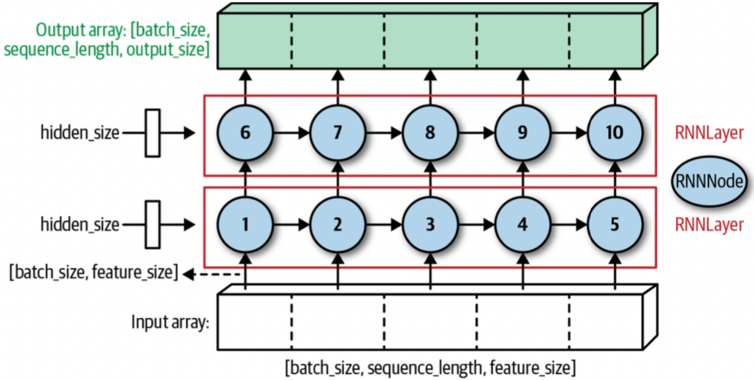
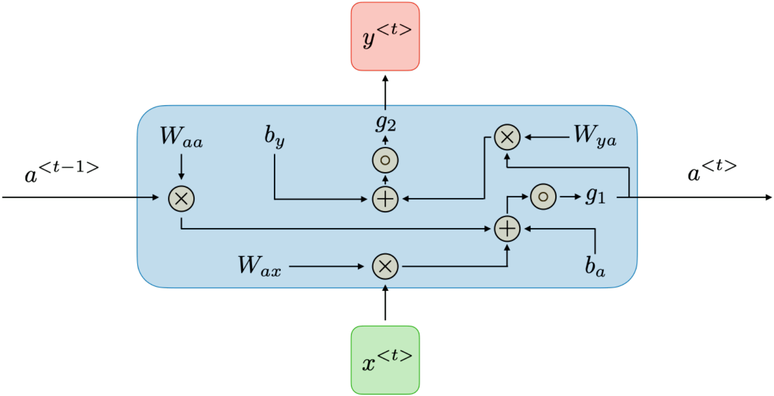


RNN Architecture

Two key components of the RNN architecture:

- **RNN Node:** It is the building block of the RNN layer. It processes the input at each time step with the information learned from the previous time step.
- **RNN Layer:** It is a group of RNN nodes that process the input sequence and can be cascaded for better overall performance.

RNN Node



RNN Node

- RNN Node receive two inputs:
  - The data inputs to the network, of shape `(batch_size, num_features)`
  - The learned representation "hidden state" up to this RNN node, shape `(batch_size, hidden_size)`
- RNN Node has two outputs:
  - The outputs of the network at that time step, of shape `(batch_size, output_size)`
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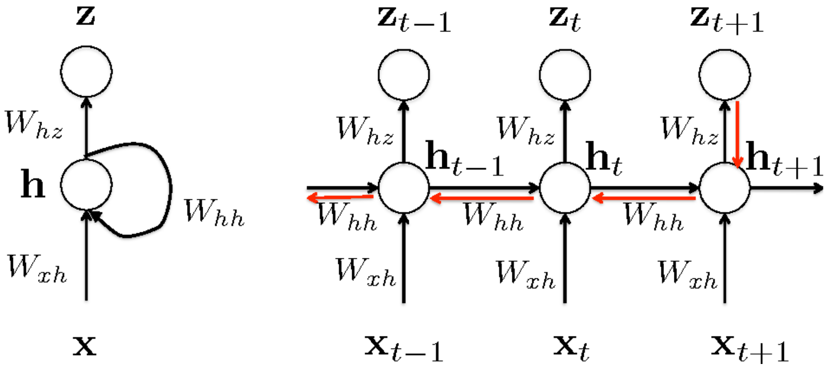
4. Continue until all `sequence_length` passed through the layer.
5. Concatenate all the results together to get an output from that layer of shape `(batch_size,sequence_length, output_size)`

Outline

Another Perspective of RNN



- It should be noted that the weights and biases are Shared through the time

Back Propagation Through Time

- Back propagation is done at each point in time.
- At timestep T, the derivative of the loss $\mathcal{L}$ with respect to each weight matrix $W_{(.)}$ is calculated, and the same $W_{(.)}$ are updated.
- This cause a problem widely known as vanishing/exploding gradient problem

Vanishing/Exploding Gradient Problem - Vanilla RNN

Assume we have a hidden state a_t at time step t. If we make things simple and remove biases and inputs, we have

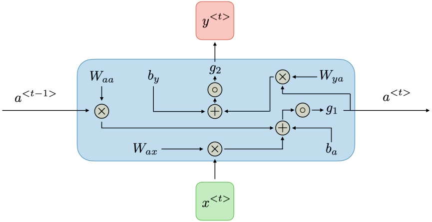
$$a_t = \sigma(w.a_{t-1})$$

we can show that

$$\frac{\partial a_{t_n}}{\partial a_t} = \prod_{i=1}^{i=t_n-t} w.\sigma'(a_{t_n-i})$$

$$= w^{t_n-t} \prod_{i=1}^{i=t_n-t} .\sigma'(a_{t_n-i})$$

The factored w^{t_n-t} is a crucial term.



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- The answer is yes, but if we are able to get rid of this term $w^{t_n - t}$, the decay/growth rate will be lessened.
- Note, the original proof is very mathematically rigor

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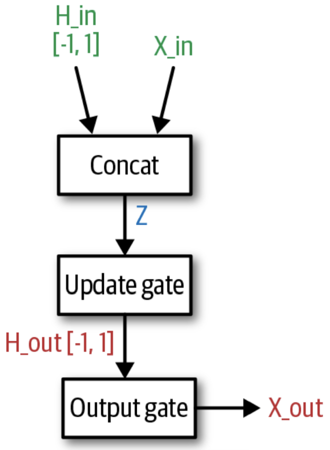
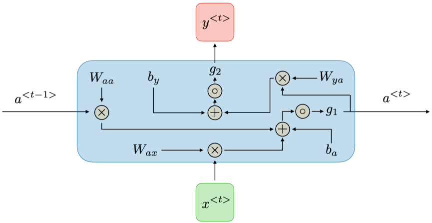
Vanilla RNN Two Perspectives





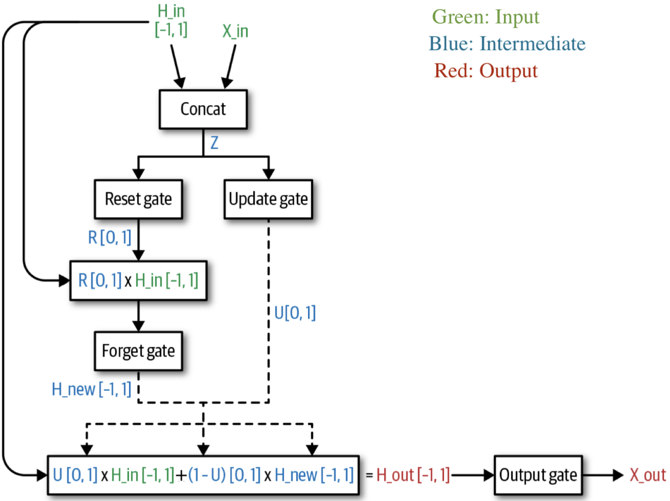
Gate is simply weight multiplication, bias addition, and activation function (sigmoid[0,1]/tanh[-1,1]).

Modifications

We will update the previous architecture by introducing some gates :

- **Update Gate [0,1]:** How much past should matter now?
- **Reset Gate [0,1]:** Reset previous information?
- **Forget Gate:** Erase a cell or not? (Important in LSTM)
- **Output Gate:** How much to reveal to the output?

Gated Recurrent Unit (GRU)



Green: Input
Blue: Intermediate
Red: Output

Back propagation with GRU

We can show that the gradient received by the hidden state is in the form

$$\frac{\partial s_{t_n}}{\partial s_t} = \prod_{i=1}^{i=t_n-t} \sigma'(.)$$

Long Short Term Memory (LSTM)

- LSTM is the first solution to the vanishing gradient problem
- It is much more complicated than the GRU
- Each LSTM node has two inputs as usual and three outputs
  - Hidden State
  - Cell State
  - Output
- The cell state is meant to encode a kind of aggregation of data from all previous time-steps that have been processed, while the hidden state is meant to encode a kind of characterization of the previous time-step's data.

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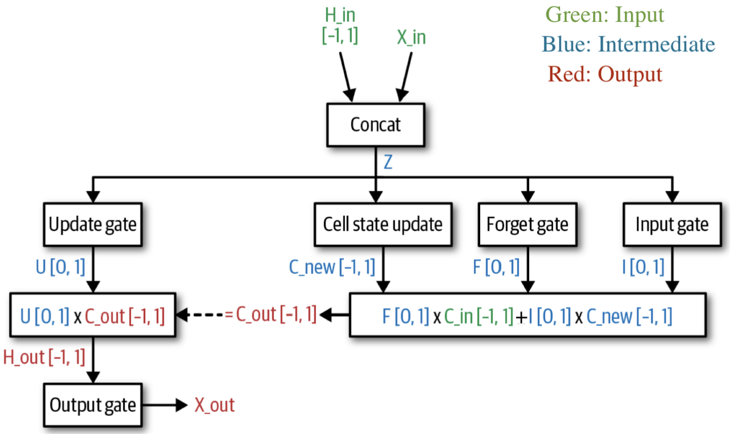
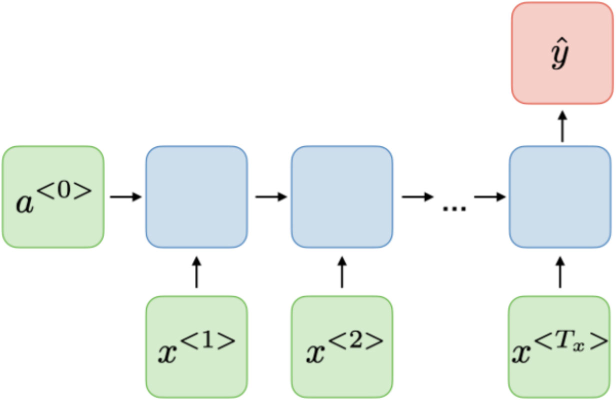


Outline

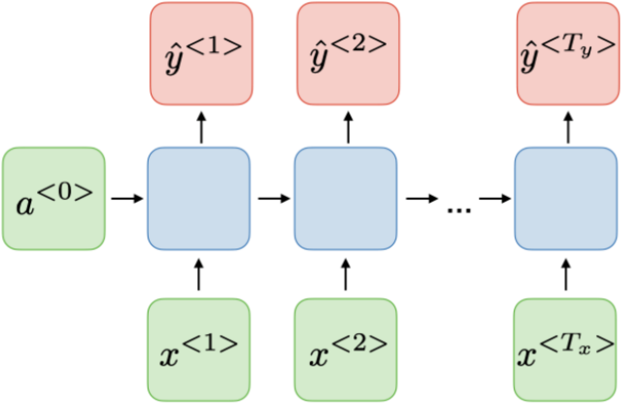
Language Modeling

- Language modeling is one of the most common tasks RNNs are used for.
- A neural network that learns to write text in the style of Shakespeare !!
- The hardest part is building the training data !!
- We can use one hot encoding to represent each word as big vector of zeros and a single one at the word position in the vocabulary dictionary
- Then determining the sequence length, and start building the training data

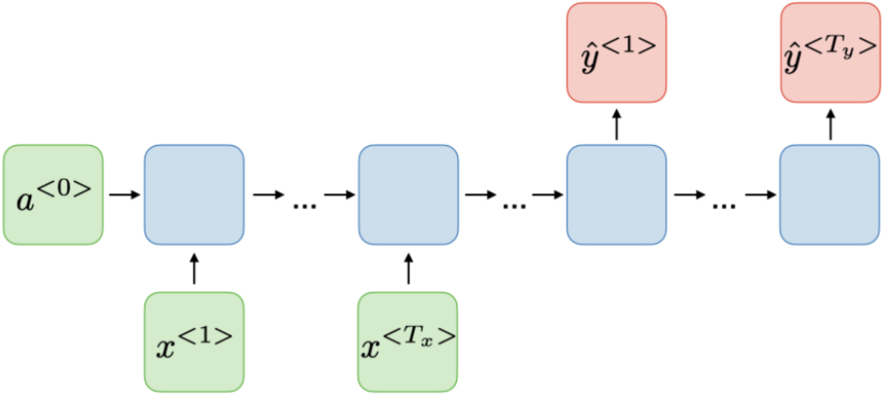
Sentiment Classification



Named Entity Recognition



Machine Translation



Questions