Applied Deep Learning

Chapter 6: Recurrent NNs

Ali Bereyhi

ali.bereyhi@utoronto.ca

Department of Electrical and Computer Engineering

University of Toronto

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RNN: *Dataset and Learning Setting*

We are now looking into a supervised learning problem where we are to

learn label from a sequence of data that has generally a temporal correlation

Let's denote the sequence with $\mathbf{x}[1], \ldots, \mathbf{x}[T]$

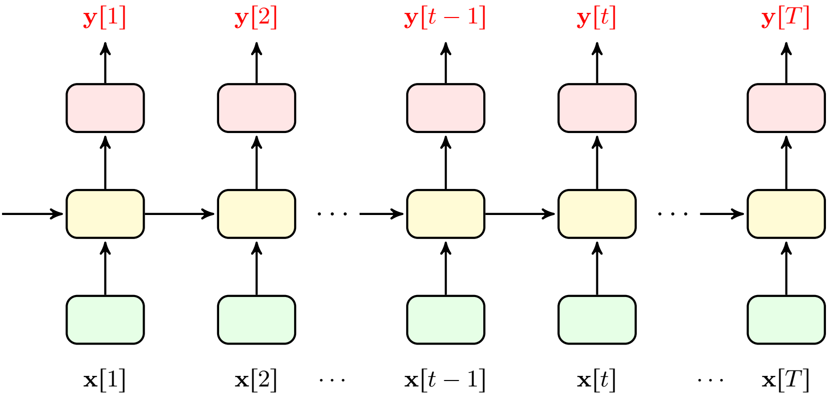
Temporal Correlation

By temporal correlation we mean that entries at other time instances carry information about one particular entry $\mathbf{x}[t]$

+ *But how is a label assigned to this sequence?*
– Well, that can be of various forms!

Types of Problems with Sequence Data

We considered a very simple case: many-to-many type I

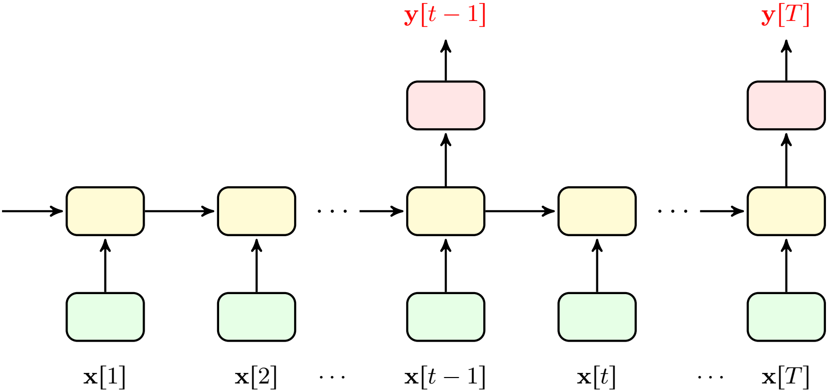


In this case, every entry has a label

↳ *speech tagging: $\mathbf{x}[t]$ is a part of speech and $\mathbf{y}[t]$ is its tag*

Types of Problems with Sequence Data

We considered a very simple case: many-to-many type II

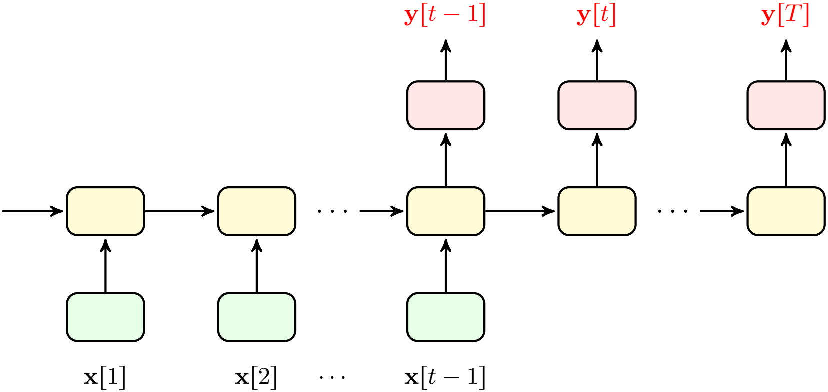


In this case, we get a label once after multiple entries

↳ *speech recognition: $\mathbf{x}[t]$ is a small part of speech and $\mathbf{y}[t]$ says what is a every couple of minutes about*

Types of Problems with Sequence Data

We considered a very simple case: many-to-many type III

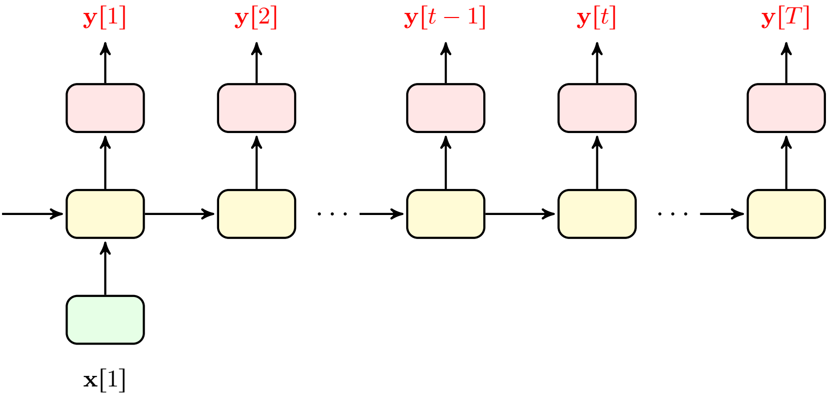


In this case, we start to get labels after some delay

↳ *language translation:* $\mathbf{x}[1], \ldots, \mathbf{x}[t-1]$ *is a sentence in German and* $\mathbf{y}[t-1], \ldots, \mathbf{y}[T]$ *is its translation to English*

Types of Problems with Sequence Data

We considered a very simple case: one-to-many

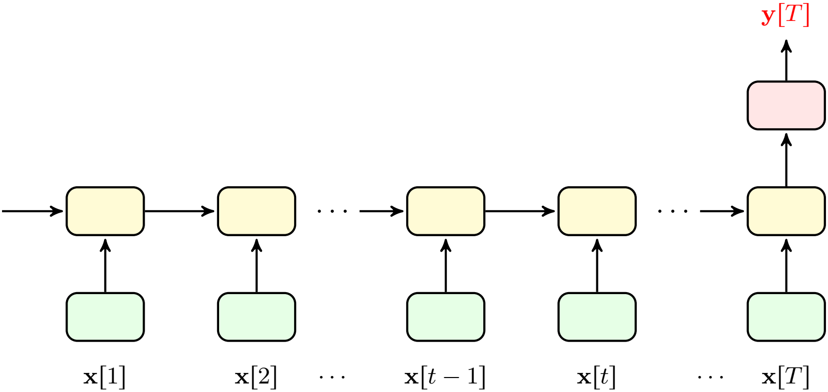


In this case, we get only one input data and have a sequence of labels

↳ *image captioning: $\mathbf{x}[1]$ is an image and $\mathbf{y}[1], \dots, \mathbf{y}[T]$ is a caption describing what is inside the image*

Types of Problems with Sequence Data

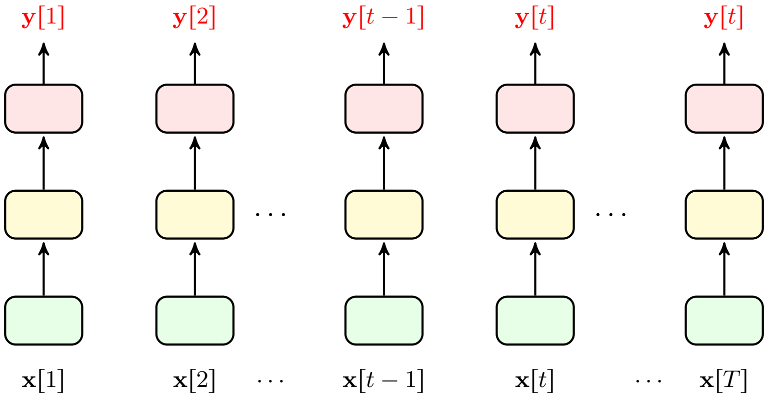
We considered a very simple case: many-to-one



In this case, we get only one label for a whole input sequence

↳ *sequence classification:* $\mathbf{x}[1], \ldots, \mathbf{x}[T]$ *is a speech and* $\mathbf{y}[T]$ *says if this speech is constructive or destructive*

Types of Problems with Sequence Data: *FNNs*



In fact, FNNs are one-to-one RNNs

↳ *we can think of every data-point as a sequence of length one, or*

↳ *we may think of dataset as a long sequence with no temporal correlation*

RNN: *General Form*

To construct an RNN, we can use any module that we have learned:

- *we can use a fully-connected layer*
- *we can use a convolutional layer*
- *we can use a residual unit*
- *we may use an inception unit used in GoogLeNet*

  $\dots$

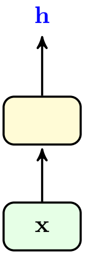
But, classical implementations use fully-connected layers

We can use one layer to make a shallow RNN or multiple to make a deep RNN

+ *Don't we do any change to them?*
- Not a serious change
  - ↳ *We may change the activation to* $\tanh(\cdot)$: *we will see later why*
  - ↳ *We expand the input dimension: since we need to also give memory as input*

Shallow RNN

Let's break it down a bit: *say the yellow box is a fully-connected layer*

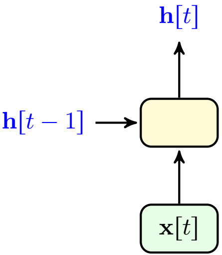


This layer gets input $\mathbf{x} \in \mathbb{R}^N$ *and returns activated feature* $\mathbf{h} \in \mathbb{R}^M$

- *We replace its activation by* $\tanh(\cdot)$
  - ↳ *Not necessary, but usually suggested*
- *We modify it to get a new input in* $\mathbb{R}^{N+M}$
  - ↳ N *entries for data inputs* $\mathbf{x}$ *in time* t
  - ↳ M *entries for features* $\mathbf{h}$ *in time* $t-1$

Shallow RNN

Let's break it down a bit: *say the yellow box is a fully-connected layer*

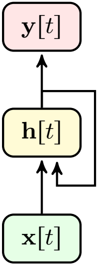


We show it this way now

- *We call $\mathbf{h}[t]$ usually the hidden state*
- *We pass the hidden state through an output layer*
  - ↳ *Output is not necessarily corresponding to label*

Shallow RNN

We may show our shallow RNN compactly via the following diagram



In this diagram

- *Each edge is a set of weights, e.g., a weight matrix*
- *The return edge also has a delay in time*

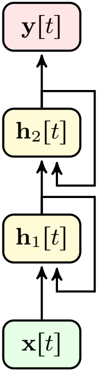
\+ *But, isn't that simply Elman Network?*

– If we use a fully-connected layer and sigmoid activation; then, Yes! *But, Remember that*

  - *Elman did not train it over time*
  - *Elman in its model used sigmoid activation*

Deep RNN

We can add more layers to make a deep RNN

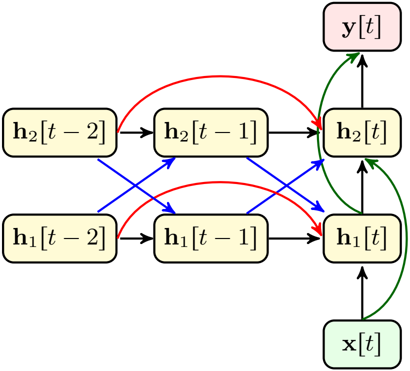


In this diagram

- *Each edge is a set of weights, e.g., a weight matrix*
- *The return edge also has a delay in time*
- *And, it's no more Elman Network*

Deep RNN

It might be easier to think of it as the following diagram



We can use any module that we like

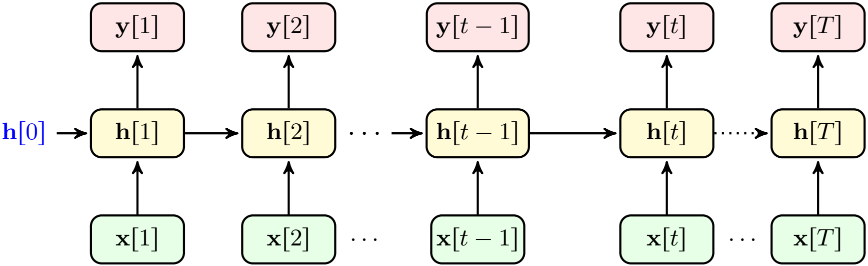
- *We may add skip connection*
- *We could make dense connections*
- *We may skip over time*
- *We may replace hidden layers with convolutions or anything else*

Shallow RNN: *Elman-Like Network*

Let's start with simple RNN: *a shallow RNN with fully-connected hidden layer*

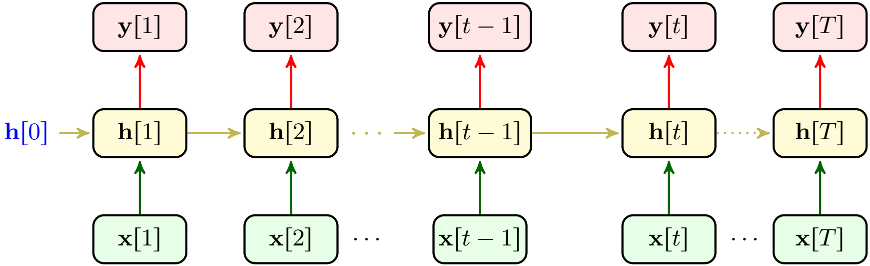
- \+ *You mean Elman Network?*
- – Yes, but *we now try to address the challenges that Elman did not address*

Let's look at the flow of information once again



Shallow RNN: *Forward Propagation*

Let's specify the learnable parameters with some colors



Say we set the activation to $f(\cdot)$

1. *We have* $\mathbf{y}[t] = f(\mathbf{W}_2\mathbf{h}[t])$: *we can learn* $\mathbf{W}_2$
2. *We have* $\mathbf{h}[t] = f(\mathbf{W}_1\mathbf{x}[t] + \mathbf{W}_\mathrm{m}\mathbf{h}[t-1])$: *we can learn* $\mathbf{W}_1$ *and* $\mathbf{W}_\mathrm{m}$
3. *We can start with any hidden state: this means we can learn* $\mathbf{h}[0]$ *too*