RNN in action: Understanding sequences

We will study a toy example that is typical of many tasks involving sequences

- Given a prefix of a sequence
- Predict the next element

For example

- Predict the next word in a sentence
- Predict the next price in a timeseries of prices

Being able to predict the next element may be key to understanding the "logic" underlying a sequence

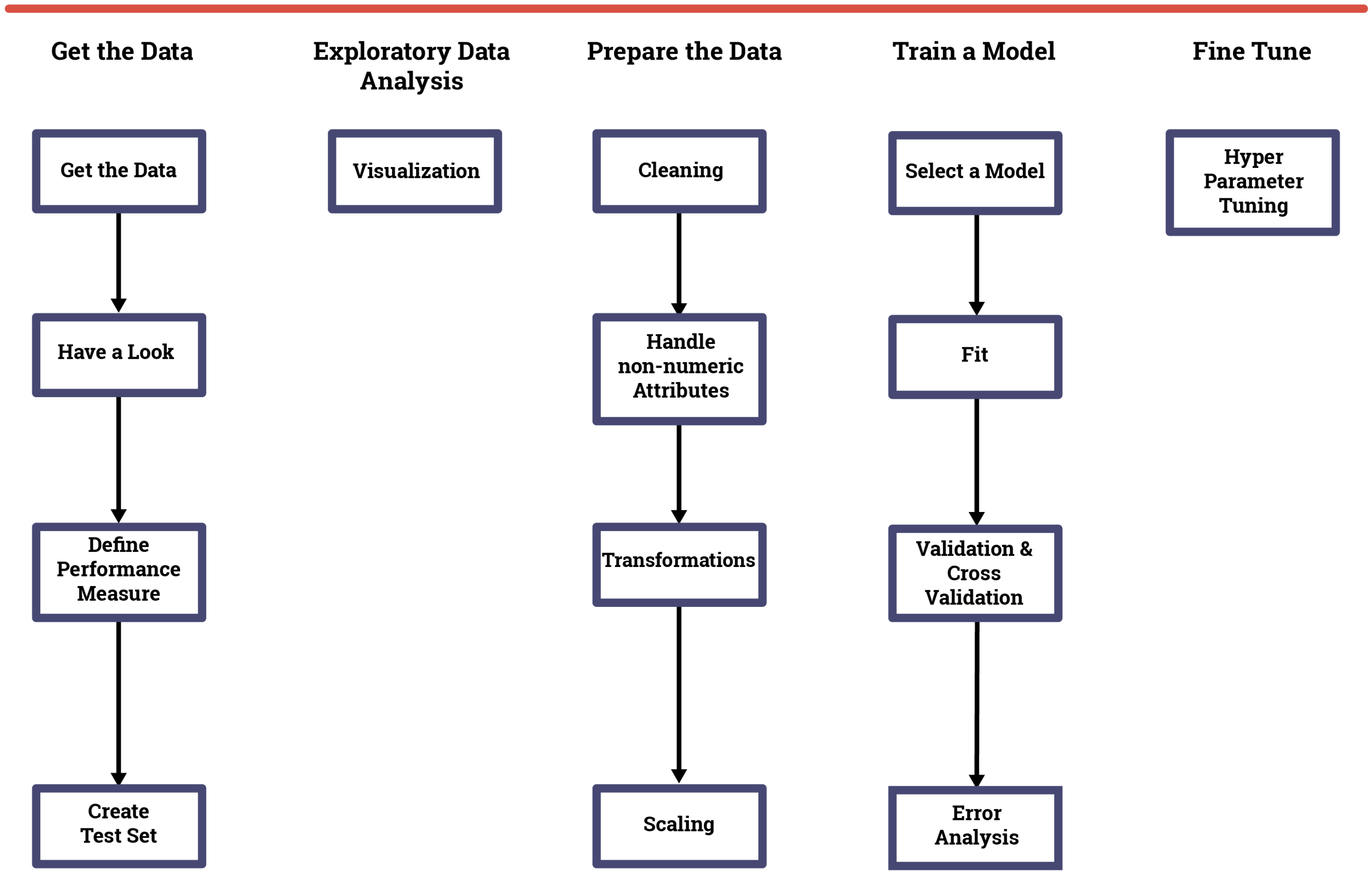
- You have to understand context and domain
- You have to understand how earlier elements influence latter elements

Predict the next: Data preparation

It is our belief that Machine Learning is a *process* and not just a collection of models.

We have recently been emphasizing the models but let's review the process.

Recipe for Machine Learning



It is usually the case that Sequence data involves substantial Data Preparation.

Suppose our task is to predict the next word in a sentence.

We are given (or must obtain) a collection of sentences (e.g., one or more documents) as our raw data.

But a sentence is not the format required for the training set of the "Predict the next word" task.

Data preparation is usually a substantial prerequisite for solving tasks involving sequences.

To be precises, the "Predict the next word" task involves

- Training a many to one RNN with examples created from a sequence.
- The elements of a single example are the prefix of a sentence
- The target of the example is the next word in the sentence

Let

$$[\ \mathbf{s}_{(t)} | 1 \leq t \leq T\ ]$$

be the sequence of words in sentence $\mathbf{s}$.

We will prepare $(T - 1)$ examples from this single sentence.

$\langle \mathbf{X}, \mathbf{y} \rangle =$

i	$\mathbf{x^{(i)}}$	$\mathbf{y^{(i)}}$
1	$\mathbf{s}_{(1)}$	$\mathbf{s}_{(2)}$
2	$\mathbf{s}_{(1),(2)}$	$\mathbf{s}_{(3)}$
$\vdots$		
i	$\mathbf{s}_{(1),\ldots,(i)}$	$\mathbf{s}_{(i+1)}$
$\vdots$		
$(T-1)$	$\mathbf{s}_{(1),\ldots,(T-1)}$	$\mathbf{s}_{(T)}$

For example

$\mathbf{s} =$ "I am taking a class in Machine Learning"

i	$\mathbf{x^{(i)}}$	$\mathbf{y^{(i)}}$
1	[I]	am
2	[I, am]	taking
3	[I, am, taking]	a

Predict the next: data shape

We had warned earlier about the explosion of the number of dimensions of our data. Now is a good time to take stock

- $\mathbf{X}$, the training set, is a matrix with m rows
- Each row is an example $\mathbf{x^{(i)}}$
- Each example is a sequence $[\ \mathbf{x}^{\mathbf{(i)}}_{(t)} \mid 1 \le t \le ||\mathbf{x^{(i)}}||\ ]$
- Each element $\mathbf{x}^{\mathbf{(i)}}_{(t)}$ of the sequence encodes a word
- A word is encoded as a One Hot Encoded binary vector of length $||V||$ where V is the set of words in the vocabulary

Target $\mathbf{y^{(i)}}$ is also a word (so is vector of length $||V||$).

- Many to one: target is *not* a sequence

Predict the next: training

Just like training any other type of layer, but more expensive

- Each example involves multiple time steps: forward pass time consuming
- The derivatives (needed for Gradient Descent) are more complex; backward pass complex and time consuming

RNN as a generative model (fun with RNN’s)

The "Predict the next" word task is interesting on its own

- But a slight twist will make it extremely interesting

Suppose

- We train the RNN on a large number of sentences of the same type (e.g., same author)
- Create a few words to create the prefix of a sentence
- Ask the RNN to predict the next word
- Append this word to the prefix
- Repeat !

Voila: the RNN can *generate* a story in the same style as the training sentences.

Using Machine Learning to *create* data is called *generative*.

Using Machine Learning to classify/predict (as we've been doing thus far) is called *discriminative*.

Architecture

How do we construct a model to solve this task ?

We construct a two part model in what is known as an *Encoder/Decoder* architecture

The *Encoder* is a many to one RNN

- Takes the variable length "seed" sequence
- Outputs a fixed length representation of the seed
    - This is one of the strengths of an RNN

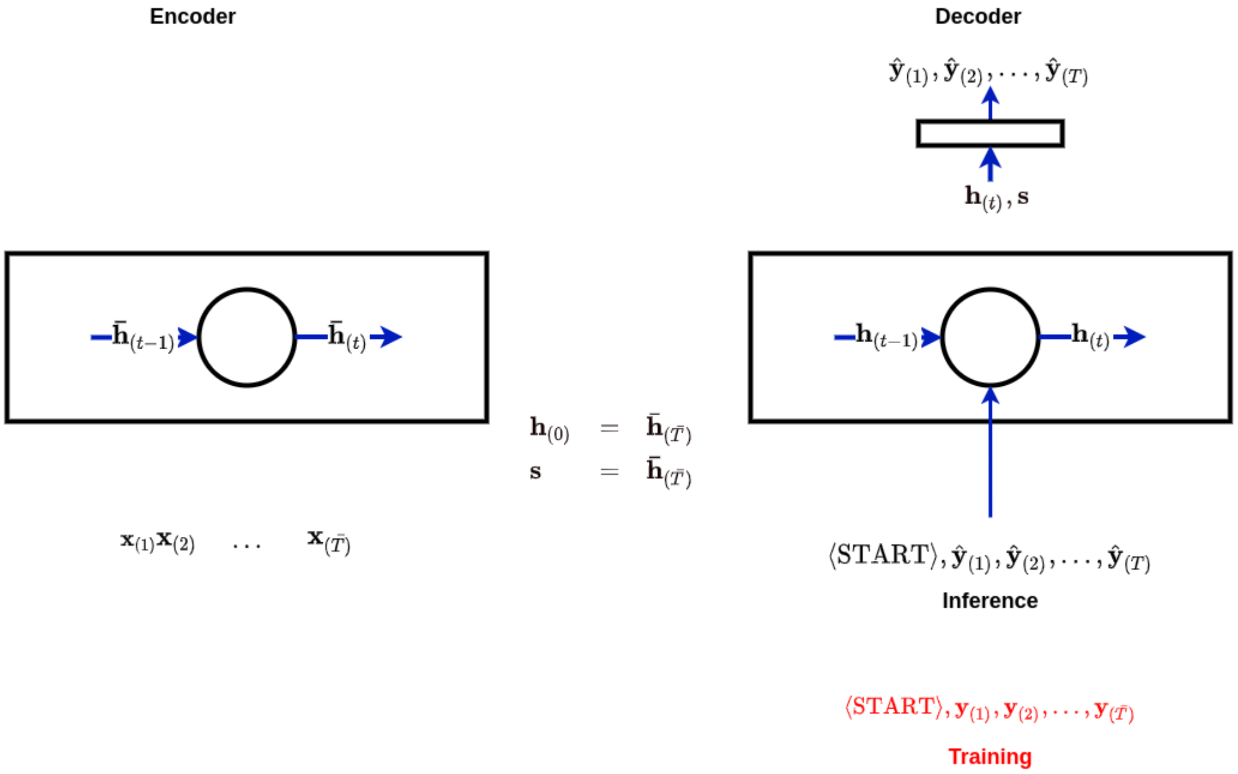
The *Decoder* is a one to many RNN

- Takes the fixed length representation of the seed produced by the Encoder
    - Used to initialized the Decoder's latent state $\mathbf{h}_{(0)}$
- Outputs a variable length sequence

The only thing unusual about the Decoder is how its input sequence is constructed

- All the elements of its input $\mathbf{x}$ are *generated* by the Decoder
- The first element of $\mathbf{x}$ is set to a special "start of output" symbol
$$\mathbf{x}_{(1)} = \langle \text{START} \rangle$$
- $\mathbf{x}_{(t)}$ is extending *dynamically*, using the previous prediction $\hat{\mathbf{y}}_{(t-1)}$
$$\mathbf{x}^{(\mathbf{i})}_{(t)} = \mathbf{y}_{(t-1)}$$
- The Decoder stops when it generates a special "end of output" symbol $\langle \text{END} \rangle$

Sequence to Sequence: inference



That is

- The output is fed as the next input
- Thus extending the sequence
- And making sure that subsequent elements are influenced by all previously *generated* elements
- Continuing until the special $\langle \mathrm{END} \rangle$ symbol is generated

Training: Teacher forcing

Some issues arise in using an RNN in the generative manner.

The first issue:

- Is the prediction a single word or a probability distribution over the vocabulary $||V||$
- If it's a single word: the output is deterministic
    - Problematic once one word is wrong: the error propagates forward

The output of the multinomial classifier is a vector of length $||V||$

- With values in the range $[0, 1]$ that can be interpretted as probabilities
- Rather than choosing the single word with highest probability
- We *sample* one word at random, according to the probability distribution

This makes the output non-deterministic: running the model twice with the same "seed" may give different stories.

A second issue

- If a wrong word is chosen at step t: it affects the generation of all words at step $t > t'$
- This is particularly problematic at *training* time: makes learning difficult

The solution for training an RNN for this task is a method known as *teacher forcing*

- Rather than extending the seed example $\mathbf{x^{(i)}} = [\ \mathbf{x}_{(t)}^{\mathbf{(i)}} \,|\, 1 \le t \le t'\ ]$
  - With $\hat{\mathbf{y}}_{(t)}$, the *predicted* t^{th} word for $(t > t')$
  - Which is what would happen at inference/test time
  - Extend it with $\mathbf{y}_{(t)}$, the *target* (i.e., correct t^{th} word)

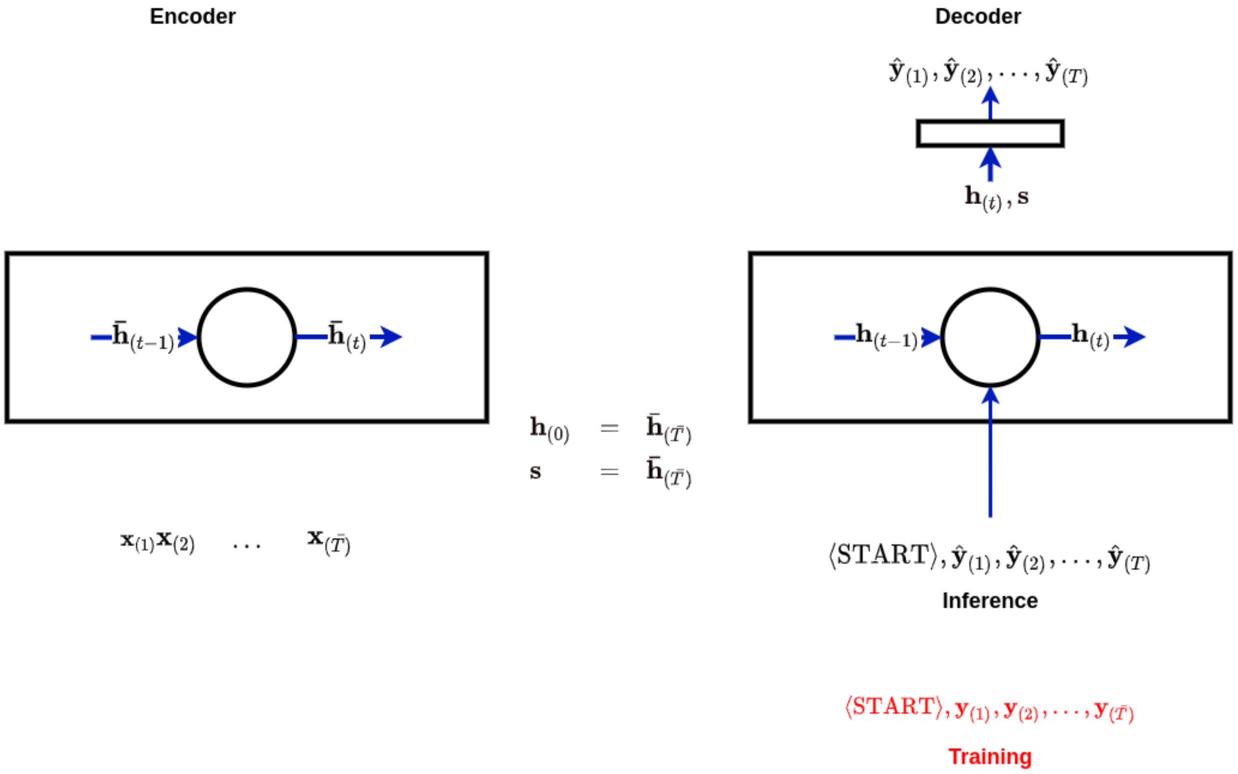
In other words: to speed up training

- When extending the prefix
- A teacher forces the student (model) to continue with the *correct* answer
- Rather than the student's answer

$$\mathbf{x}_{(t)}^{\mathbf{(i)}} = \mathbf{y}_{(t-1)}$$

for $t > t'$.

Sequence to Sequence: training (teacher forcing)



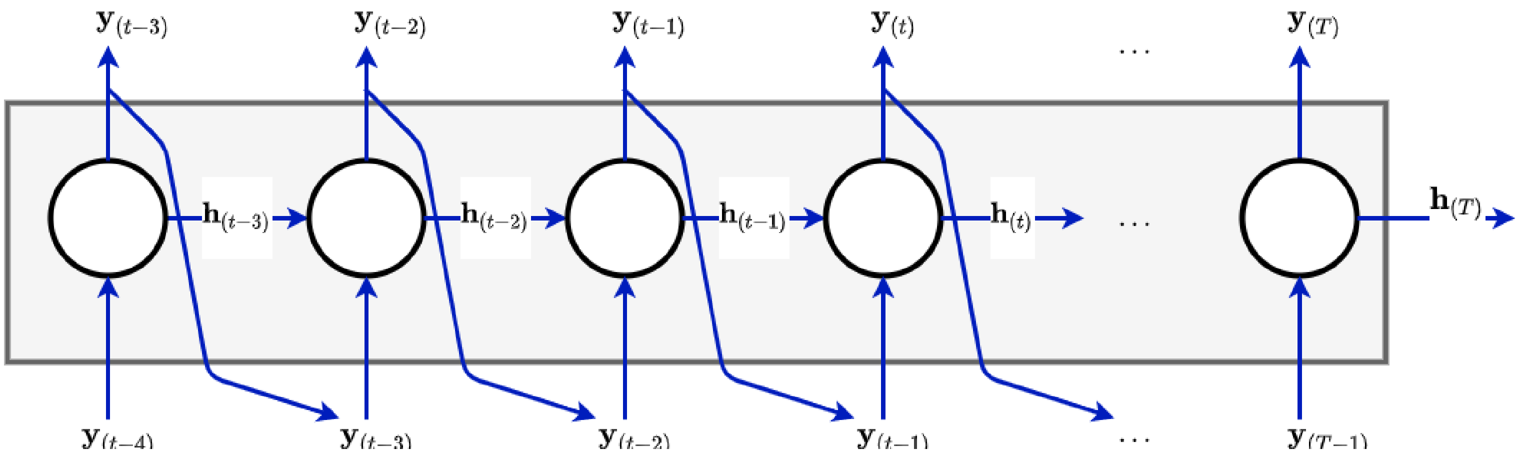
Teacher forcing is indicated in red

- Predictions $[\ \hat{\mathbf{y}}_{(t)} \mid 1 \le t \le T\ ]$ **are not** used as input (lower right)
- Only correct targets $[\ \mathbf{y}_{(t)} \mid 1 \le t \le T\ ]$ are used

Summary

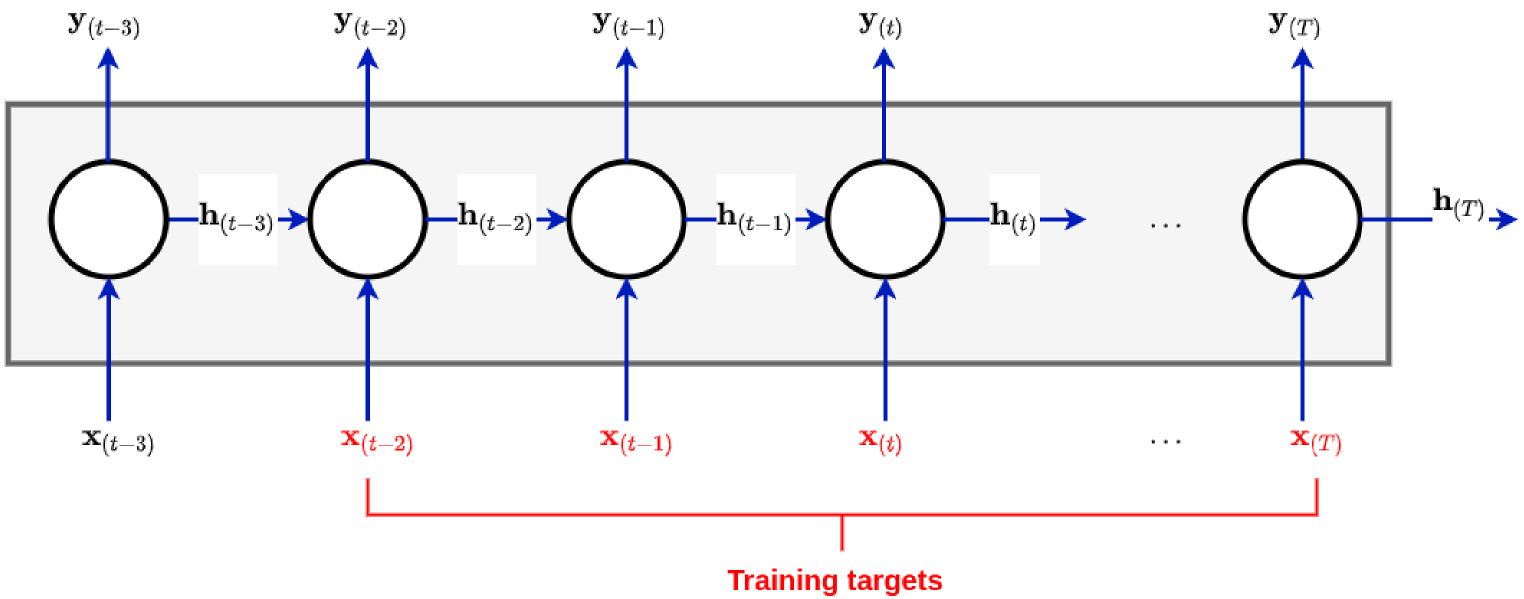
Here is an unrolled graph at inference/test time

Test time: no forcing



And here is a depiction of the graph used at *training* time

Training, with Teacher Forcing



Generating strange things

Generating stories from seeds was very popular a few years back.

Let's look at some examples.

But first, a surprise:

- Rather than solving a "predict the next word" task
- All of the following examples were generated by a "predict the next **character**" task !

It is somewhat amazing that what is generated

- Has correctly spelled words/keywords
- Is Syntactically correct (sentences end with a ".", parentheses/brackets are balanced)
- Is meaningful: the elements/words are arranged in a logical order

Even though

- We have not explicilty identified any of these concepts
- Nor forced training to respect them (via a loss function)

Remember

- All of this behavior was "learned" by identifying the correct next **character**

- Fake Shakespeare (http://karpathy.github.io/2015/05/21/rnn-effectiveness/#shakespeare), or fake politician-speak
- Fake code
- Fake math textbooks (http://karpathy.github.io/2015/05/21/rnn-effectiveness/#algebraic-geometry-latex)
- Click bait headline generator (http://clickotron.com/about)

In [2]:

```
print("Done")
```

Done