

Applied Deep Learning

Chapter 7: Sequence-to-Sequence Models

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Learning Sequence from Sequence

In many applications, our dataset contains data-points that of the form

$$(\mathbf{x}[t], \mathbf{v}[t])$$

This is still standard *supervised learning* where

- *input data* is a sequence, and
- *label* is a sequence

We have already seen several examples with RNNs

- We want to train a machine translator
 - ↳ Dataset contains sequences of German sentences with English translations
- We want to caption an image
 - ↳ Dataset contains images with sequences of caption sentences
- We want to predict next words
 - ↳ Dataset contains sequences of sentences with label being last word

Sequence-to-Sequence Problem

- + What is the key point in such learning problems?
- They are often called a **sequence-to-sequence problem**, since we intend to learn an **output sequence** from an **input sequence**

Sequence-to-Sequence (Seq2Seq) Models

A Seq2Seq model is a model, e.g., a NN, that takes a **sequence** as an **input** and returns an **output sequence**

- + Then isn't RNN a Seq2Seq model?
- Sure! Strictly speaking even **MLPs** and **CNNs** are **Seq2Seq** models with sequences of length 1!

Despite this definition, when we talk about **Seq2Seq models** in practice, we mainly refer to **architectures** with **encoder** and **decoder**

First Seq2Seq Model

Let's start with a simple task:

*we intend to **train a model** that generates **coherent sentences***

- After training it should be able to generate **meaningful sentences**
 - ↳ If we give in an **incomplete sentence**, it can **complete it**
 - ↳ If we **don't give it an input**, it generates a **random meaningful sentence**

Since, we only know RNNs up to now, we are going to use an RNN

- As **model** we want to **train an RNN**
 - ↳ It could be an **LSTM**, a **GRU**, or even a **basic RNN**
 - ↳ It can be **shallow** or **deep**
- We are going to train this RNN via a given **dataset**
 - ↳ We compute the **loss** by some loss function, e.g., **cross-entropy**

Seq2Seq Model: Basic Language Model

We intend to train a **model** that generates **coherent sentences**

*this is a basic **natural language model***

You learn in detail about it in **ECE 1786: Creative Applications of NLP**

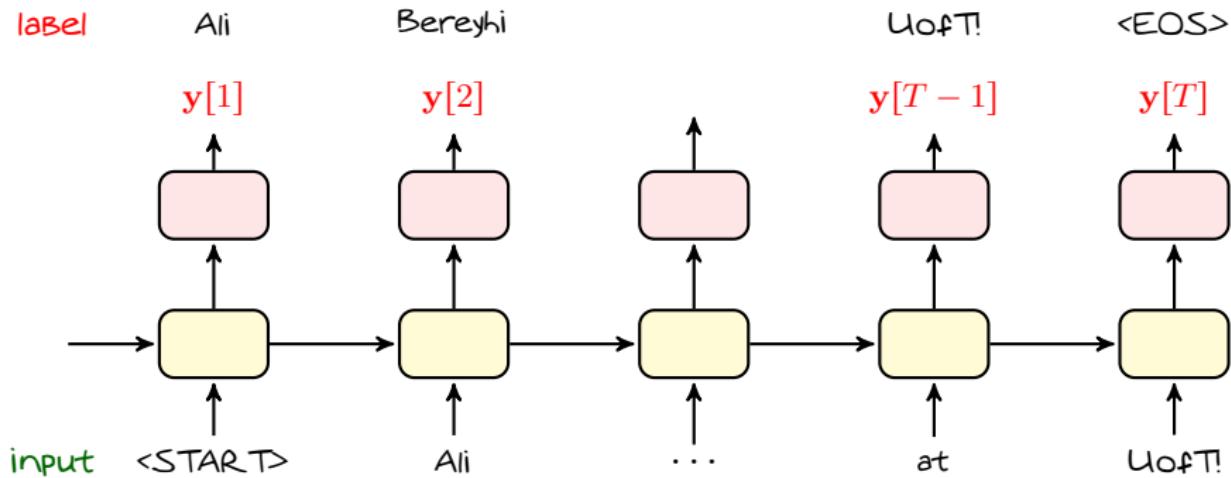
↳ You may consider taking it in the next **fall semester**

Let's write our dataset first: it contains **sequences** of **coherent** English sentences

Ali Bereyhi is the coolest professor at UoFT!

- Sentences are of **different** lengths, i.e., T is **different** for each sequence
 - ↳ Each **word** in a **sentence** is **one input entry**
 - ↳ We **label** each word with its **next word in the sentence**

Basic Language Model: Dataset



- To be able to predict first word and end of sentence we add two new words
 - ↳ We tag the beginning of sentence with <START>
 - ↳ We label the end of sentence with <EOS>
- We do not have the correspondence issue in this problem

Basic Language Model: Dataset

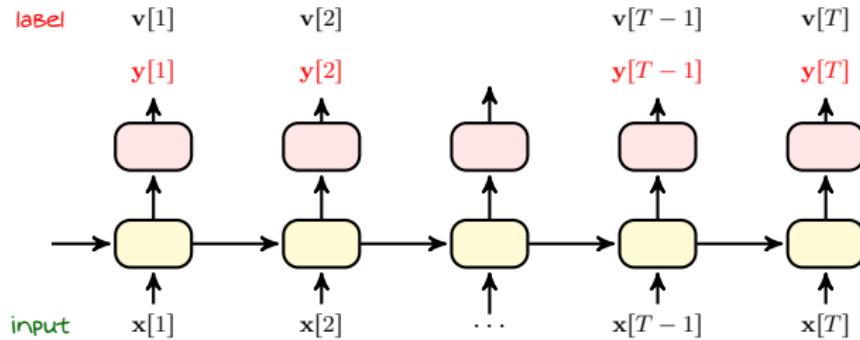
- + How can we feed those **words** to our RNN?
- We convert them to **vectors** by some method
 - ↳ You can learn those methods in ECE 1786

The **basic approach** is to make a **token** for each **word**

- We list **all possible words** and index them by 1 to D
 - ↳ D could be **very large**: just imagine how **many words** we could say!
 - ↳ The set of these words is what we call **vocabulary**
- We add **<START>** with **index 0** and **<EOS>** with $D + 1$
- We show each character by its **one-hot vector** which is called **token**, e.g.,

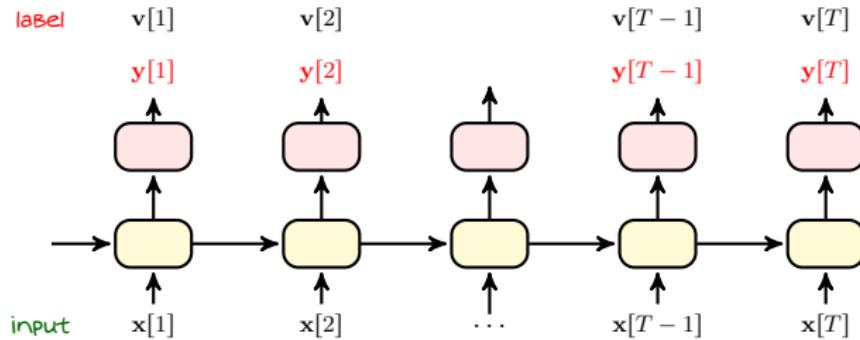
$$\text{<START>} \mapsto \begin{bmatrix} 1 \\ 0 \\ \vdots \end{bmatrix} \in \{0, 1\}^{D+2} \quad \text{<EOS>} \mapsto \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \in \{0, 1\}^{D+2}$$

Basic Language Model: Dataset



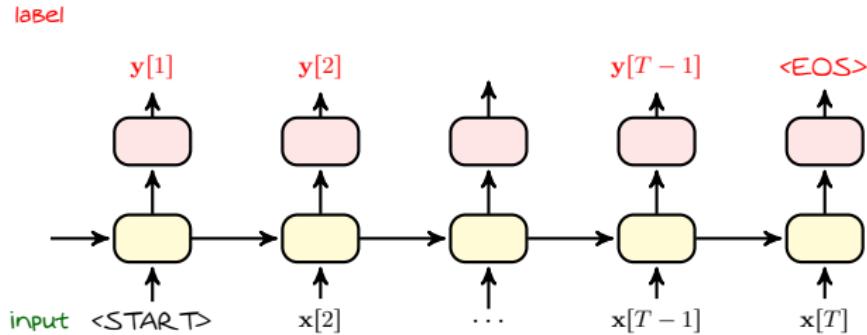
- We can replace every word with its **token**
 - ↳ We now have a standard **many-to-many** setting
 - ↳ We could also use “embedding” to assign **vectors** to **words**
 - ↳ This will be taught in ECE 1786

Basic Language Model: Training



- We now train the RNN with our dataset
 - ↳ We break dataset into **mini-batches**
 - ↳ For each **data-point** we pass first **forward** and then **backward** through time
 - ↳ We compute **aggregated loss** for each point and **average** over mini-batch
- After a certain number of epochs, we have the **trained RNN**

Basic Language Model: Inference



- If we want to generate a *random sentence*, we can give $\langle \text{START} \rangle$
 - ↳ It generates a *word* in each time step
 - ↳ Intuitively, *these sentences* are correlated to what RNN learned from dataset
- If we want to *complete the sentence*, we give the *initial part*
 - ↳ It keeps on generating till $\langle \text{EOS} \rangle$
 - ↳ Intuitively, this is correlated to what RNN learned and the *input part*

Sequence Generation: Caption Generation

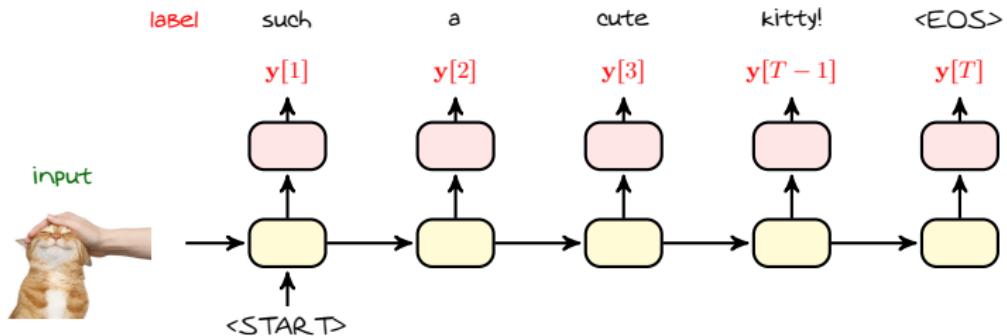
Sentence completion worked **simply** with RNN: *mainly following the fact that entries of **input** and **output** sequences are of **same nature***

- ↳ They are both **tokens**
- ↳ But in practice, we may have **different types of sequences**

Let's consider another example: we want to train an NN that gets an image and writes a caption for it

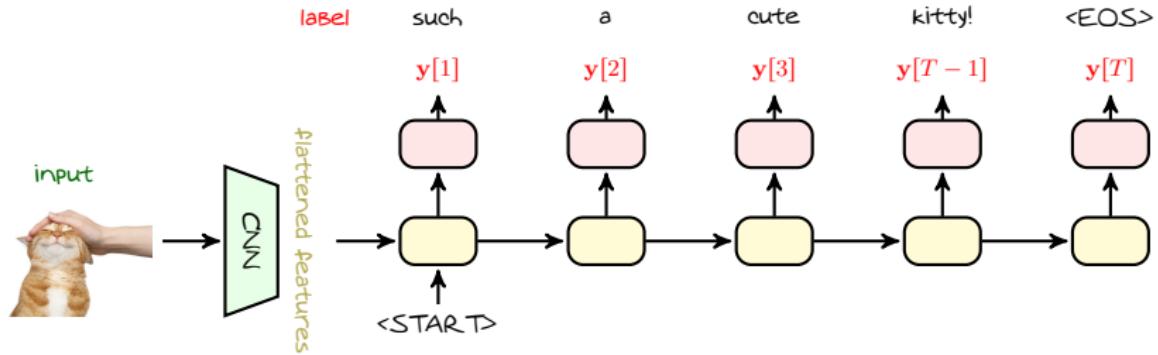
- It gets as input a single image: a **sequence of length one**
 - ↳ For instance a 256×256 RGB image of a cat
- It returns a **sentence**: potentially a **long sequence**
 - ↳ For instance the **sentence** such a cute kitty!

Caption Generation: Model



- We can generate a **meaningful sentence** with our **basic language model**
 - ↳ The **sentence** is probably not relevant to the **image**
 - ↳ We need to make the RNN **speak about the cat image**
- Maybe, we could set **initial state** of the RNN **depending on the image**
 - ↳ We need to **extract features** of image
 - ↳ Those **features** are going to **explain what is inside the image**

Caption Generation: Encoder-Decoder



- We can extract a **rich vector** of **features** from the image via a **CNN**
 - ↳ We use **multiple convolutional layers** to extract **features**
 - ↳ We **flatten** those **features** and give it as a **initial state** to the **RNN**

This architecture is called an **encoder-decoder model**

- ↳ A **CNN** is used to **encode input** to a good vector of features
- ↳ An **RNN** is used to **decode** extracted features to a desired **label sequence**