Selected topics in AI – TPs 5-6

(taken from Stanford CS224n Assignment #4)

The notation and implementation of the NMT system is a bit tricky, so if you ever get stuck along the way, please ask.

Neural Machine Translation with RNNs

In Machine Translation, our goal is to convert a sentence from the *source* language (e.g. Spanish) to the *target* language (e.g. English). In this assignment, we will implement a sequence-to-sequence (Seq2Seq) network with attention, to build a Neural Machine Translation (NMT) system. In this section, we describe the **training procedure** for the proposed NMT system, which uses a Bidirectional LSTMEncoder and a Unidirectional LSTM Decoder.

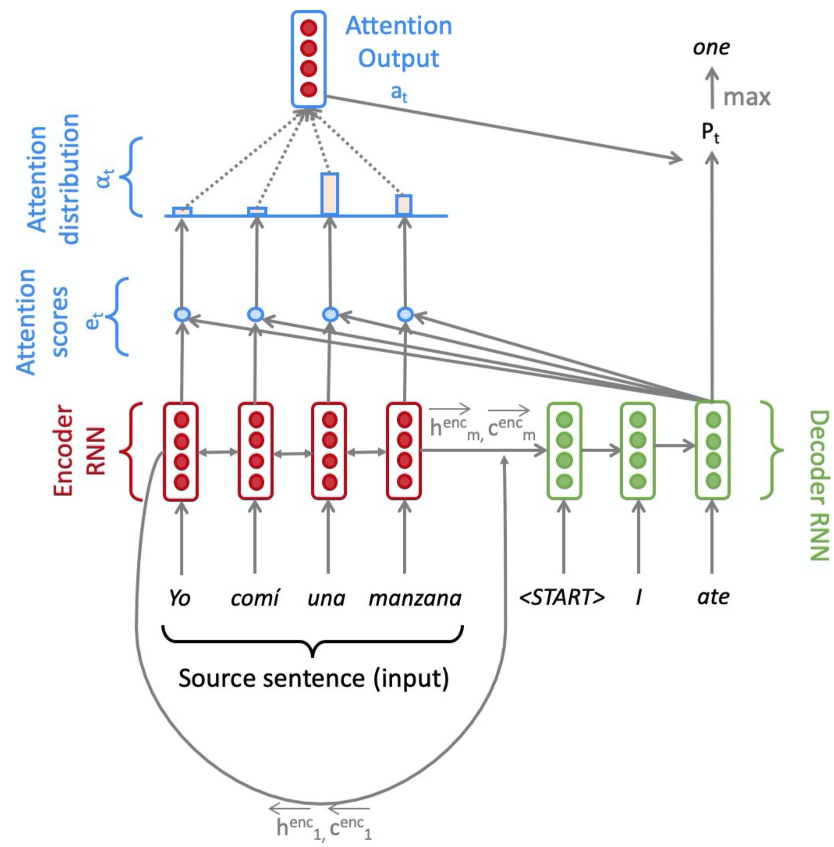

Figure 1: Seq2Seq Model with Multiplicative Attention, shown on the third step of the decoder. Hidden states $\mathbf{h}_i^{\text{enc}}$ and cell states $\mathbf{c}_i^{\text{enc}}$ are defined in the next page.

Model description (training procedure)

Given a sentence in the source language, we look up the word embeddings from an embeddings matrix, yielding $\mathbf{x}_1, \ldots, \mathbf{x}_m$ ($\mathbf{x}_i \in \mathbb{R}^{e\times 1}$), where m is the length of the source sentence and e is the embedding size. We feed these embeddings to the bidirectional encoder, yielding hidden states and cell states for both the forwards (→) and backwards (←) LSTMs. The forwards and backwards versions are concatenated to give hidden states $\mathbf{h}_i^{\text{enc}}$ and cell states $\mathbf{c}_i^{\text{enc}}$:

$$\mathbf{h}_i^{\text{enc}} = [\overleftarrow{\mathbf{h}_i^{\text{enc}}}; \overrightarrow{\mathbf{h}_i^{\text{enc}}}] \text{ where } \mathbf{h}_i^{\text{enc}} \in \mathbb{R}^{2h\times 1}, \overleftarrow{\mathbf{h}_i^{\text{enc}}}, \overrightarrow{\mathbf{h}_i^{\text{enc}}} \in \mathbb{R}^{h\times 1} \qquad 1 \le i \le m \tag{1}$$

$$\mathbf{c}_i^{\text{enc}} = [\overleftarrow{\mathbf{c}_i^{\text{enc}}}; \overrightarrow{\mathbf{c}_i^{\text{enc}}}] \text{ where } \mathbf{c}_i^{\text{enc}} \in \mathbb{R}^{2h\times 1}, \overleftarrow{\mathbf{c}_i^{\text{enc}}}, \overrightarrow{\mathbf{c}_i^{\text{enc}}} \in \mathbb{R}^{h\times 1} \qquad 1 \le i \le m \tag{2}$$

We then initialize the decoder's first hidden state $\mathbf{h}_0^{\text{dec}}$ and cell state $\mathbf{c}_0^{\text{dec}}$ with a linear projection of the encoder's final hidden state and final cell state.[1]

$$\mathbf{h}_0^{\text{dec}} = \mathbf{W}_h[\overleftarrow{\mathbf{h}_1^{\text{enc}}}; \overrightarrow{\mathbf{h}_m^{\text{enc}}}] \text{ where } \mathbf{h}_0^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{W}_h \in \mathbb{R}^{h\times 2h} \tag{3}$$

$$\mathbf{c}_0^{\text{dec}} = \mathbf{W}_c[\overleftarrow{\mathbf{c}_1^{\text{enc}}}; \overrightarrow{\mathbf{c}_m^{\text{enc}}}] \text{ where } \mathbf{c}_0^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{W}_c \in \mathbb{R}^{h\times 2h} \tag{4}$$

With the decoder initialized, we must now feed it a target sentence. On the t^{th} step, we look up the embedding for the t^{th} word, $\mathbf{y}_t \in \mathbb{R}^{e\times 1}$. We then concatenate $\mathbf{y}_t$ with the *combined-output vector* $\mathbf{o}_{t-1} \in \mathbb{R}^{h\times 1}$ from the previous timestep (we will explain what this is later down this page!) to produce $\overline{\mathbf{y}_t} \in \mathbb{R}^{(e+h)\times 1}$. Note that for the first target word (i.e. the start token) $\mathbf{o}_0$ is a zero-vector. We then feed $\overline{\mathbf{y}_t}$ as input to the decoder.

$$\mathbf{h}_t^{\text{dec}}, \mathbf{c}_t^{\text{dec}} = \text{Decoder}(\overline{\mathbf{y}_t}, \mathbf{h}_{t-1}^{\text{dec}}, \mathbf{c}_{t-1}^{\text{dec}}) \text{ where } \mathbf{h}_t^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{c}_t^{\text{dec}} \in \mathbb{R}^{h\times 1} \tag{5}$$

$$\tag{6}$$

We then use $\mathbf{h}_t^{\text{dec}}$ to compute multiplicative attention over $\mathbf{h}_1^{\text{enc}}, \ldots, \mathbf{h}_m^{\text{enc}}$:

$$\mathbf{e}_{t,i} = (\mathbf{h}_t^{\text{dec}})^T \mathbf{W}_{\text{attProj}} \mathbf{W} \mathbf{h}_i^{\text{enc}} \text{ where } \mathbf{e}_t \in \mathbb{R}^{m\times 1}, \mathbf{W}_{\text{attProj}} \in \mathbb{R}^{h\times 2h} \qquad 1 \le i \le m \tag{7}$$

$$\alpha_t = \text{softmax}(\mathbf{e}_t) \text{ where } \alpha_t \in \mathbb{R}^{m\times 1} \tag{8}$$

$$\mathbf{a}_t = \sum_{i=1}^{m} \alpha_{t,i} \mathbf{h}_i^{\text{enc}} \text{ where } \mathbf{a}_t \in \mathbb{R}^{2h\times 1} \tag{9}$$

We now concatenate the attention output $\mathbf{a}_t$ with the decoder hidden state $\mathbf{h}_t^{\text{dec}}$ and pass this through a linear layer, tanh, and dropout to attain the *combined-output* vector $\mathbf{o}_t$.

$$\mathbf{u}_t = [\mathbf{a}_t; \mathbf{h}_t^{\text{dec}}] \text{ where } \mathbf{u}_t \in \mathbb{R}^{3h\times 1} \tag{10}$$

$$\mathbf{v}_t = \mathbf{W}_u \mathbf{u}_t \text{ where } \mathbf{v}_t \in \mathbb{R}^{h\times 1}, \mathbf{W}_u \in \mathbb{R}^{h\times 3h} \tag{11}$$

$$\mathbf{o}_t = \text{dropout}(\tanh(\mathbf{v}_t)) \text{ where } \mathbf{o}_t \in \mathbb{R}^{h\times 1} \tag{12}$$

Then, we produce a probability distribution $\mathbf{P}_t$ over target words at the t^{th} timestep:

[1] If it's not obvious, think about why we regard $[\overleftarrow{\mathbf{h}_1^{\text{enc}}}, \overrightarrow{\mathbf{h}_m^{\text{enc}}}]$ as the 'final hidden state' of the Encoder.

$$\mathbf{P}_t = \text{softmax}(\mathbf{W}_{\text{vocab}}\mathbf{o}_t) \text{ where } \mathbf{P}_t \in \mathbb{R}^{V_t \times 1}, \mathbf{W}_{\text{vocab}} \in \mathbb{R}^{V_t \times h} \tag{13}$$

Here, V_t is the size of the target vocabulary. Finally, to train the network we then compute the softmax cross entropy loss between $\mathbf{P}_t$ and $\mathbf{g}_t$, where $\mathbf{g}_t$ is the one-hot vector of the target word at timestep t:

$$J_t(\theta) = CrossEntropy(\mathbf{P}_t, \mathbf{g}_t) \tag{14}$$

Here, θ represents all the parameters of the model and $J_t(\theta)$ is the loss on step t of the decoder. Now that we have described the model, let's try implementing it for Spanish to English translation!

Setting up your Environment

In order to run the model code on your **local** machine, please run the following command to create the proper virtual environment:

```
conda env create --file local_env.yml
conda activate ENV_NAME
```

Implementation

(a) (coding) In order to apply tensor operations, we must ensure that the sentences in a given batch are of the same length. Thus, we must identify the longest sentence in a batch and pad others to be the same length. Implement the pad_sents function in utils.py, which shall produce these padded sentences.

(b) (coding) Implement the init function in model_embeddings.py to initialize the necessary source and target embeddings.

(c) (coding) Implement the init function in nmt_model.py to initialize the necessary model embeddings (using the ModelEmbeddings class from model_embeddings.py) and layers (LSTM, projection, and dropout) for the NMT system.

(d) (coding) Implement the encode function in nmt_model.py. This function converts the padded source sentences into the tensor $\mathbf{X}$, generates $\mathbf{h}_1^{\text{enc}}, \ldots, \mathbf{h}_m^{\text{enc}}$, and computes the initial state $\mathbf{h}_0^{\text{dec}}$ and initial cell $\mathbf{c}_0^{\text{dec}}$ for the Decoder.

(e) ~~(coding) Implement the decode function in nmt model.py. This function constructs $\bar{\mathbf{y}}$ and runs the step function over every timestep for the input.~~

(f) (coding) Implement the step function in nmt model.py. This function applies the Decoder's LSTM cell for a single timestep, computing the encoding of the target word $\mathbf{h}_t^{\text{dec}}$, the attention scores $\mathbf{e}_t$, attention distribution α_t, the attention output $\mathbf{a}_t$, and finally the combined output $\mathbf{o}_t$.

The generate sent masks() function in nmt model.py produces a tensorcalled enc masks. It has shape (batch size, max source sentence length) and contains 1s in positions corresponding to 'pad' tokens in the input, and 0s for non-pad tokens. Look at how the masks are used during the attention computation in the step() function (lines 295-296). First explain (in around three sentences) what effect the masks have on the entire attention computation. Then explain (in one or two sentences) why it is necessary to use the masks in thisway.

Run the code

Now it's time to get things running! Execute the following to generate the necessary vocab file:

```
sh run.sh vocab
```

As noted earlier, we recommend that you develop the code on your personal computer. Confirm that you are running in the proper conda environment and then execute the following command to train the model on your local machine:

```
sh run.sh train_local
```

Once your model is done training (**this should take about 4 hours on a GPU**), execute the following command to test the model:

```
sh run.sh test
```

Please report the model's corpus BLEU Score. It should be larger than 21.

In class, we learned about dot product attention, multiplicative attention, and additive attention. Please explain one advantage and one disadvantage of dot product attention compared to multiplicative attention. Then explain one advantage and one disadvantage of additive attention compared to multiplicative attention. As a reminder, dot product attention is $\mathbf{e}_{t,i} = \mathbf{s}_t^{\mathrm{T}}\mathbf{h}_i$, multiplicative attention is $\mathbf{e}_{t,i} = \mathbf{s}_t^{\mathrm{T}}\mathbf{W}\mathbf{h}_i$, and additive attention is $\mathbf{e}_{t,i} = \mathbf{v}^T\tanh(\mathbf{W}_1\mathbf{h}_i + \mathbf{W}_2\mathbf{s}_t)$.

Answer these questions, about the model

1. It might be useful to reduce e. How would you do that?

2. Why is $\mathbf{y}_t$ called a *combined* output?

3. Why is $\mathbf{y}_t$ used as input to the decoder despite the fact that it is called an output?

4. Why do we use $\mathbf{y}_t$ as input to the decoder despite the fact that the decoder already as a state $\mathbf{h}_t^{\text{dec}}$ and $\mathbf{c}_t^{\text{dec}}$

5. Why is $\mathbf{h}_i^{\text{enc}}$ used two times in the attention model, on time in Eq. 7, and another time in Eq. 9.

6. Why is $\mathbf{u}_t \in \mathrm{R}^{3h\times 1}$

7. What is the total number of parameters of the encoded, of the decoder, and of the complete model? Use h, e, and possibly other meta-parameters to express your answer and explain it.

8. Cite two ways you could use to increase the complexity (number of parameters of this model), to possibly be able to train on larger data sets and get better performance.

Answer these questions, about the implementation

9. Why do we need `pack_padded_sequence()` and `pad_packed sequence()`? Is there something fundamental to it?

10. Why are `squeeze()` and `unsqueeze()` necessary? (Something to do with `bmm()` limitations)

11. Do a drawing of *end_hidden* tensor. How many dimensions does it have. Indicate what is the role and number of elements along each of those dimensions.

12. Do the same for *last_hidden*[0]. What does the '[0]' mean?

13. Explain the difference between *dec_hidden* before and after it is "unsqueezed".

14. There was one bug left intentionally in the code framework provided. Can you find it?

15. It is possible to give name to tensor dimensions in torch. How would you do that? Give an example.

Answer these questions, about the main takeaways of the TPs

16. Summarize what you have learned in TP1-4 (10 lines)

17. Summarize what you have learn in TP5-6 (10 lines)