Sequence-to-Sequence Learning

Chapter 5 – (Introduction to Deep Learning)

Introduction

- Sequence to sequence learning is a deep learning technique to map a sequence of symbols to the other.
  - Used specifically when mapping symbols individually is not possible.
  - Machine Translation is the typical application of this algorithm.

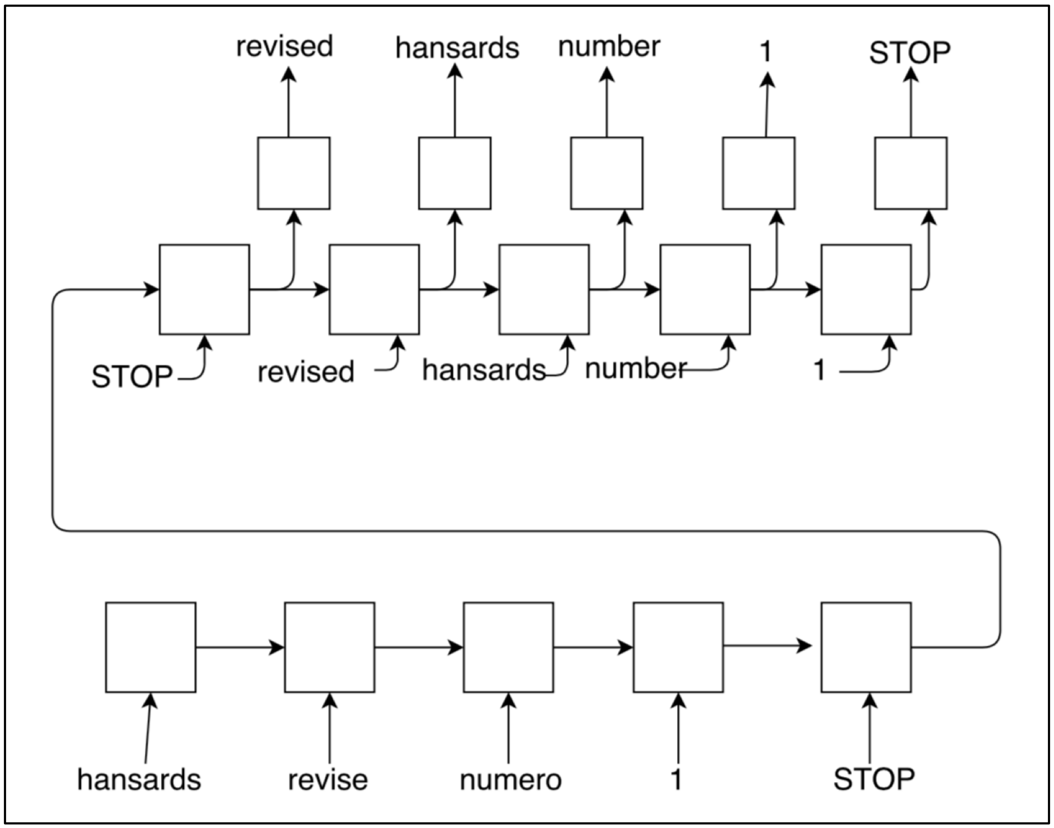
- Word by word translation does not help in most of the cases.

this being the day on which parliament was convoked by proclamation of his excellency ...
parlement ayant été convoqué pour aujourd ' hui , par proclamation de son excellence ...

Sequence-to-Sequence Paradigm

- The model consists of two RNNs.
- Uses GRU – Gated Recurrent Unit which passes a single memory line between time units.
- Total two passes:
  - Encoding: First phase of the seq2seq process, set of symbols (in source language) are passed through GRU. The goal of this pass is to produce a sentence embeddings which summarizes the sentence.
  - Decoding: Second phase of the seq2seq process, passing through symbols in target language. The goal of this pass is to predict the word/symbol after each word/symbol is input.

Sequence-to-Sequence Paradigm



Sequence-to-sequence Paradigm

- The image is shown as back propagation through time.
  - So all the RNN units at the bottom row are actually the same recurrent unit but at successive time.
  - Same goes for the units in the top as well.

- The book assumes a few simplifications:
  - Every sentences starts and ends with STOP word.
  - Machine translation complexity is ignored to predict the next word given the previous word.
  - All sentences are limited to the length of 13 words. Sentences shorter are padded with extra STOP word(s).

Sequence-to-sequence Program

```
with tf.variable_scope("enc"):
```

```
with tf.variable_scope("dec"):
```

- Variable scope is used here to differentiate the encoding and decoding parts of the program.
    - It helps with TF program design as well because TF uses same name variable to insert into TF graph while working with multiple dynamic_rnn calls.
    - Variable scope stops multiple dynamic_rnn calls step on each other and avoid error.
    - Lines in above diagram, defines scope for encoding and decoding respectively.

Sequence-to-sequence Program

```
F = tf.Variable(tf.random_normal((vfSz,embedSz),stddev=.1))
embs = tf.nn.embedding_lookup(F, encIn)
embs = tf.nn.dropout(embs, keepPrb)
cell = tf.contrib.rnn.GRUCell(rnnSz)
initState = cell.zero_state(bSz, tf.float32)
encOut, encState = tf.nn.dynamic_rnn(cell, embs,
                                     initial_state=initState)
```

- First, the French word embeddings are created of by passing the French word indices in the shape of batch size by window size.
- The lookup function will return the 3D tensor of batch size by window size by embedding size.

Sequence-to-sequence Program – cont’d

- Dropout with probability of keeping the connection is applied to the output of the lookup.
- Then RNN cell is created through GRU variant of LSTM.
- This cell is used to create output and the next state through dynamic RNN.

```
E = tf.Variable(tf.random_normal((veSz,embedSz),stddev=.1))
embs = tf.nn.embedding_lookup(E, decIn)
embs = tf.nn.dropout(embs, keepPrb)
cell = tf.contrib.rnn.GRUCell(rnnSz)
decOut,_ = tf.nn.dynamic_rnn(cell, embs, initial_state=encState)
```

Sequence-to-sequence Program – cont'd

- In the decoder variable scope, the output of the encoding RNN is used by the dynamic_rnn of the decoder.
- The output of decoder also feeds into loss computation which can be done using below code.

```
W = tf.Variable(tf.random_normal([rnnSz,veSz],stddev=.1))
b = tf.Variable(tf.random_normal([veSz,stddev=.1))
logits = tf.tensordot(decOut,W,axes=[[2],[0]])+b
loss = tf.contrib.seq2seq.sequence_loss(logits, ans,
                                        tf.ones([bSz, wSz]))
```

- Seq2seq.sequence_loss is a specialized version of cross-entropy loss.

Sequence-to-sequence sentence summary

- The idea of seq2seq translation is to create a summary of a sentence in source language by passing it through GRU.
- There are multiple ways to create sentence summaries. Instead of passing just the encoder state output, sum of all encoder states can be passed to decoder.
- Another possibility is to pass the average value of all encoder states instead of passing the sum.
- According to the book, passing the sum seems to more informative compared one final vector.

Attention in Sequence-to-sequence

- Concept of attention in seq2seq comes from the fact that a patch of target word translations depend more on some part of the source sentence than the other.
- Encoding phase output is fed into all decoder states indicating equal importance to all states.
  - For attention models, some encoding states' output are mixed together in different proportion before feeding them into decoding scope.
  - This is called 'position-only attention'.
- For attention model scheme, attention paid by the word of source language at position i to the target language word at position j depends only on i and j. Attention is higher for close i and j.

Multilength Sequence-to-sequence

- One of the simplification considered for seq2seq is to have sentence limited to 13 words.
  - In reality, this is very small limit but increasing the limit might impact sentences with less number of words.
- In the seq2seq program, dynamic_rnn call takes in embds which is of dimension, batch size by window size by embed size.

```
cell = tf.contrib.rnn.GRUCell(rnnSz)
encOutSmall, encStateS = tf.nn.dynamic_rnn(cell, smallerEmbs, ...)
encOutLarge, encStateL= tf.nn.dynamic_rnn(cell, largerEmbs, ...)
```

- Because there is a single GRU cell which is used for smaller and larger window size, they learn and share same knowledge for source and target language.