Word Embeddings and Recurrent NNs

Chapter 4 – (Introduction to Deep Learning)

Word Embedding for Language Models

- Language model is the probability distribution over all strings.
  - Language translation programs need to identify differences in sentence from one language to the other.
  - Language model helps with the above idea.
- Sentences can be broken into words and probabilities of each word following the previous can be counted.
- E.g. "We live in a small world".
  - $P(\text{We live in a small world}) = P(\text{We})P(\text{live}|\text{We})P(\text{in}|\text{We live}) \ldots$

Language Models

$P(\text{We live in a small world}) = P(\text{We})P(\text{live}|\text{We})P(\text{in}|\text{We live})$ ..

- Each word probability is calculated given all previous words are present in a sentence.
- Not a practical approach, as sentences can be very long.

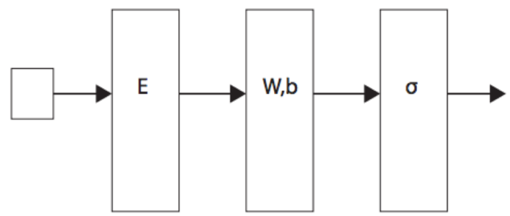
Bigram language model:

- Probability for each word in a sentence is calculated based on just the previous word.

Word Embeddings

- Given a word in a vocabulary, a probability distribution of all other words following the previous one can be created in a table.
- Using deep network for a word W_i, a reasonable probability distribution can be calculated over possible next word.
- As deep network only work with floating numbers, each word can be mapped to a vector of float which is called Word Embeddings.
    - Each embedding is initialized as a vector of e floats.
    - Here, e is the system hyperparameter
- For the number of of words are |V| then an array E is initialized to be |V| by e to hold all word embeddings.

Feed Forward Network for Language Model



- Small square represents the input to the network, the integer index of current word e_i.
- Output of the network is the probability assignment for possible next word.
- The layer E, converts the word index to the embedding and all operations after that point are done on these embeddings.

Cosine similarity

- The cosine similarity of two vectors is a standard measure of how close the vectors are.
- For a two dimensional vectors,
  - if both vectors are pointing in same direction then the cosine similarity would be 1.0.
  - If both are pointing in opposite direction then it would be -1.0.
  - If both vectors are orthogonal then cosine similarity would be 0.
- For arbitrary dimensions, cosine similarity can be calculated using,

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{(\sqrt{(}\sum_{i=1}^{i=n} x_i^2)(\sqrt{(}\sum_{i=1}^{i=n} y_i^2)}$$

Feed Forward Language Model

- First input for the NN is the word index. It is used to get the word embedding E.

```
inpt=tf.placeholder(tf,int32, shape=[batchSz])
answr=tf.placeholder(tf.int32, shape=[batchSz])
E = tf.Variable(tf.random_normal([vocabSz, embedSz],
                                 std_dev = 0.1))
embed = tf.nn.embedding_lookup(E, inpt)
```

- In the above code, inpt points to the word indices.
- And, answr points to the correct similarity index for each word.
- E is the embedding lookup array of the size |V| by e.
- All future operations will be done on embed.

Feed Forward Language Model Loss

- In a language model, each training example is a word probability.
- The loss in a language model is calculated per word.

$$f(d) = e^{-\frac{x_d}{|d|}}$$

- Here if the corpus d of total words |d| has loss of x_d then *f*(*d*) represents the perplexity of the corpus d.
- As the training moves forward, the perplexity decreases.

Improving Language Model Efficiency

- Moving from a bigram language model to a trigram language model can help improve the efficiency.
- The previous model used two words (bigram) to create the model. That is each word is assigned probability based on the previous word.
- Trigram model calculates probability based on two previous words rather than one.
- Below is the code to support trigram model along with bigram model,

```
embed2 = tf.nn.embedding_lookup(E, inpt2)

both = tf.concat([embed, embed2], 1)
```

Overfitting

- An ideal training data set covers all possible test dataset samples.
  - Improving the model efficiency on test dataset.
- Training samples do not always include all possible examples for test dataset.
  - Hence there is a chance of a good performance on training dataset by the model
  - The same model fails with high loss/perplexity on test dataset.
  - This scenario is classified as overfitting of training dataset.
- Mnist dataset can be characterized as very ideal while PTB contains the combination of handwritten words which has potential for overfitting the training dataset.

Regularization

- Regularization is the modification to fix overfitting.
- Early stopping is a type of regularization.
  - The model stops training when the development perplexity is the lowest.
  - Not the best technique to fix overfitting.
  - Dropout and L2 regularization are much better solutions.

Dropout Regularization

- Here pieces of computation is dropped randomly from one layer of the network to the other.
- Next layer sees more zeros in random locations. This makes training data different for each epoch.
- Classifier cannot depend on the coincidence of a lot of features of the data lining up in a particular way so the generalization is better.
- Preferred method of regularization.

```
keepP = tf.placeholder(tf.float32)
w1Out = tf.nn.dropout(w1Out, keepP)
```

- KeepP is set to 0.5 for 50% dropout in training phase and 1.0 for testing phase.

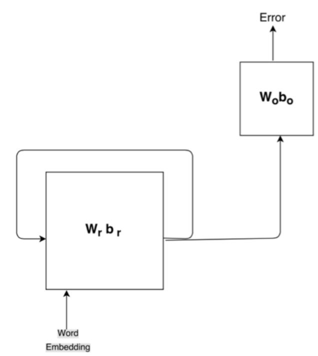
L2 Regularization

- In many machine learning overfitting problems are accompanied by model parameters getting too large or too small.
- Seeing the same data again and again contributes to probabilities being overestimated.
- This overestimate is achieved by large absolute weight values.
- L2 Regularization adds a quantity proportional to the sum of squared weights to the loss function.
- Following is added to the loss function in Tensorflow for l2 regularization.

```
0.1 * tf.nn.loss(W1)
```

Recurrent Networks

- Recurrent Neural Networks are opposite of Feed forward NNs.
- If feed forward NNs are directed acyclic graphs then recurrent neural networks would be directed cyclic graphs.
- A part of the network's output is feed as its own input.



Recurrent Neural Network – cont'd

- The previous figure can be explained with below equations

$S_0 = 0$

$s_{t+1} = relu((e_{t+1} \, . \, s_t) \, W_r + b_r)$

$o = s_{t+1}W_o + b_o$

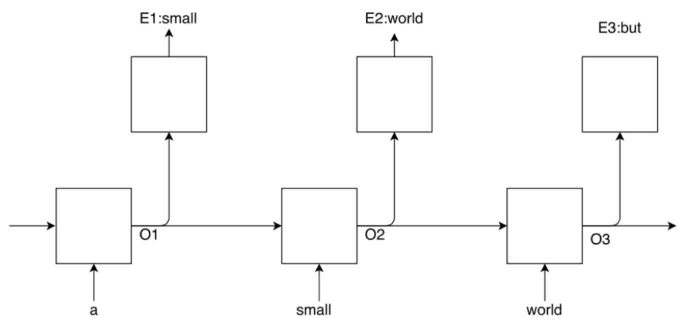
- S_0 represents state vector and its dimension is a hyperparameter.
- By concatenating the next s_t and feeding it to linear unit.
- The output is passed through relu activation function.
- Finally output o is obtained by feeding current state through second linear unit.
- Loss is calculated on o.

RNN

- Recurrent Neural Networks are used when previous input requires to influence arbitrarily far into the future.
- Language models are one of the cases where a word in a sentence can have effects on other word choices.
- Current explanation makes the recurrent neural network approach impractical.
  - Not practical to change all words' weights and biases for the last word in the corpus in a backward pass.
  - Brute force method can be used to cut off backward pass calculation after certain iterations.

RNN Back propagation and Window size

- The number of iterations used to stop backward pass is called a window size.
  - It is a system hyperparameter.



- Above figure shows back propagation through time with window size set to three.

RNN Batch size and Window size

STOP	It	is	a	small	world
but	I	like	it	that	way

STOP	It	is
but	I	like

a	small	world
it	that	way

- If the corpus is “It is a small world but I like it that way”,
  - The batch size of two divides the sentence in half including STOP padding.
  - Window size 3 divides the batch size so input would be batchSz by window size.

RNN Tensorflow

```
rnn = tf.contrib.rnn.BasicRNNCell(rnnSz)
initialState = rnn.zero_state(batchSz, tf.float32)
Outputs, nextState = tf.nn.dynamic_rnn(rnn, embeddings, initial_state =
initialState)
```

- First line adds recurrent network to the computation.
  - RNN’s weight array is rnnSz.
- The last line calls RNN. It takes in three parameters and outputs two.
  - The first parameter is rnn, the second is words divided in batchSz by windowSz and the last is the initial state which comes from the previous run.
  - When the first call to RNN happens, there is no previous state so initial_state is set to a dummy value.

RNN Tensorflow – cont'd

- The two outputs represents outputs and nextState.
- In previously shown RNN figure, outputs are represented as O1, O2 and O3.
  - Outputs has a shape of [batch-size, window-size, hidden-size].
  - The first dimension represents the batch-size of words.
  - The second dimension consists of O1, O2 and O3 for each word.
  - The last is the vector of size rnn-size floats.
- nextState consists the last output from the current pass. The next pass will have initial_state set to nextState from the current pass.

RNN Tensorflow – cont'd

- The loss calculation can be done with little modification.
- As we know the output of RNN is a three dimensional array of [batch-size, window-size, hidden-size].
  - The output has to be reshaped for the next layer.

```
output2 = tf.reshape(output, [batchSz*windowSz, rnnSz])
logits = matmul(output2, W)
```

- The logits can be handed to `tf.nn.sparse_softmax_cross_entropy_with_logits` to get a column vector of loss values which then can be passed to `tf.reduce_mean` to get the loss value. This loss value can be exponentiated to get perplexity.

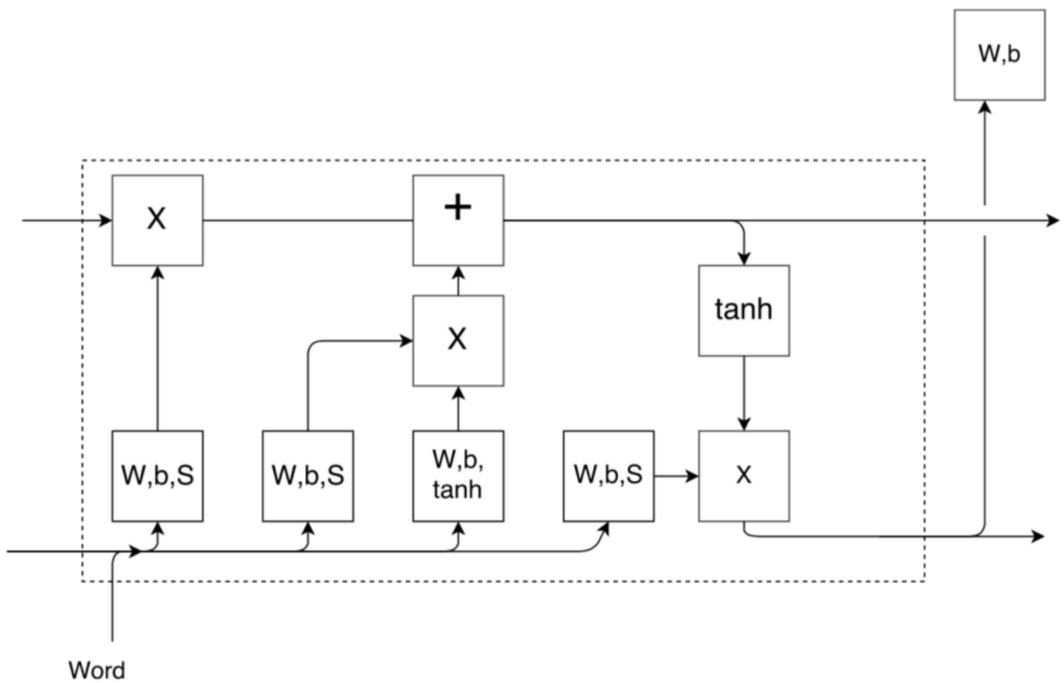
Long Short Term Memory NN

- A type of recurrent neural network which almost always outperforms simple recurrent neural network.
- RNN's goal is to remember things from far back while simple RNN forgets things quickly.
- LSTM NN's goal is to improve RNN's memory of past by training it to remember important things and forget everything else.

```
tf.contrib.rnn.LSTMCell(runSz)
```

- LSTM takes longer to train than simple RNN.

LSTM RNN Diagram



LSTM RNN Diagram – cont'd

- On the left, we have information coming from previous word with two tensors.
- At bottom left, the next word is coming in and at top right, the information about next word probability and loss is coming out.
- Memories are removed at times units in the diagram and added back at the plus units.
- Current word embedding goes through a layer of linear unit followed by sigmoid activation function.

LSTM RNN Diagram – cont’d

$h' = h_t \,.\, e$

$f = S(h' W_f + b_f)$

- Center . presents the concatenation of vectors. Previous word line ht and current word embedding e are concatenated to create h’ which is fed to forgetting unit to produce f.
- The output of the sigmoid function is multiplied element-wise with memory line c.
- As sigmoid output varies between 0 and 1, the multiplication must reduce the incoming absolute values.

LSTM RNN Diagram – cont'd

- The next stop is the plus unit where the word embedding has gone through two linear units prior to reaching here.
  - One is sigmoid function and the second is hyperbolic tangent (tanh) function.

$$a_1 = S(h' W_{a1} + b_{a1})$$

$$a_2 = \tanh((h_t \cdot e) W_{a2} + b_{a2})$$

- The result of this is added to the + unit.

$$c_{t+1} = c'_t + (a_1 \cdot a_2)$$

- After this, one copy goes out and the other goes to tanh function followed by linear transformation of the more local history to become h line.

$$h'' = h' W_h + b_h$$

$$h_{t+1} = h'' + a_2$$