Charles Ashby's blog

About

TensorFlow Tutorial - Analysing Tweet's Sentiment with Character-Level LSTMs

Jun 5, 2017

This blog first started as a platform for presenting a project I worked on during the course of the winter's 2017 Deep Learning class given by prof Aaron Courville.

Since then, I've been very inspired by Andrej Karpathy's blog and decided to try to give this blog a second life by dedicating some of my free time to contribute to the community by sharing the projects I work on in a manner that, I wish, will be accessible to anyone with a very limited background in deep learning. Therefore, if this post helped you, please, DO let me know!

The Project

Since my background is in Mathematical Finance, I thought that sentiment analysis would be a great fit for this blog's first real post considering how closely related it is to stock price prediction.

I decided to work with Tweets for two main reasons: First, there is a humongous amount of data available (Twitter even let's you categorize tweets with those who contains happy/sad emoticons i.e. there is an almost infinite amount of training data). Second, I have a strong feeling that if a network can generalize well with Tweets where there is a great deal of spelling mistakes and ambiguous sentences, it should have no problem to generalize somewhere else.

In this tutorial, we will train a neural network to categorize a Tweet as having a positive or negative connotation, we will use the **Stanford's Sentiment140 dataset** available for download here.

> *Given a sentence, tell whether it has a positive or negative connotation.*

I will also be showing how we can merge **Stanford CoreNLP library** with our network to extract the "entity-wise sentiment" of a sentence.

```
# e.g. Sentence: Jeanne is sad, but Jean is really happy!
# Jeanne: negative
# Jean: positive
```

Preprocessing the data

The first thing we need to do when working with natural language is to decide the way we are going to process the text (i.e. how to embed the words), like I mentioned earlier, Tweets are flooded with spelling errors and awkward syntax, therefore, since a lot of words will not exist, a Word2Vec approach (embedding each word as a vector in R^n where n is smaller then the size of our vocabulary) is likely to miss out on a lot of information since it will have to completely ignore words that are not in our dictionary.

Instead, I opted for a character-level embedding, we first embed the words as a one-hot encoding of a “character-vocabulary” (which is, basically, an alphabet), in our case, we use every ASCII characters.

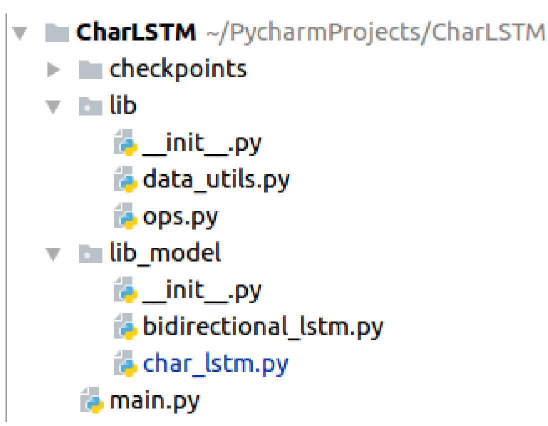
```
# e.g. the word "hi" will be a matrix where it has a 1 at
# positions (0, 7) and (1, 8) and 0's everywhere
# else considering our alphabet is given by:
emb_alphabet = 'abcdefghijklmnopqrstuvwxyz0123456789-,;' \
               '.!?:\'"/\\|_@#$%^&*~`+-=<>()[]{} '
```

Afterward, we feed this embedding to a CharCNN network [1], it is composed of multiple convolutional filters with different kernel widths used to capture the information of distinct character n-grams, we will get in the details of its implementation in just a second, but first, I would like to provide further motivation for this approach.

From the top of my head, there are three main advantages:

- The biggest one is probably that the model will be much smaller (around ~50-100 mb for the whole model compared to over 3GB for the classic Word2Vec from Google - this is only taking into account the embedding, not the actual model);
- The model can understand the underlying emotion of repetitive letters (e.g. hellooooo!!);
- and finally, it is almost immune to typos

Now that we have a rough idea of how we will pre-process the data, let’s get into the coding; when I start a new project I like to separate my code into two main directory: one for my model and another for basically everything else, the following code will all fall into the `data_utils.py` file.



The first thing we need to do is shuffle our dataset, I won’t really get into the details of what I’m doing here, I think it is pretty straight-forward.

```
import random, csv

def reshape_lines(lines):
    # Hacky function to make it easier to process the data
    data = []
    for l in lines:
        #
        split = l.split('","')
        data.append((split[0][1:], split[-1][:-2]))
    return data

def save_csv(out_file, data):
    # Save a file
    with open(out_file, 'wb') as f:
        writer = csv.writer(f)
        writer.writerows(data)
    print('Data saved to file: %s' % out_file)

def shuffle_datasets(valid_perc=0.05):
    """ Shuffle the datasets """
    # TRAIN_SET and TEST_SET are respectively the path for
    # training.1600000.processed.noemoticon.csv and
    # testdata.manual.2009.06.14.csv, this function will create two
    # new files called "valid_set.csv" and "train_set.csv".

    # Make sure the paths exists, otherwise send some help messages...
    assert os.path.exists(TRAIN_SET), 'Download the training set at ' \
                                      'http://help.sentiment140.com/for-students/'
    assert os.path.exists(TEST_SET), 'Download the testing set at ' \
                                     'http://help.sentiment140.com/for-students/'

    # Create training and validation set - We take 5% of the training set
    # for the validation set by default
    print('Creating training & validation set...')

    with open(TRAIN_SET, 'r') as f:
        lines = f.readlines()
        random.shuffle(lines)
        lines_train = lines[:int(len(lines) * (1 - valid_perc))]
        lines_valid = lines[int(len(lines) * (1 - valid_perc)):]

    save_csv(PATH + 'datasets/valid_set.csv', reshape_lines(lines_valid))
    save_csv(PATH + 'datasets/train_set.csv', reshape_lines(lines_train))

    print('Creating testing set...')

    with open(TEST_SET, 'r') as f:
        lines = f.readlines()
        random.shuffle(lines)
```

```
    save_csv(PATH + 'datasets/test_set.csv', reshape_lines(lines))
    print('All datasets have been created!')

# Once this is done, we rename the new training and testing set...
TRAIN_SET = PATH + 'datasets/train_set.csv'
TEST_SET = PATH + 'datasets/test_set.csv'
VALID_SET = PATH + 'datasets/valid_set.csv'
```

Before going any further, `shuffle_datasets()` needs to be ran once. Next, we will create our `TextReader()` class, this class will help us loop through the data and create minibatches that will be fed to our network during training. It opens a CSV file (our training, validation or test set) and reads it through a buffer by loading a small amount of lines at a time to the RAM.

```
# Some packages we will need:
import numpy as np
from nltk.tokenize import word_tokenize
from unidecode import unidecode
import string
import os

# Our alphabet
emb_alphabet = 'abcdefghijklmnopqrstuvwxyz0123456789-' \
               ',;.!?:\'"/\\|_@#$%^&*~`+-=<>()[]{} '

# we associate every character in our alphabet to a number:
# e.g. b => 1 d => 3 etc.
DICT = {ch: ix for ix, ch in enumerate(emb_alphabet)}

# The size of our alphabet (~70)
ALPHABET_SIZE = len(emb_alphabet)

class TextReader(object):
    """ Util for Reading the Stanford CSV Files """

    def __init__(self, file, max_word_length):
        # TextReader() takes a CSV file as input that it will read
        # through a buffer

        # we can also feed TextReader() our own sentences, therefore
        # sometimes it will not need a file
        if file != None:
            self.file = file

        # The maximum number of character in a word, default is 16 (we
        # will get to this later)
        self.max_word_length = max_word_length
```

Once this is done, we need to convert the sentences as a one-hot tensor of shape `[sentence_length x word_length x alphabet_size]`. Basically, we encode every character as a one-hot vector of length `ALPHABET_SIZE`, then we concatenate the characters together to form words, and then concatenate words to form the sentence, thus, yielding a tensor of shape `[sentence_length x word_length x alphabet_size]`.

```
    def encode_one_hot(self, sentence):
        # Convert Sentences to np.array of Shape
        # ('sent_length', 'word_length', 'emb_size')

        max_word_length = self.max_word_length
        sent = []

        # We need to keep track of the maximum length of the sentence in a minibatch
        # so that we can pad them with zeros, this is why we return the length of every
        # sentences after they are converted to one-hot tensors
        SENT_LENGTH = 0

        # Here, we remove any non-printable characters in a sentence (mostly
        # non-ASCII characters)
        printable = string.printable
        encoded_sentence = filter(lambda x: x in printable, sentence)

        # word_tokenize() splits a sentence into an array where each element is
        # a word in the sentence, for example,
        # "My name is Charles" => ["My", "name", "is", Charles"]
        # Unidecode convert characters to utf-8
        for word in word_tokenize(unidecode(encoded_sentence)):

            # Encode one word as a matrix of shape [max_word_length x ALPHABET_SIZE]
            word_encoding = np.zeros(shape=(max_word_length, ALPHABET_SIZE))

            for i, char in enumerate(word):

                # If the character is not in the alphabet, ignore it
                try:
                    char_encoding = DICT[char]
                    one_hot = np.zeros(ALPHABET_SIZE)
                    one_hot[char_encoding] = 1
                    word_encoding[i] = one_hot

                except Exception as e:
                    pass

            sent.append(np.array(word_encoding))
            SENT_LENGTH += 1

        return np.array(sent), SENT_LENGTH
```

Now, we simply need to concatenate a bunch of sentences together to create a minibatch that we will feed to the network. Note that a minibatch will have shape `[batch_size x maximum_sentence_length x maximum_word_length x alphabet_size]`, but at the moment the sentences all have different lengths, therefore, we need to pad every sentences with lengths lower than `maximum_sentence_length` so that there are no holes in our tensor.

```
    def make_minibatch(self, sentences):
        # Create a minibatch of sentences and convert sentiment
        # to a one-hot vector, also takes care of padding

        max_word_length = self.max_word_length
        minibatch_x = []
        minibatch_y = []
        max_length = 0

        for sentence in sentences:
            # Append the one-hot encoding of the sentiment to the minibatch of Y
            # 0: Negative 1: Positive
            minibatch_y.append(np.array([0, 1]) if sentence[:1] == '0' else np.array([1, 0])

            # One-hot encoding of the sentence
            one_hot, length = self.encode_one_hot(sentence[2:-1])

            # Calculate maximum_sentence_length
            if length >= max_length:
                max_length = length

            # Append encoded sentence to the minibatch of X
            minibatch_x.append(one_hot)


        # data is a np.array of shape ('b', 's', 'w', 'e') we want to
        # pad it with np.zeros of shape ('e',) to get
        # ('b', 'SENTENCE_MAX_LENGTH', 'WORD_MAX_LENGTH', 'e')
        def numpy_fillna(data):
            """ This is a very useful function that fill the holes in our tensor """

            # Get lengths of each row of data
            lens = np.array([len(i) for i in data])

            # Mask of valid places in each row
            mask = np.arange(lens.max()) < lens[:, None]

            # Setup output array and put elements from data into masked positions
            out = np.zeros(shape=(mask.shape + (max_word_length, ALPHABET_SIZE)),
                           dtype='float32')

            out[mask] = np.concatenate(data)
            return out
```

```
        # Padding...
        minibatch_x = numpy_fillna(minibatch_x)

        return minibatch_x, np.array(minibatch_y)
```

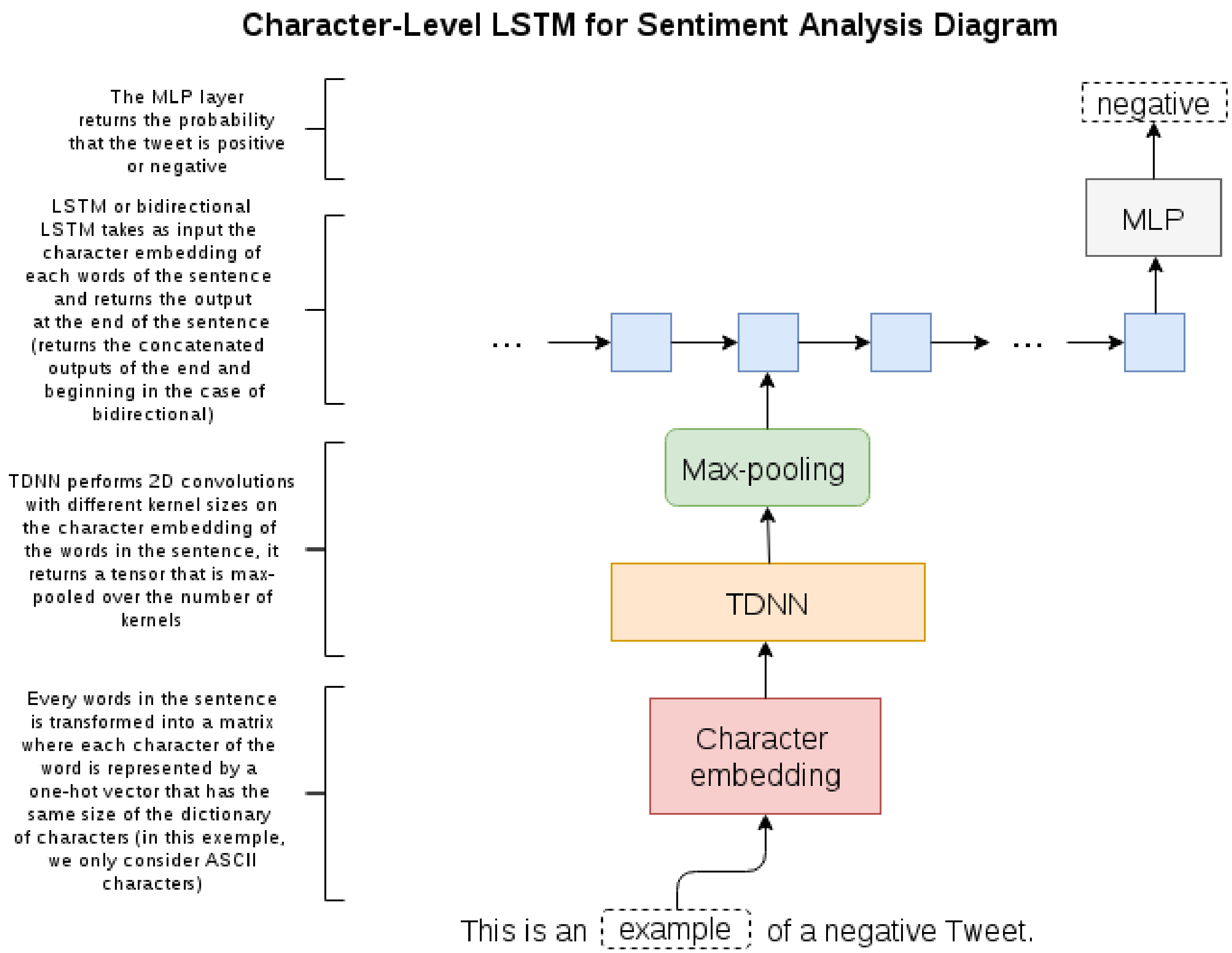
Finally, we need an iterator function that loads some lines to our RAM, converts them to one-hot vectors, concatenate them to minibatches and return the minibatches, ready to be fed to the network.

```
    def load_to_ram(self, batch_size):
        """ Load n Rows from File f to Ram """
        # Returns True if there are still lines in the buffer,
        # otherwise returns false - the epoch is over

        self.data = []
        n_rows = batch_size
        while n_rows > 0:
            self.data.append(next(self.file))
            n_rows -= 1
        if n_rows == 0:
            return True
        else:
            return False

    def iterate_minibatch(self, batch_size, dataset=TRAIN_SET):
        """ Returns Next Batch """

        # I realize this could be more
        if dataset == TRAIN_SET:
            n_samples = 1600000 * 0.95
        elif dataset == VALID_SET:
            n_samples = 1600000 * 0.05
        elif dataset == TEST_SET:
            n_samples = 498

        # Number of batches / number of iterations per epoch
        n_batch = int(n_samples // batch_size)

        # Creates a minibatch, loads it to RAM and feed it to the network
        # until the buffer is empty
        for i in range(n_batch):
            if self.load_to_ram(batch_size):
                inputs, targets = self.make_minibatch(self.data)
                yield inputs, targets
```

The model

Now that we got the nitty-gritty stuff out of the way, let's finally get into our actual model, I sketched what we will do in the next picture. Before you move on, you should take a while to stare at this schema until you're comfortable with most of the concepts in there. The following code will all be part of the `char_lstm.py` file unless specified otherwise.

NB: In the following picture, the TDNN block (Time-Delay Neural Network) is actually the CharCNN network, when I made this picture I kept the wording of the original paper.



As I mentioned earlier, the first part of our model is a CharCNN network, I'll try to give you as much information as I can on this model, but if you are interested in knowing more I highly suggest that you read this paper, also if you feel kind of lost, don't worry, it will all get clearer when we get to the actual implementation.

The CharCNN model is composed of multiple convolutional layers with different kernel widths (in this implementation, I use 25 x kernels of size 1, 50 x kernels of size 2, …, 175 x kernels of size 7 - height is always the same as the length of our character-alphabet). Each of them take as input ONE word of the sentence at a time (the CharCNN is used as an embedding of the words that will then be fed to the LSTM where each time step in the LSTM is a word).

After the convolution, we do a max pooling operation for every kernels over the resulting width of the convolution, this operation acts as a sort of arrangement of the most important features of the word for every n-grams. For example, a kernel with a width of 4 might have learned to detect repetitive characters and would “fire” when it sees “oooo” in “helloooo!”.

We then concatenate the results of all the max pooling operation in a tensor of shape `[25 * 50 * ... * 175 x 1]` (one max-pool for every kernel) for every words (the resulting tensor for the minibatch will then be of shape `[batch_size x sentence_length x 25 * 50 * ... * 175 x 1]`).

```
# This goes in ops.py
import tensorflow as tf

def conv2d(input_, output_dim, k_h, k_w, name="conv2d"):
    """ Straight-forward convvolutional layer """
    # w is the kernel, b the bias, no strides and VALID padding

    with tf.variable_scope(name):
        w = tf.get_variable('w', [k_h, k_w, input_.get_shape()[-1], output_dim])
        b = tf.get_variable('b', [output_dim])

    return tf.nn.conv2d(input_, w, strides=[1, 1, 1, 1], padding='VALID') + b
```

```
from lib.ops import *
import tensorflow as tf

def tdnn(input_, kernels, kernel_features, scope='TDNN'):
    ''' Time Delay Neural Network
    :input:           input float tensor of shape
                      [(batch_size*num_unroll_steps) x max_word_length x embed_size]
    :kernels:         array of kernel sizes
    :kernel_features: array of kernel feature sizes (parallel to kernels)
    '''
    assert len(kernels) == len(kernel_features), 'Kernel and Features must have the same siz

    # input_ is a np.array of shape ('b', 'sentence_length', 'max_word_length', 'embed_size'
    # need to convert it to shape ('b * sentence_length', 1, 'max_word_length', 'embed_size'
    # use conv2D
    # It might not seem obvious why we need to use this small hack at first sight, the reaso
    # is that sentence_length will change across the different minibatches, but if we kept i
    # as is sentence_length would act as the number of channels in the convnet which NEEDS t
    # stay the same
    input_ = tf.reshape(input_, [-1, self.max_word_length, ALPHABET_SIZE])
    input_ = tf.expand_dims(input_, 1)

    layers = []
    with tf.variable_scope(scope):
        for kernel_size, kernel_feature_size in zip(kernels, kernel_features):
            reduced_length = self.max_word_length - kernel_size + 1
```

```
            # [batch_size * sentence_length x max_word_length x embed_size x kernel_feature_
            conv = conv2d(input_, kernel_feature_size, 1,
                          kernel_size, name="kernel_%d" % kernel_size)

            # [batch_size * sentence_length x 1 x 1 x kernel_feature_size]
            pool = tf.nn.max_pool(tf.tanh(conv), [1, 1, reduced_length, 1], [1, 1, 1, 1], 'V

            layers.append(tf.squeeze(pool, [1, 2]))

        if len(kernels) > 1:
            output = tf.concat(layers, 1)
        else:
            output = layers[0]

    return output
```

At this point, we could simply feed the tensor to the LSTM, but we can actually get better results by passing it through a “highway network” before.

Highway Network

A “highway network” is a gated multi-layer perceptron equipped with a “skip-connection”, that is, a connection to the output layer with no activation function. These kinds of network are extremely popular these days and have achieved state-of-the-art results in image classification tasks. They are especially useful in very deep neural networks because they help backpropagate the error better (the fact that there is a path with no squashing function seems to be very beneficial during the training of these networks).

```
# This goes in ops.py

def linear(input_, output_size, scope=None):
    """
    Linear map: output[k] = sum_i(Matrix[k, i] * args[i] ) + Bias[k]

    Args:
        args: a tensor or a list of 2D, batch x n, Tensors.
        output_size: int, second dimension of W[i].
        scope: VariableScope for the created subgraph; defaults to "Linear".

    Returns:
        A 2D Tensor with shape [batch x output_size] equal to
        sum_i(args[i] * W[i]), where W[i]s are newly created matrices.

    Raises:
        ValueError: if some of the arguments has unspecified or wrong shape.
    """
```

```
    shape = input_.get_shape().as_list()
    if len(shape) != 2:
        raise ValueError("Linear is expecting 2D arguments: %s" % str(shape))
    if not shape[1]:
        raise ValueError("Linear expects shape[1] of arguments: %s" % str(shape))
    input_size = shape[1]

    # Now the computation.
    with tf.variable_scope(scope or "SimpleLinear"):
        matrix = tf.get_variable("Matrix", [output_size, input_size],
                                 dtype=input_.dtype)
        bias_term = tf.get_variable("Bias", [output_size], dtype=input_.dtype)

    return tf.matmul(input_, tf.transpose(matrix)) + bias_term
```

```
def highway(input_, size, num_layers=1, bias=-2.0, f=tf.nn.relu, scope='Highway'):
    """Highway Network (cf. http://arxiv.org/abs/1505.00387).
    t = sigmoid(Wy + b)
    z = t * g(Wy + b) + (1 - t) * y
    where g is nonlinearity, t is transform gate, and (1 - t) is carry gate.
    """

    with tf.variable_scope(scope):
        for idx in range(num_layers):
            g = f(linear(input_, size, scope='highway_lin_%d' % idx))

            t = tf.sigmoid(linear(input_, size, scope='highway_gate_%d' % idx) + bias)

            output = t * g + (1. - t) * input_
            input_ = output

    return output
```

Now, let's create our `LSTM()` class, the first thing we do is initialize it with placeholders for the one-hot encoded sentences and the sentiments, those will be the input to our computational graph.

```
class LSTM(object):
    """ Character-Level LSTM Implementation """

    def __init__(self):
        # Get the hyperparameters
        self.hparams = self.get_hparams()

        # maximum length of each words
        max_word_length = self.hparams['max_word_length']

        # X is of shape ('b', 'sentence_length', 'max_word_length', 'alphabet_size']
        # Placeholder for the one-hot encoded sentences
```

```
        self.X = tf.placeholder('float32',
                                shape=[None, None, max_word_length, ALPHABET_SIZE],
                                name='X')

        # Placeholder for the one-hot encoded sentiment
        self.Y = tf.placeholder('float32', shape=[None, 2], name='Y')

    def get_hparams(self):
        ''' Get Hyperparameters '''

        return {
            'BATCH_SIZE':       64,
            'EPOCHS':           500,
            'max_word_length':  16,
            'learning_rate':    0.0001,
            'patience':         10000,
        }
```

We are now ready to build the computational graph, note that the softmax function is simply a multi-layer perceptron with a softmax activation function to output the probability that the sentence is positive or negative.

```
# This goes in ops.py
def softmax(input_, out_dim, scope=None):
    """ SoftMax Output """

    with tf.variable_scope(scope or 'softmax'):
        W = tf.get_variable('W', [input_.get_shape()[1], out_dim])
        b = tf.get_variable('b', [out_dim])

    return tf.nn.softmax(tf.matmul(input_, W) + b)
```

```
    def build(self,
              training=False,
              testing_batch_size=1000,
              kernels=[1, 2, 3, 4, 5, 6, 7],
              kernel_features=[25, 50, 75, 100, 125, 150, 175],
              rnn_size=650,
              dropout=0.0,
              size=700,
              train_samples=1600000 * 0.95,
              valid_samples=1600000 * 0.05):
        """
        Build the computational graph

        :param training:
            Boolean whether we are training (True) or testing (False)
```

```
        :param testing_batch_size:
            Batch size to use during testing

        :param kernels:
            Kernel width for each convolutional layer

        :param kernel_features:
            Number of kernels for each convolutional layer

        :param rnn_size:
            Size of the LSTM output

        :param dropout:
            Retain probability when using dropout

        :param size:
            Size of the Highway embeding

        :param train_samples:
            Number of training samples

        :param valid_samples:
            Number of validation samples
        """
        self.size = size
        self.hparams = self.get_hparams()
        self.max_word_length = self.hparams['max_word_length']
        self.train_samples = train_samples
        self.valid_samples = valid_samples

        # If we are training use the BATCH_SIZE from the hyperparameters
        # else use the testing batch size
        if training == True:
            BATCH_SIZE = self.hparams['BATCH_SIZE']
            self.BATCH_SIZE = BATCH_SIZE
        else:
            BATCH_SIZE = testing_batch_size
            self.BATCH_SIZE = BATCH_SIZE

        # Pass the sentences through the CharCNN network
        cnn = tdnn(self.X, kernels, kernel_features)

        # tdnn() returns a tensor of shape [batch_size * sentence_length x kernel_features]
        # highway() returns a tensor of shape [batch_size * sentence_length x size] to use
        # tensorflow dynamic_rnn module we need to reshape it to
        # [batch_size x sentence_length x size]
        cnn = highway(cnn, self.size)
        cnn = tf.reshape(cnn, [BATCH_SIZE, -1, self.size])
```

```
        # Build the LSTM
        with tf.variable_scope('LSTM'):

            # The following is pretty straight-forward, create a cell and add dropout if
            # necessary. Note that I did not use dropout to get my results, but using it
            # will probably help
            def create_rnn_cell():
                cell = rnn.BasicLSTMCell(rnn_size, state_is_tuple=True,
                                         forget_bias=0.0, reuse=False)

                if dropout > 0.0:
                    cell = tf.contrib.rnn.DropoutWrapper(cell, output_keep_prob=1. - dropout

                return cell

            cell = create_rnn_cell()

            # Initial state of the LSTM cell
            initial_rnn_state = cell.zero_state(BATCH_SIZE, dtype='float32')

            # This function returns the outputs at every steps of
            # the LSTM (i.e. one output for every word)
            outputs, final_rnn_state = tf.nn.dynamic_rnn(cell, cnn,
                                                         initial_state=initial_rnn_state,
                                                         dtype=tf.float32)

            # In this implementation, we only care about the last outputs of the RNN
            # i.e. the output at the end of the sentence
            outputs = tf.transpose(outputs, [1, 0, 2])
            last = outputs[-1]

        self.prediction = softmax(last, 2)
```

Now that the computational graph has been built, we need to train it, note that the `train()` method expects some arguments such as the `LOGGING_PATH, SAVE_PATH, TRAIN_SET` and `TEST_SET`, which are, respectively, the path to the logging file, saving files, training set and testing set. In my case:

```
PATH = '/NOBACKUP/ashbylepoc/PycharmProjects/CharLSTM/'
TRAIN_SET = PATH + 'datasets/train_set.csv'
TEST_SET = PATH + 'datasets/test_set.csv'
VALID_SET = PATH + 'datasets/valid_set.csv'
SAVE_PATH = PATH + 'checkpoints/lstm'
LOGGING_PATH = PATH + 'checkpoints/log.txt'
```

```
from tensorflow.contrib import rnn
import numpy as np
```

```
    def train(self):
        BATCH_SIZE = self.hparams['BATCH_SIZE']
        EPOCHS = self.hparams['EPOCHS']
        max_word_length = self.hparams['max_word_length']
        learning_rate = self.hparams['learning_rate']

        # the probability for each sentiment (pos, neg)
        pred = self.prediction

        # Binary cross-entropy loss
        cost = - tf.reduce_sum(self.Y * tf.log(tf.clip_by_value(pred, 1e-10, 1.0)))

        # The number of "predictions" we got right, we assign a sentence with
        # a positive connotation when the probability to be positive is greater then
        # the probability of being negative and vice-versa.
        predictions = tf.equal(tf.argmax(pred, 1), tf.argmax(self.Y, 1))

        # Accuracy: # predictions right / total number of predictions
        acc = tf.reduce_mean(tf.cast(predictions, 'float32'))

        # We use the Adam Optimizer
        optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(cost)

        n_batch = self.train_samples // BATCH_SIZE

        # parameters for saving and early stopping
        saver = tf.train.Saver()
        patience = self.hparams['patience']

        with tf.Session() as sess:
            sess.run(tf.initialize_all_variables())
            best_acc = 0.0
            DONE = False
            epoch = 0

            while epoch <= EPOCHS and not DONE:
                loss = 0.0
                batch = 1
                epoch += 1

                with open(TRAIN_SET, 'r') as f:
                    # Load the file in a TextReader object until we've read it all
                    # then create a new TextReader Object for how many epochs we
                    # want to loop on
                    reader = TextReader(f, max_word_length)
                    for minibatch in reader.iterate_minibatch(BATCH_SIZE, dataset=TRAIN_SET)
                        batch_x, batch_y = minibatch

                        # Do backprop and compute the cost and accuracy on this minibatch
```

```
_, c, a = sess.run([optimizer, cost, acc],
                   feed_dict={self.X: batch_x, self.Y: batch_y})

loss += c

if batch % 100 == 0:
    # Compute Accuracy on the Training set and print some info
    print('Epoch: %5d/%5d -- batch: %5d/%5d -- Loss: %.4f -- Train A
          (epoch, EPOCHS, batch, n_batch, loss/batch, a))

    # Write loss and accuracy to some file
    log = open(LOGGING_PATH, 'a')
    log.write('%s, %6d, %.5f, %.5f \n' % ('train', epoch * batch, lo
    log.close()

# --------------
# EARLY STOPPING
# --------------

# Compute Accuracy on the Validation set, check if validation has im
if batch % 500 == 0:
    accuracy = []

    # Validation set is very large, so accuracy is computed on testi
    # instead of valid set, change TEST_SET to VALID_SET to compute
    with open(TEST_SET, 'r') as ff:
        valid_reader = TextReader(ff, max_word_length)
        for mb in valid_reader.iterate_minibatch(BATCH_SIZE, dataset
            valid_x, valid_y = mb
            a = sess.run([acc], feed_dict={self.X: valid_x, self.Y:
            accuracy.append(a)
        mean_acc = np.mean(accuracy)

        # if accuracy has improved, save model and boost patience
        if mean_acc > best_acc:
            best_acc = mean_acc
            save_path = saver.save(sess, SAVE_PATH)
            patience = self.hparams['patience']
            print('Model saved in file: %s' % save_path)

        # else reduce patience and break loop if necessary
        else:
            patience -= 500
            if patience <= 0:
                DONE = True
                break

        print('Epoch: %5d/%5d -- batch: %5d/%5d -- Valid Accuracy: %
             (epoch, EPOCHS, batch, n_batch, mean_acc))
```

```
                    # Write validation accuracy to log file
                    log = open(LOGGING_PATH, 'a')
                    log.write('%s, %6d, %.5f \n' % ('valid', epoch * batch, mean
                    log.close()

                batch += 1
```

Finally, we want to evaluate the test set to see how well we have done, this function is very repetitive and most of it is a copy-paste of the `train()` method.

```
    def evaluate_test_set(self):
        """
        Evaluate Test Set
        On a model that trained for around 5 epochs it achieved:
        # Valid loss: 23.50035 -- Valid Accuracy: 0.83613
        """
        BATCH_SIZE = self.hparams['BATCH_SIZE']
        max_word_length = self.hparams['max_word_length']

        pred = self.prediction

        cost = - tf.reduce_sum(self.Y * tf.log(tf.clip_by_value(pred, 1e-10, 1.0)))

        predictions = tf.equal(tf.argmax(pred, 1), tf.argmax(self.Y, 1))

        acc = tf.reduce_mean(tf.cast(predictions, 'float32'))

        # parameters for restoring variables
        saver = tf.train.Saver()

        with tf.Session() as sess:
            print('Loading model %s...' % SAVE_PATH)
            saver.restore(sess, SAVE_PATH)
            print('Done!')
            loss = []
            accuracy = []

            with open(VALID_SET, 'r') as f:
                reader = TextReader(f, max_word_length)
                for minibatch in reader.iterate_minibatch(BATCH_SIZE, dataset=VALID_SET):
                    batch_x, batch_y = minibatch

                    c, a = sess.run([cost, acc], feed_dict={self.X: batch_x, self.Y: batch_y
                    loss.append(c)
                    accuracy.append(a)
```

```
                loss = np.mean(loss)
                accuracy = np.mean(accuracy)
                print('Valid loss: %.5f -- Valid Accuracy: %.5f' % (loss, accuracy))
                return loss, accuracy
```

And there we have it, your own character-level LSTM, it should train for about 5 epochs before the early-stopping criteria fires and you should achieve an accuracy on the validation set (around 80,000 samples) of 82-83% - remember that validation loss was computer on the test set, because it was much smaller, therefore, we do testing on the validation set.

Training is quite slow, therefore, I have made available a pre-trained model for those who dont want to / can't wait, you can find it in here.

I won't be sharing the methods for evaluating your own sentences on this blog, if you're interested you can find them in my github repository.

For those who are interested I also created a bi-directional character-level LSTM, the code is available in my Github repo as well.

Handling Multiple Entities

The last subject I want to address is how to handle sentences with multiple entities, that is, how to capture the sentiment towards different people (here, we will focus only on "human" entities i.e. no organization, etc., but generalizing to organization is very easy to do once you understand the main concept).

To do so, we will be using the **Stanford CoreNLP Toolkit**, you can download the files to run the server locally here.

```
# Run the server with the following commands in a terminal:
$ cd stanford-corenlp-*
$ java -mx4g -cp "*" edu.stanford.nlp.pipeline.StanfordCoreNLPServer -port 9000 -timeout 150
```

The API is in Java, but, fortunately, there are wrappers in almost every popular languages we will be using `pycorenlp`, you can install it with a simple pip install.

The first thing we want to do here is to separate the sentences into chunks of words where each chunk is associated with it's corresponding entity. For example, we want to convert "Jeanne is sad, but Marie is really happy!" to ["Jeanne is sad", "Marie is really happy"].

Once this is done we can simply use our LSTM to go over each sentence and report the connotation.

At the same time we will also want to fix "coreferences", take the following sentence for example: "Marie came home yesterday, she was really sad.", after the chunking we would get something like: ["Marie came home yesterday", "she was really sad"] what we would really want is ["Marie came home yesterday", "Marie was really sad"]. Otherwise we would not be able to assign a sentiment to any entity for the second sentence, this process is known as anaphora resolution.

> *Stanford CoreNLP tutorial starts here…*

The following code is all part of the `parse_doc.py` file, this file should be outside the directories and act as your main file. Now, let's create a `StanfordCoreNLP` object that will be used to make API calls, make sure you started the server before you import `pycorenlp`.

```
from pycorenlp import StanfordCoreNLP
from nltk.tokenize import sent_tokenize
from nltk import Tree
from lib_model.char_lstm import *

# StanfordCoreNLP object used for making API calls
nlp = StanfordCoreNLP('http://localhost:9000')
```

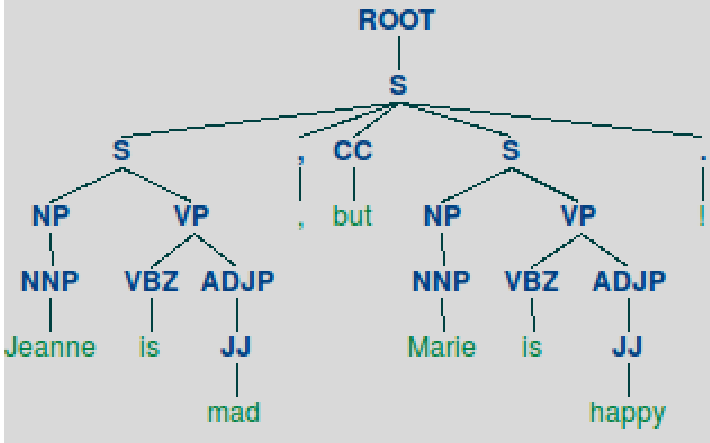
I will not be going over how the **Stanford CoreNLP** algorithms work, but if you are interested you can read more about it here, I will only say that, to my knowledge, this is the best parser available online.

Let's create a method that resolve coreferences, it will take a sentence as input and return a new sentence with the pronouns transformed to their corresponding entity.

```
def get_rep_mention(coreference):
    """
    This function will make more sense if you go through the
    coreference_resolution() method first.
    """

    for reference in coreference:
        if reference['isRepresentativeMention'] == True:
            pos = (reference['startIndex'], reference['headIndex'])
            text = reference['text']
            return text, pos

def coreference_resolution(sentence):
    """ Coreference/Anaphora Resolution"""

    # This is where Stanford CoreNLP does its magic: it takes a sentence
    # and returns a dictionary where the keys are the named entity and
    # the values are dictionaries with every coreferences (usually pronouns)
    # associated with the entity - I highly suggest that you take a
    # close look at the output of the API calls before you move on
    output = nlp.annotate(sentence, properties={'annotators':   'coref',
                                                'outputFormat': 'json'})
    tokens = word_tokenize(sentence)
    coreferences = output['corefs']
```

```
    entity_keys = coreferences.keys()

    for k in entity_keys:
        # skip non PERSON NP; is NP is a person it gender will either be
        # MALE or FEMALE
        if coreferences[k][0]['gender'] == 'MALE' or coreferences[k][0]['gender'] == 'FEMALE

            # if isRepresentativeMention is True then the word is a
            # proper noun - we want those
            rep_mention, pos = get_rep_mention(coreferences[k])

            # coreferences is a list with all the pronouns that
            # needs to be replaced by the rep_mention
            for reference in coreferences[k]:

                # Don't remplace the noun with itself...
                if not reference['isRepresentativeMention']:

                    # 'startIndex' and 'headIndex' are respectively
                    # the starting and ending position token-wise of
                    # the noun/pronoun, note that tokens are words, therefore,
                    # if reference['startIndex'] = 3 it actually means that
                    # we're looking for the 4th word in the sentence
                    start, end = reference['startIndex'] - 1, reference['headIndex'] - 1

                    # if 'startIndex' == 'headIndex' which should almost always
                    # be the case, then there is only one word to replace
                    if start == end:
                        tokens[start] = rep_mention
                    else:
                        # Otherwise we need to replace multiple words
                        # and delete the words we are not going to be
                        # using anymore
                        tokens[start] = rep_mention
                        del tokens[start + 1: end]

    # Join the words together with spaces to return the
    # sentence
    sentence = ' '.join(tokens)
    return sentence.encode('utf-8')
```

Next, we want to take this new sentence and divide it into chunks where each chunk of words is associated with its corresponding entity. We will do this with the "parse" annotator, in the following picture you can see a tree visualization of what it did for the sentence "Jeanne is mad, but Marie is happy!".



You can reproduce this tree with the following code:

```
import nltk

def parse_sentence(sentence):
    """ sentence --> named-entity chunked tree """
    output = nlp.annotate(sentence, properties={'annotators':   'tokenize, ssplit, pos,'
                                                                ' lemma, ner, parse',
                                                'outputFormat': 'json'})
    # print_tree(output)
    return Tree.fromstring(output['sentences'][0]['parse'])

def draw_tree(tree):
    """ Draw a tree """
    pattern = "NP: {<DT>?<JJ>*<NN>}"
    NPChunker = nltk.RegexpParser(pattern)
    result = NPChunker.parse(tree)
    result.draw()

draw_tree(parse_sentence("Jeanne is mad, but Marie is happy!"))
```

As you can see, the only thing left to do is to grab the noun and associate it to all the leaves of his subtree, to do this we will traverse the tree using breadth-first search.

```
import Queue

def tree_to_str(tree):
    """ Convert a tree/subtree to a string """
    return ' '.join([w for w in tree.leaves()])

def get_subtrees(tree):
    """ Return chunked sentences """

    subtrees = []

    # FIFO queue used to store the child
```

```python
    # elements of the tree during traversal
    queue = Queue.Queue()

    # First element is the root node
    queue.put(tree)

    while not queue.empty():
        node = queue.get()

        # Put all the childs of a node in the Queue
        # to process them later
        for child in node:
            if isinstance(child, Tree):
                queue.put(child)

        # nouns are always childs of an "S" node
        if node.label() == "S":
            # if childs are (respectively) 'NP' and 'VP'
            # convert subtree to string, else keep looking

            # Get the labels for all the childs
            child_labels = [child.label() for child in node]

            if "NP" in child_labels and "VP" in child_labels:

                # Convert the subtree to string and look for the
                # noun
                sentence = tree_to_str(node)
                for child in node:
                    if child.label() == "NP":
                        # look for NNP - keep only the names
                        subchild_labels = [subchild.label() for subchild in child]
                        if "NNP" in subchild_labels:
                            noun = ""
                            for subchild in child:
                                if subchild.label() == "NNP":
                                    noun = ' '.join([noun, subchild.leaves()[0]])

                            # Append the noun with it's associated
                            # sentence
                            subtrees.append((noun, sentence))
    return subtrees
```

Finally, we could put all of this together, call the neural network and predict the connotation, but we will go one step further, at the moment, our code is only suited for handling single sentences, let’s make it compatible with documents of any length.

Note that the `predict_sentences()` and `categorize_document()` methods used below are available in my Github repo.

```
def flatten(list):
    """ Flatten a list of lists
    i.e. [[element], [more element]] => [element, more element]
    """
    return [val for sublist in list for val in sublist]

def parse_doc(document):
    """ Extract relevant entities in a document """

    # sent_tokenize() returns an array where each element
    # is a sentence
    sentences = sent_tokenize(document)

    # Context of all named entities
    ne_context = []

    for sentence in sentences:
        # change pronouns to their respective nouns
        print('Anaphora resolution for sentence: %s' % sentence)
        tree = parse_sentence(coreference_resolution(sentence))
        print('Done!')

        # get context for each noun
        print('Named Entity Clustering:')

        # context is a tuple with the noun and
        # the sentence associated to the noun
        context = get_subtrees(tree)

        for n, s in context:
            print('%s' % s)

        # We return the context for every entity in
        # the document
        ne_context.append(context)

    return flatten(ne_context)

def init_dict(contexts):
    """ Initialize a dictionary with all the entities in the contexts """
    dict = {}
    for k, _ in contexts:
        if not k in dict:
            dict[k] = None
    return dict

def get_sentiment(document, network):
    """ Create a dict of every entities with their associated sentiment """
```

```
    print('Parsing Document...')
    contexts = parse_doc(document)
    print('Done!')

    entities = init_dict(contexts)

    # Encode the sentences as utf-8
    sentences = [sentence.encode('utf-8') for _, sentence in contexts]

    # Use the neural network to predict the connotations for
    # every sentences, note that if you plan on analyzing multiple
    # sentences (> BATCH_SIZE ~ 64) you should use the categorize_document()
    # method available in my github repo https://github.com/charlesashby/CharLSTM
    predictions = network.predict_sentences(sentences)

    # When an entity appears multiple times in a document we
    # take the mean sentiment as our prediction, note that the
    # prediction is a floating point in [-1, 1] it is defined as
    # mean(pred(pos) - pred(neg))
    for i, c in enumerate(contexts):
        key = c[0]
        if entities[key] != None:
            entities[key] += (predictions[0][i][0] - predictions[0][i][1])
            entities[key] /= 2
        else:
            entities[key] = (predictions[0][i][0] - predictions[0][i][1])

    # Print the sentiment
    for e in entities.keys():
        print('Entity: %s -- sentiment: %s' % (e, entities[e]))
```

And that is it! Here are the results you can expect with the pretrained unidirectional LSTM model:

```
# Results for sentence: Jean is really sad, but Adam is the happiest guy ever
# Entity:  Jean -- sentiment: -0.197092 (neg)
# Entity:  Adam -- sentiment: 0.885632  (pos)
```

Got Questions?

Hit me up in the comment section below and I will do my best to answer.

Also, if you like this kind of tutorial,I'll be releasing a new tutorial on reinforcement learning in the upcoming weeks, like always, I'll be covering slightly advanced subjects, but in a manner that should be understandable by everybody.

With all that being said, thanks so much for reading this post. I will catch you in the next tutorial!

- Charles Ashby

36 Comments **Charles Ashby's Blog** 1 Login

Recommend Share Sort by Best

Join the discussion…

LOG IN WITH

OR SIGN UP WITH DISQUS ?

Name

Suzana Ilić • 8 months ago

wow! this is exactly what I was looking for, thank you!

1 • Reply • Share ›

Charles Ashby Mod → Suzana Ilić • 8 months ago

Glad I could help!

• Reply • Share ›

Sai Pavan • 5 months ago

I am stuck with this error. I was just trying execute the code posted by you.Please help me.

tensorflow.python.framework.errors_impl.InvalidArgumentError: Assign requires shapes of both tensors to match. lhs shape= [1,2,109,50] rhs shape= [1,2,70,50]

• Reply • Share ›

neeraj godbole • 7 months ago

Is it normal for the accuracy to be stuck at a really low value for the first few hundred batches? Is this due to the learning rate?

• Reply • Share ›

Charles Ashby Mod → neeraj godbole • 7 months ago

Yes, at the beginning the accuracy is very bad... It takes a while for the network to learn to categorize the sentences

• Reply • Share ›

neeraj godbole → Charles Ashby • 7 months ago

Hmm mine has been stuck at 1% for the first 10,000 batches.

• Reply • Share ›

Charles Ashby Mod → neeraj godbole • 7 months ago

You probably have a bug somewhere you should expect something close to 1/2

• Reply • Share ›

neeraj godbole → Charles Ashby • 7 months ago

Yeah must be because my cost and accuracy just dont change. Do we need to give the tensors some initial values or something. My code structure is quite similar to yours so I am surprised that nothing seems to be changing.

^ | v • Reply • Share ›

Charles Ashby Mod ➦ neeraj godbole • 7 months ago

Actually, I think you have a problem with the way you compute your accuracy... maybe try to compare with my code and see what's wrong

^ | v • Reply • Share ›

neeraj godbole ➦ Charles Ashby • 7 months ago

The issue was in my embeddings file. Now the training seems to be working, however the valid accuracy has been hovering around 48-52 % and it has trained through 17000 batches in the first epoch. Is this to be expected?

^ | v • Reply • Share ›

Charles Ashby Mod ➦ neeraj godbole • 7 months ago

Yes, don't worry!

^ | v • Reply • Share ›

neeraj godbole ➦ Charles Ashby • 7 months ago

The problem is that the model keeps stopping early (towards end of epoch 1 or halfway through epoch 2 with accuracy still being in the 50% region) due to the accuracy not improving. Should I increase the patience value from 10000 to maybe 50000 or so, to ensure that this doesn't happen?

^ | v • Reply • Share ›

Charles Ashby Mod ➦ neeraj godbole • 7 months ago

Yes, if you're going to stay close to your computer while you train it, you can simply set it to inf and stop when you're happy with the results you got

^ | v • Reply • Share ›

neeraj godbole ➦ Charles Ashby • 7 months ago

Yeah that's a good idea, I just set it to a huge value. Its strange though even nearly done with the 4th epoch, the loss is still stuck at 44 and the accuracy is still around 50. Was it in epoch 5 that the loss suddenly plummeted?

^ | v • Reply • Share ›

Charles Ashby Mod ➦ neeraj godbole • 7 months ago

Sorry, I don't have the training plots anymore.. I don't remember when it happened, but just give it some time.

^ | v • Reply • Share ›

neeraj godbole ➦ Charles Ashby • 7 months ago

Would increasing the learning rate to 0.001 be a good idea, or is this too high for this model. I was thinking start it off at 0.001 and then lower it as the cost gets lower.

^ | v • Reply • Share ›

Charles Ashby Mod ➦ neeraj godbole • 7 months ago

It's always a good idea to try new things in this field :)

^ | v • Reply • Share ›

Tony Fu • 7 months ago

Thanks for all the info! I did run into this issue: no matter my input, I got the same output--yielded results (pos/neg): 0.50248/0.49752, prediction: pos. Do you know why this is happening? Thanks!*

*nvm it seems like there was an issue with my terminal. However, I did run into this error when I attempted to use your pre-trained dataset: tensorflow.python.framework.errors_impl.NotFoundError: Key LSTM/rnn/basic_lstm_cell/bias not found in checkpoint. I suspect this resulted from a difference in our operating systems. Thus, I think I can only start testing when I finish training. Out of curiosity, how long did it take you to fully train lstm?

Additionally, is it normal for the loss to get stuck at 44-45?

^ | v • Reply • Share ›

Charles Ashby Mod → Tony Fu • 7 months ago

Hello Tony! I trained the model for around 4 hours*** on a GTX1070. Unfortunately, I don't have the training plots anymore, but I remember the loss being stuck for most of the training and then suddenly dive down very quickly.

As for your NotFoundError, it's probably because you don't have any checkpoints yet. You can download the pretrained model for the unidirectional LSTM here: https://github.com/charlesa...

^ | v • Reply • Share ›

Tony Fu → Charles Ashby • 7 months ago

Hi Charles, thanks for the reply! I had downloaded the checkpoints from your pretrained models, but the error persisted despite the presence of the three checkpoint files. I read up a bit about the error and it appears to be that some variables are named differently upon sourcing saved model.

One more question, I have been testing some input while training concurrently, and I noticed my pos/neg ratio hover very close to 50/50. In fact, all my samples were classified as positive. Is this something to expect during early training? (I'm still on epoch 1 on my mac)

^ | v • Reply • Share ›

Tony Fu → Tony Fu • 7 months ago

understood, thanks!

^ | v • Reply • Share ›

Sai Pavan → Tony Fu • 5 months ago

I have downloaded the checkpoints. Can tell me where to change the names of the variables.

^ | v • Reply • Share ›

Charles Ashby Mod → Tony Fu • 7 months ago

I would wait a bit before worrying about that kind of details. Like I said early during training the model can only see a bunch of characters, it takes a while before it can associate meaning to words, therefore, at this point, the best way to minimize the loss might be to just predict "positive" or "negative" no matter what the input is.

I'll try to load the checkpoint from my computer later on, I might have changed something that is causing the bug. I'll update here if I can reproduce the error.

^ | v • Reply • Share ›

Tony Fu → Charles Ashby • 7 months ago

I was also curious, would it be viable for me to tweak the algorithm to make a classify

3 classes (pos/neg/neu)? If I didn't misread, the stanford dataset is given as 3-classes with 0,2,4 representing the three categories right?

Reply • Share ›

Charles Ashby Mod → Tony Fu • 7 months ago

Not at all, all you have to do is change the number of units in the output layer to 3 instead of 2, note that you will need to download a different dataset, the one I used only has pos/neg (only the test set has 3 categories)

Reply • Share ›

Tony Fu → Charles Ashby • 7 months ago

Gotcha. Aside from gathering more data, how else would you surmise that I could further improve the accuracy? Are there any existing models that can achieve >= 85% ? Thanks again!

Reply • Share ›

Charles Ashby Mod → Tony Fu • 7 months ago

The first thing I would try to do is add DropOut. Also, it would be interesting to see if memory networks could help with sentiment analysis (https://arxiv.org/abs/1410.....
Let me know if you try it!

Reply • Share ›

Tony Fu → Charles Ashby • 7 months ago

One more question. I have been trying to run the trained algorithm on a a csv with 1000 sentences to test accuracy, but it takes an exceedingly long time (25-30) seconds and uses considerable memory (5GB sometimes). Is there something that I can do to speed that up while optimizing resources used?

Reply • Share ›

Charles Ashby Mod → Tony Fu • 7 months ago

Try using a smaller batch size

Reply • Share ›

neeraj godbole • 7 months ago

This might be a slightly long question,
On the tensorflow API page, it says the input tensor for conv2d is [batch, in_height, in_width, in_channels].
You said that we have to use a hack to convert input_ from [b, sentence_length, word_length, alphabet] to [b * sentence_length, 1, word_length, alphabet] because the sentences act as the number of channels.
From the API page it seems as though the alphabet size would be the number of channels, not sentence length.
Could you please explain why the hack is necessary in this case and why sentence length acts as the number of channels, when it seems as though it would be the input height?
Otherwise, great guide!
Thanks!

Reply • Share ›

Charles Ashby Mod → neeraj godbole • 7 months ago

Hi! You are completely right, I got mixed up with Theano's convolutions (there the channel size is at position 2). I meant to write that we need to convert the input to [b * sentence_length, word_length, alphabet, 1] (Thus, the number of channels would be 1, the word_length and alphabet sizes -- the height and width of the matrix that is being convoluted -- remain fixed and the new batch size -- b * sentence_length -- can change without hurting us), thanks for letting me know!

PS: The figure at page 2 of this article might help you understand what I did better
https://arxiv.org/pdf/1508.....

Reply • Share ›

neeraj godbole → Charles Ashby • 7 months ago

I have written up a completed model, but the output dimensions of my max_pool (same parameters provided as yours) are not (b*s, 1, 1, feature_size). Do you think that might be due to the strides provided?

Reply • Share ›

Charles Ashby Mod → neeraj godbole • 7 months ago

Probably, I don't use any strides in my max-pool layer

Reply • Share ›

neeraj godbole → Charles Ashby • 7 months ago

Just a quick followup, or more like a clarification.
Our kernel height is 1, because the each row is one word and we are convolving one word at a time?

Reply • Share ›

Charles Ashby Mod → neeraj godbole • 7 months ago

Not exactly, actually our kernel height is the same as the height of the input, which is the alphabet size. It is the resulting output of the convolution that is of height 1.

The fact that we are convolving one word at a time does not affect that since we process all the words of all the sentences of our batch in parallel. (This is actually the reason I converted the input size to [b * sentence_length, word_length, alphabet_size, 1])

I highly suggest you take a look at the actual paper they have much more details about the model!

Reply • Share ›

neeraj godbole → Charles Ashby • 7 months ago

Thanks, that clears things up a lot. Also thank you for the fast response! :)

Reply • Share ›

Charles Ashby's blog

charlesashby

Deep Learning Blog