Tutorial VI: Recurrent Neural Networks

Bern Winter School on Machine Learning, 28.01-01.02 2019 Mykhailo Vladymyrov

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In this session we will see what RNN is. We will use it to predict/generate text sequence, but same approach can be applied to any sequential data.

(Largely adopted from https://github.com/roatienza/Deep-Learning-Experiments)

So far we looked at the data available altogether. In many cases the data is sequential (weather, speach, sensor signals etc). RNNs are specifically designed for such tasks.



unpack libraries

if using colab, upload the material.tgz and run the next cell

```
!tar -xvzf material.tgz
```

▼ 1. Load necessary libraries

```
import sys
import numpy as np
import matplotlib.pyplot as plt
import IPython.display as ipyd
import tensorflow as tf
import collections
import time
# We'll tell matplotlib to inline any drawn figures like so:
%matplotlib inline
plt.style.use('ggplot')
from utils import gr_disp
from IPython.core.display import HTML
HTML("""<style> .rendered_html code {
   padding: 2px 5px;
   color: #0000aa;
   background-color: #ccccc;
} </style>""")
```

2. Load the text data

```
def read_data(fname):
    with open(fname) as f:
```

```
content = f.readlines()
content = [x.strip() for x in content]
content = [word for i in range(len(content)) for word in content[i].split()]
content = np.array(content)
return content

training_file = 'RNN/rnn.txt'

training_data = read_data(training_file)

print(training_data[:100])
```

3. Build dataset

We will assign an id to each word, and make dictionaries word->id and id->word. The most frequently repeating words have lowest id

```
def build_dataset(words):
    count = collections.Counter(words).most_common()
    dictionary = dict()
    for word, _ in count:
        dictionary[word] = len(dictionary)
    reverse_dictionary = dict(zip(dictionary.values(), dictionary.keys()))
    return dictionary, reverse_dictionary

dictionary, reverse_dictionary = build_dataset(training_data)
vocab_size = len(dictionary)

print(dictionary)

Then the whole text will look as a sequence of word ids:
```

print([dictionary[w] for w in training_data])


```
# Parameters
learning rate = 0.001
training_iters = 100000
display step = 1000
n input = 5
# number of units in RNN cell
n \text{ hidden} = [1024, 512]
def RNN(x, n_vocab, n_hid):
    x = tf.unstack(x, n_input, 1)
   basic_cells = [tf.nn.rnn_cell.LSTMCell(n) for n in n_hid]
    rnn_cell = tf.nn.rnn_cell.MultiRNNCell(basic_cells)
    # generate prediction
    outputs, states = tf.nn.static rnn(rnn cell, x, dtype=tf.float32)
    # there are n input outputs but
    # we only want the last output
    last_output = outputs[-1]
```

```
w = tf.Variable(tf.random normal([n hid[-1], n vocab]))
    b = tf.Variable(tf.random normal([n vocab]))
    y = tf.matmul(last_output, w) + b
    return y
g = tf.Graph()
with g.as default():
    # tf Graph input
    x = tf.placeholder("float", [None, n_input, 1])
y = tf.placeholder("float", [None, vocab_size])
    pred = RNN(x, vocab size, n hidden)
    # Loss and optimizer
    cost = tf.reduce mean(tf.nn.softmax cross entropy with logits v2(logits=pred, 1
    optimizer = tf.train.RMSPropOptimizer(learning rate=learning rate).minimize(cos
    # Model evaluation
    correct pred = tf.equal(tf.argmax(pred,1), tf.argmax(y,1))
    accuracy = tf.reduce mean(tf.cast(correct pred, tf.float32))
gr_disp.show(g.as_graph_def())
```

→ 5. Run!

```
with tf.Session(graph=g) as session:
    session.run(tf.global variables initializer())
    step = 0
   offset = np.random.randint(0,n input+1)
   end offset = n input + 1
    acc total = 0
    loss total = 0
   start time = time.time()
   while step < training iters:
        # Generate a minibatch. Add some randomness on selection process.
        if offset > (len(training data)-end offset):
            offset = np.random.randint(0, n_input+1)
        symbols_in_keys = [ [dictionary[ str(training_data[i])]] for i in range(off
        symbols_in_keys = np.reshape(np.array(symbols_in_keys), [-1, n_input, 1])
        symbols_out_onehot = np.zeros([vocab_size], dtype=float)
        symbols_out_onehot[dictionary[str(training_data[offset+n_input])]] = 1.0
        symbols_out_onehot = np.reshape(symbols_out_onehot,[1,-1])
        _, acc, loss, onehot_pred = session.run([optimizer, accuracy, cost, pred],
                                                feed_dict={x: symbols_in_keys, y: s
       loss total += loss
        acc total += acc
        if (step+1) % display_step == 0:
            print("Iter= " + str(step+1) + ", Average Loss= " + \
                  "{:.6f}".format(loss total/display step) + ", Average Accuracy "
                  "{:.2f}%".format(100*acc_total/display_step))
            acc total = 0
            loss\_total = 0
            symbols_in = [training_data[i] for i in range(offset, offset + n_input)
            symbols out = training data[offset + n input]
            symbols_out_pred = reverse_dictionary[int(tf.argmax(onehot_pred, 1).eva
            print("%s - [%s] vs [%s]" % (symbols_in,symbols_out,symbols_out_pred))
        step += 1
        offset += (n input+1)
    print("Optimization Finished!")
    print("Elapsed time: ", time.time() - start_time)
    for itr in range(100):
```

```
prompt = "%s words: " % n input
sentence = input(prompt)
sentence = sentence.strip()
words = sentence.split('
if len(words) != n input:
    continue
try:
    symbols in keys = [dictionary[str(words[i])] for i in range(len(words))
    for i in range(128):
        keys = np.reshape(np.array(symbols in keys), [-1, n input, 1])
        onehot pred = session.run(pred, feed dict={x: keys})
        onehot pred index = int(tf.argmax(onehot pred, 1).eval())
        sentence = "%s %s" % (sentence, reverse dictionary onehot pred index
        symbols in keys = symbols in keys[1:]
        symbols in keys.append(onehot pred index)
    print(sentence)
except:
    print("Word not in dictionary")
```

6. Excercice

- Run with 5-7 input words instead of 3.
- increase number of training iterations, since convergance will take much longer (training as well!).

▼ 7. Further reading

Illustrated Guide to Recurrent Neural Networks

Illustrated Guide to LSTM's and GRU's: A step by step explanation