

vanilla_rnn

April 22, 2019

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In [0]: import numpy as np
import matplotlib.pyplot as plt
# Load the Drive helper and mount
from google.colab import drive
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In [2]: # This will prompt for authorization.
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive/My Drive/speeches.txt")

```
In [0]: # softmax of a numpy array
def softmax(x):
    e_x = np.exp(x - np.max(x))
    return e_x / e_x.sum(axis=0)
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In [0]: # forward pass for one-to-one RNN architecture
def forward_pass(X, Y, h_init, parameters):

    # dictionaries to store values at each time step
    h = {} # to keep hidden states
    x = {} # to keep input states
    y = {} # to keep softmax output (array of probs with vocab size)

    # retrieve the model parameters
    W_xh, W_hh, W_hy, b_h, b_y = parameters

    # set initial hidden state to start RNN loop
    h[-1] = np.copy(h_init)
    loss = 0

    # for each character in the input/output
    for t in range(len(X)):

        # one hot representation of character t
        x[t] = np.zeros((vocab_size,1))
        x[t][X[t]] = 1
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    # rnn cell calculations given by formula
    h[t] = np.tanh(np.dot(W_hh,h[t-1]) + np.dot(W_xh,x[t]) + b_h)
    y[t] = softmax(np.dot(W_hy,h[t]) + b_y)

    # get the softmax probability of output character t
    softmax_out = y[t][Y[t],0]

    # update the cross entropy (softmax) loss at each time step
    loss += -np.log(softmax_out)

    return loss, y, x, h, h[len(X)-1] # rnn input and hidden states are needed for bac

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In [0]: def backward_pass(X, Y, parameters,y,x,h):
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    # retrieve model parameters
    W_xh,W_hh,W_hy,b_h,b_y = parameters

    # initialize the gradients of same shape with parameters
    dW_xh,dW_hh,dW_hy,db_h,db_y = np.zeros(W_xh.shape),np.zeros(W_hh.shape),np.zeros(W_hy.shape),np.zeros(b_h.shape),np.zeros(b_y.shape)
    dh_next = np.zeros(h[0].shape)

    # backpropagation for each time step
    for t in reversed(range(len(X))):

        # calculate gradients for all parameters
        d_y = np.copy(y[t])
        d_y[Y[t]] = d_y[Y[t]] - 1
        dW_hy += np.dot(d_y,h[t].T)
        db_y += d_y
        d_h = np.dot(W_hy.T, d_y) + dh_next
        d_tanh = (1- h[t]*h[t]) *d_h # derivative of tanh (1-t^2)dt
        db_h += d_tanh
        dW_xh += np.dot(d_tanh, x[t].T)
        dW_hh += np.dot(d_tanh, h[t-1].T)
        dh_next = np.dot(W_hh.T,d_tanh)

    return (dW_xh,dW_hh,dW_hy,db_h,db_y)

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In [0]: def SGD(X, Y, h_init, parameters, learning_rate):
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    loss, y_preds, x, h, h_init = forward_pass(X,Y,h_init,parameters)
    gradients = backward_pass(X,Y,parameters,y_preds,x,h)
    #gradients = gradient_clip(gradients)

    new_params = []
    for i in range(len(parameters)):

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        new_params.append(parameters[i] - learning_rate * gradients[i] )
    return tuple(new_params), h_init, loss

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In [0]: def initialize_parameters(num_hiddens,vocab_size):

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    # weight matrices
    W_hx = np.random.randn(num_hiddens, vocab_size) * 0.01
    W_hh = np.random.randn(num_hiddens, num_hiddens) * 0.01
    W_yh = np.random.randn(vocab_size, num_hiddens) * 0.01

    # biases
    b_h = np.zeros((num_hiddens, 1))
    b_y = np.zeros((vocab_size, 1))

    return (W_hx,W_hh,W_yh,b_h,b_y)

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In [0]: def train(data, num_hiddens, vocab_size, batch_size, learning_rate, num_epoch, char_to_index, char_from_index):

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    num_iteration = int((len(data)/batch_size) * num_epoch) # total number of iterations
    parameters = initialize_parameters(num_hiddens,vocab_size) # get model parameters
    h_init = np.zeros((num_hiddens, 1)) # get initial hidden vector
    smooth_loss = -np.log(1.0/vocab_size)*batch_size # smooth loss not to see high oscillations

    losses = []
    cnt = 1
    epoch_cnt = 1
    for i in range(num_iteration):

        # get batch of training data
        X_batch = []
        Y_batch = []
        for j in range(batch_size):
            X_batch.append(char_to_index[data[cnt-1]])
            Y_batch.append(char_to_index[data[cnt]])
            cnt+=1

        # forward/backward pass and update parameters
        parameters, h_init, loss = SGD(X_batch, Y_batch, h_init, parameters, learning_rate)
        smooth_loss = smooth_loss * 0.999 + loss * 0.001
        losses.append(smooth_loss)

        # epoch is completed print progress and reset counter
        if (len(data) - cnt) <= batch_size or (i == 0):
            print ("Epoch:", epoch_cnt, "\tBatch:", str(cnt-1) + "/" + str(len(data)), "\tLoss:", loss)
            cnt = 1
            epoch_cnt+=1

    return parameters,h_init,losses

```

```

In [0]: def sampling(parameters, h_init, sample_size, index_to_char):

    # retrieve model parameters
    W_xh,W_hh,W_hy,b_h,b_y = parameters

    # get the hyper parameters
    vocab_size = b_y.shape[0]
    num_hiddens = W_hh.shape[1]

    # initialize the sequence and first hidden state
    x = np.zeros((vocab_size,1))
    #h_init = np.zeros((num_hiddens,1))
    # store all sampled indices
    indices = []

    for i in range(sample_size):

        # make forward pass
        h_init = np.tanh(np.dot(W_hh,h_init) + np.dot(W_xh,x) + b_h)
        y = softmax(np.dot(W_hy,h_init) + b_y)

        # get a random index in vocab within the probability distribution of y (ravel()
        index = np.random.choice(range(vocab_size), p=y.ravel())

        # add the sampled char into one hot vector
        x = np.zeros((vocab_size, 1))
        x[index] = 1

        # append chosen index at each iteration
        indices.append(index)

    sampled_text = ''
    for index in indices:
        sampled_text += index_to_char[index]

    return sampled_text

In [0]: def data_preprocess(file_path):
    data = open(file_path, 'r',encoding = 'utf-8').read()
    data = data.lower()
    data = ''.join([i for i in data if not i.isdigit()])
    data = (data.translate({ord(i): None for i in ' '}&=)-@\\ufe00;_é$(')))
    char_set = list(set(data))
    vocab_size = len(char_set)
    data_size = len(data)
    char_to_index = { ch:i for i,ch in enumerate(char_set) } # to index each char in d
    index_to_char = { i:ch for i,ch in enumerate(char_set) } # to print generated char

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return data, vocab_size, char_to_index, index_to_char
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1 Trump Speech

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In [0]: data, vocab_size, char_to_index, index_to_char = data_preprocess("/content/drive/My Dr
```

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In [0]: # hyperparameters (chosen by experiments)
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num_hiddens = 150
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batch_size = 100
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learning_rate = 0.001
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num_epoch = 12
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In [13]: parameters, h_init, loss_history = train(data, num_hiddens, vocab_size, batch_size, le
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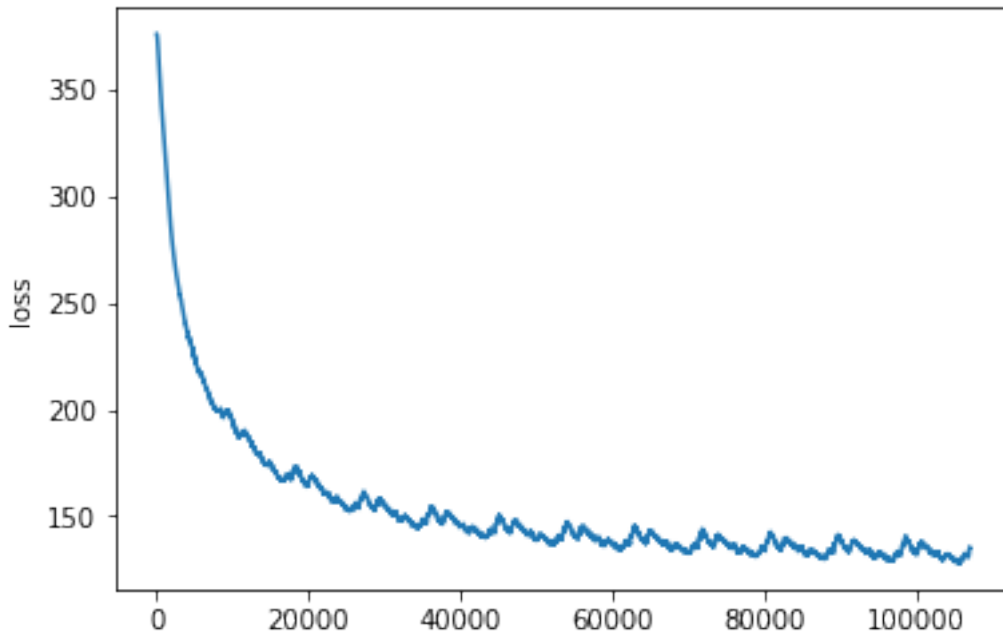
Epoch: 1	Batch: 100/891479	Loss: 376.1199891113728
Epoch: 2	Batch: 891400/891479	Loss: 198.5989692792207
Epoch: 3	Batch: 891400/891479	Loss: 170.3894478995746
Epoch: 4	Batch: 891400/891479	Loss: 157.60121457779493
Epoch: 5	Batch: 891400/891479	Loss: 150.44044000065216
Epoch: 6	Batch: 891400/891479	Loss: 145.9852464188745
Epoch: 7	Batch: 891400/891479	Loss: 142.9700438330822
Epoch: 8	Batch: 891400/891479	Loss: 140.81607290079847
Epoch: 9	Batch: 891400/891479	Loss: 139.1327426461128
Epoch: 10	Batch: 891400/891479	Loss: 137.84397843322512
Epoch: 11	Batch: 891400/891479	Loss: 136.83862173950166
Epoch: 12	Batch: 891400/891479	Loss: 135.84353882700896
Epoch: 13	Batch: 891400/891479	Loss: 134.9228162700672

```
In [14]: import matplotlib.pyplot as plt
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plt.plot(loss_history)
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```
plt.ylabel('loss')
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plt.show()
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In [15]: print("Generated text: ",sampling(parameters, h_init, 1000, index_to_char))
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Generated text: . we have great for somethrust hape. and i have a creatia.

whor time for it would we're go to believe than should country. it justll so says write trade t

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2 Shakespeare Sonnets

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In [0]: data, vocab_size, char_to_index, index_to_char = data_preprocess("/content/drive/My Dr
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```
In [0]: # hyperparameters (chosen by experiments)
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```
num_hiddens = 75
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```
batch_size = 50
```

```
learning_rate = 0.001
```

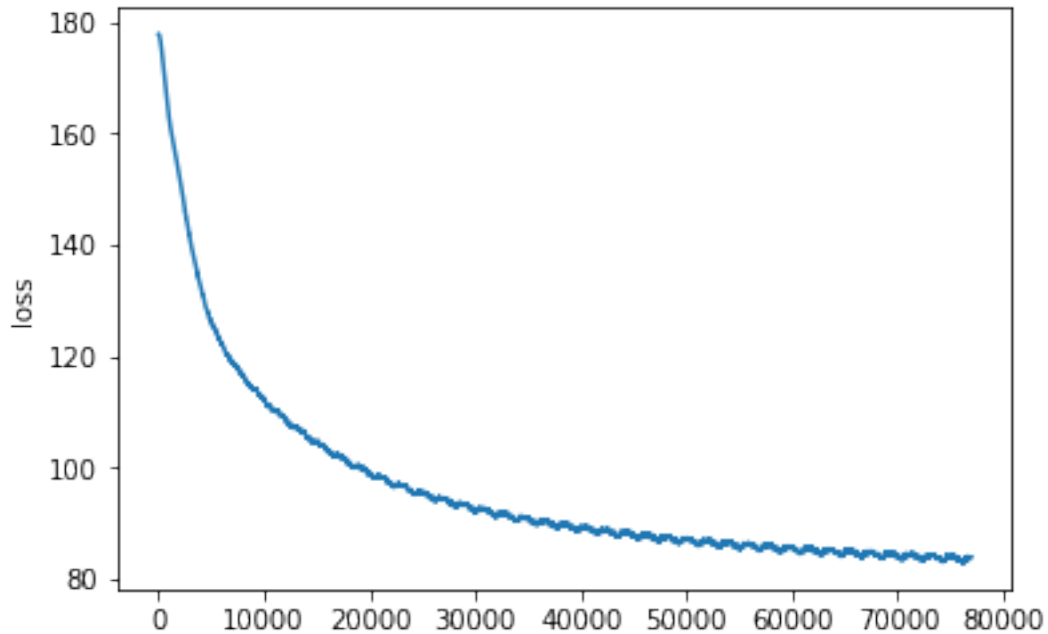
```
num_epoch = 40
```

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In [30]: parameters, h_init, loss_history = train(data,num_hiddens, vocab_size, batch_size, lea
```

Epoch: 1	Batch: 50/96141	Loss: 177.76740676292425
Epoch: 2	Batch: 96100/96141	Loss: 152.87332345994457
Epoch: 3	Batch: 96100/96141	Loss: 133.48517373835352
Epoch: 4	Batch: 96100/96141	Loss: 122.98104313356272

Epoch: 5	Batch: 96100/96141	Loss: 117.2566426211953
Epoch: 6	Batch: 96100/96141	Loss: 112.97279295517684
Epoch: 7	Batch: 96100/96141	Loss: 109.52457368012955
Epoch: 8	Batch: 96100/96141	Loss: 106.63987367592102
Epoch: 9	Batch: 96100/96141	Loss: 104.12809151900247
Epoch: 10	Batch: 96100/96141	Loss: 101.93276277396208
Epoch: 11	Batch: 96100/96141	Loss: 99.99024230016366
Epoch: 12	Batch: 96100/96141	Loss: 98.30579146634021
Epoch: 13	Batch: 96100/96141	Loss: 96.85819599826198
Epoch: 14	Batch: 96100/96141	Loss: 95.60277932213847
Epoch: 15	Batch: 96100/96141	Loss: 94.4982531963851
Epoch: 16	Batch: 96100/96141	Loss: 93.51305087532857
Epoch: 17	Batch: 96100/96141	Loss: 92.62718008772738
Epoch: 18	Batch: 96100/96141	Loss: 91.82938195606005
Epoch: 19	Batch: 96100/96141	Loss: 91.11222545893507
Epoch: 20	Batch: 96100/96141	Loss: 90.46793798439523
Epoch: 21	Batch: 96100/96141	Loss: 89.88722931454213
Epoch: 22	Batch: 96100/96141	Loss: 89.36083794675807
Epoch: 23	Batch: 96100/96141	Loss: 88.88049029211619
Epoch: 24	Batch: 96100/96141	Loss: 88.43936330917548
Epoch: 25	Batch: 96100/96141	Loss: 88.03292520142264
Epoch: 26	Batch: 96100/96141	Loss: 87.65776193851777
Epoch: 27	Batch: 96100/96141	Loss: 87.30961738176757
Epoch: 28	Batch: 96100/96141	Loss: 86.98376729332455
Epoch: 29	Batch: 96100/96141	Loss: 86.675704684499
Epoch: 30	Batch: 96100/96141	Loss: 86.38220440881477
Epoch: 31	Batch: 96100/96141	Loss: 86.1021769578767
Epoch: 32	Batch: 96100/96141	Loss: 85.83527253864459
Epoch: 33	Batch: 96100/96141	Loss: 85.58124590625765
Epoch: 34	Batch: 96100/96141	Loss: 85.33962784585829
Epoch: 35	Batch: 96100/96141	Loss: 85.10998066427449
Epoch: 36	Batch: 96100/96141	Loss: 84.89229702799874
Epoch: 37	Batch: 96100/96141	Loss: 84.68656177978453
Epoch: 38	Batch: 96100/96141	Loss: 84.49256842112965
Epoch: 39	Batch: 96100/96141	Loss: 84.30754739935313
Epoch: 40	Batch: 96100/96141	Loss: 84.12963874704366
Epoch: 41	Batch: 96100/96141	Loss: 83.95895816560346

```
In [31]: plt.plot(loss_history)
         plt.ylabel('loss')
         plt.show()
```



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In [32]: print("Generated text:")
          print(sampling(parameters, h_init, 500, index_to_char))
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Generated text:

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