

## Problem 1

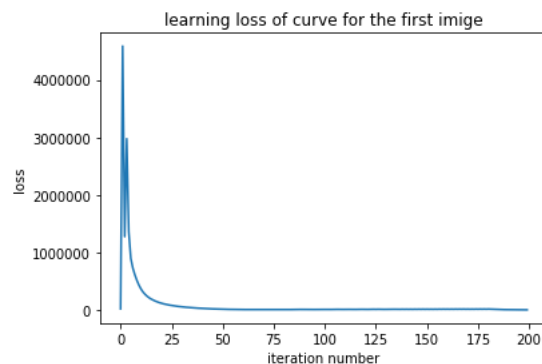
1. Train-model function is implemented.
2. visualize-model function is implemented.
3. finetune function is implemented.
4. freeze function is implemented.
5. the accuracy on validation daaset for these tow scenarios:

Finetune	0.954248
Freeze	0.960784

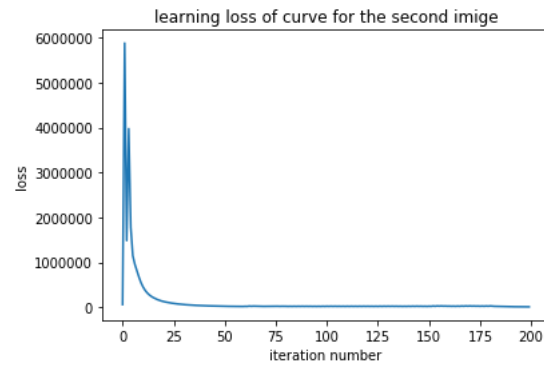
## Problem 2

1. content-loss function is implemented.
2. style-loss function is implemented.
3. tv-loss function is implemented.
4. style-transfer function is implemented.

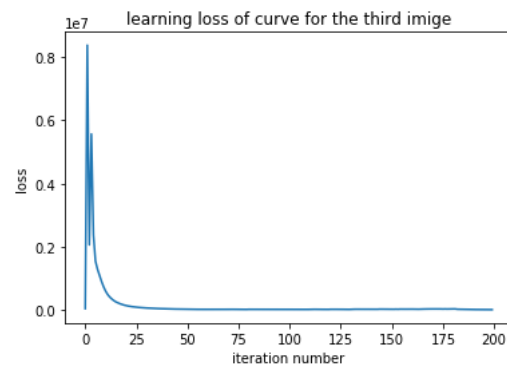
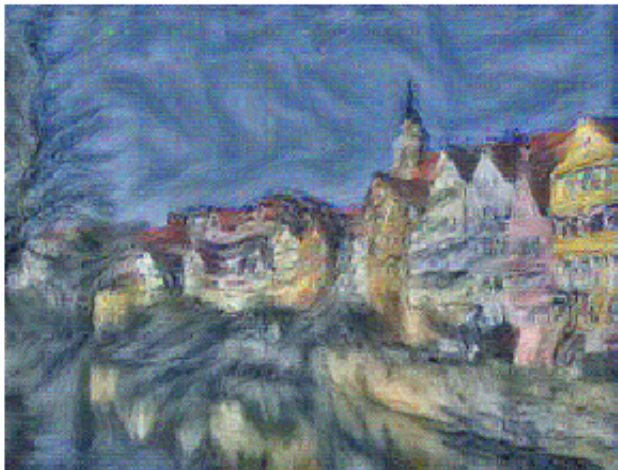
tubingen using composition-vii style:



tubingen using the-scream style:



tubingen using starry-night style:



## Problem 3

1. rnn-step-forward function is implemented
2. derive the gradient for step backward.

$$\frac{\partial L}{\partial X_t} = \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right] W_x^T$$

$$\frac{\partial L}{\partial W_x} = X_t^T \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right]$$

$$\frac{\partial L}{\partial h_{t-1}} = \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right] W_h^T$$

$$\frac{\partial L}{\partial W_h} = h_{t-1}^T \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right]$$

$$\frac{\partial L}{\partial b} = \sum_n \left[ \frac{\partial L}{\partial h_{tn}} (1 - h_{tn}^2) \right]$$

3. rnn forward function is implemented.

4. derive the gradient for rnn backward.

$$\begin{aligned} \frac{\partial L}{\partial h_{t-1}} &= \frac{\partial D}{\partial h_{t-1}} + \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right] W_h^T \\ \frac{\partial L}{\partial h_0} &= \left[ \frac{\partial L}{\partial h_1} (1 - h_1^2) \right] W_h^T \end{aligned}$$

$$\frac{\partial L}{\partial X_t} = \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right] W_x^T$$

$$\frac{\partial L}{\partial W_x} = \sum_t X_t^T \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right]$$

$$\frac{\partial L}{\partial W_h} = \sum_t h_{t-1}^T \left[ \frac{\partial L}{\partial h_t} (1 - h_t^2) \right]$$

$$\frac{\partial L}{\partial b} = \sum_t \sum_n \left[ \frac{\partial L}{\partial h_{tn}} (1 - h_{tn}^2) \right]$$

## Problem 4

1. lstm-step-forward function is implemented.

2. derive the gradient for step backward.

define  $\theta_{t-fc} = W_x^\theta x_t + W_H^\theta H_{t-1} + b^\theta$  for  $\theta = \{f, i, \tilde{c}, o\}$ , then we can derive:

$$\begin{aligned}\frac{\partial L}{\partial f_{t-fc}} &= \frac{\partial L}{\partial h_t} c_{t-1} f_t (1 - f_t) \\ \frac{\partial L}{\partial i_{t-fc}} &= \frac{\partial L}{\partial c_t} \tilde{c}_t i_t (1 - i_t) \\ \frac{\partial L}{\partial \tilde{c}_t} &= \frac{\partial L}{\partial c_t} i_t (1 - \tilde{c}_t^2) \\ \frac{\partial L}{\partial o_{t-fc}} &= \frac{\partial L}{\partial h_t} \tanh(c_t) o_t (1 - o_t)\end{aligned}$$

then we have:

$$\begin{aligned}\frac{\partial L}{\partial x_t} &= \sum_{\theta} \frac{\partial L}{\partial \theta_{t-fc}} W_x^{\theta T} \\ \frac{\partial L}{\partial h_{t-1}} &= \sum_{\theta} \frac{\partial L}{\partial \theta_{t-fc}} W_h^{\theta T} \\ \frac{\partial L}{\partial c_{t-1}} &= \sum_{\theta} \frac{\partial L}{\partial c_t} + \frac{\partial L}{\partial h_t} o_t (1 - \tanh^2(c_t))\end{aligned}$$

and

$$\begin{aligned}\frac{\partial L}{\partial W_x^\theta} &= x_t^T \frac{\partial L}{\partial \theta_{t-fc}} \\ \frac{\partial L}{\partial W_h^\theta} &= h_{t-1}^T \frac{\partial L}{\partial \theta_{t-fc}} \\ \frac{\partial L}{\partial b^\theta} &= \mathbf{1}^T \frac{\partial L}{\partial \theta_{t-fc}}\end{aligned}$$

3. lstm-forward function is implemented.

4. derive the gradient for lstm backward. define  $\theta_{t-fc} = W_x^\theta x_t + W_H^\theta H_{t-1} + b^\theta$  for  $\theta = \{f, i, \tilde{c}, o\}$ , then we can derive:

$$\begin{aligned}
\frac{\partial L}{\partial f_{t-fc}} &= \frac{\partial L}{\partial h_t} c_{t-1} f_t (1 - f_t) \\
\frac{\partial L}{\partial i_{t-fc}} &= \frac{\partial L}{\partial c_t} \tilde{c}_t i_t (1 - i_t) \\
\frac{\partial L}{\partial \tilde{c}_t} &= \frac{\partial L}{\partial c_t} i_t (1 - \tilde{c}_t^2) \\
\frac{\partial L}{\partial o_{t-fc}} &= \frac{\partial L}{\partial h_t} \tanh(c_t) o_t (1 - o_t)
\end{aligned}$$

then we have:

$$\begin{aligned}
\frac{\partial L}{\partial x_t} &= \sum_{\theta} \frac{\partial L}{\partial \theta_{t-fc}} W_x^{\theta T} \\
\frac{\partial L}{\partial h_0} &= \sum_{\theta} \frac{\partial L_1}{\partial \theta_{1-fc}} W_h^{\theta T}
\end{aligned}$$

and

$$\begin{aligned}
\frac{\partial L}{\partial W_x^{\theta}} &= \sum_t x_t^T \frac{\partial L}{\partial \theta_{t-fc}} \\
\frac{\partial L}{\partial W_h^{\theta}} &= \sum_t h_{t-1}^T \frac{\partial L}{\partial \theta_{t-fc}} \\
\frac{\partial L}{\partial b^{\theta}} &= \sum_t \mathbf{1}^T \frac{\partial L}{\partial \theta_{t-fc}}
\end{aligned}$$

additionally:

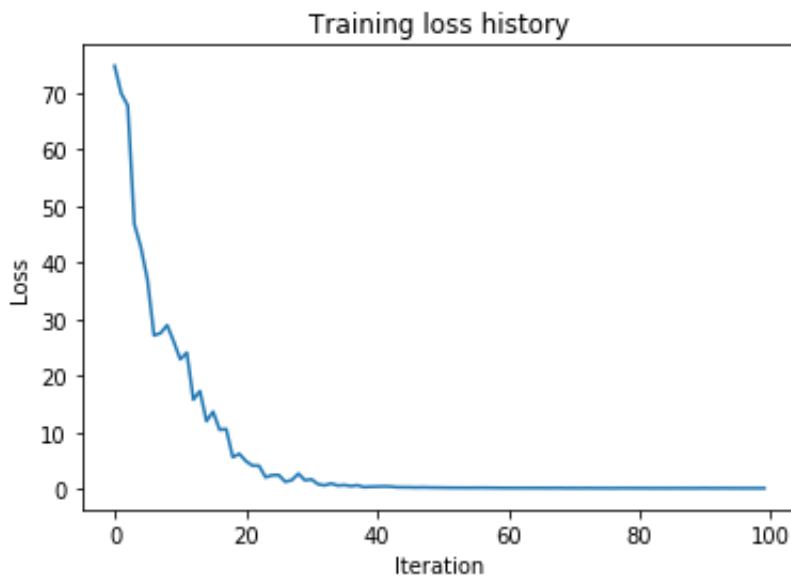
$$\frac{\partial L_t}{\partial h_t} = \frac{\partial D(y_t - \tilde{y}_t)}{\partial h_t} + \sum_{\theta} \frac{\partial L}{\partial \theta_{t+1-fc}} W_h^{\theta T}$$

## Problem 5

1. the forward and backward of temporal fc is implemented.

## Homework 2

2. the temporal-softmax-loss is implemented.
3. sample function is implemented.
4. learning curves of training loss and learned captions for samples. the learning curve of training loss of RNN:



the sample of train captions of RNN:

train  
a bathroom with shower toilet and sink is shown <END>  
GT:<START> a bathroom with shower toilet and sink is shown <END>

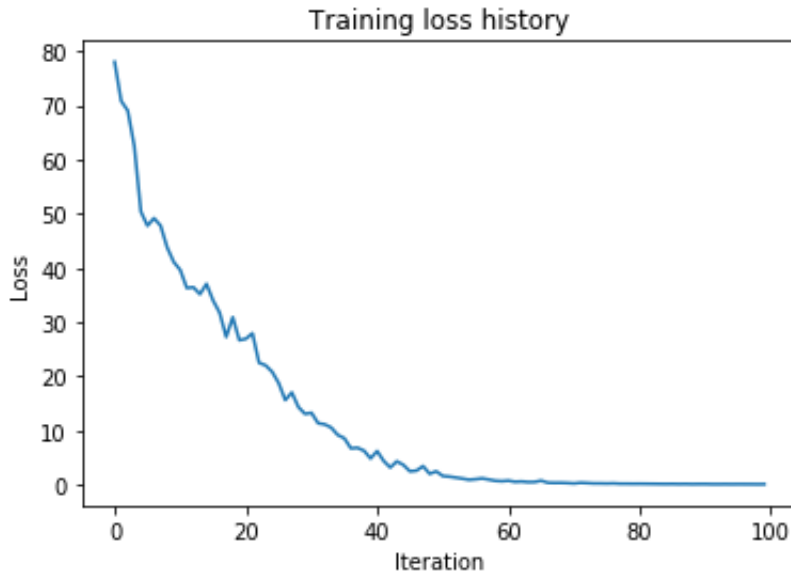


the sample of validation captions of RNN:

val  
a the on in a is with at a traffic light <END>  
GT:<START> some tracks for a rail way <UNK> near a building <END>



the learning curve of training loss of LSTM:



the sample of train captions of LSTM:

train  
a little bird sitting on the top of a <UNK> chair <END>  
GT:<START> a little bird sitting on the top of a <UNK> chair <END>



the sample of validation captions of LSTM:

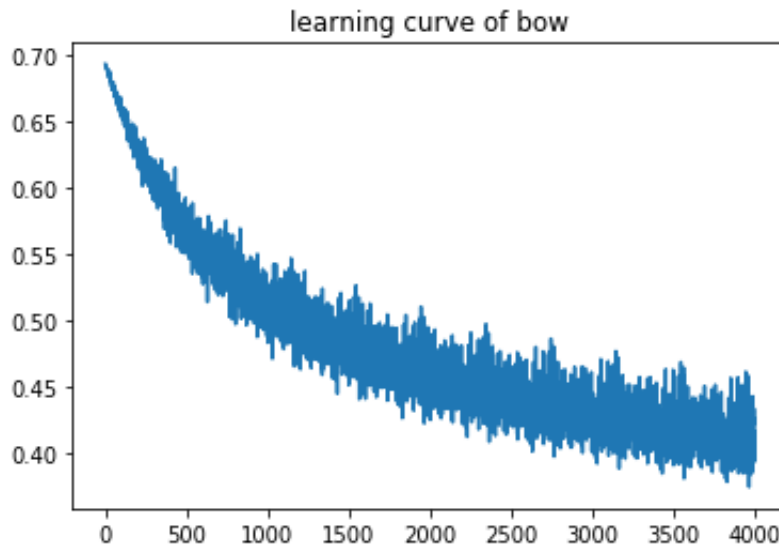


val  
a lone with a <UNK> on a <UNK> <END>  
GT:<START> a snowboarder jumps very high as he <UNK> a <UNK> <END>



### Problem 6

1. bag of words is implemented in bow.py  
The learning curve of training loss is:



The accuracy of bow is:

**Finished Training**

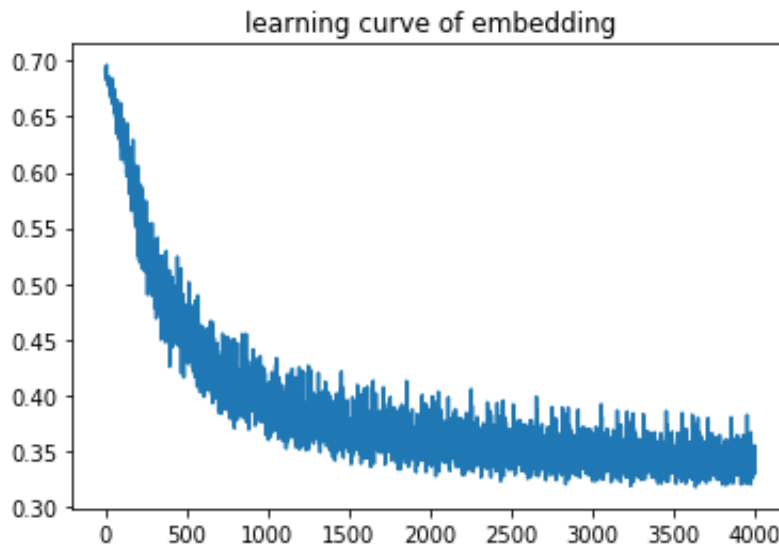
**Accuracy of the network on the 40000 train images: 94.872500 %**

**Accuracy of the network on the 10000 dev images: 93.960000 %**

**Accuracy of the network on the 10000 test images: 93.700000 %**

2. word embedding is implemented in embedding.py.

The learning curve of training loss is:



The accuracy of embedding is:

**Finished Training**

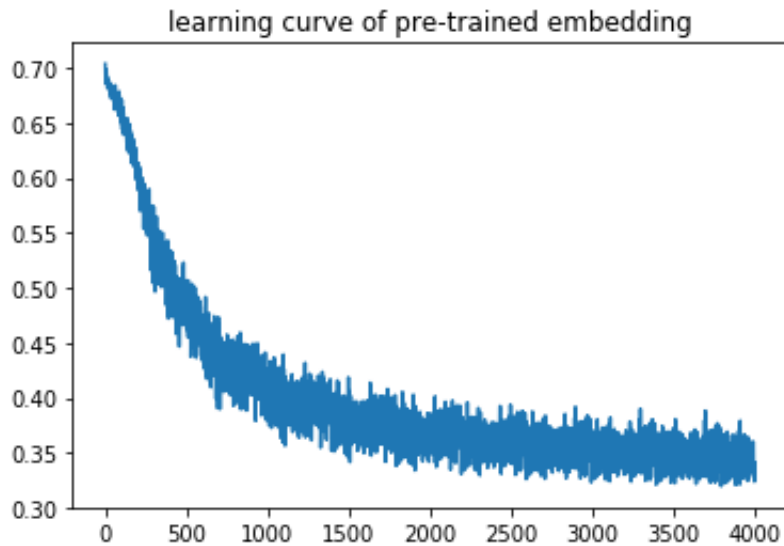
**Accuracy of the network on the 40000 train images: 98.092500 %**

**Accuracy of the network on the 10000 dev images: 95.810000 %**

**Accuracy of the network on the 10000 test images: 95.810000 %**

3. word embedding with pre-trained weight is implemented in glove.py

The learning curve of glove is:



The accuracy of embedding is:

**Finished Training**

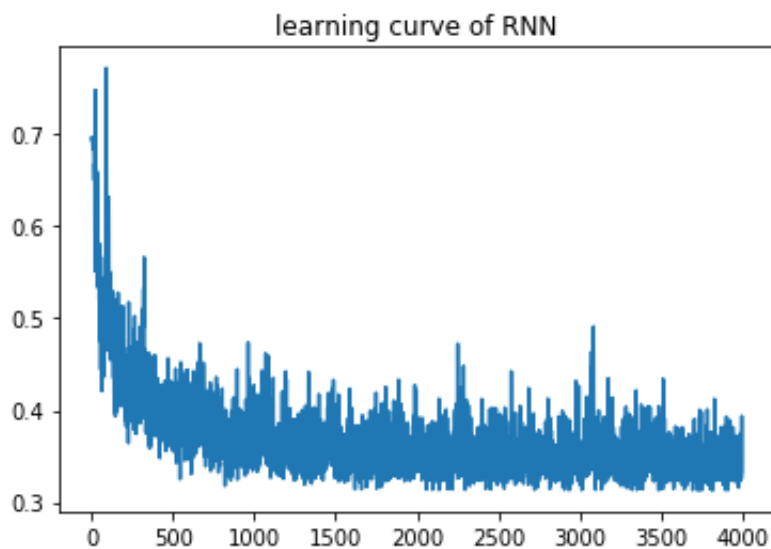
**Accuracy of the network on the 40000 train images: 97.760000 %**

**Accuracy of the network on the 10000 dev images: 95.950000 %**

**Accuracy of the network on the 10000 test images: 95.420000 %**

4. rnn is implemented in rnn.py with style='RNN' in prob6 folder.

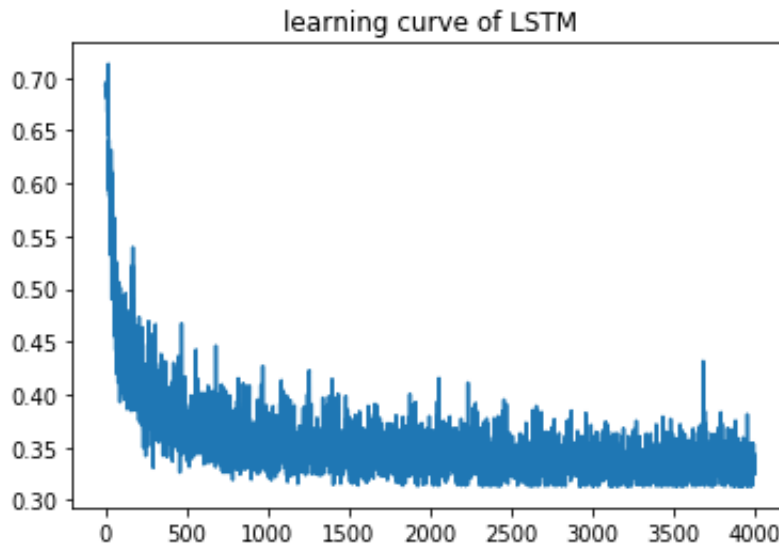
The learning curve of rnn is:



The accuracy of rnn is:

**Finished Training****Accuracy of the network on the 40000 train images: 95.782500 %****Accuracy of the network on the 10000 dev images: 94.180000 %****Accuracy of the network on the 10000 test images: 93.670000 %**

5. lstm is implemented in lstm.py with style='LSTM' in prob6 folder.  
The learning curve of lstm is:



The accuracy of lstm is:

**Accuracy of the network on the 40000 train images: 98.222500 %****Accuracy of the network on the 10000 dev images: 96.420000 %****Accuracy of the network on the 10000 test images: 96.050000 %**