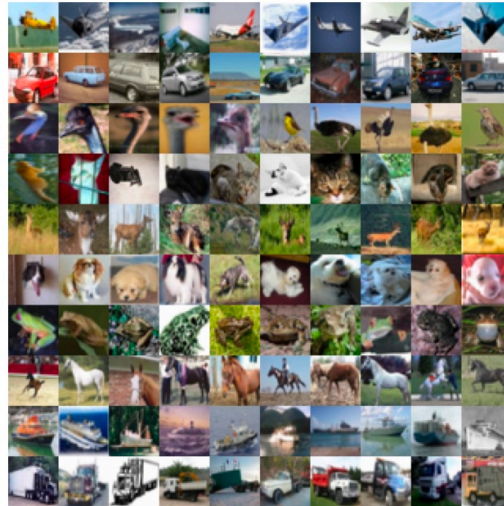


1) CNNs for Multi-class Classification

a) Autograder

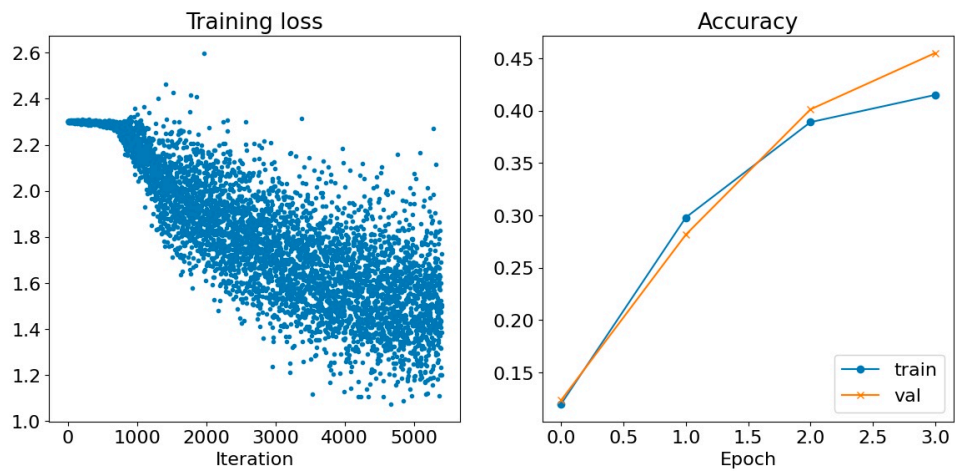
b) Autograder



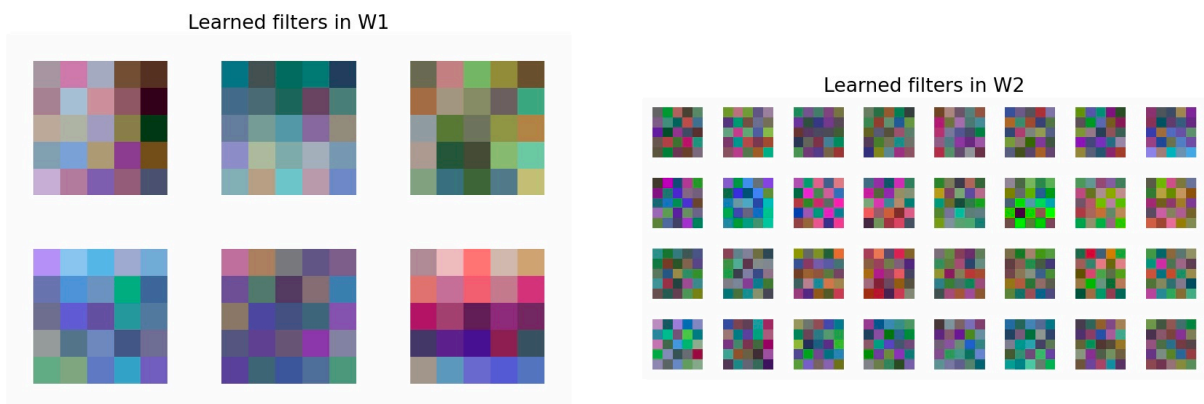
(Iteration 1 / 5400) loss: 2.301563
(Epoch 0 / 3) train acc: 12.00% val_acc: 12.36%
(Iteration 201 / 5400) loss: 2.299032
(Iteration 401 / 5400) loss: 2.294829
(Iteration 601 / 5400) loss: 2.292795
(Iteration 801 / 5400) loss: 2.239551
(Iteration 1001 / 5400) loss: 2.110933
(Iteration 1201 / 5400) loss: 2.084381
(Iteration 1401 / 5400) loss: 2.037848
(Iteration 1601 / 5400) loss: 1.980791
(Epoch 1 / 3) train acc: 29.80% val_acc: 28.16%
(Iteration 1801 / 5400) loss: 1.992676
(Iteration 2001 / 5400) loss: 1.923459
(Iteration 2201 / 5400) loss: 1.522694
(Iteration 2401 / 5400) loss: 2.085683
(Iteration 2601 / 5400) loss: 1.694311
(Iteration 2801 / 5400) loss: 1.973651
(Iteration 3001 / 5400) loss: 1.549451
(Iteration 3201 / 5400) loss: 1.939619
(Iteration 3401 / 5400) loss: 1.613157
(Epoch 2 / 3) train acc: 38.90% val_acc: 40.12%
(Iteration 3601 / 5400) loss: 1.709699
(Iteration 3801 / 5400) loss: 1.254350
(Iteration 4001 / 5400) loss: 1.589834

(Iteration 4201 / 5400) loss: 1.302215
...
(Iteration 4801 / 5400) loss: 1.333149
(Iteration 5001 / 5400) loss: 1.675020
(Iteration 5201 / 5400) loss: 1.180103
(Epoch 3 / 3) train acc: 41.50% val_acc: 45.50%

c)



Test accuracy: 45.15%

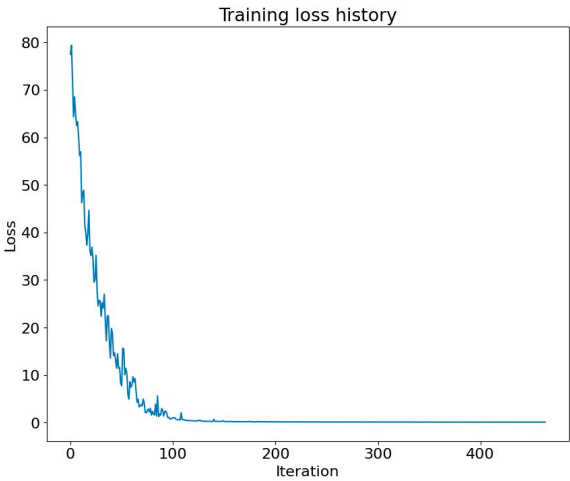












2) Application to Image Captioning

a) Autograder


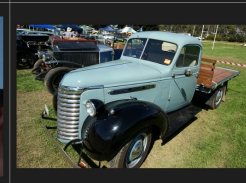


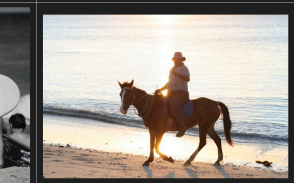

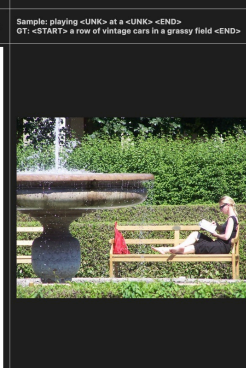
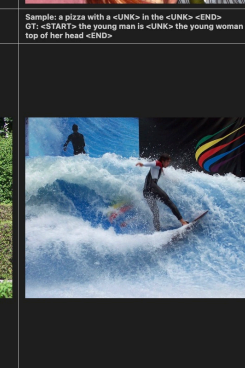
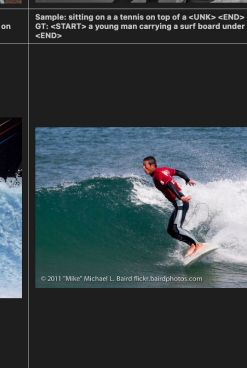
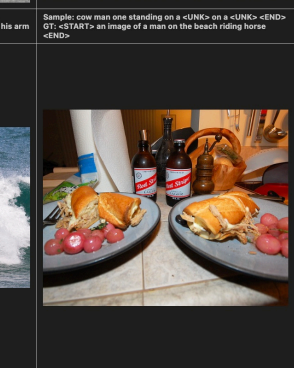
b) Autograder

c)



Training samples				
				
Sample: two people walking down a street holding an umbrella <END> GT: <START> two people walking down a street holding an umbrella <END>	Sample: the plate is filled with meat and vegetables <END> GT: <START> the plate is filled with meat and vegetables <END>	Sample: tennis player in a tennis court <UNK> with her tennis racket <END> GT: <START> tennis player in a tennis court <UNK> with her tennis racket <END>	Sample: a man in a blue shirt holding a white plate with some food on it <END> GT: <START> a man in a blue shirt holding a white plate with some food on it <END>	Sample: a <UNK> vase being displayed in a <UNK> <END> GT: <START> a <UNK> vase being displayed in a <UNK> <END>
				
Sample: a person is standing on the water on a <UNK> board <END> GT: <START> a person is standing on the water on a <UNK> board <END>	Sample: a traffic signal with a very big pretty building by it <END> GT: <START> a traffic signal with a very big pretty building by it <END>	Sample: a very big room with a big pretty clock <END> GT: <START> a very big room with a big pretty clock <END>	Sample: many beautiful fruit <UNK> line the shelves in the market <END> GT: <START> many beautiful fruit <UNK> line the shelves in the market <END>	Sample: a double decker green bus driving down a <UNK> road near a lake <END> GT: <START> a double decker green bus driving down a <UNK> road near a lake <END>

Validation samples

				
Sample: <UNK> <UNK> on a table near the boat <END> GT: <START> a herd of sheep that are walking through a large group of people <END>	Sample: playing <UNK> at a <UNK> <END> GT: <START> a row of vintage cars in a grassy field <END>	Sample: a pizza with a <UNK> in the <UNK> <END> GT: <START> the young man is <UNK> the young woman on top of her head <END>	Sample: sitting on a tennis on top of a <UNK> <END> GT: <START> a young man carrying a surf board under his arm <END>	Sample: cow man one standing on a <UNK> on a <UNK> <END> GT: <START> an image of a man on the beach riding horse <END>
				
Sample: a man and a the <UNK> on a baseball across a <UNK> <END> GT: <START> a person holding a baseball bat in a <UNK> cage <END>	Sample: a man and up a truck <UNK> with a <UNK> street <END> GT: <START> a woman is reading on a park bench beside a <UNK> <END>	Sample: a person on a jacket and on <UNK> <UNK> to the <END> GT: <START> a person who is surfing in a wave pool <END>	Sample: there woman a woman next to a forest <END> GT: <START> a man that is surfing on a wave in water <END>	Sample: the <UNK> with a <UNK> on <UNK> <UNK> a the <UNK> <END> GT: <START> a meal of sandwiches potatoes and red <UNK> beer <END>

3) Transfer Learning

a)

transfer learning		
Test Case	Passed	Score
submitted transfer_learning.py?	✓	1/1
submitted transfer_learning.ipynb?	✓	1/1

b)

Performance of pre-trained model without finetuning

Training complete in 0m 26s

Best val Acc: 0.509804

Finetune the model

Epoch 0/4

train Loss: 0.6573 Acc: 0.6762

val Loss: 0.2386 Acc: 0.9346

Epoch 1/4

train Loss: 0.4575 Acc: 0.8197

val Loss: 0.3018 Acc: 0.8954

Epoch 2/4

train Loss: 0.4725 Acc: 0.7992

val Loss: 0.4032 Acc: 0.8497

Epoch 3/4

train Loss: 0.6934 Acc: 0.7664

val Loss: 0.2935 Acc: 0.9150

Epoch 4/4

train Loss: 0.5843 Acc: 0.7459

val Loss: 0.2266 Acc: 0.9216

Training complete in 4m 49s

Best val Acc: 0.934641

Performance of pre-trained model without finetuning

Training complete in 0m 25s

Best val Acc: 0.555556

Finetune the model

Epoch 0/4

train Loss: 0.6224 Acc: 0.6762

val Loss: 0.4306 Acc: 0.8235

Epoch 1/4

train Loss: 0.5809 Acc: 0.7213

val Loss: 0.1828 Acc: 0.9412

Epoch 2/4

train Loss: 0.4972 Acc: 0.7705

val Loss: 0.2076 Acc: 0.9346

Epoch 3/4

train Loss: 0.4346 Acc: 0.8033

val Loss: 0.2356 Acc: 0.9085

Epoch 4/4

train Loss: 0.3156 Acc: 0.8811

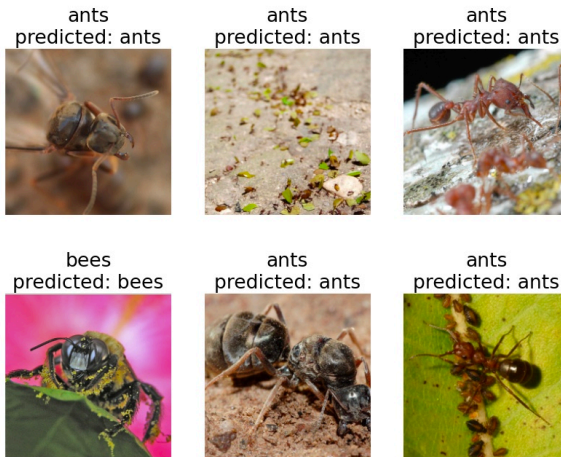
val Loss: 0.1979 Acc: 0.9412

Training complete in 4m 11s

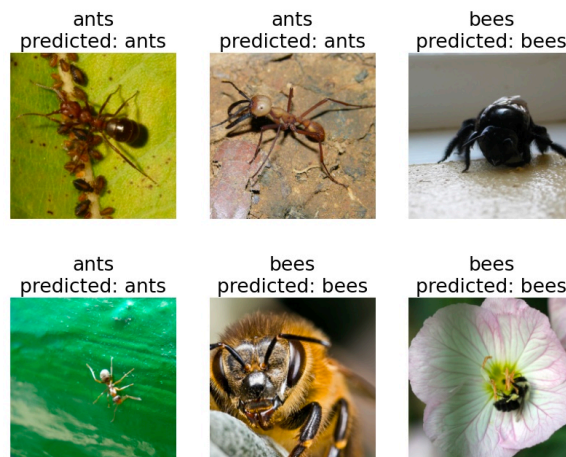
Best val Acc: 0.941176

c)

Finetuned Model Predictions



Frozen Model Predictions

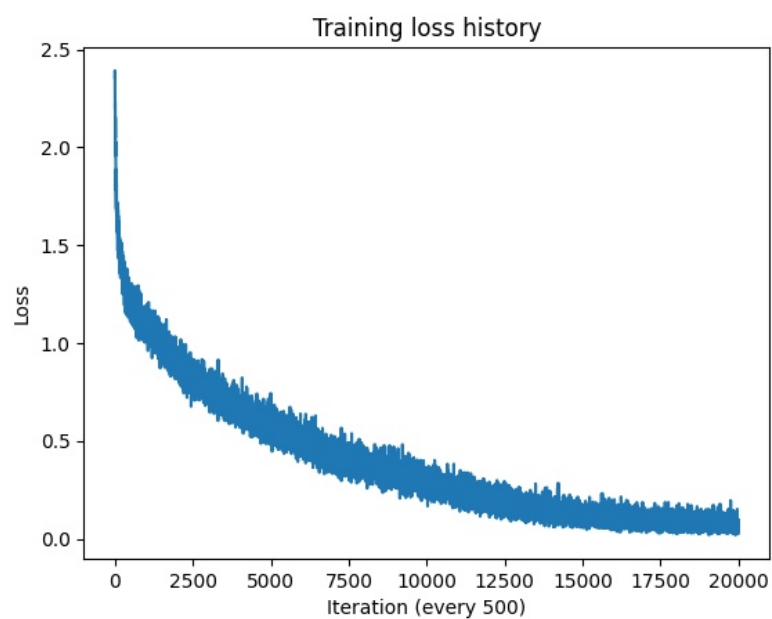


4) Transformer Neural Networks

a) Autograder

b) train accuracy: 98.91%

test accuracy: 85.00%



c)

Iteration 15000/15000: training loss 0.6190

Story (1):

Once upon a time, there was a little bird named Tweety. Tweety loved to play with his rock with all kinds of toys. One day, he found a crack that made him go vroom. They were very happy to see the crack hiding some pictures.

The crack bought the story and checkered her eyes.

Tweety ran to the city and said to the crack. But it would not come true. Sam saved the rick to think where he would find it. Mr. Smith looked around and saw many different things to do. He had no finguing to come inside next to the forest.

At the end of the dark, Lily found a small hole in the window. She was so happy to have found the honey for a long time ago. They said, "Let's go inside, Mom!" They hugged Lily and said, "Thank you for taught us to be kind. And take the honey soon soon." From then on, Lily practiced pupping and hit hands on the wallet. They had so much fun with their new honey that took Lily honked in dough.

Story (2):

Once there was an old man. He wanted to back to his truck. He could not wait to try it.

"Let's go, Tom," his mom replied. "Maybe we can have something else too."

"OK, Ben," Tom said. "We can make something big and beautiful."

They worked together to display the truck. Lily was happy to show them how to fix them them. Her favorite toys mixed so they could show them all her friends. They were happy and gentle with their friends.

Story (3):

One day, Tim was playing with his friend, a little fish, came and saw a big tree with a big rock, and said, "Help, what's inside?" Tim agreed, and Tim followed Tim for a long time. They scooped the rock and turned around the tree, packing from the tree. They were happy to be their friends.