

深度視覺

HW5 : Neural Network

notebook 執行過程

依照說明，forward 代表實現該函數，backward 代表計算 gradient

實現 layer 中的 Sigmoid 函數

Task: Implement

Open the file `exercise_code/networks/layer.py`. Implement the `forward` and the `backward` method in the `Sigmoid` class, and test your implementation by running the following cell.

```
[5] # Test your sigmoid implementation
print(SigmoidTestWrapper())
```

SigmoidForwardTest passed.
SigmoidBackwardTest passed.
Congratulations! You have passed all the unit tests!!! Tests passed: 2/2
Score: 100/100
You secured a score of: 100

```
8     def forward(self, x):
9         """
10            :param x: Inputs, of any shape
11
12            :return outputs: Outputs, of the same shape as x
13            :return cache: Cache, stored for backward computation, of the same shape as x
14            """
15         shape = x.shape
16         outputs, cache = np.zeros(shape), np.zeros(shape)
17         #####
18         # TODO:
19         # Implement the forward pass of Sigmoid activation function
20         #####
21
22         outputs = 1 / (1 + np.exp(-x))
23         cache = (x, outputs)
24
25         #####
26         #                                     END OF YOUR CODE
27         #####
28         return outputs, cache
```

```
30     def backward(self, dout, cache):
31         """
32            :return: dx: the gradient w.r.t. input X, of the same shape as X
33            """
34         dx = None
35         #####
36         # TODO:
37         # Implement the backward pass of Sigmoid activation function
38         #####
39
40         dx = cache[1] * (1-cache[1]) * dout
41
42         #####
43         #                                     END OF YOUR CODE
44         #####
45         return dx
```

實現 layers 中的 ReLU 函數(max(0, x))

Task: Implement

Open the file `exercise_code/networks/layer.py`. Implement the `forward` and the `backward` method in the `Relu` class, and test your implementation by running the following cell.

```
[6] # Test your ReLu implementation
    print(ReluTestWrapper())

ReluForwardTest passed.
ReluBackwardTest passed.
Congratulations! You have passed all the unit tests!!! Tests passed: 2/2
Score: 100/100
You secured a score of: 100
```

```
52     def forward(self, x):
53         """
54         :param x: Inputs, of any shape
55
56         :return out: Outputs, of the same shape as x
57         :return cache: Cache, stored for backward computation, of the same shape as x
58         """
59         outputs = None
60         cache = None
61         #####
62         # TODO:
63         # Implement the forward pass of Relu activation function
64         #####
65
66         outputs = np.array(list(map(lambda x: x if x > 0 else 0, x.ravel()))).reshape(x.shape)
67         cache = (x, outputs)
68
69         #####
70         #                                     END OF YOUR CODE
71         #####
72         return outputs, cache
73
74     def backward(self, dout, cache):
75         """
76         :return: dx: the gradient w.r.t. input X, of the same shape as X
77         """
78         dx = None
79         #####
80         # TODO:
81         # Implement the backward pass of Relu activation function
82         #####
83
84         dx = np.array(list(map(lambda x: 1 if x > 0 else 0, cache[1].ravel()))).reshape(cache[1].shape) * dout
85
86         #####
87         #                                     END OF YOUR CODE
88         #####
89         return dx
```

實作 layer 中的 affine_forward、affine_backward

Task: Implement

Open the file `exercise_code/networks/layer.py`. Implement the `affine_forward` and the `affine_backward` function and test your implementation by running the following cell.

```
[7] # Test your affine layer implementations
    print(AffineTestWrapper())

AffineForwardTest passed.
AffineBackwardTestDx passed.
AffineBackwardTestDw passed.
AffineBackwardTestDb passed.
Congratulations! You have passed all the unit tests!!! Tests passed: 4/4
Score: 100/100
You secured a score of: 100
```

Forward : 計算 $WX+b$

```
92 def affine_forward(x, w, b):
93     """
94     Computes the forward pass for an affine (fully-connected) layer.
95     The input x has shape (N, d_1, ..., d_k) and contains a minibatch of N
96     examples, where each example x[i] has shape (d_1, ..., d_k). We will
97     reshape each input into a vector of dimension D = d_1 * ... * d_k, and
98     then transform it to an output vector of dimension M.
99     Inputs:
100     :param x: A numpy array containing input data, of shape (N, d_1, ..., d_k)
101     :param w: A numpy array of weights, of shape (D, M)
102     :param b: A numpy array of biases, of shape (M,)
103     :return out: output, of shape (N, M)
104     :return cache: (x, w, b)
105     """
106     N, M = x.shape[0], b.shape[0]
107     out = np.zeros((N, M))
108     #####
109     # TODO: Implement the affine forward pass. Store the result in out.      #
110     # You will need to reshape the input into rows.                        #
111     #####
112
113     out = np.dot(w.T, x.reshape(N, -1).T).T + b
114
115     #####
116     #                                     END OF YOUR CODE
117     #####
118     cache = (x, w, b)
119     return out, cache
```

Backward 計算 x 、 w 、 b 之 gradient

```
122 def affine_backward(dout, cache):
123     """
124     Computes the backward pass for an affine layer.
125     Inputs:
126     :param dout: Upstream derivative, of shape (N, M)
127     :param cache: Tuple of:
128         - x: Input data, of shape (N, d_1, ... d_k)
129         - w: Weights, of shape (D, M)
130         - b: A numpy array of biases, of shape (M,)
131     :return dx: Gradient with respect to x, of shape (N, d_1, ..., d_k)
132     :return dw: Gradient with respect to w, of shape (D, M)
133     :return db: Gradient with respect to b, of shape (M,)
134     """
135     x, w, b = cache
136     dx, dw, db = None, None, None
137     #####
138     # TODO: Implement the affine backward pass.
139     # Hint: Don't forget to average the gradients dw and db
140     #####
141
142     dx = np.dot(w, dout.T).T.reshape(x.shape)
143     dw = np.dot(x.reshape(x.shape[0], -1).T, dout).reshape(w.shape) / x.shape[0]
144     db = dout.sum(axis = 0).reshape(b.shape) / x.shape[0]
145
146     #####
147     #                                     END OF YOUR CODE
148     #####
149     return dx, dw, db
```

CIFAR10 Dataset 建立與測試

```
[9] os.chdir('/content')

[10] # Define output path similar to exercise 3
i2dl_exercises_path = os.path.dirname(os.path.abspath(os.getcwd()))
cifar_root = os.path.join(i2dl_exercises_path, "datasets", "cifar10")

# Dictionary so that we can convert label indices to actual label names
classes = [
    'plane', 'car', 'bird', 'cat', 'deer',
    'dog', 'frog', 'horse', 'ship', 'truck',
]

# Simply call dataset class
dataset = ImageFolderDataset(
    root=cifar_root
)

Downloading https://cdn3.vision.in.tum.de/~dl4cv/cifar10.zip to /datasets/cifar10/cifar10.zip
120725504it [00:06, 19719567.34it/s]
```

Now we can set up a dataset iterate over it and visualize images as well as labels easily just like that.

```
[11] num_images = 3

for i in range(num_images):
    item = dataset[i]
    image = item['image']
    label = item['label']

    # Print shape and label
    print('Sample {} \nimage shape: {} \nlabel: {}'.format(
        i, image.shape, classes[label]))

    # Visualize image
    plt.subplot(1, num_images, 1 + i)
    plt.imshow(image.astype('uint8'))

print('\nSample images')
plt.show()

Sample 0
image shape: (32, 32, 3)
label: bird
Sample 1
image shape: (32, 32, 3)
label: cat
Sample 2
image shape: (32, 32, 3)
label: truck

Sample images
```


Task: Proof

Think about why this solves the numerical stability problem and prove that $\sigma(x) = \sigma(x + c)$ for any constant vector $c \in \mathbb{R}^n$.

With that proof, we can simply switch out the softmax computation with the new vector above and avoid numerical instabilities.

證明若將 softmax 的輸入 x 的每一項都加上一個常數後，結果會與原本相同

$$\sigma(x+c) = \frac{e^{x_i+c}}{\sum_{i=1}^n e^{x_i+c}} = \frac{e^{x_i} \cdot e^c}{\sum_{i=1}^n (e^{x_i} \cdot e^c)} = \frac{e^c \cdot e^{x_i}}{e^c \sum_{i=1}^n e^{x_i}} = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_i}} = \sigma(x)$$

Sanity Check

Let's quickly check if our loss formulation works as intended. Let's compute the loss of a random vector from our network defined above.

```
[17] # Set up loss
loss_func = CrossEntropyFromLogits()

# Sample input from a single image
sample_image = dataset[0]['image']
sample_label = dataset[0]['label']
single_image_batch = np.expand_dims(sample_image, 0)
single_label_batch = np.expand_dims(sample_label, 0)

# Feed forward using our network
model_output = model.forward(single_image_batch)

# Loss computation
computed_loss, _ = loss_func(model_output, single_label_batch)
print('Loss of single image sample:', computed_loss)
```

Loss of single image sample: 2.3025235137032287

Task: Reason

Why do we expect our loss to be close to $-\log(0.1)$? Explain briefly.

$\text{CE}(y, \hat{y})$ 可以透過 $\text{softmax}(x)$ 模擬。又因為 $\text{softmax}(x)$ 是一個代表機率的函數(部分/全體)，所以可知 $\text{softmax}(x) \leq 1$ ，且

$$-\log(0.1) = -\log(10^{-1}) = (-1) * (-\log(10)) = \log(10) = 1$$

所以可以預期 loss 會近似於 $-\log(0.1) = 1$

計算 Neural Network 的大小

Optional: Check Code

Check our implementation to compute the size of a network forward pass in bytes in `exercise_code/networks/compute_network_size.py`, which simply sums up the caches values as well as gradients. You should also think about how and why those caches/gradients are populated using the steps above.

Nice! That is the amount of memory required to do a full training forward and backward pass using our small batch.

However, if we wanted to compute the memory required to do a full gradient update for the CIFAR10 dataset using our small network, you'd need...

```
[22] # A current batch consists of 8 images. The whole dataset would require 50000/8 times the amount of memory
num_bytes = num_bytes * 50000 / 8

print('Total number of bytes used by network for the whole dataset', GetHumanReadable(num_bytes))
```

Total number of bytes used by network for the whole dataset 36.81GB

SGD 實作

Note: Good Practice

Always, always, always when starting a new project or defining a new network: **overfit on a small set first and then generalize**. The 500 images we are using here are already too many sample for most cases. Start with a single sample, then 10 and finally a few hundred. Don't cheap out on this step! More often, your network will fail to generalize properly and you have to first know if it has enough capacity to overfit and that the full training pipeline is working!

In order to run these experiments, you don't necessarily need a validation set. Just a few training samples are enough to make those checks!

```
[23] # Redefine model and loss function
      model = ClassificationNet(input_size=input_size,
                               hidden_size=128,
                               activation=Relu(),
                               num_layer=2,
                               num_classes=10)

      loss_func = CrossEntropyFromLogits()

[24] learning_rate = 1e-2

      # We use our training dataloader for validation as well as testing
      solver = Solver(model, dataloader, dataloader,
                      learning_rate=learning_rate, loss_func=loss_func, optimizer=SGD)

      # This might take a while depending on your hardware. When in doubt: use google colab
      solver.train(epochs=20)

(Epoch 1 / 20) train loss: 2.302592; val loss: 2.302594
(Epoch 2 / 20) train loss: 2.302559; val loss: 2.302325
(Epoch 3 / 20) train loss: 2.302292; val loss: 2.302050
```

SGD + Momentum 實作：藉由更新 velocity 來計算 learning rating

4.3 SGD + Momentum

As you can see, the loss is going down smoothly which indicates that we are easily overfitting. Great. However, plain SGD is rarely used in practice (as it is usually too slow) which is why we will focus on implementing SGD+Momentum now, which is a straightforward extension to SGD.

Recall that its update rule is defined by:

$$\begin{aligned} v^{k+1} &= \beta v^k - \alpha \nabla_{\theta} L(\theta^k), \\ \theta^{k+1} &= \theta^k + v^{k+1}. \end{aligned}$$

Task: Check Code and Implement

Familiarize yourself with the SGD implementation in `exercise_code/networks/optimizer.py` as well as our general optimization class structure.

Then, implement the `SGDMomentum_update` function which is very similar to the update rule of SGD above.

```
[25] #Test your SGD momentum implementations
      print(SGDMTestWrapper())

SGDM_Weight_Test passed.
SGDM_Velocity_Test passed.
Congratulations you have passed all the unit tests!!! Tests passed: 2/2
Score: 100/100
You secured a score of :100
```

為了以防原先 config["momentum"] 為空，先將 0.9 加入字典中

```
103 def _update(self, w, dw, config, lr):
104     """
105     Update a model parameter
106     """
107     if config is None:
108         config = {}
109     config.setdefault('momentum', 0.9)
110     v = config.get('velocity', np.zeros_like(w))
111     next_w = None
112
113     #####
114     # TODO: Implement the momentum update formula. Store the updated value in
115     # the next_w variable. You should also use and update the velocity v.
116     #####
117
118     b = config.get('momentum')
119     v = b * v - lr * dw
120     next_w = w + v
121
122     #####
123     #                                     END OF YOUR CODE
124     #####
125     config['velocity'] = v
126
127     return next_w, config
```

測試與比較 SGD、SGD+Momentum、Adam

```
[26] learning_rate = 1e-3
num_epochs = 20
loss_func = CrossEntropyFromLogits()

# Compute loss histories for all optimizers
loss_histories = {}

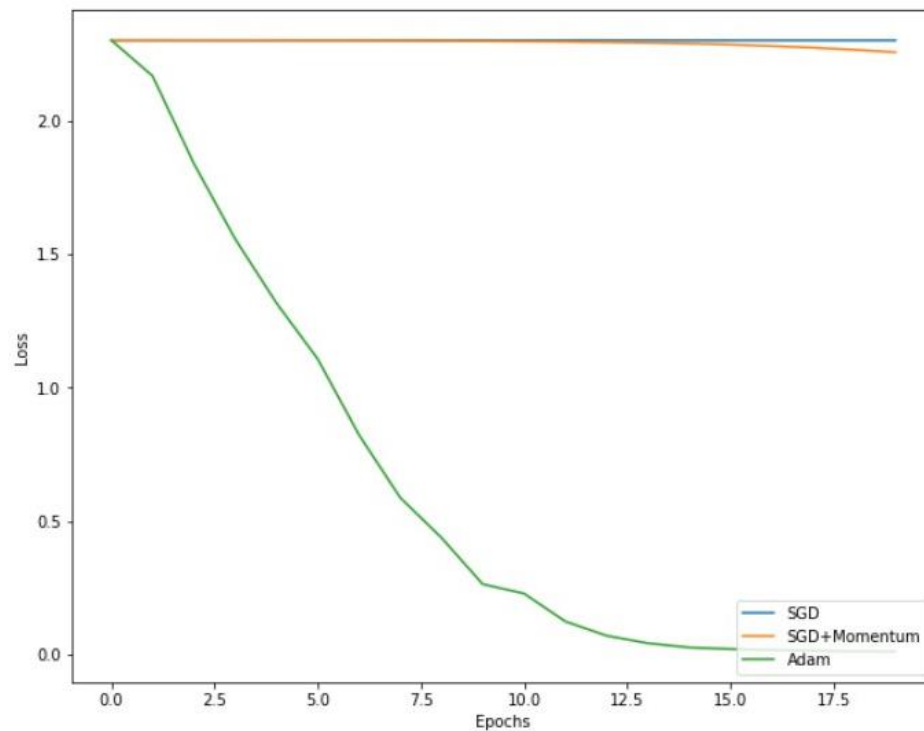
for name, optimizer in zip(['SGD', 'SGD+Momentum', 'Adam'], [SGD, SGDMomentum, Adam]):
    print('Starting {}'.format(name))
    # Reset model
    model = ClassificationNet(input_size=input_size,
                              hidden_size=128,
                              activation=Relu(),
                              num_layer=2,
                              num_classes=10)

    # Set up solver
    solver = Solver(model, dataloader, dataloader,
                    learning_rate=learning_rate, loss_func=loss_func,
                    optimizer=optimizer)

    solver.train(epochs=num_epochs)
    # Save train history to plot later
    loss_histories[name] = solver.train_loss_history
    print()

# Plot them in a shared plot
for name in loss_histories:
    plt.plot(loss_histories[name], '-', label=name)
plt.legend(loc='lower right')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.show()
```

比較結果：



存檔與繳交

7. Submission Instructions

Hooooooray, you trained your model! The model will be saved as a pickle file to `models/NN.p`.

```
[27] from exercise_code.tests import save_pickle
      from exercise_code.networks.layer import *
      from exercise_code.networks.optimizer import SGDMomentum

      save_pickle(
          data_dict={
              "SGD_Momentum_update": SGDMomentum._update,
              "AffineForward": affine_forward,
              "AffineBackward": affine_backward,
              "Sigmoid": Sigmoid,
              "Relu": Relu,
          },
          file_name="NN.p"
      )

[28] from exercise_code.submit import submit_exercise

      submit_exercise('exercise05')

relevant folders: ['models']
notebooks files: []
Adding folder models
Zipping successful! Zip is stored under: /content/exercise05.zip
```