Problem 1: Basics of Neural Networks

- **Learning Objective:** In this problem, you are asked to implement a basic multi-layer fully connected neural network from scratch, including forward and backward passes of certain essential layers, to perform an image classification task on the CIFAR100 dataset. You need to implement essential functions in different indicated python files under directory `lib`.
- **Provided Code:** We provide the skeletons of classes you need to complete. Forward checking and gradient checkings are provided for verifying your implementation as well.
- **TODOs:** You are asked to implement the forward passes and backward passes for standard layers and loss functions, various widely-used optimizers, and part of the training procedure. And finally we want you to train a network from scratch on your own. Also, there are inline questions you need to answer. See `README.md` to set up your environment.

In [1]:
```
from lib.mlp.fully_conn import *
from lib.mlp.layer_utils import *
from lib.datasets import *
from lib.mlp.train import *
from lib.grad_check import *
from lib.optim import *
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ip
%load_ext autoreload
%autoreload 2
```

Loading the data (CIFAR-100 with 20 superclasses)

In this homework, we will be classifying images from the CIFAR-100 dataset into the 20 superclasses. More information about the CIFAR-100 dataset and the 20 superclasses can be found here.

Download the CIFAR-100 data files here, and save the `.mat` files to the `data/cifar100` directory.

Load the dataset.

In [2]:
```
data = CIFAR100_data('data/cifar100/')
for k, v in data.items():
    if type(v) == np.ndarray:
        print ("Name: {} Shape: {}, {}".format(k, v.shape, type(v)))
    else:
        print("{}: {}".format(k, v))
label_names = data['label_names']
mean_image = data['mean_image'][0]
std_image = data['std_image'][0]
```

```
Name: data_train Shape: (40000, 32, 32, 3), <class 'numpy.ndarray'>
Name: labels_train Shape: (40000,), <class 'numpy.ndarray'>
Name: data_val Shape: (10000, 32, 32, 3), <class 'numpy.ndarray'>
Name: labels_val Shape: (10000,), <class 'numpy.ndarray'>
Name: data_test Shape: (10000, 32, 32, 3), <class 'numpy.ndarray'>
Name: labels_test Shape: (10000,), <class 'numpy.ndarray'>
label_names: ['aquatic_mammals', 'fish', 'flowers', 'food_containers', 'fru
it_and_vegetables', 'household_electrical_devices', 'household_furniture',
'insects', 'large_carnivores', 'large_man-made_outdoor_things', 'large_natu
ral_outdoor_scenes', 'large_omnivores_and_herbivores', 'medium_mammals', 'n
on-insect_invertebrates', 'people', 'reptiles', 'small_mammals', 'trees',
'vehicles_1', 'vehicles_2']
Name: mean_image Shape: (1, 1, 1, 3), <class 'numpy.ndarray'>
Name: std_image Shape: (1, 1, 1, 3), <class 'numpy.ndarray'>
```

Implement Standard Layers

You will now implement all the following standard layers commonly seen in a fully connected neural network (aka multi-layer perceptron, MLP). Please refer to the file `lib/mlp/layer_utils.py`. Take a look at each class skeleton, and we will walk you through the network layer by layer. We provide results of some examples we pre-computed for you for checking the forward pass, and also the gradient checking for the backward pass.

FC Forward [2pt]

In the class skeleton `flatten` and `fc` in `lib/mlp/layer_utils.py`, please complete the forward pass in function `forward`. The input to the `fc` layer may not be of dimension (batch size, features size), it could be an image or any higher dimensional data. We want to convert the input to have a shape of (batch size, features size). Make sure that you handle this dimensionality issue.

In [3]:
```
%reload_ext autoreload

# Test the fc forward function
input_bz = 3 # batch size
input_dim = (7, 6, 4)
```

```
output_dim = 4

input_size = input_bz * np.prod(input_dim)
weight_size = output_dim * np.prod(input_dim)

flatten_layer = flatten(name="flatten_test")
single_fc = fc(np.prod(input_dim), output_dim, init_scale=0.02, name="fc_tes

x = np.linspace(-0.1, 0.4, num=input_size).reshape(input_bz, *input_dim)
w = np.linspace(-0.2, 0.2, num=weight_size).reshape(np.prod(input_dim), outp
b = np.linspace(-0.3, 0.3, num=output_dim)

single_fc.params[single_fc.w_name] = w
single_fc.params[single_fc.b_name] = b

out = single_fc.forward(flatten_layer.forward(x))

correct_out = np.array([[0.63910291, 0.83740057, 1.03569824, 1.23399591],
                        [0.61401587, 0.82903823, 1.04406058, 1.25908294],
                        [0.58892884, 0.82067589, 1.05242293, 1.28416997]])

# Compare your output with the above pre-computed ones.
# The difference should not be larger than 1e-8
print ("Difference: ", rel_error(out, correct_out))
```

```
Difference:  4.0260162945880345e-09
```

FC Backward [2pt]

Please complete the function `backward` as the backward pass of the `flatten` and `fc` layers. Follow the instructions in the comments to store gradients into the predefined dictionaries in the attributes of the class. Parameters of the layer are also stored in the predefined dictionary.

In [4]:
```
%reload_ext autoreload

# Test the fc backward function
inp = np.random.randn(15, 2, 2, 3)
w = np.random.randn(12, 15)
b = np.random.randn(15)
dout = np.random.randn(15, 15)

flatten_layer = flatten(name="flatten_test")
x = flatten_layer.forward(inp)
single_fc = fc(np.prod(x.shape[1:]), 15, init_scale=5e-2, name="fc_test")
single_fc.params[single_fc.w_name] = w
single_fc.params[single_fc.b_name] = b

dx_num = eval_numerical_gradient_array(lambda x: single_fc.forward(x), x, do
dw_num = eval_numerical_gradient_array(lambda w: single_fc.forward(x), w, do
db_num = eval_numerical_gradient_array(lambda b: single_fc.forward(x), b, do

out = single_fc.forward(x)
dx = single_fc.backward(dout)
```

```
dw = single_fc.grads[single_fc.w_name]
db = single_fc.grads[single_fc.b_name]
dinp = flatten_layer.backward(dx)

# The error should be around 1e-9
print("dx Error: ", rel_error(dx_num, dx))
# The errors should be around 1e-10
print("dw Error: ", rel_error(dw_num, dw))
print("db Error: ", rel_error(db_num, db))
# The shapes should be same
print("dinp Shape: ", dinp.shape, inp.shape)
```

```
dx Error:  2.8355684912930893e-09
dw Error:  1.0635671541838665e-09
db Error:  7.493461688506616e-11
dinp Shape:  (15, 2, 2, 3) (15, 2, 2, 3)
```

GeLU Forward [2pt]

In the class skeleton `gelu` in `lib/mlp/layer_utils.py`, please complete the `forward` pass.

GeLU is a smooth version of ReLU and it's used in pre-training LLMs such as GPT-3 and BERT.

$$\mathrm{GeLU}(x) = x\Phi(x) \approx 0.5x(1 + \tanh(\sqrt{2/\pi}(x + 0.044715x^3)))$$

Where $\Phi(x)$ is the CDF for standard Gaussian random variables. You should use the approximate version to compute forward and backward pass.

In [5]:
```
%reload_ext autoreload

# Test the leaky_relu forward function
x = np.linspace(-1.5, 1.5, num=12).reshape(3, 4)
gelu_f = gelu(name="gelu_f")

out = gelu_f.forward(x)
correct_out = np.array([[-0.10042842, -0.13504766, -0.16231757, -0.1689214 ]
                        [-0.13960493, -0.06078651,  0.07557713,  0.26948598]
                        [ 0.51289678,  0.79222788,  1.09222506,  1.39957158]

# Compare your output with the above pre-computed ones.
# The difference should not be larger than 1e-7
print ("Difference: ", rel_error(out, correct_out))
```

```
Difference:  1.8037541876132445e-08
```

GeLU Backward [2pt]

Please complete the `backward` pass of the class `gelu`.

In [6]:
```
%reload_ext autoreload

# Test the relu backward function
x = np.random.randn(15, 15)
dout = np.random.randn(*x.shape)
gelu_b = gelu(name="gelu_b")

dx_num = eval_numerical_gradient_array(lambda x: gelu_b.forward(x), x, dout)

out = gelu_b.forward(x)
dx = gelu_b.backward(dout)

# The error should not be larger than 1e-4, since we are using an approximat
print ("dx Error: ", rel_error(dx_num, dx))
```

```
dx Error:  1.1785849688294396e-09
```

Dropout Forward [2pt]

In the class `dropout` in `lib/mlp/layer_utils.py`, please complete the `forward` pass.

Remember that the dropout is **only applied during training phase**, you should pay attention to this while implementing the function.

Important Note1: The probability argument input to the function is the "keep probability": probability that each activation is kept.

Important Note2: If the keep_prob is set to 1, make it as no dropout.

In [7]:
```
%reload_ext autoreload

x = np.random.randn(100, 100) + 5.0

print ("----------------------------------------------------------------")
for p in [0, 0.25, 0.50, 0.75, 1]:
    dropout_f = dropout(keep_prob=p)
    out = dropout_f.forward(x, True)
    out_test = dropout_f.forward(x, False)

    # Mean of output should be similar to mean of input
    # Means of output during training time and testing time should be simila
    print ("Dropout Keep Prob = ", p)
    print ("Mean of input: ", x.mean())
    print ("Mean of output during training time: ", out.mean())
    print ("Mean of output during testing time: ", out_test.mean())
    print ("Fraction of output set to zero during training time: ", (out ==
    print ("Fraction of output set to zero during testing time: ", (out_test
    print ("----------------------------------------------------------------
```

```
----------------------------------------------------------------
Dropout Keep Prob =  0
Mean of input:  4.992512948311678
Mean of output during training time:  4.992512948311678
Mean of output during testing time:  4.992512948311678
Fraction of output set to zero during training time:  0.0
Fraction of output set to zero during testing time:  0.0
----------------------------------------------------------------
Dropout Keep Prob =  0.25
Mean of input:  4.992512948311678
Mean of output during training time:  4.759288997009822
Mean of output during testing time:  4.992512948311678
Fraction of output set to zero during training time:  0.7622
Fraction of output set to zero during testing time:  0.0
----------------------------------------------------------------
Dropout Keep Prob =  0.5
Mean of input:  4.992512948311678
Mean of output during training time:  4.8880787586487395
Mean of output during testing time:  4.992512948311678
Fraction of output set to zero during training time:  0.5093
Fraction of output set to zero during testing time:  0.0
----------------------------------------------------------------
Dropout Keep Prob =  0.75
Mean of input:  4.992512948311678
Mean of output during training time:  5.033513627010743
Mean of output during testing time:  4.992512948311678
Fraction of output set to zero during training time:  0.2454
Fraction of output set to zero during testing time:  0.0
----------------------------------------------------------------
Dropout Keep Prob =  1
Mean of input:  4.992512948311678
Mean of output during training time:  4.992512948311678
Mean of output during testing time:  4.992512948311678
Fraction of output set to zero during training time:  0.0
Fraction of output set to zero during testing time:  0.0
----------------------------------------------------------------
```

Dropout Backward [2pt]

Please complete the `backward` pass. Again remember that the dropout is only applied during training phase, handle this in the backward pass as well.

In [8]:
```
%reload_ext autoreload

x = np.random.randn(5, 5) + 5
dout = np.random.randn(*x.shape)

keep_prob = 0.75
dropout_b = dropout(keep_prob, seed=100)
out = dropout_b.forward(x, True, seed=1)
dx = dropout_b.backward(dout)
dx_num = eval_numerical_gradient_array(lambda xx: dropout_b.forward(xx, True
```

```
# The error should not be larger than 1e-10
print ('dx relative error: ', rel_error(dx, dx_num))
```

```
dx relative error:  3.003119399167029e-11
```

Testing cascaded layers: FC + GeLU [2pt]

Please find the `TestFCGeLU` function in `lib/mlp/fully_conn.py`.
You only need to complete a few lines of code in the TODO block.
Please design an `Flatten -> FC -> GeLU` network where the parameters of them match the given x, w, and b.
Please insert the corresponding names you defined for each layer to param_name_w, and param_name_b respectively. Here you only modify the param_name part, the `_w`, and `_b` are automatically assigned during network setup

In [9]:
```
%reload_ext autoreload

x = np.random.randn(3, 5, 3)  # the input features
w = np.random.randn(15, 5)   # the weight of fc layer
b = np.random.randn(5)       # the bias of fc layer
dout = np.random.randn(3, 5) # the gradients to the output, notice the shape

tiny_net = TestFCGeLU()

###################################################
# TODO: param_name should be replaced accordingly #
###################################################
tiny_net.net.assign("fc_w", w)
tiny_net.net.assign("fc_b", b)
###################################################
#                 END OF YOUR CODE                #
###################################################

out = tiny_net.forward(x)
dx = tiny_net.backward(dout)

###################################################
# TODO: param_name should be replaced accordingly #
###################################################
dw = tiny_net.net.get_grads("fc_w")
db = tiny_net.net.get_grads("fc_b")
###################################################
#                 END OF YOUR CODE                #
###################################################

dx_num = eval_numerical_gradient_array(lambda x: tiny_net.forward(x), x, dou
dw_num = eval_numerical_gradient_array(lambda w: tiny_net.forward(x), w, dou
db_num = eval_numerical_gradient_array(lambda b: tiny_net.forward(x), b, dou

# The errors should not be larger than 1e-7
print ("dx error: ", rel_error(dx_num, dx))
```

```
print ("dw error: ", rel_error(dw_num, dw))
print ("db error: ", rel_error(db_num, db))
```

```
dx error:  2.875124252987862e-10
dw error:  5.166650955492451e-05
db error:  9.525096079066106e-08
```

SoftMax Function and Loss Layer [2pt]

In the `lib/mlp/layer_utils.py`, please first complete the function `softmax`, which will be used in the function `cross_entropy`. Then, implement `corss_entropy` using `softmax`. Please refer to the lecture slides of the mathematical expressions of the cross entropy loss function, and complete its forward pass and backward pass. You should also take care of `size_average` on whether or not to divide by the batch size.

In [10]:
```
%reload_ext autoreload

num_classes, num_inputs = 6, 100
x = 0.001 * np.random.randn(num_inputs, num_classes)
y = np.random.randint(num_classes, size=num_inputs)

test_loss = cross_entropy()

dx_num = eval_numerical_gradient(lambda x: test_loss.forward(x, y), x, verbo

loss = test_loss.forward(x, y)
dx = test_loss.backward()

# Test softmax_loss function. Loss should be around 1.792
# and dx error should be at the scale of 1e-8 (or smaller)
print ("Cross Entropy Loss: ", loss)
print ("dx error: ", rel_error(dx_num, dx))
```

```
Cross Entropy Loss:  1.7917983721983493
dx error:  1.0827842449141255e-08
```

Test a Small Fully Connected Network [2pt]

Please find the `SmallFullyConnectedNetwork` function in `lib/mlp/fully_conn.py`.
Again you only need to complete few lines of code in the TODO block.
Please design an `FC --> GeLU --> FC` network where the shapes of parameters match the given shapes.
Please insert the corresponding names you defined for each layer to param_name_w, and param_name_b respectively.
Here you only modify the param_name part, the `_w`, and `_b` are automatically assigned during network setup.

In [11]:
```
%reload_ext autoreload

seed = 1234
np.random.seed(seed=seed)

model = SmallFullyConnectedNetwork()
loss_func = cross_entropy()

N, D, = 4, 4  # N: batch size, D: input dimension
H, C  = 30, 7 # H: hidden dimension, C: output dimension
std = 0.02
x = np.random.randn(N, D)
y = np.random.randint(C, size=N)

print ("Testing initialization ... ")

###################################################
# TODO: param_name should be replaced accordingly  #
###################################################
w1_std = abs(model.net.get_params("fc1_w").std() - std)
print(w1_std, std / 10)
b1 = model.net.get_params("fc1_b").std()
w2_std = abs(model.net.get_params("fc2_w").std() - std)
b2 = model.net.get_params("fc2_b").std()
###################################################
#                END OF YOUR CODE                 #
###################################################

assert w1_std < std / 10, "First layer weights do not seem right"
assert np.all(b1 == 0), "First layer biases do not seem right"
assert w2_std < std / 10, "Second layer weights do not seem right"
assert np.all(b2 == 0), "Second layer biases do not seem right"
print ("Passed!")

print ("Testing test-time forward pass ... ")
w1 = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
w2 = np.linspace(-0.2, 0.2, num=H*C).reshape(H, C)
b1 = np.linspace(-0.6, 0.2, num=H)
b2 = np.linspace(-0.9, 0.1, num=C)

###################################################
# TODO: param_name should be replaced accordingly  #
###################################################
model.net.assign("fc1_w", w1)
model.net.assign("fc1_b", b1)
model.net.assign("fc2_w", w2)
model.net.assign("fc2_b", b2)
###################################################
#                END OF YOUR CODE                 #
###################################################

feats = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
scores = model.forward(feats)
correct_scores = np.asarray([[-2.33881897, -1.92174121, -1.50466344, -1.0875
                             [-1.57214916, -1.1857013 , -0.79925345, -0.4128
```

```
                                [-0.80178618, -0.44604469, -0.0903032 ,  0.2654
                                [-0.00331319,  0.32124836,  0.64580991,  0.9703
scores_diff = np.sum(np.abs(scores - correct_scores))
assert scores_diff < 1e-6, "Your implementation might be wrong!"
print ("Passed!")

print ("Testing the loss ...",)
y = np.asarray([0, 5, 1, 4])
loss = loss_func.forward(scores, y)
dLoss = loss_func.backward()
correct_loss = 2.4248995879903195
assert abs(loss - correct_loss) < 1e-10, "Your implementation might be wrong
print ("Passed!")

print ("Testing the gradients (error should be no larger than 1e-6) ...")
din = model.backward(dLoss)
for layer in model.net.layers:
    if not layer.params:
        continue
    for name in sorted(layer.grads):
        f = lambda _: loss_func.forward(model.forward(feats), y)
        grad_num = eval_numerical_gradient(f, layer.params[name], verbose=Fa
        print ('%s relative error: %.2e' % (name, rel_error(grad_num, layer.
```

```
Testing initialization ...
0.00047324457430174965 0.002
Passed!
Testing test-time forward pass ...
Passed!
Testing the loss ...
Passed!
Testing the gradients (error should be no larger than 1e-6) ...
fc1_b relative error: 5.94e-09
fc1_w relative error: 1.06e-08
fc2_b relative error: 4.01e-10
fc2_w relative error: 2.50e-08
```

Test a Fully Connected Network regularized with Dropout [2pt]

Please find the `DropoutNet` function in `fully_conn.py` under `lib/mlp` directory.
For this part you don't need to design a new network, just simply run the following test code.
If something goes wrong, you might want to double check your dropout implementation.

In [12]:
```
%reload_ext autoreload

seed = 1234
np.random.seed(seed=seed)

N, D, C = 3, 15, 10
X = np.random.randn(N, D)
y = np.random.randint(C, size=(N,))
```

```
for keep_prob in [0, 0.25, 0.5]:
    np.random.seed(seed=seed)
    print ("Dropout p =", keep_prob)
    model = DropoutNet(keep_prob=keep_prob, seed=seed)
    loss_func = cross_entropy()
    output = model.forward(X, True, seed=seed)
    loss = loss_func.forward(output, y)
    dLoss = loss_func.backward()
    dX = model.backward(dLoss)
    grads = model.net.grads

    print ("Error of gradients should be around or less than 1e-3")
    for name in sorted(grads):
        if name not in model.net.params.keys():
            continue
        f = lambda _: loss_func.forward(model.forward(X, True, seed=seed), y
        grad_num = eval_numerical_gradient(f, model.net.params[name], verbos
        print ("{} relative error: {}".format(name, rel_error(grad_num, grad
    print ()
```

```
Dropout p = 0
Error of gradients should be around or less than 1e-3
fc1_b relative error: 9.824168508277432e-08
fc1_w relative error: 4.706355825013066e-06
fc2_b relative error: 1.133402768221828e-08
fc2_w relative error: 3.1672231525171774e-05
fc3_b relative error: 2.0518174276833617e-10
fc3_w relative error: 2.720304740415546e-06

Dropout p = 0.25
Error of gradients should be around or less than 1e-3
fc1_b relative error: 3.999389219427179e-07
fc1_w relative error: 8.179318698085921e-06
fc2_b relative error: 1.1076481195535879e-08
fc2_w relative error: 1.6687639406224407e-05
fc3_b relative error: 2.457979279712419e-10
fc3_w relative error: 8.853121862924033e-07

Dropout p = 0.5
Error of gradients should be around or less than 1e-3
fc1_b relative error: 1.1627314962924926e-07
fc1_w relative error: 1.1142454961437094e-06
fc2_b relative error: 1.4365119640657006e-07
fc2_w relative error: 5.060201349801403e-06
fc3_b relative error: 2.3684339866586803e-10
fc3_w relative error: 6.610872364250095e-06
```

Training a Network

In this section, we defined a `TinyNet` class for you to fill in the TODO block in `lib/mlp/fully_conn.py`.

- Here please design a two layer fully connected network with Leaky ReLU activation (`Flatten --> FC --> GeLU --> FC`).
- You can adjust the number of hidden neurons, batch_size, epochs, and learning rate decay parameters.
- Please read the `lib/train.py` carefully and complete the TODO blocks in the `train_net` function first. Codes in "Test a Small Fully Connected Network" can be helpful.
- Implement SGD in `lib/optim.py`, you will be asked to complete weight decay and Adam in the later sections.

In [13]:
```
# Arrange the data
data_dict = {
    "data_train": (data["data_train"], data["labels_train"]),
    "data_val": (data["data_val"], data["labels_val"]),
    "data_test": (data["data_test"], data["labels_test"])
}
```

In [14]:
```
print("Data shape:", data["data_train"].shape)
print("Flattened data input size:", np.prod(data["data_train"].shape[1:]))
print("Number of data classes:", max(data['labels_train']) + 1)
```

```
Data shape: (40000, 32, 32, 3)
Flattened data input size: 3072
Number of data classes: 20
```

Now train the network to achieve at least 30% validation accuracy [5pt]

You may only adjust the hyperparameters inside the TODO block

In [15]:
```
%autoreload
```

In [16]:
```
%reload_ext autoreload

seed = 123
np.random.seed(seed=seed)

model = TinyNet()
loss_f = cross_entropy()
optimizer = SGD(model.net, 0.1)

results = None
############################################################################
# TODO: Use the train_net function you completed to train a network
############################################################################
batch_size = 100
epochs = 5
lr_decay = 0.99
lr_decay_every = 100
############################################################################
#                              END OF YOUR CODE
```

```
#######################################################################
results = train_net(data_dict, model, loss_f, optimizer, batch_size, epochs,
                    lr_decay, lr_decay_every, show_every=10000, verbose=True
opt_params, loss_hist, train_acc_hist, val_acc_hist = results
```

```
  1%|▏         | 5/400 [00:00<00:16, 24.36it/s]
(Iteration 1 / 2000) Average loss: 3.0628587499151663
100%|██████████| 400/400 [00:13<00:00, 29.31it/s]
(Epoch 1 / 5) Training Accuracy: 0.31385, Validation Accuracy: 0.2855
100%|██████████| 400/400 [00:15<00:00, 25.70it/s]
(Epoch 2 / 5) Training Accuracy: 0.36775, Validation Accuracy: 0.3152
100%|██████████| 400/400 [00:14<00:00, 27.68it/s]
(Epoch 3 / 5) Training Accuracy: 0.39525, Validation Accuracy: 0.3165
 63%|██████▎   | 252/400 [00:08<00:04, 32.80it/s]/Users/dch239/Desktop/USC/
Spring 2023/CSCI 566/csci566-assignment1/lib/mlp/layer_utils.py:242: Runtim
eWarning: overflow encountered in power
  df = 0.5*(1 + np.tanh(temp)) + (feat / (np.sqrt(2*np.pi))) * (0.134145 *
np.power(feat, 2) + 1) * (1 / (np.power(np.cosh(temp), 2)))
100%|██████████| 400/400 [00:12<00:00, 31.17it/s]
(Epoch 4 / 5) Training Accuracy: 0.442775, Validation Accuracy: 0.3341
100%|██████████| 400/400 [00:12<00:00, 31.21it/s]
(Epoch 5 / 5) Training Accuracy: 0.444775, Validation Accuracy: 0.3164
```

In [17]:

```
# Take a look at what names of params were stored
print (opt_params.keys())
```

```
dict_keys(['fc1_w', 'fc1_b', 'fc2_w', 'fc2_b'])
```

In [18]:

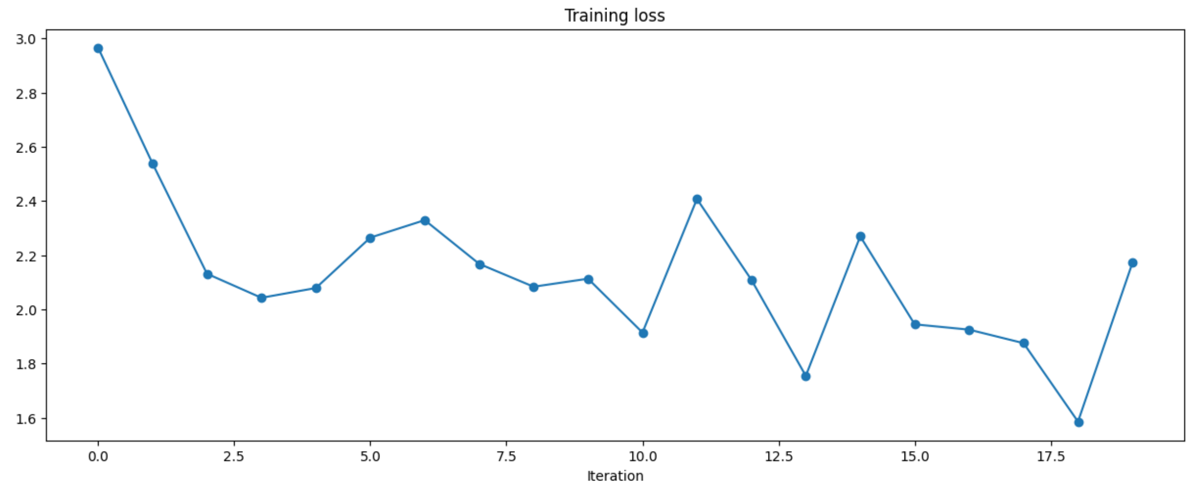
```
# Demo: How to load the parameters to a newly defined network
model = TinyNet()
model.net.load(opt_params)
val_acc = compute_acc(model, data["data_val"], data["labels_val"])
print ("Validation Accuracy: {}%".format(val_acc*100))
test_acc = compute_acc(model, data["data_test"], data["labels_test"])
print ("Testing Accuracy: {}%".format(test_acc*100))
```

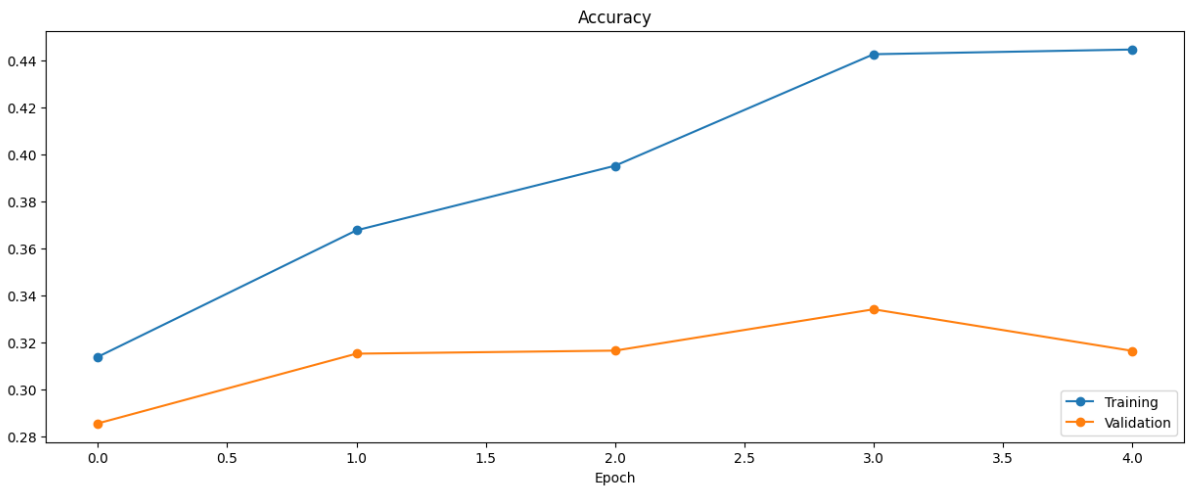
```
Loading Params: fc1_w Shape: (3072, 500)
Loading Params: fc1_b Shape: (500,)
Loading Params: fc2_w Shape: (500, 20)
Loading Params: fc2_b Shape: (20,)
Validation Accuracy: 31.64%
Testing Accuracy: 31.259999999999998%
```

In [19]:

```
# Plot the learning curves
plt.subplot(2, 1, 1)
plt.title('Training loss')
loss_hist_ = loss_hist[1::100] # sparse the curve a bit
plt.plot(loss_hist_, '-o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(train_acc_hist, '-o', label='Training')
plt.plot(val_acc_hist, '-o', label='Validation')
plt.xlabel('Epoch')
```

```
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```





Different Optimizers and Regularization Techniques

There are several more advanced optimizers than vanilla SGD, and there are many regularization tricks. You'll implement them in this section. Please complete the TODOs in the `lib/optim.py`.

SGD + Weight Decay [2pt]

The update rule of SGD plus weigh decay is as shown below:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta J(\theta_t) - \lambda \theta_t$$

Update the `SGD()` function in `lib/optim.py`, and also incorporate weight decay options.

In [20]:
```
%reload_ext autoreload

# Test the implementation of SGD with Momentum
```

```
seed = 1234
np.random.seed(seed=seed)

N, D = 4, 5
test_sgd = sequential(fc(N, D, name="sgd_fc"))

w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)

test_sgd.layers[0].params = {"sgd_fc_w": w}
test_sgd.layers[0].grads = {"sgd_fc_w": dw}


test_sgd_wd = SGD(test_sgd, 1e-3, 1e-4)
test_sgd_wd.step()

updated_w = test_sgd.layers[0].params["sgd_fc_w"]


expected_updated_w = np.asarray([
       [-0.39936   , -0.34678632, -0.29421263, -0.24163895, -0.18906526],
       [-0.13649158, -0.08391789, -0.03134421,  0.02122947,  0.07380316],
       [ 0.12637684,  0.17895053,  0.23152421,  0.28409789,  0.33667158],
       [ 0.38924526,  0.44181895,  0.49439263,  0.54696632,  0.59954   ]])


print ('The following errors should be around or less than 1e-6')
print ('updated_w error: ', rel_error(updated_w, expected_updated_w))
```

```
The following errors should be around or less than 1e-6
updated_w error:  8.677112905190533e-08
```

Comparing SGD and SGD with Weight Decay [2pt]

Run the following code block to train a multi-layer fully connected network with both SGD and SGD plus Weight Decay. You are expected to see Weight Decay have better validation accuracy than vinilla SGD.

In [22]:
```
seed = 1234

# Arrange a small data
num_train = 20000
small_data_dict = {
    "data_train": (data["data_train"][:num_train], data["labels_train"][:num
    "data_val": (data["data_val"], data["labels_val"]),
    "data_test": (data["data_test"], data["labels_test"])
}

reset_seed(seed=seed)
model_sgd      = FullyConnectedNetwork()
loss_f_sgd     = cross_entropy()
optimizer_sgd  = SGD(model_sgd.net, 0.01)
print ("Training with Vanilla SGD...")
results_sgd = train_net(small_data_dict, model_sgd, loss_f_sgd, optimizer_sg
```

```
                         max_epochs=50, show_every=10000, verbose=True)

reset_seed(seed=seed)
model_sgdw     = FullyConnectedNetwork()
loss_f_sgdw    = cross_entropy()
optimizer_sgdw = SGD(model_sgdw.net, 0.01, 1e-4)
print ("\nTraining with SGD plus Weight Decay...")
results_sgdw = train_net(small_data_dict, model_sgdw, loss_f_sgdw, optimizer
                          max_epochs=50, show_every=10000, verbose=True)

opt_params_sgd,  loss_hist_sgd,  train_acc_hist_sgd,  val_acc_hist_sgd  = re
opt_params_sgdw, loss_hist_sgdw, train_acc_hist_sgdw, val_acc_hist_sgdw = re

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 3)
plt.title('Validation accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd, 'o', label="Vanilla SGD")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd, '-o', label="Vanilla SGD")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd, '-o', label="Vanilla SGD")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgdw, 'o', label="SGD with Weight Decay")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgdw, '-o', label="SGD with Weight Decay")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgdw, '-o', label="SGD with Weight Decay")

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
plt.gcf().set_size_inches(15, 15)
plt.show()
```

```
Training with Vanilla SGD...
  0%|          | 1/200 [00:00<00:21,  9.29it/s]
(Iteration 1 / 10000) Average loss: 3.3332154539088985
100%|██████████| 200/200 [00:06<00:00, 30.46it/s]
(Epoch 1 / 50) Training Accuracy: 0.15095, Validation Accuracy: 0.1474
100%|██████████| 200/200 [00:03<00:00, 55.85it/s]
(Epoch 2 / 50) Training Accuracy: 0.18815, Validation Accuracy: 0.1805
100%|██████████| 200/200 [00:04<00:00, 47.18it/s]
(Epoch 3 / 50) Training Accuracy: 0.2107, Validation Accuracy: 0.2029
100%|██████████| 200/200 [00:04<00:00, 42.83it/s]
```

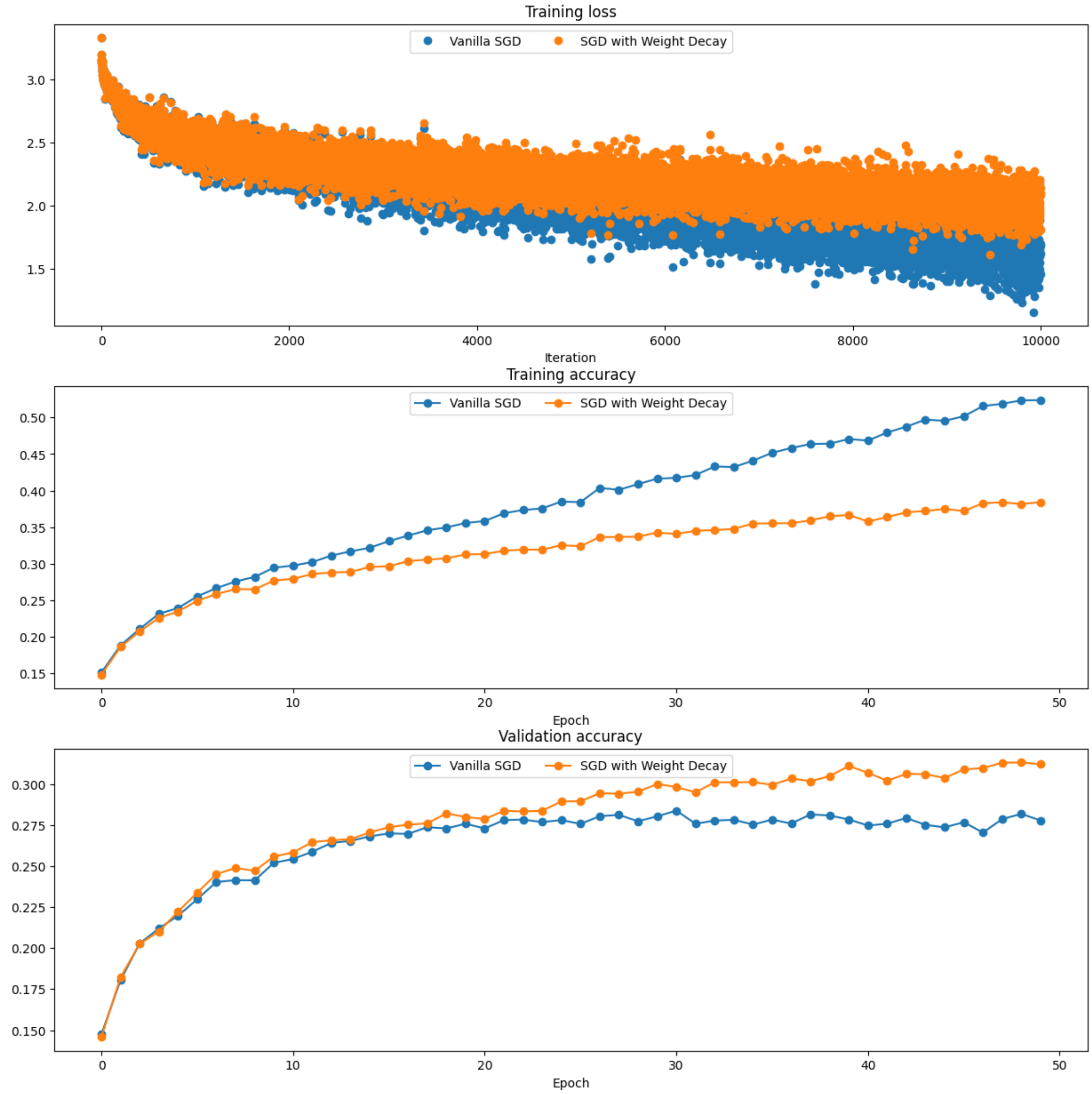
```
(Epoch 4 / 50) Training Accuracy: 0.2314, Validation Accuracy: 0.212
100%|██████████| 200/200 [00:03<00:00, 50.46it/s]
(Epoch 5 / 50) Training Accuracy: 0.23915, Validation Accuracy: 0.2197
100%|██████████| 200/200 [00:04<00:00, 46.19it/s]
(Epoch 6 / 50) Training Accuracy: 0.2552, Validation Accuracy: 0.2298
100%|██████████| 200/200 [00:04<00:00, 43.14it/s]
(Epoch 7 / 50) Training Accuracy: 0.26645, Validation Accuracy: 0.2403
100%|██████████| 200/200 [00:07<00:00, 25.85it/s]
(Epoch 8 / 50) Training Accuracy: 0.27555, Validation Accuracy: 0.2414
100%|██████████| 200/200 [00:05<00:00, 35.10it/s]
(Epoch 9 / 50) Training Accuracy: 0.28185, Validation Accuracy: 0.2413
100%|██████████| 200/200 [00:05<00:00, 38.76it/s]
(Epoch 10 / 50) Training Accuracy: 0.2944, Validation Accuracy: 0.252
100%|██████████| 200/200 [00:05<00:00, 37.36it/s]
(Epoch 11 / 50) Training Accuracy: 0.29735, Validation Accuracy: 0.2543
100%|██████████| 200/200 [00:05<00:00, 38.90it/s]
(Epoch 12 / 50) Training Accuracy: 0.3021, Validation Accuracy: 0.2587
100%|██████████| 200/200 [00:05<00:00, 37.74it/s]
(Epoch 13 / 50) Training Accuracy: 0.31105, Validation Accuracy: 0.2641
100%|██████████| 200/200 [00:04<00:00, 42.28it/s]
(Epoch 14 / 50) Training Accuracy: 0.3168, Validation Accuracy: 0.2653
100%|██████████| 200/200 [00:05<00:00, 36.98it/s]
(Epoch 15 / 50) Training Accuracy: 0.3217, Validation Accuracy: 0.2681
100%|██████████| 200/200 [00:05<00:00, 39.96it/s]
(Epoch 16 / 50) Training Accuracy: 0.3307, Validation Accuracy: 0.2699
100%|██████████| 200/200 [00:04<00:00, 47.40it/s]
(Epoch 17 / 50) Training Accuracy: 0.33835, Validation Accuracy: 0.2696
100%|██████████| 200/200 [00:04<00:00, 46.70it/s]
(Epoch 18 / 50) Training Accuracy: 0.34565, Validation Accuracy: 0.2737
100%|██████████| 200/200 [00:04<00:00, 49.37it/s]
(Epoch 19 / 50) Training Accuracy: 0.3495, Validation Accuracy: 0.2729
100%|██████████| 200/200 [00:04<00:00, 43.91it/s]
(Epoch 20 / 50) Training Accuracy: 0.35565, Validation Accuracy: 0.2758
100%|██████████| 200/200 [00:04<00:00, 44.49it/s]
(Epoch 21 / 50) Training Accuracy: 0.35825, Validation Accuracy: 0.2729
100%|██████████| 200/200 [00:05<00:00, 38.21it/s]
(Epoch 22 / 50) Training Accuracy: 0.36895, Validation Accuracy: 0.278
100%|██████████| 200/200 [00:06<00:00, 28.96it/s]
(Epoch 23 / 50) Training Accuracy: 0.3734, Validation Accuracy: 0.2783
100%|██████████| 200/200 [00:08<00:00, 24.05it/s]
(Epoch 24 / 50) Training Accuracy: 0.3756, Validation Accuracy: 0.2768
100%|██████████| 200/200 [00:06<00:00, 29.37it/s]
(Epoch 25 / 50) Training Accuracy: 0.38495, Validation Accuracy: 0.278
100%|██████████| 200/200 [00:07<00:00, 27.55it/s]
(Epoch 26 / 50) Training Accuracy: 0.38415, Validation Accuracy: 0.2757
100%|██████████| 200/200 [00:08<00:00, 22.82it/s]
(Epoch 27 / 50) Training Accuracy: 0.40365, Validation Accuracy: 0.2804
100%|██████████| 200/200 [00:06<00:00, 29.03it/s]
(Epoch 28 / 50) Training Accuracy: 0.40105, Validation Accuracy: 0.2812
```

```
100%|██████████| 200/200 [00:05<00:00, 33.49it/s]
(Epoch 29 / 50) Training Accuracy: 0.40885, Validation Accuracy: 0.2773
100%|██████████| 200/200 [00:05<00:00, 38.41it/s]
(Epoch 30 / 50) Training Accuracy: 0.4163, Validation Accuracy: 0.2803
100%|██████████| 200/200 [00:06<00:00, 31.58it/s]
(Epoch 31 / 50) Training Accuracy: 0.41745, Validation Accuracy: 0.2838
100%|██████████| 200/200 [00:05<00:00, 39.49it/s]
(Epoch 32 / 50) Training Accuracy: 0.42125, Validation Accuracy: 0.2758
100%|██████████| 200/200 [00:05<00:00, 33.40it/s]
(Epoch 33 / 50) Training Accuracy: 0.433, Validation Accuracy: 0.2777
100%|██████████| 200/200 [00:04<00:00, 43.25it/s]
(Epoch 34 / 50) Training Accuracy: 0.4322, Validation Accuracy: 0.2782
100%|██████████| 200/200 [00:03<00:00, 58.24it/s]
(Epoch 35 / 50) Training Accuracy: 0.44095, Validation Accuracy: 0.2753
100%|██████████| 200/200 [00:03<00:00, 52.21it/s]
(Epoch 36 / 50) Training Accuracy: 0.4517, Validation Accuracy: 0.2783
100%|██████████| 200/200 [00:03<00:00, 52.24it/s]
(Epoch 37 / 50) Training Accuracy: 0.4583, Validation Accuracy: 0.2759
100%|██████████| 200/200 [00:04<00:00, 40.27it/s]
(Epoch 38 / 50) Training Accuracy: 0.4637, Validation Accuracy: 0.2815
100%|██████████| 200/200 [00:04<00:00, 42.02it/s]
(Epoch 39 / 50) Training Accuracy: 0.4642, Validation Accuracy: 0.2808
100%|██████████| 200/200 [00:04<00:00, 48.23it/s]
(Epoch 40 / 50) Training Accuracy: 0.47055, Validation Accuracy: 0.2784
100%|██████████| 200/200 [00:03<00:00, 50.97it/s]
(Epoch 41 / 50) Training Accuracy: 0.4684, Validation Accuracy: 0.2747
100%|██████████| 200/200 [00:07<00:00, 26.74it/s]
(Epoch 42 / 50) Training Accuracy: 0.4795, Validation Accuracy: 0.2758
100%|██████████| 200/200 [00:06<00:00, 33.29it/s]
(Epoch 43 / 50) Training Accuracy: 0.48745, Validation Accuracy: 0.2793
100%|██████████| 200/200 [00:05<00:00, 38.22it/s]
(Epoch 44 / 50) Training Accuracy: 0.49715, Validation Accuracy: 0.2751
100%|██████████| 200/200 [00:05<00:00, 38.95it/s]
(Epoch 45 / 50) Training Accuracy: 0.49545, Validation Accuracy: 0.2736
100%|██████████| 200/200 [00:03<00:00, 51.58it/s]
(Epoch 46 / 50) Training Accuracy: 0.50175, Validation Accuracy: 0.2767
100%|██████████| 200/200 [00:03<00:00, 51.92it/s]
(Epoch 47 / 50) Training Accuracy: 0.51565, Validation Accuracy: 0.2704
100%|██████████| 200/200 [00:03<00:00, 54.43it/s]
(Epoch 48 / 50) Training Accuracy: 0.51875, Validation Accuracy: 0.2786
100%|██████████| 200/200 [00:04<00:00, 45.04it/s]
(Epoch 49 / 50) Training Accuracy: 0.5235, Validation Accuracy: 0.2818
100%|██████████| 200/200 [00:03<00:00, 50.50it/s]
(Epoch 50 / 50) Training Accuracy: 0.52375, Validation Accuracy: 0.2778

Training with SGD plus Weight Decay...
  3%|▎         | 6/200 [00:00<00:03, 57.33it/s]
(Iteration 1 / 10000) Average loss: 3.3332154539088985
100%|██████████| 200/200 [00:04<00:00, 42.33it/s]
```

```
(Epoch 1 / 50) Training Accuracy: 0.148, Validation Accuracy: 0.1458
100%|██████████| 200/200 [00:06<00:00, 29.32it/s]
(Epoch 2 / 50) Training Accuracy: 0.186, Validation Accuracy: 0.1822
100%|██████████| 200/200 [00:06<00:00, 29.17it/s]
(Epoch 3 / 50) Training Accuracy: 0.2073, Validation Accuracy: 0.2027
100%|██████████| 200/200 [00:04<00:00, 49.00it/s]
(Epoch 4 / 50) Training Accuracy: 0.22575, Validation Accuracy: 0.2101
100%|██████████| 200/200 [00:04<00:00, 42.34it/s]
(Epoch 5 / 50) Training Accuracy: 0.2345, Validation Accuracy: 0.2223
100%|██████████| 200/200 [00:03<00:00, 54.08it/s]
(Epoch 6 / 50) Training Accuracy: 0.24915, Validation Accuracy: 0.2338
100%|██████████| 200/200 [00:03<00:00, 56.89it/s]
(Epoch 7 / 50) Training Accuracy: 0.2584, Validation Accuracy: 0.2451
100%|██████████| 200/200 [00:04<00:00, 47.34it/s]
(Epoch 8 / 50) Training Accuracy: 0.2651, Validation Accuracy: 0.2488
100%|██████████| 200/200 [00:03<00:00, 51.74it/s]
(Epoch 9 / 50) Training Accuracy: 0.2648, Validation Accuracy: 0.2471
100%|██████████| 200/200 [00:06<00:00, 30.38it/s]
(Epoch 10 / 50) Training Accuracy: 0.27685, Validation Accuracy: 0.2558
100%|██████████| 200/200 [00:06<00:00, 30.17it/s]
(Epoch 11 / 50) Training Accuracy: 0.2792, Validation Accuracy: 0.2583
100%|██████████| 200/200 [00:04<00:00, 47.46it/s]
(Epoch 12 / 50) Training Accuracy: 0.28575, Validation Accuracy: 0.2646
100%|██████████| 200/200 [00:04<00:00, 43.35it/s]
(Epoch 13 / 50) Training Accuracy: 0.2879, Validation Accuracy: 0.2657
100%|██████████| 200/200 [00:04<00:00, 47.86it/s]
(Epoch 14 / 50) Training Accuracy: 0.28865, Validation Accuracy: 0.2664
100%|██████████| 200/200 [00:04<00:00, 49.56it/s]
(Epoch 15 / 50) Training Accuracy: 0.29545, Validation Accuracy: 0.2705
100%|██████████| 200/200 [00:03<00:00, 55.34it/s]
(Epoch 16 / 50) Training Accuracy: 0.2964, Validation Accuracy: 0.2737
100%|██████████| 200/200 [00:04<00:00, 40.51it/s]
(Epoch 17 / 50) Training Accuracy: 0.30345, Validation Accuracy: 0.2752
100%|██████████| 200/200 [00:03<00:00, 51.40it/s]
(Epoch 18 / 50) Training Accuracy: 0.30555, Validation Accuracy: 0.276
100%|██████████| 200/200 [00:04<00:00, 48.68it/s]
(Epoch 19 / 50) Training Accuracy: 0.30715, Validation Accuracy: 0.2821
100%|██████████| 200/200 [00:03<00:00, 51.49it/s]
(Epoch 20 / 50) Training Accuracy: 0.31265, Validation Accuracy: 0.2799
100%|██████████| 200/200 [00:04<00:00, 44.39it/s]
(Epoch 21 / 50) Training Accuracy: 0.31315, Validation Accuracy: 0.2787
100%|██████████| 200/200 [00:05<00:00, 35.53it/s]
(Epoch 22 / 50) Training Accuracy: 0.31755, Validation Accuracy: 0.2836
100%|██████████| 200/200 [00:04<00:00, 49.56it/s]
(Epoch 23 / 50) Training Accuracy: 0.3192, Validation Accuracy: 0.2833
100%|██████████| 200/200 [00:04<00:00, 44.43it/s]
(Epoch 24 / 50) Training Accuracy: 0.31905, Validation Accuracy: 0.2837
100%|██████████| 200/200 [00:05<00:00, 39.08it/s]
(Epoch 25 / 50) Training Accuracy: 0.32525, Validation Accuracy: 0.2894
```

```
100%|██████████| 200/200 [00:04<00:00, 41.15it/s]
(Epoch 26 / 50) Training Accuracy: 0.3238, Validation Accuracy: 0.2895
100%|██████████| 200/200 [00:05<00:00, 36.66it/s]
(Epoch 27 / 50) Training Accuracy: 0.33645, Validation Accuracy: 0.2944
100%|██████████| 200/200 [00:04<00:00, 42.78it/s]
(Epoch 28 / 50) Training Accuracy: 0.33645, Validation Accuracy: 0.2941
100%|██████████| 200/200 [00:04<00:00, 45.63it/s]
(Epoch 29 / 50) Training Accuracy: 0.33695, Validation Accuracy: 0.2953
100%|██████████| 200/200 [00:03<00:00, 56.42it/s]
(Epoch 30 / 50) Training Accuracy: 0.3425, Validation Accuracy: 0.3
100%|██████████| 200/200 [00:03<00:00, 60.23it/s]
(Epoch 31 / 50) Training Accuracy: 0.3406, Validation Accuracy: 0.2982
100%|██████████| 200/200 [00:03<00:00, 62.26it/s]
(Epoch 32 / 50) Training Accuracy: 0.34505, Validation Accuracy: 0.2949
100%|██████████| 200/200 [00:03<00:00, 57.95it/s]
(Epoch 33 / 50) Training Accuracy: 0.34595, Validation Accuracy: 0.3011
100%|██████████| 200/200 [00:04<00:00, 40.93it/s]
(Epoch 34 / 50) Training Accuracy: 0.34755, Validation Accuracy: 0.301
100%|██████████| 200/200 [00:04<00:00, 49.37it/s]
(Epoch 35 / 50) Training Accuracy: 0.3548, Validation Accuracy: 0.3012
100%|██████████| 200/200 [00:03<00:00, 53.53it/s]
(Epoch 36 / 50) Training Accuracy: 0.3552, Validation Accuracy: 0.2995
100%|██████████| 200/200 [00:03<00:00, 57.71it/s]
(Epoch 37 / 50) Training Accuracy: 0.35525, Validation Accuracy: 0.3034
100%|██████████| 200/200 [00:03<00:00, 51.93it/s]
(Epoch 38 / 50) Training Accuracy: 0.3593, Validation Accuracy: 0.3017
100%|██████████| 200/200 [00:03<00:00, 56.83it/s]
(Epoch 39 / 50) Training Accuracy: 0.3648, Validation Accuracy: 0.3048
100%|██████████| 200/200 [00:03<00:00, 55.25it/s]
(Epoch 40 / 50) Training Accuracy: 0.36665, Validation Accuracy: 0.311
100%|██████████| 200/200 [00:03<00:00, 62.61it/s]
(Epoch 41 / 50) Training Accuracy: 0.35765, Validation Accuracy: 0.3068
100%|██████████| 200/200 [00:03<00:00, 62.53it/s]
(Epoch 42 / 50) Training Accuracy: 0.36375, Validation Accuracy: 0.302
100%|██████████| 200/200 [00:03<00:00, 63.63it/s]
(Epoch 43 / 50) Training Accuracy: 0.3702, Validation Accuracy: 0.3062
100%|██████████| 200/200 [00:06<00:00, 31.77it/s]
(Epoch 44 / 50) Training Accuracy: 0.37215, Validation Accuracy: 0.306
100%|██████████| 200/200 [00:06<00:00, 30.35it/s]
(Epoch 45 / 50) Training Accuracy: 0.37475, Validation Accuracy: 0.3037
100%|██████████| 200/200 [00:04<00:00, 43.53it/s]
(Epoch 46 / 50) Training Accuracy: 0.37205, Validation Accuracy: 0.3089
100%|██████████| 200/200 [00:04<00:00, 45.11it/s]
(Epoch 47 / 50) Training Accuracy: 0.3827, Validation Accuracy: 0.3097
100%|██████████| 200/200 [00:04<00:00, 45.19it/s]
(Epoch 48 / 50) Training Accuracy: 0.38395, Validation Accuracy: 0.313
100%|██████████| 200/200 [00:03<00:00, 50.61it/s]
(Epoch 49 / 50) Training Accuracy: 0.38155, Validation Accuracy: 0.3131
100%|██████████| 200/200 [00:03<00:00, 56.19it/s]
```

```
(Epoch 50 / 50) Training Accuracy: 0.38415, Validation Accuracy: 0.3121
```



SGD with L1 Regularization [2pts]

With L1 Regularization, your regularized loss becomes $\tilde{J}_{\ell_1}(\theta)$ and it's defined as

$$\tilde{J}_{\ell_1}(\theta) = J(\theta) + \lambda \|\theta\|_{\ell_1}$$

where

$$\|\theta\|_{\ell_1} = \sum_{l=1}^{n} \sum_{k=1}^{n_l} |\theta_{l,k}|$$

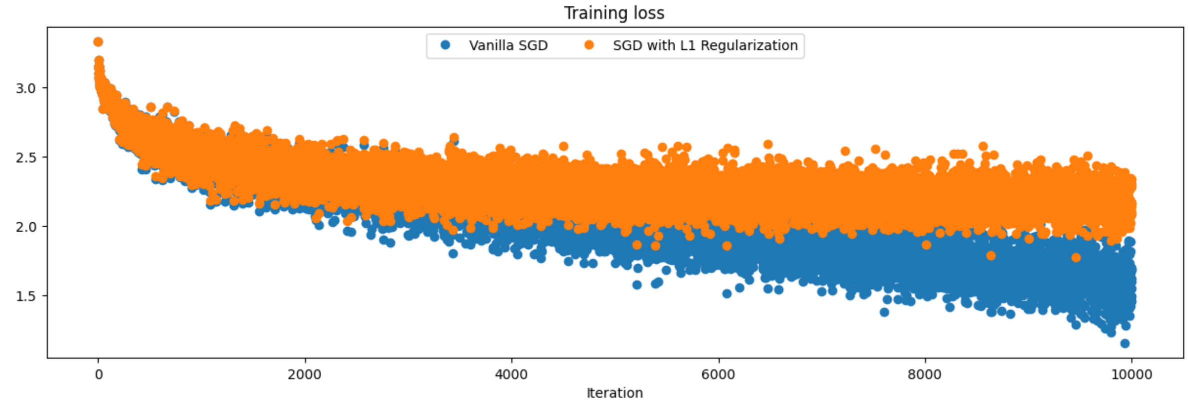
Please implmemt TODO block of `apply_l1_regularization` in `lib/layer_utils`. Such regularization funcationality is called after gradient gathering in the `backward` process.

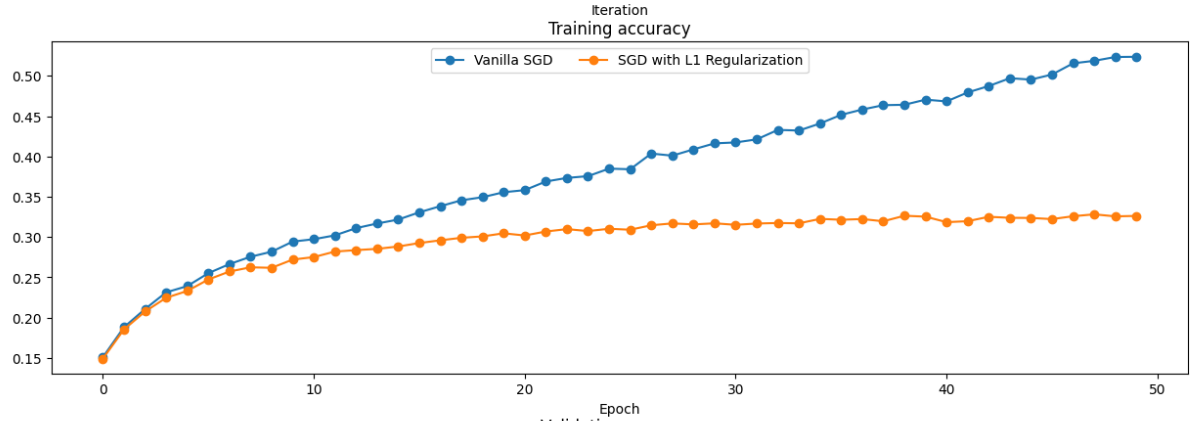
In [23]:
```
reset_seed(seed=seed)
model_sgd_l1     = FullyConnectedNetwork()
loss_f_sgd_l1    = cross_entropy()
optimizer_sgd_l1 = SGD(model_sgd_l1.net, 0.01)

print ("\nTraining with SGD plus L1 Regularization...")
results_sgd_l1 = train_net(small_data_dict, model_sgd_l1, loss_f_sgd_l1, opt
                         max_epochs=50, show_every=10000, verbose=True, regu

opt_params_sgd_l1, loss_hist_sgd_l1, train_acc_hist_sgd_l1, val_acc_hist_sgc

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 3)
plt.title('Validation accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd, 'o', label="Vanilla SGD")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd, '-o', label="Vanilla SGD")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd, '-o', label="Vanilla SGD")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd_l1, 'o', label="SGD with L1 Regularization")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd_l1, '-o', label="SGD with L1 Regularization")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd_l1, '-o', label="SGD with L1 Regularization")

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
plt.gcf().set_size_inches(15, 15)
plt.show()
```

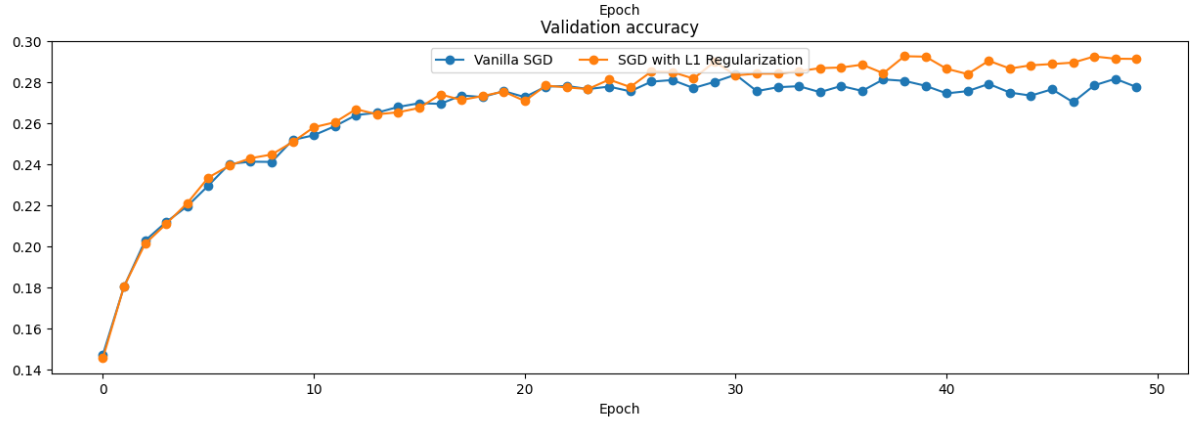
```
Training with SGD plus L1 Regularization...
  0%|          | 0/200 [00:00<?, ?it/s]
(Iteration 1 / 10000) Average loss: 3.3332154539088985
100%|██████████| 200/200 [00:04<00:00, 40.55it/s]
(Epoch 1 / 50) Training Accuracy: 0.1491, Validation Accuracy: 0.1457
100%|██████████| 200/200 [00:06<00:00, 32.67it/s]
(Epoch 2 / 50) Training Accuracy: 0.1854, Validation Accuracy: 0.1806
100%|██████████| 200/200 [00:05<00:00, 39.91it/s]
(Epoch 3 / 50) Training Accuracy: 0.20755, Validation Accuracy: 0.2014
100%|██████████| 200/200 [00:04<00:00, 43.91it/s]
(Epoch 4 / 50) Training Accuracy: 0.22465, Validation Accuracy: 0.2111
```

```
100%|██████████| 200/200 [00:04<00:00, 43.23it/s]
(Epoch 5 / 50) Training Accuracy: 0.2331, Validation Accuracy: 0.2212
100%|██████████| 200/200 [00:04<00:00, 45.98it/s]
(Epoch 6 / 50) Training Accuracy: 0.24735, Validation Accuracy: 0.2337
100%|██████████| 200/200 [00:04<00:00, 41.66it/s]
(Epoch 7 / 50) Training Accuracy: 0.25725, Validation Accuracy: 0.2395
100%|██████████| 200/200 [00:04<00:00, 45.14it/s]
(Epoch 8 / 50) Training Accuracy: 0.26245, Validation Accuracy: 0.2431
100%|██████████| 200/200 [00:05<00:00, 36.13it/s]
(Epoch 9 / 50) Training Accuracy: 0.26185, Validation Accuracy: 0.2449
100%|██████████| 200/200 [00:05<00:00, 38.68it/s]
(Epoch 10 / 50) Training Accuracy: 0.27205, Validation Accuracy: 0.251
100%|██████████| 200/200 [00:04<00:00, 44.07it/s]
(Epoch 11 / 50) Training Accuracy: 0.27515, Validation Accuracy: 0.2582
100%|██████████| 200/200 [00:04<00:00, 41.60it/s]
(Epoch 12 / 50) Training Accuracy: 0.282, Validation Accuracy: 0.2606
100%|██████████| 200/200 [00:04<00:00, 48.55it/s]
(Epoch 13 / 50) Training Accuracy: 0.2838, Validation Accuracy: 0.267
100%|██████████| 200/200 [00:04<00:00, 44.05it/s]
(Epoch 14 / 50) Training Accuracy: 0.28535, Validation Accuracy: 0.2645
100%|██████████| 200/200 [00:04<00:00, 46.02it/s]
(Epoch 15 / 50) Training Accuracy: 0.2883, Validation Accuracy: 0.2655
100%|██████████| 200/200 [00:05<00:00, 35.72it/s]
(Epoch 16 / 50) Training Accuracy: 0.2926, Validation Accuracy: 0.2676
100%|██████████| 200/200 [00:04<00:00, 44.57it/s]
(Epoch 17 / 50) Training Accuracy: 0.296, Validation Accuracy: 0.2742
100%|██████████| 200/200 [00:06<00:00, 32.73it/s]
(Epoch 18 / 50) Training Accuracy: 0.2991, Validation Accuracy: 0.2715
100%|██████████| 200/200 [00:04<00:00, 40.16it/s]
(Epoch 19 / 50) Training Accuracy: 0.30085, Validation Accuracy: 0.2734
100%|██████████| 200/200 [00:04<00:00, 40.49it/s]
(Epoch 20 / 50) Training Accuracy: 0.30465, Validation Accuracy: 0.2756
100%|██████████| 200/200 [00:04<00:00, 45.13it/s]
(Epoch 21 / 50) Training Accuracy: 0.30195, Validation Accuracy: 0.271
100%|██████████| 200/200 [00:04<00:00, 41.38it/s]
(Epoch 22 / 50) Training Accuracy: 0.3069, Validation Accuracy: 0.2785
100%|██████████| 200/200 [00:04<00:00, 40.39it/s]
(Epoch 23 / 50) Training Accuracy: 0.30985, Validation Accuracy: 0.2776
100%|██████████| 200/200 [00:05<00:00, 37.56it/s]
(Epoch 24 / 50) Training Accuracy: 0.30745, Validation Accuracy: 0.2768
100%|██████████| 200/200 [00:04<00:00, 46.18it/s]
(Epoch 25 / 50) Training Accuracy: 0.3103, Validation Accuracy: 0.2814
100%|██████████| 200/200 [00:05<00:00, 37.97it/s]
(Epoch 26 / 50) Training Accuracy: 0.3091, Validation Accuracy: 0.2778
100%|██████████| 200/200 [00:05<00:00, 38.59it/s]
(Epoch 27 / 50) Training Accuracy: 0.31465, Validation Accuracy: 0.2853
100%|██████████| 200/200 [00:04<00:00, 45.10it/s]
(Epoch 28 / 50) Training Accuracy: 0.31695, Validation Accuracy: 0.2851
100%|██████████| 200/200 [00:04<00:00, 42.26it/s]
```

```
(Epoch 29 / 50) Training Accuracy: 0.3157, Validation Accuracy: 0.2819
100%|██████████| 200/200 [00:04<00:00, 46.96it/s]
(Epoch 30 / 50) Training Accuracy: 0.31705, Validation Accuracy: 0.2901
100%|██████████| 200/200 [00:04<00:00, 47.15it/s]
(Epoch 31 / 50) Training Accuracy: 0.3152, Validation Accuracy: 0.2835
100%|██████████| 200/200 [00:03<00:00, 54.35it/s]
(Epoch 32 / 50) Training Accuracy: 0.3168, Validation Accuracy: 0.2843
100%|██████████| 200/200 [00:03<00:00, 54.88it/s]
(Epoch 33 / 50) Training Accuracy: 0.31745, Validation Accuracy: 0.2843
100%|██████████| 200/200 [00:04<00:00, 46.91it/s]
(Epoch 34 / 50) Training Accuracy: 0.31705, Validation Accuracy: 0.2855
100%|██████████| 200/200 [00:04<00:00, 41.05it/s]
(Epoch 35 / 50) Training Accuracy: 0.32255, Validation Accuracy: 0.287
100%|██████████| 200/200 [00:03<00:00, 52.07it/s]
(Epoch 36 / 50) Training Accuracy: 0.3215, Validation Accuracy: 0.2873
100%|██████████| 200/200 [00:04<00:00, 49.84it/s]
(Epoch 37 / 50) Training Accuracy: 0.32235, Validation Accuracy: 0.2887
100%|██████████| 200/200 [00:04<00:00, 47.79it/s]
(Epoch 38 / 50) Training Accuracy: 0.3196, Validation Accuracy: 0.2845
100%|██████████| 200/200 [00:04<00:00, 42.21it/s]
(Epoch 39 / 50) Training Accuracy: 0.32645, Validation Accuracy: 0.2928
100%|██████████| 200/200 [00:04<00:00, 45.26it/s]
(Epoch 40 / 50) Training Accuracy: 0.32535, Validation Accuracy: 0.2926
100%|██████████| 200/200 [00:04<00:00, 46.91it/s]
(Epoch 41 / 50) Training Accuracy: 0.3185, Validation Accuracy: 0.2867
100%|██████████| 200/200 [00:04<00:00, 44.32it/s]
(Epoch 42 / 50) Training Accuracy: 0.3197, Validation Accuracy: 0.2841
100%|██████████| 200/200 [00:04<00:00, 46.85it/s]
(Epoch 43 / 50) Training Accuracy: 0.32515, Validation Accuracy: 0.2906
100%|██████████| 200/200 [00:04<00:00, 47.03it/s]
(Epoch 44 / 50) Training Accuracy: 0.3239, Validation Accuracy: 0.2868
100%|██████████| 200/200 [00:03<00:00, 51.48it/s]
(Epoch 45 / 50) Training Accuracy: 0.32375, Validation Accuracy: 0.2884
100%|██████████| 200/200 [00:04<00:00, 48.23it/s]
(Epoch 46 / 50) Training Accuracy: 0.3223, Validation Accuracy: 0.289
100%|██████████| 200/200 [00:03<00:00, 59.47it/s]
(Epoch 47 / 50) Training Accuracy: 0.32585, Validation Accuracy: 0.2897
100%|██████████| 200/200 [00:03<00:00, 58.82it/s]
(Epoch 48 / 50) Training Accuracy: 0.3282, Validation Accuracy: 0.2927
100%|██████████| 200/200 [00:04<00:00, 49.42it/s]
(Epoch 49 / 50) Training Accuracy: 0.3257, Validation Accuracy: 0.2916
100%|██████████| 200/200 [00:03<00:00, 55.44it/s]
(Epoch 50 / 50) Training Accuracy: 0.32625, Validation Accuracy: 0.2915
```







SGD with L2 Regularization [2pts]

With L2 Regularization, your regularized loss becomes $\tilde{J}_{\ell_2}(\theta)$ and it's defined as

$$\tilde{J}_{\ell_2}(\theta) = J(\theta) + \lambda \|\theta\|_{\ell_2}$$

where

$$\|\theta\|_{\ell_2} = \sum_{l=1}^{n} \sum_{k=1}^{n_l} \theta_{l,k}^2$$

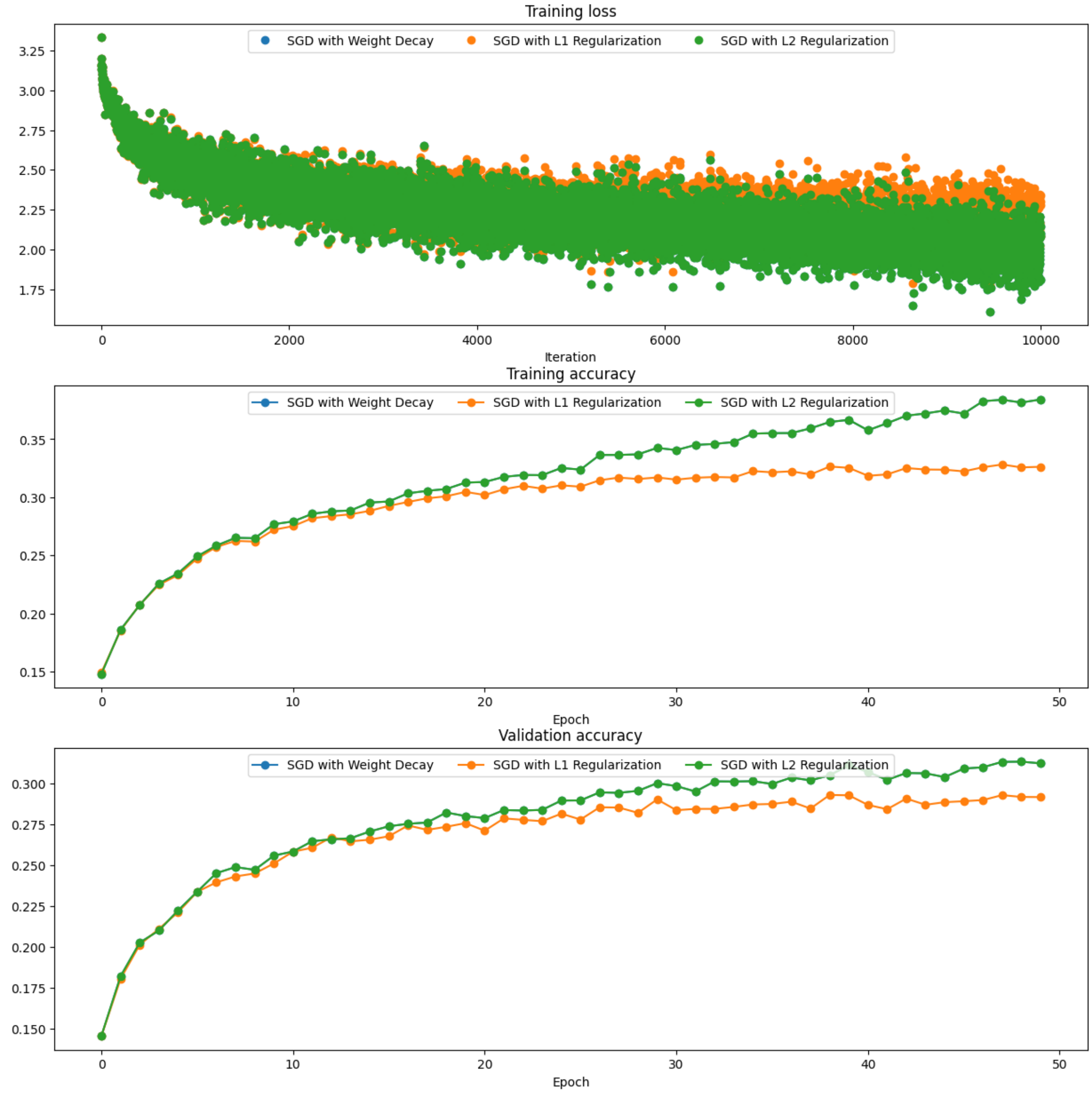
Similarly, implmemt TODO block of `apply_l2_regularization` in `lib/layer_utils`. For SGD, you're also asked to find the λ for L2 Regularization such that it achives the EXACTLY SAME effect as weight decay in the previous cells. As a reminder, learning rate is the same as previously, and the weight decay paramter was 1e-4.

In [24]:
```
reset_seed(seed=seed)
model_sgd_l2     = FullyConnectedNetwork()
loss_f_sgd_l2    = cross_entropy()
optimizer_sgd_l2 = SGD(model_sgd_l2.net, 0.01)
######################################################################
#### Find lambda for L2 regularization so that                   ####
#### it achieves EXACTLY THE SAME learning curve as weight decay ####
l2_lambda = 0.005
######################################################################

print ("\nTraining with SGD plus L2 Regularization...")
results_sgd_l2 = train_net(small_data_dict, model_sgd_l2, loss_f_sgd_l2, opt
                           max_epochs=50, show_every=10000, verbose=False, r

opt_params_sgd_l2, loss_hist_sgd_l2, train_acc_hist_sgd_l2, val_acc_hist_sgc

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 3)
plt.title('Validation accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgdw, 'o', label="SGD with Weight Decay")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgdw, '-o', label="SGD with Weight Decay")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgdw, '-o', label="SGD with Weight Decay")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd_l1, 'o', label="SGD with L1 Regularization")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd_l1, '-o', label="SGD with L1 Regularization")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd_l1, '-o', label="SGD with L1 Regularization")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd_l2, 'o', label="SGD with L2 Regularization")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd_l2, '-o', label="SGD with L2 Regularization")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd_l2, '-o', label="SGD with L2 Regularization")

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
```

```
plt.gcf().set_size_inches(15, 15)
plt.show()
```

```
Training with SGD plus L2 Regularization...
```

```
100%|██████████| 200/200 [00:03<00:00, 55.33it/s]
100%|██████████| 200/200 [00:02<00:00, 67.05it/s]
100%|██████████| 200/200 [00:02<00:00, 68.54it/s]
100%|██████████| 200/200 [00:04<00:00, 49.48it/s]
100%|██████████| 200/200 [00:03<00:00, 56.40it/s]
100%|██████████| 200/200 [00:03<00:00, 51.43it/s]
100%|██████████| 200/200 [00:03<00:00, 60.17it/s]
100%|██████████| 200/200 [00:03<00:00, 58.81it/s]
100%|██████████| 200/200 [00:03<00:00, 62.68it/s]
100%|██████████| 200/200 [00:03<00:00, 61.74it/s]
100%|██████████| 200/200 [00:02<00:00, 71.55it/s]
100%|██████████| 200/200 [00:03<00:00, 54.51it/s]
100%|██████████| 200/200 [00:03<00:00, 66.32it/s]
100%|██████████| 200/200 [00:03<00:00, 63.12it/s]
100%|██████████| 200/200 [00:02<00:00, 67.57it/s]
100%|██████████| 200/200 [00:03<00:00, 66.23it/s]
100%|██████████| 200/200 [00:03<00:00, 53.58it/s]
100%|██████████| 200/200 [00:04<00:00, 48.87it/s]
100%|██████████| 200/200 [00:04<00:00, 48.59it/s]
100%|██████████| 200/200 [00:03<00:00, 57.72it/s]
100%|██████████| 200/200 [00:04<00:00, 48.25it/s]
100%|██████████| 200/200 [00:04<00:00, 45.09it/s]
100%|██████████| 200/200 [00:04<00:00, 49.04it/s]
100%|██████████| 200/200 [00:03<00:00, 51.89it/s]
100%|██████████| 200/200 [00:04<00:00, 48.57it/s]
100%|██████████| 200/200 [00:04<00:00, 45.67it/s]
100%|██████████| 200/200 [00:04<00:00, 48.62it/s]
100%|██████████| 200/200 [00:04<00:00, 43.73it/s]
100%|██████████| 200/200 [00:04<00:00, 44.14it/s]
100%|██████████| 200/200 [00:03<00:00, 51.55it/s]
100%|██████████| 200/200 [00:03<00:00, 52.04it/s]
100%|██████████| 200/200 [00:03<00:00, 55.59it/s]
100%|██████████| 200/200 [00:03<00:00, 50.79it/s]
100%|██████████| 200/200 [00:03<00:00, 57.93it/s]
100%|██████████| 200/200 [00:03<00:00, 59.34it/s]
100%|██████████| 200/200 [00:03<00:00, 50.97it/s]
100%|██████████| 200/200 [00:03<00:00, 56.41it/s]
100%|██████████| 200/200 [00:03<00:00, 56.91it/s]
100%|██████████| 200/200 [00:04<00:00, 49.20it/s]
100%|██████████| 200/200 [00:04<00:00, 45.61it/s]
100%|██████████| 200/200 [00:03<00:00, 50.13it/s]
100%|██████████| 200/200 [00:04<00:00, 47.47it/s]
100%|██████████| 200/200 [00:04<00:00, 49.19it/s]
100%|██████████| 200/200 [00:03<00:00, 52.73it/s]
100%|██████████| 200/200 [00:04<00:00, 43.40it/s]
100%|██████████| 200/200 [00:04<00:00, 49.29it/s]
100%|██████████| 200/200 [00:04<00:00, 47.98it/s]
100%|██████████| 200/200 [00:03<00:00, 54.12it/s]
100%|██████████| 200/200 [00:05<00:00, 38.01it/s]
100%|██████████| 200/200 [00:03<00:00, 50.17it/s]
```



Adam [2pt]

The update rule of Adam is as shown below:

$$
\begin{aligned}
t &= t + 1 \\
g_t &: \text{gradients at update step } t \\
m_t &= \beta_1 m_{t-1} + (1 - \beta_1) g_t \\
v_t &= \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \\
\hat{m}_t &= m_t / (1 - \beta_1^t) \\
\hat{v}_t &= v_t / (1 - \beta_2^t) \\
\theta_{t+1} &= \theta_t - \frac{\eta \, \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}
\end{aligned}
$$

Complete the `Adam()` function in `lib/optim.py` Important Notes:

1. t must be updated before everything else
2. β_1^t is β_1 exponentiated to the t'th power
3. You should also enable weight decay in Adam, similar to what you did in SGD

In [25]:
```
%reload_ext autoreload

seed = 1234
np.random.seed(seed=seed)

# Test Adam implementation; you should see errors around 1e-7 or less
N, D = 4, 5
test_adam = sequential(fc(N, D, name="adam_fc"))

w = np.linspace(-0.4, 0.6, num=N*D).reshape(N, D)
dw = np.linspace(-0.6, 0.4, num=N*D).reshape(N, D)
m = np.linspace(0.6, 0.9, num=N*D).reshape(N, D)
v = np.linspace(0.7, 0.5, num=N*D).reshape(N, D)

test_adam.layers[0].params = {"adam_fc_w": w}
test_adam.layers[0].grads = {"adam_fc_w": dw}

opt_adam = Adam(test_adam, 1e-2, 0.9, 0.999, t=5)
opt_adam.mt = {"adam_fc_w": m}
opt_adam.vt = {"adam_fc_w": v}
opt_adam.step()

updated_w = test_adam.layers[0].params["adam_fc_w"]
mt = opt_adam.mt["adam_fc_w"]
vt = opt_adam.vt["adam_fc_w"]

expected_updated_w = np.asarray([
  [-0.40094747, -0.34836187, -0.29577703, -0.24319299, -0.19060977],
  [-0.1380274,  -0.08544591, -0.03286534,  0.01971428,  0.0722929],
  [ 0.1248705,   0.17744702,  0.23002243,  0.28259667,  0.33516969],
  [ 0.38774145,  0.44031188,  0.49288093,  0.54544852,  0.59801459]])
expected_v = np.asarray([
  [ 0.69966,     0.68908382,  0.67851319,  0.66794809,  0.65738853,],
  [ 0.64683452,  0.63628604,  0.6257431,   0.61520571,  0.60467385,],
  [ 0.59414753,  0.58362676,  0.57311152,  0.56260183,  0.55209767,],
  [ 0.54159906,  0.53110598,  0.52061845,  0.51013645,  0.49966,   ]])
expected_m = np.asarray([
  [ 0.48,        0.49947368,  0.51894737,  0.53842105,  0.55789474],
  [ 0.57736842,  0.59684211,  0.61631579,  0.63578947,  0.65526316],
  [ 0.67473684,  0.69421053,  0.71368421,  0.73315789,  0.75263158],
  [ 0.77210526,  0.79157895,  0.81105263,  0.83052632,  0.85      ]])

print ('The following errors should be around or less than 1e-7')
print ('updated_w error: ', rel_error(expected_updated_w, updated_w))
print ('mt error: ', rel_error(expected_m, mt))
print ('vt error: ', rel_error(expected_v, vt))
```

```
The following errors should be around or less than 1e-7
updated_w error:  1.1355763428905147e-07
mt error:  4.214963193114416e-09
vt error:  4.208314038113071e-09
```

Comparing the Weight Decay v.s. L2 Regularization in Adam [5pt]

Run the following code block to compare the plotted results between effects of weight decay and L2 regularization on Adam. Are they still the same? (we can make them the same as in SGD, can we also do it in Adam?)

Answer: In Adam, weight decay and L2 regularization can be different because Adam includes a momentum term that SGD does not have. The momentum term in Adam can counteract the effect of weight decay on the weight updates. As a result, the effect of weight decay and L2 regularization on the weights may not be the same in Adam as in SGD.

To make the effects of weight decay and L2 regularization the same in Adam, we can use the L2 regularization term directly in the Adam optimizer instead of weight decay. This can be achieved by adding the L2 regularization term to the loss function and using it to compute the gradients for the weight updates in Adam. By doing this, the effect of L2 regularization on the weights would be the same in Adam as in SGD.

In [26]:
```
seed = 1234
reset_seed(seed)
model_adam_wd      = FullyConnectedNetwork()
loss_f_adam_wd     = cross_entropy()
optimizer_adam_wd  = Adam(model_adam_wd.net, lr=1e-4, weight_decay=1e-6)


print ("Training with AdamW...")
results_adam_wd = train_net(small_data_dict, model_adam_wd, loss_f_adam_wd,
                        max_epochs=50, show_every=10000, verbose=False)

reset_seed(seed)
model_adam_l2      = FullyConnectedNetwork()
loss_f_adam_l2     = cross_entropy()
optimizer_adam_l2 = Adam(model_adam_l2.net, lr=1e-4)
reg_lambda_l2 = 1e-4
print ("\nTraining with Adam + L2...")
results_adam_l2 = train_net(small_data_dict, model_adam_l2, loss_f_adam_l2,
                         max_epochs=50, show_every=10000, verbose=False, reg

opt_params_adam_wd, loss_hist_adam_wd, train_acc_hist_adam_wd, val_acc_hist_
opt_params_adam_l2, loss_hist_adam_l2, train_acc_hist_adam_l2, val_acc_hist_

plt.subplot(3, 1, 1)
plt.title('Training loss')
plt.xlabel('Iteration')

plt.subplot(3, 1, 2)
plt.title('Training accuracy')
plt.xlabel('Epoch')
```

```
plt.subplot(3, 1, 3)
plt.title('Validation accuracy')
plt.xlabel('Epoch')

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgd, 'o', label="Vanilla SGD")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgd, '-o', label="Vanilla SGD")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgd, '-o', label="Vanilla SGD")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_sgdw, 'o', label="SGD with Weight Decay")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_sgdw, '-o', label="SGD with Weight Decay")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_sgdw, '-o', label="SGD with Weight Decay")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_adam_wd, 'o', label="Adam with Weight Decay")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_adam_wd, '-o', label="Adam with Weight Decay")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_adam_wd, '-o', label="Adam with Weight Decay")

plt.subplot(3, 1, 1)
plt.plot(loss_hist_adam_l2, 'o', label="Adam with L2")
plt.subplot(3, 1, 2)
plt.plot(train_acc_hist_adam_l2, '-o', label="Adam with L2")
plt.subplot(3, 1, 3)
plt.plot(val_acc_hist_adam_l2, '-o', label="Adam with L2")

for i in [1, 2, 3]:
  plt.subplot(3, 1, i)
  plt.legend(loc='upper center', ncol=4)
plt.gcf().set_size_inches(15, 15)
plt.show()
```

```
Training with AdamW...
```

```
100%|██████████| 200/200 [00:04<00:00, 44.15it/s]
100%|██████████| 200/200 [00:03<00:00, 52.38it/s]
100%|██████████| 200/200 [00:04<00:00, 47.59it/s]
100%|██████████| 200/200 [00:04<00:00, 47.77it/s]
100%|██████████| 200/200 [00:04<00:00, 46.85it/s]
100%|██████████| 200/200 [00:04<00:00, 42.70it/s]
100%|██████████| 200/200 [00:04<00:00, 46.61it/s]
100%|██████████| 200/200 [00:04<00:00, 48.03it/s]
100%|██████████| 200/200 [00:04<00:00, 48.77it/s]
100%|██████████| 200/200 [00:03<00:00, 55.37it/s]
100%|██████████| 200/200 [00:03<00:00, 51.54it/s]
100%|██████████| 200/200 [00:03<00:00, 51.01it/s]
100%|██████████| 200/200 [00:04<00:00, 46.89it/s]
100%|██████████| 200/200 [00:04<00:00, 47.91it/s]
100%|██████████| 200/200 [00:03<00:00, 53.04it/s]
100%|██████████| 200/200 [00:04<00:00, 44.08it/s]
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100%|██████████| 200/200 [00:05<00:00, 39.28it/s]
100%|██████████| 200/200 [00:04<00:00, 43.34it/s]
100%|██████████| 200/200 [00:05<00:00, 37.75it/s]
100%|██████████| 200/200 [00:05<00:00, 36.67it/s]
100%|██████████| 200/200 [00:04<00:00, 40.03it/s]
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100%|██████████| 200/200 [00:04<00:00, 42.42it/s]
100%|██████████| 200/200 [00:04<00:00, 44.20it/s]
100%|██████████| 200/200 [00:05<00:00, 37.01it/s]
100%|██████████| 200/200 [00:31<00:00,  6.30it/s]
100%|██████████| 200/200 [00:53<00:00,  3.73it/s]
100%|██████████| 200/200 [00:31<00:00,  6.39it/s]
100%|██████████| 200/200 [00:03<00:00, 51.28it/s]
100%|██████████| 200/200 [00:04<00:00, 49.96it/s]
100%|██████████| 200/200 [00:04<00:00, 40.11it/s]
100%|██████████| 200/200 [00:05<00:00, 34.05it/s]
100%|██████████| 200/200 [00:05<00:00, 36.07it/s]
100%|██████████| 200/200 [00:04<00:00, 43.84it/s]
100%|██████████| 200/200 [00:05<00:00, 34.13it/s]
100%|██████████| 200/200 [00:05<00:00, 36.48it/s]
100%|██████████| 200/200 [00:04<00:00, 42.46it/s]
100%|██████████| 200/200 [00:05<00:00, 38.77it/s]
100%|██████████| 200/200 [00:06<00:00, 31.50it/s]
100%|██████████| 200/200 [00:05<00:00, 37.77it/s]
100%|██████████| 200/200 [00:04<00:00, 41.46it/s]
100%|██████████| 200/200 [00:04<00:00, 44.44it/s]
100%|██████████| 200/200 [00:04<00:00, 43.00it/s]
100%|██████████| 200/200 [00:04<00:00, 41.68it/s]
100%|██████████| 200/200 [00:04<00:00, 41.64it/s]
```

```
Training with Adam + L2...
```

```
100%|██████████| 200/200 [00:05<00:00, 37.21it/s]
100%|██████████| 200/200 [00:04<00:00, 40.37it/s]
100%|██████████| 200/200 [00:05<00:00, 36.60it/s]
100%|██████████| 200/200 [00:04<00:00, 45.46it/s]
100%|██████████| 200/200 [00:04<00:00, 47.71it/s]
100%|██████████| 200/200 [00:04<00:00, 43.32it/s]
100%|██████████| 200/200 [00:04<00:00, 42.70it/s]
100%|██████████| 200/200 [00:04<00:00, 42.72it/s]
100%|██████████| 200/200 [00:06<00:00, 30.75it/s]
100%|██████████| 200/200 [00:05<00:00, 34.44it/s]
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100%|██████████| 200/200 [00:04<00:00, 44.69it/s]
100%|██████████| 200/200 [00:04<00:00, 43.36it/s]
100%|██████████| 200/200 [00:04<00:00, 41.65it/s]
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100%|██████████| 200/200 [00:04<00:00, 44.85it/s]
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100%|██████████| 200/200 [00:13<00:00, 15.10it/s]
100%|██████████| 200/200 [00:04<00:00, 40.83it/s]
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100%|██████████| 200/200 [00:06<00:00, 30.27it/s]
100%|██████████| 200/200 [00:04<00:00, 42.18it/s]
100%|██████████| 200/200 [00:04<00:00, 43.92it/s]
100%|██████████| 200/200 [00:05<00:00, 38.17it/s]
100%|██████████| 200/200 [00:05<00:00, 39.16it/s]
100%|██████████| 200/200 [00:04<00:00, 41.04it/s]
100%|██████████| 200/200 [00:05<00:00, 37.51it/s]
100%|██████████| 200/200 [00:04<00:00, 46.38it/s]
100%|██████████| 200/200 [00:04<00:00, 46.88it/s]
100%|██████████| 200/200 [00:04<00:00, 41.66it/s]
100%|██████████| 200/200 [00:05<00:00, 36.31it/s]
100%|██████████| 200/200 [00:04<00:00, 40.07it/s]
100%|██████████| 200/200 [00:05<00:00, 39.34it/s]
100%|██████████| 200/200 [00:05<00:00, 38.71it/s]
100%|██████████| 200/200 [00:04<00:00, 40.27it/s]
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100%|██████████| 200/200 [00:04<00:00, 40.74it/s]
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100%|██████████| 200/200 [00:04<00:00, 41.45it/s]
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100%|██████████| 200/200 [00:06<00:00, 31.99it/s]
100%|██████████| 200/200 [00:04<00:00, 45.30it/s]
```

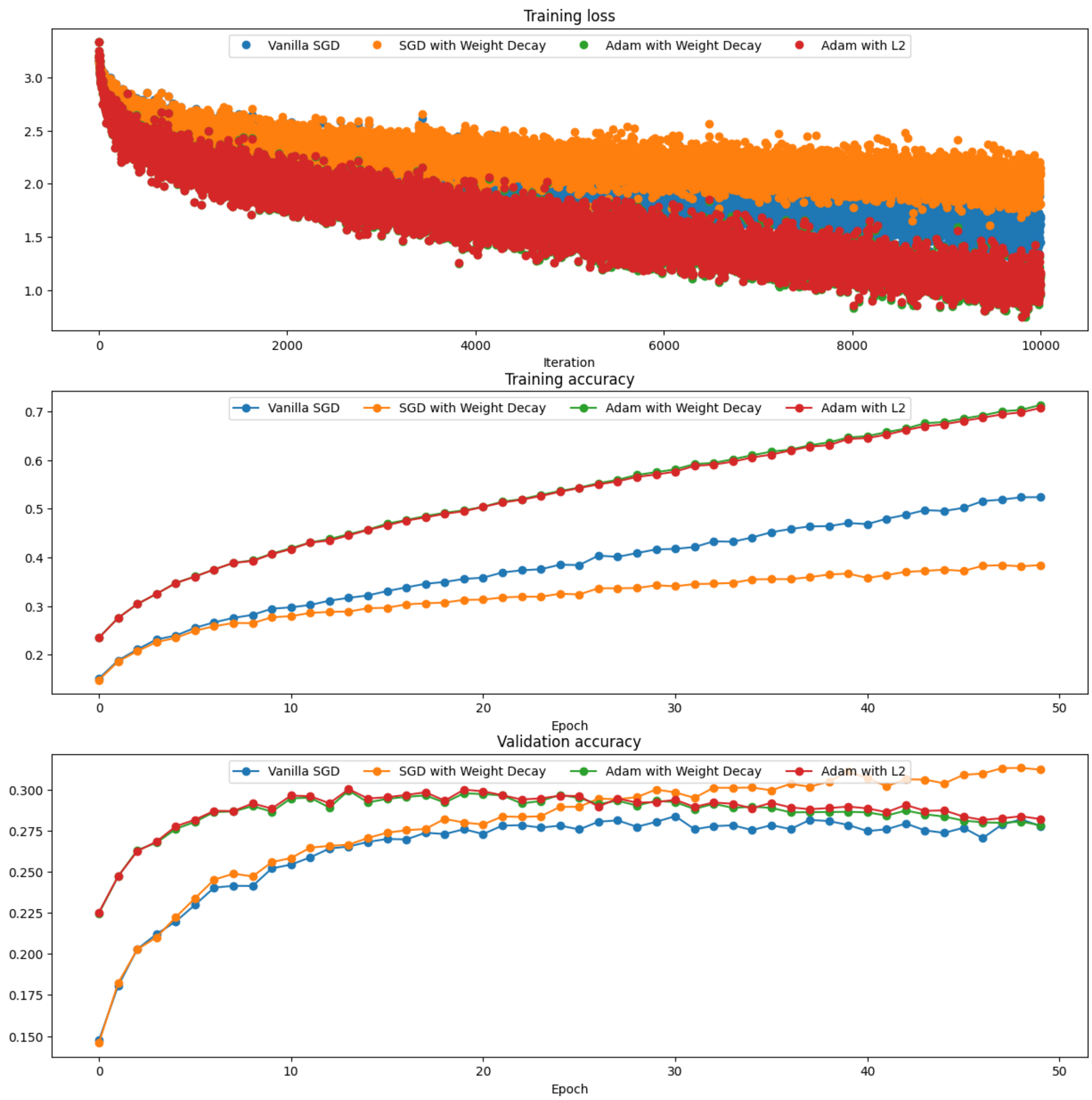

Submission

Please prepare a PDF document `problem_1_solution.pdf` in the root directory of this repository with all plots and inline answers of your solution. Concretely, the document should contain the following items in strict order:

1. Training loss / accuracy curves for the simple neural network training with > 30% validation accuracy
2. Plots for comparing vanilla SGD to SGD + Weight Decay, SGD + L1 and SGD + L2
3. "Comparing different Regularizations with Adam" plots

Note that you still need to submit the jupyter notebook with all generated solutions. We will randomly pick submissions and check that the plots in the PDF and in the notebook are equivalent.

In [ ]:

```
```