knn

April 28, 2023

1 ECE 285 Assignment 1: KNN

For this part of assignment, you are tasked to implement KNN algorithm and test it on the a subset of CIFAR10 dataset.

You sould run the whole notebook and answer the question in the notebook.

TO SUBMIT: PDF of this notebook with all the required outputs and answers.

[1]:
```
# Import Packages
import numpy as np
import matplotlib.pyplot as plt
```

1.1 Prepare Dataset

Since CIFAR10 is a relative large dataset, and KNN is quite time-consuming method, we only a small sub-set of CIFAR10 for KNN part

[2]:
```
from ece285.utils.data_processing import get_cifar10_data

# Use a subset of CIFAR10 for KNN assignments
dataset = get_cifar10_data(subset_train=5000, subset_val=250, subset_test=500)

print(dataset.keys())
print("Training Set Data  Shape: ", dataset["x_train"].shape)
print("Training Set Label Shape: ", dataset["y_train"].shape)
```

```
dict_keys(['x_train', 'y_train', 'x_val', 'y_val', 'x_test', 'y_test'])
Training Set Data  Shape:  (5000, 3072)
Training Set Label Shape:  (5000,)
```

1.2 Implementation (60%)

You need to implement the KNN method in `algorithms/knn.py`. You need to fill in the prediction function(since the training of KNN is just remembering the training set).

For KNN implementation, you are tasked to implement two version of it.

- Two Loop Version: use one loop to iterate through training samples and one loop to iterate through test samples

- One Loop Version: use one loop to iterate through test samples and use broadcast feature of numpy to calculate all the distance at once

Note: It is possible to build a Fully Vectorized Version without explicit for loop to calculate the distance, but you do not have to do it in this assignment. You could use the fully vectorized version to replace the loop versions as well.

For distance function, in this assignment, we use Eucliean distance between samples.

[3]:
```
from ece285.algorithms import KNN

knn = KNN(num_class=10)
knn.train(
    x_train=dataset["x_train"],
    y_train=dataset["y_train"],
    k=5,
)
```

1.2.1 Compare the time consumption of different method

In this section, you will test your different implementation of KNN method, and compare their speed.

[4]:
```
from ece285.utils.evaluation import get_classification_accuracy
```

[5]:
```
knn = KNN(num_class=10)
knn.train(
    x_train=dataset["x_train"],
    y_train=dataset["y_train"],
    k=5,
)
```

Two Loop Version:

[6]:
```
import time

c_t = time.time()
prediction = knn.predict(dataset["x_test"], loop_count=2)
print("Two Loop Prediction Time:", time.time() - c_t)

test_acc = get_classification_accuracy(prediction, dataset["y_test"])
print("Test Accuracy:", test_acc)
```

```
Two Loop Prediction Time: 32.387789249420166
Test Accuracy: 0.29
```

One Loop Version

[8]:
```
import time

c_t = time.time()
prediction = knn.predict(dataset["x_test"], loop_count=1)
print("One Loop Prediction Time:", time.time() - c_t)

test_acc = get_classification_accuracy(prediction, dataset["y_test"])
print("Test Accuracy:", test_acc)
```

```
One Loop Prediction Time: 107.23934006690979
Test Accuracy: 0.29
```

Your different implementation should output the exact same result

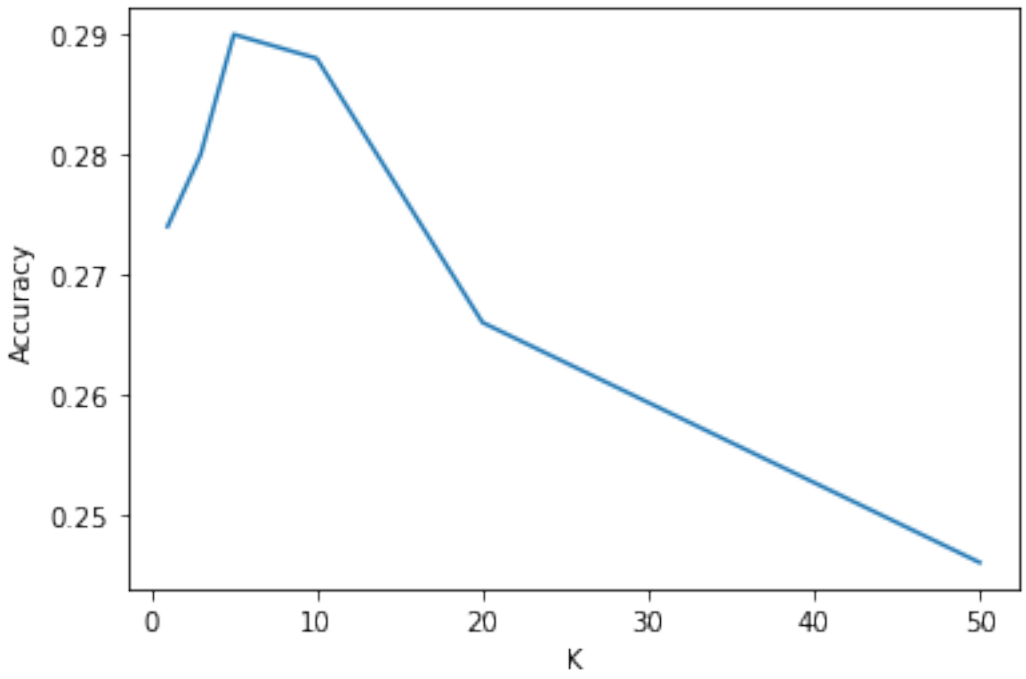
1.3 Test different Hyper-parameter(20%)

For KNN, there is only one hyper-parameter of the algorithm: How many nearest neighbour to use(**K**).

Here, you are provided the code to test different k for the same dataset.

[11]:
```
accuracies = []

k_candidates = [1, 3, 5, 10, 20, 50]
# k_candidates = [1]
for k_cand in k_candidates:
    prediction = knn.predict(x_test=dataset["x_test"], k=k_cand)
    acc = get_classification_accuracy(prediction, dataset["y_test"])
    accuracies.append(acc)
    print("Finish k = {}, acc = {}".format(k_cand, acc))
plt.ylabel("Accuracy")
plt.xlabel("K")
plt.plot(k_candidates, accuracies)
plt.show()
```

```
Finish k = 1, acc = 0.274
Finish k = 3, acc = 0.28
Finish k = 5, acc = 0.29
Finish k = 10, acc = 0.288
Finish k = 20, acc = 0.266
Finish k = 50, acc = 0.246
```



1.3.1 Inline Question 1:

Please describe the output result you get, and provide some explanation as well.

1.3.2 Your Answer:

Put Your Answer Here

I found that the accuracy would be affected by k, but the result is not linear dependent. When k is around 5, we could get the highest accuracy. However, when k is lower or higher than the value, the performance degrades. If k is too low, it takes a little number of labels to predict. If k is too high, the result would be affected by unreliable samples.

1.4 Try different feature representation(20%)

Since machine learning method rely heavily on the feature extraction, you will see how different feature representation affect the performance of the algorithm in this section.

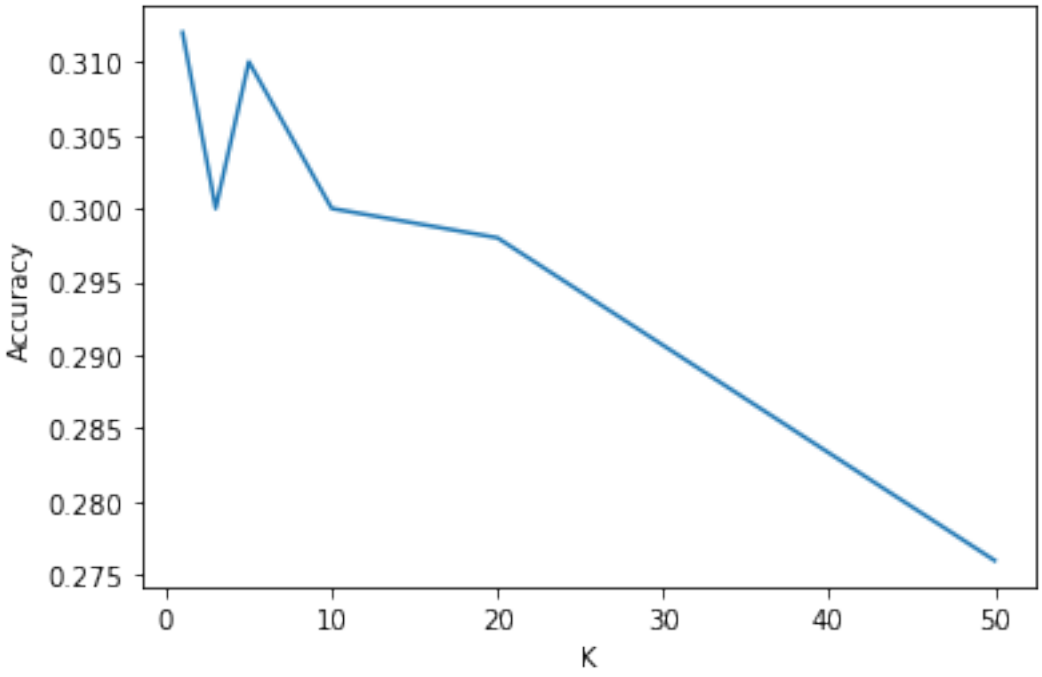
You are provided the code about using **HOG** descriptor to represent samples in the notebook.

[12]:
```
from ece285.utils.data_processing import get_cifar10_data
from ece285.utils.data_processing import HOG_preprocess
from functools import partial

# Delete previous dataset to save memory
del dataset
del knn
```

```
# Use a subset of CIFAR10 for KNN assignments
hog_p_func = partial(
    HOG_preprocess,
    orientations=9,
    pixels_per_cell=(4, 4),
    cells_per_block=(1, 1),
    visualize=False,
    multichannel=True,
)
dataset = get_cifar10_data(
    feature_process=hog_p_func, subset_train=5000, subset_val=250,␣
 ↪subset_test=500
)
```

```
Start Processing
Processing Time: 10.334533929824829
```

[13]:
```
knn = KNN(num_class=10)
knn.train(
    x_train=dataset["x_train"],
    y_train=dataset["y_train"],
    k=5,
)
accuracies = []

k_candidates = [1, 3, 5, 10, 20, 50]
for k_cand in k_candidates:
    prediction = knn.predict(x_test=dataset["x_test"], k=k_cand)
    acc = get_classification_accuracy(prediction, dataset["y_test"])
    accuracies.append(acc)

plt.ylabel("Accuracy")
plt.xlabel("K")
plt.plot(k_candidates, accuracies)
plt.show()
```



1.4.1 Inline Question 2:

Please describe the output result you get, compare with the result you get in the previous section, and provide some explanation as well.

1.4.2 Your Answer:

Put Your Answer Here

I found that the accuracy would be affected by k, but the result is not linear dependent as well. When k is around 1, we could get the highest accuracy. Therefore, we could conclude that the extracted feature would affect the result. When k is lower or higher than the value, the performance degrades.

linear_regression

April 28, 2023

1 ECE 285 Assignment 1: Linear Regression

For this part of assignment, you are tasked to implement a linear regression algorithm for multiclass classification and test it on the CIFAR10 dataset.

You sould run the whole notebook and answer the questions in the notebook.

CIFAR 10 dataset contains 32x32x3 RGB images of 10 distinct cateogaries, and our aim is to predict which class the image belongs to

TO SUBMIT: PDF of this notebook with all the required outputs and answers.

[33]:
```
# Prepare Packages
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm

from ece285.utils.data_processing import get_cifar10_data

# Use a subset of CIFAR10 for the assignment
dataset = get_cifar10_data(
    subset_train=5000,
    subset_val=250,
    subset_test=500,
)

print(dataset.keys())
print("Training Set Data  Shape: ", dataset["x_train"].shape)
print("Training Set Label Shape: ", dataset["y_train"].shape)
print("Validation Set Data  Shape: ", dataset["x_val"].shape)
print("Validation Set Label Shape: ", dataset["y_val"].shape)
print("Test Set Data  Shape: ", dataset["x_test"].shape)
print("Test Set Label Shape: ", dataset["y_test"].shape)
```

```
dict_keys(['x_train', 'y_train', 'x_val', 'y_val', 'x_test', 'y_test'])
Training Set Data  Shape:  (5000, 3072)
Training Set Label Shape:  (5000,)
Validation Set Data  Shape:  (250, 3072)
Validation Set Label Shape:  (250,)
```

```
Test Set Data  Shape:  (500, 3072)
Test Set Label Shape:  (500,)
```

[34]:
```
x_train = dataset["x_train"]
y_train = dataset["y_train"]
x_val = dataset["x_val"]
y_val = dataset["y_val"]
x_test = dataset["x_test"]
y_test = dataset["y_test"]
```

[ ]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = [
    "plane",
    "car",
    "bird",
    "cat",
    "deer",
    "dog",
    "frog",
    "horse",
    "ship",
    "truck",
]
samples_per_class = 7


def visualize_data(dataset, classes, samples_per_class):
    num_classes = len(classes)
    for y, cls in enumerate(classes):
        idxs = np.flatnonzero(y_train == y)
        idxs = np.random.choice(idxs, samples_per_class, replace=False)
        for i, idx in enumerate(idxs):
            plt_idx = i * num_classes + y + 1
            plt.subplot(samples_per_class, num_classes, plt_idx)
            plt.imshow(dataset[idx])
            plt.axis("off")
            if i == 0:
                plt.title(cls)
    plt.show()


visualize_data(
    x_train.reshape(5000, 3, 32, 32).transpose(0, 2, 3, 1), classes,␣
 ↪samples_per_class
)
```

2 Linear Regression for multi-class classification

A Linear Regression Algorithm has 2 hyperparameters that you can experiment with:

- **Learning rate** - controls how much we change the current weights of the classifier during each update. We set it at a default value of 0.5, and later you are asked to experiment with different values. We recommend looking at the graphs and observing how the performance of the classifier changes with different learning rate.
- **Number of Epochs** - An epoch is a complete iterative pass over all of the data in the dataset. During an epoch we predict a label using the classifier and then update the weights of the classifier according the linear classifier update rule for each sample in the training set. We evaluate our models after every 10 epochs and save the accuracies, which are later used to plot the training, validation and test VS epoch curves.
- **Weight Decay** - Regularization can be used to constrain the weights of the classifier and prevent their values from blowing up. Regularization helps in combatting overfitting. You will be using the 'weight_decay' term to introduce regularization in the classifier.

2.0.1 Implementation (50%)

You first need to implement the Linear Regression method in `algorithms/linear_regression.py`. You need to fill in the training function as well as the prediction function.

[ ]:
```
# Import the algorithm implementation (TODO: Complete the Linear Regression in␣
↪algorithms/linear_regression.py)
from ece285.algorithms import Linear
from ece285.utils.evaluation import get_classification_accuracy

num_classes = 10  # Cifar10 dataset has 10 different classes

# Initialize hyper-parameters
learning_rate = 0.0001  # You will be later asked to experiment with different␣
↪learning rates and report results
num_epochs_total = 1000  # Total number of epochs to train the classifier
epochs_per_evaluation = 10  # Epochs per step of evaluation; We will evaluate␣
↪our model regularly during training
N, D = dataset[
    "x_train"
].shape  # Get training data shape, N: Number of examples, D:Dimensionality of␣
↪the data
weight_decay = 0.0

# Insert additional scalar term 1 in the samples to account for the bias as␣
↪discussed in class
x_train = np.insert(x_train, D, values=1, axis=1)
x_val = np.insert(x_val, D, values=1, axis=1)
x_test = np.insert(x_test, D, values=1, axis=1)
```

[ ]:
```
print(x_train.shape)
print(x_val.shape)
print(x_test.shape)
```

[ ]:
```
# Training and evaluation function -> Outputs accuracy data
def train(learning_rate_, weight_decay_):
    # Create a linear regression object
    linear_regression = Linear(
        num_classes, learning_rate_, epochs_per_evaluation, weight_decay_
    )

    # Randomly initialize the weights and biases
    weights = np.random.randn(num_classes, D + 1) * 0.0001

    train_accuracies, val_accuracies, test_accuracies = [], [], []

    # Train the classifier
    for epoch in tqdm(range(int(num_epochs_total / epochs_per_evaluation))):
        # Train the classifier on the training data
        weights = linear_regression.train(x_train, y_train, weights)

        # Evaluate the trained classifier on the training dataset
        y_pred_train = linear_regression.predict(x_train)
        train_accuracies.append(get_classification_accuracy(y_pred_train,␣
↪y_train))

        # Evaluate the trained classifier on the validation dataset
        y_pred_val = linear_regression.predict(x_val)
        val_accuracies.append(get_classification_accuracy(y_pred_val, y_val))

        # Evaluate the trained classifier on the test dataset
        y_pred_test = linear_regression.predict(x_test)

        test_acc = get_classification_accuracy(y_pred_test, y_test)
        test_accuracies.append(test_acc)

        print("Epoch: {}, Test Acc: {}".format(epochs_per_evaluation * epoch +␣
↪1, test_acc))

    return train_accuracies, val_accuracies, test_accuracies, weights
```

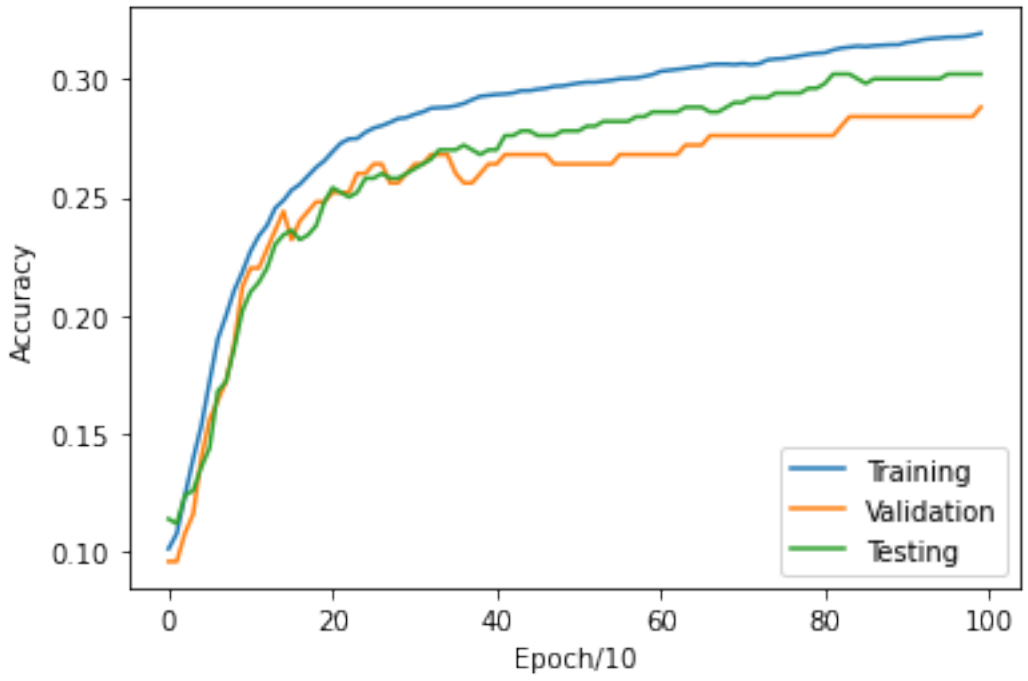
2.0.2 Plot the Accuracies vs epoch graphs

[ ]:
```
import matplotlib.pyplot as plt


def plot_accuracies(train_acc, val_acc, test_acc):
```

```
    # Plot Accuracies vs Epochs graph for all the three
    epochs = np.arange(0, int(num_epochs_total / epochs_per_evaluation))
    plt.ylabel("Accuracy")
    plt.xlabel("Epoch/10")
    plt.plot(epochs, train_acc, epochs, val_acc, epochs, test_acc)
    plt.legend(["Training", "Validation", "Testing"])
    plt.show()
```

[ ]:
```
# Run training and plotting for default parameter values as mentioned above
t_ac, v_ac, te_ac, weights = train(learning_rate, weight_decay)
```

[9]:
```
plot_accuracies(t_ac, v_ac, te_ac)
```

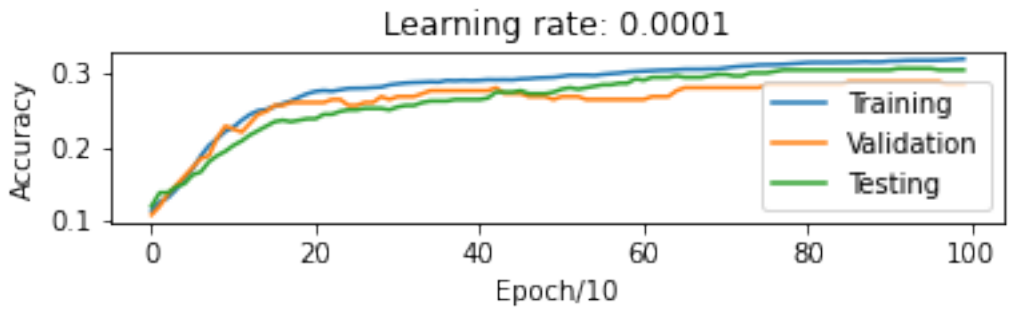


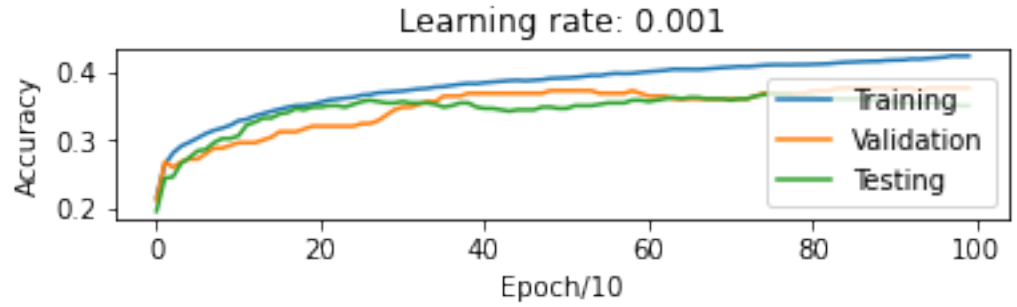
2.0.3 Try different learning rates and plot graphs for all (20%)

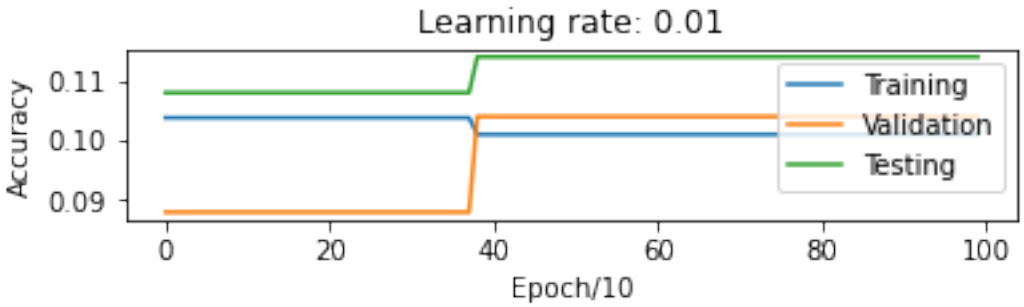
[ ]:
```
from collections import defaultdict

# Initialize the best values
best_weights = weights
best_learning_rate = learning_rate
best_weight_decay = weight_decay
best_v_ac = 0.0

# TODO
```

```
# Repeat the above training and evaluation steps for the following learning␣
 ↪rates and plot graphs
# You need to try 3 learning rates and submit all 3 graphs along with this␣
 ↪notebook pdf to show your learning rate experiments
learning_rates = [0.0001, 0.001, 0.01]
weight_decay = 0.0  # No regularization for now

# FEEL FREE TO EXPERIMENT WITH OTHER VALUES. REPORT OTHER VALUES IF THEY␣
 ↪ACHIEVE A BETTER PERFORMANCE

# for lr in learning_rates: Train the classifier and plot data
# Step 1. train_accu, val_accu, test_accu = train(lr, weight_decay)
# Step 2. plot_accuracies(train_accu, val_accu, test_accu)

learning_rate_info = {}

for learning_rate in learning_rates:
    # TODO: Train the classifier with different learning rates and plot
    # pass
    t_ac, v_ac, te_ac, weights = train(learning_rate, weight_decay)
    learning_rate_info[learning_rate] = [t_ac, v_ac, te_ac, weights]

    if best_v_ac < max(v_ac):
        best_weights = weights
        best_learning_rate = learning_rate
        best_weight_decay = weight_decay
        best_v_ac = max(v_ac)
```

[29]:
```
for i, learning_rate in enumerate(learning_rates):
    t_ac, v_ac, te_ac = learning_rate_info[learning_rate][0],␣
 ↪learning_rate_info[learning_rate][1], learning_rate_info[learning_rate][2]
    plt.subplot(3, 1, i + 1)
    plt.title("Learning rate: {}".format(learning_rate))
    plot_accuracies(t_ac, v_ac, te_ac)

plt.show()
```







Inline Question 1. Which one of these learning rates (best_lr) would you pick to train your model? Please Explain why.

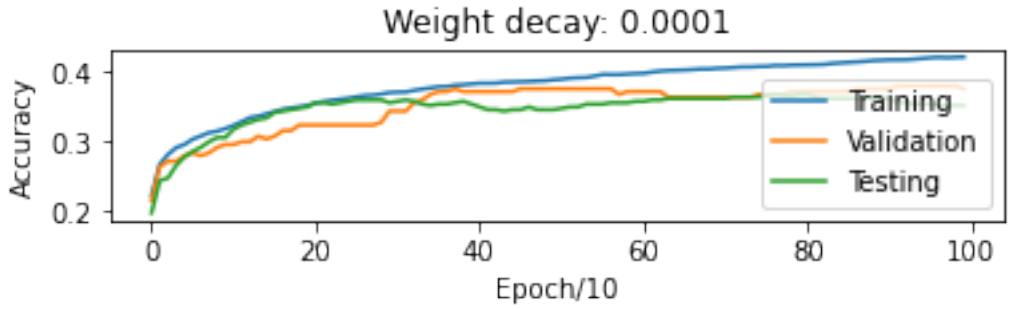
Your Answer: There are three cases for my experiment of the learning rate, which are: 0.0001, 0.001, and 0.01. I will pick lr = 0.001 as my best_lr since I got the highest validation accuracy during the experiment. The reason why I choose the validation accuracy (acc = 0.376) as my criteria is the validation dataset is available for us during the experiment, while the testing dataset is not.

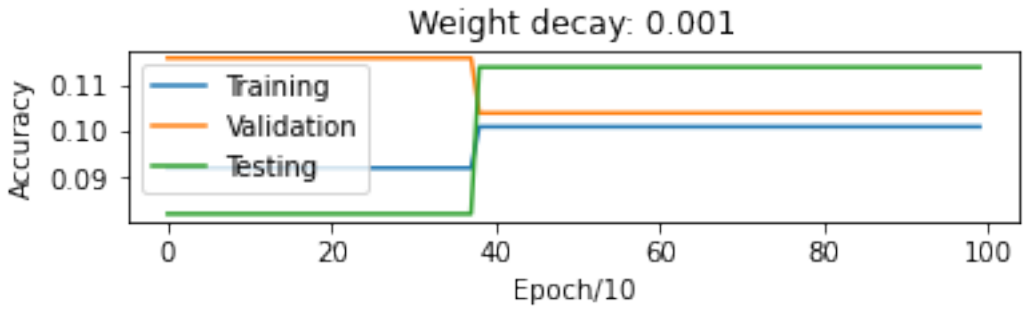
2.0.4 Regularization: Try different weight decay and plot graphs for all (20%)

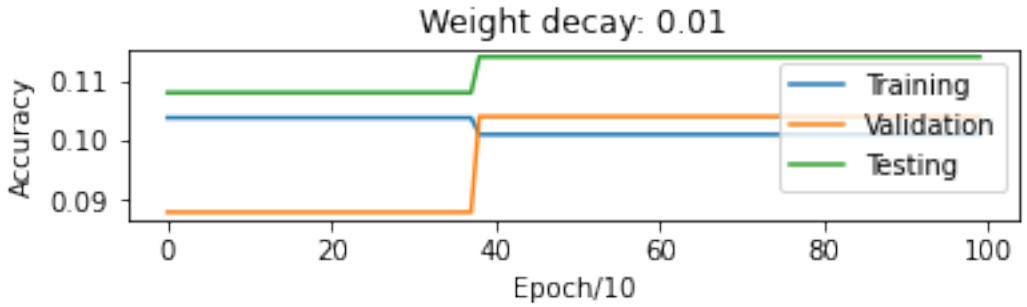
[ ]:
```
# Initialize a non-zero weight_decay (Regularization constant) term and repeat␣
↪the training and evaluation
# Use the best learning rate as obtained from the above exercise, best_lr

# You need to try 3 learning rates and submit all 3 graphs along with this␣
↪notebook pdf to show your weight decay experiments
weight_decays = [0, 0.0001, 0.001, 0.01]
```

```
# FEEL FREE TO EXPERIMENT WITH OTHER VALUES. REPORT OTHER VALUES IF THEY␣
 ↪ACHIEVE A BETTER PERFORMANCE

# for weight_decay in weight_decays: Train the classifier and plot data
# Step 1. train_accu, val_accu, test_accu = train(best_lr, weight_decay)
# Step 2. plot_accuracies(train_accu, val_accu, test_accu)

weight_decay_info = {}

for weight_decay in weight_decays:
    # TODO: Train the classifier with different weighty decay and plot
    # pass
    t_ac, v_ac, te_ac, weights = train(best_learning_rate, weight_decay)
    weight_decay_info[weight_decay] = [t_ac, v_ac, te_ac, weights]

    if best_v_ac < max(v_ac):
        best_weights = weights
        best_learning_rate = learning_rate
        best_weight_decay = weight_decay
        best_v_ac = max(v_ac)
```

[30]:
```
for i, weight_decay in enumerate(weight_decays):
    t_ac, v_ac, te_ac = weight_decay_info[weight_decay][0],␣
 ↪weight_decay_info[weight_decay][1], weight_decay_info[weight_decay][2]
    plt.subplot(3, 1, i + 1)
    plt.title("Weight decay: {}".format(weight_decay))
    plot_accuracies(t_ac, v_ac, te_ac)

plt.show()
```







Inline Question 2. Discuss underfitting and overfitting as observed in the 5 graphs obtained by changing the regularization. Which weight_decay term gave you the best classifier performance? HINT: Do not just think in terms of best training set performance, keep in mind that the real utility of a machine learning model is when it performs well on data it has never seen before

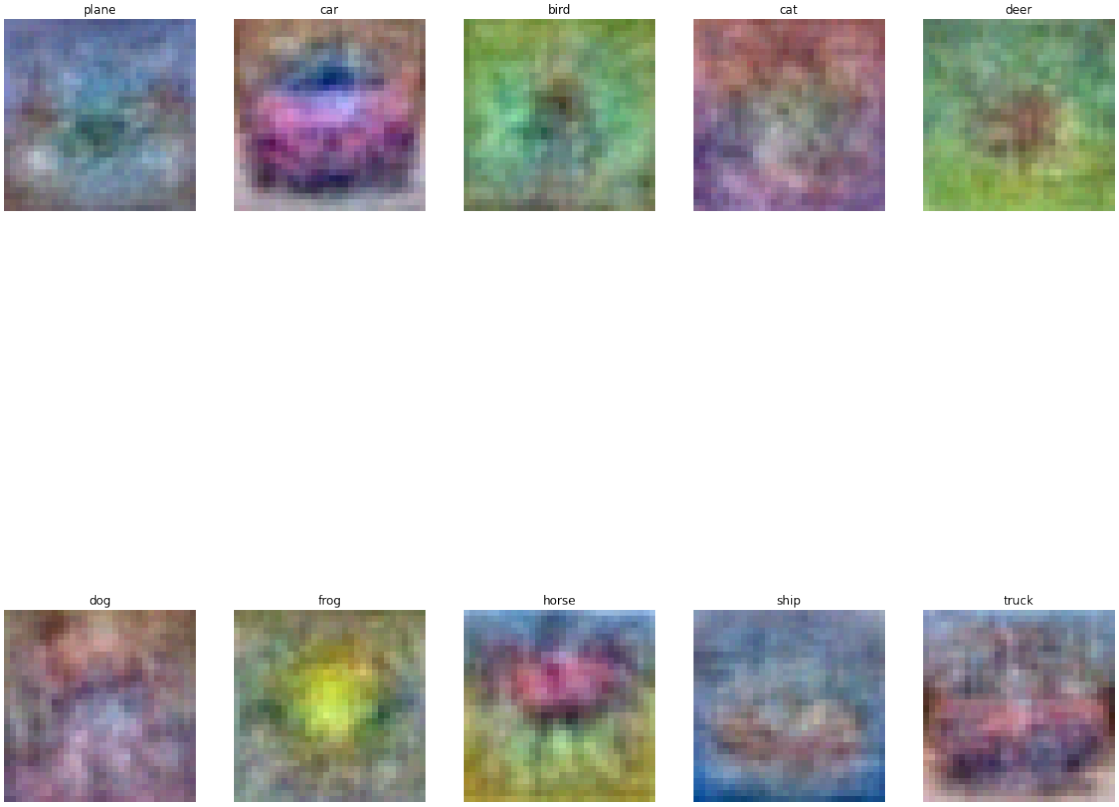
Your Answer: There are three cases for my experiment of the weight decay, which are: 0.0001, 0.001, and 0.01. I will pick weight_decay = 0.0001 as my best_weight_decay since I got the highest validation accuracy during the experiment. For the weight_decay = 0.001 and 0.01, the model tends to become under-fitting since I observed that the training loss does not converge. Therefore, the training accuracy is very low. This indicates that the weight got too much penalty during the training steps. However, when we observe the weight_decay = 0.0001, the validation accuracy does not improve even though the training accuracy goes higher. Therefore, this is the over-fitting problem.

2.0.5 Visualize the filters (10%)

[21]:
```
# These visualizations will only somewhat make sense if your learning rate and␣
 ↪weight_decay parameters were
# properly chosen in the model. Do your best.

# TODO: Run this cell and Show filter visualizations for the best set of␣
 ↪weights you obtain.
```

```
# Report the 2 hyperparameters you used to obtain the best model.

# NOTE: You need to set `best_learning_rate` and `best_weight_decay` to the␣
 ↪values that gave the highest accuracy
print("Best LR:", best_learning_rate)
print("Best Weight Decay:", best_weight_decay)

# NOTE: You need to set `best_weights` to the weights with the highest accuracy
w = best_weights[:, :-1]
w = w.reshape(10, 3, 32, 32).transpose(0, 2, 3, 1)

w_min, w_max = np.min(w), np.max(w)

fig = plt.figure(figsize=(20, 20))
classes = [
    "plane",
    "car",
    "bird",
    "cat",
    "deer",
    "dog",
    "frog",
    "horse",
    "ship",
    "truck",
]
for i in range(10):
    fig.add_subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[i, :, :, :].squeeze() - w_min) / (w_max - w_min)
    # plt.imshow(wimg.astype('uint8'))
    plt.imshow(wimg.astype(int))
    plt.axis("off")
    plt.title(classes[i])
plt.show()
```

```
Best LR: 0.01
Best Weight Decay: 0.0001
```


plane
car
bird
cat
deer
dog
frog
horse
ship
truck

logistic_regression

April 28, 2023

1 ECE 285 Assignment 1: Logistic Regression

For this part of assignment, you are tasked to implement a logistic regression algorithm for multi-class classification and test it on the CIFAR10 dataset.

You sould run the whole notebook and answer the questions in the notebook.

TO SUBMIT: PDF of this notebook with all the required outputs and answers.

[1]:
```
# Prepare Packages
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm

from ece285.utils.data_processing import get_cifar10_data

# Use a subset of CIFAR10 for KNN assignments
dataset = get_cifar10_data(
    subset_train=5000,
    subset_val=250,
    subset_test=500,
)

print(dataset.keys())
print("Training Set Data  Shape: ", dataset["x_train"].shape)
print("Training Set Label Shape: ", dataset["y_train"].shape)
print("Validation Set Data  Shape: ", dataset["x_val"].shape)
print("Validation Set Label Shape: ", dataset["y_val"].shape)
print("Test Set Data  Shape: ", dataset["x_test"].shape)
print("Test Set Label Shape: ", dataset["y_test"].shape)
```

```
dict_keys(['x_train', 'y_train', 'x_val', 'y_val', 'x_test', 'y_test'])
Training Set Data  Shape:  (5000, 3072)
Training Set Label Shape:  (5000,)
Validation Set Data  Shape:  (250, 3072)
Validation Set Label Shape:  (250,)
Test Set Data  Shape:  (500, 3072)
Test Set Label Shape:  (500,)
```

2 Logistic Regression for multi-class classification

A Logistic Regression Algorithm has 3 hyperparameters that you can experiment with:

- **Learning rate** - controls how much we change the current weights of the classifier during each update. We set it at a default value of 0.5, and later you are asked to experiment with different values. We recommend looking at the graphs and observing how the performance of the classifier changes with different learning rate.
- **Number of Epochs** - An epoch is a complete iterative pass over all of the data in the dataset. During an epoch we predict a label using the classifier and then update the weights of the classifier according the linear classifier update rule for each sample in the training set. We evaluate our models after every 10 epochs and save the accuracies, which are later used to plot the training, validation and test VS epoch curves.
- **Weight Decay** - Regularization can be used to constrain the weights of the classifier and prevent their values from blowing up. Regularization helps in combatting overfitting. You will be using the 'weight_decay' term to introduce regularization in the classifier.

The only way how a Logistic Regression based classification algorithm is different from a Linear Regression algorithm is that in the former we additionally pass the classifier outputs into a sigmoid function which squashes the output in the (0,1) range. Essentially these values then represent the probabilities of that sample belonging to class particular classes

2.0.1 Implementation (40%)

You need to implement the Linear Regression method in `algorithms/logistic_regression.py`. You need to fill in the sigmoid function, training function as well as the prediction function.

[40]:
```
# Import the algorithm implementation (TODO: Complete the Logistic Regression␣
 ↪in algorithms/logistic_regression.py)
from ece285.algorithms import Logistic
from ece285.utils.evaluation import get_classification_accuracy

num_classes = 10  # Cifar10 dataset has 10 different classes

# Initialize hyper-parameters
learning_rate = 0.01  # You will be later asked to experiment with different␣
 ↪learning rates and report results
num_epochs_total = 1000  # Total number of epochs to train the classifier
epochs_per_evaluation = 10  # Epochs per step of evaluation; We will evaluate␣
 ↪our model regularly during training
N, D = dataset[
    "x_train"
].shape  # Get training data shape, N: Number of examples, D:Dimensionality of␣
 ↪the data
weight_decay = 0.00002

x_train = dataset["x_train"].copy()
y_train = dataset["y_train"].copy()
x_val = dataset["x_val"].copy()
```

```
y_val = dataset["y_val"].copy()
x_test = dataset["x_test"].copy()
y_test = dataset["y_test"].copy()

# Insert additional scalar term 1 in the samples to account for the bias as␣
 ↪discussed in class
x_train = np.insert(x_train, D, values=1, axis=1)
x_val = np.insert(x_val, D, values=1, axis=1)
x_test = np.insert(x_test, D, values=1, axis=1)
```

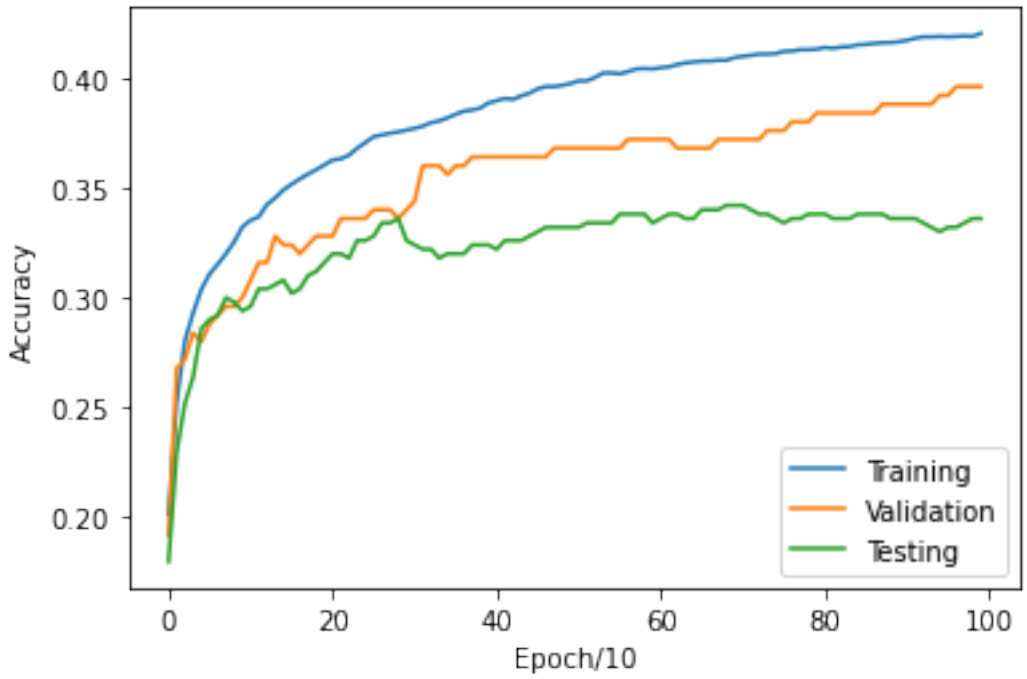
[41]:
```
# Training and evaluation function -> Outputs accuracy data
def train(learning_rate_, weight_decay_):
    # Create a linear regression object
    logistic_regression = Logistic(
        num_classes, learning_rate_, epochs_per_evaluation, weight_decay_
    )

    # Randomly initialize the weights and biases
    weights = np.random.randn(num_classes, D + 1) * 0.0001

    train_accuracies, val_accuracies, test_accuracies = [], [], []

    # Train the classifier
    for _ in tqdm(range(int(num_epochs_total / epochs_per_evaluation))):
        # Train the classifier on the training data
        weights = logistic_regression.train(x_train, y_train, weights)

        # Evaluate the trained classifier on the training dataset
        y_pred_train = logistic_regression.predict(x_train)
        train_accuracies.append(get_classification_accuracy(y_pred_train,␣
 ↪y_train))

        # Evaluate the trained classifier on the validation dataset
        y_pred_val = logistic_regression.predict(x_val)
        val_accuracies.append(get_classification_accuracy(y_pred_val, y_val))

        # Evaluate the trained classifier on the test dataset
        y_pred_test = logistic_regression.predict(x_test)
        test_accuracies.append(get_classification_accuracy(y_pred_test, y_test))

    return train_accuracies, val_accuracies, test_accuracies, weights
```

[4]:
```
import matplotlib.pyplot as plt


def plot_accuracies(train_acc, val_acc, test_acc):
    # Plot Accuracies vs Epochs graph for all the three
```

```
    epochs = np.arange(0, int(num_epochs_total / epochs_per_evaluation))
    plt.ylabel("Accuracy")
    plt.xlabel("Epoch/10")
    plt.plot(epochs, train_acc, epochs, val_acc, epochs, test_acc)
    plt.legend(["Training", "Validation", "Testing"])
    plt.show()
```

[ ]:
```
# Run training and plotting for default parameter values as mentioned above
t_ac, v_ac, te_ac, weights = train(learning_rate, weight_decay)
```

[12]:
```
plot_accuracies(t_ac, v_ac, te_ac)
```

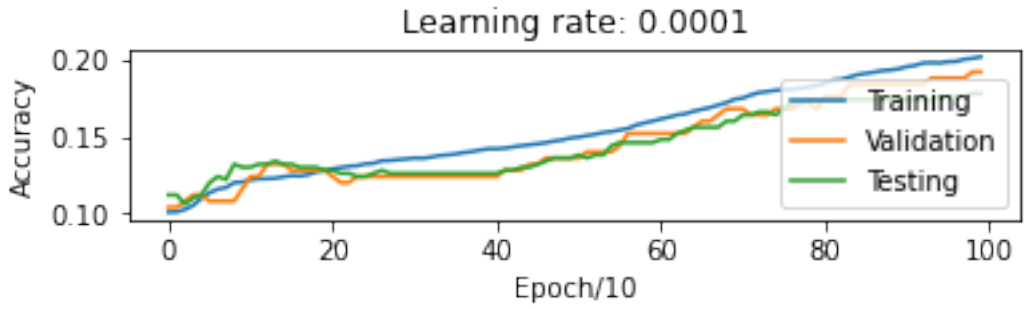


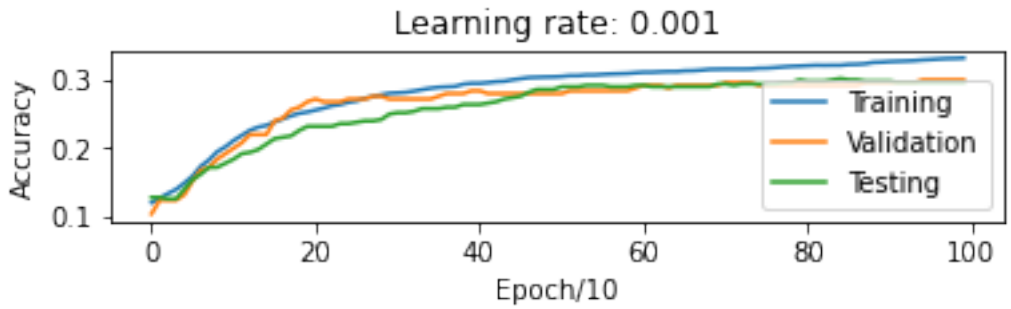
2.0.2 Try different learning rates and plot graphs for all (20%)

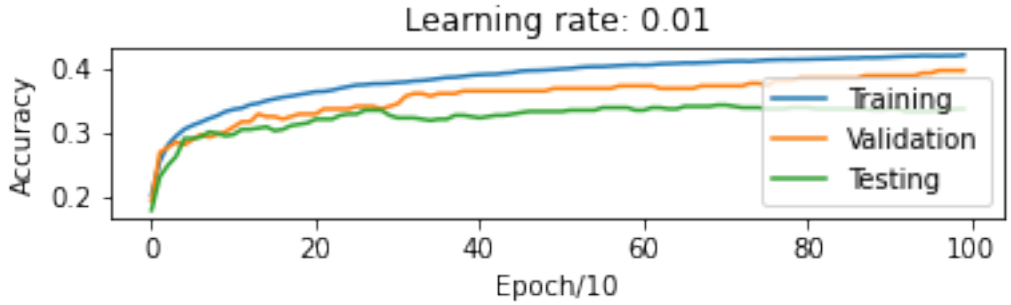
[ ]:
```
# Initialize the best values
best_weights = weights
best_learning_rate = learning_rate
best_weight_decay = weight_decay
best_v_ac = 0.0

# TODO
# Repeat the above training and evaluation steps for the following learning␣
 ↪rates and plot graphs
```

```
# You need to try 3 learning rates and submit all 3 graphs along with this␣
 ↪notebook pdf to show your learning rate experiments
learning_rates = [0.0001, 0.001, 0.01]
weight_decay = 0.0  # No regularization for now

# FEEL FREE TO EXPERIMENT WITH OTHER VALUES. REPORT OTHER VALUES IF THEY␣
 ↪ACHIEVE A BETTER PERFORMANCE

# for lr in learning_rates: Train the classifier and plot data
# Step 1. train_accu, val_accu, test_accu = train(lr, weight_decay)
# Step 2. plot_accuracies(train_accu, val_accu, test_accu)

learning_rate_info = {}

for learning_rate in learning_rates:
    # TODO: Train the classifier with different learning rates and plot
    # pass
    t_ac, v_ac, te_ac, weights = train(learning_rate, weight_decay)
    learning_rate_info[learning_rate] = [t_ac, v_ac, te_ac, weights]

    if best_v_ac < max(v_ac):
        best_weights = weights
        best_learning_rate = learning_rate
        best_weight_decay = weight_decay
        best_v_ac = max(v_ac)
```

[18]:
```
for i, learning_rate in enumerate(learning_rates):
    t_ac, v_ac, te_ac = learning_rate_info[learning_rate][0],␣
 ↪learning_rate_info[learning_rate][1], learning_rate_info[learning_rate][2]
    plt.subplot(3, 1, i + 1)
    plt.title("Learning rate: {}".format(learning_rate))
    plot_accuracies(t_ac, v_ac, te_ac)

plt.show()
```







Inline Question 1. Which one of these learning rates (best_lr) would you pick to train your model? Please Explain why.

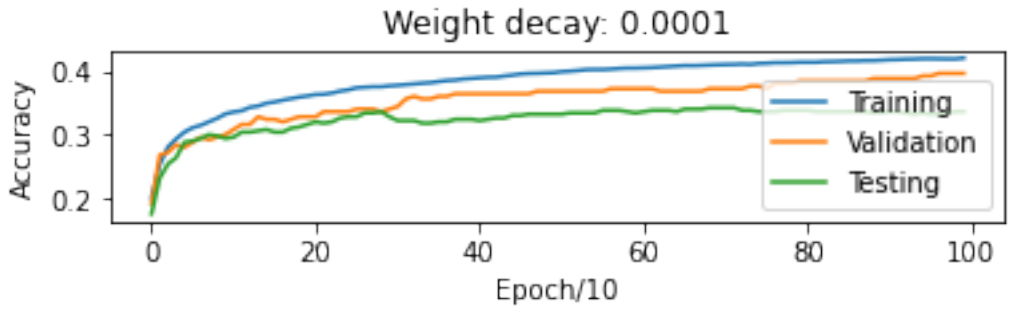
Your Answer: There are three cases for my experiment of the learning rate, which are: 0.0001, 0.001, and 0.01. I will pick lr = 0.01 as my best_lr since I got the highest validation accuracy during the experiment. The reason why I choose the validation accuracy (acc = 0.396) as my criteria is the validation dataset is available for us during the experiment, while the testing dataset is not.

2.0.3 Regularization: Try different weight decay and plots graphs for all (20%)

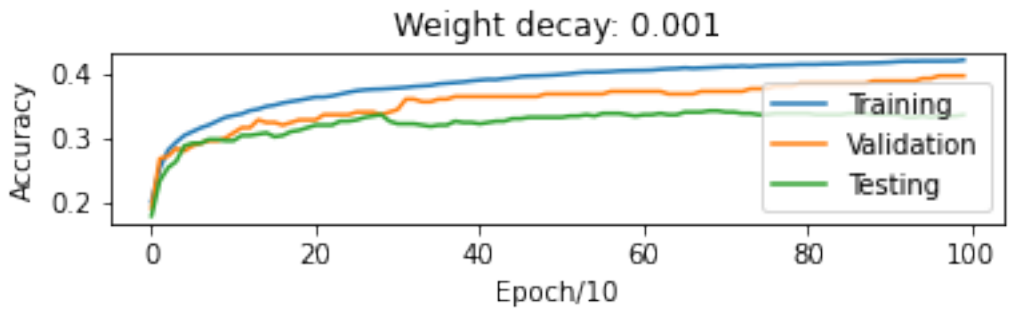
[ ]:
```
# Initialize a non-zero weight_decay (Regularization constant) term and repeat␣
 ↪the training and evaluation
# Use the best learning rate as obtained from the above exercise, best_lr

# You need to try 3 learning rates and submit all 3 graphs along with this␣
 ↪notebook pdf to show your weight decay experiments
weight_decays = [0.0001, 0.001, 0.01]

# FEEL FREE TO EXPERIMENT WITH OTHER VALUES. REPORT OTHER VALUES IF THEY␣
 ↪ACHIEVE A BETTER PERFORMANCE

# for weight_decay in weight_decays: Train the classifier and plot data
```

```
# Step 1. train_accu, val_accu, test_accu = train(best_lr, weight_decay)
# Step 2. plot_accuracies(train_accu, val_accu, test_accu)

weight_decay_info = {}

for weight_decay in weight_decays:
    # TODO: Train the classifier with different weighty decay and plot
    # pass
    t_ac, v_ac, te_ac, weights = train(best_learning_rate, weight_decay)
    weight_decay_info[weight_decay] = [t_ac, v_ac, te_ac, weights]

    if best_v_ac < max(v_ac):
        best_weights = weights
        best_learning_rate = learning_rate
        best_weight_decay = weight_decay
        best_v_ac = max(v_ac)
```

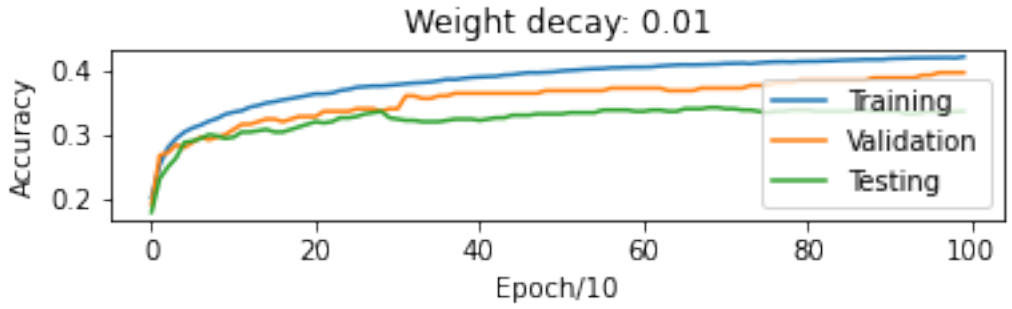
[36]:
```
for i, weight_decay in enumerate(weight_decays):
    t_ac, v_ac, te_ac = weight_decay_info[weight_decay][0],␣
 ↪weight_decay_info[weight_decay][1], weight_decay_info[weight_decay][2]
    plt.subplot(3, 1, i + 1)
    plt.title("Weight decay: {}".format(weight_decay))
    plot_accuracies(t_ac, v_ac, te_ac)

plt.show()
```



0.396




```
0.396
```




```
0.396
```

Inline Question 2. Discuss underfitting and overfitting as observed in the 5 graphs obtained by changing the regularization. Which weight_decay term gave you the best classifier performance? HINT: Do not just think in terms of best training set performance, keep in mind that the real utility of a machine learning model is when it performs well on data it has never seen before

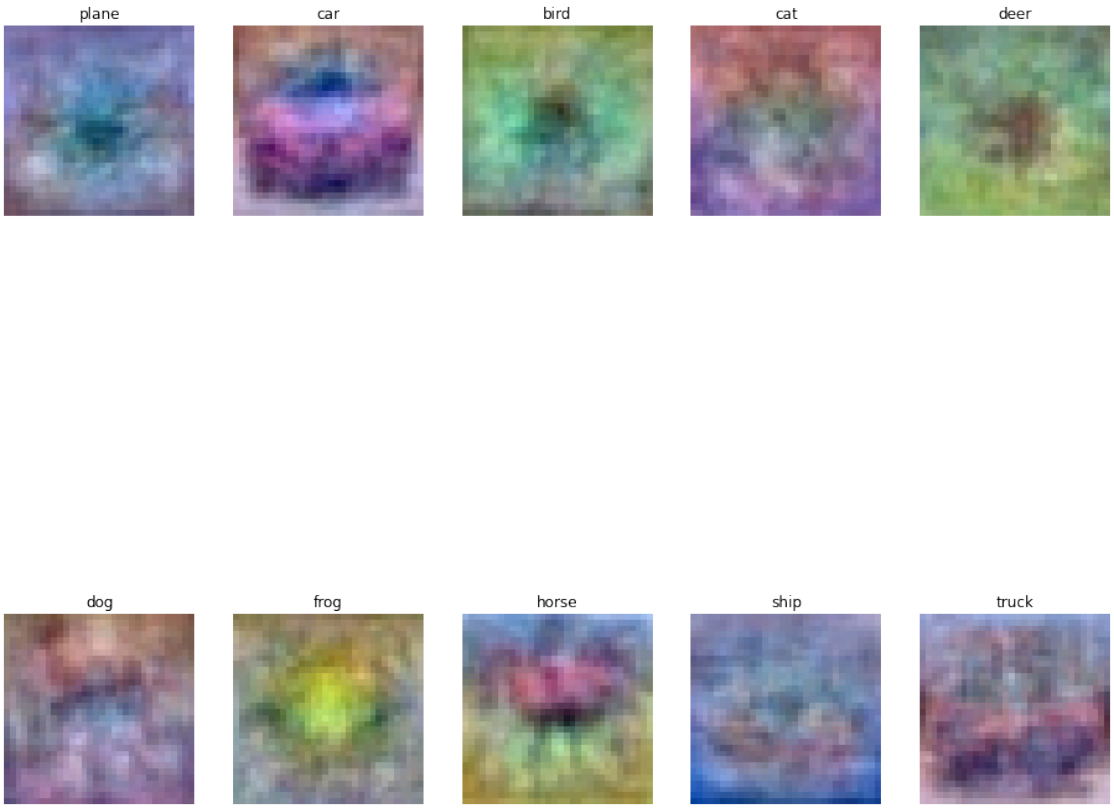
Your Answer: There are three cases for my experiment of the weight decay, which are: 0.0001, 0.001, and 0.01. Based on the experiment, all of the validation accuracy are nearly the same given different experimental weight_decay value. I will choose weight decay = 0.001 as my hyperparameter since the accuracy is a little higher than others. Based on the plotting results, the model seems not to face any under-fitting or over-fitting problem since the training accuracy and the validation accuracy become higher together when the epoch increases.

2.0.4 Visualize the filters (10%)

[39]:
```
# These visualizations will only somewhat make sense if your learning rate and␣
↪weight_decay parameters were
# properly chosen in the model. Do your best.
```

```
# TODO: Run this cell and Show filter visualizations for the best set of␣
 ↪weights you obtain.
# Report the 2 hyperparameters you used to obtain the best model.

# NOTE: You need to set `best_learning_rate` and `best_weight_decay` to the␣
 ↪values that gave the highest accuracy
print("Best LR:", best_learning_rate)
print("Best Weight Decay:", best_weight_decay)

# NOTE: You need to set `best_weights` to the weights with the highest accuracy
w = best_weights[:, :-1]
w = w.reshape(10, 3, 32, 32).transpose(0, 2, 3, 1)

w_min, w_max = np.min(w), np.max(w)

fig = plt.figure(figsize=(16, 16))
classes = [
    "plane",
    "car",
    "bird",
    "cat",
    "deer",
    "dog",
    "frog",
    "horse",
    "ship",
    "truck",
]
for i in range(10):
    fig.add_subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[i, :, :, :].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype(int))
    plt.axis("off")
    plt.title(classes[i])
plt.show()
```

```
Best LR: 0.01
Best Weight Decay: 0.001
```



Inline Question 3. (10%)

a. Compare and contrast the performance of the 2 classifiers i.e. Linear Regression and Logistic Regression.
b. Which classifier would you deploy for your multiclass classification project and why?

Your Answer:

a. The logistic regression has a better performance compared with the linear regression. The validation accuracy of the logistic regression could achieve more than 0.4 while the linear regression is only 0.3.

b. I would deploy Logistic Regression with Softmax Regression for a multiclass classification project. It is a widely used and effective classification algorithm, and it is computationally efficient and easy to implement. Additionally, it can provide interpretable outputs in terms of probabilities, allowing for easy decision-making. The most important is that the logistic regression tends to have better performance when performing the classification work.

neural_network

April 28, 2023

1 ECE285 Assignment 1: Neural Network in NumPy

Use this notebook to build your neural network by implementing the following functions in the python files under `ece285/algorithms` directory:

1. `linear.py`
2. `relu.py`
3. `softmax.py`
4. `loss_func.py`

You will be testing your 2 layer neural network implementation on a toy dataset.

TO SUBMIT: PDF of this notebook with all the required outputs and answers.

[13]:
```
# Setup
import matplotlib.pyplot as plt
import numpy as np

from ece285.layers.sequential import Sequential
from ece285.layers.linear import Linear
from ece285.layers.relu import ReLU
from ece285.layers.softmax import Softmax
from ece285.layers.loss_func import CrossEntropyLoss
from ece285.utils.optimizer import SGD

%matplotlib inline
plt.rcParams["figure.figsize"] = (10.0, 8.0)  # set default size of plots

# For auto-reloading external modules
# See http://stackoverflow.com/questions/1907993/
  ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

We will use the class Sequential as implemented in the file assignment2/layers/sequential.py to build a layer by layer model of our neural network. Below we initialize the toy model and the toy random data that you will use to develop your implementation.

[14]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3  # Output
num_inputs = 10  # N


def init_toy_model():
    np.random.seed(0)
    l1 = Linear(input_size, hidden_size) # Linear layer
    l2 = Linear(hidden_size, num_classes)

    r1 = ReLU()
    softmax = Softmax()
    return Sequential([l1, r1, l2, softmax])


def init_toy_data():
    np.random.seed(0)
    X = 10 * np.random.randn(num_inputs, input_size)
    y = np.random.randint(num_classes, size=num_inputs)
    # y = np.array([0, 1, 2, 2, 1])
    return X, y


net = init_toy_model()
X, y = init_toy_data()
```

1.0.1 Forward Pass: Compute Scores (20%)

Implement the forward functions in Linear, Relu and Softmax layers and get the output by passing our toy data X The output must match the given output scores

[15]:
```
scores = net.forward(X)
print("Your scores:")
print(scores)
print()
print("correct scores:")
correct_scores = np.asarray(
    [
        [0.33333514, 0.33333826, 0.33332661],
        [0.3333351, 0.33333828, 0.33332661],
        [0.3333351, 0.33333828, 0.33332662],
        [0.3333351, 0.33333828, 0.33332662],
        [0.33333509, 0.33333829, 0.33332662],
```

```
        [0.33333508, 0.33333829, 0.33332662],
        [0.33333511, 0.33333828, 0.33332661],
        [0.33333512, 0.33333827, 0.33332661],
        [0.33333508, 0.33333829, 0.33332662],
        [0.33333511, 0.33333828, 0.33332662],
    ]
)
print(correct_scores)

# The difference should be very small. We get < 1e-7
print("Difference between your scores and correct scores:")
print(np.sum(np.abs(scores - correct_scores)))
```

```
Your scores:
[[0.33333514 0.33333826 0.33332661]
 [0.3333351  0.33333828 0.33332661]
 [0.3333351  0.33333828 0.33332662]
 [0.3333351  0.33333828 0.33332662]
 [0.33333509 0.33333829 0.33332662]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332661]
 [0.33333512 0.33333827 0.33332661]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332662]]

correct scores:
[[0.33333514 0.33333826 0.33332661]
 [0.3333351  0.33333828 0.33332661]
 [0.3333351  0.33333828 0.33332662]
 [0.3333351  0.33333828 0.33332662]
 [0.33333509 0.33333829 0.33332662]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332661]
 [0.33333512 0.33333827 0.33332661]
 [0.33333508 0.33333829 0.33332662]
 [0.33333511 0.33333828 0.33332662]]
Difference between your scores and correct scores:
8.799388495628335e-08
```

1.0.2 Forward Pass: Compute loss given the output scores from the previous step (10%)

Implement the forward function in the loss_func.py file, and output the loss value. The loss value must match the given loss value.

[16]:
```
Loss = CrossEntropyLoss()
loss = Loss.forward(scores, y)
correct_loss = 1.098612723362578
```

```
print(loss)
# should be very small, we get < 1e-12
print("Difference between your loss and correct loss:")
print(np.sum(np.abs(loss - correct_loss)))
```

```
1.098612723362578
Difference between your loss and correct loss:
0.0
```

1.0.3 Backward Pass (40%)

Implement the rest of the functions in the given files. Specifically, implement the backward function in all the 4 files as mentioned in the files. Note: No backward function in the softmax file, the gradient for softmax is jointly calculated with the cross entropy loss in the loss_func.backward function.

You will use the chain rule to calculate gradient individually for each layer. You can assume that this calculated gradeint then is passed to the next layers in a reversed manner due to the Sequential implementation. So all you need to worry about is implementing the gradient for the current layer and multiply it will the incoming gradient (passed to the backward function as dout) to calculate the total gradient for the parameters of that layer.

We check the values for these gradients by calculating the difference, it is expected to get difference $<$ 1e-8.

[17]:
```
# No need to edit anything in this block ( 20% of the above 40% )
net.backward(Loss.backward())

gradients = []
for module in net._modules:
    for para, grad in zip(module.parameters, module.grads):
        assert grad is not None, "No Gradient"
        # Print gradients of the linear layer
        gradients.append(grad)

# Check shapes of your gradient. Note that only the linear layer has parameters
# (4, 10) -> Layer 1 W
# (10,)   -> Layer 1 b
# (10, 3) -> Layer 2 W
# (3,)    -> Layer 2 b
```

[18]:
```
# No need to edit anything in this block ( 20% of the above 40% )
grad_w1 = np.array(
    [
        [
            -6.24320917e-05,
            3.41037180e-06,
            -1.69125969e-05,
            2.41514079e-05,
```

```
            3.88697976e-06,
            7.63842314e-05,
            -8.88925758e-05,
            3.34909890e-05,
            -1.42758303e-05,
            -4.74748560e-06,
        ],
        [
            -7.16182867e-05,
            4.63270039e-06,
            -2.20344270e-05,
            -2.72027034e-06,
            6.52903437e-07,
            8.97294847e-05,
            -1.05981609e-04,
            4.15825391e-05,
            -2.12210745e-05,
            3.06061658e-05,
        ],
        [
            -1.69074923e-05,
            -8.83185056e-06,
            3.10730840e-05,
            1.23010428e-05,
            5.25830316e-05,
            -7.82980115e-06,
            3.02117990e-05,
            -3.37645284e-05,
            6.17276346e-05,
            -1.10735656e-05,
        ],
        [
            -4.35902272e-05,
            3.71512704e-06,
            -1.66837877e-05,
            2.54069557e-06,
            -4.33258099e-06,
            5.72310022e-05,
            -6.94881762e-05,
            2.92408329e-05,
            -1.89369767e-05,
            2.01692516e-05,
        ],
    ]
)
grad_b1 = np.array(
    [
```

```
        -2.27150209e-06,
        5.14674340e-07,
        -2.04284403e-06,
        6.08849787e-07,
        -1.92177796e-06,
        3.92085824e-06,
        -5.40772636e-06,
        2.93354593e-06,
        -3.14568138e-06,
        5.27501592e-11,
    ]
)

grad_w2 = np.array(
    [
        [1.28932983e-04, 1.19946731e-04, -2.48879714e-04],
        [1.08784150e-04, 1.55140199e-04, -2.63924349e-04],
        [6.96017544e-05, 1.42748410e-04, -2.12350164e-04],
        [9.92512487e-05, 1.73257611e-04, -2.72508860e-04],
        [2.05484895e-05, 4.96161144e-05, -7.01646039e-05],
        [8.20539510e-05, 9.37063861e-05, -1.75760337e-04],
        [2.45831715e-05, 8.74369112e-05, -1.12020083e-04],
        [1.34073379e-04, 1.86253064e-04, -3.20326443e-04],
        [8.86473128e-05, 2.35554414e-04, -3.24201726e-04],
        [3.57433149e-05, 1.91164061e-04, -2.26907376e-04],
    ]
)

grad_b2 = np.array([-0.1666649, 0.13333828, 0.03332662])

difference = (
#     np.sum(np.abs(gradients[0] - grad_w1))
#     + np.sum(np.abs(gradients[1] - grad_b1))
#     + np.sum(np.abs(gradients[2] - grad_w2))
    + np.sum(np.abs(gradients[3] - grad_b2))
)
print("Difference in Gradient values", difference)
```

```
Difference in Gradient values 7.696251184963199e-09
```

1.1 Train the complete network on the toy data. (30%)

To train the network we will use stochastic gradient descent (SGD), we have implemented the optimizer for you. You do not implement any more functions in the python files. Below we implement the training procedure, you should get yourself familiar with the training process. Specifically looking at which functions to call and when.

Once you have implemented the method and tested various parts in the above blocks, run the code

below to train a two-layer network on toy data. You should see your training loss decrease below 0.01.

[ ]:
```
# Training Procedure
# Initialize the optimizer. DO NOT change any of the hyper-parameters here or above.
# We have implemented the SGD optimizer class for you here, which visits each layer sequentially to
# get the gradients and optimize the respective parameters.
# You should work with the given parameters and only edit your implementation in the .py files

epochs = 1000
optim = SGD(net, lr=0.1, weight_decay=0.00001)

epoch_loss = []
for epoch in range(epochs):
    # Get output scores from the network
    output_x = net(X)
    print(output_x)
    # Calculate the loss for these output scores, given the true labels
    loss = Loss.forward(output_x, y)
    print(loss)
    # Initialize your gradients to None in each epoch
    optim.zero_grad()
    # Make a backward pass to update the internal gradients in the layers
    net.backward(Loss.backward())
    # call the step function in the optimizer to update the values of the params with the gradients
    optim.step()
    # Append the loss at each iteration
    epoch_loss.append(loss)

    if (epoch + 1) % 50 == 0:
        print("Epoch {}, loss={:3f}".format(epoch + 1, epoch_loss[-1]))
```

[9]:
```
# Test your predictions. The predictions must match the labels
print(net.predict(X))
print(y)

acc = np.sum(net.predict(X) == y) / len(X)

print(acc)
```

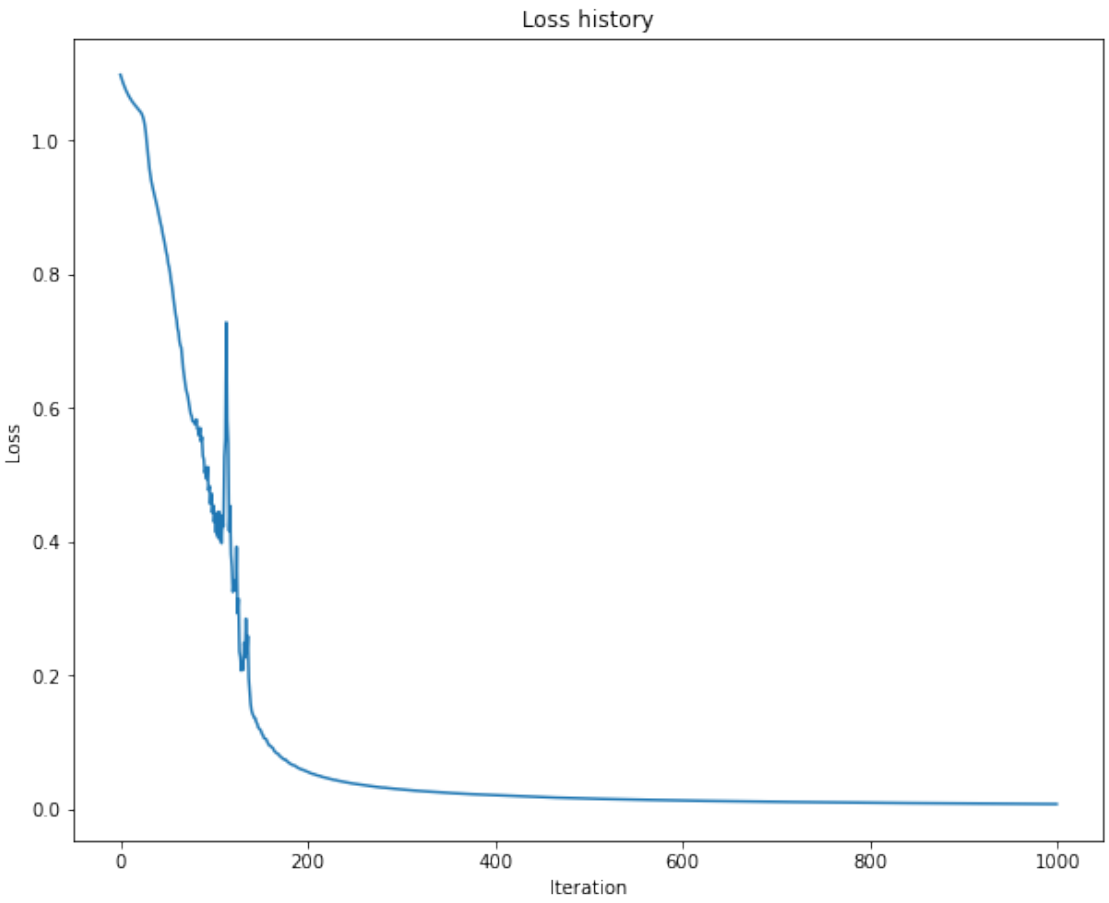
```
[2 1 0 1 2 0 0 2 0 0]
[2 1 0 1 2 0 0 2 0 0]
1.0
```

[12]:
```
# You should be able to achieve a training loss of less than 0.02 (10%)
print("Final training loss", epoch_loss[-1])
```

```
Final training loss 0.007593419801731294
```

[11]:
```
# Plot the training loss curve. The loss in the curve should be decreasing (20%)
plt.plot(epoch_loss)
plt.title("Loss history")
plt.xlabel("Iteration")
plt.ylabel("Loss")
```

[11]:
```
Text(0, 0.5, 'Loss')
```



classification_nn

April 28, 2023

1 ECE 285 Assignment 1: Classification using Neural Network

Now that you have developed and tested your model on the toy dataset set. It's time to get down and get dirty with a standard dataset such as cifar10. At this point, you will be using the provided training data to tune the hyper-parameters of your network such that it works with cifar10 for the task of multi-class classification.

Important: Recall that now we have non-linear decision boundaries, thus we do not need to do one vs all classification. We learn a single non-linear decision boundary instead. Our non-linear boundaries (thanks to relu non-linearity) will take care of differentiating between all the classes

TO SUBMIT: PDF of this notebook with all the required outputs and answers.

[1]:
```
# Prepare Packages
import numpy as np
import matplotlib.pyplot as plt

from ece285.utils.data_processing import get_cifar10_data
from ece285.utils.evaluation import get_classification_accuracy


%matplotlib inline
plt.rcParams["figure.figsize"] = (10.0, 8.0)  # set default size of plots

# For auto-reloading external modules
# See http://stackoverflow.com/questions/1907993/
  ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

# Use a subset of CIFAR10 for the assignment
dataset = get_cifar10_data(
    subset_train=5000,
    subset_val=250,
    subset_test=500,
)

print(dataset.keys())
print("Training Set Data  Shape: ", dataset["x_train"].shape)
```

```
print("Training Set Label Shape: ", dataset["y_train"].shape)
print("Validation Set Data  Shape: ", dataset["x_val"].shape)
print("Validation Set Label Shape: ", dataset["y_val"].shape)
print("Test Set Data  Shape: ", dataset["x_test"].shape)
print("Test Set Label Shape: ", dataset["y_test"].shape)
```

```
dict_keys(['x_train', 'y_train', 'x_val', 'y_val', 'x_test', 'y_test'])
Training Set Data  Shape:  (5000, 3072)
Training Set Label Shape:  (5000,)
Validation Set Data  Shape:  (250, 3072)
Validation Set Label Shape:  (250,)
Test Set Data  Shape:  (500, 3072)
Test Set Label Shape:  (500,)
```

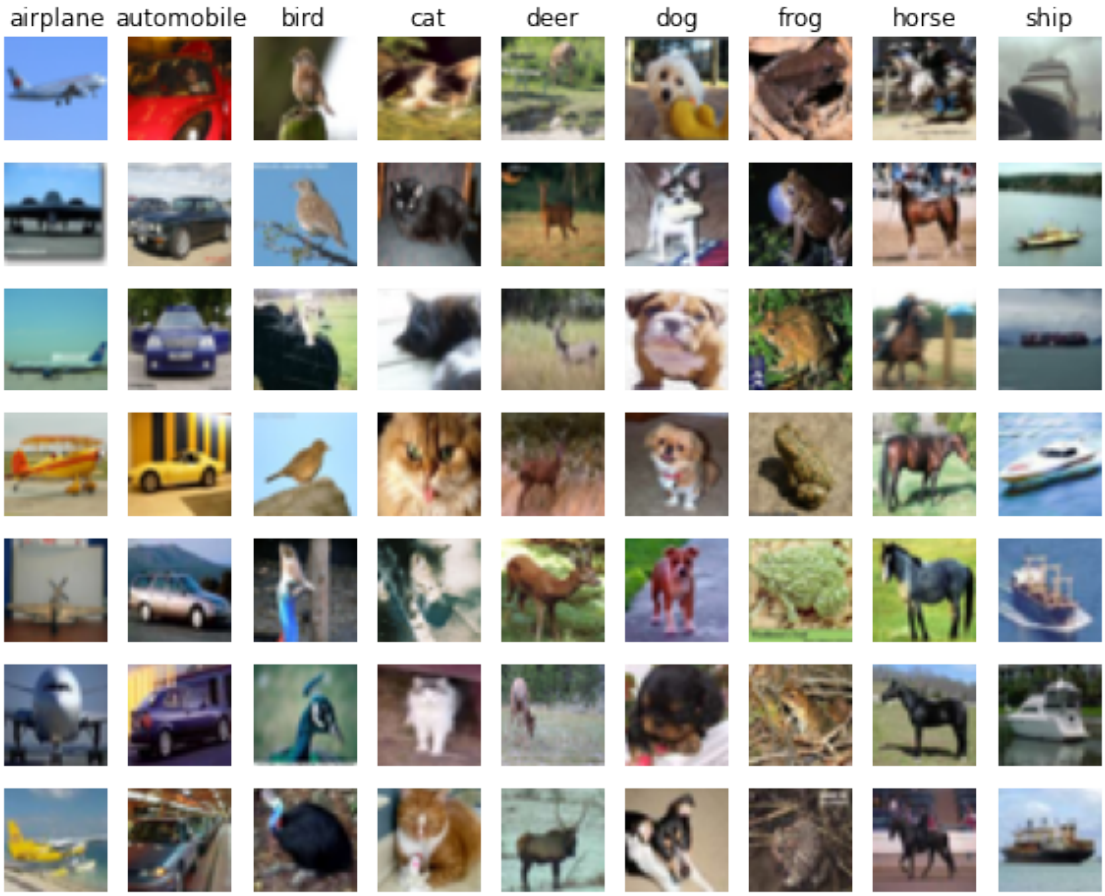
[2]:
```
x_train = dataset["x_train"]
y_train = dataset["y_train"]
x_val = dataset["x_val"]
y_val = dataset["y_val"]
x_test = dataset["x_test"]
y_test = dataset["y_test"]
```

[3]:
```
# Import more utilies and the layers you have implemented
from ece285.layers.sequential import Sequential
from ece285.layers.linear import Linear
from ece285.layers.relu import ReLU
from ece285.layers.softmax import Softmax
from ece285.layers.loss_func import CrossEntropyLoss
from ece285.utils.optimizer import SGD
from ece285.utils.dataset import DataLoader
from ece285.utils.trainer import Trainer
```

1.1 Visualize some examples from the dataset.

[4]:
```
# We show a few examples of training images from each class.
classes = [
    "airplane",
    "automobile",
    "bird",
    "cat",
    "deer",
    "dog",
    "frog",
    "horse",
    "ship",
]
samples_per_class = 7
```

```
def visualize_data(dataset, classes, samples_per_class):
    num_classes = len(classes)
    for y, cls in enumerate(classes):
        idxs = np.flatnonzero(y_train == y)
        idxs = np.random.choice(idxs, samples_per_class, replace=False)
        for i, idx in enumerate(idxs):
            plt_idx = i * num_classes + y + 1
            plt.subplot(samples_per_class, num_classes, plt_idx)
            plt.imshow(dataset[idx])
            plt.axis("off")
            if i == 0:
                plt.title(cls)
    plt.show()


# Visualize the first 10 classes
visualize_data(
    x_train.reshape(5000, 3, 32, 32).transpose(0, 2, 3, 1),
    classes,
    samples_per_class,
)
```



1.2 Initialize the model

[84]:
```
input_size = 3072
hidden_size = 100  # Hidden layer size (Hyper-parameter)
num_classes = 10  # Output

# For a default setting we use the same model we used for the toy dataset.
# This tells you the power of a 2 layered Neural Network. Recall the Universal␣
 ↪Approximation Theorem.
# A 2 layer neural network with non-linearities can approximate any function,␣
 ↪given large enough hidden layer
def init_model(hidden_size):
    # np.random.seed(0) # No need to fix the seed here
    l1 = Linear(input_size, hidden_size)
    l2 = Linear(hidden_size, num_classes)

    r1 = ReLU()
    softmax = Softmax()
```

```
    return Sequential([l1, r1, l2, softmax])
```

[48]:
```
# Initialize the dataset with the dataloader class
dataset = DataLoader(x_train, y_train, x_val, y_val, x_test, y_test)
net = init_model(hidden_size)
optim = SGD(net, lr=0.01, weight_decay=0.01)
loss_func = CrossEntropyLoss()
epoch = 200  # (Hyper-parameter)
batch_size = 200  # (Reduce the batch size if your computer is unable to handle␣
 ↪it)
```

[49]:
```
# Initialize the trainer class by passing the above modules
trainer = Trainer(
    dataset, optim, net, loss_func, epoch, batch_size, validate_interval=3
)
```

[ ]:
```
# Call the trainer function we have already implemented for you. This trains␣
 ↪the model for the given
# hyper-parameters. It follows the same procedure as in the last ipython␣
 ↪notebook you used for the toy-dataset
train_error, validation_accuracy = trainer.train()
```

1.2.1 Print the training and validation accuracies for the default hyper-parameters provided

[51]:
```
from ece285.utils.evaluation import get_classification_accuracy

out_train = net.predict(x_train)
acc = get_classification_accuracy(out_train, y_train)
print("Training acc: ", acc)
out_val = net.predict(x_val)
acc = get_classification_accuracy(out_val, y_val)
print("Validation acc: ", acc)
```

```
Training acc:  0.3448
Validation acc:  0.312
```

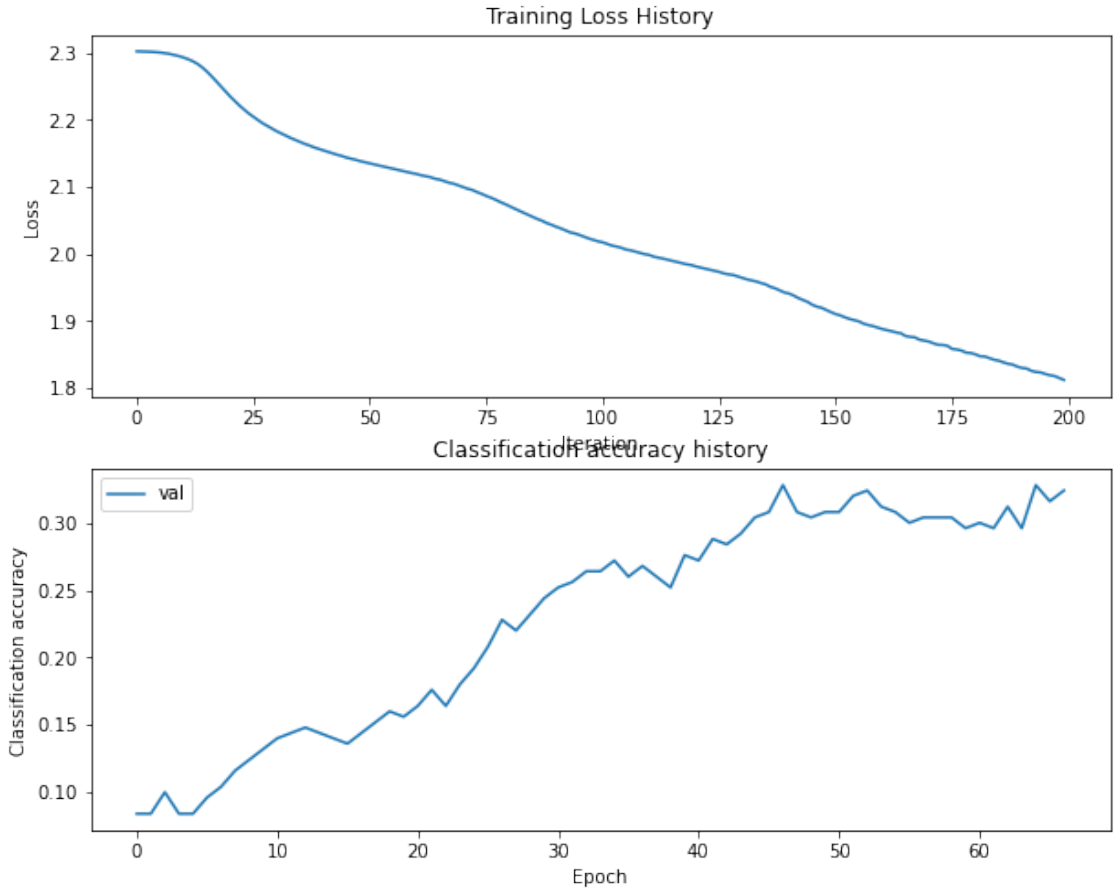
1.2.2 Debug the training

With the default parameters we provided above, you should get a validation accuracy of around ~0.2 on the validation set. This isn't very good.

One strategy for getting insight into what's wrong is to plot the training loss function and the validation accuracies during optimization.

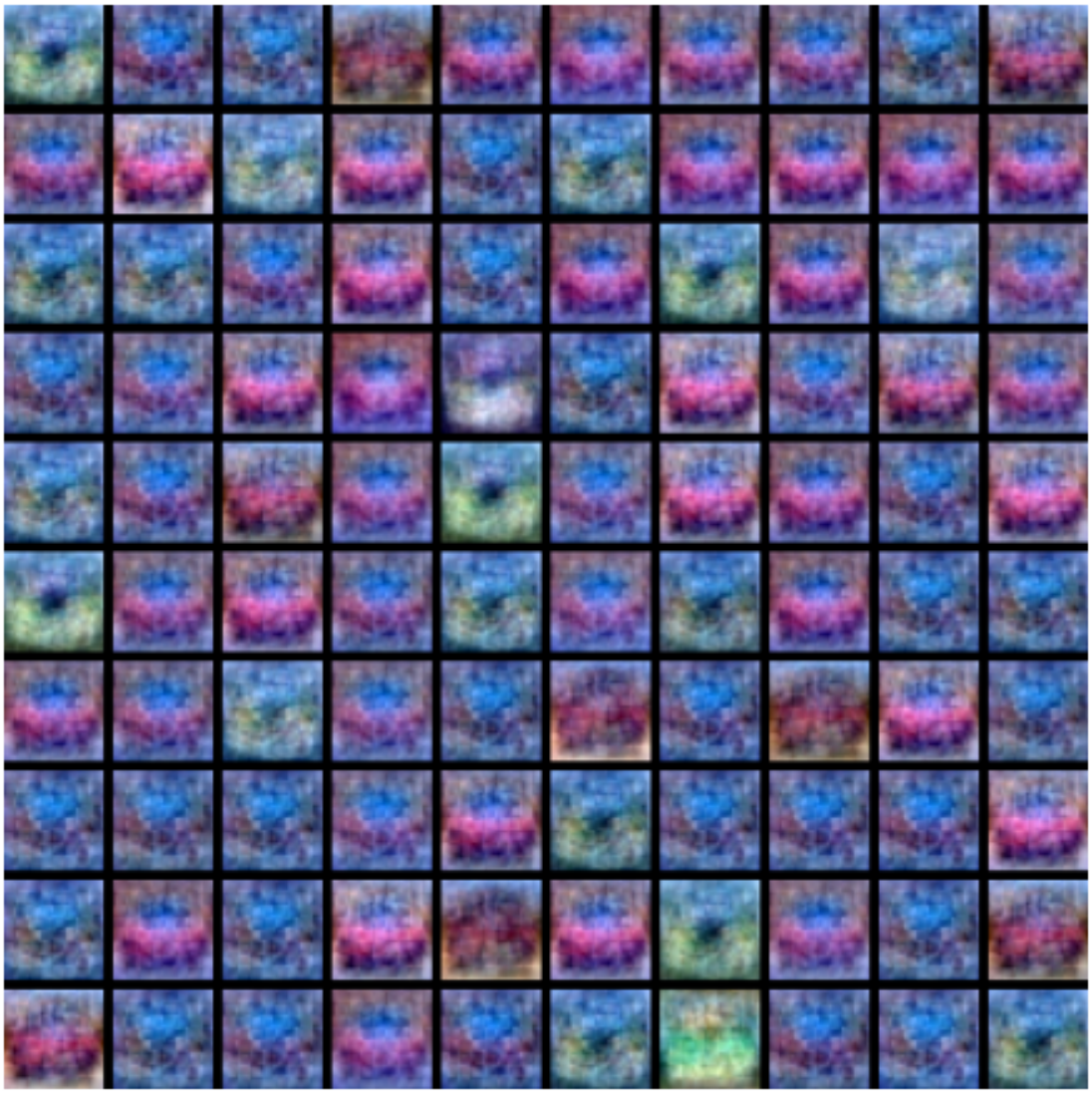
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

[52]:
```
# Plot the training loss function and validation accuracies
plt.subplot(2, 1, 1)
plt.plot(train_error)
plt.title("Training Loss History")
plt.xlabel("Iteration")
plt.ylabel("Loss")

plt.subplot(2, 1, 2)
# plt.plot(stats['train_acc_history'], label='train')
plt.plot(validation_accuracy, label="val")
plt.title("Classification accuracy history")
plt.xlabel("Epoch")
plt.ylabel("Classification accuracy")
plt.legend()
plt.show()
```



[53]:
```
from ece285.utils.vis_utils import visualize_grid

# Credits: http://cs231n.stanford.edu/
```

```
# Visualize the weights of the network

def show_net_weights(net):
    W1 = net._modules[0].parameters[0]
    W1 = W1.reshape(3, 32, 32, -1).transpose(3, 1, 2, 0)
    plt.imshow(visualize_grid(W1, padding=3).astype("uint8"))
    plt.gca().axis("off")
    plt.show()


show_net_weights(net)
```



2 Tune your hyperparameters (50%)

What's wrong?. Looking at the visualizations above, we see that the loss is decreasing more or less linearly, which seems to suggest that the learning rate may be too low. Moreover, there is no gap between the training and validation accuracy, suggesting that the model we used has low capacity, and that we should increase its size. On the other hand, with a very large model we would expect to see more overfitting, which would manifest itself as a very large gap between the training and validation accuracy.

Tuning. Tuning the hyperparameters and developing intuition for how they affect the final performance is a large part of using Neural Networks, so we want you to get a lot of practice. Below, you should experiment with different values of the various hyperparameters, including hidden layer size, learning rate, numer of training epochs, and regularization strength.

Approximate results. You should be aim to achieve a classification accuracy of greater than 40% on the validation set. Our best network gets over 40% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on cifar10 as you can (40% could serve as a reference), with a fully-connected Neural Network.

Explain your hyperparameter tuning process below.

Your Answer:

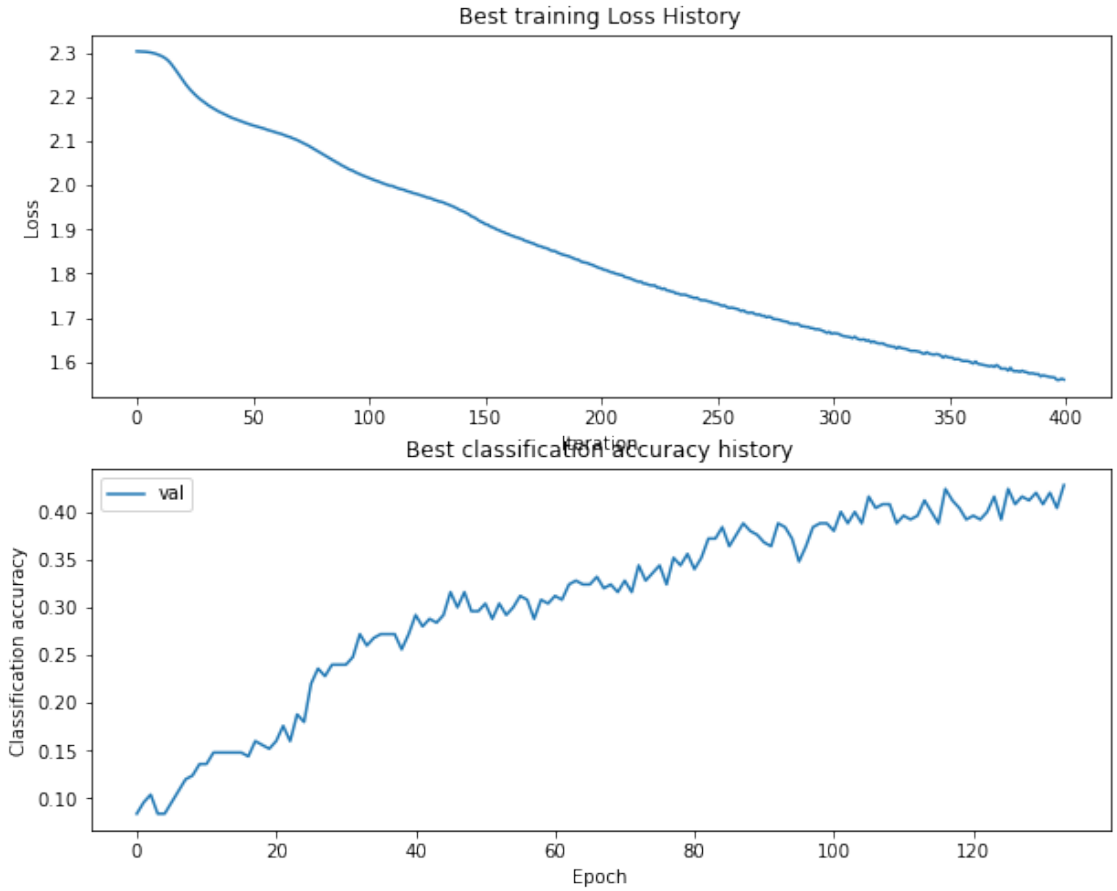
[95]:
```
best_net_hyperparams = None  # store the best model into this

################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained #
# model hyperparams in best_net.                                               #
#                                                                              #
# To help debug your network, it may help to use visualizations similar to the #
# ones we used above; these visualizations will have significant qualitative   #
# differences from the ones we saw above for the poorly tuned network.         #
#                                                                              #
# You are now free to test different combinations of hyperparameters to build  #
# various models and test them according to the above plots and visualization  #


# TODO: Show the above plots and visualizations for the default params (already#
```

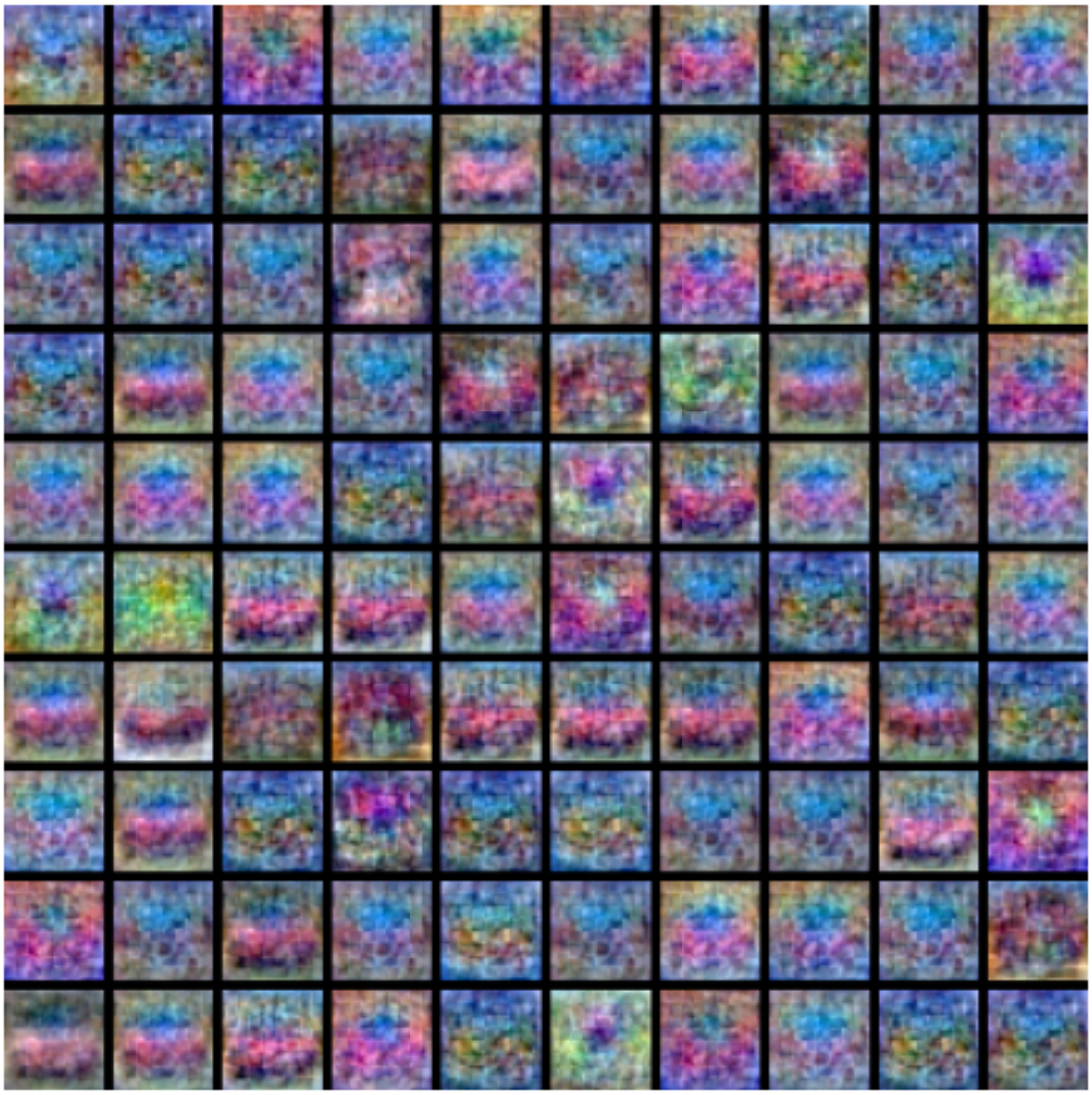
```
# done) and the best hyper-params you obtain. You only need to show this for 2 ␣
 ↪#
# sets of hyper-params.                                                        ␣
 ↪#
# You just need to store values for the hyperparameters in best_net_hyperparams␣
 ↪#
# as a list in the order
# best_net_hyperparams = [lr, weight_decay, epoch, hidden_size]
################################################################################

# pass
# Initialize the dataset with the dataloader class
best_hidden_size = 150
best_lr = 0.02
best_weight_decay = 0.01
best_epoch = 400  # (Hyper-parameter)
best_optim = SGD(best_net, lr=best_lr, weight_decay=best_weight_decay)

best_net = init_model(best_hidden_size)

# Initialize the trainer class by passing the above modules
best_trainer = Trainer(
    dataset, best_optim, best_net, loss_func, best_epoch, batch_size,␣
 ↪validate_interval=3
)
```

[ ]:
```
# Call the trainer function we have already implemented for you. This trains␣
 ↪the model for the given
# hyper-parameters. It follows the same procedure as in the last ipython␣
 ↪notebook you used for the toy-dataset
best_train_error, best_validation_accuracy = best_trainer.train()
```

[81]:
```
# TODO: Plot the training_error and validation_accuracy of the best network (5%)
# Plot the training loss function and validation accuracies
plt.subplot(2, 1, 1)
plt.plot(best_train_error)
plt.title("Best training Loss History")
plt.xlabel("Iteration")
plt.ylabel("Loss")

plt.subplot(2, 1, 2)
# plt.plot(stats['train_acc_history'], label='train')
plt.plot(best_validation_accuracy, label="val")
plt.title("Best classification accuracy history")
plt.xlabel("Epoch")
plt.ylabel("Classification accuracy")
```

```
plt.legend()
plt.show()


# TODO: visualize the weights of the best network (5%)
show_net_weights(best_net)
```





[7]:
```
best_net_hyperparams = [best_lr, best_weight_decay, best_epoch,␣
 ↪best_hidden_size]
print("best_net_hyperparams are: lr = {}, weight_decay = {}, epoch = {},␣
 ↪hidden_size = {}" \
      .format(best_net_hyperparams[0], best_net_hyperparams[1],␣
 ↪best_net_hyperparams[2], best_net_hyperparams[3]))
```

```
best_net_hyperparams are: lr = 0.02, weight_decay = 0.01, epoch = 400,
hidden_size = 150
```

3 Run on the test set (30%)

When you are done experimenting, you should evaluate your final trained network on the test set; you should get above 35%.

[83]:
```
test_acc = (best_net.predict(x_test) == y_test).mean()
print("Test accuracy: ", test_acc)
```

```
Test accuracy:  0.362
```

Inline Question (10%) Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Select all that apply.

1. Train on a larger dataset.
2. Add more hidden units.
3. Increase the regularization strength.
4. None of the above.

Your Answer: 1, 3

Your Explanation: The problem is called over-fitting. There are some tips we could avoid the issue. 1. Yes. It can increase the variation of the training data. 2. No. It would lead to a larger model, which makes the over-fitting problem worse. 3. Yes. it could let the model parameters not too overfit to the training data.