Assignment Twelve

CS 499

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Python Program:

```
# <-- BEGIN IMPORTS / HEADERS -->
import os
import urllib
import urllib.request
import pandas as pd
import numpy as np
import plotnine as p9
import torch
import torchvision

import sklearn
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split


from statistics import mode
import inspect
import warnings
# <-- END IMPORTS / HEADERS -->

# <-- BEGIN INITIALIZATION -->
# FILE VARIABLES
download_directory = "."

# - Spam data variables
spam_data_url = "https://hastie.su.domains/ElemStatLearn/datasets/spam.data"
spam_data_file = "spam.data"
spam_file_path = os.path.join(download_directory, spam_data_file)

# - Zip data (Training) variables
ziptrain_url = "https://hastie.su.domains/ElemStatLearn/datasets/zip.train.gz"
ziptrain_file = "zip.train.gz"
```

```
ziptrain_file_path = os.path.join(download_directory, ziptrain_file)

# - Zip data (Test) variables
ziptest_url = "https://hastie.su.domains/ElemStatLearn/datasets/zip.test.gz"
ziptest_file = "zip.test.gz"
ziptest_file_path = os.path.join(download_directory, ziptest_file)

# CONSTANT VARIABLES
spam_label_col = 57
zip_empty_col = 257

MAX_EPOCHS_VAR = 100
BATCH_SIZE_VAR = 256
STEP_SIZE_VAR = 0.01
HIDDEN_LAYERS_VAR = 10
CV_VAL = 2
N_FOLDS = 2

global ncol
global n_classes

# MISC. VARIABLES
kf = KFold( n_splits=N_FOLDS, shuffle=True, random_state=1 )
test_acc_df_list = []
pipe = make_pipeline(StandardScaler(), LogisticRegression(max_iter=1000))

#CLASS DEFINITIONS
class CSV(torch.utils.data.Dataset):
    def __init__(self, features, labels):
        self.features = features
        self.labels = labels
    def __getitem__(self, item):
        return self.features[item,:], self.labels[item]
    def __len__(self):
        return len(self.labels)

class TorchModel(torch.nn.Module):
   def __init__(self, *units_per_layer):
      super(TorchModel, self).__init__()
      seq_args = []
      for layer_i in range(len(units_per_layer)-1):
         units_in = units_per_layer[layer_i]
         units_out = units_per_layer[layer_i+1]
         seq_args.append( torch.nn.Linear( units_in, units_out ) )
         if layer_i != len(units_per_layer)-2:
```

```
            seq_args.append(torch.nn.ReLU())
        self.stack = torch.nn.Sequential(*seq_args)

    def forward(self, feature_mat):
        return self.stack(feature_mat.float())

class OptimizerMLP:
    def __init__(self, **kwargs):
        """Store hyper-parameters, TorchModel instance, loss, etc."""
        kwargs.setdefault("max_epochs", 2)
        kwargs.setdefault("batch_size", BATCH_SIZE_VAR)
        kwargs.setdefault("step_size", 0.01)
        kwargs.setdefault("units_per_layer", ( ncol, 1000, 100, n_classes ) )
        kwargs.setdefault("hidden_layers", 3)
        kwargs.setdefault("opt_name", torch.optim.SGD)
        kwargs.setdefault("opt_params", {'lr':0.1})

        for key, value in kwargs.items():
            setattr(self, key, value)

        units_per_layer = [ncol]
        for L in range(self.hidden_layers):
            units_per_layer.append(100)
        units_per_layer.append(n_classes)

        self.best_epoch = -1                    # Best Epoch
        self.loss_df = pd.DataFrame()           # Dataframe of Loss per Epoch

        self.model = TorchModel(*self.units_per_layer)

        self.optimizer = self.opt_name(self.model.parameters(), **self.opt_params)
        self.loss_fun = torch.nn.CrossEntropyLoss()

    def take_step(self, X, y):
        """compute predictions, loss, gradients, take one step"""
        self.optimizer.zero_grad()
        pred_tensor = self.model.forward(X)#.reshape(len(y))
        loss_tensor = self.loss_fun(pred_tensor, y.long())
        loss_tensor.backward()
        self.optimizer.step()

    def fit(self, X, y):
        """Gradient descent learning of weights"""
        units_per_layer = [ncol]
        for L in range(self.hidden_layers):
```

```
        units_per_layer.append(100)
    units_per_layer.append(n_classes)

    ds = CSV( X, y )
    dl = torch.utils.data.DataLoader( ds, batch_size = self.batch_size,
                                      shuffle = True )
    loss_df_list = []
    best_loss_val = 10000

    for epoch in range(self.max_epochs):
      for batch_features, batch_labels in dl:
        self.take_step(batch_features, batch_labels)
        pred = self.model(batch_features)
        loss_value = self.loss_fun(pred, batch_labels.long())

        if( loss_value < best_loss_val ):
            self.best_epoch = epoch
            best_loss_val = loss_value

      loss_df_list.append(pd.DataFrame({
          #"set_name":set_name,
          "loss":float(loss_value),
          "epoch":epoch,
      }, index=[0]))#subtrain/validation loss using current weights.

    self.loss_df = pd.concat( loss_df_list )

  def predict(self, X):
    """Return numpy vector of predictions"""
    pred_vec = []
    for row in self.model(torch.from_numpy(X)):
        best_label = -1
        highest_prob = -1000
        itera = 0
        for iter in row.long():
            if(iter.item() > highest_prob):
                highest_prob = iter.item()
                best_label = itera
            itera += 1
        pred_vec.append(best_label)

    return pred_vec

class TorchLearnerCV:
```

```
    def __init__(self, max_epochs, batch_size, step_size, units_per_layer,
**kwargs):
        self.subtrain_learner = OptimizerMLP( max_epochs=max_epochs,
                                              batch_size=batch_size,
                                              step_size=step_size,
                                              units_per_layer=units_per_layer )

        for key, value in kwargs.items():
            setattr(self, key, value)

        self.batch_size = batch_size
        self.step_size = step_size
        self.units_per_layer = units_per_layer

        self.plotting_df = pd.DataFrame()

    def fit(self, X, y):
        """cross-validation for selecting the best number of epochs"""
        fold_vec = np.random.randint(low=0, high=5, size=y.size)
        validation_fold = 0
        is_set_dict = {
            "validation":fold_vec == validation_fold,
            "subtrain":fold_vec != validation_fold,
        }

        set_features = {}
        set_labels = {}

        for set_name, is_set in is_set_dict.items():
            set_features[set_name] = X[is_set,:]
            set_labels[set_name] = y[is_set]
        {set_name:array.shape for set_name, array in set_features.items()}

        self.subtrain_learner.validation_data = set_features["validation"]
        self.subtrain_learner.fit( set_features["subtrain"],
set_labels["subtrain"], "subtrain" )
        self.plotting_df = pd.concat([self.plotting_df,
self.subtrain_learner.loss_df])

        best_epochs = self.subtrain_learner.best_epoch

        self.train_learner = OptimizerMLP( max_epochs=best_epochs,
                                           batch_size=self.batch_size,
                                           step_size=self.step_size,
                                           units_per_layer=self.units_per_layer )
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```
      self.train_learner.fit( set_features["validation"],
set_labels["validation"], "validation" )
      self.plotting_df = pd.concat([self.plotting_df,
self.train_learner.loss_df])

   def predict(self, X):
      return self.train_learner.predict(X)

class RegularizedMLP:
    def __init__(self, **kwargs):
        kwargs.setdefault("max_epochs", 2)
        kwargs.setdefault("batch_size", BATCH_SIZE_VAR)
        kwargs.setdefault("step_size", 0.001)
        kwargs.setdefault("units_per_layer", ( ncol, 1000, 100, n_classes ) )

        for key, value in kwargs.items():
            setattr(self, key, value)

        self.estimator = estimator()

    def fit(self, X, y):
        self.estimator.fit(X, y)

    def predict(self, X):
        return self.estimator.predict(X)

class MyCV():
    def __init__(self, **kwargs):
        # Initialize parameters and setup variables
        self.train_features = []
        self.train_labels = []
        self.training_data = None

        kwargs.setdefault("num_folds", 5)
        for key, value in kwargs.items():
            setattr(self, key, value)

        self.estimator = self.estimator()
        self.best_model = None

        self.plotting_df = pd.DataFrame()

    def fit(self, X, y):
        # Populate internal data structures
        self.train_features = X
```

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        self.train_labels = y
        self.training_data = {'X':self.train_features, 'y':self.train_labels}

        # Create a dataframe to temporarily hold results from each fold
        best_paramter_df = pd.DataFrame()

        # Calculate folds
        fold_indicies = []

        # Pick random entries for validation/subtrain
        fold_vec = np.random.randint(low=0,
                                     high=self.num_folds,
                                     size=self.train_labels.size)

        # for each fold,
        for fold_number in range(self.num_folds):
            subtrain_indicies = []
            validation_indicies = []
            # check if index goes into subtrain or validation list
            for index in range(len(self.train_features)):
                if fold_vec[index] == fold_number:
                    validation_indicies.append(index)
                else:
                    subtrain_indicies.append(index)

            fold_indicies.append([subtrain_indicies, validation_indicies])


        printing_df = pd.DataFrame()
        # Loop over the folds
        for foldnum, indicies in enumerate(fold_indicies):
            print("(MyCV) Subfold #" + str(foldnum))

            # Get indicies of data chosen for this fold
            index_dict = dict(zip(["subtrain", "validation"], indicies))
            set_data_dict = {}

            # Dictionary for test and train data
            for set_name, index_vec in index_dict.items():
                set_data_dict[set_name] = {
                    "X":self.train_features[index_vec],
                    "y":self.train_labels[index_vec]
                }

            # Create a dictionary to hold the results of the fitting
```

```python
        results_dict = {}

        parameter_index = 0
        # Loop over each parameter in the param_grid
        for parameter_entry in self.param_grid:
            for param_name, param_value in parameter_entry.items():
                setattr(self.estimator, param_name, param_value)

            # Fit fold data to estimator
            self.estimator.fit(**set_data_dict["subtrain"])

            printing_df = self.estimator.loss_df
            for param_name, param_value in parameter_entry.items():
                printing_df[param_name] = str(param_value)
            printing_df['set'] = 'subtrain'
            printing_df['subfold'] = foldnum
            self.plotting_df = pd.concat([self.plotting_df, printing_df])

            self.estimator.fit(**set_data_dict["validation"])

            printing_df = self.estimator.loss_df
            for param_name, param_value in parameter_entry.items():
                printing_df[param_name] = str(param_value)
            printing_df['set'] = 'validation'
            printing_df['subfold'] = foldnum
            self.plotting_df = pd.concat([self.plotting_df, printing_df])

            # Make a prediction of current fold's test data
            prediction = \
                self.estimator.predict(set_data_dict["validation"]['X'])

            # Determine accuracy of the prediction
            results_dict[parameter_index] = \
            (prediction == set_data_dict["validation"]["y"]).mean()*100

            # index only serves to act as key for results dictionary
            parameter_index += 1

        # Store the results of this param entry into dataframe
        best_paramter_df = best_paramter_df.append(results_dict,
                                                   ignore_index=True)

    # Average across all folds for each parameter
    averaged_results = dict(best_paramter_df.mean())
```

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        # From the averaged data, get the single best model
        best_result = max(averaged_results, key = averaged_results.get)

        # Store best model for future reference
        self.best_model = self.param_grid[best_result]

    def predict(self, test_features):
        # Load best model into estimator
        for param_name, param_value in self.best_model.items():
            setattr(self.estimator, param_name, param_value)

        # Fit estimator to training data
        self.estimator.fit(**self.training_data)

        # Make a prediction of the test features
        prediction = self.estimator.predict(test_features)

        return(prediction)


# <-- END INITIALIZATION -->

# <-- BEGIN FUNCTIONS -->
# FUNCTION: MAIN
#   Description  : Main driver for Assignment Ten
#   Inputs       : None
#   Outputs      : PlotNine graphs, printed and saved to directory
#   Dependencies : build_image_df_from_dataframe
def main():
    # Display the title
    print("\nCS 499: Homework 12 Program Start")
    print("================================\n")

    # Suppress annoying plotnine warnings
    warnings.filterwarnings('ignore')

    # Download data files
    download_data_file(ziptrain_file, ziptrain_url, ziptrain_file_path)
    download_data_file(ziptest_file, ziptest_url, ziptest_file_path)
    download_data_file(spam_data_file, spam_data_url, spam_file_path)

    # Open each dataset as a pandas dataframe
    zip_train_df = pd.read_csv(ziptrain_file, header=None, sep=" ")
    zip_test_df = pd.read_csv(ziptest_file, header=None, sep=" ")
    spam_df = pd.read_csv(spam_data_file, header=None, sep=" ")
```

```python
# Concat the two zip dataframes together
zip_df = pd.concat([zip_train_df, zip_test_df])
zip_df[0] = zip_df[0].astype(int)
# Drop empty col from zip dataframe
zip_df = zip_df.drop(columns=[zip_empty_col])

zip_features = zip_df.iloc[:,:-1].to_numpy()
zip_labels = zip_df[0].to_numpy()

spam_features = spam_df.iloc[:,:-1].to_numpy()
spam_labels = spam_df.iloc[:,-1].to_numpy()

# 1. feature scaling.
spam_mean = spam_features.mean(axis=0)
spam_sd = np.sqrt(spam_features.var(axis=0))
spam_features = (spam_features-spam_mean)/spam_sd
spam_features.mean(axis=0)
spam_features.var(axis=0)

# Create data dictionary
data_dict = {
    'spam' : [spam_features, spam_labels],
    'zip' : [zip_features, zip_labels]
}

final_df_list = []
final_deep_print_list = []

final_deep_df = pd.DataFrame()

# Loop through each data set
for data_set, (input_data, output_array) in data_dict.items():
    current_set = str(data_set)
    print("")
    print("Working on set: " + current_set)

    # Loop over each fold for each data set
    for foldnum, indicies in enumerate(kf.split(input_data)):
        print("Fold #" + str(foldnum))

        # Set up input data structs
        global ncol
        nrow, ncol = input_data.shape
        index_dict = dict(zip(["train", "test"], indicies))
```

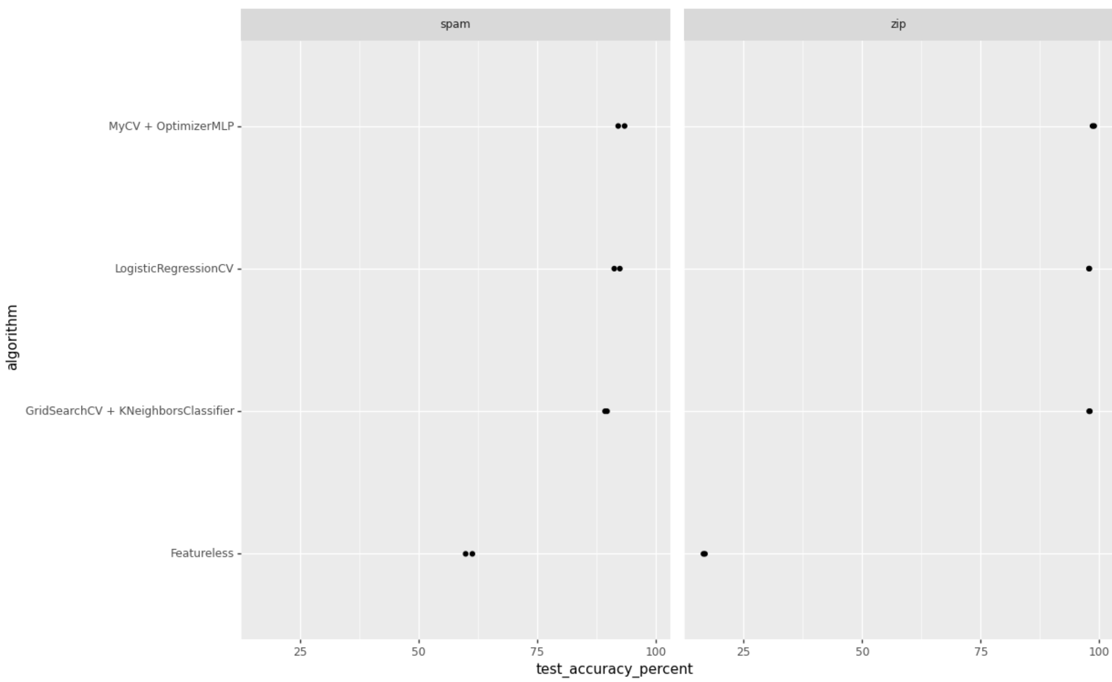
```python
# Creating dictionary with input and outputs
set_data_dict = {}
for set_name, index_vec in index_dict.items():
    set_data_dict[set_name] = {
        "X":input_data[index_vec],
        "y":output_array[index_vec]
    }

# Finalizing variables for CV construction
param_dicts = [{'n_neighbors':[x]} for x in range(1, 21)]
global n_classes
n_classes = len( np.unique( set_data_dict['test']['y'] ) )
UNITS_PER_VAR = ( int(ncol), 1000, 100, int(n_classes) )

param_grid = []

for momentum in 0.1, 0.5, 0.9:
    for lr in 0.1, 0.01, 0.001:
        param_grid.append({
            "opt_name":torch.optim.SGD,
            "opt_params":{"momentum":momentum, "lr":lr}
        })
for beta1 in 0.85, 0.9, 0.95:
    for beta2 in 0.99, 0.999, 0.9999:
        param_grid.append({
            "opt_name":torch.optim.Adam,
            "opt_params":{"betas":(beta1, beta2)}
        })

clf = GridSearchCV(KNeighborsClassifier(), param_dicts)
linear_model = sklearn.linear_model.LogisticRegressionCV(cv=CV_VAL)
DeepTorchCV = MyCV( max_epochs = MAX_EPOCHS_VAR,
                    batch_size = BATCH_SIZE_VAR,
                    step_size = STEP_SIZE_VAR,
                    units_per_layer = UNITS_PER_VAR,
                    estimator = OptimizerMLP,
                    param_grid = param_grid,
                    num_folds = CV_VAL )

# Train the models with given data
clf.fit(**set_data_dict["train"])
linear_model.fit(**set_data_dict["train"])
DeepTorchCV.fit(**set_data_dict["train"])
```

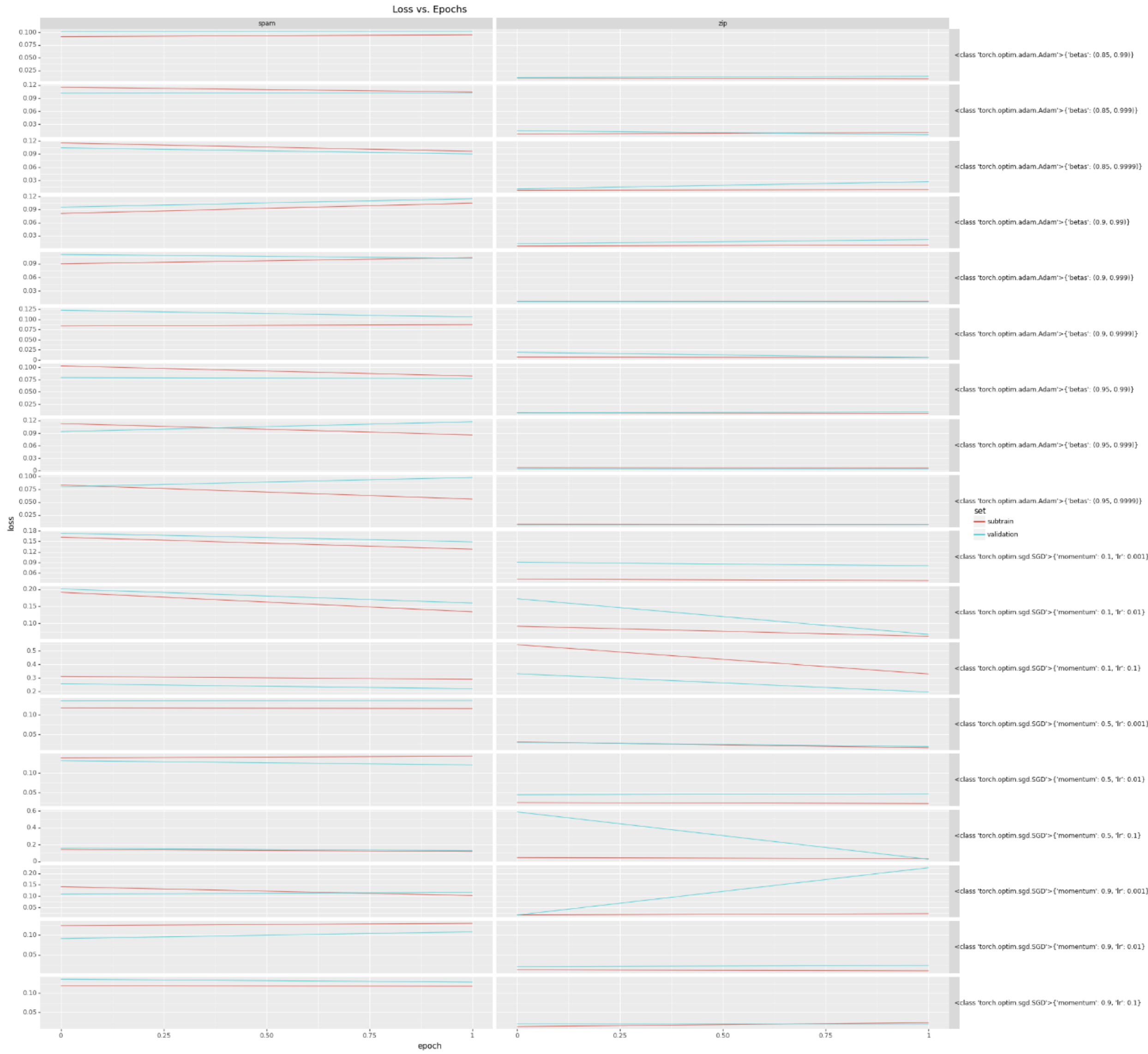
```
        # Get most common output from outputs for featureless set
        most_common_element = mode(set_data_dict["train"]['y'])

        buffer_df = DeepTorchCV.plotting_df
        buffer_df['fold'] = foldnum
        buffer_df['data_set'] = data_set
        final_deep_print_list.append(buffer_df)

        # Get results
        pred_dict = {
            "GridSearchCV + KNeighborsClassifier": \
                clf.predict(set_data_dict["test"]["X"]),
            "LogisticRegressionCV": \
                linear_model.predict(set_data_dict["test"]["X"]),
            "MyCV + OptimizerMLP": \
                DeepTorchCV.predict(set_data_dict["test"]["X"]),
            "Featureless":most_common_element
        }

        # Build results dataframe for each algo/fold
        for algorithm, pred_vec in pred_dict.items():
            test_acc_dict = {
                "test_accuracy_percent":(
                    pred_vec == set_data_dict["test"]["y"]).mean()*100,
                "data_set":data_set,
                "fold_id":foldnum,
                "algorithm":algorithm
            }
            test_acc_df_list.append(pd.DataFrame(test_acc_dict, index=[0]))

final_deep_df = pd.concat(final_deep_print_list)

# Build accuracy results dataframe
test_acc_df = pd.concat(test_acc_df_list)

# Print results
print("\n")
print(test_acc_df)
print("")

# Plot results
plot = (p9.ggplot(test_acc_df,
                    p9.aes(x='test_accuracy_percent',
                    y='algorithm'))
               + p9.facet_grid('. ~ data_set')
```

```
                   + p9.geom_point()
                   + p9.theme(subplots_adjust={'left': 0.2}))

    print(plot)

    # Epoch vector for plotting
    """epoch_vec = np.arange(MAX_EPOCHS_VAR)
    epoch_vec = np.tile(epoch_vec, 1)
    epoch_vec = epoch_vec.flatten()"""


    print(final_deep_df)

    final_deep_df = final_deep_df.groupby(['set', 'data_set', 'epoch',
'opt_name'], as_index=False).mean()
    #final_deep_df['epochs'] = epoch_vec
    print(final_deep_df)
    deepplot = (p9.ggplot(final_deep_df,
                        p9.aes(x='epoch',
                               y='loss',
                               color='set'))
                   + p9.facet_grid('opt_name ~ data_set', scales='free')
                   + p9.geom_line()
                   + p9.theme(subplots_adjust={'left': 0.2})
                   + p9.ggtitle("Hidden Layers vs. Loss"))

    print(plot)
    deepplot.save("DeepTorch Loss Graph.png")

    print("\nCS 499: Homework 12 Program End")
    print("==============================\n")

# FUNCTION : DOWNLOAD_DATA_FILE
#   Description: Downloads file from source, if not already downloaded
#   Inputs:
#       - file      : Name of file to download
#       - file_url  : URL of file
#       - file_path : Absolute path of location to download file to.
#                     Defaults to the local directory of this program.
#   Outputs: None
def download_data_file(file, file_url, file_path):
    # Check for data file. If not found, download
    if not os.path.isfile(file_path):
        try:
            print("Getting file: " + str(file) + "...\n")
```

```
            urllib.request.urlretrieve(file_url, file_path)
            print("File downloaded.\n")
        except(error):
            print(error)
    else:
        print("File: " + str(file) + " is already downloaded.\n")

# Launch main
if __name__ == "__main__":
    main()
```

Program Output:


spam
zip
MyCV + OptimizerMLP
LogisticRegressionCV
GridSearchCV + KNeighborsClassifier
Featureless
algorithm
25
50
75
100
test_accuracy_percent


Loss vs. Epochs
spam
zip
loss
epoch
set
subtrain
validation
<class 'torch.optim.adam.Adam'>{'betas': (0.85, 0.99)}
<class 'torch.optim.adam.Adam'>{'betas': (0.85, 0.999)}
<class 'torch.optim.adam.Adam'>{'betas': (0.85, 0.9999)}
<class 'torch.optim.adam.Adam'>{'betas': (0.9, 0.99)}
<class 'torch.optim.adam.Adam'>{'betas': (0.9, 0.999)}
<class 'torch.optim.adam.Adam'>{'betas': (0.9, 0.9999)}
<class 'torch.optim.adam.Adam'>{'betas': (0.95, 0.99)}
<class 'torch.optim.adam.Adam'>{'betas': (0.95, 0.999)}
<class 'torch.optim.adam.Adam'>{'betas': (0.95, 0.9999)}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.1, 'lr': 0.001}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.1, 'lr': 0.01}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.1, 'lr': 0.1}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.5, 'lr': 0.001}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.5, 'lr': 0.01}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.5, 'lr': 0.1}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.9, 'lr': 0.001}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.9, 'lr': 0.01}
<class 'torch.optim.sgd.SGD'>{'momentum': 0.9, 'lr': 0.1}

	test_accuracy_percent	data_set	fold_id	algorithm
0	89.265537	spam	0	GridSearchCV + KNeighborsClassifier
0	92.394611	spam	0	LogisticRegressionCV
0	92.829205	spam	0	MyCV + OptimizerMLP
0	59.887006	spam	0	Featureless
0	89.695652	spam	1	GridSearchCV + KNeighborsClassifier
0	91.217391	spam	1	LogisticRegressionCV
0	92.869565	spam	1	MyCV + OptimizerMLP
0	61.304348	spam	1	Featureless
0	97.849000	zip	0	GridSearchCV + KNeighborsClassifier
0	97.892020	zip	0	LogisticRegressionCV
0	98.515810	zip	0	MyCV + OptimizerMLP
0	16.541192	zip	0	Featureless
0	97.999570	zip	1	GridSearchCV + KNeighborsClassifier
0	97.805980	zip	1	LogisticRegressionCV
0	98.752420	zip	1	MyCV + OptimizerMLP
0	16.863842	zip	1	Featureless

Question Answers / Commentary:

For this assignment I was able to implement the two different optimization functions – Adam and SGD. I found that in implementing these, my model would only train to one or two epochs. After this point, it would not select any higher epoch as the best one. Regardless of this, the test accuracy remained high. Because the model did not train past 1 epoch, the loss graphs for sub train and validation are not as expected.

I also trained learning rate along with the optimizers.