Assignment Eleven

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 = 10
BATCH_SIZE_VAR = 256
STEP_SIZE_VAR = 0.001
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:
```

```python
            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 TorchLearner:
   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", 0.001)
      kwargs.setdefault("units_per_layer", ( ncol, 1000, 100, n_classes ) )
      kwargs.setdefault("hidden_layers", 3)

      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 = torch.optim.SGD(self.model.parameters(), lr=0.1)
      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):
      self.subtrain_learner = TorchLearner( max_epochs=max_epochs,
                                            batch_size=batch_size,
```

```
                                             step_size=step_size,
                                             units_per_layer=units_per_layer )

      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 = TorchLearner( max_epochs=best_epochs,
                                          batch_size=self.batch_size,
                                          step_size=self.step_size,
                                          units_per_layer=self.units_per_layer )
      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)
```

```python
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
        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
```

```python
        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
            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] = 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] = 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)

        # all of this stuff is for plotting loss vs iterations...
#         printing_df = printing_df.groupby(['step_size',
'iterations']).loss.apply(list)
#        printing_df = printing_df.to_frame().reset_index()
#        printing_df['iteration_list'] = ""
#        for index, row in printing_df.iterrows():
#            new_loss_row = row['loss']
#            new_loss_row = np.mean(new_loss_row, axis=0)
#            printing_df.at[index, 'loss'] = new_loss_row
```

```
#            new_iter_row = row['iterations']
#            new_iter_row = np.arange(new_iter_row)
#            printing_df.at[index, 'iteration_list'] = new_iter_row
#
#        printing_df = printing_df.explode(['loss', 'iteration_list'])

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

        # 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 11 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=" ")

    # 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)
```

```python
# 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))

    # 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) )

    deep_param_dict = \
        [{'hidden_layers': L,
          'max_epochs': max_epochs} \
          for L in [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] \
          for max_epochs in [10, 20, 50]]

    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 = TorchLearner,
                        param_grid = deep_param_dict,
                        num_folds = CV_VAL )

    eep_param_dict = \
        [{'hidden_layers': L} \
          for L in [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]]

    DeepTorchCVEpoch = MyCV( max_epochs = MAX_EPOCHS_VAR,
```

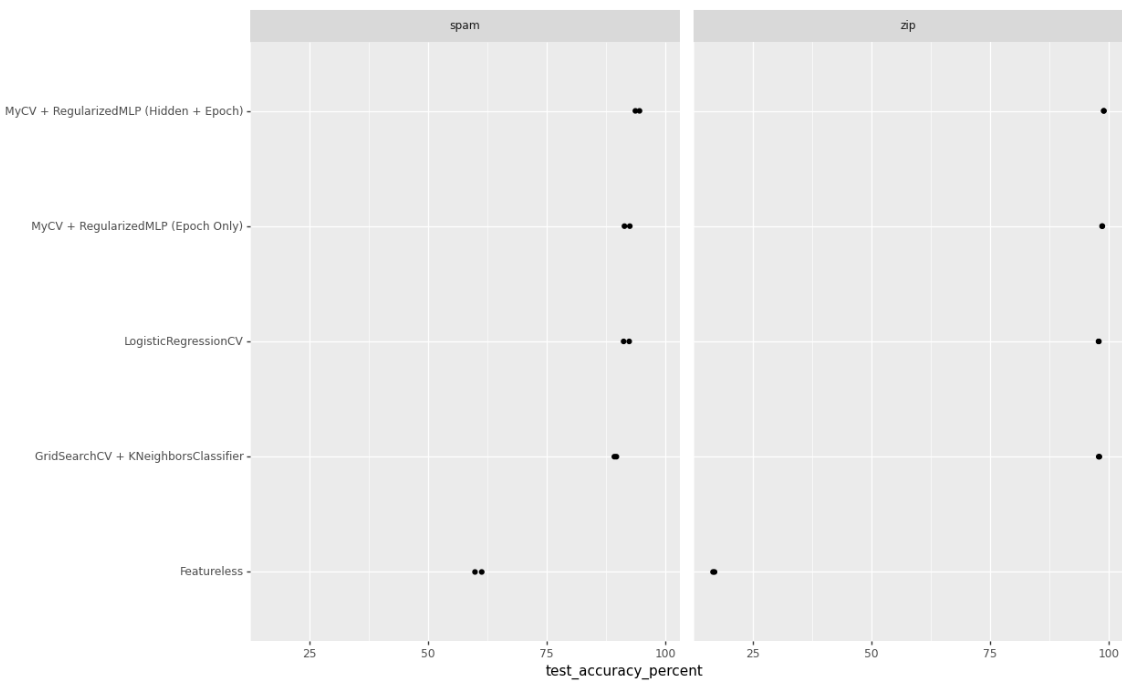
```python
                            batch_size = BATCH_SIZE_VAR,
                            step_size = STEP_SIZE_VAR,
                            units_per_layer = UNITS_PER_VAR,
                            estimator = TorchLearner,
                            param_grid = eep_param_dict,
                            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"])
            DeepTorchCVEpoch.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 + RegularizedMLP (Hidden + Epoch)": \
                    DeepTorchCV.predict(set_data_dict["test"]["X"]),
                "MyCV + RegularizedMLP (Epoch Only)": \
                    DeepTorchCVEpoch.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]))
```

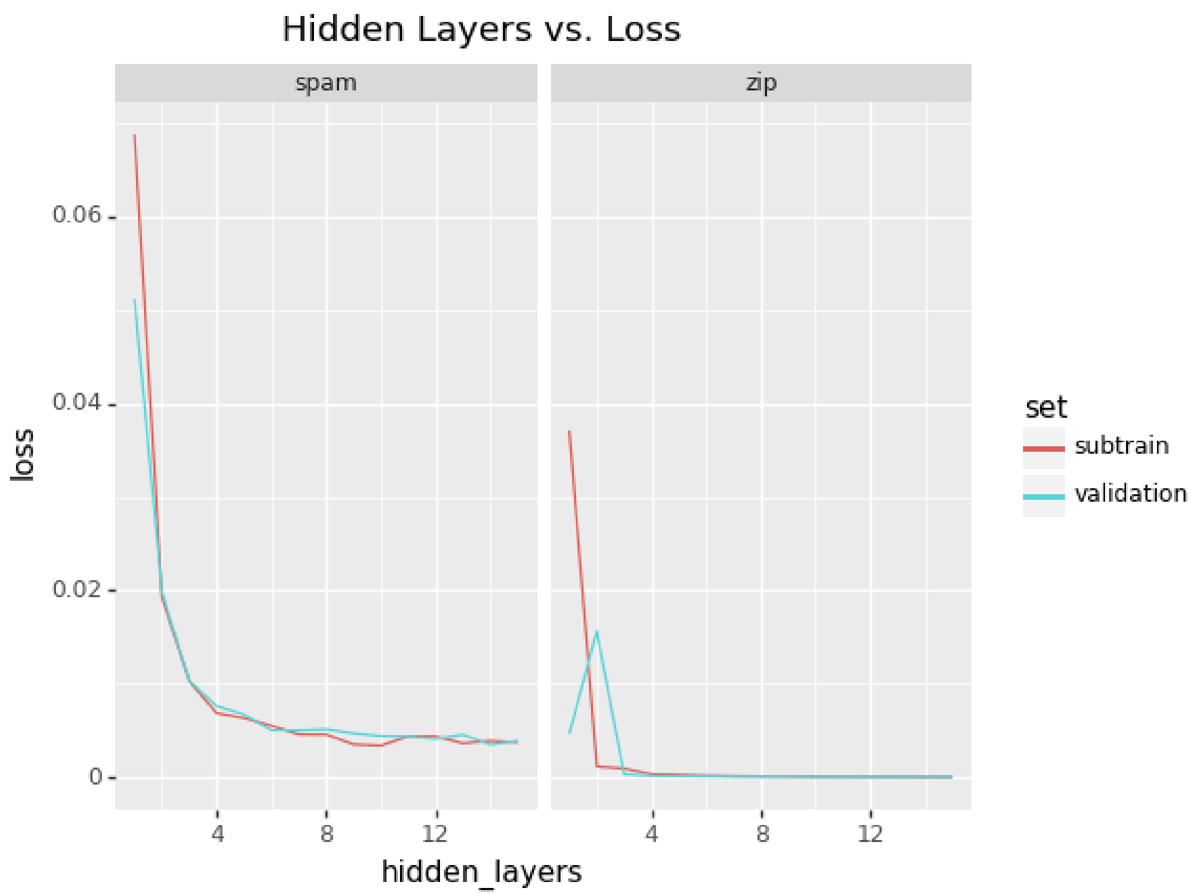
```
    final_deep_df = pd.concat(final_deep_print_list)

    # 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}))

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

    final_deep_df = final_deep_df.groupby(['set', 'data_set', 'hidden_layers'],
as_index=False).mean()
    #final_deep_df['epochs'] = epoch_vec

    deepplot = (p9.ggplot(final_deep_df,
                      p9.aes(x='hidden_layers',
                             y='loss',
                             color='set'))
                 + p9.facet_grid('. ~ 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 11 Program End")
    print("==============================\n")

# FUNCTION : DOWNLOAD_DATA_FILE
#   Description: Downloads file from source, if not already downloaded
#   Inputs:
```

```python
#       - 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:

```
   test_accuracy_percent data_set  fold_id                                algorithm
0              89.265537     spam        0     GridSearchCV + KNeighborsClassifier
0              92.394611     spam        0                    LogisticRegressionCV
0              93.698392     spam        0  MyCV + RegularizedMLP (Hidden + Epoch)
0              91.395046     spam        0     MyCV + RegularizedMLP (Epoch Only)
0              59.887006     spam        0                             Featureless
0              89.695652     spam        1     GridSearchCV + KNeighborsClassifier
0              91.217391     spam        1                    LogisticRegressionCV
0              94.565217     spam        1  MyCV + RegularizedMLP (Hidden + Epoch)
0              92.521739     spam        1     MyCV + RegularizedMLP (Epoch Only)
0              61.304348     spam        1                             Featureless
0              97.849000      zip        0     GridSearchCV + KNeighborsClassifier
0              97.892020      zip        0                    LogisticRegressionCV
0              98.946010      zip        0  MyCV + RegularizedMLP (Hidden + Epoch)
0              98.558830      zip        0     MyCV + RegularizedMLP (Epoch Only)
0              16.541192      zip        0                             Featureless
0              97.999570      zip        1     GridSearchCV + KNeighborsClassifier
0              97.805980      zip        1                    LogisticRegressionCV
0              98.902990      zip        1  MyCV + RegularizedMLP (Hidden + Epoch)
0              98.623360      zip        1     MyCV + RegularizedMLP (Epoch Only)
0              16.863842      zip        1                             Featureless
```





Hidden Layers vs. Loss
spam
zip
0.06
0.04
0.02
0
loss
4
8
12
4
8
12
hidden_layers
set
subtrain
validation

Question Answers / Commentary:

For this assignment, I was able to implement a hyper-parameter learning solution for my multi-class neural network. The results show that implementing hidden layer learning increased accuracy of the model significantly, and that implementing epoch learning next to hidden layer learning increased the accuracy of the model beyond that of the two SciKit models.

Looking at the loss vs hidden layers plot, it appears that increasing the number of hidden layers decreases the total loss per iteration of the model. It is likely that adding additional training for other parameters, such as batch size or step size, would further increase the model's accuracy.