Assignment Four

CS 499

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<u>Python Program:</u>

```
# <-- 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 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 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
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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
MyKNN_N_NEIGHBORS_VAL = 20
CV_VAL = 5

# MISC. VARIABLES
kf = KFold(n_splits=2, shuffle=True, random_state=1)
test_acc_df_list = []
pipe = make_pipeline(StandardScaler(), LogisticRegression(max_iter=1000))

#CLASS DEFINITIONS
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)

    def getitem(self, item):
        weights, intercept = [p for p in self.weight_vec.parameters()]
        return weights.data[0][item]

class TorchLearner(torch.nn.Module):
    def __init__( self, **kwargs ):
        super(TorchLearner, self).__init__()

        kwargs.setdefault("step_size", 0.0001) # trained through cv
        kwargs.setdefault("max_epochs", 10)
        kwargs.setdefault("batch_size", 2)
        kwargs.setdefault("units_per_layer")
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        for key, value in kwargs.items():
            setattr(self, key, value)

        self.loss_df_list = []

        self.train_data = None
        self.train_labels = None
        self.coef_ = None
        self.intercept_ = None

        self.model = TorchModel( self.units_per_layer )
        self.optimizer = torch.optim.SGD(self.model.parameters(), lr=0.1)
        self.loss_fun = torch.nn.BCEWithLogitsLoss()

        self.loss_df = {}

    def take_step(self, X, y):
        self.optimizer.zero_grad()
        pred_tensor = self.model.forward(X.float()).reshape(len(y))
        loss_tensor = self.loss_fun(pred_tensor, y.float())
        loss_tensor.backward()
        self.optimizer.step()

    def fit(self, X, y):
        np.random.seed(1)
        n_folds = 5
        fold_vec = np.random.randint(low=0, high=n_folds, 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()}

        ds = CSV(X, y)
        dl = torch.utils.data.DataLoader(
            ds, batch_size=2, shuffle=True)
        for batch_features, batch_labels in dl:
            pass
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        for epoch in range(self.max_epochs):
            for batch_features, batch_labels in dl:
                self.take_step(batch_features, batch_labels)

            for set_name in set_features:
                set_X = set_features[set_name]
                set_y = set_labels[set_name]
                set_X_tensor = torch.from_numpy(set_X).float()
                set_y_tensor = torch.from_numpy(set_y)
                set_pred = self.model(set_X_tensor).reshape(len(set_y))
                set_loss = self.loss_fun(set_pred, set_y_tensor.float())

                pred_vec = set_pred.detach().numpy()
                pred_vec[pred_vec > 0] = 1
                pred_vec[pred_vec <= 0] = 0

                self.loss_df_list.append(pd.DataFrame({
                    "set_name":set_name,
                    "loss":float(set_loss),
                    "epoch":epoch,
                    "test_accuracy_percent":(
                        pred_vec == set_y).mean()*100,
                }, index=[0]))

        self.loss_df = pd.concat(self.loss_df_list)
        #self.pred_vec = pred_vec

    def decision_function(self, X):
        pred_vec = np.matmul(X,
                             self.model.stack[-1].weight[0].detach().numpy()) \
                             + self.model.stack[-1].bias[0].detach().numpy()

        return pred_vec

    def predict(self, X):
        pred_vec = self.decision_function(X)

        pred_vec[pred_vec > 0] = 1
        pred_vec[pred_vec <= 0] = 0

        pred_vec = np.stack(pred_vec, axis=0)

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

        kwargs.setdefault("num_folds", 3)

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

        self.estimator = self.estimator(
            units_per_layer=self.param_grid[0]['units_per_layer'])
        self.best_model = None

        self.printing_list = []

        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
        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)
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                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_list = printing_df.append({'loss':
self.estimator.avg_loss, 'iterations': self.estimator.max_iterations,
'step_size': self.estimator.step_size, 'fold':foldnum}, ignore_index=True)

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

                self.printing_list.append(self.estimator.loss_df)


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

        self.plotting_df = pd.concat(self.printing_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)

class LinearModel(torch.nn.Module):
    def __init__(self, num_inputs):
        super(LinearModel, self).__init__()
        self.weight_vec = torch.nn.Linear(num_inputs, 1)
    def getitem(self, item):
        weights, intercept = [p for p in self.weight_vec.parameters()]
        return weights.data[0][item]
    def forward(self, feature_mat):
        return self.weight_vec(feature_mat)
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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 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
        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 = []
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            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 = printing_df.append({'loss':
self.estimator.avg_loss, 'iterations': self.estimator.max_iterations,
'step_size': self.estimator.step_size, 'fold':foldnum}, ignore_index=True)

                # Make a prediction of current fold's test data
                prediction = \
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                    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)
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        # Make a prediction of the test features
        prediction = self.estimator.predict(test_features)

        return(prediction)

class MyLogReg():
    def __init__(self, **kwargs):
        kwargs.setdefault("num_folds", 5)
        kwargs.setdefault("max_iterations", 10) # trained through cv
        kwargs.setdefault("step_size", 0.0001) # trained through cv

        self.train_data = None
        self.train_labels = None

        self.coef_ = None
        self.intercept_ = None

        self.plotting_df = {}

        #self.pipe = \
        #    make_pipeline(StandardScaler(), LogisticRegression(max_iter=1000))

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

    def fit(self, X, y):
        self.train_data = X
        self.train_labels = y

        self.avg_loss = []

        # Create a dictionary to hold the results of the fitting
        results_dict = {}
        best_weights = {}

        # If input labels are 0/1 then make sure to convert labels to -1 and 1
        # for learning with the logistic loss.
        self.train_labels = np.where(self.train_labels==1, 1, -1)

        # Calculate folds
        fold_indicies = []

        self.plotting_dict = {
            "max_iterations": [],
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        "avg_loss": []
    }

    # 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_data)):
            if fold_vec[index] == fold_number:
                validation_indicies.append(index)
            else:
                subtrain_indicies.append(index)

        fold_indicies.append([subtrain_indicies, validation_indicies])

    # Loop over the folds
    for foldnum, indicies in enumerate(fold_indicies):
        # 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_data[index_vec],
                "y":self.train_labels[index_vec]
            }

        # Define a variable called scaled_mat which has
        subtrain_data = set_data_dict["subtrain"]['X']
        subtrain_labels = set_data_dict["subtrain"]['y']

        scaled_mat = subtrain_data

        # (1) filtered/removed any zero variance features
        #non_variant_indicies = \
#           np.argwhere(np.all(scaled_mat[..., :] == 0, axis=0))

        #scaled_mat = np.delete(scaled_mat,
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        #                       non_variant_indicies,
        #                       axis=1)

        # (2) scaled any other features
        # self.pipe.fit(scaled_mat, self.train_labels)

        # (3) and an extra column of ones (for learning the intercept).
        #intercept_col = np.ones((len(scaled_mat), 1))
        #scaled_mat = np.append(scaled_mat,
        #                       intercept_col,
        #                       axis=1)

        # Initialize an weight vector with size equal to the number of
columns

        # in scaled_mat.
        nrow, ncol = scaled_mat.shape

        learn_features = np.column_stack([
            np.repeat(1, nrow),
            scaled_mat
        ])

        weight_vec = np.zeros(ncol+1)

        #learn_features = learn_features[:,0]

        subtrain_mean = subtrain_data.mean(axis=0)
        subtrain_sd = np.sqrt(subtrain_data.var(axis=0))

        # Then use a for loop from 0 to max_iterations to iteratively compute
        # linear model parameters that minimize the average logistic loss
over

        #the subtrain data.
        min_loss = np.array([10])
        best_iter = 0
        best_coef = weight_vec

        avg_iter_loss = []

        # Loop for each of the max iterations
        for index in range(self.max_iterations):
            # Calculate prediction and log loss
            pred_vec = np.matmul(learn_features, weight_vec)
            log_loss = np.ma.log(1+np.exp(-subtrain_labels * pred_vec))
            #print("iteration=%d log_loss=%s"%(index,log_loss.mean()))
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                grad_loss_pred = -subtrain_labels / \
                                    (1+np.exp(subtrain_labels * pred_vec))
                grad_loss_pred = grad_loss_pred
                grad_loss_weight_mat = grad_loss_pred * learn_features.T
                grad_vec = grad_loss_weight_mat.sum(axis=1)
                weight_vec -= self.step_size * grad_vec
                # get the smallest log loss
                if( not np.isinf(log_loss.mean()) <= min_loss.mean() ):
                    min_loss = log_loss
                    best_iter = index
                    best_coef = weight_vec
                # build list of loss values
                avg_iter_loss.append(log_loss.mean())

            # save best stuff from each pass
            results_dict[best_iter] = min_loss.mean()
            best_weights[best_iter] = best_coef
            self.avg_loss.append(avg_iter_loss)

        # get single best weight and intercept
        best_result = max(results_dict, key = results_dict.get)
        self.coef_ = best_weights[best_result][1:]
        self.intercept_ = best_weights[best_result][0]

        # these get saved for plotting
        self.avg_loss = np.asarray(self.avg_loss)
        self.avg_loss = self.avg_loss.mean(axis=0)

        # At the end of the algorithm you should save the learned
        # weights/intercept (on original scale) as the coef_ and intercept_
        # attributes of the class (values should be similar to attributes of
        # LogisticRegression class in scikit-learn).

    def decision_function(self, X):
        # Implement a decision_function(X) method which uses the learned weights
        # and intercept to compute a real-valued score (larger for more likely
        # to be predicted positive)

        # use best coef and inter to build result
        pred_vec = np.matmul(X, self.coef_) + self.intercept_

        return pred_vec

    def predict(self, test_features):
        # Implement a predict(X) method which uses np.where to threshold the
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        # predicted values from decision_function, and obtain a vector of
        # predicted classes (1 if predicted value is positive, 0 otherwise).
        pred_vec = self.decision_function(test_features)

        # positive values are 1, anything else is 0
        pred_vec[pred_vec > 0] = 1
        pred_vec[pred_vec <= 0] = 0

        # predicted values using either scaled or unscaled features agree:
        # print(pred_vec)
        return( pred_vec )

# <-- END INITIALIZATION -->

# <-- BEGIN FUNCTIONS -->
# FUNCTION: MAIN
#   Description  : Main driver for Assignment Three
#   Inputs       : None
#   Outputs      : PlotNine graphs saved to program directory
#   Dependencies : build_image_df_from_dataframe
def main():
    # Display the title
    print("\nCS 499: Homework 6 Program Start")
    print("================================\n")

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

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

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

    # Concat the two zip dataframes together
    zip_df = pd.concat([zip_train_df, zip_test_df])

    # Drop rows of dataframes where the label is not ( 0 or 1)
    zip_df[0] = zip_df[0].astype(int)
    zip_df = zip_df[zip_df[0].isin([0, 1])]
    # Drop empty col from zip dataframe
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zip_df = zip_df.drop(columns=[zip_empty_col])

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)

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

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

final_df_list = []
final_deep_print_list = []
final_linear_print_list = []

final_deep_df = pd.DataFrame()
final_linear_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("Working on set: " + current_set)

    #torchLean = TorchLearner(units_per_layer=(ncol, 100, 10, 100, 1) )
    #torchLean.fit( input_data, output_array )

    # 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

        nrow, ncol = input_data.shape
        index_dict = dict(zip(["train", "test"], indicies))
        param_dicts = [{'n_neighbors':[x]} for x in range(1, 21)]
        logreg_param_dicts = \
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    [{'max_iterations':max_it, 'step_size':steps} \
        for max_it in [100, 1000, 2000] \
        for steps in [0.1, 0.01, 0.001, 0.0001, 0.00001, 0.000001]]

logreg_param_nosteps_dicts = \
    [{'max_iterations':max_it} \
        for max_it in [100, 1000, 2000]]

deep_param_dict = \
    [{'units_per_layer': (ncol, 100, 10, 100, ncol, 1),
      'max_epochs':max_ep} \
         for max_ep in [10]]

linear_param_dict = \
    [{'units_per_layer': (ncol, 1),
      'max_epochs':max_ep} \
         for max_ep in [10]]


clf = GridSearchCV(KNeighborsClassifier(), param_dicts)
linear_model = sklearn.linear_model.LogisticRegressionCV(cv=5)
DeepTorchCV = TorchLearnerCV(estimator=TorchLearner,
                    param_grid=deep_param_dict,
                    cv=CV_VAL)
LinearTorchCV = TorchLearnerCV(estimator=TorchLearner,
                    param_grid=linear_param_dict,
                    cv=CV_VAL)


# 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]
    }

# 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"])
LinearTorchCV.fit(**set_data_dict["train"])

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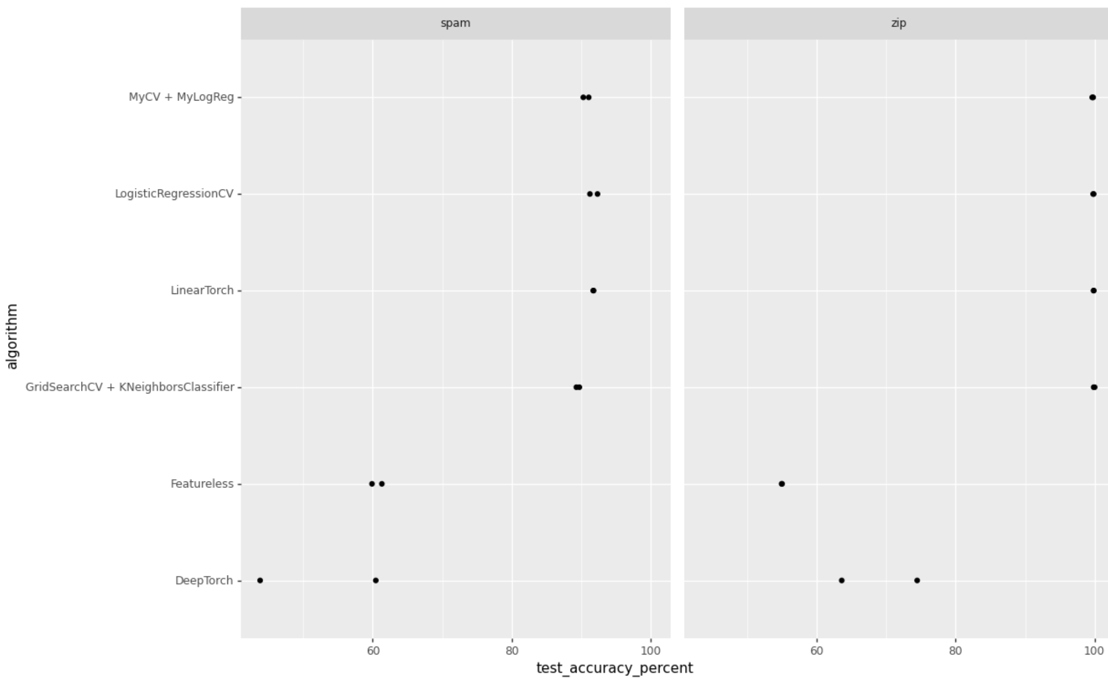
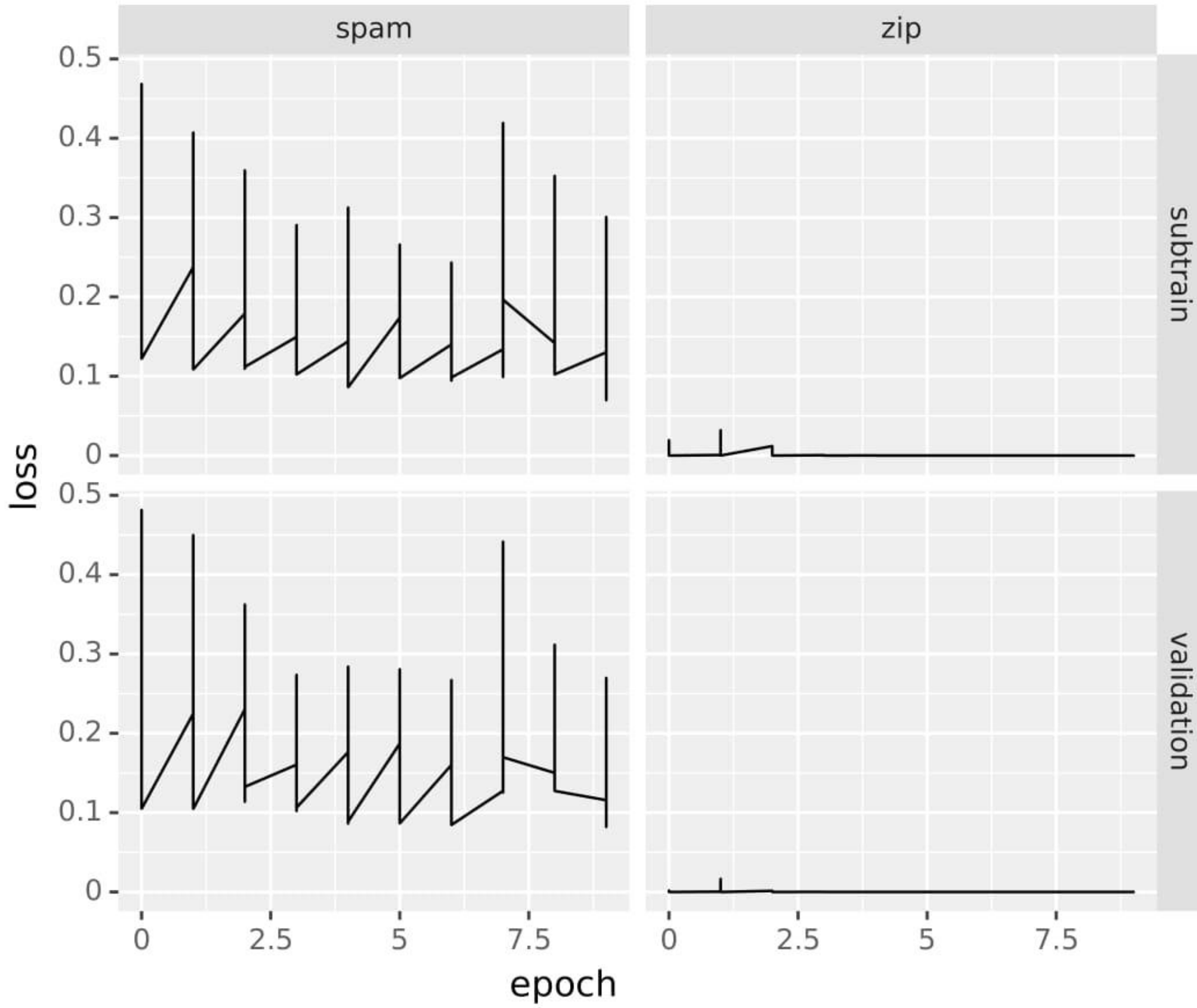

```
        buffer_df = DeepTorchCV.plotting_df
        buffer_df['subfold'] = foldnum
        buffer_df['set'] = data_set
        final_deep_print_list.append(DeepTorchCV.plotting_df)

        buffer_df = LinearTorchCV.plotting_df
        buffer_df['subfold'] = foldnum
        buffer_df['set'] = data_set
        final_linear_print_list.append(LinearTorchCV.plotting_df)

        # Get results
        cv_df = pd.DataFrame(clf.cv_results_)
        cv_df.loc[:, ["param_n_neighbors", "mean_test_score"]]
        pred_dict = {
            "GridSearchCV + KNeighborsClassifier": \
                clf.predict(set_data_dict["test"]["X"]),
            "LogisticRegressionCV": \
                linear_model.predict(set_data_dict["test"]["X"]),
            "DeepTorch": \
                DeepTorchCV.predict(set_data_dict["test"]["X"]),
            "LinearTorch": \
                LinearTorchCV.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)
    final_linear_df = pd.concat(final_deep_print_list)

    #print(final_deep_df)
    #print(final_deep_df.groupby(['set_name', 'set', 'epoch']).mean())

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

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

    # 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(final_deep_df.groupby(['subfold', 'set', 'epoch']).mean())
    deepplot = (p9.ggplot(final_deep_df.groupby(['subfold', 'set',
'epoch']).mean(),
                        p9.aes(x='epoch',
                        y='loss'))
                   + p9.facet_grid('. ~ set', scales='free')
                   + p9.geom_line()
                   + p9.theme(subplots_adjust={'left': 0.2})
                   + p9.ggtitle("DeepTorch Subtrain/Validation Loss"))

    linearplot = (p9.ggplot(final_linear_df.groupby(['subfold', 'set',
'epoch']).mean(),
                        p9.aes(x='epoch',
                        y='loss'))
                   + p9.facet_grid('. ~ set', scales='free')
                   + p9.geom_line()
                   + p9.theme(subplots_adjust={'left': 0.2})
                   + p9.ggtitle("LinearTorch Subtrain/Validation Loss"))

    print(plot)
    deepplot.save()
    #print(deepplot)

    print("\nCS 499: Homework 6 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
```

```python
#       - 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
subtrain
validation
loss
epoch
0.5
0.4
0.3
0.2
0.1
0
0
2.5
5
7.5

	test_accuracy_percent	data_set	fold_id	algorithm
0	89.265537	spam	0	GridSearchCV + KNeighborsClassifier
0	92.307692	spam	0	LogisticRegressionCV
0	43.807040	spam	0	DeepTorch
0	91.742721	spam	0	LinearTorch
0	90.265102	spam	0	MyCV + MyLogReg
0	59.887006	spam	0	Featureless
0	89.695652	spam	1	GridSearchCV + KNeighborsClassifier
0	91.217391	spam	1	LogisticRegressionCV
0	60.434783	spam	1	DeepTorch
0	91.695652	spam	1	LinearTorch
0	91.043478	spam	1	MyCV + MyLogReg
0	61.304348	spam	1	Featureless
0	99.858257	zip	0	GridSearchCV + KNeighborsClassifier
0	99.858257	zip	0	LogisticRegressionCV
0	63.642807	zip	0	DeepTorch
0	99.858257	zip	0	LinearTorch
0	99.787385	zip	0	MyCV + MyLogReg
0	55.067328	zip	0	Featureless
0	100.000000	zip	1	GridSearchCV + KNeighborsClassifier
0	99.787385	zip	1	LogisticRegressionCV
0	74.486180	zip	1	DeepTorch
0	99.858257	zip	1	LinearTorch
0	99.645641	zip	1	MyCV + MyLogReg
0	54.996456	zip	1	Featureless

Question Answers / Commentary:

In this assignment I was unable to implement a deep neural network using the PyTorch tools. My best attempt was only able to create a prediction that was similar in accuracy to a featureless model. However, I was able to implement a linear model using PyTorch methods that achieved very high accuracy.

I used the same Torch model for both the linear and deep CV's. I believe that the results in this project are due to a misunderstanding of how the prediction result is derived from the trained model, as the trained model was able to produce higher accuracy results than the predictions.

For the extra-credit portion of the assignment, I was able to implement my original logistic regression CV and compare it to my new PyTorch linear CV, and the new CV showed a small but significant improvement in accuracy.