

CS599 (Deep Learning)

Homework – 12

1. Python Code:

```
import torch
import pandas as pd
import matplotlib
matplotlib.use("agg")
import numpy as np
import plotnine as p9
import math
import pdb[]

from sklearn.model_selection import KFold, GridSearchCV, ParameterGrid
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegressionCV
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from collections import Counter

data_set_dict = {"zip": ("zip.test.gz", 0),
                 "spam": ("spam.data", 57)}
data_dict = {}

for data_name, (file_name, label_col_num) in data_set_dict.items():
    data_df = pd.read_csv(file_name, sep=" ", header=None)
    data_label_vec = data_df.iloc[:, label_col_num]
    is_label_col = data_df.columns == label_col_num
    data_features = data_df.iloc[:, ~is_label_col]
    data_labels = data_df.iloc[:, is_label_col]
    data_dict[data_name] = (data_features, data_labels)

spam_features, spam_labels = data_dict.pop("spam")
spam_nrow, spam_ncol = spam_features.shape
spam_mean = spam_features.mean().to_numpy().reshape(1, spam_ncol)
spam_std = spam_features.std().to_numpy().reshape(1, spam_ncol)
spam_scaled = (spam_features - spam_mean)/spam_std
data_dict["spam_scaled"] = (spam_scaled, spam_labels)
{data_name:X.shape for data_name, (X,y) in data_dict.items()}

class TorchModel(torch.nn.Module):
    def __init__(self, units_per_layer):
        super(TorchModel, self).__init__()
        seq_args = []
        second_to_last = len(units_per_layer)-1
        for layer_i in range(second_to_last):
            next_i = layer_i+1
            layer_units = units_per_layer[layer_i]
            next_units = units_per_layer[next_i]
            seq_args.append(torch.nn.Linear(layer_units, next_units))
            if layer_i < second_to_last-1:
                seq_args.append(torch.nn.ReLU())
        self.stack = torch.nn.Sequential(*seq_args)
    def forward(self, features):
        return self.stack(features)

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 TorchLearner:
    def __init__(
        self, units_per_layer, opt_name, opt_params,
        batch_size=20, max_epochs=100):
        self.max_epochs = max_epochs
        self.batch_size=batch_size
        self.model = TorchModel(units_per_layer)
        self.loss_fun = torch.nn.CrossEntropyLoss()
        self.initial_step_size = 0.1
        self.end_step_size = 0.001
        self.last_step_number = 50
        self.opt_name = opt_name
        self.opt_params = opt_params
    def get_step_size(self, iteration):
        if iteration > self.last_step_number:
            return self.end_step_size
        prop_to_last_step = iteration/self.last_step_number
        return (1 - prop_to_last_step) * self.initial_step_size +\
            prop_to_last_step * self.end_step_size
    def fit(self, split_data_dict):
        ds = CSV(
            split_data_dict["subtrain"]["X"],
            split_data_dict["subtrain"]["y"])
        dl = torch.utils.data.DataLoader(
            ds, batch_size=self.batch_size, shuffle=True)
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train_df_list = []
for epoch_number in range(self.max_epochs):
    step_size = self.get_step_size(epoch_number)
    #print(f"epoch = {epoch_number}, step = {step_size}")
    #print(f"opt_name = {self.opt_name}, opt_params = {self.opt_params}")
    if self.opt_name == "SGD":
        self.optimizer = torch.optim.SGD(self.model.parameters(), **self.opt_params, lr = step_size)
    elif self.opt_name == "Adam":
        self.optimizer = torch.optim.Adam(self.model.parameters(), **self.opt_params, lr = step_size)
    #print(epoch_number)
    for batch_features, batch_labels in dl:
        #pdb.set_trace()
        self.optimizer.zero_grad()
        loss_value = self.loss_fun(
            self.model(batch_features), batch_labels)
        loss_value.backward()
        self.optimizer.step()
    for set_name, set_data in split_data_dict.items():
        pred_vec = self.model(set_data["X"])
        set_loss_value = self.loss_fun(pred_vec, set_data["Y"])
        train_df_list.append(pd.DataFrame({
            "set_name": [set_name],
            "loss": [float(set_loss_value)],
            "epoch": [epoch_number]
        }))
    self.train_df = pd.concat(train_df_list)
def decision_function(self, test_features):
    with torch.no_grad():
        pred_vec = self.model(test_features)
    return pred_vec

def predict(self, test_features):
    pred_scores = self.decision_function(test_features)
    _, predicted = torch.max(pred_scores, 1)
    return predicted

class TorchLearnerCV:
    def __init__(self, n_folds, units_per_layer, opt_name = 'SGD', opt_params = {'momentum': 0.5}):
        self.units_per_layer = units_per_layer
        self.opt_name = opt_name
        self.opt_params = opt_params
        self.n_folds = n_folds
    def fit(self, train_features, train_labels):
        train_nrow, train_ncol = train_features.shape
        times_to_repeat = int(math.ceil(train_nrow/self.n_folds))
        fold_id_vec = np.tile(torch.arange(self.n_folds), times_to_repeat)[:train_nrow]
        np.random.shuffle(fold_id_vec)
        cv_data_list = []
        for validation_fold in range(self.n_folds):
            is_split = {
                "subtrain": fold_id_vec != validation_fold,
                "validation": fold_id_vec == validation_fold
            }
            split_data_dict = {}
            for set_name, is_set in is_split.items():
                set_y = train_labels[is_set]
                split_data_dict[set_name] = {
                    "X": train_features[is_set,:],
                    "Y": set_y
                }
            learner = TorchLearner(self.units_per_layer, self.opt_name, self.opt_params)
            learner.fit(split_data_dict)
            cv_data_list.append(learner.train_df)
        self.cv_data = pd.concat(cv_data_list)
        self.train_df = self.cv_data.groupby(["set_name", "epoch"]).mean().reset_index()
        #print(self.train_df)
        valid_df = self.train_df.query("set_name=='validation'")
        #print(valid_df)
        best_epochs = valid_df["loss"].argmin()
        self.min_df = valid_df.query("epoch==s"%(best_epochs))
        print("Best Epoch: ", best_epochs)
        #pdb.set_trace()
        self.final_learner = TorchLearner(self.units_per_layer, self.opt_name, self.opt_params, +\
                                           max_epochs=(best_epochs + 1))
        self.final_learner.fit({"subtrain": {"X": train_features, "Y": train_labels}})
        return self.cv_data
    def predict(self, test_features):
        return self.final_learner.predict(test_features)

class MyCV:
    def __init__(self, estimator, param_grid, cv):
        """estimator: learner instance
        param_grid: list of dictionaries
        cv: number of folds"""
        self.cv = cv
        self.param_grid = param_grid
        self.estimator = estimator

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def fit_one(self, param_dict, X, y):
    """Run self.estimated.fit on one parameter combination"""
    for param_name, param_value in param_dict.items():
        #print(f"param_name = {param_name}, param_value = {param_value}")
        setattr(self.estimated, param_name, param_value)
    self.estimated.fit(X, y)

def fit(self, X, y):
    """cross-validation for selecting the best dictionary is param_grid"""
    validation_df_list = []
    train_nrow, train_ncol = X.shape
    times_to_repeat = int(math.ceil(train_nrow/self.cv))
    fold_id_vec = np.tile(np.arange(self.cv), times_to_repeat)[:train_nrow]
    np.random.shuffle(fold_id_vec)
    for validation_fold in range(self.cv):
        is_split = {
            "subtrain": fold_id_vec != validation_fold,
            "validation": fold_id_vec == validation_fold
        }
        split_data_dict = {}
        for set_name, is_set in is_split.items():
            split_data_dict[set_name] = (
                X[is_set],
                y[is_set])
        for param_number, param_dict in enumerate(self.param_grid):
            self.fit_one(param_dict, *split_data_dict["subtrain"])
            X_valid, y_valid = split_data_dict["validation"]
            pred_valid = self.estimated.predict(X_valid)
            #pdb.set_trace()
            is_correct = pred_valid == y_valid
            #self.estimated.fit(*split_data_dict["validation"])
            valid_loss = self.estimated.train_df.query("set_name=='validation'")["loss"].mean()
            subtrain_loss = self.estimated.train_df.query("set_name=='subtrain'")["loss"].mean()
            validation_row1 = pd.DataFrame({
                "set_name": "subtrain",
                "validation_fold": validation_fold,
                "accuracy_percent": float(is_correct.float().mean()),
                "param_number": [param_number],
                "loss": float(subtrain_loss)
            }, index = [0])
            validation_row2 = pd.DataFrame({
                "set_name": "validation",
                "validation_fold": validation_fold,
                "accuracy_percent": float(is_correct.float().mean()),
                "param_number": [param_number],
                "loss": float(valid_loss)
            }, index = [0])
            validation_df_list.append(validation_row1)
            validation_df_list.append(validation_row2)
        self.validation_df = pd.concat(validation_df_list)
        self.mean_valid_loss = self.validation_df.groupby("param_number")["loss"].mean().reset_index()
        self.train_df = self.validation_df.groupby(["set_name", "loss"]).mean().reset_index()
        best_index = self.mean_valid_loss["loss"].argmin()
        #pdb.set_trace()
        valid_df = self.train_df.query("set_name == 'validation'")
        self.min_df = valid_df.query("param_number==s"%(best_index))
        self.best_param_dict = self.param_grid[best_index]
        self.fit_one(self.best_param_dict, X, y)

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

accuracy_data_frames = []
loss_data_dict = {}
min_df_dict = {}
best_param_dict = {}
for data_name, (data_features, data_labels) in data_dict.items():
    kf = KFold(n_splits=3, shuffle=True, random_state=3)
    enum_obj = enumerate(kf.split(data_features))
    for fold_num, index_tup in enum_obj:
        zip_obj = zip(["train", "test"], index_tup)
        split_data = {}
        for set_name, set_indices in zip_obj:
            split_data[set_name] = (torch.from_numpy(data_features.iloc[set_indices, :].to_numpy()).float(),
                                    torch.from_numpy(np.ravel(data_labels.iloc[set_indices])).flatten())
        #x = {data_name:X.shape for data_name, (X,y) in split_data.items()}
        #print(f"{data_name}: ", x)
        train_features, train_labels = split_data["train"]
        nrow, ncol = train_features.shape
        print(f"{data_name}: ", nrow, ncol)
        test_features, test_labels = split_data["test"]

#kneighbors
knn = KNeighborsClassifier()
hp_parameters = {"n_neighbors": list(range(1, 21))}
grid = GridSearchCV(knn, hp_parameters, cv=3)

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        grid.fit(train_features, train_labels)
        best_n_neighbors = grid.best_params_['n_neighbors']
        print("Best N-Neighbors = ", best_n_neighbors)
        knn = KNeighborsClassifier(n_neighbors=best_n_neighbors)
        knn.fit(train_features, train_labels)
        knn_pred = knn.predict(test_features)
        #print(knn_pred)
        #loss = mean_squared_error(test_labels, knn_pred)
        #print(f"Knn Loss {data_name} : ", loss)

    #linear model
    pipe = make_pipeline(StandardScaler(), LogisticRegressionCV(cv=3, max_iter=2000))
    pipe.fit(train_features, train_labels)
    lr_pred = pipe.predict(test_features)
    #print(lr_pred)
    #loss_linear = mean_squared_error(test_labels, lr_pred)
    #print(f"Linear_loss {data_name} : ", loss_linear)

    #Featureless
    y_train_series = pd.Series(train_labels)
    #mean_train_label = y_train_series.mean()
    #print("Mean Train Label = ", mean_train_label)

    # create a featureless baseline
    most_frequent_label = y_train_series.value_counts().idxmax()
    print("Most Frequent Label = ", most_frequent_label)

    featureless_pred = np.repeat(most_frequent_label, len(test_features))
    #featureless_loss = mean_squared_error(test_labels, featureless_pred)
    #print(f"Featureless Loss {data_name} : ", featureless_loss)

    param_grid = []
    for momentum in 0.1, 0.5:
        param_grid.append({
            "opt_name": "SGD",
            "opt_params": {"momentum": momentum}
        })
    for beta1 in 0.85, 0.9, 0.95:
        for beta2 in 0.99, 0.999, 0.9999:
            param_grid.append({
                "opt_name": "Adam",
                "opt_params": {"betas": (beta1, beta2)}
            })

    #MyCV + OptimizerMLP
    my_cv_learner = MyCV(
        estimator = TorchLearnerCV(3, [ncol, 100, 10, 10]),
        param_grid = param_grid,
        cv = 2)
    my_cv_learner.fit(train_features, train_labels)
    print(f"Best param_dict: {my_cv_learner.best_param_dict}")
    best_param_dict[data_name] = {'Best param_dict': my_cv_learner.best_param_dict}
    my_cv_pred = my_cv_learner.predict(test_features)

    min_df_dict[data_name] = {'min_df_estimator': my_cv_learner.estimator.min_df,
                             'min_df': my_cv_learner.min_df}

    loss_data_dict[data_name] = {'my_cv_learner_estimator': my_cv_learner.estimator.train_df,
                                 'my_cv_learner': my_cv_learner.validation_df}

    # store predict data in dict
    pred_dict = {'KNeighborsClassifier + GridSearchCV': knn_pred,
                 'LogisticRegressionCV': lr_pred,
                 'MyCV + OptimizerMLP': my_cv_pred,
                 'featureless': featureless_pred}
    test_accuracy = {}
    for algorithm, predictions in pred_dict.items():
        #print(f"{algorithm}:", predictions.shape)
        #test_loss = mean_squared_error(test_labels, predictions)
        accuracy = accuracy_score(test_labels, predictions)
        test_accuracy[algorithm] = accuracy

    for algorithm, accuracy in test_accuracy.items():
        print(f"{algorithm} Test Accuracy: {accuracy * 100}")
        accuracy_df = pd.DataFrame({
            "data_set": [data_name],
            "fold_id": [fold_num],
            "algorithm": [algorithm],
            "accuracy": [test_accuracy[algorithm]]})
        accuracy_data_frames.append(accuracy_df)
    print(f"*****End of {data_name}({fold_num})*****")

total_accuracy_df = pd.concat(accuracy_data_frames, ignore_index = True)
print(total_accuracy_df)

```

```

import plotnine as p9
gg = p9.ggplot(total_accuracy_df, p9.aes(x='accuracy', y='algorithm'))+\
    p9.facet_grid('~data_set') + p9.geom_point()

gg.save("output.png", height = 8, width = 12)

gg1 = p9.ggplot() +\
    p9.geom_line(
        p9.aes(
            x = "epoch",
            y = "loss",
            color = "set_name"
        ),
        data = loss_data_dict["zip"]["my_cv_learner_estimator"]) +\
    p9.geom_point(
        p9.aes(
            x = "epoch",
            y = "loss",
            color = "set_name"
        ),
        data = min_df_dict["zip"]["min_df_estimator"]) +\
    p9.ggtitle("Subtrain/Validation Loss vs Epochs (Zip - Data)")

gg1.save("Torch_validation_graph1.png", height = 8, width = 12)

gg2 = p9.ggplot() +\
    p9.geom_line(
        p9.aes(
            x = "epoch",
            y = "loss",
            color = "set_name"
        ),
        data = loss_data_dict["spam_scaled"]["my_cv_learner_estimator"]) +\
    p9.geom_point(
        p9.aes(
            x = "epoch",
            y = "loss",
            color = "set_name"
        ),
        data = min_df_dict["spam_scaled"]["min_df_estimator"]) +\
    p9.ggtitle("Subtrain/Validation Loss vs Epochs (Spam_scaled - Data)")

gg2.save("Torch_validation_graph2.png", height = 8, width = 12)

gg3 = p9.ggplot() +\
    p9.geom_line(
        p9.aes(
            x = "param_number",
            y = "loss",
            color = "set_name"
        ),
        data = loss_data_dict["zip"]["my_cv_learner"]) +\
    p9.geom_point(
        p9.aes(
            x = "param_number",
            y = "loss",
            color = "set_name"
        ),
        data = min_df_dict["zip"]["min_df"]) +\
    p9.facet_grid('~validation fold') +\
    p9.ggtitle(f"Subtrain/Validation Loss vs param_grid {best_param_dict['zip']} (Zip - Data)")

gg3.save("l1loss_graph1.png", height = 10, width = 16)

gg4 = p9.ggplot() +\
    p9.geom_line(
        p9.aes(
            x = "param_number",
            y = "loss",
            color = "set_name"
        ),
        data = loss_data_dict["spam_scaled"]["my_cv_learner"]) +\
    p9.geom_point(
        p9.aes(
            x = "param_number",
            y = "loss",
            color = "set_name"
        ),
        data = min_df_dict["spam_scaled"]["min_df"]) +\
    p9.facet_grid('~validation fold') +\
    p9.ggtitle(f"Subtrain/Validation Loss vs param_grid {best_param_dict['spam_scaled']} (Spam_scaled - Data)")

gg4.save("l1loss_graph2.png", height = 10, width = 16)

```

2. Output:

```
>> for data_name, (data_features, data_labels) in data_dict.items():
...     kf = KFold(n_splits=3, shuffle=True, random_state=3)
...     enum_obj = enumerate(kf.split(data_features))
...     for fold_num, index_tup in enum_obj:
...         zip_obj = zip(["train", "test"], index_tup)
...         split_data = {}
...         for set_name, set_indices in zip_obj:
...             split_data[set_name] = (torch.from_numpy(data_features.iloc[set_indices, :].to_numpy()).float(),
...                                     torch.from_numpy(np.ravel(data_labels.iloc[set_indices])).flatten())
...         #x = {data_name:X.shape for data_name, (X,y) in split_data.items()}
...     ...
...     for algorithm, accuracy in test_accuracy.items():
...         print(f"{algorithm} Test Accuracy: {accuracy * 100}")
...         accuracy_df = pd.DataFrame({
...             "data_set": [data_name],
...             "fold_id": [fold_num],
...             "algorithm": [algorithm],
...             "accuracy": [test_accuracy[algorithm]]})
...         accuracy_data_frames.append(accuracy_df)
...     print(f"*****End of {data_name}({fold_num})*****")

zip: 1338 256
Best N-Neighbors = 1
Most Frequent Label = 0
Best Epoch: 8
Best Epoch: 3
Best Epoch: 0
Best Epoch: 11
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0
Best Epoch: 0
Best Epoch: 17
Best Epoch: 1
Best Epoch: 8
Best Epoch: 6
Best Epoch: 41
Best Epoch: 0
Best Epoch: 19
Best Epoch: 0
Best Epoch: 2
Best Epoch: 0
Best Epoch: 5
Best Epoch: 19
Best Epoch: 28
Best Epoch: 10
Best param_dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 90.5829596412556
LogisticRegressionCV Test Accuracy: 89.8355754857997
MyCV + OptimizerMLP Test Accuracy: 89.98505231689087
featureless Test Accuracy: 18.53512705530643
*****End of zip(0)*****

zip: 1338 256
Best N-Neighbors = 1
Most Frequent Label = 0
Best Epoch: 14
Best Epoch: 10
Best Epoch: 0
Best Epoch: 0
Best Epoch: 2
Best Epoch: 26
Best Epoch: 4
Best Epoch: 13
Best Epoch: 0
Best Epoch: 41
Best Epoch: 0
Best Epoch: 13
Best Epoch: 7
Best Epoch: 1
Best Epoch: 1
Best Epoch: 19
Best Epoch: 1
Best Epoch: 1
Best Epoch: 0
Best Epoch: 4
Best Epoch: 2
Best Epoch: 0
Best Epoch: 4
Best param_dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.5}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 91.18086696562034
LogisticRegressionCV Test Accuracy: 88.34080717488789
MyCV + OptimizerMLP Test Accuracy: 87.14499252615845
featureless Test Accuracy: 17.638266068759343
*****End of zip(1)*****

zip: 1338 256
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└─
Best N-Neighbors = 1
Most Frequent Label = 0
Best Epoch: 13
Best Epoch: 8
Best Epoch: 9
Best Epoch: 34
Best Epoch: 0
Best Epoch: 7
Best Epoch: 18
Best Epoch: 8
Best Epoch: 13
Best Epoch: 6
Best Epoch: 0
Best Epoch: 10
Best Epoch: 10
Best Epoch: 0
Best Epoch: 3
Best Epoch: 0
Best Epoch: 0
Best Epoch: 13
Best Epoch: 0
Best Epoch: 14
Best Epoch: 37
Best Epoch: 1
Best Epoch: 11
Best param dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 89.98505231689087
LogisticRegressionCV Test Accuracy: 89.98505231689087
MyCV + OptimizerMLP Test Accuracy: 89.68609865470853
featureless Test Accuracy: 17.48878923766816
*****End of zip(2)*****
spam_scaled: 3067 57
Best N-Neighbors = 4
Most Frequent Label = 0
Best Epoch: 4
Best Epoch: 8
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 2
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 5
Best Epoch: 10
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 1
Best Epoch: 2
Best Epoch: 2
Best Epoch: 0
Best Epoch: 0
Best Epoch: 3
Best param dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.5}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 88.72229465449804
LogisticRegressionCV Test Accuracy: 91.52542372881356
MyCV + OptimizerMLP Test Accuracy: 93.48109517601043
featureless Test Accuracy: 60.88657105606258
*****End of spam_scaled(0)*****
spam_scaled: 3067 57
Best N-Neighbors = 5
Most Frequent Label = 0
Best Epoch: 9
Best Epoch: 4
Best Epoch: 0
Best Epoch: 8
Best Epoch: 2
Best Epoch: 2
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 1
Best Epoch: 4
Best Epoch: 3
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0

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Best Epoch: 0
Best Epoch: 1
Best Epoch: 7
Best param dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 90.80834419817471
LogisticRegressionCV Test Accuracy: 91.78617992177314
MyCV + OptimizerMLP Test Accuracy: 92.24250325945242
featureless Test Accuracy: 60.104302477183836
*****End of spam_scaled(1)*****
spam_scaled: 3068 57
Best N-Neighbors = 9
Most Frequent Label = 0
Best Epoch: 4
Best Epoch: 3
Best Epoch: 2
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0
Best Epoch: 0
Best Epoch: 12
Best Epoch: 0
Best Epoch: 1
Best Epoch: 0
Best Epoch: 6
Best Epoch: 2
Best Epoch: 0
Best Epoch: 4
Best Epoch: 1
Best Epoch: 3
Best Epoch: 3
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 0
Best Epoch: 10
Best param dict: {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}
KNeighborsClassifier + GridSearchCV Test Accuracy: 90.54142204827136
LogisticRegressionCV Test Accuracy: 92.49836921069797
MyCV + OptimizerMLP Test Accuracy: 92.82452707110241
featureless Test Accuracy: 60.79582517938682
*****End of spam_scaled(2)*****

```

```
>>> total_accuracy_df = pd.concat(accuracy_data_frames, ignore_index = True)
```

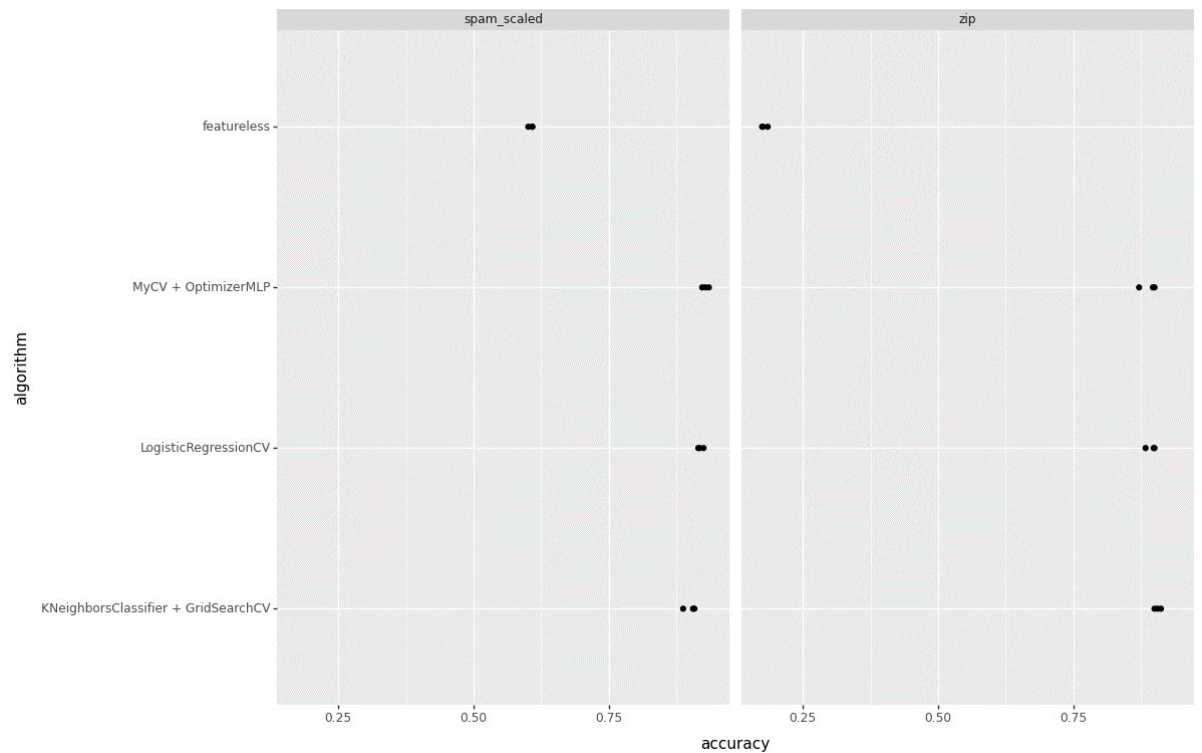
```
>>> print(total_accuracy_df)
```

	data_set	fold_id	algorithm	accuracy
0	zip	0	KNeighborsClassifier + GridSearchCV	0.905830
1	zip	0	LogisticRegressionCV	0.898356
2	zip	0	MyCV + OptimizerMLP	0.899851
3	zip	0	featureless	0.185351
4	zip	1	KNeighborsClassifier + GridSearchCV	0.911809
5	zip	1	LogisticRegressionCV	0.883408
6	zip	1	MyCV + OptimizerMLP	0.871450
7	zip	1	featureless	0.176383
8	zip	2	KNeighborsClassifier + GridSearchCV	0.899851
9	zip	2	LogisticRegressionCV	0.899851
10	zip	2	MyCV + OptimizerMLP	0.896861
11	zip	2	featureless	0.174888
12	spam_scaled	0	KNeighborsClassifier + GridSearchCV	0.887223
13	spam_scaled	0	LogisticRegressionCV	0.915254
14	spam_scaled	0	MyCV + OptimizerMLP	0.934811
15	spam_scaled	0	featureless	0.608866
16	spam_scaled	1	KNeighborsClassifier + GridSearchCV	0.908083
17	spam_scaled	1	LogisticRegressionCV	0.917862
18	spam_scaled	1	MyCV + OptimizerMLP	0.922425
19	spam_scaled	1	featureless	0.601043
20	spam_scaled	2	KNeighborsClassifier + GridSearchCV	0.905414
21	spam_scaled	2	LogisticRegressionCV	0.924984
22	spam_scaled	2	MyCV + OptimizerMLP	0.928245
23	spam_scaled	2	featureless	0.607958

```
>>> import plotnine as p9
```

```
>>> gg = p9.ggplot(total_accuracy_df, p9.aes(x='accuracy', y='algorithm')) + \
...     p9.facet_grid('~data_set') + p9.geom_point()
```

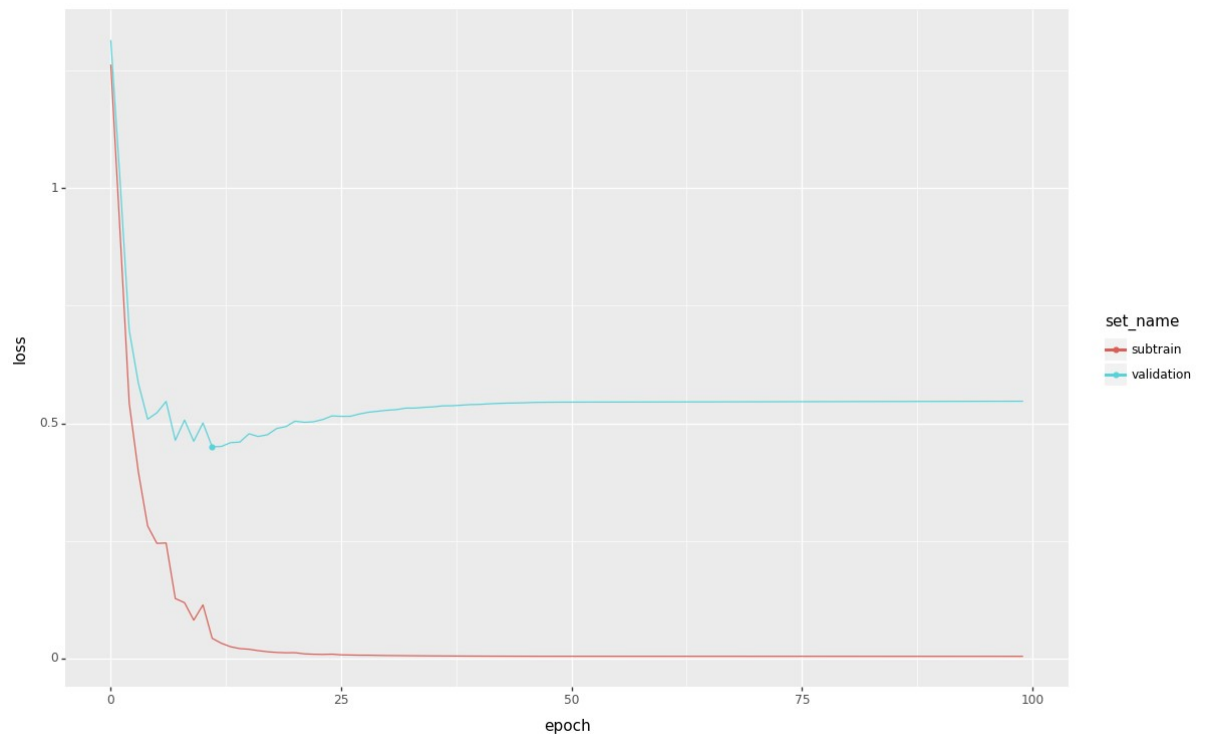
```
>>> gg.save("c:/Users/Anudeep Kumar/OneDrive/Desktop/Fall 2023/CS599-Deep Learning/Homework/HW12/output.png", height = 8, width = 12)
```

```
>>> gg1 = p9.ggplot() +\
...   p9.geom_line(\
...     p9.aes(\
...       x = "epoch",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = loss_data_dict["zip"]["my_cv_learner_estimator"]) +\
...   p9.geom_point(\
...     p9.aes(\
...       x = "epoch",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = min_df_dict["zip"]["min_df_estimator"]) +\
...   p9.ggtitle("Subtrain/Validation Loss vs Epochs (Zip - Data)")

>>> gg1.save("c:/Users/Anudeep Kumar/OneDrive/Desktop/Fall 2023/CS599-Deep Learning/Homework/HW12/Torch_validation_2\
graph1.png", height = 8, width = 12)
```

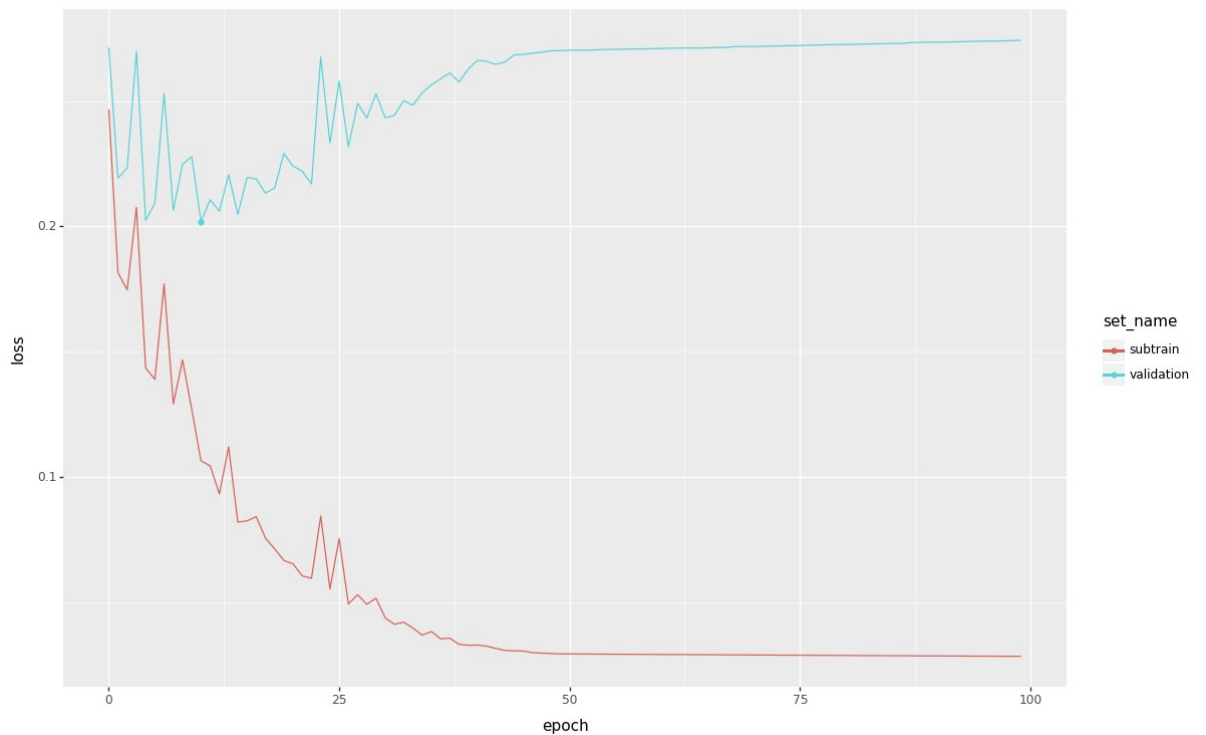
Subtrain/Validation Loss vs Epochs(Zip - Data)



```
>>> gg2 = p9.ggplot() +\
...   p9.geom_line(\
...     p9.aes(\
...       x = "epoch",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = loss_data_dict["spam_scaled"]["my_cv_learner_estimator"]) +\
...   p9.geom_point(\
...     p9.aes(\
...       x = "epoch",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = min_df_dict["spam_scaled"]["min_df_estimator"]) +\
...   p9.ggtitle("Subtrain/Validation Loss vs Epochs (Spam_scaled - Data)")

>>> gg2.save("c:/Users/Anudeep Kumar/OneDrive/Desktop/Fall 2023/CS599-Deep Learning/Homework/HW12/Torch_validation_2\
graph2.png", height = 8, width = 12)
```

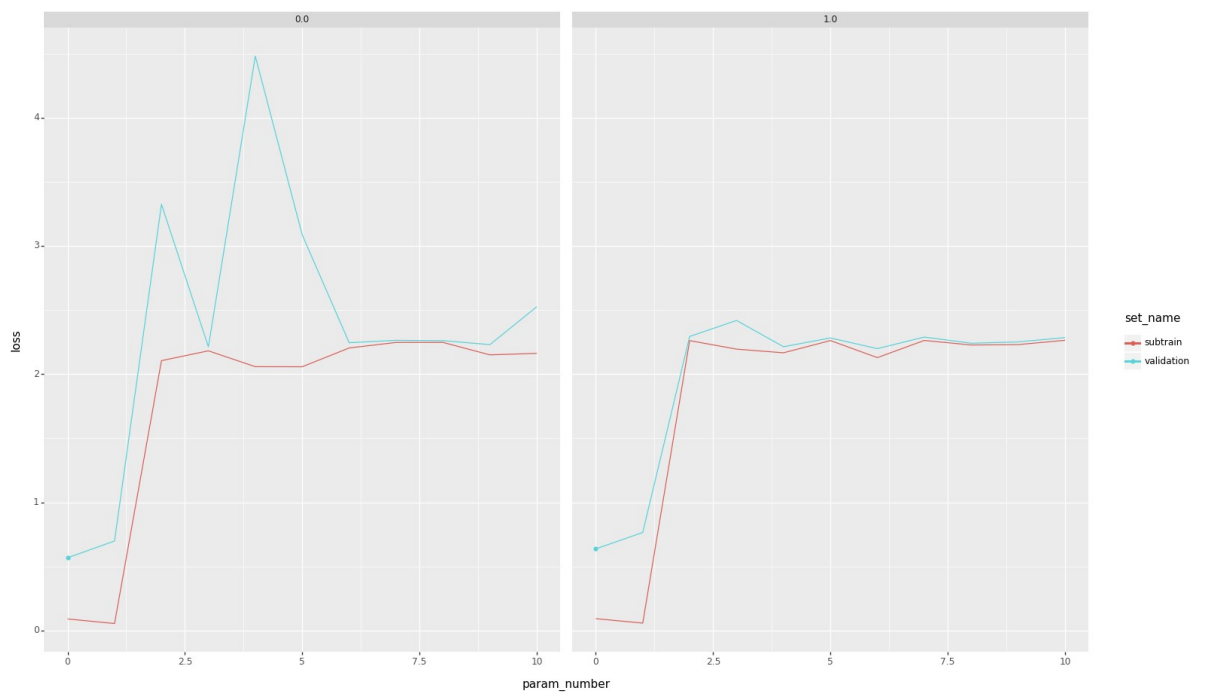
Subtrain/Validation Loss vs Epochs(Spam_scaled - Data)



```
>>> gg3 = p9.ggplot() +\
...   p9.geom_line(\
...     p9.aes(\
...       x = "param_number",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = loss_data_dict["zip"]["my_cv_learner"]) +\
...   p9.geom_point(\
...     p9.aes(\
...       x = "param_number",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = min_df_dict["zip"]["min_df"]) +\
...   p9.facet_grid('~validation_fold') +\
...   p9.ggtitle(f"Subtrain/Validation Loss vs param_grid {best_param_dict['zip']} (Zip - Data)")

>>> gg3.save("c:/Users/Anudeep Kumar/OneDrive/Desktop/Fall 2023/CS599-Deep Learning/Homework/HW12/01loss_graph1.png")
```

Subtrain/Validation Loss vs param_grid {'Best param_dict': {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}} (Zip - Data)



```
>>> gg4 = p9.ggplot() +\
...   p9.geom_line(\
...     p9.aes(\
...       x = "param_number",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = loss_data_dict["spam_scaled"]["my_cv_learner"]) +\
...   p9.geom_point(\
...     p9.aes(\
...       x = "param_number",\
...       y = "loss",\
...       color = "set_name"\
...     ),\
...     data = min_df_dict["spam_scaled"]["min_df"]) +\
...   p9.facet_grid('~validation_fold') +\
...   p9.ggtitle(f"Subtrain/Validation Loss vs param_grid {best_param_dict['spam_scaled']} (Spam_scaled - Data)")

>>> gg4.save("c:/Users/Anudeep Kumar/OneDrive/Desktop/Fall 2023/CS599-Deep Learning/Homework/HW12/01loss_graph2.png")
```

Subtrain/Validation Loss vs param_grid {'Best param_dict': {'opt_name': 'SGD', 'opt_params': {'momentum': 0.1}}}(Spam_scaled - Data)

