## hw3

October 20, 2024

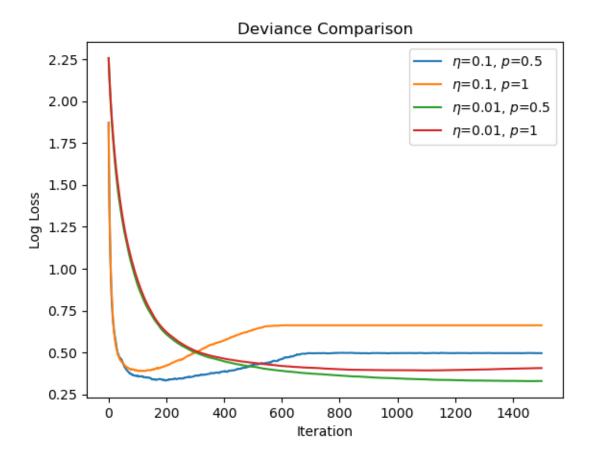
## 1 Problem 4

```
[117]: from sklearn.datasets import load_digits
       from sklearn.metrics import log_loss, accuracy_score
       from sklearn.ensemble import GradientBoostingClassifier
       from sklearn.model_selection import GridSearchCV
       import matplotlib.pyplot as plt
[85]: digits = load_digits()
       X = digits.data
       y = digits.target
       X_train, X_test = X[:1000], X[1000:]
       y_train, y_test = y[:1000], y[1000:]
 []: deviance_dct = {
           (0.1,0.5): None,
           (0.1, 1): None,
           (0.01, 0.5): None,
           (0.01, 1): None
       }
       for lr in [0.1, 0.01]:
           for p in [0.5, 1]:
               gb_clf = GradientBoostingClassifier(n_estimators=1500, # T = 1500
                                                   learning_rate=lr, # 0.1 and 0.01
                                                   max_leaf_nodes=4,
                                                   min_samples_split=5,
                                                   subsample=p, # 0.5 and 1
                                                   random_state=42)
               gb_clf.fit(X_train, y_train)
               y_pred_proba_stages = gb_clf.staged_predict_proba(X_test)
```

```
deviances = []
for y_pred_proba in y_pred_proba_stages:
    deviance = log_loss(y_test, y_pred_proba)
    deviances.append(deviance)

deviance_dct[(lr, p)] = deviances
```

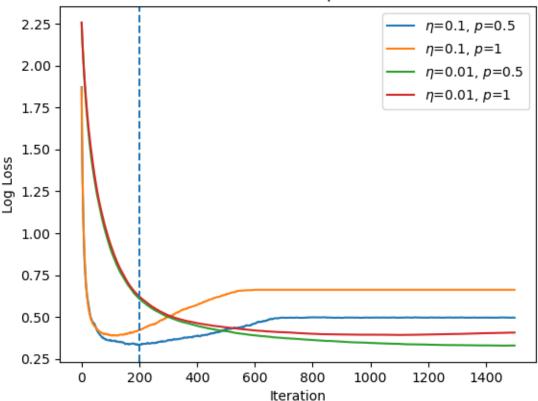
[101]: Text(0, 0.5, 'Log Loss')



```
[103]: param_grid = {
           'n_estimators': [20, 30, 40, 60, 80, 100, 200, 500]
       }
       gb_clf = GradientBoostingClassifier(learning_rate=0.1, # Example learning rate
                                             max_leaf_nodes=4,
                                             min_samples_split=5,
                                             subsample=0.5,
                                                                 # Example subsample
                                             random state=42)
       grid_search = GridSearchCV(estimator=gb_clf,
                                   param_grid=param_grid,
                                   cv=10,
                                   scoring='neg_log_loss',
                                   n_jobs=-1
       grid_search.fit(X_train, y_train)
       best_n_estimators = grid_search.best_params_['n_estimators']
[108]: import pandas as pd
       pd.DataFrame(grid search.cv results )
[108]:
          mean_fit_time
                         std_fit_time mean_score_time std_score_time
               1.113934
                             0.024499
                                               0.006466
                                                               0.004081
       0
       1
               1.633280
                             0.044832
                                               0.003623
                                                               0.000530
       2
               2.151802
                             0.046762
                                               0.003758
                                                               0.000719
       3
               3.099959
                             0.082132
                                               0.004153
                                                               0.000775
       4
               4.124060
                             0.086896
                                               0.004514
                                                               0.000750
       5
               5.278415
                             0.084862
                                               0.005714
                                                               0.002679
       6
              10.710508
                             0.210531
                                               0.006764
                                                               0.000723
                                               0.009756
              21.778956
                             0.112896
                                                               0.000930
         param_n_estimators
                                             params
                                                     split0_test_score
                              {'n_estimators': 20}
                                                             -0.634718
                         20
                              {'n_estimators': 30}
       1
                         30
                                                             -0.517642
       2
                         40
                              {'n_estimators': 40}
                                                             -0.462130
                              {'n_estimators': 60}
       3
                         60
                                                             -0.414317
       4
                              {'n_estimators': 80}
                         80
                                                             -0.384714
                             {'n estimators': 100}
       5
                        100
                                                              -0.352984
       6
                        200
                             {'n_estimators': 200}
                                                             -0.326890
       7
                        500 {'n_estimators': 500}
                                                             -0.484325
          split1_test_score split2_test_score split3_test_score split4_test_score \
       0
                  -0.410750
                                      -0.357796
                                                         -0.463038
                                                                             -0.542924
                  -0.306412
                                      -0.261578
                                                         -0.343196
                                                                             -0.406640
       1
       2
                  -0.256677
                                      -0.211052
                                                         -0.306566
                                                                             -0.337621
```

```
3
                  -0.200579
                                      -0.160666
                                                          -0.253328
                                                                              -0.285509
       4
                  -0.179854
                                      -0.145694
                                                          -0.217918
                                                                              -0.251432
       5
                  -0.166531
                                      -0.121922
                                                          -0.189873
                                                                              -0.226205
       6
                  -0.137073
                                      -0.098897
                                                          -0.120130
                                                                              -0.223812
       7
                  -0.171181
                                      -0.106960
                                                          -0.103007
                                                                              -0.292377
          split5_test_score split6_test_score split7_test_score split8_test_score \
                                                          -0.511252
       0
                  -0.585417
                                      -0.483604
                                                                              -0.511213
       1
                  -0.407291
                                      -0.317340
                                                          -0.397742
                                                                              -0.420775
       2
                  -0.341101
                                      -0.251725
                                                          -0.328141
                                                                              -0.387675
       3
                                      -0.167223
                                                          -0.262561
                  -0.274873
                                                                              -0.316265
       4
                  -0.235531
                                      -0.128219
                                                          -0.246509
                                                                              -0.282631
       5
                  -0.204619
                                      -0.102296
                                                          -0.232413
                                                                              -0.245616
                                                          -0.227744
       6
                  -0.159400
                                      -0.048569
                                                                              -0.165468
       7
                  -0.157914
                                      -0.016387
                                                          -0.301402
                                                                              -0.141732
                              mean_test_score std_test_score
                                                                rank_test_score
          split9_test_score
       0
                  -0.462232
                                    -0.496294
                                                      0.076584
                                                                               7
       1
                  -0.341912
                                    -0.372053
                                                      0.069221
       2
                  -0.290532
                                    -0.317322
                                                      0.068645
                                                                               6
       3
                  -0.212774
                                    -0.254810
                                                      0.072020
                                                                               5
       4
                  -0.179247
                                    -0.225175
                                                      0.070668
                                                                               4
       5
                  -0.159207
                                    -0.200167
                                                      0.067655
                                                                               3
       6
                                                                               1
                  -0.117145
                                    -0.162513
                                                      0.075221
       7
                  -0.160283
                                    -0.193557
                                                      0.125934
                                                                               2
[115]: for lr in [0.1, 0.01]:
           for p in [0.5, 1]:
               plt.plot(deviance_dct[(lr,p)], label=f'$\eta$={lr}, $p$={p}')
       plt.axvline(best_n_estimators, linestyle='--')
       plt.title('Deviance Comparison')
       plt.legend()
       plt.xlabel('Iteration')
       plt.ylabel('Log Loss')
```

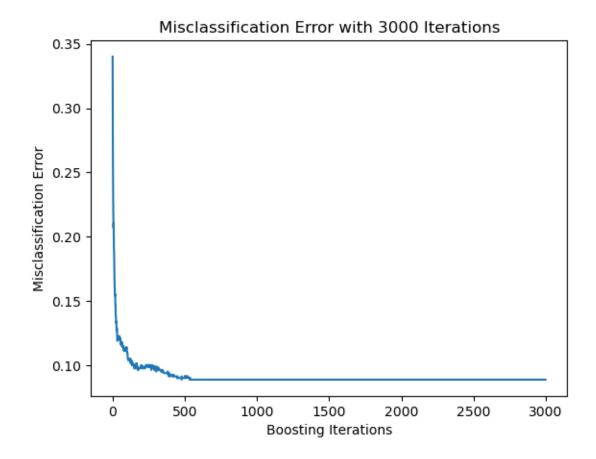
## **Deviance Comparison**



```
[124]: errors = []
for y_pred in gb_clf.staged_predict(X_test):
    errors.append(
        1 - accuracy_score(y_pred, y_test)
    )
```

```
[132]: plt.plot(errors)
# plt.yscale('log')
# plt.ylim(0,0.1)
plt.xlabel("Boosting Iterations")
plt.ylabel("Misclassification Error")
plt.title("Misclassification Error with 3000 Iterations")
```

[132]: Text(0.5, 1.0, 'Misclassification Error with 3000 Iterations')



## 2 Problem 5

```
[206]: from sklearn . neighbors import RadiusNeighborsClassifier
  from collections import Counter
  import random
  import numpy as np
[142]: d=2
mu0 = [
      [-2,-3.5],
```

```
[0,0],[2,-3.5]
       ]
       Id = [
           [25,0],
           [0,25]
       def Data_Generate(n):
           outX = []
           outY = np.random.choice(
               list(range(3)), n, replace=True, p=[0.5,0.25,0.25]
           for i in range(n):
               mu = mu0[outY[i]]
               X = np.random.multivariate_normal(mu,Id,1)[0].tolist()
               outX.append(X)
           return np.array(outX), np.array(outY)
[183]: n = 500
       testX, testY = Data_Generate(n)
[169]: def q_quantile_interpoint_distance(data, q):
           distances = np.linalg.norm(data[:, np.newaxis, :] - data[np.newaxis, :, :],
        ⇒axis=2)
           # print(distances)
           # print(distances.shape)
           interpoint_distances = distances[np.triu_indices_from(distances, k=1)]
           # print(interpoint_distances)
           # print(interpoint_distances.shape)
           return np.quantile(interpoint_distances, q)
  [ ]: NUM_EXPERIMENT = 100
       well_defined_proportions = [[] for _ in range(11)]
       errors = [[] for _ in range(11)]
       # repeat 1000 times
       for experiment in range(NUM_EXPERIMENT):
           trainX, trainY = Data_Generate(n)
           for q in range(1, 11):
               dist = q_quantile_interpoint_distance(trainX, q/10)
               # print(q/10, dist)
```

```
ENN = RadiusNeighborsClassifier(radius=dist)
      ENN.fit(trainX, trainY)
      neigh_indices = ENN.radius_neighbors(testX, return_distance=False)
      well_defined_count = 0
      for indices in (neigh_indices):
          if len(indices):
               well_defined_count += 1
      # print(experiment, q, well_defined_count, well_defined_count / n)
      well_defined_proportion = well_defined_count / n
      well_defined_proportions[q].append(well_defined_proportion)
      try:
          y_pred = ENN.predict(testX)
          test_error = 1 - accuracy_score(testY, y_pred)
          errors[q].append(test_error)
           # print(neigh_indices)
           # print(len(neigh_indices))
           # print(neigh_indices[0].shape, neigh_indices[39].shape, ___
→neigh_indices[139].shape)
      except ValueError as e:
           # print(e)
          pass
```

plot error

```
[246]: mus = []
stds = []

for q in range(1, 11):
    err = np.array(errors[q])
    mu = err.mean()
    std = err.std()

    mus.append(mu)
    stds.append(std)

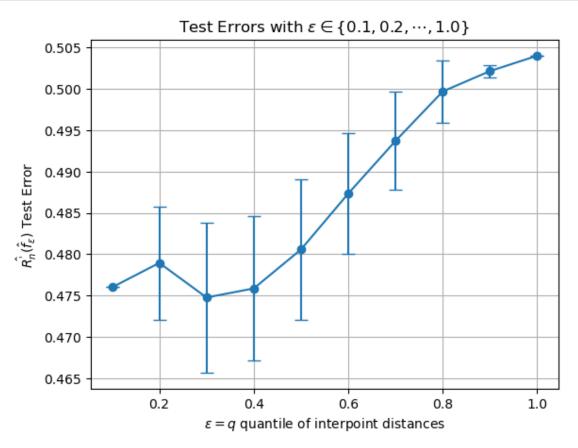
x_values = np.arange(1, 11) / 10

plt.errorbar(x_values, mus, yerr=stds, fmt='o-', capsize=5)

# Add labels and title
plt.xlabel("$\epsilon = q$ quantile of interpoint distances")
```

```
plt.ylabel("$\hat{R_n^'} (\hat{f}_\epsilon)$ Test Error")
plt.title("Test Errors with $\epsilon \in \{0.1, 0.2, \cdots, 1.0 \}$")

# Show the plot
plt.grid(True)
plt.show()
```



```
[275]: mus = []
    stds = []

for q in range(1, 11):
    arr = np.array(well_defined_proportions[q])
    # print(arr)
    mu = arr.mean()
    std = arr.std()

    mus.append(mu)
    stds.append(std)

x_values = np.arange(1, 11) / 10
```

```
plt.errorbar(x_values, mus, yerr=stds, fmt='o-', capsize=5)

# Add labels and title
plt.xlabel("$\epsilon = q$ quantile of interpoint distances")
plt.ylabel("Ratio of well-defined $\hat{f}_\epsilon$")
plt.title("Ratio of well-defined $\hat{f}_\epsilon$ with $\epsilon \in \{0.1, 0.
$\infty 2, \cdots, 1.0 \}$")

# Show the plot
plt.grid(True)
plt.show()
```

