Homework 2

May 2, 2019

1 Homework 2

1.1 Data

```
In [1]: import pandas as pd
        import numpy as np
        from sklearn.model_selection import train_test_split
        import matplotlib.pyplot as plt
```

```
In [2]: X_train = pd.read_csv('./mnist_train_data.csv', header= None)
        y_train = pd.read_csv('./mnist_train_labels.csv', names=['labels'])
        X_test = pd.read_csv('./mnist_test_data.csv', header= None)
        y_test = pd.read_csv('./mnist_test_labels.csv', names=['labels'])
```

1.2 Generative Learning

Problem 1:

```
In [3]: # Prior label probabilities:
        print(y_train['labels'].value_counts().sort_index()/len(y_train))
        prior_probs = y_train['labels'].value_counts().sort_index()/len(y_train)

        prior_prob_list = prior_probs.tolist()
```

```
0    0.098667
1    0.111833
2    0.096833
3    0.101333
4    0.103833
5    0.085667
6    0.101333
7    0.108500
8    0.091833
9    0.100167
Name: labels, dtype: float64
```

Problem 2:

```
In [20]: total_train = pd.concat([X_train, y_train], axis = 1)
         prob_tab = np.zeros(shape=[10, 784])

         for i in np.sort(y_train['labels'].unique()):
             a = total_train.loc[total_train['labels'] == i]
             # Remove label column
             a = a.drop('labels', 1)
             sum_val = (a.values).sum(axis = 0)

             # Laplacian smoothing
             probabilities = (sum_val +1 ) / (a.shape[0] + 2)
             prob_tab[i, :] = probabilities
             print ("Max Pji for label", i,   " = ",probabilities.max())

         log_prob_tab = np.log(prob_tab.T)
```

```
Max Pji for label 0  =  0.851851851852
Max Pji for label 1  =  0.98514115899
Max Pji for label 2  =  0.728987993139
Max Pji for label 3  =  0.808196721311
Max Pji for label 4  =  0.8496
Max Pji for label 5  =  0.711240310078
Max Pji for label 6  =  0.849180327869
Max Pji for label 7  =  0.794793261868
Max Pji for label 8  =  0.875226039783
Max Pji for label 9  =  0.867330016584
```

Problem 3:

```
In [23]: mm_l = np.matmul(X_test, log_prob_tab)
         mm_r = np.matmul((1-X_test), np.log(1-prob_tab).T )

         final_matrix = np.add((mm_l+mm_r), np.log(prior_prob_list))
         y_pred = np.argmax(final_matrix, axis = 1)
```

```
In [24]: from sklearn import metrics
         import itertools
         print('The accuracy is', metrics.accuracy_score(y_test, y_pred))
```

```
The accuracy is 0.809
```

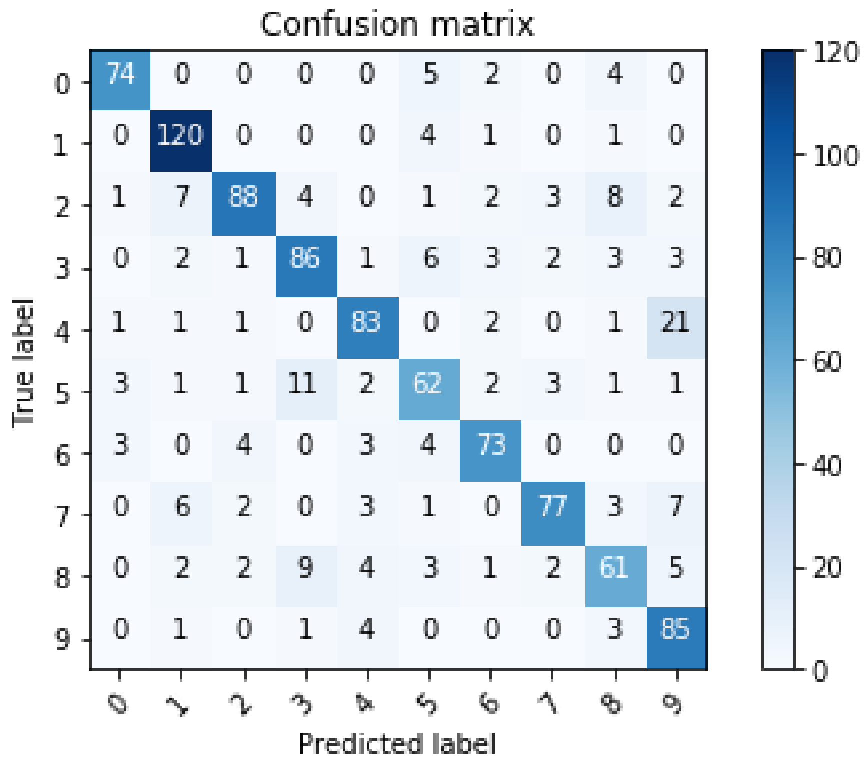
```
In [25]: def plot_confusion_matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Blues):
             """
             This function prints and plots the confusion matrix.
```

```
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()
```

Problem 4:

In [26]:
```
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=np.sort(y_test['labels'].unique()),
                      title='Confusion matrix')
```

```
[[ 74   0   0   0   0   5   2   0   4   0]
 [  0 120   0   0   0   4   1   0   1   0]
 [  1   7  88   4   0   1   2   3   8   2]
 [  0   2   1  86   1   6   3   2   3   3]
 [  1   1   1   0  83   0   2   0   1  21]
 [  3   1   1  11   2  62   2   3   1   1]
 [  3   0   4   0   3   4  73   0   0   0]
 [  0   6   2   0   3   1   0  77   3   7]
 [  0   2   2   9   4   3   1   2  61   5]
 [  0   1   0   1   4   0   0   0   3  85]]
```



According to the confusion matrix, we can see that the biggest misclassification pairs are:

- 4 being misclassified as a 9 (21 times)
- 5 being misclassified as a 3 (11 times)
- 8 being misclassified as a 3 (9 times)

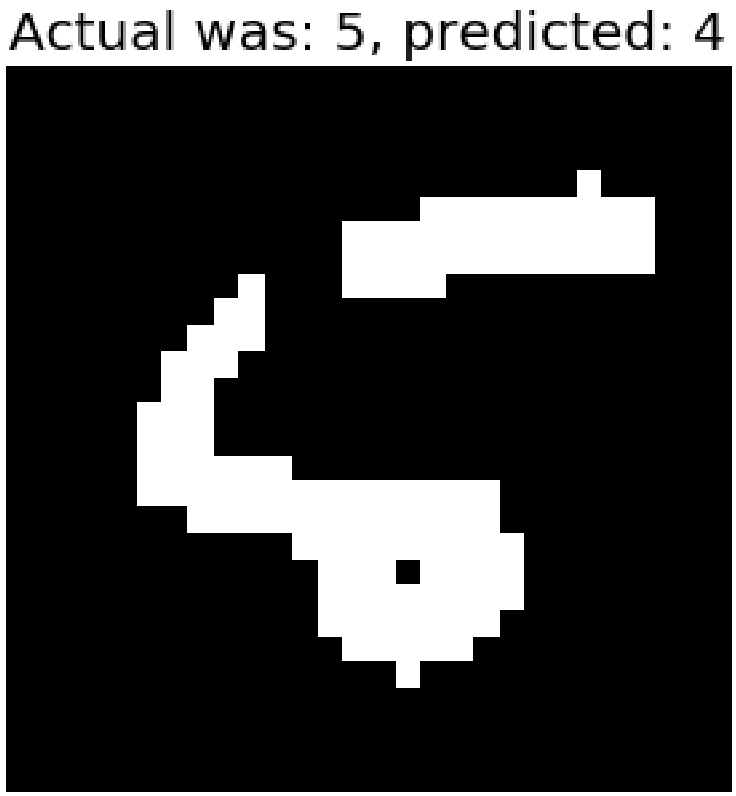
```
In [30]: def displaychar(image):
             plt.imshow(np.reshape(image, (28,28)), cmap=plt.cm.gray)
             plt.axis('off')
             plt.show()
```

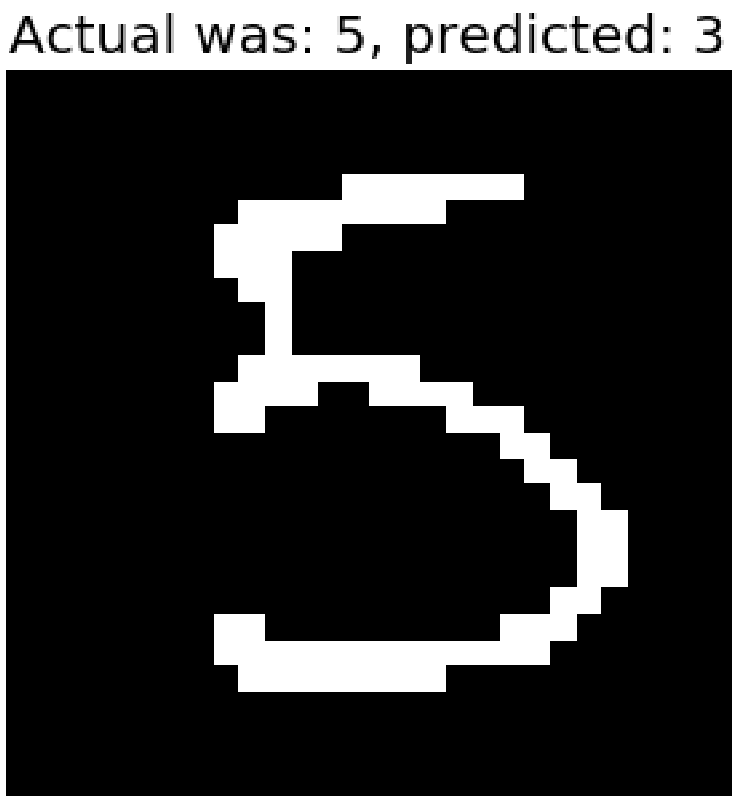
Problem 5:

```
In [32]: index_error = np.array(np.where((y_test['labels'] != y_pred)==True))[0]
```

```
In [33]: incorrect = index_error[:2]
         actual = y_test.iloc[incorrect]['labels']
         miss = y_pred[incorrect]
         for i in range(len(incorrect)):
             b = incorrect[i]
             plt.figure(figsize=(10,5))
             plt.title('Actual was: %i, predicted: %i' % (actual.iloc[i], miss[i]), fontsize = 2
             displaychar(X_test.iloc[b]);
```

```
/Users/kkannapp/anaconda/lib/python3.6/site-packages/numpy/core/fromnumeric.py:57: FutureWarning
  return getattr(obj, method)(*args, **kwds)
```





Breast Cancer Data for problems 6,7:

```
In [36]: from sklearn.datasets import load_breast_cancer
         from sklearn.model_selection import train_test_split
         bc = load_breast_cancer()
         X, X_test, y, y_test = train_test_split(bc.data, bc.target, test_size=0.4, random_state
         X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.33, random_stat
         print('Train', y_train.shape, 'Valid', y_valid.shape, 'Test', y_test.shape)

         # For final predictions:
         X_train_fin = np.concatenate((X_train,X_valid))
         y_train_fin = np.concatenate((y_train,y_valid))
```

```
Train (228,) Valid (113,) Test (228,)
```

Problem 6:

```
In [51]: from sklearn.mixture import GaussianMixture
         best_acc = 0
         cov_parameter = ['spherical', 'tied', 'diag', 'full']
         for i in cov_parameter:
```

```
            clf = GaussianMixture(n_components=2, covariance_type = i)
            clf.fit(X_train, y_train)
            y_pred = clf.predict(X_valid)
            accuracy = np.sum(y_pred == y_valid)*1.0/len(y_valid)
            print('For criterion =', i, 'the validation accuracy = ' + str(accuracy))
            if (accuracy > best_acc):
                best_cov = i
                best_acc = accuracy
        print('The best criterion is', best_cov, 'with a validation accuracy of', best_acc)

        clf = GaussianMixture(n_components=2, covariance_type = best_cov)
        clf.fit(X_train_fin, y_train_fin)
        predictions = clf.predict(X_test)
        fin_accuracy = metrics.accuracy_score(y_test, predictions)
        print('\n')
        print('Final accuracy on total training data = ' + str(fin_accuracy))
```

```
For criterion = spherical the validation accuracy = 0.115044247788
For criterion = tied the validation accuracy = 0.212389380531
For criterion = diag the validation accuracy = 0.0973451327434
For criterion = full the validation accuracy = 0.83185840708
The best criterion is full with a validation accuracy of 0.83185840708


Final accuracy on total training data = 0.938596491228
```

Problem 7:

```
In [56]: from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
         clf = LinearDiscriminantAnalysis()
         clf.fit(X_train_fin, y_train_fin)
         predictions = clf.predict(X_test)
         print('The test accuracy = ' + str(sum(predictions == y_test)/len(y_test)))
```

```
The test accuracy = 0.964912280702
```

```
In [59]: print('The transformation matrix is \n', clf.coef_)
         print('\n')
         print('The intercept is', clf.intercept_[0])
```

```
The transformation matrix is
 [[  1.35e+00  -1.27e-01  -1.36e-01  -2.44e-04  -2.24e+01   8.56e+01
    1.39e+01  -1.22e+02   1.60e+01   7.43e+00  -1.48e+01   4.83e-01
    1.73e+00  -1.64e-02  -4.69e+02  -1.96e+00   1.60e+01  -9.78e+01
   -6.14e+01   5.59e+02  -1.26e+00  -2.00e-01  -2.62e-01   1.93e-02
    3.19e+01   4.09e+00  -1.27e+01  -9.32e+00  -1.49e+01  -1.72e+02]]
```

```
The intercept is 51.8553297822
```

1.3 Evaluating Classifiers

Problem 8:

```
In [61]: from sklearn.neighbors import KNeighborsClassifier
         from sklearn.datasets import load_digits
         digits = load_digits()
         print(digits.data.shape)

         # Last 1300 as training, beginning 497 as test
         X_train = digits.data[:497]
         y_train = digits.target[:497]
         X_test = digits.data[497:]
         y_test = digits.target[497:]
```

```
(1797, 64)
```

```
In [64]: # Fit the model:
         clf = KNeighborsClassifier(n_neighbors=5, metric = 'chebyshev')
         clf.fit(X_train, y_train)
         y_pred = clf.predict(X_test)

         # Evaluation metrics:
         TP = sum(y_pred[y_test == 3] == 3)
         FP = sum(y_pred[y_test != 3] == 3)
         TN = sum(y_pred[y_test != 3] != 3)
         FN = sum(y_pred[y_test == 3] != 3)
```

```
In [67]: print('Specificity:', TN/(TN+FP))
         print('Sensitivity:', TP/(TP+FN))
         print('True Positive Rate (TPR):', TP/(TP+FN))
         print('True Negative Rate (TNR):', TN/(TN+FP))
         print('False Negative Rate (FNR):', FN/(TP+FN))
         print('False Positive Rate (FPR):', FP/(FP+TN))
         print('Precision:', TP/(TP+FP))
         print('Recall:', TP/(TP+FN))
```

```
Specificity: 0.988888888889
Sensitivity: 0.869230769231
True Positive Rate (TPR): 0.869230769231
True Negative Rate (TNR): 0.988888888889
False Negative Rate (FNR): 0.130769230769
False Positive Rate (FPR): 0.0111111111111
Precision: 0.896825396825
```

```
Recall: 0.869230769231
```

From my experience, these are exceptional evaluation metrics!

1.4 Regression

Problem 9:

```
In [70]: from sklearn.datasets import load_diabetes
         diabetes = load_diabetes()

         # Form data-set:
         X_train, X_test, y_train, y_test = train_test_split(diabetes.data, diabetes.target, tes

In [71]: from sklearn.linear_model import LinearRegression
         clf = LinearRegression()
         clf.fit(X_train, y_train)
         predictions = clf.predict(X_test)

         print('Test MSE:', metrics.mean_squared_error(y_test, predictions))
         print('Test MAE:', metrics.mean_absolute_error(y_test, predictions))

Test MSE: 2155.96465103
Test MAE: 36.3181336987
```

Problem 10:

```
In [73]: for i in range(10):
             X_ablation = np.delete(diabetes.data, [i], axis=1)
             X_train, X_test, y_train, y_test = train_test_split(X_ablation, diabetes.target, te
             clf = LinearRegression()
             clf.fit(X_train, y_train)
             predictions = clf.predict(X_test)
             print('Removing feature', i, ', test MSE:', metrics.mean_squared_error(y_test, pred

Removing feature 0 , test MSE: 2152.80664218
Removing feature 1 , test MSE: 2259.13307937
Removing feature 2 , test MSE: 2783.51448185
Removing feature 3 , test MSE: 2424.772348
Removing feature 4 , test MSE: 2187.59951938
Removing feature 5 , test MSE: 2167.51760615
Removing feature 6 , test MSE: 2159.15148251
Removing feature 7 , test MSE: 2153.06317113
Removing feature 8 , test MSE: 2335.17338461
Removing feature 9 , test MSE: 2165.86619219
```

Problem 11:

Feature 2 is the most valuable, as indicated by that the model has its test MSE increase the most without the feature included.