CS441: Applied ML - HW 1

▼ Part I: MNIST Classification

```
Include all the code for Part 1 in this section
# initialization code
import numpy as np
from keras datasets import mnist
%matplotlib inline
from matplotlib import pyplot as plt
from scipy import stats
from sklearn.linear_model import LogisticRegression
from numpy import linalg as la
# loads MNIST data and reformat to 768-d vectors with values in range 0 to 1
# splits into train/val/test sets and provides indices for subsets of train
def load mnist():
    (x\_train, \quad y\_train), \quad (x\_test, \quad y\_test) \quad = \quad mnist. \, load\_data \, ()
    x_train = np.reshape(x_train, (len(x_train), 28*28))
   x \text{ test} = \text{np.reshape}(x \text{ test}, (1\text{en}(x \text{ test}), 28*28))
    maxval = x_train.max()
   x_train = x_train/maxval
    x_{test} = x_{test/maxval}
    x_val = x_train[:10000]
   y val = y train[:10000]
    x_{train} = x_{train}[10000:]
    y_train = y_train[10000:]
    train_indices = dict()
    train_indices['xs'] = np.arange(50)
    train_indices['s'] = np.arange(500)
    train_indices['m'] = np.arange(5000)
    train_indices['all'] = np.arange(50000)
    return (x_train, y_train), (x_val, y_val), (x_test, y_test), train indices
# displays a set of mnist images
\label{lem:cols} \mbox{def display\_mnist(x, subplot\_rows=1, subplot\_cols=1):}
    if subplot_rows>1 or subplot_cols>1:
       fig, ax = plt.subplots(subplot_rows, subplot_cols, figsize=(15,15))
        for i in np.arange(len(x)):
           ax[i]. imshow(np. reshape(x[i], (28, 28)), cmap='gray')
           ax[i].axis('off')
           plt.imshow(np.reshape(x, (28,28)), cmap='gray')
           plt.axis('off')
    plt.show()
# counts the number of examples per class
def class count mnist(y):
    count = np. zeros((10,), dtype='uint32')
    for i in np.arange(10):
      count[i] = sum(v==i)
    return count
# example of using MNIST load, display, indices, and count functions
(x_{train}, y_{train}), (x_{val}, y_{val}), (x_{test}, y_{test}), train_indices = load_mnist()
display_mnist(x_train[:10], 1, 10)
print(x_test.shape)
print('Total size: train=\{\}, val=\{\}, test = \{\}'.format(len(x\_train), len(x\_val), len(x\_test))\}
print('Train subset size: xs={}, s={}, m={}, all={}'.format(len(train_indices['xs']),len(train_indices['s']),len(train_indices['m']),len(train_indices['all'])))
print('Class count for s: {}'.format(class_count_mnist(y_train[train_indices['s']])))
                  879901152
     (10000, 784)
     Total size: train=50000, val=10000, test =10000
     Train subset size: xs=50, s=500, m=5000, all=50000
     Class count for s: [56 57 51 49 46 46 50 51 40 54]
# This is a suggested function definition for KNN, but feel free to change it
\label{eq:classify_KNN} \mbox{ ($X_{trn}$, $y_{trn}$, $X_{tst}$, $K=1$):}
```

Output: return y_pred , where $y_pred[i]$ is the predicted ith test label

 $Input: \ X_trn[i] \ is \ the \ ith \ training \ data. \ y_trn[i] \ is \ the \ ith \ training \ label.$

Classify each data point in X_tst using a K-nearest neighbor classifier based on (X_trn, y_trn), with L2 distance.

X_tst[i] is the ith example to classify. K is the number of closest neighbors to use.

```
# needs code here
    y_pred = []
    for elem in X tst:
       smallest = float('inf')
       index = -1
       for i in range(len(X_{trn})):
          value = la.norm(np.abs(elem - x_train[i]), 2)
           if value < smallest:
               smallest = value
              index = y trn[i]
       y_pred.append(index)
    y_pred = np.array(y_pred)
    return y_pred
# This is a suggested function definition for training Naive Bayes, but feel free to change it
def train_NB_mnist(X, y, alpha=1):
     \text{Train } P(x\_f=v \mid y=c) \quad \text{for each feature f, value v, and class c.} \quad \text{Can assume 10 classes and that the features are binary variables} 
   Input: X[i] is the ith training data. y[i] is the ith training label. alpha is the count prior Output: return pxy of shape (Nf, 10, 2), where Nf is the number of features; pxy[f,c,v] is P(x\_f=v|y=c)
    # needs code here
   n_{data} = len(X)
    n_{feature} = 1en(X[0])
    labels = list(set(y))
    n labels = len(set(y))
    for i in range (n_{data}):
       for j in range(n feature):
          if X[i, j] > 0.5:
              X[i, j] = 1.00000
           else:
              X[i, j] = 0.000000
    pxy1 = []
    for i in range(n_labels):
       labe1 = labe1s[i]
       fit_data = []
        for j in range(n_data):
         if y[j] == label:
              fit_data.append(X[j])
       number_fits = len(fit_data)
       fit data = np.array(fit data)
        total = np.sum(fit_data, axis = 0)
       for k in range(len(total)):
         total[k] = (total[k] + alpha) / (number_fits)
           + n_feature * alpha)
       pxyl.append(total)
    pxy1 = np.array(pxy1)
    pxy = pxy1
    return pxy
# This is a suggested function definition for evauating Naive Bayes, but feel free to change it
def eval_NB_mnist(pxy, X):
    y_pred = []
    for i in range(len(X)):
       data = X[i]
       probs = []
       for j in range(len(pxy)):
        prob = pxy[j] @ data
          probs. append (prob)
       probs = np.array(probs)
       label = np.argmax(probs)
       y_pred.append(label)
    return y_pred
    Evaluate naive bayes for mnist
    Input: pxy is the trained model; X is the test data
    Output: return y_pred, where y_pred[i] is the predicted ith test label
```

```
# don't forget logistic regression!
from sklearn.linear_model import LogisticRegression
def log_reg(x_train, y_train, x_test):
   logR = LogisticRegression(max iter=100000)
   logR.fit(x_train, y_train)
   y_pred = logR.predict(x_test)
   return y_pred
# experiments code
  display_mnist(x_test, 1, 10000)
\# X_{trn} = x_{train}[0:5]
# Y trn = y train[0:5]
\# X_{tst} = x_{test}
  def func(matrix, value, y_pred, y_val):
Ħ
      for i in range(10000):
         row = y_val[i] ## should be i
         col = y_pred[i] ## the label we get is matched or not
          confusion[row][col] += 1 ## the diagonal will be the correctness
#
         if y_pred[i] != y_val[i]:
            value += 1
#
      return value, confusion
  y_pred = classify_KNN(X_trn, Y_trn, x_val, K=1)
  confusion = np.zeros((10, 10))
  count = 0
# count, confusion = func(confusion, count, y pred, y val)
# print(confusion)
# naive bayes
# pxy = train_NB_mnist(X_trn, Y_trn, 1)
# y_pred = eval_NB_mnist(pxy, X_tst)
  count = 0
  for i in range (10000):
Ħ
      if y_pred[i] != y_test[i]:
         count = count + 1
 print(count / 10000)
# logistic
# y_pred = log_reg(x_train, y_train, X_tst)
  count = 0
# for i in range(10000):
     if y_pred[i] != y_test[i]:
        count = count + 1
# print(count / 10000)
# print(y_pred)
```

▼ Part 2: Temperature Regression

Include all your code for part 2 in this section. You can copy-paste code from part 1 if it is re-usable.

```
import numpy as np
from google.colab import drive
%matplotlib inline
from matplotlib import pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
# load data (modify to match your data directory or comment)
def load_temp_data():
            drive.mount('/content/drive/')
            datadir = "/content/drive/MyDrive/cs441/hw1/"
            T = np.load(datadir + "temperature_data.npz")
            x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, feature_to_city, feature_to_day = \
            T['x\_train'], \quad T['y\_train'], \quad T['x\_val'], \quad T['y\_val'], \quad T['x\_test'], \quad T['dates\_train'], \quad T['dates\_val'], \quad T['dates\_test'], \quad T['feature\_to\_city'], \quad T['feature\_to\_ci
            # plot one data point for listed cities and target temperature
\label{lem:continuous} \mbox{def plot\_temps(x, y, cities, feature\_to\_city, feature\_to\_day, target\_date):}
           nc = len(cities)
           ndays = 5
           xplot = np.array([-5,-4,-3,-2,-1])
```

```
for f in np.arange(len(x)):
       for c in np. arange(nc):
           if cities[c] == feature_to_city[f]:
              yplot[feature to day[f]+ndays, c] = x[f]
   plt.plot(xplot, yplot)
   plt.legend(cities)
   plt.plot(0, y, 'b*', markersize=10)
   plt.title('Predict Temp for Cleveland on ' + target date)
   plt.xlabel('Day')
   plt.ylabel('Avg Temp (C)')
   plt.show()
# load data (may need to modify file location in preceding cell)
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, feature_to_city, feature_to_day) = load_temp_data()
# example of displaying information related to a feature index
print('Feature {}: city = {}, day= {}'.format(f,feature_to_city[f], feature_to_day[f]))
# example of computing RMSE and median absolute error (for baseline of predicting based on previous day's temperature in Cleveland)
baseline_rmse = np.sqrt(np.mean((y_val[1:]-y_val[:-1])**2)) # root mean squared error
baseline mae = np.sqrt(np.median(np.abs(y val[1:]-y val[:-1]))) # median absolute error
print('Baseline - predict same as previous day: RMSE={}'.format(baseline_rmse, baseline_mae))
# plots temperatures for preceding days for given cities, and target (Cleveland) temp
plot_temps(x_val[0], y_val[0], ['Cleveland', 'New York', 'Chicago', 'Denver', 'St. Louis'], feature_to_city, feature_to_day, dates_val[0])
plot_temps(x_val[100], y_val[100], ['Cleveland', 'New York', 'Chicago', 'Denver', 'St. Louis'], feature_to_city, feature_to_day, dates_val[1])
     Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive.mount("/content/drive/", for
     Feature 361: city = Cleveland, day= -1
     Baseline - predict same as previous day: RMSE=3.460601246750482, MAE=1.3964240043768943
                Predict Temp for Cleveland on 2018-09-27
        24
                                                 Cleveland
                                                Chicago
        22
                                                Denver
      ⊙ 20
     g
18
      Avg 1
        16
        14
                                Day
                 Predict Temp for Cleveland on 2018-09-28
         10
          5
      Avg Temp (C)
          0
        -5
                                                  Cleveland
                                                  New York
        -10
                                                  Chicago
                                                  Denver
                                                  St. Louis
        -15
                                               -1
                      -4
from google.colab import drive
drive.mount('/content/drive')
     Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
# This is a suggested function definition for KNN, but feel free to change it
\label{eq:classify_KNN} \mbox{ def classify\_KNN} \mbox{ ($X$\_trn, $y$\_trn, $X$\_tst, $K$=$1): }
   Classify each data point in X_tst using a K-nearest neighbor classifier based on (X_trn, y_trn), with L2 distance.
   Input: X_trn[i] is the ith training data, y_trn[i] is the ith training label. K is the number of closest neighbors to use.
   Output: return y_pred, where y_pred[i] is the predicted ith test label
   # needs code
   n = 1en(X_trn)
   v pred = []
    for value in X_tst:
       temp = []
       pred_y = 0
```

yplot = np.zeros((nc, ndays))

for i in range(n):

```
distance = la.norm(X_trn[i] - value)
           temp.append(distance)
        temp = np.array(temp)
        choose = np.argsort(temp)
        sum = y_trn[choose[0]] + y_trn[choose[1]] + y_trn[choose[2]]
       pred_y = sum / 3
       y_pred. append (pred_y)
    return y_pred
# Suggested function definition for NB for temperature regression, but feel free to change
def train_NB_temp(X, y, std_prior=0):
    Train NB, assuming that X[f]-y is a Gaussian
   Input: X[i] is the ith training data. y[i] is the ith training label. std_prior is a value to add to std Output: return pxy['mu'] and pxy['std'] each with number of values equal to number of features
   # needs code
    n \text{ features} = 1en(X[0])
    pxy = np. zeros((2, n features))
    for i in range(n_{\text{features}}):
       temp = np.mean(y - X[:, i], axis=0)
       temp2 = np.std(y - X[:, i], axis=0) + std_prior
       pxy[0][i] = temp
       pxy[1][i] = temp2
    return pxy
def eval_NB_temp(pxy, X):
    Evaluate naive bayes for temp
    Input: pxy is the trained model; X is the test data
    Output: return y_pred, where y_pred[i] is the predicted ith test value
   # needs code
   n_{data} = 1en(X)
    y_pred = []
    for i in range (n_{data}):
       temp = (1/np. sum(1/pxy[1]**2))
       temp2 = np. sum((X[i]+pxy[0])/pxy[1]**2)
       total = temp * temp2
       y_pred.append(total)
    return y_pred
# Don't forget linear regression!
from sklearn.linear_model import LinearRegression
def linear_reg(x_train, y_train, x_test):
    linearR = LinearRegression()
    linearR.fit(x_train, y_train)
    y pred = linearR.predict(x test)
    return y_pred
# Feature analysis
from sklearn import linear model
temp = linear model.Lasso()
temp.fit(x_train, y_train)
y_pred = temp.predict(x_val)
temp1 = np.argsort(abs(temp.coef_))[:10]
argsort_vector = temp1[::-1]
x_{new\_train} = np.zeros((len(x_train), 10))
x_{new_val} = np.zeros((1en(x_val), 10))
for i in range(10):
   idx = argsort_vector[i]
print("index: " + str(idx) + " city: " + feature_to_city[idx] + " day: " + str(feature_to_day[idx]))
   x_new_train[:,i] = x_train[:,idx]
    x_{new\_val[:,i]} = x_val[:, idx]
# experiment code
# knn
\# y_pred = classify_KNN(x_train, y_train, x_val , K = 3)
# Naive bayes
# pxy = train_NB_temp(x_train, y_train, 0)
\# y_pred = eval_NB_temp(pxy, x_val)
# linear regression
# y_pred = linear_reg(x_train, y_train, x_val)
# rmse = np.sqrt(np.mean((y_pred-y_val)**2))
# mae = np. sqrt(np. median(np. abs(y_pred-y_val)))
# print(rmse)
# print(mae)
```

index: 269 city: Baltimore day: -2
index: 270 city: Riverside day: -2
index: 271 city: St. Louis day: -2
index: 272 city: Las Vegas day: -2
index: 273 city: Portland day: -2
index: 274 city: San Antonio day: -2
index: 275 city: Sacramento day: -2
index: 276 city: San Jose day: -2
index: 277 city: Orlando day: -2
index: 0 city: New York day: -5
2. 444692756154613

▼ Part 3: Stretch Goals

1. 2823643380425092

Include all your code used for part 3 in this section. You can copy-paste code from parts 1 or 2 if it is re-usable.

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