cs441-sp24-hw1-starter

February 6, 2024

0.1 CS441: Applied ML - HW 1

0.1.1 Parts 1-2: MNIST

Include all the code for generating MNIST results below

[1]:
```
# initialization code
import numpy as np
from keras.datasets import mnist
%matplotlib inline
from matplotlib import pyplot as plt
from scipy import stats


def load_mnist():
  '''
  Loads, reshapes, and normalizes the data
  '''
  (x_train, y_train), (x_test, y_test) = mnist.load_data() # loads MNIST data
  x_train = np.reshape(x_train, (len(x_train), 28*28))  # reformat to 768-d␣
 ↪vectors
  x_test = np.reshape(x_test, (len(x_test), 28*28))
  maxval = x_train.max()
  x_train = x_train/maxval  # normalize values to range from 0 to 1
  x_test = x_test/maxval
  return (x_train, y_train), (x_test, y_test)

def display_mnist(x, subplot_rows=1, subplot_cols=1):
  '''
  Displays one or more examples in a row or a grid
  '''
  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')
  else:
      plt.imshow(np.reshape(x, (28,28)), cmap='gray')
      plt.axis('off')
```

```
  plt.show()
```

```
WARNING:tensorflow:From D:\CODE\School\cs441\venv\Lib\site-
packages\keras\src\losses.py:2976: The name
tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

[2]:
```
# example of using MNIST load, display, indices, and count functions
(x_train, y_train), (x_test, y_test) = load_mnist()
display_mnist(x_train[:10],1,10)
print('Total size: train={}, test ={}'.format(len(x_train), len(x_test)))
```

```
Total size: train=60000, test =10000
```

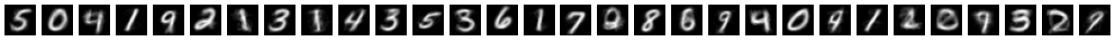
1. Retrieval, Clustering, and NN Classification

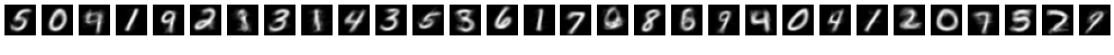
[3]:
```
# Retrieval

def get_nearest(X_query, X):
  ''' Return the index of the sample in X that is closest to X_query according
      to L2 distance '''
  return np.argmin([np.sum((X_query - x) ** 2) for x in X])

j = get_nearest(x_test[0], x_train)
print(j)
j = get_nearest(x_test[1], x_train)
print(j)
```

```
53843
28882
```

[4]:
```
# K-means
import copy
def kmeans(X, K, niter=10):
  '''
  Starting with the first K samples in X as cluster centers, iteratively assign␣
 ↪each
  point to the nearest cluster and compute the mean of each cluster.
  Input: X[i] is the ith sample, K is the number of clusters, niter is the␣
 ↪number of iterations
  Output: K cluster centers
```

```
  '''
  # TO DO -- add code to display cluster centers at each iteration also
  clusters = [[] for _ in range(K)]
  cluster_centers = copy.deepcopy(X[:K])

  for i in range(niter):

    # For each x_i, compute the closest cluster it belongs
    for x_i in X:
      nearest_center = get_nearest(x_i, cluster_centers)
      clusters[nearest_center].append(x_i)
    # Update centers
    for j in range(len(cluster_centers)):
      cluster_centers[j] = np.mean(clusters[j], axis=0)

    display_mnist(cluster_centers, 1, K)
    # reset clusters
    clusters = [[] for _ in range(K)]

  return cluster_centers

K=30
centers = kmeans(x_train[:1000], K)
```





[5]:
```
# 1-NN
def one_nn(X_test, Y_test, X_train, Y_train):
  correct_labels = Y_test

  predictions = [get_nearest(x_t, X_train) for x_t in X_test]
  predictions = np.take(Y_train, predictions, axis=0)

  accuracy = (predictions == correct_labels).sum() / len(X_test)

  return 1 - accuracy


# TO DO
n_test = 100
n_train = 10000
error_rate = one_nn(x_test[:n_test], y_test[:n_test], x_train[:n_train],␣
 ↪y_train[:n_train])
print('Error rate: {:0.5f}'.format(error_rate))
```

```
Error rate: 0.08000
```

2. Make it fast

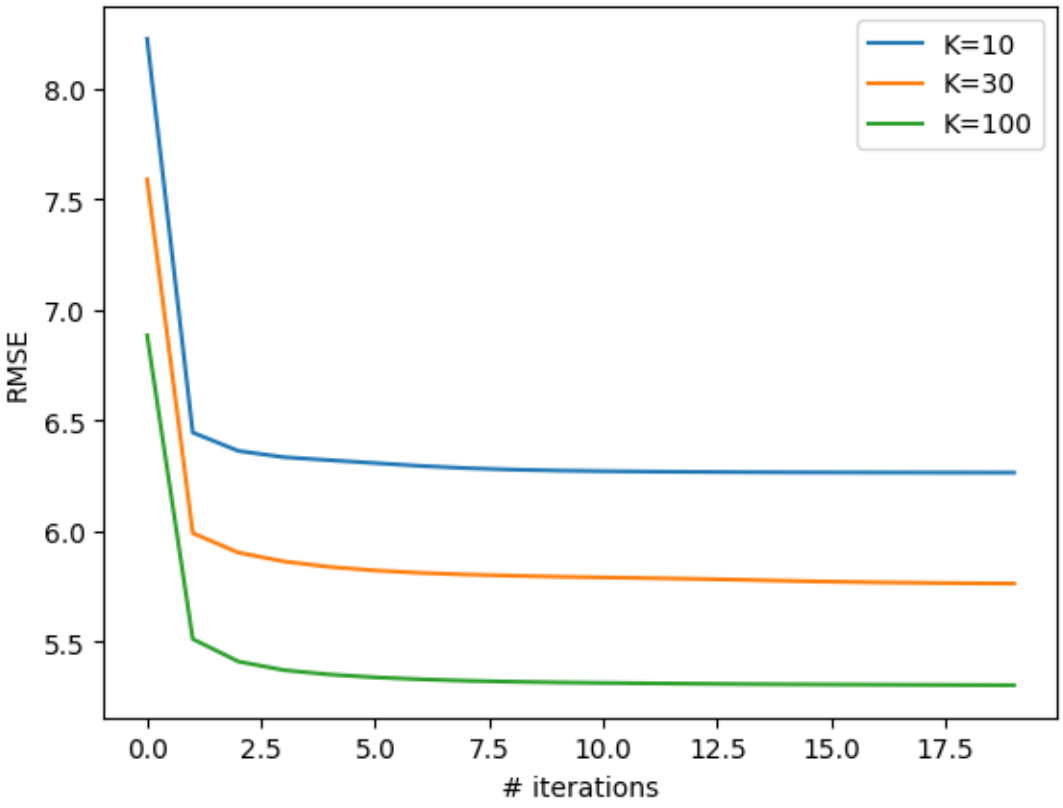
[6]:
```
# install libraries you need for part 2
import faiss
import time
```

[7]:
```
# retrieval

# TO DO (check that you're using FAISS correctly)
def get_nearest_faiss(X_query, X):
  index = faiss.IndexFlatL2(X.shape[1])
  index.add(X)
  dist, idx = index.search(X_query,1)

  return dist.item(), idx.item()

j = get_nearest_faiss(x_test[0].reshape(1,-1), x_train)
print(j)
j = get_nearest_faiss(x_test[1].reshape(1,-1), x_train)
print(j)
```

```
(7.039846420288086, 53843)
(20.798309326171875, 28882)
```

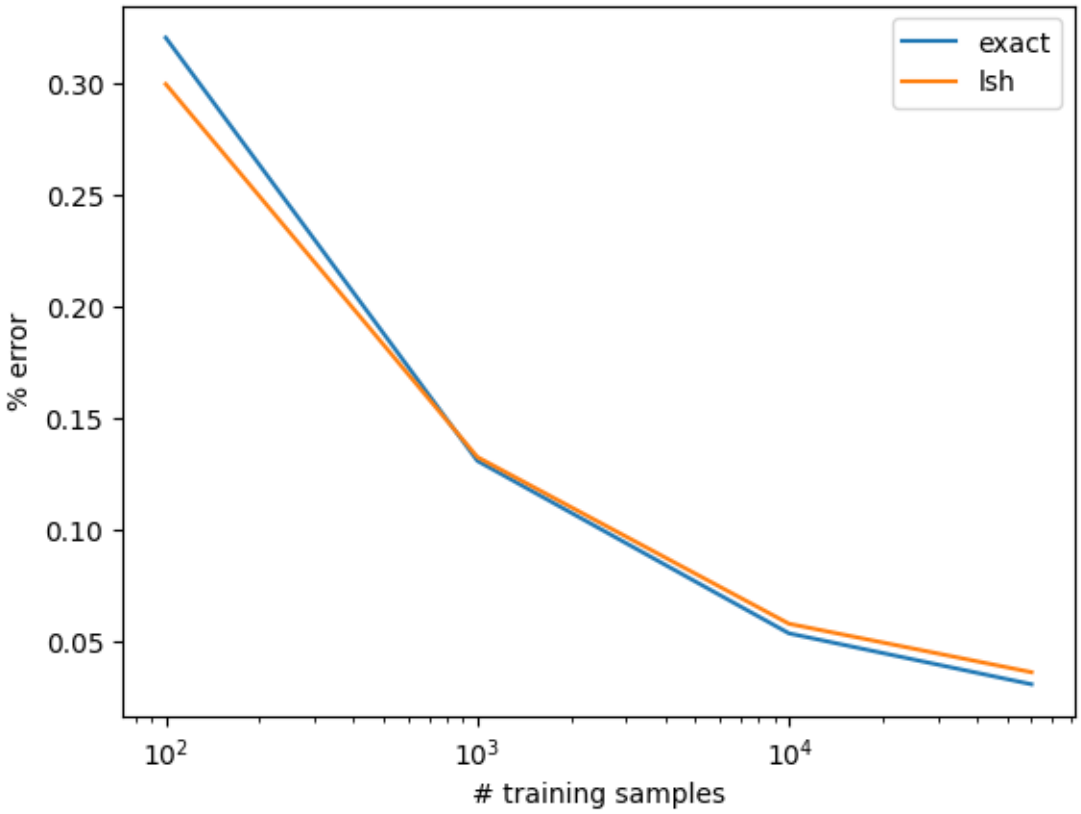
[8]:
```
# K-means
from collections import defaultdict
def create_index(index_dataset):
  index = faiss.IndexFlatL2(index_dataset.shape[1])
  index.add(index_dataset)
  return index

def find_with_index(index: faiss.IndexFlatL2, query):
  dist, idx = index.search(query,1)
  return dist, idx

def kmeans_fast(X, K, niter=10):
  '''
  Starting with the first K samples in X as cluster centers, iteratively assign␣
 ↪each
  point to the nearest cluster using faiss and compute the mean of each cluster.
  Input: X[i] is the ith sample, K is the number of clusters, niter is the␣
 ↪number of iterations
  Output: K cluster centers
  '''

  # TO DO (you can base this on part 1, but use FAISS for search)
  # if you include display code, you need to re-organize the plotting code below

  clusters = defaultdict(list)
  distances = []
  cluster_centers = copy.deepcopy(X[:K])

  for i in range(niter):
```

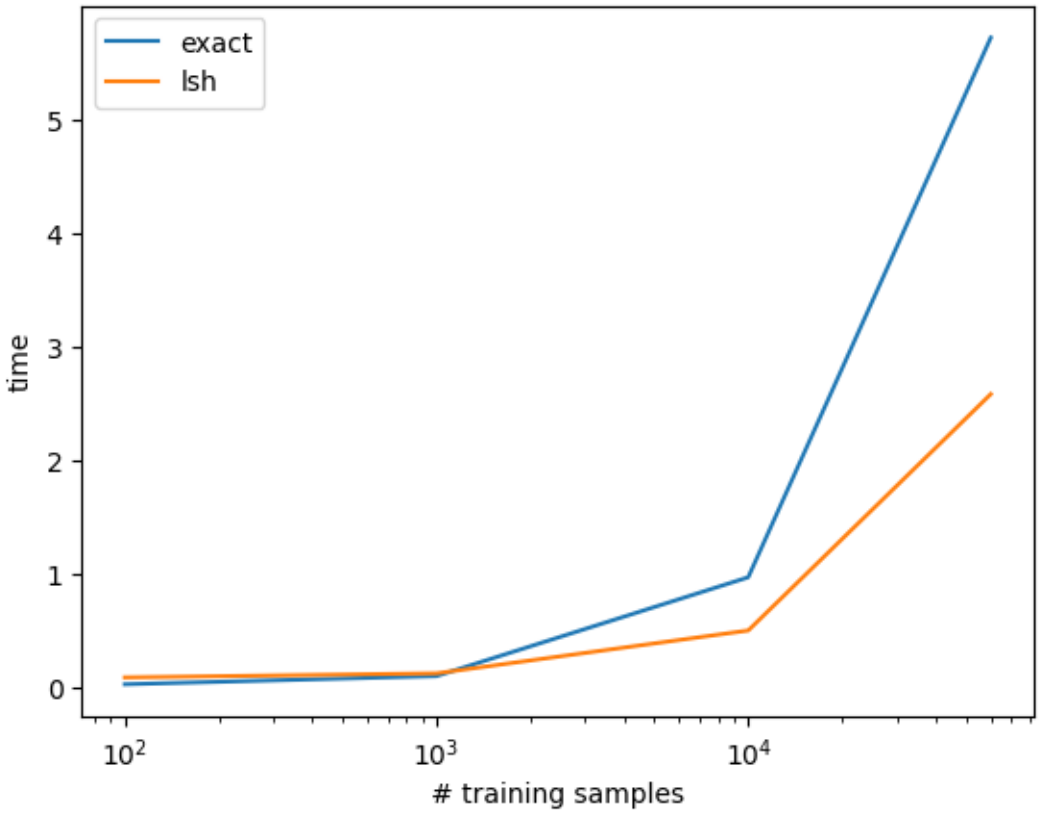
```
    faiss_index = create_index(cluster_centers)
    dist, nearest_center = find_with_index(faiss_index, X)
    dist, nearest_center = dist.flatten(), nearest_center.flatten()
    distances.append(np.sqrt(np.mean(dist)))

    # Populate clusters
    for img_idx, center_idx in enumerate(nearest_center):
      clusters[center_idx].append(X[img_idx])

    # Update centers
    for j in range(len(cluster_centers)):
      cluster_centers[j] = np.mean(clusters[j], axis=0)

    # reset
    clusters = defaultdict(list)

  return cluster_centers, distances

K=10
centers, rmse = kmeans_fast(x_train, K, niter=20)
plt.plot(np.arange(len(rmse)), rmse, label='K=10')

K=30
centers, rmse = kmeans_fast(x_train, K, niter=20)
plt.plot(np.arange(len(rmse)), rmse, label='K=30')

K=100
centers, rmse = kmeans_fast(x_train, K, niter=20)
plt.plot(np.arange(len(rmse)), rmse, label='K=100')
plt.legend(), plt.ylabel('RMSE'), plt.xlabel('# iterations')
plt.show()
```



[9]:
```
# 1-NN
from time import time
nsample = [100, 1000, 10000, 60000]

calc_acc = lambda actual, prediction: (prediction == actual).sum() /␣
 ↪len(prediction)
get_predictions = lambda indices: np.take(y_train, indices, axis=0)
acc = lambda actual, prediction: calc_acc(actual, get_predictions(prediction))

acc_exact = []
acc_lsh = []

timing_exact = []
timing_lsh = []

exact_predictions = None

# TO DO
for samp in nsample:
  # setup index for exact
  dim = x_train.shape[1]
```

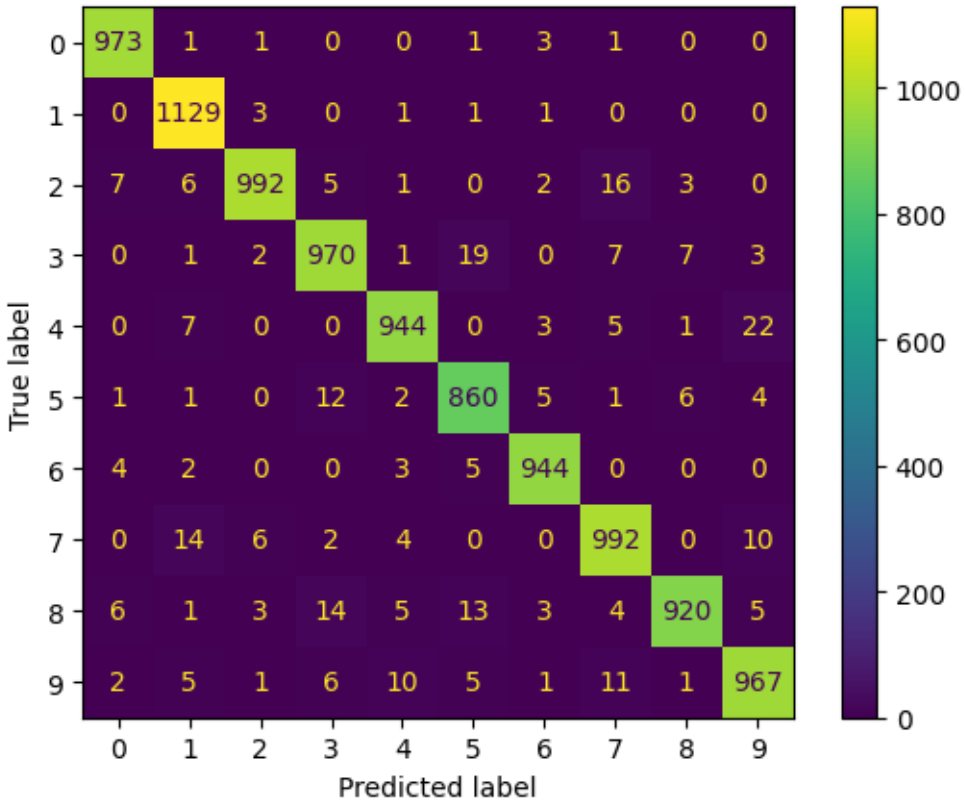
```
  exact_idx = faiss.IndexFlatL2(dim)
  exact_idx.add(x_train[:samp])

  # search for exact
  t1 = time()
  _, idx = exact_idx.search(x_test, 1) # full test set search
  t2 = time()
  timing_exact.append(t2 - t1)
  acc_exact.append(acc(y_test, idx.reshape(-1))) # take out the extra dimension␣
↪using reshape
  exact_predictions = get_predictions(idx)

  # setup index for lsh
  lsh_idx = faiss.IndexLSH(dim, dim)
  lsh_idx.add(x_train[:samp])

  # search for lsh
  t1 = time()
  _, idx = lsh_idx.search(x_test, 1)
  t2 = time()
  timing_lsh.append(t2 - t1)
  acc_lsh.append(acc(y_test, idx.reshape(-1)))

acc_exact = np.array(acc_exact)
acc_lsh = np.array(acc_lsh)

plt.semilogx(nsample, 1-acc_exact, label='exact')
plt.semilogx(nsample, 1-acc_lsh, label='lsh')
plt.legend(), plt.ylabel('% error'), plt.xlabel('# training samples')
plt.show()

plt.semilogx(nsample, timing_exact, label='exact')
plt.semilogx(nsample, timing_lsh, label='lsh')
plt.legend(), plt.ylabel('time'), plt.xlabel('# training samples')
plt.show()
```


exact
lsh
0.30
0.25
0.20
0.15
0.10
0.05
% error
10^2
10^3
10^4
training samples



[10]:
```
# Confusion matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm = confusion_matrix(y_test, exact_predictions)
disp = ConfusionMatrixDisplay(cm)
disp.plot()

# TO DO
```

[10]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x278f2054cd0>



0.2 Part 3: Temperature Regression

Include all your code used for part 2 in this section.

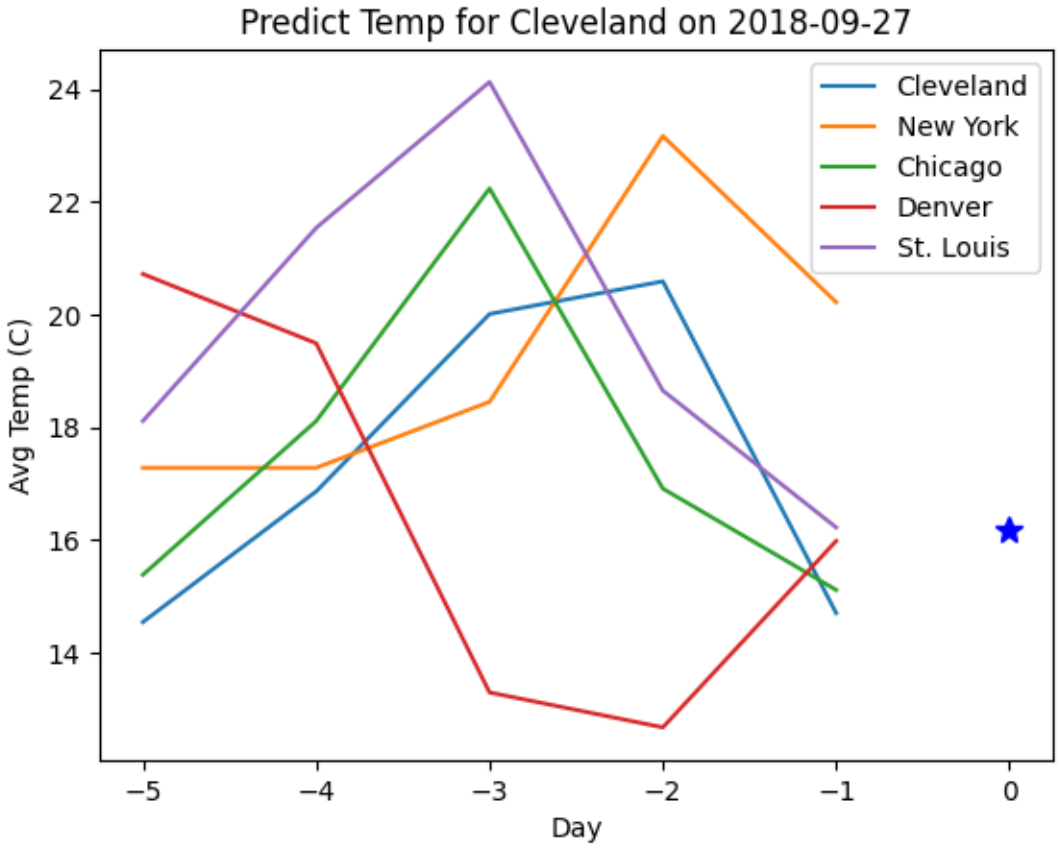
[11]:
```
import numpy as np
%matplotlib inline
from matplotlib import pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso

# load data (modify to match your data directory or comment)
def load_temp_data():
  datadir = "./"
  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'], T['y_train'], T['x_val'], T['y_val'], T['x_test'], T['y_test'],␣
 ↪T['dates_train'], T['dates_val'], T['dates_test'], T['feature_to_city'],␣
 ↪T['feature_to_day']
  return (x_train, y_train, x_val, y_val, x_test, y_test, dates_train,␣
 ↪dates_val, dates_test, feature_to_city, feature_to_day)
```

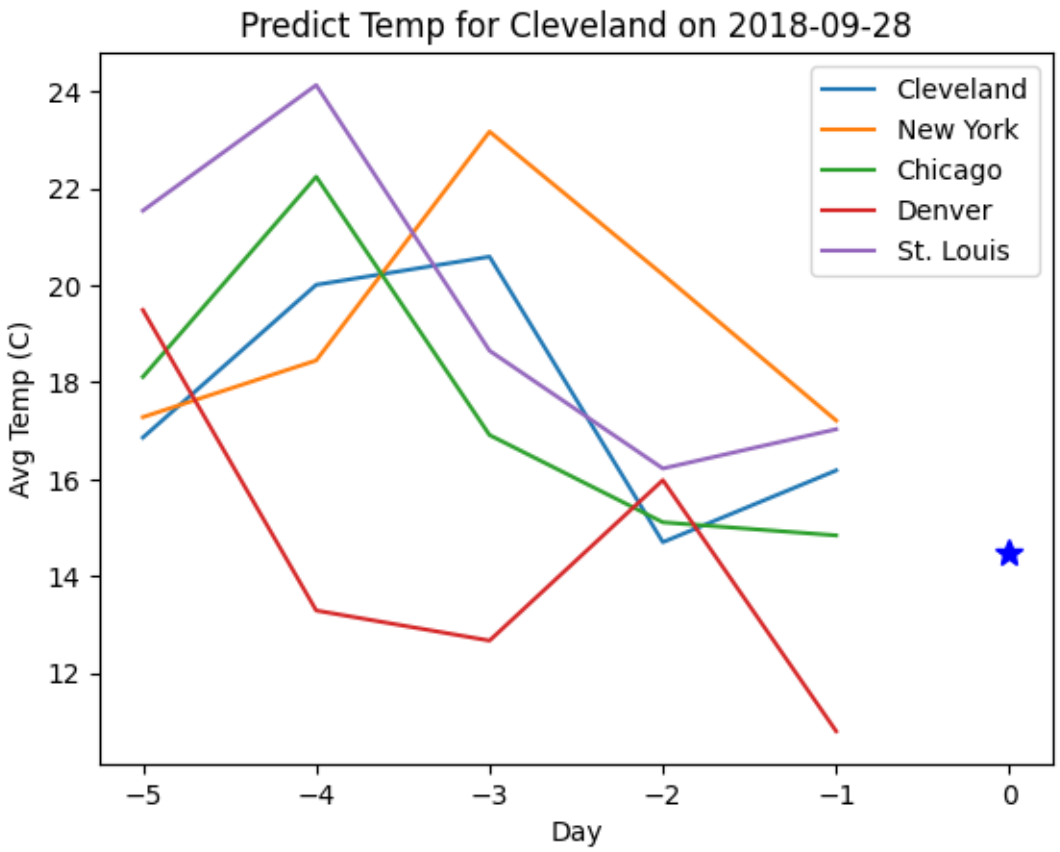
```
# plot one data point for listed cities and target date
def plot_temps(x, y, cities, feature_to_city, feature_to_day, target_date):
  nc = len(cities)
  ndays = 5
  xplot = np.array([-5,-4,-3,-2,-1])
  yplot = np.zeros((nc,ndays))
  for f in np.arange(len(x)):
    for c in np.arange(nc):
      if 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()
```

[12]:
```
# load data
(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()
''' Data format:
      x_train, y_train: features and target value for each training sample␣
 ↪(used to fit model)
      x_val, y_val: features and target value for each validation sample (used␣
 ↪to select hyperparameters, such as regularization and K)
      x_test, y_test: features and target value for each test sample (used to␣
 ↪evaluate final performance)
      dates_xxx: date of the target value for the corresponding sample
      feature_to_city: maps from a feature number to the city
      feature_to_day: maps from a feature number to a day relative to the␣
 ↪target value, e.g. -2 means two days before
      Note: 361 is the temperature of Cleveland on the previous day
'''
f = 361
print('Feature {}: city = {}, day= {}'.format(f,feature_to_city[f],␣
 ↪feature_to_day[f]))
baseline_rmse = np.sqrt(np.mean((y_val[1:]-y_val[:-1])**2)) # root mean squared␣
 ↪error example
print('Baseline - prediction using previous day: RMSE={}'.format(baseline_rmse))

# plot first two x/y for val
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[1], y_val[1], ['Cleveland', 'New York', 'Chicago', 'Denver',␣
  ↪'St. Louis'], feature_to_city, feature_to_day, dates_val[1])
```

```
Feature 361: city = Cleveland, day= -1
Baseline - prediction using previous day: RMSE=3.460601246750482
```





[13]:
```python
# K-NN Regression

def regress_KNN(X_trn, y_trn, X_tst, K=1):
    '''
    Predict the target value for each data point in X_tst using a
    K-nearest neighbor regressor 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 value
    '''
    # TO DO
    faiss_index = create_index(X_trn)
    dist, idx = faiss_index.search(X_tst, K)

    # get prediction
    predictions = np.take(y_trn, idx, axis=0)
    predictions = np.mean(predictions, axis=1)

    return predictions
```

```
def normalize_features(x, y, fnum):
  ''' Normalize the features in x and y.
      For each data sample i:
        x2[i] = x[i]-x[i,fnum]
        y2[i] = y[i]-x[i,fnum]
  '''
  # TO DO
  return (x - np.take(x, fnum, axis=1).reshape(-1, 1)), (y - np.take(x, fnum,␣
 ↪axis=1))


# KNN with original features
res = regress_KNN(x_train, y_train, x_test, 5)
print(np.sqrt(np.mean((res - y_test) ** 2)))

# TO DO

# KNN with normalized features
fnum = 361 # previous day temp in Cleveland

# TO DO
x_train_norm, y_train_norm = normalize_features(x_train, y_train, fnum)
x_test_norm, y_test_norm = normalize_features(x_test, y_test, fnum)
# KNN with normalized features
res = regress_KNN(x_train_norm, y_train_norm, x_test_norm, 5)
print(np.sqrt(np.mean((res - y_test_norm) ** 2)))
```

```
3.249556245363484
2.9324389176041588
```

0.3 Part 5: Stretch Goals

Include all your code used for part 5 in this section. You can copy-paste code from parts 1-3 if it is re-usable.

[14]:
```
# Stretch: KNN classification (Select K)
from sklearn.neighbors import KNeighborsClassifier

(x_train, y_train), (x_test, y_test) = load_mnist()

p5a_train_x, p5a_train_y = x_train[:50000], y_train[:50000]
p5a_val_x, p5a_val_y = x_train[50000:], y_train[50000:]

# for i in [1,3,5,11,25]:
#   neigh = KNeighborsClassifier(n_neighbors=i)
#   neigh.fit(p5a_train_x, p5a_train_y)
#   print(f'n = {i}, error rate = {1 - neigh.score(p5a_val_x, p5a_val_y)}')
```

```
neigh = KNeighborsClassifier(n_neighbors=3)
neigh.fit(x_train, y_train)
1 - neigh.score(x_test, y_test)
```

[14]: 0.02949999999999997

[15]:
```
# Stretch: KNN regression (Select K)
```

[16]:
```
# Stretch: K-means (more iters vs redos

params = [(20, 1), (4, 5), (50, 1), (10, 5)]

for (iteration, restart) in params:
  rmses = []
  for _ in range(5):
    fkmeans = faiss.Kmeans(x_train.shape[1], 30, niter=iteration,␣
 ↪nredo=restart, seed=int(time()))
    fkmeans.train(x_train)
    dist, idx = fkmeans.index.search(x_train,1)
    rmses.append(np.sqrt(np.sum(dist) / x_train.shape[0]))

  std = np.std(rmses)
  avg = np.mean(rmses)

  print(f'iteration: {iteration}, redos: {restart}, mean: {avg}, std: {std}')
```

```
iteration: 20, redos: 1, mean: 5.79427435672978, std: 0.013635576397397473
iteration: 4, redos: 5, mean: 5.824453619315952, std: 0.0014559432134116084
iteration: 50, redos: 1, mean: 5.780731385540949, std: 0.008345551020031898
iteration: 10, redos: 5, mean: 5.780008829446705, std: 0.003928297103671805
```