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CS 441 - HW1: Instance-based Methods

Complete the claimed points and sections below. *There is a 5 point penalty for failing to complete this section.*

Total Points Claimed	**[145] / 145**
1. Retrieval, K-means, 1-NN on MNIST	
a. Retrieval	[5] / 5
b. K-means	[15] / 15
c. 1-NN	[10] / 10
2. Make it fast	
a. K-means plot	[15] / 15
b. 1-NN error plots	[8] / 8
c. 1-NN time plots	[7] / 7
d. Most confused label	[5] / 5
3. Temperature Regression	
a. RMSE Tables	[20] / 20
4. Conceptual questions	[15] / 15
5. Stretch Goals	
a. Evaluate effect of K for MNIST	[15] / 15
b. Evaluate effect of K for Temp Reg.	[15] / 15
c. Compare Kmeans more iterations vs. restarts	[15] / 15

1. Retrieval, K-means, 1-NN on MNIST

a. What index is returned for x_test[1]?

28882

b. Paste the display of clusters after the 1st and 10th iteration for K=30.

1st iteration:

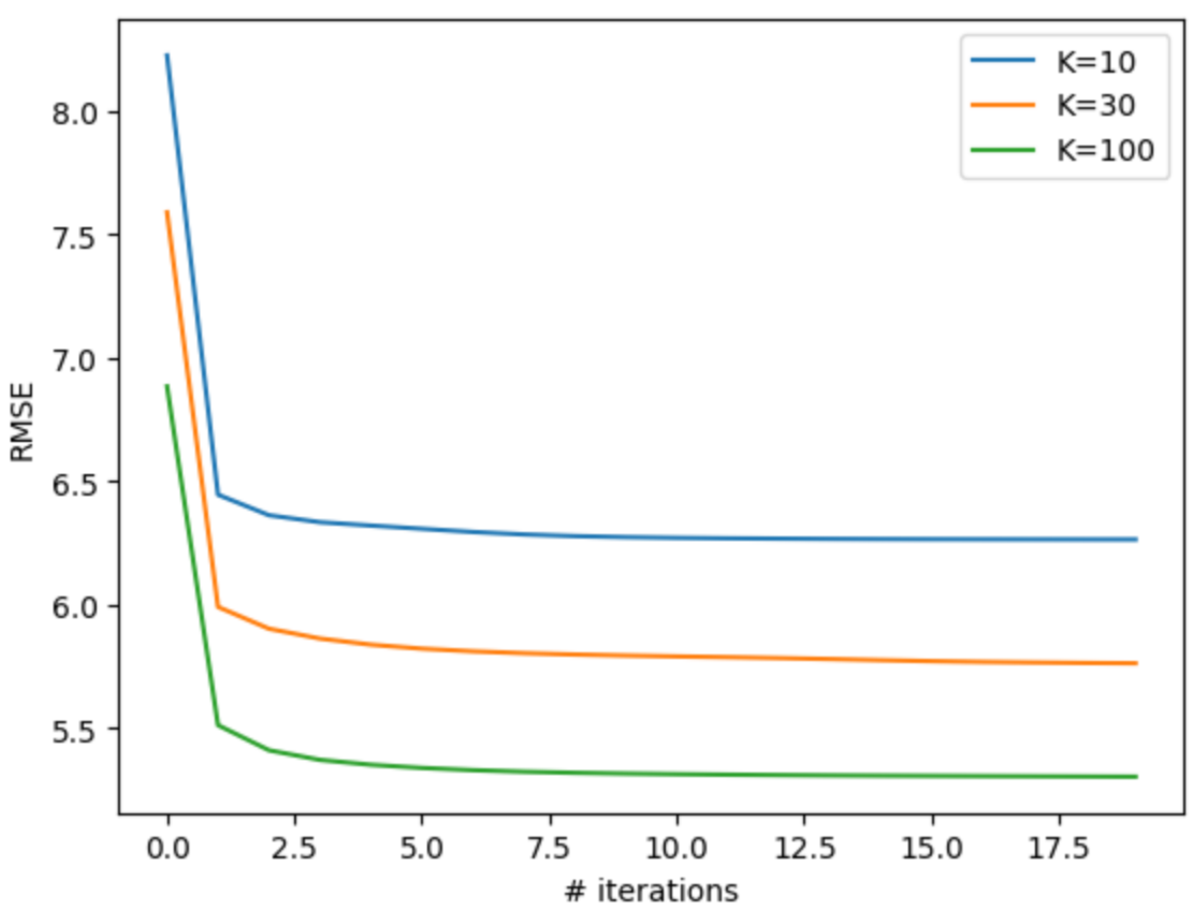
10th iteration:

c. Error rate for first 100 test samples, using first 10,000 training samples (x.x)

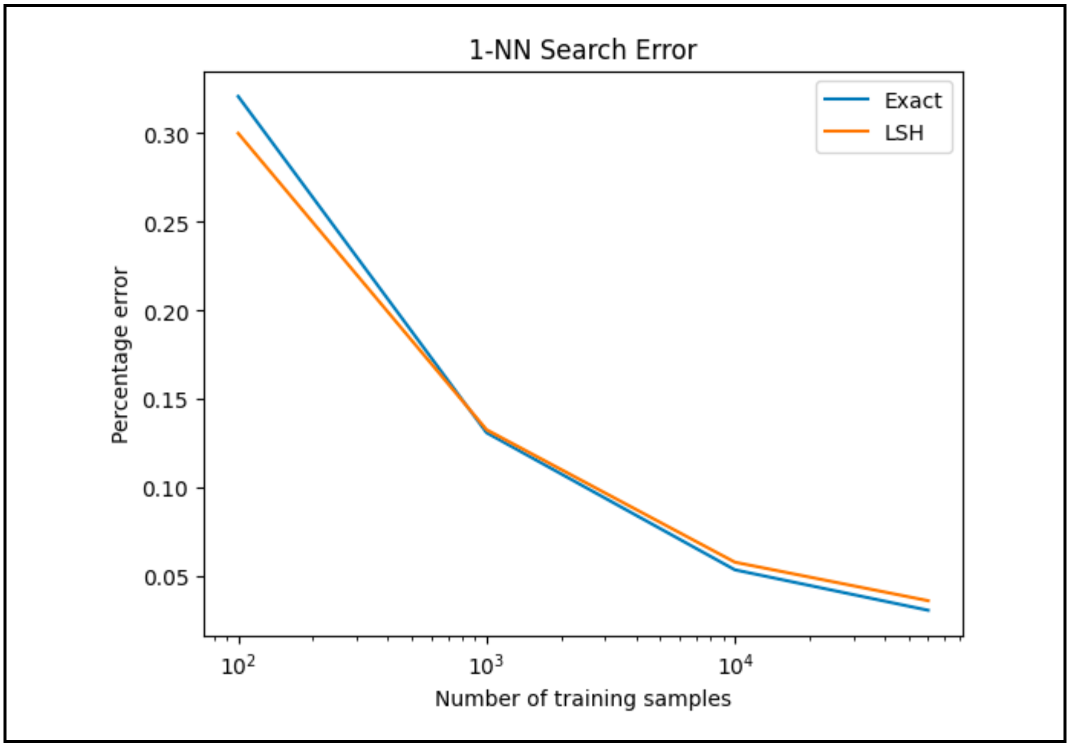
0.1

2. Make it fast

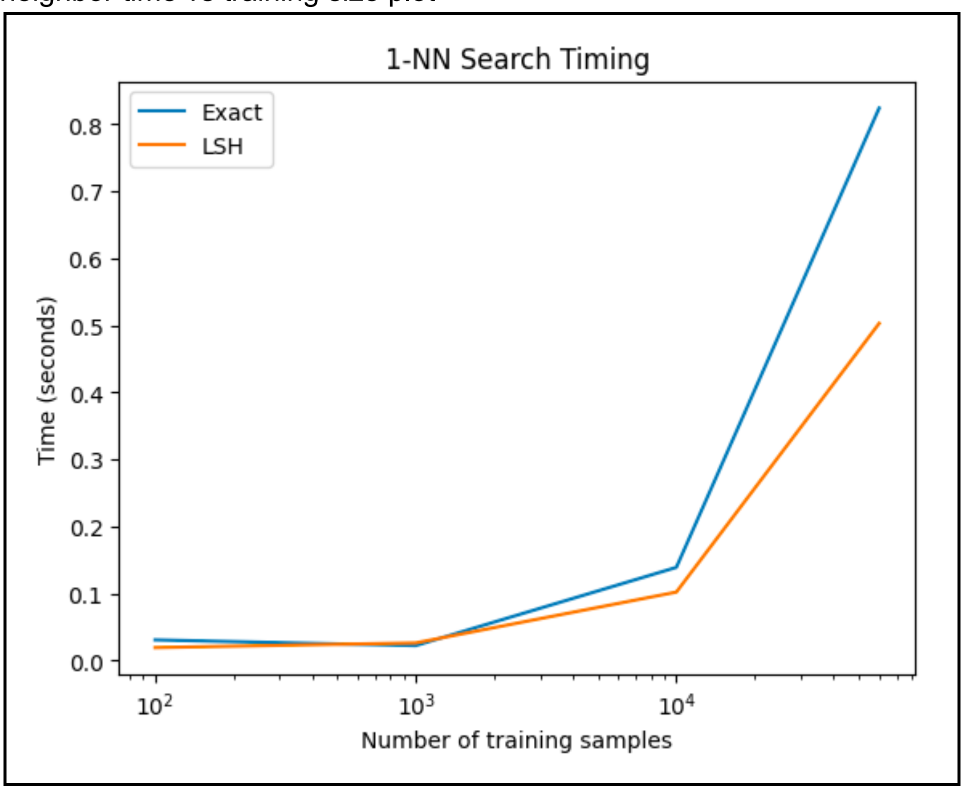
a. KMeans plot of RMSE vs iterations for K=10, 30, 100



b. Nearest neighbor error vs training size plot



c. Nearest neighbor time vs training size plot



d. What label is most commonly confused with ‘2’?

7

3. Temperature Regression

a. Table of RMSE for KNN with K=5 (x.xx)

	KNN (K=5)
Original Features	3.25
Normalized Features	3.17

4. Test your understanding

Fill in the letter corresponding to the answer. If you’re not sure, you can sometimes run small experiments to check.

1. Is K-means guaranteed to decrease RMSE between nearest cluster and samples at each iteration until convergence?
    a. Yes
    b. No

Yes, in the update step the recalibration of cluster centers to the mean of assigned samples ensures distances are minimized for future iterations.

2. If you increase K, is K-means expected or guaranteed to achieve lower RMSE?
    a. Guaranteed
    b. Expected but not guaranteed
    c. Not expected

Guaranteed, each additional cluster provides an opportunity to reduce the distance between points and their nearest center. Therefore, average squared distance between points and centroids is reduced resulting in a lower RMSE.

3. In K-NN regression, for training labels y, what is the lowest target value that can possibly be predicted for any query?
    a. Min(y)
    b. Mean(y)
    c. Can’t be determined

Min(y), the theoretical lower bound for a K-NN regression is the minimum value of the training label y, nothing else in KNN results in a value less than Min(y)

4. Would you expect the “training error” for 1-NN to be higher or lower than 3-NN for classification? Training error is the error if you test on the training data.
    a. Higher
    b. Lower
    c. It’s problem-dependent

Lower, the training error for 1-NN is zero since its neighbor is its own point (has no neighbors).

5. Would you expect the test error for 1-NN to be higher or lower than for 3-NN for regression?
    a. Higher
    b. Lower
    c. It’s problem-dependent

It’s problem-dependent, 3-NN would normally decrease test error due to its relative insensitivity to noisy neighbors however for some datasets a smaller K might capture trends more accurately – depending on the kind of data and its variance.

5. Stretch Goals (optional)

a. Select best K parameter for K-NN MNIST classification in K=1, 3, 5, 11, 25.

(x.xx)

Validation Set Performance	K=1	K=3	K=5	K=11	K=25
% error	2.88	2.80	2.82	3.08	3.82

Best K:

3

Test % error (x.xx)

2.83

b. Select best K parameter for K-NN temperature regression in K=1, 3, 5, 11, 25.

Validation Set RMSE	K=1	K=3	K=5	K=11	K=25
Original Features	4.33	3.23	3.10	3.06	3.06
Normalized Features	3.87	3.17	3.03	2.89	2.91

Best Setting (K, feature type):

11, normalized

Test RMSE (x.xx)

2.77

c. Kmeans: compare average and standard deviation RMSE based on number of iterations and number of restarts

(4 digit precision)

K=30	RMSE avg	RMSE std
20 iterations, 1 restart	5.7863	0.0076
4 iterations, 5 restarts	5.8228	0.0121
50 iterations, 1 restart	5.7771	0.0055
10 iterations, 5 restarts	5.7876	0.0037

Acknowledgments / Attribution

https://www.w3schools.com/python/python_ml_k-means.asp

https://stackoverflow.com/questions/33458834/k-means-clustering-in-python

https://codereview.stackexchange.com/questions/154609/knn-algorithm-implemented-in-python

CS441: Applied ML - HW 1

Darian Irani - irani2 - CS441

Parts 1-2: MNIST

Include all the code for generating MNIST results below

In [55]:

```
# 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()
```

In [56]:

```
# 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**

In [57]:

```
    dist_min = np.inf
    idx_min = -1

    for n in range(len(X)):
        dist = np.sum((X[n] - x_q) ** 2)
        if dist < dist_min:
            dist_min = dist
            idx_min = n

    return idx_min


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

```
53843
28882
```

In [58]:

```
def kmeans(X, K, niter=10):
    centers = X[:K].copy()
    assignments = np.zeros(len(X), dtype=int)

    for iteration in range(niter):
        # Reset assignments at the start of each iteration
        assignments.fill(0)

        # Assign each data point to the nearest center
        for i in range(len(X)):
            assignments[i] = get_nearest(X[i], centers)

        # Update the centers
        for k in range(K):
            if np.any(assignments == k):
                centers[k] = np.mean(X[assignments == k], axis=0)
            else:
                # If no points are assigned to a cluster, skip updating that center
                continue

        # Display the cluster centers after the 1st and 10th iterations for K=30
        if K == 30 and (iteration == 0 or iteration == niter - 1):
            print(f"Displaying cluster centers after iteration {iteration + 1}")
            display_mnist(centers, 1, K)   # Assuming K can be accommodated in a single r
ow

    return centers, assignments

# Load and display MNIST data
(x_train, y_train), (x_test, y_test) = load_mnist()

# Running kmeans with K=30 and displaying centers after 1st and 10th iterations
K = 30
centers, idx = kmeans(x_train[:1000], K)
```

```
Displaying cluster centers after iteration 1
```

```
Displaying cluster centers after iteration 10
```

In [59]:

```
def k_nn(x_test, x_train, y_train):

    predictions = []

    for x in x_test:
        min_index = get_nearest(x, x_train)
        predictions.append(y_train[min_index])
    return predictions


def error(predictions, y_test):
    error_rate = (sum(pred != true for pred, true in zip(predictions, y_test))) / len(y_
test)
    return error_rate

predictions_1k = k_nn(x_test[:100], x_train[:1000], y_train[:1000])
error_rate_1k = error(predictions_1k, y_test[:100])
print(f"Error rate using 1000 training samples: {error_rate_1k}")

predictions_10k = k_nn(x_test[:100], x_train[:10000], y_train[:10000])
error_rate_10k = error(predictions_1k, y_test[:100])
print(f"Error rate using 10000 training samples: {error_rate_10k }")
```

```
Error rate using 1000 training samples: 0.17
Error rate using 10000 training samples: 0.17
```

1. **Make it fast**

In [62]:

```
# install libraries you need for part 2

import faiss
import time
```

In [63]:

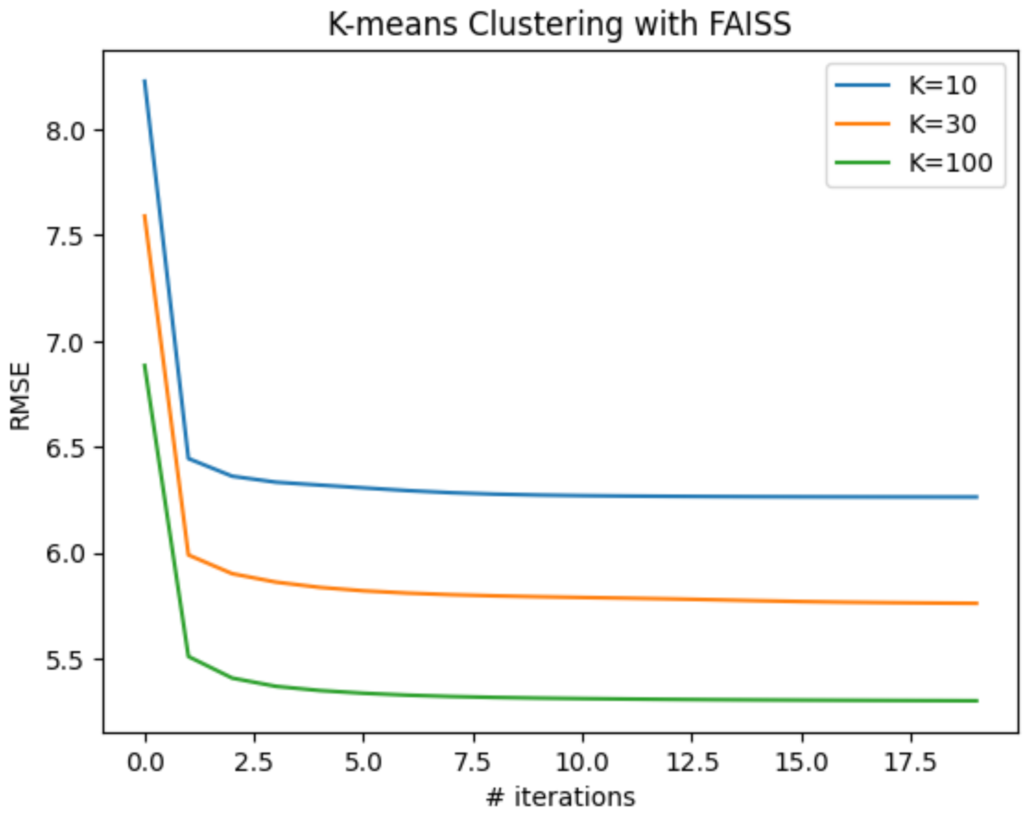
```
# retrieval

# TO DO (check that you're using FAISS correctly)

# exact search
index = faiss.IndexFlatL2(x_train.shape[1])
index.add(x_train)
dist, idx = index.search(x_test[:2],1)

print("FAISS indices:", idx.flatten())
print("get_nearest indices:", [get_nearest(x_test[i], x_train) for i in range(2)])
```

```
FAISS indices: [53843 28882]
get_nearest indices: [53843, 28882]
```

In [64]:

```
def kmeans_fast(X, K, niter=20):

    centers = X[:K].copy()
    # Convert centers to float32
    centers = centers.astype(np.float32)

    rmse_list = []

    for iteration in range(niter):
        # Create a new index for FAISS
        index = faiss.IndexFlatL2(X.shape[1])
        index.add(centers)
```

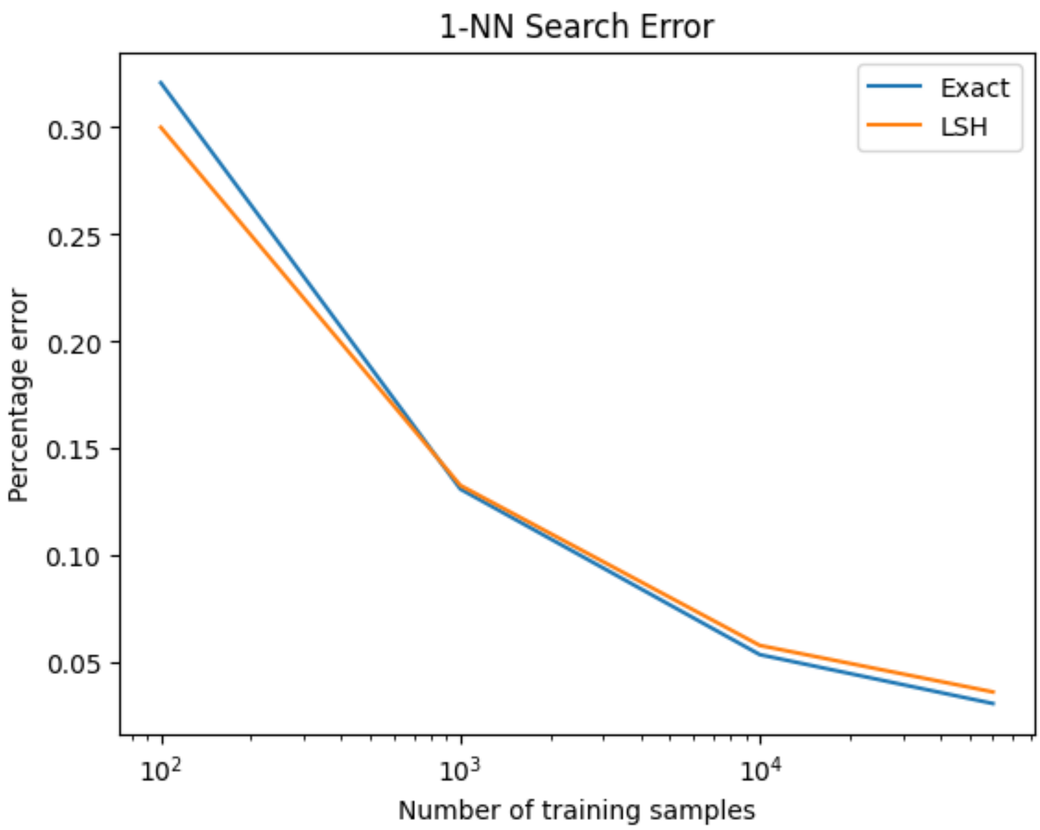
```
        # Compute RMSE
        rmse = np.sqrt(np.mean(dists))
        # rmse = np.sqrt(np.mean((x_train - centers[idx])**2))
        rmse_list.append(rmse)

        # Update cluster centers
        new_centers = np.zeros_like(centers)
        for k in range(K):
            # Select points that belong to cluster k
            points_in_cluster = X[idx.reshape(-1) == k]
            if len(points_in_cluster) > 0:
                new_centers[k] = np.mean(points_in_cluster, axis=0)
            else:
                # If no points are assigned to the cluster, use the old center
                new_centers[k] = centers[k]

        # Check for convergence (if centers didn't change, break)
        if np.allclose(centers, new_centers):
            break

        centers = new_centers

    return centers, rmse_list

for K in [10, 30, 100]:
    centers, rmse = kmeans_fast(x_train.astype(np.float32), K, niter=20)
    plt.plot(np.arange(len(rmse)), rmse, label=f'K={K}')

plt.legend(), plt.ylabel('RMSE'), plt.xlabel('# iterations')
plt.title('K-means Clustering with FAISS')
plt.show()
```

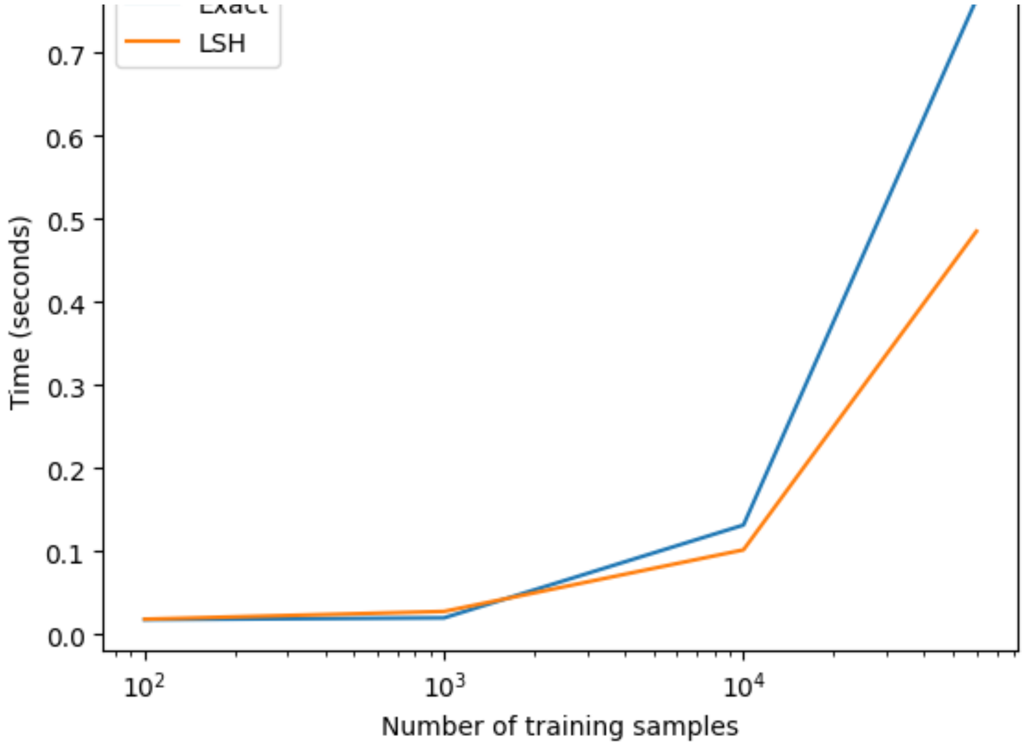


In [65]:

```
# # 1-NN

nsample = [100, 1000, 10000, 60000]
acc_exact = []
acc_lsh = []
```

```python
for s in nsample:
    # Exact search
    index_exact = faiss.IndexFlatL2(x_train[:s].shape[1])
    index_exact.add(x_train[:s].astype(np.float32))

    start_time = time.time()
    _, idx_exact = index_exact.search(x_test.astype(np.float32), 1)
    timing_exact.append(time.time() - start_time)

    # Calculate accuracy for exact search
    acc_exact.append(np.mean(y_train[idx_exact.reshape(-1)] == y_test))

    # LSH approximate search
    dim = x_train[:s].shape[1]
    index_lsh = faiss.IndexLSH(dim, dim)
    index_lsh.train(x_train[:s].astype(np.float32))
    index_lsh.add(x_train[:s].astype(np.float32))

    start_time = time.time()
    _, idx_lsh = index_lsh.search(x_test.astype(np.float32), 1)
    timing_lsh.append(time.time() - start_time)

    # Calculate accuracy for LSH search
    acc_lsh.append(np.mean(y_train[idx_lsh.reshape(-1)] == y_test))


error_exact = [1 - acc for acc in acc_exact]
error_lsh = [1 - acc for acc in acc_lsh]

plt.semilogx(nsample, error_exact, label='Exact')
plt.semilogx(nsample, error_lsh, label='LSH')
plt.legend(), plt.ylabel('Percentage error'), plt.xlabel('Number of training samples')
plt.title('1-NN Search Error')
plt.show()

plt.semilogx(nsample, timing_exact, label='Exact')
plt.semilogx(nsample, timing_lsh, label='LSH')
plt.legend(), plt.ylabel('Time (seconds)'), plt.xlabel('Number of training samples')
plt.title('1-NN Search Timing')
plt.show()
```





In [66]:

```
# Confusion matrix
from sklearn.metrics import confusion_matrix

# TO DO

x_train_faiss = x_train.astype(np.float32)
x_test_faiss = x_test.astype(np.float32)
index = faiss.IndexFlatL2(x_train_faiss.shape[1])
index.add(x_train_faiss)

# Perform the search on the full test set for the 1 nearest neighbor.
_, indices = index.search(x_test_faiss, 1)

# Retrieve the predicted labels using the indices returned by the search.
predicted_labels = y_train[indices.flatten()]

confuse = confusion_matrix(y_test, predicted_labels)

# Find out which label is most often confused with '2'.
confuse[2][np.argsort(confuse[2])[-2]]

# Label '7' is misclassified 16 times
```

Out[66]:

```
16
```

Part 3: Temperature Regression

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

In [46]:

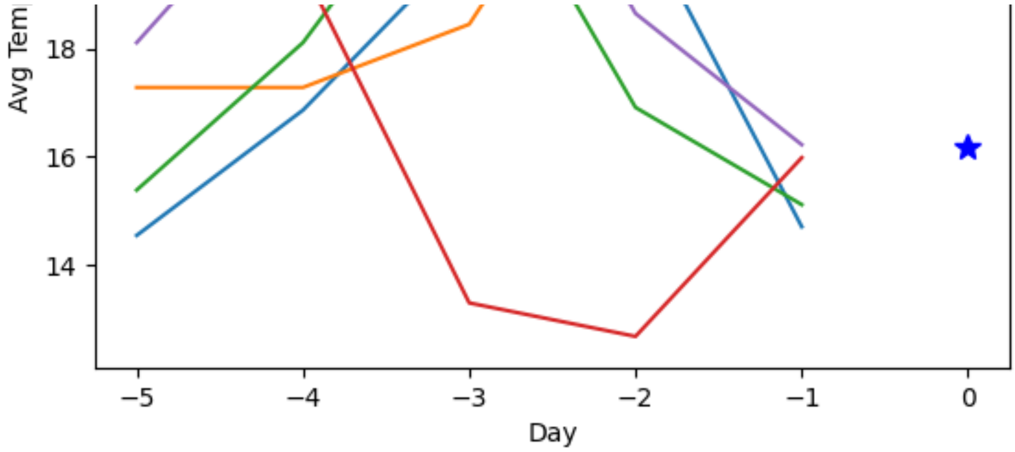
```
import numpy as np
# from google.colab import drive
%matplotlib inline
from matplotlib import pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
```

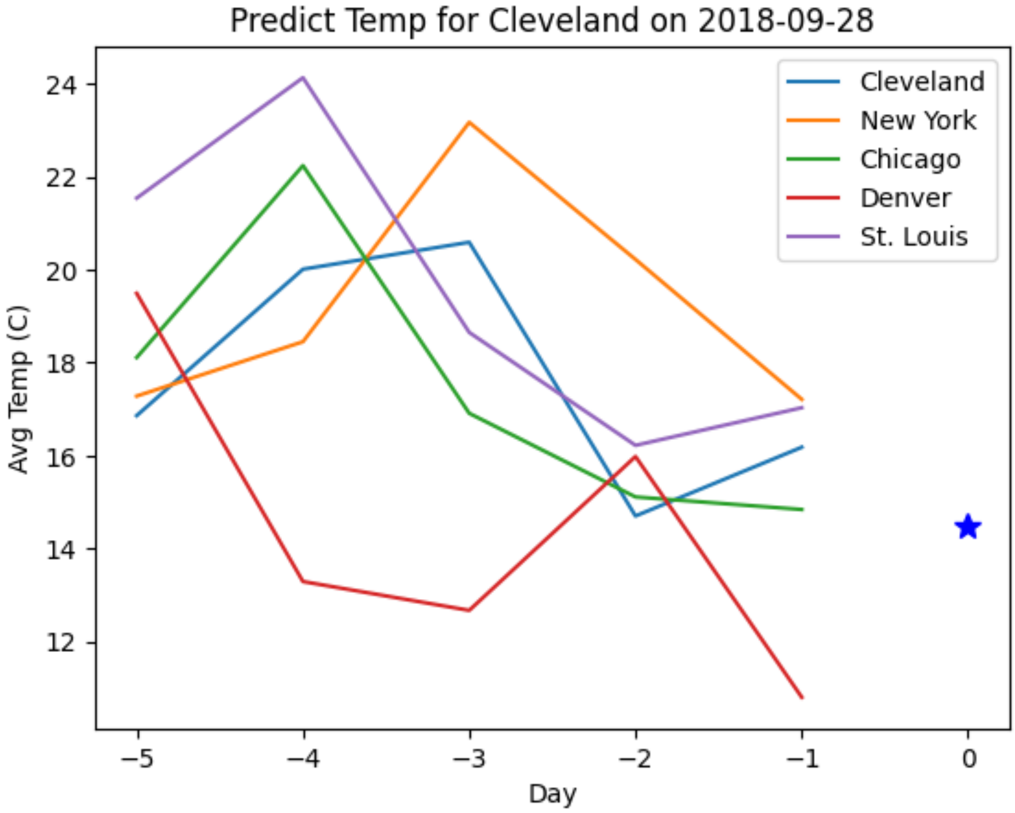
```
  datadir = "/Users/darian/Desktop/UIUC/Applied ML/HW1/Code/temperature_data.npz"
  T = np.load(datadir)
  x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, fe
ature_to_city, feature_to_day = \
  T['x_train'], T['y_train'], T['x_val'], T['y_val'], T['x_test'], T['y_test'], 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()
```

In [47]:

```
# load data
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, fea
ture_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 m
odel)
      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 fi
nal 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 ex
ample
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
```





In [48]:

```
# K-NN Regression

def get_distances(X_trn, x_tst):
    """
    Calculate L2 distances from a test point to all training points.
    """
    distances = np.sqrt(np.sum((X_trn - x_tst) ** 2, axis=1))
    return distances



def regress_KNN(X_trn, y_trn, X_tst, K=3):
  '''
  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

  y_pred = []
```

```
function
      dists = get_distances(X_trn, x_tst)
      nearest_indices = np.argsort(dists)[:K]  # Get indices of K nearest neighbors
      # Predict by averaging the labels of K nearest neighbors
      y_pred.append(np.mean(y_trn[nearest_indices]))

  return np.array(y_pred)



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

  x2 = x - x[:, fnum][:, np.newaxis]
  y2 = y - x[:, fnum]
  return x2, y2


def calculate_rmse(y_pred, y_true):
    return np.sqrt(np.mean((y_true - y_pred) ** 2))


# KNN with original features

# TO DO

# Run K-NN regression
y_pred = regress_KNN(X_trn=x_train, y_trn=y_train, X_tst=x_test, K=5)

# Calculate and print RMSE for original features
rmse_original = calculate_rmse(y_test, y_pred)
print(f"RMSE for original features with K={5}: {rmse_original}")


# Normalize features
x_train_norm, y_train_norm = normalize_features(x_train, y_train, fnum=361)
x_val_norm, y_val_norm = normalize_features(x_val, y_val, fnum=361)

# KNN with normalized features
y_pred_normalized = regress_KNN(x_train_norm, y_train_norm, x_val_norm, K=3)
rmse_normalized = calculate_rmse(y_pred_normalized, y_val_norm)
print(f"RMSE for normalized features: {rmse_normalized}")
```

```
RMSE for original features with K=5: 3.249556245363484
RMSE for normalized features: 3.174005914679923
```

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.

In [11]:

```
# Stretch: KNN MNIST

from keras.datasets import mnist
import numpy as np
import faiss

def load_mnist():
    '''
    Loads, reshapes, and normalizes the data
    '''
```

```python
    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)

# Assuming the load_mnist function correctly loads and preprocesses the data
(x_train, y_train), (x_test, y_test) = load_mnist()

# Splitting the training data into actual training and validation sets
# First 50000 for training, remaining for validation
# x_val = x_train[50000:]
# y_val = y_train[50000:]
# x_train = x_train[:50000]
# y_train = y_train[:50000]

# Full training, full test set
x_val = x_test
y_val = y_test
x_train = x_train
y_train = y_train

def KNN_MNIST_faiss(x_train, y_train, x_val, K=3):
    x_train_faiss = x_train.astype(np.float32)
    x_val_faiss = x_val.astype(np.float32)

    d = x_train_faiss.shape[1]

    index = faiss.IndexFlatL2(d)
    index.add(x_train_faiss)

    D, I = index.search(x_val_faiss, K)  # D: Distances, I: Indices

    y_pred = []
    for i in range(len(x_val)):
        # Get labels of K nearest neighbors
        labels = y_train[I[i]]

        # Count occurrences of each label
        label_counts = np.bincount(labels, minlength=10)

        # Find the most common label(s)
        max_count = np.max(label_counts)
        common_labels = np.where(label_counts == max_count)[0]

        if len(common_labels) > 1:
            # Tie: choose the label of the closest sample among the tied labels
            for idx in I[i]:
                if y_train[idx] in common_labels:
                    y_pred.append(y_train[idx])
                    break
        else:
            # No tie: choose the most common label
            y_pred.append(common_labels[0])

    return np.array(y_pred)

def error_MNIST(y_pred, y_val):
    error_rate = np.mean(y_pred != y_val)
    return error_rate


K_values = [1, 3, 5, 11, 25]
for K in K_values:
    y_pred = KNN_MNIST_faiss(x_train, y_train, x_val, K=K)
    error_rate = error_MNIST(y_pred, y_val)
    print(f"Error rate for K={K}: {error_rate*100}%")
```

```
Error rate for K=1: 3.09%
```

In [19]:

```
# Stretch: KNN regression (Select K)

import numpy as np

def load_temp_data():

  datadir = "/Users/darian/Desktop/UIUC/Applied ML/HW1/Code/temperature_data.npz"
  T = np.load(datadir)
  x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, fe
ature_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)

# Load temperature data
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val, dates_test, fea
ture_to_city, feature_to_day) = load_temp_data()

def get_distances(X_trn, x_tst):
    """
    Calculate L2 distances from a test point to all training points.
    """
    distances = np.sqrt(np.sum((X_trn - x_tst) ** 2, axis=1))
    return distances

def regress_KNN(X_trn, y_trn, X_tst, K=3):
  '''
  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

  y_pred = []

  for x_tst in X_tst:
      # Calculate distances from the test point to all training points using the revised
function
      dists = get_distances(X_trn, x_tst)
      nearest_indices = np.argsort(dists)[:K]  # Get indices of K nearest neighbors
      # Predict by averaging the labels of K nearest neighbors
      y_pred.append(np.mean(y_trn[nearest_indices]))

  return np.array(y_pred)

# Define the normalization function
def normalize_features(x, y, fnum):
    x2 = x - x[:, fnum][:, np.newaxis]
    y2 = y - x[:, fnum]
    return x2, y2

# Define RMSE calculation function
def calculate_rmse(y_pred, y_true):
    return np.sqrt(np.mean((y_true - y_pred) ** 2))

# # KNN with original features
# K_values = [1, 3, 5, 11, 25]
# print("Original Features:")
# for K in K_values:
#     y_pred = regress_KNN(X_trn=x_train, y_trn=y_train, X_tst=x_val, K=K)  # Use x_val
for validation
#     rmse_original = calculate_rmse(y_pred, y_val)  # Use y_val for validation
```

```
e in Cleveland
# x_train_norm, y_train_norm = normalize_features(x_train, y_train, fnum)
# x_val_norm, y_val_norm = normalize_features(x_val, y_val, fnum)

# # KNN with normalized features
# print("\nNormalized Features:")
# for K in K_values:
#     y_pred_normalized = regress_KNN(x_train_norm, y_train_norm, x_val_norm, K=K)
#     rmse_normalized = calculate_rmse(y_pred_normalized, y_val_norm)
#     print(f"RMSE for normalized features with K={K}: {rmse_normalized}")



# For K = 11 and normalized:

# Normalize features for the training and validation set
fnum = 361  # Assuming this is the correct feature number for previous day's temperature
in Cleveland
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
print("\nNormalized Features:")

y_pred_normalized = regress_KNN(x_train_norm, y_train_norm, x_test_norm, K=11)
rmse_normalized = calculate_rmse(y_pred_normalized, y_test_norm)
print(f"RMSE for normalized features with K={11}: {rmse_normalized}")
```

```
Normalized Features:
RMSE for normalized features with K=11: 2.7671311757775685
```

In [39]:

```
import faiss
import numpy as np


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)

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




def run_faiss_kmeans(X, K, niter, nredo, seed=123):
    d = X.shape[1]
    kmeans = faiss.Kmeans(d, K, niter=niter, nredo=nredo, seed=seed)
    kmeans.train(X)
    # After training, compute the sum of squared distances from each point to its cluster
center
    D, _ = kmeans.index.search(X, 1)
    # Compute RMSE
    rmse = np.sqrt(np.mean(D))
    return rmse

# Assuming x_train is loaded and preprocessed correctly
x_train_faiss = x_train.astype(np.float32)
```

```
    {"niter": 4, "nredo": 5},
    {"niter": 20, "nredo": 1}
]

# Run experiments
K = 30
results = {config: [] for config in range(len(configs))}

for i, config in enumerate(configs):
    print(f"Running configuration: {config}")
    for seed in range(5):  # Repeat test five times with different seeds
        rmse = run_faiss_kmeans(x_train_faiss, K, config["niter"], config["nredo"], seed
=seed)
        results[i].append(rmse)
        print(f"Run {seed + 1}, RMSE: {rmse}")

# Calculate and print mean and standard deviation of RMSE for each configuration
for i, config in enumerate(configs):
    mean_rmse = np.mean(results[i])
    std_rmse = np.std(results[i])
    print(f"Configuration {config}, Mean RMSE: {mean_rmse}, Std RMSE: {std_rmse}")
```

```
Running configuration: {'niter': 10, 'nredo': 5}
Run 1, RMSE: 5.791625022888184
Run 2, RMSE: 5.789511203765869
Run 3, RMSE: 5.789932727813721
Run 4, RMSE: 5.785751819610596
Run 5, RMSE: 5.781244277954102
Running configuration: {'niter': 50, 'nredo': 1}
Run 1, RMSE: 5.78638219833374
Run 2, RMSE: 5.77720832824707
Run 3, RMSE: 5.7691240310668945
Run 4, RMSE: 5.776084899902344
Run 5, RMSE: 5.776626110076904
Running configuration: {'niter': 4, 'nredo': 5}
Run 1, RMSE: 5.8296637535095215
Run 2, RMSE: 5.835312366485596
Run 3, RMSE: 5.819028854370117
Run 4, RMSE: 5.829253196716309
Run 5, RMSE: 5.800961494445801
Running configuration: {'niter': 20, 'nredo': 1}
Run 1, RMSE: 5.789977550506592
Run 2, RMSE: 5.7789764404296875
Run 3, RMSE: 5.7753987312316895
Run 4, RMSE: 5.792483806610107
Run 5, RMSE: 5.794531345367432
Configuration {'niter': 10, 'nredo': 5}, Mean RMSE: 5.7876129150390625, Std RMSE: 0.00371
76674231886864
Configuration {'niter': 50, 'nredo': 1}, Mean RMSE: 5.777085304260254, Std RMSE: 0.005496
197380125523
Configuration {'niter': 4, 'nredo': 5}, Mean RMSE: 5.8228440284729, Std RMSE: 0.012136279
605329037
Configuration {'niter': 20, 'nredo': 1}, Mean RMSE: 5.78627347946167, Std RMSE: 0.0076418
26756298542
```

In [ ]:

```
# from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27b343dca4abba

import os
# @title Convert Notebook to PDF. Save Notebook to given directory
NOTEBOOKS_DIR = "/content/drive/My Drive/CS441/24SP/hw1" # @param {type:"string"}
NOTEBOOK_NAME = "CS441_SP24_HW1_Solution.ipynb" # @param {type:"string"}
#------------------------------------------------------------------------------#
from google.colab import drive
drive.mount("/content/drive/", force_remount=True)
NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK NOT FOUND: {NOTEBOOK_PATH}"
```

```
assert os.path.exists(NOTEBOOK_PDF), f"ERROR MAKING PDF: {NOTEBOOK_PDF}"
print(f"PDF CREATED: {NOTEBOOK_PDF}")
```