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CS 441 - HW2: PCA and Linear Models

Complete the sections below. You do not need to fill out the checklist.

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b. Display scatterplot	[ ] / 5
c. Plot cumulative explained variance	[ ] / 5
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2. MNIST Classification with Linear Models	
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4. Stretch Goals	
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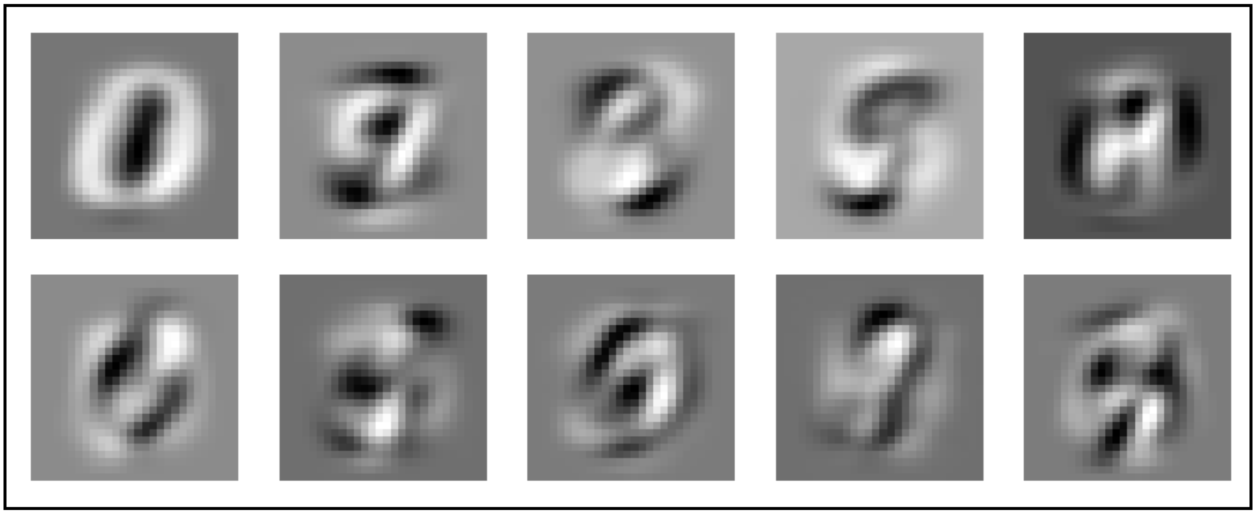
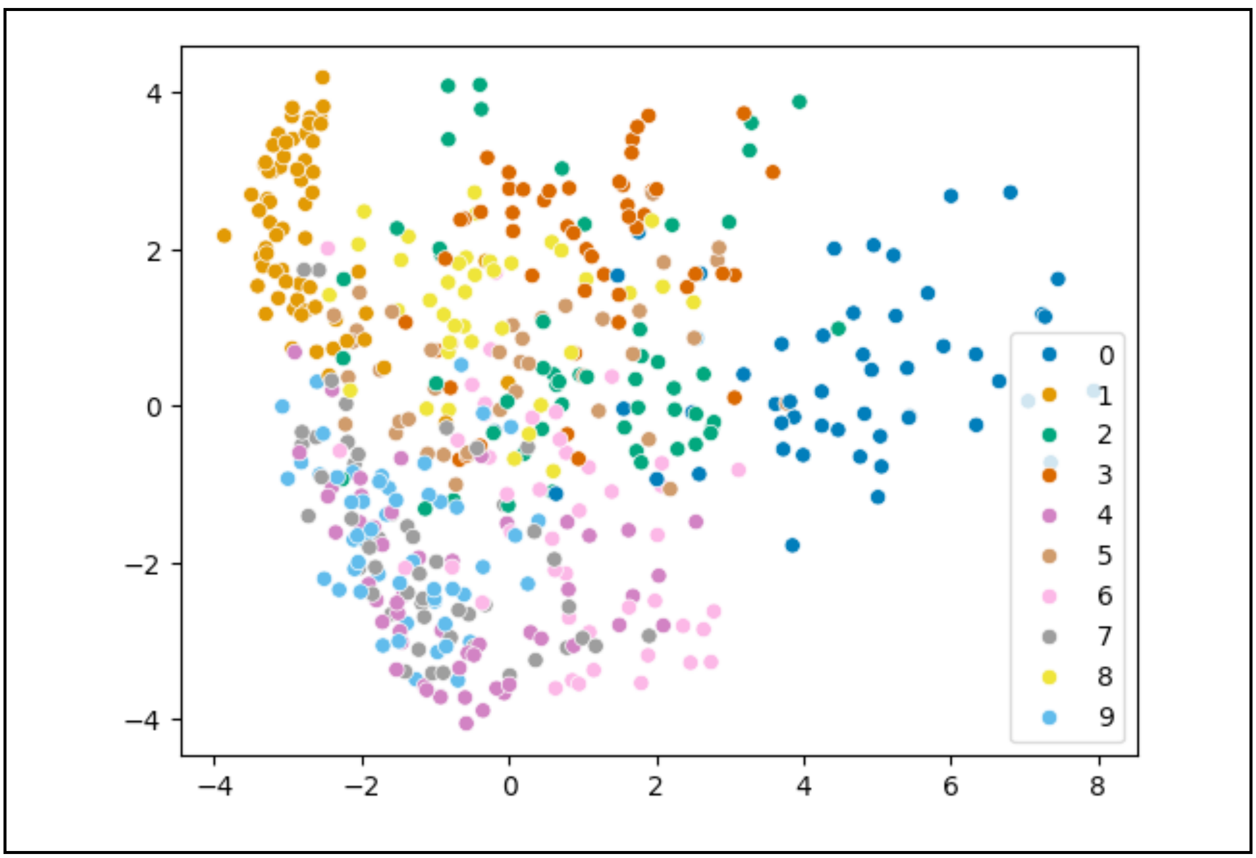
1. PCA on MNIST

a. Display 10 principal component vectors

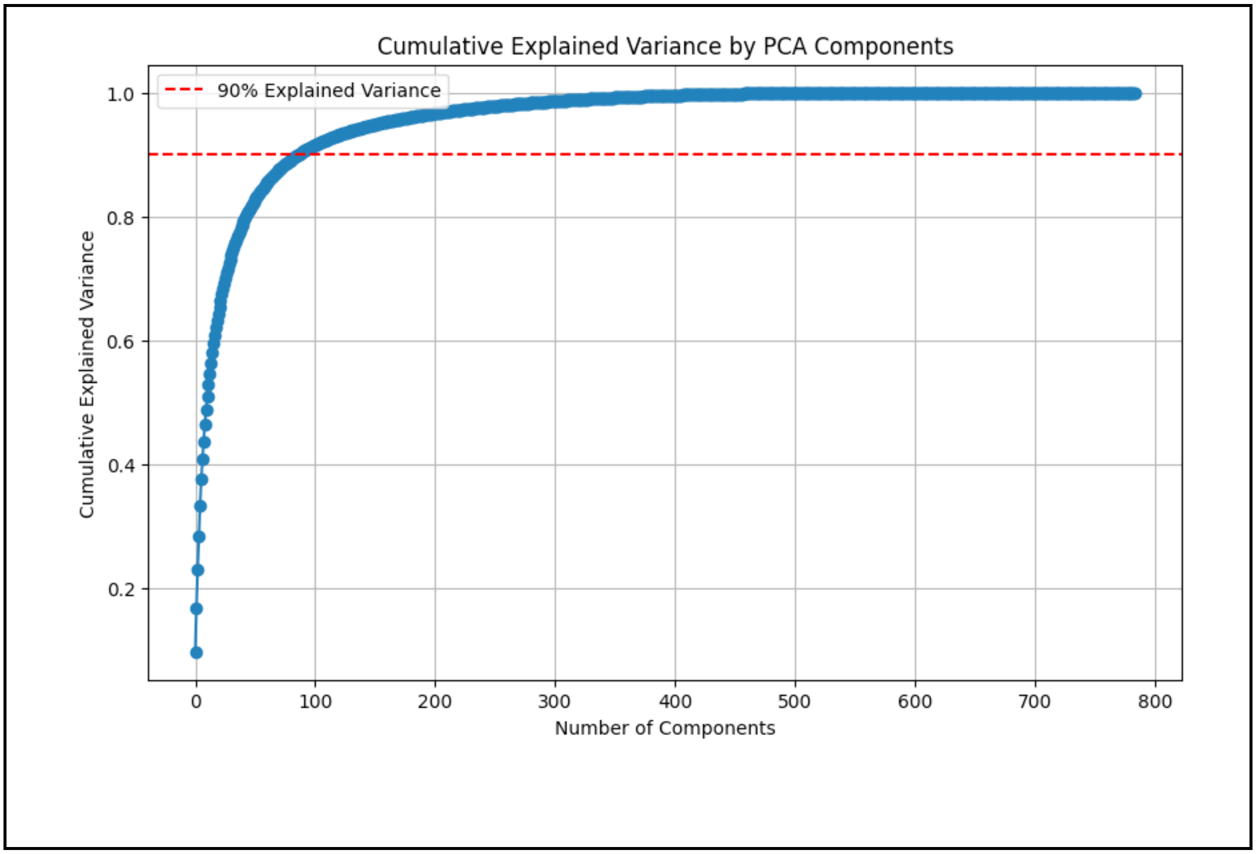


b. Display scatterplot

Scatterplot `x_train[:500]` for the first two PCA dimensions. Show a different color for each label.



c. Plot cumulative explained variance



d. Compression and 1-NN experiment

Number of components selected:

	Total Time (s)	Test Error (%)	Dimensions
Brute Force (PCA)	0.38	2.7	87
Brute Force	0.82	3.1	784

2. MNIST Classification with Linear Models

a. LLR / SVM error vs training size

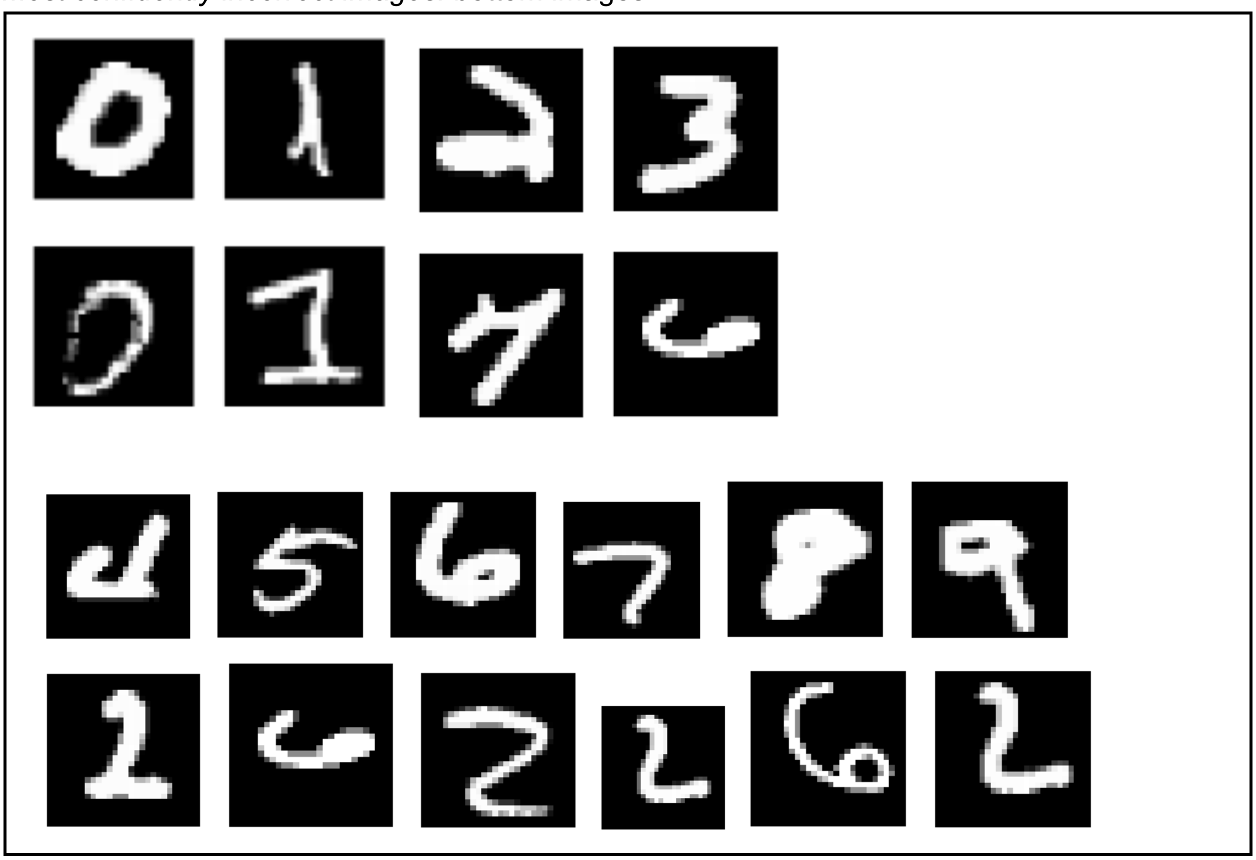
Test error (%)

# training samples	LLR	SVM
100	32.5%	32.4%
1,000	13.8%	16.1%
10,000	9.5%	11.1%
60,000	7.4%	8.2%

b. Error visualization

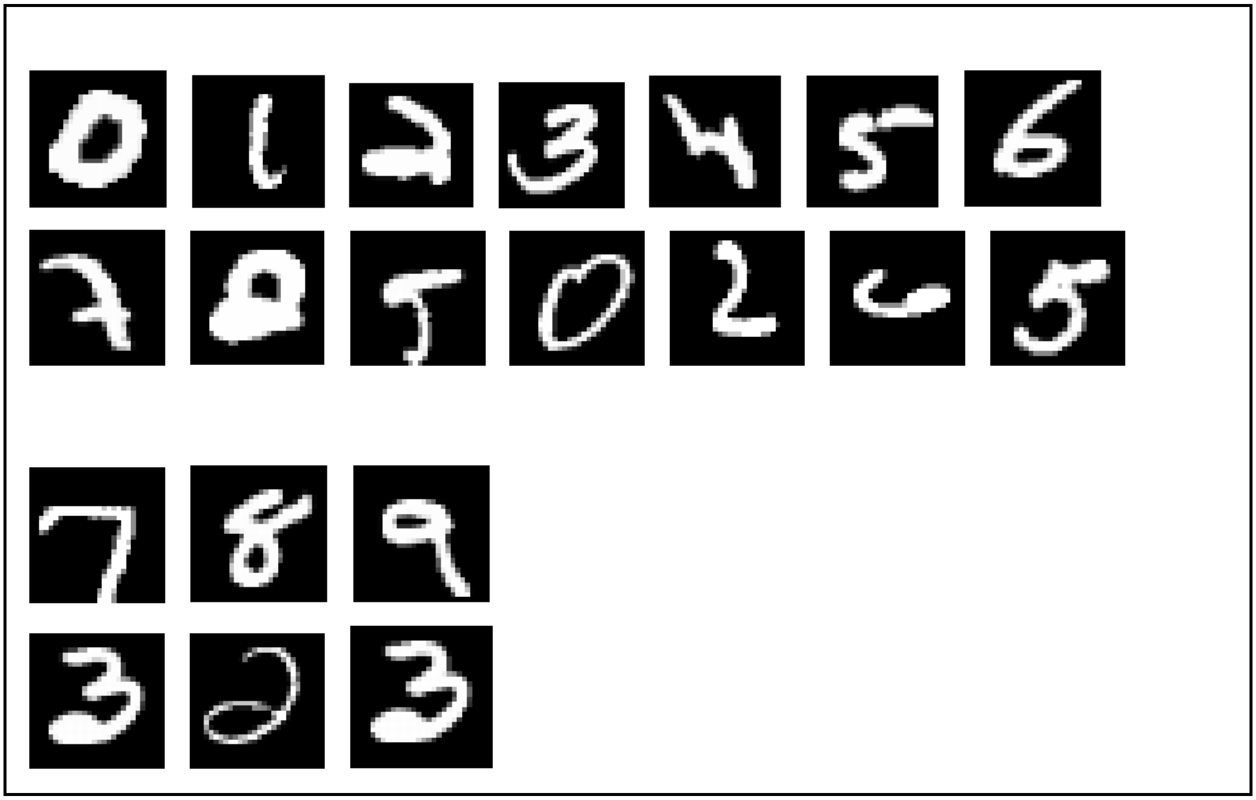
LLR

Most confidently correct: top images
Most confidently incorrect images: bottom images



SVM

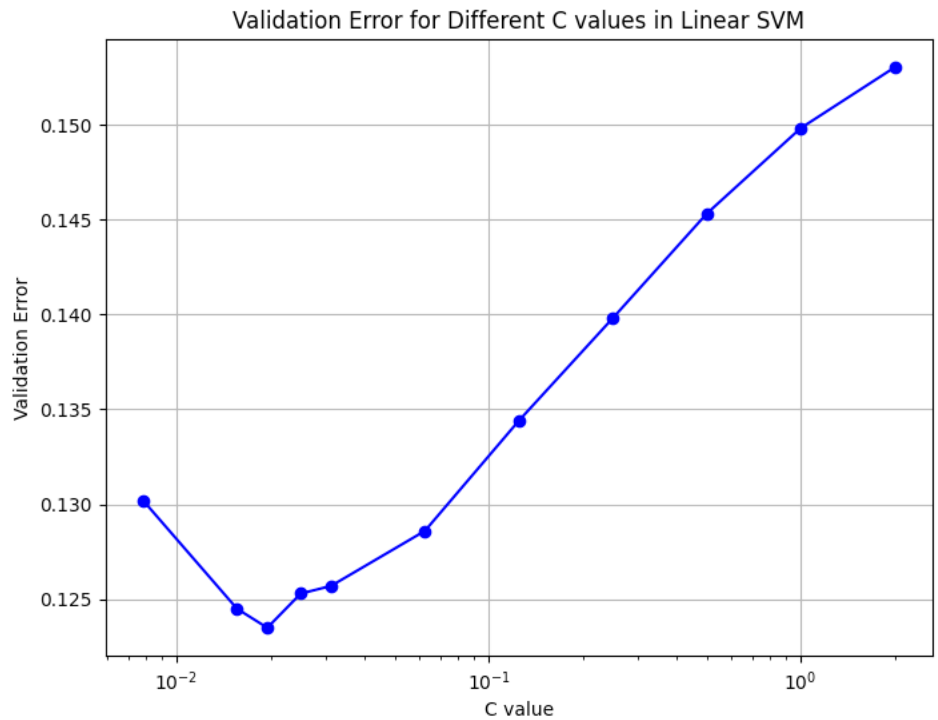
Most confidently correct: top images
Most confidently incorrect images: bottom images



c. Parameter selection experiments

	SVM
Best C value	0.025
Validation error (%)	12.35
Test error (%)	14.65

Plot C value vs validation error for values tested



3. Temperature Regression

a. Linear regression test

Test RMSE

	Linear regression
Original features	1.7744
Normalized features	1.7726

Why might normalizing features in this way not be as helpful as it is for KNN?

As seen above, the RMSE for the normalized and original features of L2-regularized linear regression is very similar. Since KNN is a distance based algorithm, large numeric ranges can skew results and hence normalizing prevents any skewed results from affecting the dataset. Ridge regression uses a linear model with a regularization term, feature scaling is less effective than KNN. Ridge regression relies on a linear relationship where coefficients are adjusted to minimize the regularized loss function, rather than relying on distance metrics between points.

b. Feature selection results

Feature Rank	Feature number	City	Day
1	405	Grand Rapids	-1
2	347	Minneapolis	-1
3	345	Detroit	-1
4	334	Chicago	-1
5	345	Detroit	-1
6	350	Brooklyn	-1
7	412	New Haven	-1
8	348	Tampa	-1
9	361	Cleveland	-1
10	314	Fresno	-2

Test error using only the 10 most important features for regression

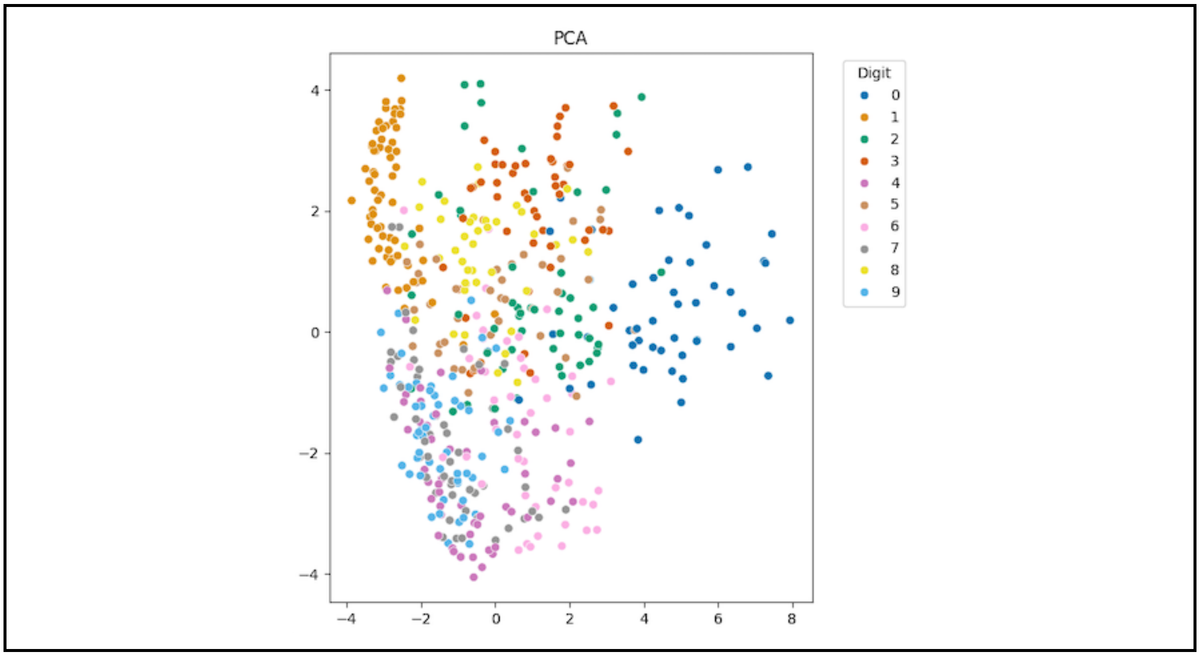
	Linear Regression
RMS Error	2.353

4. Stretch Goals

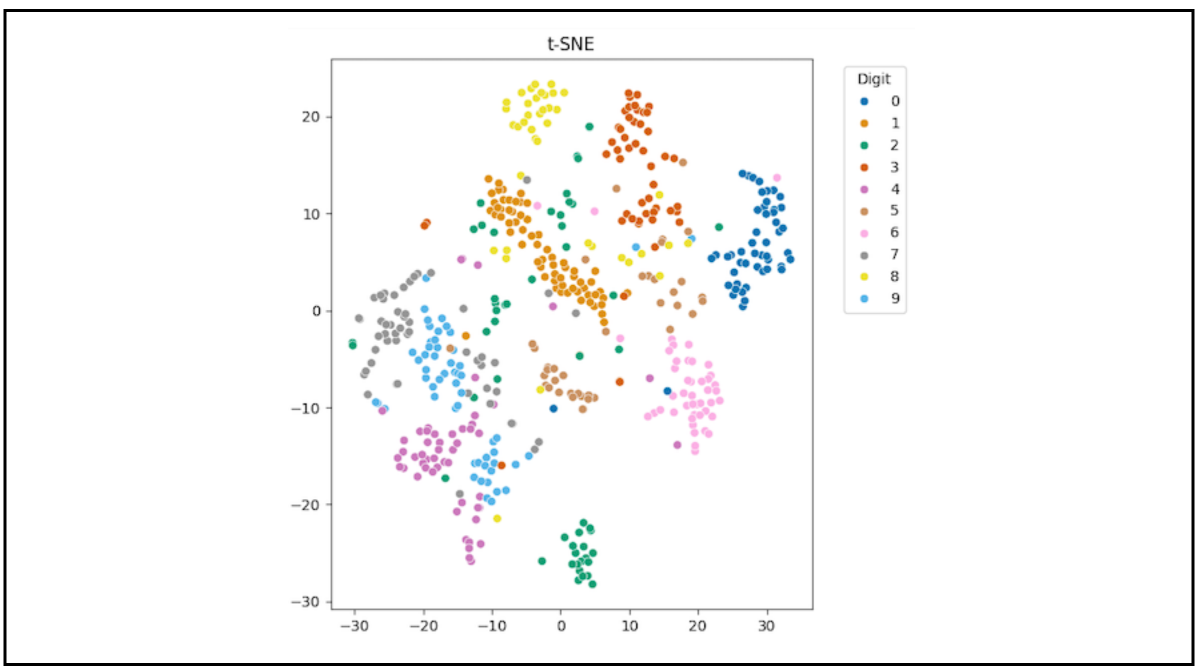
c. Other embeddings

Display 2+ plots for TSNE, MDA, and/or LDA, and copy PCA plot from 1b here.

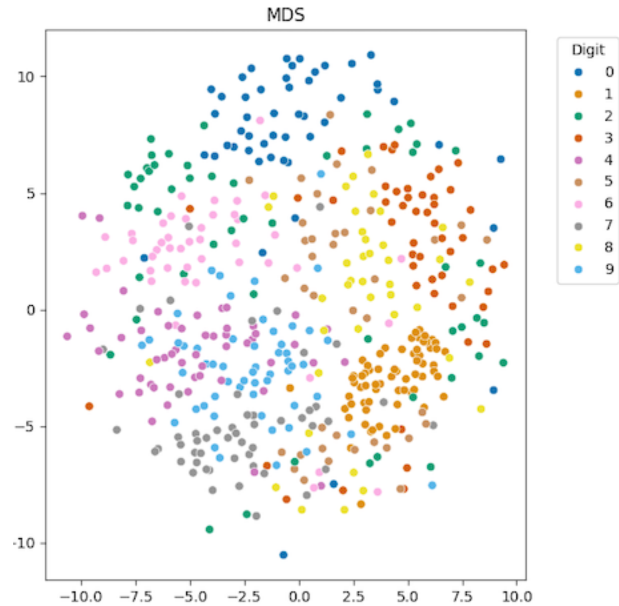
PCA



t-SNE



MDS



d. One city is all you need

City

St. Louis

Test error using features only from that city

2.8659

Explain your process (in words):

Once the dataset is loaded and a model is selected. The aim is to use that model and validation data to obtain a RMSE value for each city. Once that city is identified I run the model on the test data to obtain a temperature prediction and a test error % for that city.

e. Compare linear SVM and SVM with RBF kernel

Test accuracy (%)

# training samples	SVM-Linear	SVM-RBF
100	32.4%	34.4%
1,000	16.1%	9.2%
10,000	11.1%	4.1%
60,000	8.2%	2.1%

Acknowledgments / Attribution

List any outside sources for code or ideas or “None”.

https://stackoverflow.com/questions/46241578/feature-selection-scikit-learn

https://stackoverflow.com/questions/59851961/how-to-calculate-confidence-score-of-a-neural-network-prediction

CS441: Applied ML - HW 2

Parts 1-2: MNIST

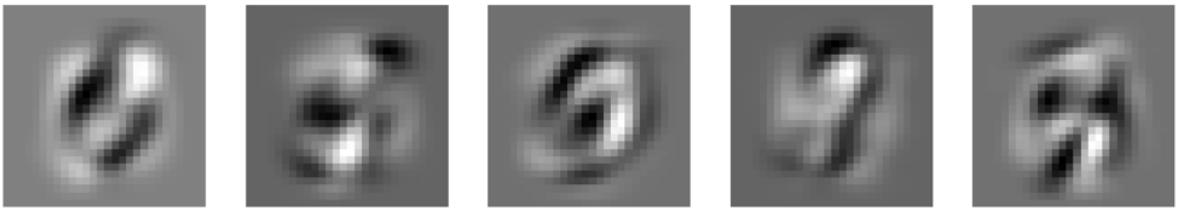
Include all the code for generating MNIST results below

In [83]:
```
# 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


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()
```

Part 1: PCA and Data Compression

In [84]:

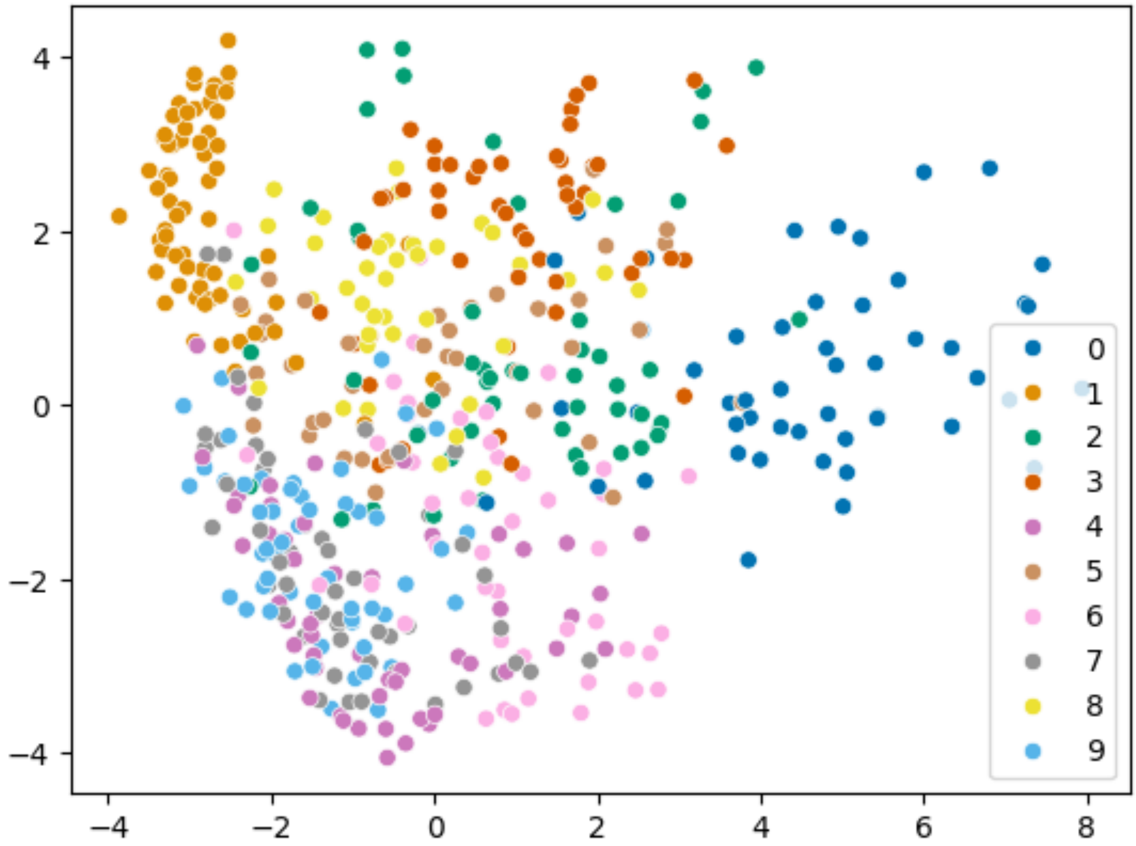
```python
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

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

# Modified display_mnist func
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 or len(x) > 1:
        fig, ax = plt.subplots(subplot_rows, subplot_cols, figsize=
(15,15))
        for i in range(len(x)):
            if subplot_rows > 1 or subplot_cols > 1:
                ax.ravel()[i].imshow(x[i], cmap='gray')
                ax.ravel()[i].axis('off')
            else:
                plt.imshow(x[i], cmap='gray')
                plt.axis('off')
    else:
        plt.imshow(x[0], cmap='gray')
        plt.axis('off')
    plt.show()


# Compute the first 10 principal components using x_train

# TO DO

# Display First 10 Components

pca = PCA(n_components=10)
pca.fit(x_train)

# Retrieve the principal components and transform them back to 28x2
8 format for visualization
components = pca.components_
images = np.reshape(components, (10, 28, 28))  # Reshape components
to 28x28 images

# Display the first 10 components in a 2x5 grid
display_mnist(images, subplot_rows=2, subplot_cols=5)
```



In [ ]:

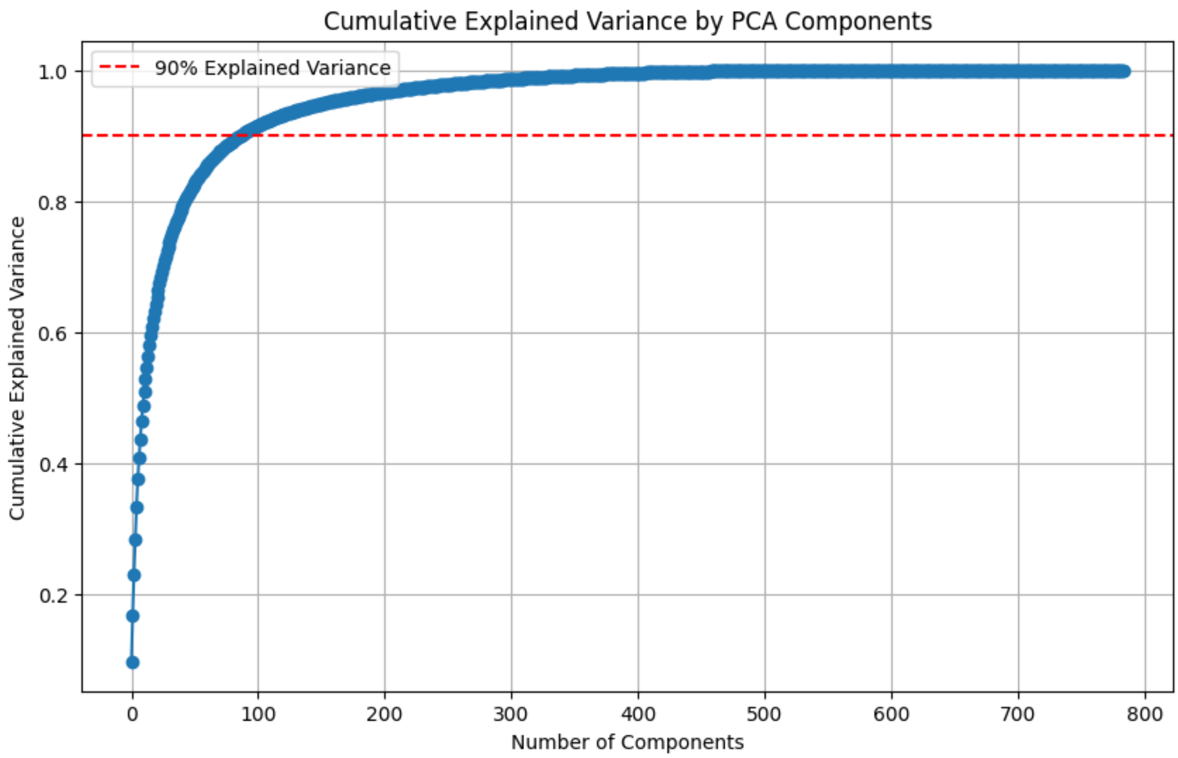
In [85]:
```
# Scatter plot of first two PCA dimensions
import seaborn as sns

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

pca = PCA(n_components=10)
x_pca = pca.fit_transform(x_train[:500])

# use pca.transform
# TO DO
ind = np.arange(500)
sns.scatterplot(x=x_pca[ind,0],y=x_pca[ind,1], hue=y_train[ind], pa
lette="colorblind")
```

Out[85]: <Axes: >



In [34]:

```
# Plot cumulative explained variance ratio
# cumsum and pca.explained_variance_ratio_ will be useful
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import numpy as np

# TO DO
(x_train, y_train), (x_test, y_test) = load_mnist()

pca = PCA()
pca.fit(x_train)

cum_var = np.cumsum(pca.explained_variance_ratio_)


# Plotting
plt.figure(figsize=(10, 6))
plt.plot(cum_var, marker='o')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Explained Variance by PCA Components')
plt.grid(True)
plt.axhline(y=0.9, color='r', linestyle='--', label='90% Explained
Variance')
plt.legend(loc='best')

plt.show()
```



In [51]:

```python
# Select number of dimensions that explains 90% of variance, accord
ing to your plot above
from sklearn.decomposition import PCA
import numpy as np
import faiss
import time
from sklearn.metrics import accuracy_score

pca_87 = PCA(n_components=87)
pca_87.fit(x_train)
x_train_pca = pca_87.transform(x_train)
x_test_pca = pca_87.transform(x_test)

# Convert data type for Faiss compatibility
x_train_faiss = x_train.astype('float32')
x_test_faiss = x_test.astype('float32')
x_train_pca_faiss = x_train_pca.astype('float32')
x_test_pca_faiss = x_test_pca.astype('float32')

# Create a Faiss index (L2 distance) for original features
index_original = faiss.IndexFlatL2(x_train_faiss.shape[1])
index_original.add(x_train_faiss)  # add the vectors to the index

# Create a Faiss index for compressed features
index_compressed = faiss.IndexFlatL2(x_train_pca_faiss.shape[1])
index_compressed.add(x_train_pca_faiss)


# Function to perform 1-NN search and calculate accuracy
def perform_search(index, x_query, y_true):
    start_time = time.time()
    _, I = index.search(x_query, k=1)  # Perform 1-NN search
    end_time = time.time()
    y_pred = y_train[I.flatten()]  # Retrieve predictions
    accuracy = accuracy_score(y_true, y_pred)

    total_time = end_time - start_time
    error = 1 - accuracy

    return total_time, error

# Compute time and error for 1-NN with original features
time_original, error_original = perform_search(index_original, x_te
st_faiss, y_test)

# Compute time and error for 1-NN with compressed features
time_compressed, error_compressed = perform_search(index_compressed
, x_test_pca_faiss, y_test)

print(f"Original Features Time: {time_original:.2f} s, Error: {erro
r_original:.4f}")
print(f"Compressed Features Time: {time_compressed:.2f} s, Error: {
error_compressed:.4f}")
```

```
Original Features Time: 0.82 s, Error: 0.0309
Compressed Features Time: 0.38 s, Error: 0.0270
```

Part 2: MNIST Classification with Linear Models

In [37]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn import svm
```

LLR/SVM vs training size

In [40]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score
import numpy as np

nsample = [100, 1000, 10000, 60000]
results = []

for N in nsample:
    x_train_N = x_train[:N]
    y_train_N = y_train[:N]

    # Train Logistic Regression
    lr = LogisticRegression(max_iter=10000)
    lr.fit(x_train_N, y_train_N)
    y_pred_lr = lr.predict(x_test)
    error_lr = 1 - accuracy_score(y_test, y_pred_lr)

    # Train Linear SVM
    svm = LinearSVC(max_iter=10000)
    svm.fit(x_train_N, y_train_N)
    y_pred_svm = svm.predict(x_test)
    error_svm = 1 - accuracy_score(y_test, y_pred_svm)

    # Store the results
    results.append({
        'Training Size': N,
        'LR Error': error_lr,
        'SVM Error': error_svm
    })

# Display the results
for result in results:
    print(f"Training Size: {result['Training Size']}, LR Error: {result['LR Error']:.4f}, SVM Error: {result['SVM Error']:.4f}")
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
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press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
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press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

Training Size: 100, LR Error: 0.3250, SVM Error: 0.3236
Training Size: 1000, LR Error: 0.1378, SVM Error: 0.1611
Training Size: 10000, LR Error: 0.0950, SVM Error: 0.1112
Training Size: 60000, LR Error: 0.0744, SVM Error: 0.0817
```

Error visualization

In [50]:

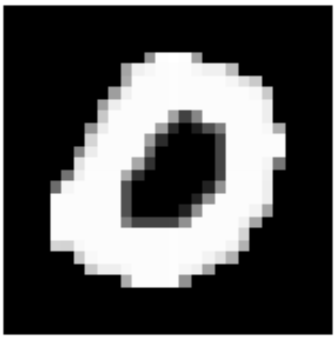
```
# to get scores for logistic regression use: scores = model_lr.pred
ict_proba(x_test)
# TO DO

# to get scores for SVM use: scores = model_svm.decision_function(x
_test)
# TO DO

from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score
import numpy as np
from sklearn.preprocessing import label_binarize



# Train Logistic Regression
llr = LogisticRegression(max_iter=10000)
llr.fit(x_train, y_train)
y_pred_llr = lr.predict(x_test)
llr_score = llr.predict_proba(x_test)

# Train Linear SVM
svm = LinearSVC(max_iter=10000, C=1.5)
svm.fit(x_train, y_train)
y_pred_svm = svm.predict(x_test)
svm_score = svm.decision_function(x_test)
```

```
# For Logistic Regression
scores_lr = llr.predict_proba(x_test)
predictions_lr = np.argmax(scores_lr, axis=1)
correctness_lr = predictions_lr == y_test

# For Linear SVM
scores_svm = svm.decision_function(x_test)
predictions_svm = np.argmax(scores_svm, axis=1)
correctness_svm = predictions_svm == y_test

def display_mnist(x, subplot_rows=1, subplot_cols=1, img_size = (2,
2)):
  '''
  Displays one or more examples in a row or a grid. Adjust figsize
for smaller images.
  '''
  # Calculate figure size dynamically based on the number of column
s; adjust width per image and height
  figure_width = subplot_cols * 2
  figure_height = subplot_rows * 2
  fig, ax = plt.subplots(subplot_rows, subplot_cols, figsize=(figur
e_width, figure_height))

  if subplot_rows > 1 or subplot_cols > 1:
    for i in range(len(x)):
      ax.ravel()[i].imshow(x[i].reshape(28, 28), cmap='gray')
      ax.ravel()[i].axis('off')
  else:
      plt.imshow(x[0].reshape(28, 28), cmap='gray')
      plt.axis('off')
  plt.show()


for label in range(10):
    # Logistic Regression
    label_scores_lr = scores_lr[:, label]
    correct_indices_lr = np.where((predictions_lr == label) & corre
ctness_lr)[0]
    incorrect_indices_lr = np.where((predictions_lr != label) & ~co
rrectness_lr)[0]

    if len(correct_indices_lr) > 0:
        most_confident_correct_lr = correct_indices_lr[np.argmax(la
bel_scores_lr[correct_indices_lr])]
        print(f"LR: Most confidently correct for label {label}:")
        display_mnist(x_test[most_confident_correct_lr].reshape(1,
28, 28),img_size=(1, 1))

    if len(incorrect_indices_lr) > 0:
        most_confident_incorrect_lr = incorrect_indices_lr[np.argmi
n(label_scores_lr[incorrect_indices_lr])]
        print(f"LR: Most confidently incorrect for label {label}:")
        display_mnist(x_test[most_confident_incorrect_lr].reshape(1
, 28, 28), img_size=(1, 1))
```

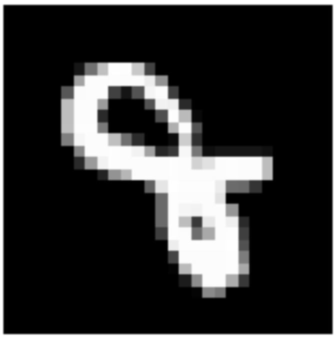
```
    # SVM
    label_scores_svm = scores_svm[:, label]
    correct_indices_svm = np.where((predictions_svm == label) & cor
rectness_svm)[0]
    incorrect_indices_svm = np.where((predictions_svm != label) & ~
correctness_svm)[0]

    if len(correct_indices_svm) > 0:
        most_confident_correct_svm = correct_indices_svm[np.argmax(
label_scores_svm[correct_indices_svm])]
        print(f"SVM: Most confidently correct for label {label}:")
        display_mnist(x_test[most_confident_correct_svm].reshape(1,
28, 28), img_size=(1, 1))

    if len(incorrect_indices_svm) > 0:
        most_confident_incorrect_svm = incorrect_indices_svm[np.arg
min(label_scores_svm[incorrect_indices_svm])]
        print(f"SVM: Most confidently incorrect for label {label}:"
)
        display_mnist(x_test[most_confident_incorrect_svm].reshape(
1, 28, 28), img_size=(1, 1))
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
```

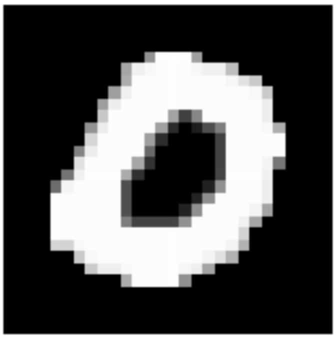
LR: Most confidently correct for label 0:



LR: Most confidently incorrect for label 0:

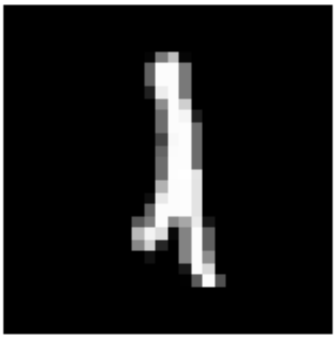


SVM: Most confidently correct for label 0:

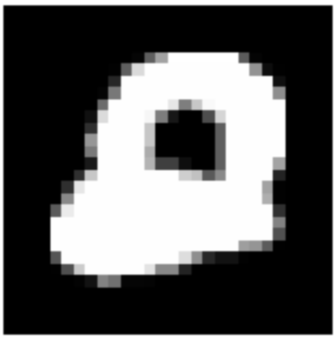


SVM: Most confidently incorrect for label 0:

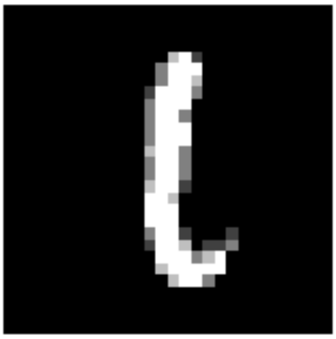
LR: Most confidently correct for label 1:



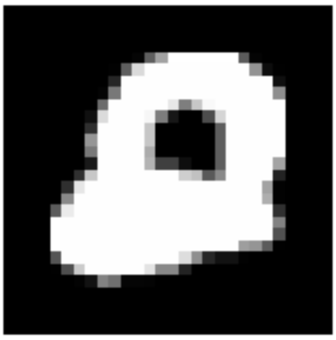
LR: Most confidently incorrect for label 1:



SVM: Most confidently correct for label 1:



SVM: Most confidently incorrect for label 1:

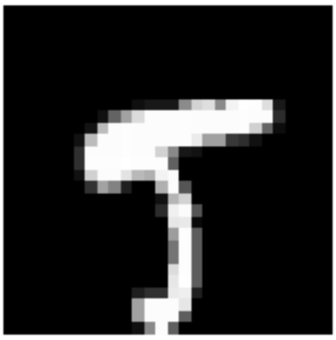


LR: Most confidently correct for label 2:

LR: Most confidently incorrect for label 2:

SVM: Most confidently correct for label 2:

SVM: Most confidently incorrect for label 2:

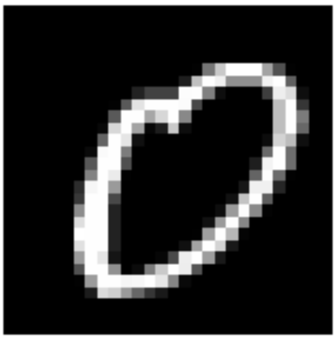


LR: Most confidently correct for label 3:

LR: Most confidently incorrect for label 3:

SVM: Most confidently correct for label 3:

SVM: Most confidently incorrect for label 3:



LR: Most confidently correct for label 4:

LR: Most confidently incorrect for label 4:

SVM: Most confidently correct for label 4:

SVM: Most confidently incorrect for label 4:

LR: Most confidently correct for label 5:

LR: Most confidently incorrect for label 5:

SVM: Most confidently correct for label 5:

SVM: Most confidently incorrect for label 5:

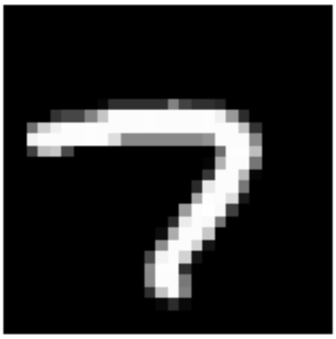
LR: Most confidently correct for label 6:

LR: Most confidently incorrect for label 6:

SVM: Most confidently correct for label 6:

SVM: Most confidently incorrect for label 6:

LR: Most confidently correct for label 7:



LR: Most confidently incorrect for label 7:

SVM: Most confidently correct for label 7:

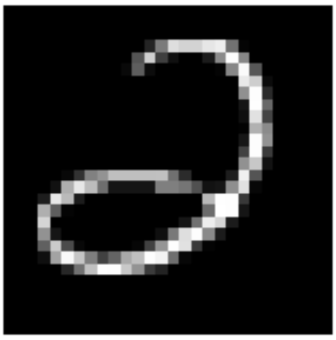
SVM: Most confidently incorrect for label 7:

LR: Most confidently correct for label 8:

LR: Most confidently incorrect for label 8:

SVM: Most confidently correct for label 8:

SVM: Most confidently incorrect for label 8:



LR: Most confidently correct for label 9:

LR: Most confidently incorrect for label 9:

SVM: Most confidently correct for label 9:

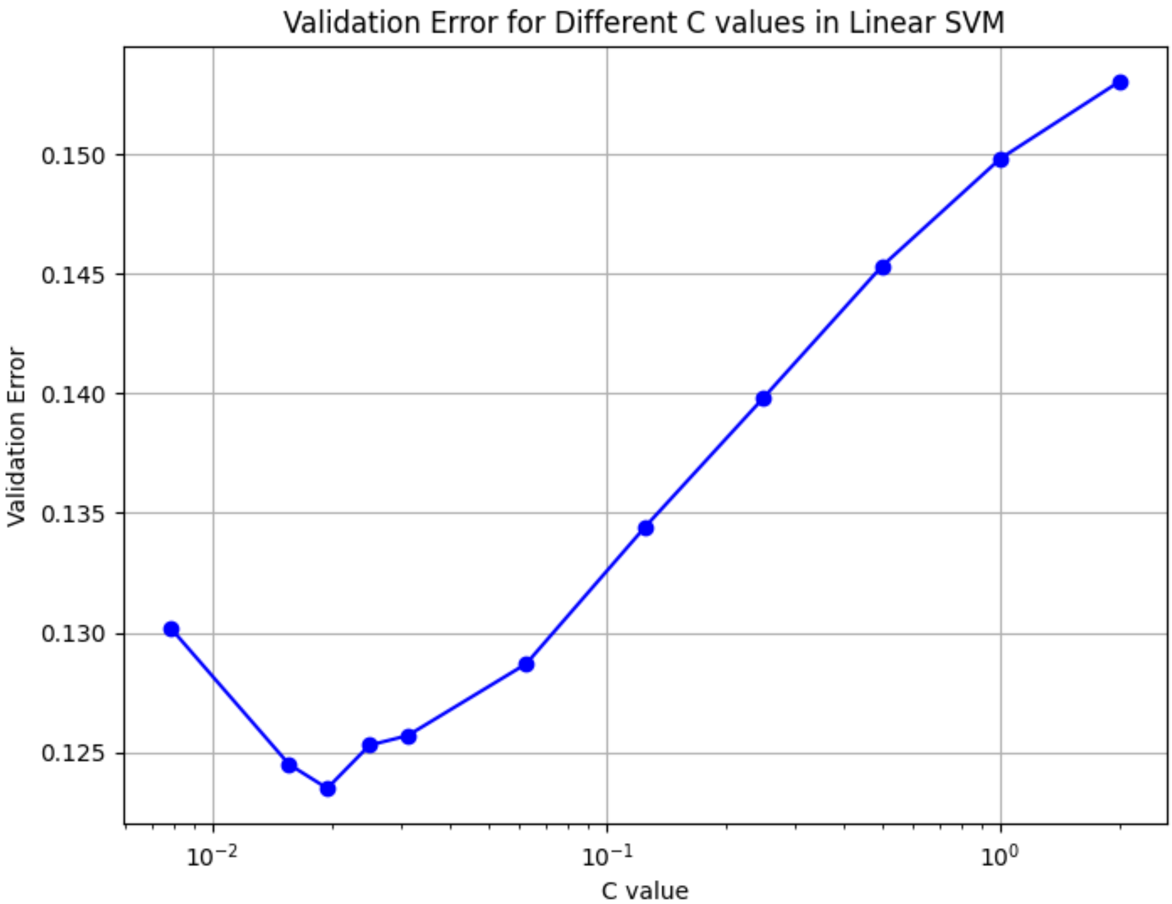
SVM: Most confidently incorrect for label 9:

Parameter selection

In [90]:
```python
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import numpy as np

# Assuming x_train, y_train, and x_test, y_test are already loaded

# Split the data for this experiment
x_train_small = x_train[:1000]
y_train_small = y_train[:1000]
x_val = x_train[50000:]
y_val = y_train[50000:]

# Range of C values to test
C_values = [0.0078125,0.015625,0.0195325,0.025,0.03125,0.0625,0.125
,0.25,0.5,1.0,2.0]
val_errors = []

# Iterate over the range of C values
for C in C_values:
    # Train Linear SVM
    svm = LinearSVC(C=C, max_iter=10000)
    svm.fit(x_train_small, y_train_small)

    # Evaluate on the validation set
    y_pred_val = svm.predict(x_val)
    val_accuracy = accuracy_score(y_val, y_pred_val)
    val_error = 1 - val_accuracy
    val_errors.append(val_error)

    print(f"C={C}, Validation Error: {val_error:.4f}")

# Find the best C value and its corresponding validation error
best_index = np.argmin(val_errors)
best_C = C_values[best_index]
best_error = val_errors[best_index]

# Plotting the validation error for each C value
plt.figure(figsize=(8, 6))
plt.semilogx(C_values, val_errors, marker='o', linestyle='-', color
='b')
plt.xlabel('C value')
plt.ylabel('Validation Error')
plt.title('Validation Error for Different C values in Linear SVM')
plt.grid(True)
plt.show()
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=0.0078125, Validation Error: 0.1302
C=0.015625, Validation Error: 0.1245

/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=0.0195325, Validation Error: 0.1235
C=0.025, Validation Error: 0.1253
C=0.03125, Validation Error: 0.1257
C=0.0625, Validation Error: 0.1287

/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=0.125, Validation Error: 0.1344

/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=0.25, Validation Error: 0.1398
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=0.5, Validation Error: 0.1453

/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=1.0, Validation Error: 0.1498

/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

C=2.0, Validation Error: 0.1530
```



In [89]:

```
# Get test result for selected parameter

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# TO DO

x_train_compressed = x_train[:1000]
y_train_compressed = y_train[:1000]
x_val = x_train[50000:]
y_val = y_train[50000:]

best_C = 0.025

# Train a new model with the best C value on the larger initial tra
ining set
lr_best = LogisticRegression(C=best_C, max_iter=10000)
lr_best.fit(x_train_compressed, y_train_compressed)

# Evaluate on the test set
y_pred_test = lr_best.predict(x_test)
test_accuracy = accuracy_score(y_test, y_pred_test)
test_error = 1 - test_accuracy

print(f"Best C: {best_C}, Validation Error: {best_error:.4f}, Test
Error: {test_error:.4f}")
```

```
Best C: 0.025, Validation Error: 0.1235, Test Error: 0.1465
```

Part 3: Temperature Regression

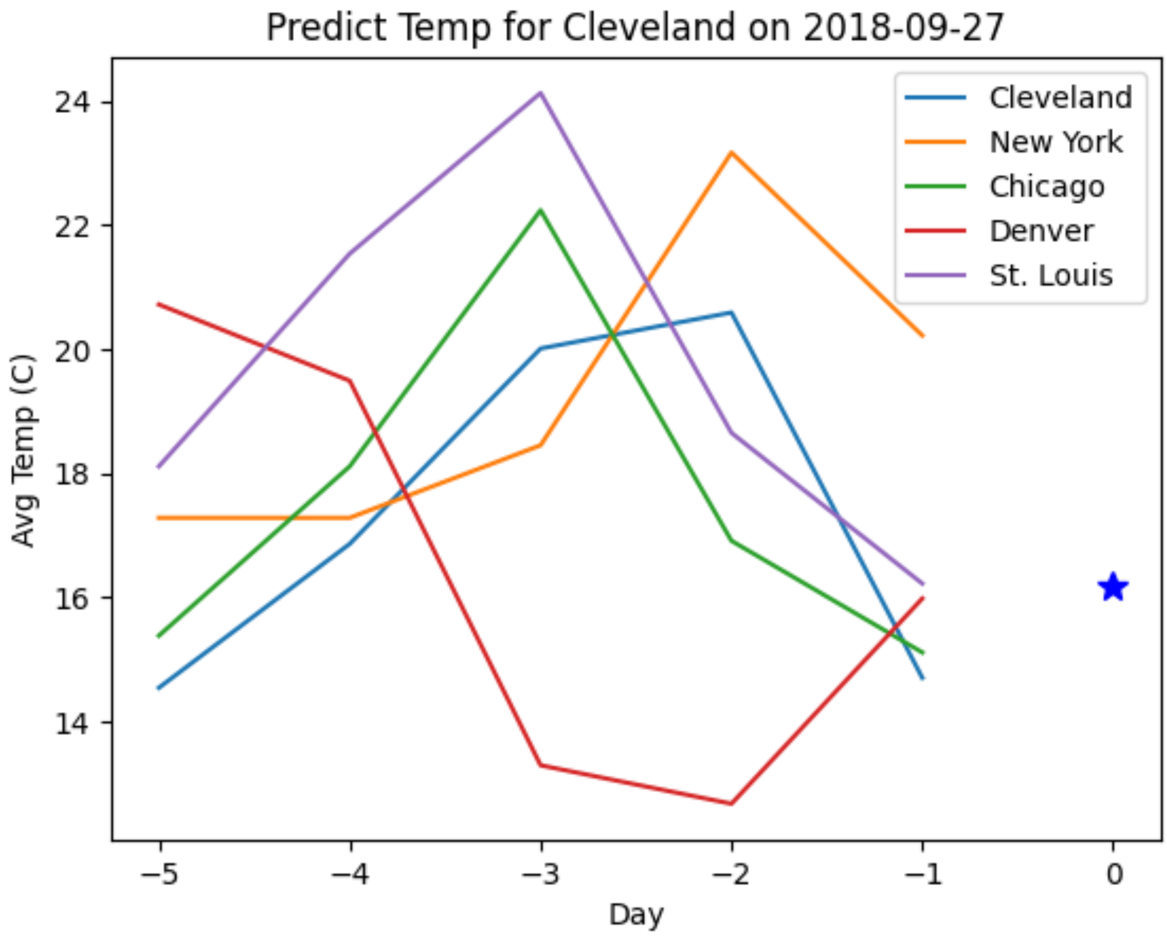
In [156]:

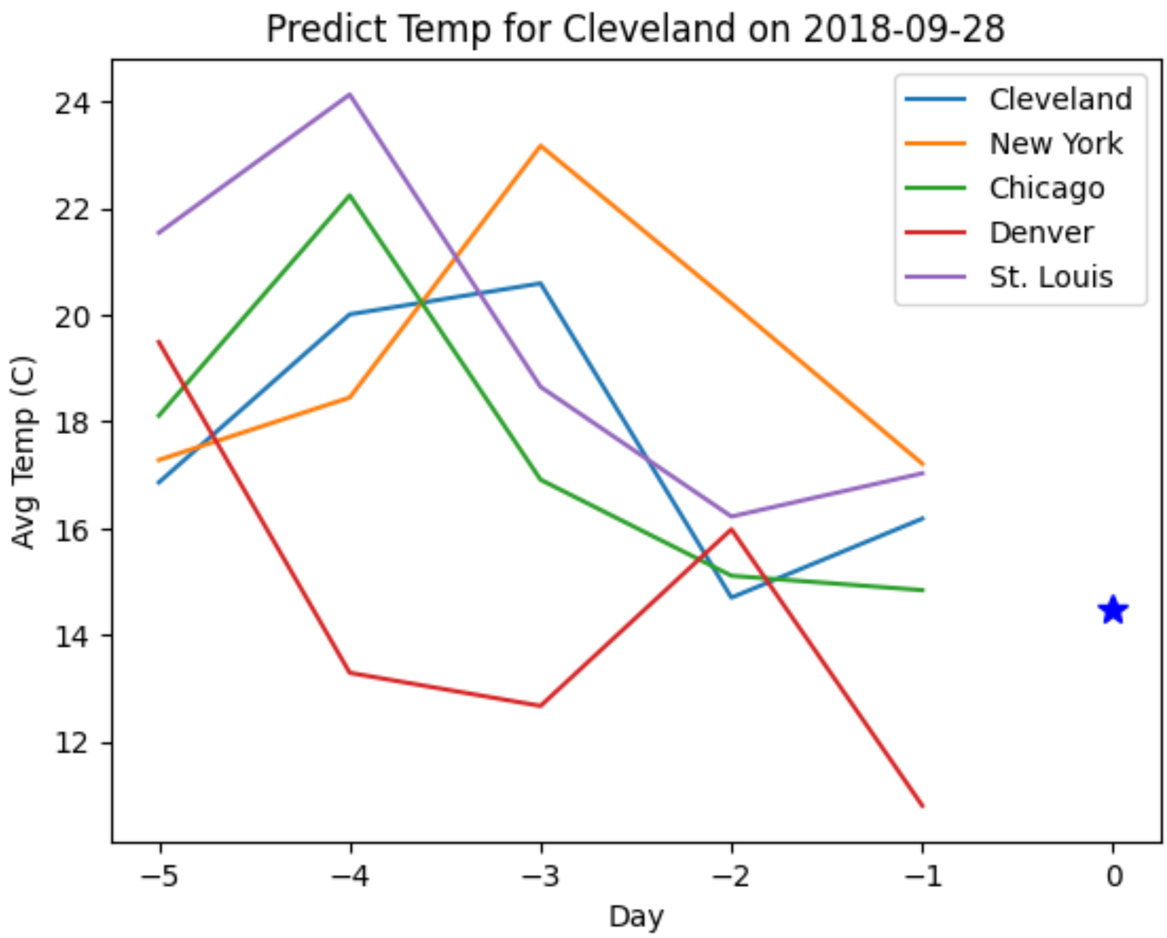
```
import numpy as np
from matplotlib import pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso

# load data (modify to match your data directory or comment)
def load_temp_data():

  datadir = "/Users/darian/Desktop/UIUC/Applied ML/HW2/Code/tempera
ture_data.npz"
  T = np.load(datadir)
  x_train, y_train, x_val, y_val, x_test, y_test, dates_train, date
s_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_tra
in, 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, targe
t_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 [210]:

```
# 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 s
ample (used to select hyperparameters, such as regularization and K
)
      x_test, y_test: features and target value for each test sampl
e (used to evaluate final performance)
      dates_xxx: date of the target value for the corresponding sam
ple
      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
print('Baseline - prediction using previous day: RMSE={}'.format(ba
seline_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
```


Predict Temp for Cleveland on 2018-09-27
Cleveland
New York
Chicago
Denver
St. Louis
Avg Temp (C)
24
22
20
18
16
14
−5
−4
−3
−2
−1
0
Day


Predict Temp for Cleveland on 2018-09-28
Cleveland
New York
Chicago
Denver
St. Louis
Avg Temp (C)
24
22
20
18
16
14
12
−5
−4
−3
−2
−1
0
Day

Linear regression test

In [158]:
```
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]
  '''
  x2 = x.copy()
  y2 = y.copy()
  for i in np.arange(len(x)):
    x2[i] = x[i] - x[i, fnum]
    y2[i] = y[i] - x[i,fnum]
  return x2, y2
```

In [173]:

```python
# linear regression (use Ridge)
from sklearn.linear_model import Ridge
import numpy as np

# original features
# TO DO

lin_regression_original = Ridge(alpha=1)
lin_regression_original.fit(x_train, y_train)
y_pred = lin_regression_original.predict(x_test)


# normalized features
# TO DO

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]
  '''
  x2 = x.copy()
  y2 = y.copy()
  for i in np.arange(len(x)):
    x2[i] = x[i] - x[i, fnum]
    y2[i] = y[i] - x[i,fnum]
  return x2, y2

fnum = 361

x_train_norm, y_train_norm = normalize_features(x_train, y_train, f
num)
x_test_norm, y_test_norm = normalize_features(x_test, y_test, fnum)

lin_regression_normalized = Ridge(alpha=1)
lin_regression_normalized.fit(x_train_norm, y_train_norm)
y_pred_norm = lin_regression_normalized.predict(x_test_norm)

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

rmse_original = calculate_rmse(y_pred, y_test)
rmse_normalized = calculate_rmse(y_pred_norm, y_test_norm)

print(f"RMSE orginal: ", rmse_original)
print(f"RMSE normalized: ", rmse_normalized)
```

```
RMSE orginal:  1.7743829555451878
RMSE normalized:  1.7725575696489029
```

Feature selection

In [160]:

```
from sklearn import linear_model
from sklearn.linear_model import Ridge


def load_temp_data():

  datadir = "/Users/darian/Desktop/UIUC/Applied ML/HW2/Code/tempera
ture_data.npz"
  T = np.load(datadir)
  x_train, y_train, x_val, y_val, x_test, y_test, dates_train, date
s_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_tra
in, dates_val, dates_test, feature_to_city, feature_to_day)

# feature analysis (select important features using Lasso)
# TO DO

lasso = linear_model.Lasso(alpha = 0.01).fit(x_train, y_train)
optimal_features = []
imp_features = lasso.coef_

for i in range(len(imp_features)):
    if abs(imp_features[i]) > 0.001:
        optimal_features.append((abs(imp_features[i]),i))

features_10 = sorted(optimal_features, reverse=True)[:10]
features_10_idx = []

for i in features_10:
    features_10_idx.append(i[1])

    print("Feature: {} City: {} Day: {}".format(i[1], feature_to_ci
ty[i[1]], feature_to_day[i[1]]))


# predict using best features
# TO DO

x_train_10 = x_train[:, features_10_idx]
x_test_10 = x_test[:, features_10_idx]

ridge = linear_model.Ridge(alpha = 0.01).fit(x_train_10, y_train)
y_pred_10 = ridge.predict(x_test_10)

rmse_features = np.sqrt(np.mean((y_pred_10-y_test)**2))

print("RMSE: {}".format(rmse_features))
```

```
Feature: 332 City: New York Day: -1
Feature: 361 City: Cleveland Day: -1
Feature: 348 City: Tampa Day: -1
Feature: 412 City: New Haven Day: -1
Feature: 350 City: Brooklyn Day: -1
Feature: 334 City: Chicago Day: -1
Feature: 345 City: Detroit Day: -1
Feature: 405 City: Grand Rapids Day: -1
Feature: 347 City: Minneapolis Day: -1
Feature: 314 City: Fresno Day: -2
RMSE: 2.3531757895767713
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/linear_model/_co
ordinate_descent.py:628: ConvergenceWarning: Objective did not con
verge. You might want to increase the number of iterations, check
the scale of the features or consider increasing regularisation. D
uality gap: 2.727e+03, tolerance: 2.049e+01
  model = cd_fast.enet_coordinate_descent(
```

Part 4: Stretch Goals

Include all your code used for any stretch goals in this section. Add headings where appropriate.

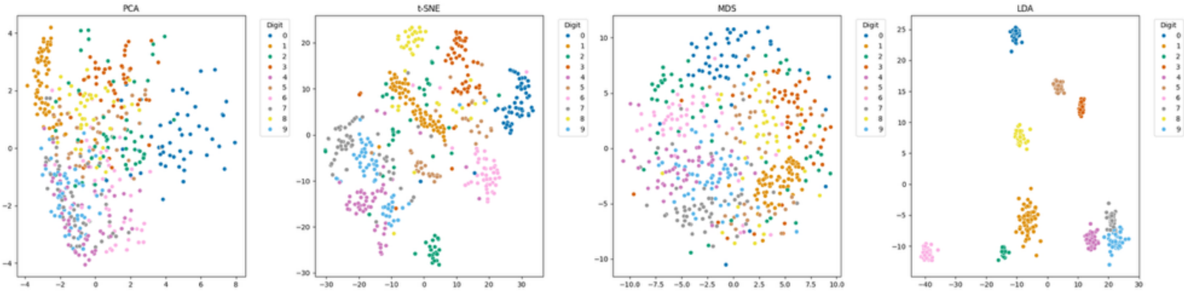
4a: PR and ROC curves:

4c: Other embeddings

In [167]:

```python
from sklearn.manifold import TSNE, MDS
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

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

x_compressed = x_train[:500]
y_compressed = y_train[:500]

# PCA transformation
pca = PCA(n_components=2)
x_pca = pca.fit_transform(x_compressed)

# t-SNE transformation
tsne = TSNE(n_components=2, random_state=42)
x_tsne = tsne.fit_transform(x_compressed)

# MDS transformation
mds = MDS(n_components=2, random_state=42)
x_mds = mds.fit_transform(x_compressed)

# LDA transformation
lda = LDA(n_components=2)
x_lda = lda.fit_transform(x_compressed, y_compressed)

# Plotting
fig, axes = plt.subplots(1, 4, figsize=(24, 6))
plot_labels = ['PCA', 't-SNE', 'MDS', 'LDA']

for i, (x_transformed, title) in enumerate(zip([x_pca, x_tsne, x_mds, x_lda], plot_labels)):
    sns.scatterplot(ax=axes[i], x=x_transformed[:,0], y=x_transformed[:,1], hue=y_compressed, palette="colorblind", legend="full")
    axes[i].set_title(title)
    axes[i].legend(title='Digit', bbox_to_anchor=(1.05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/manifold/_mds.p
y:298: FutureWarning: The default value of `normalized_stress` wil
l change to `'auto'` in version 1.4. To suppress this warning, man
ually set the value of `normalized_stress`.
  warnings.warn(
```



4d. Best city for temp prediction

In [212]:

```
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

def load_temp_data():

  datadir = "/Users/darian/Desktop/UIUC/Applied ML/HW2/Code/tempera
ture_data.npz"
  T = np.load(datadir)
  x_train, y_train, x_val, y_val, x_test, y_test, dates_train, date
s_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_tra
in, dates_val, dates_test, feature_to_city, feature_to_day)

# Load the 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()

def evaluate_city(city_index):
    # Select data for the specified city
    x_train_city = x_train[:, city_index].reshape(-1, 1)
    x_val_city = x_val[:, city_index].reshape(-1, 1)

    # Train a linear regression model
    model = LinearRegression()
    model.fit(x_train_city, y_train)

    # Predict on the validation set
    y_val_pred = model.predict(x_val_city)

    # Calculate RMSE
    rmse = np.sqrt(mean_squared_error(y_val, y_val_pred))

    return rmse

# Dictionary to hold city names and their corresponding RMSE values
city_rmse = {}

# Iterate over all cities (assuming one feature per city)
for city_index in range(x_train.shape[1]):
    rmse = evaluate_city(city_index)
    city_name = feature_to_city[city_index]  # Assuming feature_to_
city is a list mapping feature indices to city names
    city_rmse[city_name] = rmse

# Sort cities by RMSE and print the results
sorted_cities_by_rmse = sorted(city_rmse.items(), key=lambda item:
item[1])

print("Cities and their RMSE on validation data:")
for city, rmse in sorted_cities_by_rmse:
    print(f"{city}: {rmse:.4f}")
```

```
Cities and their RMSE on validation data:
```

Chicago: 2.8442
St. Louis: 2.8659
Indianapolis: 2.9853
Grand Rapids: 3.1193
Milwaukee: 3.1711
Detroit: 3.3436
Kansas City: 3.4068
Cleveland: 3.4079
Dayton: 3.4296
Cincinnati: 3.4822
Louisville: 3.5352
Tulsa: 3.6153
Akron: 3.6754
Minneapolis: 3.6967
Columbus: 3.7233
Memphis: 3.7251
Nashville: 3.8208
Oklahoma City: 3.8307
Omaha: 3.9372
Buffalo: 3.9613
Dallas: 4.1461
Pittsburgh: 4.1886
Fort Worth: 4.2271
Rochester: 4.3033
Knoxville: 4.3504
Austin: 4.4012
San Antonio: 4.4939
Birmingham: 4.5117
Manhattan: 4.5320
New York: 4.5342
Brooklyn: 4.5348
Bronx: 4.5359
Queens: 4.5470
Baltimore: 4.5659
Bridgeport: 4.5908
New Orleans: 4.5965
New Haven: 4.6441
Albany: 4.6873
Allentown: 4.6877
Houston: 4.6955
Philadelphia: 4.7579
Washington: 4.7773
Springfield: 4.7908
Atlanta: 4.8338
Hartford: 4.8475
Baton Rouge: 4.9067
Boston: 4.9734
Providence: 4.9836
Virginia Beach: 5.0083
Colorado Springs: 5.0569
Charlotte: 5.1007
El Paso: 5.2057
Albuquerque: 5.2148
Richmond: 5.2229
Denver: 5.2366
Raleigh: 5.3124
Ogden: 5.4174

```
Columbia: 5.4431
McAllen: 5.4881
Salt Lake City: 5.4916
Charleston: 5.5216
Seattle: 5.5735
Las Vegas: 5.5946
Phoenix: 5.6157
Portland: 5.6385
Sacramento: 5.6967
Fresno: 5.7408
Tucson: 5.8491
Jacksonville: 5.9406
Bakersfield: 5.9406
Sarasota: 6.0134
Cape Coral: 6.2157
Concord: 6.2443
Tampa: 6.3157
Honolulu: 6.4835
Orlando: 6.5291
Miami: 6.5451
Riverside: 6.6221
San Jose: 6.7731
Los Angeles: 6.9142
San Francisco: 6.9842
Mission Viejo: 7.1521
San Diego: 7.3052
```

In [207]:

```
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

def load_temp_data():
    # Placeholder for the actual load_temp_data function
    pass

def train_and_evaluate_city(x_train, y_train, x_test, y_test, featu
re_to_city, city_name):
    """
    Trains a Linear Regression model for a specific city's temperat
ure data and evaluates it on the test set.

    Parameters:
    - x_train: Training feature data
    - y_train: Training target data
    - x_test: Test feature data
    - y_test: Test target data
    - feature_to_city: List mapping feature indices to city names
    - city_name: The name of the city to evaluate

    Returns:
    - rmse_test: The RMSE of the model on the test set for the spec
ified city
    """
    # Load the data
    x_train, y_train, x_val, y_val, x_test, y_test, dates_train, da
tes_val, dates_test, feature_to_city, feature_to_day = load_temp_da
ta()
```

```
    # Find the index for the specified city
    try:
        index = feature_to_city.index(city_name)
    except ValueError:
        print(f"{city_name} not found in the feature_to_city mappin
g.")
        return

    # Select the temperature data for the specified city
    x_train_city = x_train[:, index].reshape(-1, 1)
    x_test_city = x_test[:, index].reshape(-1, 1)

    # Train a Linear Regression model on the training data for the
city
    model = LinearRegression()
    model.fit(x_train_city, y_train)

    # Predict the temperature on the test set
    y_test_pred = model.predict(x_test_city)

    # Calculate the RMSE on the test set
    rmse_test = np.sqrt(mean_squared_error(y_test, y_test_pred))

    print(f"Test RMSE for {city_name}: {rmse_test:.4f}")
    return rmse_test

# Example usage
# Assuming the load_temp_data function is defined elsewhere and loa
ds your dataset correctly
# rmse_test_st_louis = train_and_evaluate_city(x_train, y_train, x_
test, y_test, feature_to_city, 'St. Louis')
```

4e. SVM with RBF Kernel

In [190]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC, SVC
from sklearn.metrics import accuracy_score
import numpy as np

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

nsample = [100, 1000, 10000, 60000]
results_lin = []
results_rbf = []

for N in nsample:
    x_train_N = x_train[:N]
    y_train_N = y_train[:N]

    # Train Linear SVM
    svm = LinearSVC(max_iter=10000)
    svm.fit(x_train_N, y_train_N)
    y_pred_svm = svm.predict(x_test)
    error_svm = 1 - accuracy_score(y_test, y_pred_svm)

    # Train RBF SVM
    svm_rbf = SVC(max_iter=10000, kernel="rbf")
    svm_rbf.fit(x_train_N, y_train_N)
    y_pred_svm_rbf = svm_rbf.predict(x_test)
    error_svm_rbf = 1 - accuracy_score(y_test, y_pred_svm_rbf)

    # Store the results
    results_lin.append({
        'Training Size': N,
        'Linear SVM Error': error_svm
    })

    results_rbf.append({
        'Training Size': N,
        'RBF SVM Error': error_svm_rbf
    })

# Display the results
for result in results_lin:
    print(f"Training Size: {result['Training Size']}, Linear SVM Er
ror: {result['Linear SVM Error']:.4f}")

for result in results_rbf:
    print(f"Training Size: {result['Training Size']}, RBF SVM Error
: {result['RBF SVM Error']:.4f}")
```

```
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
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  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
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  warnings.warn(
/opt/homebrew/lib/python3.8/site-packages/sklearn/svm/_classes.py:
32: FutureWarning: The default value of `dual` will change from `T
rue` to `'auto'` in 1.5. Set the value of `dual` explicitly to sup
press the warning.
  warnings.warn(

Training Size: 100, Linear SVM Error: 0.3235
Training Size: 1000, Linear SVM Error: 0.1611
Training Size: 10000, Linear SVM Error: 0.1112
Training Size: 60000, Linear SVM Error: 0.0817
Training Size: 100, RBF SVM Error: 0.3441
Training Size: 1000, RBF SVM Error: 0.0917
Training Size: 10000, RBF SVM Error: 0.0406
Training Size: 60000, RBF SVM Error: 0.0208
```

In [122]:

```
# from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27
b343dca4abba
# install can take a minute

import os
# @title Convert Notebook to PDF. Save Notebook to given directory
NOTEBOOKS_DIR = "/content/drive/My Drive/CS441/24SP/hw2" # @param {
type:"string"}
NOTEBOOK_NAME = "CS441_SP24_HW2_Solution.ipynb" # @param {type:"str
ing"}
#-----------------------------------------------------------------
------------#
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: {NOTEBO
OK_PATH}"
!apt install -y texlive-xetex texlive-fonts-recommended texlive-pla
in-generic > /dev/null 2>&1
!jupyter nbconvert "$NOTEBOOK_PATH" --to pdf > /dev/null 2>&1
NOTEBOOK_PDF = NOTEBOOK_PATH.rsplit('.', 1)[0] + '.pdf'
assert os.path.exists(NOTEBOOK_PDF), f"ERROR MAKING PDF: {NOTEBOOK_
PDF}"
print(f"PDF CREATED: {NOTEBOOK_PDF}")
```

```
-----------------------------------------------------------------
---------
ModuleNotFoundError                       Traceback (most recent c
all last)
Cell In[122], line 9
      7 NOTEBOOK_NAME = "CS441_SP24_HW2_Solution.ipynb" # @param {
type:"string"}
      8 #-------------------------------------------------------
---------------------#
----> 9 from google.colab import drive
     10 drive.mount("/content/drive/", force_remount=True)
     11 NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"

ModuleNotFoundError: No module named 'google.colab'
```

In [ ]: