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CS 441 - HW2: PCA and Linear Models

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

Total Points Available **[ ] / 160**

1. PCA on MNIST
    a. Display 10 principal component vectors [ ] / 5
    b. Display scatterplot [ ] / 5
    c. Plot cumulative explained variance [ ] / 5
    d. Compression and 1-NN experiment [ ] / 15
2. MNIST Classification with Linear Models
    a. LLR / SVM error vs training size [ ] / 20
    b. Error visualization [ ] / 10
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3. Temperature Regression
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4. Stretch Goals
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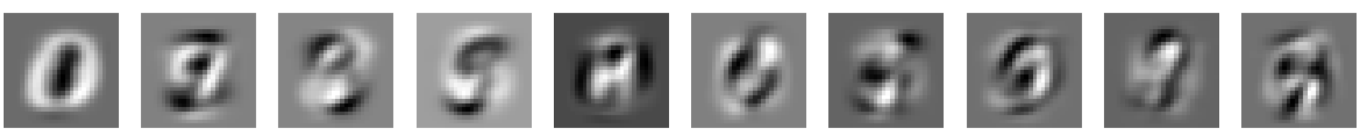
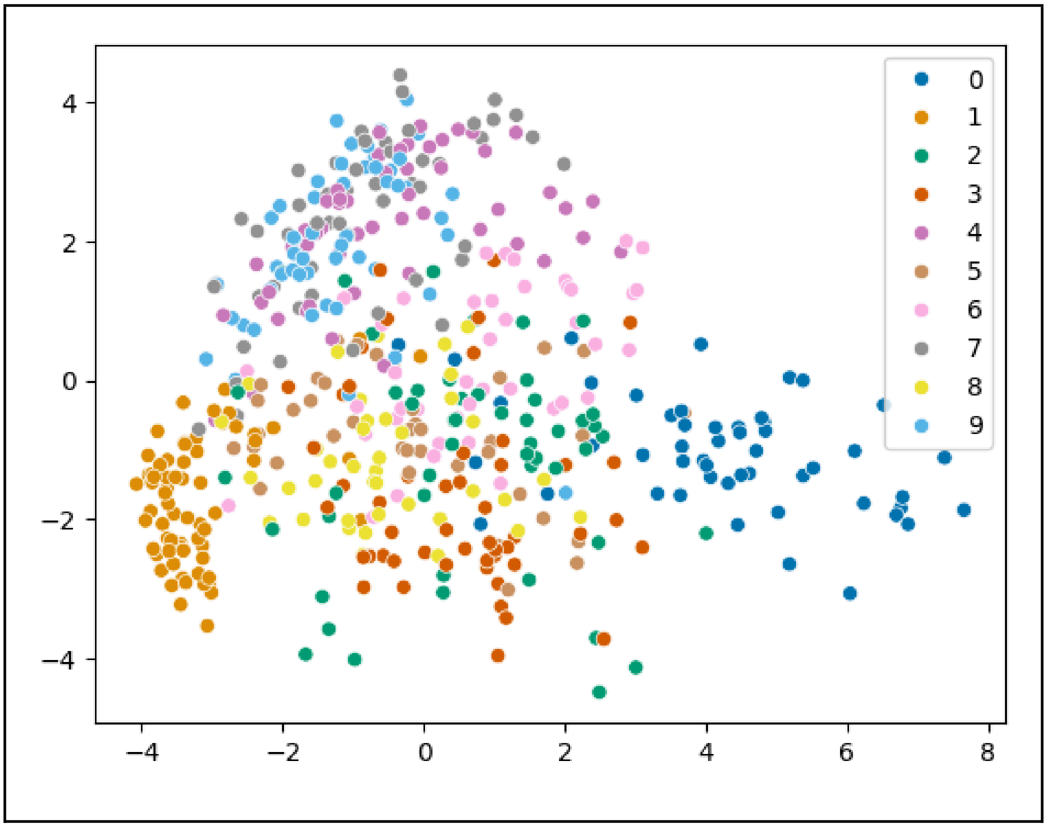
1. PCA on MNIST

a. Display 10 principal component vectors

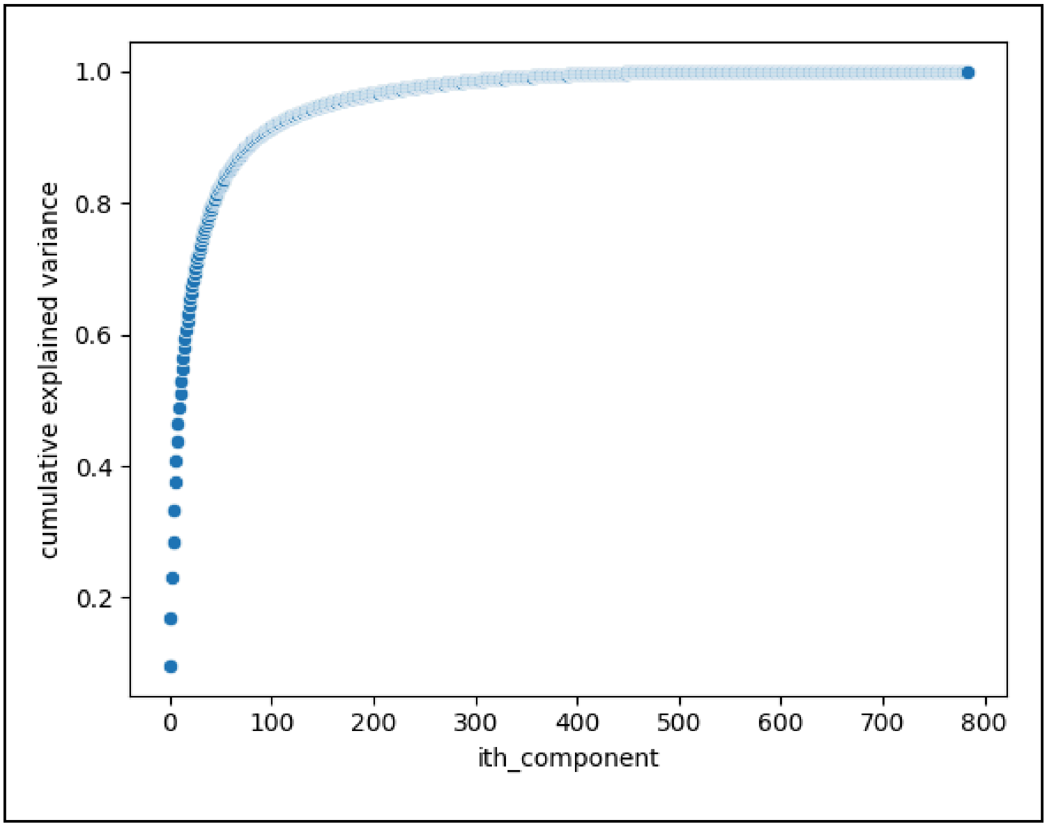


b. Display scatterplot

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)	1.28	2.68	87
Brute Force	5.49	3.09	784

2. MNIST Classification with Linear Models

a. LLR / SVM error vs training size

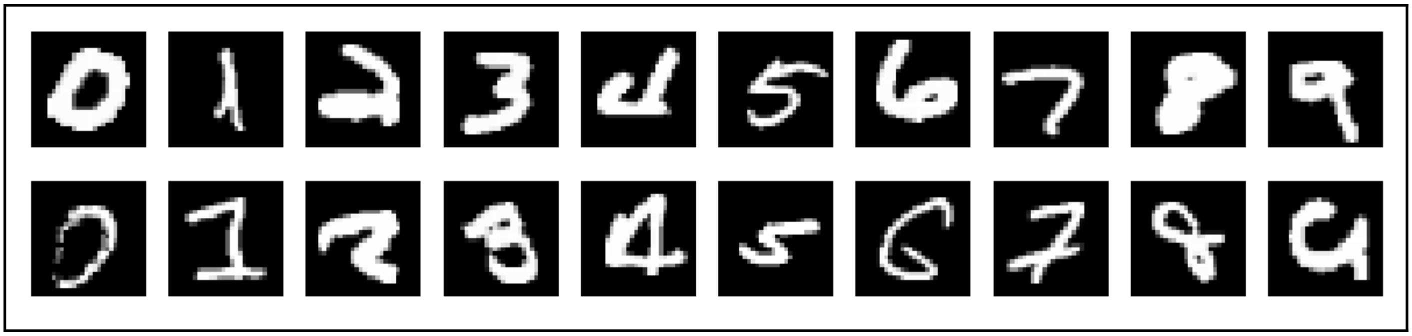
Test error (%)

# training samples	LLR	SVM
100	32.5%	32.4%
1,000	13.64	16.11

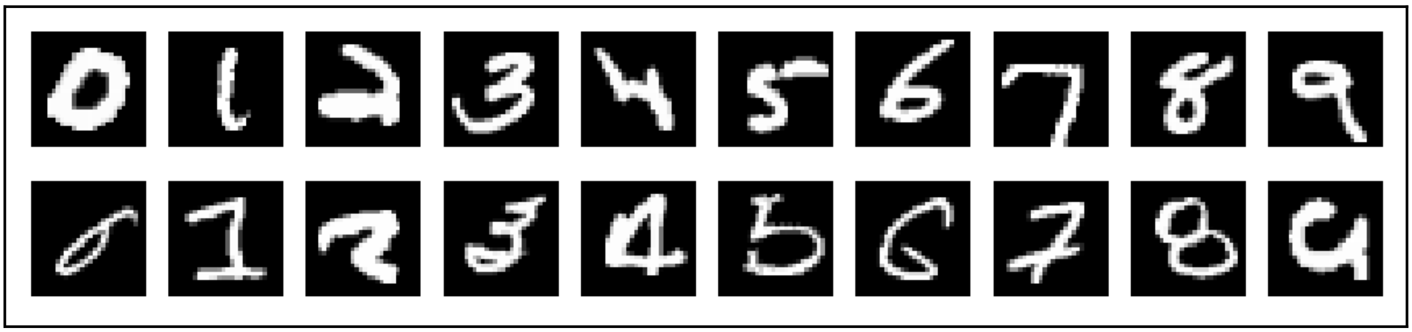
10,000	9.5	11.12
60,000	7.39	8.17

b. Error visualization

LLR



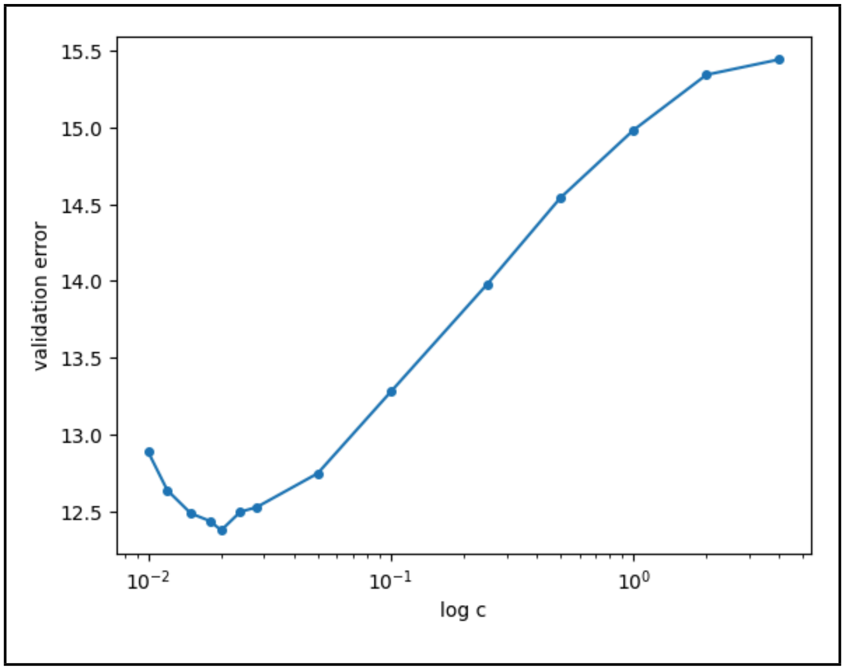
SVM



c. Parameter selection experiments

	Logistic Regression
Best C value	0.02
Validation error (%)	12.38
Test error (%)	13.57

Plot C value vs validation error for values tested



3. Temperature Regression

a. Linear regression test

Test RMSE

	Linear regression
Original features	2.161
Normalized features	2.163

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

Linear regression is not sensitive to the scale of the features as much as KNN. Additionally, if the relationship between the features and the target variable is non-linear, normalizing the data might not necessarily improve performance and could even lead to an increase in RMSE.

b. Feature selection results

Feature Rank	Feature number	City	Day
1	334	Chicago	-1
2	347	Minneapolis	-1
3	405	Grand Rapids	-1
4	336	Kansas City	-1
5	361	Cleveland	-1
6	307	Omaha	-2
7	367	Indianapolis	-1
8	264	Minneapolis	-2
9	9	Boston	-5
10	236	Springfield	-3

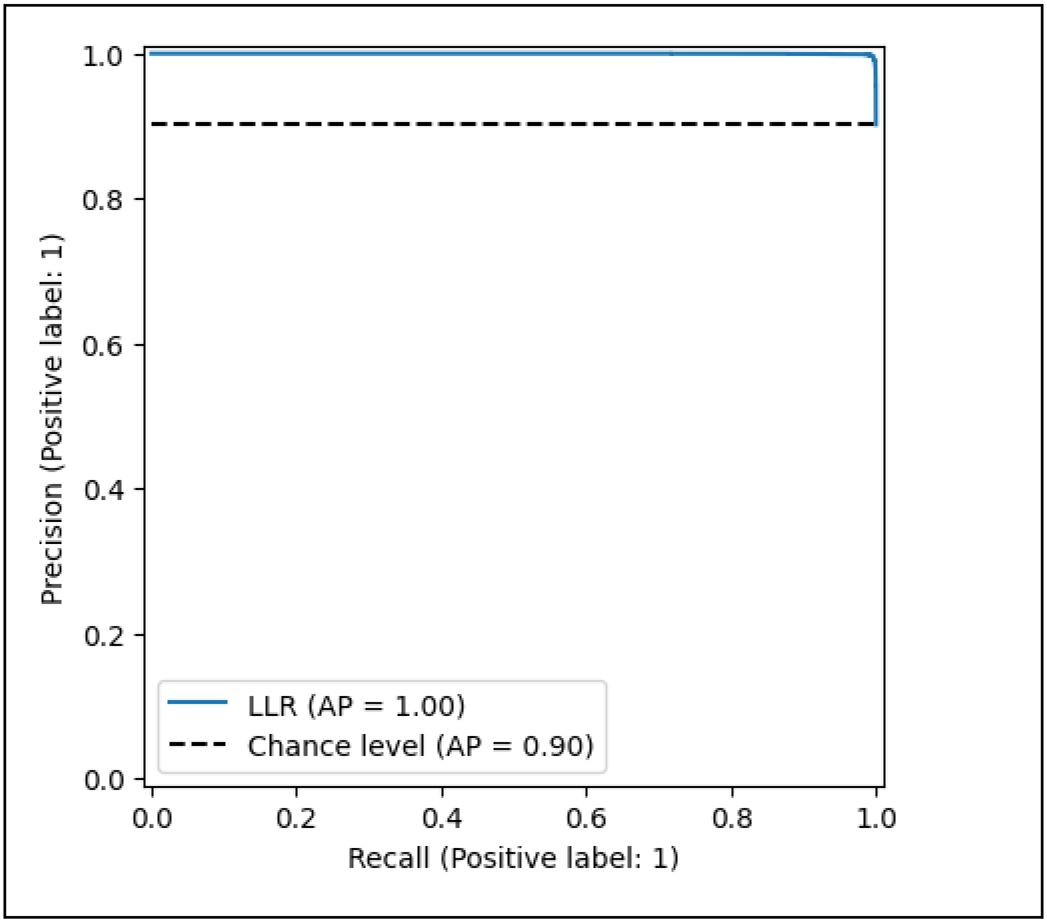
Test error using only the 10 most important features for regression

	Linear Regression
RMS Error	2.058

4. Stretch Goals

a. PR and ROC curves

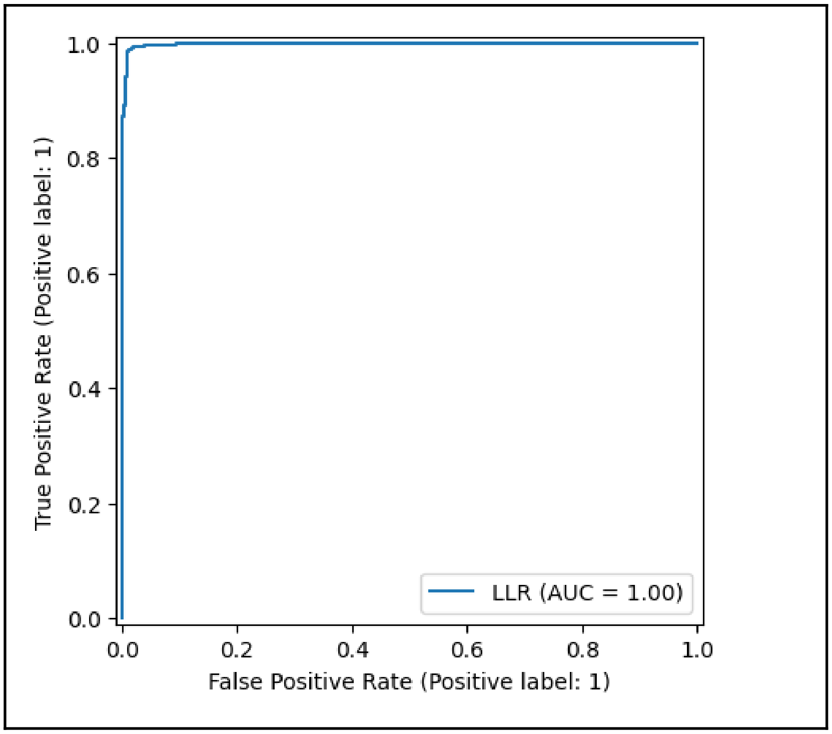
PR plot



Average Precision

1.0

ROC plot

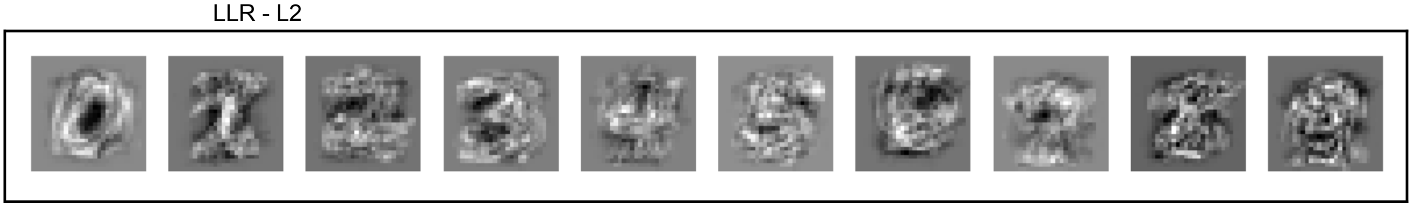


Area under the curve (AUC)

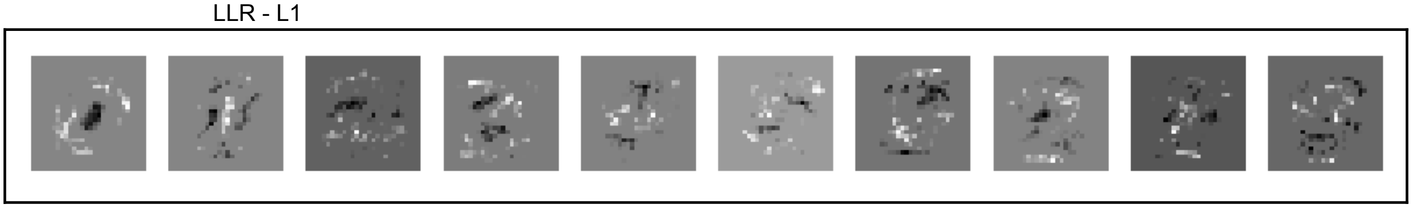
1.0

b. Visualize weights

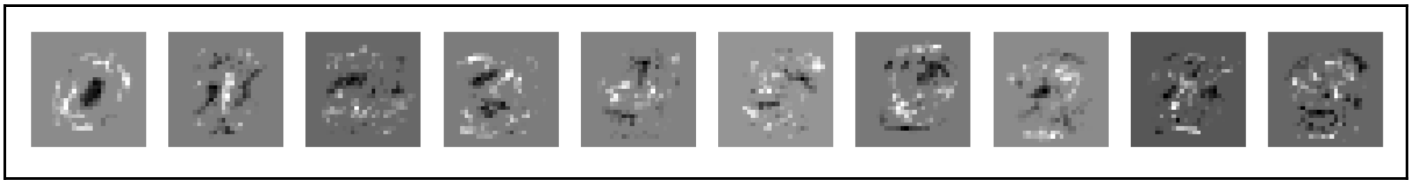
LLR - L2



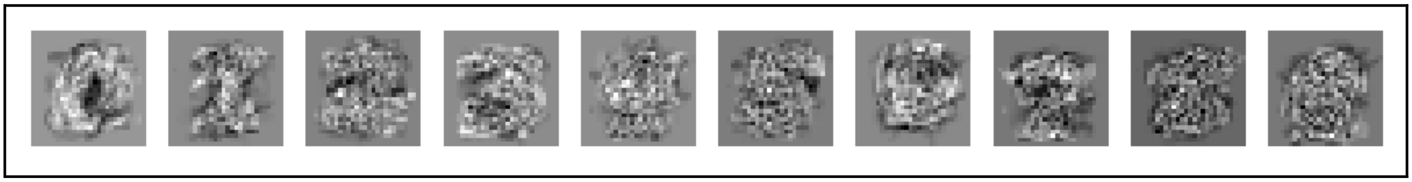
LLR - L1



LLR - elastic



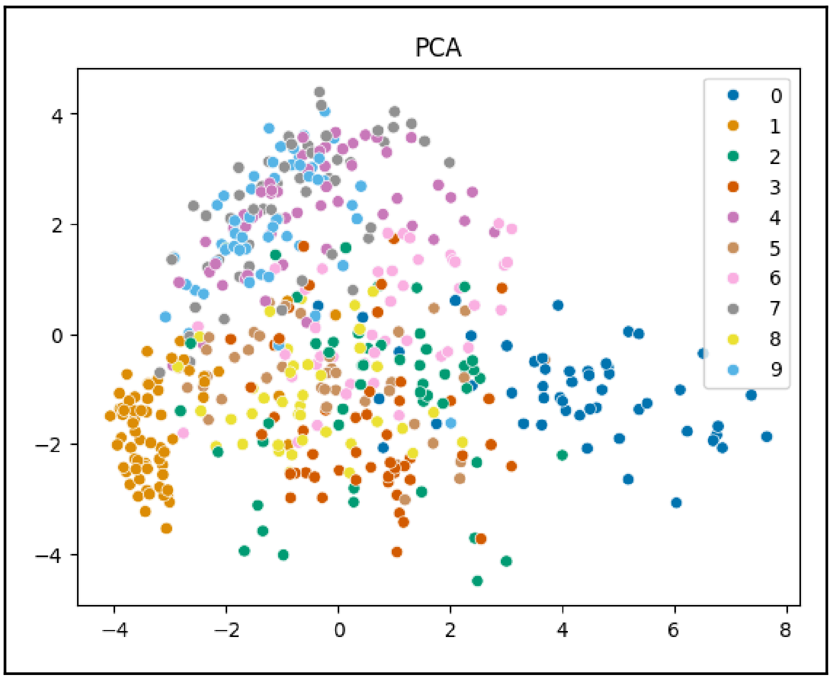
SVM



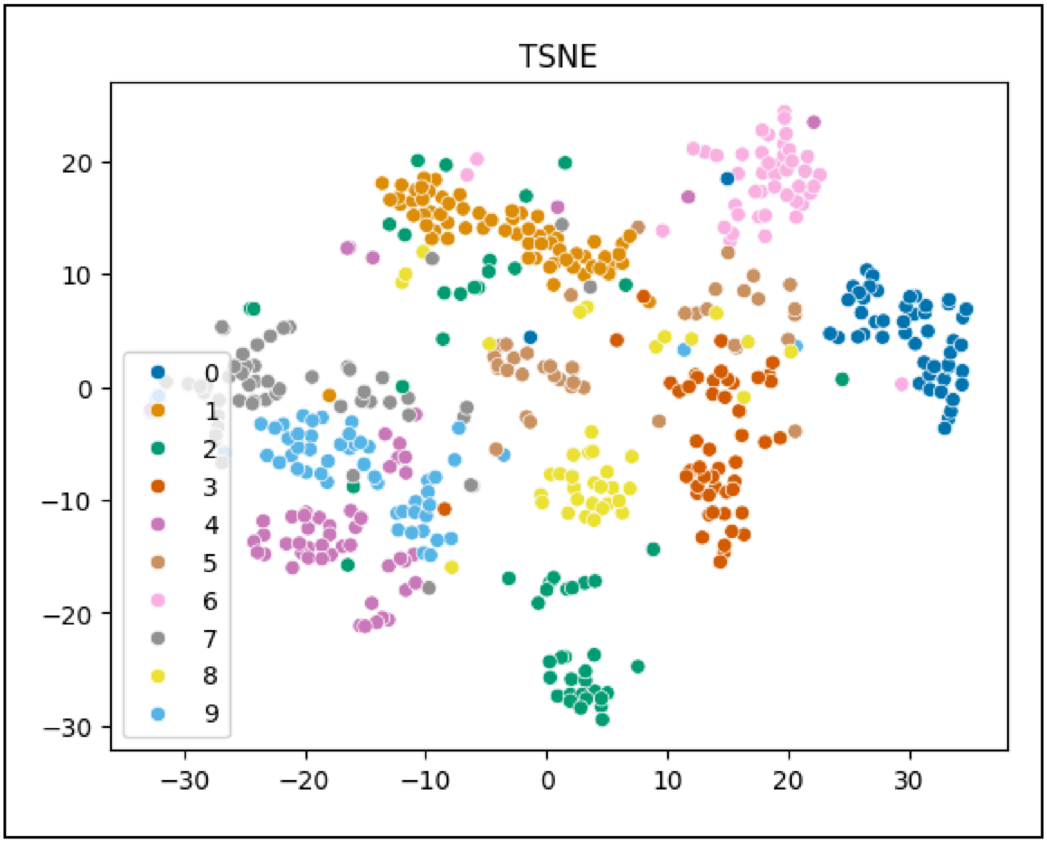
c. Other embeddings

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

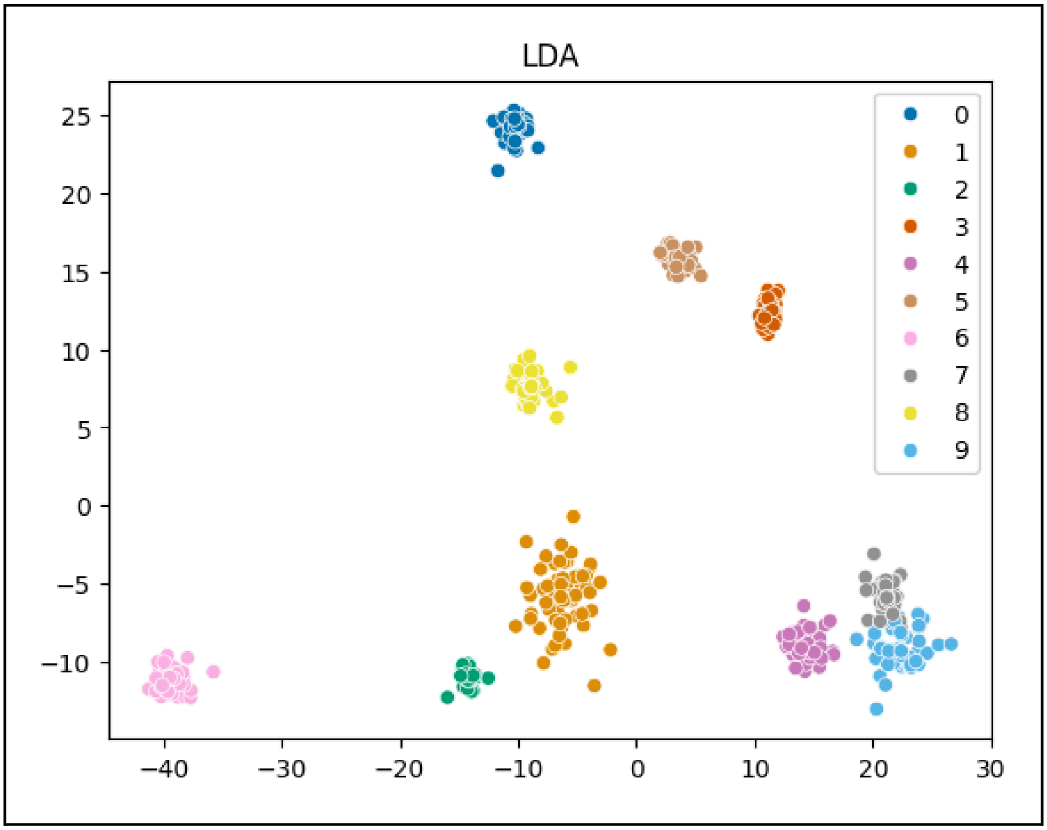
PCA



[TSNE]



[LDA]



d. One city is all you need

City

Test error using features only from that city

Explain your process (in words):

e. Compare linear SVM and SVM with RBF kernel

Test accuracy (%)

# training samples	SVM-Linear	SVM-RBF
100	67.5%	65.59%
1,000	86.36%	90.83%
10,000	90.5%	95.94%
60,000	92.61%	97.92%

Acknowledgments / Attribution

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

None

cs441-sp24-hw2-starter

February 20, 2024

0.1 CS441: Applied ML - HW 2

0.1.1 Parts 1-2: MNIST

Include all the code for generating MNIST results below

[80]:
```
# 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
import cache_magic

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()
```

0.1.2 Part 1: PCA and Data Compression

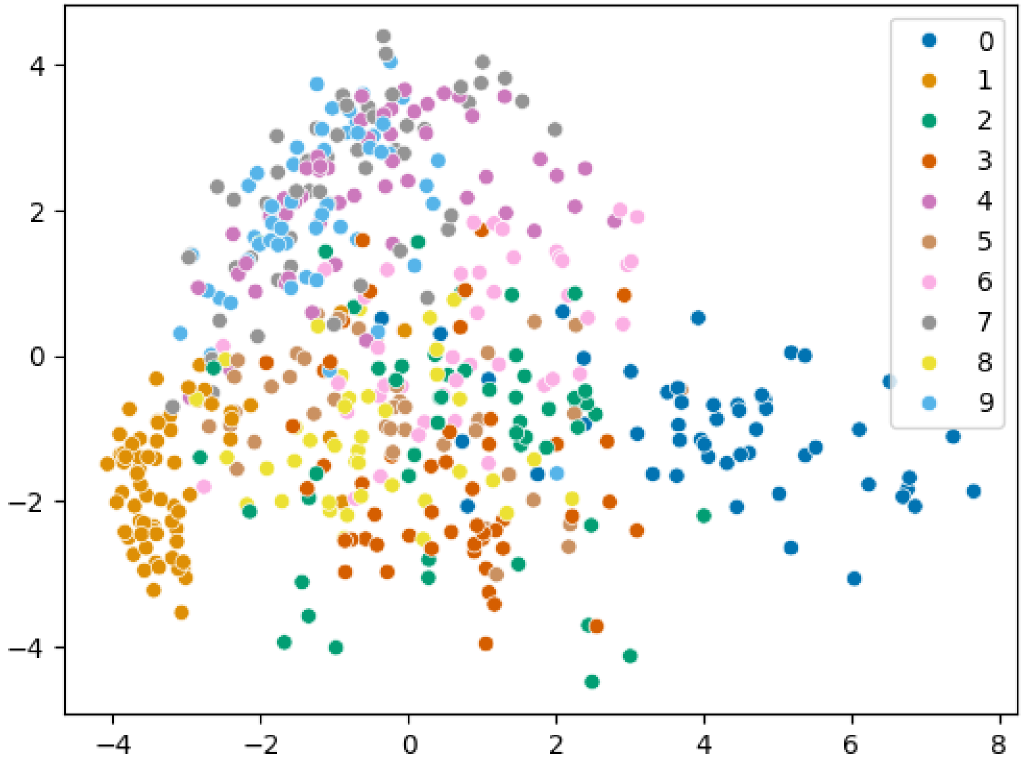
[81]:
```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

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

# Compute the first 10 principal components using x_train

%cache pca1a = PCA(n_components=10).fit(x_train)

print(pca1a.components_.shape)
# Display First 10 Components
display_mnist(pca1a.components_, subplot_rows=1, subplot_cols=10)
```

```
Loading cached value for variable 'pca1a'. Time since caching: 8 days,
1:38:03.816843
(10, 784)
```

[82]:
```
# Scatter plot of first two PCA dimensions
import seaborn as sns

# use pca.transform
%cache pca1b = PCA(n_components=2).fit(x_train)
x = pca1b.transform(x_train[:500])
ind = np.arange(500)
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind")
```

```
Loading cached value for variable 'pca1b'. Time since caching: 8 days,
1:40:06.955217
```

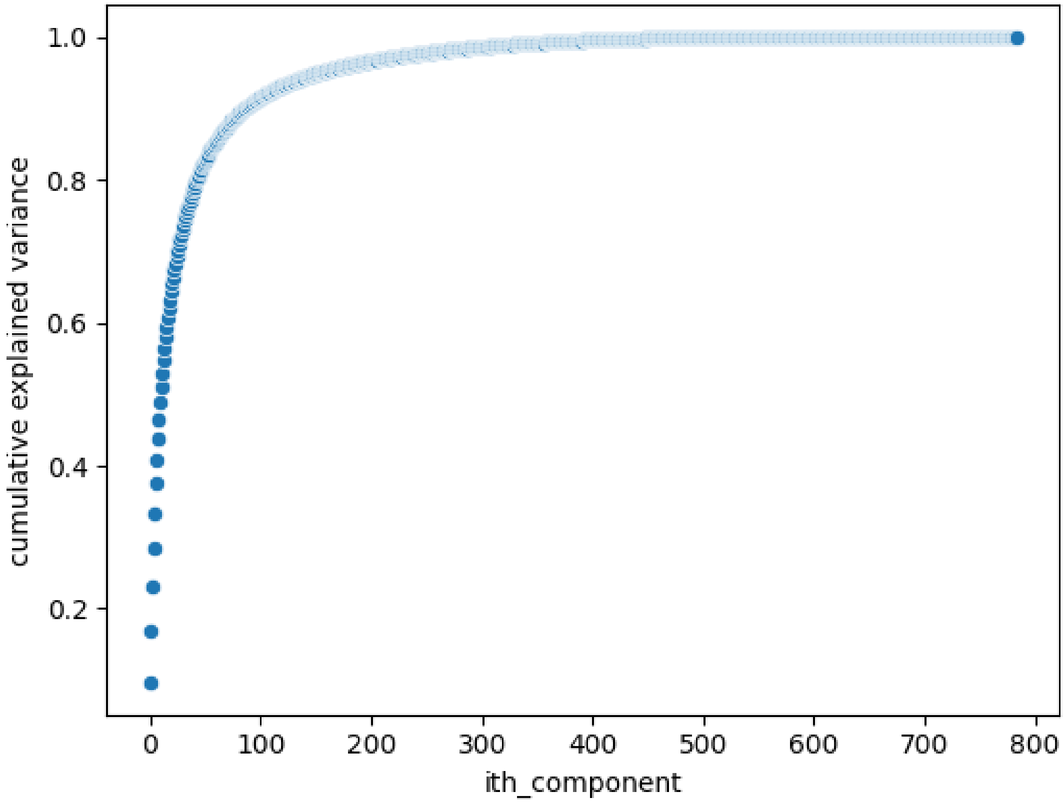
[82]: <Axes: >



[83]:
```
# Plot cumulative explained variance ratio
# cumsum and pca.explained_variance_ratio_ will be useful

%cache pca1c = PCA().fit(x_train)
cumul = np.cumsum(pca1c.explained_variance_ratio_)
sns.scatterplot(
    data = {
        "ith_component": np.arange(0, len(cumul), 1),
        "cumulative explained variance": cumul
    },
    x = "ith_component",
    y = "cumulative explained variance"
)
```

```
Loading cached value for variable 'pca1c'. Time since caching: 8 days,
1:37:55.480961
```

[83]: `<Axes: xlabel='ith_component', ylabel='cumulative explained variance'>`



[84]:
```
# Select number of dimensions that explains 90% of variance, according to your
↪plot above
# !apt install libomp-dev > /dev/null 2>&1
# !pip install faiss-cpu > /dev/null 2>&1
import faiss
import time

# plus 1 because of 0 indexing
M = np.argwhere(cumul >= 0.9)[0].item() + 1
print(f"M = {M}")

# compress training data and test data
%cache pca1d = PCA(n_components=M).fit(x_train)
compressed_train, compressed_test = pca1d.transform(x_train), pca1d.
↪transform(x_test)

def create_and_add(dim, data):
    idx = faiss.IndexFlatL2(dim)
    idx.add(data)
    return idx
# Get time and error when using original features with brute force 1-NN
```

```
%cache original_index = create_and_add(x_train.shape[1], x_train)
t1 = time.time()
dist, prediction = original_index.search(x_test, 1)
t2 = time.time()
timing = t2 - t1
# prediction = y_train[prediction]
# error = prediction[prediction != y_test.reshape(-1, 1)].sum() /
↪len(prediction) * 100
error = np.mean(y_train[prediction.flatten()] != y_test) * 100
print(f"original error = {error}% | time = {timing}")
# print(np.mean(dist))

# Get time and error when using compressed features with brute force 1-NN
%cache comp_index = create_and_add(compressed_train.shape[1], compressed_train)
t1 = time.time()
dist, prediction = comp_index.search(compressed_test, 1)
t2 = time.time()
timing = t2 - t1
# prediction = y_train[prediction]
error = np.mean(y_train[prediction.flatten()] != y_test) * 100
print(f"compressed error = {error}% | time = {timing}")
# print(np.mean(dist))
```

```
M = 87
Loading cached value for variable 'pca1d'. Time since caching: 8 days,
1:37:52.756670
Loading cached value for variable 'original_index'. Time since caching: 8 days,
1:37:50.756619
original error = 3.09% | time = 5.727076530456543
Loading cached value for variable 'comp_index'. Time since caching: 8 days,
1:37:50.332103
compressed error = 2.68% | time = 1.317983627319336
```

[85]:
```
%cache
```

```
<IPython.core.display.HTML object>
```

0.1.3 Part 2: MNIST Classification with Linear Models

[86]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.metrics import accuracy_score
```

LLR/SVM vs training size

[87]:
```
# LLR
sizes = [100, 1000, 10000, 60000]
```

```
train_llr = lambda: [LogisticRegression(max_iter=10000).fit(x_train[:sz],␣
 ↪y_train[:sz]) for sz in sizes]
%cache llr_estimators = train_llr()
print([1 - accuracy_score(llr.predict(x_test), y_test) for llr in␣
 ↪llr_estimators])
```

```
Loading cached value for variable 'llr_estimators'. Time since caching: 8 days,
1:37:11.062065
[0.32499999999999996, 0.13639999999999997, 0.09499999999999997,
0.07389999999999997]
```

[88]:
```
# SVM
train_svm = lambda: [svm.LinearSVC(max_iter=10000, dual='auto').fit(x_train[:
 ↪sz], y_train[:sz]) for sz in sizes]
%cache svm_estimators = train_svm()
errors = [(svm.predict(x_test) != y_test).sum() / len(y_test) * 100 for svm in␣
 ↪svm_estimators]
print([1 - accuracy_score(svm.predict(x_test), y_test) for svm in␣
 ↪svm_estimators])
```

```
Loading cached value for variable 'svm_estimators'. Time since caching: 7 days,
23:17:33.032995
[0.3235, 0.16110000000000002, 0.11119999999999997, 0.0817]
```

Error visualization

[89]:
```
scores = llr_estimators[-1].predict_proba(x_test)

llrhigh, llrlow = [], []
for cls in range(10):
    # get samples with true label of class
    cls_sample = x_test[y_test == cls]
    # get their scores
    cls_sample_scores = scores[y_test == cls][:, cls]
    # show
    llrhigh.append(cls_sample[np.argmax(cls_sample_scores)])
    llrlow.append(cls_sample[np.argmin(cls_sample_scores)])

print("LLR high and low confidence")
display_mnist(llrhigh, subplot_rows=1, subplot_cols=10)
display_mnist(llrlow, subplot_rows=1, subplot_cols=10)

scores = svm_estimators[-1].decision_function(x_test)
svmhigh, svmlow = [], []
for cls in range(10):
    # get samples with true label of class
    cls_sample = x_test[y_test == cls]
    # get their scores
```

```
    cls_sample_scores = scores[y_test == cls][:, cls]
    # show
    svmhigh.append(cls_sample[np.argmax(cls_sample_scores)])
    svmlow.append(cls_sample[np.argmin(cls_sample_scores)])

print("SVM high and low confidence")
display_mnist(svmhigh, subplot_rows=1, subplot_cols=10)
display_mnist(svmlow, subplot_rows=1, subplot_cols=10)
```

```
LLR high and low confidence
```

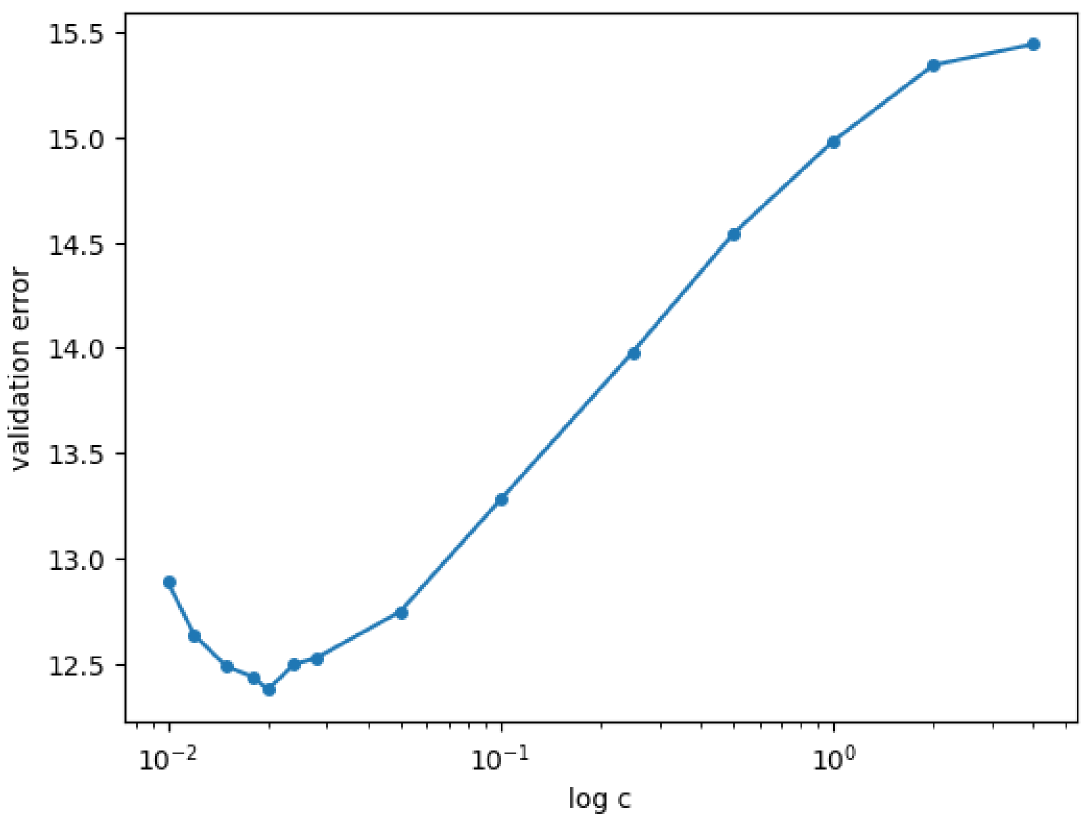
```
SVM high and low confidence
```

Parameter selection

[90]:
```
# Try multiple C parameters, select one that minimizes validation error
# Often, you need to try a few values and see those results to determine what␣
↪other values to try

get_error = lambda pred, y: (pred != y).sum() / len(y) * 100
C = [0.01, 0.012, 0.015, 0.018, 0.02, 0.024, 0.028, 0.05, 0.1, 0.25, 0.5, 1, 2,␣
↪4]
x_train2c, x_val2c = x_train[:1000], x_train[50000:]
```

```
y_train2c, y_val2c = y_train[:1000], y_train[50000:]
val_err = []
for c in C:
    model = svm.LinearSVC(max_iter=10000, dual='auto', C=c)
    model.fit(x_train2c, y_train2c)
    val_err.append(get_error(model.predict(x_val2c), y_val2c))
plt.semilogx(C, val_err, marker='o', markersize=4)
plt.xlabel('log c')
plt.ylabel('validation error')
```

[90]: Text(0, 0.5, 'validation error')



[91]:
```
# Get test result for selected parameter
%cache best_svm_model = svm.LinearSVC(max_iter=10000, dual='auto', C=0.02).
 ↪fit(x_train2c, y_train2c)
print(f"Validation error: {get_error(best_svm_model.predict(x_val2c),␣
 ↪y_val2c)}")
print(f"Test error: {get_error(best_svm_model.predict(x_test), y_test)}")
```

```
Loading cached value for variable 'best_svm_model'. Time since caching: 7 days,
15:46:20.024406
```

```
Validation error: 12.379999999999999
Test error: 13.569999999999999
```

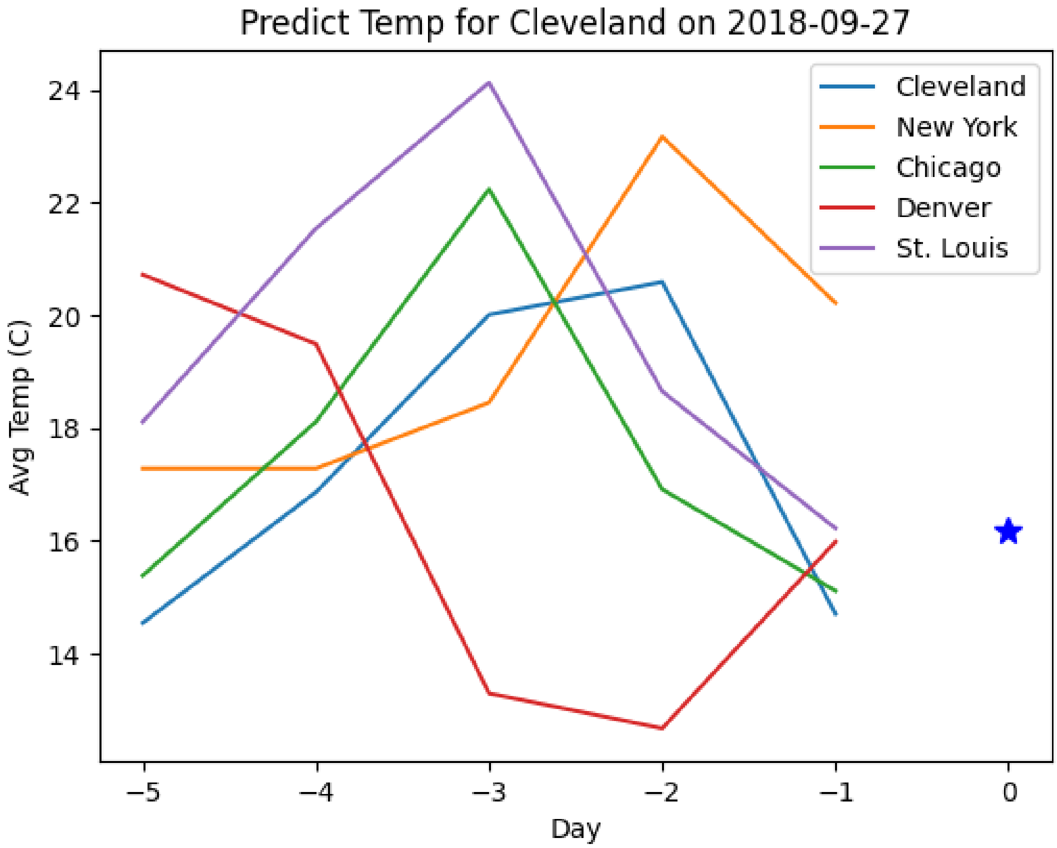
0.2 Part 3: Temperature Regression

[92]:
```
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():
  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()
```

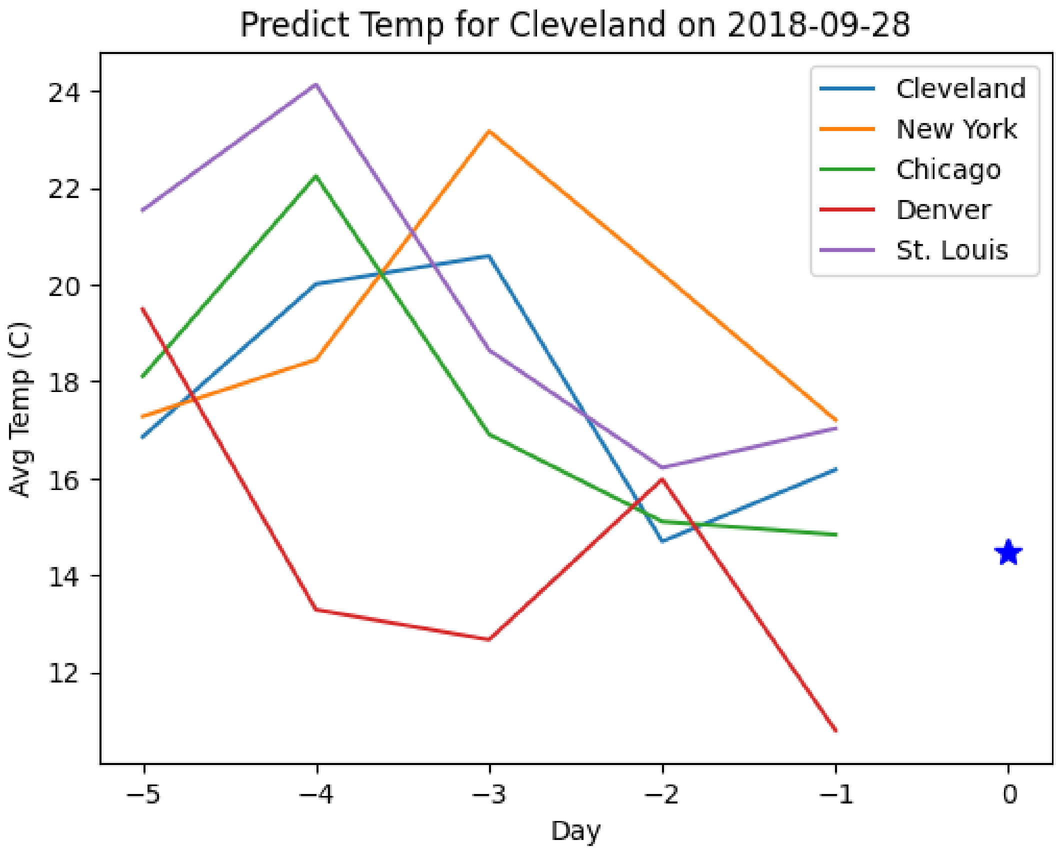
[93]:
```
# load data
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val,␣
↪dates_test, feature_to_city, feature_to_day) = load_temp_data()
''' Data format:
```

```python
    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
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
```



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



Linear regression test

[94]:
```
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
```

[95]:
```
F = 361
from sklearn.metrics import root_mean_squared_error
# linear regression (use Ridge)
# original features
%cache original_ridge = Ridge().fit(x_train, y_train)
```

```
print(f"original features rmse: {np.sqrt(np.mean((original_ridge.
 ↪predict(x_test) - y_test) ** 2))}")
# normalized features
(x_train_norm, y_train_norm), (x_test_norm, y_test_norm) =␣
 ↪normalize_features(x_train, y_train, F), normalize_features(x_test, y_test,␣
 ↪F)
%cache normalized_ridge = Ridge().fit(x_train_norm, y_train_norm)
print(f"normalized features rmse: {np.sqrt(np.mean((normalized_ridge.
 ↪predict(x_test_norm) - y_test_norm) ** 2))}")
```

```
Loading cached value for variable 'original_ridge'. Time since caching: 6 days,
0:30:16.487390
original features rmse: 2.160860526080926
Loading cached value for variable 'normalized_ridge'. Time since caching: 6
days, 0:22:20.693291
normalized features rmse: 2.1630698027573665
```

Feature selection

[96]:
```
# feature analysis (select important features using Lasso)
lasso = Lasso().fit(x_train, y_train)
lasso_indices = [(i, v) for i, v in enumerate(np.abs(lasso.coef_)) if v > 0.001]
lasso_indices.sort(key = lambda x: x[1], reverse=True)
top10_indices = [x[0] for x in lasso_indices[:10]]
print(f"Top 10: {top10_indices}")
print(f"Top 10 cities: {[feature_to_city[x] for x in top10_indices]}")
print(f"Top 10 days: {[feature_to_day[x] for x in top10_indices]}")

# predict using best features
selected_indices = [x[0] for x in lasso_indices]
root_mean_squared_error(
    Ridge().fit(
        np.take(x_train, selected_indices, axis=1), y_train)
        .predict(np.take(x_test, selected_indices, axis=1))
    , y_test
)
```

```
Top 10: [334, 347, 405, 366, 361, 307, 367, 264, 9, 236]
Top 10 cities: ['Chicago', 'Minneapolis', 'Grand Rapids', 'Kansas City',
'Cleveland', 'Omaha', 'Indianapolis', 'Minneapolis', 'Boston', 'Springfield']
Top 10 days: [-1, -1, -1, -1, -1, -2, -1, -2, -5, -3]
```

[96]: 2.0579879892446384

[97]:
```
%cache
```

```
<IPython.core.display.HTML object>
```

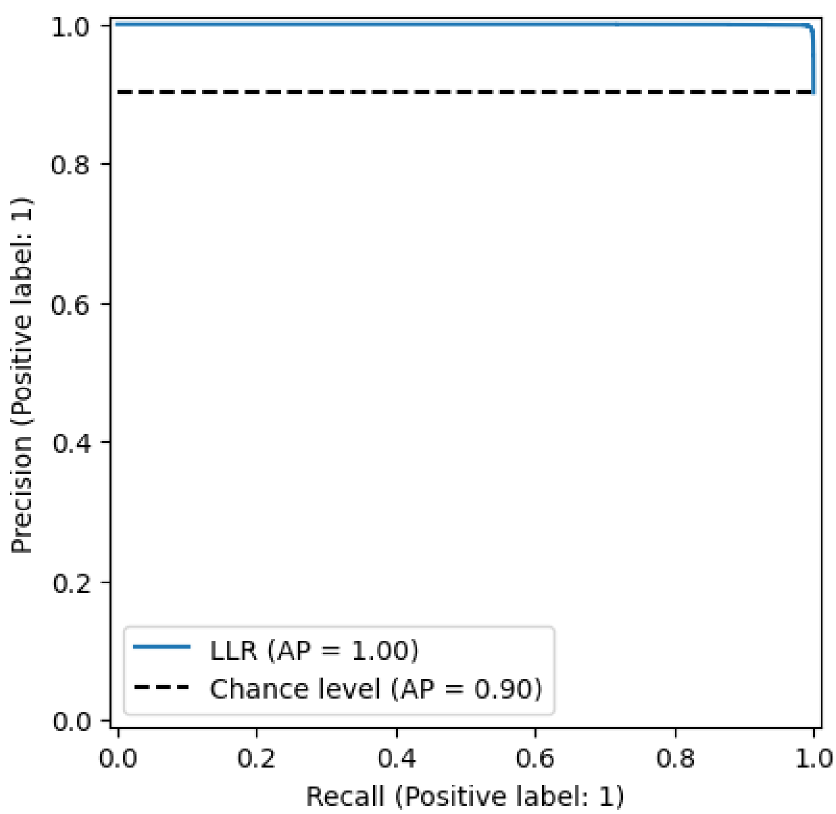
0.3 Part 4: Stretch Goals

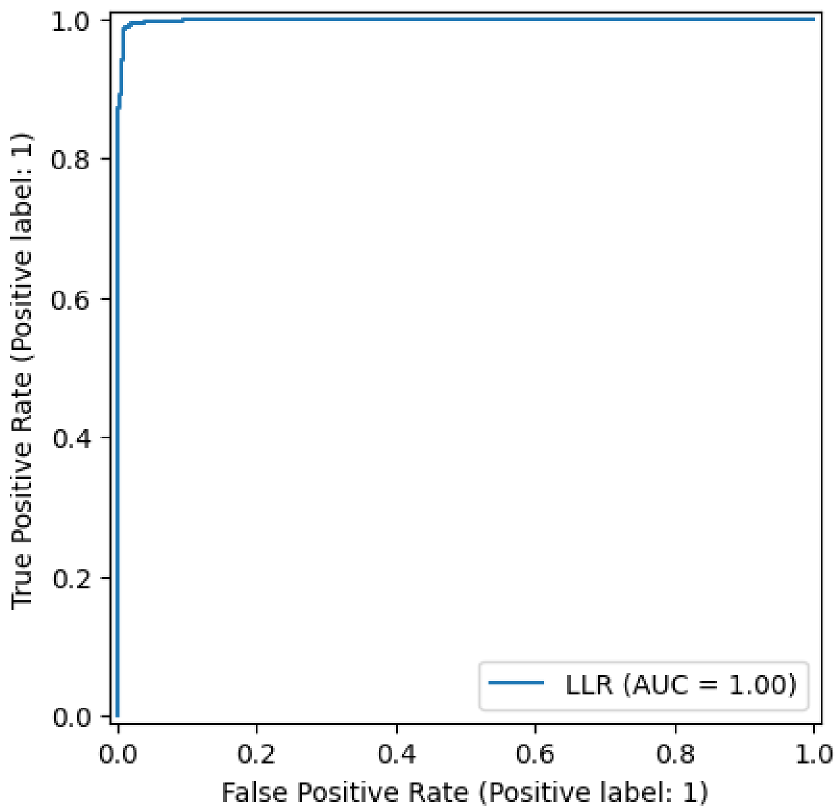
Include all your code used for any stretch goals in this section. Add headings where appropriate.

a) PR and ROC curves

[98]:
```
(x_train, y_train), (x_test, y_test) = load_mnist()
# change label to 0 or 1
p4a_y_train = y_train.copy()
p4a_y_train[p4a_y_train > 0] = 1
p4a_y_test = y_test.copy()
p4a_y_test[p4a_y_test > 0] = 1

p4allr = LogisticRegression().fit(x_train, p4a_y_train)
from sklearn.metrics import PrecisionRecallDisplay, RocCurveDisplay
PrecisionRecallDisplay.from_estimator(
    p4allr, x_test, p4a_y_test, name="LLR", plot_chance_level=True
)
RocCurveDisplay.from_estimator(
    p4allr, x_test, p4a_y_test, name="LLR"
)
```

[98]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1da02c62b90>



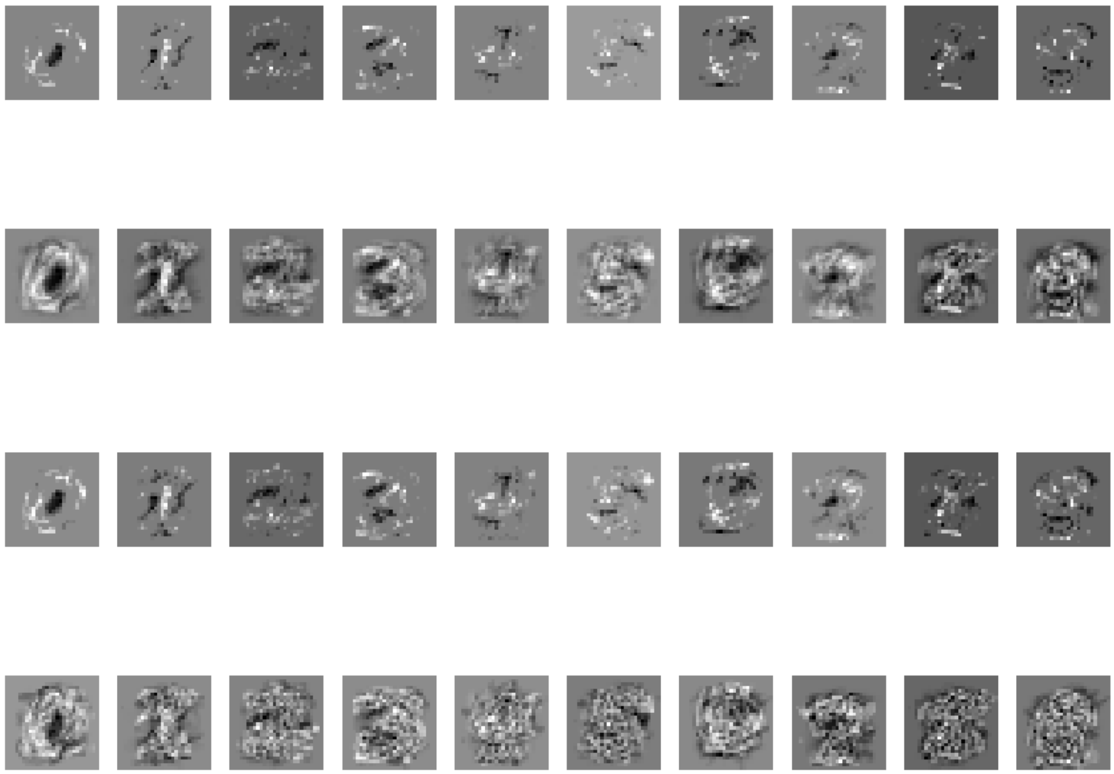


b) Visualize weights

[99]:
```
# train using fewer samples
N = 1000
%cache p4bllrl1 = LogisticRegression(solver='saga', penalty='l1').fit(x_train[:
↪N], y_train[:N])
%cache p4bllrl2 = LogisticRegression(solver='saga', penalty='l2').fit(x_train[:
↪N], y_train[:N])
%cache p4bllrel = LogisticRegression(solver='saga', penalty='elasticnet',␣
↪l1_ratio=.5).fit(x_train[:N], y_train[:N])

display_mnist(p4bllrl1.coef_, subplot_rows=1, subplot_cols=10)
display_mnist(p4bllrl2.coef_, subplot_rows=1, subplot_cols=10)
display_mnist(p4bllrel.coef_, subplot_rows=1, subplot_cols=10)

p4bsvm = svm.LinearSVC(dual='auto').fit(x_train[:N], y_train[:N])
display_mnist(p4bsvm.coef_, subplot_rows=1, subplot_cols=10)
```

```
Loading cached value for variable 'p4bllrl1'. Time since caching: 5 days,
18:34:20.956202
```

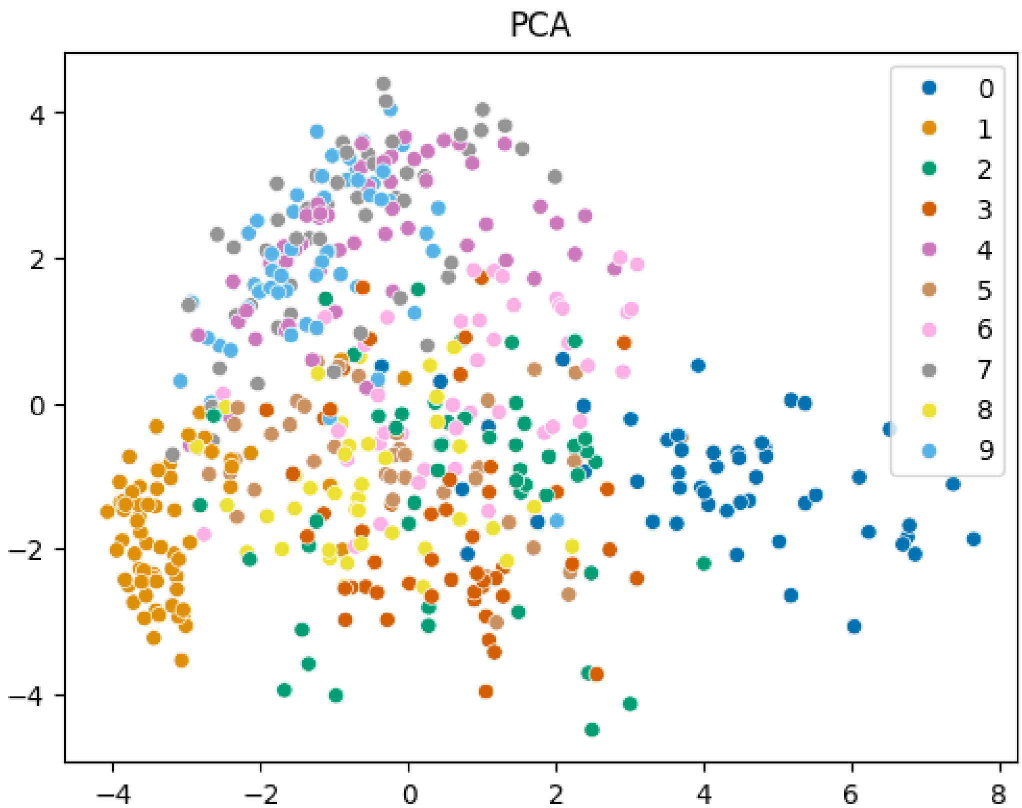
```
Loading cached value for variable 'p4bllrl2'. Time since caching: 5 days,
18:34:17.953454
Loading cached value for variable 'p4bllrel'. Time since caching: 5 days,
18:33:02.574848
```



c) Other embeddings

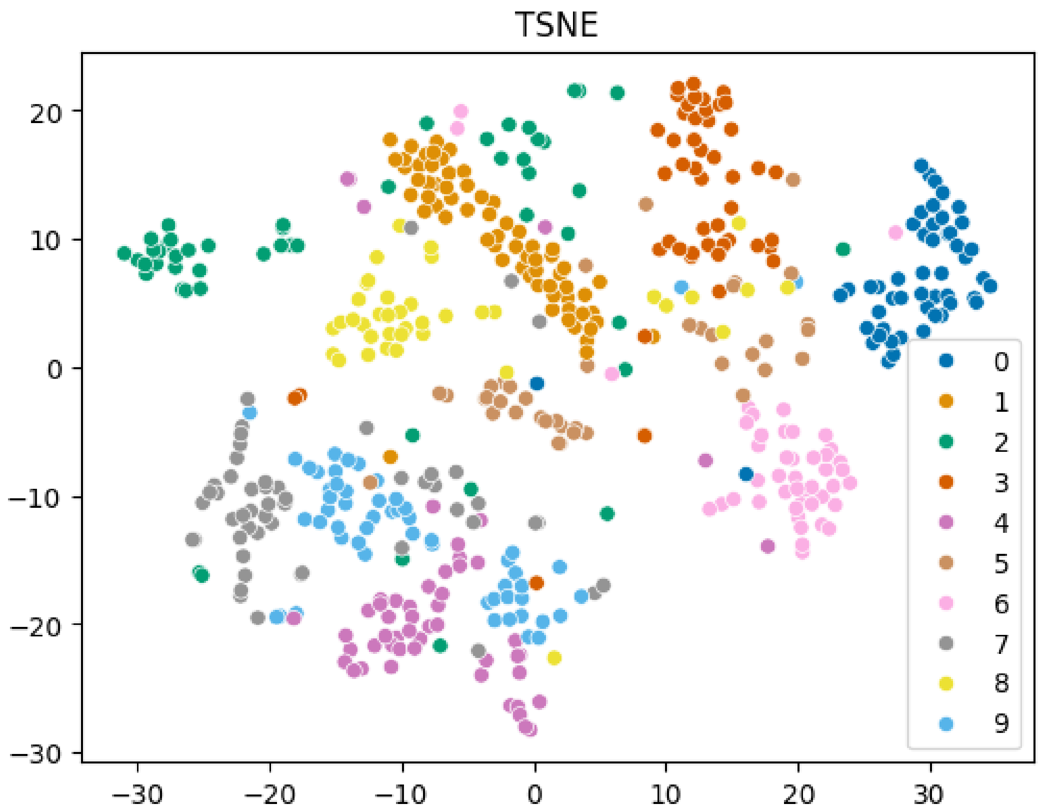
[100]:
```python
x = pca1b.transform(x_train[:500])
ind = np.arange(500)
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind").
    ↪set(title='PCA')
```

[100]:
```
[Text(0.5, 1.0, 'PCA')]
```



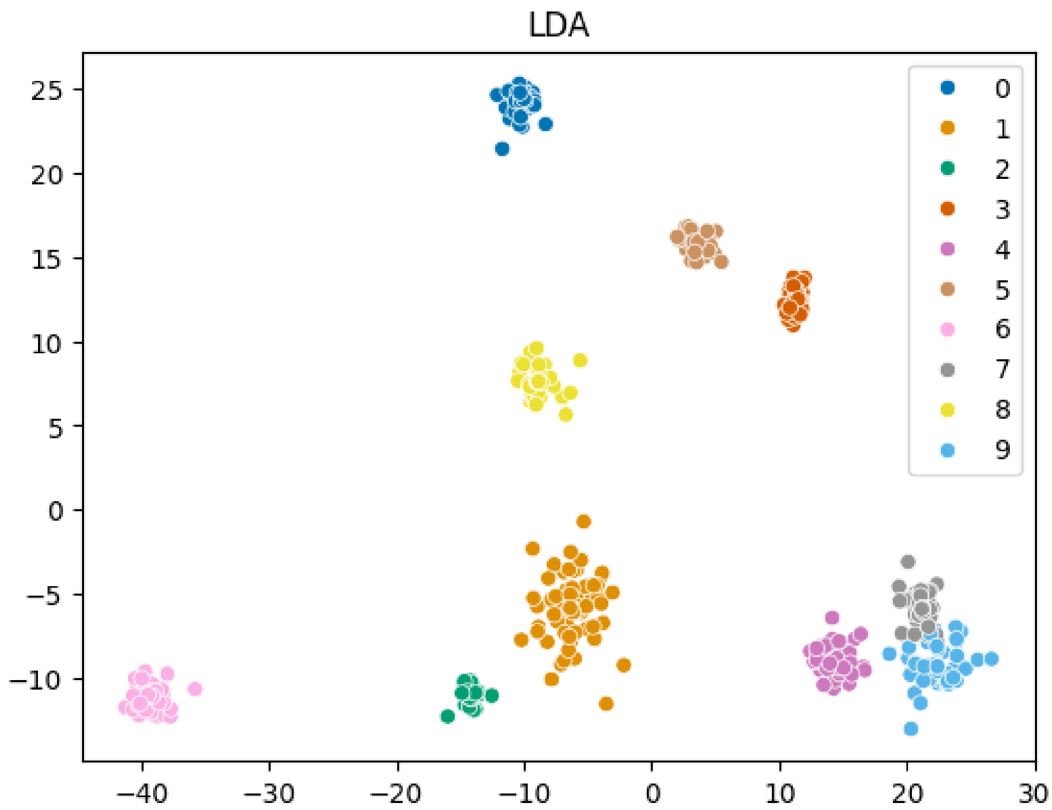
[101]:
```
from sklearn.manifold import TSNE
p4ctsne = TSNE()
x = p4ctsne.fit_transform(x_train[:500])
ind = np.arange(500)
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind").
 ↪set(title='TSNE')
```

[101]: [Text(0.5, 1.0, 'TSNE')]



[102]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
p4clda = LinearDiscriminantAnalysis(n_components=2).fit(x_train[:500], y_train[:
 ↪500])
x = p4clda.transform(x_train[:500])
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind").
 ↪set(title='LDA')
```

[102]: [Text(0.5, 1.0, 'LDA')]



e) SVM with RBF Kernel

[103]:
```
print([accuracy_score(llr.predict(x_test), y_test) for llr in llr_estimators])

sizes = [100, 1000, 10000, 60000]
train_svmrbf = lambda : [svm.SVC(kernel='rbf').fit(x_train[:sz], y_train[:sz])␣
 ↪for sz in sizes]
%cache svmrbf_estimators = train_svmrbf()
score_svmrbf = lambda : [accuracy_score(svm.predict(x_test), y_test) for svm in␣
 ↪svmrbf_estimators]
%cache svmrbfscores = score_svmrbf()
print(svmrbfscores)
```

```
[0.675, 0.8636, 0.905, 0.9261]
Loading cached value for variable 'svmrbf_estimators'. Time since caching: 5
days, 17:37:32.071795
Loading cached value for variable 'svmrbfscores'. Time since caching: 5 days,
17:30:58.110247
[0.6559, 0.9083, 0.9594, 0.9792]
```

[104]:
```
%cache
```

<IPython.core.display.HTML object>

[105]:
```
# from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27b343dca4abba
# 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:"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}"
# !apt install -y texlive-xetex texlive-fonts-recommended texlive-plain-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}")
```