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CS 441 - HW2: PCA and Linear Models

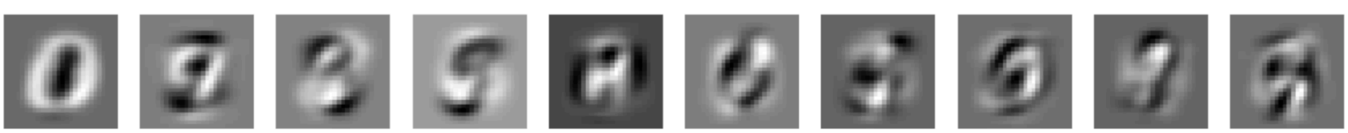
Complete the sections below. You do not need to fill out the checklist.

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
    c. Parameter selection experiments [ ] / 15
3. Temperature Regression
    a. Linear regression test [ ] / 10
    b. Feature selection results [ ] / 15
4. Stretch Goals
    a. PR and ROC curves [ ] / 10
    b. Visualize weights [ ] / 10
    c. Other embeddings [ ] / 15
    d. One city is all you need [ ] / 15
    e. SVM with RBF kernel [ ] / 10

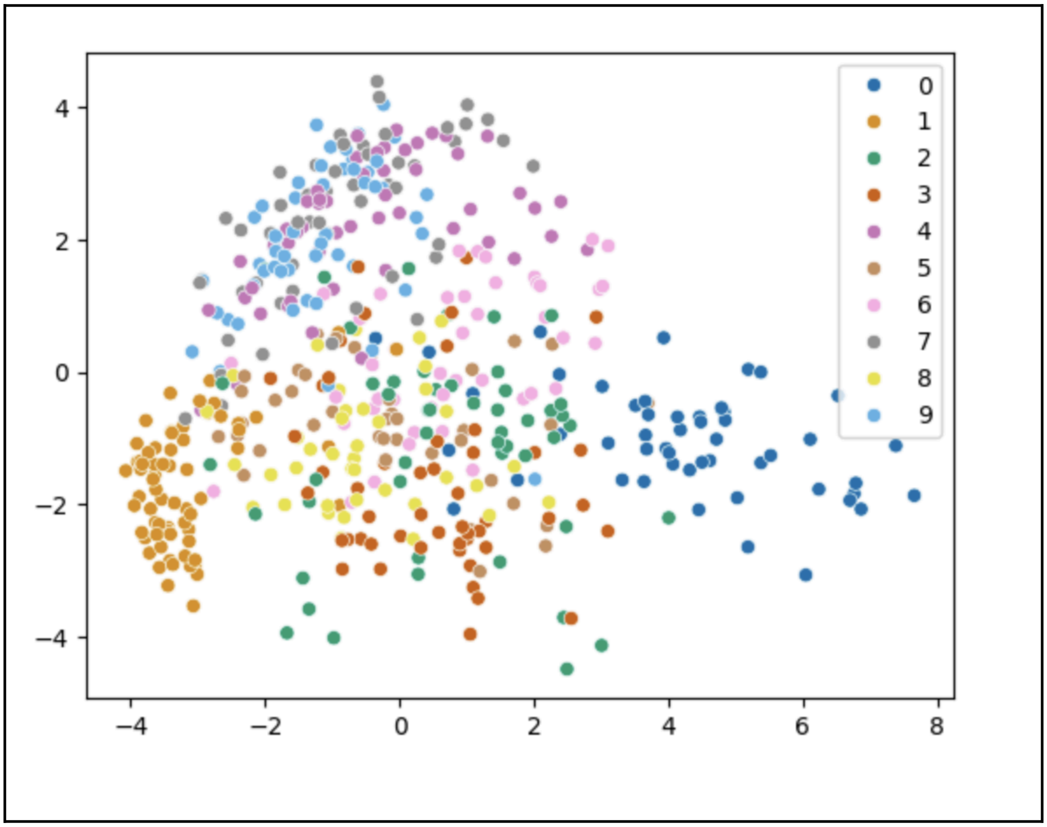
1. PCA on MNIST

a. Display 10 principal component vectors

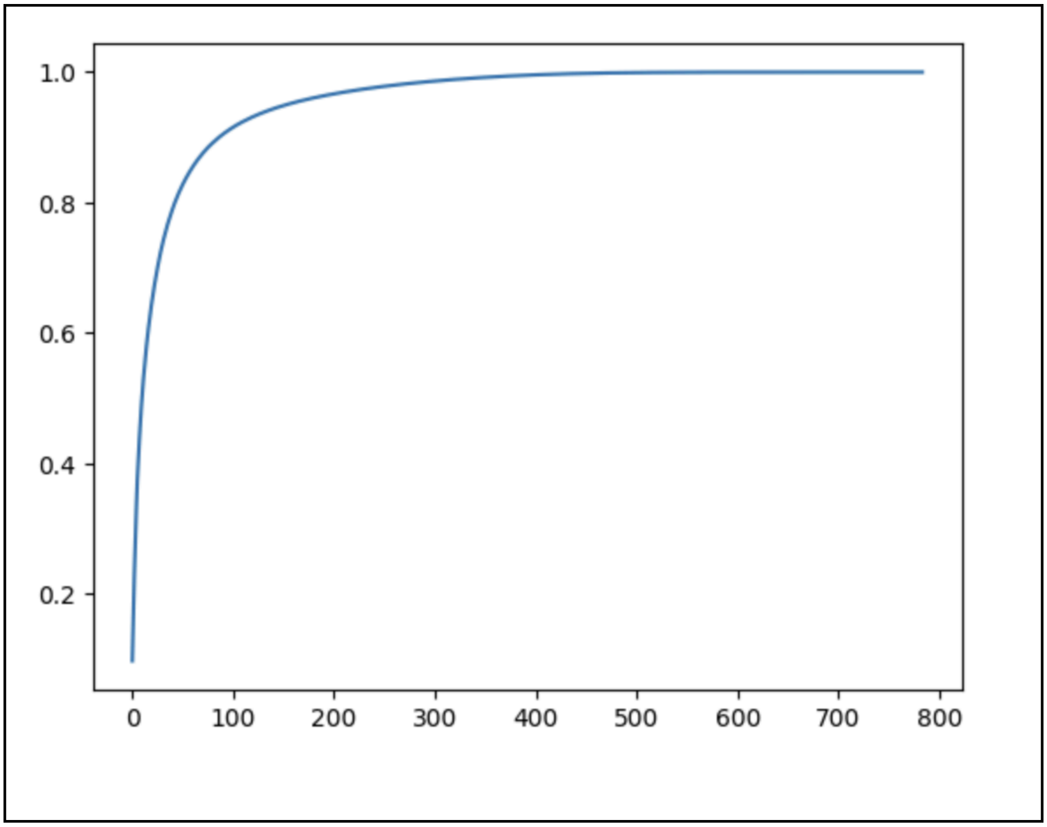


b. Display scatterplot

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)	4.545	2.73%	87
Brute Force	36.031	3.09%	784

2. MNIST Classification with Linear Models

a. LLR / SVM error vs training size

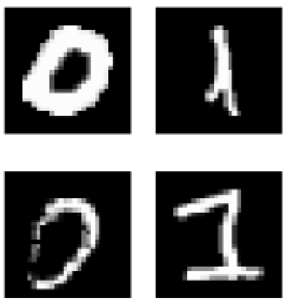
Test error (%)

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

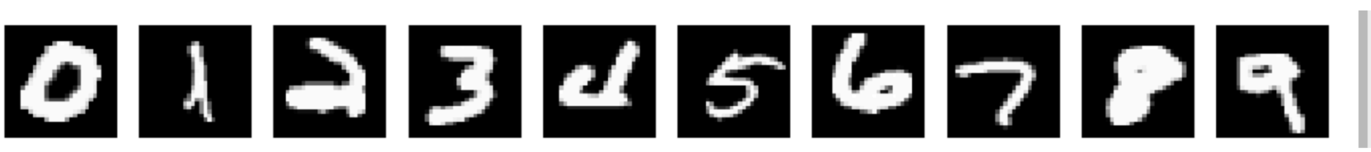
10,000	9.5 %	11.12 %
60,000	7.38 %	8.17 %

b. Error visualization

LLR



LLR Most confident correct:



LLR Most confident incorrect:

SVM

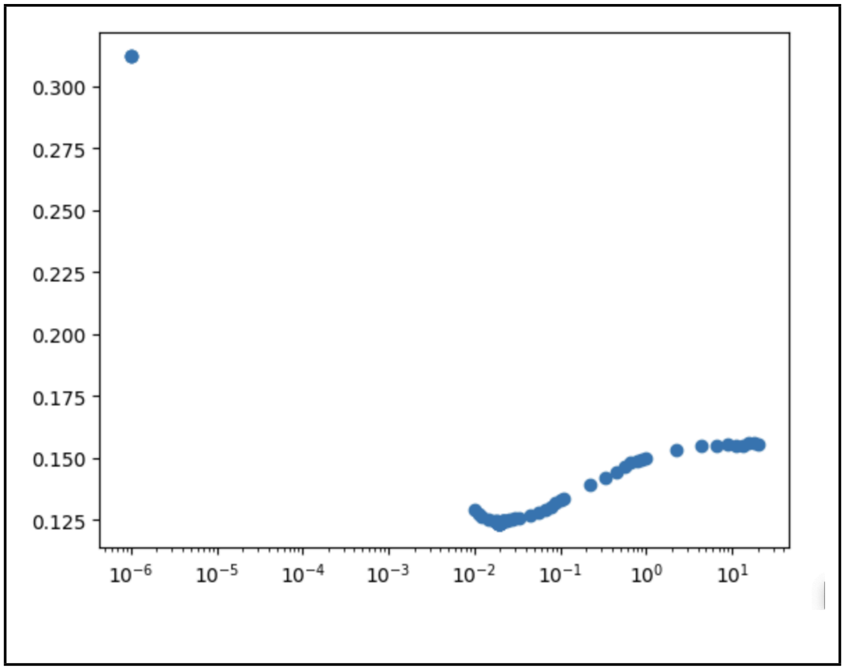
Most confident correct:

Most confident incorrect:

c. Parameter selection experiments

	SVM
Best C value	0.0196
Validation error (%)	12.35 %
Test error (%)	13.58 %

Plot C value vs validation error for values tested



3. Temperature Regression

a. Linear regression test

Test RMSE

	Linear regression
Original features	2.1608
Normalized features	2.1631

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

Because KNN uses distances, it is sensitive to the scale of features. Linear regression can learn weights to scale features so it is less sensitive. This normalization essentially centers/rescales features.

b. Feature selection results

Feature Rank	Feature number	City	Day
1	334	Chicago	-1
2	347	Minneapolis	-1
3	405	Grand Rapids	-1
4	366	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

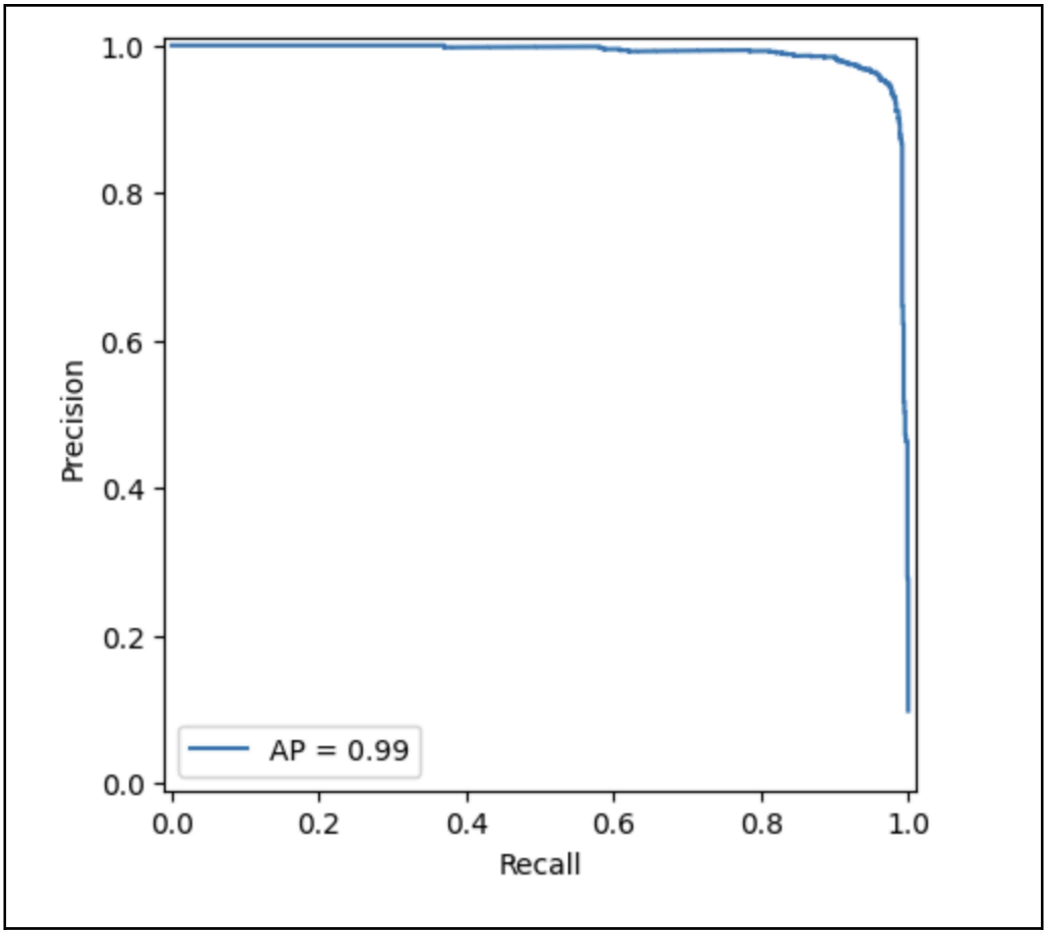
Test error using only the 10 most important features for regression

	Linear Regression
RMS Error	2.0621

4. Stretch Goals

a. PR and ROC curves

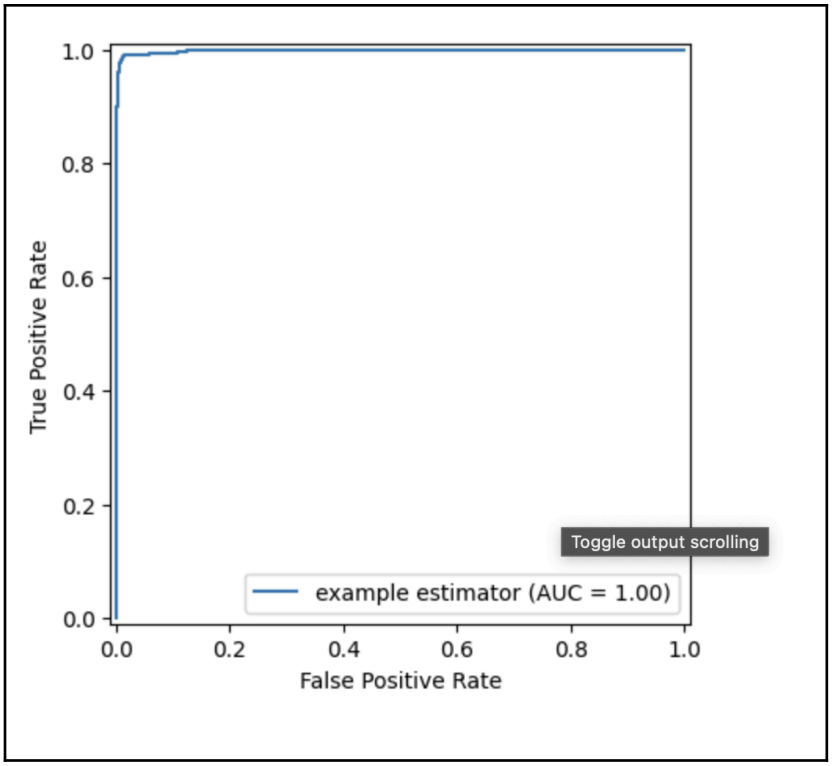
PR plot



Average Precision

0.98883

ROC plot

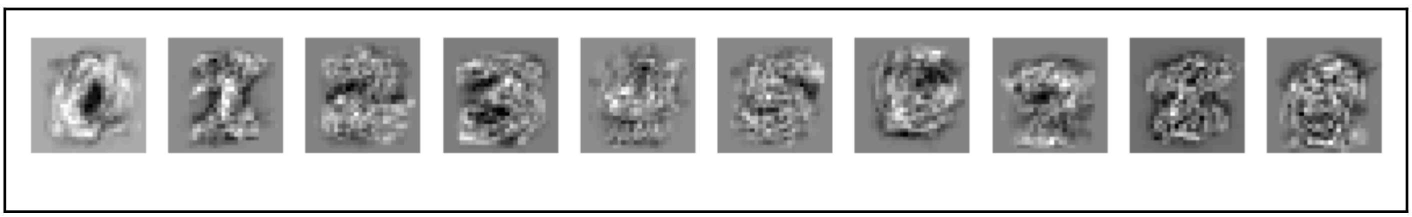


Area under the curve (AUC)

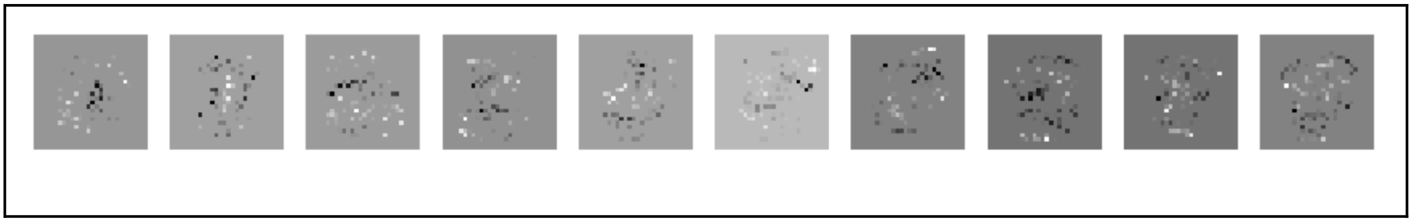
0.9983

b. Visualize weights

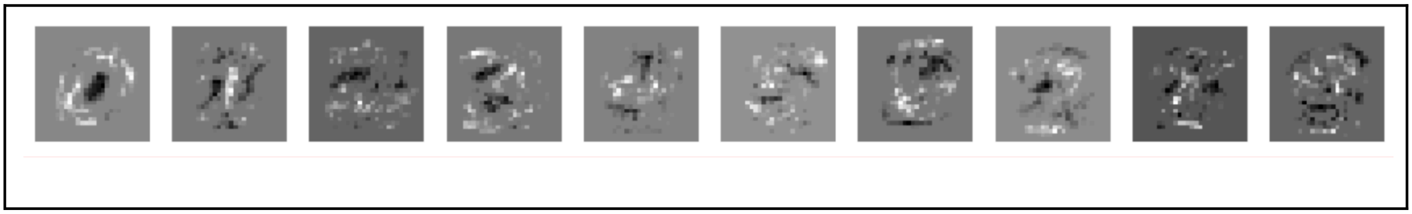
LLR - L2



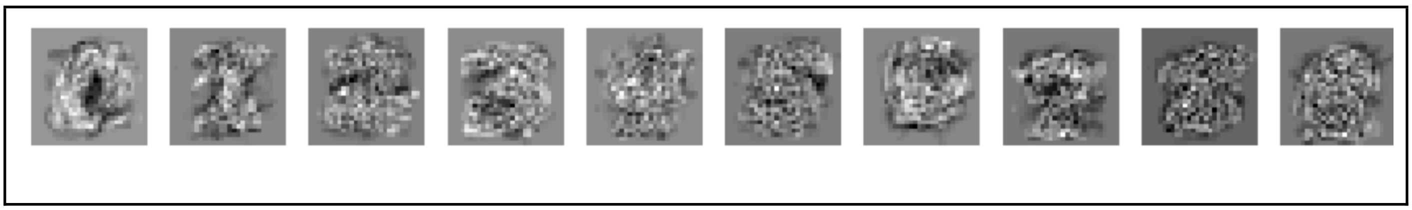
LLR - L1



LLR - elastic



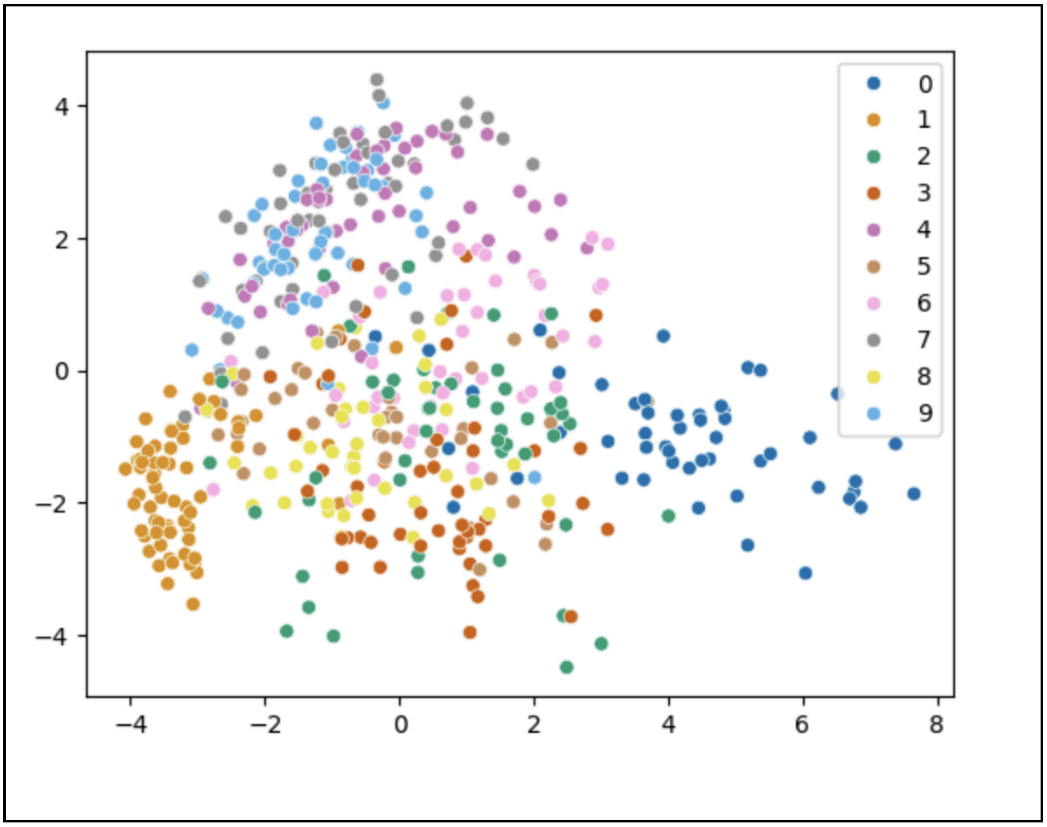
SVM



c. Other embeddings

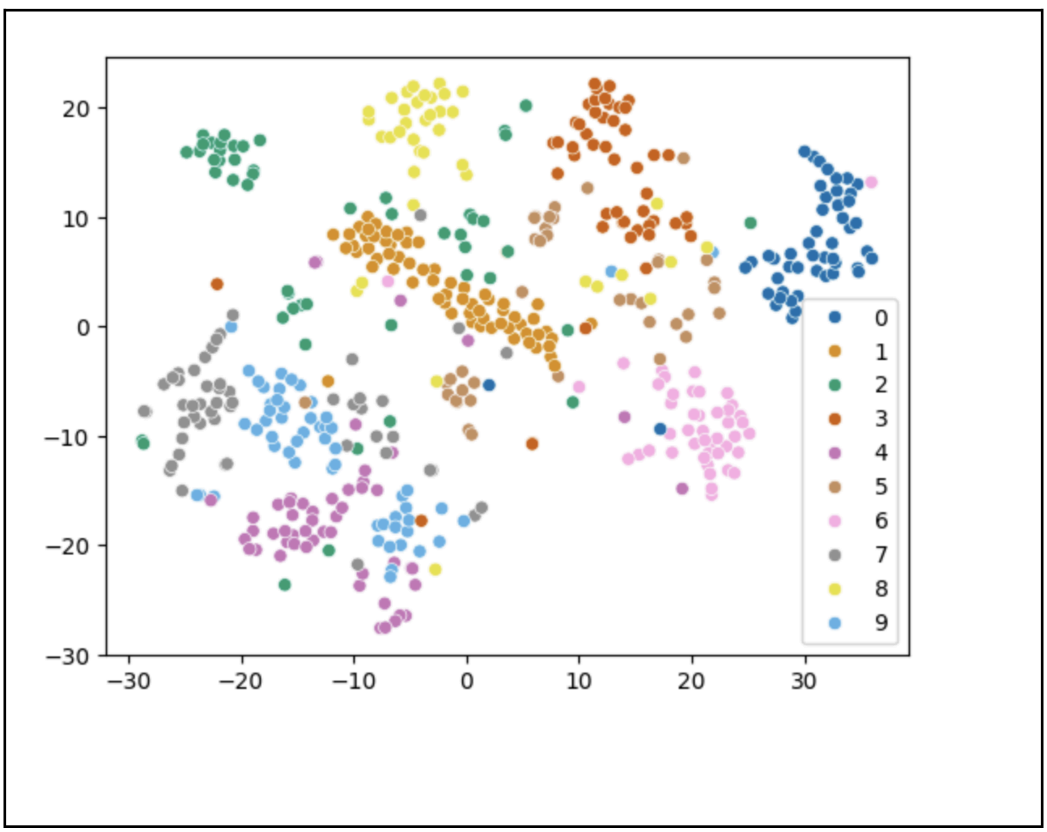
Display 2+ plots for TSNE, MDA, and/or LDA, and copy PCA plot from 1b here.

PCA



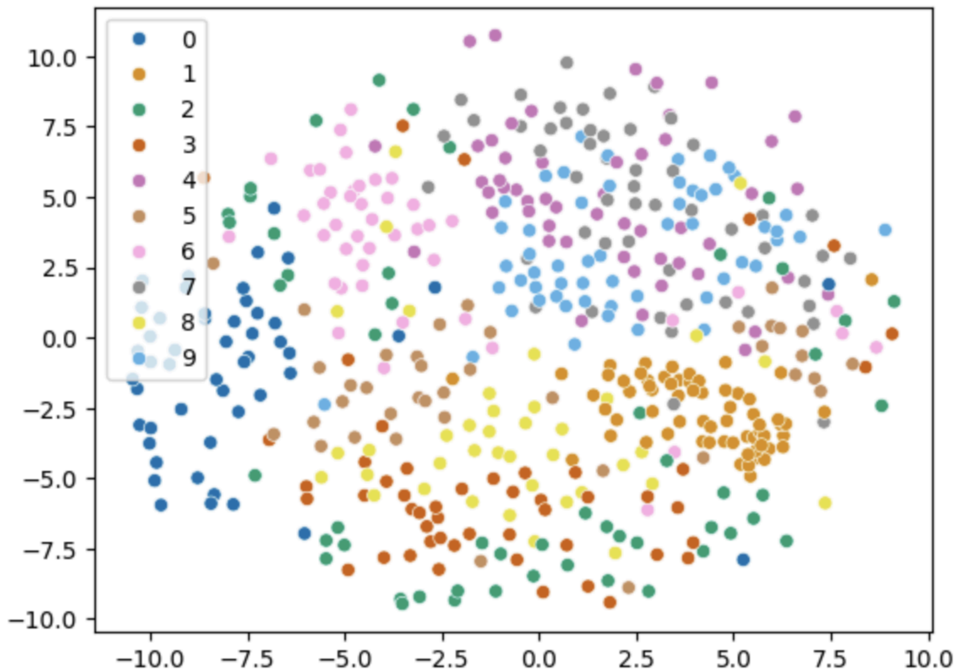
4
2
0
−2
−4
−4
−2
0
2
4
6
8
0
1
2
3
4
5
6
7
8
9

TNSE



20
10
0
−10
−20
−30
−30
−20
−10
0
10
20
30
0
1
2
3
4
5
6
7
8
9

MDS



d. One city is all you need

City

St. Louis

Test error using features only from that city

3.1263 RMSE

Explain your process (in words):

Iterated through every city, and trained a Ridge model (no feature normalization, default parameters) using only days from that city as input features. Then I took the validation error for each of these models, and took the city with the minimum validation error.

e. Compare linear SVM and SVM with RBF kernel

Test accuracy (%)

# training samples	SVM-Linear	SVM-RBF
100	32.4%	34.4%
1,000	16.11 %	9.17%
10,000	11.12 %	4.06%
60,000	8.17 %	2.08%

Acknowledgments / Attribution

List any outside sources for code or ideas or “None”.
Stackoverflow + sklearn docs

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

[253]:
```
# 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

!apt install libomp-dev > /dev/null 2>&1
!pip install faiss-cpu > /dev/null 2>&1
import faiss
import time

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)):
```

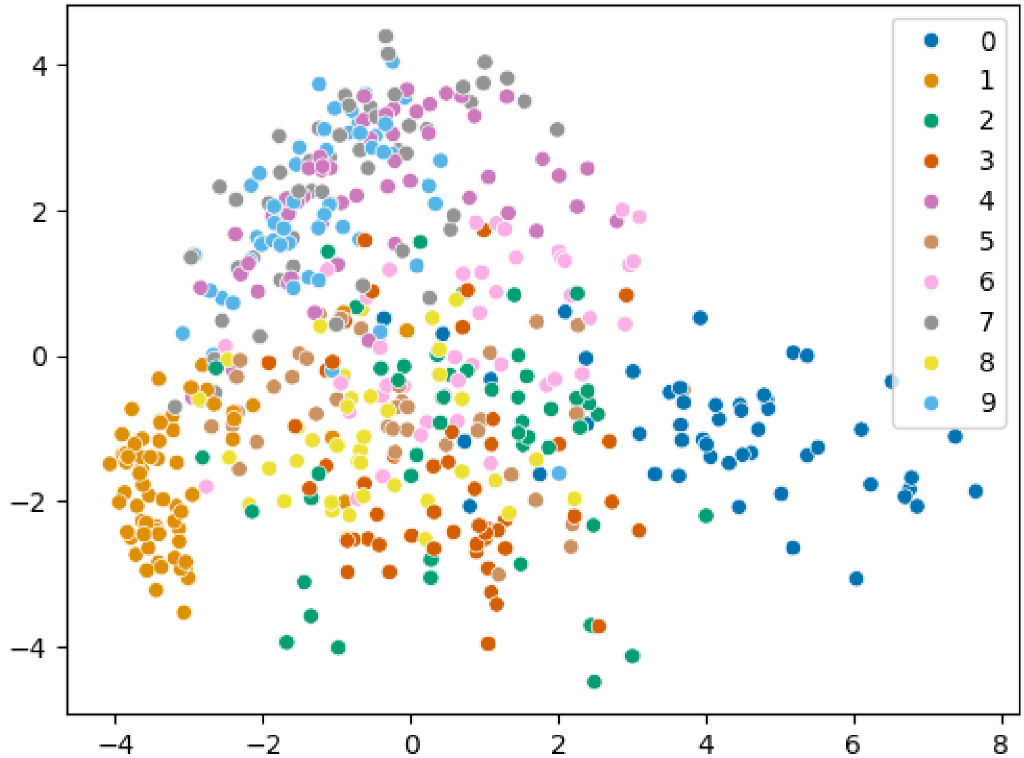
```
        ax[i].imshow(np.reshape(x[i], (28,28)), cmap='gray')
        ax[i].axis('off')
    else:
        plt.imshow(np.reshape(x, (28,28)), cmap='gray')
        plt.axis('off')
    plt.show()
```

0.1.2 Part 1: PCA and Data Compression

[254]:
```
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
pca_model = PCA()
pca_model.fit(x_train)
principal_components = pca_model.components_[:10]

# Display First 10 Components
display_mnist(principal_components, 1, 10)
```

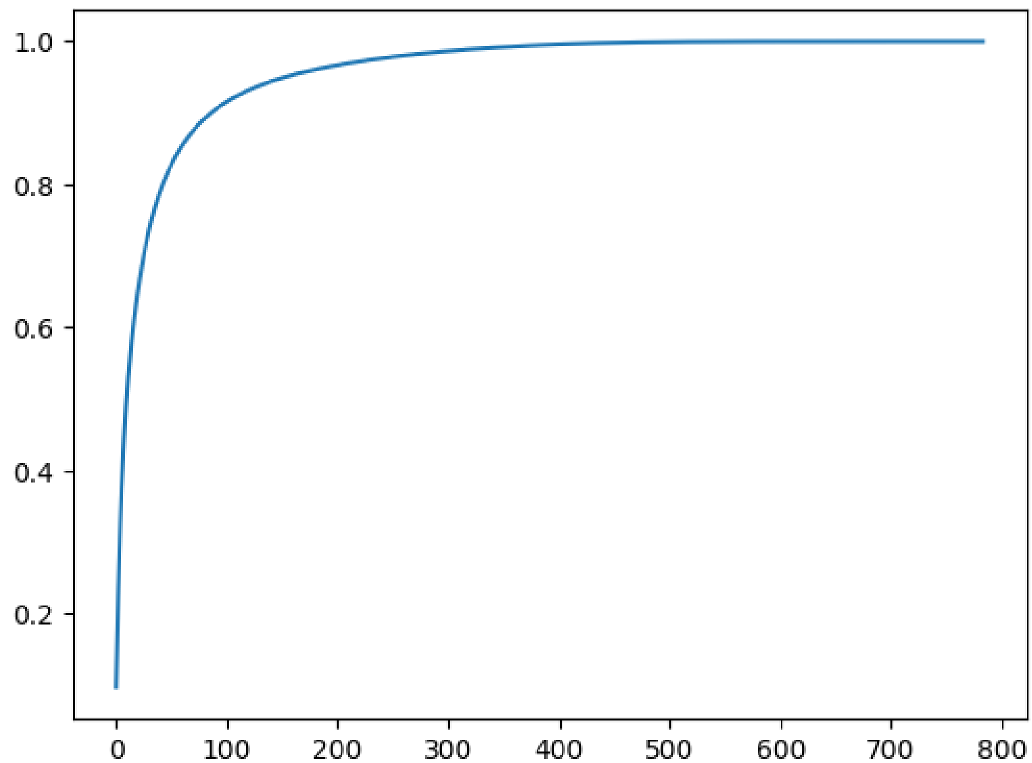
[57]:
```
# Scatter plot of first two PCA dimensions
import seaborn as sns

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

[57]: <Axes: >



[58]:
```
# Plot cumulative explained variance ratio
# cumsum and pca.explained_variance_ratio_ will be useful

# TO DO
cum_var = np.cumsum(pca_model.explained_variance_ratio_)
plt.plot(cum_var)
```

[58]: [<matplotlib.lines.Line2D at 0x7f3a416a2190>]



[59]:
```
# Select number of dimensions that explains 90% of variance, according to your
 ↪plot above
m = (cum_var >= 0.9).argmax() + 1
print(m)

pca_model = PCA(n_components=m).fit(x_train)

# Get time and error when using original features with brute force 1-NN
# TO DO
start = time.time()
index = faiss.IndexFlatL2(x_train.shape[1])
index.add(x_train)
dist, idx = index.search(x_test,1)
pred = y_train[idx.squeeze()]
err = (pred != y_test).mean()
print(err)
print(time.time() - start)

# Get time and error when using compressed features with brute force 1-NN
# TO DO
x_train_comp = pca_model.transform(x_train)
x_test_comp = pca_model.transform(x_test)
```

```
start = time.time()
index = faiss.IndexFlatL2(x_train_comp.shape[1])
index.add(x_train_comp)
dist, idx = index.search(x_test_comp,1)
pred = y_train[idx.squeeze()]
err = (pred != y_test).mean()
print(err)
print(time.time() - start)
```

```
87
0.0309
36.031790018081665
0.0273
4.545729160308838
```

0.1.3 Part 2: MNIST Classification with Linear Models

[6]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
```

LLR/SVM vs training size

[14]:
```
# LLR
for n in [100, 1000, 10000, 60000]:
  LLR = LogisticRegression(max_iter = 10000).fit(x_train[:n],y_train[:n])
  pred = LLR.predict(x_test)
  err = 100*(pred != y_test).mean()
  print(err)
```

```
32.5
13.639999999999999
9.5
7.380000000000001
```

[7]:
```
# SVM
for n in [100, 1000, 10000, 60000]:
  SVM = LinearSVC(max_iter = 10000).fit(x_train[:n],y_train[:n])
  pred = SVM.predict(x_test)
  err = 100*(pred != y_test).mean()
  print(err)
```

```
/home/matty/.local/lib/python3.11/site-packages/sklearn/svm/_classes.py:31:
FutureWarning: The default value of `dual` will change from `True` to `'auto'`
in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
/home/matty/.local/lib/python3.11/site-packages/sklearn/svm/_classes.py:31:
FutureWarning: The default value of `dual` will change from `True` to `'auto'`
```

```
in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
```

```
32.35
16.11
```

```
/home/matty/.local/lib/python3.11/site-packages/sklearn/svm/_classes.py:31:
FutureWarning: The default value of `dual` will change from `True` to `'auto'`
in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
```

```
11.12
```

```
/home/matty/.local/lib/python3.11/site-packages/sklearn/svm/_classes.py:31:
FutureWarning: The default value of `dual` will change from `True` to `'auto'`
in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
```

```
8.17
```

Error visualization

[54]:
```
# to get scores for logistic regression use: scores = model_lr.
 ↪predict_proba(x_test)
def makeplots(scores):
  mostcorrect = np.empty((10, x_test.shape[1]))
  mostwrong = mostcorrect.copy()
  for i in range(10):
    print(f"idx {i}")
    probs = scores[:,i]
    islabel = (y_test == i).astype(int)

    maxidx = (probs * islabel).argmax()
    minidx = ((1-probs) * islabel).argmax()
    print(probs[maxidx], probs[minidx])
    # display_mnist(x_test[minidx])
    # display_mnist(x_test[maxidx])
    mostcorrect[i] = x_test[maxidx]
    mostwrong[i] = x_test[minidx]

  display_mnist(mostcorrect,subplot_cols=10)
  display_mnist(mostwrong,subplot_cols=10)

makeplots(LLR.predict_proba(x_test))
# to get scores for SVM use: scores = model_svm.decision_function(x_test)
makeplots(SVM.decision_function(x_test))
```

```
idx 0
0.9999999963899942 0.00025819211990930365
idx 1
0.9996567977883941 3.0877626333995e-07
```

```
idx 2
0.9999999744316168 8.143784266293726e-08
idx 3
0.9999989329684581 2.559199561611065e-05
idx 4
0.9999997898596669 1.332051810719343e-07
idx 5
0.9999795469879909 0.00011521805519352722
idx 6
0.9999992170012151 9.196212267621756e-05
idx 7
0.9999978520581978 2.8968218320809687e-06
idx 8
0.9999939555425639 2.7513009347682197e-05
idx 9
0.9999710313820391 1.0870533123166027e-07
```

```
idx 0
4.61895263661966 -2.6070372181055292
idx 1
2.4273329555515355 -5.02282639157594
idx 2
4.3457220804306536 -4.503737615673133
idx 3
4.294225965182193 -4.2211613082993695
idx 4
3.769328884272958 -4.4923061471241255
idx 5
4.0326785525818565 -4.385248350034097
idx 6
3.9589625796426087 -3.189884761323814
idx 7
5.565132589995729 -4.641314083206345
idx 8
2.6371411849356683 -2.8530038389350647
```

```
idx 9
3.0858680559435063 -4.077201020006369
```

Parameter selection

[255]:
```python
cs = []
errs = []
```

[264]:
```python
# 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


def geterr(c):
  model = LinearSVC(C=c, dual='auto').fit(x_train[:1000], y_train[:1000])
  pred = model.predict(x_train[50000:])
  err = (pred != y_train[50000:]).mean()
  print(c, err)
  cs.append(c)
  errs.append(err)
  return err

minval = 1000
minc = -1

for c in np.linspace(0.0185,0.0199,10):
  err = geterr(c)
  if err < minval:
    minval = err
    minc = c

print(minc, minval)
```

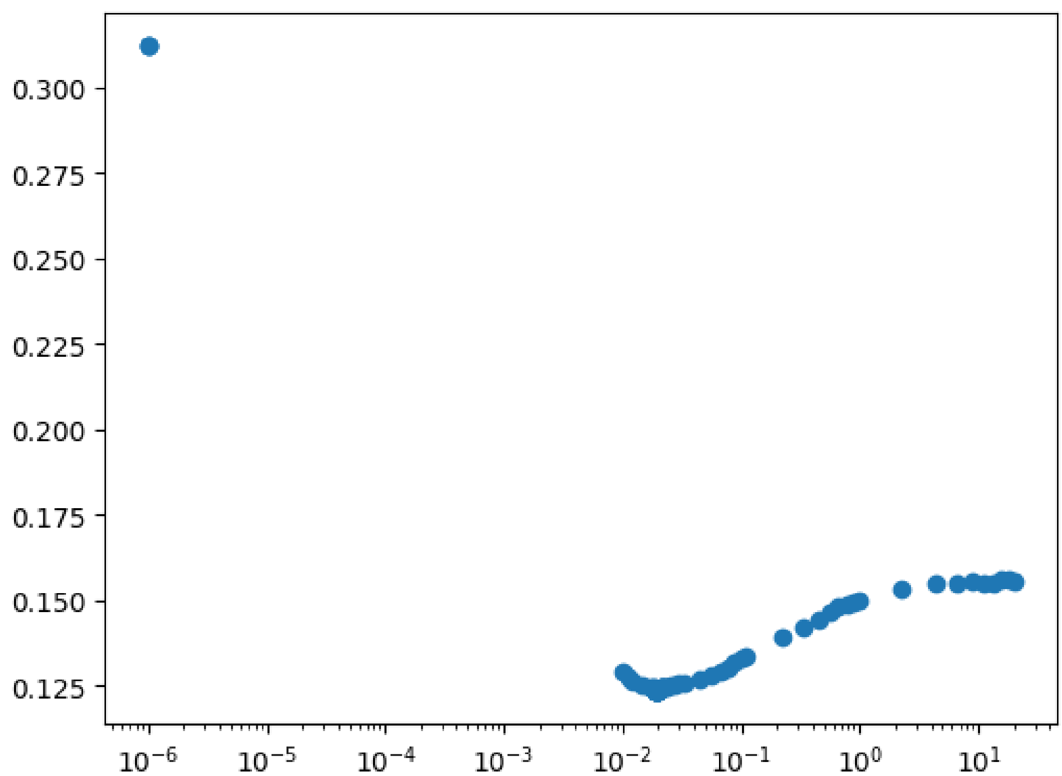
```
0.0185 0.1239
0.018655555555555554 0.1238
0.018811111111111112 0.1237
```

```
0.018966666666666666 0.1236
0.019122222222222222 0.1237
0.019277777777777778 0.1238
0.019433333333333334 0.1237
0.019588888888888889 0.1235
0.019744444444444446 0.1237
0.0199 0.1238
0.019588888888888889 0.1235
```

[265]:

```python
# Get test result for selected parameter
plt.semilogx(cs,errs, marker='o', linestyle='')
# TO DO
c = cs[np.argmin(errs)]
print(min(errs))
model = LinearSVC(C=c, dual='auto').fit(x_train[:1000], y_train[:1000])
pred = model.predict(x_test)
err = (pred != y_test).mean()
print(err)
```

```
0.1235
0.1358
```



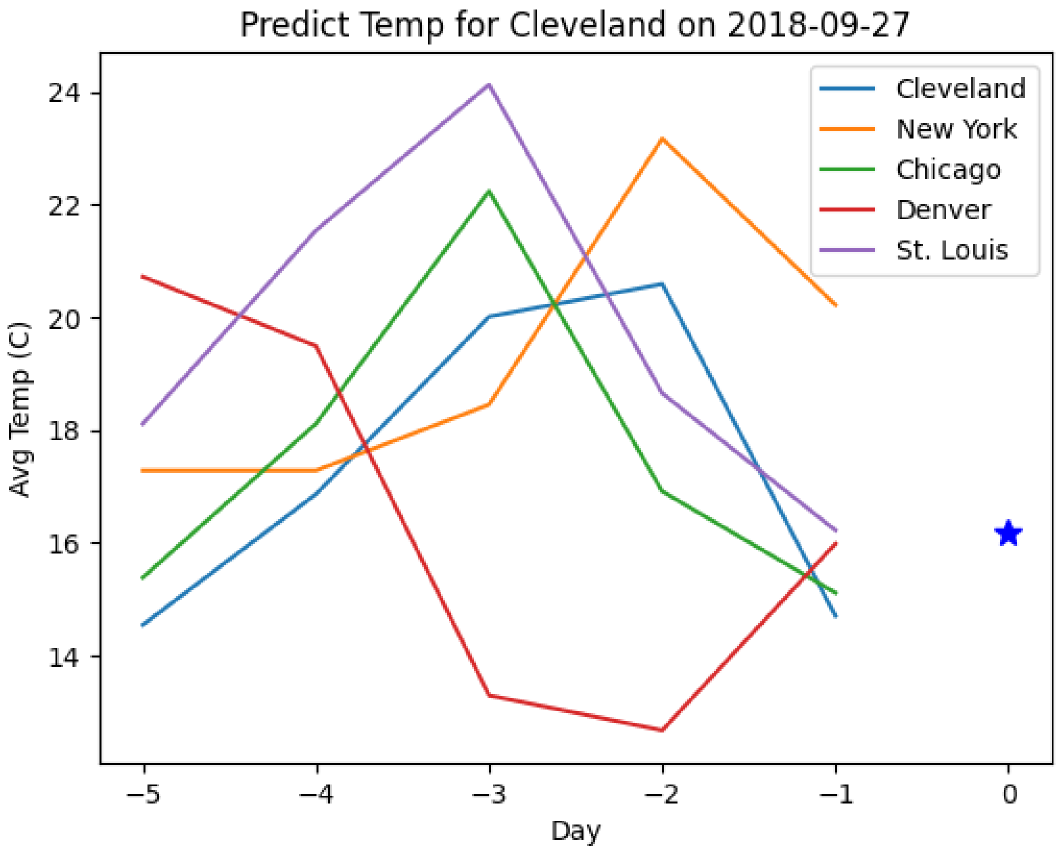
0.2 Part 3: Temperature Regression

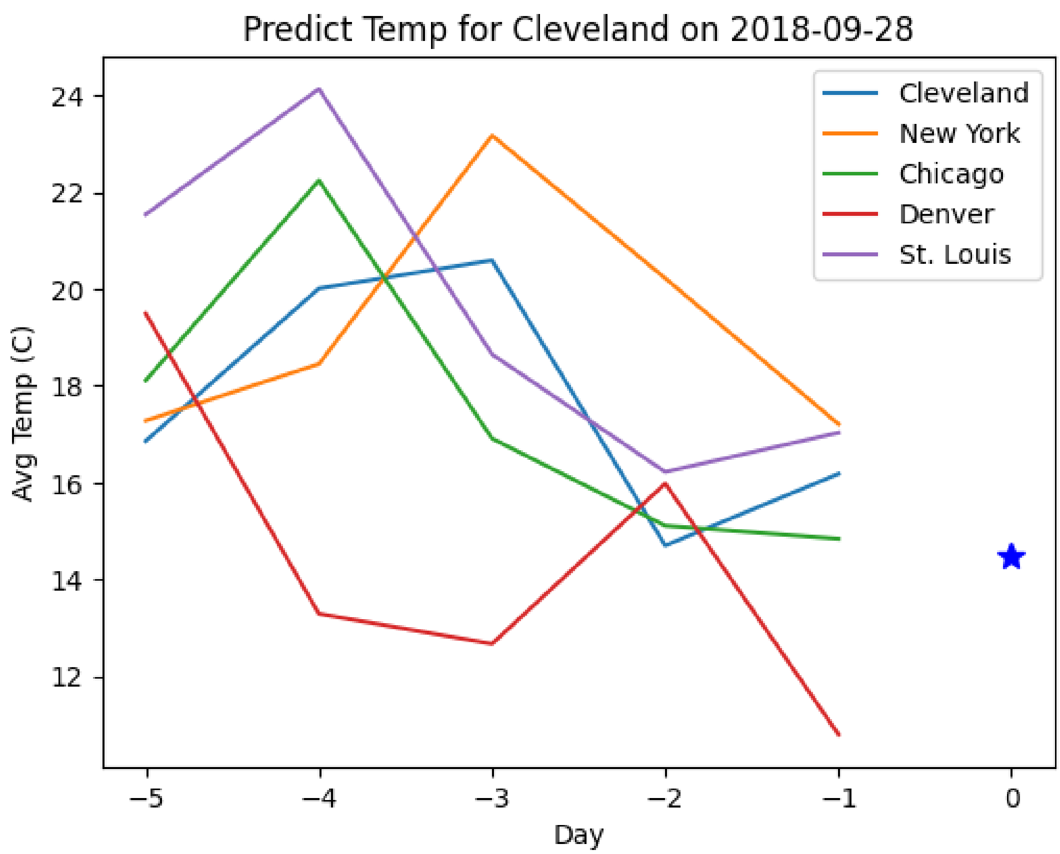
[125]:
```
import numpy as np
# from google.colab import drive
%matplotlib inline
from matplotlib import pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso

# load data (modify to match your data directory or comment)
def load_temp_data():
  # drive.mount('/content/drive')
  # datadir = "/content/drive/My Drive/CS441/24SP/hw1/"
  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()
```

[126]:
```
# load data
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val,␣
↪dates_test, feature_to_city, feature_to_day) = load_temp_data()
''' Data format:
      x_train, y_train: features and target value for each training sample␣
↪(used to fit model)
```

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

[127]:
```
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
```

[135]:
```
# linear regression (use Ridge)

# original features
model = Ridge().fit(x_train,y_train)
pred = model.predict(x_test)
```

```
print(np.sqrt(np.square(pred-y_test).mean()))

# normalized features
fnum=361
xnorm_train,ynorm_train = normalize_features(x_train,y_train,fnum)
xnorm_test, ynorm_test = normalize_features(x_test,y_test,fnum)


y_pred = Ridge().fit(xnorm_train,ynorm_train).predict(xnorm_test)

print(np.square(y_pred - ynorm_test).mean()**0.5)
# TO DO
```

```
2.1608605260795755
2.1630698027575606
```

Feature selection

[169]:
```
# feature analysis (select important features using Lasso)
# TO DO
model = Lasso().fit(x_train,y_train)
fidx = (np.abs(model.coef_)>0.001)
fidx = np.arange(x_train.shape[1])[fidx]

import pandas as pd
df = pd.DataFrame({
'coef': np.abs(model.coef_[fidx]),
    'fnum':fidx,
'city':feature_to_city[fidx],
  'day':feature_to_day[fidx],

})
df = df.sort_values('coef',ascending=False)
df
```

[169]:

	coef	fnum	city	day
6	0.279599	334	Chicago	-1
7	0.225942	347	Minneapolis	-1
12	0.180130	405	Grand Rapids	-1
10	0.162950	366	Kansas City	-1
9	0.138357	361	Cleveland	-1
5	0.111248	307	Omaha	-2
11	0.046103	367	Indianapolis	-1
3	0.043280	264	Minneapolis	-2
0	0.025518	9	Boston	-5
2	0.025198	236	Springfield	-3
4	0.015140	290	Providence	-2
1	0.005399	175	Boston	-3

8   0.001785   354   St. Louis   -1

[267]:
```
# predict using best features
idxs = df['fnum'][:10].values
model = Ridge().fit(x_train[:,idxs],y_train)
pred = model.predict(x_test[:,idxs])
print(np.sqrt(np.square(pred-y_test).mean()))
```

2.7350935573443653

0.3 Part 4: Stretch Goals

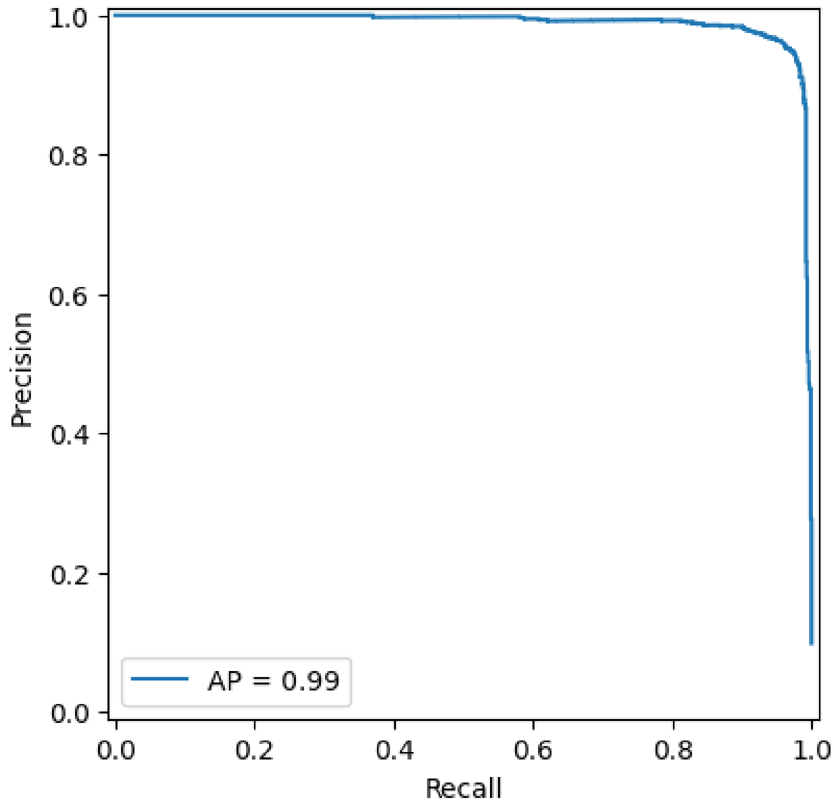
Include all your code used for any stretch goals in this section. Add headings where appropriate.

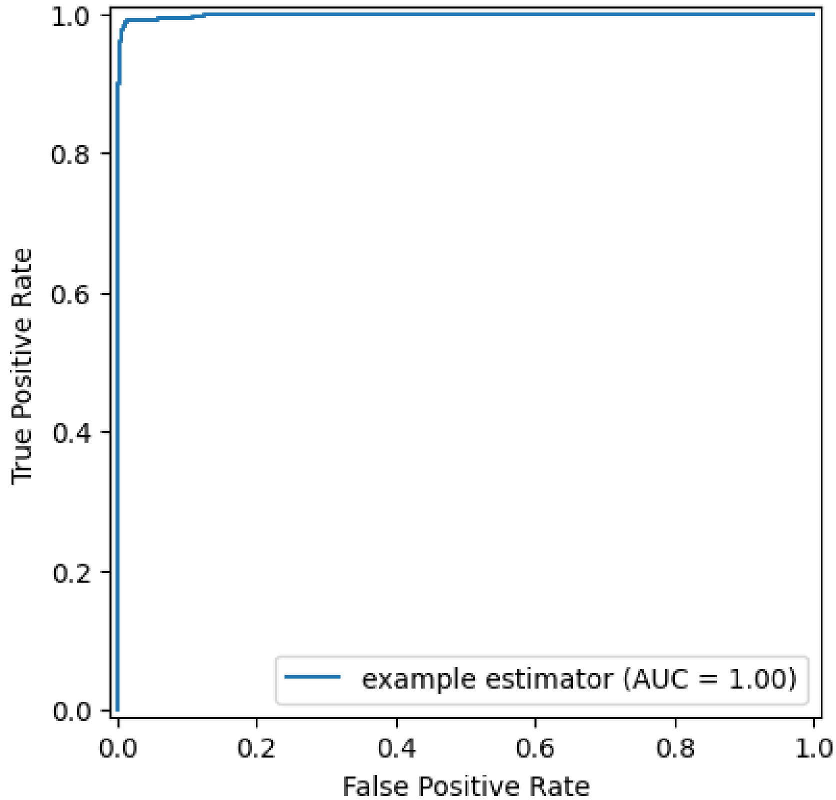
1 4a

[190]:
```
from sklearn.metrics import precision_recall_curve, roc_curve,␣
↪average_precision_score, auc,roc_auc_score,PrecisionRecallDisplay
import sklearn.metrics as metrics


(x_train, y_train), (x_test, y_test) = load_mnist()
y_train = y_train == 0
y_test = y_test == 0
model = LogisticRegression().fit(x_train,y_train)
```

[192]:
```
probs = model.predict_proba(x_test)[:,1]

average_precision = average_precision_score(y_test, probs)
print('Average Precision (AP):', average_precision)

auroc = roc_auc_score(y_test,probs)
print('Area under the ROC curve (AuROC):', auroc)

precision, recall, _ = precision_recall_curve(y_test, probs)
disp = PrecisionRecallDisplay(precision=precision, recall=recall,␣
↪average_precision=average_precision)
disp.plot()


precision, recall, _ = precision_recall_curve(y_test, probs)
fpr, tpr, thresholds = metrics.roc_curve(y_test, probs)
auroc = roc_auc_score(y_test,probs)
display = metrics.RocCurveDisplay(fpr=fpr, tpr=tpr,␣
↪roc_auc=auroc,estimator_name='example estimator')
display.plot()
fpr, tpr, _ = roc_curve(y_test, probs)
```

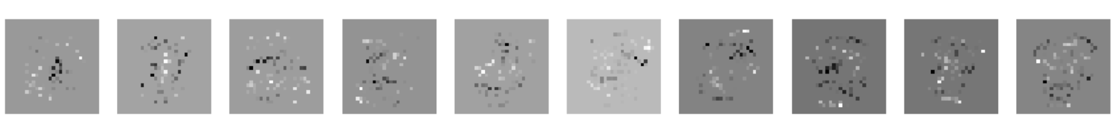
```
Average Precision (AP): 0.9888354276370754
Area under the ROC curve (AuROC): 0.9983122539481425
```

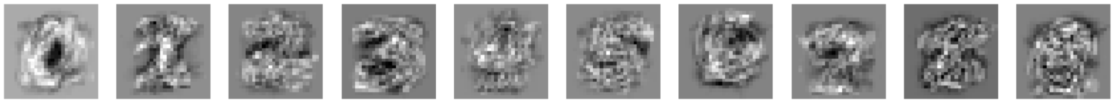




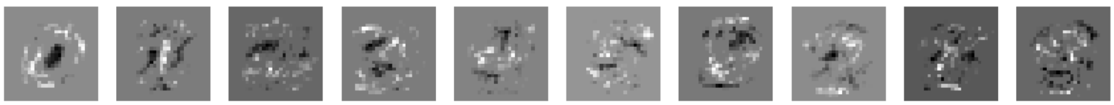
2 4b

[212]:
```
(x_train, y_train), (x_test, y_test) = load_mnist()


def go(model):
  model.fit(x_train[:1000],y_train[:1000])
  display_mnist(model.coef_, subplot_cols=10)


go(LogisticRegression(penalty='l1',solver='liblinear'))
go(LogisticRegression(penalty='l2',solver='liblinear'))
go(LogisticRegression(penalty='elasticnet',solver='saga',l1_ratio=0.5))
go(LinearSVC())
```

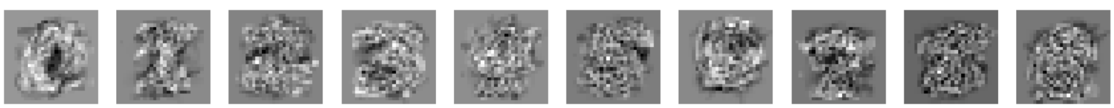




```
/home/matty/.local/lib/python3.11/site-
packages/sklearn/linear_model/_sag.py:350: ConvergenceWarning: The max_iter was
reached which means the coef_ did not converge
  warnings.warn(
```



```
/home/matty/.local/lib/python3.11/site-packages/sklearn/svm/_classes.py:31:
FutureWarning: The default value of `dual` will change from `True` to `'auto'`
in 1.5. Set the value of `dual` explicitly to suppress the warning.
  warnings.warn(
```

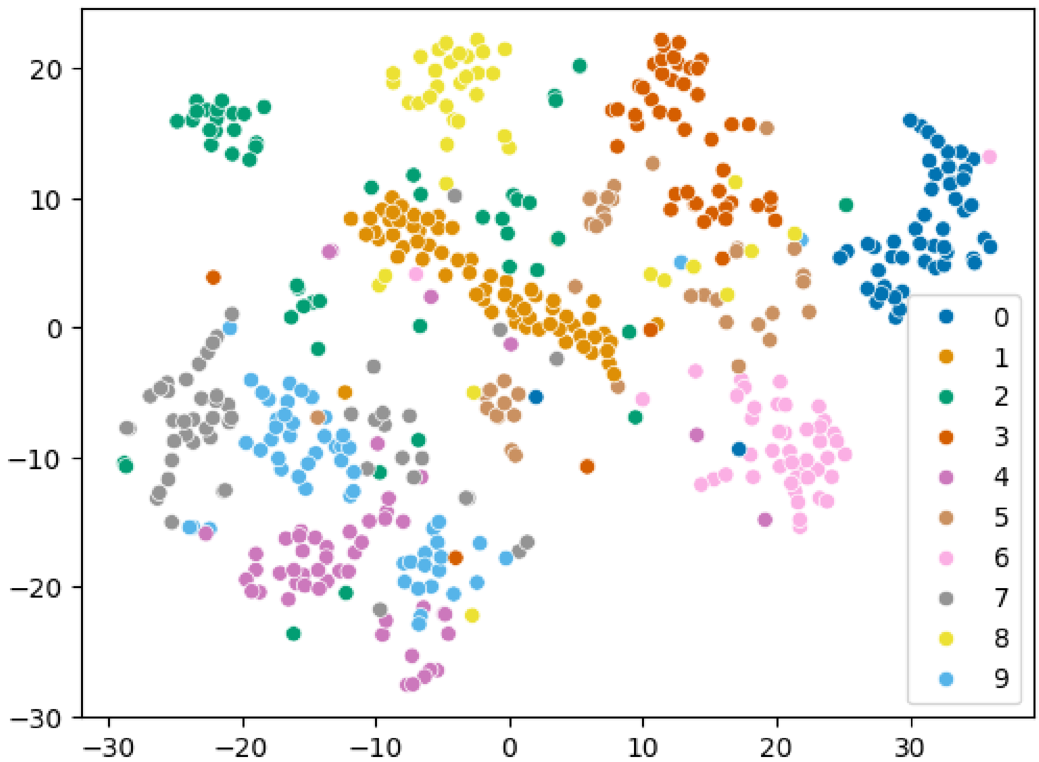


3 4c

[218]:

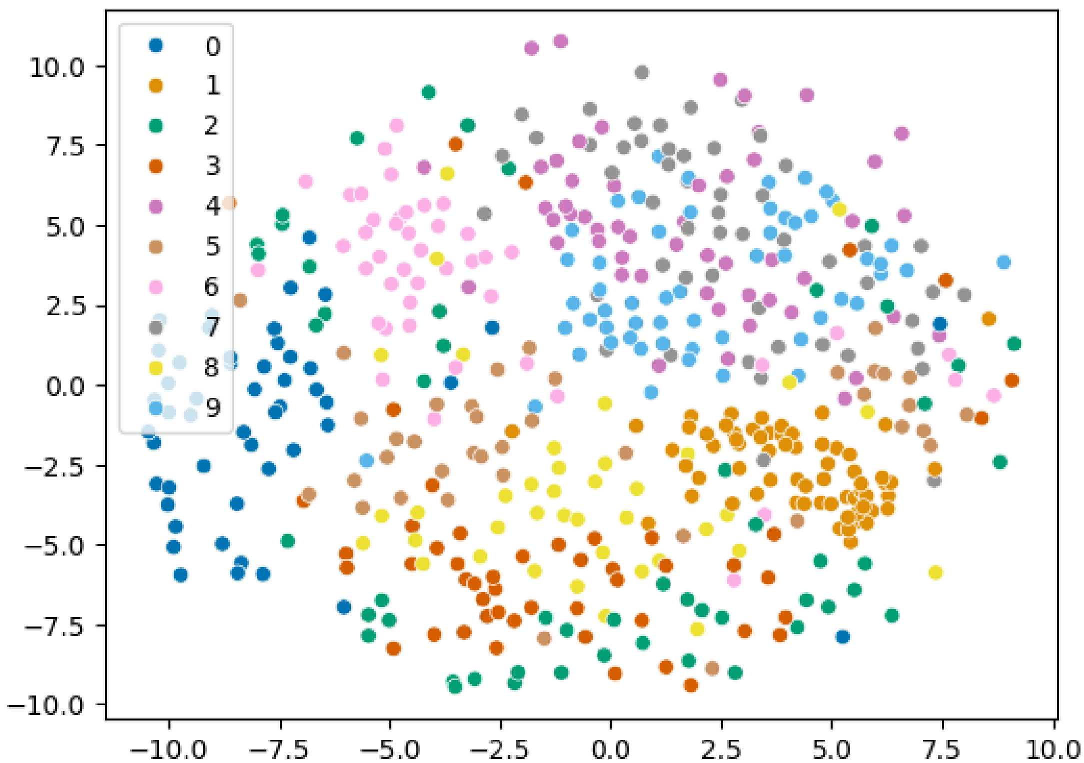
```
from sklearn.manifold import TSNE
from sklearn.manifold import MDS
(x_train, y_train), (x_test, y_test) = load_mnist()

tsne = TSNE(n_components=2)
X_tsne = tsne.fit_transform(x_train[:500])

# MDS
mds = MDS(n_components=2)
X_mds = mds.fit_transform(x_train[:500])

# Plotting

sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=y_train[:500],
 ↪palette="colorblind")
```

[218]: <Axes: >



[217]:
```
sns.scatterplot(x=X_mds[:, 0], y=X_mds[:, 1], hue=y_train[:500],␣
↪palette="colorblind")
```

[217]: <Axes: >



4 4D

[246]:
```
# 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()

def RMSE(a,b):
  return np.sqrt(np.square(a-b).mean())

errs  = []
for i in range(83):
  x = x_train[:, i:415:83]
  xv = x_val[:,i:415:83]
  model = Ridge().fit(x, y_train)
  pred = model.predict(xv)
  err = RMSE(pred, y_val)
  errs.append(err)

imin = np.argmin(errs)
print(imin, feature_to_city[imin])
x = x_train[:, imin:415:83]
```

```
model = Ridge().fit(x, y_train)
pred = model.predict(x_test[:,imin:415:83])
err = RMSE(pred, y_test)
print(err)
```

```
22 St. Louis
3.1263272970544764
```

5 4e

[220]:
```
from sklearn.svm import SVC
# SVM
for n in [100, 1000, 10000, 60000]:
  SVM = SVC(max_iter = 10000).fit(x_train[:n],y_train[:n])
  pred = SVM.predict(x_test)
  err = 100*(pred != y_test).mean()
  print(err)
```

```
34.410000000000004
9.17
4.06
2.08
```

[ ]:
```
# 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}")
```

```
Mounted at /content/drive/
PDF CREATED: /content/drive/My Drive/CS441/24SP/hw1/CS441_SP24_HW1_Solution.pdf
```