optical_character_recognition

December 29, 2024

In [27]:
```
#loading data
import pickle
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler


with open('digits.pkl', 'rb') as file:
    data = pickle.load(file)

data.head(10)
print(data.isna().sum())
```

```
0           0
1           0
2           0
3           0
4           0
          ...
60          0
61          0
62          0
63          0
Value    1350
Length: 65, dtype: int64
```

In [28]:
```
#summary of data statistics and adding range column
summary = data.describe()
```

In [29]:
```
summary.loc['range'] = summary.loc['max'] - summary.loc['min']
print(summary)
```

```
              0            1            2            3            4  \
count  1400.0  1400.000000  1400.000000  1400.000000  1400.000000
mean      0.0     0.290000     5.172857    11.781429    12.011429
std       0.0     0.871378     4.721566     4.287982     4.202336
```

```
min       0.0     0.000000     0.000000     0.000000     0.000000
25%       0.0     0.000000     1.000000    10.000000    10.000000
50%       0.0     0.000000     4.000000    13.000000    13.000000
75%       0.0     0.000000     9.000000    15.000000    15.000000
max       0.0     8.000000    16.000000    16.000000    16.000000
range     0.0     8.000000    16.000000    16.000000    16.000000

                5            6            7            8            9  ...  \
count  1400.000000  1400.000000  1400.000000  1400.000000  1400.000000  ...
mean      5.892857     1.437143     0.147143     0.007143     1.980000  ...
std       5.646605     3.446774     1.090504     0.106704     3.124695  ...
min       0.000000     0.000000     0.000000     0.000000     0.000000  ...
25%       0.000000     0.000000     0.000000     0.000000     0.000000  ...
50%       4.000000     0.000000     0.000000     0.000000     0.000000  ...
75%      11.000000     0.000000     0.000000     0.000000     3.000000  ...
max      16.000000    16.000000    14.000000     2.000000    16.000000  ...
range    16.000000    16.000000    14.000000     2.000000    16.000000  ...

               55           56           57           58           59  \
count  1400.000000  1400.000000  1400.000000  1400.000000  1400.000000
mean      0.240714     0.000714     0.266429     5.537857    12.085714
std       1.056610     0.026726     0.880096     5.071892     4.329670
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     1.000000    11.000000
50%       0.000000     0.000000     0.000000     4.000000    13.000000
75%       0.000000     0.000000     0.000000    10.000000    16.000000
max      13.000000     1.000000     9.000000    16.000000    16.000000
range    13.000000     1.000000     9.000000    16.000000    16.000000

               60           61           62           63        Value
count  1400.000000  1400.000000  1400.000000  1400.000000  50.000000
mean     11.990714     7.027857     2.302857     0.435000   4.540000
std       4.882821     5.989979     4.357963     2.048393   3.051998
min       0.000000     0.000000     0.000000     0.000000   0.000000
25%      10.000000     0.000000     0.000000     0.000000   2.000000
50%      14.000000     6.500000     0.000000     0.000000   5.000000
75%      16.000000    13.000000     2.000000     0.000000   7.000000
max      16.000000    16.000000    16.000000    16.000000   9.000000
range    16.000000    16.000000    16.000000    16.000000   9.000000

[9 rows x 65 columns]
```

```
In [30]: q1 = data.quantile(0.25)
         q3 = data.quantile(0.75)
         outlier_count = 0
         for index, row in data.iterrows():
             for col in data.columns:
```

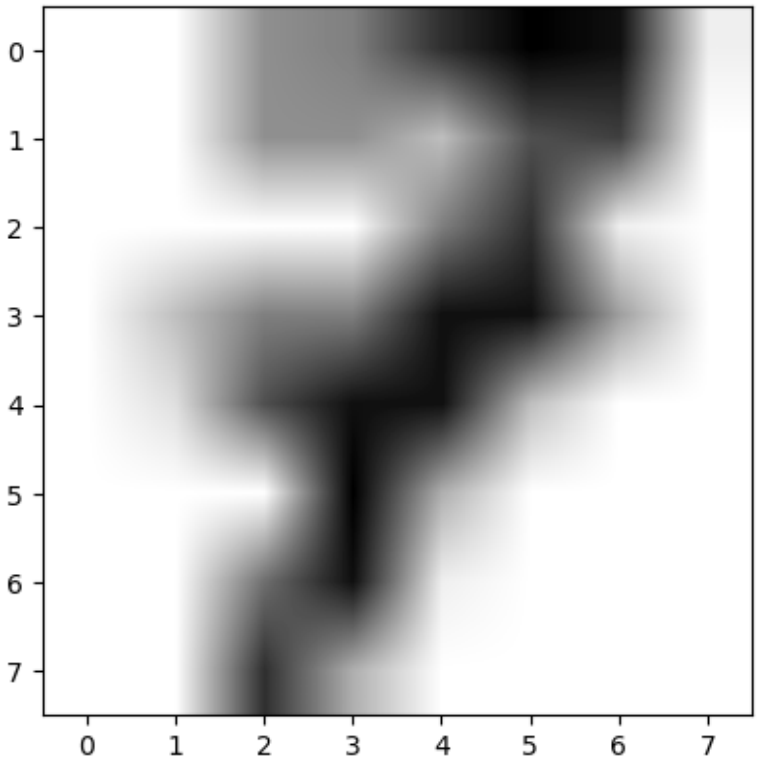
```
            if row[col] > q3[col]:
                outlier_count = outlier_count + 1
            elif row[col] < q1[col]:
                outlier_count = outlier_count + 1
    print(outlier_count)
    #from the table we can clearly see that the columns with
    #numerical data can have values from 0 to 2 to 16, and etc.
    #I coded up a for loop to calculate the # of outliers within the dataset.
    #22537/896000=0.02% of outliers which is acceptable
```

```
22537
```

In [31]:
```
#created a data frame that contains 64 pixel values for each number (X)
#created a series object containing data labels (y)
X = data.iloc[:, :-1]
y = data["Value"]
```

In [32]:
```
#converted both data frame and a series to NumPy arrays
numbers_np = X.to_numpy()
labels_np = y.to_numpy()
```

In [33]:
```
#used Pyplot to confirm digits upclose
plt.imshow(numbers_np[7].reshape(8, 8), cmap="binary",
           interpolation="bilinear")
plt.show()
```



In [34]:
```
#used Pyplot to examine multiple digits and confirmed labels
for i in range(50):
    plt.subplot(5, 10, i + 1)
    plt.imshow(numbers_np[i].reshape(8, 8), cmap="binary",
               interpolation="bilinear")
    plt.axis('off')

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

In [35]:
```
for i in range(50):
    print(f"{i} {labels_np[i]}")
#as we can see from the output,
#the first 50 numbers match the Values column
```

```
0 0.0
1 1.0
2 2.0
3 3.0
4 4.0
5 5.0
```

```
6 6.0
7 7.0
8 8.0
9 9.0
10 0.0
11 1.0
12 2.0
13 3.0
14 4.0
15 5.0
16 6.0
17 7.0
18 8.0
19 9.0
20 0.0
21 1.0
22 2.0
23 3.0
24 4.0
25 5.0
26 6.0
27 7.0
28 8.0
29 9.0
30 0.0
31 9.0
32 5.0
33 5.0
34 6.0
35 5.0
36 0.0
37 9.0
38 8.0
39 9.0
40 8.0
41 4.0
42 1.0
43 7.0
44 7.0
45 3.0
46 5.0
47 1.0
48 0.0
49 0.0
```

```
In [36]: #used labelled digits (y) to train a Logistic Regression
         #classifier from the features of individually labelled digits (X)
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

scaler = StandardScaler()
X_scaled = scaler.fit_transform(numbers_np[:50])
y = labels_np[:50]

regression = LogisticRegression(max_iter=500, solver='lbfgs')
regression.fit(X_scaled, y)
```

Out[36]:
```
LogisticRegression(max_iter=500)
```

In [37]:
```
#loaded a labelled test set
with open('digits_labeled.pkl', 'rb') as file:
    data2 = pickle.load(file)
data2.head(5)
```

Out[37]:

	0	1	2	3	4	5	6	7	8	9	...	55	56	57	\
0	0.0	1.0	10.0	13.0	2.0	0.0	0.0	0.0	0.0	10.0	...	0.0	0.0	0.0	
1	0.0	0.0	15.0	13.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
2	0.0	0.0	1.0	10.0	14.0	13.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
3	0.0	1.0	10.0	16.0	15.0	2.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
4	0.0	0.0	4.0	14.0	15.0	6.0	0.0	0.0	0.0	5.0	...	0.0	0.0	0.0	

	58	59	60	61	62	63	Value
0	9.0	13.0	11.0	10.0	9.0	0.0	2
1	10.0	13.0	10.0	6.0	2.0	0.0	2
2	0.0	12.0	14.0	4.0	0.0	0.0	5
3	10.0	15.0	2.0	0.0	0.0	0.0	7
4	4.0	13.0	15.0	9.0	0.0	0.0	9

[5 rows x 65 columns]

In [38]:
```
#used Logistic Regression model to determine
#the accuracy of labelling numbers
X_test = data2.iloc[:, :-1]
y_test = data2.iloc[:, -1]

X_test_scaled = scaler.transform(X_test)

y_pred = regression.predict(X_test_scaled)

# evaluating accuracy
test_accuracy = accuracy_score(y_test, y_pred)
print(test_accuracy)
```

```
0.8666666666666667
```

In [39]:
```
#created a cluster that has 50 classes of images based on the labeled data
from sklearn.cluster import KMeans
X_50 = numbers_np[:50]
kmeans = KMeans(n_clusters=50, random_state=42)

kmeans.fit(X_50)
clusters = kmeans.labels_
print(clusters)
```

```
[ 2 20 14 16 29  8 12 41 33 23 42 47 10 21 48 30  5 17  0 45 25  4 34 13
 18 22 46  6 39  1 40 35 24 49 38 11 43 28 32 19 15  3 44 37  9 36  7 26
 31 27]
```

```
/software/anaconda3/2023.07-2/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1412: Fut
  super()._check_params_vs_input(X, default_n_init=10)
```

In [40]:
```
#for each of the 50 classes determined a centroid
#and a representative image that is closest to the value
distances = kmeans.fit_transform(X_50)

closest_indices = []

for cluster_idx in range(50):
    cluster_distances = distances[:, cluster_idx]

    closest_idx = np.argmin(cluster_distances)
    closest_indices.append(closest_idx)

print(closest_indices)
```

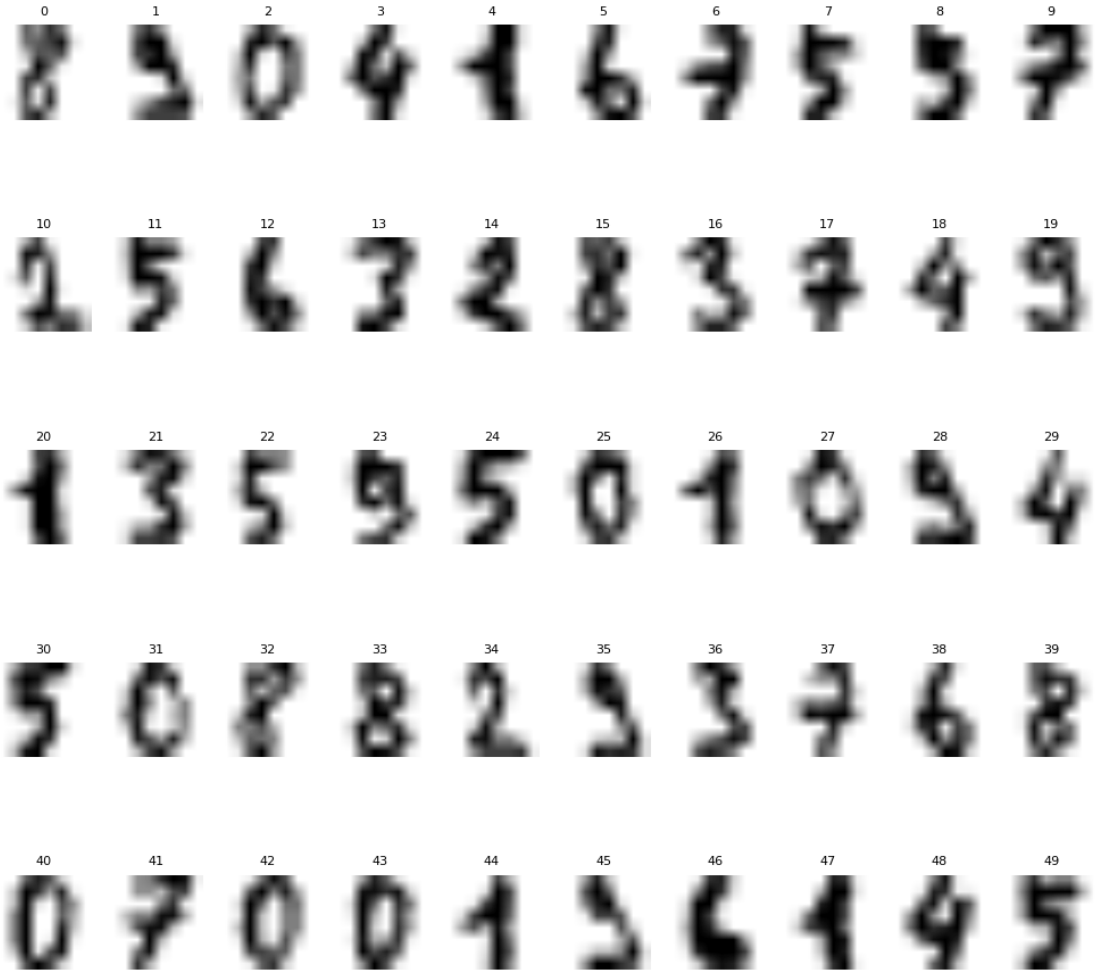
```
[18, 29, 0, 41, 21, 16, 27, 46, 5, 44, 12, 35, 6, 23, 2, 40, 3, 17, 24, 39, 1, 13, 25, 9, 32, 1
```

```
/software/anaconda3/2023.07-2/lib/python3.11/site-packages/sklearn/cluster/_kmeans.py:1412: Fut
  super()._check_params_vs_input(X, default_n_init=10)
```

In [41]:
```
#visualizing images using Pyplot
plt.figure(figsize=(10, 10))

for i, idx in enumerate(closest_indices):
    plt.subplot(5, 10, i + 1)  # Create a grid of 5 rows and 10 columns
    plt.imshow(numbers_np[idx].reshape(8, 8), cmap="binary",
               interpolation="bilinear")
    plt.title(f"{i}", fontsize=8)
    plt.axis("off")
```

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



In [42]:
```
#propagated labels from each representative image
#to each one of the images in the individual 50 clusters
all_labels = kmeans.predict(numbers_np)
representative_labels = labels_np[closest_indices]
propagated_labels = np.empty(len(numbers_np), dtype=int)

# assigns labels to all images based on their cluster
for cluster_idx in range(50):
    # finds all images assigned to the current cluster
    cluster_mask = all_labels == cluster_idx

    propagated_labels[cluster_mask] = representative_labels[cluster_idx]

print(representative_labels)
print(propagated_labels)
```

```
[8. 9. 0. 4. 1. 6. 7. 5. 5. 7. 2. 5. 6. 3. 2. 8. 3. 7. 4. 9. 1. 3. 5. 9.
 5. 0. 1. 0. 9. 4. 5. 0. 8. 8. 2. 9. 3. 7. 6. 8. 0. 7. 0. 0. 1. 9. 6. 1.
 4. 5.]
[0 1 2 ... 4 4 7]
```

In [43]:
```
#trained a Logistic Regression model using
#newly labelled data and determined accuracy (results in the comment below)
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(numbers_np,
                                                    propagated_labels,
                                                    test_size=0.2,
                                                    random_state=42)


scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

log_reg = LogisticRegression(max_iter=500, random_state=42)
log_reg.fit(X_train_scaled, y_train)

y_pred = log_reg.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
#clustering data to provide learned labels has proved to bring
#better accuracy (0.89 vs 0.86 prior to that)
```

```
0.8928571428571429
```