# Reading and Importing Data

In [1]:

```
#importing csv file
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import scale
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import classification_report
from sklearn.metrics import classification_report, confusion_matrix
data = pd.read_csv("digit_svm.csv")
```

Data understanding and exploration¶

In [2]:

```
data.head()
```

Out[2]:

| | label | pixel0 | pixel1 | pixel2 | pixel3 | pixel4 | pixel5 | pixel6 | pixel7 | pixel8 | ... | pixel774 | pixel775 | pixel776 | pixel777 | pixel778 | pixel779 | pixel78 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | |
| **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | |
| **2** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | |
| **3** | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | |
| **4** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | |

5 rows × 785 columns

In [3]:

```
data.shape
```

Out[3]:

```
(42000, 785)
```

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42000 entries, 0 to 41999
Columns: 785 entries, label to pixel783
dtypes: int64(785)
memory usage: 251.5 MB
```

In [5]:

```
data.describe()
```

Out[5]:

| | label | pixel0 | pixel1 | pixel2 | pixel3 | pixel4 | pixel5 | pixel6 | pixel7 | pixel8 | ... | pixel774 | pixel775 | pixe |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 42000.000000 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | 42000.0 | ... | 42000.000000 | 42000.000000 | 42000.000 |
| **mean** | 4.456643 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.219286 | 0.117095 | 0.059 |
| **std** | 2.887730 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 6.312890 | 4.633819 | 3.274 |
| **min** | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 | 0.000 |
| **25%** | 2.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 | 0.000 |
| **50%** | 4.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 | 0.000 |
| **75%** | 7.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.000000 | 0.000000 | 0.000 |
| **max** | 9.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 254.000000 | 254.000000 | 253.000 |

8 rows × 785 columns

In [6]:

```
data.isnull().sum()
```

Out[6]:

```
label       0
pixel0      0
```

```
pixel1      0
pixel2      0
pixel3      0
           ..
pixel779    0
pixel780    0
pixel781    0
pixel782    0
pixel783    0
Length: 785, dtype: int64
```

# Viualisation

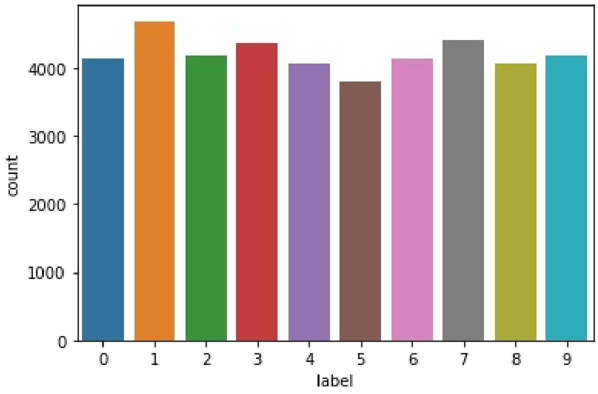
In [7]:

```
sns.countplot(data["label"])
```

```
C:\Users\KIIT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable a
s a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[7]:

```
<AxesSubplot:xlabel='label', ylabel='count'>
```



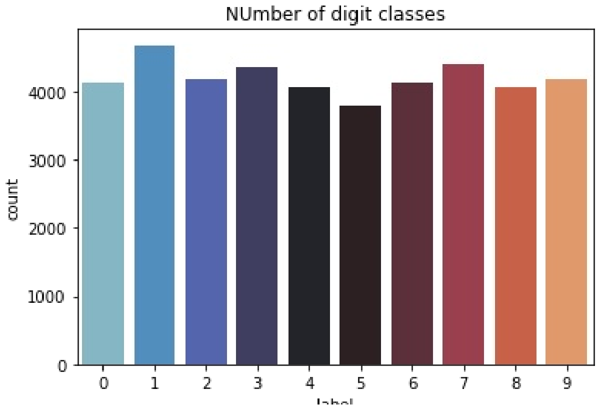
In [8]:

```
plt.plot(figure = (16,10))
g = sns.countplot( data["label"], palette = 'icefire')
plt.title('NUmber of digit classes')
data.label.astype('category').value_counts()
```

```
C:\Users\KIIT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable a
s a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[8]:

```
1    4684
7    4401
3    4351
9    4188
2    4177
6    4137
0    4132
4    4072
8    4063
5    3795
Name: label, dtype: int64
```



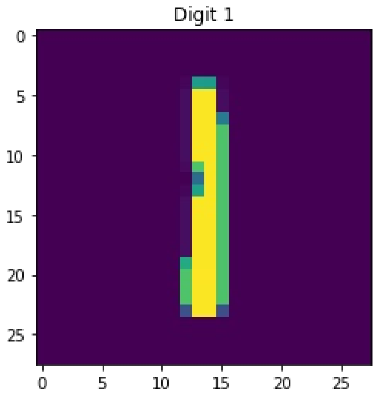
label

In [9]:

```python
one = data.iloc[2, 1:]
one = one.values.reshape(28,28)
plt.imshow(one)
plt.title("Digit 1")
```

Out[9]:

```
Text(0.5, 1.0, 'Digit 1')
```

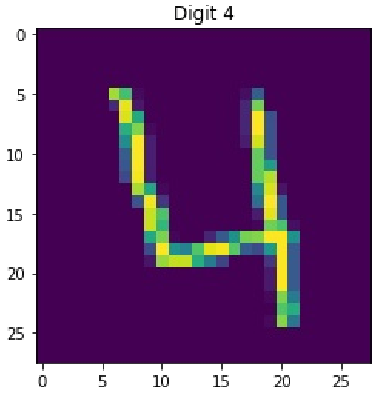


In [10]:

```python
four = data.iloc[3, 1:]
four = four.values.reshape(28,28)
plt.imshow(four)
plt.title("Digit 4")
```

Out[10]:

```
Text(0.5, 1.0, 'Digit 4')
```

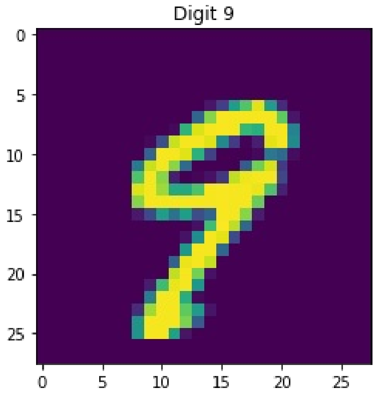


In [11]:

```python
nine = data.iloc[11, 1:]
nine = nine.values.reshape(28,28)
plt.imshow(nine)
plt.title("Digit 9")
```

Out[11]:

```
Text(0.5, 1.0, 'Digit 9')
```



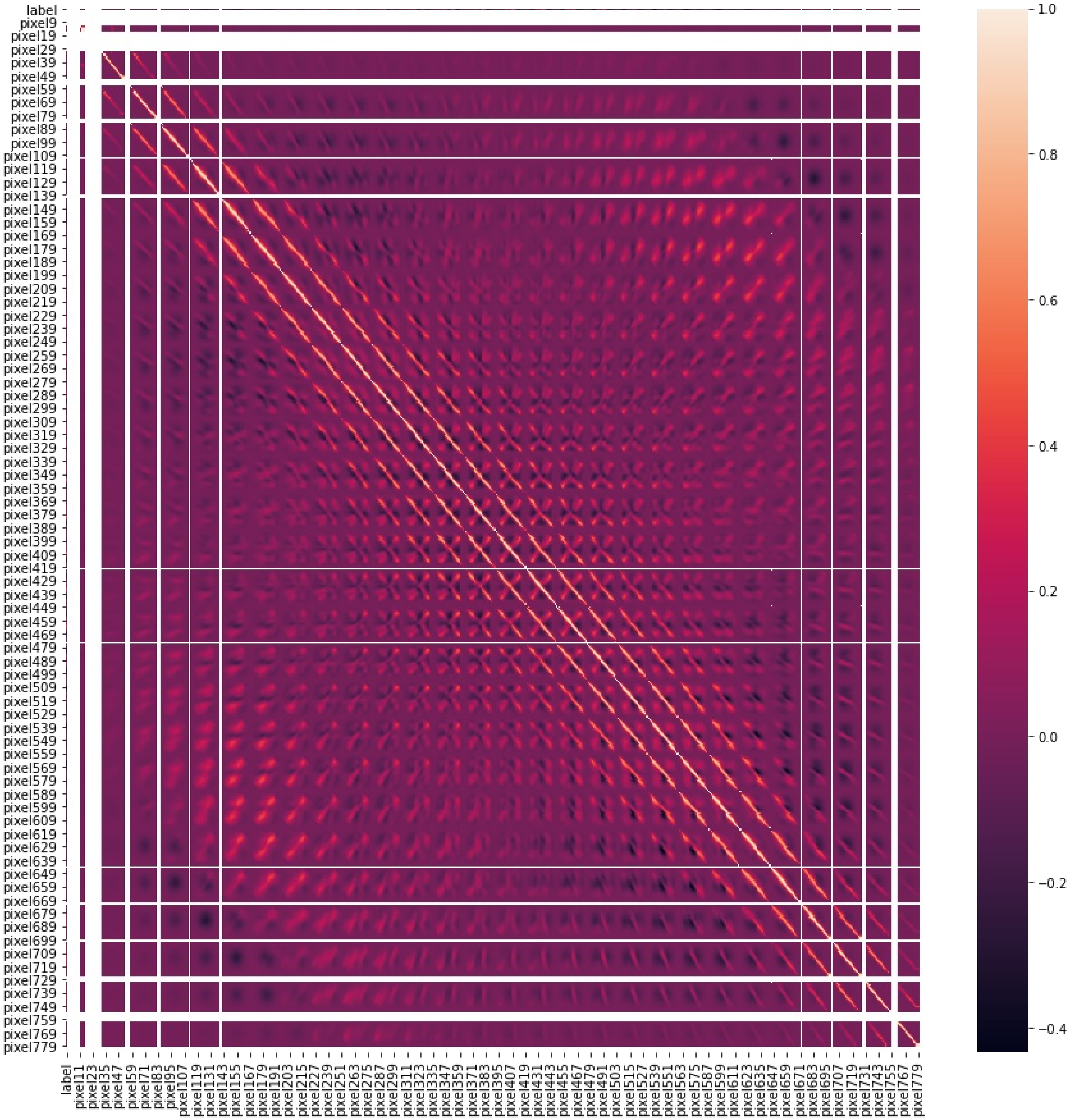
# Heatmap

In [12]:

```
plt.figure(figsize=(15,15))
sns.heatmap(data=data.corr(),annot=False)
```

Out[12]:

```
<AxesSubplot:>
```



In [13]:

```
data.corr()
```

Out[13]:

| | label | pixel0 | pixel1 | pixel2 | pixel3 | pixel4 | pixel5 | pixel6 | pixel7 | pixel8 | ... | pixel774 | pixel775 | pixel776 | pixel777 | pixel778 | p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **label** | 1.000000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | 0.033424 | 0.025050 | 0.019558 | 0.014490 | 0.009790 | 0 |
| **pixel0** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | |
| **pixel1** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | |
| **pixel2** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | |
| **pixel3** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **pixel779** | 0.006075 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | -0.000240 | -0.000174 | -0.000124 | 0.236633 | 0.905835 | 1 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **pixel780** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN |
| **pixel781** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN |
| **pixel782** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN |
| **pixel783** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN | NaN | NaN | NaN | NaN |

785 rows × 785 columns

# Splitting and scalling

In [14]:

```
# splitting into X and y
X = data.drop("label", axis = 1)
y = data['label']
X_scaled = scale(X)
from sklearn.model_selection import train_test_split
# train test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, train_size=0.2,test_size = 0.8, random_state = 1
```

In [15]:

```
print('X_train shape:',X_train.shape)
print('y_train shape:',y_train.shape)
print('X_test shape:',X_test.shape)
print('y_test shape:',y_test.shape)
```

```
X_train shape: (8400, 784)
y_train shape: (8400,)
X_test shape: (33600, 784)
y_test shape: (33600,)
```

# Model Building

In [16]:

```
from sklearn import svm
from sklearn import metrics
from sklearn.svm import SVC


model_linear = SVC(kernel='linear')
model_linear.fit(X_train, y_train)
y_pred = model_linear.predict(X_test)

# accuracy
print("accuracy:", metrics.accuracy_score(y_true=y_test, y_pred=y_pred), "\n")

# cm
print(metrics.confusion_matrix(y_true=y_test, y_pred=y_pred))
```

```
accuracy: 0.913125

[[3188    0   10    5   11   20   32    3   15    1]
 [   0 3677   14   11    5    7    4    8   30    4]
 [  36   29 3027   54   55   10   30   42   48   12]
 [  13   12  104 3051    9  181    5   21   54   25]
 [   8   14   33    2 3057    4   25   31    6  110]
 [  30   23   29  136   44 2622   44   12   72   27]
 [  26   11   44    4   28   33 3113    0   18    0]
 [   7   24   36   19   59    9    2 3210    4  134]
 [  13   46   50  120   21  110   30   18 2843   21]
 [  19   17   21   22  172   20    4  161   26 2893]]
```

In [17]:

```
scores=metrics.classification_report(y_test, y_pred, labels=[0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
print(scores)
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      3285
           1       0.95      0.98      0.97      3760
           2       0.90      0.91      0.90      3343
           3       0.89      0.88      0.88      3475
           4       0.88      0.93      0.91      3290
           5       0.87      0.86      0.87      3039
           6       0.95      0.95      0.95      3277
           7       0.92      0.92      0.92      3504
           8       0.91      0.87      0.89      3272
           9       0.90      0.86      0.88      3355

    accuracy                           0.91     33600
   macro avg       0.91      0.91      0.91     33600
weighted avg       0.91      0.91      0.91     33600
```

## Non-Linear SVM

In [18]:

```
# rbf kernel with other hyperparameters kept to default
svm_rbf = svm.SVC(kernel='rbf')
svm_rbf.fit(X_train, y_train)
```

Out[18]:

```
SVC()
```

In [19]:

```
# predict
predictions = svm_rbf.predict(X_test)

# accuracy
print(metrics.accuracy_score(y_true=y_test, y_pred=predictions))
```

```
0.9396130952380952
```

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