MNIST

Lisää informaatio datasta ja kilpailusta: https://www.kaggle.com/c/digit-recognizer/data

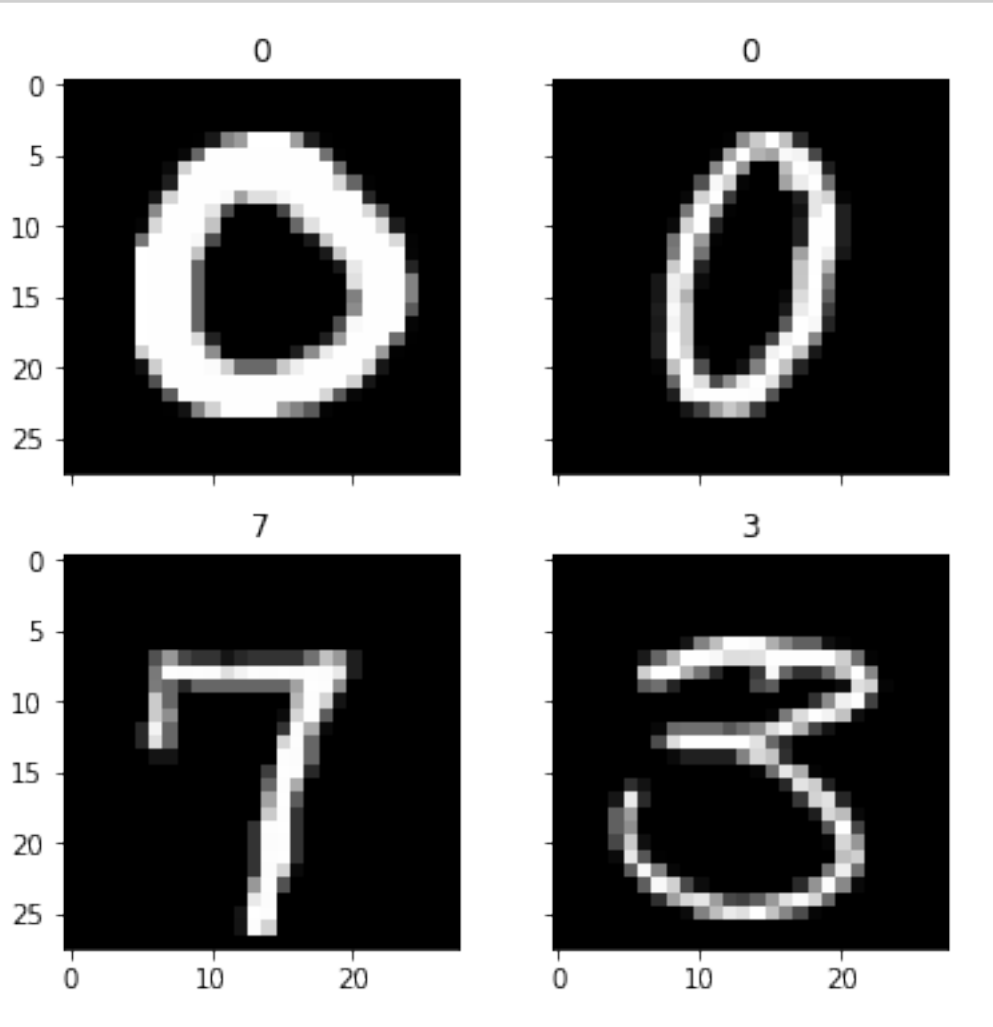
Datan lataus ja tarkastelu ¶

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import ndimage
from sklearn import model_selection
%matplotlib inline
```

In [2]:
```
#Luetaan data
df_test = pd.read_csv('test.csv')
df_train = pd.read_csv('train.csv')
```

Katsotaan miltä data näyttää

In [3]:
```
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(nrows = 2, ncols = 2, sharex=True, sharey=True, figsize=(6,6))

ax1.imshow(df_train.loc[4,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28)), cmap='gray')
ax2.imshow(df_train.loc[5,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28)), cmap='gray')
ax3.imshow(df_train.loc[6,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28)), cmap='gray')
ax4.imshow(df_train.loc[7,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28)), cmap='gray')
#fig.tight_layout()
ax1.set(title=df_train.loc[4,df_train.columns[0]])
ax2.set(title=df_train.loc[5,df_train.columns[0]])
ax3.set(title=df_train.loc[6,df_train.columns[0]])
ax4.set(title=df_train.loc[7,df_train.columns[0]])
plt.show()
```

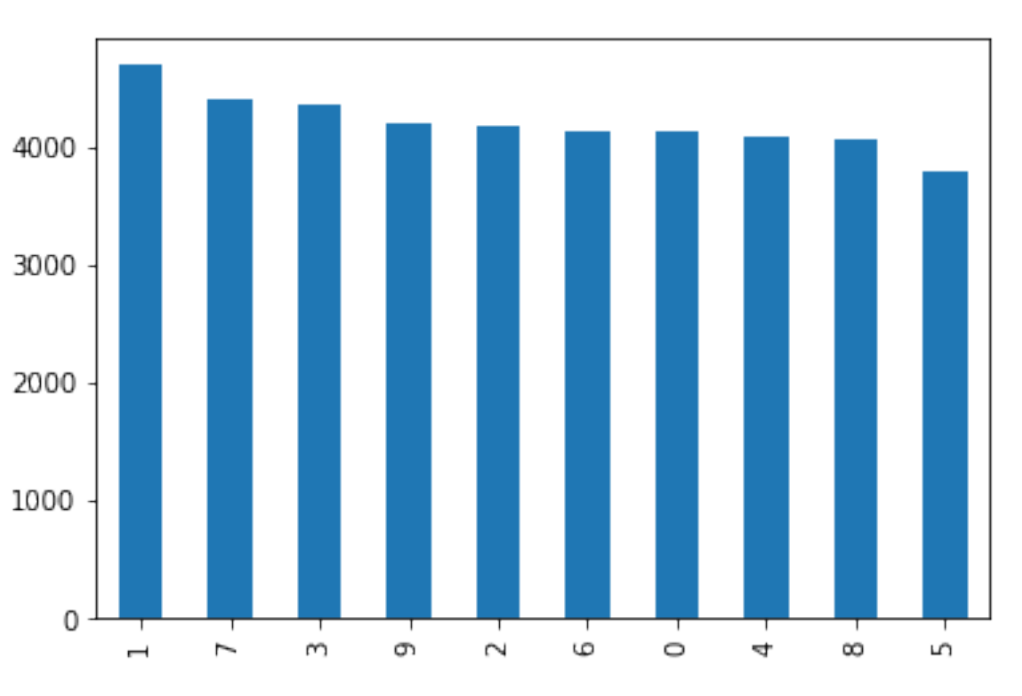


In [4]:
```
print(f"Koulutus setissä: {df_train.shape[0]} kuvaa")
print(f"Testi setissä: {df_test.shape[0]} kuvaa")
```

```
Koulutus setissä: 42000 kuvaa
Testi setissä: 28000 kuvaa
```

In [5]:
```
df_train['label'].value_counts().plot(kind='bar')
```

Out[5]:
```
<AxesSubplot:>
```



Train-data näyttäisi olevan tasapainossa.

Data augmentaatio

Augmentaatiossa luodaan lisää dataa muokkaamalla olemassa olevia kuvia. Augmentaatio toimii regularisaatio metodina ja vähentää ylisovituksen riskin määrää. Tässä tapauksessa kuviin lisätään satunnaisesti eri määriä kohinaa ja kiertoa.

Rotaatio

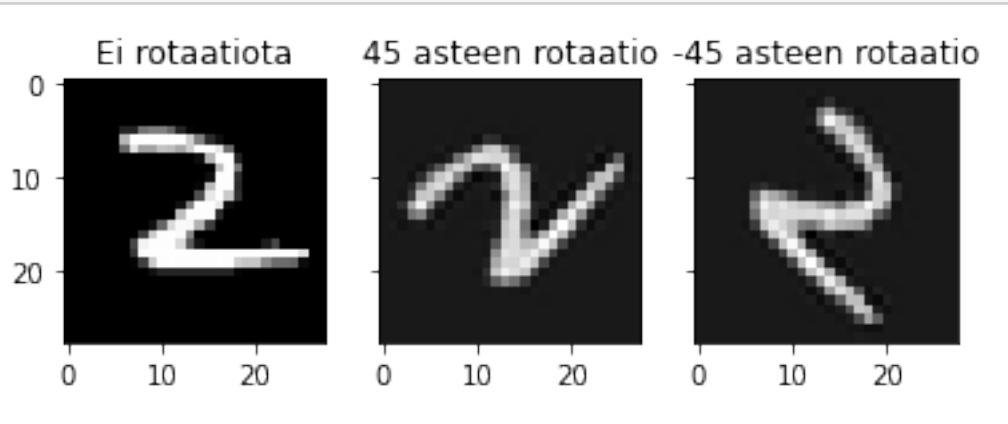
Kutakin kuvan pikseliä (x, y) voidaan kuvata paikkavektorilla. Uudet paikat θ suuruisen rotaation jälkeen ovat

$$x' = xcos(\theta) - ysin(\theta)$$

$$y' = xsin(\theta) + ycos(\theta)$$

Esimerkki

In [6]:
```
fig, (ax1, ax2, ax3) = plt.subplots(nrows=1, ncols=3,sharey=True)
ax1.imshow(df_train.loc[56,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28)), cmap='gray')
picture = df_train.loc[56,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28))
picture2 = ndimage.rotate(picture, -45, reshape=False)
picture = ndimage.rotate(picture, 45, reshape=False)
ax2.imshow(picture, cmap='gray')
ax3.imshow(picture2, cmap='gray')
ax1.set(title='Ei rotaatiota')
ax2.set(title='45 asteen rotaatio')
ax3.set(title='-45 asteen rotaatio')
plt.show()
```



In [7]:
```
def random_rotation(image):
    theta = np.random.randint(-45, 45) #random angle
    rotated_image = ndimage.rotate(image, theta, reshape=False)
    return rotated_image

def pick_random_image(dataframe):
    random_row = np.random.randint(0, dataframe.shape[0])
    random_image = df_train.loc[random_row,df_train.columns[1]:df_train.columns[-1]].to_numpy().reshape((28,28))
    return random_image
```

Augmentoidaan 400 kuvaa per numero. (n. 10% lisää dataa)

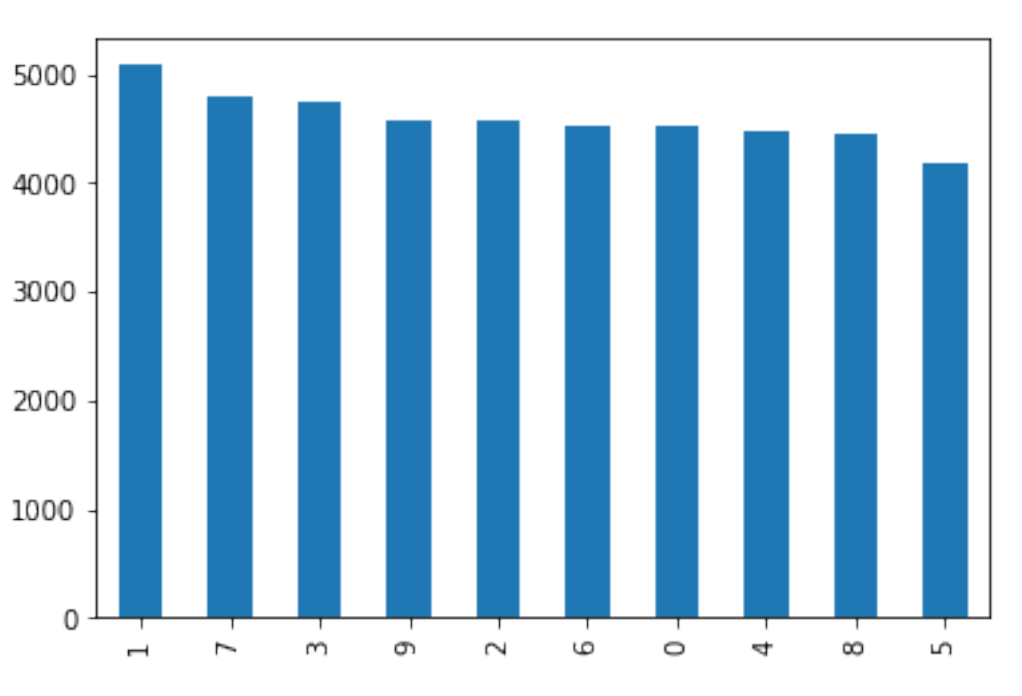
In [8]:
```
def augment(dataframe, label):
    rows_list=[]
    sample_data = dataframe[dataframe['label']==label]
    for i in range(0,400):
        rotated_image = random_rotation(pick_random_image(sample_data))
        row = np.append(label, rotated_image.flatten())
        rows_list.append(row)

    return pd.DataFrame(rows_list, columns=dataframe.columns)

matrix_train = df_train.to_numpy()
print(f"Ennen augmentointia: {matrix_train.shape}")
for i in range(0,10):
    aug = augment(df_train.sample(frac=0.1), i)
    tmp_matrix = np.vstack([matrix_train, aug])
    matrix_train = tmp_matrix

print(f"Augmentoinnin jälkeen: {matrix_train.shape}")
```

```
Ennen augmentointia: (42000, 785)
Augmentoinnin jälkeen: (46000, 785)
```

Tarkistetaan vielä, että jakauma on pysynyt hyvänä

In [9]:
```
pd.DataFrame(matrix_train)[0].value_counts().plot(kind='bar')
```

Out[9]:
```
<AxesSubplot:>
```

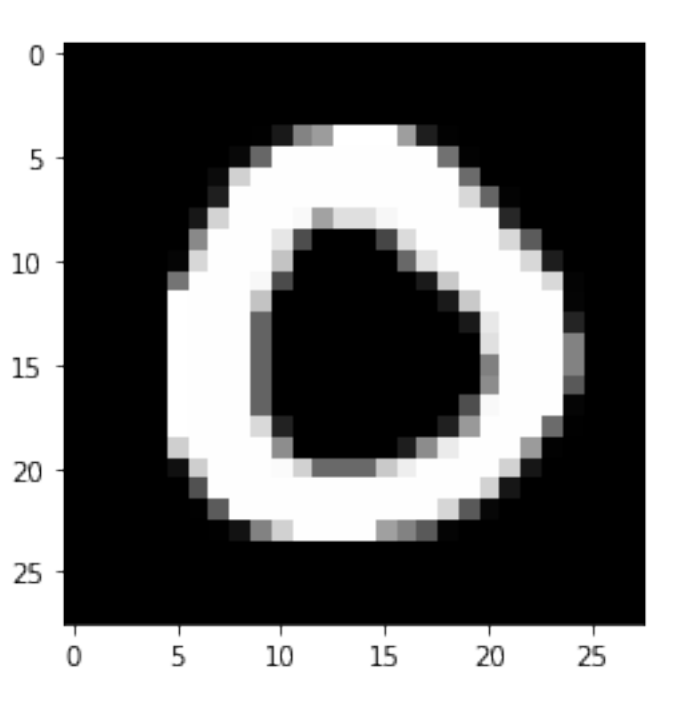


Datan skaalaus

Kaikki pikseli arvot on nyt välillä $0 - 255$, mutta skaalataan ne välille $[0..1]$. Skaalaus helpottaa optimisointi algoritmia löytämään globaalin minimin. Skaalaus tapahtuu jakamalla kaikki arvot 255.

In [10]:
```
df_train_augmented = pd.DataFrame(matrix_train)
df_train_augmented_norm = df_train_augmented.iloc[:, 1:] / 255
plt.imshow(df_train_augmented_norm.loc[4,1:784].to_numpy().reshape((28,28)), cmap='gray')
```

Out[10]:
```
<matplotlib.image.AxesImage at 0x1244387f0>
```



Train test split

Jaetaan data kahteen osaan suhteessa 90/10, jossa 90% datasta käytetään mallin kouluttamiseen ja 10 % käytetään mallin arviointiin. Tämä siksi, koska annetussa testi datassa ei ole annettu oikeaa vastausta.

In [11]:
```
X = df_train_augmented_norm.loc[:, 1:784]
y = df_train_augmented.iloc[:, 0]
```

In [12]:
```
X_train, X_test, y_train, y_test = model_selection.train_test_split(X,y,test_size=0.1, random_state=42)
#Set random state for pseudorandomness
```

In [13]:
```
print(f"X_train shape: {X_train.shape}; y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}; y_test shape: {y_test.shape}")
```

```
X_train shape: (41400, 784); y_train shape: (41400,)
X_test shape: (4600, 784); y_test shape: (4600,)
```

Mallin luominen

CNN - Convolutional neural networks

In [14]:
```
import torch
import torch.nn as nn
from torch.autograd import Variable
```

In [15]:
```
class CNNModel(nn.Module):
    def __init__(self):
        super(CNNModel, self).__init__()

        #1. konvoluutio
        self.cnn1 = nn.Conv2d(in_channels=1, out_channels=16, kernel_size = 6, stride = 1, padding = 0)
        self.relu1 = nn.ReLU()
        #22x22x16

        #1. Max pooling
        self.maxpool1 = nn.MaxPool2d(kernel_size=2)
        #11x11x16


        #2. konvoluutio
        self.cnn2 = nn.Conv2d(in_channels=16, out_channels= 32, kernel_size = 3, stride=1, padding =0)
        self.relu2 = nn.ReLU()
        #9x9x32

        # 2. maxpooling
        self.maxpool2 = nn.MaxPool2d(kernel_size=2)
        #4x4x32

        #FC
        self.fc1 = nn.Linear(32*4*4,10)

    def forward(self, x):
        out = self.cnn1(x)
        out=self.relu1(out)  #1.konv
        out = self.maxpool1(out)  #1.max
        out= self.cnn2(out)
        out=self.relu2(out) #2.conv
        out=self.maxpool2(out)#2.max
        out = out.view(out.size(0), -1) #flatten for fc
        out = self.fc1(out) #linear out
        return out

model = CNNModel()
```

In [41]:
```
import torch.optim as optim

features_train = torch.from_numpy(X_train.to_numpy().astype(np.float32))
label_train = torch.from_numpy(y_train.to_numpy().astype(np.float32)).type(torch.LongTensor)
features_test = torch.from_numpy(X_test.to_numpy().astype(np.float32))
label_test = torch.from_numpy(y_test.to_numpy().astype(np.float32)).type(torch.LongTensor)
train = torch.utils.data.TensorDataset(features_train, label_train)
test = torch.utils.data.TensorDataset(features_test, label_test)

train_loader = torch.utils.data.DataLoader(train, batch_size = 100, shuffle = True)
test_loader = torch.utils.data.DataLoader(test, batch_size = 100, shuffle = True)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr = 0.001)
```

In [42]:
```
count = 0
loss_list = []
iteration_list = []
accuracy_list = []
for epoch in range(8):
    for i, (images,labels) in enumerate(train_loader):
        train = Variable(images.view(100,1,28,28))
        labels = Variable(labels)

        optimizer.zero_grad()

        outputs = model(train)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        count += 1

        if count % 50 == 0:
            correct = 0
            total = 0
            for images, labels in test_loader:
                test = Variable(images.view(100,1,28,28))

                outputs = model(test)

                predicted = torch.max(outputs.data, 1)[1]

                total += len(labels)
                correct += (predicted == labels).sum()

            accuracy = 100 * correct / float(total)

            loss_list.append(loss.data)
            iteration_list.append(count)
            accuracy_list.append(accuracy)
        if count % 250 == 0:
            print(f"Iteration: {count} \n Loss: {loss.data} \n Accuracy: {accuracy}.")
```

```
Iteration: 250
 Loss: 0.45241475105285645
 Accuracy: 90.63043212890625.
Iteration: 500
 Loss: 0.6133931279182434
 Accuracy: 90.65217590332031.
Iteration: 750
 Loss: 0.5700414776802063
 Accuracy: 90.4565200805664.
Iteration: 1000
 Loss: 0.26190468668937683
 Accuracy: 90.67391204833984.
Iteration: 1250
 Loss: 0.5478730797767639
 Accuracy: 90.67391204833984.
Iteration: 1500
 Loss: 0.6204952001571655
 Accuracy: 90.76087188720703.
Iteration: 1750
 Loss: 0.3303655982017517
 Accuracy: 90.63043212890625.
Iteration: 2000
 Loss: 0.2510245740413666
 Accuracy: 90.5434799194336.
Iteration: 2250
 Loss: 0.40671417117118835
 Accuracy: 90.67391204833984.
Iteration: 2500
 Loss: 0.36767876148223877
 Accuracy: 90.5.
Iteration: 2750
 Loss: 0.35545843839645386
 Accuracy: 90.47826385498047.
Iteration: 3000
 Loss: 0.2771175503730774
 Accuracy: 90.21739196777344.
Iteration: 3250
 Loss: 0.5785958170890808
 Accuracy: 90.60869598388672.
```

Evaluaatio

In [43]:
```
torch.save(model, './mnist_model.pt')
validate = df_test.to_numpy().astype(np.float32) / 255
validate_features = torch.from_numpy(validate)
```

In [77]:
```
val_loader = torch.utils.data.DataLoader(validate_features, batch_size = 100)
outputs = np.array([])
with torch.no_grad():
    for i, data in enumerate(val_loader):
        data = Variable(data.view(100,1,28,28))
        output = model(data)
        predicted = torch.max(output.data, 1)[1]
        #outputs.append(predicted.numpy())
        outputs = np.append(outputs, predicted.numpy())
```

In [84]:
```
df_val = pd.DataFrame(outputs.flatten().astype(int))
df_val.index += 1
```

In [85]:
```
df_val.to_csv('./submission.csv', index=True)
```

https://www.kaggle.com/jaka0206

Tämä malli saavutti kilpailussa n. 98% tarkkuuden.

In [ ]: