Gaussian naive bayes model for handwritten digits recognition

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Import libs

In [1]:
```
import os
from PIL import Image
import PIL.ImageOps
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import mpl_toolkits.mplot3d as m3d
from sklearn.naive_bayes import GaussianNB
```

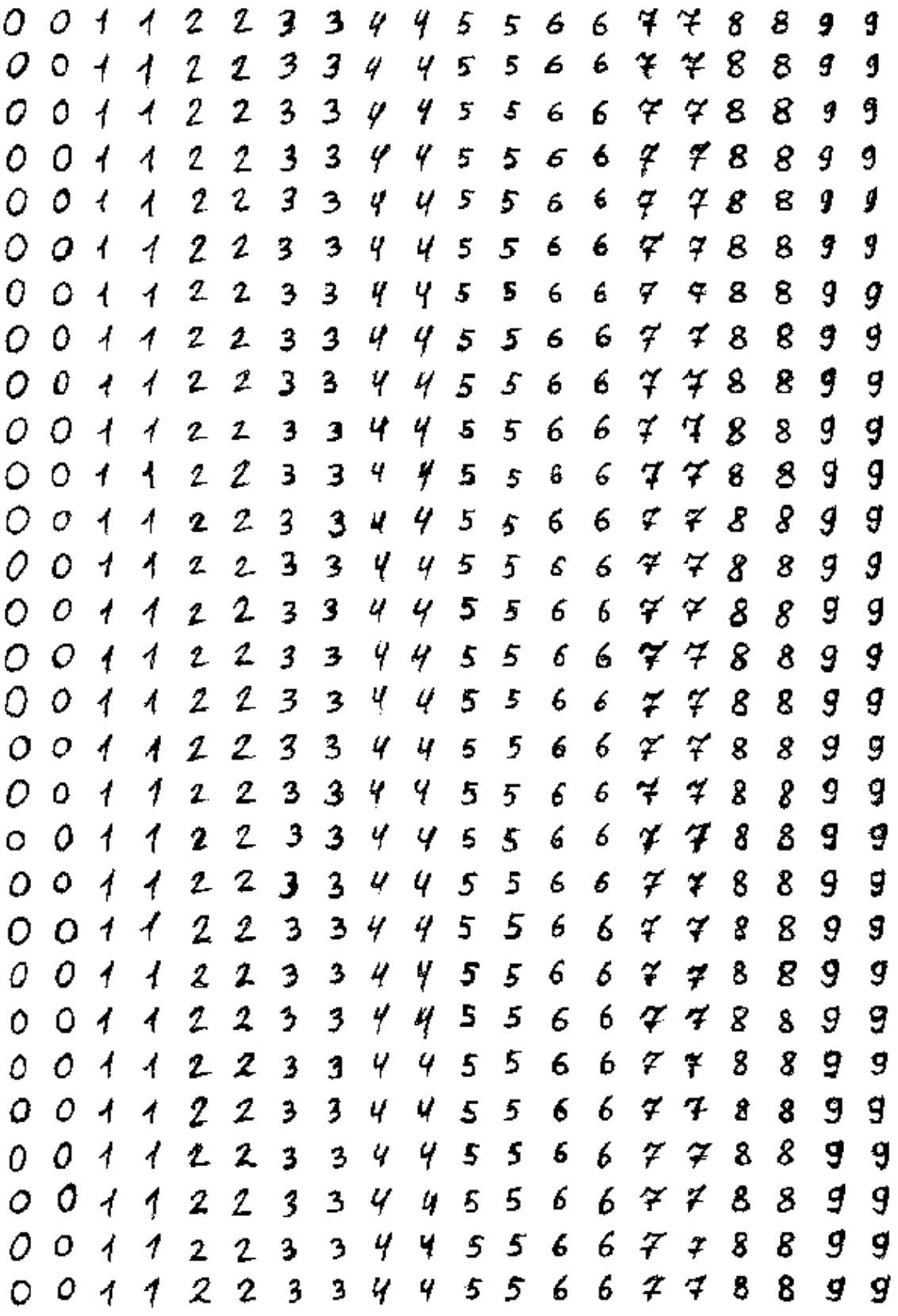
List of images with digits for future train and prediction sets

In [2]:
```
imagearr = []
for filename in os.listdir('C:\\Users\\NULL\\Desktop\\BS_project\\scan'):
    image = Image.open('C:\\Users\\NULL\\Desktop\\BS_project\\scan\\' + filename)
    imagearr.append(image)
    del image
```

Digits set 1

In [3]:
```
imagearr[0]
```

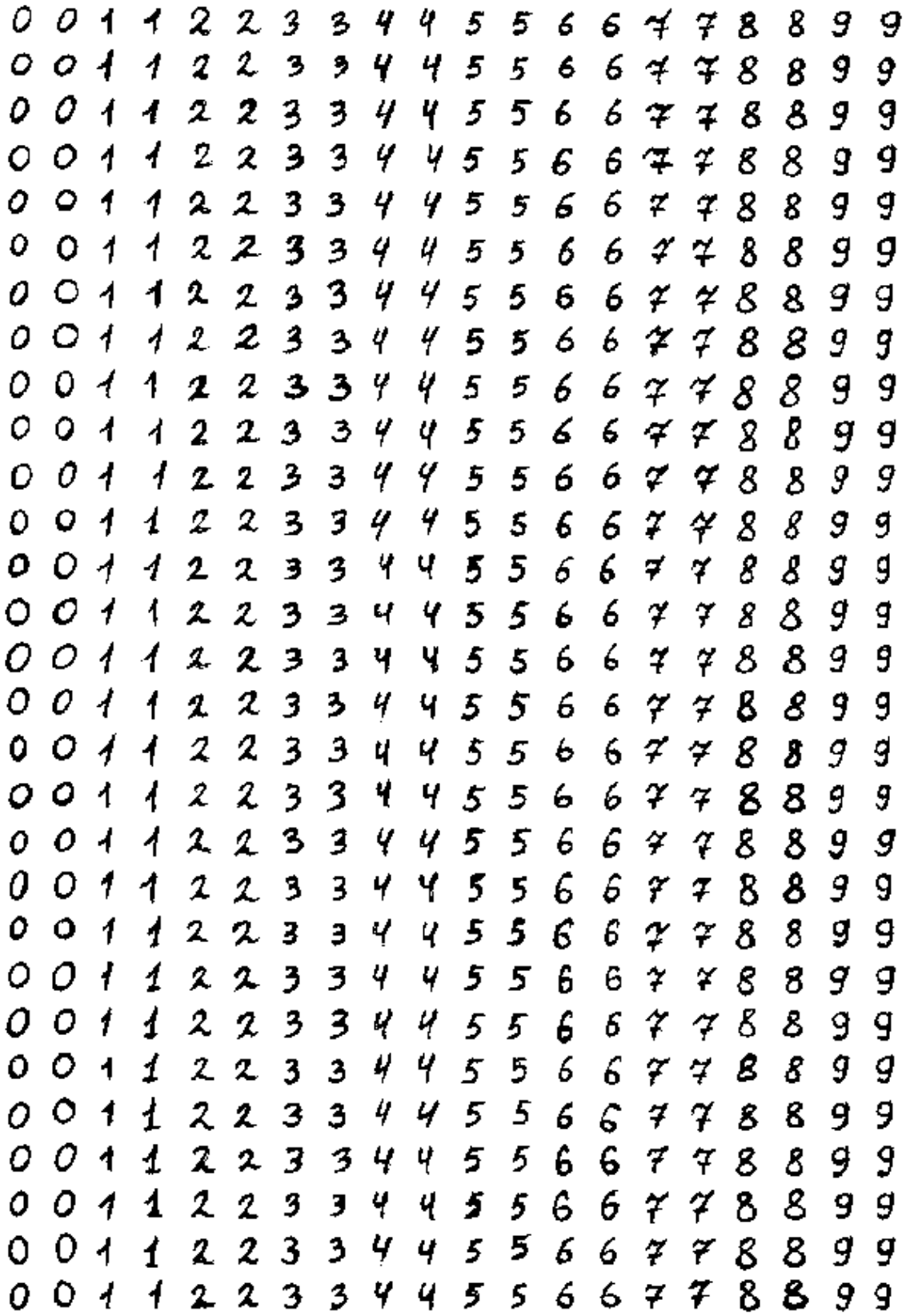
Out[3]:



Digits set 2

In [4]:
```
imagearr[1]
```

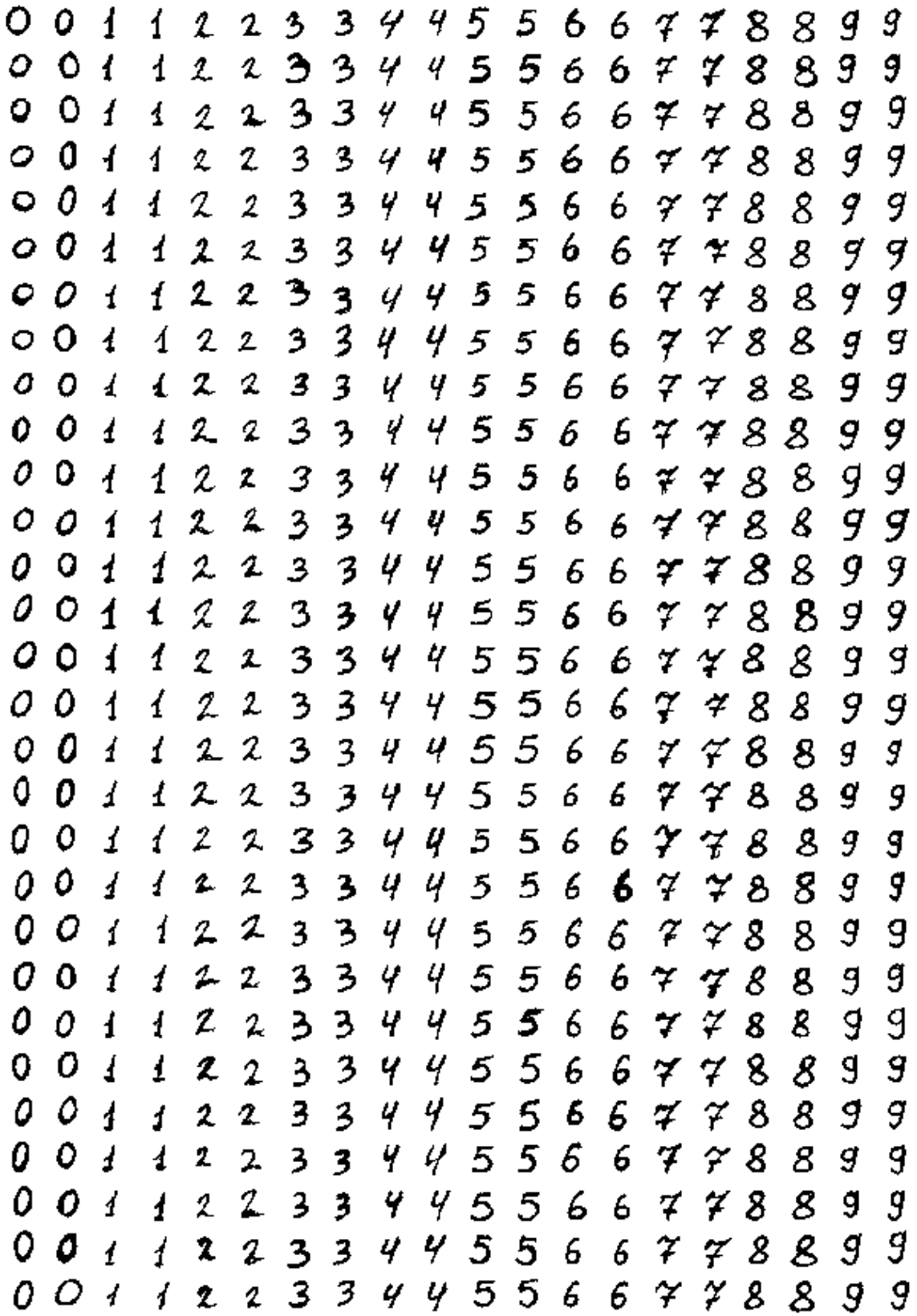
Out[4]:



Digits set 3

In [5]:
```
imagearr[2]
```

Out[5]:



Func for search exact coordinates of the digit (helps with cropping and stretching images)

In [6]:
```
def naive_cords2(image):
    start_list = list(image.getdata())
    err1 = 1

    left_pixel = []
    top_pixel = []
    right_pixel = []
    bottom_pixel = []
    arr_rng = range(err1, 30-err1)

    for count in arr_rng:
        left_pixel.append([0,0])
        top_pixel.append([0,0])
        right_pixel.append([0,0])
        bottom_pixel.append([0,0])

    for search in arr_rng:
        counter = err1
        for item in left_pixel:
            item[0] = search if ((start_list[counter*30 + search] == 0) and (item
[0] == 0)) else item[0]
            item[1] += 1 if (start_list[counter*30 + search] == 0) else item [1]
            counter+=1

        counter = err1
        for item in top_pixel:
            item[0] = search if ((start_list[search*30 + counter] == 0) and (item
[0] == 0)) else item[0]
            item[1] += 1 if (start_list[search*30 + counter] == 0) else item [1]
            counter+=1

        counter = err1
        for item in right_pixel:
            item[0] = (30 - search) if ((start_list[counter*30 + 30 - search] ==
0) and (item[0] == 0)) else item [0]
            item[1] += 1 if (start_list[counter*30 + 30 - search] == 0) else item
 [1]
            counter+=1

        counter = err1
        for item in bottom_pixel:
            item[0] = (30 - search) if ((start_list[(30-search)*30 + counter] ==
0) and (item[0] == 0)) else item [0]
            item[1] += 1 if (start_list[counter*30 + search] == 0) else item [1]
            counter+=1

    left, top, right, bottom = 0, 0, 0, 0

    left = 30 - err1;
    for i in left_pixel:
        left = i[0] if ((i[0] < left) and i[0] > 0) else left
    top = 30 - err1;
    for i in top_pixel:
        top = i[0] if ((i[0] < top) and i[0] > 0) else top
    right = err1;
    for i in right_pixel:
        right = i[0] if ((i[0] > right) and i[0] > 0) else right
    bottom = err1;
    for i in bottom_pixel:
```

```
            bottom = i[0] if ((i[0] > bottom) and i[0] > 0) else bottom

        return left, top, right, bottom
```

Func for partial image stretching 20x20 (used before rotation func to prevent data loss)

In [7]:
```
def resizeim2020(image):
    temp_image = image.convert('1')
    #factor = (32 / temp_image.height) if (temp_image.height > temp_image.width) el
se (32 / temp_image.width)
    factorh = 20 / temp_image.height
    factorw = 20 / temp_image.width
    temp_image = temp_image.resize((round(temp_image.height * factorh), round(temp_
image.width * factorw)))
    fin_image = Image.new('1', (30,30), 'white')
    #x = round(15 - (int((x2+1)*factor) - (int((x1-1)*factor)))/2)
    #y = round(15 - (int((y2+1)*factor) - (int((y1-1)*factor)))/2)
    x = round((30 - temp_image.width)/2)
    y = round((30 - temp_image.height)/2)
    fin_image.paste(temp_image, box = (x, y))
    del temp_image
    return fin_image
```

Func for full image stretching 30x30 (used after rotation to fill empty spaces near the edge in case if some left)

In [8]:
```
def resizeim(image):
    temp_image = image.convert('1')
    factorh = 28 / temp_image.height
    factorw = 28 / temp_image.width
    temp_image = temp_image.resize((int(temp_image.height * factorh), int(temp_imag
e.width * factorw)))
    fin_image = Image.new('1', (30,30), 'white')
    x = round((30 - temp_image.width)/2)
    y = round((30 - temp_image.height)/2)
    fin_image.paste(temp_image, box = (x, y))
    del temp_image
    return fin_image
```

Func for crop with cords and temporary resize to 20x20 (used before rotation) returns new image

In [9]:
```
def naive_crop_temp(image, x1, y1, x2, y2):
    if(((x1>0)and(x2>0))and((y1>0)and(y1>0))):
        temp_image = image.convert('1')
        temp_image = temp_image.crop((x1-1, y1-1, x2+1, y2+1))
        new_image = resizeim2020(temp_image)
        del temp_image
        return new_image
```

Func for crop with new cords and resize to 30x30 (after rotation) returns new image

In [10]:
```
def naive_crop2(image, x1, y1, x2, y2):
    if(((x1>0)and(x2>0))and((y1>0)and(y1>0))):
        temp_image = image.convert('1')
        temp_image = temp_image.crop((x1-1, y1-1, x2+1, y2+1))
        new_image = resizeim(temp_image)
        del temp_image
        return new_image
```

Func for image rotation in negative mode (after 20x20 resize)

In [11]:
```
def rotateim(image, angle):
    image = image.convert('L')
    image2 = PIL.ImageOps.invert(image)
    image2 = image2.rotate(angle)
    image = PIL.ImageOps.invert(image2)
    image = image.convert('1')
    del image2
    return image
```

Crop, Convert, Align, Resize (20x20), Rotate, Resize (30x30), Random Split (on Train and Predict sets)

In [12]:
```
def croptrain_fin(image, imagecounter):
    for i in range(20):
        for j in range(29):
            for angle in range(-16, 17, 2):
                new_image = image.crop((i*30+2, j*30+2, 28+i*30, 28+j*30)) #CROP
                fin_image = Image.new('1',(30, 30), 'white')

                new_image = new_image.convert("1") #CONVERT

                x = round((30 - new_image.width)/2) #ALIGN
                y = round((30 - new_image.height)/2)
                fin_image.paste(new_image, box = (x, y))

                x1, y1, x2, y2 = naive_cords2(fin_image)
                fin_image = naive_crop_temp(fin_image, x1, y1, x2, y2) #RESIZE 20x2
0

                new_image = rotateim(fin_image, angle) #ROTATE
                del fin_image

                x1, y1, x2, y2 = naive_cords2(new_image)
                new_image = naive_crop2(new_image, x1, y1, x2, y2) #RESIZE 33x33

                if (np.random.randint(0, 10)<2): #RANDOM SPLIT
                    new_image.save('C:\\Users\\NULL\\Desktop\\BS_project\\check\\'
+ str(i//2) + '_' + str(imagecounter) + '.tiff', 'TIFF')
                    imagecounter+=1
                else:
                    new_image.save('C:\\Users\\NULL\\Desktop\\BS_project\\train\\'
+ str(i//2) + '_' + str(imagecounter) + '.tiff', 'TIFF')
                    imagecounter+=1
                del new_image
    del image
    return imagecounter
```

Finally process the list with our main images with digits set through these wheel reinventing functions

In [13]:
```
imcounter = 0
for image in imagearr:
    imcounter = croptrain_fin(image, imcounter)
    del image
```

Digit examples after processing

In [14]:
```
images = os.listdir('C:\\Users\\NULL\\Desktop\\BS_project\\train')
image = []
for x in range ((len(images)//10)//2, len(images), len(images)//10):
    image.append([Image.open('C:\\Users\\NULL\\Desktop\\BS_project\\train\\' + imag
es[x]), images[x][0]])
```

In [15]:
```
image[0][0]
```

Out[15]: 

In [16]:
```
image[1][0]
```

Out[16]: 

In [17]:
```
image[2][0]
```

Out[17]: 

In [18]:
```
image[3][0]
```

Out[18]: 

In [19]:
```
image[4][0]
```

Out[19]: 

In [20]:
```
image[5][0]
```

Out[20]: 

In [21]:
```
image[6][0]
```

Out[21]: 

In [22]:
```
image[7][0]
```

Out[22]: 

In [23]:
```
image[8][0]
```

Out[23]: 

In [24]:
```
image[9][0]
```

Out[24]: 

Dataframe for 3D scatter with x, y, z coords

In [25]:
```
c = 0
df3d = pd.DataFrame(columns = [['x','y','z']])
for item, value in image:
    df_temp = pd.DataFrame({'x':list(np.arange(900)), 'y':list(item.getdata()),
'z':int(value)}, index=range(c, c+900))
    del item
    df3d = pd.concat([df3d, df_temp], axis=0)
    c+=900
```

In [26]:
```
df3d.head()
```

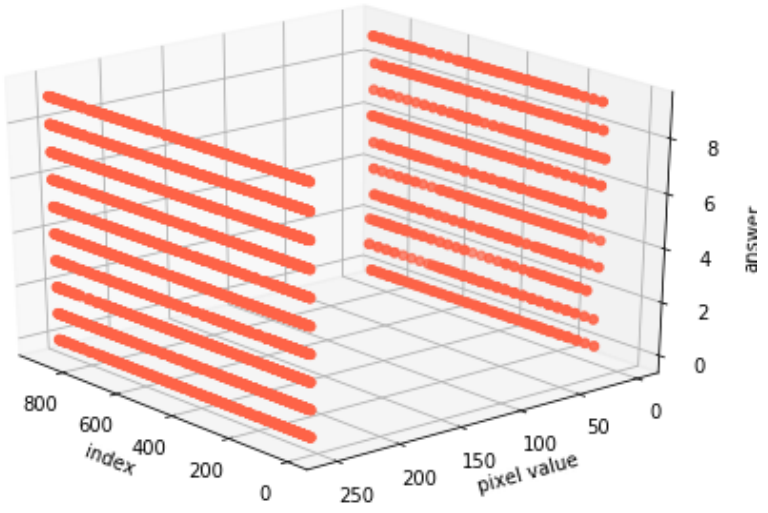
Out[26]:

	x	y	z
0	0	255	0
1	1	255	0
2	2	255	0
3	3	255	0
4	4	255	0

In [27]:
```
fig3d = m3d.Axes3D(plt.figure())
fig3d.scatter3D(df3d['x'], df3d['y'], df3d['z'], color='tomato')

fig3d.set_xlabel('index')
fig3d.set_ylabel('pixel value')
fig3d.set_zlabel('answer')

fig3d.view_init(25, 140)
plt.show()
```



In [28]:
```
del image
```

Copy data from the images (training folder) to the training dataset

In [29]:
```
c = 0
for filename in os.listdir('C:\\Users\\NULL\\Desktop\\BS_project\\train'):
    image = Image.open('C:\\Users\\NULL\\Desktop\\BS_project\\train\\' + filename)
    image_list = list(image.getdata())
    del image

    df = pd.DataFrame(image_list, columns=[filename])
    del image_list

    if c>0:
        df_final = pd.concat([df_final, df], axis=1)
    else:
        df_final = df
    c+=1
```

Int data

In [30]:
```
df_final.head(4)
```

Out[30]:

	0_0.tiff	0_1.tiff	0_10.tiff	0_100.tiff	0_10000.tiff	0_10001.tiff	0_10002.tiff	0_10003.tiff	0_100
0	255	255	255	255	255	255	255	255	255
1	255	255	255	255	255	255	255	255	255
2	255	255	255	255	255	255	255	255	255
3	255	255	255	255	255	255	255	255	255

4 rows × 23635 columns

Bool data

In [31]:
```
df_b = df_final.astype('bool')
df_b.head(4)
```

Out[31]:

	0_0.tiff	0_1.tiff	0_10.tiff	0_100.tiff	0_10000.tiff	0_10001.tiff	0_10002.tiff	0_10003.tiff	0_100
0	True	True	True	True	True	True	True	True	True
1	True	True	True	True	True	True	True	True	True
2	True	True	True	True	True	True	True	True	True
3	True	True	True	True	True	True	True	True	True

4 rows × 23635 columns

Bool data transposed

In [32]:
```
df_b.T.head(4)
```

Out[32]:

	0	1	2	3	4	5	6	7	8	9	...	890	891	892	893	8
0_0.tiff	True	True	True	True	True	True	True	True	True	True	...	True	True	True	True	Tr
0_1.tiff	True	True	True	True	True	True	True	True	True	True	...	True	True	True	True	Tr
0_10.tiff	True	True	True	True	True	True	True	True	True	True	...	True	True	True	True	Tr
0_100.tiff	True	True	True	True	True	True	True	True	True	True	...	True	True	True	True	Tr

4 rows × 900 columns

List of True values for prediction and accuracy with "1000" step

In [33]:
```
zz = []
for z in df_b.columns:
    zz.append(z[0])
zz = list(map(int, zz))
zz[::1000]
```

Out[33]: `[0, 0, 0, 1, 1, 2, 2, 2, 3, 3, 4, 4, 5, 5, 5, 6, 6, 7, 7, 8, 8, 8, 9, 9]`

Fit the data in the model

In [34]:
```
X = df_b.T
Y = zz
model = GaussianNB()
model.fit(X, Y)
```

Out[34]: `GaussianNB(priors=None)`

Copy data from check folder to the predict dataset, compare predictions with True values and calc "accuracy"

In [35]:
```
c, c2 = 0, 0
for filename in os.listdir('C:\\Users\\NULL\\Desktop\\BS_project\\check'):
    image = Image.open('C:\\Users\\NULL\\Desktop\\BS_project\\check\\' + filename)
    image_list = list(image.getdata())
    del image
    df = pd.DataFrame(image_list, columns=[filename])
    df = df.T.astype('bool')
    del image_list
    if c>0:
        dfp_final = pd.concat([dfp_final, df], axis=0)
    else:
        dfp_final = df
    c+=1

    predicted = model.predict(df)
    if (int(filename[0]) == predicted[0]):
        c2+=1

accuracy = c2*100/c
```

In [36]:
```
accuracy
```

Out[36]: 90.46257359125316

How I should to calculare accuracy in the first place

In [37]:
```
from sklearn.metrics import accuracy_score
```

In [38]:
```
zoz = [] #VERY MEANINGFUL VARIABLE NAME FOR THE LIST
for z in dfp_final.T.columns:
    zoz.append(z[0])
zoz = list(map(int, zoz)) #LIST WITH TRUE VALUES

model_pred = model.predict(dfp_final) #LIST WITH PREDICTED VALUES
accuracy_score(zoz, model_pred, normalize = True) #last was 0.90322
```

Out[38]: 0.90462573591253159

Fail predictions

In [39]:
```
c = 0
for guess in model_pred:
    if (guess != zoz[c]):
        print("Prediction:  %s        True:  %s" % (guess, zoz[c]))
    c+=1
```

```
Prediction:  8       True:  0
Prediction:  9       True:  0
Prediction:  5       True:  0
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  2       True:  1
Prediction:  2       True:  1
Prediction:  5       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  6       True:  1
Prediction:  2       True:  1
Prediction:  6       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  1
Prediction:  7       True:  2
Prediction:  7       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  8       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  7       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  7       True:  2
Prediction:  7       True:  2
Prediction:  7       True:  2
Prediction:  7       True:  2
Prediction:  7       True:  2
Prediction:  1       True:  2
Prediction:  8       True:  2
Prediction:  1       True:  2
Prediction:  7       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  1       True:  2
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  7       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
```

```
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  5       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  5       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
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Prediction:  8       True:  3
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Prediction:  8       True:  3
Prediction:  9       True:  3
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Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  5       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
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Prediction:  9       True:  3
Prediction:  5       True:  3
Prediction:  5       True:  3
Prediction:  5       True:  3
Prediction:  5       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  1       True:  3
Prediction:  1       True:  3
Prediction:  1       True:  3
Prediction:  9       True:  3
```

```
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  8       True:  3
Prediction:  9       True:  3
Prediction:  1       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
Prediction:  8       True:  3
Prediction:  5       True:  3
Prediction:  5       True:  3
Prediction:  9       True:  3
Prediction:  9       True:  3
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Prediction:  9       True:  3
Prediction:  8       True:  3
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Prediction:  9       True:  4
Prediction:  7       True:  4
Prediction:  9       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
```

```
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  8       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  9       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  8       True:  4
Prediction:  8       True:  4
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Prediction:  1       True:  4
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Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
```

```
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  9       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
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Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  9       True:  4
Prediction:  9       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
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Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
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Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
```

```
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
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Prediction:  1       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  7       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  9       True:  4
Prediction:  9       True:  4
Prediction:  9       True:  4
Prediction:  1       True:  4
Prediction:  1       True:  4
Prediction:  6       True:  5
Prediction:  3       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
Prediction:  6       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  3       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  1       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
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Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  3       True:  5
Prediction:  6       True:  5
Prediction:  7       True:  5
Prediction:  2       True:  5
Prediction:  2       True:  5
```

```
Prediction:  2       True:  5
Prediction:  7       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  1       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
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Prediction:  1       True:  5
Prediction:  8       True:  5
Prediction:  6       True:  5
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Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  3       True:  5
Prediction:  3       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  8       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  1       True:  5
Prediction:  6       True:  5
Prediction:  7       True:  5
Prediction:  6       True:  5
Prediction:  8       True:  5
Prediction:  2       True:  5
Prediction:  2       True:  5
Prediction:  6       True:  5
Prediction:  2       True:  5
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
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Prediction:  8       True:  6
Prediction:  5       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  5       True:  6
Prediction:  8       True:  6
```

```
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  8       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  6
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  2       True:  7
Prediction:  2       True:  7
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Prediction:  2       True:  7
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Prediction:  2       True:  7
Prediction:  1       True:  7
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Prediction:  1       True:  7
Prediction:  4       True:  7
Prediction:  1       True:  7
Prediction:  8       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
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Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  2       True:  7
Prediction:  9       True:  7
Prediction:  9       True:  7
Prediction:  9       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
```

```
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  1       True:  7
Prediction:  6       True:  8
Prediction:  6       True:  8
Prediction:  1       True:  8
Prediction:  1       True:  8
Prediction:  2       True:  8
Prediction:  5       True:  8
Prediction:  5       True:  8
Prediction:  5       True:  8
Prediction:  6       True:  8
Prediction:  6       True:  8
Prediction:  1       True:  8
Prediction:  1       True:  8
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Prediction:  1       True:  8
Prediction:  6       True:  8
Prediction:  1       True:  8
Prediction:  1       True:  8
Prediction:  1       True:  8
Prediction:  1       True:  8
Prediction:  6       True:  8
Prediction:  1       True:  8
Prediction:  9       True:  8
Prediction:  9       True:  8
Prediction:  9       True:  8
Prediction:  9       True:  8
Prediction:  9       True:  8
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  3       True:  9
Prediction:  7       True:  9
Prediction:  7       True:  9
Prediction:  7       True:  9
Prediction:  1       True:  9
Prediction:  2       True:  9
Prediction:  7       True:  9
Prediction:  8       True:  9
```

```
Prediction:  7       True:  9
Prediction:  7       True:  9
Prediction:  7       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  3       True:  9
Prediction:  3       True:  9
Prediction:  1       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  4       True:  9
Prediction:  3       True:  9
Prediction:  3       True:  9
Prediction:  1       True:  9
Prediction:  5       True:  9
Prediction:  1       True:  9
Prediction:  1       True:  9
Prediction:  1       True:  9
Prediction:  1       True:  9
Prediction:  1       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  8       True:  9
Prediction:  1       True:  9
```

In [40]:
```
ete = Image.open('C:\\Users\\NULL\\Desktop\\BS_project\\meme.png')
ete
```

Out[40]:

In [41]:
```
del ete
```

After presentation additional code

Here I finally compare models. GaussianNB is almost the worst for this task

I should compare them earlier, however, due to the good data preprocess even with

GNB I got 90-93% accuracy while KNN is the best for this task with a ~99.9% result

In [42]:
```
seed = 666
```

In [43]:
```
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.svm import SVC
```

In [44]:
```
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
```

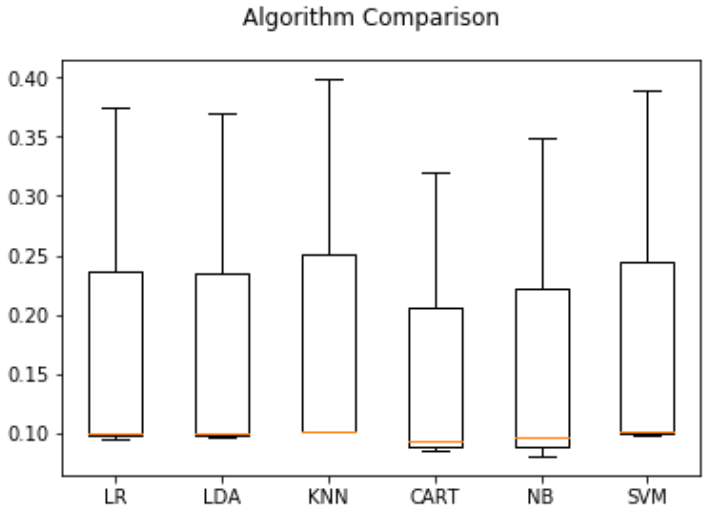
In [45]:
```
results = []
names = []
scoring = 'accuracy'
for name, model in models:
    kfold = model_selection.KFold(n_splits=3, random_state=seed)
    cv_results =  model_selection.cross_val_score(model, X, Y, cv=kfold, scoring=sc
oring)
    results.append(cv_results)
    names.append(name)
    msg = "%s : %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR : 0.189892 (0.130790)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.py:442: U
serWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.py:388: U
serWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.py:388: U
serWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.py:442: U
serWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.py:388: U
serWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")

LDA : 0.188665 (0.127888)
KNN : 0.200427 (0.140025)
CART : 0.165859 (0.108965)
NB : 0.175295 (0.123132)
SVM : 0.196408 (0.136318)
```

In [46]:
```
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



In [47]:
```
model1 = models[2][1] #KNN #1st best
model1.fit(X, Y)
model1_pred = model1.predict(dfp_final) #LIST WITH PREDICTED VALUES
```

Ta-da!

In [48]:
```
accuracy_score(zoz, model1_pred, normalize = True)
```

Out[48]: 1.0

In [49]:
```
c = 0
for guess in model1_pred:
    if (guess != zoz[c]):
        print("Prediction:  %s        True:  %s" % (guess, zoz[c]))
    c+=1
```

In [50]:
```
model2 = models[5][1] #SVM #2nd best
model2.fit(X, Y)
model2_pred = model2.predict(dfp_final) #LIST WITH PREDICTED VALUES
accuracy_score(zoz, model2_pred, normalize = True)
```

Out[50]: 0.99646761984861232

In [51]:
```
c = 0
for guess in model2_pred:
    if (guess != zoz[c]):
        print("Prediction:  %s        True:  %s" % (guess, zoz[c]))
    c+=1
```

```
Prediction:  7        True:  1
Prediction:  2        True:  1
Prediction:  9        True:  3
Prediction:  9        True:  3
Prediction:  5        True:  3
Prediction:  5        True:  3
Prediction:  9        True:  3
Prediction:  7        True:  4
Prediction:  8        True:  5
Prediction:  6        True:  5
Prediction:  6        True:  5
Prediction:  6        True:  5
Prediction:  6        True:  5
Prediction:  8        True:  6
Prediction:  8        True:  6
Prediction:  1        True:  7
Prediction:  1        True:  7
Prediction:  4        True:  7
Prediction:  1        True:  7
Prediction:  6        True:  8
Prediction:  6        True:  8
```

In [52]:
```
model3 = models[0][1] #LR #3rd best
model3.fit(X, Y)
model3_pred = model3.predict(dfp_final) #LIST WITH PREDICTED VALUES
accuracy_score(zoz, model3_pred, normalize = True)
```

Out[52]: 0.99243061396131205

In [53]:
```
c = 0
for guess in model3_pred:
    if (guess != zoz[c]):
        print("Prediction:  %s        True:  %s" % (guess, zoz[c]))
    c+=1
```

```
Prediction:  7        True:  1
Prediction:  7        True:  1
Prediction:  7        True:  2
Prediction:  9        True:  3
Prediction:  9        True:  3
Prediction:  1        True:  3
Prediction:  9        True:  3
Prediction:  9        True:  3
Prediction:  8        True:  3
Prediction:  8        True:  3
Prediction:  5        True:  3
Prediction:  7        True:  4
Prediction:  8        True:  5
Prediction:  3        True:  5
Prediction:  6        True:  5
Prediction:  1        True:  5
Prediction:  8        True:  5
Prediction:  6        True:  5
Prediction:  6        True:  5
Prediction:  4        True:  5
Prediction:  6        True:  5
Prediction:  8        True:  5
Prediction:  1        True:  5
Prediction:  6        True:  5
Prediction:  8        True:  6
Prediction:  8        True:  6
Prediction:  8        True:  6
Prediction:  0        True:  6
Prediction:  5        True:  6
Prediction:  8        True:  7
Prediction:  4        True:  7
Prediction:  4        True:  7
Prediction:  2        True:  7
Prediction:  9        True:  7
Prediction:  4        True:  7
Prediction:  1        True:  7
Prediction:  6        True:  8
Prediction:  6        True:  8
Prediction:  6        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  3        True:  9
Prediction:  5        True:  9
```

Combined from the best 3 models just for fun

In [54]:
```
def combined(a, b, c):
    return b if (b == c) else a
```

In [55]:
```
model_comb = []
for counter in range(len(model1_pred)):
    model_comb.append(combined(model1_pred[counter], model2_pred[counter], model3_p
red[counter]))
accuracy_score(zoz, model_comb, normalize = True)
```

Out[55]: 0.99848612279226245

In [56]:
```
c = 0
for guess in model3_pred:
    if (guess != zoz[c]):
        print("Prediction:  %s        True:  %s" % (guess, zoz[c]))
    c+=1
```

```
Prediction:  7        True:  1
Prediction:  7        True:  1
Prediction:  7        True:  2
Prediction:  9        True:  3
Prediction:  9        True:  3
Prediction:  1        True:  3
Prediction:  9        True:  3
Prediction:  9        True:  3
Prediction:  8        True:  3
Prediction:  8        True:  3
Prediction:  5        True:  3
Prediction:  7        True:  4
Prediction:  8        True:  5
Prediction:  3        True:  5
Prediction:  6        True:  5
Prediction:  1        True:  5
Prediction:  8        True:  5
Prediction:  6        True:  5
Prediction:  6        True:  5
Prediction:  4        True:  5
Prediction:  6        True:  5
Prediction:  8        True:  5
Prediction:  1        True:  5
Prediction:  6        True:  5
Prediction:  8        True:  6
Prediction:  8        True:  6
Prediction:  8        True:  6
Prediction:  0        True:  6
Prediction:  5        True:  6
Prediction:  8        True:  7
Prediction:  4        True:  7
Prediction:  4        True:  7
Prediction:  2        True:  7
Prediction:  9        True:  7
Prediction:  4        True:  7
Prediction:  1        True:  7
Prediction:  6        True:  8
Prediction:  6        True:  8
Prediction:  6        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  9        True:  8
Prediction:  3        True:  9
Prediction:  5        True:  9
```

I can actually implement "combined" function better based on models' prediction percentage instead of just strict comparing 2nd and 3rd models and then to the 1st, however, I think it's enough programming for this project. Also you need some time to check this and other projects, so KNN is still the best for this task, even compare to the simple "combined" function

Thank you