Dataset1-Regression_output_12

October 7, 2021

1 Dataset 1 - Regression

1.1 Import Libraries

[1]:
```
import train_test
import ABC_train_test
import regressionDataset
import network
import statsModel
import performanceMetrics
import dataset
import sanityChecks
import torch
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
from torch.utils.data import Dataset,DataLoader
from torch import nn
import warnings
warnings.filterwarnings('ignore')
```

1.2 Parameters

General Parameters

1. Number of Samples

Discriminator Parameters

1. Size : number of hidden nodes

ABC-Generator parameters are as mentioned below: 1. mean : 1 ($\beta \sim N(\beta^*, \sigma)$ where β^* are coefficients of statistical model) or 1 ($\beta \sim N(0, \sigma)$ 2. std : $\sigma = 1, 0.1, 0.01$ (standard deviation)

[2]:
```
n_features = 10
sample_size = 100
#Discriminator Parameters
hidden_nodes = 25
#ABC Generator Parameters
mean = 1
```

```
variance = 0.001
```

1.3 Dataset

Generate a random regression problem

$Y = 1 + \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_3 + ... + \beta_n x_n + N(0, \sigma)$ where $\sigma = 0.1$

[3]:
```
X,Y = regressionDataset.regression_data(sample_size,n_features)
```

```
         X1        X2        X3        X4        X5        X6        X7  \
0  1.019419 -0.348530 -2.453278 -1.385382  0.027489  0.857707  0.310409
1 -0.355626  0.828089 -1.500913 -0.280003 -0.076394 -0.340453 -0.199560
2 -0.208233  0.357357  1.164037  0.353566  2.303539 -0.930240 -1.081422
3  0.875442  0.849547  0.622432 -1.530370  0.528268  1.607151  0.648693
4  1.362796  1.029631  0.860897  0.594007 -1.084402 -1.405882 -0.680652

         X8        X9       X10           Y
0  2.077641 -1.035411  0.328783    4.042960
1  1.032006 -1.563911  0.670816 -151.798457
2 -2.416419  0.669253 -0.525355  -64.486498
3  0.670541 -1.552191  0.058923  282.664840
4 -2.021125 -0.842296  1.243716 -276.206244
```

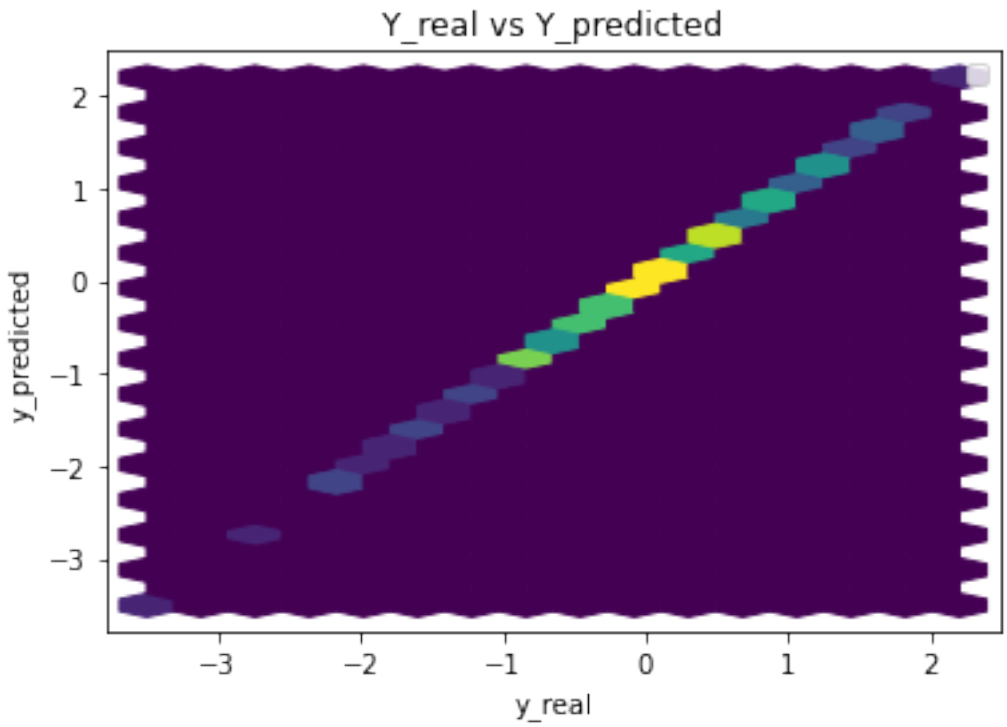
1.4 Stats Model

[4]:
```
[coeff,y_pred] = statsModel.statsModel(X,Y)
```

```
No handles with labels found to put in legend.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 3.749e+07
Date:                Thu, 07 Oct 2021   Prob (F-statistic):          3.28e-290
Time:                        19:01:54   Log-Likelihood:                620.78
No. Observations:                 100   AIC:                            -1220.
Df Residuals:                      89   BIC:                            -1191.
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -2.776e-17   5.16e-05  -5.37e-13      1.000      -0.000       0.000
x1             0.1919   5.22e-05   3674.844      0.000       0.192       0.192
x2             0.0932   5.27e-05   1767.981      0.000       0.093       0.093
x3             0.4910   5.28e-05   9308.108      0.000       0.491       0.491
x4             0.1860   5.27e-05   3532.975      0.000       0.186       0.186
x5             0.3833   5.23e-05   7332.039      0.000       0.383       0.383
```

```
x6             0.3927   5.44e-05   7223.784      0.000       0.393       0.393
x7             0.3100    5.4e-05   5740.910      0.000       0.310       0.310
x8             0.5228   5.29e-05   9882.494      0.000       0.523       0.523
x9             0.1848   5.45e-05   3389.117      0.000       0.185       0.185
x10            0.0606   5.29e-05   1146.017      0.000       0.061       0.061
==============================================================================
Omnibus:                        2.752   Durbin-Watson:                   2.003
Prob(Omnibus):                  0.253   Jarque-Bera (JB):                2.149
Skew:                           0.251   Prob(JB):                        0.341
Kurtosis:                       3.513   Cond. No.                         1.49
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
Parameters:  const   -2.775558e-17
x1       1.919068e-01
x2       9.316367e-02
x3       4.910205e-01
x4       1.860242e-01
x5       3.832744e-01
x6       3.927479e-01
x7       3.100232e-01
x8       5.228482e-01
x9       1.847538e-01
x10      6.061683e-02
dtype: float64
```




```
Performance Metrics
Mean Squared Error: 2.373965774884984e-07
Mean Absolute Error: 0.00036645423828874903
Manhattan distance: 0.03664542382887491
Euclidean distance: 0.00487233596428344
```

2 Generator and Discriminator Networks

GAN Generator

[5]:
```
class Generator(nn.Module):

  def __init__(self,n_input):
    super().__init__()
    self.output = nn.Linear(n_input,1)

  def forward(self, x):
    x = self.output(x)
    return x
```

GAN Discriminator

[6]:
```
class Discriminator(nn.Module):
```

```
  def __init__(self,n_input,n_hidden):

    super().__init__()
    self.hidden = nn.Linear(n_input,n_hidden)
    self.output = nn.Linear(n_hidden,1)
    self.relu = nn.ReLU()

  def forward(self, x):
    x = self.hidden(x)
    x = self.relu(x)
    x = self.output(x)
    return x
```

ABC Generator

The ABC generator is defined as follows:

$Y = 1 + \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_3 + ... + \beta_n x_n + N(0, \sigma)$ where $\sigma = 0.1$

$\beta_i \sim N(0, \sigma^*)$ when $\mu = 0$ else

$\beta_i \sim N(\beta_i^*, \sigma^*)$ where $\beta_i^* s$ are coefficients obtained from stats model

Parameters : μ and σ^*

σ^* takes the values 0.01,0.1 and 1

[7]:
```
def ABC_pre_generator(x_batch,coeff,variance,mean,device):

  coeff_len = len(coeff)

  if mean == 0:
    weights = np.random.normal(0,variance,size=(coeff_len,1))
    weights = torch.from_numpy(weights).reshape(coeff_len,1)
  else:
    weights = []
    for i in range(coeff_len):
      weights.append(np.random.normal(coeff[i],variance))
    weights = torch.tensor(weights).reshape(coeff_len,1)

  y_abc =  torch.matmul(x_batch,weights.float())
  gen_input = torch.cat((x_batch,y_abc),dim = 1).to(device)
  return gen_input
```

3 GAN Model

[8]:
```
real_dataset = dataset.CustomDataset(X,Y)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

[9]:
```
generator = Generator(n_features+2)
discriminator = Discriminator(n_features+2,hidden_nodes)

criterion = torch.nn.BCEWithLogitsLoss()
gen_opt = torch.optim.Adam(generator.parameters(), lr=0.01, betas=(0.5, 0.999))
disc_opt = torch.optim.Adam(discriminator.parameters(), lr=0.01, betas=(0.5, 0.
↪999))
```

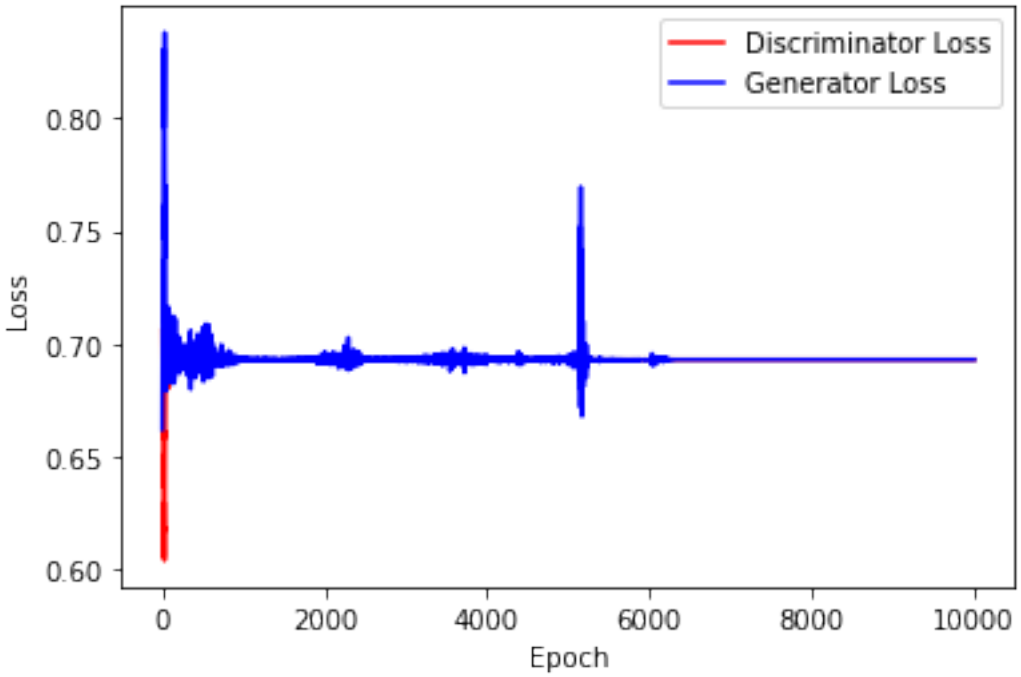
[10]:
```
print(generator)
print(discriminator)
```

```
Generator(
  (output): Linear(in_features=12, out_features=1, bias=True)
)
Discriminator(
  (hidden): Linear(in_features=12, out_features=25, bias=True)
  (output): Linear(in_features=25, out_features=1, bias=True)
  (relu): ReLU()
)
```

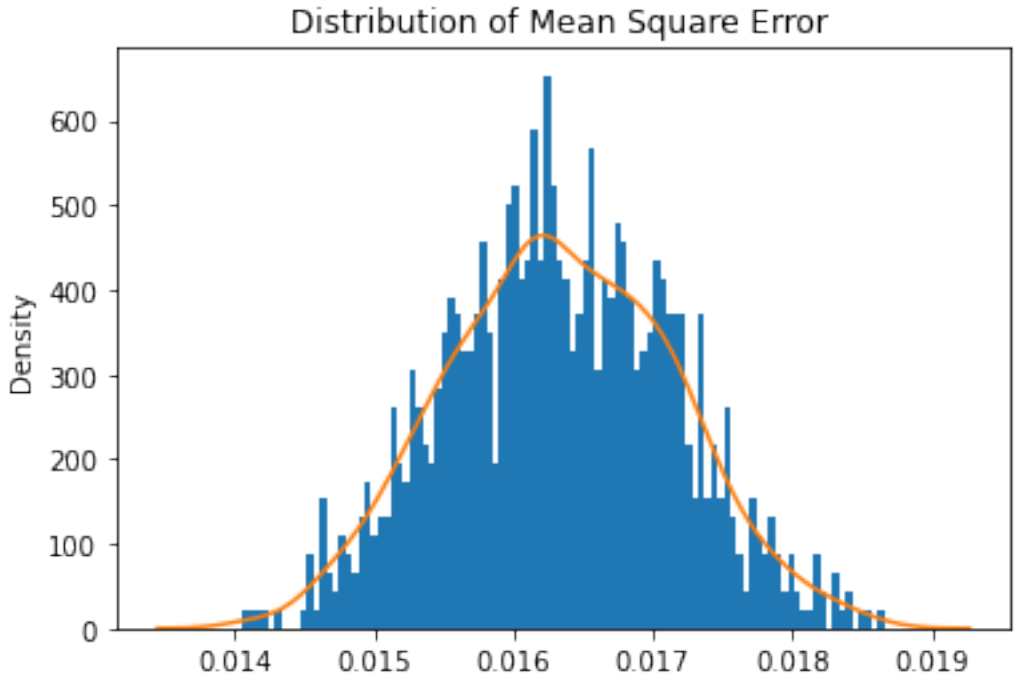
[11]:
```
n_epochs = 5000
batch_size = sample_size//2
```

[12]:
```
# Parameters
sample_size = 1000000
mean = 0
std = 1
```

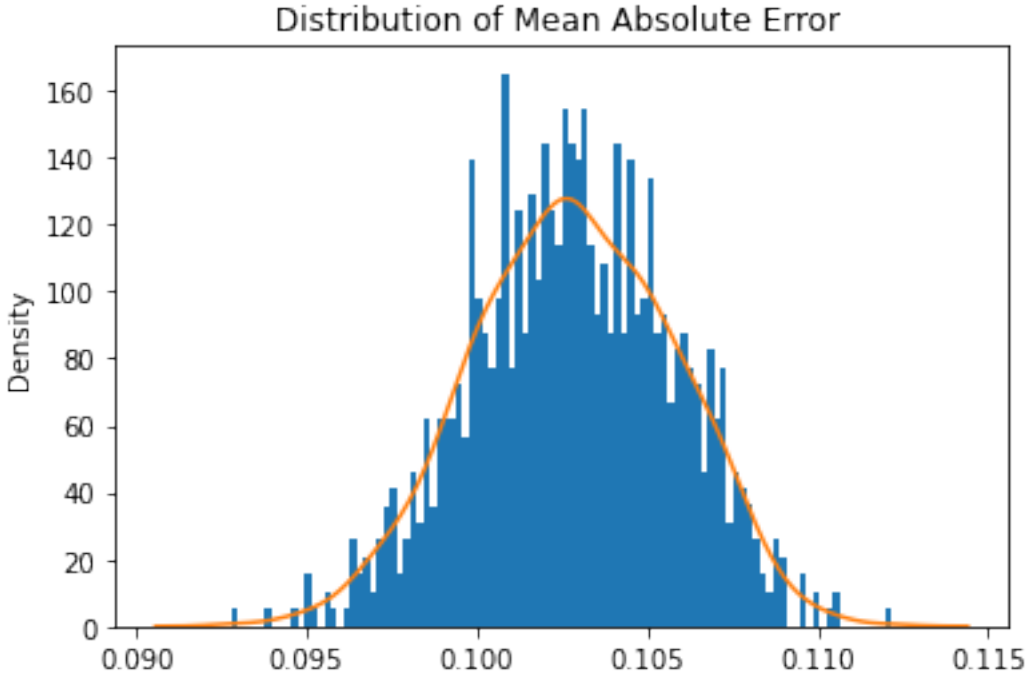
[13]:
```
train_test.
↪training_GAN(discriminator,generator,disc_opt,gen_opt,real_dataset,batch_size,␣
↪n_epochs,criterion,device)
```



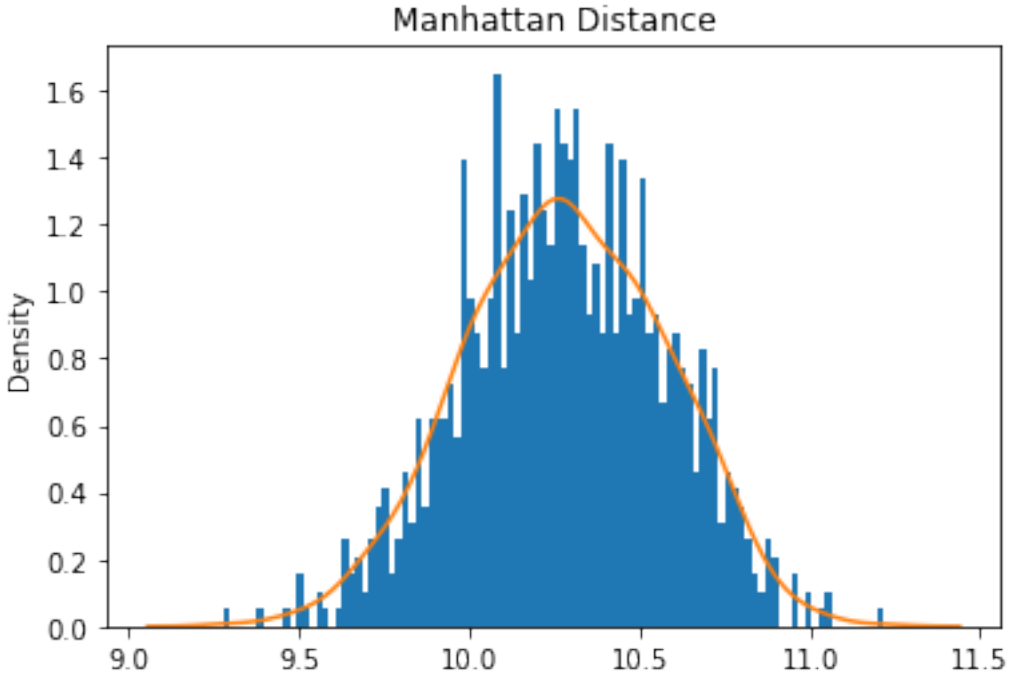
[14]:
```
train_test.test_generator(generator,real_dataset,device)
```



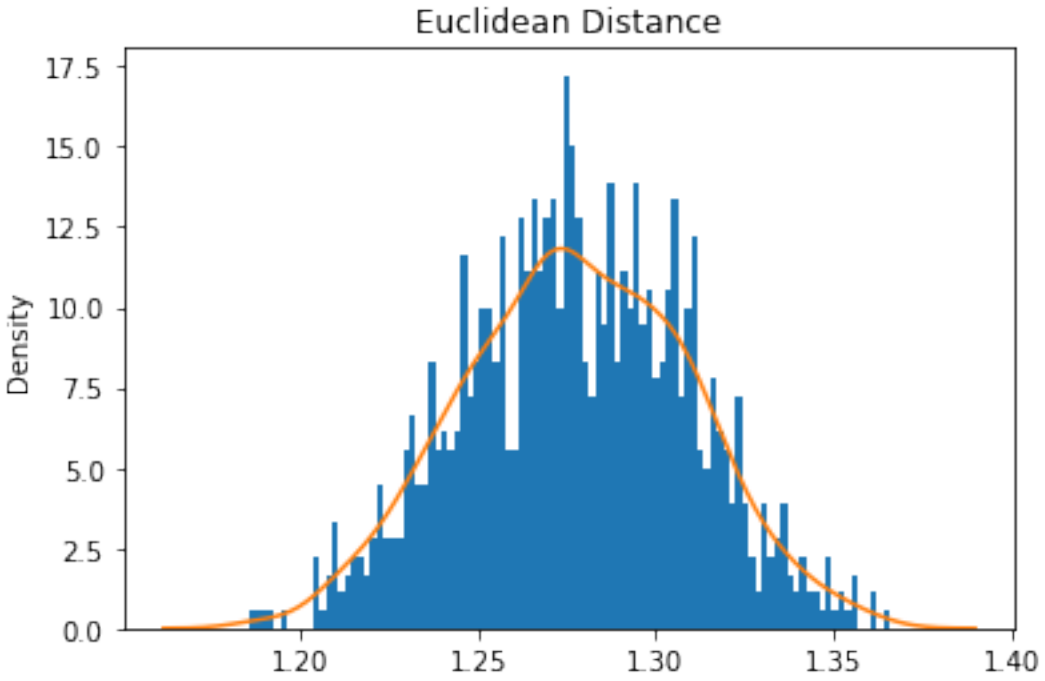
```
Mean Square Error: 0.016332300127777759
```




```
Mean Absolute Error: 0.10280930770398118
```



```
Mean Manhattan Distance: 10.280930770398118
```




```
Mean Euclidean Distance: 10.280930770398118
```

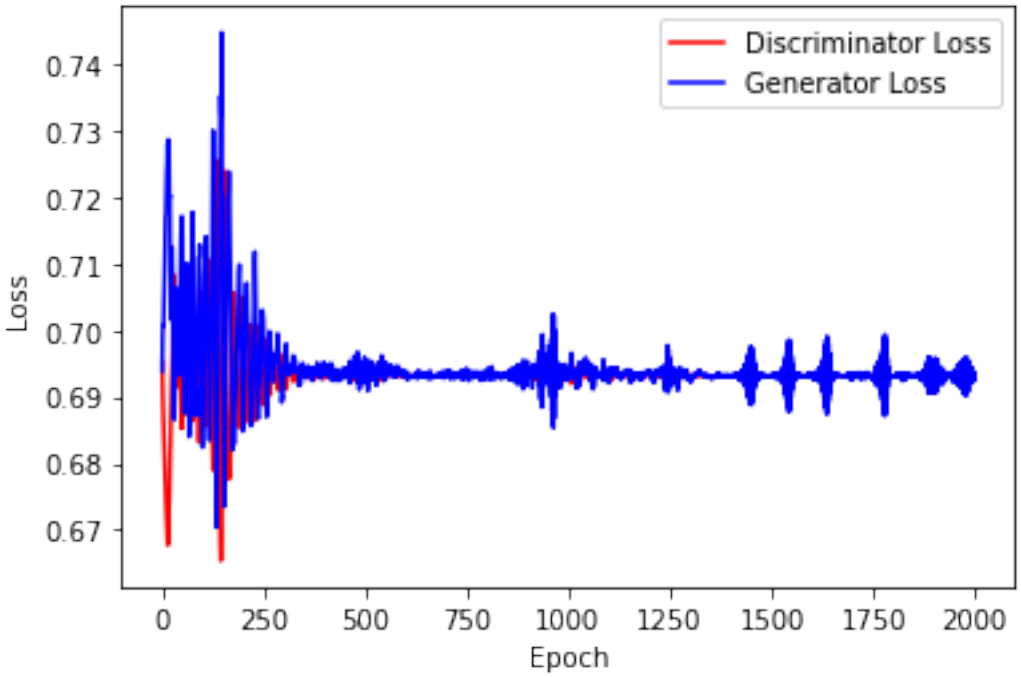
4 ABC GAN Model

Training the network

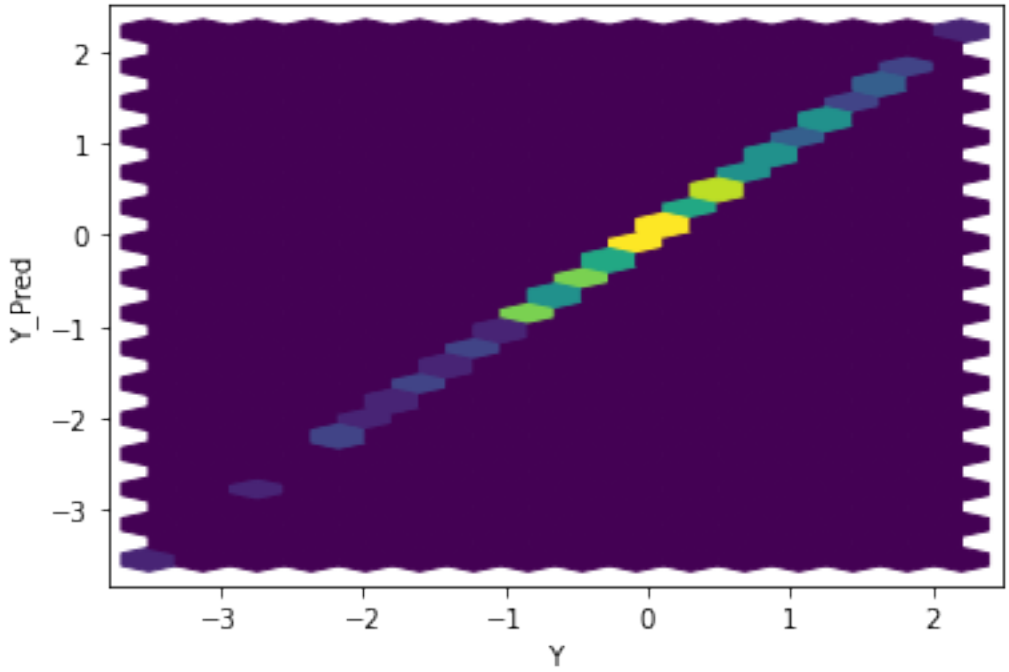
[15]:
```
gen = Generator(n_features+2)
disc = Discriminator(n_features+2,hidden_nodes)

criterion = torch.nn.BCEWithLogitsLoss()
gen_opt = torch.optim.Adam(gen.parameters(), lr=0.01, betas=(0.5, 0.999))
disc_opt = torch.optim.Adam(disc.parameters(), lr=0.01, betas=(0.5, 0.999))
```

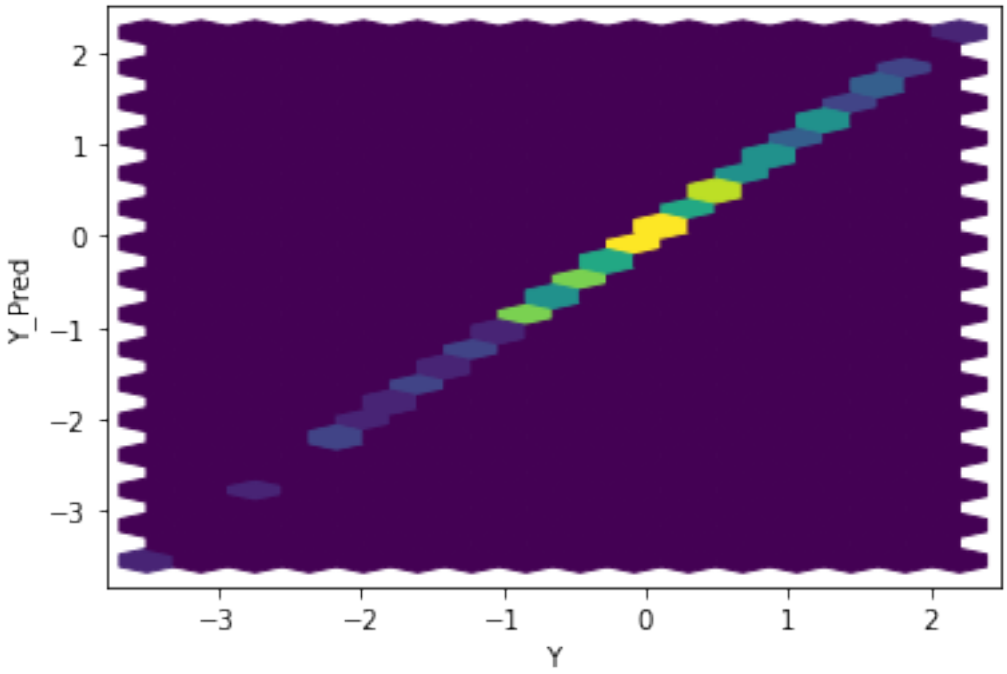
[16]:
```
n_epoch_abc = 2000
batch_size = sample_size//2
```

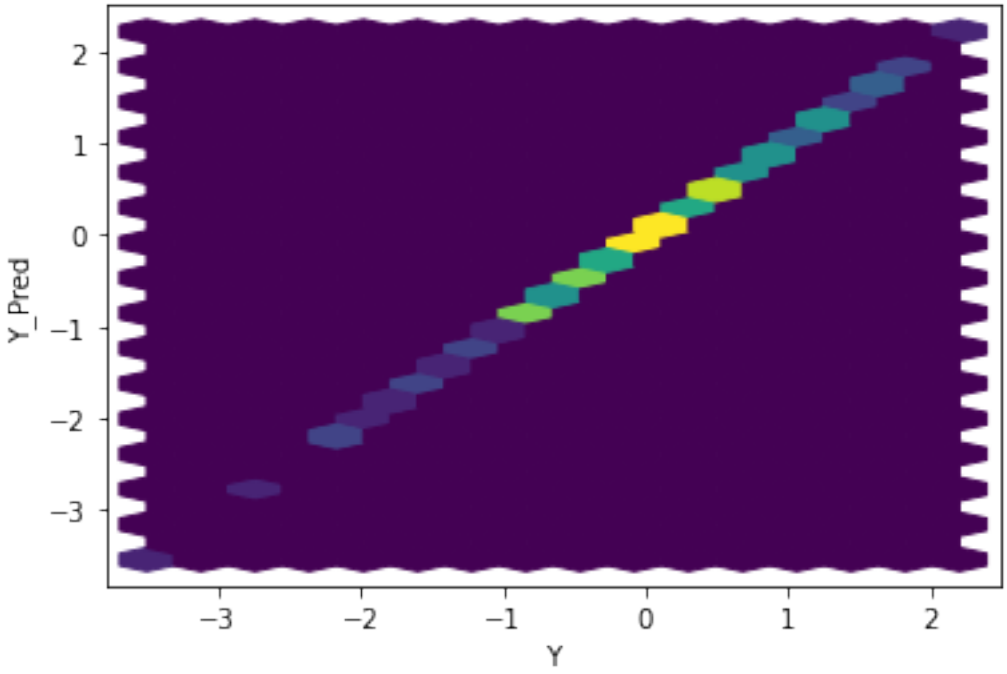
[17]:
```
ABC_train_test.training_GAN(disc, gen,disc_opt,gen_opt,real_dataset,␣
↪batch_size, n_epoch_abc,criterion,coeff,mean,variance,device)
```

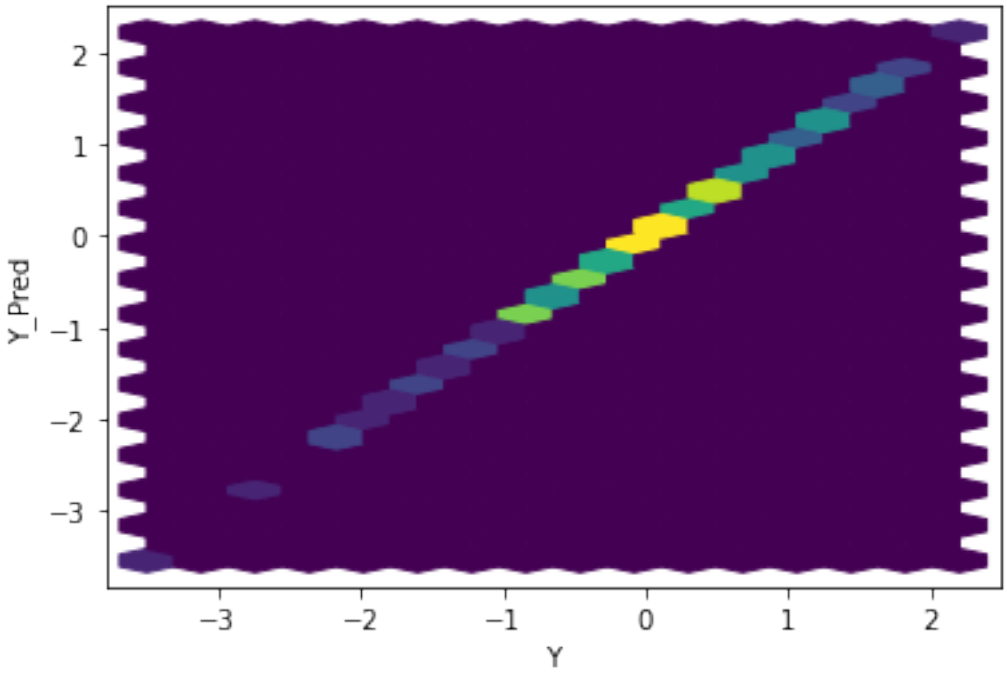


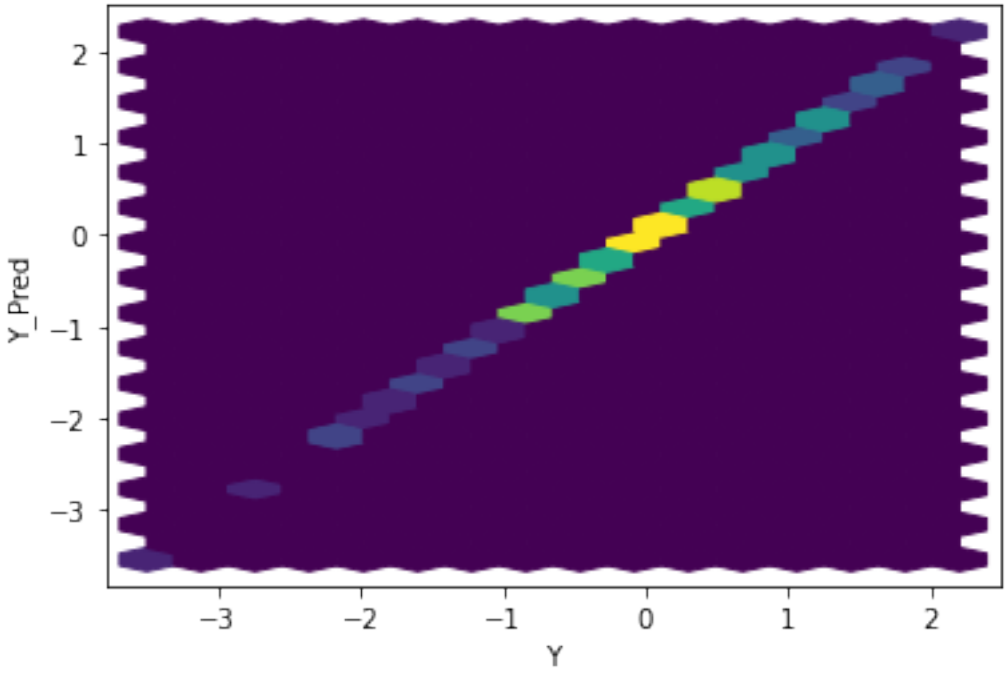
[18]:
```
ABC_train_test.test_generator(gen,real_dataset,coeff,mean,variance,device)
```

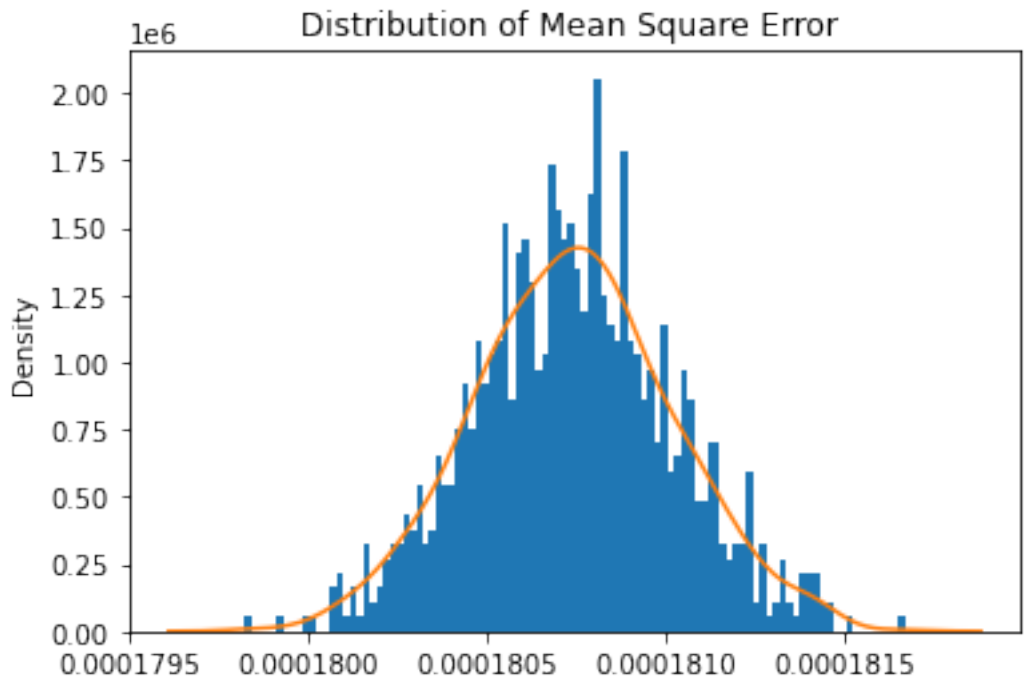



Y_Pred
Y
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2

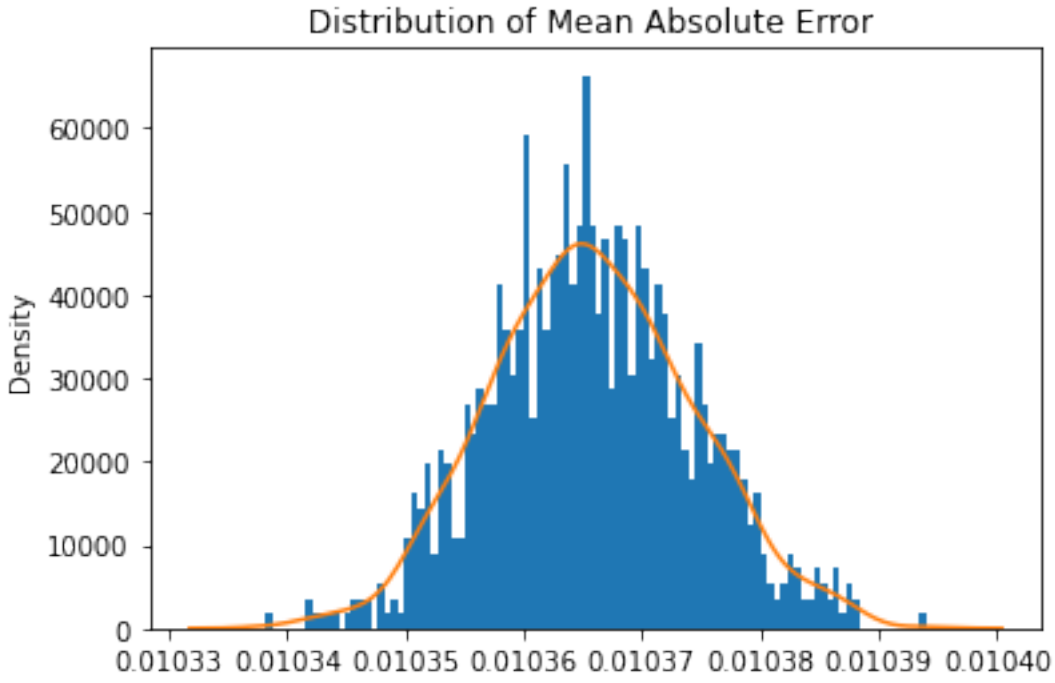

Y_Pred
Y
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2


Y_Pred
Y
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2

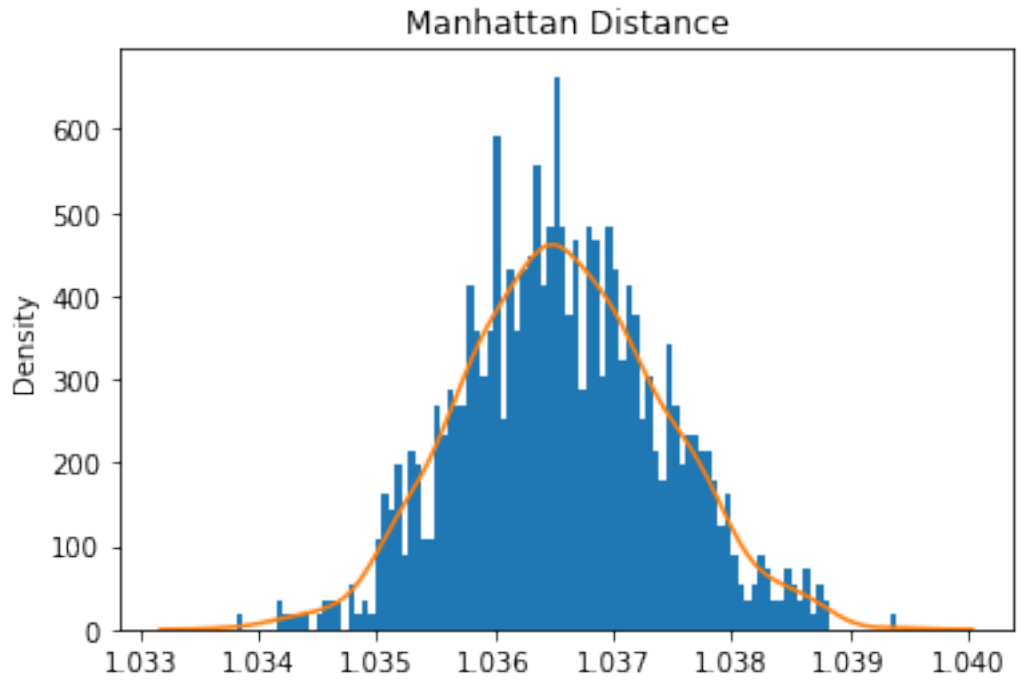

Y_Pred
Y
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2



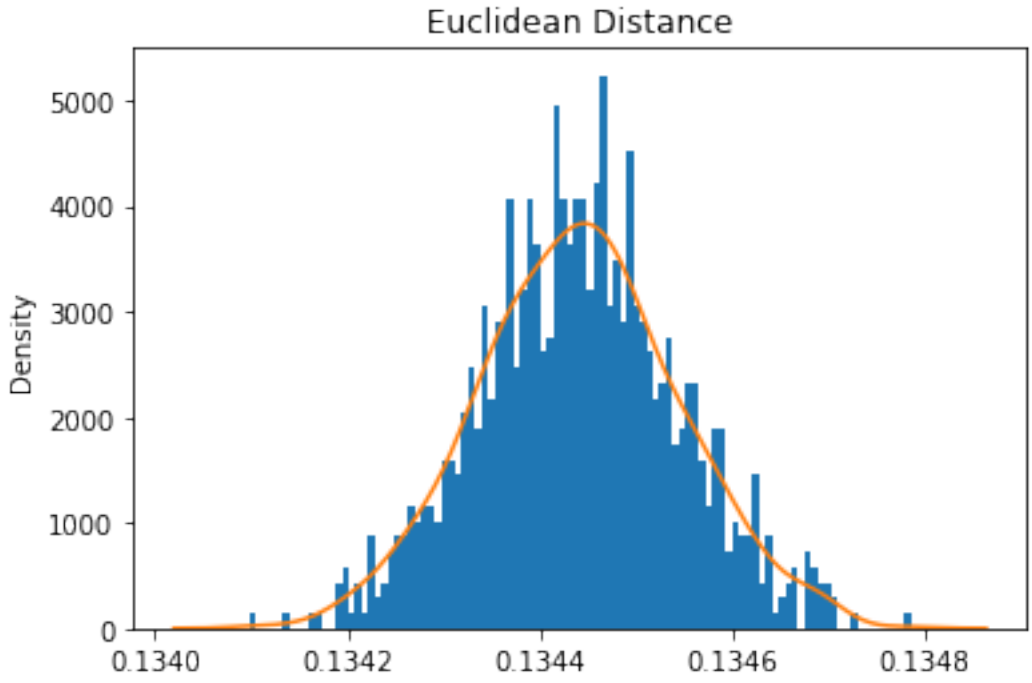

```
Mean Square Error: 0.00018074479328959966
```



```
Mean Absolute Error: 0.010365754132531583
Mean Manhattan Distance: 1.0365754132531584
```

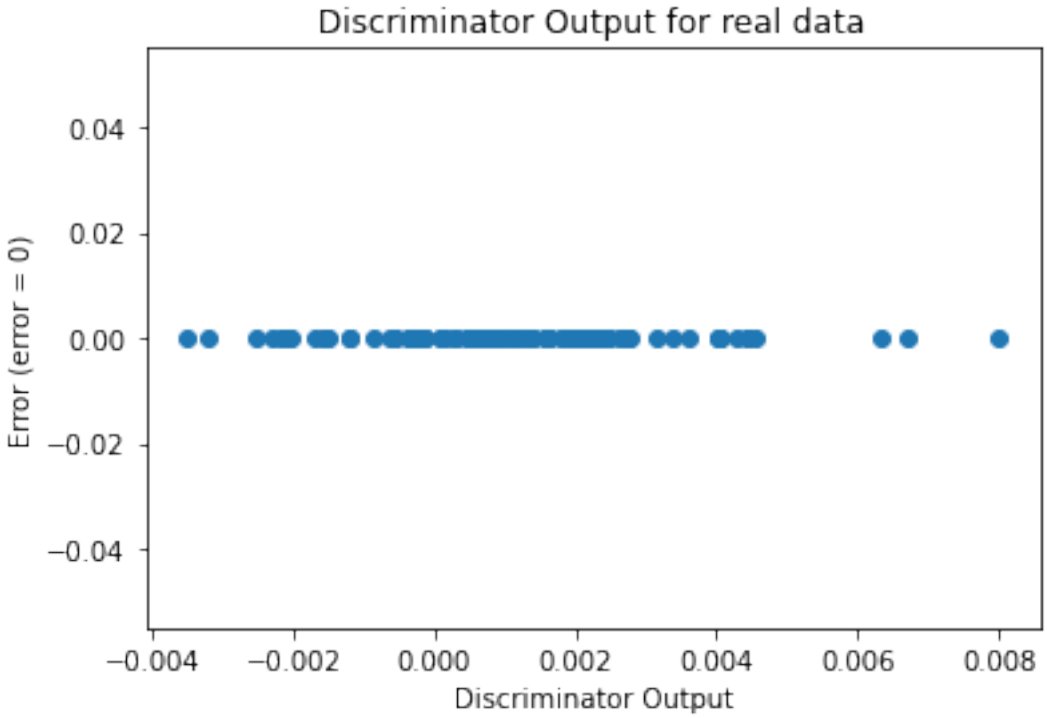


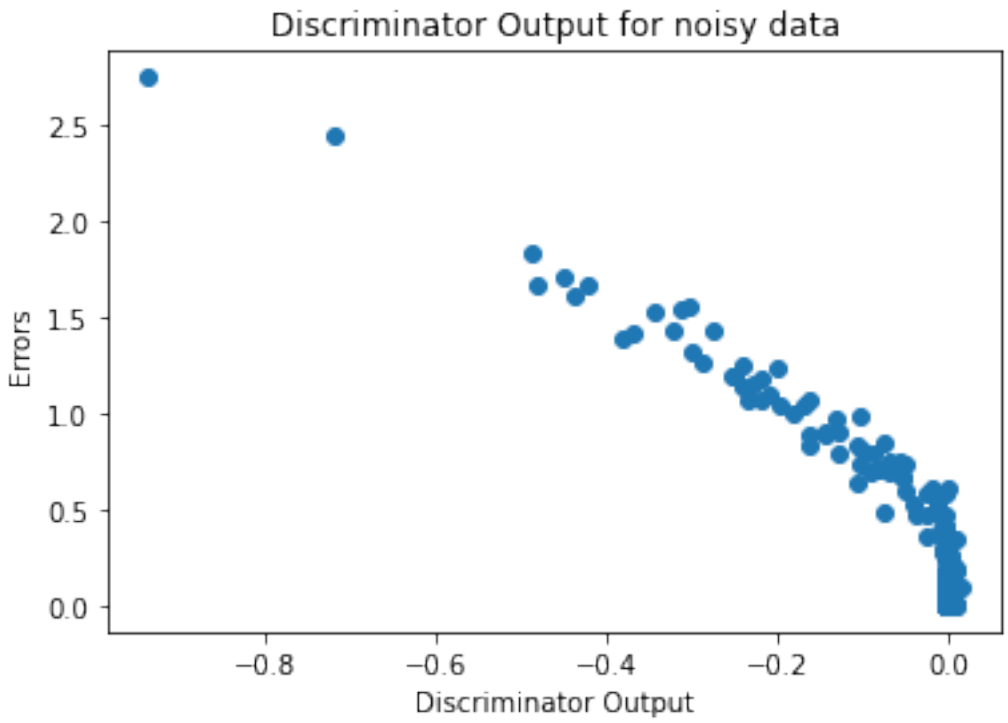

```
Mean Euclidean Distance: 0.13444131981405855
```



Sanity Checks

[19]:
```
sanityChecks.discProbVsError(real_dataset,disc,device)
```





4.1 Visualization of trained GAN generator

[20]:
```
for name, param in gen.named_parameters():
    print(name,param)
```

```
output.weight Parameter containing:
tensor([[ 0.2179,  0.1939,  0.0913,  0.4959,  0.1936,  0.3853,  0.3918,  0.3056,
          0.5301,  0.1867,  0.0621, -0.0106]], requires_grad=True)
output.bias Parameter containing:
tensor([-0.2235], requires_grad=True)
```