Dataset2-Dummy_Linear_output_28

October 7, 2021

1 Dataset 2 : Dummy Linear Data

1.1 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 0 ($\beta \sim N(0, \sigma)$ 2. std : $\sigma = 1, 0.1, 0.01$ (standard deviation) 3. prior: 0 (Correct) or 1 (Misspecified)

[1]:
```
n_samples = 100

#Discriminator Parameters
hidden_nodes = 25

#ABC Generator Parameters
meanVal = 1
std = 1
prior = 0
```

[2]:
```
# Parameters
sample_size = 100
std = 1
mean = 1
prior = 1
```

1.2 Import Libraries

[3]:
```
import train_test
import ABC_train_test
import linearDataset
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 statistics import mean
from sklearn.metrics import mean_squared_error,mean_absolute_error
from torch import nn
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

1.3 Dataset

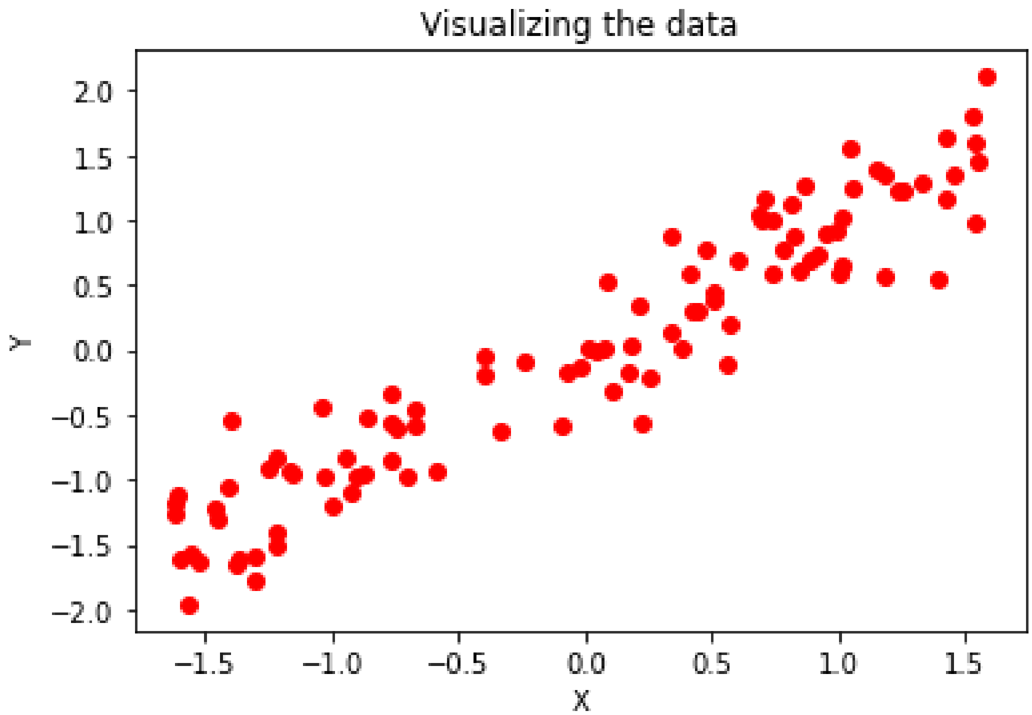
Generate the linear dataset

$y = m * x + c + e$ where $m = 1$, $c = 0.5$ and $e \sim N(0, 1)$

$x \sim 10 * U(-0.5, 0.5)$

[4]:
```
X,Y = linearDataset.linear_data(n_samples)
n_features = 1
```

```
          X         Y
0 -3.595274 -3.806086
1  3.277697  5.823070
2 -4.661033 -5.627130
3  2.461562  3.241949
4 -2.166268 -1.216861
```



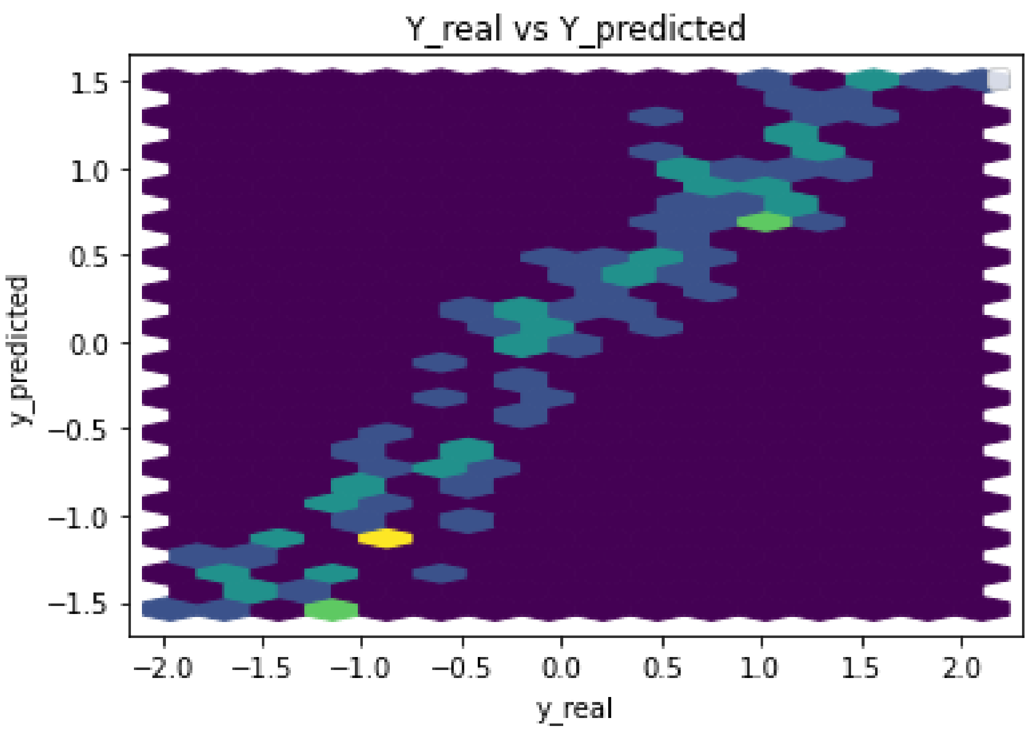
1.4 Stats Model

The statistical model is assumed to be $Y = \beta X + \mu$ where $\mu \sim N(0, 1)$

[5]:
```
[coeff,y_pred] = statsModel.statsModel(X,Y)
```

```
No handles with labels found to put in legend.
                            OLS Regression Results
================================================================================
=======
Dep. Variable:                      Y   R-squared (uncentered):
0.900
Model:                            OLS   Adj. R-squared (uncentered):
0.899
Method:                 Least Squares   F-statistic:
888.5
Date:                Thu, 07 Oct 2021   Prob (F-statistic):
3.02e-51
Time:                        16:28:40   Log-Likelihood:
-26.890
No. Observations:                 100   AIC:
55.78
Df Residuals:                      99   BIC:
58.39
```

```
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.9486      0.032     29.808      0.000       0.885       1.012
==============================================================================
Omnibus:                        0.562   Durbin-Watson:                   2.380
Prob(Omnibus):                  0.755   Jarque-Bera (JB):                0.699
Skew:                          -0.093   Prob(JB):                        0.705
Kurtosis:                       2.635   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
Parameters:  x1    0.948551
dtype: float64
```




```
Performance Metrics
Mean Squared Error: 0.10025129396187253
Mean Absolute Error: 0.2582909550551534
```

```
Manhattan distance: 25.829095505515333
Euclidean distance: 3.1662484735388756
```

1.5 Generator and Discriminator Networks

Generator Model

A simple generator consisting of 2 input nodes and an output node

[6]:
```python
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
```

Discriminator Model

Discriminator Model consisting of 2 input nodes,1 hidden layer and one output node.The input to the discriminator will be (x, y_{real}) and (x, y_{pred})

[7]:
```python
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 Generators

1. *Correctly Specified Prior* : The 1st ABC Generator is defined as $Y = m * X + c + e$ where $m \sim N(\mu, \sigma)$, $c = 0.5$ and $e \sim N(0, 1)$
2. *Misspecified Prior* : The 2nd ABC Generator is defined as $Y = 1 + m * X + c + e$ where $m \sim N(\mu, \sigma)$, $c = 0.5$ and $e \sim N(0, 1)$

Here μ and σ are parameters and can take the values $\mu = 0, 1$ and $\sigma = 1, 0.1, 0.01$

[8]:
```python
def ABC_Generator_Correct(X,mu,sigma,batch_size,device):
    m = np.random.normal(mu,sigma)
    c = 0.5
    X = X.numpy().reshape(1,batch_size)[0]
    Y = m*X + c + np.random.normal(0,1,size = batch_size)
```

```
    X = torch.from_numpy(X).reshape(batch_size,1)
    Y = torch.from_numpy(Y).reshape(batch_size,1)
    gen_input = torch.cat((X,Y),dim = 1).to(device)
    return gen_input
```

[9]:
```
def ABC_Generator_Misspecified(X,mu,sigma,batch_size,device):
    m = np.random.normal(mu,sigma)
    c = 0.5
    X = X.numpy().reshape(1,batch_size)[0]
    Y = 1 + m*X + c + np.random.normal(0,1,size = batch_size)
    X = torch.from_numpy(X).reshape(batch_size,1)
    Y = torch.from_numpy(Y).reshape(batch_size,1)
    gen_input = torch.cat((X,Y),dim = 1).to(device)
    return gen_input
```

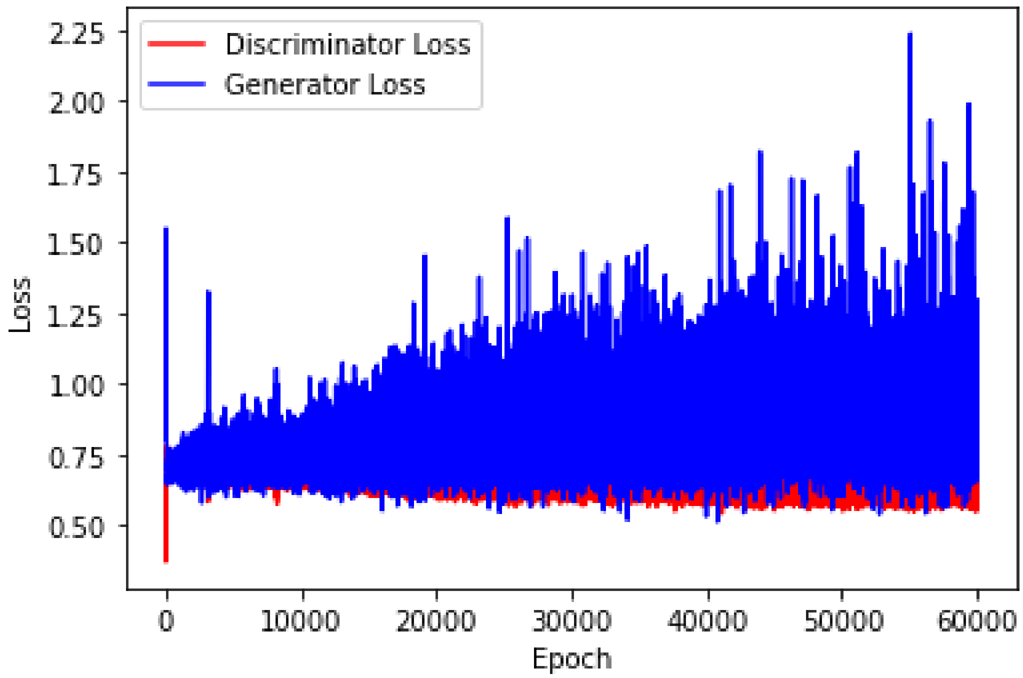
1.6 GAN Model

[10]:
```
real_dataset = dataset.CustomDataset(X,Y)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

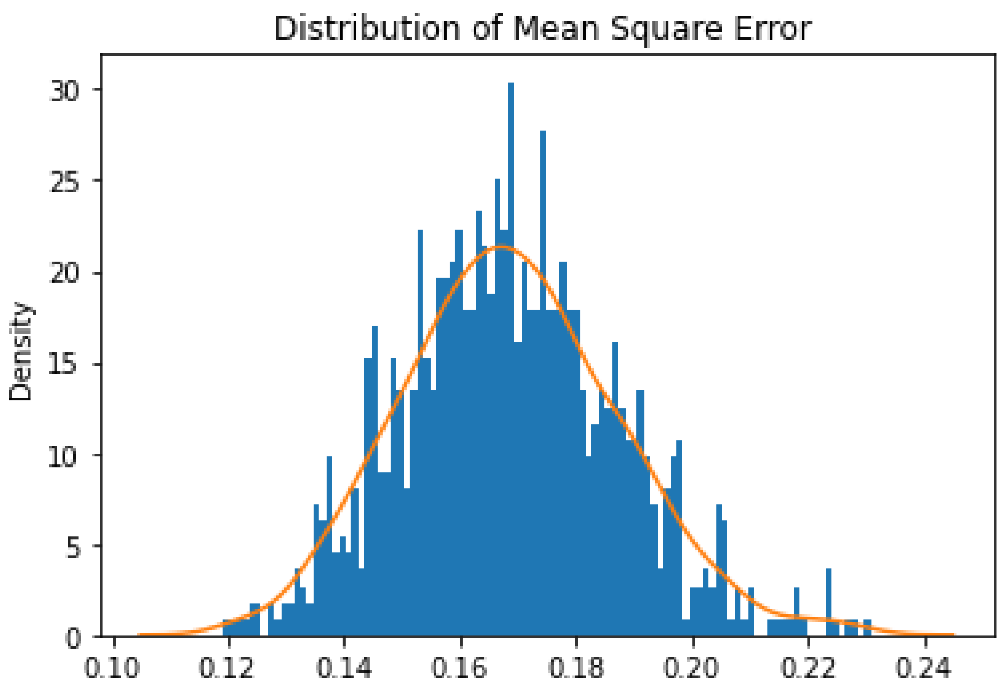
[11]:
```
generator = Generator(n_features+1)
discriminator = Discriminator(n_features+1,hidden_nodes)

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))
```

[12]:
```
n_epochs = 30000
batch_size = n_samples//2
```

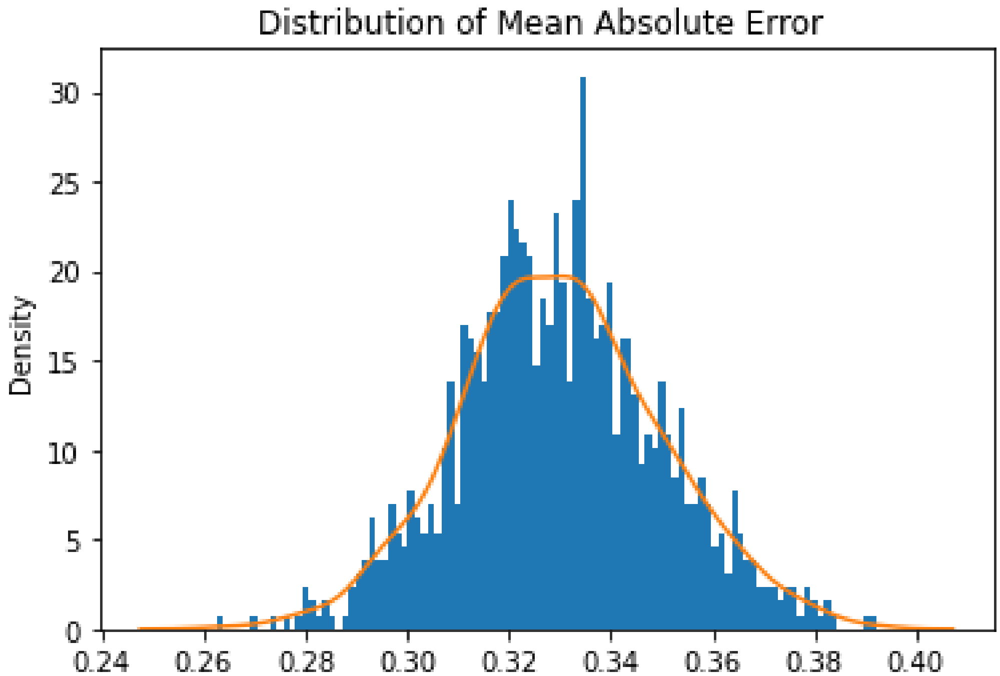
[13]:
```
train_test.
 ↪training_GAN(discriminator,generator,disc_opt,gen_opt,real_dataset,batch_size,␣
 ↪n_epochs,criterion,device)
```



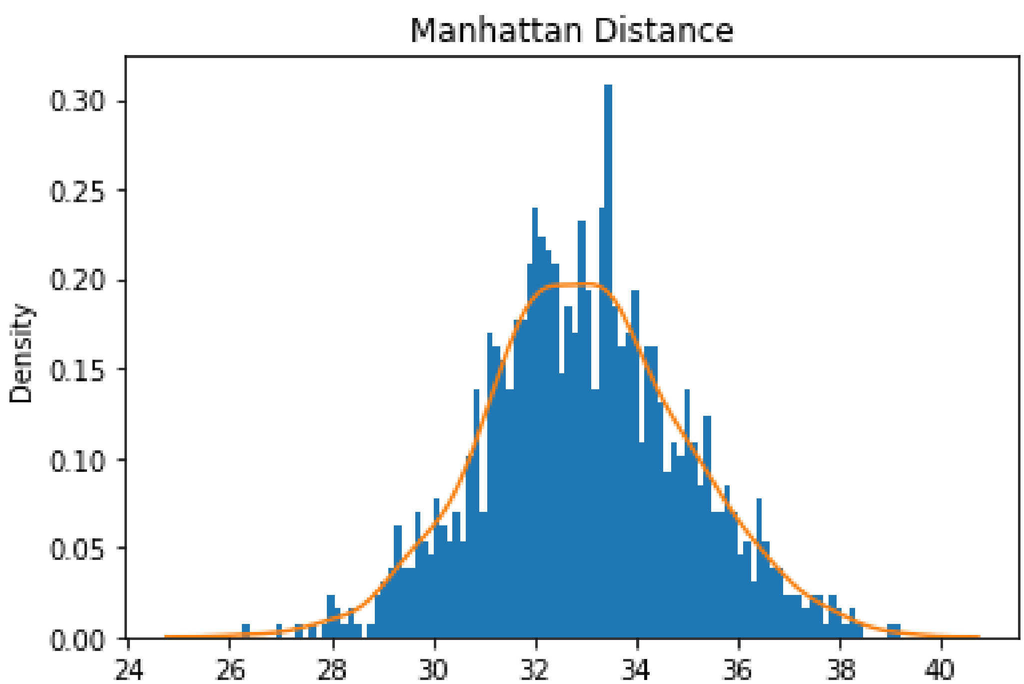
[14]:
```
train_test.test_generator(generator,real_dataset,device)
```



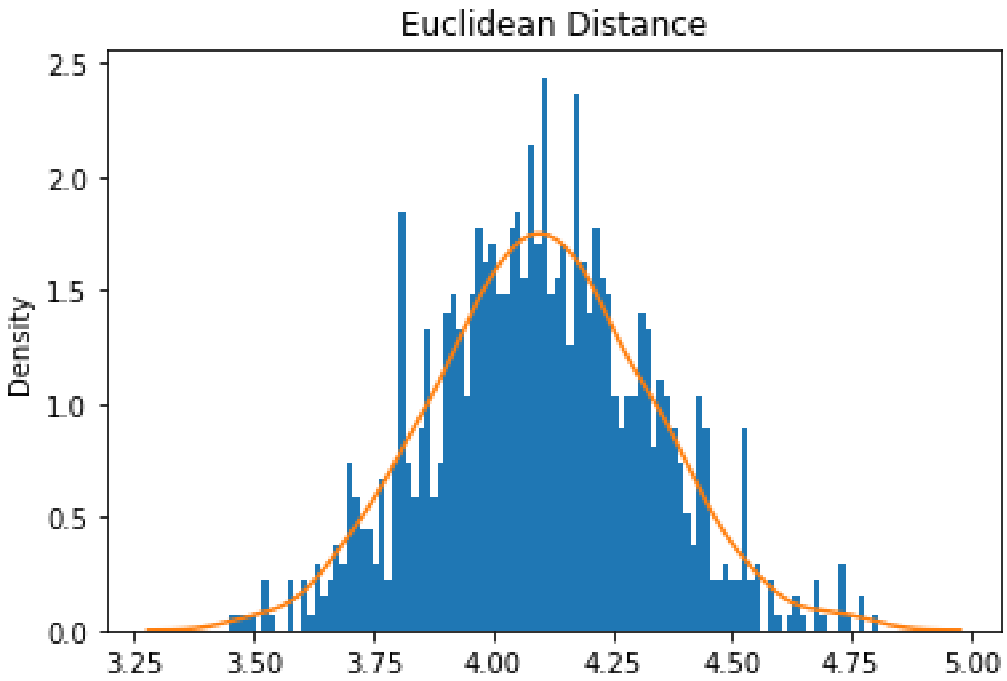
```
Mean Square Error: 0.168672483837347
```




```
Mean Absolute Error: 0.3299261477966886
```



```
Mean Manhattan Distance: 32.99261477966886
```




```
Mean Euclidean Distance: 32.99261477966886
```

1.7 ABC - GAN Model

[15]:
```python
gen = Generator(n_features+1)
disc = Discriminator(n_features+1,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]:
```python
n_epoch_abc = 2000
batch_size = n_samples//2
```

[17]:
```python
def training_GAN(disc, gen,disc_opt,gen_opt,dataset, batch_size,␣
 ↪n_epochs,criterion,coeff,mean,std,prior,device):
    discriminatorLoss = []
    generatorLoss = []
    train_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

    for epoch in range(n_epochs):
```

```
        for x_batch,y_batch in train_loader:
            y_shape = list(y_batch.size())
            curr_batch_size = y_shape[0]
            y_batch = torch.reshape(y_batch,(curr_batch_size,1))

            #Create the labels
            real_labels = torch.ones(curr_batch_size,1).to(device)
            fake_labels = torch.zeros(curr_batch_size,1).to(device)

            #-------------------------
            #Update the discriminator
            #-------------------------
            disc_opt.zero_grad()

            #Get discriminator loss for real data
            inputs_real = torch.cat((x_batch,y_batch),dim=1).to(device)
            disc_real_pred = disc(inputs_real)
            disc_real_loss = criterion(disc_real_pred,real_labels)

            #Get discriminator loss for fake data
            gen_input =␣
↪ABC_Generator_Misspecified(x_batch,mean,std,curr_batch_size,device)
            if(prior == 0):
                gen_input = ␣
↪ABC_Generator_Correct(x_batch,mean,std,curr_batch_size,device)
            generated_y = gen(gen_input.float())
            x_batch = x_batch.to(device)
            inputs_fake = torch.cat((x_batch,generated_y),dim=1).to(device)
            x_batch = x_batch.detach().cpu()
            disc_fake_pred = disc(inputs_fake)
            disc_fake_loss = criterion(disc_fake_pred,fake_labels)

            #Get the discriminator loss
            disc_loss = (disc_fake_loss + disc_real_loss) / 2
            discriminatorLoss.append(disc_loss.item())

            # Update gradients
            disc_loss.backward(retain_graph=True)
            # Update optimizer
            disc_opt.step()

            #-------------------------
            #Update the Generator
            #-------------------------
            gen_opt.zero_grad()

            #Generate input to generator using ABC pre-generator
```

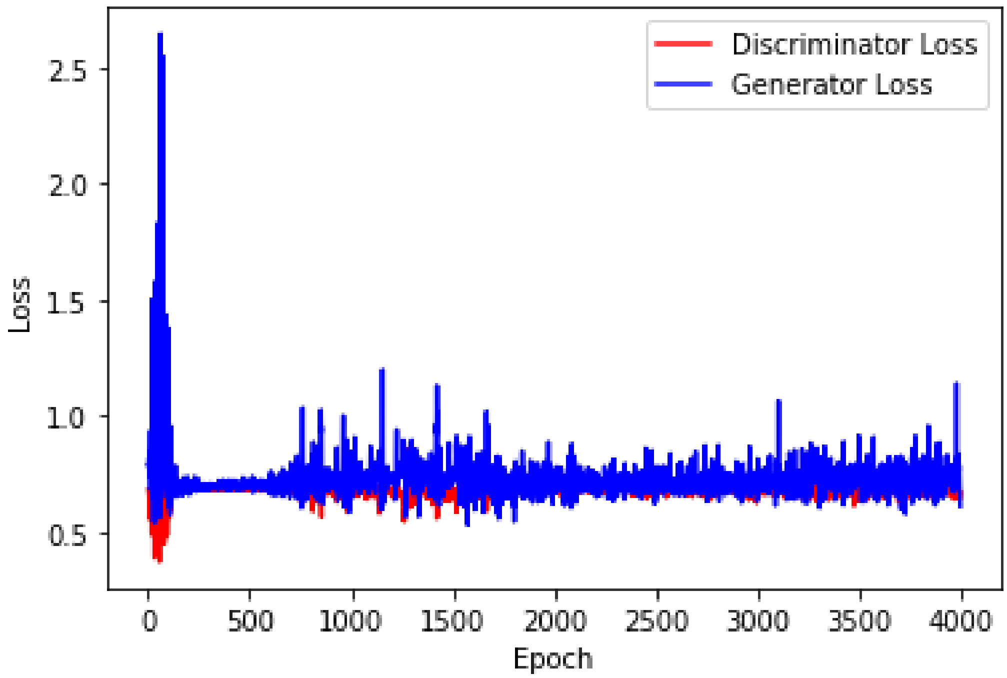
```
            gen_input = ␣
↪ABC_Generator_Misspecified(x_batch,mean,std,curr_batch_size,device)
            if(prior == 0):
                gen_input = ␣
↪ABC_Generator_Correct(x_batch,mean,std,curr_batch_size,device)
            generated_y = gen(gen_input.float())
            x_batch = x_batch.to(device)
            inputs_fake = torch.cat((x_batch,generated_y),dim=1).to(device)
            x_batch = x_batch.detach().cpu()
            disc_fake_pred = disc(inputs_fake)

            gen_loss = criterion(disc_fake_pred,real_labels)
            generatorLoss.append(gen_loss.item())

            #Update gradients
            gen_loss.backward()
            #Update optimizer
            gen_opt.step()

    #Plotting the Discriminator and Generator Loss
    plt.plot(discriminatorLoss,color = "red",label="Discriminator Loss")
    plt.plot(generatorLoss,color="blue",label ="Generator Loss")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
```

[18]:

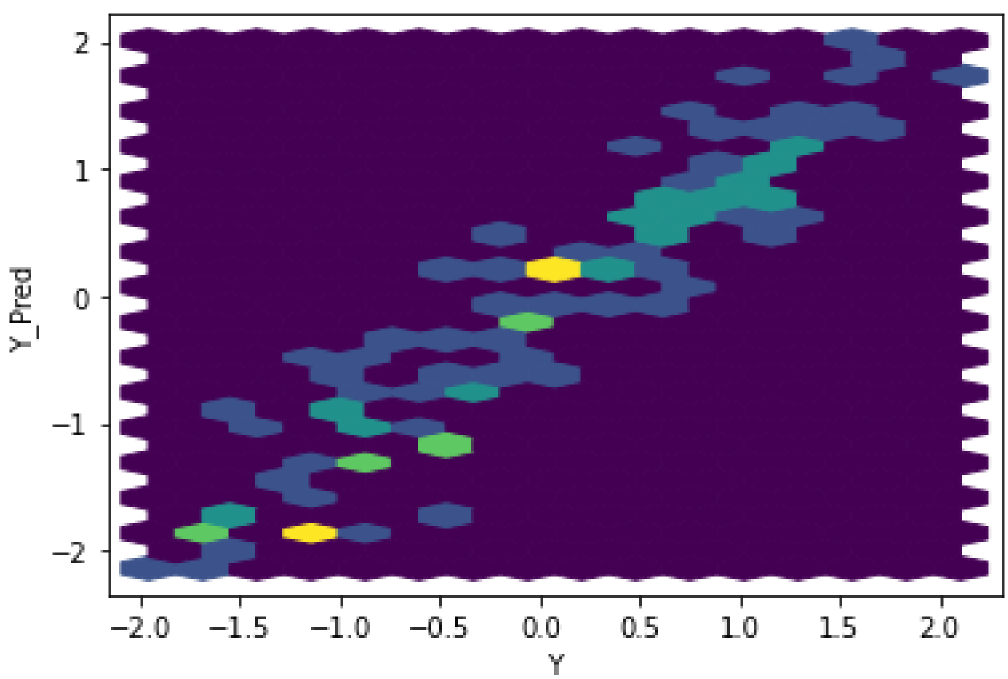
```
def test_generator(gen,dataset,coeff,w,std,prior,device):
    test_loader = DataLoader(dataset, batch_size=len(dataset), shuffle=False)
    mse=[]
    mae=[]
    distp1 = []
    distp2 = []
    for epoch in range(1000):
        for x_batch, y_batch in test_loader:
            gen_input = ␣
↪ABC_Generator_Misspecified(x_batch,w,std,len(dataset),device)
            if(prior == 0):
                gen_input = ␣
↪ABC_Generator_Correct(x_batch,w,std,len(dataset),device)
            generated_y = gen(gen_input.float())
            generated_y = generated_y.cpu().detach()
            generated_data = torch.reshape(generated_y,(-1,))
            gen_data = generated_data.numpy().reshape(1,len(dataset)).tolist()
            real_data = y_batch.numpy().reshape(1,len(dataset)).tolist()
            #Plot the data
            if(epoch%200==0):
```

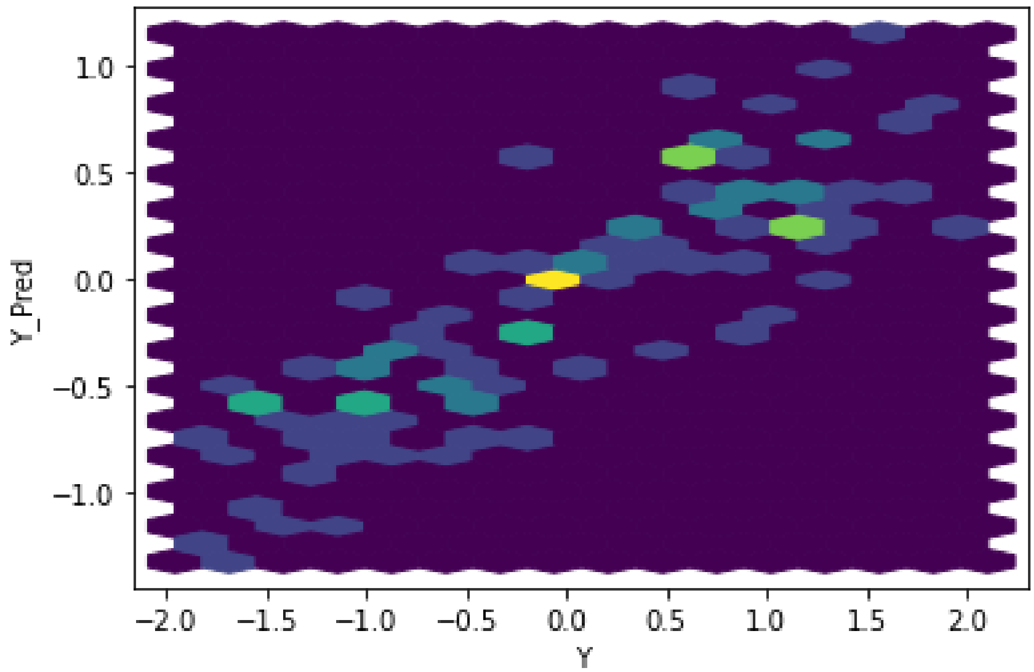
```
                gen_data1 = generated_data.numpy().tolist()
                real_data1 = y_batch.numpy().tolist()
                plt.hexbin(real_data1,gen_data1,gridsize=(15,15))
                plt.xlabel("Y")
                plt.ylabel("Y_Pred")
                plt.show()
            meanSquaredError = mean_squared_error(real_data,gen_data)
            meanAbsoluteError = mean_absolute_error(real_data, gen_data)
            mse.append(meanSquaredError)
            mae.append(meanAbsoluteError)
            dist1 = ABC_train_test.minkowski_distance(np.array(real_data)[0],np.
↪array(gen_data)[0], 1)
            dist2 = ABC_train_test.minkowski_distance(np.array(real_data)[0],np.
↪array(gen_data)[0], 2)
            distp1.append(dist1)
            distp2.append(dist2)

    #Distribution of Metrics
    #Mean Squared Error
    n,x,_=plt.hist(mse,bins=100,density=True)
    plt.title("Distribution of Mean Square Error ")
    sns.distplot(mse,hist=False)
    plt.show()
    print("Mean Square Error:",mean(mse))

    #Mean Absolute Error
    n,x,_=plt.hist(mae,bins=100,density=True)
    plt.title("Distribution of Mean Absolute Error ")
    sns.distplot(mae,hist=False)
    plt.show()
    print("Mean Absolute Error:",mean(mae))

    #Minkowski Distance 1st Order
    n,x,_=plt.hist(distp1,bins=100,density=True)
    plt.title("Manhattan Distance")
    sns.distplot(distp1,hist=False)
    print("Mean Manhattan Distance:",mean(distp1))
    plt.show()

    #Minkowski Distance 2nd Order
    n,x,_=plt.hist(distp2,bins=100,density=True)
    plt.title("Euclidean Distance")
    sns.distplot(distp2,hist=False)
    print("Mean Euclidean Distance:",mean(distp2))
    plt.show()
```

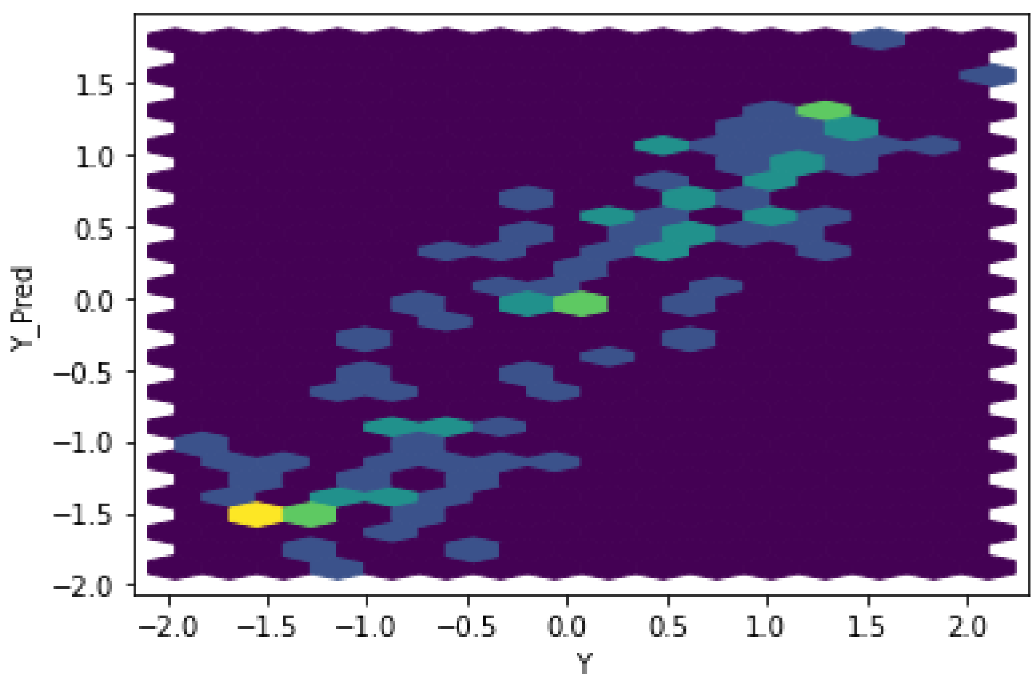
[19]:
```
training_GAN(disc,gen,disc_opt,gen_opt,real_dataset,batch_size,n_epoch_abc,criterion,coeff,mea
```

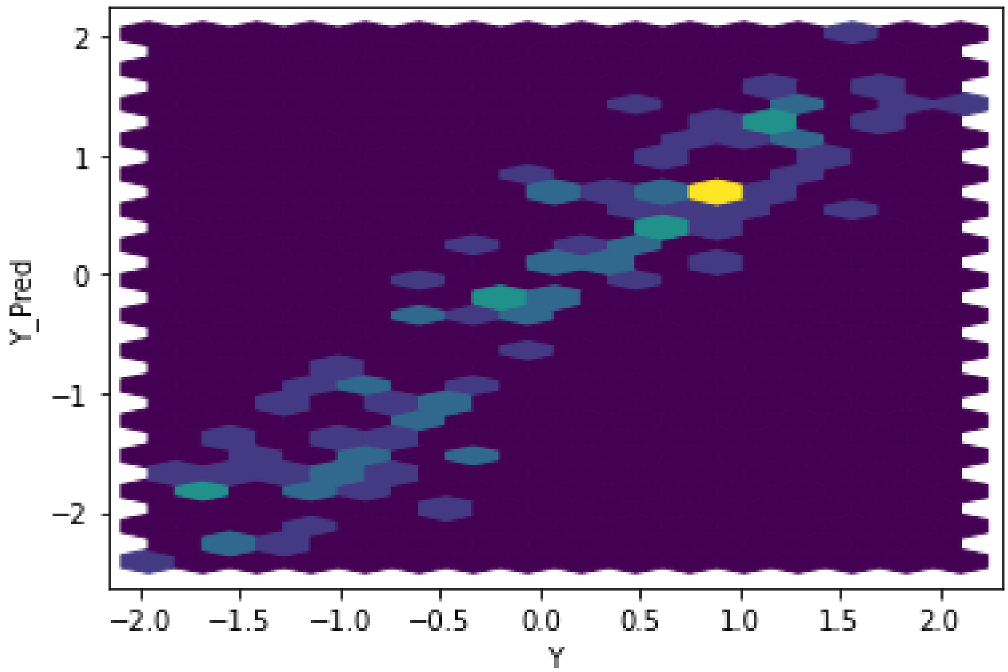


[20]:
```
test_generator(gen,real_dataset,coeff,meanVal,std,prior,device)
```

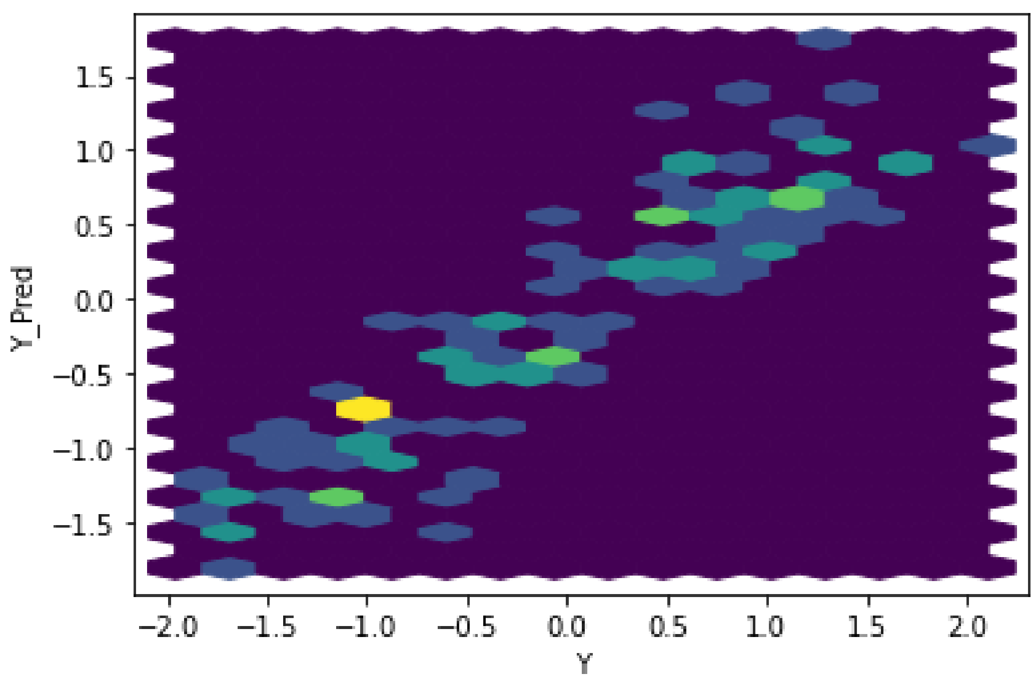



1.0
0.5
0.0
−0.5
−1.0
Y_Pred
−2.0 −1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0
Y

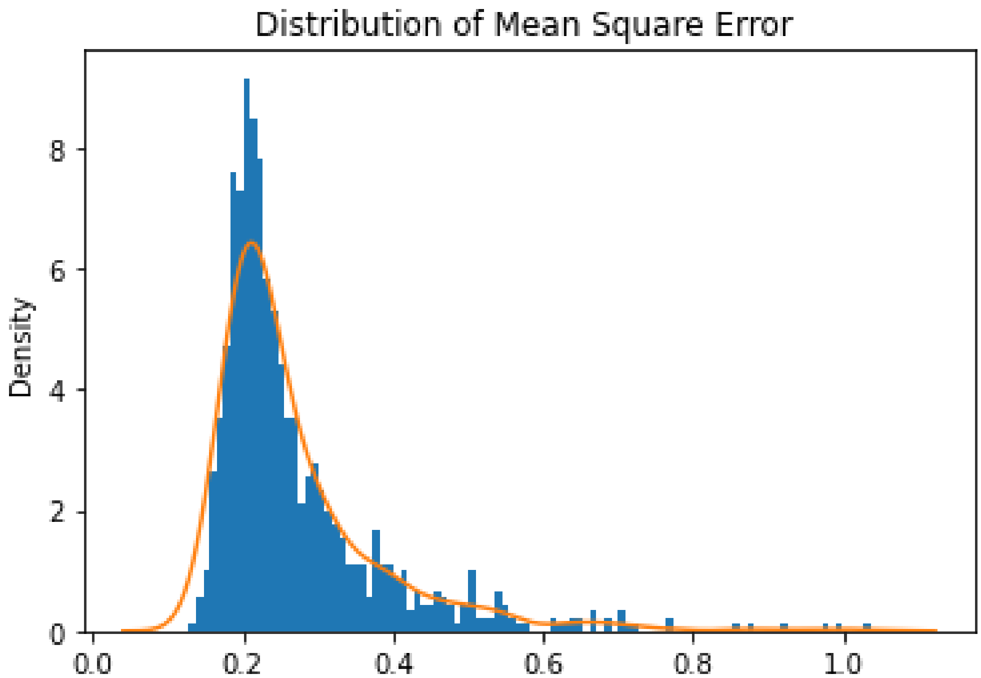

1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
Y_Pred
−2.0 −1.5 −1.0 −0.5 0.0 0.5 1.0 1.5 2.0
Y



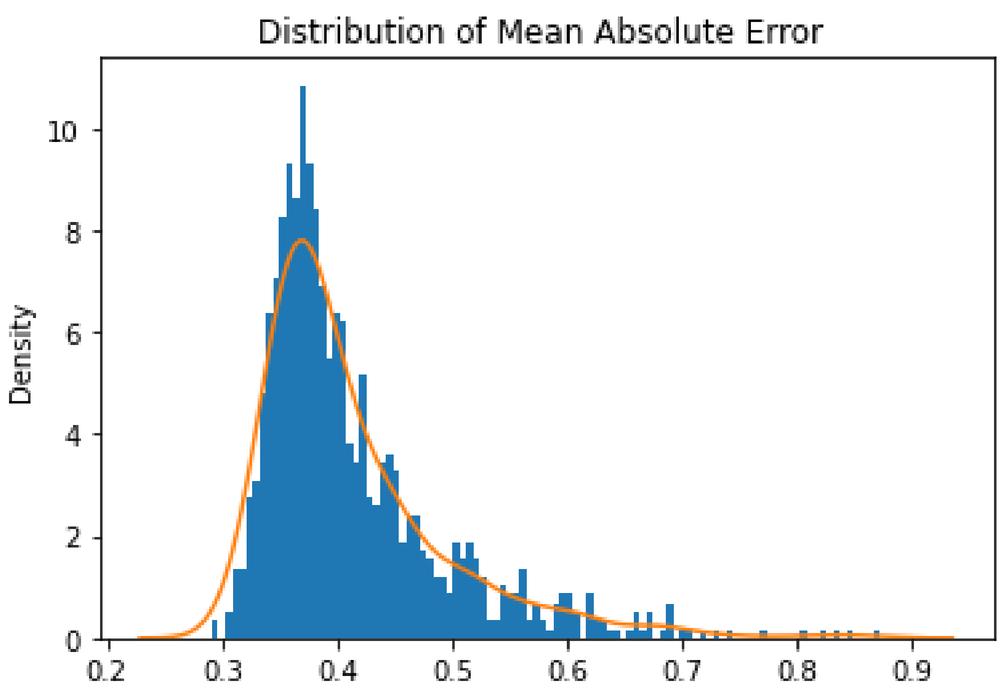
Y_Pred
Y
2
1
0
−1
−2
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



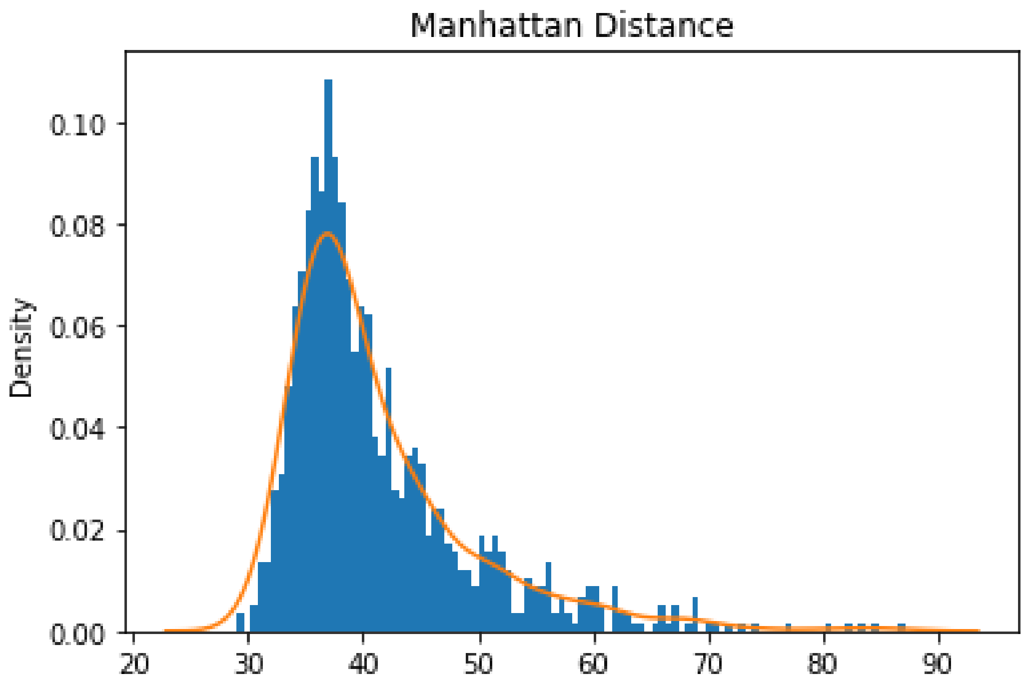
Y_Pred
Y
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



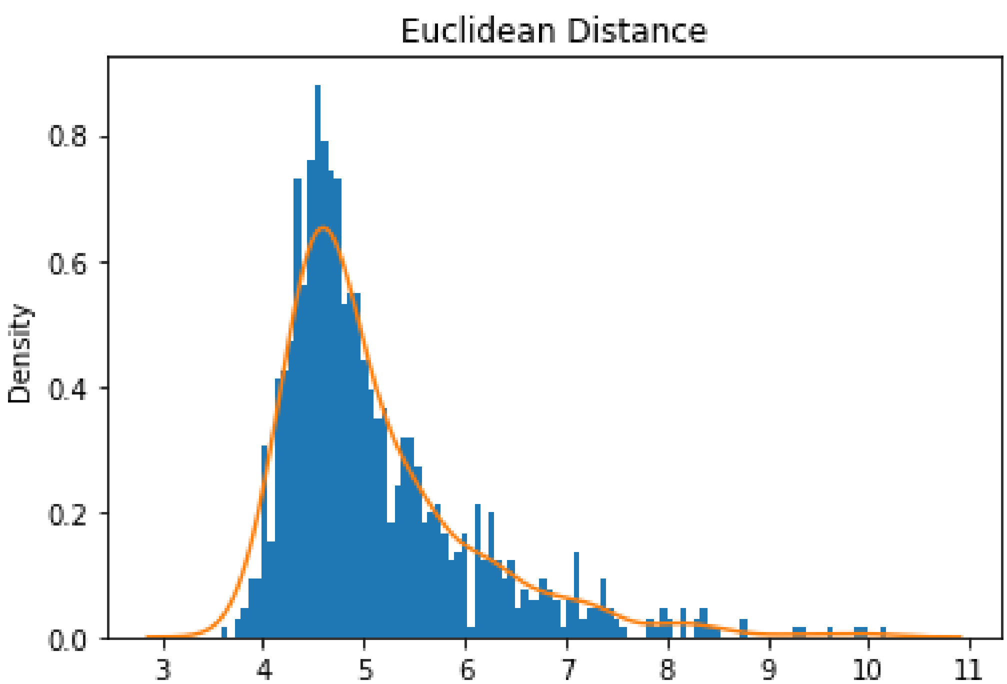
Mean Square Error: 0.27112973312104244



```
Mean Absolute Error: 0.41335140882176347
Mean Manhattan Distance: 41.33514088217635
```



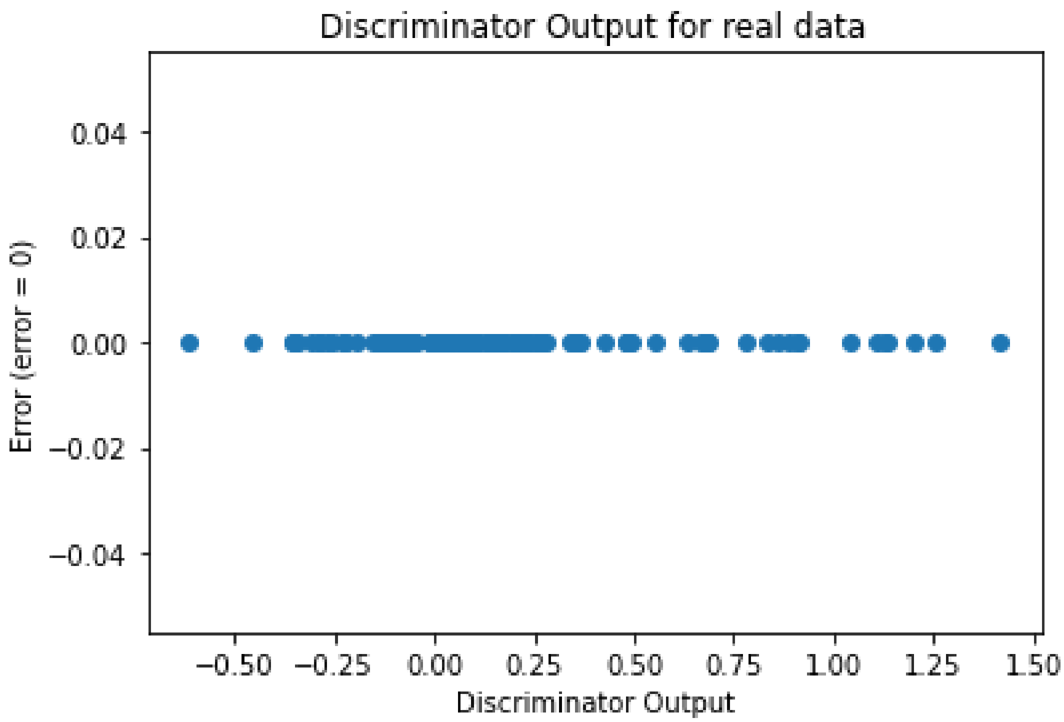

```
Mean Euclidean Distance: 5.11658800871561
```

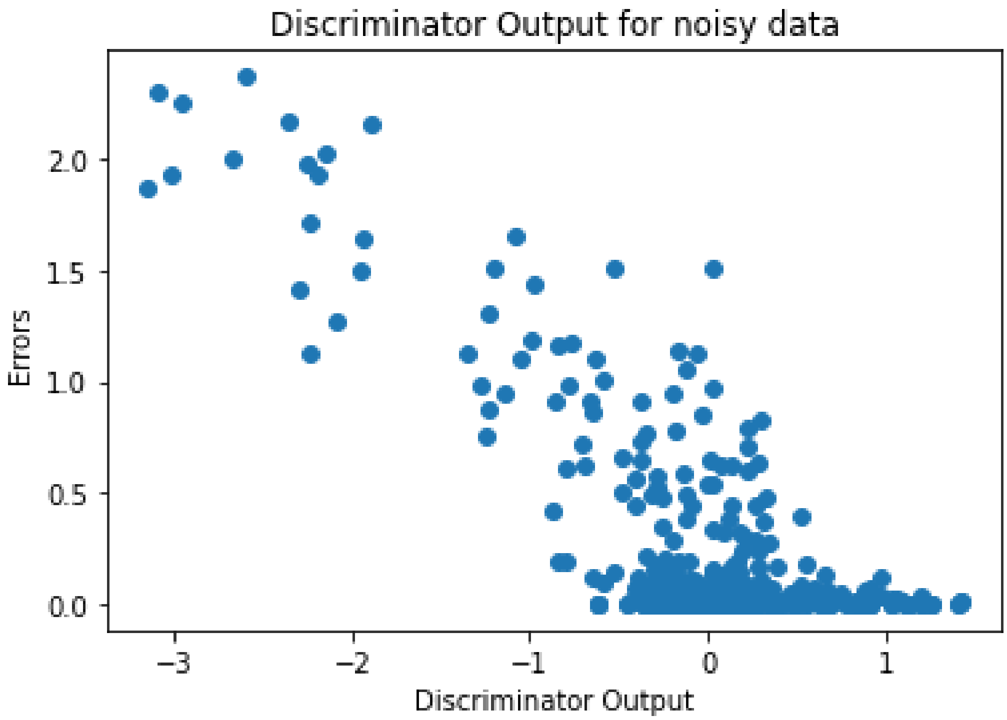


1.7.1 Sanity Check

We plot the discriminator output vs the noise in the input to verify that the discriminator functions correctly. We expect that discriminator output and noise are inversely proportional

[21]:
```
sanityChecks.discProbVsError(real_dataset,disc,device)
```





1.7.2 Visualization of Trained GAN Generator

[22]:
```
for name, param in gen.named_parameters():
    print(name,param)
```

```
output.weight Parameter containing:
tensor([[ 1.0871, -0.2627]], requires_grad=True)
output.bias Parameter containing:
tensor([0.2543], requires_grad=True)
```