Dataset2-Dummy_Linear_output_14

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 = 10000
std = 1
mean = 0.1
prior = 0
```

1.2 Import Libraries

[3]:
```
import train_test
import ABC_train_test
import linearDataset
import network
import statsModel
import performanceMetrics
```

```python
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

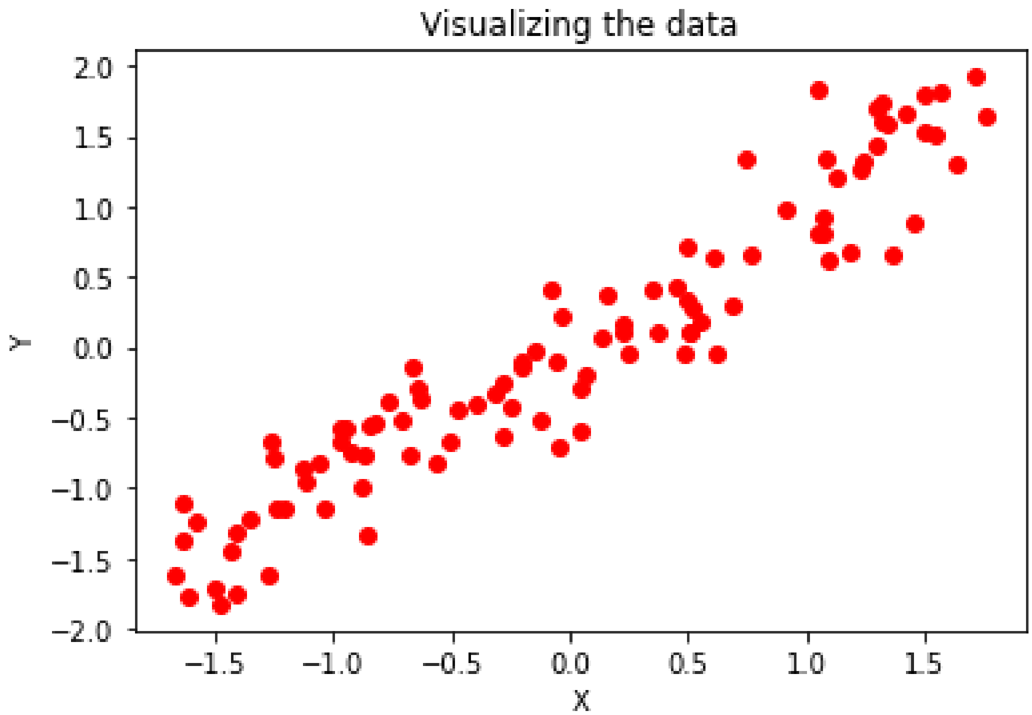
Generate the linear dataset

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

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

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

```
          X         Y
0 -0.840081 -1.463260
1  1.407469  0.729693
2  0.966175  1.665507
3 -1.664791 -2.054066
4  4.421772  5.846094
```



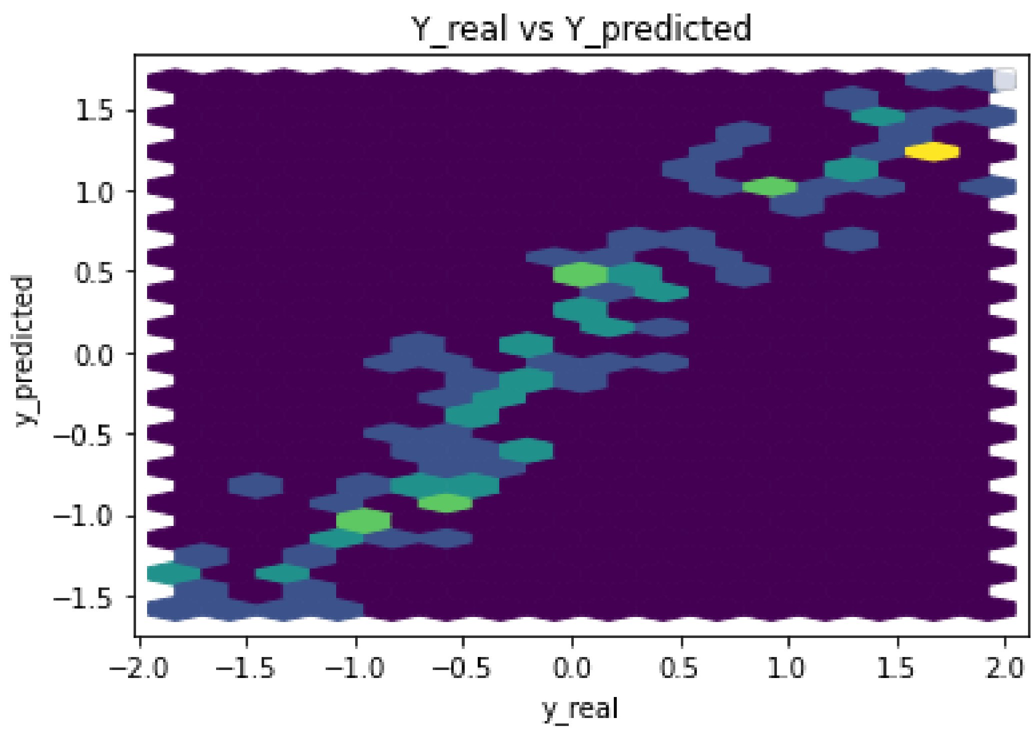
1.4 Stats Model

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):
0.903
Model:                            OLS   Adj. R-squared (uncentered):
0.902
Method:                 Least Squares   F-statistic:
917.4
Date:                Thu, 07 Oct 2021   Prob (F-statistic):
7.21e-52
Time:                        15:54:53   Log-Likelihood:
-25.446
No. Observations:                 100   AIC:
52.89
Df Residuals:                      99   BIC:
55.50
```

```
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.9501      0.031     30.289      0.000       0.888       1.012
==============================================================================
Omnibus:                        0.911   Durbin-Watson:                   1.791
Prob(Omnibus):                  0.634   Jarque-Bera (JB):                0.912
Skew:                          -0.055   Prob(JB):                        0.634
Kurtosis:                       2.545   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    0.950054
dtype: float64
```




```
Performance Metrics
Mean Squared Error: 0.09739802543266751
Mean Absolute Error: 0.2557156831439636
```

```
Manhattan distance: 25.571568314396362
Euclidean distance: 3.120865672095925
```

1.5 Generator and Discriminator Networks

Generator Model

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

[6]:
```
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]:
```
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]:
```
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
```

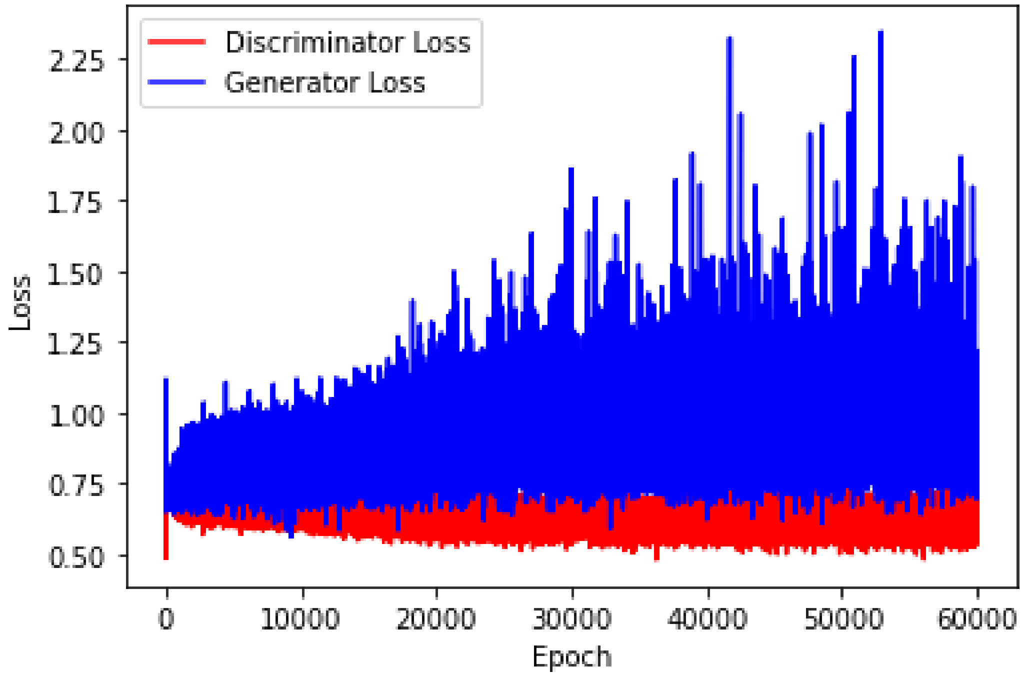
1.6 GAN Model

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

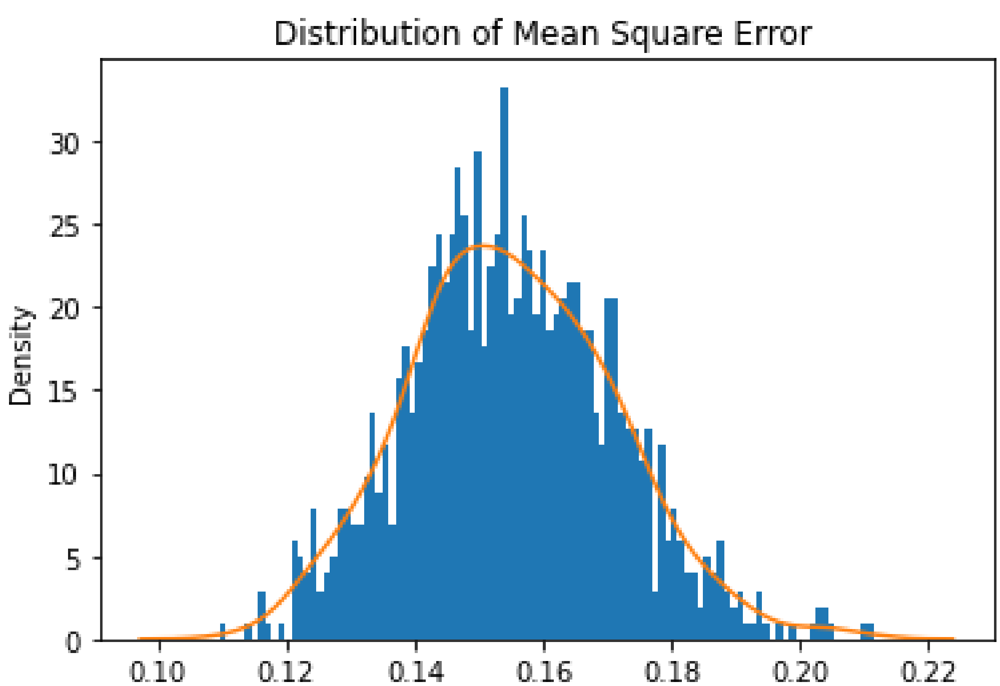
[11]:
```
generator = Generator(n_features+1)
discriminator = Discriminator(n_features+1,hidden_nodes)

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
```

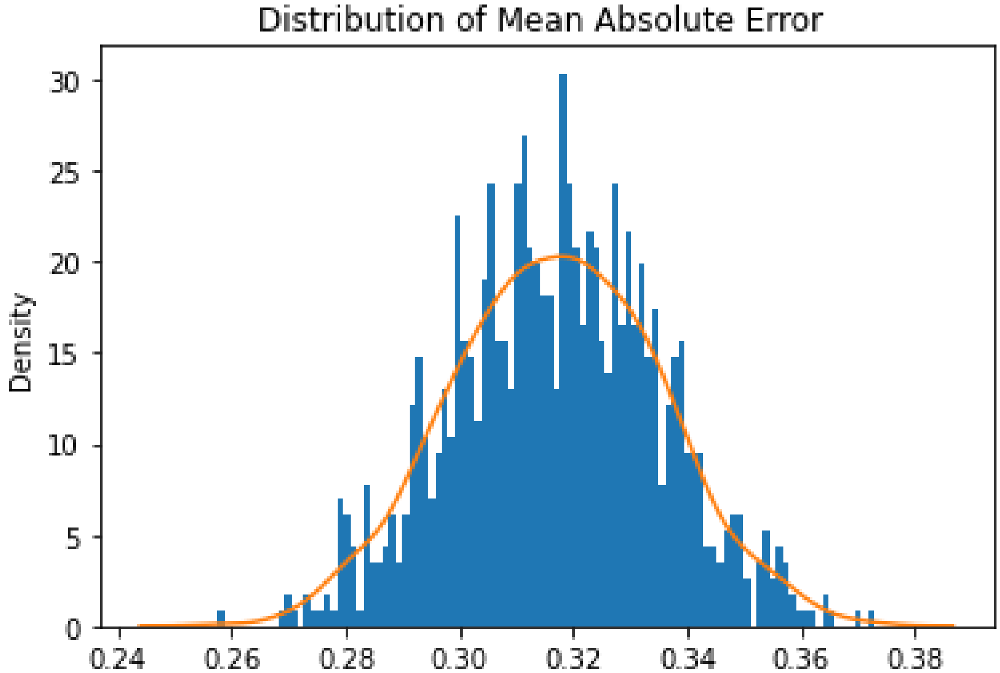
[13]:
```
train_test.
 ↪training_GAN(discriminator,generator,disc_opt,gen_opt,real_dataset,batch_size,␣
 ↪n_epochs,criterion,device)
```



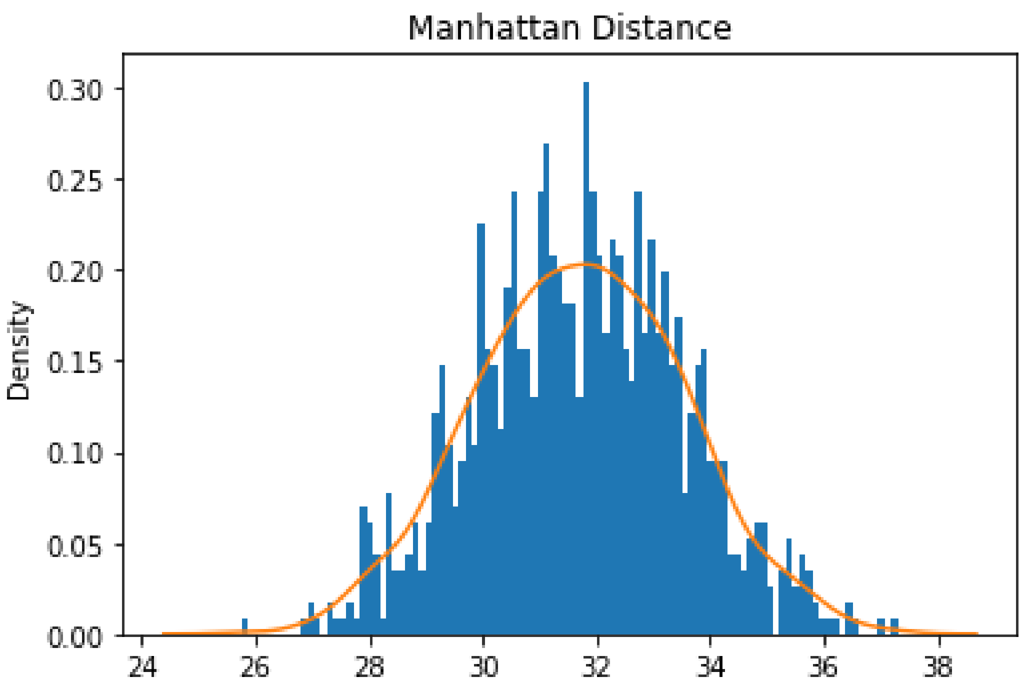
[14]:
```
train_test.test_generator(generator,real_dataset,device)
```



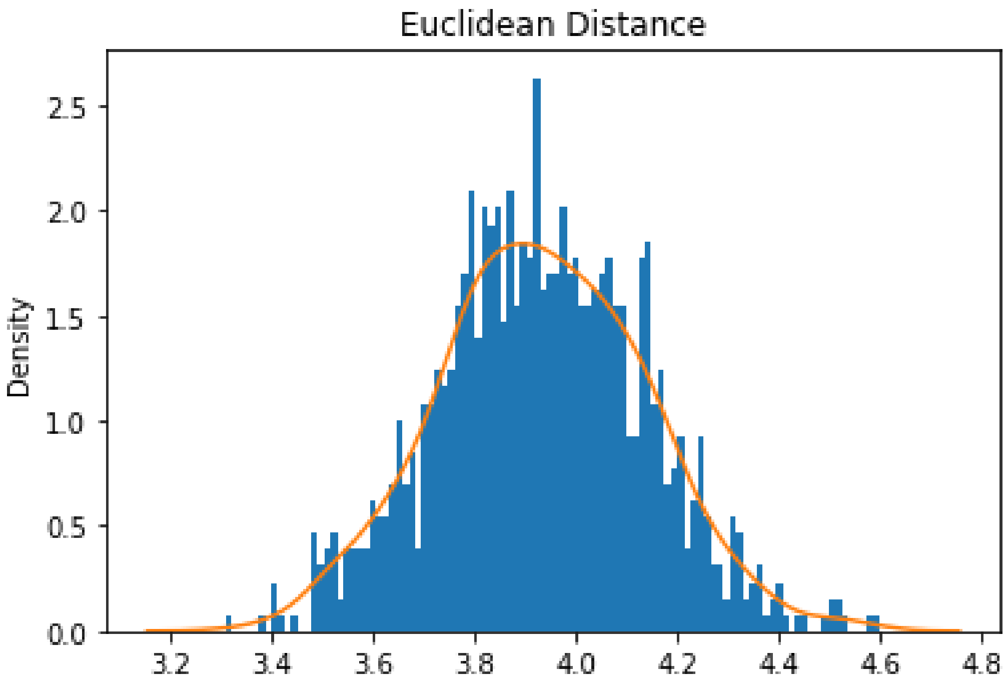
Mean Square Error: 0.15503096387655116



Mean Absolute Error: 0.3170201495877653



```
Mean Manhattan Distance: 31.702014958776534
```




```
Mean Euclidean Distance: 31.702014958776534
```

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
```

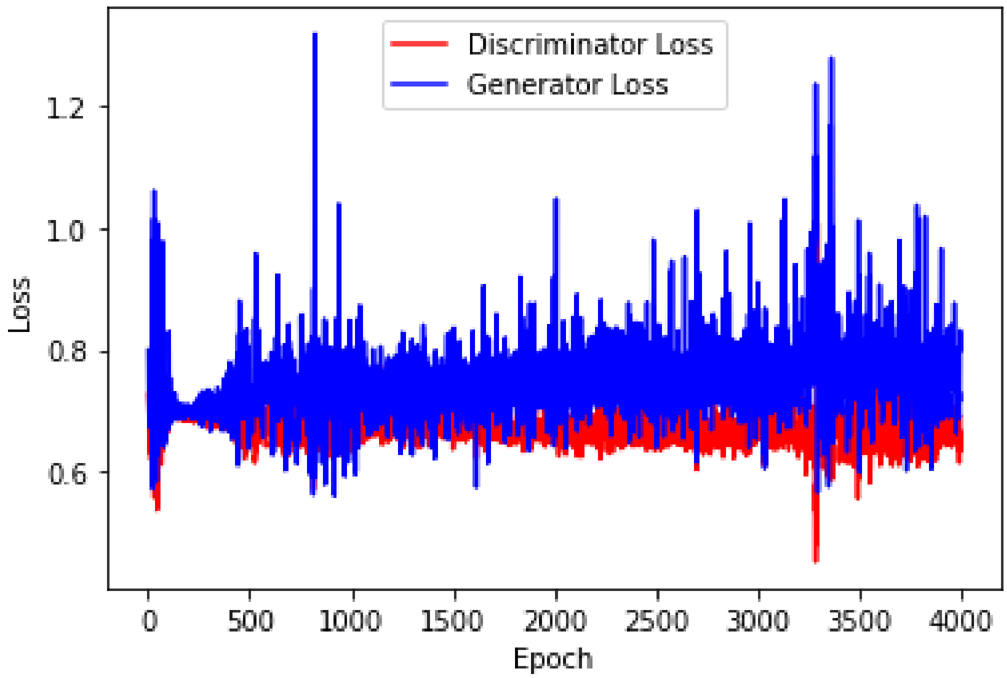
```
            gen_input = ␣
↪ABC_Generator_Misspecified(x_batch,mean,std,curr_batch_size,device)
            if(prior == 0):
                gen_input = ␣
↪ABC_Generator_Correct(x_batch,mean,std,curr_batch_size,device)
            generated_y = gen(gen_input.float())
            x_batch = x_batch.to(device)
            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):
```

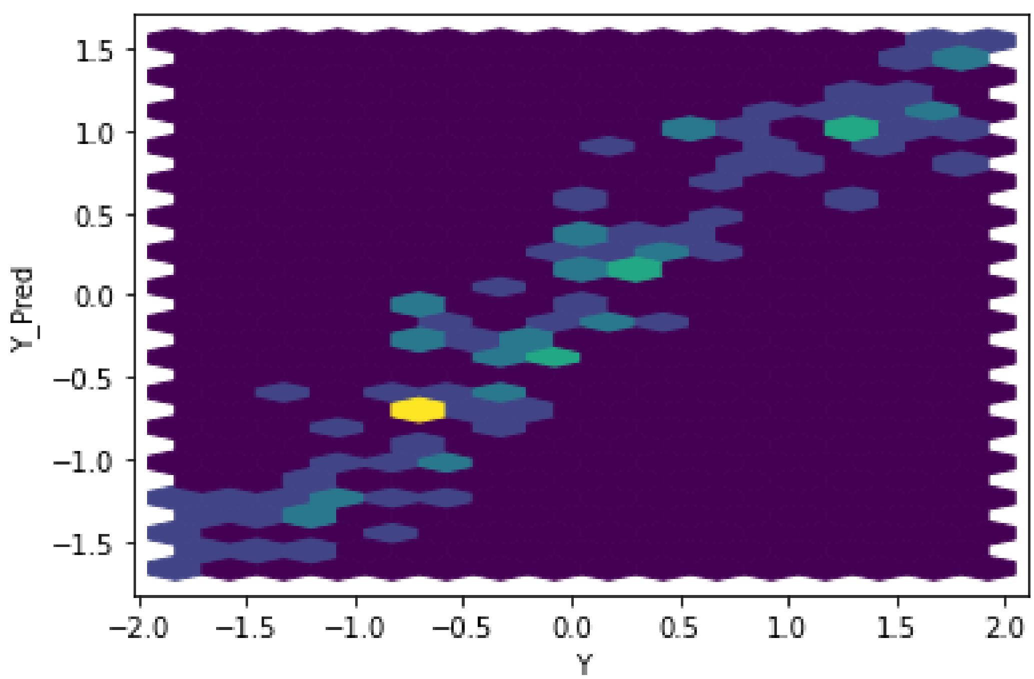
```
                gen_data1 = generated_data.numpy().tolist()
                real_data1 = y_batch.numpy().tolist()
                plt.hexbin(real_data1,gen_data1,gridsize=(15,15))
                plt.xlabel("Y")
                plt.ylabel("Y_Pred")
                plt.show()
            meanSquaredError = 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()
```

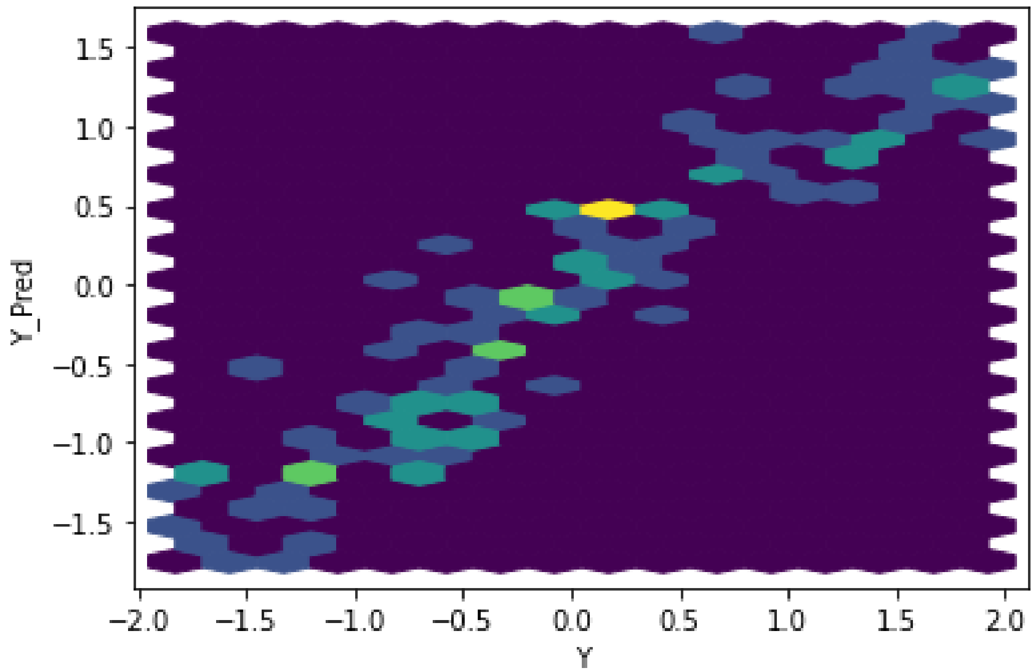
[19]:

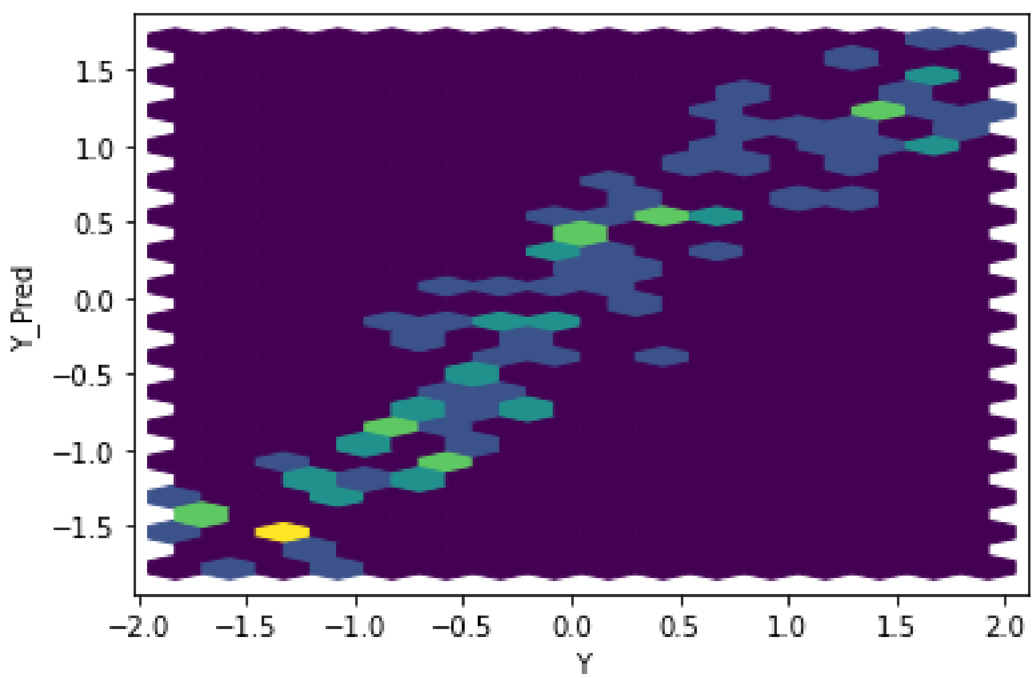
```
training_GAN(disc,gen,disc_opt,gen_opt,real_dataset,batch_size,n_epoch_abc,criterion,coeff,mea
```

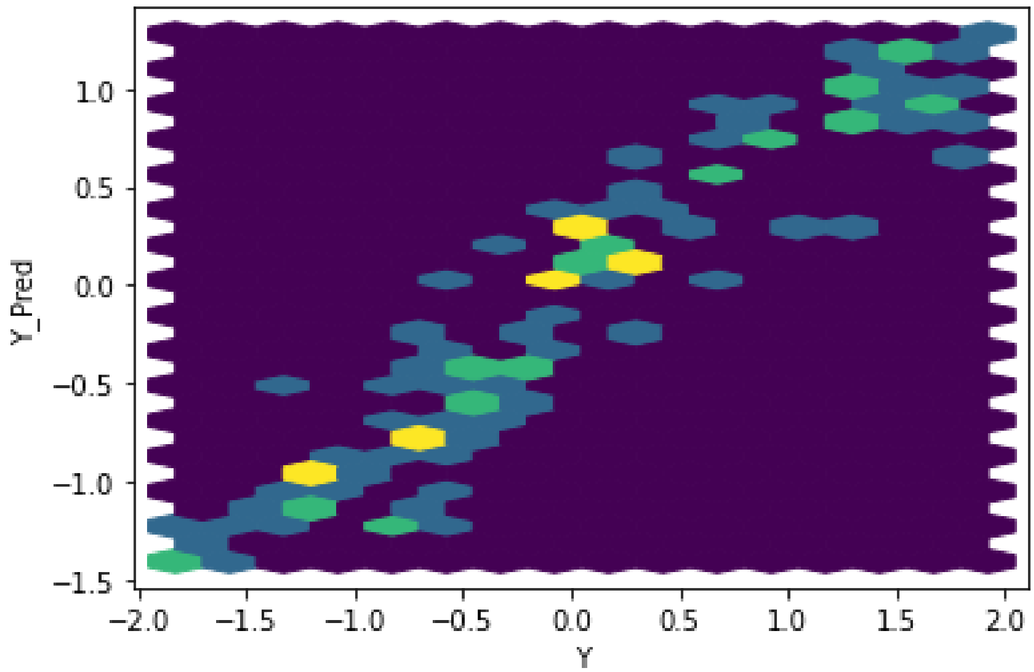


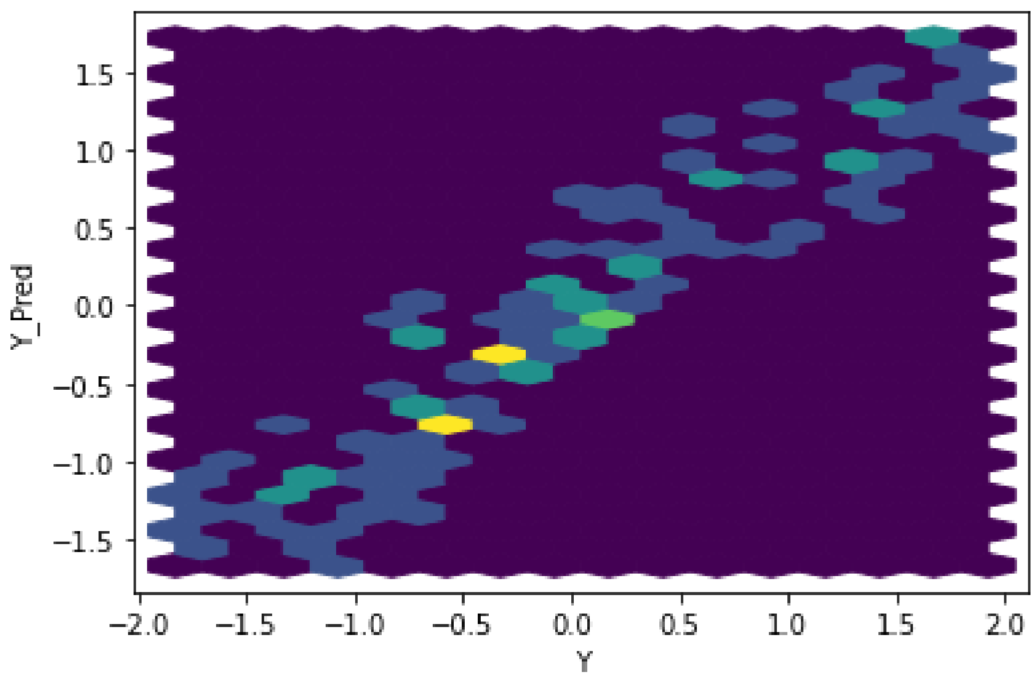
[20]:
```
test_generator(gen,real_dataset,coeff,meanVal,std,prior,device)
```

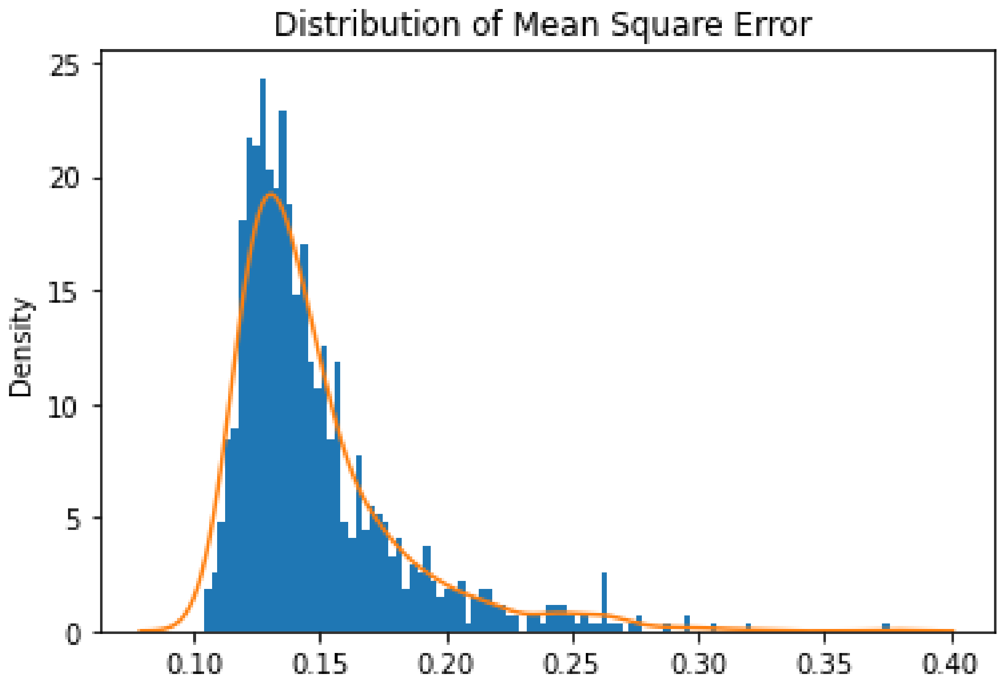



Y_Pred
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Y

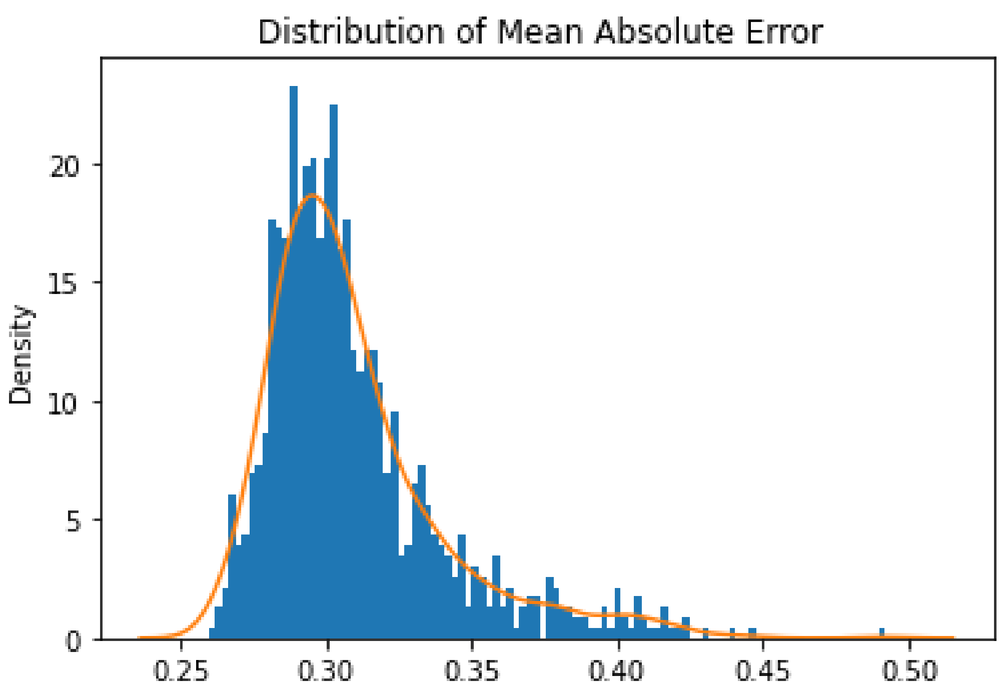

Y_Pred
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Y


Y_Pred
Y
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

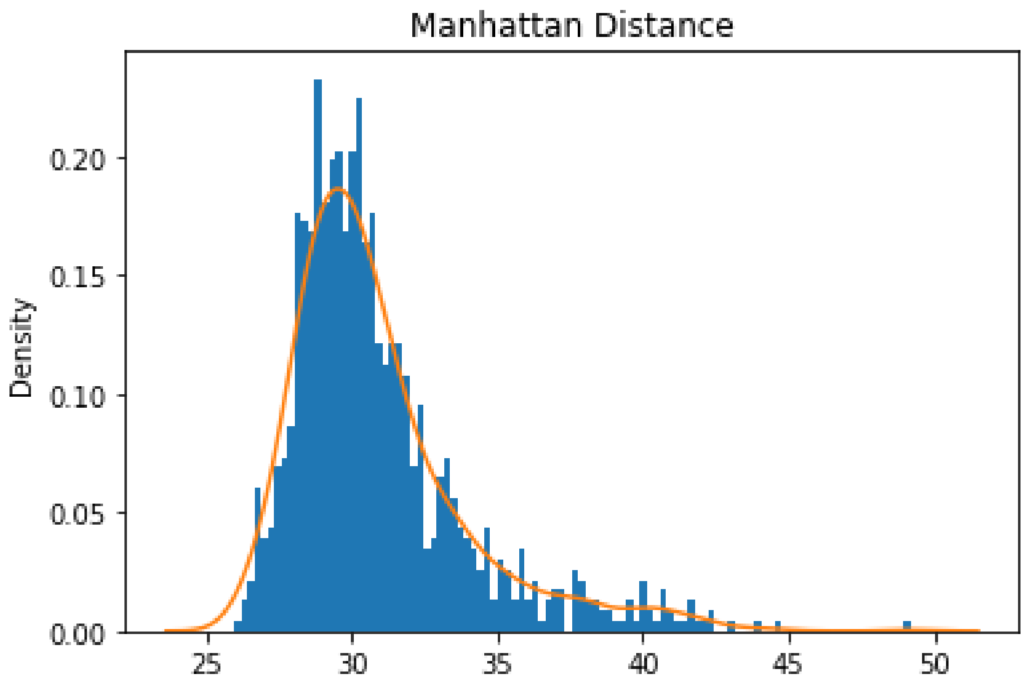

Y_Pred
Y
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



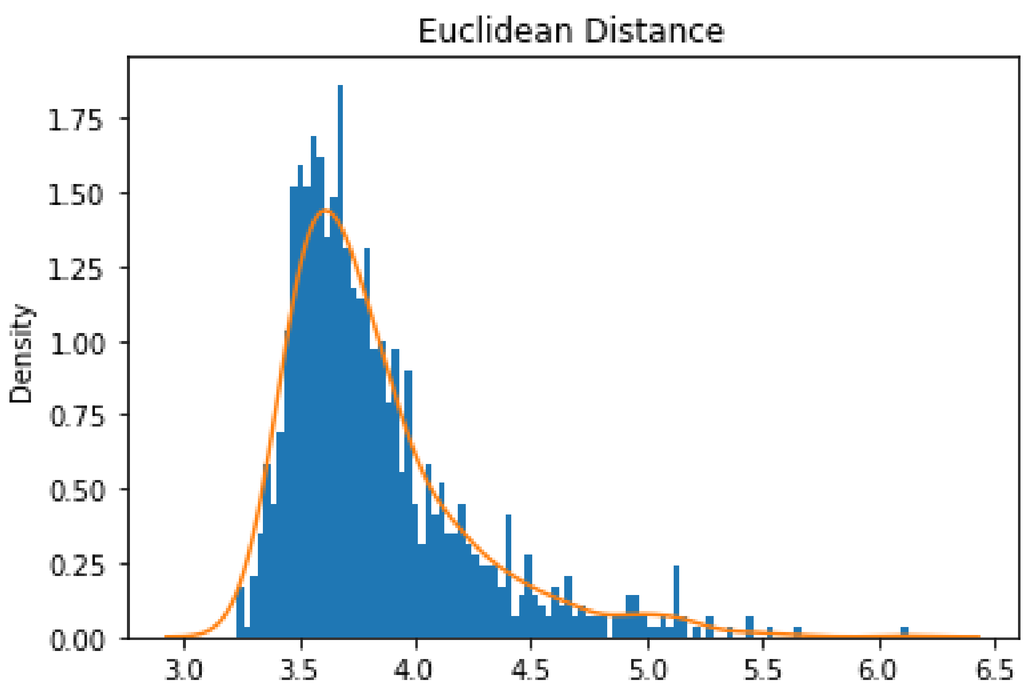

```
Mean Square Error: 0.14835449687882163
```



```
Mean Absolute Error: 0.3092937923701853
Mean Manhattan Distance: 30.929379237018527
```



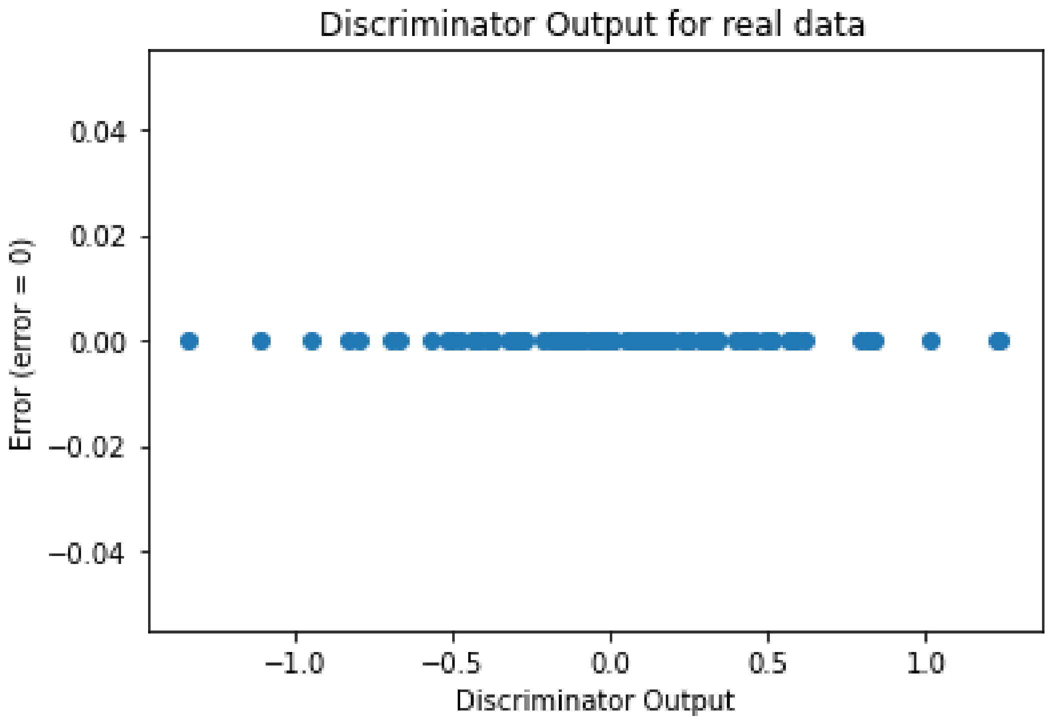

```
Mean Euclidean Distance: 3.8306294890601698
```

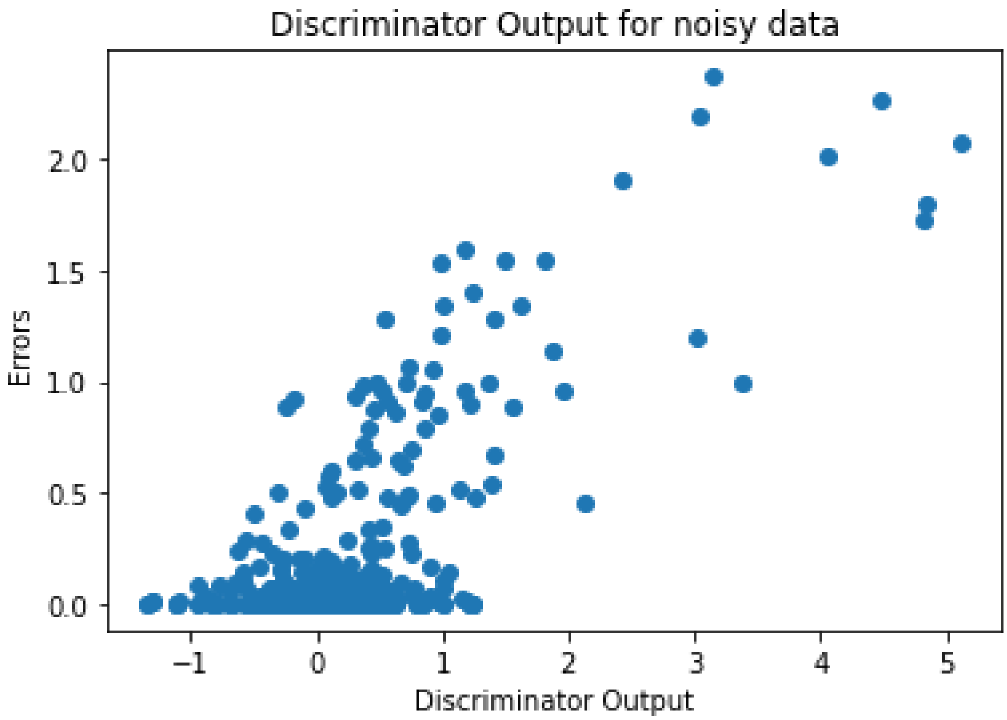


1.7.1 Sanity Check

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([[0.7981, 0.1482]], requires_grad=True)
output.bias Parameter containing:
tensor([-0.1494], requires_grad=True)
```