Dataset2-Dummy_Linear_output_8

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 = 0.01
     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

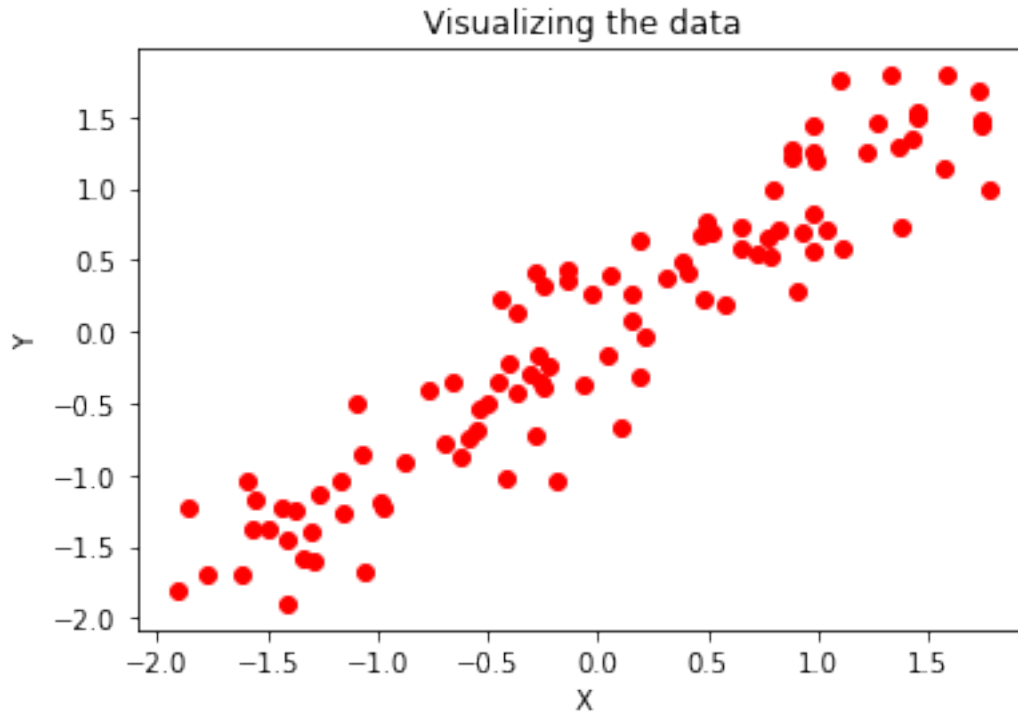$y = m * x + c + e$ where $m = 1$, $c = 0.5$ and $e \sim N(0, 1)$

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

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

```
          X          Y
0 -1.298180 -0.943587
1 -2.453451 -2.810255
2 -0.581163  0.095977
3  2.685541  2.856504
4 -0.246245  1.774130
```

Visualizing the data

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):
0.885
Model:                             OLS   Adj. R-squared (uncentered):
0.883
Method:                  Least Squares   F-statistic:
758.2
Date:                 Thu, 07 Oct 2021   Prob (F-statistic):
3.36e-48
Time:                         15:40:08   Log-Likelihood:
-33.969
No. Observations:                  100   AIC:
69.94
Df Residuals:                       99   BIC:
72.54
```

```
Df Model:                              1
Covariance Type:              nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.9405      0.034     27.535      0.000       0.873       1.008
==============================================================================
Omnibus:                        0.508   Durbin-Watson:                   2.155
Prob(Omnibus):                  0.776   Jarque-Bera (JB):                0.658
Skew:                          -0.129   Prob(JB):                        0.720
Kurtosis:                       2.698   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     0.940479
dtype: float64
```
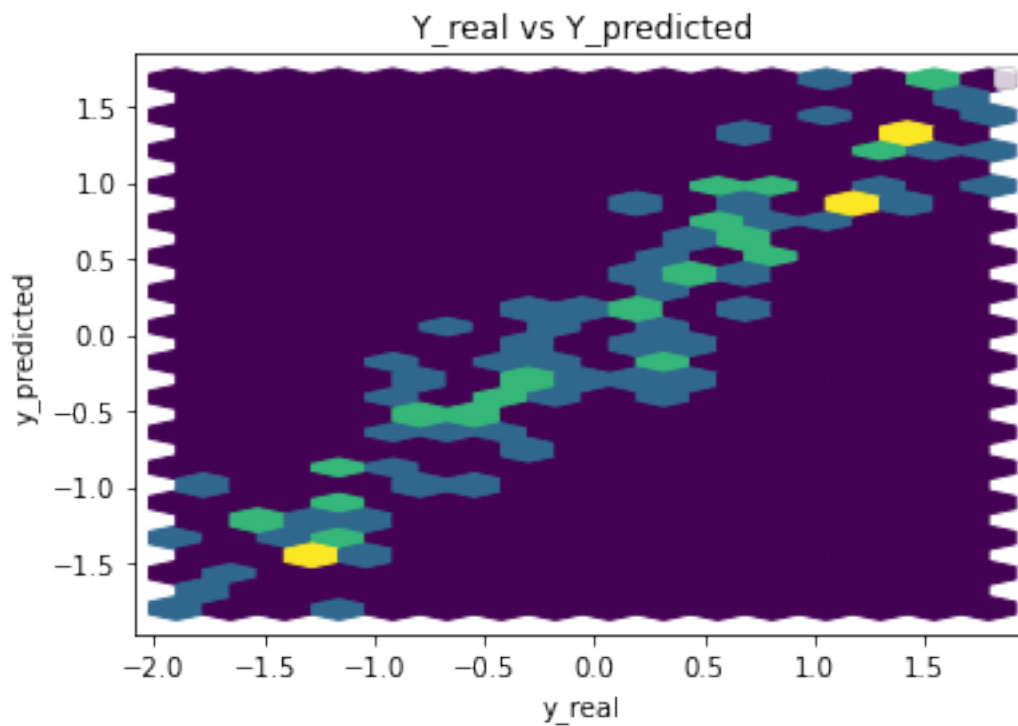

Y_real vs Y_predicted

```
Performance Metrics
Mean Squared Error: 0.1154985236556028
Mean Absolute Error: 0.2701054285184451
```

```
Manhattan distance: 27.010542851844498
Euclidean distance: 3.3985073731802133
```

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))
```
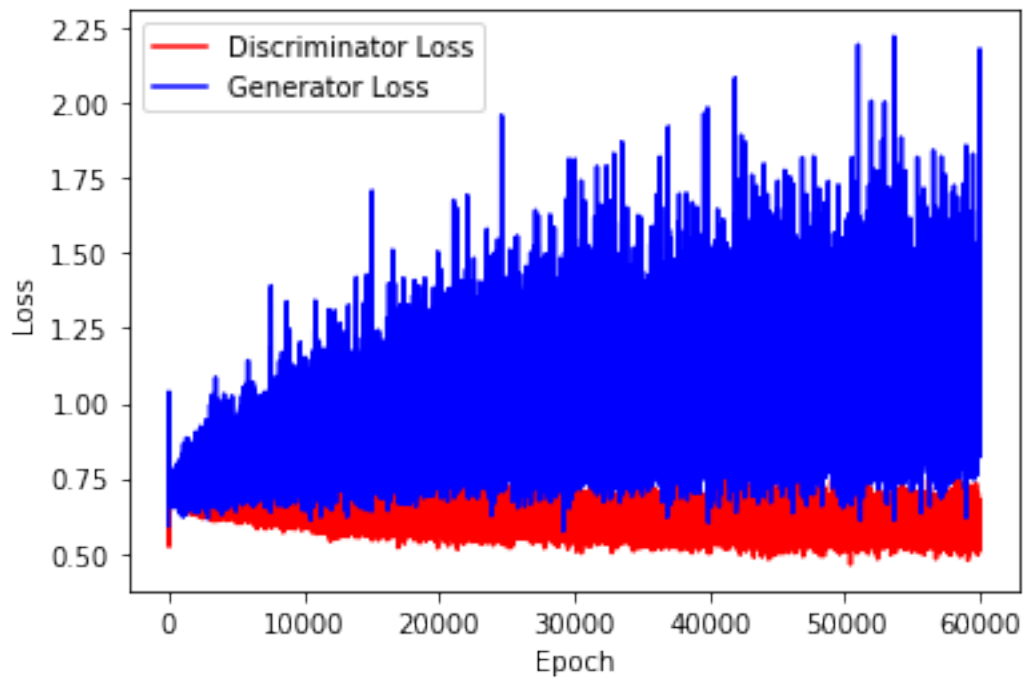
```
[12]: n_epochs = 30000
      batch_size = n_samples//2
```
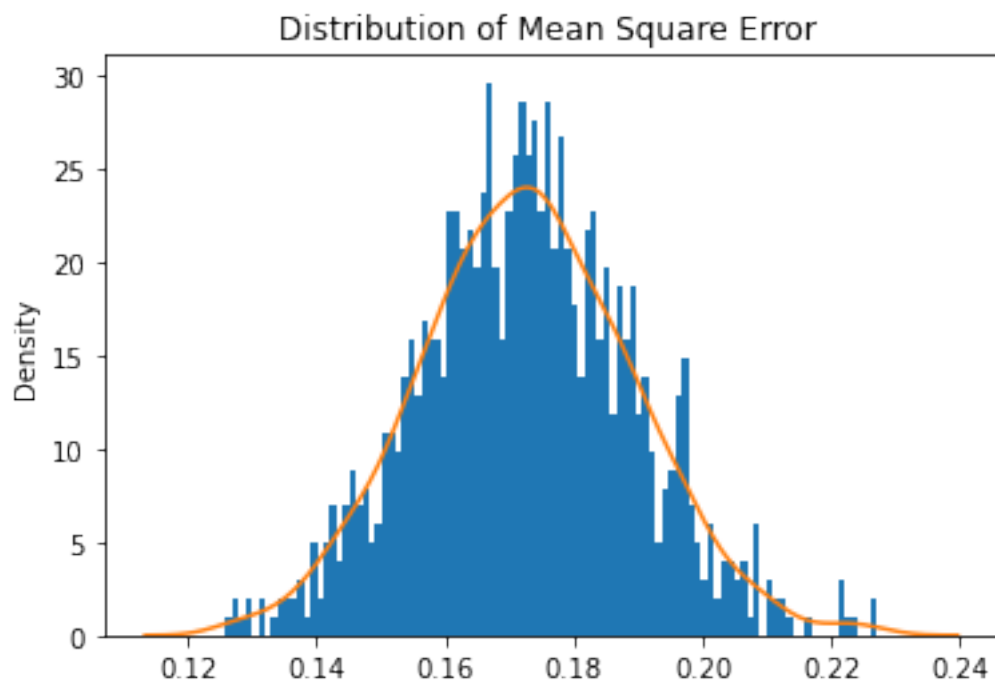
```
[13]: train_test.
        →training_GAN(discriminator,generator,disc_opt,gen_opt,real_dataset,batch_size,
        →n_epochs,criterion,device)
```
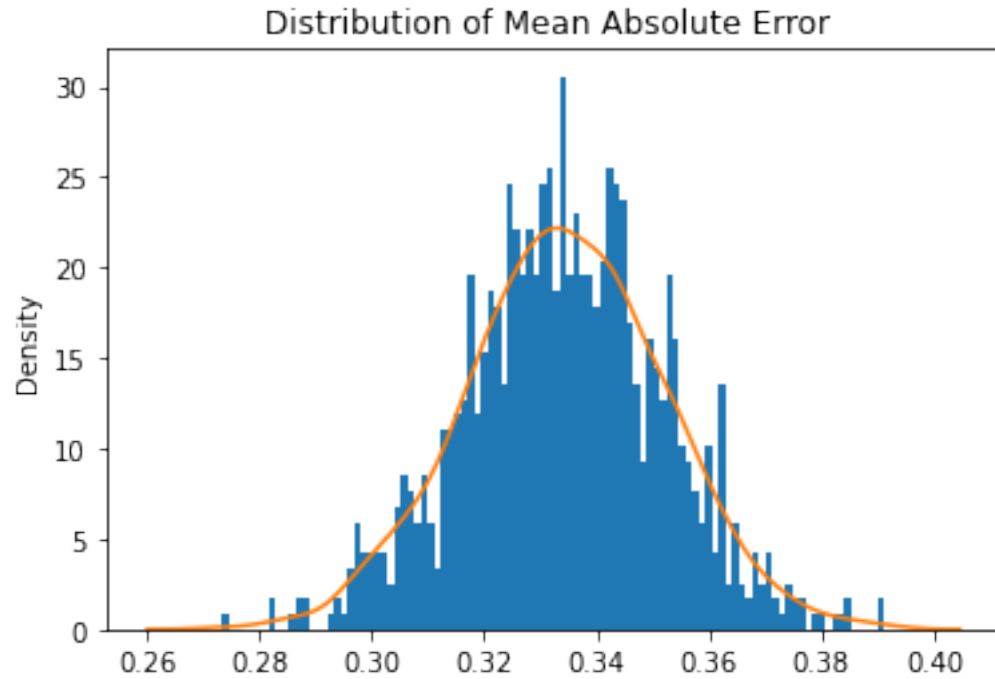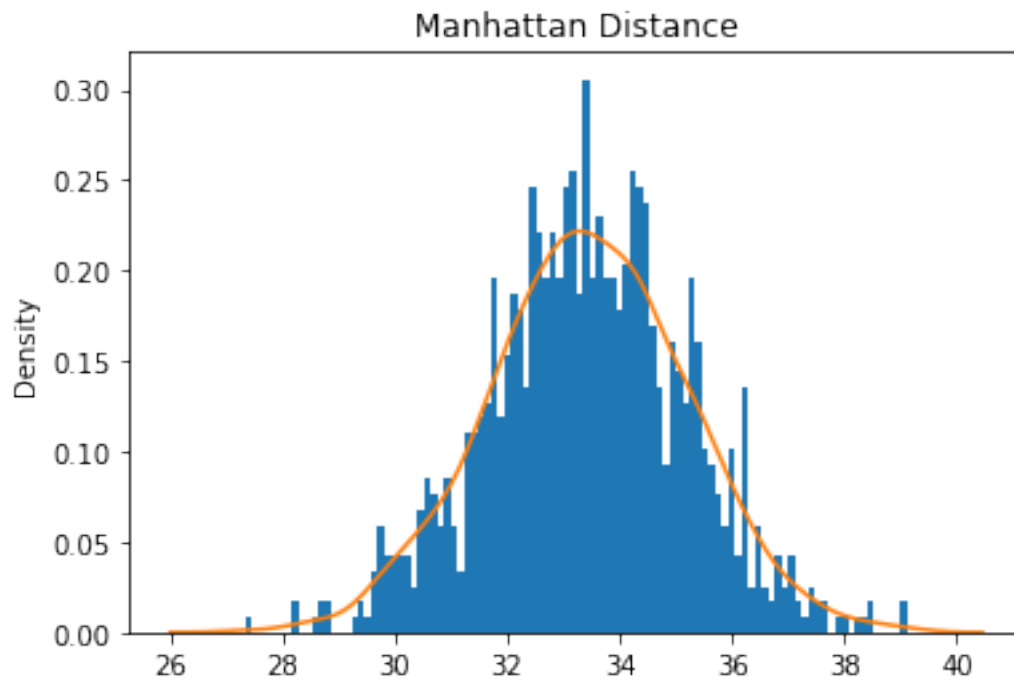
```
[14]: train_test.test_generator(generator,real_dataset,device)
```
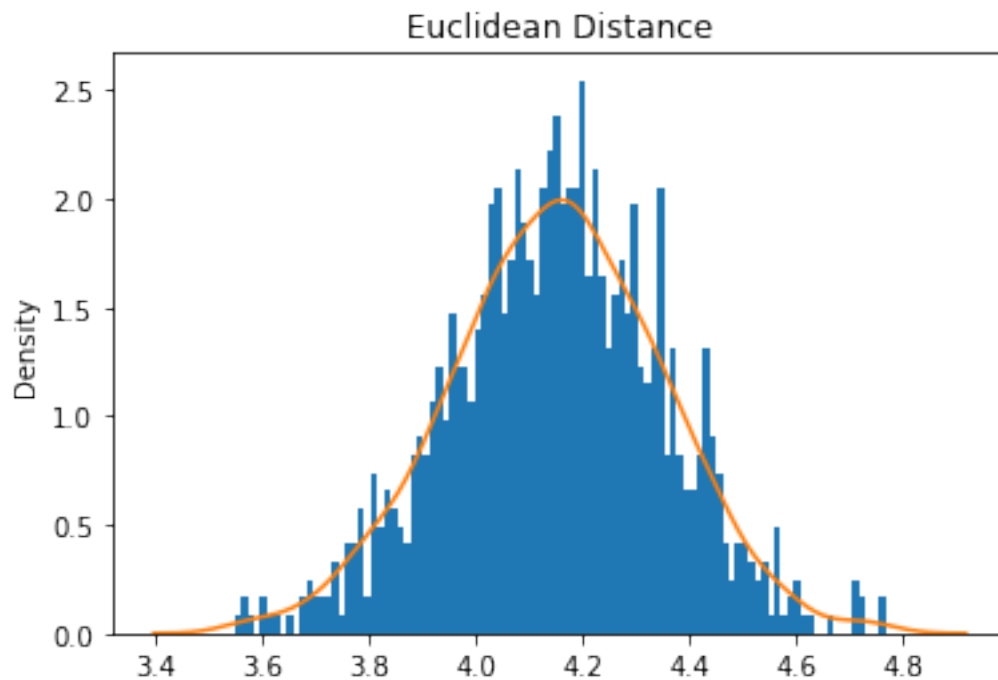
Distribution of Mean Square Error

Mean Square Error: 0.17261010249585648

Distribution of Mean Absolute Error

Mean Absolute Error: 0.33431813743392935

Manhattan Distance

```
Mean Manhattan Distance: 33.43181374339294
```


Euclidean Distance

```
Mean Euclidean Distance: 33.43181374339294
```

1.7 ABC - GAN Model

```
[15]: 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]: n_epoch_abc = 2000
      batch_size = n_samples//2
```

```
[17]: 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):
```

```python
    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
```

```python
                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()
```

```python
[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):
```

```python
                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()
```
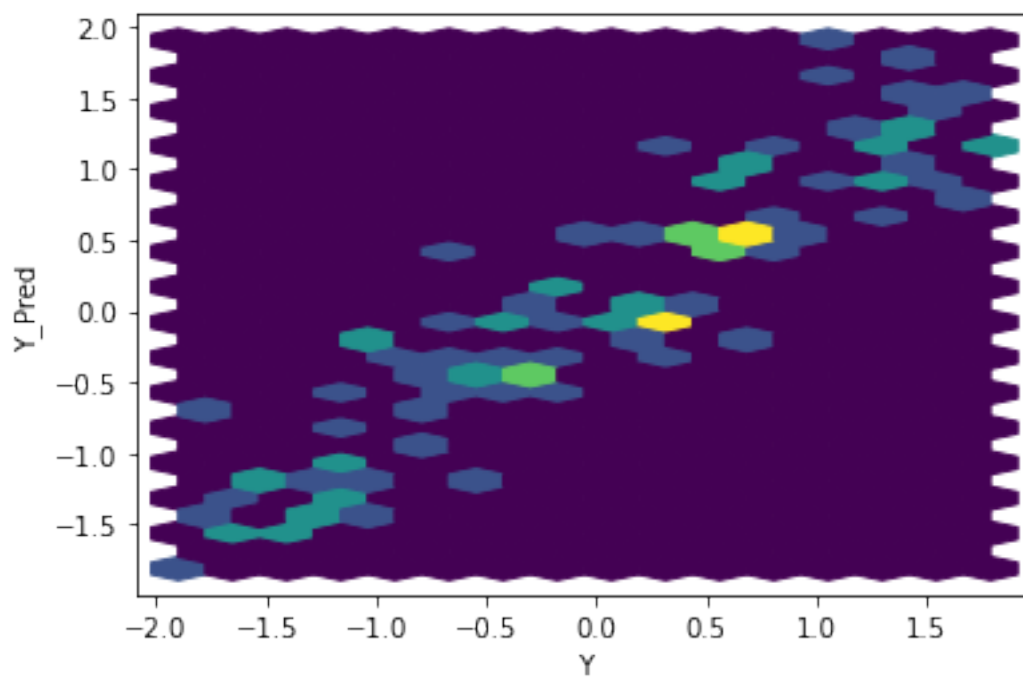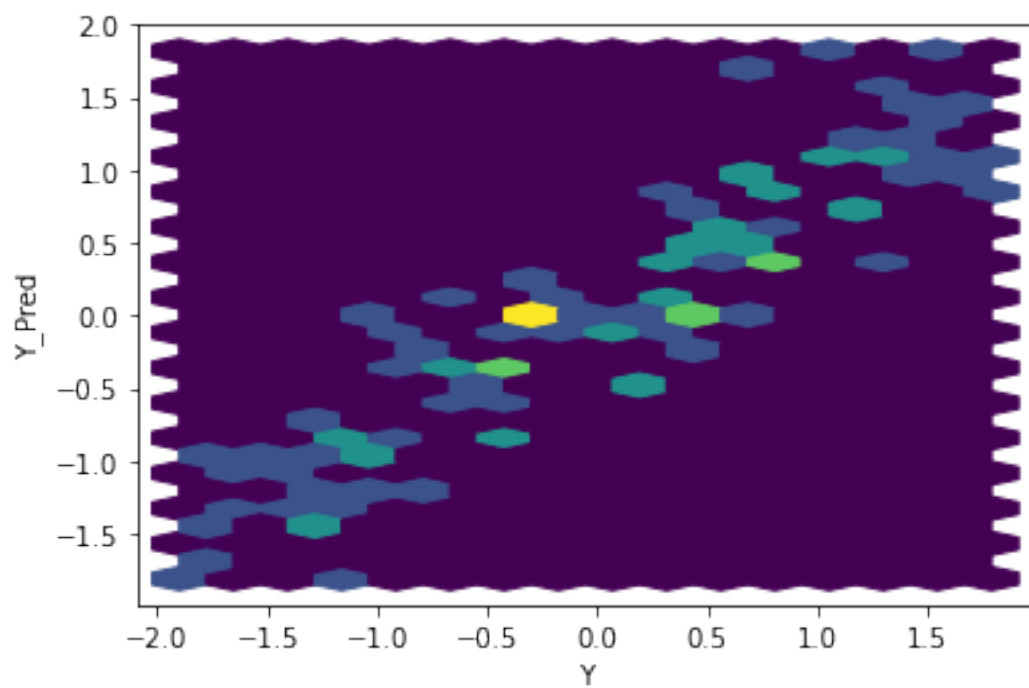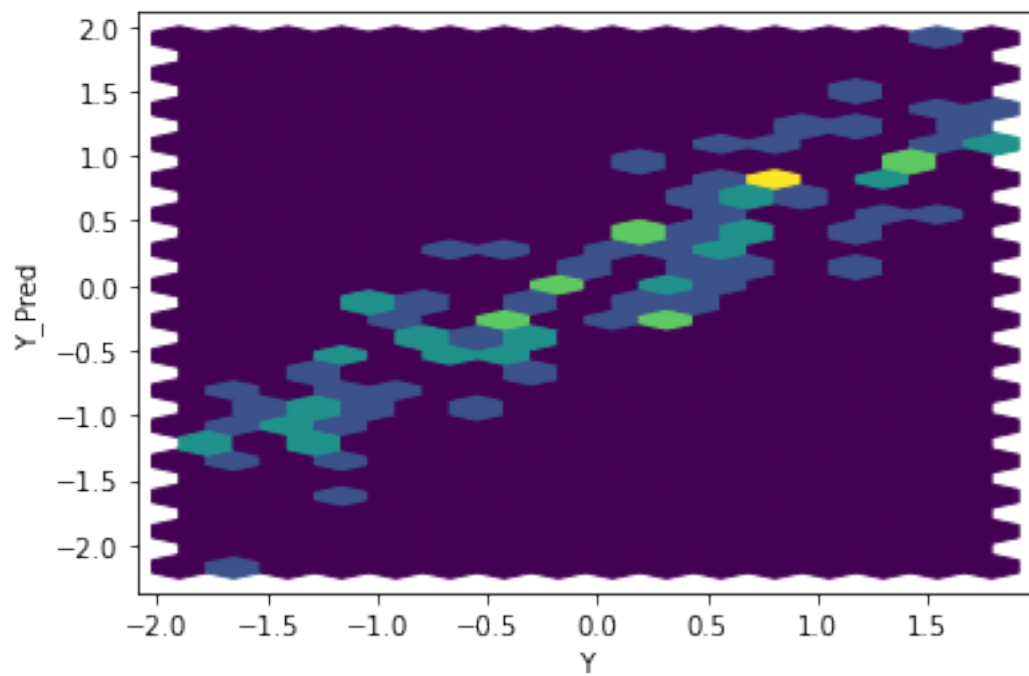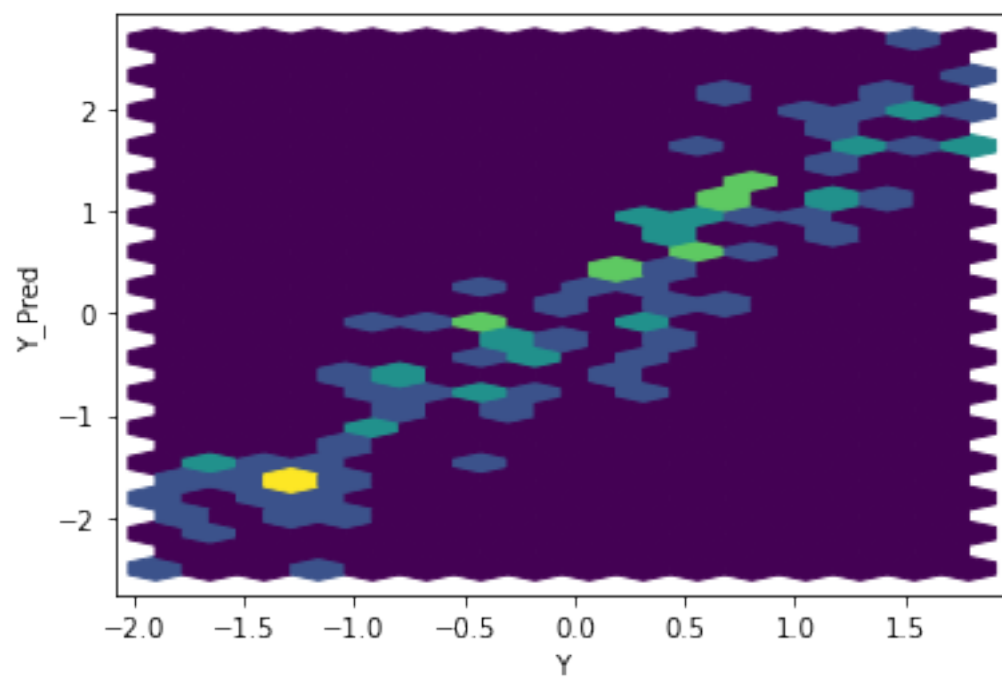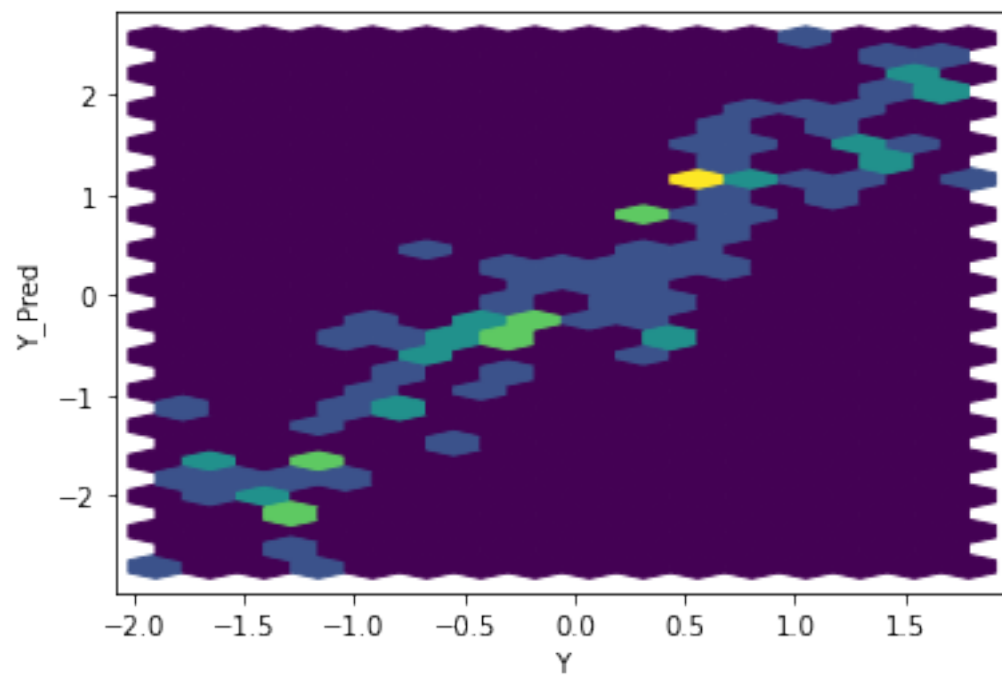
```
[19]: training_GAN(disc,gen,disc_opt,gen_opt,real_dataset,batch_size,n_epoch_abc,criterion,coeff,mea
```
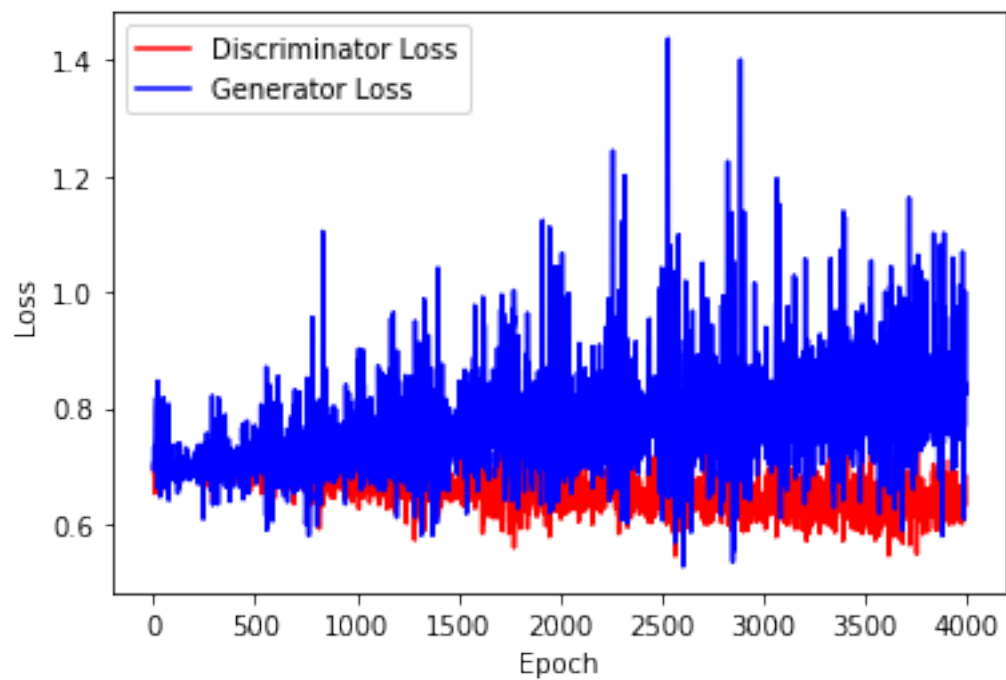
```
[20]: test_generator(gen,real_dataset,coeff,meanVal,std,prior,device)
```
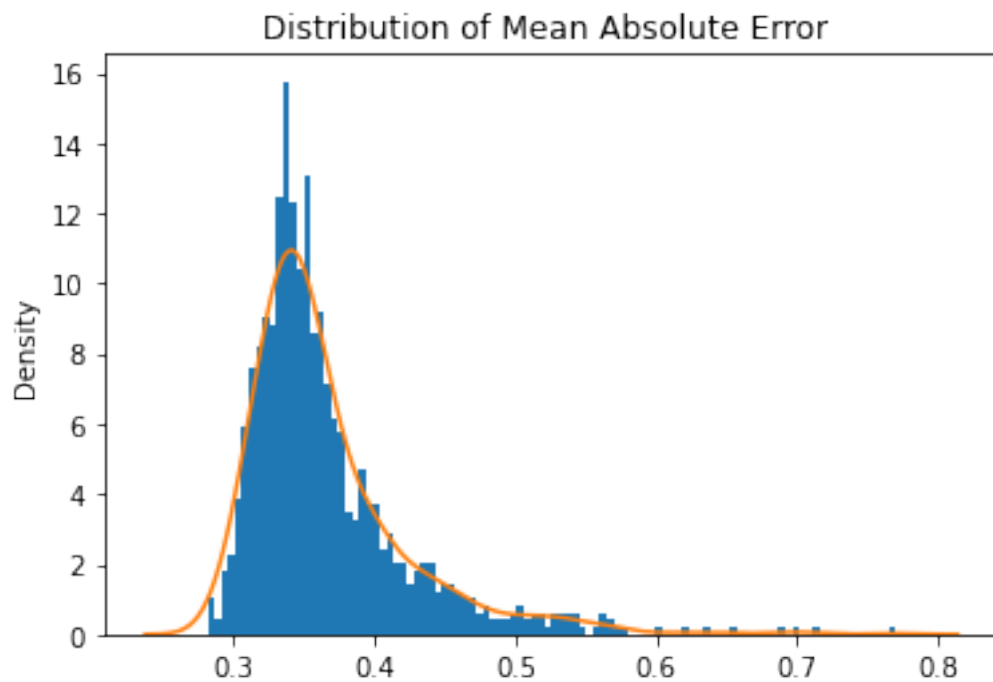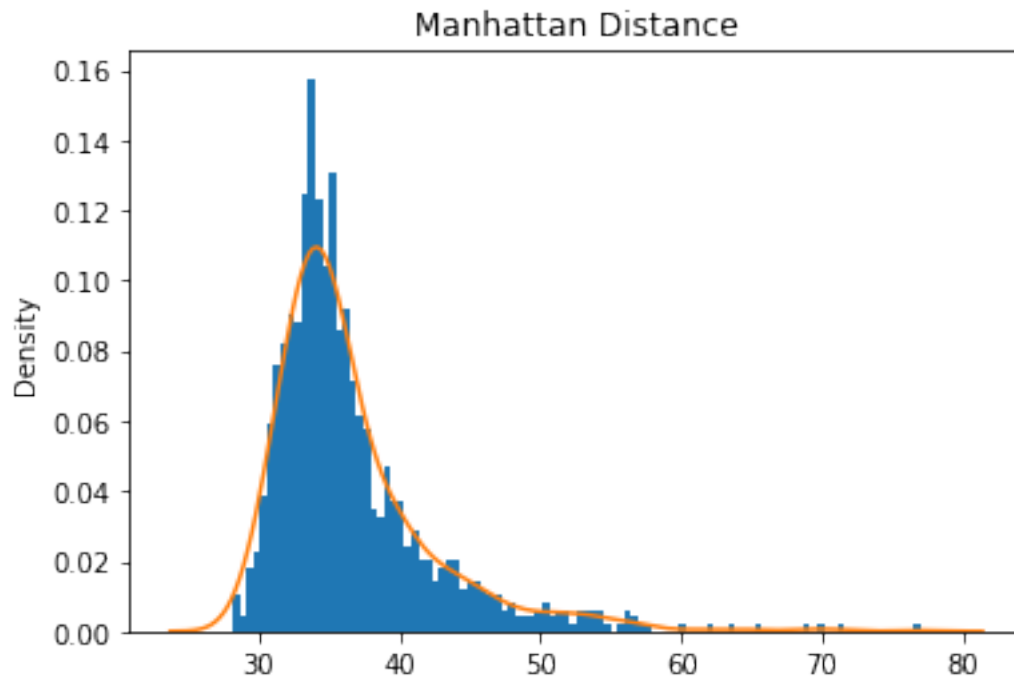
Distribution of Mean Square Error
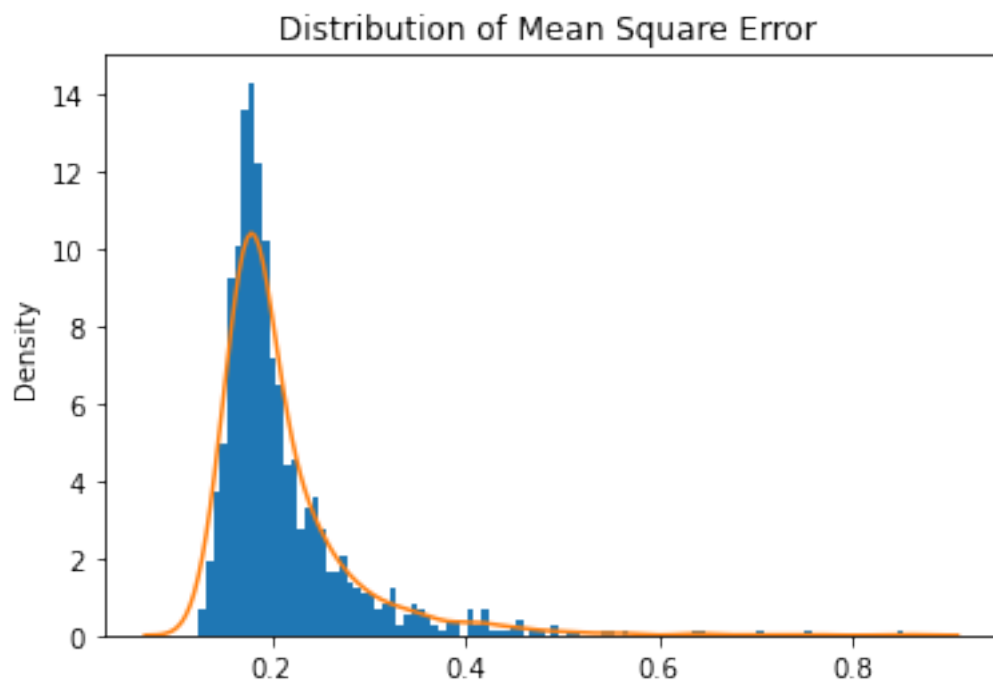
Mean Square Error: 0.21196482576925768
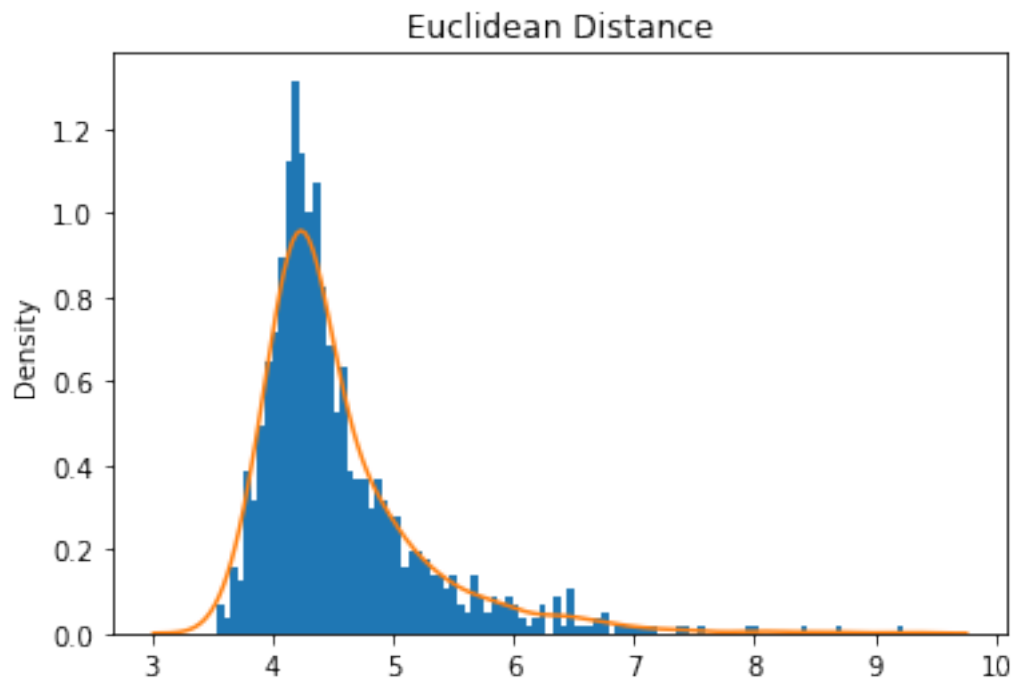

Distribution of Mean Absolute Error

Mean Absolute Error: 0.3664543240585178
Mean Manhattan Distance: 36.64543240585178

Manhattan Distance

Mean Euclidean Distance: 4.551728526247181
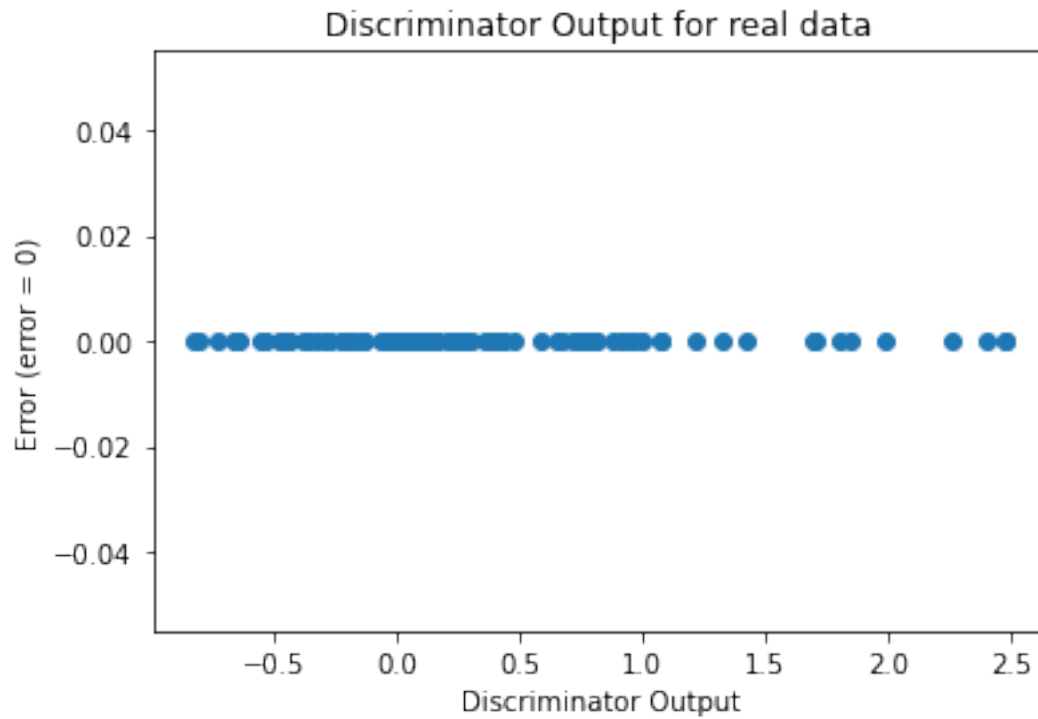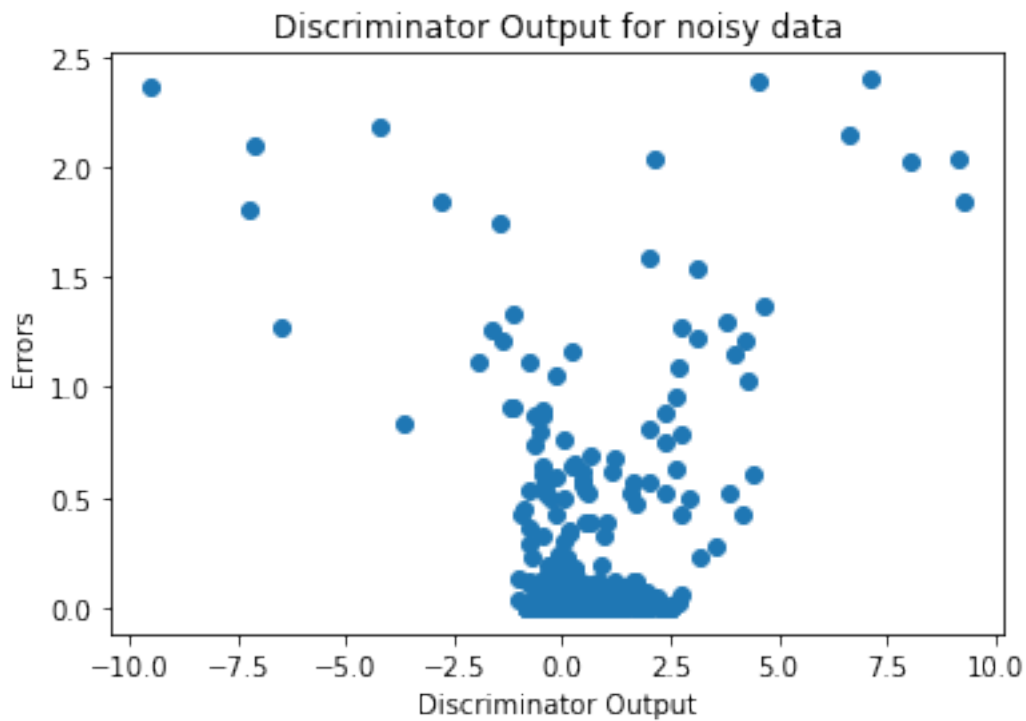

Euclidean Distance

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)
```

Discriminator Output for noisy data

1.7.2 Visualization of Trained GAN Generator

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

```
output.weight Parameter containing:
tensor([[0.7438, 0.2202]], requires_grad=True)
output.bias Parameter containing:
tensor([-0.0810], requires_grad=True)
```