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First initializations

I have assumed that datasets are mounted from a google drive.

```
# For question 1
import numpy as np
from sklearn.metrics import mean_squared_error, r2_score
from scipy.stats import pearsonr
from sklearn.linear_model import LinearRegression
from yellowbrick.datasets import load_concrete
from yellowbrick.regressor import ResidualsPlot
from sklearn.linear_model import RidgeCV, LinearRegression, LassoCV,
ElasticNetCV, Ridge
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import SplineTransformer
import warnings
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline

# Question 2
from sklearn.preprocessing import scale
from sklearn.decomposition import PCA
from scipy.linalg import svd
import pandas as pd

# Question 3
import torch
import torch.nn as nn
from torch.nn.functional import normalize
from torch.utils.data import Dataset
from torchvision import datasets
from torchvision.transforms import ToTensor
import torchvision.transforms as T
import os
from torchvision.io import read_image
from torchvision.transforms.functional import resize
%matplotlib inline
import matplotlib.pyplot as plt
import math

# Question 4
import glob
import shutil
```

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
ass_path = os.getcwd()
```

Mounting the data directory

This notebook assumes that all datafiles will be accessed from a google drive. Please modify the ass_path variable below in accordance with where the data is stored for evaluation.

```
# Set the data files directory to the directory stored on my google
drive
# for the purposes of doing the assessment
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
ass_path = os.path.join('/content', 'drive', 'MyDrive', 'INT3
Assessment', 'Assessment')
```

```
Mounted at /content/drive
```

Question 1 - Using regression

Begin by initializing the data and a dictionary to keep track of my best performing models as I experiment with different model variations

```
# Store the best models of each experiment here
best_models = {}
# Import data ignoring first row since we will not be making any
calculations with these labels
data = np.genfromtxt(os.path.join(ass_path,'data.csv'),delimiter=',')
[1:,:]
# Extract inputs, ignoring the last row based on the constraints of
the assignment
X = data[:-1,:]
# Take D as the target, one time lag down from the inputs
y = data[1:,-1]
```

Evaluation pipeline

In order to evaluate the effectiveness of each regression model, I will write the following function.

It will be used to fine tune parameters such as the amount of training data (in order to avoid over fitting and underfitting).

It will calculate the r2 score of each model which has been passed as a parameter into the function.

It will store the model with the highest r2 score from each run into a "best_models" dictionary for evaluation later on.

```
# Parameters are the models to be evaluated along with the features of
the
# training set. Features are set to the unmodified features by
defeault, but can
# be modified for polynomial and piecewise regression by passing the
new features.
def model_pipeline(models, pline=None):

    # Evaluate the input models and save the best performing model
into the
    # "best_models" dictionary
    optim_model, score, train_size = eval_model(models, pline=pline)
    best_models[score] = optim_model

    # Create a residuals plot graph to verify the bias of the model
and the
    # significance of the r2 score as well as show the difference
between the
    # training r2 score and the testing r2 score to detect overfitting
    resid_plot(optim_model, train_size)

def eval_model(models, pline):
    training_sizes = []
    for i in range(20,len(X)-20, 5):
        training_sizes.append(i)
    # Keep track of the r2 scores and the corresponding models for
final evaluation
    model_scores = {}
    r2_scores = []
    # Go through different sizes of training data to find a balance
between overfitting and
    # underfitting
    for train in training_sizes:
        X_train = X[:train]
        X_test = X[train:]
        y_train = y[:train]
        y_test = y[train:]
        # Cylce through and fit the models given for evaluation
        for model in models:
            if pline != None:
                reg = Pipeline([('trans', pline),('reg', model())])
            else:
                reg = model()
            reg.fit(X_train, y_train)

            # Extract the scores for each model and associate with the
model in a dictionary
            y_pred = reg.predict(X_test)
            score = r2_score(y_test, y_pred)
            r2_scores.append(score)
```

```
            model_scores[score] = [reg, train]

    # Return the best perfroming model from the run along with its
relevant
    # attributes for demonstration purposes.
    optim_model, score, train_size = get_best(r2_scores, model_scores)
    return optim_model, score, train_size

# Used to extract the optimal model from a run along with its score
and training
# data split
def get_best(r2_scores, model_scores):
    best = np.max(r2_scores)

    name = model_scores[best][0]
    if isinstance(model_scores[best][0], Pipeline):
        name = model_scores[best][0].named_steps['reg']

    print('The best performing model in the run was: {}\n\
          With an r2 score of: {:.4f}\n\
          With a training data size of: {}\n'
          .format(name, best, model_scores[best][1]))
    return model_scores[best][0], best, model_scores[best][1]

# This residual plot function will be used as my main method for
evaluating the
# validity of the r2 scores produced by each model. If the plot
indicates bias,
# this means that the r2 score produced by the model is unreliable and
would not
# generalize well to new data.
def resid_plot(optim_model, train_size):
    visualizer = ResidualsPlot(optim_model)
    visualizer.fit(X[:train_size], y[:train_size])
    visualizer.score(X[train_size:], y[train_size:])
    visualizer.show()
```

Basic Linear Regression

I will begin by creating and evaluating the most basic of regression models: a basic linear regression model.

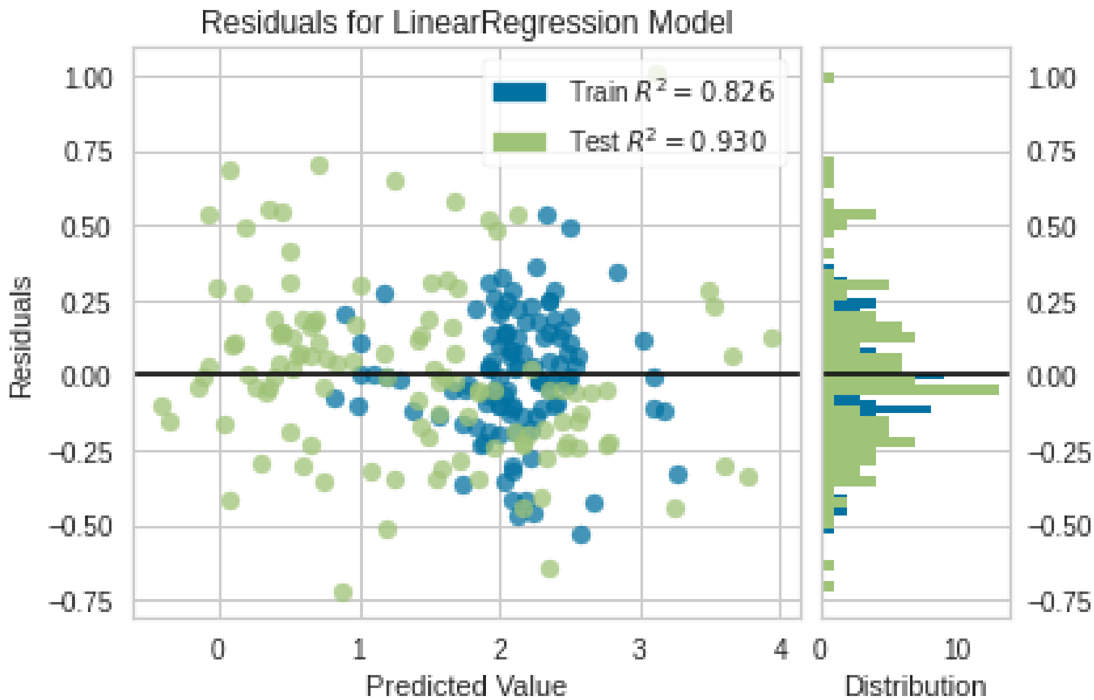
This should be a good place to start and will allow me to approximately see whether the data I am working with has a linear shape. I will cycle through the different sizes of training data and find which size gives the best r2 score, indicating it has been balanced between over and underfitting.

I will then plot a Residuals Plot graph in order to check whether the model is biased and whether the r2 score should be taken at face value

This model with a fine-tuned training data size will be stored as one of my best models for further inspection and comparison moving forward.

```
models = [LinearRegression]
model_pipeline(models=models)
```

```
The best performing model in the run was: LinearRegression()
         With an r2 score of: 0.9303
         With a training data size of: 110
```



Basic Linear Regression evaluation

As we can see, the basic Linear Regression model works quite well with the data. It has achieved a relatively high r2 score of 0.93 with a training data size of 110, indicating that the shape of the data is reasonably linear.

The residuals plot graph indicates that there is no significant bias in the model, and that for this reason we can accept the r2 score as significant.

Regularisation models

The next natural step is to implement and evaluate the three main regularisation methods: L1, L2 and Elastic (a combination of L1 and L2) to see if this improves over the performance of the previous model.

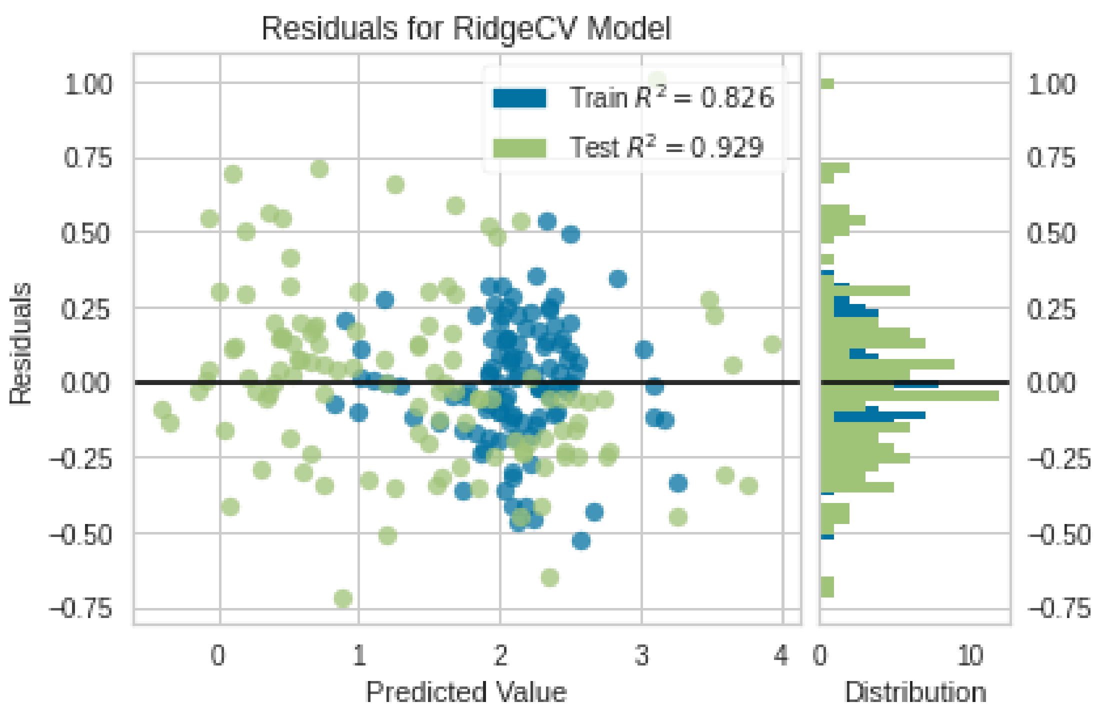
I will be using the CV implementations of these models in order to compute the complexity penalties for each in a robust, user friendly way using their default "Leave-One-Out" method.

My model evaluation function will tell me which of these three models achieved the highest r2 score and the optimal training data size to avoid over and underfitting.

As with basic linear regression, I will plot a Residuals Plot graph in order to verify that the model is unbiased and that the r2 score is significant.

```
models = [RidgeCV, LassoCV, ElasticNetCV]
model_pipeline(models)
```

```
The best performing model in the run was: RidgeCV(alphas=array([ 0.1,
1. , 10. ]))
          With an r2 score of: 0.9293
          With a training data size of: 110
```



Regularisation models evaluation

As we can see, there is a negligable difference between the r2 score for the basic linear regression model and the regularization method models.

This indicates that implementing a basic regularization method by itself does nothing to improve on the performance of the model. It also suggests that the complexity parameter is so small as to be negligable since it does not alter the outcome of the basic LinearRegression model.

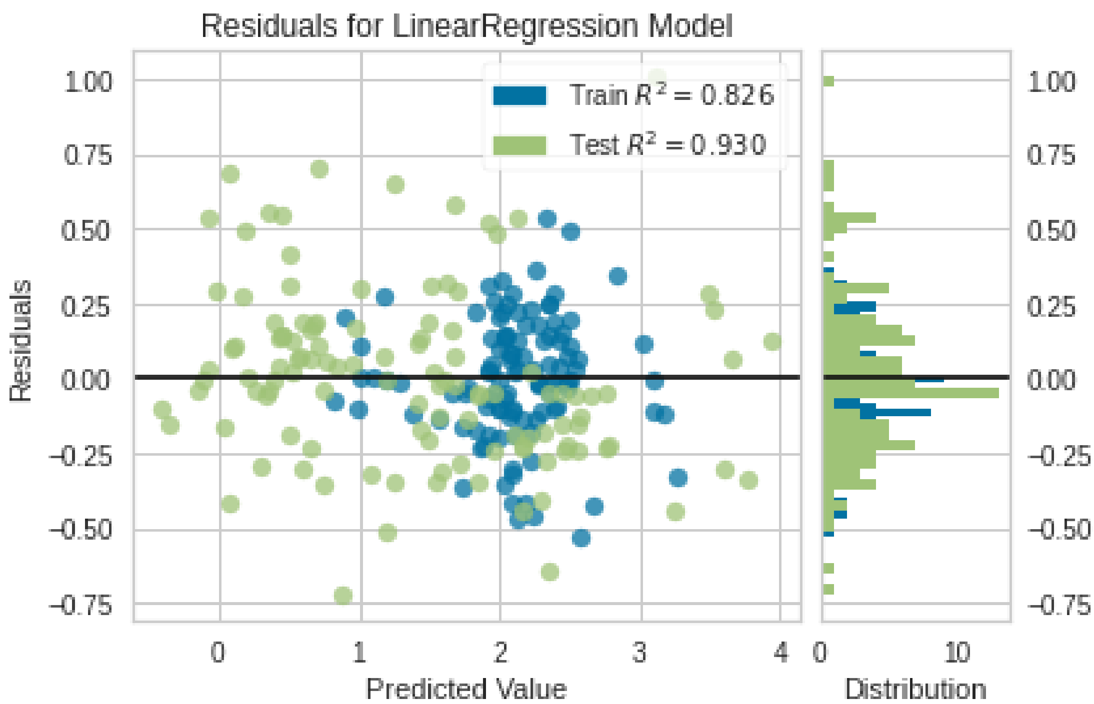
The residual plots graph indicates that there is no visual bias in the model and the r2 score is significant.

Polynomial regression

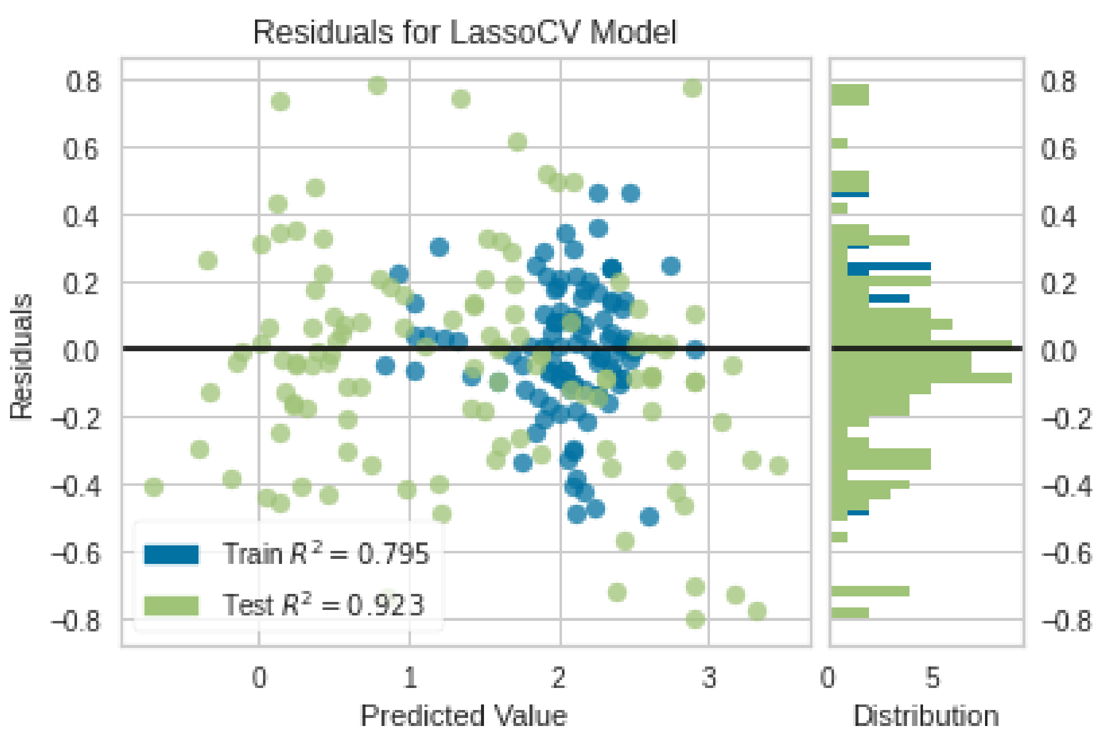
I will now continue to explore the effects of polynomial regression on all of the previously explored models, in order to see whether adding these parameters will improve the previously evaluated r2 scores in any significant way.

```
# When evaluating these models with the amount of training data
provided,
# a convergence warning consistently appears. For the purposes of a
clear printout
# these warnings will be omitted but later addressed when evaluating
the strength
# of the evaluated models.
warnings.filterwarnings('ignore')

models=[LinearRegression, RidgeCV, LassoCV, ElasticNetCV]
for degree in [1,2,3,4,5]:
    print('Polynomial regression with degree: {}'.format(degree))
    # Generate polynomial features
    poly_reg = PolynomialFeatures(degree=degree, include_bias=True)

    model_pipeline(models, poly_reg)

# Reset warning printout to default
warnings.filterwarnings('default')
```

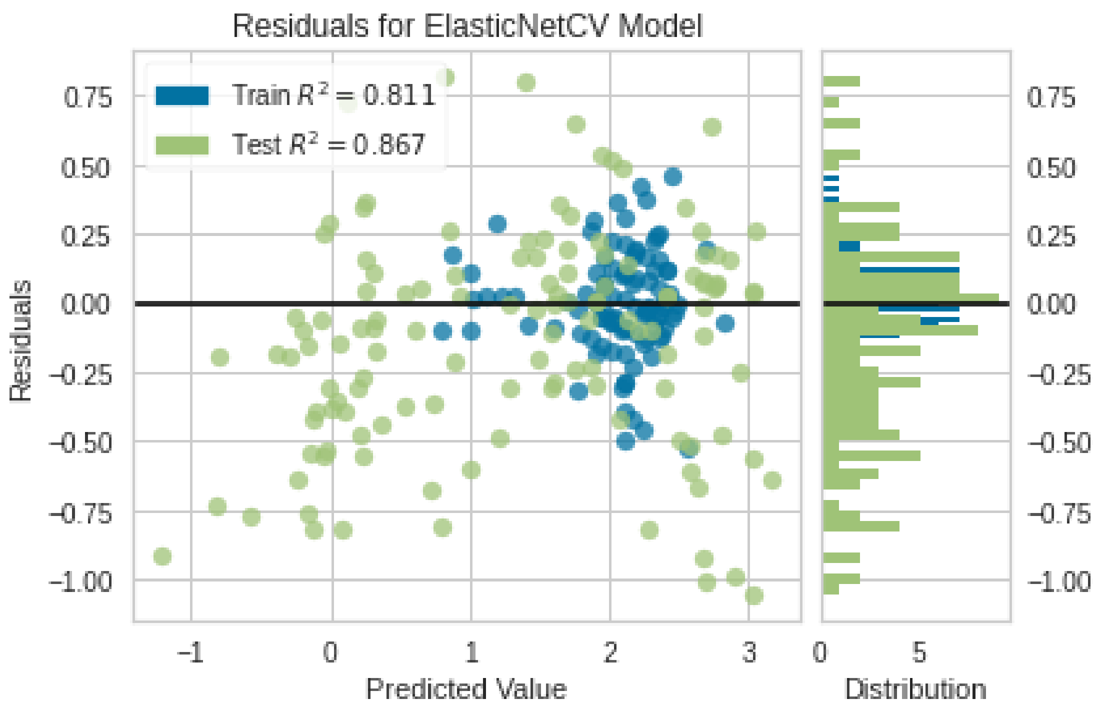
```
Polynomial regression with degree: 1
The best performing model in the run was: LinearRegression()
          With an r2 score of: 0.9303
          With a training data size of: 110
```



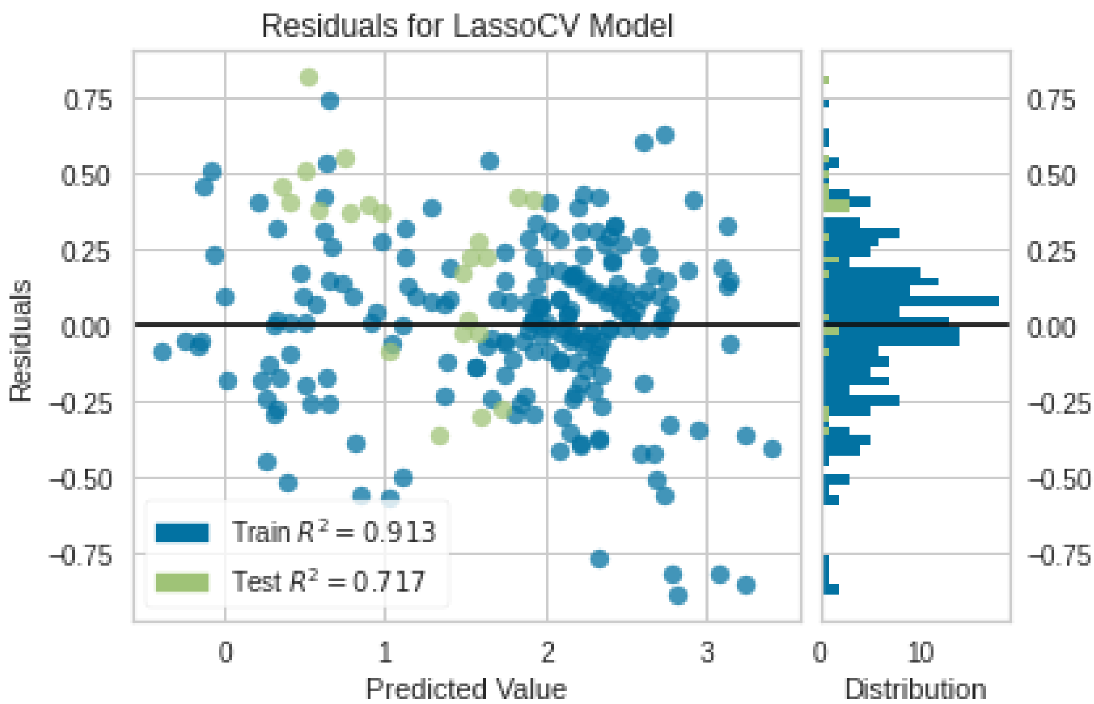

```
Polynomial regression with degree: 2
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.9229
          With a training data size of: 105
```



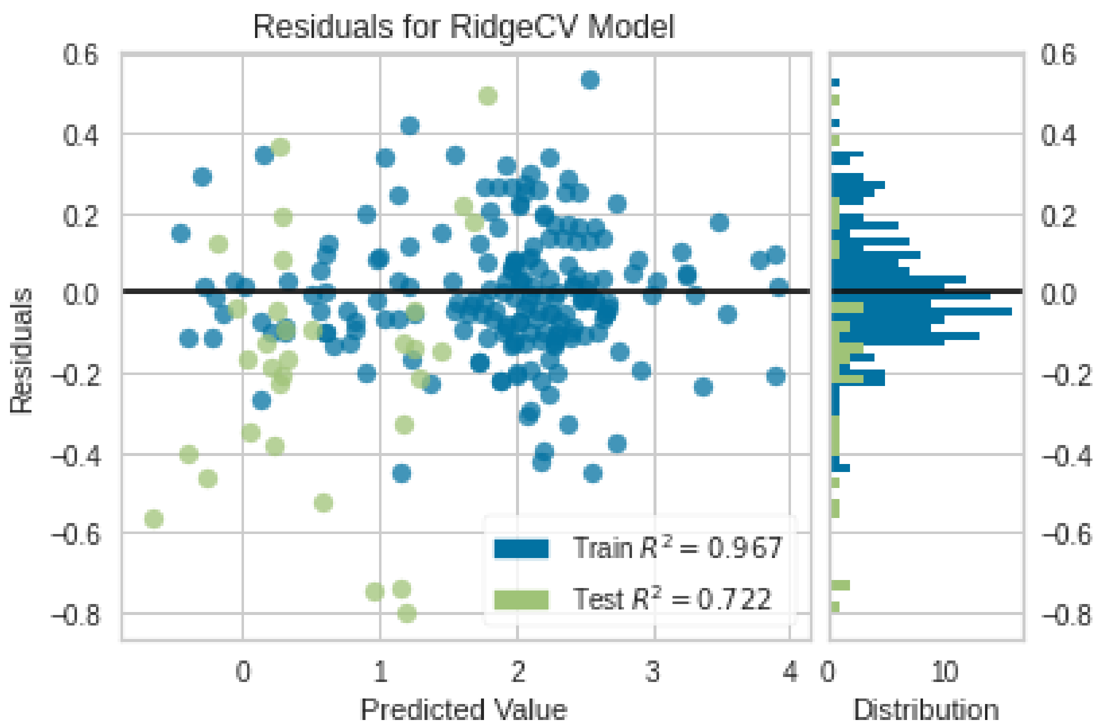
```
Polynomial regression with degree: 3
The best performing model in the run was: ElasticNetCV()
          With an r2 score of: 0.8669
          With a training data size of: 100
```




```
Polynomial regression with degree: 4
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.7172
          With a training data size of: 205
```




```
Polynomial regression with degree: 5
The best performing model in the run was: RidgeCV(alphas=array([ 0.1,
1. , 10. ]))
          With an r2 score of: 0.7216
          With a training data size of: 195
```



Polynomial regression evaluation

As we can see, the only polynomial degree to work somewhat competitively against our original basic linear regression model is degree 2. The most effective polynomial degree combined with the most effective model for this degree, extracted by our evaluation function, is slightly worse than out basic linear regression model.

We can see in our residuals plot graphs that as we increase our polynomial degree, the training r2 score continues to increase while the testing r2 score continues to decrease.

This indicates to us that by adding polynomial features, we are overfitting to our training data and not generalizing to the testing data.

We can deduce from this that while polynomial regression does work well for fitting onto a specific set of data, the actual structure of our data is closer to a linear shape than it is to any polynomial shape.

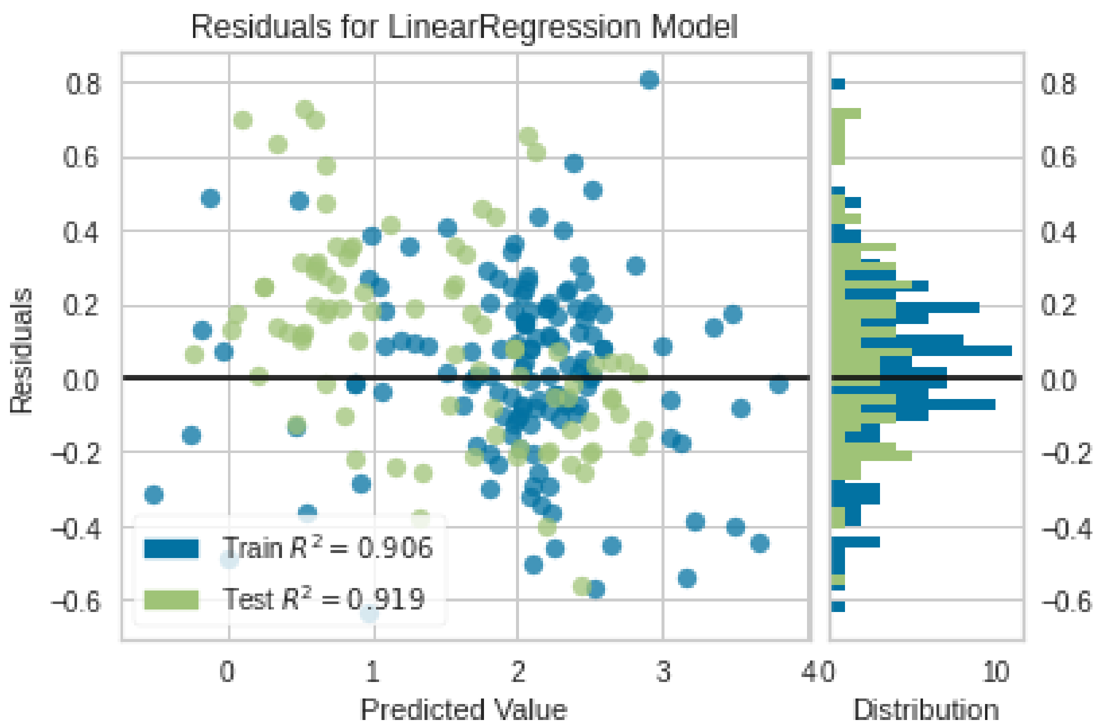
We must also keep in mind that trying to fit a polynomial regression model using ElasticCV and LassoCV regularisation methods leads to a convergence warning. This indicates that we do not have enough data provided to us in order to properly evaluate the efficacy of polynomial regression with these regularization methods.

All of the previous points indicate to us that polynomial regression is too computationally demanding and ineffective compared to our previous methods, that the generalizable testing data is poorly fit to polynomial regression indicating that the true shape of the data is not polynomial and that polynomial regression should be discarded for this particular set of data.

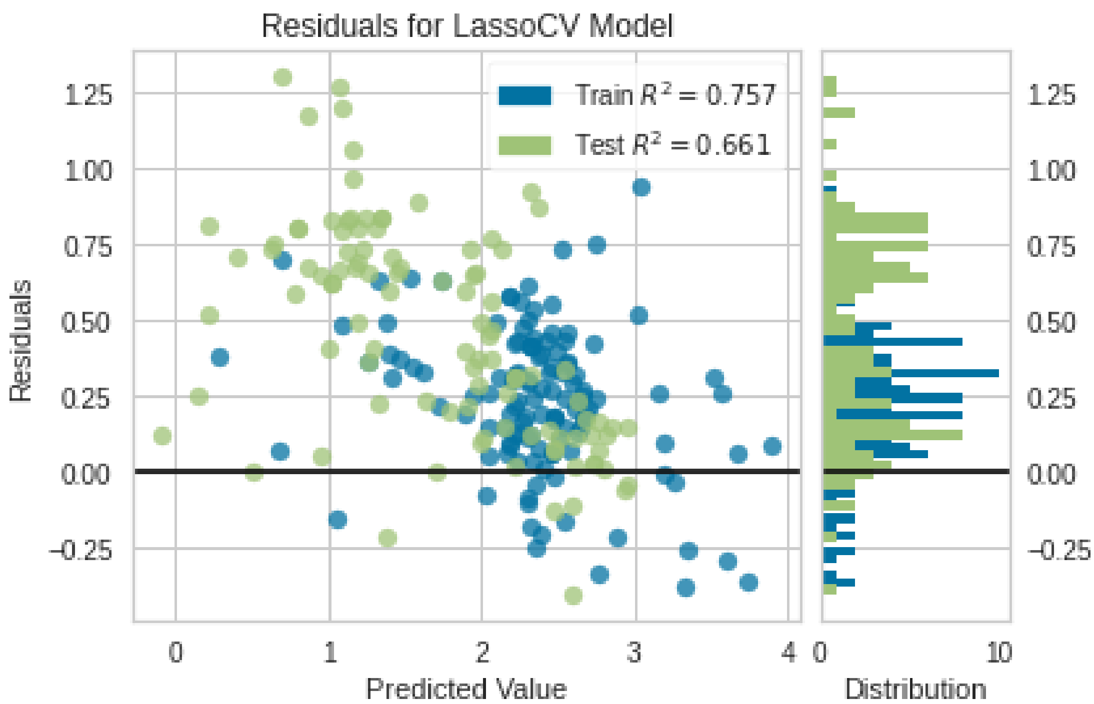
Piecewise Regression

```
# When evaluating these models with the amount of training data provided,
# a convergence warning consistently appears. For the purposes of a clear printout
# these warnings will be omitted but later addressed when evaluating the strength
# of the evaluated models.
warnings.filterwarnings('ignore')

models=[LinearRegression, RidgeCV, LassoCV, ElasticNetCV]
# Cycle through preselected number of degrees and knots in order to evaluate a
# pattern of behaviour
for degree in [1,2,3,4,5]:
    for knots in [2,3,4,5]:
        print('Piecewise regression with degree: {}\n and knots: {}'.format(degree, knots))

        # Generate piecewise features
        spline = SplineTransformer(degree=degree, n_knots=knots)

        # Pass spline transformer into the model pipeline to call "make_pipeline with",
        # along with models
        # to evaluate
        model_pipeline(models, pline=spline)

# Reset warnings printout to default
warnings.filterwarnings('default')
```

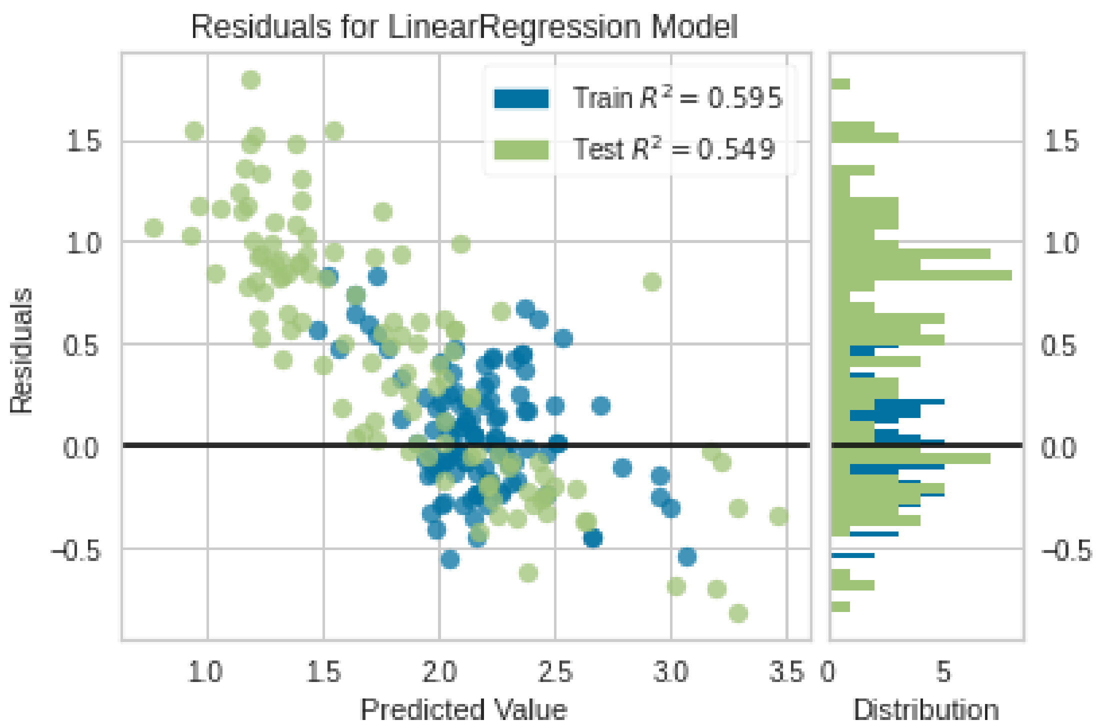
```
Piecewise regression with degree: 1
 and knots: 2
The best performing model in the run was: LinearRegression()
          With an r2 score of: 0.9265
          With a training data size of: 140
```



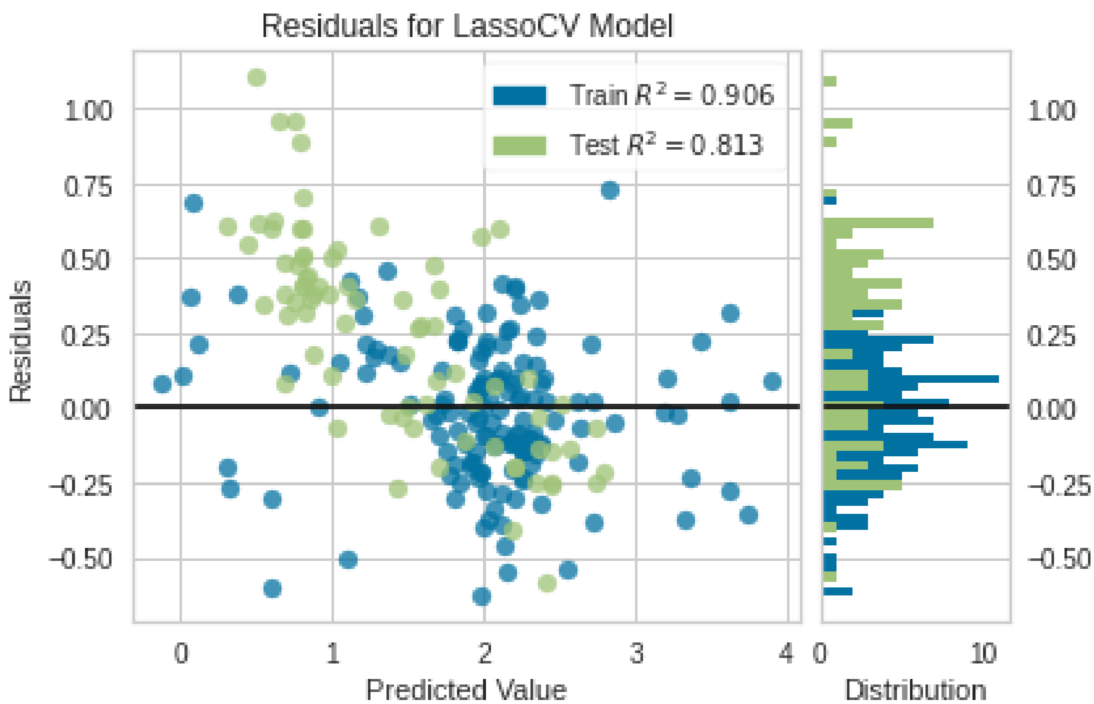

```
Piecewise regression with degree: 1
 and knots: 3
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8827
          With a training data size of: 125
```



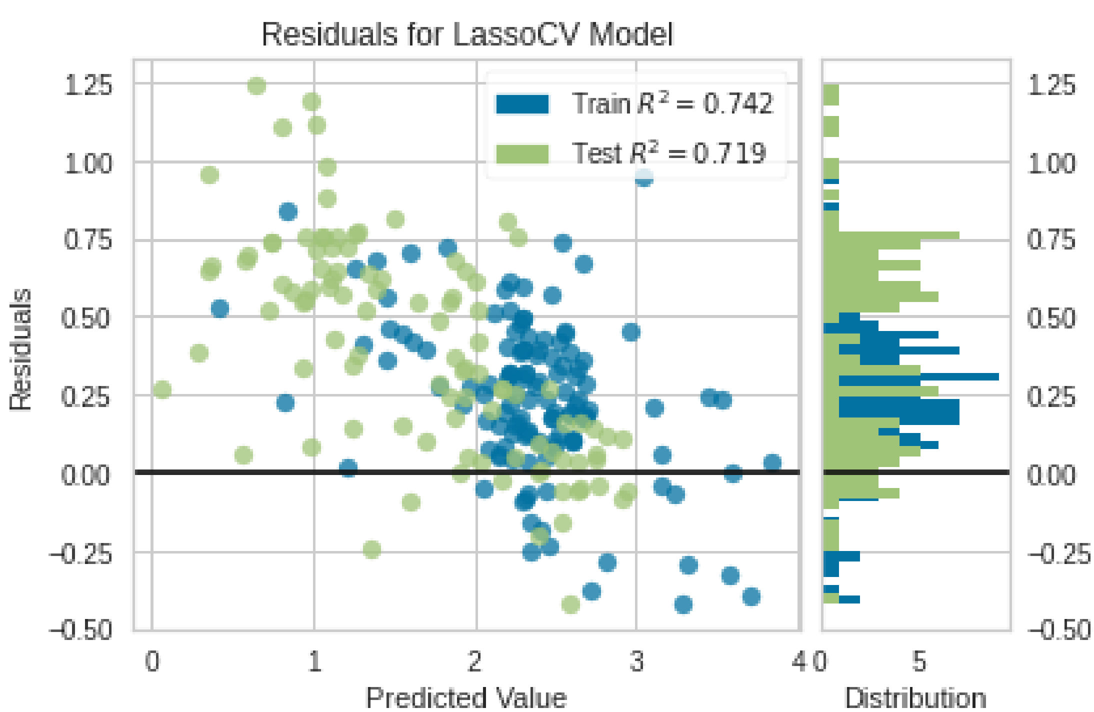

```
Piecewise regression with degree: 1
 and knots: 4
The best performing model in the run was: LinearRegression()
          With an r2 score of: 0.8115
          With a training data size of: 110
```



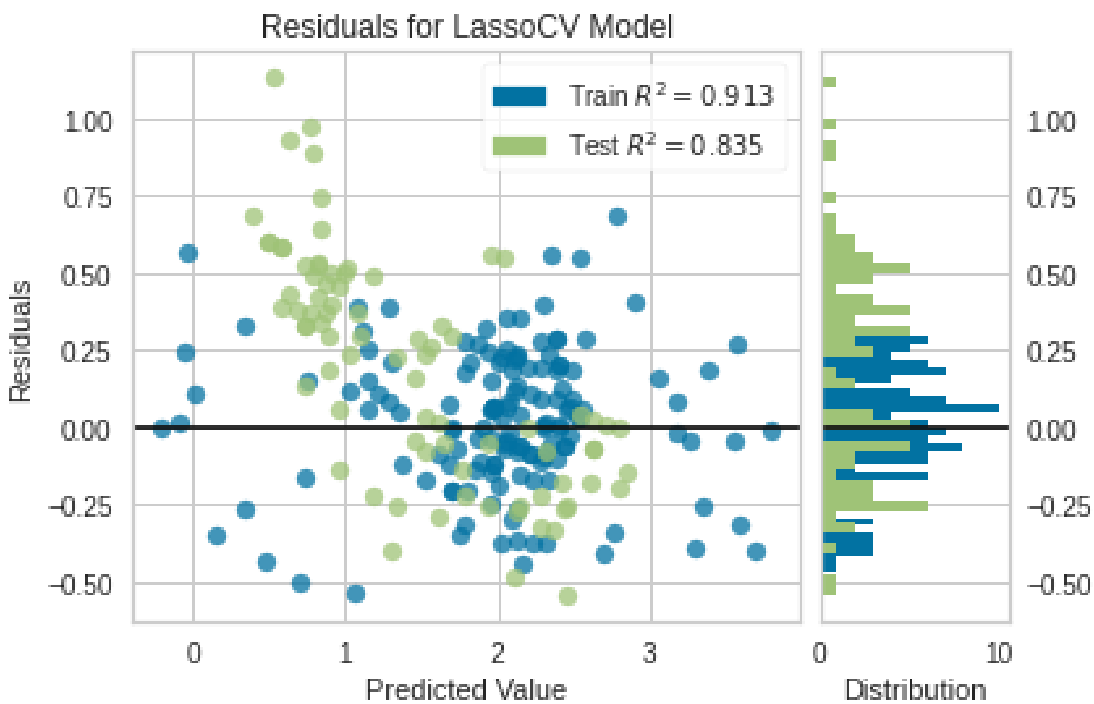

```
Piecewise regression with degree: 1
 and knots: 5
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.7951
          With a training data size of: 150
```



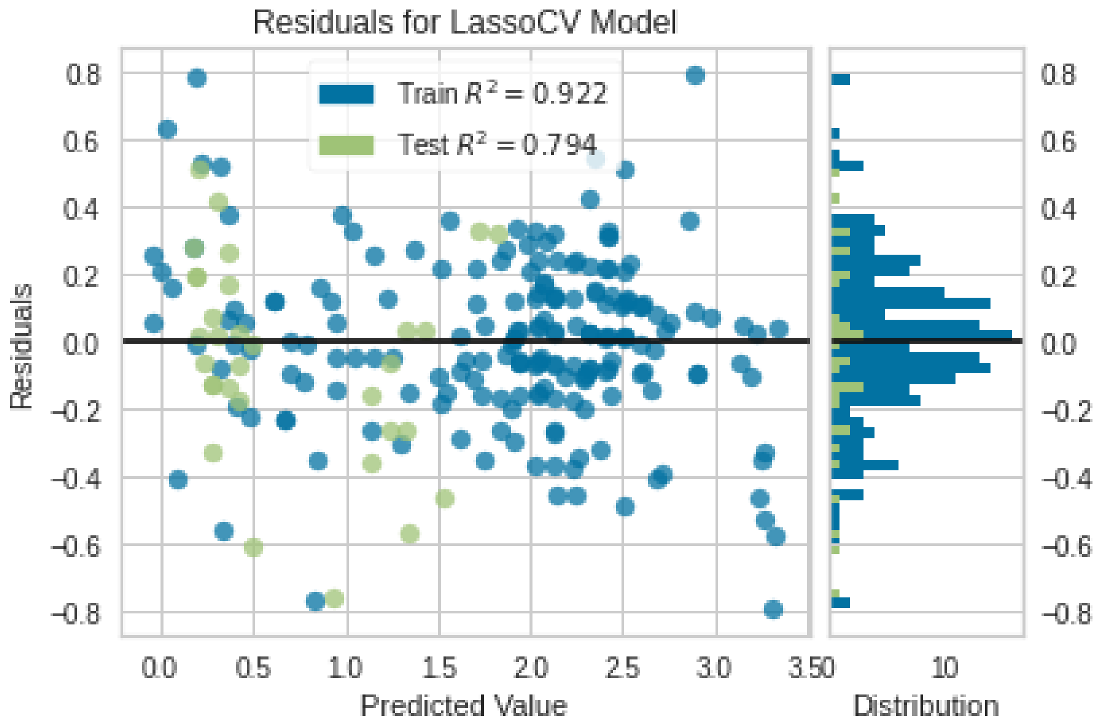

```
Piecewise regression with degree: 2
 and knots: 2
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8960
          With a training data size of: 125
```



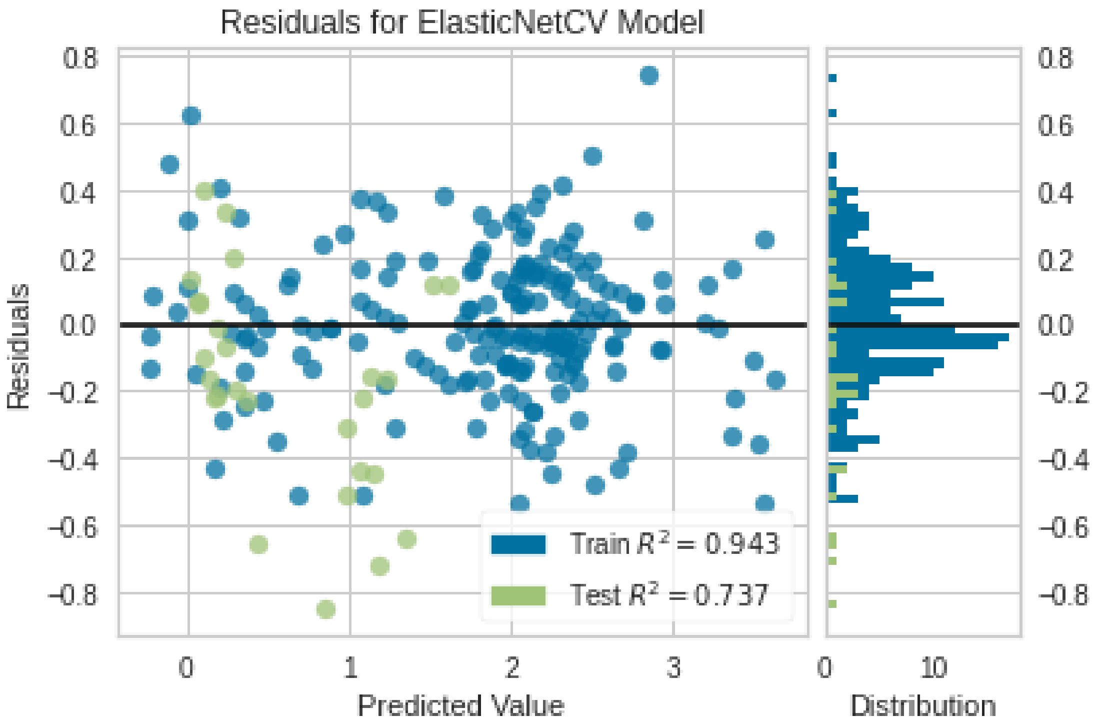
```
Piecewise regression with degree: 2
 and knots: 3
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8358
          With a training data size of: 145
```



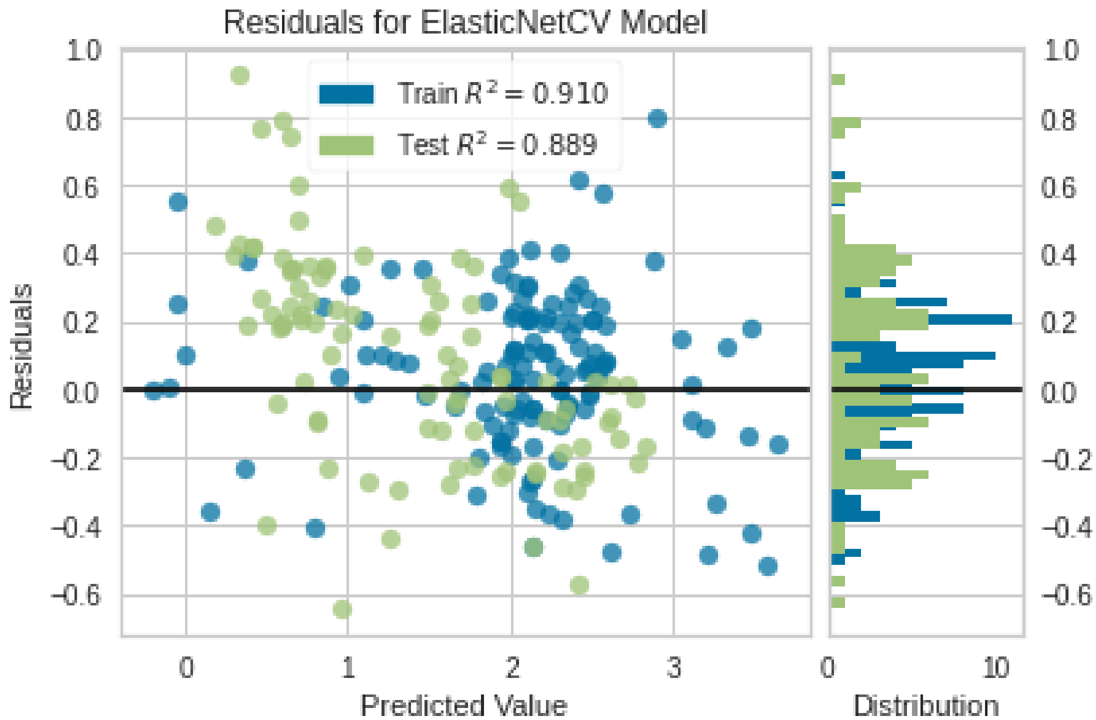

```
Piecewise regression with degree: 2
 and knots: 4
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.7941
          With a training data size of: 195
```



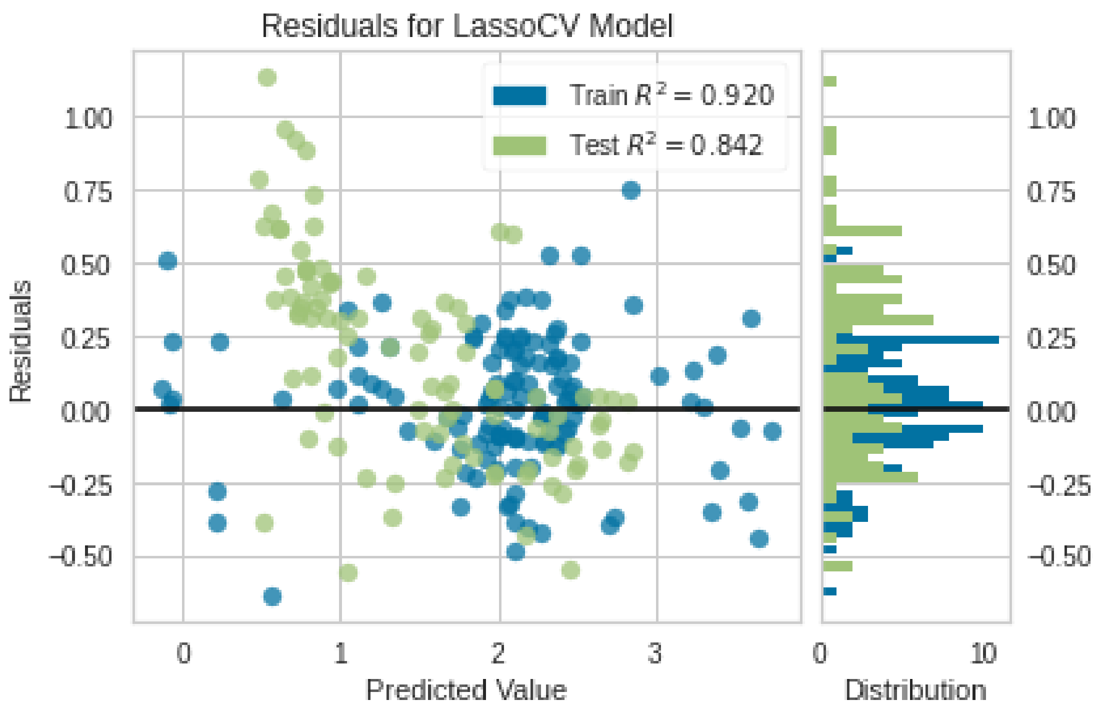

```
Piecewise regression with degree: 2
 and knots: 5
The best performing model in the run was: ElasticNetCV()
          With an r2 score of: 0.7371
          With a training data size of: 200
```



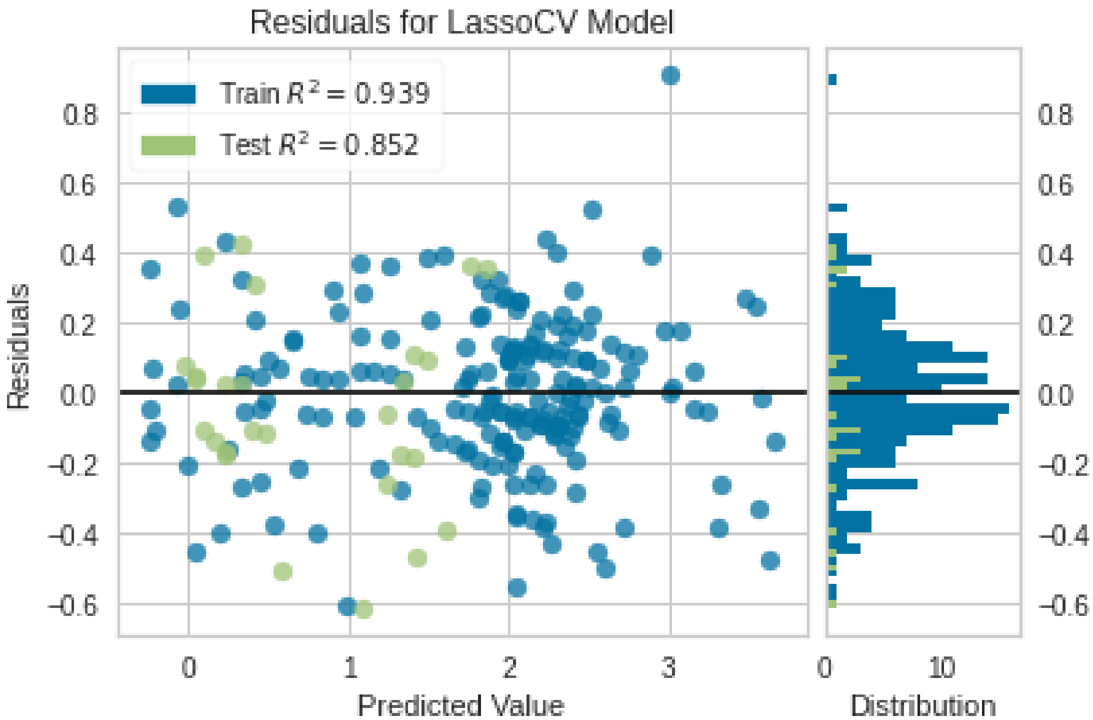

```
Piecewise regression with degree: 3
 and knots: 2
The best performing model in the run was: ElasticNetCV()
          With an r2 score of: 0.8932
          With a training data size of: 130
```



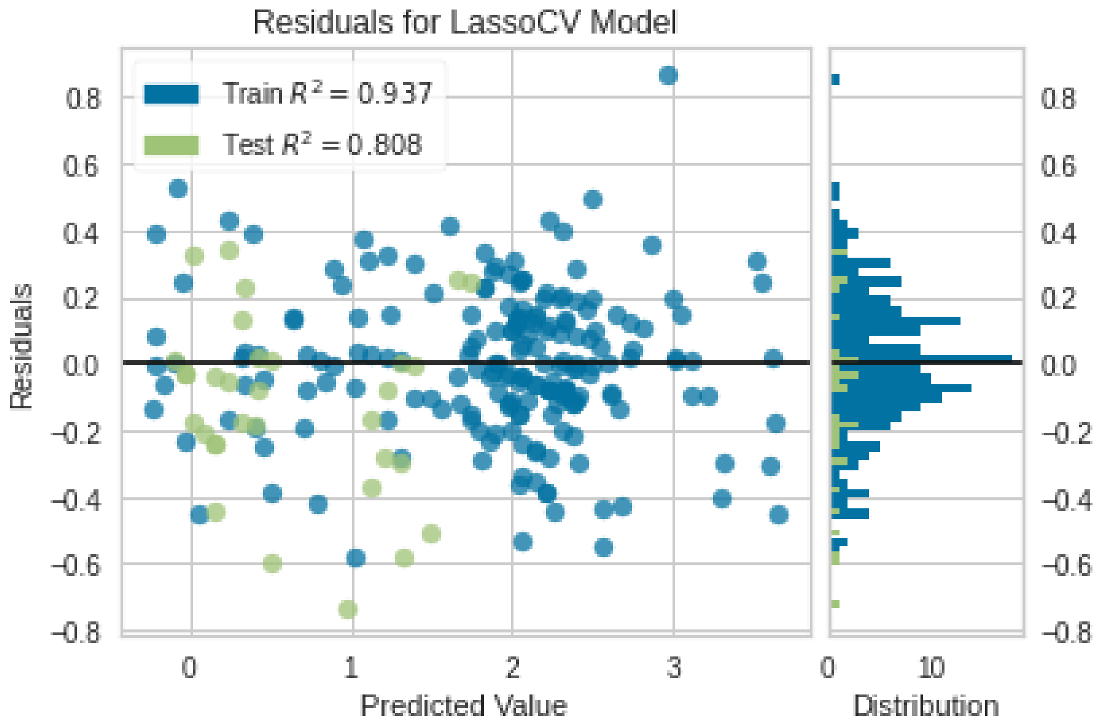

```
Piecewise regression with degree: 3
 and knots: 3
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8578
          With a training data size of: 130
```



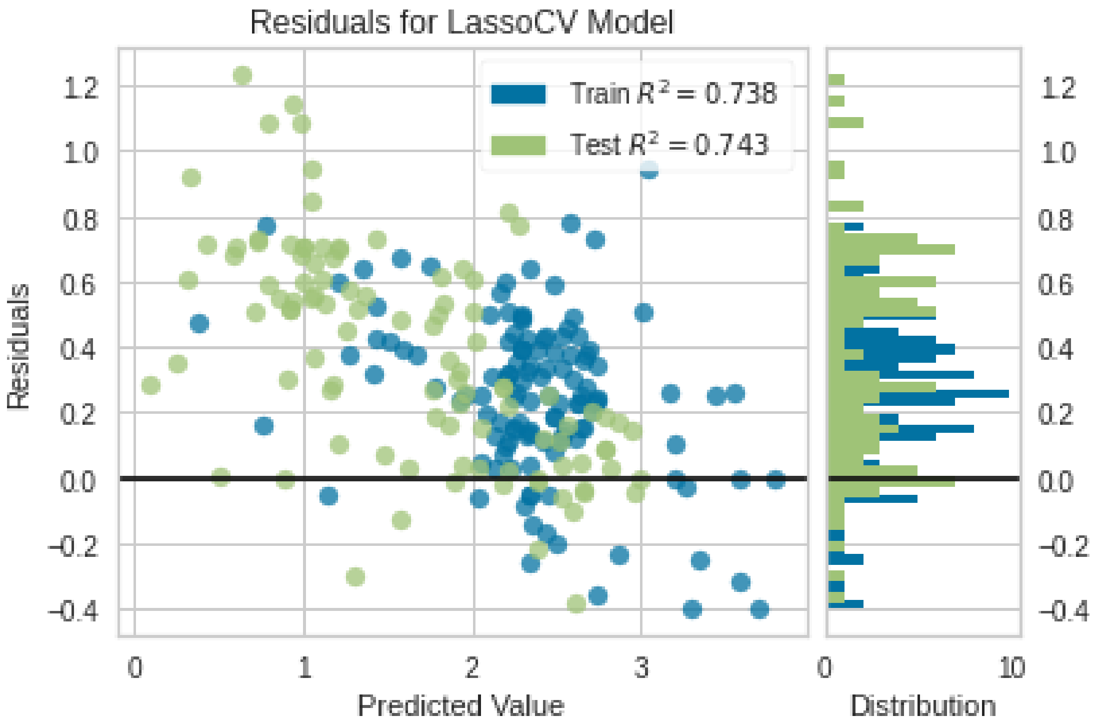

```
Piecewise regression with degree: 3
 and knots: 4
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8517
          With a training data size of: 200
```



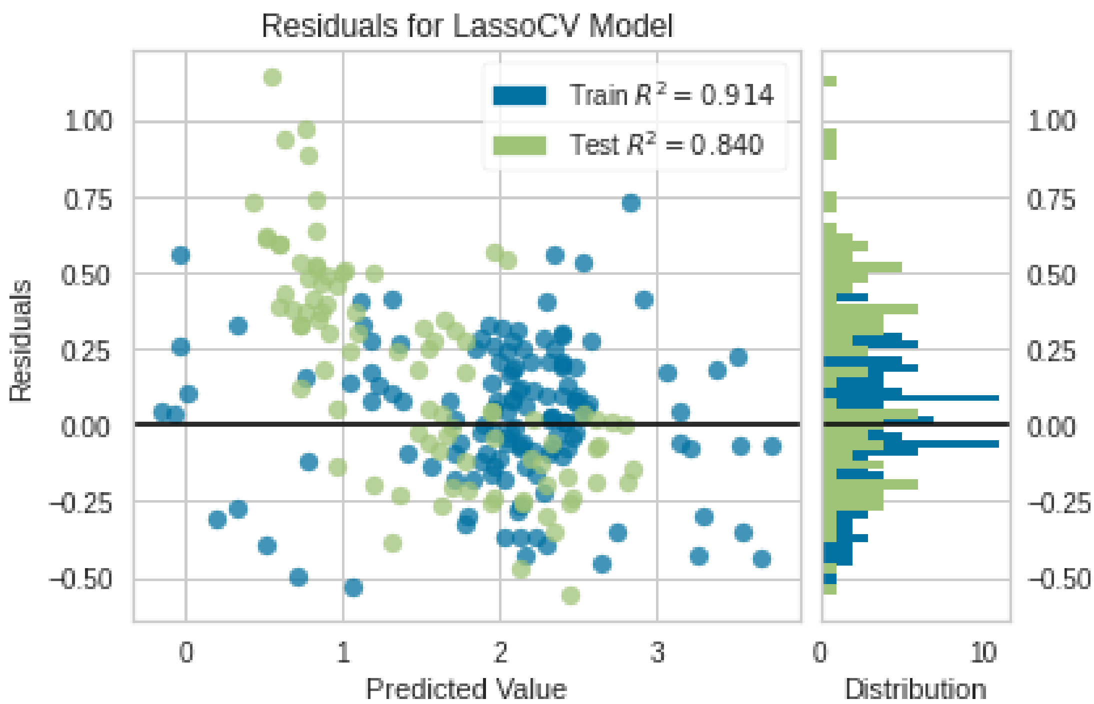

```
Piecewise regression with degree: 3
 and knots: 5
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8082
          With a training data size of: 195
```



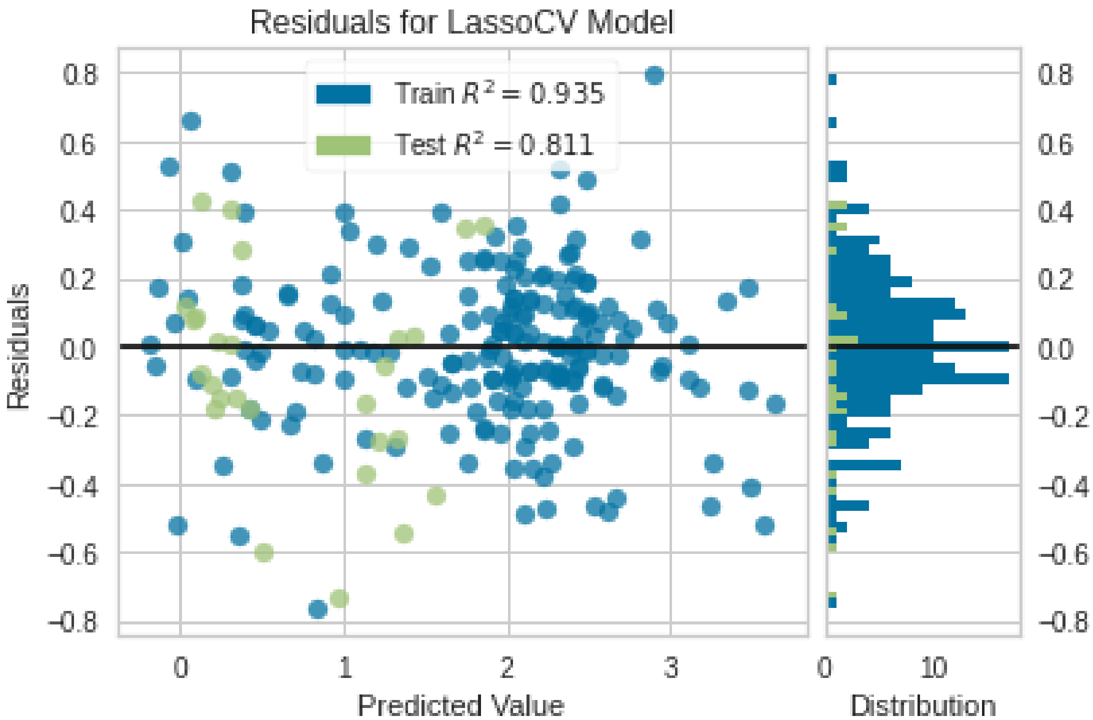

```
Piecewise regression with degree: 4
 and knots: 2
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8940
          With a training data size of: 125
```



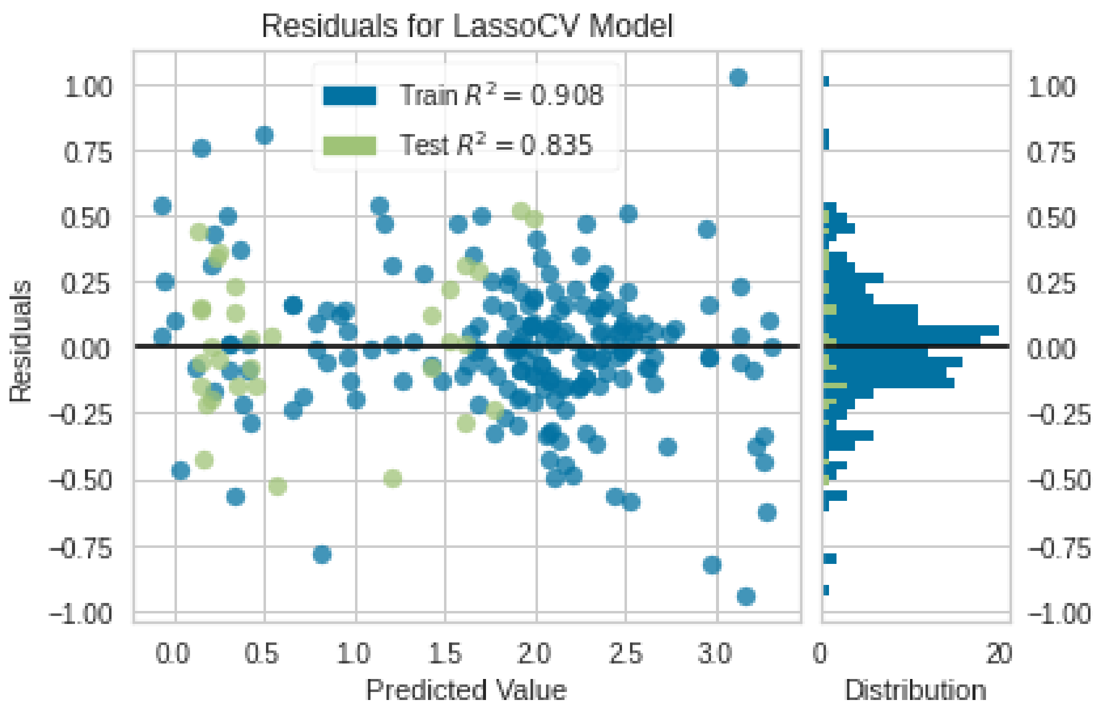

```
Piecewise regression with degree: 4
 and knots: 3
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8420
          With a training data size of: 135
```



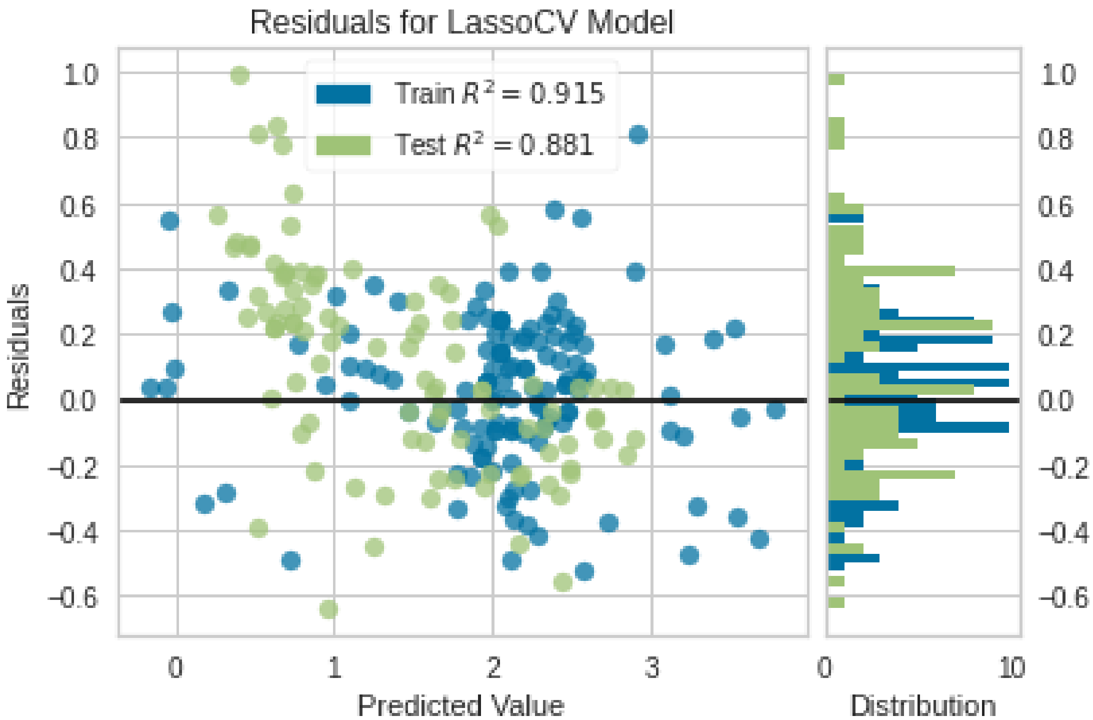

```
Piecewise regression with degree: 4
 and knots: 4
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8108
          With a training data size of: 200
```



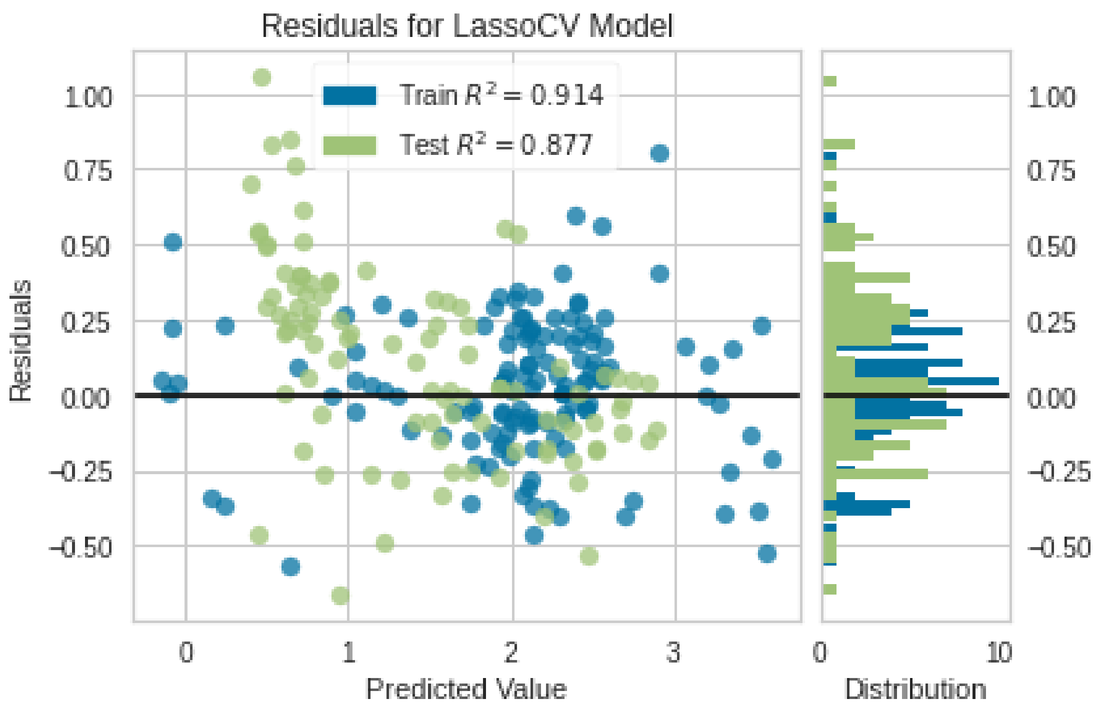

```
Piecewise regression with degree: 4
 and knots: 5
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8347
          With a training data size of: 195
```



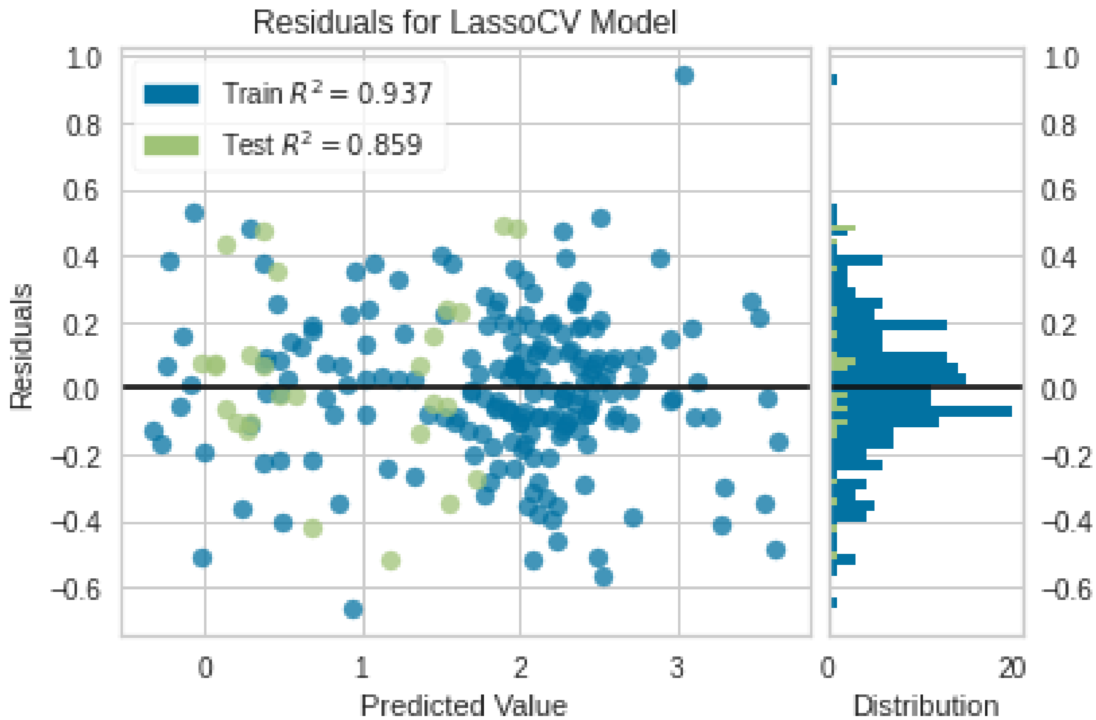

```
Piecewise regression with degree: 5
 and knots: 2
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8839
          With a training data size of: 130
```



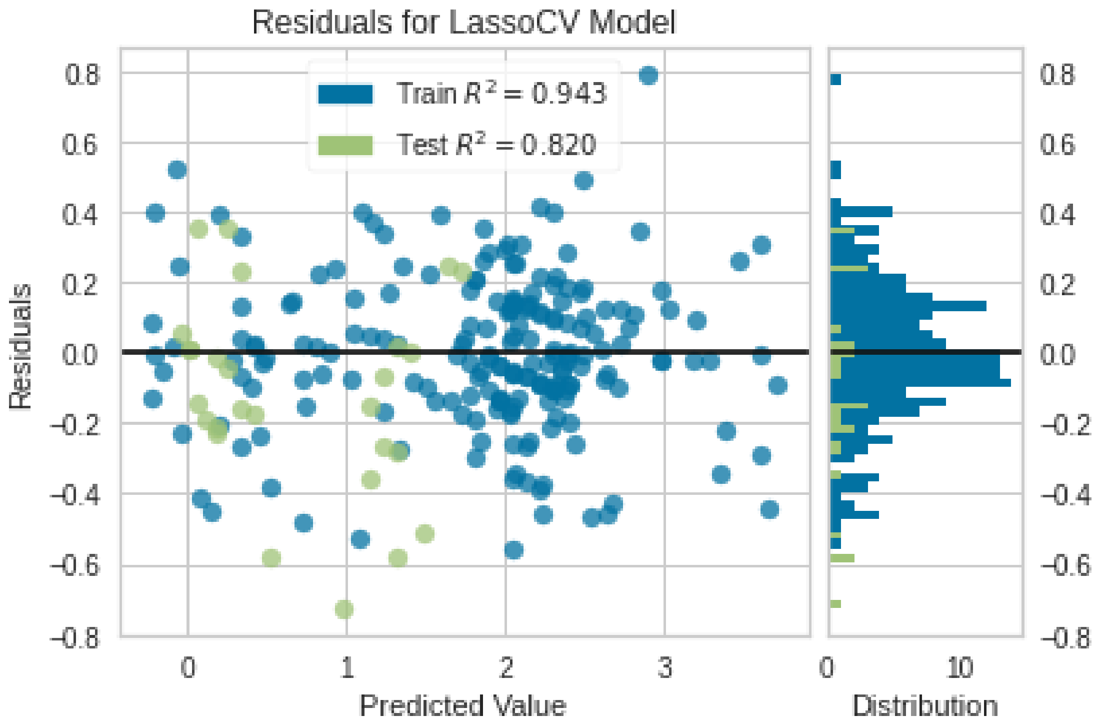

```
Piecewise regression with degree: 5
 and knots: 3
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8778
          With a training data size of: 130
```




```
Piecewise regression with degree: 5
 and knots: 4
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8589
          With a training data size of: 200
```




```
Piecewise regression with degree: 5
 and knots: 5
The best performing model in the run was: LassoCV()
          With an r2 score of: 0.8202
          With a training data size of: 200
```



Piecewise Regression evaluation

As we can see from our evaluation of different piecewise regression models over varying knots and degrees, even the best performing models result in a negligably similar r2 score to our initial LinearRegression model and in the vast majority of cases are objectively worse.

Not only this, but the highest scoring piecewise regression model is the one which most closely simulates a basic LinearRegression model.

As we increase our number of knots, as a general trend, we can see that the model overfits to the training data and begins to generalize more poorly to the evaluation data. The best performing model is the one with the minimum number of permissible knots.

This indicates that the shape of our provided data is more closely correlated with a linear model than a set of discretely divided patterns.

For these reasons, we can deduce that our data does not follow a piecewise pattern and that this model should be discarded.

Selection of model

The primary features we want out of the model are r2 accuracy and ability to generalize to other training sets.

Becuase of this, I will be evaluating my models based on how good their r2 scores are, whether the particular regression method is appropriate for the shape of the data and how well they should generalize to other datasets (based on whether it has overfit and the variance of the model).

These parameters are good for evaluation because it will allow me to pick the highest performing model with the highest ability to generalize in order to get a good score on a set of new, previously unseen data.

The basic LinearRegression model provides a reasonably good r2 score when optimally fit on the provided data. This indicates that the data is at quite linearly distributed. In terms of generalization, both the training and validation r2 scores are close together which suggests that the model is neither under nor over-fit. Linear regression is also a low variance method which is good for generalization.

In terms of the r2 score, the output of the best performing regularization methods and the output of the best performing LinearRegression model are negligably similar. This indicates that the most effective complexity parameters cause a negligable difference to fitting the linear regression model and hence there is no reason to add a regularization method to the final model. Not only this, but regularization is a higher variance method than linear regression which would harm the model's ability to generalize. For these reasons, the regularization models are worse than the basic linear regression model.

The best model utilizing polynomial features has a degree of 1. In other words, simulating a basic linear regression model using a polynomial method is the most effective way of fitting to and generalizing from the data. Every other degree value offers a worse performance compared to the basic linear regression model and demonstrates that the data fits a linear shape far more than it does any degree of polynomial shape. This suggests very poor generalization ability and for these reasons, the basic linear regression model is better than the polynomial method.

Finally, our evaluations of the piecewise regression models have shown us that the best performing model is the one which most closely simulates a basic linear regression model. This is something we already know from evaluating the data polynomially. The more knots we add, the more it overfits to the training data as a general trend. While certain combinations of knots and degrees provide a competitive r2 score to the basic linear regression model, even the best scores are negligably different. This indicates that this model performs best when it either approximates itself to a linear model as much as possible, or artificially fits itself to a shape approximating a linear distribution. Artificially fitting to a linear shape is a high variance and poorly generalizable method. Either way, a basic LinearRegression model offers less risk of overfitting, less computation, complexity and a better approach to fit to a seemingly linear distribution of data. For these reasons, the linear regression model is better than the piecewise regression method.

For all of these reasons, no other model has proven itself to be competitive in any significant way to the initally evaluated LinearRegression model. Hence, the initial LinearRegression model with a training data of size 110 is the most optimal model we have evaluated and will be selected for the assessment.

Evaluation segment

The following tile will evaluate my selected model on the "unseendata.csv" file and provide its according r2 score.

Please replace the 'data.csv' file with the unseen data

```
# Format data in the same way as previously done since that data is in
the same format.
# Set the whole dataset as test data for evaluation.
data = np.genfromtxt(os.path.join(ass_path,'data.csv'),delimiter=',')
[1:,:]
X_test = data[:-1,:]
y_test = data[1:,-1]

# Extract the first trained LinearRegression model which has been
chosen for evaluation.
model = list(best_models.values())[0]

# Evaluate and extract the r2 score.
y_pred = model.predict(X_test)
score = r2_score(y_test, y_pred)

print(score)
```

```
0.9275942558524233
```

Question 2

```
# Preprocess and normalize the data before applying PCA
pca_data = data

# Extend the table with 8 additional time-lagged columns
for i in range(pca_data.shape[1]*2):
    col = []
    for j in range(pca_data.shape[0]):
        if j-1>=0:
            col.append(pca_data[j-1][i])
        else:
            col.append(0)
    pca_data = np.c_[pca_data, col]

# Remove initial lines with incomplete data
pca_data = pca_data[2:,:]

# Scale the data
pca_data = scale(pca_data)

# Create a PCA object with the same amount of principle components as
variables (12)
```

```
pca = PCA(n_components=12)
new_data = pca.fit_transform(pca_data)

# Simple calculator to generate the variance over each given dimension
as well as
# the total variance over all dimensions
def variance_calculator(data, dim_name):
    total_var = 0
    for i in range(data.shape[1]):
        var = np.var(data[:,i])
        total_var += var
        print('Variance over {}{}: {:.4f}'.format(dim_name, i+1, var))

    print("Total variance = {:.4f}".format(total_var))
```

Calculate variance of original data

```
# Calculate the variance of each dimension from the original data as
well as
# the variance sum over all dimensions
variance_calculator(pca_data, 'Dimension')
```

```
Variance over Dimension1: 1.0000
Variance over Dimension2: 1.0000
Variance over Dimension3: 1.0000
Variance over Dimension4: 1.0000
Variance over Dimension5: 1.0000
Variance over Dimension6: 1.0000
Variance over Dimension7: 1.0000
Variance over Dimension8: 1.0000
Variance over Dimension9: 1.0000
Variance over Dimension10: 1.0000
Variance over Dimension11: 1.0000
Variance over Dimension12: 1.0000
Total variance = 12.0000
```

Calculate variance of pca data

```
# Calculate the variance of each PC as well as the variance sum over
all PCs
variance_calculator(new_data, 'PCA')
```

```
Variance over PCA1: 7.1624
Variance over PCA2: 2.5760
Variance over PCA3: 1.4930
Variance over PCA4: 0.5946
Variance over PCA5: 0.0788
Variance over PCA6: 0.0444
Variance over PCA7: 0.0200
Variance over PCA8: 0.0127
Variance over PCA9: 0.0102
```

```
Variance over PCA10: 0.0055
Variance over PCA11: 0.0019
Variance over PCA12: 0.0004
Total variance = 12.0000
```

Comparison of the sum of variances before and after PCA

The sum of the variances before applying the PCA is the same as after applying the PCA! This is due to the fact that we set the number of PCs to be equal to the number of variables (i.e. 12). Because of this, none of the variables were discarded.

Since variance is simply the sum of squared differences, you simply get the euclidean distance. The euclidean distance is not going to change if all we do is transpose our system. For this reason we get the same sum of variance between the two.

Linear equations for each PC1 - 4

The linear equations derived from the independant variables for each PC will be printed below in descending order based on their contribution to the PC

```
# Manually assign each dimension with its corresponding label for
visualization
variables = {1:'A', 2:'B', 3:'C', 4:'D', 5:'A-1', 6:'B-1', 7:'C-1',
8:'D-1', 9:'A-2', 10:'B-2',
            11:'C-2', 12:'D-2'}

# Print out the loading scores in descending order (contribution of
each dimension)
# for each of the  first 4 PCs
for i in range(4):
    # Extract and sort loading scores
    loading_scores = list(zip([variables[i] for i in range(1,13)],
pca.components_[i]))
    loading_scores.sort(key=lambda score: abs(score[1]), reverse=True)
    print('PCA{} equation sorted by internal
contribution:'.format(i+1))
    for j in range(len(loading_scores)):
        print('({}) * {:.4f},'.format(loading_scores[j][0],
loading_scores[j][1]))
    print()
```

```
PCA1 equation sorted by internal contribution:
(C) * 0.3433,
(C-1) * 0.3415,
(C-2) * 0.3374,
(A-1) * -0.3283,
(A) * -0.3283,
(A-2) * -0.3267,
(D) * 0.2907,
(D-1) * 0.2865,
```

```
(D-2) * 0.2768,
(B-2) * 0.1887,
(B-1) * 0.1697,
(B) * 0.1474,

PCA2 equation sorted by internal contribution:
(B) * -0.5626,
(B-1) * -0.5492,
(B-2) * -0.5233,
(D-2) * 0.1876,
(D-1) * 0.1481,
(C-2) * 0.1232,
(D) * 0.1068,
(C-1) * 0.0959,
(A-2) * -0.0855,
(C) * 0.0694,
(A-1) * -0.0519,
(A) * -0.0192,

PCA3 equation sorted by internal contribution:
(D-1) * -0.4718,
(D-2) * -0.4586,
(D) * -0.4584,
(A) * -0.3190,
(A-1) * -0.3129,
(A-2) * -0.3074,
(C-2) * 0.1306,
(C-1) * 0.1219,
(C) * 0.1168,
(B-2) * -0.0919,
(B-1) * -0.0761,
(B) * -0.0541,

PCA4 equation sorted by internal contribution:
(C) * -0.4408,
(C-1) * -0.4402,
(C-2) * -0.4360,
(A-1) * -0.3542,
(A-2) * -0.3538,
(A) * -0.3528,
(D) * 0.1319,
(D-1) * 0.1294,
(D-2) * 0.1098,
(B) * -0.0208,
(B-1) * -0.0104,
(B-2) * 0.0003,
```

Analysis of independant variable contribution to PCs

As you can see, each PCA is most strongly influenced by clusters of one of the original input variables along with its time permutations (for eg A, A-1, A-2).

This makes a lot of sense since each variable is closer (during the vast majority of the data) in value to itself one step in either time direction than to another variable.

This is due to the fact that each variable only changes a small, incremental amount per timestep.

For this reason if variable C, for example, aligns very strongly with one of the PCs, due to the small difference between variable C, C-1 and C-2, they will all align with the PC a very similar amount.

Question 3 - CNN light source prediction

I will start by creating Dataset object customized to work with the format of the data provided. This will allow me to pass it into a dataloader and make it a lot easier to write a training loop.

```
class LightSourceDataset(Dataset):

    def __init__(self, img_dir, labels_file=None, transform=None):
        super(LightSourceDataset, self).__init__()
        # Init the attributes of the class needed for training, as
well as the
        # transform option for data pre-processing
        self.labels = pd.read_csv(labels_file, header=None)
        self.img_dir = img_dir
        self.transform = transform

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        img_path = os.path.join(self.img_dir, self.labels.iloc[idx,0])

        # Normalize image data in between -1 and 1 to for better
training.
        # This has proven to give better results than simply
normalizing between
        # 0 and 1, and for this reason has been hard coded in.
        image = (read_image(img_path).float()/255)*2 -1

        # Perform any desired transformations to the data to evaluate
performance
        # differences. This gives us flexibility instead of hard
coding a given
```

```
        # transformation
        if self.transform:
            image = self.transform(image)

        label = 
torch.from_numpy(self.labels.iloc[idx,1:].to_numpy(dtype=float))

        # Return an image tensor along with its corresponding label 
tensor
        return image, label
```

The resolution on the images is currently too high to perform adequate training. For this reason I will apply a simple resizing transformation, and only give a single int value. This means that the smallest edge will be of my defined length, and the larger side will be computed in order to maintain the same aspect ratio.

This should allow me to train my CNN more effectively without losing any significant data, as well as not distorting the image by changing its aspect ratio.

```
transform = T.Resize(30)
train_data = LightSourceDataset(os.path.join(ass_path, "train/"), 
os.path.join(ass_path, "train/labels.csv"), transform=transform)
val_data = LightSourceDataset(os.path.join(ass_path,"validate/"), 
os.path.join(ass_path,"validate/labels.csv"), transform=transform)

batch_size=50
train_loader = torch.utils.data.DataLoader(train_data, 
batch_size=batch_size,
                                           shuffle=True, 
num_workers=1)
test_loader = torch.utils.data.DataLoader(val_data, 
batch_size=batch_size,
                                          shuffle=True, num_workers=1)

# Choose batch size for training
batch_size=50
# Implement both shuffled dataloaders with correct parameters
train_loader = torch.utils.data.DataLoader(train_data, 
batch_size=batch_size,
                                           shuffle=True, 
num_workers=1)
val_loader = torch.utils.data.DataLoader(val_data, 
batch_size=batch_size,
                                          shuffle=True, num_workers=1)
```

Network architecture

Regression or classification

Since the original data was specified to only have 64 different light source directions, I was tempted to go for a classification method.

This would be incorrect, however, as this would be an assumption on the structure of the test set which could lead to an error when tested.

i.e. I do not know how many classes the test set would have, and so it would be a poor design decision to base my architecture on an unverified assumption

For these reasons I have chosen a regression method.

Depth

I wanted to balance the relative complexity of deriving a 3 dimensional vector from an image, with the amount of data we have been given.

I did not have a very large dataset, and so I did not want to create an architecture that was too powerful that would end up overfitting on the limited amount of data. I also did not want an architecture too weak to derive the abstract feature of a light vector from the images.

I made the architecture deep and narrow instead of broad and shallow in order to abstract away the unnecessary features and effectively learn the desired features.

After validating the architecture and finetuning architecture along with the hyperparameters, a standard architecture of three convolutional layers attached to three dense layers seemed like an appropriate compromise.

In between layers

By applying the batch-normalization, along with the ReLU non-linearity to each of my layers, I have managed to stabilize the architecture.

Batch normalization will lead to better generalization (which is very important for this assessment), will allow stable training with a higher learning rate (which will allow me to more effectively fit my model to the data), and will require less hyperparameter tuning, something which I am not very experienced in as of yet. It also has the added benefit of providing all of the benefits of dropout.

ReLU will allow me to add non-linearity to my layers which is necessary for learning complex features, and has proven to be one of the most robust activation function for deep networks.

I have also added standard MaxPool2d layers in order to facilitate feature extraction for the next layer and decrease the resolution of the output in order to abstract features away from the image.

```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.convlayers = nn.Sequential(
            # Choose a kernel size of 3x3 since odd sized filters 
symmetrically divide
            # the previous layer pixels, and 1x1 provides no
```

```
information on neighbouring pixels
            nn.Conv2d(in_channels=1, out_channels=6, kernel_size=3,
stride=1, padding=1),
            nn.BatchNorm2d(6),
            nn.ReLU(),
            # Halve the resolution
            nn.MaxPool2d(kernel_size=2, stride=2),
            # Remove padding to decrease the resolution a little bit
more
            nn.Conv2d(in_channels=6, out_channels=12, kernel_size=3,
stride=1, padding=0),
            nn.BatchNorm2d(12),
            nn.ReLU(),
            # Halve the resolution
            nn.MaxPool2d(kernel_size=2, stride=2),
            # Remove padding to decrease the resolution a little bit
more
            nn.Conv2d(in_channels=12, out_channels=24, kernel_size=3,
stride=1, padding=0),
            nn.BatchNorm2d(24),
            nn.ReLU()
        )

        self.MLP = nn.Sequential(
            # Use three densely connected layers to extract patterns
from the
            # output of the convolutional layer and output the final
prediction
            nn.Linear(in_features=24*6*4, out_features=250),
            nn.BatchNorm1d(250),
            nn.ReLU(),
            nn.Linear(in_features=250, out_features=100),
            nn.BatchNorm1d(100),
            nn.ReLU(),
            nn.Linear(in_features=100, out_features=3),
        )

    def forward(self,x):
        x = self.convlayers(x)
        x = x.view(x.size(0), -1)
        x = self.MLP(x)

        # Normalize output into a unit vector
        x = normalize(x, p=2, dim=1)
        return x

model = CNN()
model = model.to(device)
```

Loss function

Since I have decided to use a regression model, rather than a classification model and hence will choose a loss function from this category. I also have the choice of designing a custom loss function for this particular problem, but I will start off by evaluating the industry standard methods before deciding whether a custom approach is needed.

The two most robust and industry driven loss functions for regression models are MSE and L1. MSE is better for punishing outliers whereas L1 is more lineant on them. MSE is also more appropriate for complex problems.

Since MSE is less forgiving of errors, and the data we are provided is very difficult to evaluate objectively (some faces have different shapes and light shines on them differently), I will be choosing the method which is more lenient on minor errors, since I am aiming for a model which provides a good approximation of the feature without needing it to be exact. Also, through experimentation I have found that the MSE loss function is much more prone to occasional spiking compared to L1.

For these reasons, I will implement the L1Loss function for my model.

```
loss_func = nn.L1Loss()
```

Train and validation pipeline

The declaration of all of the relevant functions and helper functions to be used for training and validating the model.

```
# Implement a training cycle which calculates the mean angular error
as well as the
# mean training loss for each epoch
def train_cycle(epoch, train_loader, optim, loss_func):
    # Set model to train in order to update weights
    model.train()
    ang_errors = []
    total_loss = 0
    for i, (images, labels) in enumerate(train_loader):
        images, labels = images.to(device), labels.to(device)
        output = model(images)

        # Calculate and store angular error
        for j in range(len(output)):
            error = get_angle(output[j].cpu().detach().numpy(),
labels[j].cpu().detach().numpy())
            ang_errors.append(error)

        # Update the model
        loss = loss_func(output.float(),labels.float())
        optim.zero_grad()
        loss.backward()
        optim.step()
```

```
        # Update the running loss
        total_loss += loss

    # Calculate mean loss, mean angular error and print out each for
the epoch
    # Save each of these for graph visualization to check for
convergence and
    # learning pattern
    mean_loss = total_loss / len(train_loader)
    training_losses.append(mean_loss)
    print('Mean training loss for Epoch [{}/{}]: {:.4f}'.
          format(epoch + 1, num_epochs, mean_loss))
    sum_ang = sum(ang_errors)
    mean_ang = sum_ang/len(ang_errors)
    training_ang_errors.append(mean_ang)
    print('Mean angular error over training epoch {}: {}'.
          format(epoch+1, sum_ang/len(ang_errors)))

# Implement a validation cycle which calculates the mean angular error
as well as the
# mean validation loss for each epoch
def val_cycle(epoch, val_loader):

    # Switch to eval mode to avoid accidentally updating weights
    model.eval()
    with torch.no_grad():
        ang_errors = []
        total_loss = 0
        for images, labels in val_loader:
            images = images.to(device)
            labels = labels.to(device)
            output = model(images)
            loss = loss_func(output.float(),labels.float())

            # Caculate and store angular error
            for j in range(len(output)):
                error = get_angle(output[j].cpu().detach().numpy(),
labels[j].cpu().detach().numpy())
                ang_errors.append(error)

            # Update the running loss
            total_loss += loss

        # Calculate mean loss, mean angular error and print out each
for the epoch
        # Save each of these for graph visualization to check for
convergence and
        # learning pattern
        mean_loss = total_loss / len(val_loader)
```

```
        print('Mean validation loss for Epoch [{}/{}]: {:.4f}'.
              format(epoch + 1, num_epochs, mean_loss))
        sum_ang = sum(ang_errors)
        mean_ang = sum_ang/len(ang_errors)
        validation_losses.append(mean_loss)
        validation_ang_errors.append(mean_ang)
        print('Mean angular error over validation epoch {}: {}\n'.
              format(epoch+1, sum_ang/len(ang_errors)))

# Set of helper functions used to calculate mean angular error in the
training and
# validation cycles
def unit_vector(vector):
    return vector / np.linalg.norm(vector)
def get_angle(vec1, vec2):
    v1_u = unit_vector(vec1)
    v2_u = unit_vector(vec2)
    return np.rad2deg(np.arccos(np.clip(np.dot(v1_u, v2_u), -1.0,
1.0)))

images, labels = next(iter(train_loader))
print(images[0].size())
output = model(images)
print(output.shape)
loss = loss_func(output,labels)
print(loss)

torch.Size([1, 36, 30])
torch.Size([50, 3])
tensor(0.7562, grad_fn=<L1LossBackward0>)

num_epochs = 175

# Use Adam optimiser since it is the least sensitive to
hyperparameters and most likely to
# work robustly
optim_cnn = torch.optim.Adam(model.parameters(), lr = 0.003)

# Initialise some variables to track mean angular errors for
visualization
iterations_per_epoch = math.ceil(len(train_data)/batch_size)
training_ang_errors = []
validation_ang_errors = []
training_losses = []
validation_losses = []

for epoch in range(num_epochs):
    train_cycle(epoch, train_loader, optim_cnn, loss_func)
    val_cycle(epoch, val_loader)
```

```
Mean training loss for Epoch [1/175]: 0.1716
Mean angular error over training epoch 1: 21.249999419776373
Mean validation loss for Epoch [1/175]: 0.1519
Mean angular error over validation epoch 1: 17.598418771086777

Mean training loss for Epoch [2/175]: 0.0956
Mean angular error over training epoch 2: 11.27327234948301
Mean validation loss for Epoch [2/175]: 0.1033
Mean angular error over validation epoch 2: 11.49150444295237

Mean training loss for Epoch [3/175]: 0.0790
Mean angular error over training epoch 3: 9.279271488206781
Mean validation loss for Epoch [3/175]: 0.0725
Mean angular error over validation epoch 3: 9.265425229152374

Mean training loss for Epoch [4/175]: 0.0803
Mean angular error over training epoch 4: 9.440441193278852
Mean validation loss for Epoch [4/175]: 0.0840
Mean angular error over validation epoch 4: 9.14084865579263

Mean training loss for Epoch [5/175]: 0.0692
Mean angular error over training epoch 5: 8.027126996407857
Mean validation loss for Epoch [5/175]: 0.0708
Mean angular error over validation epoch 5: 9.035805659399504

Mean training loss for Epoch [6/175]: 0.0656
Mean angular error over training epoch 6: 7.742480254356495
Mean validation loss for Epoch [6/175]: 0.0698
Mean angular error over validation epoch 6: 8.526912651746958

Mean training loss for Epoch [7/175]: 0.0654
Mean angular error over training epoch 7: 7.64573615617059
Mean validation loss for Epoch [7/175]: 0.0752
Mean angular error over validation epoch 7: 8.83282397223545

Mean training loss for Epoch [8/175]: 0.0652
Mean angular error over training epoch 8: 7.697157681536725
Mean validation loss for Epoch [8/175]: 0.0672
Mean angular error over validation epoch 8: 8.097242883790987

Mean training loss for Epoch [9/175]: 0.0642
Mean angular error over training epoch 9: 7.5060844284390456
Mean validation loss for Epoch [9/175]: 0.0613
Mean angular error over validation epoch 9: 7.65848627588962

Mean training loss for Epoch [10/175]: 0.0569
Mean angular error over training epoch 10: 6.675403961791657
Mean validation loss for Epoch [10/175]: 0.0675
Mean angular error over validation epoch 10: 8.012924093704946
```

```
Mean training loss for Epoch [11/175]: 0.0584
Mean angular error over training epoch 11: 6.879485807127238
Mean validation loss for Epoch [11/175]: 0.0610
Mean angular error over validation epoch 11: 7.085582078309851

Mean training loss for Epoch [12/175]: 0.0548
Mean angular error over training epoch 12: 6.424355404550014
Mean validation loss for Epoch [12/175]: 0.0594
Mean angular error over validation epoch 12: 6.8771795414603725

Mean training loss for Epoch [13/175]: 0.0584
Mean angular error over training epoch 13: 6.851637994557616
Mean validation loss for Epoch [13/175]: 0.0645
Mean angular error over validation epoch 13: 7.37490406347648

Mean training loss for Epoch [14/175]: 0.0512
Mean angular error over training epoch 14: 5.971761370346267
Mean validation loss for Epoch [14/175]: 0.0581
Mean angular error over validation epoch 14: 7.18538979942677

Mean training loss for Epoch [15/175]: 0.0540
Mean angular error over training epoch 15: 6.335573914628581
Mean validation loss for Epoch [15/175]: 0.0565
Mean angular error over validation epoch 15: 7.321594883528333

Mean training loss for Epoch [16/175]: 0.0542
Mean angular error over training epoch 16: 6.379642760355941
Mean validation loss for Epoch [16/175]: 0.0793
Mean angular error over validation epoch 16: 9.261866679196494

Mean training loss for Epoch [17/175]: 0.0513
Mean angular error over training epoch 17: 6.039627526155702
Mean validation loss for Epoch [17/175]: 0.0596
Mean angular error over validation epoch 17: 7.062157515744146

Mean training loss for Epoch [18/175]: 0.0494
Mean angular error over training epoch 18: 5.768778725994532
Mean validation loss for Epoch [18/175]: 0.0574
Mean angular error over validation epoch 18: 7.237271378019792

Mean training loss for Epoch [19/175]: 0.0539
Mean angular error over training epoch 19: 6.298493237537806
Mean validation loss for Epoch [19/175]: 0.0619
Mean angular error over validation epoch 19: 6.892163797582735

Mean training loss for Epoch [20/175]: 0.0508
Mean angular error over training epoch 20: 5.950201073455786
Mean validation loss for Epoch [20/175]: 0.0599
```

```
Mean angular error over validation epoch 20: 7.115295735757689

Mean training loss for Epoch [21/175]: 0.0474
Mean angular error over training epoch 21: 5.565151840444147
Mean validation loss for Epoch [21/175]: 0.0532
Mean angular error over validation epoch 21: 6.695696771540732

Mean training loss for Epoch [22/175]: 0.0454
Mean angular error over training epoch 22: 5.307979753915438
Mean validation loss for Epoch [22/175]: 0.0616
Mean angular error over validation epoch 22: 7.300170902322175

Mean training loss for Epoch [23/175]: 0.0484
Mean angular error over training epoch 23: 5.686334529259742
Mean validation loss for Epoch [23/175]: 0.0553
Mean angular error over validation epoch 23: 6.95010647478925

Mean training loss for Epoch [24/175]: 0.0468
Mean angular error over training epoch 24: 5.518713568679237
Mean validation loss for Epoch [24/175]: 0.0565
Mean angular error over validation epoch 24: 6.672057020360711

Mean training loss for Epoch [25/175]: 0.0466
Mean angular error over training epoch 25: 5.485809507285824
Mean validation loss for Epoch [25/175]: 0.0519
Mean angular error over validation epoch 25: 6.394341342397602

Mean training loss for Epoch [26/175]: 0.0426
Mean angular error over training epoch 26: 4.979951418116912
Mean validation loss for Epoch [26/175]: 0.0620
Mean angular error over validation epoch 26: 7.129666683539516

Mean training loss for Epoch [27/175]: 0.0419
Mean angular error over training epoch 27: 4.962038206365535
Mean validation loss for Epoch [27/175]: 0.0553
Mean angular error over validation epoch 27: 6.693071639657541

Mean training loss for Epoch [28/175]: 0.0428
Mean angular error over training epoch 28: 5.014315761686416
Mean validation loss for Epoch [28/175]: 0.0537
Mean angular error over validation epoch 28: 6.450426276250637

Mean training loss for Epoch [29/175]: 0.0436
Mean angular error over training epoch 29: 5.131928267885766
Mean validation loss for Epoch [29/175]: 0.0560
Mean angular error over validation epoch 29: 6.778960020270609

Mean training loss for Epoch [30/175]: 0.0424
Mean angular error over training epoch 30: 5.007520845173451
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Mean validation loss for Epoch [30/175]: 0.0562
Mean angular error over validation epoch 30: 7.092799217496556

Mean training loss for Epoch [31/175]: 0.0418
Mean angular error over training epoch 31: 4.925023224177466
Mean validation loss for Epoch [31/175]: 0.0542
Mean angular error over validation epoch 31: 6.237384286017963

Mean training loss for Epoch [32/175]: 0.0388
Mean angular error over training epoch 32: 4.574234001706982
Mean validation loss for Epoch [32/175]: 0.0609
Mean angular error over validation epoch 32: 7.077103828789743

Mean training loss for Epoch [33/175]: 0.0396
Mean angular error over training epoch 33: 4.6757674272808485
Mean validation loss for Epoch [33/175]: 0.0563
Mean angular error over validation epoch 33: 7.168230809408439

Mean training loss for Epoch [34/175]: 0.0431
Mean angular error over training epoch 34: 5.101760868108947
Mean validation loss for Epoch [34/175]: 0.0511
Mean angular error over validation epoch 34: 6.525419369194158

Mean training loss for Epoch [35/175]: 0.0397
Mean angular error over training epoch 35: 4.651259814129589
Mean validation loss for Epoch [35/175]: 0.0476
Mean angular error over validation epoch 35: 6.036704688167409

Mean training loss for Epoch [36/175]: 0.0380
Mean angular error over training epoch 36: 4.467571317279426
Mean validation loss for Epoch [36/175]: 0.0496
Mean angular error over validation epoch 36: 5.877884148909111

Mean training loss for Epoch [37/175]: 0.0373
Mean angular error over training epoch 37: 4.38221469457999
Mean validation loss for Epoch [37/175]: 0.0555
Mean angular error over validation epoch 37: 7.013491637108156

Mean training loss for Epoch [38/175]: 0.0389
Mean angular error over training epoch 38: 4.554059991890379
Mean validation loss for Epoch [38/175]: 0.0503
Mean angular error over validation epoch 38: 6.304804496375587


Mean training loss for Epoch [39/175]: 0.0400
Mean angular error over training epoch 39: 4.724742870670765
Mean validation loss for Epoch [39/175]: 0.0564
Mean angular error over validation epoch 39: 6.540759217862176
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Mean training loss for Epoch [40/175]: 0.0389
Mean angular error over training epoch 40: 4.564296477868515
Mean validation loss for Epoch [40/175]: 0.0741
Mean angular error over validation epoch 40: 6.776691950370185

Mean training loss for Epoch [41/175]: 0.0364
Mean angular error over training epoch 41: 4.277745111709925
Mean validation loss for Epoch [41/175]: 0.0505
Mean angular error over validation epoch 41: 5.953715156997842

Mean training loss for Epoch [42/175]: 0.0363
Mean angular error over training epoch 42: 4.296672865691781
Mean validation loss for Epoch [42/175]: 0.0492
Mean angular error over validation epoch 42: 6.352693502499359

Mean training loss for Epoch [43/175]: 0.0365
Mean angular error over training epoch 43: 4.274091115625507
Mean validation loss for Epoch [43/175]: 0.0522
Mean angular error over validation epoch 43: 6.612506072723661

Mean training loss for Epoch [44/175]: 0.0381
Mean angular error over training epoch 44: 4.472943412419862
Mean validation loss for Epoch [44/175]: 0.0468
Mean angular error over validation epoch 44: 5.977842650856253

Mean training loss for Epoch [45/175]: 0.0330
Mean angular error over training epoch 45: 3.897833045721021
Mean validation loss for Epoch [45/175]: 0.0757
Mean angular error over validation epoch 45: 6.663242819310657

Mean training loss for Epoch [46/175]: 0.0361
Mean angular error over training epoch 46: 4.290751447223222
Mean validation loss for Epoch [46/175]: 0.0524
Mean angular error over validation epoch 46: 6.027485715667928

Mean training loss for Epoch [47/175]: 0.0354
Mean angular error over training epoch 47: 4.151788651573089
Mean validation loss for Epoch [47/175]: 0.0668
Mean angular error over validation epoch 47: 7.088976796636909

Mean training loss for Epoch [48/175]: 0.0355
Mean angular error over training epoch 48: 4.157866593762345
Mean validation loss for Epoch [48/175]: 0.0536
Mean angular error over validation epoch 48: 6.4427209878524705

Mean training loss for Epoch [49/175]: 0.0326
Mean angular error over training epoch 49: 3.8314131809098244
Mean validation loss for Epoch [49/175]: 0.0490
Mean angular error over validation epoch 49: 5.822455032066922
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Mean training loss for Epoch [50/175]: 0.0323
Mean angular error over training epoch 50: 3.8238875985860172
Mean validation loss for Epoch [50/175]: 0.0519
Mean angular error over validation epoch 50: 6.498785319965018

Mean training loss for Epoch [51/175]: 0.0332
Mean angular error over training epoch 51: 3.935620152861482
Mean validation loss for Epoch [51/175]: 0.0504
Mean angular error over validation epoch 51: 5.797806829076758

Mean training loss for Epoch [52/175]: 0.0315
Mean angular error over training epoch 52: 3.7409023961480004
Mean validation loss for Epoch [52/175]: 0.0477
Mean angular error over validation epoch 52: 6.195229640558918

Mean training loss for Epoch [53/175]: 0.0317
Mean angular error over training epoch 53: 3.7610006435233534
Mean validation loss for Epoch [53/175]: 0.0484
Mean angular error over validation epoch 53: 6.2504413120135665

Mean training loss for Epoch [54/175]: 0.0324
Mean angular error over training epoch 54: 3.8463657817367896
Mean validation loss for Epoch [54/175]: 0.0443
Mean angular error over validation epoch 54: 5.8454608398884655

Mean training loss for Epoch [55/175]: 0.0311
Mean angular error over training epoch 55: 3.6943099900776013
Mean validation loss for Epoch [55/175]: 0.0480
Mean angular error over validation epoch 55: 6.053715590762929

Mean training loss for Epoch [56/175]: 0.0310
Mean angular error over training epoch 56: 3.674395620458766
Mean validation loss for Epoch [56/175]: 0.0493
Mean angular error over validation epoch 56: 5.972411032473278

Mean training loss for Epoch [57/175]: 0.0307
Mean angular error over training epoch 57: 3.6295528745121985
Mean validation loss for Epoch [57/175]: 0.0460
Mean angular error over validation epoch 57: 5.462214623214469

Mean training loss for Epoch [58/175]: 0.0329
Mean angular error over training epoch 58: 3.9156766278671005
Mean validation loss for Epoch [58/175]: 0.0525
Mean angular error over validation epoch 58: 6.214964062142752

Mean training loss for Epoch [59/175]: 0.0298
Mean angular error over training epoch 59: 3.506825647988569
Mean validation loss for Epoch [59/175]: 0.0459
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Mean angular error over validation epoch 59: 5.617560069999731

Mean training loss for Epoch [60/175]: 0.0310
Mean angular error over training epoch 60: 3.656819572956975
Mean validation loss for Epoch [60/175]: 0.0469
Mean angular error over validation epoch 60: 5.8307105614324986

Mean training loss for Epoch [61/175]: 0.0286
Mean angular error over training epoch 61: 3.3895665296533837
Mean validation loss for Epoch [61/175]: 0.0466
Mean angular error over validation epoch 61: 5.972629644266469

Mean training loss for Epoch [62/175]: 0.0294
Mean angular error over training epoch 62: 3.453739685620786
Mean validation loss for Epoch [62/175]: 0.0533
Mean angular error over validation epoch 62: 6.496936375412332

Mean training loss for Epoch [63/175]: 0.0280
Mean angular error over training epoch 63: 3.3405969740921218
Mean validation loss for Epoch [63/175]: 0.0531
Mean angular error over validation epoch 63: 5.753612493089607

Mean training loss for Epoch [64/175]: 0.0293
Mean angular error over training epoch 64: 3.45087545308604
Mean validation loss for Epoch [64/175]: 0.0721
Mean angular error over validation epoch 64: 6.213113033285097

Mean training loss for Epoch [65/175]: 0.0308
Mean angular error over training epoch 65: 3.6527521209779317
Mean validation loss for Epoch [65/175]: 0.0519
Mean angular error over validation epoch 65: 6.153792531818242

Mean training loss for Epoch [66/175]: 0.0303
Mean angular error over training epoch 66: 3.601333252204117
Mean validation loss for Epoch [66/175]: 0.0471
Mean angular error over validation epoch 66: 5.9204923979339314

Mean training loss for Epoch [67/175]: 0.0274
Mean angular error over training epoch 67: 3.284177246073058
Mean validation loss for Epoch [67/175]: 0.0470
Mean angular error over validation epoch 67: 5.585349734157187

Mean training loss for Epoch [68/175]: 0.0269
Mean angular error over training epoch 68: 3.1954238606948473
Mean validation loss for Epoch [68/175]: 0.0434
Mean angular error over validation epoch 68: 5.9434768455233105

Mean training loss for Epoch [69/175]: 0.0276
Mean angular error over training epoch 69: 3.274274352241793
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Mean validation loss for Epoch [69/175]: 0.0459
Mean angular error over validation epoch 69: 5.819084894128208

Mean training loss for Epoch [70/175]: 0.0295
Mean angular error over training epoch 70: 3.4596792539681935
Mean validation loss for Epoch [70/175]: 0.0442
Mean angular error over validation epoch 70: 5.6113336375940275

Mean training loss for Epoch [71/175]: 0.0273
Mean angular error over training epoch 71: 3.211662199559639
Mean validation loss for Epoch [71/175]: 0.0518
Mean angular error over validation epoch 71: 5.358529390651936

Mean training loss for Epoch [72/175]: 0.0283
Mean angular error over training epoch 72: 3.3398055130054365
Mean validation loss for Epoch [72/175]: 0.0459
Mean angular error over validation epoch 72: 5.92479653564525

Mean training loss for Epoch [73/175]: 0.0328
Mean angular error over training epoch 73: 3.9202285305644655
Mean validation loss for Epoch [73/175]: 0.0462
Mean angular error over validation epoch 73: 6.097811959886853

Mean training loss for Epoch [74/175]: 0.0283
Mean angular error over training epoch 74: 3.391731219558578
Mean validation loss for Epoch [74/175]: 0.0654
Mean angular error over validation epoch 74: 5.590704417273401

Mean training loss for Epoch [75/175]: 0.0285
Mean angular error over training epoch 75: 3.399637286227971
Mean validation loss for Epoch [75/175]: 0.0436
Mean angular error over validation epoch 75: 5.713916334582914

Mean training loss for Epoch [76/175]: 0.0260
Mean angular error over training epoch 76: 3.0972679432329495

Mean validation loss for Epoch [76/175]: 0.0465
Mean angular error over validation epoch 76: 5.916015864204285

Mean training loss for Epoch [77/175]: 0.0274
Mean angular error over training epoch 77: 3.2594973507066576
Mean validation loss for Epoch [77/175]: 0.0437
Mean angular error over validation epoch 77: 5.7076233555048175

Mean training loss for Epoch [78/175]: 0.0262
Mean angular error over training epoch 78: 3.1017692323850485
Mean validation loss for Epoch [78/175]: 0.0397
Mean angular error over validation epoch 78: 5.290736041457529
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Mean training loss for Epoch [79/175]: 0.0253
Mean angular error over training epoch 79: 3.0047679135087955
Mean validation loss for Epoch [79/175]: 0.0431
Mean angular error over validation epoch 79: 5.41087238778769

Mean training loss for Epoch [80/175]: 0.0240
Mean angular error over training epoch 80: 2.8489885616365065
Mean validation loss for Epoch [80/175]: 0.0448
Mean angular error over validation epoch 80: 5.767138810725888

Mean training loss for Epoch [81/175]: 0.0252
Mean angular error over training epoch 81: 2.9998844792648462
Mean validation loss for Epoch [81/175]: 0.0424
Mean angular error over validation epoch 81: 5.3126277416673

Mean training loss for Epoch [82/175]: 0.0263
Mean angular error over training epoch 82: 3.1402607147101063
Mean validation loss for Epoch [82/175]: 0.0432
Mean angular error over validation epoch 82: 5.214438199891053

Mean training loss for Epoch [83/175]: 0.0262
Mean angular error over training epoch 83: 3.1022431550445444
Mean validation loss for Epoch [83/175]: 0.0430
Mean angular error over validation epoch 83: 5.546764520921384

Mean training loss for Epoch [84/175]: 0.0251
Mean angular error over training epoch 84: 3.007602879551456
Mean validation loss for Epoch [84/175]: 0.0459
Mean angular error over validation epoch 84: 5.518265193273405

Mean training loss for Epoch [85/175]: 0.0250
Mean angular error over training epoch 85: 2.9674136088700704
Mean validation loss for Epoch [85/175]: 0.0426
Mean angular error over validation epoch 85: 5.602420272248535

Mean training loss for Epoch [86/175]: 0.0256
Mean angular error over training epoch 86: 3.0451655515829583
Mean validation loss for Epoch [86/175]: 0.0418
Mean angular error over validation epoch 86: 5.142202737762158

Mean training loss for Epoch [87/175]: 0.0236
Mean angular error over training epoch 87: 2.8233627054708
Mean validation loss for Epoch [87/175]: 0.0450
Mean angular error over validation epoch 87: 5.5317951295921235

Mean training loss for Epoch [88/175]: 0.0245
Mean angular error over training epoch 88: 2.9071524647122358
Mean validation loss for Epoch [88/175]: 0.0390
Mean angular error over validation epoch 88: 5.192520132866248
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Mean training loss for Epoch [89/175]: 0.0246
Mean angular error over training epoch 89: 2.925723109882883
Mean validation loss for Epoch [89/175]: 0.0472
Mean angular error over validation epoch 89: 5.3319206075431795

Mean training loss for Epoch [90/175]: 0.0248
Mean angular error over training epoch 90: 2.9098601434340465
Mean validation loss for Epoch [90/175]: 0.0493
Mean angular error over validation epoch 90: 6.288093089136201

Mean training loss for Epoch [91/175]: 0.0254
Mean angular error over training epoch 91: 2.99500941254802
Mean validation loss for Epoch [91/175]: 0.0493
Mean angular error over validation epoch 91: 5.608126920208987

Mean training loss for Epoch [92/175]: 0.0259
Mean angular error over training epoch 92: 3.0713461090285
Mean validation loss for Epoch [92/175]: 0.0405
Mean angular error over validation epoch 92: 5.518696842486954

Mean training loss for Epoch [93/175]: 0.0252
Mean angular error over training epoch 93: 3.014149192805041
Mean validation loss for Epoch [93/175]: 0.0415
Mean angular error over validation epoch 93: 5.491947485150893

Mean training loss for Epoch [94/175]: 0.0233
Mean angular error over training epoch 94: 2.7569647514239026
Mean validation loss for Epoch [94/175]: 0.0452
Mean angular error over validation epoch 94: 5.451928775440648

Mean training loss for Epoch [95/175]: 0.0246
Mean angular error over training epoch 95: 2.9528837698815127
Mean validation loss for Epoch [95/175]: 0.0408
Mean angular error over validation epoch 95: 5.259000851344757

Mean training loss for Epoch [96/175]: 0.0231
Mean angular error over training epoch 96: 2.743005454113931
Mean validation loss for Epoch [96/175]: 0.0456
Mean angular error over validation epoch 96: 5.336484748660834

Mean training loss for Epoch [97/175]: 0.0239
Mean angular error over training epoch 97: 2.8391052222005975
Mean validation loss for Epoch [97/175]: 0.0401
Mean angular error over validation epoch 97: 4.884676177260536

Mean training loss for Epoch [98/175]: 0.0234
Mean angular error over training epoch 98: 2.8004546603218046
Mean validation loss for Epoch [98/175]: 0.0444
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Mean angular error over validation epoch 98: 5.523827280387316

Mean training loss for Epoch [99/175]: 0.0220
Mean angular error over training epoch 99: 2.6350062359196964
Mean validation loss for Epoch [99/175]: 0.0403
Mean angular error over validation epoch 99: 5.299990251016237

Mean training loss for Epoch [100/175]: 0.0240
Mean angular error over training epoch 100: 2.8494288910915504
Mean validation loss for Epoch [100/175]: 0.0397
Mean angular error over validation epoch 100: 5.134749308052887

Mean training loss for Epoch [101/175]: 0.0251
Mean angular error over training epoch 101: 2.988449555059314
Mean validation loss for Epoch [101/175]: 0.0400
Mean angular error over validation epoch 101: 5.01720515406792

Mean training loss for Epoch [102/175]: 0.0233
Mean angular error over training epoch 102: 2.7749270371926555
Mean validation loss for Epoch [102/175]: 0.0401
Mean angular error over validation epoch 102: 5.048617998467132

Mean training loss for Epoch [103/175]: 0.0216
Mean angular error over training epoch 103: 2.589455957200829
Mean validation loss for Epoch [103/175]: 0.0385
Mean angular error over validation epoch 103: 4.797772056577502

Mean training loss for Epoch [104/175]: 0.0229
Mean angular error over training epoch 104: 2.733106927041509
Mean validation loss for Epoch [104/175]: 0.0354
Mean angular error over validation epoch 104: 4.855479925615642

Mean training loss for Epoch [105/175]: 0.0206
Mean angular error over training epoch 105: 2.460233963454601
Mean validation loss for Epoch [105/175]: 0.0459
Mean angular error over validation epoch 105: 5.278365045113074

Mean training loss for Epoch [106/175]: 0.0214
Mean angular error over training epoch 106: 2.5488851283510523
Mean validation loss for Epoch [106/175]: 0.0363
Mean angular error over validation epoch 106: 4.87411594027247

Mean training loss for Epoch [107/175]: 0.0239
Mean angular error over training epoch 107: 2.8440327276160065
Mean validation loss for Epoch [107/175]: 0.0394
Mean angular error over validation epoch 107: 5.166439406062917

Mean training loss for Epoch [108/175]: 0.0210
Mean angular error over training epoch 108: 2.5276594638147323
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Mean validation loss for Epoch [108/175]: 0.0388
Mean angular error over validation epoch 108: 5.015916620693677

Mean training loss for Epoch [109/175]: 0.0205
Mean angular error over training epoch 109: 2.463652983352912
Mean validation loss for Epoch [109/175]: 0.0425
Mean angular error over validation epoch 109: 5.133677320483833

Mean training loss for Epoch [110/175]: 0.0214
Mean angular error over training epoch 110: 2.5406341533455077
Mean validation loss for Epoch [110/175]: 0.0445
Mean angular error over validation epoch 110: 5.1283167246269885

Mean training loss for Epoch [111/175]: 0.0212
Mean angular error over training epoch 111: 2.5498197948153414
Mean validation loss for Epoch [111/175]: 0.0378
Mean angular error over validation epoch 111: 4.780473709278742

Mean training loss for Epoch [112/175]: 0.0216
Mean angular error over training epoch 112: 2.5569313320698313
Mean validation loss for Epoch [112/175]: 0.0418
Mean angular error over validation epoch 112: 5.238687836926773

Mean training loss for Epoch [113/175]: 0.0198
Mean angular error over training epoch 113: 2.374653610311664
Mean validation loss for Epoch [113/175]: 0.0414
Mean angular error over validation epoch 113: 5.095130418105521


Mean training loss for Epoch [114/175]: 0.0207
Mean angular error over training epoch 114: 2.495289597747349
Mean validation loss for Epoch [114/175]: 0.0402
Mean angular error over validation epoch 114: 4.989227459267325

Mean training loss for Epoch [115/175]: 0.0199
Mean angular error over training epoch 115: 2.3931418510988327
Mean validation loss for Epoch [115/175]: 0.0616
Mean angular error over validation epoch 115: 4.811108251738567

Mean training loss for Epoch [116/175]: 0.0201
Mean angular error over training epoch 116: 2.409400418080149
Mean validation loss for Epoch [116/175]: 0.0374
Mean angular error over validation epoch 116: 4.821187846413974

Mean training loss for Epoch [117/175]: 0.0209
Mean angular error over training epoch 117: 2.492307466010581
Mean validation loss for Epoch [117/175]: 0.0456
Mean angular error over validation epoch 117: 4.973689561209816
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Mean training loss for Epoch [118/175]: 0.0210
Mean angular error over training epoch 118: 2.503970961115536
Mean validation loss for Epoch [118/175]: 0.0401
Mean angular error over validation epoch 118: 5.3513525448923245

Mean training loss for Epoch [119/175]: 0.0195
Mean angular error over training epoch 119: 2.32245593940961
Mean validation loss for Epoch [119/175]: 0.0418
Mean angular error over validation epoch 119: 5.018419001454067

Mean training loss for Epoch [120/175]: 0.0215
Mean angular error over training epoch 120: 2.5644735469511275
Mean validation loss for Epoch [120/175]: 0.0369
Mean angular error over validation epoch 120: 5.017062962978525

Mean training loss for Epoch [121/175]: 0.0220
Mean angular error over training epoch 121: 2.653018339909384
Mean validation loss for Epoch [121/175]: 0.0369
Mean angular error over validation epoch 121: 4.964434436813417

Mean training loss for Epoch [122/175]: 0.0215
Mean angular error over training epoch 122: 2.5534021432475824
Mean validation loss for Epoch [122/175]: 0.0370
Mean angular error over validation epoch 122: 4.778136483401115

Mean training loss for Epoch [123/175]: 0.0221
Mean angular error over training epoch 123: 2.657058812492731
Mean validation loss for Epoch [123/175]: 0.0403
Mean angular error over validation epoch 123: 5.250503468851576

Mean training loss for Epoch [124/175]: 0.0198
Mean angular error over training epoch 124: 2.3794379181577385
Mean validation loss for Epoch [124/175]: 0.0438
Mean angular error over validation epoch 124: 5.453012354812546

Mean training loss for Epoch [125/175]: 0.0200
Mean angular error over training epoch 125: 2.3936615924804414
Mean validation loss for Epoch [125/175]: 0.0362
Mean angular error over validation epoch 125: 4.775732008378144

Mean training loss for Epoch [126/175]: 0.0188
Mean angular error over training epoch 126: 2.2400737995993274
Mean validation loss for Epoch [126/175]: 0.0376
Mean angular error over validation epoch 126: 4.957353237851898

Mean training loss for Epoch [127/175]: 0.0196
Mean angular error over training epoch 127: 2.3482412156200447
Mean validation loss for Epoch [127/175]: 0.0371
Mean angular error over validation epoch 127: 4.782499448701933
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Mean training loss for Epoch [128/175]: 0.0189
Mean angular error over training epoch 128: 2.25103276273319
Mean validation loss for Epoch [128/175]: 0.0382
Mean angular error over validation epoch 128: 4.716941892328031

Mean training loss for Epoch [129/175]: 0.0201
Mean angular error over training epoch 129: 2.4240444149344764
Mean validation loss for Epoch [129/175]: 0.0367
Mean angular error over validation epoch 129: 4.74554983003525

Mean training loss for Epoch [130/175]: 0.0194
Mean angular error over training epoch 130: 2.318434356040261
Mean validation loss for Epoch [130/175]: 0.0391
Mean angular error over validation epoch 130: 5.072064133821903

Mean training loss for Epoch [131/175]: 0.0186
Mean angular error over training epoch 131: 2.2368323472960157
Mean validation loss for Epoch [131/175]: 0.0376
Mean angular error over validation epoch 131: 5.021898063937175

Mean training loss for Epoch [132/175]: 0.0204
Mean angular error over training epoch 132: 2.444184728912354
Mean validation loss for Epoch [132/175]: 0.0540
Mean angular error over validation epoch 132: 4.5021332720324985

Mean training loss for Epoch [133/175]: 0.0188
Mean angular error over training epoch 133: 2.2640619644913547
Mean validation loss for Epoch [133/175]: 0.0338
Mean angular error over validation epoch 133: 4.741851279457945

Mean training loss for Epoch [134/175]: 0.0178
Mean angular error over training epoch 134: 2.1252116927250984
Mean validation loss for Epoch [134/175]: 0.0391
Mean angular error over validation epoch 134: 4.926486290592132

Mean training loss for Epoch [135/175]: 0.0205
Mean angular error over training epoch 135: 2.433790608160823
Mean validation loss for Epoch [135/175]: 0.0462
Mean angular error over validation epoch 135: 5.774003221622239

Mean training loss for Epoch [136/175]: 0.0187
Mean angular error over training epoch 136: 2.230294809044549
Mean validation loss for Epoch [136/175]: 0.0395
Mean angular error over validation epoch 136: 5.250340580683071

Mean training loss for Epoch [137/175]: 0.0194
Mean angular error over training epoch 137: 2.3419875376857338
Mean validation loss for Epoch [137/175]: 0.0406
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Mean angular error over validation epoch 137: 5.3750138114153545

Mean training loss for Epoch [138/175]: 0.0186
Mean angular error over training epoch 138: 2.217828191274918
Mean validation loss for Epoch [138/175]: 0.0399
Mean angular error over validation epoch 138: 5.073851968259794

Mean training loss for Epoch [139/175]: 0.0186
Mean angular error over training epoch 139: 2.2480199215990107
Mean validation loss for Epoch [139/175]: 0.0366
Mean angular error over validation epoch 139: 4.776438461764609

Mean training loss for Epoch [140/175]: 0.0189
Mean angular error over training epoch 140: 2.279558495996105
Mean validation loss for Epoch [140/175]: 0.0361
Mean angular error over validation epoch 140: 4.671911164165089

Mean training loss for Epoch [141/175]: 0.0183
Mean angular error over training epoch 141: 2.1807664745718522
Mean validation loss for Epoch [141/175]: 0.0370
Mean angular error over validation epoch 141: 4.789364314118993

Mean training loss for Epoch [142/175]: 0.0185
Mean angular error over training epoch 142: 2.199513412590019
Mean validation loss for Epoch [142/175]: 0.0361
Mean angular error over validation epoch 142: 5.002273491793978

Mean training loss for Epoch [143/175]: 0.0191
Mean angular error over training epoch 143: 2.2922619204741705
Mean validation loss for Epoch [143/175]: 0.0371
Mean angular error over validation epoch 143: 5.055379051986012

Mean training loss for Epoch [144/175]: 0.0185
Mean angular error over training epoch 144: 2.21633503336555
Mean validation loss for Epoch [144/175]: 0.0413
Mean angular error over validation epoch 144: 4.986032200389594

Mean training loss for Epoch [145/175]: 0.0203
Mean angular error over training epoch 145: 2.43370382277116
Mean validation loss for Epoch [145/175]: 0.0356
Mean angular error over validation epoch 145: 4.74209025049744

Mean training loss for Epoch [146/175]: 0.0193
Mean angular error over training epoch 146: 2.2969065858298796
Mean validation loss for Epoch [146/175]: 0.0406
Mean angular error over validation epoch 146: 4.8046158236423215

Mean training loss for Epoch [147/175]: 0.0170
Mean angular error over training epoch 147: 2.03409260866471
```
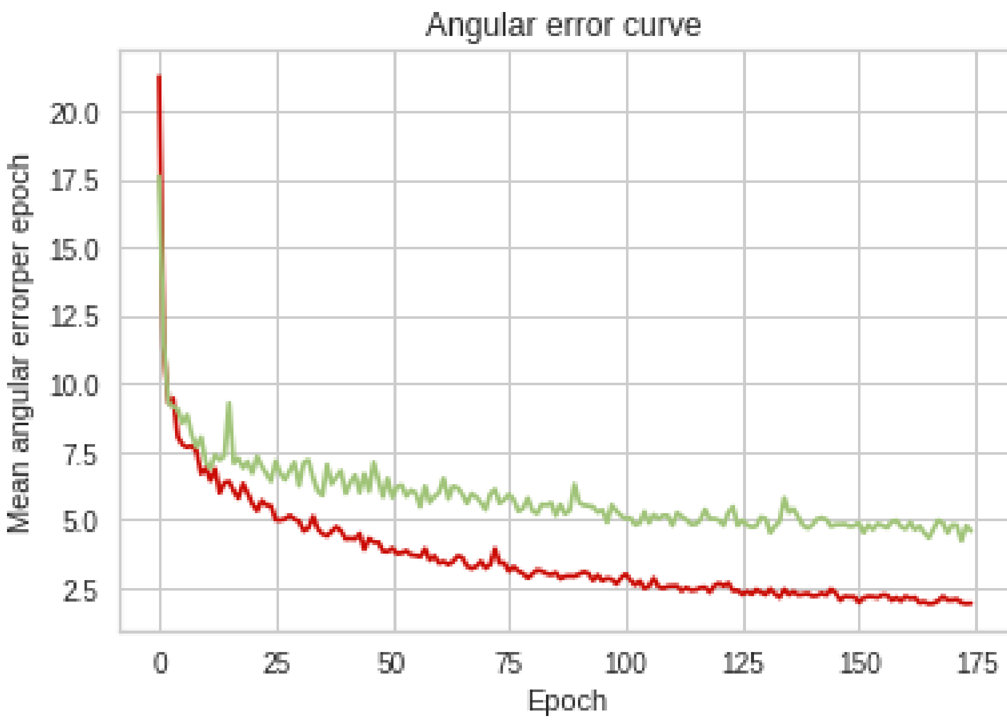

```
Mean validation loss for Epoch [147/175]: 0.0409
Mean angular error over validation epoch 147: 4.805169772093434

Mean training loss for Epoch [148/175]: 0.0182
Mean angular error over training epoch 148: 2.1775782469844156
Mean validation loss for Epoch [148/175]: 0.0362
Mean angular error over validation epoch 148: 4.820814021436956

Mean training loss for Epoch [149/175]: 0.0178
Mean angular error over training epoch 149: 2.1507623833977587
Mean validation loss for Epoch [149/175]: 0.0387
Mean angular error over validation epoch 149: 4.7372485292811675

Mean training loss for Epoch [150/175]: 0.0182
Mean angular error over training epoch 150: 2.1598319606174425
Mean validation loss for Epoch [150/175]: 0.0366
Mean angular error over validation epoch 150: 4.759170227603258


Mean training loss for Epoch [151/175]: 0.0162
Mean angular error over training epoch 151: 1.9503209421822407
Mean validation loss for Epoch [151/175]: 0.0359
Mean angular error over validation epoch 151: 4.864414514976047

Mean training loss for Epoch [152/175]: 0.0179
Mean angular error over training epoch 152: 2.1163365222479436
Mean validation loss for Epoch [152/175]: 0.0341
Mean angular error over validation epoch 152: 4.505461255251409

Mean training loss for Epoch [153/175]: 0.0182
Mean angular error over training epoch 153: 2.1733836137893845
Mean validation loss for Epoch [153/175]: 0.0382
Mean angular error over validation epoch 153: 4.801351398325638

Mean training loss for Epoch [154/175]: 0.0180
Mean angular error over training epoch 154: 2.160513295916749
Mean validation loss for Epoch [154/175]: 0.0343
Mean angular error over validation epoch 154: 4.62494885420292

Mean training loss for Epoch [155/175]: 0.0177
Mean angular error over training epoch 155: 2.1250832130771324
Mean validation loss for Epoch [155/175]: 0.0362
Mean angular error over validation epoch 155: 4.83170531384536

Mean training loss for Epoch [156/175]: 0.0186
Mean angular error over training epoch 156: 2.2273115907452747
Mean validation loss for Epoch [156/175]: 0.0415
Mean angular error over validation epoch 156: 4.767701899547587
```

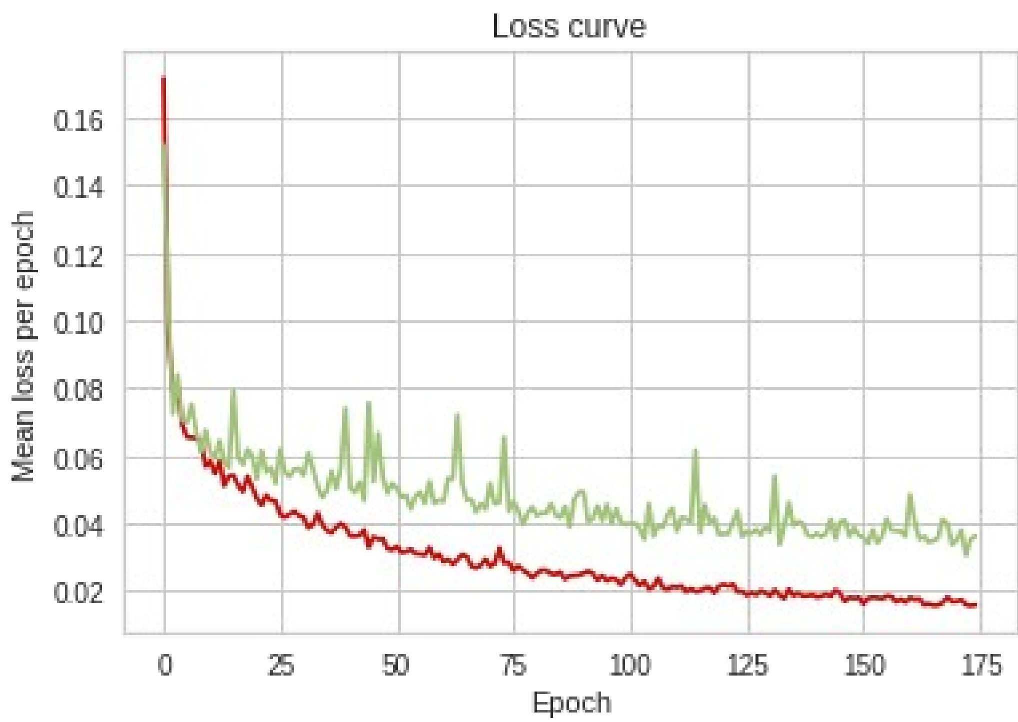
```
Mean training loss for Epoch [157/175]: 0.0184
Mean angular error over training epoch 157: 2.22011929167499
Mean validation loss for Epoch [157/175]: 0.0380
Mean angular error over validation epoch 157: 4.690099506035681

Mean training loss for Epoch [158/175]: 0.0168
Mean angular error over training epoch 158: 2.0292637353364245
Mean validation loss for Epoch [158/175]: 0.0378
Mean angular error over validation epoch 158: 4.905596095536535

Mean training loss for Epoch [159/175]: 0.0176
Mean angular error over training epoch 159: 2.1224004775953613
Mean validation loss for Epoch [159/175]: 0.0378
Mean angular error over validation epoch 159: 4.953398175550426

Mean training loss for Epoch [160/175]: 0.0167
Mean angular error over training epoch 160: 2.0064739283411055
Mean validation loss for Epoch [160/175]: 0.0362
Mean angular error over validation epoch 160: 4.729756732314091

Mean training loss for Epoch [161/175]: 0.0181
Mean angular error over training epoch 161: 2.1727050555127407
Mean validation loss for Epoch [161/175]: 0.0484
Mean angular error over validation epoch 161: 4.64409013018048

Mean training loss for Epoch [162/175]: 0.0175
Mean angular error over training epoch 162: 2.0950194099808757
Mean validation loss for Epoch [162/175]: 0.0404
Mean angular error over validation epoch 162: 4.883304144935871

Mean training loss for Epoch [163/175]: 0.0177
Mean angular error over training epoch 163: 2.1256747650018792
Mean validation loss for Epoch [163/175]: 0.0353
Mean angular error over validation epoch 163: 4.614367110434717

Mean training loss for Epoch [164/175]: 0.0160
Mean angular error over training epoch 164: 1.9348239773986389
Mean validation loss for Epoch [164/175]: 0.0363
Mean angular error over validation epoch 164: 4.744083426025331

Mean training loss for Epoch [165/175]: 0.0163
Mean angular error over training epoch 165: 1.9745414360319982
Mean validation loss for Epoch [165/175]: 0.0345
Mean angular error over validation epoch 165: 4.499351935559416

Mean training loss for Epoch [166/175]: 0.0158
Mean angular error over training epoch 166: 1.8960874641725773
Mean validation loss for Epoch [166/175]: 0.0350
Mean angular error over validation epoch 166: 4.318411850609046
```

```
Mean training loss for Epoch [167/175]: 0.0159
Mean angular error over training epoch 167: 1.9166100296302444
Mean validation loss for Epoch [167/175]: 0.0357
Mean angular error over validation epoch 167: 4.633293023476164

Mean training loss for Epoch [168/175]: 0.0167
Mean angular error over training epoch 168: 2.0119124722901316
Mean validation loss for Epoch [168/175]: 0.0413
Mean angular error over validation epoch 168: 4.965793691163492

Mean training loss for Epoch [169/175]: 0.0182
Mean angular error over training epoch 169: 2.1717410820749934
Mean validation loss for Epoch [169/175]: 0.0400
Mean angular error over validation epoch 169: 4.856014959220673

Mean training loss for Epoch [170/175]: 0.0169
Mean angular error over training epoch 170: 2.0341731037960487
Mean validation loss for Epoch [170/175]: 0.0337
Mean angular error over validation epoch 170: 4.4990176139272835

Mean training loss for Epoch [171/175]: 0.0170
Mean angular error over training epoch 171: 2.0370287667544615
Mean validation loss for Epoch [171/175]: 0.0351
Mean angular error over validation epoch 171: 4.790230245550577

Mean training loss for Epoch [172/175]: 0.0174
Mean angular error over training epoch 172: 2.067341779122165
Mean validation loss for Epoch [172/175]: 0.0381
Mean angular error over validation epoch 172: 4.780920419525932

Mean training loss for Epoch [173/175]: 0.0160
Mean angular error over training epoch 173: 1.9348085114175428
Mean validation loss for Epoch [173/175]: 0.0306
Mean angular error over validation epoch 173: 4.210571265917752

Mean training loss for Epoch [174/175]: 0.0157
Mean angular error over training epoch 174: 1.9020756274296367
Mean validation loss for Epoch [174/175]: 0.0355
Mean angular error over validation epoch 174: 4.758033723792855

Mean training loss for Epoch [175/175]: 0.0160
Mean angular error over training epoch 175: 1.9170938418279306
Mean validation loss for Epoch [175/175]: 0.0363
Mean angular error over validation epoch 175: 4.5748866859581785
```

```
plt.title("Angular error curve")
plt.plot(range(len(training_ang_errors)),training_ang_errors,'r')
```

```
plt.plot(range(len(validation_ang_errors)),validation_ang_errors,'g')
plt.xlabel("Epoch")
plt.ylabel("Mean angular errorper epoch")
plt.show()

plt.title("Loss curve")
plt.plot(range(len(training_losses)),training_losses,'r')
plt.plot(range(len(validation_losses)),validation_losses,'g')
plt.xlabel("Epoch")
plt.ylabel("Mean loss per epoch")
plt.show()
```





Save the model when good enough

```
torch.save(model.state_dict(), os.path.join(ass_path,
'question_3_weights'))
```

Hyper-parameter tuning

By studying the graphs produced during the training of my model, I have tuned the hyper-parameters in order to reach a point of reasonable convergence comfortably below the 10% angular mean error requested for the assessment.

As we can see, the model successfully converges with a reasonable amount of generalization error at around 5% mean angular loss for the validation set. While the training set mean angular error continues to decrease the more I train it, this would indicate the possibility of the model learning and overfitting towards the training data. Since the amount of data provided is not sufficiently large, this cannot be verified. I have chosen to only train the model for this number of epochs in order to avoid accidentally overfitting and hurting the generalization strength of the model.

Since the model has fulfilled every requirement stated by the assessment with a comfortable margin of error, it has proven itself to not need further tuning and is good enough for submission.

Evaluation segment

```
# Load weights from pre-trained model
model.load_state_dict(torch.load(os.path.join(ass_path,
'question_3_weights'),
                                  map_location=torch.device(device)))
```

```
<All keys matched successfully>
```

```
# Load assessment testing data onto test_loader
test_folder_name = "validate/"
transform = T.Resize(30)
test_data = LightSourceDataset(os.path.join(ass_path,
test_folder_name),
                               os.path.join(ass_path,
test_folder_name, 'labels.csv'),
                               transform=transform)
batch_size=50
test_loader = torch.utils.data.DataLoader(test_data,
batch_size=batch_size,
                                            shuffle=True,
num_workers=1)

# Run a validation cycle for one epoch over the loaded testing data
num_epochs = 1
val_cycle(0, test_loader)
```

```
Mean validation loss for Epoch [1/1]: 0.0357
Mean angular error over validation epoch 1: 4.574895904211679
```

Question 4

Set up gan data and dataloaders

```
# Create a gan_data directory in order to create a dataset with both
test and validation
# images. Since GANs do not need a validation set of data, this will
allow us to improve its
# performance at no cost
directory = "gan_data"
path = os.path.join(ass_path, directory)
if not os.path.exists(path):
    os.mkdir(path)

train_images = sorted(glob.glob(os.path.join(ass_path,
"train/*.jpg")))
val_images =
sorted(glob.glob(os.path.join(ass_path,"validate/*.jpg")))
gan_images = train_images + val_images

# If the directory is already contains all of the images and the
labels file,
# ignore
if len(os.listdir(path)) != len(gan_images)+1:
    for im_name in gan_images:
        shutil.copy2(os.path.join(im_name), path)
```

```
    # Concatenate csv files into a new merged csv file to facilitate
dataloader implementation
    csv1 = os.path.join(ass_path,"train/labels.csv")
    csv2 = os.path.join(ass_path, "validate/labels.csv")
    df1 = pd.read_csv(csv1, header=None)
    df2 = pd.read_csv(csv2, header=None)
    df_merged = pd.concat([df1, df2], ignore_index=True)
    df_merged.to_csv(os.path.join(ass_path,"gan_data/labels.csv"),
index=False, header=None)

images, labels = next(iter(train_loader))
print(images[0].size())
output = model(images)
print(output.shape)
loss = loss_func(output,labels)
print(loss)# Create a composition of transformations preprocess the
data with
batch_size = 50
trans1=T.Resize(40)
transform = T.Compose([trans1])

# Pass the new gan_data folder into the custom LightSourceDataset
gan_train_data = LightSourceDataset(os.path.join(ass_path,
"gan_data"),

os.path.join(ass_path,"gan_data/labels.csv"),
                                    transform=transform)

# Pass the gan dataset into a trainloader to faciliate training
gan_train_loader = torch.utils.data.DataLoader(gan_train_data,
batch_size=batch_size,
                                               shuffle=True,
num_workers=1)

torch.Size([1, 36, 30])
torch.Size([50, 3])
tensor(0.0079, grad_fn=<L1LossBackward0>)
```

Network architecture

Loss function

Since GANs work by applying a binary real or fake classification to its features, I will be using the appropriate BCELoss function to carry out this task.

Depth and layer shapes

I modelled the structure of the generator along with the discriminator according to the aspect ratio of my data.

For the discriminator, I followed a basic structure where I halved the resolution each layer by using a kernel size of 4, a stride of 2 and a padding of 1 (an industry standard approach) until I reached the final layer. Here I used a rectangular kernel to fully reduce the resolution.

For the generator, I followed the same approach but mirrored. I used the first layer to set the aspect ratio of the resolution I wanted to generate with a rectangular kernel, and continued with the standard approach of a kernel size of 4, a stride of 2 and a padding of 1 to double the resolution until it reached the same resolution as my training data.

4 layers appeared to be a good balance for both the generator and the discriminator. For the generator, it meant that there weren't too many filters which would harm the quality of images it produced. For the discriminator, it offered enough complexity to be able to effectively classify the images it was fed. The number of layers was found through experimentation, training and evaluation.

In between layers

By applying the batch-normalization, along with the ReLU non-linearity to each of my layers, I have managed to stabilize the architecture.

Batch normalization will allow us to combat the vanishing gradient problem and help with low value signals.

LeakyReLU will allow me to add non-linearity to my layers as well as combat the issue of sparse gradients.

The output of the generator goes through a tanh function in order to normalize the image data between -1 and 1.

The ouptut of the discriminator is sigmoid in order to provide a binary prediction value on the fakeness of the image.

```
nz = 100 # Size of latent vector
ngf = 64 # Size of feature maps in generator
ndf = 64 # Size of feature maps in discriminator

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.main = nn.Sequential(
            nn.Conv2d(1, ndf, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf, ndf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 2),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf * 2, ndf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 4),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf * 4, 1, (6,5), 1, 0, bias=False),
```

```
            nn.Sigmoid()
        )

    def forward(self, x):
        x = self.main(x)
        return x

netD = Discriminator()
netD = netD.to(device)

class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.main = nn.Sequential(
            nn.ConvTranspose2d( nz, ngf * 4, (6,5), 1, 0, bias=False),
            nn.BatchNorm2d(ngf * 4),
            nn.ReLU(True),
            nn.ConvTranspose2d(ngf * 4, ngf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 2),
            nn.ReLU(True),
            nn.ConvTranspose2d(ngf * 2, ngf, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf),
            nn.ReLU(True),
            nn.ConvTranspose2d( ngf, 1, 4, 2, 1, bias=False),
            nn.Tanh()
        )

    def forward(self, x):
        x = self.main(x)
        return x

netG = Generator()
netG = netG.to(device)
```

Training loop

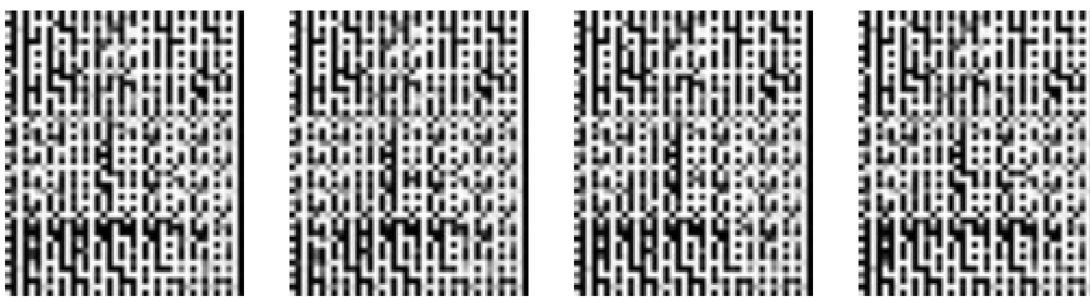
```
num_epochs = 1000

loss_func_gan = nn.BCELoss()

real_label = 1.
fake_label = 0.

optimD = torch.optim.Adam(netD.parameters(), lr=0.001)
optimG = torch.optim.Adam(netG.parameters(), lr=0.001)

print("starting training loop...")

for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(gan_train_loader):
```

```
        real_images = images.to(device)

        # Create fake labels of length of actual labels from the
original dataset. Avoids
        # mismatch between output and label sizes since the batch size
is not a perfect
        # multiple of the training data
        label = torch.full((len(labels),), real_label,
dtype=torch.float, device = device)

        # Train discriminator on real images
        output = netD(real_images).view(-1)
        netD.zero_grad()
        errD_real = loss_func_gan(output, label)
        errD_real.backward()
        D_x = output.mean().item()

        # Train discrimnator on fake images
        z = torch.randn(len(labels), nz, 1, 1, device=device)
        fake = netG(z)
        label.fill_(fake_label)
        output = netD(fake.detach()).view(-1)
        errD_fake = loss_func_gan(output, label)
        errD_fake.backward()
        D_G_z1 = output.mean().item()
        errD = errD_real + errD_fake
        optimD.step()

        #############

        # Train generator adversarially against the discriminator
        netG.zero_grad()
        label.fill_(real_label)
        output = netD(fake).view(-1)
        errG = loss_func_gan(output, label)
        errG.backward()
        D_G_z2 = output.mean().item()
        optimG.step()

        # Print progress every 20 iterations
        if i % 20 == 0:
            print('[%d/%d][%d/%d]\tLoss_D: %.4f\tLoss_G: %.4f\tD(x):
%.4f\tD(G(z)): %.4f / %.4f'
                % (epoch+1, num_epochs, i, len(gan_train_loader),
                    errD.item(), errG.item(), D_x, D_G_z1, D_G_z2))

    # Every 10 epochs print an image of generated by the generator
    if (epoch+1) % 10 == 0:
        z = torch.randn(25,nz,1,1,device=device)
        cols, rows = 4, 1
```

```
        images = netG(z)
        figure = plt.figure(figsize=(9, 6))
        for i in range(4):
            figure.add_subplot(rows, cols, i+1)
            plt.axis("off")
            plt.imshow(images[i,:].cpu().detach().squeeze(),
cmap="gray")
        plt.show()
```

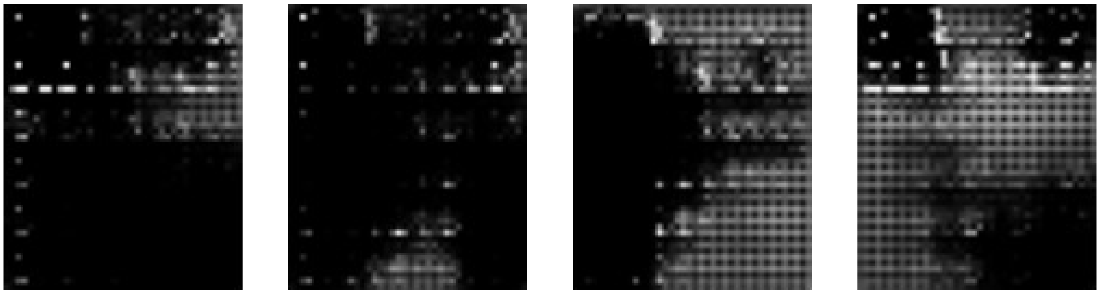
```
starting training loop...
[1/1000][0/42]  Loss_D: 1.4568  Loss_G: 4.3168  D(x): 0.5090
     D(G(z)): 0.5320 / 0.0148
[1/1000][20/42] Loss_D: 0.0140  Loss_G: 10.5774 D(x): 0.9912
     D(G(z)): 0.0050 / 0.0000
[1/1000][40/42] Loss_D: 0.0039  Loss_G: 11.9563 D(x): 0.9965
     D(G(z)): 0.0004 / 0.0000
[2/1000][0/42]  Loss_D: 0.0031  Loss_G: 14.7855 D(x): 0.9970
     D(G(z)): 0.0000 / 0.0000
[2/1000][20/42] Loss_D: 0.0074  Loss_G: 11.8183 D(x): 0.9941
     D(G(z)): 0.0008 / 0.0000
[2/1000][40/42] Loss_D: 0.0022  Loss_G: 11.5357 D(x): 0.9979
     D(G(z)): 0.0001 / 0.0000
[3/1000][0/42]  Loss_D: 0.0136  Loss_G: 8.0143  D(x): 0.9969
     D(G(z)): 0.0102 / 0.0006
[3/1000][20/42] Loss_D: 0.0005  Loss_G: 16.9702 D(x): 0.9995
     D(G(z)): 0.0000 / 0.0000
[3/1000][40/42] Loss_D: 0.0020  Loss_G: 9.7854  D(x): 0.9989
     D(G(z)): 0.0009 / 0.0001
[4/1000][0/42]  Loss_D: 0.0022  Loss_G: 9.1535  D(x): 0.9993
     D(G(z)): 0.0014 / 0.0001
[4/1000][20/42] Loss_D: 0.0106  Loss_G: 12.8859 D(x): 0.9909
     D(G(z)): 0.0012 / 0.0000
[4/1000][40/42] Loss_D: 0.0002  Loss_G: 9.9776  D(x): 1.0000
     D(G(z)): 0.0001 / 0.0001
[5/1000][0/42]  Loss_D: 0.0230  Loss_G: 7.7083  D(x): 0.9997
     D(G(z)): 0.0216 / 0.0008
[5/1000][20/42] Loss_D: 0.0005  Loss_G: 10.3653 D(x): 0.9998
     D(G(z)): 0.0003 / 0.0003
[5/1000][40/42] Loss_D: 0.0024  Loss_G: 8.6543  D(x): 0.9994
     D(G(z)): 0.0018 / 0.0007
[6/1000][0/42]  Loss_D: 0.0122  Loss_G: 8.6104  D(x): 0.9996
     D(G(z)): 0.0111 / 0.0007
[6/1000][20/42] Loss_D: 0.0073  Loss_G: 8.6696  D(x): 0.9997
     D(G(z)): 0.0069 / 0.0008
[6/1000][40/42] Loss_D: 0.0033  Loss_G: 9.6034  D(x): 0.9989
     D(G(z)): 0.0022 / 0.0004
[7/1000][0/42]  Loss_D: 0.0026  Loss_G: 9.6096  D(x): 0.9997
     D(G(z)): 0.0023 / 0.0004
[7/1000][20/42] Loss_D: 0.0008  Loss_G: 14.8401 D(x): 0.9993
     D(G(z)): 0.0000 / 0.0000
```

```
[7/1000][40/42] Loss_D: 0.0009  Loss_G: 9.0251  D(x): 0.9998
      D(G(z)): 0.0007 / 0.0002
[8/1000][0/42]  Loss_D: 0.0012  Loss_G: 9.3262  D(x): 0.9997
      D(G(z)): 0.0009 / 0.0002
[8/1000][20/42] Loss_D: 0.0003  Loss_G: 10.9923 D(x): 0.9997
      D(G(z)): 0.0001 / 0.0000
[8/1000][40/42] Loss_D: 0.0007  Loss_G: 9.4829  D(x): 0.9998
      D(G(z)): 0.0005 / 0.0001
[9/1000][0/42]  Loss_D: 0.0011  Loss_G: 9.5270  D(x): 0.9993
      D(G(z)): 0.0005 / 0.0001
[9/1000][20/42] Loss_D: 0.0010  Loss_G: 10.2005 D(x): 0.9997
      D(G(z)): 0.0007 / 0.0001
[9/1000][40/42] Loss_D: 0.0004  Loss_G: 10.0159 D(x): 0.9998
      D(G(z)): 0.0002 / 0.0001
[10/1000][0/42] Loss_D: 0.0003  Loss_G: 10.0730 D(x): 0.9999
      D(G(z)): 0.0002 / 0.0001
[10/1000][20/42]Loss_D: 0.0002  Loss_G: 10.0171 D(x): 0.9998
      D(G(z)): 0.0001 / 0.0001
[10/1000][40/42]Loss_D: 0.0007  Loss_G: 9.7183  D(x): 0.9995
      D(G(z)): 0.0002 / 0.0001
```



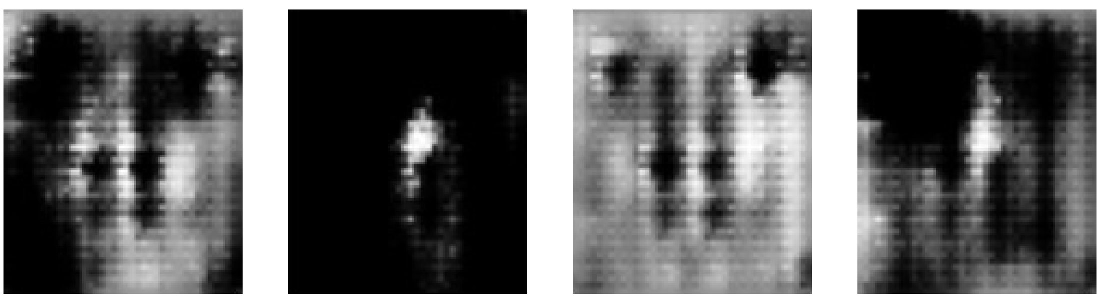
```
[11/1000][0/42] Loss_D: 0.0005  Loss_G: 9.6171  D(x): 0.9997
      D(G(z)): 0.0002 / 0.0001
[11/1000][20/42]Loss_D: 0.0005  Loss_G: 9.2581  D(x): 0.9999
      D(G(z)): 0.0004 / 0.0001
[11/1000][40/42]Loss_D: 0.0005  Loss_G: 9.1686  D(x): 0.9999
      D(G(z)): 0.0004 / 0.0001
[12/1000][0/42] Loss_D: 0.0004  Loss_G: 9.3464  D(x): 0.9999
      D(G(z)): 0.0003 / 0.0001
[12/1000][20/42]Loss_D: 0.0005  Loss_G: 8.6779  D(x): 0.9998
      D(G(z)): 0.0004 / 0.0002
[12/1000][40/42]Loss_D: 0.0004  Loss_G: 9.2329  D(x): 0.9999
      D(G(z)): 0.0002 / 0.0001
[13/1000][0/42] Loss_D: 0.0004  Loss_G: 9.4821  D(x): 0.9998
      D(G(z)): 0.0002 / 0.0001
[13/1000][20/42]Loss_D: 0.0002  Loss_G: 9.9239  D(x): 0.9999
      D(G(z)): 0.0001 / 0.0001
[13/1000][40/42]Loss_D: 0.0031  Loss_G: 7.8922  D(x): 0.9996
      D(G(z)): 0.0028 / 0.0004
[14/1000][0/42] Loss_D: 0.0017  Loss_G: 9.8798  D(x): 0.9995
```

```
      D(G(z)): 0.0011 / 0.0001
[14/1000][20/42] Loss_D: 0.0004  Loss_G: 9.3082  D(x): 0.9999
      D(G(z)): 0.0002 / 0.0001
[14/1000][40/42] Loss_D: 0.0009  Loss_G: 8.8149  D(x): 0.9997
      D(G(z)): 0.0006 / 0.0002
[15/1000][0/42]  Loss_D: 0.0009  Loss_G: 8.8176  D(x): 0.9998
      D(G(z)): 0.0007 / 0.0002
[15/1000][20/42] Loss_D: 0.0010  Loss_G: 9.1425  D(x): 0.9995
      D(G(z)): 0.0005 / 0.0001
[15/1000][40/42] Loss_D: 0.0005  Loss_G: 9.6556  D(x): 0.9999
      D(G(z)): 0.0003 / 0.0001
[16/1000][0/42]  Loss_D: 0.0009  Loss_G: 9.0724  D(x): 0.9997
      D(G(z)): 0.0006 / 0.0001
[16/1000][20/42] Loss_D: 0.0005  Loss_G: 8.8621  D(x): 0.9999
      D(G(z)): 0.0004 / 0.0002
[16/1000][40/42] Loss_D: 0.0004  Loss_G: 9.4514  D(x): 0.9998
      D(G(z)): 0.0002 / 0.0001
[17/1000][0/42]  Loss_D: 0.0004  Loss_G: 9.1306  D(x): 0.9999
      D(G(z)): 0.0003 / 0.0001
[17/1000][20/42] Loss_D: 0.0002  Loss_G: 10.1611 D(x): 0.9999
      D(G(z)): 0.0002 / 0.0000
[17/1000][40/42] Loss_D: 0.0008  Loss_G: 8.2520  D(x): 0.9999
      D(G(z)): 0.0007 / 0.0003
[18/1000][0/42]  Loss_D: 0.0010  Loss_G: 8.8594  D(x): 0.9999
      D(G(z)): 0.0009 / 0.0002
[18/1000][20/42] Loss_D: 0.0027  Loss_G: 9.8651  D(x): 0.9974
      D(G(z)): 0.0001 / 0.0001
[18/1000][40/42] Loss_D: 0.0763  Loss_G: 14.6675 D(x): 0.9996
      D(G(z)): 0.0533 / 0.0000
[19/1000][0/42]  Loss_D: 0.1130  Loss_G: 12.7894 D(x): 0.9249
      D(G(z)): 0.0000 / 0.0001
[19/1000][20/42] Loss_D: 0.0091  Loss_G: 12.5535 D(x): 0.9930
      D(G(z)): 0.0008 / 0.0006
[19/1000][40/42] Loss_D: 0.0618  Loss_G: 12.9399 D(x): 0.9784
      D(G(z)): 0.0069 / 0.0007
[20/1000][0/42]  Loss_D: 0.0193  Loss_G: 12.7704 D(x): 0.9887
      D(G(z)): 0.0059 / 0.0072
[20/1000][20/42] Loss_D: 0.0054  Loss_G: 11.4937 D(x): 0.9953
      D(G(z)): 0.0005 / 0.0004
[20/1000][40/42] Loss_D: 0.0037  Loss_G: 17.6702 D(x): 0.9967
      D(G(z)): 0.0002 / 0.0000
```



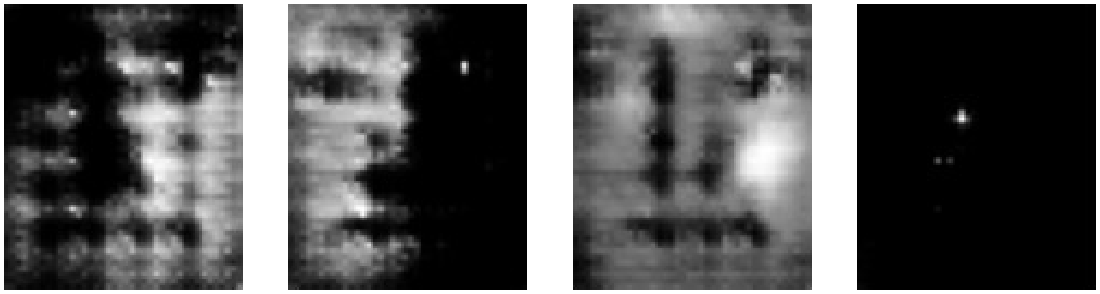
```
[21/1000][0/42] Loss_D: 0.0174  Loss_G: 13.7712 D(x): 0.9848
     D(G(z)): 0.0008 / 0.0004
[21/1000][20/42]Loss_D: 0.0018  Loss_G: 14.6751 D(x): 0.9983
     D(G(z)): 0.0000 / 0.0000
[21/1000][40/42]Loss_D: 0.0159  Loss_G: 12.6482 D(x): 0.9934
     D(G(z)): 0.0088 / 0.0001
[22/1000][0/42] Loss_D: 0.0685  Loss_G: 10.8246 D(x): 0.9474
     D(G(z)): 0.0002 / 0.0004
[22/1000][20/42]Loss_D: 0.0448  Loss_G: 7.3390  D(x): 0.9845
     D(G(z)): 0.0202 / 0.0062
[22/1000][40/42]Loss_D: 0.0191  Loss_G: 8.1380  D(x): 0.9992
     D(G(z)): 0.0174 / 0.0014
[23/1000][0/42] Loss_D: 0.0285  Loss_G: 9.1442  D(x): 0.9891
     D(G(z)): 0.0128 / 0.0010
[23/1000][20/42]Loss_D: 0.0048  Loss_G: 13.6665 D(x): 0.9954
     D(G(z)): 0.0002 / 0.0000
[23/1000][40/42]Loss_D: 0.0314  Loss_G: 10.3814 D(x): 0.9741
     D(G(z)): 0.0019 / 0.0003
[24/1000][0/42] Loss_D: 0.0126  Loss_G: 9.4139  D(x): 0.9971
     D(G(z)): 0.0093 / 0.0022
[24/1000][20/42]Loss_D: 0.0177  Loss_G: 8.8471  D(x): 0.9891
     D(G(z)): 0.0060 / 0.0051
[24/1000][40/42]Loss_D: 0.0262  Loss_G: 13.1875 D(x): 0.9789
     D(G(z)): 0.0026 / 0.0010
[25/1000][0/42] Loss_D: 0.3737  Loss_G: 11.2328 D(x): 0.8099
     D(G(z)): 0.0034 / 0.0006
[25/1000][20/42]Loss_D: 0.1726  Loss_G: 13.7488 D(x): 0.9245
     D(G(z)): 0.0008 / 0.0001
[25/1000][40/42]Loss_D: 0.0252  Loss_G: 12.1227 D(x): 0.9987
     D(G(z)): 0.0178 / 0.0001
[26/1000][0/42] Loss_D: 0.0034  Loss_G: 16.1067 D(x): 0.9967
     D(G(z)): 0.0000 / 0.0000
[26/1000][20/42]Loss_D: 0.0316  Loss_G: 11.7796 D(x): 0.9742
     D(G(z)): 0.0012 / 0.0001
[26/1000][40/42]Loss_D: 0.0433  Loss_G: 10.4049 D(x): 0.9748
     D(G(z)): 0.0152 / 0.0013
[27/1000][0/42] Loss_D: 0.0404  Loss_G: 7.0424  D(x): 0.9678
     D(G(z)): 0.0045 / 0.0057
[27/1000][20/42]Loss_D: 0.1495  Loss_G: 9.3241  D(x): 0.9110
     D(G(z)): 0.0031 / 0.0069
```

```
[27/1000][40/42] Loss_D: 0.0091  Loss_G: 9.3441  D(x): 0.9993
      D(G(z)): 0.0080 / 0.0007
[28/1000][0/42]  Loss_D: 0.0277  Loss_G: 11.0844 D(x): 0.9848
      D(G(z)): 0.0039 / 0.0014
[28/1000][20/42] Loss_D: 0.2643  Loss_G: 10.5142 D(x): 0.9148
      D(G(z)): 0.0727 / 0.0007
[28/1000][40/42] Loss_D: 0.0381  Loss_G: 8.6912  D(x): 0.9767
      D(G(z)): 0.0120 / 0.0028
[29/1000][0/42]  Loss_D: 0.0209  Loss_G: 11.2188 D(x): 0.9917
      D(G(z)): 0.0115 / 0.0008
[29/1000][20/42] Loss_D: 0.0145  Loss_G: 12.9837 D(x): 0.9988
      D(G(z)): 0.0125 / 0.0048
[29/1000][40/42] Loss_D: 0.0888  Loss_G: 11.1167 D(x): 0.9855
      D(G(z)): 0.0306 / 0.0143
[30/1000][0/42]  Loss_D: 0.1912  Loss_G: 11.8888 D(x): 0.9285
      D(G(z)): 0.0082 / 0.0007
[30/1000][20/42] Loss_D: 0.2435  Loss_G: 7.3833  D(x): 0.9881
      D(G(z)): 0.1021 / 0.0222
[30/1000][40/42] Loss_D: 0.1025  Loss_G: 13.6058 D(x): 0.9487
      D(G(z)): 0.0008 / 0.0081
```



```
[31/1000][0/42]  Loss_D: 0.0319  Loss_G: 11.3500 D(x): 0.9898
      D(G(z)): 0.0152 / 0.0183
[31/1000][20/42] Loss_D: 0.3017  Loss_G: 11.2952 D(x): 0.9681
      D(G(z)): 0.0944 / 0.0232
[31/1000][40/42] Loss_D: 0.2443  Loss_G: 7.6327  D(x): 0.9195
      D(G(z)): 0.0615 / 0.0241
[32/1000][0/42]  Loss_D: 0.0360  Loss_G: 10.4929 D(x): 0.9788
      D(G(z)): 0.0109 / 0.0006
[32/1000][20/42] Loss_D: 0.0291  Loss_G: 10.8275 D(x): 0.9937
      D(G(z)): 0.0190 / 0.0121
[32/1000][40/42] Loss_D: 0.0639  Loss_G: 12.1649 D(x): 0.9635
      D(G(z)): 0.0126 / 0.0009
[33/1000][0/42]  Loss_D: 0.0628  Loss_G: 11.6383 D(x): 0.9626
      D(G(z)): 0.0072 / 0.0020
[33/1000][20/42] Loss_D: 0.1481  Loss_G: 9.5817  D(x): 0.9568
      D(G(z)): 0.0593 / 0.0026
[33/1000][40/42] Loss_D: 0.1577  Loss_G: 8.4090  D(x): 0.9677
      D(G(z)): 0.0558 / 0.0167
[34/1000][0/42]  Loss_D: 0.0405  Loss_G: 9.6668  D(x): 0.9829
```

```
    D(G(z)): 0.0192 / 0.0042
[34/1000][20/42] Loss_D: 0.1481  Loss_G: 9.0284  D(x): 0.9634
    D(G(z)): 0.0704 / 0.0254
[34/1000][40/42] Loss_D: 0.0727  Loss_G: 8.2189  D(x): 0.9953
    D(G(z)): 0.0576 / 0.0039
[35/1000][0/42]  Loss_D: 0.2466  Loss_G: 11.5024 D(x): 0.9333
    D(G(z)): 0.0705 / 0.0005
[35/1000][20/42] Loss_D: 0.1523  Loss_G: 10.6718 D(x): 0.9450
    D(G(z)): 0.0478 / 0.0018
[35/1000][40/42] Loss_D: 0.0247  Loss_G: 11.0313 D(x): 0.9779
    D(G(z)): 0.0006 / 0.0016
[36/1000][0/42]  Loss_D: 0.1809  Loss_G: 7.1652  D(x): 0.9452
    D(G(z)): 0.0360 / 0.0451
[36/1000][20/42] Loss_D: 0.1152  Loss_G: 7.0106  D(x): 0.9767
    D(G(z)): 0.0605 / 0.0222
[36/1000][40/42] Loss_D: 0.1655  Loss_G: 7.8501  D(x): 0.9704
    D(G(z)): 0.0869 / 0.0052
[37/1000][0/42]  Loss_D: 0.1186  Loss_G: 11.5241 D(x): 0.9230
    D(G(z)): 0.0014 / 0.0001
[37/1000][20/42] Loss_D: 0.0973  Loss_G: 7.1959  D(x): 0.9531
    D(G(z)): 0.0179 / 0.0144
[37/1000][40/42] Loss_D: 0.1154  Loss_G: 11.1401 D(x): 0.9870
    D(G(z)): 0.0325 / 0.0221
[38/1000][0/42]  Loss_D: 0.1127  Loss_G: 11.1090 D(x): 0.9767
    D(G(z)): 0.0415 / 0.0035
[38/1000][20/42] Loss_D: 0.0321  Loss_G: 17.2890 D(x): 0.9726
    D(G(z)): 0.0011 / 0.0001
[38/1000][40/42] Loss_D: 0.5694  Loss_G: 10.7594 D(x): 0.8390
    D(G(z)): 0.0183 / 0.0060
[39/1000][0/42]  Loss_D: 0.5780  Loss_G: 7.8040  D(x): 0.9815
    D(G(z)): 0.2358 / 0.0280
[39/1000][20/42] Loss_D: 0.1412  Loss_G: 9.9342  D(x): 0.9336
    D(G(z)): 0.0058 / 0.0039
[39/1000][40/42] Loss_D: 0.0890  Loss_G: 7.0526  D(x): 0.9988
    D(G(z)): 0.0624 / 0.0499
[40/1000][0/42]  Loss_D: 0.1501  Loss_G: 9.8196  D(x): 0.9893
    D(G(z)): 0.0977 / 0.0045
[40/1000][20/42] Loss_D: 0.1313  Loss_G: 6.0552  D(x): 0.9819
    D(G(z)): 0.0816 / 0.0559
[40/1000][40/42] Loss_D: 0.2831  Loss_G: 10.1043 D(x): 0.8825
    D(G(z)): 0.0075 / 0.0019
```

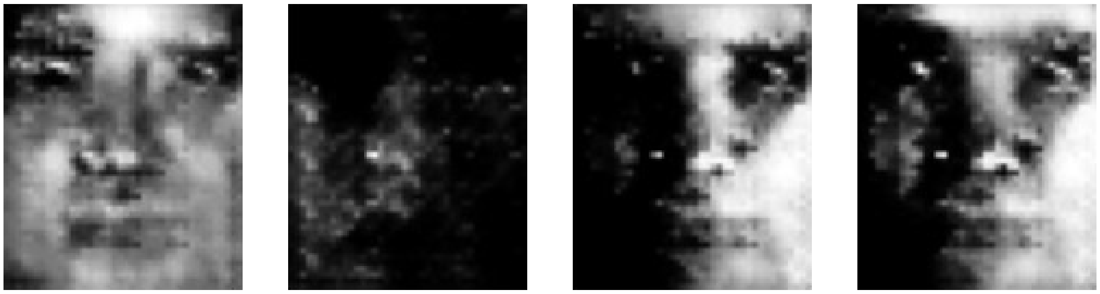


```
[41/1000][0/42] Loss_D: 0.2310  Loss_G: 6.8817  D(x): 0.9378
      D(G(z)): 0.0678 / 0.0560
[41/1000][20/42]Loss_D: 0.1431  Loss_G: 9.8598  D(x): 0.9293
      D(G(z)): 0.0250 / 0.0092
[41/1000][40/42]Loss_D: 0.0218  Loss_G: 9.6607  D(x): 0.9994
      D(G(z)): 0.0193 / 0.0150
[42/1000][0/42] Loss_D: 0.0486  Loss_G: 9.3591  D(x): 0.9976
      D(G(z)): 0.0321 / 0.0056
[42/1000][20/42]Loss_D: 0.0876  Loss_G: 8.0477  D(x): 0.9717
      D(G(z)): 0.0426 / 0.0926
[42/1000][40/42]Loss_D: 0.2141  Loss_G: 9.7148  D(x): 0.9008
      D(G(z)): 0.0305 / 0.0176
[43/1000][0/42] Loss_D: 0.0673  Loss_G: 9.3556  D(x): 0.9811
      D(G(z)): 0.0315 / 0.0034
[43/1000][20/42]Loss_D: 0.1555  Loss_G: 9.5082  D(x): 0.9510
      D(G(z)): 0.0417 / 0.0178
[43/1000][40/42]Loss_D: 0.2643  Loss_G: 7.9200  D(x): 0.9909
      D(G(z)): 0.1091 / 0.0059
[44/1000][0/42] Loss_D: 0.1196  Loss_G: 8.6419  D(x): 0.9599
      D(G(z)): 0.0489 / 0.0088
[44/1000][20/42]Loss_D: 0.5534  Loss_G: 6.3290  D(x): 0.8926
      D(G(z)): 0.1554 / 0.0392
[44/1000][40/42]Loss_D: 0.2469  Loss_G: 6.2644  D(x): 0.9276
      D(G(z)): 0.1033 / 0.0169
[45/1000][0/42] Loss_D: 0.1733  Loss_G: 7.1235  D(x): 0.9621
      D(G(z)): 0.0888 / 0.0173
[45/1000][20/42]Loss_D: 0.1837  Loss_G: 9.9480  D(x): 0.9789
      D(G(z)): 0.0791 / 0.0088
[45/1000][40/42]Loss_D: 0.2359  Loss_G: 9.0062  D(x): 0.9399
      D(G(z)): 0.0073 / 0.0023
[46/1000][0/42] Loss_D: 0.0532  Loss_G: 7.4808  D(x): 0.9938
      D(G(z)): 0.0409 / 0.0041
[46/1000][20/42]Loss_D: 0.5851  Loss_G: 8.4353  D(x): 0.7866
      D(G(z)): 0.0140 / 0.0467
[46/1000][40/42]Loss_D: 0.1172  Loss_G: 10.6535 D(x): 0.9355
      D(G(z)): 0.0013 / 0.0003
[47/1000][0/42] Loss_D: 0.0231  Loss_G: 7.1668  D(x): 0.9843
      D(G(z)): 0.0065 / 0.0055
[47/1000][20/42]Loss_D: 0.2853  Loss_G: 10.0635 D(x): 0.8715
      D(G(z)): 0.0176 / 0.0143
```

```
[47/1000][40/42] Loss_D: 0.3056  Loss_G: 7.6518  D(x): 0.8835
     D(G(z)): 0.0363 / 0.0146
[48/1000][0/42]  Loss_D: 0.2578  Loss_G: 7.8773  D(x): 0.9494
     D(G(z)): 0.1142 / 0.0146
[48/1000][20/42] Loss_D: 0.0559  Loss_G: 10.5960 D(x): 0.9899
     D(G(z)): 0.0324 / 0.0112
[48/1000][40/42] Loss_D: 0.1067  Loss_G: 9.8583  D(x): 0.9258
     D(G(z)): 0.0037 / 0.0008
[49/1000][0/42]  Loss_D: 0.0495  Loss_G: 8.5227  D(x): 0.9701
     D(G(z)): 0.0122 / 0.0058
[49/1000][20/42] Loss_D: 0.1328  Loss_G: 10.0327 D(x): 0.9439
     D(G(z)): 0.0333 / 0.0038
[49/1000][40/42] Loss_D: 0.3744  Loss_G: 7.5863  D(x): 0.9990
     D(G(z)): 0.1913 / 0.0203
[50/1000][0/42]  Loss_D: 0.3489  Loss_G: 11.0831 D(x): 0.8576
     D(G(z)): 0.0062 / 0.0009
[50/1000][20/42] Loss_D: 0.1412  Loss_G: 5.9238  D(x): 0.9810
     D(G(z)): 0.0736 / 0.0592
[50/1000][40/42] Loss_D: 0.2062  Loss_G: 9.8907  D(x): 0.8971
     D(G(z)): 0.0329 / 0.0453
```

```
[51/1000][0/42]  Loss_D: 0.7757  Loss_G: 8.4844  D(x): 0.9236
     D(G(z)): 0.1704 / 0.0386
[51/1000][20/42] Loss_D: 0.0952  Loss_G: 8.0838  D(x): 0.9860
     D(G(z)): 0.0645 / 0.0132
[51/1000][40/42] Loss_D: 0.1724  Loss_G: 7.7417  D(x): 0.9855
     D(G(z)): 0.1129 / 0.0667
[52/1000][0/42]  Loss_D: 0.3335  Loss_G: 8.1656  D(x): 0.9445
     D(G(z)): 0.1034 / 0.0119
[52/1000][20/42] Loss_D: 0.0373  Loss_G: 9.5489  D(x): 0.9788
     D(G(z)): 0.0126 / 0.0021
[52/1000][40/42] Loss_D: 0.0579  Loss_G: 8.0334  D(x): 0.9929
     D(G(z)): 0.0363 / 0.0086
[53/1000][0/42]  Loss_D: 0.2027  Loss_G: 8.8975  D(x): 0.9480
     D(G(z)): 0.0383 / 0.0157
[53/1000][20/42] Loss_D: 0.1822  Loss_G: 10.5819 D(x): 0.9133
     D(G(z)): 0.0114 / 0.0050
[53/1000][40/42] Loss_D: 0.2007  Loss_G: 9.2393  D(x): 0.9194
     D(G(z)): 0.0115 / 0.0036
[54/1000][0/42]  Loss_D: 0.1349  Loss_G: 8.2362  D(x): 0.9605
```

```
    D(G(z)): 0.0384 / 0.0139
[54/1000][20/42] Loss_D: 0.1621  Loss_G: 6.7998  D(x): 0.9647
    D(G(z)): 0.0762 / 0.0177
[54/1000][40/42] Loss_D: 0.0228  Loss_G: 8.8188  D(x): 0.9901
    D(G(z)): 0.0113 / 0.0024
[55/1000][0/42]  Loss_D: 0.0813  Loss_G: 7.3873  D(x): 0.9888
    D(G(z)): 0.0411 / 0.0137
[55/1000][20/42] Loss_D: 0.1759  Loss_G: 10.6894 D(x): 0.9335
    D(G(z)): 0.0330 / 0.0015
[55/1000][40/42] Loss_D: 0.0890  Loss_G: 13.7539 D(x): 0.9764
    D(G(z)): 0.0165 / 0.0274
[56/1000][0/42]  Loss_D: 0.1470  Loss_G: 14.1986 D(x): 0.9980
    D(G(z)): 0.0904 / 0.0202
[56/1000][20/42] Loss_D: 0.2105  Loss_G: 10.6791 D(x): 0.9153
    D(G(z)): 0.0250 / 0.0134
[56/1000][40/42] Loss_D: 0.2225  Loss_G: 10.7695 D(x): 0.9405
    D(G(z)): 0.0690 / 0.0019
[57/1000][0/42]  Loss_D: 0.2623  Loss_G: 13.9886 D(x): 0.8620
    D(G(z)): 0.0017 / 0.0005
[57/1000][20/42] Loss_D: 0.1439  Loss_G: 8.5929  D(x): 0.9919
    D(G(z)): 0.1056 / 0.0132
[57/1000][40/42] Loss_D: 0.2556  Loss_G: 7.1617  D(x): 0.9748
    D(G(z)): 0.1137 / 0.0594
[58/1000][0/42]  Loss_D: 0.2637  Loss_G: 7.8355  D(x): 0.9616
    D(G(z)): 0.1302 / 0.0258
[58/1000][20/42] Loss_D: 0.2337  Loss_G: 7.2598  D(x): 0.9342
    D(G(z)): 0.1041 / 0.0054
[58/1000][40/42] Loss_D: 0.0702  Loss_G: 10.0707 D(x): 0.9861
    D(G(z)): 0.0443 / 0.0183
[59/1000][0/42]  Loss_D: 0.1840  Loss_G: 7.7557  D(x): 0.9580
    D(G(z)): 0.0880 / 0.0141
[59/1000][20/42] Loss_D: 0.2951  Loss_G: 5.6623  D(x): 0.9876
    D(G(z)): 0.1737 / 0.0293
[59/1000][40/42] Loss_D: 0.3407  Loss_G: 7.7071  D(x): 0.8826
    D(G(z)): 0.0962 / 0.0105
[60/1000][0/42]  Loss_D: 0.0883  Loss_G: 8.7242  D(x): 0.9722
    D(G(z)): 0.0454 / 0.0051
[60/1000][20/42] Loss_D: 0.2221  Loss_G: 8.4027  D(x): 0.9456
    D(G(z)): 0.0942 / 0.0163
[60/1000][40/42] Loss_D: 0.2321  Loss_G: 10.4165 D(x): 0.9391
    D(G(z)): 0.0409 / 0.0020
```

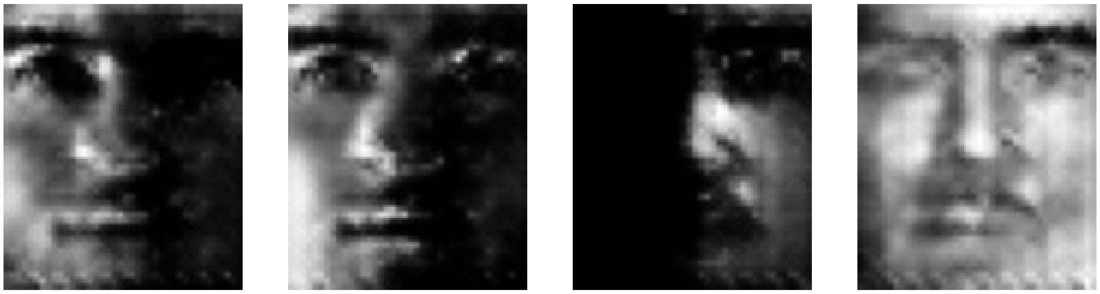


```
[61/1000][0/42] Loss_D: 0.2706  Loss_G: 8.2038  D(x): 0.9035
      D(G(z)): 0.0580 / 0.0409
[61/1000][20/42]Loss_D: 0.3323  Loss_G: 10.0602 D(x): 0.8971
      D(G(z)): 0.0105 / 0.0007
[61/1000][40/42]Loss_D: 0.1630  Loss_G: 7.2454  D(x): 0.9389
      D(G(z)): 0.0446 / 0.0341
[62/1000][0/42] Loss_D: 0.1075  Loss_G: 8.2157  D(x): 0.9956
      D(G(z)): 0.0483 / 0.0200
[62/1000][20/42]Loss_D: 0.2132  Loss_G: 9.2025  D(x): 0.8808
      D(G(z)): 0.0161 / 0.0042
[62/1000][40/42]Loss_D: 0.1108  Loss_G: 10.1915 D(x): 0.9314
      D(G(z)): 0.0028 / 0.0011
[63/1000][0/42] Loss_D: 0.2347  Loss_G: 9.2891  D(x): 0.9459
      D(G(z)): 0.0215 / 0.0198
[63/1000][20/42]Loss_D: 0.1568  Loss_G: 7.8862  D(x): 0.9487
      D(G(z)): 0.0588 / 0.0129
[63/1000][40/42]Loss_D: 0.5598  Loss_G: 9.3008  D(x): 0.7857
      D(G(z)): 0.0124 / 0.0149
[64/1000][0/42] Loss_D: 0.6688  Loss_G: 6.3927  D(x): 0.9330
      D(G(z)): 0.2661 / 0.1040
[64/1000][20/42]Loss_D: 0.1265  Loss_G: 8.4169  D(x): 0.9917
      D(G(z)): 0.0799 / 0.0503
[64/1000][40/42]Loss_D: 0.1346  Loss_G: 11.4886 D(x): 0.9301
      D(G(z)): 0.0105 / 0.0009
[65/1000][0/42] Loss_D: 0.2259  Loss_G: 7.0675  D(x): 0.8850
      D(G(z)): 0.0188 / 0.0447
[65/1000][20/42]Loss_D: 0.1657  Loss_G: 9.1279  D(x): 0.9306
      D(G(z)): 0.0143 / 0.0055
[65/1000][40/42]Loss_D: 0.2638  Loss_G: 8.4036  D(x): 0.9988
      D(G(z)): 0.1271 / 0.0147
[66/1000][0/42] Loss_D: 0.1555  Loss_G: 11.0858 D(x): 0.9118
      D(G(z)): 0.0109 / 0.0005
[66/1000][20/42]Loss_D: 0.5045  Loss_G: 7.2224  D(x): 0.8693
      D(G(z)): 0.0554 / 0.0376
[66/1000][40/42]Loss_D: 0.2460  Loss_G: 7.5522  D(x): 0.9201
      D(G(z)): 0.0291 / 0.0195
[67/1000][0/42] Loss_D: 0.0918  Loss_G: 6.4676  D(x): 0.9950
      D(G(z)): 0.0597 / 0.0192
[67/1000][20/42]Loss_D: 0.3260  Loss_G: 8.3619  D(x): 0.8734
      D(G(z)): 0.0369 / 0.0089
```

```
[67/1000][40/42] Loss_D: 0.3010  Loss_G: 7.8484  D(x): 0.9113
      D(G(z)): 0.1099 / 0.0343
[68/1000][0/42]  Loss_D: 0.3491  Loss_G: 8.0779  D(x): 0.9461
      D(G(z)): 0.0813 / 0.0131
[68/1000][20/42] Loss_D: 0.1368  Loss_G: 7.4169  D(x): 0.9564
      D(G(z)): 0.0454 / 0.0316
[68/1000][40/42] Loss_D: 0.3341  Loss_G: 7.0265  D(x): 0.9883
      D(G(z)): 0.1353 / 0.0434
[69/1000][0/42]  Loss_D: 0.3630  Loss_G: 8.4296  D(x): 0.8448
      D(G(z)): 0.0636 / 0.0153
[69/1000][20/42] Loss_D: 0.0726  Loss_G: 6.5827  D(x): 0.9979
      D(G(z)): 0.0603 / 0.0373
[69/1000][40/42] Loss_D: 0.6156  Loss_G: 4.7257  D(x): 0.8103
      D(G(z)): 0.1087 / 0.1013
[70/1000][0/42]  Loss_D: 0.3015  Loss_G: 6.7070  D(x): 0.9445
      D(G(z)): 0.1207 / 0.0225
[70/1000][20/42] Loss_D: 0.1694  Loss_G: 8.9005  D(x): 0.9897
      D(G(z)): 0.0969 / 0.0059
[70/1000][40/42] Loss_D: 0.1759  Loss_G: 7.2261  D(x): 0.9699
      D(G(z)): 0.0816 / 0.0264
```

```
[71/1000][0/42]  Loss_D: 0.2136  Loss_G: 8.3944  D(x): 0.9700
      D(G(z)): 0.0891 / 0.0327
[71/1000][20/42] Loss_D: 0.3382  Loss_G: 6.0499  D(x): 0.9626
      D(G(z)): 0.1480 / 0.0605
[71/1000][40/42] Loss_D: 0.1685  Loss_G: 6.0932  D(x): 0.9568
      D(G(z)): 0.0803 / 0.0315
[72/1000][0/42]  Loss_D: 0.1124  Loss_G: 8.6544  D(x): 0.9716
      D(G(z)): 0.0563 / 0.0094
[72/1000][20/42] Loss_D: 0.3020  Loss_G: 6.1502  D(x): 0.9770
      D(G(z)): 0.1782 / 0.0288
[72/1000][40/42] Loss_D: 0.2869  Loss_G: 7.8303  D(x): 0.8910
      D(G(z)): 0.0257 / 0.0056
[73/1000][0/42]  Loss_D: 0.3216  Loss_G: 5.2598  D(x): 0.8927
      D(G(z)): 0.0984 / 0.0259
[73/1000][20/42] Loss_D: 0.2351  Loss_G: 6.3896  D(x): 0.8965
      D(G(z)): 0.0621 / 0.0487
[73/1000][40/42] Loss_D: 0.3051  Loss_G: 8.2939  D(x): 0.9475
      D(G(z)): 0.1336 / 0.0232
[74/1000][0/42]  Loss_D: 0.1982  Loss_G: 11.5400 D(x): 0.8741
```

```
     D(G(z)): 0.0031 / 0.0005
[74/1000][20/42] Loss_D: 0.2420  Loss_G: 9.3402  D(x): 0.8875
     D(G(z)): 0.0373 / 0.0113
[74/1000][40/42] Loss_D: 0.4047  Loss_G: 6.6242  D(x): 0.8688
     D(G(z)): 0.0803 / 0.0231
[75/1000][0/42]  Loss_D: 0.4868  Loss_G: 7.2149  D(x): 0.8433
     D(G(z)): 0.0435 / 0.0371
[75/1000][20/42] Loss_D: 0.2725  Loss_G: 3.6341  D(x): 0.9772
     D(G(z)): 0.1572 / 0.2279
[75/1000][40/42] Loss_D: 0.3113  Loss_G: 6.4973  D(x): 0.8939
     D(G(z)): 0.0924 / 0.0260
[76/1000][0/42]  Loss_D: 0.4080  Loss_G: 7.2634  D(x): 0.8188
     D(G(z)): 0.0191 / 0.0126
[76/1000][20/42] Loss_D: 0.3438  Loss_G: 6.1550  D(x): 0.9371
     D(G(z)): 0.1672 / 0.0627
[76/1000][40/42] Loss_D: 0.0872  Loss_G: 8.6656  D(x): 0.9602
     D(G(z)): 0.0331 / 0.0557
[77/1000][0/42]  Loss_D: 0.5953  Loss_G: 7.4339  D(x): 0.9014
     D(G(z)): 0.1859 / 0.0594
[77/1000][20/42] Loss_D: 0.3694  Loss_G: 6.5845  D(x): 0.9590
     D(G(z)): 0.1314 / 0.0413
[77/1000][40/42] Loss_D: 0.1122  Loss_G: 7.3523  D(x): 0.9580
     D(G(z)): 0.0493 / 0.0086
[78/1000][0/42]  Loss_D: 0.2925  Loss_G: 6.4930  D(x): 0.9539
     D(G(z)): 0.1467 / 0.0286
[78/1000][20/42] Loss_D: 0.5513  Loss_G: 5.4244  D(x): 0.9372
     D(G(z)): 0.2344 / 0.0622
[78/1000][40/42] Loss_D: 0.1112  Loss_G: 5.5875  D(x): 0.9775
     D(G(z)): 0.0659 / 0.0541
[79/1000][0/42]  Loss_D: 0.0949  Loss_G: 6.7712  D(x): 0.9693
     D(G(z)): 0.0346 / 0.0228
[79/1000][20/42] Loss_D: 0.1239  Loss_G: 6.1747  D(x): 0.9806
     D(G(z)): 0.0821 / 0.0167
[79/1000][40/42] Loss_D: 0.2375  Loss_G: 6.6527  D(x): 0.9444
     D(G(z)): 0.0551 / 0.0210
[80/1000][0/42]  Loss_D: 0.4253  Loss_G: 5.5296  D(x): 0.9159
     D(G(z)): 0.1274 / 0.0666
[80/1000][20/42] Loss_D: 0.1798  Loss_G: 6.4769  D(x): 0.9577
     D(G(z)): 0.0807 / 0.0355
[80/1000][40/42] Loss_D: 0.1453  Loss_G: 8.0318  D(x): 0.9024
     D(G(z)): 0.0054 / 0.0046
```

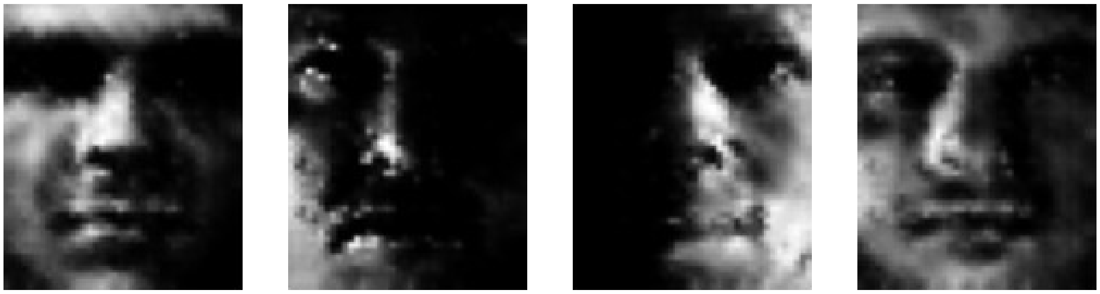


```
[81/1000][0/42] Loss_D: 0.4345  Loss_G: 6.1902  D(x): 0.9275
      D(G(z)): 0.1553 / 0.0729
[81/1000][20/42] Loss_D: 0.8825  Loss_G: 6.5992  D(x): 0.9531
      D(G(z)): 0.2760 / 0.0671
[81/1000][40/42] Loss_D: 0.2574  Loss_G: 7.3562  D(x): 0.8977
      D(G(z)): 0.0335 / 0.0133
[82/1000][0/42] Loss_D: 0.5277  Loss_G: 5.2756  D(x): 0.9535
      D(G(z)): 0.1735 / 0.0786
[82/1000][20/42] Loss_D: 0.5999  Loss_G: 8.4396  D(x): 0.7677
      D(G(z)): 0.0763 / 0.0044
[82/1000][40/42] Loss_D: 0.3049  Loss_G: 7.4612  D(x): 0.9525
      D(G(z)): 0.0979 / 0.0053
[83/1000][0/42] Loss_D: 0.4981  Loss_G: 9.0489  D(x): 0.8042
      D(G(z)): 0.0263 / 0.0255
[83/1000][20/42] Loss_D: 0.2746  Loss_G: 7.1457  D(x): 0.9227
      D(G(z)): 0.0663 / 0.0445
[83/1000][40/42] Loss_D: 0.8191  Loss_G: 6.8639  D(x): 0.7342
      D(G(z)): 0.0673 / 0.0607
[84/1000][0/42] Loss_D: 0.3373  Loss_G: 4.1862  D(x): 0.9469
      D(G(z)): 0.1714 / 0.1659
[84/1000][20/42] Loss_D: 0.3349  Loss_G: 8.2088  D(x): 0.8665
      D(G(z)): 0.0503 / 0.0226
[84/1000][40/42] Loss_D: 0.7042  Loss_G: 5.5929  D(x): 0.7649
      D(G(z)): 0.0821 / 0.0926
[85/1000][0/42] Loss_D: 0.2269  Loss_G: 5.4466  D(x): 0.9599
      D(G(z)): 0.1063 / 0.0637
[85/1000][20/42] Loss_D: 0.3347  Loss_G: 6.1941  D(x): 0.9201
      D(G(z)): 0.1109 / 0.0298
[85/1000][40/42] Loss_D: 0.3137  Loss_G: 7.1388  D(x): 0.9240
      D(G(z)): 0.0878 / 0.0318
[86/1000][0/42] Loss_D: 0.1164  Loss_G: 6.9498  D(x): 0.9552
      D(G(z)): 0.0471 / 0.0102
[86/1000][20/42] Loss_D: 0.3131  Loss_G: 5.8874  D(x): 0.9183
      D(G(z)): 0.0907 / 0.0620
[86/1000][40/42] Loss_D: 0.4741  Loss_G: 4.9521  D(x): 0.8804
      D(G(z)): 0.1919 / 0.0817
[87/1000][0/42] Loss_D: 0.4045  Loss_G: 6.6879  D(x): 0.9158
      D(G(z)): 0.1570 / 0.0305
[87/1000][20/42] Loss_D: 1.0711  Loss_G: 6.4945  D(x): 0.7169
      D(G(z)): 0.1219 / 0.0617
```

```
[87/1000][40/42] Loss_D: 0.2851  Loss_G: 4.8087  D(x): 0.9374
      D(G(z)): 0.1128 / 0.0595
[88/1000][0/42]  Loss_D: 0.2784  Loss_G: 5.8747  D(x): 0.9950
      D(G(z)): 0.1614 / 0.0403
[88/1000][20/42] Loss_D: 0.2251  Loss_G: 7.3225  D(x): 0.8963
      D(G(z)): 0.0620 / 0.0346
[88/1000][40/42] Loss_D: 0.4050  Loss_G: 6.0392  D(x): 0.9107
      D(G(z)): 0.1575 / 0.0440
[89/1000][0/42]  Loss_D: 0.1799  Loss_G: 7.8619  D(x): 0.9149
      D(G(z)): 0.0348 / 0.0063
[89/1000][20/42] Loss_D: 0.2586  Loss_G: 5.4693  D(x): 0.9359
      D(G(z)): 0.1000 / 0.0375
[89/1000][40/42] Loss_D: 0.2363  Loss_G: 5.8653  D(x): 0.8883
      D(G(z)): 0.0674 / 0.0175
[90/1000][0/42]  Loss_D: 0.2950  Loss_G: 5.2771  D(x): 0.8702
      D(G(z)): 0.0429 / 0.0393
[90/1000][20/42] Loss_D: 0.2892  Loss_G: 8.4050  D(x): 0.8579
      D(G(z)): 0.0169 / 0.0049
[90/1000][40/42] Loss_D: 0.1065  Loss_G: 6.5432  D(x): 0.9921
      D(G(z)): 0.0789 / 0.0271
```

```
[91/1000][0/42]  Loss_D: 0.2380  Loss_G: 6.9468  D(x): 0.9211
      D(G(z)): 0.0587 / 0.0219
[91/1000][20/42] Loss_D: 0.1340  Loss_G: 6.1459  D(x): 0.9351
      D(G(z)): 0.0397 / 0.0249
[91/1000][40/42] Loss_D: 0.2593  Loss_G: 7.1752  D(x): 0.8884
      D(G(z)): 0.0355 / 0.0113
[92/1000][0/42]  Loss_D: 0.2730  Loss_G: 6.4912  D(x): 0.9056
      D(G(z)): 0.0634 / 0.0704
[92/1000][20/42] Loss_D: 0.3238  Loss_G: 6.7953  D(x): 0.9537
      D(G(z)): 0.1328 / 0.0344
[92/1000][40/42] Loss_D: 0.4269  Loss_G: 5.6015  D(x): 0.8366
      D(G(z)): 0.0929 / 0.0347
[93/1000][0/42]  Loss_D: 0.4341  Loss_G: 5.9158  D(x): 0.8107
      D(G(z)): 0.0769 / 0.0227
[93/1000][20/42] Loss_D: 0.1950  Loss_G: 6.0551  D(x): 0.9179
      D(G(z)): 0.0450 / 0.0307
[93/1000][40/42] Loss_D: 0.3505  Loss_G: 4.5487  D(x): 0.8920
      D(G(z)): 0.1346 / 0.0949
[94/1000][0/42]  Loss_D: 0.1009  Loss_G: 5.9021  D(x): 0.9872
```

```
     D(G(z)): 0.0686 / 0.0205
[94/1000][20/42] Loss_D: 0.2948  Loss_G: 8.1290  D(x): 0.8443
     D(G(z)): 0.0173 / 0.0098
[94/1000][40/42] Loss_D: 0.2001  Loss_G: 6.3179  D(x): 0.9531
     D(G(z)): 0.0913 / 0.0357
[95/1000][0/42]  Loss_D: 0.2854  Loss_G: 5.3877  D(x): 0.8950
     D(G(z)): 0.0826 / 0.0656
[95/1000][20/42] Loss_D: 0.1258  Loss_G: 7.9219  D(x): 0.9495
     D(G(z)): 0.0478 / 0.0110
[95/1000][40/42] Loss_D: 0.4122  Loss_G: 4.6097  D(x): 0.9449
     D(G(z)): 0.2352 / 0.1095
[96/1000][0/42]  Loss_D: 0.5847  Loss_G: 5.5575  D(x): 0.9169
     D(G(z)): 0.1550 / 0.0696
[96/1000][20/42] Loss_D: 0.3605  Loss_G: 5.4607  D(x): 0.9656
     D(G(z)): 0.1579 / 0.0943
[96/1000][40/42] Loss_D: 0.2225  Loss_G: 6.2849  D(x): 0.9606
     D(G(z)): 0.0889 / 0.0566
[97/1000][0/42]  Loss_D: 0.1621  Loss_G: 6.8422  D(x): 0.9255
     D(G(z)): 0.0408 / 0.0218
[97/1000][20/42] Loss_D: 0.2331  Loss_G: 6.2106  D(x): 0.9710
     D(G(z)): 0.1197 / 0.0283
[97/1000][40/42] Loss_D: 0.3181  Loss_G: 5.7408  D(x): 0.9626
     D(G(z)): 0.1363 / 0.0523
[98/1000][0/42]  Loss_D: 0.1442  Loss_G: 7.2727  D(x): 0.9507
     D(G(z)): 0.0487 / 0.0155
[98/1000][20/42] Loss_D: 0.4670  Loss_G: 5.1398  D(x): 0.9422
     D(G(z)): 0.2107 / 0.0735
[98/1000][40/42] Loss_D: 0.3398  Loss_G: 5.3188  D(x): 0.8943
     D(G(z)): 0.0991 / 0.0549
[99/1000][0/42]  Loss_D: 0.3679  Loss_G: 5.2904  D(x): 0.9426
     D(G(z)): 0.1836 / 0.0765
[99/1000][20/42] Loss_D: 0.2098  Loss_G: 6.0337  D(x): 0.9433
     D(G(z)): 0.0868 / 0.0448
[99/1000][40/42] Loss_D: 0.2833  Loss_G: 6.7617  D(x): 0.9068
     D(G(z)): 0.0876 / 0.0222
[100/1000][0/42] Loss_D: 0.2609  Loss_G: 7.5099  D(x): 0.8700
     D(G(z)): 0.0262 / 0.0147
[100/1000][20/42]     Loss_D: 0.3585  Loss_G: 8.4349  D(x): 0.7985
     D(G(z)): 0.0113 / 0.0042
[100/1000][40/42]     Loss_D: 0.3619  Loss_G: 4.9418  D(x): 0.9703
     D(G(z)): 0.1902 / 0.1075
```



```
[101/1000][0/42]Loss_D: 0.0904  Loss_G: 6.5435  D(x): 0.9852
      D(G(z)): 0.0633 / 0.0131
[101/1000][20/42]     Loss_D: 0.2336  Loss_G: 7.5646  D(x): 0.8631
      D(G(z)): 0.0321 / 0.0185
[101/1000][40/42]     Loss_D: 0.3502  Loss_G: 6.0391  D(x): 0.9274
      D(G(z)): 0.1391 / 0.0287
[102/1000][0/42]Loss_D: 0.1607  Loss_G: 5.4537  D(x): 0.9398
      D(G(z)): 0.0676 / 0.0507
[102/1000][20/42]     Loss_D: 0.1665  Loss_G: 5.9159  D(x): 0.9773
      D(G(z)): 0.0979 / 0.0296
[102/1000][40/42]     Loss_D: 0.1603  Loss_G: 5.6533  D(x): 0.9301
      D(G(z)): 0.0492 / 0.0194
[103/1000][0/42]Loss_D: 0.1485  Loss_G: 5.0783  D(x): 0.9444
      D(G(z)): 0.0682 / 0.0316
[103/1000][20/42]     Loss_D: 0.1299  Loss_G: 5.3725  D(x): 0.9701
      D(G(z)): 0.0739 / 0.0415
[103/1000][40/42]     Loss_D: 0.2703  Loss_G: 5.4233  D(x): 0.8964
      D(G(z)): 0.0799 / 0.0472
[104/1000][0/42]Loss_D: 0.1438  Loss_G: 5.0240  D(x): 0.9556
      D(G(z)): 0.0746 / 0.0312
[104/1000][20/42]     Loss_D: 0.1834  Loss_G: 6.4116  D(x): 0.9390
      D(G(z)): 0.0660 / 0.0185
[104/1000][40/42]     Loss_D: 0.1784  Loss_G: 4.9419  D(x): 0.9949
      D(G(z)): 0.1303 / 0.0487
[105/1000][0/42]Loss_D: 0.1199  Loss_G: 7.2963  D(x): 0.9678
      D(G(z)): 0.0478 / 0.0125
[105/1000][20/42]     Loss_D: 0.4416  Loss_G: 6.9162  D(x): 0.7586
      D(G(z)): 0.0136 / 0.0142
[105/1000][40/42]     Loss_D: 0.2694  Loss_G: 6.4522  D(x): 0.9650
      D(G(z)): 0.1219 / 0.0222
[106/1000][0/42]Loss_D: 0.0945  Loss_G: 9.6350  D(x): 0.9313
      D(G(z)): 0.0061 / 0.0019
[106/1000][20/42]     Loss_D: 0.2402  Loss_G: 5.0741  D(x): 0.8868
      D(G(z)): 0.0223 / 0.0229
[106/1000][40/42]     Loss_D: 0.2183  Loss_G: 5.4306  D(x): 0.9414
      D(G(z)): 0.0989 / 0.0587
[107/1000][0/42]Loss_D: 0.2350  Loss_G: 5.0177  D(x): 0.9490
      D(G(z)): 0.1184 / 0.0364
[107/1000][20/42]     Loss_D: 0.0752  Loss_G: 8.9005  D(x): 0.9520
      D(G(z)): 0.0105 / 0.0019
```

```
[107/1000][40/42]     Loss_D: 0.0661  Loss_G: 5.8361  D(x): 0.9757
      D(G(z)): 0.0346 / 0.0215
[108/1000][0/42] Loss_D: 0.2161  Loss_G: 4.8659  D(x): 0.9730
      D(G(z)): 0.1123 / 0.0611
[108/1000][20/42]     Loss_D: 0.4248  Loss_G: 4.4014  D(x): 0.8587
      D(G(z)): 0.1123 / 0.1230
[108/1000][40/42]     Loss_D: 0.1578  Loss_G: 5.9082  D(x): 0.9685
      D(G(z)): 0.0881 / 0.0267
[109/1000][0/42] Loss_D: 0.2095  Loss_G: 6.6589  D(x): 0.9030
      D(G(z)): 0.0540 / 0.0132
[109/1000][20/42]     Loss_D: 0.1077  Loss_G: 4.5783  D(x): 0.9603
      D(G(z)): 0.0568 / 0.0874
[109/1000][40/42]     Loss_D: 0.2843  Loss_G: 6.3479  D(x): 0.8627
      D(G(z)): 0.0340 / 0.0147
[110/1000][0/42] Loss_D: 0.1753  Loss_G: 4.9268  D(x): 0.9727
      D(G(z)): 0.1019 / 0.0602
[110/1000][20/42]     Loss_D: 0.6091  Loss_G: 7.1499  D(x): 0.7960
      D(G(z)): 0.0404 / 0.0233
[110/1000][40/42]     Loss_D: 0.2799  Loss_G: 4.5521  D(x): 0.8729
      D(G(z)): 0.0513 / 0.0967
```

```
[111/1000][0/42] Loss_D: 0.6797  Loss_G: 5.2490  D(x): 0.9969
      D(G(z)): 0.2623 / 0.1113
[111/1000][20/42]     Loss_D: 0.1017  Loss_G: 8.1413  D(x): 0.9349
      D(G(z)): 0.0182 / 0.0041
[111/1000][40/42]     Loss_D: 0.1114  Loss_G: 4.4288  D(x): 0.9745
      D(G(z)): 0.0716 / 0.0569
[112/1000][0/42] Loss_D: 0.2898  Loss_G: 5.3767  D(x): 0.9738
      D(G(z)): 0.1767 / 0.0491
[112/1000][20/42]     Loss_D: 0.2237  Loss_G: 6.0874  D(x): 0.9530
      D(G(z)): 0.1110 / 0.0373
[112/1000][40/42]     Loss_D: 0.1835  Loss_G: 5.6346  D(x): 0.9243
      D(G(z)): 0.0634 / 0.0555
[113/1000][0/42] Loss_D: 0.1919  Loss_G: 6.5078  D(x): 0.9765
      D(G(z)): 0.0728 / 0.0380
[113/1000][20/42]     Loss_D: 0.1823  Loss_G: 6.3684  D(x): 0.9489
      D(G(z)): 0.0792 / 0.0129
[113/1000][40/42]     Loss_D: 0.1775  Loss_G: 7.9685  D(x): 0.9276
      D(G(z)): 0.0413 / 0.0106
[114/1000][0/42] Loss_D: 0.2196  Loss_G: 7.1621  D(x): 0.8877
```

```
    D(G(z)): 0.0333 / 0.0263
[114/1000][20/42]    Loss_D: 0.4749  Loss_G: 4.6859  D(x): 0.9621
    D(G(z)): 0.2009 / 0.0969
[114/1000][40/42]    Loss_D: 0.1511  Loss_G: 5.3496  D(x): 0.9452
    D(G(z)): 0.0582 / 0.0219
[115/1000][0/42]Loss_D: 0.1111  Loss_G: 5.6631  D(x): 0.9576
    D(G(z)): 0.0387 / 0.0270
[115/1000][20/42]    Loss_D: 0.2193  Loss_G: 6.2450  D(x): 0.9108
    D(G(z)): 0.0423 / 0.0373
[115/1000][40/42]    Loss_D: 0.2259  Loss_G: 5.8716  D(x): 0.9855
    D(G(z)): 0.1209 / 0.0714
[116/1000][0/42]Loss_D: 0.2030  Loss_G: 5.7726  D(x): 0.9835
    D(G(z)): 0.1073 / 0.0433
[116/1000][20/42]    Loss_D: 0.1702  Loss_G: 5.9263  D(x): 0.9172
    D(G(z)): 0.0459 / 0.0269
[116/1000][40/42]    Loss_D: 0.2633  Loss_G: 4.4667  D(x): 0.9570
    D(G(z)): 0.1490 / 0.0743
[117/1000][0/42]Loss_D: 0.2143  Loss_G: 6.8157  D(x): 0.9596
    D(G(z)): 0.1007 / 0.0219
[117/1000][20/42]    Loss_D: 0.0909  Loss_G: 6.2749  D(x): 0.9828
    D(G(z)): 0.0617 / 0.0231
[117/1000][40/42]    Loss_D: 0.1192  Loss_G: 6.3673  D(x): 0.9238
    D(G(z)): 0.0217 / 0.0101
[118/1000][0/42]Loss_D: 0.1226  Loss_G: 5.6487  D(x): 0.9330
    D(G(z)): 0.0373 / 0.0306
[118/1000][20/42]    Loss_D: 0.0931  Loss_G: 6.0425  D(x): 0.9547
    D(G(z)): 0.0276 / 0.0150
[118/1000][40/42]    Loss_D: 0.2120  Loss_G: 6.1691  D(x): 0.9669
    D(G(z)): 0.1151 / 0.0367
[119/1000][0/42]Loss_D: 0.3524  Loss_G: 5.9893  D(x): 0.8476
    D(G(z)): 0.0521 / 0.0286
[119/1000][20/42]    Loss_D: 0.3601  Loss_G: 5.1665  D(x): 0.9772
    D(G(z)): 0.1406 / 0.0985
[119/1000][40/42]    Loss_D: 0.0500  Loss_G: 7.0816  D(x): 0.9939
    D(G(z)): 0.0371 / 0.0192
[120/1000][0/42]Loss_D: 0.0348  Loss_G: 7.2174  D(x): 0.9823
    D(G(z)): 0.0154 / 0.0089
[120/1000][20/42]    Loss_D: 0.2199  Loss_G: 6.7374  D(x): 0.8766
    D(G(z)): 0.0244 / 0.0286
[120/1000][40/42]    Loss_D: 0.0854  Loss_G: 6.8741  D(x): 0.9686
    D(G(z)): 0.0405 / 0.0253
```

```
[121/1000][0/42] Loss_D: 0.1976  Loss_G: 6.4093  D(x): 0.9841
     D(G(z)): 0.1077 / 0.0371
[121/1000][20/42]    Loss_D: 0.3257  Loss_G: 6.9837  D(x): 0.8094
     D(G(z)): 0.0288 / 0.0225
[121/1000][40/42]    Loss_D: 0.3734  Loss_G: 5.6556  D(x): 0.7974
     D(G(z)): 0.0410 / 0.0244
[122/1000][0/42] Loss_D: 0.2237  Loss_G: 4.8227  D(x): 0.9519
     D(G(z)): 0.1188 / 0.0756
[122/1000][20/42]    Loss_D: 0.1314  Loss_G: 6.6925  D(x): 0.9538
     D(G(z)): 0.0546 / 0.0199
[122/1000][40/42]    Loss_D: 0.1613  Loss_G: 5.8644  D(x): 0.9740
     D(G(z)): 0.0934 / 0.0497
[123/1000][0/42] Loss_D: 0.2632  Loss_G: 5.7222  D(x): 0.9743
     D(G(z)): 0.1309 / 0.0467
[123/1000][20/42]    Loss_D: 0.1087  Loss_G: 8.5482  D(x): 0.9331
     D(G(z)): 0.0192 / 0.0133
[123/1000][40/42]    Loss_D: 0.1593  Loss_G: 5.5519  D(x): 0.9861
     D(G(z)): 0.0880 / 0.0397
[124/1000][0/42] Loss_D: 0.1307  Loss_G: 7.1595  D(x): 0.9498
     D(G(z)): 0.0508 / 0.0202
[124/1000][20/42]    Loss_D: 0.1743  Loss_G: 6.3069  D(x): 0.9227
     D(G(z)): 0.0544 / 0.0262
[124/1000][40/42]    Loss_D: 0.2010  Loss_G: 5.7621  D(x): 0.9412
     D(G(z)): 0.0885 / 0.0441
[125/1000][0/42] Loss_D: 0.1622  Loss_G: 6.3060  D(x): 0.9072
     D(G(z)): 0.0203 / 0.0150
[125/1000][20/42]    Loss_D: 0.2389  Loss_G: 4.4107  D(x): 0.9877
     D(G(z)): 0.1382 / 0.0635
[125/1000][40/42]    Loss_D: 0.1732  Loss_G: 6.0351  D(x): 0.9046
     D(G(z)): 0.0297 / 0.0204
[126/1000][0/42] Loss_D: 0.1265  Loss_G: 4.7926  D(x): 0.9748
     D(G(z)): 0.0806 / 0.0335
[126/1000][20/42]    Loss_D: 0.1338  Loss_G: 5.7591  D(x): 0.9810
     D(G(z)): 0.0744 / 0.0375
[126/1000][40/42]    Loss_D: 0.1414  Loss_G: 4.0469  D(x): 0.9806
     D(G(z)): 0.0879 / 0.0716
[127/1000][0/42] Loss_D: 0.1727  Loss_G: 5.4916  D(x): 0.9794
     D(G(z)): 0.1149 / 0.0295
[127/1000][20/42]    Loss_D: 0.2093  Loss_G: 5.8264  D(x): 0.9778
     D(G(z)): 0.1148 / 0.0289
```

```
[127/1000][40/42]     Loss_D: 0.0670  Loss_G: 5.2357  D(x): 0.9627
      D(G(z)): 0.0223 / 0.0233
[128/1000][0/42] Loss_D: 0.1048  Loss_G: 6.3157  D(x): 0.9741
      D(G(z)): 0.0515 / 0.0176
[128/1000][20/42]     Loss_D: 0.1692  Loss_G: 4.8884  D(x): 0.9397
      D(G(z)): 0.0782 / 0.0779
[128/1000][40/42]     Loss_D: 0.0925  Loss_G: 5.7703  D(x): 0.9741
      D(G(z)): 0.0544 / 0.0350
[129/1000][0/42] Loss_D: 0.1835  Loss_G: 5.9819  D(x): 0.9380
      D(G(z)): 0.0768 / 0.0305
[129/1000][20/42]     Loss_D: 0.1582  Loss_G: 6.6264  D(x): 0.9212
      D(G(z)): 0.0241 / 0.0091
[129/1000][40/42]     Loss_D: 0.2991  Loss_G: 5.0785  D(x): 0.8264
      D(G(z)): 0.0192 / 0.0315
[130/1000][0/42] Loss_D: 0.2069  Loss_G: 4.6972  D(x): 0.9951
      D(G(z)): 0.1477 / 0.0551
[130/1000][20/42]     Loss_D: 0.3093  Loss_G: 5.8902  D(x): 0.8810
      D(G(z)): 0.1000 / 0.0286
[130/1000][40/42]     Loss_D: 0.0964  Loss_G: 7.4528  D(x): 0.9481
      D(G(z)): 0.0272 / 0.0163
```

```
[131/1000][0/42] Loss_D: 0.0954  Loss_G: 6.0091  D(x): 0.9648
      D(G(z)): 0.0436 / 0.0149
[131/1000][20/42]     Loss_D: 0.1109  Loss_G: 6.3215  D(x): 0.9637
      D(G(z)): 0.0515 / 0.0321
[131/1000][40/42]     Loss_D: 0.2237  Loss_G: 5.3781  D(x): 0.9112
      D(G(z)): 0.0741 / 0.0366
[132/1000][0/42] Loss_D: 0.1446  Loss_G: 5.9912  D(x): 0.9665
      D(G(z)): 0.0635 / 0.0283
[132/1000][20/42]     Loss_D: 0.0588  Loss_G: 6.5015  D(x): 0.9774
      D(G(z)): 0.0304 / 0.0145
[132/1000][40/42]     Loss_D: 0.2370  Loss_G: 7.4304  D(x): 0.8580
      D(G(z)): 0.0344 / 0.0081
[133/1000][0/42] Loss_D: 0.2333  Loss_G: 7.7333  D(x): 0.8754
      D(G(z)): 0.0177 / 0.0159
[133/1000][20/42]     Loss_D: 0.0953  Loss_G: 6.7267  D(x): 0.9517
      D(G(z)): 0.0193 / 0.0331
[133/1000][40/42]     Loss_D: 0.1479  Loss_G: 5.6852  D(x): 0.9587
      D(G(z)): 0.0661 / 0.0613
[134/1000][0/42] Loss_D: 0.3362  Loss_G: 6.3039  D(x): 0.9500
```

```
      D(G(z)): 0.1400 / 0.0415
[134/1000][20/42]     Loss_D: 0.1303  Loss_G: 6.7606  D(x): 0.9439
      D(G(z)): 0.0375 / 0.0260
[134/1000][40/42]     Loss_D: 0.1178  Loss_G: 6.9455  D(x): 0.9345
      D(G(z)): 0.0194 / 0.0104
[135/1000][0/42] Loss_D: 0.1465  Loss_G: 5.5219  D(x): 0.9585
      D(G(z)): 0.0772 / 0.0536
[135/1000][20/42]     Loss_D: 0.1230  Loss_G: 7.6826  D(x): 0.9297
      D(G(z)): 0.0252 / 0.0176
[135/1000][40/42]     Loss_D: 0.0762  Loss_G: 6.1233  D(x): 0.9590
      D(G(z)): 0.0267 / 0.0127
[136/1000][0/42] Loss_D: 0.0897  Loss_G: 6.5092  D(x): 0.9801
      D(G(z)): 0.0560 / 0.0179
[136/1000][20/42]     Loss_D: 0.1507  Loss_G: 6.5866  D(x): 0.9618
      D(G(z)): 0.0793 / 0.0135
[136/1000][40/42]     Loss_D: 0.1241  Loss_G: 6.0429  D(x): 0.9847
      D(G(z)): 0.0678 / 0.0290
[137/1000][0/42] Loss_D: 0.1285  Loss_G: 7.2072  D(x): 0.9470
      D(G(z)): 0.0431 / 0.0133
[137/1000][20/42]     Loss_D: 0.1143  Loss_G: 6.4574  D(x): 0.9801
      D(G(z)): 0.0618 / 0.0446
[137/1000][40/42]     Loss_D: 0.0758  Loss_G: 8.4186  D(x): 0.9813
      D(G(z)): 0.0420 / 0.0291
[138/1000][0/42] Loss_D: 0.1079  Loss_G: 7.0783  D(x): 0.9587
      D(G(z)): 0.0489 / 0.0356
[138/1000][20/42]     Loss_D: 0.0637  Loss_G: 6.9787  D(x): 0.9710
      D(G(z)): 0.0297 / 0.0225
[138/1000][40/42]     Loss_D: 0.1397  Loss_G: 6.2437  D(x): 0.9807
      D(G(z)): 0.0651 / 0.0421
[139/1000][0/42] Loss_D: 0.1114  Loss_G: 6.9488  D(x): 0.9423
      D(G(z)): 0.0333 / 0.0109
[139/1000][20/42]     Loss_D: 0.0591  Loss_G: 6.2168  D(x): 0.9733
      D(G(z)): 0.0262 / 0.0306
[139/1000][40/42]     Loss_D: 0.2441  Loss_G: 9.1626  D(x): 0.9012
      D(G(z)): 0.0336 / 0.0173
[140/1000][0/42] Loss_D: 0.3134  Loss_G: 6.3080  D(x): 0.8139
      D(G(z)): 0.0076 / 0.0194
[140/1000][20/42]     Loss_D: 0.1487  Loss_G: 5.9178  D(x): 0.9589
      D(G(z)): 0.0604 / 0.0393
[140/1000][40/42]     Loss_D: 0.2044  Loss_G: 5.6812  D(x): 0.9768
      D(G(z)): 0.1184 / 0.0375
```

```
[141/1000][0/42]Loss_D: 0.0287  Loss_G: 8.2700  D(x): 0.9811
    D(G(z)): 0.0081 / 0.0029
[141/1000][20/42]    Loss_D: 0.1242  Loss_G: 7.1461  D(x): 0.9192
    D(G(z)): 0.0278 / 0.0128
[141/1000][40/42]    Loss_D: 0.1918  Loss_G: 5.6684  D(x): 0.9859
    D(G(z)): 0.1094 / 0.0421
[142/1000][0/42]Loss_D: 0.1164  Loss_G: 6.8324  D(x): 0.9862
    D(G(z)): 0.0790 / 0.0151
[142/1000][20/42]    Loss_D: 0.1954  Loss_G: 5.0393  D(x): 0.9629
    D(G(z)): 0.0789 / 0.0642
[142/1000][40/42]    Loss_D: 0.0975  Loss_G: 6.2141  D(x): 0.9553
    D(G(z)): 0.0405 / 0.0283
[143/1000][0/42]Loss_D: 0.1108  Loss_G: 5.2451  D(x): 0.9864
    D(G(z)): 0.0734 / 0.0468
[143/1000][20/42]    Loss_D: 0.0939  Loss_G: 5.6606  D(x): 0.9920
    D(G(z)): 0.0679 / 0.0181
[143/1000][40/42]    Loss_D: 0.1182  Loss_G: 6.3738  D(x): 0.9426
    D(G(z)): 0.0268 / 0.0356
[144/1000][0/42]Loss_D: 0.1000  Loss_G: 5.7034  D(x): 0.9636
    D(G(z)): 0.0491 / 0.0332
[144/1000][20/42]    Loss_D: 0.0734  Loss_G: 6.6156  D(x): 0.9707
    D(G(z)): 0.0296 / 0.0086
[144/1000][40/42]    Loss_D: 0.1363  Loss_G: 4.4368  D(x): 0.9806
    D(G(z)): 0.0905 / 0.0641
[145/1000][0/42]Loss_D: 0.0832  Loss_G: 6.3782  D(x): 0.9917
    D(G(z)): 0.0606 / 0.0148
[145/1000][20/42]    Loss_D: 0.1424  Loss_G: 6.0550  D(x): 0.9211
    D(G(z)): 0.0176 / 0.0280
[145/1000][40/42]    Loss_D: 0.0881  Loss_G: 5.9350  D(x): 0.9627
    D(G(z)): 0.0348 / 0.0369
[146/1000][0/42]Loss_D: 0.0366  Loss_G: 6.3683  D(x): 0.9964
    D(G(z)): 0.0305 / 0.0127
[146/1000][20/42]    Loss_D: 0.1016  Loss_G: 5.7217  D(x): 0.9885
    D(G(z)): 0.0709 / 0.0286
[146/1000][40/42]    Loss_D: 0.1592  Loss_G: 6.2342  D(x): 0.9429
    D(G(z)): 0.0559 / 0.0215
[147/1000][0/42]Loss_D: 0.2375  Loss_G: 5.5727  D(x): 0.9454
    D(G(z)): 0.0956 / 0.0677
[147/1000][20/42]    Loss_D: 0.1583  Loss_G: 6.1966  D(x): 0.9398
    D(G(z)): 0.0528 / 0.0261
```

```
[147/1000][40/42]	Loss_D: 0.0678	Loss_G: 8.0893	D(x): 0.9703
	D(G(z)): 0.0266 / 0.0228
[148/1000][0/42]	Loss_D: 0.1577	Loss_G: 6.2745	D(x): 0.9986
	D(G(z)): 0.0946 / 0.0532
[148/1000][20/42]	Loss_D: 0.0513	Loss_G: 7.6885	D(x): 0.9704
	D(G(z)): 0.0151 / 0.0073
[148/1000][40/42]	Loss_D: 0.1508	Loss_G: 6.8554	D(x): 0.8997
	D(G(z)): 0.0152 / 0.0168
[149/1000][0/42]	Loss_D: 0.3260	Loss_G: 5.4738	D(x): 0.9693
	D(G(z)): 0.1420 / 0.0729
[149/1000][20/42]	Loss_D: 0.1563	Loss_G: 5.9904	D(x): 0.9076
	D(G(z)): 0.0174 / 0.0491
[149/1000][40/42]	Loss_D: 0.2743	Loss_G: 5.2430	D(x): 0.9821
	D(G(z)): 0.1477 / 0.0851
[150/1000][0/42]	Loss_D: 0.1071	Loss_G: 6.1793	D(x): 0.9908
	D(G(z)): 0.0690 / 0.0195
[150/1000][20/42]	Loss_D: 0.1197	Loss_G: 6.2201	D(x): 0.9431
	D(G(z)): 0.0317 / 0.0234
[150/1000][40/42]	Loss_D: 0.0821	Loss_G: 7.2156	D(x): 0.9499
	D(G(z)): 0.0184 / 0.0073
```

```
[151/1000][0/42]	Loss_D: 0.1926	Loss_G: 6.8998	D(x): 0.9322
	D(G(z)): 0.0477 / 0.0164
[151/1000][20/42]	Loss_D: 0.1018	Loss_G: 5.0171	D(x): 0.9753
	D(G(z)): 0.0612 / 0.0368
[151/1000][40/42]	Loss_D: 0.1059	Loss_G: 7.9682	D(x): 0.9565
	D(G(z)): 0.0283 / 0.0102
[152/1000][0/42]	Loss_D: 0.0676	Loss_G: 9.0523	D(x): 0.9482
	D(G(z)): 0.0064 / 0.0055
[152/1000][20/42]	Loss_D: 0.1546	Loss_G: 5.5114	D(x): 0.9709
	D(G(z)): 0.0770 / 0.0294
[152/1000][40/42]	Loss_D: 0.1034	Loss_G: 5.9737	D(x): 0.9829
	D(G(z)): 0.0732 / 0.0242
[153/1000][0/42]	Loss_D: 0.0389	Loss_G: 6.9181	D(x): 0.9865
	D(G(z)): 0.0226 / 0.0081
[153/1000][20/42]	Loss_D: 0.1687	Loss_G: 6.7766	D(x): 0.9288
	D(G(z)): 0.0417 / 0.0167
[153/1000][40/42]	Loss_D: 0.0606	Loss_G: 6.8045	D(x): 0.9688
	D(G(z)): 0.0227 / 0.0148
[154/1000][0/42]	Loss_D: 0.1414	Loss_G: 4.5553	D(x): 0.9885
```

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      D(G(z)): 0.1024 / 0.0541
[154/1000][20/42]     Loss_D: 0.1477  Loss_G: 6.1993  D(x): 0.9238
      D(G(z)): 0.0265 / 0.0231
[154/1000][40/42]     Loss_D: 0.2261  Loss_G: 9.7367  D(x): 0.8782
      D(G(z)): 0.0189 / 0.0063
[155/1000][0/42]Loss_D: 0.0444  Loss_G: 7.9729  D(x): 0.9652
      D(G(z)): 0.0061 / 0.0099
[155/1000][20/42]     Loss_D: 0.0447  Loss_G: 8.6730  D(x): 0.9748
      D(G(z)): 0.0169 / 0.0300
[155/1000][40/42]     Loss_D: 0.0795  Loss_G: 7.5985  D(x): 0.9625
      D(G(z)): 0.0308 / 0.0168
[156/1000][0/42]Loss_D: 0.0764  Loss_G: 7.1128  D(x): 0.9838
      D(G(z)): 0.0433 / 0.0251
[156/1000][20/42]     Loss_D: 0.2635  Loss_G: 5.4072  D(x): 0.9341
      D(G(z)): 0.0867 / 0.0514
[156/1000][40/42]     Loss_D: 0.1004  Loss_G: 6.8172  D(x): 0.9431
      D(G(z)): 0.0234 / 0.0101
[157/1000][0/42]Loss_D: 0.1792  Loss_G: 6.5818  D(x): 0.9730
      D(G(z)): 0.0863 / 0.0310
[157/1000][20/42]     Loss_D: 0.0780  Loss_G: 7.2679  D(x): 0.9452
      D(G(z)): 0.0104 / 0.0093
[157/1000][40/42]     Loss_D: 0.3353  Loss_G: 5.8882  D(x): 0.9685
      D(G(z)): 0.1384 / 0.0422
[158/1000][0/42]Loss_D: 0.0807  Loss_G: 8.0956  D(x): 0.9735
      D(G(z)): 0.0383 / 0.0079
[158/1000][20/42]     Loss_D: 0.1055  Loss_G: 7.1161  D(x): 0.9789
      D(G(z)): 0.0425 / 0.0327
[158/1000][40/42]     Loss_D: 0.1171  Loss_G: 6.0857  D(x): 0.9819
      D(G(z)): 0.0591 / 0.0209
[159/1000][0/42]Loss_D: 0.0766  Loss_G: 7.1545  D(x): 0.9581
      D(G(z)): 0.0263 / 0.0093
[159/1000][20/42]     Loss_D: 0.3307  Loss_G: 5.7428  D(x): 0.9658
      D(G(z)): 0.1382 / 0.0485
[159/1000][40/42]     Loss_D: 0.0837  Loss_G: 4.3152  D(x): 0.9986
      D(G(z)): 0.0680 / 0.0855
[160/1000][0/42]Loss_D: 0.1253  Loss_G: 6.3447  D(x): 0.9998
      D(G(z)): 0.0877 / 0.0252
[160/1000][20/42]     Loss_D: 0.0809  Loss_G: 8.0541  D(x): 0.9584
      D(G(z)): 0.0186 / 0.0103
[160/1000][40/42]     Loss_D: 0.1109  Loss_G: 5.9580  D(x): 0.9644
      D(G(z)): 0.0579 / 0.0304
```

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[161/1000][0/42] Loss_D: 0.1253  Loss_G: 7.3656  D(x): 0.9710
      D(G(z)): 0.0655 / 0.0336
[161/1000][20/42]     Loss_D: 0.1331  Loss_G: 8.6279  D(x): 0.9501
      D(G(z)): 0.0406 / 0.0217
[161/1000][40/42]     Loss_D: 0.0736  Loss_G: 8.5975  D(x): 0.9582
      D(G(z)): 0.0203 / 0.0049
[162/1000][0/42] Loss_D: 0.1028  Loss_G: 7.3461  D(x): 0.9314
      D(G(z)): 0.0070 / 0.0128
[162/1000][20/42]     Loss_D: 0.1097  Loss_G: 4.7014  D(x): 0.9936
      D(G(z)): 0.0834 / 0.0427
[162/1000][40/42]     Loss_D: 0.1633  Loss_G: 6.0842  D(x): 0.8928
      D(G(z)): 0.0185 / 0.0197
[163/1000][0/42] Loss_D: 0.1704  Loss_G: 4.8129  D(x): 0.9914
      D(G(z)): 0.1148 / 0.0635
[163/1000][20/42]     Loss_D: 0.2087  Loss_G: 5.3588  D(x): 0.9678
      D(G(z)): 0.1048 / 0.0468
[163/1000][40/42]     Loss_D: 0.1898  Loss_G: 7.2168  D(x): 0.8879
      D(G(z)): 0.0137 / 0.0116
[164/1000][0/42] Loss_D: 0.2740  Loss_G: 5.2197  D(x): 0.8951
      D(G(z)): 0.0648 / 0.0515
[164/1000][20/42]     Loss_D: 0.1623  Loss_G: 4.7707  D(x): 0.9445
      D(G(z)): 0.0754 / 0.0523
[164/1000][40/42]     Loss_D: 0.0849  Loss_G: 6.7794  D(x): 0.9795
      D(G(z)): 0.0518 / 0.0326
[165/1000][0/42] Loss_D: 0.0688  Loss_G: 7.9741  D(x): 0.9841
      D(G(z)): 0.0449 / 0.0072
[165/1000][20/42]     Loss_D: 0.1156  Loss_G: 7.5697  D(x): 0.9523
      D(G(z)): 0.0311 / 0.0224
[165/1000][40/42]     Loss_D: 0.0668  Loss_G: 6.2468  D(x): 0.9806
      D(G(z)): 0.0399 / 0.0167
[166/1000][0/42] Loss_D: 0.0745  Loss_G: 7.4098  D(x): 0.9590
      D(G(z)): 0.0187 / 0.0050
[166/1000][20/42]     Loss_D: 0.1464  Loss_G: 5.6794  D(x): 0.9533
      D(G(z)): 0.0680 / 0.0408
[166/1000][40/42]     Loss_D: 0.0350  Loss_G: 7.5404  D(x): 0.9780
      D(G(z)): 0.0058 / 0.0064
[167/1000][0/42] Loss_D: 0.0629  Loss_G: 6.3198  D(x): 0.9807
      D(G(z)): 0.0367 / 0.0189
[167/1000][20/42]     Loss_D: 0.0732  Loss_G: 7.4422  D(x): 0.9722
      D(G(z)): 0.0352 / 0.0110
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[167/1000][40/42]	Loss_D: 0.1499	Loss_G: 5.8202	D(x): 0.9673
D(G(z)): 0.0828 / 0.0232
[168/1000][0/42]	Loss_D: 0.0811	Loss_G: 7.4469	D(x): 0.9834
D(G(z)): 0.0360 / 0.0354
[168/1000][20/42]	Loss_D: 0.0281	Loss_G: 6.5702	D(x): 0.9914
D(G(z)): 0.0186 / 0.0072
[168/1000][40/42]	Loss_D: 0.0850	Loss_G: 8.7099	D(x): 0.9420
D(G(z)): 0.0088 / 0.0040
[169/1000][0/42]	Loss_D: 0.1910	Loss_G: 6.4700	D(x): 0.8918
D(G(z)): 0.0224 / 0.0527
[169/1000][20/42]	Loss_D: 0.0983	Loss_G: 8.8708	D(x): 0.9532
D(G(z)): 0.0048 / 0.0018
[169/1000][40/42]	Loss_D: 0.1860	Loss_G: 8.0729	D(x): 0.9095
D(G(z)): 0.0127 / 0.0091
[170/1000][0/42]	Loss_D: 0.0915	Loss_G: 7.2015	D(x): 0.9674
D(G(z)): 0.0394 / 0.0255
[170/1000][20/42]	Loss_D: 0.1287	Loss_G: 7.1214	D(x): 0.9391
D(G(z)): 0.0337 / 0.0126
[170/1000][40/42]	Loss_D: 0.0947	Loss_G: 6.5825	D(x): 0.9872
D(G(z)): 0.0632 / 0.0215

[171/1000][0/42]	Loss_D: 0.0608	Loss_G: 7.5950	D(x): 0.9568
D(G(z)): 0.0100 / 0.0041
[171/1000][20/42]	Loss_D: 0.0282	Loss_G: 6.4192	D(x): 0.9876
D(G(z)): 0.0146 / 0.0154
[171/1000][40/42]	Loss_D: 0.0928	Loss_G: 6.6482	D(x): 0.9593
D(G(z)): 0.0279 / 0.0099
[172/1000][0/42]	Loss_D: 0.0968	Loss_G: 6.4333	D(x): 0.9346
D(G(z)): 0.0108 / 0.0063
[172/1000][20/42]	Loss_D: 0.1441	Loss_G: 7.8797	D(x): 0.9788
D(G(z)): 0.0719 / 0.0348
[172/1000][40/42]	Loss_D: 0.0792	Loss_G: 7.6498	D(x): 0.9730
D(G(z)): 0.0328 / 0.0108
[173/1000][0/42]	Loss_D: 0.0770	Loss_G: 5.9114	D(x): 0.9465
D(G(z)): 0.0175 / 0.0322
[173/1000][20/42]	Loss_D: 0.0756	Loss_G: 6.1797	D(x): 0.9745
D(G(z)): 0.0377 / 0.0139
[173/1000][40/42]	Loss_D: 0.5193	Loss_G: 6.0734	D(x): 0.9889
D(G(z)): 0.2235 / 0.0628
[174/1000][0/42]	Loss_D: 0.1492	Loss_G: 8.2352	D(x): 0.9566

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    D(G(z)): 0.0448 / 0.0081
[174/1000][20/42]    Loss_D: 0.1051  Loss_G: 8.2414  D(x): 0.9623
    D(G(z)): 0.0299 / 0.0141
[174/1000][40/42]    Loss_D: 0.1251  Loss_G: 7.0339  D(x): 0.9387
    D(G(z)): 0.0272 / 0.0143
[175/1000][0/42] Loss_D: 0.1237  Loss_G: 5.3309  D(x): 0.9487
    D(G(z)): 0.0532 / 0.0249
[175/1000][20/42]    Loss_D: 0.0964  Loss_G: 6.8408  D(x): 0.9845
    D(G(z)): 0.0382 / 0.0150
[175/1000][40/42]    Loss_D: 0.0340  Loss_G: 7.0767  D(x): 0.9884
    D(G(z)): 0.0194 / 0.0088
[176/1000][0/42] Loss_D: 0.0369  Loss_G: 7.7012  D(x): 0.9792
    D(G(z)): 0.0124 / 0.0062
[176/1000][20/42]    Loss_D: 0.1756  Loss_G: 4.5714  D(x): 0.9899
    D(G(z)): 0.0761 / 0.0716
[176/1000][40/42]    Loss_D: 0.0777  Loss_G: 8.7159  D(x): 0.9501
    D(G(z)): 0.0141 / 0.0045
[177/1000][0/42] Loss_D: 0.0567  Loss_G: 8.8392  D(x): 0.9580
    D(G(z)): 0.0060 / 0.0035
[177/1000][20/42]    Loss_D: 0.0996  Loss_G: 8.1058  D(x): 0.9677
    D(G(z)): 0.0468 / 0.0180
[177/1000][40/42]    Loss_D: 0.1203  Loss_G: 8.5176  D(x): 0.9112
    D(G(z)): 0.0103 / 0.0042
[178/1000][0/42] Loss_D: 0.1524  Loss_G: 6.0975  D(x): 0.9017
    D(G(z)): 0.0090 / 0.0166
[178/1000][20/42]    Loss_D: 0.0574  Loss_G: 7.2159  D(x): 0.9834
    D(G(z)): 0.0299 / 0.0131
[178/1000][40/42]    Loss_D: 0.0440  Loss_G: 5.9095  D(x): 0.9776
    D(G(z)): 0.0195 / 0.0221
[179/1000][0/42] Loss_D: 0.0434  Loss_G: 6.1553  D(x): 0.9902
    D(G(z)): 0.0287 / 0.0189
[179/1000][20/42]    Loss_D: 0.1006  Loss_G: 9.0315  D(x): 0.9349
    D(G(z)): 0.0078 / 0.0021
[179/1000][40/42]    Loss_D: 0.1758  Loss_G: 6.9070  D(x): 0.9231
    D(G(z)): 0.0410 / 0.0334
[180/1000][0/42] Loss_D: 0.0373  Loss_G: 8.1714  D(x): 0.9918
    D(G(z)): 0.0257 / 0.0126
[180/1000][20/42]    Loss_D: 0.0493  Loss_G: 8.0503  D(x): 0.9753
    D(G(z)): 0.0167 / 0.0111
[180/1000][40/42]    Loss_D: 0.1163  Loss_G: 6.5236  D(x): 0.9693
    D(G(z)): 0.0628 / 0.0259
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[181/1000][0/42] Loss_D: 0.0498  Loss_G: 7.7477  D(x): 0.9684
     D(G(z)): 0.0144 / 0.0041
[181/1000][20/42]    Loss_D: 0.1443  Loss_G: 7.1961  D(x): 0.9790
     D(G(z)): 0.0780 / 0.0341
[181/1000][40/42]    Loss_D: 0.0505  Loss_G: 6.6783  D(x): 0.9854
     D(G(z)): 0.0313 / 0.0094
[182/1000][0/42] Loss_D: 0.0401  Loss_G: 7.2896  D(x): 0.9891
     D(G(z)): 0.0217 / 0.0092
[182/1000][20/42]    Loss_D: 0.0768  Loss_G: 5.8946  D(x): 0.9768
     D(G(z)): 0.0436 / 0.0210
[182/1000][40/42]    Loss_D: 0.1497  Loss_G: 5.6876  D(x): 0.9904
     D(G(z)): 0.0755 / 0.0372
[183/1000][0/42] Loss_D: 0.0468  Loss_G: 6.7874  D(x): 0.9927
     D(G(z)): 0.0342 / 0.0147
[183/1000][20/42]    Loss_D: 0.0985  Loss_G: 4.8357  D(x): 0.9703
     D(G(z)): 0.0476 / 0.0465
[183/1000][40/42]    Loss_D: 0.0666  Loss_G: 6.8190  D(x): 0.9867
     D(G(z)): 0.0412 / 0.0146
[184/1000][0/42] Loss_D: 0.2520  Loss_G: 8.1853  D(x): 0.9180
     D(G(z)): 0.0796 / 0.0085
[184/1000][20/42]    Loss_D: 0.1046  Loss_G: 6.9801  D(x): 0.9464
     D(G(z)): 0.0271 / 0.0181
[184/1000][40/42]    Loss_D: 0.1238  Loss_G: 7.4713  D(x): 0.9380
     D(G(z)): 0.0205 / 0.0110
[185/1000][0/42] Loss_D: 0.0757  Loss_G: 6.8377  D(x): 0.9540
     D(G(z)): 0.0121 / 0.0127
[185/1000][20/42]    Loss_D: 0.1063  Loss_G: 5.9774  D(x): 0.9668
     D(G(z)): 0.0414 / 0.0196
[185/1000][40/42]    Loss_D: 0.1890  Loss_G: 6.1917  D(x): 0.9541
     D(G(z)): 0.0692 / 0.0496
[186/1000][0/42] Loss_D: 0.1767  Loss_G: 6.8504  D(x): 0.9939
     D(G(z)): 0.0916 / 0.0271
[186/1000][20/42]    Loss_D: 0.1483  Loss_G: 7.5632  D(x): 0.9797
     D(G(z)): 0.0899 / 0.0234
[186/1000][40/42]    Loss_D: 0.2555  Loss_G: 8.7936  D(x): 0.8678
     D(G(z)): 0.0134 / 0.0174
[187/1000][0/42] Loss_D: 0.1039  Loss_G: 6.8620  D(x): 0.9680
     D(G(z)): 0.0357 / 0.0417
[187/1000][20/42]    Loss_D: 0.1560  Loss_G: 6.5939  D(x): 0.9444
     D(G(z)): 0.0600 / 0.0473
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[187/1000][40/42]	Loss_D: 0.0642	Loss_G: 7.8370	D(x): 0.9678
	D(G(z)): 0.0177 / 0.0069
[188/1000][0/42]	Loss_D: 0.0942	Loss_G: 8.5498	D(x): 0.9545
	D(G(z)): 0.0267 / 0.0121
[188/1000][20/42]	Loss_D: 0.1380	Loss_G: 7.8925	D(x): 0.9469
	D(G(z)): 0.0276 / 0.0176
[188/1000][40/42]	Loss_D: 0.0420	Loss_G: 6.5135	D(x): 0.9838
	D(G(z)): 0.0213 / 0.0227
[189/1000][0/42]	Loss_D: 0.2015	Loss_G: 5.8909	D(x): 0.9927
	D(G(z)): 0.1184 / 0.0411
[189/1000][20/42]	Loss_D: 0.0899	Loss_G: 8.7471	D(x): 0.9631
	D(G(z)): 0.0315 / 0.0084
[189/1000][40/42]	Loss_D: 0.0938	Loss_G: 7.3949	D(x): 0.9538
	D(G(z)): 0.0284 / 0.0190
[190/1000][0/42]	Loss_D: 0.0385	Loss_G: 7.3619	D(x): 0.9920
	D(G(z)): 0.0257 / 0.0138
[190/1000][20/42]	Loss_D: 0.0630	Loss_G: 6.9633	D(x): 0.9952
	D(G(z)): 0.0425 / 0.0118
[190/1000][40/42]	Loss_D: 0.0316	Loss_G: 8.4562	D(x): 0.9832
	D(G(z)): 0.0130 / 0.0030
```

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[191/1000][0/42]	Loss_D: 0.1701	Loss_G: 8.3699	D(x): 0.9030
	D(G(z)): 0.0010 / 0.0016
[191/1000][20/42]	Loss_D: 0.0830	Loss_G: 5.1391	D(x): 0.9953
	D(G(z)): 0.0626 / 0.0561
[191/1000][40/42]	Loss_D: 0.0981	Loss_G: 6.9273	D(x): 0.9553
	D(G(z)): 0.0343 / 0.0094
[192/1000][0/42]	Loss_D: 0.0512	Loss_G: 7.8908	D(x): 0.9679
	D(G(z)): 0.0141 / 0.0075
[192/1000][20/42]	Loss_D: 0.1505	Loss_G: 6.3687	D(x): 0.9192
	D(G(z)): 0.0225 / 0.0187
[192/1000][40/42]	Loss_D: 0.1044	Loss_G: 6.3699	D(x): 0.9754
	D(G(z)): 0.0504 / 0.0386
[193/1000][0/42]	Loss_D: 0.0685	Loss_G: 7.7865	D(x): 0.9846
	D(G(z)): 0.0379 / 0.0142
[193/1000][20/42]	Loss_D: 0.1123	Loss_G: 6.8363	D(x): 0.9432
	D(G(z)): 0.0241 / 0.0158
[193/1000][40/42]	Loss_D: 0.0724	Loss_G: 8.1639	D(x): 0.9564
	D(G(z)): 0.0129 / 0.0071
[194/1000][0/42]	Loss_D: 0.0458	Loss_G: 5.9243	D(x): 0.9743
```

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	D(G(z)): 0.0175 / 0.0223
[194/1000][20/42]	Loss_D: 0.1094	Loss_G: 5.9765	D(x): 0.9422
	D(G(z)): 0.0322 / 0.0560
[194/1000][40/42]	Loss_D: 0.0716	Loss_G: 7.3222	D(x): 0.9909
	D(G(z)): 0.0492 / 0.0178
[195/1000][0/42]	Loss_D: 0.1711	Loss_G: 8.8845	D(x): 0.9060
	D(G(z)): 0.0111 / 0.0032
[195/1000][20/42]	Loss_D: 0.1014	Loss_G: 7.9630	D(x): 0.9345
	D(G(z)): 0.0170 / 0.0111
[195/1000][40/42]	Loss_D: 0.0378	Loss_G: 5.9236	D(x): 0.9898
	D(G(z)): 0.0256 / 0.0221
[196/1000][0/42]	Loss_D: 0.1209	Loss_G: 6.5863	D(x): 0.9911
	D(G(z)): 0.0726 / 0.0218
[196/1000][20/42]	Loss_D: 0.0936	Loss_G: 6.3009	D(x): 0.9917
	D(G(z)): 0.0634 / 0.0241
[196/1000][40/42]	Loss_D: 0.0667	Loss_G: 6.8581	D(x): 0.9807
	D(G(z)): 0.0311 / 0.0214
[197/1000][0/42]	Loss_D: 0.0719	Loss_G: 5.7570	D(x): 0.9883
	D(G(z)): 0.0504 / 0.0226
[197/1000][20/42]	Loss_D: 0.1007	Loss_G: 6.2580	D(x): 0.9665
	D(G(z)): 0.0291 / 0.0150
[197/1000][40/42]	Loss_D: 0.0592	Loss_G: 7.7413	D(x): 0.9523
	D(G(z)): 0.0053 / 0.0080
[198/1000][0/42]	Loss_D: 0.1497	Loss_G: 6.1448	D(x): 0.9942
	D(G(z)): 0.0829 / 0.0423
[198/1000][20/42]	Loss_D: 0.0708	Loss_G: 7.7271	D(x): 0.9707
	D(G(z)): 0.0233 / 0.0067
[198/1000][40/42]	Loss_D: 0.1115	Loss_G: 6.3431	D(x): 0.9658
	D(G(z)): 0.0510 / 0.0200
[199/1000][0/42]	Loss_D: 0.0777	Loss_G: 8.6941	D(x): 0.9459
	D(G(z)): 0.0136 / 0.0076
[199/1000][20/42]	Loss_D: 0.0553	Loss_G: 8.9769	D(x): 0.9544
	D(G(z)): 0.0050 / 0.0019
[199/1000][40/42]	Loss_D: 0.0439	Loss_G: 6.6244	D(x): 0.9709
	D(G(z)): 0.0096 / 0.0132
[200/1000][0/42]	Loss_D: 0.2365	Loss_G: 5.6931	D(x): 0.9955
	D(G(z)): 0.1080 / 0.0430
[200/1000][20/42]	Loss_D: 0.0719	Loss_G: 6.2444	D(x): 0.9875
	D(G(z)): 0.0477 / 0.0149
[200/1000][40/42]	Loss_D: 0.0609	Loss_G: 6.1550	D(x): 0.9985
	D(G(z)): 0.0487 / 0.0259
```

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[201/1000][0/42] Loss_D: 0.2547  Loss_G: 7.5070  D(x): 0.9569
     D(G(z)): 0.0972 / 0.0163
[201/1000][20/42]    Loss_D: 0.0217  Loss_G: 7.8321  D(x): 0.9966
     D(G(z)): 0.0172 / 0.0052
[201/1000][40/42]    Loss_D: 0.1500  Loss_G: 6.1327  D(x): 0.9553
     D(G(z)): 0.0661 / 0.0282
[202/1000][0/42] Loss_D: 0.0711  Loss_G: 6.5626  D(x): 0.9862
     D(G(z)): 0.0425 / 0.0133
[202/1000][20/42]    Loss_D: 0.0480  Loss_G: 7.3270  D(x): 0.9681
     D(G(z)): 0.0099 / 0.0128
[202/1000][40/42]    Loss_D: 0.1115  Loss_G: 8.6421  D(x): 0.9304
     D(G(z)): 0.0034 / 0.0018
[203/1000][0/42] Loss_D: 0.0554  Loss_G: 7.7190  D(x): 0.9655
     D(G(z)): 0.0150 / 0.0134
[203/1000][20/42]    Loss_D: 0.1267  Loss_G: 7.4324  D(x): 0.9745
     D(G(z)): 0.0625 / 0.0253
[203/1000][40/42]    Loss_D: 0.0899  Loss_G: 6.3906  D(x): 0.9541
     D(G(z)): 0.0262 / 0.0288
[204/1000][0/42] Loss_D: 0.1193  Loss_G: 6.2589  D(x): 0.9821
     D(G(z)): 0.0761 / 0.0202
[204/1000][20/42]    Loss_D: 0.1368  Loss_G: 8.4772  D(x): 0.9774
     D(G(z)): 0.0508 / 0.0084
[204/1000][40/42]    Loss_D: 0.2566  Loss_G: 8.8716  D(x): 0.9538
     D(G(z)): 0.0749 / 0.0358
[205/1000][0/42] Loss_D: 0.0603  Loss_G: 9.5307  D(x): 0.9559
     D(G(z)): 0.0069 / 0.0018
[205/1000][20/42]    Loss_D: 0.0338  Loss_G: 7.9900  D(x): 0.9794
     D(G(z)): 0.0089 / 0.0080
[205/1000][40/42]    Loss_D: 0.1131  Loss_G: 6.3115  D(x): 0.9580
     D(G(z)): 0.0354 / 0.0447
[206/1000][0/42] Loss_D: 0.2236  Loss_G: 6.7564  D(x): 0.9986
     D(G(z)): 0.0997 / 0.0565
[206/1000][20/42]    Loss_D: 0.1158  Loss_G: 7.0913  D(x): 0.9968
     D(G(z)): 0.0767 / 0.0199
[206/1000][40/42]    Loss_D: 0.2434  Loss_G: 7.0580  D(x): 0.9271
     D(G(z)): 0.0766 / 0.0175
[207/1000][0/42] Loss_D: 0.1256  Loss_G: 7.6533  D(x): 0.9447
     D(G(z)): 0.0336 / 0.0172
[207/1000][20/42]    Loss_D: 0.0948  Loss_G: 6.6446  D(x): 0.9659
     D(G(z)): 0.0370 / 0.0291
```

```
[207/1000][40/42]	Loss_D: 0.1931	Loss_G: 7.1544	D(x): 0.8849
	D(G(z)): 0.0078 / 0.0134
[208/1000][0/42]	Loss_D: 0.1123	Loss_G: 5.5349	D(x): 0.9820
	D(G(z)): 0.0706 / 0.0461
[208/1000][20/42]	Loss_D: 0.0347	Loss_G: 8.9508	D(x): 0.9915
	D(G(z)): 0.0220 / 0.0037
[208/1000][40/42]	Loss_D: 0.1933	Loss_G: 6.4174	D(x): 0.9326
	D(G(z)): 0.0776 / 0.0251
[209/1000][0/42]	Loss_D: 0.2014	Loss_G: 7.1256	D(x): 0.9521
	D(G(z)): 0.0569 / 0.0343
[209/1000][20/42]	Loss_D: 0.1086	Loss_G: 7.0804	D(x): 0.9499
	D(G(z)): 0.0278 / 0.0300
[209/1000][40/42]	Loss_D: 0.1235	Loss_G: 5.4746	D(x): 0.9604
	D(G(z)): 0.0648 / 0.0791
[210/1000][0/42]	Loss_D: 0.0924	Loss_G: 6.2096	D(x): 0.9985
	D(G(z)): 0.0666 / 0.0173
[210/1000][20/42]	Loss_D: 0.0269	Loss_G: 7.7817	D(x): 0.9936
	D(G(z)): 0.0170 / 0.0096
[210/1000][40/42]	Loss_D: 0.0525	Loss_G: 9.8559	D(x): 0.9807
	D(G(z)): 0.0186 / 0.0069
```

```
[211/1000][0/42]	Loss_D: 0.0829	Loss_G: 7.3737	D(x): 0.9416
	D(G(z)): 0.0069 / 0.0148
[211/1000][20/42]	Loss_D: 0.0706	Loss_G: 7.0084	D(x): 0.9922
	D(G(z)): 0.0511 / 0.0228
[211/1000][40/42]	Loss_D: 0.0845	Loss_G: 6.4110	D(x): 0.9808
	D(G(z)): 0.0484 / 0.0131
[212/1000][0/42]	Loss_D: 0.1306	Loss_G: 6.9400	D(x): 0.9243
	D(G(z)): 0.0312 / 0.0129
[212/1000][20/42]	Loss_D: 0.0794	Loss_G: 7.5412	D(x): 0.9407
	D(G(z)): 0.0058 / 0.0050
[212/1000][40/42]	Loss_D: 0.1691	Loss_G: 6.6438	D(x): 0.9318
	D(G(z)): 0.0130 / 0.0134
[213/1000][0/42]	Loss_D: 0.0714	Loss_G: 5.8386	D(x): 0.9847
	D(G(z)): 0.0453 / 0.0299
[213/1000][20/42]	Loss_D: 0.0203	Loss_G: 7.6544	D(x): 0.9947
	D(G(z)): 0.0139 / 0.0139
[213/1000][40/42]	Loss_D: 0.0759	Loss_G: 6.9451	D(x): 0.9551
	D(G(z)): 0.0139 / 0.0166
[214/1000][0/42]	Loss_D: 0.1106	Loss_G: 5.1942	D(x): 0.9961
```

```
    D(G(z)): 0.0715 / 0.0389
[214/1000][20/42]    Loss_D: 0.0934  Loss_G: 6.7337  D(x): 0.9599
    D(G(z)): 0.0224 / 0.0124
[214/1000][40/42]    Loss_D: 0.0479  Loss_G: 6.7314  D(x): 0.9898
    D(G(z)): 0.0324 / 0.0236
[215/1000][0/42] Loss_D: 0.1997  Loss_G: 5.6756  D(x): 0.9974
    D(G(z)): 0.1022 / 0.0294
[215/1000][20/42]    Loss_D: 0.0999  Loss_G: 6.6331  D(x): 0.9977
    D(G(z)): 0.0779 / 0.0128
[215/1000][40/42]    Loss_D: 0.1383  Loss_G: 7.2563  D(x): 0.9756
    D(G(z)): 0.0327 / 0.0244
[216/1000][0/42] Loss_D: 0.0479  Loss_G: 7.7718  D(x): 0.9774
    D(G(z)): 0.0196 / 0.0147
[216/1000][20/42]    Loss_D: 0.0479  Loss_G: 7.9212  D(x): 0.9847
    D(G(z)): 0.0296 / 0.0037
[216/1000][40/42]    Loss_D: 0.0217  Loss_G: 8.6006  D(x): 0.9848
    D(G(z)): 0.0053 / 0.0026
[217/1000][0/42] Loss_D: 0.0348  Loss_G: 7.6291  D(x): 0.9770
    D(G(z)): 0.0095 / 0.0081
[217/1000][20/42]    Loss_D: 0.0783  Loss_G: 5.9562  D(x): 0.9889
    D(G(z)): 0.0514 / 0.0379
[217/1000][40/42]    Loss_D: 0.0474  Loss_G: 6.8814  D(x): 0.9785
    D(G(z)): 0.0201 / 0.0226
[218/1000][0/42] Loss_D: 0.0512  Loss_G: 6.2930  D(x): 0.9933
    D(G(z)): 0.0373 / 0.0141
[218/1000][20/42]    Loss_D: 0.0825  Loss_G: 7.8148  D(x): 0.9568
    D(G(z)): 0.0176 / 0.0092
[218/1000][40/42]    Loss_D: 0.2229  Loss_G: 9.7329  D(x): 0.9663
    D(G(z)): 0.0932 / 0.0042
[219/1000][0/42] Loss_D: 0.2110  Loss_G: 11.5175 D(x): 0.8985
    D(G(z)): 0.0002 / 0.0001
[219/1000][20/42]    Loss_D: 0.2608  Loss_G: 9.2329  D(x): 0.8856
    D(G(z)): 0.0308 / 0.0131
[219/1000][40/42]    Loss_D: 0.1551  Loss_G: 7.8897  D(x): 0.9147
    D(G(z)): 0.0275 / 0.0350
[220/1000][0/42] Loss_D: 0.4193  Loss_G: 6.7273  D(x): 0.9866
    D(G(z)): 0.1821 / 0.0418
[220/1000][20/42]    Loss_D: 0.0658  Loss_G: 6.8252  D(x): 0.9928
    D(G(z)): 0.0423 / 0.0159
[220/1000][40/42]    Loss_D: 0.0759  Loss_G: 6.3106  D(x): 0.9823
    D(G(z)): 0.0453 / 0.0349
```

```
[221/1000][0/42]	Loss_D: 0.0962	Loss_G: 8.1249	D(x): 0.9994	D(G(z)): 0.0662 / 0.0143
[221/1000][20/42]	Loss_D: 0.1291	Loss_G: 8.5170	D(x): 0.9517	D(G(z)): 0.0434 / 0.0415
[221/1000][40/42]	Loss_D: 0.0485	Loss_G: 9.1024	D(x): 0.9741	D(G(z)): 0.0136 / 0.0089
[222/1000][0/42]	Loss_D: 0.0186	Loss_G: 9.7770	D(x): 0.9865	D(G(z)): 0.0035 / 0.0031
[222/1000][20/42]	Loss_D: 0.1824	Loss_G: 8.2017	D(x): 0.9710	D(G(z)): 0.0691 / 0.0238
[222/1000][40/42]	Loss_D: 0.0949	Loss_G: 6.4694	D(x): 0.9349	D(G(z)): 0.0157 / 0.0204
[223/1000][0/42]	Loss_D: 0.3005	Loss_G: 6.7891	D(x): 0.9941	D(G(z)): 0.1180 / 0.0219
[223/1000][20/42]	Loss_D: 0.0816	Loss_G: 8.1071	D(x): 0.9618	D(G(z)): 0.0245 / 0.0140
[223/1000][40/42]	Loss_D: 0.0945	Loss_G: 8.6330	D(x): 0.9960	D(G(z)): 0.0540 / 0.0202
[224/1000][0/42]	Loss_D: 0.0804	Loss_G: 9.2029	D(x): 0.9452	D(G(z)): 0.0121 / 0.0031
[224/1000][20/42]	Loss_D: 0.0974	Loss_G: 8.6701	D(x): 0.9466	D(G(z)): 0.0270 / 0.0134
[224/1000][40/42]	Loss_D: 0.0461	Loss_G: 7.9685	D(x): 0.9721	D(G(z)): 0.0151 / 0.0098
[225/1000][0/42]	Loss_D: 0.0513	Loss_G: 6.2987	D(x): 0.9704	D(G(z)): 0.0179 / 0.0169
[225/1000][20/42]	Loss_D: 0.1262	Loss_G: 8.1779	D(x): 0.9346	D(G(z)): 0.0256 / 0.0213
[225/1000][40/42]	Loss_D: 0.1937	Loss_G: 6.9940	D(x): 0.9065	D(G(z)): 0.0308 / 0.0148
[226/1000][0/42]	Loss_D: 0.0734	Loss_G: 6.8478	D(x): 0.9724	D(G(z)): 0.0336 / 0.0151
[226/1000][20/42]	Loss_D: 0.0416	Loss_G: 8.2911	D(x): 0.9848	D(G(z)): 0.0205 / 0.0182
[226/1000][40/42]	Loss_D: 0.0455	Loss_G: 7.1461	D(x): 0.9856	D(G(z)): 0.0258 / 0.0284
[227/1000][0/42]	Loss_D: 0.1386	Loss_G: 7.0745	D(x): 0.9840	D(G(z)): 0.0672 / 0.0304
[227/1000][20/42]	Loss_D: 0.0924	Loss_G: 6.4740	D(x): 0.9972	D(G(z)): 0.0736 / 0.0195
```

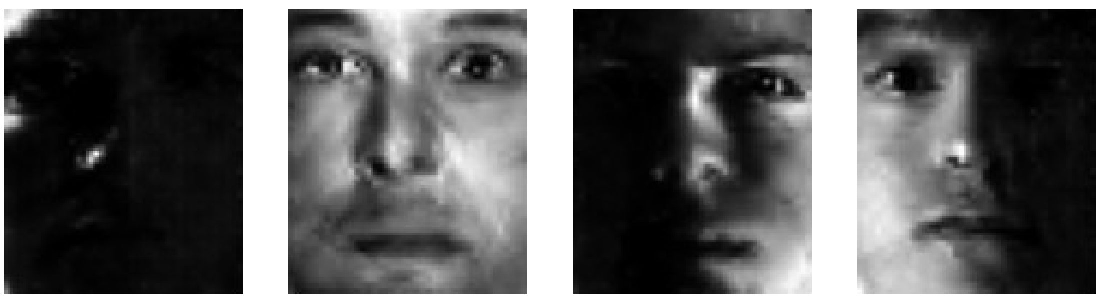
```
[227/1000][40/42]     Loss_D: 0.0511  Loss_G: 7.0965  D(x): 0.9792
      D(G(z)): 0.0252 / 0.0146
[228/1000][0/42] Loss_D: 0.0596  Loss_G: 6.1061  D(x): 0.9849
      D(G(z)): 0.0372 / 0.0175
[228/1000][20/42]     Loss_D: 0.0640  Loss_G: 7.3537  D(x): 0.9669
      D(G(z)): 0.0209 / 0.0076
[228/1000][40/42]     Loss_D: 0.1022  Loss_G: 8.2549  D(x): 0.9392
      D(G(z)): 0.0072 / 0.0071
[229/1000][0/42] Loss_D: 0.0675  Loss_G: 6.6228  D(x): 0.9828
      D(G(z)): 0.0392 / 0.0441
[229/1000][20/42]     Loss_D: 0.0153  Loss_G: 8.1019  D(x): 0.9937
      D(G(z)): 0.0085 / 0.0043
[229/1000][40/42]     Loss_D: 0.1183  Loss_G: 7.8064  D(x): 0.9321
      D(G(z)): 0.0058 / 0.0057
[230/1000][0/42] Loss_D: 0.0376  Loss_G: 7.2736  D(x): 0.9738
      D(G(z)): 0.0090 / 0.0211
[230/1000][20/42]     Loss_D: 0.1675  Loss_G: 6.8200  D(x): 0.9945
      D(G(z)): 0.0625 / 0.0408
[230/1000][40/42]     Loss_D: 0.1037  Loss_G: 5.4886  D(x): 0.9985
      D(G(z)): 0.0691 / 0.0344
```

```
[231/1000][0/42] Loss_D: 0.0392  Loss_G: 6.8740  D(x): 0.9935
      D(G(z)): 0.0291 / 0.0135
[231/1000][20/42]     Loss_D: 0.0554  Loss_G: 8.3902  D(x): 0.9638
      D(G(z)): 0.0099 / 0.0044
[231/1000][40/42]     Loss_D: 0.0656  Loss_G: 7.7103  D(x): 0.9681
      D(G(z)): 0.0217 / 0.0099
[232/1000][0/42] Loss_D: 0.1091  Loss_G: 6.4270  D(x): 0.9529
      D(G(z)): 0.0231 / 0.0202
[232/1000][20/42]     Loss_D: 0.0333  Loss_G: 6.4959  D(x): 0.9822
      D(G(z)): 0.0115 / 0.0121
[232/1000][40/42]     Loss_D: 0.0286  Loss_G: 7.6038  D(x): 0.9767
      D(G(z)): 0.0041 / 0.0034
[233/1000][0/42] Loss_D: 0.0960  Loss_G: 6.9192  D(x): 0.9852
      D(G(z)): 0.0538 / 0.0278
[233/1000][20/42]     Loss_D: 0.0696  Loss_G: 6.5794  D(x): 0.9738
      D(G(z)): 0.0359 / 0.0343
[233/1000][40/42]     Loss_D: 0.0959  Loss_G: 6.7959  D(x): 0.9810
      D(G(z)): 0.0565 / 0.0202
[234/1000][0/42] Loss_D: 0.0709  Loss_G: 7.5381  D(x): 0.9631
```

```
    D(G(z)): 0.0154 / 0.0061
[234/1000][20/42]    Loss_D: 0.0973  Loss_G: 7.9137  D(x): 0.9600
    D(G(z)): 0.0240 / 0.0073
[234/1000][40/42]    Loss_D: 0.0770  Loss_G: 5.6604  D(x): 0.9627
    D(G(z)): 0.0256 / 0.0254
[235/1000][0/42]Loss_D: 0.0611  Loss_G: 5.9635  D(x): 0.9947
    D(G(z)): 0.0477 / 0.0173
[235/1000][20/42]    Loss_D: 0.0434  Loss_G: 8.9389  D(x): 0.9704
    D(G(z)): 0.0094 / 0.0053
[235/1000][40/42]    Loss_D: 0.0753  Loss_G: 7.5449  D(x): 0.9553
    D(G(z)): 0.0175 / 0.0138
[236/1000][0/42]Loss_D: 0.0329  Loss_G: 6.8741  D(x): 0.9881
    D(G(z)): 0.0182 / 0.0175
[236/1000][20/42]    Loss_D: 0.2339  Loss_G: 6.2903  D(x): 0.8644
    D(G(z)): 0.0113 / 0.0201
[236/1000][40/42]    Loss_D: 0.0386  Loss_G: 5.8963  D(x): 0.9959
    D(G(z)): 0.0312 / 0.0225
[237/1000][0/42]Loss_D: 0.0592  Loss_G: 6.5352  D(x): 0.9977
    D(G(z)): 0.0494 / 0.0144
[237/1000][20/42]    Loss_D: 0.0536  Loss_G: 7.7523  D(x): 0.9650
    D(G(z)): 0.0109 / 0.0058
[237/1000][40/42]    Loss_D: 0.0753  Loss_G: 7.7915  D(x): 0.9690
    D(G(z)): 0.0270 / 0.0240
[238/1000][0/42]Loss_D: 0.0449  Loss_G: 6.5152  D(x): 0.9797
    D(G(z)): 0.0205 / 0.0114
[238/1000][20/42]    Loss_D: 0.0693  Loss_G: 8.9663  D(x): 0.9593
    D(G(z)): 0.0173 / 0.0022
[238/1000][40/42]    Loss_D: 0.0573  Loss_G: 8.4112  D(x): 0.9550
    D(G(z)): 0.0063 / 0.0052
[239/1000][0/42]Loss_D: 0.0483  Loss_G: 7.6009  D(x): 0.9702
    D(G(z)): 0.0138 / 0.0101
[239/1000][20/42]    Loss_D: 0.1647  Loss_G: 7.4933  D(x): 0.9052
    D(G(z)): 0.0255 / 0.0135
[239/1000][40/42]    Loss_D: 0.1168  Loss_G: 7.4003  D(x): 0.9817
    D(G(z)): 0.0622 / 0.0281
[240/1000][0/42]Loss_D: 0.0911  Loss_G: 7.9136  D(x): 0.9904
    D(G(z)): 0.0521 / 0.0099
[240/1000][20/42]    Loss_D: 0.1448  Loss_G: 9.4361  D(x): 0.9041
    D(G(z)): 0.0027 / 0.0015
[240/1000][40/42]    Loss_D: 0.2319  Loss_G: 5.9438  D(x): 0.9508
    D(G(z)): 0.0438 / 0.0505
```

```
[241/1000][0/42] Loss_D: 0.2923  Loss_G: 6.1897  D(x): 0.9913
     D(G(z)): 0.1591 / 0.0176
[241/1000][20/42]     Loss_D: 0.1475  Loss_G: 10.1479 D(x): 0.9114
     D(G(z)): 0.0098 / 0.0029
[241/1000][40/42]     Loss_D: 0.2499  Loss_G: 10.3378 D(x): 0.9714
     D(G(z)): 0.0679 / 0.0118
[242/1000][0/42] Loss_D: 0.2365  Loss_G: 12.3310 D(x): 0.9013
     D(G(z)): 0.0018 / 0.0016
[242/1000][20/42]     Loss_D: 0.0414  Loss_G: 9.5486  D(x): 0.9929
     D(G(z)): 0.0309 / 0.0024
[242/1000][40/42]     Loss_D: 0.1254  Loss_G: 7.1138  D(x): 0.9639
     D(G(z)): 0.0600 / 0.0190
[243/1000][0/42] Loss_D: 0.1200  Loss_G: 8.9550  D(x): 0.9893
     D(G(z)): 0.0670 / 0.0077
[243/1000][20/42]     Loss_D: 0.2328  Loss_G: 7.6914  D(x): 0.9283
     D(G(z)): 0.0622 / 0.0279
[243/1000][40/42]     Loss_D: 0.0340  Loss_G: 8.6058  D(x): 0.9986
     D(G(z)): 0.0245 / 0.0039
[244/1000][0/42] Loss_D: 0.1051  Loss_G: 10.4564 D(x): 0.9573
     D(G(z)): 0.0315 / 0.0047
[244/1000][20/42]     Loss_D: 0.1593  Loss_G: 7.5361  D(x): 0.9553
     D(G(z)): 0.0573 / 0.0267
[244/1000][40/42]     Loss_D: 0.1578  Loss_G: 7.4802  D(x): 0.9960
     D(G(z)): 0.0722 / 0.0197
[245/1000][0/42] Loss_D: 0.0939  Loss_G: 10.1716 D(x): 0.9437
     D(G(z)): 0.0173 / 0.0026
[245/1000][20/42]     Loss_D: 0.0512  Loss_G: 9.1151  D(x): 0.9704
     D(G(z)): 0.0145 / 0.0041
[245/1000][40/42]     Loss_D: 0.0462  Loss_G: 8.6147  D(x): 0.9844
     D(G(z)): 0.0248 / 0.0117
[246/1000][0/42] Loss_D: 0.1693  Loss_G: 8.7009  D(x): 0.9662
     D(G(z)): 0.0637 / 0.0245
[246/1000][20/42]     Loss_D: 0.1278  Loss_G: 5.9426  D(x): 0.9693
     D(G(z)): 0.0411 / 0.0354
[246/1000][40/42]     Loss_D: 0.0539  Loss_G: 7.6075  D(x): 0.9647
     D(G(z)): 0.0096 / 0.0078
[247/1000][0/42] Loss_D: 0.0082  Loss_G: 8.8643  D(x): 0.9955
     D(G(z)): 0.0036 / 0.0025
[247/1000][20/42]     Loss_D: 0.0341  Loss_G: 7.1461  D(x): 0.9862
     D(G(z)): 0.0176 / 0.0132
```

```
[247/1000][40/42]	Loss_D: 0.0801	Loss_G: 7.8216	D(x): 0.9823
	D(G(z)): 0.0321 / 0.0156
[248/1000][0/42]	Loss_D: 0.0164	Loss_G: 7.8318	D(x): 0.9909
	D(G(z)): 0.0064 / 0.0068
[248/1000][20/42]	Loss_D: 0.0607	Loss_G: 6.9774	D(x): 0.9718
	D(G(z)): 0.0233 / 0.0097
[248/1000][40/42]	Loss_D: 0.0234	Loss_G: 7.8501	D(x): 0.9926
	D(G(z)): 0.0143 / 0.0101
[249/1000][0/42]	Loss_D: 0.0480	Loss_G: 7.4514	D(x): 0.9854
	D(G(z)): 0.0264 / 0.0099
[249/1000][20/42]	Loss_D: 0.0471	Loss_G: 8.1642	D(x): 0.9684
	D(G(z)): 0.0106 / 0.0071
[249/1000][40/42]	Loss_D: 0.1322	Loss_G: 8.2817	D(x): 0.9534
	D(G(z)): 0.0209 / 0.0171
[250/1000][0/42]	Loss_D: 0.0174	Loss_G: 7.7261	D(x): 0.9884
	D(G(z)): 0.0051 / 0.0065
[250/1000][20/42]	Loss_D: 0.0570	Loss_G: 7.7288	D(x): 0.9860
	D(G(z)): 0.0251 / 0.0059
[250/1000][40/42]	Loss_D: 0.0662	Loss_G: 9.1103	D(x): 0.9622
	D(G(z)): 0.0179 / 0.0095
```



```
[251/1000][0/42]	Loss_D: 0.0453	Loss_G: 7.9959	D(x): 0.9722
	D(G(z)): 0.0126 / 0.0063
[251/1000][20/42]	Loss_D: 0.0876	Loss_G: 7.0903	D(x): 0.9537
	D(G(z)): 0.0235 / 0.0309
[251/1000][40/42]	Loss_D: 0.0191	Loss_G: 7.7254	D(x): 0.9960
	D(G(z)): 0.0136 / 0.0071
[252/1000][0/42]	Loss_D: 0.0194	Loss_G: 7.9996	D(x): 0.9973
	D(G(z)): 0.0151 / 0.0117
[252/1000][20/42]	Loss_D: 0.0661	Loss_G: 8.0541	D(x): 0.9469
	D(G(z)): 0.0057 / 0.0069
[252/1000][40/42]	Loss_D: 0.0855	Loss_G: 6.5497	D(x): 0.9731
	D(G(z)): 0.0422 / 0.0198
[253/1000][0/42]	Loss_D: 0.0283	Loss_G: 7.3478	D(x): 0.9867
	D(G(z)): 0.0140 / 0.0083
[253/1000][20/42]	Loss_D: 0.0202	Loss_G: 7.0780	D(x): 0.9940
	D(G(z)): 0.0120 / 0.0136
[253/1000][40/42]	Loss_D: 0.0192	Loss_G: 7.7770	D(x): 0.9878
	D(G(z)): 0.0060 / 0.0028
[254/1000][0/42]	Loss_D: 0.0512	Loss_G: 7.6250	D(x): 0.9683
```

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    D(G(z)): 0.0120 / 0.0099
[254/1000][20/42]   Loss_D: 0.0753  Loss_G: 7.3859  D(x): 0.9583
    D(G(z)): 0.0113 / 0.0099
[254/1000][40/42]   Loss_D: 0.0953  Loss_G: 7.4044  D(x): 0.9364
    D(G(z)): 0.0059 / 0.0207
[255/1000][0/42] Loss_D: 0.0862  Loss_G: 6.5591  D(x): 0.9900
    D(G(z)): 0.0573 / 0.0466
[255/1000][20/42]   Loss_D: 0.2699  Loss_G: 6.9666  D(x): 0.9877
    D(G(z)): 0.1078 / 0.0324
[255/1000][40/42]   Loss_D: 0.0286  Loss_G: 7.8906  D(x): 0.9935
    D(G(z)): 0.0160 / 0.0238
[256/1000][0/42] Loss_D: 0.0938  Loss_G: 7.2318  D(x): 0.9981
    D(G(z)): 0.0667 / 0.0319
[256/1000][20/42]   Loss_D: 0.0963  Loss_G: 6.1077  D(x): 0.9964
    D(G(z)): 0.0614 / 0.0372
[256/1000][40/42]   Loss_D: 0.2053  Loss_G: 5.7204  D(x): 0.9991
    D(G(z)): 0.1118 / 0.0321
[257/1000][0/42] Loss_D: 0.0768  Loss_G: 8.5337  D(x): 0.9940
    D(G(z)): 0.0449 / 0.0135
[257/1000][20/42]   Loss_D: 0.0892  Loss_G: 8.6100  D(x): 0.9797
    D(G(z)): 0.0378 / 0.0157
[257/1000][40/42]   Loss_D: 0.0279  Loss_G: 7.6805  D(x): 0.9831
    D(G(z)): 0.0097 / 0.0046
[258/1000][0/42] Loss_D: 0.0292  Loss_G: 8.9790  D(x): 0.9909
    D(G(z)): 0.0177 / 0.0084
[258/1000][20/42]   Loss_D: 0.0596  Loss_G: 7.2082  D(x): 0.9735
    D(G(z)): 0.0277 / 0.0142
[258/1000][40/42]   Loss_D: 0.0756  Loss_G: 7.2259  D(x): 0.9662
    D(G(z)): 0.0267 / 0.0133
[259/1000][0/42] Loss_D: 0.0262  Loss_G: 8.8077  D(x): 0.9807
    D(G(z)): 0.0048 / 0.0037
[259/1000][20/42]   Loss_D: 0.0792  Loss_G: 7.4901  D(x): 0.9431
    D(G(z)): 0.0097 / 0.0051
[259/1000][40/42]   Loss_D: 0.0190  Loss_G: 7.2117  D(x): 0.9921
    D(G(z)): 0.0104 / 0.0090
[260/1000][0/42] Loss_D: 0.0284  Loss_G: 7.1694  D(x): 0.9969
    D(G(z)): 0.0224 / 0.0089
[260/1000][20/42]   Loss_D: 0.1309  Loss_G: 6.5452  D(x): 0.9753
    D(G(z)): 0.0594 / 0.0389
[260/1000][40/42]   Loss_D: 0.0404  Loss_G: 8.6861  D(x): 0.9848
    D(G(z)): 0.0206 / 0.0126
```

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[261/1000][0/42]	Loss_D: 0.0191	Loss_G: 8.7153	D(x): 0.9893
	D(G(z)): 0.0075 / 0.0089
[261/1000][20/42]	Loss_D: 0.0346	Loss_G: 7.4079	D(x): 0.9819
	D(G(z)): 0.0142 / 0.0097
[261/1000][40/42]	Loss_D: 0.0607	Loss_G: 8.3622	D(x): 0.9627
	D(G(z)): 0.0169 / 0.0179
[262/1000][0/42]	Loss_D: 0.0493	Loss_G: 6.8592	D(x): 0.9984
	D(G(z)): 0.0387 / 0.0172
[262/1000][20/42]	Loss_D: 0.1351	Loss_G: 5.9559	D(x): 0.9980
	D(G(z)): 0.0786 / 0.0525
[262/1000][40/42]	Loss_D: 0.0805	Loss_G: 7.3068	D(x): 0.9955
	D(G(z)): 0.0488 / 0.0198
[263/1000][0/42]	Loss_D: 0.0450	Loss_G: 8.3079	D(x): 0.9809
	D(G(z)): 0.0212 / 0.0112
[263/1000][20/42]	Loss_D: 0.0370	Loss_G: 7.0933	D(x): 0.9874
	D(G(z)): 0.0225 / 0.0096
[263/1000][40/42]	Loss_D: 0.0365	Loss_G: 7.8482	D(x): 0.9738
	D(G(z)): 0.0084 / 0.0120
[264/1000][0/42]	Loss_D: 0.1417	Loss_G: 6.9039	D(x): 0.9481
	D(G(z)): 0.0386 / 0.0381
[264/1000][20/42]	Loss_D: 0.0698	Loss_G: 10.0904	D(x): 0.9483
	D(G(z)): 0.0033 / 0.0034
[264/1000][40/42]	Loss_D: 0.1172	Loss_G: 7.4326	D(x): 0.9871
	D(G(z)): 0.0618 / 0.0177
[265/1000][0/42]	Loss_D: 0.0549	Loss_G: 5.8374	D(x): 0.9815
	D(G(z)): 0.0317 / 0.0298
[265/1000][20/42]	Loss_D: 0.2011	Loss_G: 7.9589	D(x): 0.9523
	D(G(z)): 0.0351 / 0.0168
[265/1000][40/42]	Loss_D: 0.0773	Loss_G: 6.8324	D(x): 0.9955
	D(G(z)): 0.0545 / 0.0333
[266/1000][0/42]	Loss_D: 0.1281	Loss_G: 8.3631	D(x): 0.9953
	D(G(z)): 0.0779 / 0.0053
[266/1000][20/42]	Loss_D: 0.1615	Loss_G: 6.7569	D(x): 0.9945
	D(G(z)): 0.0844 / 0.0322
[266/1000][40/42]	Loss_D: 0.0542	Loss_G: 9.2992	D(x): 0.9577
	D(G(z)): 0.0078 / 0.0030
[267/1000][0/42]	Loss_D: 0.0181	Loss_G: 8.3628	D(x): 0.9897
	D(G(z)): 0.0067 / 0.0097
[267/1000][20/42]	Loss_D: 0.0545	Loss_G: 8.6767	D(x): 0.9876
	D(G(z)): 0.0356 / 0.0164
```

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[267/1000][40/42]    Loss_D: 0.0313  Loss_G: 10.2219 D(x): 0.9733
     D(G(z)): 0.0028 / 0.0034
[268/1000][0/42] Loss_D: 0.0375  Loss_G: 9.9887  D(x): 0.9897
     D(G(z)): 0.0205 / 0.0128
[268/1000][20/42]    Loss_D: 0.0660  Loss_G: 6.2486  D(x): 0.9930
     D(G(z)): 0.0517 / 0.0134
[268/1000][40/42]    Loss_D: 0.0673  Loss_G: 10.1209 D(x): 0.9497
     D(G(z)): 0.0034 / 0.0012
[269/1000][0/42] Loss_D: 0.1045  Loss_G: 7.0171  D(x): 0.9804
     D(G(z)): 0.0602 / 0.0392
[269/1000][20/42]    Loss_D: 0.0480  Loss_G: 6.5258  D(x): 0.9904
     D(G(z)): 0.0317 / 0.0277
[269/1000][40/42]    Loss_D: 0.0665  Loss_G: 9.2536  D(x): 0.9782
     D(G(z)): 0.0315 / 0.0062
[270/1000][0/42] Loss_D: 0.1483  Loss_G: 8.9757  D(x): 0.9268
     D(G(z)): 0.0276 / 0.0222
[270/1000][20/42]    Loss_D: 0.0394  Loss_G: 6.2906  D(x): 0.9967
     D(G(z)): 0.0302 / 0.0244
[270/1000][40/42]    Loss_D: 0.0443  Loss_G: 8.0438  D(x): 0.9785
     D(G(z)): 0.0161 / 0.0231
```

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[271/1000][0/42] Loss_D: 0.1057  Loss_G: 7.4649  D(x): 0.9714
     D(G(z)): 0.0507 / 0.0124
[271/1000][20/42]    Loss_D: 0.0118  Loss_G: 7.6510  D(x): 0.9932
     D(G(z)): 0.0047 / 0.0053
[271/1000][40/42]    Loss_D: 0.0129  Loss_G: 8.5568  D(x): 0.9943
     D(G(z)): 0.0069 / 0.0062
[272/1000][0/42] Loss_D: 0.0514  Loss_G: 6.7864  D(x): 0.9847
     D(G(z)): 0.0291 / 0.0200
[272/1000][20/42]    Loss_D: 0.0327  Loss_G: 8.5233  D(x): 0.9894
     D(G(z)): 0.0191 / 0.0052
[272/1000][40/42]    Loss_D: 0.1248  Loss_G: 8.3306  D(x): 0.9096
     D(G(z)): 0.0042 / 0.0055
[273/1000][0/42] Loss_D: 0.0145  Loss_G: 7.3019  D(x): 0.9947
     D(G(z)): 0.0089 / 0.0098
[273/1000][20/42]    Loss_D: 0.0937  Loss_G: 7.2920  D(x): 0.9713
     D(G(z)): 0.0473 / 0.0108
[273/1000][40/42]    Loss_D: 0.1646  Loss_G: 7.7905  D(x): 0.9538
     D(G(z)): 0.0815 / 0.0170
[274/1000][0/42] Loss_D: 0.0290  Loss_G: 7.3587  D(x): 0.9855
```

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    D(G(z)): 0.0126 / 0.0107
[274/1000][20/42]    Loss_D: 0.0543  Loss_G: 7.8046  D(x): 0.9894
    D(G(z)): 0.0321 / 0.0331
[274/1000][40/42]    Loss_D: 0.0536  Loss_G: 6.8255  D(x): 0.9933
    D(G(z)): 0.0352 / 0.0107
[275/1000][0/42] Loss_D: 0.0310  Loss_G: 7.8994  D(x): 0.9871
    D(G(z)): 0.0163 / 0.0082
[275/1000][20/42]    Loss_D: 0.3217  Loss_G: 10.0018 D(x): 0.8302
    D(G(z)): 0.0043 / 0.0036
[275/1000][40/42]    Loss_D: 0.0665  Loss_G: 7.5628  D(x): 0.9608
    D(G(z)): 0.0171 / 0.0254
[276/1000][0/42] Loss_D: 0.0797  Loss_G: 8.3524  D(x): 0.9916
    D(G(z)): 0.0485 / 0.0154
[276/1000][20/42]    Loss_D: 0.1310  Loss_G: 7.4880  D(x): 0.9399
    D(G(z)): 0.0288 / 0.0345
[276/1000][40/42]    Loss_D: 0.1505  Loss_G: 9.8738  D(x): 0.9812
    D(G(z)): 0.0683 / 0.0020
[277/1000][0/42] Loss_D: 0.2472  Loss_G: 11.9742 D(x): 0.8716
    D(G(z)): 0.0097 / 0.0081
[277/1000][20/42]    Loss_D: 0.0621  Loss_G: 5.9957  D(x): 0.9822
    D(G(z)): 0.0330 / 0.0467
[277/1000][40/42]    Loss_D: 0.0354  Loss_G: 10.5672 D(x): 0.9744
    D(G(z)): 0.0074 / 0.0019
[278/1000][0/42] Loss_D: 0.0547  Loss_G: 9.4010  D(x): 0.9696
    D(G(z)): 0.0132 / 0.0118
[278/1000][20/42]    Loss_D: 0.0897  Loss_G: 9.0803  D(x): 0.9536
    D(G(z)): 0.0197 / 0.0089
[278/1000][40/42]    Loss_D: 0.1238  Loss_G: 6.2067  D(x): 0.9985
    D(G(z)): 0.0640 / 0.0415
[279/1000][0/42] Loss_D: 0.0192  Loss_G: 8.4995  D(x): 0.9910
    D(G(z)): 0.0093 / 0.0031
[279/1000][20/42]    Loss_D: 0.0431  Loss_G: 9.4156  D(x): 0.9822
    D(G(z)): 0.0193 / 0.0072
[279/1000][40/42]    Loss_D: 0.0207  Loss_G: 8.5517  D(x): 0.9973
    D(G(z)): 0.0161 / 0.0047
[280/1000][0/42] Loss_D: 0.0520  Loss_G: 9.7767  D(x): 0.9699
    D(G(z)): 0.0135 / 0.0055
[280/1000][20/42]    Loss_D: 0.0224  Loss_G: 7.5614  D(x): 0.9886
    D(G(z)): 0.0099 / 0.0070
[280/1000][40/42]    Loss_D: 0.1273  Loss_G: 10.7512 D(x): 0.9099
    D(G(z)): 0.0017 / 0.0010
```

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[281/1000][0/42] Loss_D: 0.0180  Loss_G: 7.4345  D(x): 0.9877
     D(G(z)): 0.0048 / 0.0092
[281/1000][20/42]     Loss_D: 0.0201  Loss_G: 7.0487  D(x): 0.9961
     D(G(z)): 0.0156 / 0.0064
[281/1000][40/42]     Loss_D: 0.0464  Loss_G: 7.3431  D(x): 0.9682
     D(G(z)): 0.0088 / 0.0106
[282/1000][0/42] Loss_D: 0.0352  Loss_G: 6.7639  D(x): 0.9947
     D(G(z)): 0.0258 / 0.0177
[282/1000][20/42]     Loss_D: 0.0192  Loss_G: 8.7784  D(x): 0.9911
     D(G(z)): 0.0095 / 0.0086
[282/1000][40/42]     Loss_D: 0.0413  Loss_G: 6.9082  D(x): 0.9853
     D(G(z)): 0.0170 / 0.0174
[283/1000][0/42] Loss_D: 0.0718  Loss_G: 6.7706  D(x): 0.9946
     D(G(z)): 0.0445 / 0.0157
[283/1000][20/42]     Loss_D: 0.0768  Loss_G: 8.5424  D(x): 0.9934
     D(G(z)): 0.0460 / 0.0051
[283/1000][40/42]     Loss_D: 0.0772  Loss_G: 9.4283  D(x): 0.9482
     D(G(z)): 0.0013 / 0.0011
[284/1000][0/42] Loss_D: 0.0127  Loss_G: 8.3240  D(x): 0.9914
     D(G(z)): 0.0039 / 0.0100
[284/1000][20/42]     Loss_D: 0.0059  Loss_G: 9.5463  D(x): 0.9953
     D(G(z)): 0.0011 / 0.0011
[284/1000][40/42]     Loss_D: 0.0234  Loss_G: 6.8833  D(x): 0.9873
     D(G(z)): 0.0101 / 0.0050
[285/1000][0/42] Loss_D: 0.0280  Loss_G: 8.7367  D(x): 0.9814
     D(G(z)): 0.0078 / 0.0031
[285/1000][20/42]     Loss_D: 0.0277  Loss_G: 6.9183  D(x): 0.9962
     D(G(z)): 0.0213 / 0.0138
[285/1000][40/42]     Loss_D: 0.0158  Loss_G: 8.6221  D(x): 0.9933
     D(G(z)): 0.0089 / 0.0046
[286/1000][0/42] Loss_D: 0.1120  Loss_G: 7.6761  D(x): 0.9277
     D(G(z)): 0.0097 / 0.0098
[286/1000][20/42]     Loss_D: 0.0363  Loss_G: 8.3403  D(x): 0.9820
     D(G(z)): 0.0146 / 0.0113
[286/1000][40/42]     Loss_D: 0.0247  Loss_G: 10.0525 D(x): 0.9852
     D(G(z)): 0.0078 / 0.0040
[287/1000][0/42] Loss_D: 0.0350  Loss_G: 9.9683  D(x): 0.9699
     D(G(z)): 0.0026 / 0.0051
[287/1000][20/42]     Loss_D: 0.0259  Loss_G: 8.9890  D(x): 0.9831
     D(G(z)): 0.0081 / 0.0021
```

[287/1000][40/42]	Loss_D: 0.0698	Loss_G: 8.0545	D(x): 0.9692	D(G(z)): 0.0188 / 0.0098
[288/1000][0/42]	Loss_D: 0.0112	Loss_G: 8.1919	D(x): 0.9949	D(G(z)): 0.0058 / 0.0036
[288/1000][20/42]	Loss_D: 0.0247	Loss_G: 7.7247	D(x): 0.9807	D(G(z)): 0.0039 / 0.0065
[288/1000][40/42]	Loss_D: 0.0688	Loss_G: 7.5067	D(x): 0.9650	D(G(z)): 0.0230 / 0.0151
[289/1000][0/42]	Loss_D: 0.0785	Loss_G: 5.7578	D(x): 0.9773	D(G(z)): 0.0411 / 0.0182
[289/1000][20/42]	Loss_D: 0.0899	Loss_G: 7.4625	D(x): 0.9280	D(G(z)): 0.0067 / 0.0174
[289/1000][40/42]	Loss_D: 0.0933	Loss_G: 6.6473	D(x): 0.9586	D(G(z)): 0.0249 / 0.0208
[290/1000][0/42]	Loss_D: 0.0283	Loss_G: 7.4778	D(x): 0.9993	D(G(z)): 0.0246 / 0.0169
[290/1000][20/42]	Loss_D: 0.0462	Loss_G: 7.2193	D(x): 0.9984	D(G(z)): 0.0355 / 0.0227
[290/1000][40/42]	Loss_D: 0.0540	Loss_G: 7.3271	D(x): 0.9641	D(G(z)): 0.0108 / 0.0105

[291/1000][0/42]	Loss_D: 0.0343	Loss_G: 7.5017	D(x): 0.9972	D(G(z)): 0.0251 / 0.0076
[291/1000][20/42]	Loss_D: 0.0424	Loss_G: 6.9730	D(x): 0.9984	D(G(z)): 0.0339 / 0.0154
[291/1000][40/42]	Loss_D: 0.0544	Loss_G: 6.2906	D(x): 0.9895	D(G(z)): 0.0390 / 0.0140
[292/1000][0/42]	Loss_D: 0.0398	Loss_G: 9.3721	D(x): 0.9916	D(G(z)): 0.0231 / 0.0035
[292/1000][20/42]	Loss_D: 0.0617	Loss_G: 10.1179	D(x): 0.9441	D(G(z)): 0.0011 / 0.0012
[292/1000][40/42]	Loss_D: 0.2015	Loss_G: 8.9021	D(x): 0.8887	D(G(z)): 0.0013 / 0.0022
[293/1000][0/42]	Loss_D: 0.0362	Loss_G: 6.9185	D(x): 0.9933	D(G(z)): 0.0261 / 0.0259
[293/1000][20/42]	Loss_D: 0.5371	Loss_G: 6.7540	D(x): 0.9965	D(G(z)): 0.2274 / 0.0411
[293/1000][40/42]	Loss_D: 0.1373	Loss_G: 7.8438	D(x): 0.9934	D(G(z)): 0.0586 / 0.0364
[294/1000][0/42]	Loss_D: 0.1116	Loss_G: 8.6234	D(x): 0.9770

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     D(G(z)): 0.0416 / 0.0054
[294/1000][20/42]     Loss_D: 0.0692  Loss_G: 9.0427  D(x): 0.9604
     D(G(z)): 0.0084 / 0.0054
[294/1000][40/42]     Loss_D: 0.1176  Loss_G: 9.9550  D(x): 0.9746
     D(G(z)): 0.0524 / 0.0042
[295/1000][0/42] Loss_D: 0.1357  Loss_G: 10.7998 D(x): 0.9119
     D(G(z)): 0.0042 / 0.0044
[295/1000][20/42]     Loss_D: 0.1249  Loss_G: 10.2938 D(x): 0.9354
     D(G(z)): 0.0021 / 0.0029
[295/1000][40/42]     Loss_D: 0.0811  Loss_G: 12.3319 D(x): 0.9678
     D(G(z)): 0.0334 / 0.0027
[296/1000][0/42] Loss_D: 0.3460  Loss_G: 11.0047 D(x): 0.8460
     D(G(z)): 0.0016 / 0.0031
[296/1000][20/42]     Loss_D: 0.0371  Loss_G: 7.0854  D(x): 0.9938
     D(G(z)): 0.0276 / 0.0147
[296/1000][40/42]     Loss_D: 0.1160  Loss_G: 8.4435  D(x): 0.9914
     D(G(z)): 0.0596 / 0.0119
[297/1000][0/42] Loss_D: 0.1734  Loss_G: 9.1717  D(x): 0.9152
     D(G(z)): 0.0072 / 0.0040
[297/1000][20/42]     Loss_D: 0.2567  Loss_G: 7.9164  D(x): 0.9964
     D(G(z)): 0.1096 / 0.0362
[297/1000][40/42]     Loss_D: 0.0241  Loss_G: 14.4662 D(x): 0.9801
     D(G(z)): 0.0019 / 0.0002
[298/1000][0/42] Loss_D: 0.0443  Loss_G: 12.8805 D(x): 0.9628
     D(G(z)): 0.0011 / 0.0019
[298/1000][20/42]     Loss_D: 0.1919  Loss_G: 8.6945  D(x): 0.9164
     D(G(z)): 0.0356 / 0.0166
[298/1000][40/42]     Loss_D: 0.1237  Loss_G: 9.3525  D(x): 0.9336
     D(G(z)): 0.0108 / 0.0079
[299/1000][0/42] Loss_D: 0.2539  Loss_G: 8.3514  D(x): 0.8800
     D(G(z)): 0.0267 / 0.0190
[299/1000][20/42]     Loss_D: 0.0292  Loss_G: 11.1582 D(x): 0.9791
     D(G(z)): 0.0056 / 0.0168
[299/1000][40/42]     Loss_D: 0.0233  Loss_G: 7.7400  D(x): 0.9895
     D(G(z)): 0.0119 / 0.0167
[300/1000][0/42] Loss_D: 0.2549  Loss_G: 7.5903  D(x): 0.9962
     D(G(z)): 0.1094 / 0.0309
[300/1000][20/42]     Loss_D: 0.1984  Loss_G: 8.6916  D(x): 0.9939
     D(G(z)): 0.0998 / 0.0118
[300/1000][40/42]     Loss_D: 0.3382  Loss_G: 8.8063  D(x): 0.9665
     D(G(z)): 0.1149 / 0.0202
```
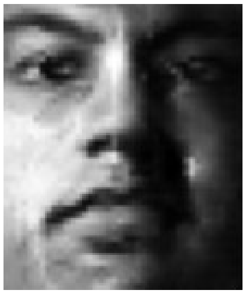
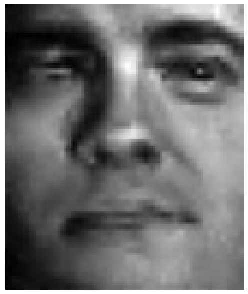
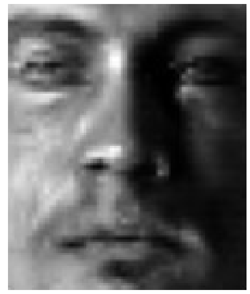
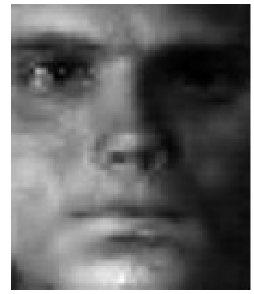

```
[301/1000][0/42]	Loss_D: 0.0632	Loss_G: 11.2490	D(x): 0.9899	D(G(z)): 0.0343 / 0.0039
[301/1000][20/42]	Loss_D: 0.0417	Loss_G: 10.9923	D(x): 0.9910	D(G(z)): 0.0225 / 0.0021
[301/1000][40/42]	Loss_D: 0.2374	Loss_G: 7.5511	D(x): 0.9748	D(G(z)): 0.0932 / 0.0267
[302/1000][0/42]	Loss_D: 0.0511	Loss_G: 9.1078	D(x): 0.9867	D(G(z)): 0.0308 / 0.0155
[302/1000][20/42]	Loss_D: 0.0345	Loss_G: 8.8652	D(x): 0.9834	D(G(z)): 0.0130 / 0.0057
[302/1000][40/42]	Loss_D: 0.0726	Loss_G: 8.4003	D(x): 0.9447	D(G(z)): 0.0032 / 0.0084
[303/1000][0/42]	Loss_D: 0.1175	Loss_G: 7.8411	D(x): 0.9988	D(G(z)): 0.0771 / 0.0305
[303/1000][20/42]	Loss_D: 0.0272	Loss_G: 7.1882	D(x): 0.9904	D(G(z)): 0.0159 / 0.0150
[303/1000][40/42]	Loss_D: 0.0624	Loss_G: 6.8519	D(x): 0.9610	D(G(z)): 0.0158 / 0.0164
[304/1000][0/42]	Loss_D: 0.0640	Loss_G: 7.9992	D(x): 0.9710	D(G(z)): 0.0209 / 0.0107
[304/1000][20/42]	Loss_D: 0.0223	Loss_G: 8.9646	D(x): 0.9849	D(G(z)): 0.0049 / 0.0035
[304/1000][40/42]	Loss_D: 0.0638	Loss_G: 8.3467	D(x): 0.9984	D(G(z)): 0.0538 / 0.0095
[305/1000][0/42]	Loss_D: 0.0276	Loss_G: 10.5503	D(x): 0.9839	D(G(z)): 0.0063 / 0.0014
[305/1000][20/42]	Loss_D: 0.0221	Loss_G: 8.5097	D(x): 0.9852	D(G(z)): 0.0052 / 0.0045
[305/1000][40/42]	Loss_D: 0.0849	Loss_G: 7.0109	D(x): 0.9952	D(G(z)): 0.0528 / 0.0186
[306/1000][0/42]	Loss_D: 0.0950	Loss_G: 8.2099	D(x): 0.9732	D(G(z)): 0.0358 / 0.0057
[306/1000][20/42]	Loss_D: 0.0352	Loss_G: 6.6407	D(x): 0.9981	D(G(z)): 0.0288 / 0.0182
[306/1000][40/42]	Loss_D: 0.0390	Loss_G: 7.2633	D(x): 0.9811	D(G(z)): 0.0105 / 0.0102
[307/1000][0/42]	Loss_D: 0.0209	Loss_G: 7.2010	D(x): 0.9887	D(G(z)): 0.0089 / 0.0086
[307/1000][20/42]	Loss_D: 0.0317	Loss_G: 7.9944	D(x): 0.9856	D(G(z)): 0.0149 / 0.0038
```

```
[307/1000][40/42]	Loss_D: 0.0507	Loss_G: 7.0771	D(x): 0.9816
	D(G(z)): 0.0257 / 0.0132
[308/1000][0/42]	Loss_D: 0.0313	Loss_G: 6.8437	D(x): 0.9818
	D(G(z)): 0.0115 / 0.0082
[308/1000][20/42]	Loss_D: 0.0907	Loss_G: 6.9623	D(x): 0.9887
	D(G(z)): 0.0482 / 0.0113
[308/1000][40/42]	Loss_D: 0.0590	Loss_G: 7.7643	D(x): 0.9972
	D(G(z)): 0.0411 / 0.0262
[309/1000][0/42]	Loss_D: 0.0526	Loss_G: 9.0766	D(x): 0.9694
	D(G(z)): 0.0175 / 0.0082
[309/1000][20/42]	Loss_D: 0.0496	Loss_G: 7.1504	D(x): 0.9915
	D(G(z)): 0.0328 / 0.0182
[309/1000][40/42]	Loss_D: 0.0086	Loss_G: 7.7256	D(x): 0.9987
	D(G(z)): 0.0070 / 0.0042
[310/1000][0/42]	Loss_D: 0.0136	Loss_G: 7.8658	D(x): 0.9934
	D(G(z)): 0.0068 / 0.0074
[310/1000][20/42]	Loss_D: 0.0725	Loss_G: 6.7063	D(x): 0.9489
	D(G(z)): 0.0082 / 0.0195
[310/1000][40/42]	Loss_D: 0.1867	Loss_G: 9.1673	D(x): 0.8779
	D(G(z)): 0.0010 / 0.0040
```

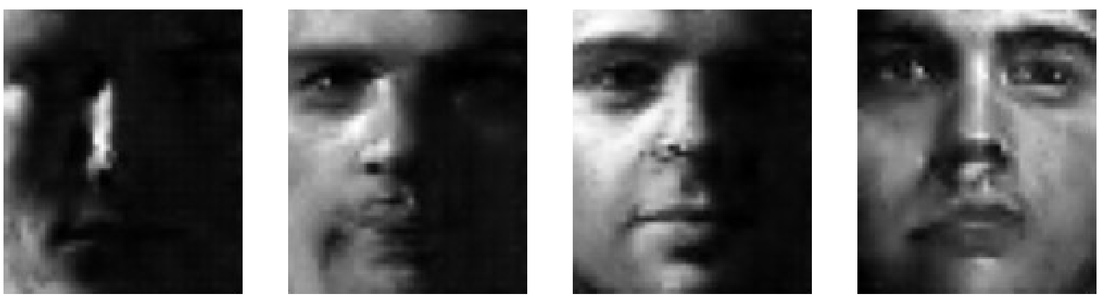
```
[311/1000][0/42]	Loss_D: 0.0124	Loss_G: 7.4255	D(x): 0.9979
	D(G(z)): 0.0098 / 0.0241
[311/1000][20/42]	Loss_D: 0.0136	Loss_G: 9.8519	D(x): 0.9918
	D(G(z)): 0.0048 / 0.0029
[311/1000][40/42]	Loss_D: 0.0234	Loss_G: 6.7609	D(x): 0.9867
	D(G(z)): 0.0081 / 0.0092
[312/1000][0/42]	Loss_D: 0.0114	Loss_G: 8.4721	D(x): 0.9996
	D(G(z)): 0.0102 / 0.0066
[312/1000][20/42]	Loss_D: 0.0538	Loss_G: 6.1744	D(x): 0.9926
	D(G(z)): 0.0387 / 0.0520
[312/1000][40/42]	Loss_D: 0.0951	Loss_G: 7.0991	D(x): 0.9899
	D(G(z)): 0.0289 / 0.0178
[313/1000][0/42]	Loss_D: 0.1319	Loss_G: 7.5945	D(x): 0.9895
	D(G(z)): 0.0669 / 0.0305
[313/1000][20/42]	Loss_D: 0.0450	Loss_G: 7.0894	D(x): 0.9841
	D(G(z)): 0.0249 / 0.0177
[313/1000][40/42]	Loss_D: 0.0474	Loss_G: 6.9385	D(x): 0.9773
	D(G(z)): 0.0197 / 0.0173
[314/1000][0/42]	Loss_D: 0.0783	Loss_G: 8.5917	D(x): 0.9820
```

```
    D(G(z)): 0.0403 / 0.0222
[314/1000][20/42]    Loss_D: 0.0653  Loss_G: 8.2488  D(x): 0.9978
    D(G(z)): 0.0335 / 0.0126
[314/1000][40/42]    Loss_D: 0.1238  Loss_G: 5.1911  D(x): 0.9985
    D(G(z)): 0.0814 / 0.0608
[315/1000][0/42]Loss_D: 0.1075  Loss_G: 6.4923  D(x): 0.9932
    D(G(z)): 0.0736 / 0.0176
[315/1000][20/42]    Loss_D: 0.0347  Loss_G: 7.4192  D(x): 0.9994
    D(G(z)): 0.0307 / 0.0198
[315/1000][40/42]    Loss_D: 0.0340  Loss_G: 7.2649  D(x): 0.9892
    D(G(z)): 0.0210 / 0.0142
[316/1000][0/42]Loss_D: 0.0288  Loss_G: 7.8321  D(x): 0.9984
    D(G(z)): 0.0232 / 0.0081
[316/1000][20/42]    Loss_D: 0.0576  Loss_G: 6.1908  D(x): 0.9937
    D(G(z)): 0.0455 / 0.0204
[316/1000][40/42]    Loss_D: 0.0203  Loss_G: 6.5463  D(x): 0.9916
    D(G(z)): 0.0110 / 0.0317
[317/1000][0/42]Loss_D: 0.2014  Loss_G: 7.5881  D(x): 0.9954
    D(G(z)): 0.0981 / 0.0174
[317/1000][20/42]    Loss_D: 0.0421  Loss_G: 9.9104  D(x): 0.9730
    D(G(z)): 0.0116 / 0.0033
[317/1000][40/42]    Loss_D: 0.0941  Loss_G: 6.6578  D(x): 0.9981
    D(G(z)): 0.0588 / 0.0249
[318/1000][0/42]Loss_D: 0.0613  Loss_G: 8.4752  D(x): 0.9955
    D(G(z)): 0.0475 / 0.0072
[318/1000][20/42]    Loss_D: 0.0765  Loss_G: 8.6523  D(x): 0.9535
    D(G(z)): 0.0132 / 0.0092
[318/1000][40/42]    Loss_D: 0.0575  Loss_G: 6.4986  D(x): 0.9666
    D(G(z)): 0.0172 / 0.0221
[319/1000][0/42]Loss_D: 0.1054  Loss_G: 7.3974  D(x): 0.9939
    D(G(z)): 0.0550 / 0.0099
[319/1000][20/42]    Loss_D: 0.1227  Loss_G: 8.2502  D(x): 0.9225
    D(G(z)): 0.0220 / 0.0150
[319/1000][40/42]    Loss_D: 0.0449  Loss_G: 9.1438  D(x): 0.9795
    D(G(z)): 0.0192 / 0.0029
[320/1000][0/42]Loss_D: 0.0539  Loss_G: 11.3349 D(x): 0.9570
    D(G(z)): 0.0006 / 0.0005
[320/1000][20/42]    Loss_D: 0.1844  Loss_G: 8.0390  D(x): 0.9575
    D(G(z)): 0.0398 / 0.0223
[320/1000][40/42]    Loss_D: 0.0426  Loss_G: 8.0090  D(x): 0.9956
    D(G(z)): 0.0286 / 0.0078
```

```
[321/1000][0/42] Loss_D: 0.0144  Loss_G: 8.8558  D(x): 0.9944
     D(G(z)): 0.0076 / 0.0023
[321/1000][20/42]    Loss_D: 0.1243  Loss_G: 8.8031  D(x): 0.9447
     D(G(z)): 0.0276 / 0.0136
[321/1000][40/42]    Loss_D: 0.0249  Loss_G: 8.2570  D(x): 0.9937
     D(G(z)): 0.0154 / 0.0051
[322/1000][0/42] Loss_D: 0.0377  Loss_G: 8.2542  D(x): 0.9848
     D(G(z)): 0.0193 / 0.0061
[322/1000][20/42]    Loss_D: 0.0323  Loss_G: 7.5065  D(x): 0.9973
     D(G(z)): 0.0234 / 0.0102
[322/1000][40/42]    Loss_D: 0.0871  Loss_G: 8.8355  D(x): 0.9803
     D(G(z)): 0.0338 / 0.0030
[323/1000][0/42] Loss_D: 0.0143  Loss_G: 10.5971 D(x): 0.9874
     D(G(z)): 0.0009 / 0.0005
[323/1000][20/42]    Loss_D: 0.0258  Loss_G: 8.4863  D(x): 0.9910
     D(G(z)): 0.0145 / 0.0083
[323/1000][40/42]    Loss_D: 0.0293  Loss_G: 9.4441  D(x): 0.9884
     D(G(z)): 0.0131 / 0.0078
[324/1000][0/42] Loss_D: 0.1140  Loss_G: 5.7253  D(x): 0.9995
     D(G(z)): 0.0690 / 0.0398
[324/1000][20/42]    Loss_D: 0.0196  Loss_G: 9.2787  D(x): 0.9847
     D(G(z)): 0.0025 / 0.0023
[324/1000][40/42]    Loss_D: 0.0248  Loss_G: 8.6486  D(x): 0.9902
     D(G(z)): 0.0134 / 0.0072
[325/1000][0/42] Loss_D: 0.0368  Loss_G: 9.3520  D(x): 0.9740
     D(G(z)): 0.0028 / 0.0035
[325/1000][20/42]    Loss_D: 0.0292  Loss_G: 9.0170  D(x): 0.9751
     D(G(z)): 0.0014 / 0.0012
[325/1000][40/42]    Loss_D: 0.0176  Loss_G: 7.0420  D(x): 0.9908
     D(G(z)): 0.0072 / 0.0058
[326/1000][0/42] Loss_D: 0.0137  Loss_G: 7.4033  D(x): 0.9980
     D(G(z)): 0.0113 / 0.0064
[326/1000][20/42]    Loss_D: 0.0391  Loss_G: 6.4091  D(x): 0.9962
     D(G(z)): 0.0304 / 0.0128
[326/1000][40/42]    Loss_D: 0.0341  Loss_G: 7.7708  D(x): 0.9801
     D(G(z)): 0.0116 / 0.0063
[327/1000][0/42] Loss_D: 0.0122  Loss_G: 8.8973  D(x): 0.9986
     D(G(z)): 0.0100 / 0.0058
[327/1000][20/42]    Loss_D: 0.0278  Loss_G: 7.6994  D(x): 0.9817
     D(G(z)): 0.0082 / 0.0087
```

```
[327/1000][40/42]    Loss_D: 0.0390  Loss_G: 8.0013  D(x): 0.9923
     D(G(z)): 0.0276 / 0.0098
[328/1000][0/42]Loss_D: 0.0121  Loss_G: 9.1975  D(x): 0.9918
     D(G(z)): 0.0036 / 0.0021
[328/1000][20/42]    Loss_D: 0.0674  Loss_G: 10.3984 D(x): 0.9608
     D(G(z)): 0.0129 / 0.0010
[328/1000][40/42]    Loss_D: 0.0792  Loss_G: 7.0963  D(x): 0.9974
     D(G(z)): 0.0560 / 0.0107
[329/1000][0/42]Loss_D: 0.0201  Loss_G: 8.8545  D(x): 0.9893
     D(G(z)): 0.0088 / 0.0020
[329/1000][20/42]    Loss_D: 0.0544  Loss_G: 8.6394  D(x): 0.9923
     D(G(z)): 0.0291 / 0.0047
[329/1000][40/42]    Loss_D: 0.1897  Loss_G: 9.2000  D(x): 0.8876
     D(G(z)): 0.0020 / 0.0057
[330/1000][0/42]Loss_D: 0.0679  Loss_G: 6.3972  D(x): 0.9982
     D(G(z)): 0.0530 / 0.0465
[330/1000][20/42]    Loss_D: 0.0655  Loss_G: 8.5796  D(x): 0.9802
     D(G(z)): 0.0237 / 0.0114
[330/1000][40/42]    Loss_D: 0.0269  Loss_G: 8.7274  D(x): 0.9854
     D(G(z)): 0.0101 / 0.0068
```

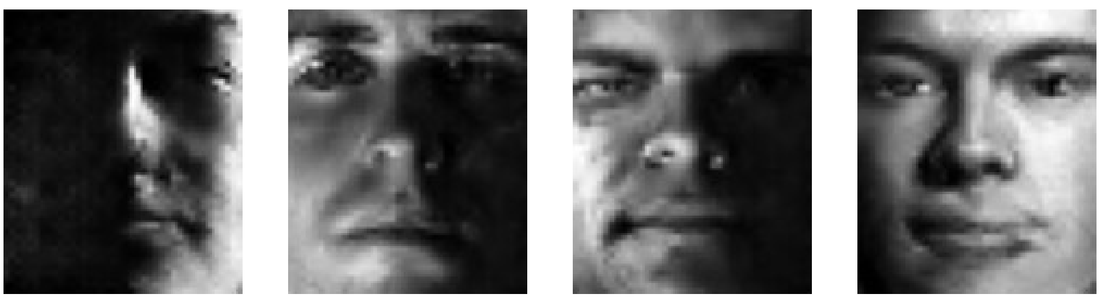


```
[331/1000][0/42]Loss_D: 0.0370  Loss_G: 9.1128  D(x): 0.9897
     D(G(z)): 0.0182 / 0.0136
[331/1000][20/42]    Loss_D: 0.0450  Loss_G: 9.8644  D(x): 0.9658
     D(G(z)): 0.0020 / 0.0025
[331/1000][40/42]    Loss_D: 0.3945  Loss_G: 8.1947  D(x): 0.8312
     D(G(z)): 0.0019 / 0.0169
[332/1000][0/42]Loss_D: 0.1046  Loss_G: 6.1284  D(x): 0.9999
     D(G(z)): 0.0408 / 0.0857
[332/1000][20/42]    Loss_D: 0.0087  Loss_G: 9.0139  D(x): 0.9974
     D(G(z)): 0.0060 / 0.0040
[332/1000][40/42]    Loss_D: 0.0735  Loss_G: 6.1775  D(x): 0.9958
     D(G(z)): 0.0524 / 0.0377
[333/1000][0/42]Loss_D: 0.0836  Loss_G: 7.8409  D(x): 0.9928
     D(G(z)): 0.0530 / 0.0166
[333/1000][20/42]    Loss_D: 0.0466  Loss_G: 9.4217  D(x): 0.9856
     D(G(z)): 0.0248 / 0.0049
[333/1000][40/42]    Loss_D: 0.1536  Loss_G: 9.1900  D(x): 0.9263
     D(G(z)): 0.0070 / 0.0072
[334/1000][0/42]Loss_D: 0.0490  Loss_G: 6.6750  D(x): 0.9982
```

```
      D(G(z)): 0.0380 / 0.0193
[334/1000][20/42]     Loss_D: 0.0403  Loss_G: 8.0850  D(x): 0.9992
      D(G(z)): 0.0323 / 0.0117
[334/1000][40/42]     Loss_D: 0.0285  Loss_G: 8.6089  D(x): 0.9941
      D(G(z)): 0.0179 / 0.0057
[335/1000][0/42] Loss_D: 0.0444  Loss_G: 8.3226  D(x): 0.9847
      D(G(z)): 0.0239 / 0.0202
[335/1000][20/42]     Loss_D: 0.0244  Loss_G: 9.9833  D(x): 0.9941
      D(G(z)): 0.0160 / 0.0140
[335/1000][40/42]     Loss_D: 0.1203  Loss_G: 8.6168  D(x): 0.9847
      D(G(z)): 0.0578 / 0.0057
[336/1000][0/42] Loss_D: 0.1311  Loss_G: 9.9460  D(x): 0.9416
      D(G(z)): 0.0127 / 0.0021
[336/1000][20/42]     Loss_D: 0.0238  Loss_G: 9.9752  D(x): 0.9930
      D(G(z)): 0.0151 / 0.0049
[336/1000][40/42]     Loss_D: 0.0336  Loss_G: 8.2351  D(x): 0.9748
      D(G(z)): 0.0054 / 0.0066
[337/1000][0/42] Loss_D: 0.0500  Loss_G: 7.6235  D(x): 0.9963
      D(G(z)): 0.0344 / 0.0164
[337/1000][20/42]     Loss_D: 0.0219  Loss_G: 7.9775  D(x): 0.9867
      D(G(z)): 0.0070 / 0.0045
[337/1000][40/42]     Loss_D: 0.0234  Loss_G: 9.5002  D(x): 0.9836
      D(G(z)): 0.0017 / 0.0018
[338/1000][0/42] Loss_D: 0.0481  Loss_G: 7.8338  D(x): 0.9944
      D(G(z)): 0.0263 / 0.0103
[338/1000][20/42]     Loss_D: 0.0974  Loss_G: 9.7839  D(x): 0.9297
      D(G(z)): 0.0014 / 0.0038
[338/1000][40/42]     Loss_D: 0.0894  Loss_G: 9.2369  D(x): 0.9418
      D(G(z)): 0.0089 / 0.0057
[339/1000][0/42] Loss_D: 0.0120  Loss_G: 9.5226  D(x): 0.9897
      D(G(z)): 0.0011 / 0.0019
[339/1000][20/42]     Loss_D: 0.0922  Loss_G: 9.3758  D(x): 0.9955
      D(G(z)): 0.0581 / 0.0174
[339/1000][40/42]     Loss_D: 0.0599  Loss_G: 8.4739  D(x): 0.9940
      D(G(z)): 0.0438 / 0.0185
[340/1000][0/42] Loss_D: 0.0870  Loss_G: 10.5533 D(x): 0.9778
      D(G(z)): 0.0302 / 0.0126
[340/1000][20/42]     Loss_D: 0.2364  Loss_G: 9.3161  D(x): 0.9867
      D(G(z)): 0.1010 / 0.0165
[340/1000][40/42]     Loss_D: 0.0338  Loss_G: 9.0337  D(x): 0.9950
      D(G(z)): 0.0243 / 0.0068
```

[341/1000][0/42] Loss_D: 0.0641 Loss_G: 11.3966 D(x): 0.9675
D(G(z)): 0.0092 / 0.0077
[341/1000][20/42] Loss_D: 0.0871 Loss_G: 7.9922 D(x): 0.9733
D(G(z)): 0.0405 / 0.0153
[341/1000][40/42] Loss_D: 0.0330 Loss_G: 7.5006 D(x): 0.9941
D(G(z)): 0.0239 / 0.0308
[342/1000][0/42] Loss_D: 0.0948 Loss_G: 8.4926 D(x): 0.9989
D(G(z)): 0.0627 / 0.0159
[342/1000][20/42] Loss_D: 0.0246 Loss_G: 8.2505 D(x): 0.9993
D(G(z)): 0.0201 / 0.0068
[342/1000][40/42] Loss_D: 0.2369 Loss_G: 6.6920 D(x): 0.9996
D(G(z)): 0.1278 / 0.0190
[343/1000][0/42] Loss_D: 0.0101 Loss_G: 12.1324 D(x): 0.9981
D(G(z)): 0.0073 / 0.0008
[343/1000][20/42] Loss_D: 0.0221 Loss_G: 9.8213 D(x): 0.9857
D(G(z)): 0.0068 / 0.0025
[343/1000][40/42] Loss_D: 0.0872 Loss_G: 8.5331 D(x): 0.9945
D(G(z)): 0.0525 / 0.0159
[344/1000][0/42] Loss_D: 0.0352 Loss_G: 8.6685 D(x): 0.9835
D(G(z)): 0.0135 / 0.0110
[344/1000][20/42] Loss_D: 0.0233 Loss_G: 9.4934 D(x): 0.9918
D(G(z)): 0.0128 / 0.0065
[344/1000][40/42] Loss_D: 0.0689 Loss_G: 9.4788 D(x): 0.9565
D(G(z)): 0.0044 / 0.0031
[345/1000][0/42] Loss_D: 0.0588 Loss_G: 8.5378 D(x): 0.9901
D(G(z)): 0.0263 / 0.0111
[345/1000][20/42] Loss_D: 0.0406 Loss_G: 8.3706 D(x): 0.9838
D(G(z)): 0.0191 / 0.0068
[345/1000][40/42] Loss_D: 0.0734 Loss_G: 9.0594 D(x): 0.9465
D(G(z)): 0.0048 / 0.0051
[346/1000][0/42] Loss_D: 0.0505 Loss_G: 7.7481 D(x): 0.9952
D(G(z)): 0.0309 / 0.0080
[346/1000][20/42] Loss_D: 0.0258 Loss_G: 7.7733 D(x): 0.9978
D(G(z)): 0.0213 / 0.0295
[346/1000][40/42] Loss_D: 0.0730 Loss_G: 7.9553 D(x): 0.9550
D(G(z)): 0.0119 / 0.0101
[347/1000][0/42] Loss_D: 0.0245 Loss_G: 8.1201 D(x): 0.9894
D(G(z)): 0.0123 / 0.0190
[347/1000][20/42] Loss_D: 0.0569 Loss_G: 9.2464 D(x): 0.9754
D(G(z)): 0.0201 / 0.0149

```
[347/1000][40/42]	Loss_D: 0.0268	Loss_G: 6.1157	D(x): 0.9989
	D(G(z)): 0.0244 / 0.0288
[348/1000][0/42]	Loss_D: 0.0582	Loss_G: 7.9673	D(x): 0.9947
	D(G(z)): 0.0402 / 0.0106
[348/1000][20/42]	Loss_D: 0.1035	Loss_G: 8.1668	D(x): 0.9988
	D(G(z)): 0.0712 / 0.0154
[348/1000][40/42]	Loss_D: 0.0655	Loss_G: 8.4725	D(x): 0.9585
	D(G(z)): 0.0028 / 0.0097
[349/1000][0/42]	Loss_D: 0.0787	Loss_G: 6.2199	D(x): 0.9996
	D(G(z)): 0.0585 / 0.0392
[349/1000][20/42]	Loss_D: 0.0649	Loss_G: 6.9277	D(x): 0.9959
	D(G(z)): 0.0385 / 0.0164
[349/1000][40/42]	Loss_D: 0.0177	Loss_G: 8.2008	D(x): 0.9945
	D(G(z)): 0.0114 / 0.0046
[350/1000][0/42]	Loss_D: 0.0564	Loss_G: 8.9003	D(x): 0.9597
	D(G(z)): 0.0047 / 0.0065
[350/1000][20/42]	Loss_D: 0.0133	Loss_G: 7.4118	D(x): 0.9952
	D(G(z)): 0.0079 / 0.0063
[350/1000][40/42]	Loss_D: 0.0434	Loss_G: 8.2599	D(x): 0.9912
	D(G(z)): 0.0272 / 0.0095
```



```
[351/1000][0/42]	Loss_D: 0.0039	Loss_G: 9.8403	D(x): 0.9989
	D(G(z)): 0.0028 / 0.0017
[351/1000][20/42]	Loss_D: 0.0144	Loss_G: 8.0521	D(x): 0.9893
	D(G(z)): 0.0034 / 0.0042
[351/1000][40/42]	Loss_D: 0.0583	Loss_G: 8.2327	D(x): 0.9583
	D(G(z)): 0.0045 / 0.0086
[352/1000][0/42]	Loss_D: 0.0212	Loss_G: 7.3833	D(x): 0.9961
	D(G(z)): 0.0157 / 0.0181
[352/1000][20/42]	Loss_D: 0.1367	Loss_G: 6.9986	D(x): 0.9985
	D(G(z)): 0.0807 / 0.0386
[352/1000][40/42]	Loss_D: 0.0161	Loss_G: 8.6007	D(x): 0.9976
	D(G(z)): 0.0121 / 0.0038
[353/1000][0/42]	Loss_D: 0.0315	Loss_G: 9.8728	D(x): 0.9914
	D(G(z)): 0.0146 / 0.0037
[353/1000][20/42]	Loss_D: 0.0355	Loss_G: 9.9525	D(x): 0.9755
	D(G(z)): 0.0074 / 0.0047
[353/1000][40/42]	Loss_D: 0.0201	Loss_G: 8.8320	D(x): 0.9989
	D(G(z)): 0.0168 / 0.0266
[354/1000][0/42]	Loss_D: 0.0518	Loss_G: 8.2875	D(x): 0.9865
```

```
D(G(z)): 0.0294 / 0.0199
[354/1000][20/42]     Loss_D: 0.0780  Loss_G: 6.6197  D(x): 0.9699
    D(G(z)): 0.0121 / 0.0176
[354/1000][40/42]     Loss_D: 0.0326  Loss_G: 8.9757  D(x): 0.9838
    D(G(z)): 0.0105 / 0.0049
[355/1000][0/42] Loss_D: 0.0256  Loss_G: 9.8569  D(x): 0.9827
    D(G(z)): 0.0066 / 0.0065
[355/1000][20/42]     Loss_D: 0.1904  Loss_G: 8.7597  D(x): 0.9252
    D(G(z)): 0.0372 / 0.0161
[355/1000][40/42]     Loss_D: 0.2393  Loss_G: 8.0257  D(x): 0.9609
    D(G(z)): 0.0526 / 0.0267
[356/1000][0/42] Loss_D: 0.0854  Loss_G: 8.6922  D(x): 0.9759
    D(G(z)): 0.0373 / 0.0037
[356/1000][20/42]     Loss_D: 0.0222  Loss_G: 10.0731 D(x): 0.9971
    D(G(z)): 0.0144 / 0.0128
[356/1000][40/42]     Loss_D: 0.0298  Loss_G: 10.1244 D(x): 0.9850
    D(G(z)): 0.0115 / 0.0036
[357/1000][0/42] Loss_D: 0.0437  Loss_G: 9.0885  D(x): 0.9721
    D(G(z)): 0.0134 / 0.0094
[357/1000][20/42]     Loss_D: 0.0296  Loss_G: 7.2460  D(x): 0.9997
    D(G(z)): 0.0257 / 0.0166
[357/1000][40/42]     Loss_D: 0.0734  Loss_G: 8.5814  D(x): 0.9970
    D(G(z)): 0.0601 / 0.0139
[358/1000][0/42] Loss_D: 0.0966  Loss_G: 9.8656  D(x): 0.9993
    D(G(z)): 0.0683 / 0.0015
[358/1000][20/42]     Loss_D: 0.1481  Loss_G: 12.3415 D(x): 0.9130
    D(G(z)): 0.0028 / 0.0035
[358/1000][40/42]     Loss_D: 0.0194  Loss_G: 11.4911 D(x): 0.9926
    D(G(z)): 0.0099 / 0.0076
[359/1000][0/42] Loss_D: 0.0157  Loss_G: 8.1650  D(x): 0.9946
    D(G(z)): 0.0097 / 0.0100
[359/1000][20/42]     Loss_D: 0.0898  Loss_G: 8.5397  D(x): 0.9989
    D(G(z)): 0.0551 / 0.0129
[359/1000][40/42]     Loss_D: 0.0485  Loss_G: 10.1126 D(x): 0.9642
    D(G(z)): 0.0073 / 0.0034
[360/1000][0/42] Loss_D: 0.1710  Loss_G: 9.8429  D(x): 0.9588
    D(G(z)): 0.0295 / 0.0228
[360/1000][20/42]     Loss_D: 0.0265  Loss_G: 10.2420 D(x): 0.9866
    D(G(z)): 0.0115 / 0.0065
[360/1000][40/42]     Loss_D: 0.1066  Loss_G: 8.7598  D(x): 0.9946
    D(G(z)): 0.0681 / 0.0126
```

```
[361/1000][0/42] Loss_D: 0.0161  Loss_G: 9.9733  D(x): 0.9966
     D(G(z)): 0.0118 / 0.0042
[361/1000][20/42]    Loss_D: 0.0424  Loss_G: 9.7337  D(x): 0.9707
     D(G(z)): 0.0096 / 0.0040
[361/1000][40/42]    Loss_D: 0.0454  Loss_G: 9.9343  D(x): 0.9841
     D(G(z)): 0.0178 / 0.0111
[362/1000][0/42] Loss_D: 0.1325  Loss_G: 7.7745  D(x): 0.9619
     D(G(z)): 0.0362 / 0.0102
[362/1000][20/42]    Loss_D: 0.0820  Loss_G: 9.2171  D(x): 0.9665
     D(G(z)): 0.0297 / 0.0068
[362/1000][40/42]    Loss_D: 0.0247  Loss_G: 7.5200  D(x): 0.9901
     D(G(z)): 0.0136 / 0.0112
[363/1000][0/42] Loss_D: 0.0363  Loss_G: 8.0966  D(x): 0.9769
     D(G(z)): 0.0084 / 0.0052
[363/1000][20/42]    Loss_D: 0.0537  Loss_G: 9.1263  D(x): 0.9626
     D(G(z)): 0.0100 / 0.0027
[363/1000][40/42]    Loss_D: 0.0428  Loss_G: 8.9623  D(x): 0.9694
     D(G(z)): 0.0077 / 0.0079
[364/1000][0/42] Loss_D: 0.0177  Loss_G: 9.0354  D(x): 0.9912
     D(G(z)): 0.0073 / 0.0092
[364/1000][20/42]    Loss_D: 0.0632  Loss_G: 7.7403  D(x): 0.9853
     D(G(z)): 0.0351 / 0.0302
[364/1000][40/42]    Loss_D: 0.0111  Loss_G: 13.3576 D(x): 0.9901
     D(G(z)): 0.0003 / 0.0004
[365/1000][0/42] Loss_D: 0.0336  Loss_G: 11.8948 D(x): 0.9699
     D(G(z)): 0.0008 / 0.0010
[365/1000][20/42]    Loss_D: 0.0488  Loss_G: 8.7750  D(x): 0.9795
     D(G(z)): 0.0173 / 0.0119
[365/1000][40/42]    Loss_D: 0.0228  Loss_G: 8.9553  D(x): 0.9907
     D(G(z)): 0.0120 / 0.0070
[366/1000][0/42] Loss_D: 0.0180  Loss_G: 9.7736  D(x): 0.9903
     D(G(z)): 0.0072 / 0.0028
[366/1000][20/42]    Loss_D: 0.0866  Loss_G: 8.0157  D(x): 0.9955
     D(G(z)): 0.0630 / 0.0046
[366/1000][40/42]    Loss_D: 0.0541  Loss_G: 8.8557  D(x): 0.9990
     D(G(z)): 0.0380 / 0.0059
[367/1000][0/42] Loss_D: 0.0427  Loss_G: 10.9774 D(x): 0.9644
     D(G(z)): 0.0009 / 0.0003
[367/1000][20/42]    Loss_D: 0.0570  Loss_G: 8.2791  D(x): 0.9551
     D(G(z)): 0.0038 / 0.0048
```

```
[367/1000][40/42]	Loss_D: 0.0087	Loss_G: 8.2269	D(x): 0.9972
	D(G(z)): 0.0057 / 0.0033
[368/1000][0/42]	Loss_D: 0.0251	Loss_G: 8.3228	D(x): 0.9966
	D(G(z)): 0.0154 / 0.0022
[368/1000][20/42]	Loss_D: 0.0226	Loss_G: 7.9227	D(x): 0.9974
	D(G(z)): 0.0177 / 0.0113
[368/1000][40/42]	Loss_D: 0.1091	Loss_G: 9.0035	D(x): 0.9390
	D(G(z)): 0.0080 / 0.0133
[369/1000][0/42]	Loss_D: 0.0552	Loss_G: 6.3169	D(x): 0.9948
	D(G(z)): 0.0319 / 0.0236
[369/1000][20/42]	Loss_D: 0.0298	Loss_G: 8.6412	D(x): 0.9821
	D(G(z)): 0.0076 / 0.0032
[369/1000][40/42]	Loss_D: 0.0270	Loss_G: 7.5621	D(x): 0.9984
	D(G(z)): 0.0226 / 0.0105
[370/1000][0/42]	Loss_D: 0.0284	Loss_G: 8.1362	D(x): 0.9905
	D(G(z)): 0.0169 / 0.0064
[370/1000][20/42]	Loss_D: 0.0093	Loss_G: 9.3125	D(x): 0.9947
	D(G(z)): 0.0038 / 0.0025
[370/1000][40/42]	Loss_D: 0.0055	Loss_G: 8.3020	D(x): 0.9972
	D(G(z)): 0.0026 / 0.0028
```

```
[371/1000][0/42]	Loss_D: 0.0260	Loss_G: 7.4227	D(x): 0.9995
	D(G(z)): 0.0229 / 0.0128
[371/1000][20/42]	Loss_D: 0.0090	Loss_G: 7.4035	D(x): 0.9983
	D(G(z)): 0.0071 / 0.0080
[371/1000][40/42]	Loss_D: 0.0216	Loss_G: 7.9319	D(x): 0.9978
	D(G(z)): 0.0172 / 0.0093
[372/1000][0/42]	Loss_D: 0.1079	Loss_G: 8.8535	D(x): 0.9995
	D(G(z)): 0.0424 / 0.0094
[372/1000][20/42]	Loss_D: 0.0441	Loss_G: 8.2863	D(x): 0.9979
	D(G(z)): 0.0318 / 0.0230
[372/1000][40/42]	Loss_D: 0.0115	Loss_G: 8.5809	D(x): 0.9964
	D(G(z)): 0.0075 / 0.0037
[373/1000][0/42]	Loss_D: 0.0704	Loss_G: 8.1909	D(x): 0.9765
	D(G(z)): 0.0348 / 0.0122
[373/1000][20/42]	Loss_D: 0.1539	Loss_G: 9.1264	D(x): 0.9510
	D(G(z)): 0.0294 / 0.0105
[373/1000][40/42]	Loss_D: 0.0515	Loss_G: 7.0724	D(x): 0.9958
	D(G(z)): 0.0288 / 0.0093
[374/1000][0/42]	Loss_D: 0.0225	Loss_G: 6.5721	D(x): 0.9998
```

```
    D(G(z)): 0.0211 / 0.0134
[374/1000][20/42]    Loss_D: 0.0075  Loss_G: 8.9225  D(x): 0.9957
    D(G(z)): 0.0031 / 0.0025
[374/1000][40/42]    Loss_D: 0.0196  Loss_G: 8.2045  D(x): 0.9949
    D(G(z)): 0.0131 / 0.0043
[375/1000][0/42] Loss_D: 0.0179  Loss_G: 10.8818 D(x): 0.9848
    D(G(z)): 0.0020 / 0.0010
[375/1000][20/42]    Loss_D: 0.0156  Loss_G: 8.7387  D(x): 0.9986
    D(G(z)): 0.0136 / 0.0059
[375/1000][40/42]    Loss_D: 0.0216  Loss_G: 8.5962  D(x): 0.9926
    D(G(z)): 0.0129 / 0.0087
[376/1000][0/42] Loss_D: 0.0365  Loss_G: 8.3052  D(x): 0.9914
    D(G(z)): 0.0242 / 0.0079
[376/1000][20/42]    Loss_D: 0.0127  Loss_G: 9.4221  D(x): 0.9915
    D(G(z)): 0.0038 / 0.0029
[376/1000][40/42]    Loss_D: 0.0257  Loss_G: 7.9042  D(x): 0.9981
    D(G(z)): 0.0176 / 0.0135
[377/1000][0/42] Loss_D: 0.0369  Loss_G: 8.8551  D(x): 0.9994
    D(G(z)): 0.0205 / 0.0041
[377/1000][20/42]    Loss_D: 0.0117  Loss_G: 7.9165  D(x): 0.9969
    D(G(z)): 0.0083 / 0.0091
[377/1000][40/42]    Loss_D: 0.0388  Loss_G: 7.8866  D(x): 0.9723
    D(G(z)): 0.0055 / 0.0050
[378/1000][0/42] Loss_D: 0.0069  Loss_G: 8.3777  D(x): 0.9973
    D(G(z)): 0.0041 / 0.0054
[378/1000][20/42]    Loss_D: 0.0082  Loss_G: 8.5475  D(x): 0.9989
    D(G(z)): 0.0067 / 0.0046
[378/1000][40/42]    Loss_D: 0.0330  Loss_G: 9.4420  D(x): 0.9875
    D(G(z)): 0.0174 / 0.0029
[379/1000][0/42] Loss_D: 0.0094  Loss_G: 8.1402  D(x): 0.9940
    D(G(z)): 0.0033 / 0.0042
[379/1000][20/42]    Loss_D: 0.0080  Loss_G: 9.4002  D(x): 0.9936
    D(G(z)): 0.0015 / 0.0014
[379/1000][40/42]    Loss_D: 0.0355  Loss_G: 7.1555  D(x): 0.9986
    D(G(z)): 0.0285 / 0.0377
[380/1000][0/42] Loss_D: 0.1043  Loss_G: 8.8962  D(x): 0.9964
    D(G(z)): 0.0643 / 0.0034
[380/1000][20/42]    Loss_D: 0.1922  Loss_G: 9.9108  D(x): 0.8862
    D(G(z)): 0.0100 / 0.0176
[380/1000][40/42]    Loss_D: 0.0143  Loss_G: 9.3562  D(x): 0.9938
    D(G(z)): 0.0067 / 0.0069
```

```
[381/1000][0/42] Loss_D: 0.0377  Loss_G: 9.7639  D(x): 0.9964
     D(G(z)): 0.0267 / 0.0103
[381/1000][20/42]    Loss_D: 0.0323  Loss_G: 10.7914 D(x): 0.9821
     D(G(z)): 0.0090 / 0.0062
[381/1000][40/42]    Loss_D: 0.0753  Loss_G: 10.2920 D(x): 0.9964
     D(G(z)): 0.0489 / 0.0022
[382/1000][0/42] Loss_D: 0.0394  Loss_G: 12.4322 D(x): 0.9739
     D(G(z)): 0.0088 / 0.0014
[382/1000][20/42]    Loss_D: 0.1426  Loss_G: 8.9110  D(x): 0.9925
     D(G(z)): 0.0700 / 0.0021
[382/1000][40/42]    Loss_D: 0.1626  Loss_G: 10.8834 D(x): 0.9208
     D(G(z)): 0.0012 / 0.0106
[383/1000][0/42] Loss_D: 0.4103  Loss_G: 8.4072  D(x): 0.9988
     D(G(z)): 0.1532 / 0.0476
[383/1000][20/42]    Loss_D: 0.1403  Loss_G: 11.4706 D(x): 0.9603
     D(G(z)): 0.0438 / 0.0012
[383/1000][40/42]    Loss_D: 0.0499  Loss_G: 13.7648 D(x): 0.9818
     D(G(z)): 0.0114 / 0.0003
[384/1000][0/42] Loss_D: 0.7608  Loss_G: 12.3412 D(x): 0.7615
     D(G(z)): 0.0044 / 0.0143
[384/1000][20/42]    Loss_D: 0.2965  Loss_G: 11.0305 D(x): 0.9658
     D(G(z)): 0.1091 / 0.0172
[384/1000][40/42]    Loss_D: 0.2572  Loss_G: 9.4404  D(x): 0.9771
     D(G(z)): 0.1007 / 0.0060
[385/1000][0/42] Loss_D: 0.6346  Loss_G: 10.6560 D(x): 0.9520
     D(G(z)): 0.1722 / 0.0221
[385/1000][20/42]    Loss_D: 0.1443  Loss_G: 9.2153  D(x): 0.9850
     D(G(z)): 0.0768 / 0.0142
[385/1000][40/42]    Loss_D: 0.1816  Loss_G: 12.7621 D(x): 0.9207
     D(G(z)): 0.0104 / 0.0064
[386/1000][0/42] Loss_D: 0.0118  Loss_G: 10.2440 D(x): 0.9950
     D(G(z)): 0.0064 / 0.0071
[386/1000][20/42]    Loss_D: 0.1752  Loss_G: 9.7745  D(x): 0.9784
     D(G(z)): 0.0640 / 0.0353
[386/1000][40/42]    Loss_D: 0.0112  Loss_G: 10.6408 D(x): 0.9948
     D(G(z)): 0.0055 / 0.0040
[387/1000][0/42] Loss_D: 0.0243  Loss_G: 9.6258  D(x): 0.9994
     D(G(z)): 0.0189 / 0.0199
[387/1000][20/42]    Loss_D: 0.2059  Loss_G: 8.0729  D(x): 0.9991
     D(G(z)): 0.1157 / 0.0316
```

```
[387/1000][40/42]	Loss_D: 0.1328	Loss_G: 9.1330	D(x): 0.9657
	D(G(z)): 0.0518 / 0.0056
[388/1000][0/42]	Loss_D: 0.1001	Loss_G: 10.4259	D(x): 0.9519
	D(G(z)): 0.0065 / 0.0018
[388/1000][20/42]	Loss_D: 0.0235	Loss_G: 10.2451	D(x): 0.9987
	D(G(z)): 0.0171 / 0.0015
[388/1000][40/42]	Loss_D: 0.0181	Loss_G: 10.6880	D(x): 0.9919
	D(G(z)): 0.0091 / 0.0056
[389/1000][0/42]	Loss_D: 0.0481	Loss_G: 9.4349	D(x): 0.9788
	D(G(z)): 0.0068 / 0.0042
[389/1000][20/42]	Loss_D: 0.0461	Loss_G: 8.9979	D(x): 0.9619
	D(G(z)): 0.0039 / 0.0024
[389/1000][40/42]	Loss_D: 0.0400	Loss_G: 9.5042	D(x): 0.9735
	D(G(z)): 0.0042 / 0.0045
[390/1000][0/42]	Loss_D: 0.0367	Loss_G: 8.5746	D(x): 0.9957
	D(G(z)): 0.0231 / 0.0138
[390/1000][20/42]	Loss_D: 0.0152	Loss_G: 8.6881	D(x): 0.9922
	D(G(z)): 0.0070 / 0.0036
[390/1000][40/42]	Loss_D: 0.0389	Loss_G: 6.5926	D(x): 0.9788
	D(G(z)): 0.0091 / 0.0122
```

```
[391/1000][0/42]	Loss_D: 0.0317	Loss_G: 7.5859	D(x): 0.9974
	D(G(z)): 0.0268 / 0.0105
[391/1000][20/42]	Loss_D: 0.0295	Loss_G: 6.6840	D(x): 0.9836
	D(G(z)): 0.0112 / 0.0171
[391/1000][40/42]	Loss_D: 0.0730	Loss_G: 9.5771	D(x): 0.9769
	D(G(z)): 0.0057 / 0.0028
[392/1000][0/42]	Loss_D: 0.0037	Loss_G: 9.6849	D(x): 0.9987
	D(G(z)): 0.0024 / 0.0018
[392/1000][20/42]	Loss_D: 0.0142	Loss_G: 10.0572	D(x): 0.9901
	D(G(z)): 0.0038 / 0.0048
[392/1000][40/42]	Loss_D: 0.0128	Loss_G: 9.1098	D(x): 0.9941
	D(G(z)): 0.0062 / 0.0034
[393/1000][0/42]	Loss_D: 0.1488	Loss_G: 9.4895	D(x): 0.8926
	D(G(z)): 0.0020 / 0.0026
[393/1000][20/42]	Loss_D: 0.0268	Loss_G: 7.0658	D(x): 0.9974
	D(G(z)): 0.0213 / 0.0171
[393/1000][40/42]	Loss_D: 0.0485	Loss_G: 7.2432	D(x): 0.9827
	D(G(z)): 0.0269 / 0.0180
[394/1000][0/42]	Loss_D: 0.0050	Loss_G: 8.7081	D(x): 0.9981
```

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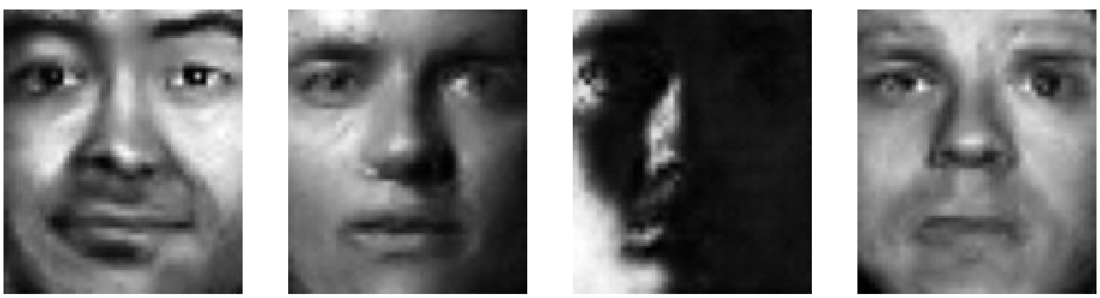
      D(G(z)): 0.0031 / 0.0022
[394/1000][20/42]     Loss_D: 0.2241  Loss_G: 9.2994  D(x): 0.8511
      D(G(z)): 0.0002 / 0.0014
[394/1000][40/42]     Loss_D: 0.0224  Loss_G: 10.2868 D(x): 0.9861
      D(G(z)): 0.0065 / 0.0030
[395/1000][0/42]Loss_D: 0.0778  Loss_G: 10.7047 D(x): 0.9482
      D(G(z)): 0.0029 / 0.0020
[395/1000][20/42]     Loss_D: 0.0498  Loss_G: 7.8721  D(x): 0.9980
      D(G(z)): 0.0378 / 0.0199
[395/1000][40/42]     Loss_D: 0.0110  Loss_G: 9.1319  D(x): 0.9960
      D(G(z)): 0.0065 / 0.0035
[396/1000][0/42]Loss_D: 0.0100  Loss_G: 9.1773  D(x): 0.9936
      D(G(z)): 0.0035 / 0.0023
[396/1000][20/42]     Loss_D: 0.0199  Loss_G: 8.3090  D(x): 0.9861
      D(G(z)): 0.0052 / 0.0085
[396/1000][40/42]     Loss_D: 0.0827  Loss_G: 7.3852  D(x): 0.9985
      D(G(z)): 0.0567 / 0.0168
[397/1000][0/42]Loss_D: 0.0332  Loss_G: 8.7120  D(x): 0.9973
      D(G(z)): 0.0271 / 0.0054
[397/1000][20/42]     Loss_D: 0.0274  Loss_G: 8.3336  D(x): 0.9969
      D(G(z)): 0.0198 / 0.0098
[397/1000][40/42]     Loss_D: 0.0241  Loss_G: 8.5470  D(x): 0.9853
      D(G(z)): 0.0067 / 0.0053
[398/1000][0/42]Loss_D: 0.0087  Loss_G: 7.9490  D(x): 0.9988
      D(G(z)): 0.0073 / 0.0070
[398/1000][20/42]     Loss_D: 0.0231  Loss_G: 7.5910  D(x): 0.9986
      D(G(z)): 0.0195 / 0.0076
[398/1000][40/42]     Loss_D: 0.0125  Loss_G: 8.8284  D(x): 0.9951
      D(G(z)): 0.0073 / 0.0039
[399/1000][0/42]Loss_D: 0.0160  Loss_G: 9.3373  D(x): 0.9962
      D(G(z)): 0.0115 / 0.0046
[399/1000][20/42]     Loss_D: 0.0195  Loss_G: 9.2079  D(x): 0.9962
      D(G(z)): 0.0115 / 0.0024
[399/1000][40/42]     Loss_D: 0.0423  Loss_G: 7.4688  D(x): 0.9793
      D(G(z)): 0.0147 / 0.0199
[400/1000][0/42]Loss_D: 0.0418  Loss_G: 7.9226  D(x): 0.9985
      D(G(z)): 0.0294 / 0.0172
[400/1000][20/42]     Loss_D: 0.0081  Loss_G: 10.3231 D(x): 0.9974
      D(G(z)): 0.0049 / 0.0040
[400/1000][40/42]     Loss_D: 0.0157  Loss_G: 11.4825 D(x): 0.9888
      D(G(z)): 0.0024 / 0.0005
```

```
[401/1000][0/42]	Loss_D: 0.1547	Loss_G: 12.1532	D(x): 0.9148
	D(G(z)): 0.0002 / 0.0003
[401/1000][20/42]	Loss_D: 0.0158	Loss_G: 6.9903	D(x): 0.9973
	D(G(z)): 0.0122 / 0.0120
[401/1000][40/42]	Loss_D: 0.0563	Loss_G: 8.9848	D(x): 0.9711
	D(G(z)): 0.0188 / 0.0055
[402/1000][0/42]	Loss_D: 0.0263	Loss_G: 10.1887	D(x): 0.9799
	D(G(z)): 0.0041 / 0.0028
[402/1000][20/42]	Loss_D: 0.0208	Loss_G: 8.0411	D(x): 0.9970
	D(G(z)): 0.0161 / 0.0159
[402/1000][40/42]	Loss_D: 0.1223	Loss_G: 8.1730	D(x): 0.9876
	D(G(z)): 0.0590 / 0.0093
[403/1000][0/42]	Loss_D: 0.0158	Loss_G: 10.6135	D(x): 0.9878
	D(G(z)): 0.0029 / 0.0017
[403/1000][20/42]	Loss_D: 0.0247	Loss_G: 8.8128	D(x): 0.9945
	D(G(z)): 0.0155 / 0.0066
[403/1000][40/42]	Loss_D: 0.0186	Loss_G: 9.9296	D(x): 0.9899
	D(G(z)): 0.0071 / 0.0053
[404/1000][0/42]	Loss_D: 0.0171	Loss_G: 8.8910	D(x): 0.9992
	D(G(z)): 0.0150 / 0.0112
[404/1000][20/42]	Loss_D: 0.0354	Loss_G: 10.5083	D(x): 0.9698
	D(G(z)): 0.0018 / 0.0018
[404/1000][40/42]	Loss_D: 0.0163	Loss_G: 8.7906	D(x): 0.9885
	D(G(z)): 0.0042 / 0.0038
[405/1000][0/42]	Loss_D: 0.0108	Loss_G: 8.6013	D(x): 0.9942
	D(G(z)): 0.0047 / 0.0037
[405/1000][20/42]	Loss_D: 0.0032	Loss_G: 9.2726	D(x): 0.9989
	D(G(z)): 0.0020 / 0.0017
[405/1000][40/42]	Loss_D: 0.0214	Loss_G: 9.4745	D(x): 0.9830
	D(G(z)): 0.0021 / 0.0015
[406/1000][0/42]	Loss_D: 0.0031	Loss_G: 10.5388	D(x): 0.9975
	D(G(z)): 0.0005 / 0.0006
[406/1000][20/42]	Loss_D: 0.0126	Loss_G: 11.0574	D(x): 0.9990
	D(G(z)): 0.0099 / 0.0017
[406/1000][40/42]	Loss_D: 0.0277	Loss_G: 9.1163	D(x): 0.9832
	D(G(z)): 0.0081 / 0.0068
[407/1000][0/42]	Loss_D: 0.0055	Loss_G: 9.3042	D(x): 0.9968
	D(G(z)): 0.0022 / 0.0015
[407/1000][20/42]	Loss_D: 0.1027	Loss_G: 10.7587	D(x): 0.9480
	D(G(z)): 0.0157 / 0.0022
```

```
[407/1000][40/42]	Loss_D: 0.0100	Loss_G: 10.0158	D(x): 0.9964
	D(G(z)): 0.0061 / 0.0019
[408/1000][0/42]	Loss_D: 0.1063	Loss_G: 9.9178	D(x): 0.9232
	D(G(z)): 0.0012 / 0.0016
[408/1000][20/42]	Loss_D: 0.0146	Loss_G: 9.7475	D(x): 0.9972
	D(G(z)): 0.0107 / 0.0066
[408/1000][40/42]	Loss_D: 0.0131	Loss_G: 7.9752	D(x): 0.9982
	D(G(z)): 0.0107 / 0.0050
[409/1000][0/42]	Loss_D: 0.0051	Loss_G: 10.5815	D(x): 0.9963
	D(G(z)): 0.0014 / 0.0006
[409/1000][20/42]	Loss_D: 0.0064	Loss_G: 8.4092	D(x): 0.9990
	D(G(z)): 0.0053 / 0.0045
[409/1000][40/42]	Loss_D: 0.0578	Loss_G: 7.9967	D(x): 0.9998
	D(G(z)): 0.0268 / 0.0043
[410/1000][0/42]	Loss_D: 0.0265	Loss_G: 10.5385	D(x): 0.9986
	D(G(z)): 0.0169 / 0.0020
[410/1000][20/42]	Loss_D: 0.0412	Loss_G: 7.2093	D(x): 0.9900
	D(G(z)): 0.0249 / 0.0280
[410/1000][40/42]	Loss_D: 0.0071	Loss_G: 11.0803	D(x): 0.9937
	D(G(z)): 0.0005 / 0.0006
```



```
[411/1000][0/42]	Loss_D: 0.0161	Loss_G: 10.1115	D(x): 0.9960
	D(G(z)): 0.0099 / 0.0050
[411/1000][20/42]	Loss_D: 0.0086	Loss_G: 8.1794	D(x): 0.9979
	D(G(z)): 0.0063 / 0.0059
[411/1000][40/42]	Loss_D: 0.0205	Loss_G: 7.6718	D(x): 0.9996
	D(G(z)): 0.0185 / 0.0089
[412/1000][0/42]	Loss_D: 0.0137	Loss_G: 8.4179	D(x): 0.9991
	D(G(z)): 0.0121 / 0.0034
[412/1000][20/42]	Loss_D: 0.0795	Loss_G: 10.3609	D(x): 0.9789
	D(G(z)): 0.0226 / 0.0055
[412/1000][40/42]	Loss_D: 0.0485	Loss_G: 9.4117	D(x): 0.9767
	D(G(z)): 0.0085 / 0.0087
[413/1000][0/42]	Loss_D: 0.0115	Loss_G: 9.1245	D(x): 0.9996
	D(G(z)): 0.0104 / 0.0056
[413/1000][20/42]	Loss_D: 0.0530	Loss_G: 8.2077	D(x): 0.9996
	D(G(z)): 0.0450 / 0.0154
[413/1000][40/42]	Loss_D: 0.0853	Loss_G: 8.0542	D(x): 0.9644
	D(G(z)): 0.0329 / 0.0168
[414/1000][0/42]	Loss_D: 0.0429	Loss_G: 9.2279	D(x): 0.9998
```

```
    D(G(z)): 0.0277 / 0.0037
[414/1000][20/42]    Loss_D: 0.0285  Loss_G: 9.5035  D(x): 0.9850
    D(G(z)): 0.0096 / 0.0039
[414/1000][40/42]    Loss_D: 0.0144  Loss_G: 8.1153  D(x): 0.9988
    D(G(z)): 0.0127 / 0.0059
[415/1000][0/42]Loss_D: 0.0414  Loss_G: 10.3310 D(x): 0.9993
    D(G(z)): 0.0354 / 0.0050
[415/1000][20/42]    Loss_D: 0.0207  Loss_G: 8.4295  D(x): 0.9923
    D(G(z)): 0.0117 / 0.0054
[415/1000][40/42]    Loss_D: 0.0585  Loss_G: 9.5829  D(x): 0.9944
    D(G(z)): 0.0276 / 0.0098
[416/1000][0/42]Loss_D: 0.0275  Loss_G: 10.3689 D(x): 0.9817
    D(G(z)): 0.0049 / 0.0025
[416/1000][20/42]    Loss_D: 0.0257  Loss_G: 11.2128 D(x): 0.9802
    D(G(z)): 0.0013 / 0.0006
[416/1000][40/42]    Loss_D: 0.0829  Loss_G: 11.2088 D(x): 0.9462
    D(G(z)): 0.0155 / 0.0039
[417/1000][0/42]Loss_D: 0.0590  Loss_G: 10.5784 D(x): 0.9689
    D(G(z)): 0.0118 / 0.0187
[417/1000][20/42]    Loss_D: 0.0415  Loss_G: 8.5894  D(x): 0.9918
    D(G(z)): 0.0291 / 0.0341
[417/1000][40/42]    Loss_D: 0.0502  Loss_G: 9.4149  D(x): 0.9989
    D(G(z)): 0.0287 / 0.0080
[418/1000][0/42]Loss_D: 0.0338  Loss_G: 10.1622 D(x): 0.9793
    D(G(z)): 0.0037 / 0.0012
[418/1000][20/42]    Loss_D: 0.0378  Loss_G: 8.3009  D(x): 0.9901
    D(G(z)): 0.0212 / 0.0106
[418/1000][40/42]    Loss_D: 0.0319  Loss_G: 11.8738 D(x): 0.9822
    D(G(z)): 0.0054 / 0.0005
[419/1000][0/42]Loss_D: 0.1533  Loss_G: 10.3984 D(x): 0.9311
    D(G(z)): 0.0022 / 0.0030
[419/1000][20/42]    Loss_D: 0.0308  Loss_G: 9.0932  D(x): 0.9922
    D(G(z)): 0.0160 / 0.0040
[419/1000][40/42]    Loss_D: 0.0513  Loss_G: 13.2097 D(x): 0.9807
    D(G(z)): 0.0024 / 0.0005
[420/1000][0/42]Loss_D: 0.1287  Loss_G: 10.7752 D(x): 0.9239
    D(G(z)): 0.0013 / 0.0027
[420/1000][20/42]    Loss_D: 0.0471  Loss_G: 11.6017 D(x): 0.9806
    D(G(z)): 0.0180 / 0.0067
[420/1000][40/42]    Loss_D: 0.1435  Loss_G: 7.9385  D(x): 0.9535
    D(G(z)): 0.0343 / 0.0184
```

```
[421/1000][0/42] Loss_D: 0.0765  Loss_G: 9.6884  D(x): 0.9966
      D(G(z)): 0.0490 / 0.0117
[421/1000][20/42]     Loss_D: 0.2010  Loss_G: 13.8181 D(x): 0.9080
      D(G(z)): 0.0074 / 0.0049
[421/1000][40/42]     Loss_D: 0.0562  Loss_G: 10.1671 D(x): 0.9695
      D(G(z)): 0.0137 / 0.0099
[422/1000][0/42] Loss_D: 0.1814  Loss_G: 6.3113  D(x): 0.9952
      D(G(z)): 0.0497 / 0.0865
[422/1000][20/42]     Loss_D: 0.2941  Loss_G: 7.9329  D(x): 0.9993
      D(G(z)): 0.1298 / 0.0458
[422/1000][40/42]     Loss_D: 0.1634  Loss_G: 10.5972 D(x): 0.9453
      D(G(z)): 0.0119 / 0.0048
[423/1000][0/42] Loss_D: 0.0554  Loss_G: 8.4851  D(x): 0.9929
      D(G(z)): 0.0409 / 0.0371
[423/1000][20/42]     Loss_D: 0.0203  Loss_G: 10.9358 D(x): 0.9988
      D(G(z)): 0.0157 / 0.0055
[423/1000][40/42]     Loss_D: 0.0435  Loss_G: 8.2000  D(x): 0.9868
      D(G(z)): 0.0234 / 0.0107
[424/1000][0/42] Loss_D: 0.0267  Loss_G: 10.5071 D(x): 0.9961
      D(G(z)): 0.0185 / 0.0026
[424/1000][20/42]     Loss_D: 0.0470  Loss_G: 11.5720 D(x): 0.9990
      D(G(z)): 0.0201 / 0.0038
[424/1000][40/42]     Loss_D: 0.0469  Loss_G: 10.6654 D(x): 0.9909
      D(G(z)): 0.0183 / 0.0019
[425/1000][0/42] Loss_D: 0.0207  Loss_G: 12.1457 D(x): 0.9921
      D(G(z)): 0.0110 / 0.0061
[425/1000][20/42]     Loss_D: 0.0447  Loss_G: 10.2217 D(x): 0.9820
      D(G(z)): 0.0222 / 0.0070
[425/1000][40/42]     Loss_D: 0.1398  Loss_G: 10.3667 D(x): 0.9512
      D(G(z)): 0.0260 / 0.0065
[426/1000][0/42] Loss_D: 0.1414  Loss_G: 9.5148  D(x): 0.9318
      D(G(z)): 0.0053 / 0.0047
[426/1000][20/42]     Loss_D: 0.0258  Loss_G: 11.2847 D(x): 0.9901
      D(G(z)): 0.0132 / 0.0047
[426/1000][40/42]     Loss_D: 0.0215  Loss_G: 8.0995  D(x): 0.9953
      D(G(z)): 0.0148 / 0.0212
[427/1000][0/42] Loss_D: 0.0120  Loss_G: 8.6094  D(x): 0.9976
      D(G(z)): 0.0089 / 0.0059
[427/1000][20/42]     Loss_D: 0.0403  Loss_G: 8.6983  D(x): 0.9701
      D(G(z)): 0.0037 / 0.0053
```

```
[427/1000][40/42]     Loss_D: 0.0295  Loss_G: 7.9721  D(x): 0.9904
      D(G(z)): 0.0167 / 0.0070
[428/1000][0/42]Loss_D: 0.1425  Loss_G: 8.6778  D(x): 0.9976
      D(G(z)): 0.0669 / 0.0100
[428/1000][20/42]     Loss_D: 0.0208  Loss_G: 10.5916 D(x): 0.9888
      D(G(z)): 0.0085 / 0.0132
[428/1000][40/42]     Loss_D: 0.0363  Loss_G: 10.1907 D(x): 0.9714
      D(G(z)): 0.0015 / 0.0007
[429/1000][0/42]Loss_D: 0.0068  Loss_G: 9.3367  D(x): 0.9957
      D(G(z)): 0.0024 / 0.0053
[429/1000][20/42]     Loss_D: 0.0057  Loss_G: 9.8742  D(x): 0.9963
      D(G(z)): 0.0018 / 0.0015
[429/1000][40/42]     Loss_D: 0.0566  Loss_G: 10.5753 D(x): 0.9530
      D(G(z)): 0.0002 / 0.0004
[430/1000][0/42]Loss_D: 0.0063  Loss_G: 8.5777  D(x): 0.9955
      D(G(z)): 0.0017 / 0.0026
[430/1000][20/42]     Loss_D: 0.0682  Loss_G: 8.3500  D(x): 0.9995
      D(G(z)): 0.0392 / 0.0111
[430/1000][40/42]     Loss_D: 0.0123  Loss_G: 9.8375  D(x): 0.9929
      D(G(z)): 0.0042 / 0.0020
```

```
[431/1000][0/42]Loss_D: 0.0272  Loss_G: 9.3586  D(x): 0.9765
      D(G(z)): 0.0011 / 0.0009
[431/1000][20/42]     Loss_D: 0.0476  Loss_G: 8.4095  D(x): 0.9721
      D(G(z)): 0.0109 / 0.0097
[431/1000][40/42]     Loss_D: 0.0116  Loss_G: 9.5420  D(x): 0.9925
      D(G(z)): 0.0037 / 0.0030
[432/1000][0/42]Loss_D: 0.0034  Loss_G: 10.8115 D(x): 0.9976
      D(G(z)): 0.0009 / 0.0005
[432/1000][20/42]     Loss_D: 0.0052  Loss_G: 9.2632  D(x): 0.9976
      D(G(z)): 0.0027 / 0.0038
[432/1000][40/42]     Loss_D: 0.0230  Loss_G: 7.9564  D(x): 0.9990
      D(G(z)): 0.0184 / 0.0066
[433/1000][0/42]Loss_D: 0.0151  Loss_G: 9.3338  D(x): 0.9898
      D(G(z)): 0.0045 / 0.0013
[433/1000][20/42]     Loss_D: 0.0221  Loss_G: 9.2238  D(x): 0.9805
      D(G(z)): 0.0011 / 0.0012
[433/1000][40/42]     Loss_D: 0.1084  Loss_G: 7.4174  D(x): 0.9990
      D(G(z)): 0.0809 / 0.0117
[434/1000][0/42]Loss_D: 0.0030  Loss_G: 11.5175 D(x): 0.9984
```

```
    D(G(z)): 0.0014 / 0.0004
[434/1000][20/42]    Loss_D: 0.0125  Loss_G: 10.7354 D(x): 0.9921
    D(G(z)): 0.0037 / 0.0025
[434/1000][40/42]    Loss_D: 0.0128  Loss_G: 9.5209  D(x): 0.9996
    D(G(z)): 0.0116 / 0.0048
[435/1000][0/42]Loss_D: 0.0056  Loss_G: 9.7200  D(x): 0.9967
    D(G(z)): 0.0022 / 0.0012
[435/1000][20/42]    Loss_D: 0.0286  Loss_G: 9.1316  D(x): 0.9885
    D(G(z)): 0.0133 / 0.0045
[435/1000][40/42]    Loss_D: 0.0599  Loss_G: 10.9533 D(x): 0.9577
    D(G(z)): 0.0002 / 0.0002
[436/1000][0/42]Loss_D: 0.0058  Loss_G: 8.5137  D(x): 0.9989
    D(G(z)): 0.0045 / 0.0154
[436/1000][20/42]    Loss_D: 0.0094  Loss_G: 10.5235 D(x): 0.9927
    D(G(z)): 0.0019 / 0.0017
[436/1000][40/42]    Loss_D: 0.0046  Loss_G: 11.0400 D(x): 0.9960
    D(G(z)): 0.0005 / 0.0004
[437/1000][0/42]Loss_D: 0.0314  Loss_G: 8.9997  D(x): 0.9778
    D(G(z)): 0.0031 / 0.0040
[437/1000][20/42]    Loss_D: 0.0075  Loss_G: 10.4693 D(x): 0.9985
    D(G(z)): 0.0057 / 0.0027
[437/1000][40/42]    Loss_D: 0.0044  Loss_G: 9.5986  D(x): 0.9966
    D(G(z)): 0.0010 / 0.0012
[438/1000][0/42]Loss_D: 0.0432  Loss_G: 9.7840  D(x): 0.9838
    D(G(z)): 0.0173 / 0.0082
[438/1000][20/42]    Loss_D: 0.0068  Loss_G: 10.6478 D(x): 0.9945
    D(G(z)): 0.0011 / 0.0006
[438/1000][40/42]    Loss_D: 0.0050  Loss_G: 8.9762  D(x): 0.9972
    D(G(z)): 0.0022 / 0.0029
[439/1000][0/42]Loss_D: 0.0225  Loss_G: 9.3258  D(x): 0.9985
    D(G(z)): 0.0173 / 0.0086
[439/1000][20/42]    Loss_D: 0.0161  Loss_G: 9.5211  D(x): 0.9875
    D(G(z)): 0.0031 / 0.0161
[439/1000][40/42]    Loss_D: 0.0218  Loss_G: 11.1459 D(x): 0.9803
    D(G(z)): 0.0008 / 0.0008
[440/1000][0/42]Loss_D: 0.0610  Loss_G: 9.7865  D(x): 0.9576
    D(G(z)): 0.0078 / 0.0078
[440/1000][20/42]    Loss_D: 0.0532  Loss_G: 9.4694  D(x): 0.9969
    D(G(z)): 0.0207 / 0.0019
[440/1000][40/42]    Loss_D: 0.0731  Loss_G: 9.4595  D(x): 0.9632
    D(G(z)): 0.0123 / 0.0027
```

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[441/1000][0/42]	Loss_D: 0.0332	Loss_G: 10.2301	D(x): 0.9852	D(G(z)): 0.0131 / 0.0040
[441/1000][20/42]	Loss_D: 0.0142	Loss_G: 9.1307	D(x): 0.9881	D(G(z)): 0.0016 / 0.0016
[441/1000][40/42]	Loss_D: 0.0242	Loss_G: 8.8443	D(x): 0.9889	D(G(z)): 0.0105 / 0.0081
[442/1000][0/42]	Loss_D: 0.0158	Loss_G: 8.3497	D(x): 0.9933	D(G(z)): 0.0081 / 0.0046
[442/1000][20/42]	Loss_D: 0.0313	Loss_G: 8.4591	D(x): 0.9968	D(G(z)): 0.0168 / 0.0027
[442/1000][40/42]	Loss_D: 0.0097	Loss_G: 7.8045	D(x): 0.9967	D(G(z)): 0.0061 / 0.0041
[443/1000][0/42]	Loss_D: 0.0054	Loss_G: 8.9692	D(x): 0.9969	D(G(z)): 0.0023 / 0.0020
[443/1000][20/42]	Loss_D: 0.0163	Loss_G: 9.3328	D(x): 0.9944	D(G(z)): 0.0094 / 0.0037
[443/1000][40/42]	Loss_D: 0.0068	Loss_G: 10.1399	D(x): 0.9945	D(G(z)): 0.0011 / 0.0010
[444/1000][0/42]	Loss_D: 0.0079	Loss_G: 8.5488	D(x): 0.9953	D(G(z)): 0.0031 / 0.0029
[444/1000][20/42]	Loss_D: 0.0703	Loss_G: 8.4056	D(x): 0.9992	D(G(z)): 0.0304 / 0.0047
[444/1000][40/42]	Loss_D: 0.0060	Loss_G: 9.9307	D(x): 0.9973	D(G(z)): 0.0032 / 0.0030
[445/1000][0/42]	Loss_D: 0.0064	Loss_G: 8.9373	D(x): 0.9967	D(G(z)): 0.0030 / 0.0033
[445/1000][20/42]	Loss_D: 0.0091	Loss_G: 9.2103	D(x): 0.9930	D(G(z)): 0.0020 / 0.0018
[445/1000][40/42]	Loss_D: 0.0235	Loss_G: 8.6560	D(x): 0.9807	D(G(z)): 0.0029 / 0.0025
[446/1000][0/42]	Loss_D: 0.0137	Loss_G: 8.8063	D(x): 0.9905	D(G(z)): 0.0032 / 0.0040
[446/1000][20/42]	Loss_D: 0.0062	Loss_G: 8.9254	D(x): 0.9980	D(G(z)): 0.0041 / 0.0029
[446/1000][40/42]	Loss_D: 0.0021	Loss_G: 9.6748	D(x): 0.9998	D(G(z)): 0.0018 / 0.0014
[447/1000][0/42]	Loss_D: 0.0032	Loss_G: 8.6762	D(x): 0.9989	D(G(z)): 0.0021 / 0.0020
[447/1000][20/42]	Loss_D: 0.0143	Loss_G: 9.5072	D(x): 0.9903	D(G(z)): 0.0040 / 0.0034
```

```
[447/1000][40/42]     Loss_D: 0.0037  Loss_G: 8.7464  D(x): 0.9990
      D(G(z)): 0.0026 / 0.0028
[448/1000][0/42] Loss_D: 0.0045  Loss_G: 8.2068  D(x): 0.9992
      D(G(z)): 0.0037 / 0.0034
[448/1000][20/42]     Loss_D: 0.0026  Loss_G: 10.1998 D(x): 0.9983
      D(G(z)): 0.0009 / 0.0014
[448/1000][40/42]     Loss_D: 0.0029  Loss_G: 10.1982 D(x): 0.9980
      D(G(z)): 0.0009 / 0.0010
[449/1000][0/42] Loss_D: 0.0078  Loss_G: 8.7828  D(x): 0.9950
      D(G(z)): 0.0028 / 0.0028
[449/1000][20/42]     Loss_D: 0.0046  Loss_G: 8.8927  D(x): 0.9992
      D(G(z)): 0.0038 / 0.0030
[449/1000][40/42]     Loss_D: 0.0077  Loss_G: 10.4587 D(x): 0.9932
      D(G(z)): 0.0007 / 0.0008
[450/1000][0/42] Loss_D: 0.0253  Loss_G: 9.5566  D(x): 0.9778
      D(G(z)): 0.0014 / 0.0018
[450/1000][20/42]     Loss_D: 0.0028  Loss_G: 9.9300  D(x): 0.9989
      D(G(z)): 0.0017 / 0.0010
[450/1000][40/42]     Loss_D: 0.0038  Loss_G: 9.8056  D(x): 0.9989
      D(G(z)): 0.0027 / 0.0023
```

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[451/1000][0/42] Loss_D: 0.0041  Loss_G: 8.7828  D(x): 0.9989
      D(G(z)): 0.0029 / 0.0030
[451/1000][20/42]     Loss_D: 0.0242  Loss_G: 10.0837 D(x): 0.9863
      D(G(z)): 0.0087 / 0.0026
[451/1000][40/42]     Loss_D: 0.0815  Loss_G: 10.0289 D(x): 0.9510
      D(G(z)): 0.0031 / 0.0024
[452/1000][0/42] Loss_D: 0.0274  Loss_G: 9.8738  D(x): 0.9924
      D(G(z)): 0.0135 / 0.0021
[452/1000][20/42]     Loss_D: 0.0880  Loss_G: 11.6226 D(x): 0.9284
      D(G(z)): 0.0007 / 0.0016
[452/1000][40/42]     Loss_D: 0.2855  Loss_G: 12.1014 D(x): 0.9976
      D(G(z)): 0.1327 / 0.0006
[453/1000][0/42] Loss_D: 0.2651  Loss_G: 12.0540 D(x): 0.8754
      D(G(z)): 0.0003 / 0.0069
[453/1000][20/42]     Loss_D: 0.1267  Loss_G: 15.6166 D(x): 0.9374
      D(G(z)): 0.0013 / 0.0003
[453/1000][40/42]     Loss_D: 0.0741  Loss_G: 12.6353 D(x): 0.9992
      D(G(z)): 0.0433 / 0.0013
[454/1000][0/42] Loss_D: 0.0239  Loss_G: 15.4287 D(x): 0.9809
```

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      D(G(z)): 0.0021 / 0.0003
[454/1000][20/42]     Loss_D: 0.0352  Loss_G: 11.7807 D(x): 0.9751
      D(G(z)): 0.0022 / 0.0002
[454/1000][40/42]     Loss_D: 0.0457  Loss_G: 10.4751 D(x): 0.9839
      D(G(z)): 0.0191 / 0.0235
[455/1000][0/42] Loss_D: 0.2117  Loss_G: 10.0565 D(x): 0.9713
      D(G(z)): 0.0917 / 0.0036
[455/1000][20/42]     Loss_D: 0.1187  Loss_G: 13.2125 D(x): 0.9444
      D(G(z)): 0.0035 / 0.0008
[455/1000][40/42]     Loss_D: 0.0589  Loss_G: 10.3567 D(x): 0.9955
      D(G(z)): 0.0396 / 0.0082
[456/1000][0/42] Loss_D: 0.0396  Loss_G: 9.8267  D(x): 0.9954
      D(G(z)): 0.0277 / 0.0077
[456/1000][20/42]     Loss_D: 0.0626  Loss_G: 9.8939  D(x): 0.9993
      D(G(z)): 0.0258 / 0.0077
[456/1000][40/42]     Loss_D: 0.1322  Loss_G: 8.0894  D(x): 0.9980
      D(G(z)): 0.0802 / 0.0203
[457/1000][0/42] Loss_D: 0.0249  Loss_G: 9.5757  D(x): 0.9912
      D(G(z)): 0.0136 / 0.0020
[457/1000][20/42]     Loss_D: 0.0814  Loss_G: 11.7058 D(x): 0.9487
      D(G(z)): 0.0111 / 0.0020
[457/1000][40/42]     Loss_D: 0.0087  Loss_G: 10.2922 D(x): 0.9991
      D(G(z)): 0.0075 / 0.0022
[458/1000][0/42] Loss_D: 0.0255  Loss_G: 10.9951 D(x): 0.9867
      D(G(z)): 0.0058 / 0.0041
[458/1000][20/42]     Loss_D: 0.0887  Loss_G: 6.0913  D(x): 0.9888
      D(G(z)): 0.0545 / 0.0227
[458/1000][40/42]     Loss_D: 0.0849  Loss_G: 7.1864  D(x): 0.9805
      D(G(z)): 0.0445 / 0.0651
[459/1000][0/42] Loss_D: 0.1255  Loss_G: 8.5607  D(x): 0.9958
      D(G(z)): 0.0791 / 0.0202
[459/1000][20/42]     Loss_D: 0.0889  Loss_G: 11.1001 D(x): 0.9903
      D(G(z)): 0.0369 / 0.0173
[459/1000][40/42]     Loss_D: 0.0953  Loss_G: 8.3561  D(x): 0.9999
      D(G(z)): 0.0641 / 0.0118
[460/1000][0/42] Loss_D: 0.0070  Loss_G: 10.6246 D(x): 0.9973
      D(G(z)): 0.0041 / 0.0014
[460/1000][20/42]     Loss_D: 0.0693  Loss_G: 9.7912  D(x): 0.9738
      D(G(z)): 0.0033 / 0.0034
[460/1000][40/42]     Loss_D: 0.0390  Loss_G: 7.9856  D(x): 0.9956
      D(G(z)): 0.0299 / 0.0147
```

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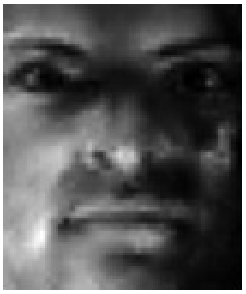
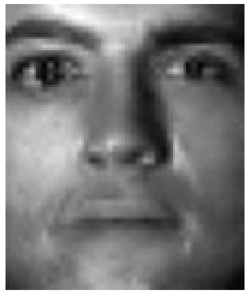
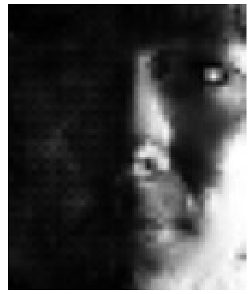
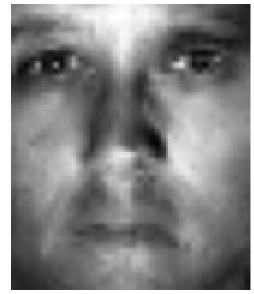
[461/1000][0/42] Loss_D: 0.0523  Loss_G: 10.3517 D(x): 0.9983
     D(G(z)): 0.0337 / 0.0135
[461/1000][20/42]    Loss_D: 0.1095  Loss_G: 11.0406 D(x): 0.9711
     D(G(z)): 0.0360 / 0.0064
[461/1000][40/42]    Loss_D: 0.0286  Loss_G: 9.0853  D(x): 0.9976
     D(G(z)): 0.0217 / 0.0080
[462/1000][0/42] Loss_D: 0.0318  Loss_G: 8.5905  D(x): 0.9881
     D(G(z)): 0.0166 / 0.0080
[462/1000][20/42]    Loss_D: 0.0143  Loss_G: 9.1845  D(x): 0.9896
     D(G(z)): 0.0031 / 0.0032
[462/1000][40/42]    Loss_D: 0.0220  Loss_G: 11.8314 D(x): 0.9803
     D(G(z)): 0.0004 / 0.0004
[463/1000][0/42] Loss_D: 0.0222  Loss_G: 9.0597  D(x): 0.9907
     D(G(z)): 0.0113 / 0.0091
[463/1000][20/42]    Loss_D: 0.0038  Loss_G: 10.4846 D(x): 0.9990
     D(G(z)): 0.0027 / 0.0021
[463/1000][40/42]    Loss_D: 0.0349  Loss_G: 8.0183  D(x): 0.9946
     D(G(z)): 0.0254 / 0.0103
[464/1000][0/42] Loss_D: 0.0107  Loss_G: 10.5394 D(x): 0.9992
     D(G(z)): 0.0093 / 0.0028
[464/1000][20/42]    Loss_D: 0.0195  Loss_G: 8.3597  D(x): 0.9987
     D(G(z)): 0.0161 / 0.0084
[464/1000][40/42]    Loss_D: 0.0157  Loss_G: 9.9161  D(x): 0.9904
     D(G(z)): 0.0047 / 0.0035
[465/1000][0/42] Loss_D: 0.0131  Loss_G: 9.1983  D(x): 0.9985
     D(G(z)): 0.0112 / 0.0078
[465/1000][20/42]    Loss_D: 0.0103  Loss_G: 7.7314  D(x): 0.9974
     D(G(z)): 0.0074 / 0.0147
[465/1000][40/42]    Loss_D: 0.0070  Loss_G: 11.4656 D(x): 0.9970
     D(G(z)): 0.0038 / 0.0040
[466/1000][0/42] Loss_D: 0.0302  Loss_G: 11.3340 D(x): 0.9798
     D(G(z)): 0.0013 / 0.0018
[466/1000][20/42]    Loss_D: 0.0430  Loss_G: 8.8429  D(x): 0.9905
     D(G(z)): 0.0275 / 0.0184
[466/1000][40/42]    Loss_D: 0.0053  Loss_G: 10.6396 D(x): 0.9987
     D(G(z)): 0.0038 / 0.0014
[467/1000][0/42] Loss_D: 0.0514  Loss_G: 10.7712 D(x): 0.9722
     D(G(z)): 0.0156 / 0.0026
[467/1000][20/42]    Loss_D: 0.0215  Loss_G: 10.2388 D(x): 0.9831
     D(G(z)): 0.0016 / 0.0021
```

```
[467/1000][40/42]     Loss_D: 0.0606  Loss_G: 10.8376 D(x): 0.9954
      D(G(z)): 0.0222 / 0.0031
[468/1000][0/42] Loss_D: 0.0708  Loss_G: 9.5175  D(x): 0.9506
      D(G(z)): 0.0015 / 0.0039
[468/1000][20/42]     Loss_D: 0.0167  Loss_G: 8.3593  D(x): 0.9936
      D(G(z)): 0.0092 / 0.0116
[468/1000][40/42]     Loss_D: 0.0564  Loss_G: 8.2686  D(x): 0.9709
      D(G(z)): 0.0143 / 0.0085
[469/1000][0/42] Loss_D: 0.0038  Loss_G: 9.4459  D(x): 0.9983
      D(G(z)): 0.0021 / 0.0023
[469/1000][20/42]     Loss_D: 0.0150  Loss_G: 9.9481  D(x): 0.9979
      D(G(z)): 0.0111 / 0.0048
[469/1000][40/42]     Loss_D: 0.0270  Loss_G: 9.8129  D(x): 0.9804
      D(G(z)): 0.0051 / 0.0057
[470/1000][0/42] Loss_D: 0.0036  Loss_G: 10.8293 D(x): 0.9992
      D(G(z)): 0.0027 / 0.0014
[470/1000][20/42]     Loss_D: 0.0127  Loss_G: 9.8085  D(x): 0.9932
      D(G(z)): 0.0050 / 0.0041
[470/1000][40/42]     Loss_D: 0.0235  Loss_G: 8.4158  D(x): 0.9972
      D(G(z)): 0.0188 / 0.0113
```

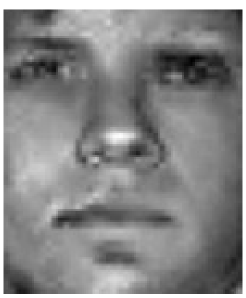
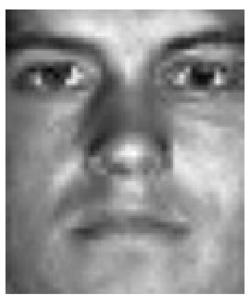
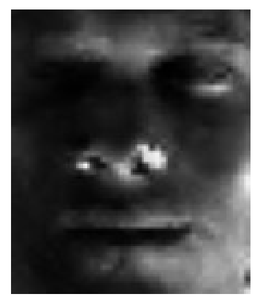
```
[471/1000][0/42] Loss_D: 0.0197  Loss_G: 8.5132  D(x): 0.9977
      D(G(z)): 0.0146 / 0.0065
[471/1000][20/42]     Loss_D: 0.0142  Loss_G: 8.9141  D(x): 0.9875
      D(G(z)): 0.0011 / 0.0093
[471/1000][40/42]     Loss_D: 0.0070  Loss_G: 8.1810  D(x): 0.9969
      D(G(z)): 0.0038 / 0.0133
[472/1000][0/42] Loss_D: 0.2256  Loss_G: 6.7107  D(x): 0.9999
      D(G(z)): 0.1423 / 0.0180
[472/1000][20/42]     Loss_D: 0.0477  Loss_G: 9.1970  D(x): 0.9997
      D(G(z)): 0.0385 / 0.0101
[472/1000][40/42]     Loss_D: 0.0860  Loss_G: 13.1489 D(x): 0.9709
      D(G(z)): 0.0262 / 0.0010
[473/1000][0/42] Loss_D: 0.0849  Loss_G: 16.3500 D(x): 0.9434
      D(G(z)): 0.0000 / 0.0000
[473/1000][20/42]     Loss_D: 0.1788  Loss_G: 11.6816 D(x): 0.9172
      D(G(z)): 0.0048 / 0.0075
[473/1000][40/42]     Loss_D: 0.0737  Loss_G: 12.0036 D(x): 0.9580
      D(G(z)): 0.0038 / 0.0014
[474/1000][0/42] Loss_D: 0.0890  Loss_G: 9.5818  D(x): 0.9490
```

```
    D(G(z)): 0.0128 / 0.0129
[474/1000][20/42]    Loss_D: 0.0594  Loss_G: 9.0250  D(x): 0.9760
    D(G(z)): 0.0099 / 0.0187
[474/1000][40/42]    Loss_D: 0.1885  Loss_G: 12.8435 D(x): 0.9153
    D(G(z)): 0.0033 / 0.0024
[475/1000][0/42] Loss_D: 0.0509  Loss_G: 9.0407  D(x): 0.9714
    D(G(z)): 0.0074 / 0.0146
[475/1000][20/42]    Loss_D: 0.0526  Loss_G: 11.7394 D(x): 0.9581
    D(G(z)): 0.0018 / 0.0008
[475/1000][40/42]    Loss_D: 0.0620  Loss_G: 10.3351 D(x): 0.9946
    D(G(z)): 0.0258 / 0.0016
[476/1000][0/42] Loss_D: 0.0207  Loss_G: 10.8988 D(x): 0.9859
    D(G(z)): 0.0035 / 0.0009
[476/1000][20/42]    Loss_D: 0.0140  Loss_G: 10.8296 D(x): 0.9931
    D(G(z)): 0.0063 / 0.0031
[476/1000][40/42]    Loss_D: 0.1807  Loss_G: 10.7429 D(x): 0.9058
    D(G(z)): 0.0036 / 0.0023
[477/1000][0/42] Loss_D: 0.0116  Loss_G: 10.3822 D(x): 0.9940
    D(G(z)): 0.0053 / 0.0037
[477/1000][20/42]    Loss_D: 0.1077  Loss_G: 7.3371  D(x): 0.9967
    D(G(z)): 0.0649 / 0.0274
[477/1000][40/42]    Loss_D: 0.0152  Loss_G: 12.1835 D(x): 0.9869
    D(G(z)): 0.0009 / 0.0007
[478/1000][0/42] Loss_D: 0.0056  Loss_G: 11.5128 D(x): 0.9951
    D(G(z)): 0.0006 / 0.0010
[478/1000][20/42]    Loss_D: 0.0418  Loss_G: 8.9642  D(x): 0.9990
    D(G(z)): 0.0207 / 0.0085
[478/1000][40/42]    Loss_D: 0.0380  Loss_G: 9.0196  D(x): 0.9909
    D(G(z)): 0.0236 / 0.0066
[479/1000][0/42] Loss_D: 0.0554  Loss_G: 10.1139 D(x): 0.9973
    D(G(z)): 0.0272 / 0.0029
[479/1000][20/42]    Loss_D: 0.0152  Loss_G: 9.7578  D(x): 0.9997
    D(G(z)): 0.0137 / 0.0051
[479/1000][40/42]    Loss_D: 0.0568  Loss_G: 8.6830  D(x): 0.9902
    D(G(z)): 0.0273 / 0.0138
[480/1000][0/42] Loss_D: 0.0191  Loss_G: 8.8018  D(x): 0.9921
    D(G(z)): 0.0088 / 0.0069
[480/1000][20/42]    Loss_D: 0.0076  Loss_G: 9.5802  D(x): 0.9977
    D(G(z)): 0.0052 / 0.0032
[480/1000][40/42]    Loss_D: 0.0286  Loss_G: 7.7449  D(x): 0.9933
    D(G(z)): 0.0196 / 0.0208
```

```
[481/1000][0/42] Loss_D: 0.0502  Loss_G: 7.7826  D(x): 0.9995
     D(G(z)): 0.0397 / 0.0122
[481/1000][20/42]    Loss_D: 0.0168  Loss_G: 9.5395  D(x): 0.9927
     D(G(z)): 0.0084 / 0.0087
[481/1000][40/42]    Loss_D: 0.0119  Loss_G: 9.2492  D(x): 0.9936
     D(G(z)): 0.0049 / 0.0036
[482/1000][0/42] Loss_D: 0.0058  Loss_G: 10.2233 D(x): 0.9975
     D(G(z)): 0.0033 / 0.0034
[482/1000][20/42]    Loss_D: 0.0426  Loss_G: 9.7484  D(x): 0.9810
     D(G(z)): 0.0136 / 0.0051
[482/1000][40/42]    Loss_D: 0.0260  Loss_G: 9.3310  D(x): 0.9976
     D(G(z)): 0.0160 / 0.0047
[483/1000][0/42] Loss_D: 0.0248  Loss_G: 8.9045  D(x): 0.9949
     D(G(z)): 0.0168 / 0.0041
[483/1000][20/42]    Loss_D: 0.0547  Loss_G: 9.6117  D(x): 0.9995
     D(G(z)): 0.0201 / 0.0018
[483/1000][40/42]    Loss_D: 0.1403  Loss_G: 9.8651  D(x): 0.9980
     D(G(z)): 0.0623 / 0.0074
[484/1000][0/42] Loss_D: 0.0109  Loss_G: 11.7124 D(x): 0.9922
     D(G(z)): 0.0022 / 0.0009
[484/1000][20/42]    Loss_D: 0.0359  Loss_G: 9.4059  D(x): 0.9993
     D(G(z)): 0.0268 / 0.0172
[484/1000][40/42]    Loss_D: 0.0669  Loss_G: 8.9592  D(x): 0.9526
     D(G(z)): 0.0050 / 0.0044
[485/1000][0/42] Loss_D: 0.0188  Loss_G: 10.1751 D(x): 0.9844
     D(G(z)): 0.0010 / 0.0015
[485/1000][20/42]    Loss_D: 0.0068  Loss_G: 11.1236 D(x): 0.9976
     D(G(z)): 0.0043 / 0.0009
[485/1000][40/42]    Loss_D: 0.0024  Loss_G: 11.5700 D(x): 0.9995
     D(G(z)): 0.0018 / 0.0011
[486/1000][0/42] Loss_D: 0.0105  Loss_G: 10.6112 D(x): 0.9967
     D(G(z)): 0.0063 / 0.0026
[486/1000][20/42]    Loss_D: 0.0092  Loss_G: 9.1271  D(x): 0.9946
     D(G(z)): 0.0034 / 0.0025
[486/1000][40/42]    Loss_D: 0.0095  Loss_G: 10.5485 D(x): 0.9920
     D(G(z)): 0.0013 / 0.0008
[487/1000][0/42] Loss_D: 0.0060  Loss_G: 9.8732  D(x): 0.9965
     D(G(z)): 0.0024 / 0.0028
[487/1000][20/42]    Loss_D: 0.0148  Loss_G: 11.4033 D(x): 0.9869
     D(G(z)): 0.0006 / 0.0003
```

```
[487/1000][40/42]     Loss_D: 0.0225  Loss_G: 10.0939 D(x): 0.9814
      D(G(z)): 0.0023 / 0.0039
[488/1000][0/42] Loss_D: 0.0499  Loss_G: 7.6154  D(x): 0.9994
      D(G(z)): 0.0385 / 0.0114
[488/1000][20/42]     Loss_D: 0.0193  Loss_G: 9.0448  D(x): 0.9855
      D(G(z)): 0.0042 / 0.0051
[488/1000][40/42]     Loss_D: 0.0202  Loss_G: 9.0763  D(x): 0.9985
      D(G(z)): 0.0140 / 0.0039
[489/1000][0/42] Loss_D: 0.0165  Loss_G: 9.1238  D(x): 0.9998
      D(G(z)): 0.0123 / 0.0015
[489/1000][20/42]     Loss_D: 0.0228  Loss_G: 8.4437  D(x): 0.9986
      D(G(z)): 0.0192 / 0.0062
[489/1000][40/42]     Loss_D: 0.0066  Loss_G: 9.5860  D(x): 0.9968
      D(G(z)): 0.0033 / 0.0028
[490/1000][0/42] Loss_D: 0.0280  Loss_G: 8.6921  D(x): 0.9945
      D(G(z)): 0.0194 / 0.0096
[490/1000][20/42]     Loss_D: 0.0684  Loss_G: 10.8679 D(x): 0.9526
      D(G(z)): 0.0011 / 0.0016
[490/1000][40/42]     Loss_D: 0.0256  Loss_G: 8.7720  D(x): 0.9964
      D(G(z)): 0.0188 / 0.0120
```

```
[491/1000][0/42] Loss_D: 0.0639  Loss_G: 8.4554  D(x): 0.9997
      D(G(z)): 0.0361 / 0.0049
[491/1000][20/42]     Loss_D: 0.0119  Loss_G: 9.2728  D(x): 0.9930
      D(G(z)): 0.0046 / 0.0110
[491/1000][40/42]     Loss_D: 0.0428  Loss_G: 8.5865  D(x): 0.9997
      D(G(z)): 0.0216 / 0.0086
[492/1000][0/42] Loss_D: 0.0296  Loss_G: 8.1060  D(x): 0.9996
      D(G(z)): 0.0192 / 0.0064
[492/1000][20/42]     Loss_D: 0.0116  Loss_G: 11.5983 D(x): 0.9970
      D(G(z)): 0.0074 / 0.0016
[492/1000][40/42]     Loss_D: 0.0018  Loss_G: 9.6771  D(x): 0.9993
      D(G(z)): 0.0011 / 0.0015
[493/1000][0/42] Loss_D: 0.0024  Loss_G: 9.3322  D(x): 0.9994
      D(G(z)): 0.0018 / 0.0021
[493/1000][20/42]     Loss_D: 0.0321  Loss_G: 7.7670  D(x): 0.9998
      D(G(z)): 0.0252 / 0.0088
[493/1000][40/42]     Loss_D: 0.0082  Loss_G: 9.3677  D(x): 0.9986
      D(G(z)): 0.0065 / 0.0028
[494/1000][0/42] Loss_D: 0.0323  Loss_G: 8.8980  D(x): 0.9735
```

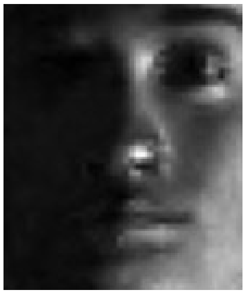
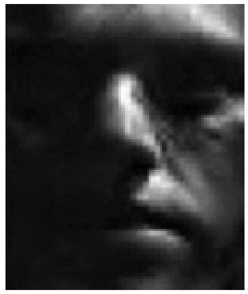
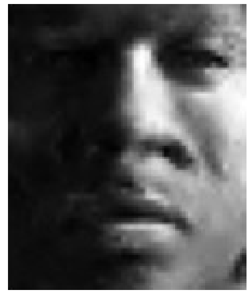
```
    D(G(z)): 0.0035 / 0.0028
[494/1000][20/42]	Loss_D: 0.0045	Loss_G: 9.3311	D(x): 0.9993
    D(G(z)): 0.0036 / 0.0017
[494/1000][40/42]	Loss_D: 0.0216	Loss_G: 9.9695	D(x): 0.9830
    D(G(z)): 0.0027 / 0.0031
[495/1000][0/42]	Loss_D: 0.0027	Loss_G: 8.6768	D(x): 0.9993
    D(G(z)): 0.0020 / 0.0022
[495/1000][20/42]	Loss_D: 0.0078	Loss_G: 10.9570	D(x): 0.9928
    D(G(z)): 0.0004 / 0.0003
[495/1000][40/42]	Loss_D: 0.0188	Loss_G: 9.2540	D(x): 0.9978
    D(G(z)): 0.0130 / 0.0023
[496/1000][0/42]	Loss_D: 0.0032	Loss_G: 11.8666	D(x): 0.9975
    D(G(z)): 0.0007 / 0.0006
[496/1000][20/42]	Loss_D: 0.0557	Loss_G: 8.9079	D(x): 0.9960
    D(G(z)): 0.0310 / 0.0048
[496/1000][40/42]	Loss_D: 0.0149	Loss_G: 9.3900	D(x): 0.9997
    D(G(z)): 0.0125 / 0.0042
[497/1000][0/42]	Loss_D: 0.0059	Loss_G: 12.2874	D(x): 0.9958
    D(G(z)): 0.0015 / 0.0009
[497/1000][20/42]	Loss_D: 0.0605	Loss_G: 8.3053	D(x): 0.9999
    D(G(z)): 0.0433 / 0.0059
[497/1000][40/42]	Loss_D: 0.0460	Loss_G: 8.3017	D(x): 0.9999
    D(G(z)): 0.0326 / 0.0281
[498/1000][0/42]	Loss_D: 0.0896	Loss_G: 9.4852	D(x): 0.9994
    D(G(z)): 0.0418 / 0.0020
[498/1000][20/42]	Loss_D: 0.1546	Loss_G: 9.9994	D(x): 0.9947
    D(G(z)): 0.0518 / 0.0083
[498/1000][40/42]	Loss_D: 0.0381	Loss_G: 12.7733	D(x): 0.9751
    D(G(z)): 0.0078 / 0.0076
[499/1000][0/42]	Loss_D: 0.0910	Loss_G: 11.8260	D(x): 0.9972
    D(G(z)): 0.0484 / 0.0173
[499/1000][20/42]	Loss_D: 0.1478	Loss_G: 9.1388	D(x): 0.9793
    D(G(z)): 0.0601 / 0.0056
[499/1000][40/42]	Loss_D: 0.0813	Loss_G: 12.5533	D(x): 0.9907
    D(G(z)): 0.0371 / 0.0027
[500/1000][0/42]	Loss_D: 0.1092	Loss_G: 11.6281	D(x): 0.9432
    D(G(z)): 0.0187 / 0.0014
[500/1000][20/42]	Loss_D: 0.2056	Loss_G: 9.3464	D(x): 0.9947
    D(G(z)): 0.0229 / 0.0224
[500/1000][40/42]	Loss_D: 0.1294	Loss_G: 10.7662	D(x): 0.9251
    D(G(z)): 0.0056 / 0.0066
```

```
[501/1000][0/42]	Loss_D: 0.1102	Loss_G: 10.0471	D(x): 0.9748
	D(G(z)): 0.0243 / 0.0138
[501/1000][20/42]	Loss_D: 0.1385	Loss_G: 13.0808	D(x): 0.9231
	D(G(z)): 0.0004 / 0.0004
[501/1000][40/42]	Loss_D: 0.0578	Loss_G: 11.6554	D(x): 0.9955
	D(G(z)): 0.0388 / 0.0096
[502/1000][0/42]	Loss_D: 0.0736	Loss_G: 10.3600	D(x): 0.9664
	D(G(z)): 0.0191 / 0.0067
[502/1000][20/42]	Loss_D: 0.1139	Loss_G: 8.1490	D(x): 0.9897
	D(G(z)): 0.0494 / 0.0069
[502/1000][40/42]	Loss_D: 0.0102	Loss_G: 7.9899	D(x): 0.9977
	D(G(z)): 0.0076 / 0.0073
[503/1000][0/42]	Loss_D: 0.0308	Loss_G: 10.6036	D(x): 0.9869
	D(G(z)): 0.0137 / 0.0028
[503/1000][20/42]	Loss_D: 0.0092	Loss_G: 12.3910	D(x): 0.9925
	D(G(z)): 0.0011 / 0.0007
[503/1000][40/42]	Loss_D: 0.0078	Loss_G: 10.8448	D(x): 0.9986
	D(G(z)): 0.0062 / 0.0035
[504/1000][0/42]	Loss_D: 0.0134	Loss_G: 9.6437	D(x): 0.9956
	D(G(z)): 0.0081 / 0.0052
[504/1000][20/42]	Loss_D: 0.0336	Loss_G: 11.1514	D(x): 0.9740
	D(G(z)): 0.0027 / 0.0027
[504/1000][40/42]	Loss_D: 0.0064	Loss_G: 11.0792	D(x): 0.9955
	D(G(z)): 0.0017 / 0.0024
[505/1000][0/42]	Loss_D: 0.0059	Loss_G: 10.4790	D(x): 0.9980
	D(G(z)): 0.0037 / 0.0047
[505/1000][20/42]	Loss_D: 0.0150	Loss_G: 10.8388	D(x): 0.9965
	D(G(z)): 0.0099 / 0.0027
[505/1000][40/42]	Loss_D: 0.0153	Loss_G: 9.6856	D(x): 0.9881
	D(G(z)): 0.0014 / 0.0030
[506/1000][0/42]	Loss_D: 0.0111	Loss_G: 8.5995	D(x): 0.9969
	D(G(z)): 0.0076 / 0.0079
[506/1000][20/42]	Loss_D: 0.0601	Loss_G: 11.7913	D(x): 0.9601
	D(G(z)): 0.0004 / 0.0011
[506/1000][40/42]	Loss_D: 0.0042	Loss_G: 14.1114	D(x): 0.9965
	D(G(z)): 0.0007 / 0.0001
[507/1000][0/42]	Loss_D: 0.1806	Loss_G: 13.5471	D(x): 0.8871
	D(G(z)): 0.0002 / 0.0007
[507/1000][20/42]	Loss_D: 0.0124	Loss_G: 8.9018	D(x): 0.9993
	D(G(z)): 0.0109 / 0.0294
```

```
[507/1000][40/42]    Loss_D: 0.2787  Loss_G: 8.6550  D(x): 0.9882
     D(G(z)): 0.1153 / 0.0150
[508/1000][0/42]Loss_D: 0.0352  Loss_G: 11.2499 D(x): 0.9997
     D(G(z)): 0.0261 / 0.0011
[508/1000][20/42]    Loss_D: 0.0411  Loss_G: 12.5483 D(x): 0.9781
     D(G(z)): 0.0101 / 0.0060
[508/1000][40/42]    Loss_D: 0.0528  Loss_G: 9.9249  D(x): 0.9828
     D(G(z)): 0.0217 / 0.0092
[509/1000][0/42]Loss_D: 0.0770  Loss_G: 11.4188 D(x): 0.9498
     D(G(z)): 0.0058 / 0.0020
[509/1000][20/42]    Loss_D: 0.0315  Loss_G: 12.4171 D(x): 0.9798
     D(G(z)): 0.0022 / 0.0007
[509/1000][40/42]    Loss_D: 0.0374  Loss_G: 10.5377 D(x): 0.9994
     D(G(z)): 0.0298 / 0.0039
[510/1000][0/42]Loss_D: 0.0072  Loss_G: 11.1073 D(x): 0.9962
     D(G(z)): 0.0032 / 0.0010
[510/1000][20/42]    Loss_D: 0.0102  Loss_G: 10.2815 D(x): 0.9945
     D(G(z)): 0.0043 / 0.0021
[510/1000][40/42]    Loss_D: 0.0115  Loss_G: 11.3337 D(x): 0.9968
     D(G(z)): 0.0078 / 0.0028
```

```
[511/1000][0/42]Loss_D: 0.0707  Loss_G: 12.2452 D(x): 0.9704
     D(G(z)): 0.0167 / 0.0015
[511/1000][20/42]    Loss_D: 0.0226  Loss_G: 11.0890 D(x): 0.9858
     D(G(z)): 0.0021 / 0.0008
[511/1000][40/42]    Loss_D: 0.0162  Loss_G: 12.4938 D(x): 0.9856
     D(G(z)): 0.0003 / 0.0005
[512/1000][0/42]Loss_D: 0.0121  Loss_G: 11.2509 D(x): 0.9982
     D(G(z)): 0.0083 / 0.0057
[512/1000][20/42]    Loss_D: 0.0169  Loss_G: 10.0109 D(x): 0.9884
     D(G(z)): 0.0043 / 0.0028
[512/1000][40/42]    Loss_D: 0.0117  Loss_G: 8.3289  D(x): 0.9986
     D(G(z)): 0.0098 / 0.0088
[513/1000][0/42]Loss_D: 0.0078  Loss_G: 9.1056  D(x): 0.9996
     D(G(z)): 0.0071 / 0.0042
[513/1000][20/42]    Loss_D: 0.0054  Loss_G: 9.8377  D(x): 0.9969
     D(G(z)): 0.0023 / 0.0016
[513/1000][40/42]    Loss_D: 0.0246  Loss_G: 12.2238 D(x): 0.9819
     D(G(z)): 0.0026 / 0.0006
[514/1000][0/42]Loss_D: 0.0383  Loss_G: 12.0802 D(x): 0.9657
```

```
	D(G(z)): 0.0003 / 0.0011
[514/1000][20/42]	Loss_D: 0.0609	Loss_G: 12.5435	D(x): 0.9574
	D(G(z)): 0.0028 / 0.0021
[514/1000][40/42]	Loss_D: 0.0036	Loss_G: 11.7202	D(x): 0.9972
	D(G(z)): 0.0006 / 0.0003
[515/1000][0/42]	Loss_D: 0.0274	Loss_G: 11.6609	D(x): 0.9849
	D(G(z)): 0.0090 / 0.0013
[515/1000][20/42]	Loss_D: 0.0023	Loss_G: 9.9414	D(x): 0.9993
	D(G(z)): 0.0016 / 0.0024
[515/1000][40/42]	Loss_D: 0.0692	Loss_G: 10.7140	D(x): 0.9509
	D(G(z)): 0.0014 / 0.0022
[516/1000][0/42]	Loss_D: 0.0111	Loss_G: 8.4173	D(x): 0.9990
	D(G(z)): 0.0087 / 0.0066
[516/1000][20/42]	Loss_D: 0.0991	Loss_G: 12.5775	D(x): 0.9657
	D(G(z)): 0.0002 / 0.0001
[516/1000][40/42]	Loss_D: 0.0176	Loss_G: 9.2933	D(x): 0.9965
	D(G(z)): 0.0118 / 0.0083
[517/1000][0/42]	Loss_D: 0.0041	Loss_G: 9.1287	D(x): 0.9991
	D(G(z)): 0.0032 / 0.0029
[517/1000][20/42]	Loss_D: 0.0243	Loss_G: 9.5509	D(x): 0.9958
	D(G(z)): 0.0156 / 0.0034
[517/1000][40/42]	Loss_D: 0.0047	Loss_G: 9.0547	D(x): 0.9972
	D(G(z)): 0.0018 / 0.0019
[518/1000][0/42]	Loss_D: 0.0075	Loss_G: 8.5291	D(x): 0.9986
	D(G(z)): 0.0059 / 0.0047
[518/1000][20/42]	Loss_D: 0.0576	Loss_G: 9.5668	D(x): 0.9920
	D(G(z)): 0.0351 / 0.0067
[518/1000][40/42]	Loss_D: 0.0071	Loss_G: 10.9587	D(x): 0.9941
	D(G(z)): 0.0011 / 0.0005
[519/1000][0/42]	Loss_D: 0.0189	Loss_G: 10.3289	D(x): 0.9915
	D(G(z)): 0.0094 / 0.0044
[519/1000][20/42]	Loss_D: 0.0033	Loss_G: 10.6443	D(x): 0.9988
	D(G(z)): 0.0021 / 0.0019
[519/1000][40/42]	Loss_D: 0.0363	Loss_G: 10.3002	D(x): 0.9695
	D(G(z)): 0.0028 / 0.0024
[520/1000][0/42]	Loss_D: 0.0324	Loss_G: 11.3625	D(x): 0.9785
	D(G(z)): 0.0003 / 0.0006
[520/1000][20/42]	Loss_D: 0.0165	Loss_G: 11.2819	D(x): 0.9899
	D(G(z)): 0.0032 / 0.0022
[520/1000][40/42]	Loss_D: 0.0262	Loss_G: 8.6538	D(x): 0.9997
	D(G(z)): 0.0205 / 0.0190
```

```
[521/1000][0/42]	Loss_D: 0.0084	Loss_G: 9.5108	D(x): 0.9994	D(G(z)): 0.0076 / 0.0037
[521/1000][20/42]	Loss_D: 0.0373	Loss_G: 8.8020	D(x): 0.9834	D(G(z)): 0.0093 / 0.0069
[521/1000][40/42]	Loss_D: 0.0805	Loss_G: 10.9410	D(x): 0.9437	D(G(z)): 0.0025 / 0.0013
[522/1000][0/42]	Loss_D: 0.0092	Loss_G: 9.5672	D(x): 0.9972	D(G(z)): 0.0062 / 0.0052
[522/1000][20/42]	Loss_D: 0.0250	Loss_G: 10.8134	D(x): 0.9821	D(G(z)): 0.0021 / 0.0019
[522/1000][40/42]	Loss_D: 0.0351	Loss_G: 11.2818	D(x): 0.9761	D(G(z)): 0.0080 / 0.0015
[523/1000][0/42]	Loss_D: 0.0122	Loss_G: 10.5241	D(x): 0.9924	D(G(z)): 0.0040 / 0.0071
[523/1000][20/42]	Loss_D: 0.0287	Loss_G: 9.5343	D(x): 0.9776	D(G(z)): 0.0016 / 0.0022
[523/1000][40/42]	Loss_D: 0.0102	Loss_G: 8.9439	D(x): 0.9995	D(G(z)): 0.0092 / 0.0066
[524/1000][0/42]	Loss_D: 0.0096	Loss_G: 9.4348	D(x): 0.9986	D(G(z)): 0.0077 / 0.0014
[524/1000][20/42]	Loss_D: 0.0063	Loss_G: 11.7515	D(x): 0.9945	D(G(z)): 0.0007 / 0.0005
[524/1000][40/42]	Loss_D: 0.0479	Loss_G: 9.4260	D(x): 0.9671	D(G(z)): 0.0022 / 0.0109
[525/1000][0/42]	Loss_D: 0.0328	Loss_G: 7.2338	D(x): 0.9998	D(G(z)): 0.0283 / 0.0221
[525/1000][20/42]	Loss_D: 0.0064	Loss_G: 12.2560	D(x): 0.9946	D(G(z)): 0.0008 / 0.0006
[525/1000][40/42]	Loss_D: 0.0059	Loss_G: 9.4805	D(x): 0.9988	D(G(z)): 0.0045 / 0.0029
[526/1000][0/42]	Loss_D: 0.0016	Loss_G: 11.5187	D(x): 0.9988	D(G(z)): 0.0003 / 0.0003
[526/1000][20/42]	Loss_D: 0.0045	Loss_G: 9.3794	D(x): 0.9989	D(G(z)): 0.0033 / 0.0058
[526/1000][40/42]	Loss_D: 0.0049	Loss_G: 9.5026	D(x): 0.9978	D(G(z)): 0.0026 / 0.0027
[527/1000][0/42]	Loss_D: 0.0248	Loss_G: 11.0112	D(x): 0.9978	D(G(z)): 0.0157 / 0.0026
[527/1000][20/42]	Loss_D: 0.0017	Loss_G: 11.0506	D(x): 0.9994	D(G(z)): 0.0011 / 0.0008
```

```
[527/1000][40/42]	Loss_D: 0.0048	Loss_G: 9.2505	D(x): 0.9983
     D(G(z)): 0.0031 / 0.0019
[528/1000][0/42]	Loss_D: 0.0061	Loss_G: 9.8368	D(x): 0.9950
     D(G(z)): 0.0010 / 0.0007
[528/1000][20/42]	Loss_D: 0.0038	Loss_G: 9.1145	D(x): 0.9988
     D(G(z)): 0.0025 / 0.0024
[528/1000][40/42]	Loss_D: 0.0527	Loss_G: 11.1529	D(x): 0.9567
     D(G(z)): 0.0008 / 0.0011
[529/1000][0/42]	Loss_D: 0.0016	Loss_G: 8.8168	D(x): 0.9997
     D(G(z)): 0.0012 / 0.0042
[529/1000][20/42]	Loss_D: 0.0027	Loss_G: 10.7117	D(x): 0.9995
     D(G(z)): 0.0021 / 0.0009
[529/1000][40/42]	Loss_D: 0.0039	Loss_G: 8.4305	D(x): 0.9986
     D(G(z)): 0.0025 / 0.0095
[530/1000][0/42]	Loss_D: 0.0210	Loss_G: 6.8536	D(x): 0.9997
     D(G(z)): 0.0194 / 0.0202
[530/1000][20/42]	Loss_D: 0.1450	Loss_G: 7.7367	D(x): 0.9966
     D(G(z)): 0.0552 / 0.0254
[530/1000][40/42]	Loss_D: 0.0615	Loss_G: 11.6122	D(x): 0.9945
     D(G(z)): 0.0368 / 0.0069
```

```
[531/1000][0/42]	Loss_D: 0.0172	Loss_G: 11.5486	D(x): 0.9946
     D(G(z)): 0.0091 / 0.0027
[531/1000][20/42]	Loss_D: 0.0382	Loss_G: 10.4014	D(x): 0.9986
     D(G(z)): 0.0246 / 0.0029
[531/1000][40/42]	Loss_D: 0.0040	Loss_G: 10.9981	D(x): 0.9989
     D(G(z)): 0.0029 / 0.0044
[532/1000][0/42]	Loss_D: 0.0070	Loss_G: 11.3368	D(x): 0.9974
     D(G(z)): 0.0042 / 0.0034
[532/1000][20/42]	Loss_D: 0.0284	Loss_G: 10.7408	D(x): 0.9989
     D(G(z)): 0.0158 / 0.0027
[532/1000][40/42]	Loss_D: 0.0286	Loss_G: 11.8234	D(x): 0.9982
     D(G(z)): 0.0231 / 0.0029
[533/1000][0/42]	Loss_D: 0.0190	Loss_G: 12.7235	D(x): 0.9896
     D(G(z)): 0.0057 / 0.0013
[533/1000][20/42]	Loss_D: 0.2209	Loss_G: 10.5754	D(x): 0.9999
     D(G(z)): 0.0950 / 0.0065
[533/1000][40/42]	Loss_D: 0.0054	Loss_G: 11.4286	D(x): 0.9991
     D(G(z)): 0.0041 / 0.0062
[534/1000][0/42]	Loss_D: 0.0390	Loss_G: 10.5047	D(x): 0.9996
```

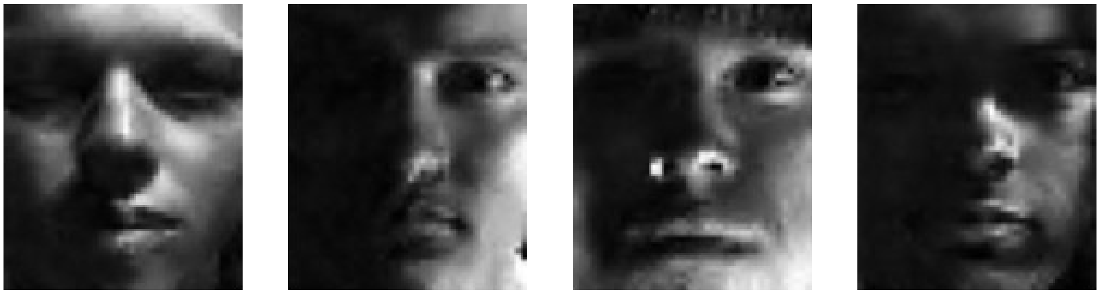
```
      D(G(z)): 0.0288 / 0.0192
[534/1000][20/42]     Loss_D: 0.0243  Loss_G: 10.7495 D(x): 0.9872
      D(G(z)): 0.0096 / 0.0099
[534/1000][40/42]     Loss_D: 0.0312  Loss_G: 10.4522 D(x): 0.9967
      D(G(z)): 0.0226 / 0.0300
[535/1000][0/42] Loss_D: 0.2727  Loss_G: 8.1528  D(x): 0.9995
      D(G(z)): 0.1087 / 0.0154
[535/1000][20/42]     Loss_D: 0.0290  Loss_G: 8.0941  D(x): 0.9892
      D(G(z)): 0.0143 / 0.0082
[535/1000][40/42]     Loss_D: 0.0219  Loss_G: 12.5523 D(x): 0.9935
      D(G(z)): 0.0134 / 0.0077
[536/1000][0/42] Loss_D: 0.1908  Loss_G: 14.3204 D(x): 0.9598
      D(G(z)): 0.0051 / 0.0009
[536/1000][20/42]     Loss_D: 0.0476  Loss_G: 10.6810 D(x): 0.9900
      D(G(z)): 0.0312 / 0.0035
[536/1000][40/42]     Loss_D: 0.1114  Loss_G: 10.6630 D(x): 0.9980
      D(G(z)): 0.0543 / 0.0083
[537/1000][0/42] Loss_D: 0.0079  Loss_G: 11.0877 D(x): 0.9989
      D(G(z)): 0.0065 / 0.0027
[537/1000][20/42]     Loss_D: 0.0897  Loss_G: 8.9846  D(x): 0.9964
      D(G(z)): 0.0567 / 0.0113
[537/1000][40/42]     Loss_D: 0.0151  Loss_G: 9.7038  D(x): 0.9998
      D(G(z)): 0.0123 / 0.0047
[538/1000][0/42] Loss_D: 0.0142  Loss_G: 11.4893 D(x): 0.9988
      D(G(z)): 0.0103 / 0.0011
[538/1000][20/42]     Loss_D: 0.0419  Loss_G: 9.7185  D(x): 0.9808
      D(G(z)): 0.0137 / 0.0026
[538/1000][40/42]     Loss_D: 0.0528  Loss_G: 8.2552  D(x): 0.9995
      D(G(z)): 0.0388 / 0.0120
[539/1000][0/42] Loss_D: 0.0270  Loss_G: 10.6754 D(x): 0.9992
      D(G(z)): 0.0228 / 0.0032
[539/1000][20/42]     Loss_D: 0.0356  Loss_G: 12.1511 D(x): 0.9752
      D(G(z)): 0.0024 / 0.0012
[539/1000][40/42]     Loss_D: 0.0189  Loss_G: 14.4822 D(x): 0.9837
      D(G(z)): 0.0008 / 0.0007
[540/1000][0/42] Loss_D: 0.0982  Loss_G: 12.7571 D(x): 0.9726
      D(G(z)): 0.0011 / 0.0012
[540/1000][20/42]     Loss_D: 0.0206  Loss_G: 14.6012 D(x): 0.9842
      D(G(z)): 0.0012 / 0.0005
[540/1000][40/42]     Loss_D: 0.0123  Loss_G: 9.4626  D(x): 0.9967
      D(G(z)): 0.0084 / 0.0059
```

```
[541/1000][0/42] Loss_D: 0.2166  Loss_G: 9.4689  D(x): 0.9806
      D(G(z)): 0.0730 / 0.0085
[541/1000][20/42]     Loss_D: 0.0669  Loss_G: 9.5601  D(x): 0.9930
      D(G(z)): 0.0440 / 0.0330
[541/1000][40/42]     Loss_D: 0.0114  Loss_G: 12.5159 D(x): 0.9907
      D(G(z)): 0.0009 / 0.0006
[542/1000][0/42] Loss_D: 0.0749  Loss_G: 12.0551 D(x): 0.9717
      D(G(z)): 0.0028 / 0.0043
[542/1000][20/42]     Loss_D: 0.0143  Loss_G: 11.1944 D(x): 0.9923
      D(G(z)): 0.0058 / 0.0022
[542/1000][40/42]     Loss_D: 0.0144  Loss_G: 9.8739  D(x): 0.9932
      D(G(z)): 0.0072 / 0.0070
[543/1000][0/42] Loss_D: 0.0101  Loss_G: 10.8945 D(x): 0.9919
      D(G(z)): 0.0011 / 0.0014
[543/1000][20/42]     Loss_D: 0.0212  Loss_G: 11.8042 D(x): 0.9807
      D(G(z)): 0.0009 / 0.0010
[543/1000][40/42]     Loss_D: 0.0268  Loss_G: 8.5105  D(x): 0.9993
      D(G(z)): 0.0226 / 0.0052
[544/1000][0/42] Loss_D: 0.0185  Loss_G: 11.1853 D(x): 0.9957
      D(G(z)): 0.0128 / 0.0070
[544/1000][20/42]     Loss_D: 0.0036  Loss_G: 11.5294 D(x): 0.9967
      D(G(z)): 0.0001 / 0.0002
[544/1000][40/42]     Loss_D: 0.0162  Loss_G: 8.6224  D(x): 0.9993
      D(G(z)): 0.0139 / 0.0062
[545/1000][0/42] Loss_D: 0.0318  Loss_G: 9.6647  D(x): 0.9992
      D(G(z)): 0.0202 / 0.0109
[545/1000][20/42]     Loss_D: 0.0381  Loss_G: 9.7366  D(x): 0.9696
      D(G(z)): 0.0017 / 0.0027
[545/1000][40/42]     Loss_D: 0.0575  Loss_G: 9.9691  D(x): 0.9971
      D(G(z)): 0.0415 / 0.0056
[546/1000][0/42] Loss_D: 0.0391  Loss_G: 13.5370 D(x): 0.9680
      D(G(z)): 0.0001 / 0.0001
[546/1000][20/42]     Loss_D: 0.0287  Loss_G: 9.8806  D(x): 0.9896
      D(G(z)): 0.0136 / 0.0053
[546/1000][40/42]     Loss_D: 0.0072  Loss_G: 9.7085  D(x): 0.9984
      D(G(z)): 0.0055 / 0.0039
[547/1000][0/42] Loss_D: 0.0088  Loss_G: 9.4519  D(x): 0.9998
      D(G(z)): 0.0080 / 0.0042
[547/1000][20/42]     Loss_D: 0.0025  Loss_G: 11.3626 D(x): 0.9987
      D(G(z)): 0.0012 / 0.0006
```

```
[547/1000][40/42]     Loss_D: 0.0035  Loss_G: 8.6779  D(x): 0.9998
      D(G(z)): 0.0033 / 0.0031
[548/1000][0/42] Loss_D: 0.0525  Loss_G: 8.5172  D(x): 0.9993
      D(G(z)): 0.0306 / 0.0050
[548/1000][20/42]     Loss_D: 0.0095  Loss_G: 9.8380  D(x): 0.9975
      D(G(z)): 0.0067 / 0.0030
[548/1000][40/42]     Loss_D: 0.0084  Loss_G: 9.3115  D(x): 0.9998
      D(G(z)): 0.0078 / 0.0078
[549/1000][0/42] Loss_D: 0.0207  Loss_G: 10.2097 D(x): 0.9977
      D(G(z)): 0.0160 / 0.0054
[549/1000][20/42]     Loss_D: 0.3106  Loss_G: 9.1113  D(x): 0.9982
      D(G(z)): 0.0602 / 0.0024
[549/1000][40/42]     Loss_D: 0.0350  Loss_G: 13.7205 D(x): 0.9901
      D(G(z)): 0.0147 / 0.0006
[550/1000][0/42] Loss_D: 0.0631  Loss_G: 13.5120 D(x): 0.9611
      D(G(z)): 0.0001 / 0.0004
[550/1000][20/42]     Loss_D: 0.0282  Loss_G: 17.0366 D(x): 0.9783
      D(G(z)): 0.0001 / 0.0002
[550/1000][40/42]     Loss_D: 0.0632  Loss_G: 11.3010 D(x): 0.9988
      D(G(z)): 0.0329 / 0.0052
```

```
[551/1000][0/42] Loss_D: 0.0459  Loss_G: 11.6011 D(x): 0.9701
      D(G(z)): 0.0035 / 0.0013
[551/1000][20/42]     Loss_D: 0.0022  Loss_G: 11.3152 D(x): 0.9998
      D(G(z)): 0.0020 / 0.0010
[551/1000][40/42]     Loss_D: 0.0970  Loss_G: 10.9825 D(x): 0.9697
      D(G(z)): 0.0207 / 0.0027
[552/1000][0/42] Loss_D: 0.0393  Loss_G: 10.5646 D(x): 0.9992
      D(G(z)): 0.0197 / 0.0073
[552/1000][20/42]     Loss_D: 0.1122  Loss_G: 7.4450  D(x): 0.9779
      D(G(z)): 0.0236 / 0.0115
[552/1000][40/42]     Loss_D: 0.1212  Loss_G: 11.3388 D(x): 0.9375
      D(G(z)): 0.0020 / 0.0025
[553/1000][0/42] Loss_D: 0.0029  Loss_G: 10.9132 D(x): 0.9976
      D(G(z)): 0.0005 / 0.0006
[553/1000][20/42]     Loss_D: 0.0069  Loss_G: 11.4119 D(x): 0.9981
      D(G(z)): 0.0049 / 0.0052
[553/1000][40/42]     Loss_D: 0.0202  Loss_G: 10.4833 D(x): 0.9945
      D(G(z)): 0.0131 / 0.0045
[554/1000][0/42] Loss_D: 0.0160  Loss_G: 9.8507  D(x): 0.9913
```

```
    D(G(z)): 0.0067 / 0.0040
[554/1000][20/42]    Loss_D: 0.0053  Loss_G: 13.4962 D(x): 0.9950
    D(G(z)): 0.0002 / 0.0001
[554/1000][40/42]    Loss_D: 0.0054  Loss_G: 9.4206  D(x): 0.9990
    D(G(z)): 0.0042 / 0.0049
[555/1000][0/42]Loss_D: 0.0429  Loss_G: 8.5599  D(x): 0.9999
    D(G(z)): 0.0311 / 0.0049
[555/1000][20/42]    Loss_D: 0.0321  Loss_G: 12.3804 D(x): 0.9759
    D(G(z)): 0.0003 / 0.0006
[555/1000][40/42]    Loss_D: 0.0047  Loss_G: 10.7323 D(x): 0.9966
    D(G(z)): 0.0013 / 0.0012
[556/1000][0/42]Loss_D: 0.0054  Loss_G: 10.0449 D(x): 0.9988
    D(G(z)): 0.0041 / 0.0031
[556/1000][20/42]    Loss_D: 0.1685  Loss_G: 8.6210  D(x): 0.9988
    D(G(z)): 0.0571 / 0.0099
[556/1000][40/42]    Loss_D: 0.0169  Loss_G: 12.9988 D(x): 0.9920
    D(G(z)): 0.0071 / 0.0026
[557/1000][0/42]Loss_D: 0.0213  Loss_G: 12.0483 D(x): 0.9803
    D(G(z)): 0.0002 / 0.0003
[557/1000][20/42]    Loss_D: 0.0546  Loss_G: 10.0868 D(x): 0.9852
    D(G(z)): 0.0179 / 0.0068
[557/1000][40/42]    Loss_D: 0.0054  Loss_G: 11.7355 D(x): 0.9957
    D(G(z)): 0.0010 / 0.0008
[558/1000][0/42]Loss_D: 0.0017  Loss_G: 10.5065 D(x): 0.9994
    D(G(z)): 0.0011 / 0.0014
[558/1000][20/42]    Loss_D: 0.0008  Loss_G: 10.5553 D(x): 0.9999
    D(G(z)): 0.0007 / 0.0006
[558/1000][40/42]    Loss_D: 0.0220  Loss_G: 10.3819 D(x): 0.9857
    D(G(z)): 0.0062 / 0.0033
[559/1000][0/42]Loss_D: 0.0012  Loss_G: 11.8606 D(x): 0.9993
    D(G(z)): 0.0005 / 0.0005
[559/1000][20/42]    Loss_D: 0.0080  Loss_G: 9.1802  D(x): 0.9997
    D(G(z)): 0.0073 / 0.0068
[559/1000][40/42]    Loss_D: 0.0047  Loss_G: 12.1043 D(x): 0.9993
    D(G(z)): 0.0037 / 0.0009
[560/1000][0/42]Loss_D: 0.0022  Loss_G: 11.8443 D(x): 0.9981
    D(G(z)): 0.0003 / 0.0004
[560/1000][20/42]    Loss_D: 0.0147  Loss_G: 10.8021 D(x): 0.9885
    D(G(z)): 0.0022 / 0.0030
[560/1000][40/42]    Loss_D: 0.0229  Loss_G: 10.3121 D(x): 0.9830
    D(G(z)): 0.0037 / 0.0025
```



```
[561/1000][0/42]	Loss_D: 0.0087	Loss_G: 9.5143	D(x): 0.9998	D(G(z)): 0.0077 / 0.0062
[561/1000][20/42]	Loss_D: 0.0037	Loss_G: 11.4687	D(x): 0.9975	D(G(z)): 0.0012 / 0.0010
[561/1000][40/42]	Loss_D: 0.0057	Loss_G: 9.9832	D(x): 0.9993	D(G(z)): 0.0049 / 0.0045
[562/1000][0/42]	Loss_D: 0.0130	Loss_G: 8.0044	D(x): 0.9996	D(G(z)): 0.0122 / 0.0079
[562/1000][20/42]	Loss_D: 0.0061	Loss_G: 10.4611	D(x): 0.9958	D(G(z)): 0.0017 / 0.0012
[562/1000][40/42]	Loss_D: 0.0046	Loss_G: 8.6074	D(x): 0.9996	D(G(z)): 0.0041 / 0.0028
[563/1000][0/42]	Loss_D: 0.0150	Loss_G: 9.6457	D(x): 0.9995	D(G(z)): 0.0119 / 0.0046
[563/1000][20/42]	Loss_D: 0.0035	Loss_G: 11.1093	D(x): 0.9977	D(G(z)): 0.0012 / 0.0007
[563/1000][40/42]	Loss_D: 0.0133	Loss_G: 10.3694	D(x): 0.9894	D(G(z)): 0.0014 / 0.0020
[564/1000][0/42]	Loss_D: 0.0537	Loss_G: 9.0425	D(x): 0.9980	D(G(z)): 0.0320 / 0.0065
[564/1000][20/42]	Loss_D: 0.0523	Loss_G: 10.6859	D(x): 0.9683	D(G(z)): 0.0115 / 0.0035
[564/1000][40/42]	Loss_D: 0.0035	Loss_G: 12.4332	D(x): 0.9975	D(G(z)): 0.0009 / 0.0012
[565/1000][0/42]	Loss_D: 0.0739	Loss_G: 10.8153	D(x): 0.9649	D(G(z)): 0.0282 / 0.0094
[565/1000][20/42]	Loss_D: 0.0091	Loss_G: 9.4180	D(x): 0.9998	D(G(z)): 0.0084 / 0.0058
[565/1000][40/42]	Loss_D: 0.0055	Loss_G: 12.1002	D(x): 0.9949	D(G(z)): 0.0002 / 0.0003
[566/1000][0/42]	Loss_D: 0.0025	Loss_G: 10.8944	D(x): 0.9988	D(G(z)): 0.0012 / 0.0016
[566/1000][20/42]	Loss_D: 0.0157	Loss_G: 11.1111	D(x): 0.9854	D(G(z)): 0.0003 / 0.0006
[566/1000][40/42]	Loss_D: 0.0117	Loss_G: 10.8075	D(x): 0.9983	D(G(z)): 0.0088 / 0.0006
[567/1000][0/42]	Loss_D: 0.0150	Loss_G: 13.0153	D(x): 0.9871	D(G(z)): 0.0012 / 0.0004
[567/1000][20/42]	Loss_D: 0.0058	Loss_G: 9.7538	D(x): 0.9984	D(G(z)): 0.0041 / 0.0027
```

```
[567/1000][40/42]	Loss_D: 0.0120	Loss_G: 11.0017	D(x): 0.9965
	D(G(z)): 0.0079 / 0.0071
[568/1000][0/42]	Loss_D: 0.0127	Loss_G: 10.0290	D(x): 0.9994
	D(G(z)): 0.0113 / 0.0097
[568/1000][20/42]	Loss_D: 0.0174	Loss_G: 11.7865	D(x): 0.9972
	D(G(z)): 0.0133 / 0.0066
[568/1000][40/42]	Loss_D: 0.0062	Loss_G: 11.9315	D(x): 0.9978
	D(G(z)): 0.0038 / 0.0050
[569/1000][0/42]	Loss_D: 0.0169	Loss_G: 10.9794	D(x): 0.9949
	D(G(z)): 0.0108 / 0.0046
[569/1000][20/42]	Loss_D: 0.1147	Loss_G: 6.6215	D(x): 0.9973
	D(G(z)): 0.0808 / 0.0472
[569/1000][40/42]	Loss_D: 0.1463	Loss_G: 13.0638	D(x): 0.9790
	D(G(z)): 0.0461 / 0.0015
[570/1000][0/42]	Loss_D: 0.0303	Loss_G: 11.1225	D(x): 0.9861
	D(G(z)): 0.0114 / 0.0094
[570/1000][20/42]	Loss_D: 0.1519	Loss_G: 7.2255	D(x): 0.9999
	D(G(z)): 0.0806 / 0.0367
[570/1000][40/42]	Loss_D: 0.0482	Loss_G: 8.5770	D(x): 0.9830
	D(G(z)): 0.0229 / 0.0343
```

```
[571/1000][0/42]	Loss_D: 0.1386	Loss_G: 9.4970	D(x): 0.9991
	D(G(z)): 0.0912 / 0.0070
[571/1000][20/42]	Loss_D: 0.1176	Loss_G: 13.5984	D(x): 0.9883
	D(G(z)): 0.0585 / 0.0047
[571/1000][40/42]	Loss_D: 0.1946	Loss_G: 9.2820	D(x): 1.0000
	D(G(z)): 0.0619 / 0.0272
[572/1000][0/42]	Loss_D: 0.0078	Loss_G: 12.2491	D(x): 0.9985
	D(G(z)): 0.0061 / 0.0007
[572/1000][20/42]	Loss_D: 0.0456	Loss_G: 10.5977	D(x): 0.9718
	D(G(z)): 0.0108 / 0.0037
[572/1000][40/42]	Loss_D: 0.0101	Loss_G: 13.5535	D(x): 0.9933
	D(G(z)): 0.0030 / 0.0005
[573/1000][0/42]	Loss_D: 0.0048	Loss_G: 13.0948	D(x): 0.9985
	D(G(z)): 0.0032 / 0.0010
[573/1000][20/42]	Loss_D: 0.0426	Loss_G: 10.6072	D(x): 0.9957
	D(G(z)): 0.0261 / 0.0184
[573/1000][40/42]	Loss_D: 0.1159	Loss_G: 10.6093	D(x): 0.9229
	D(G(z)): 0.0004 / 0.0052
[574/1000][0/42]	Loss_D: 0.0696	Loss_G: 7.2286	D(x): 1.0000
```

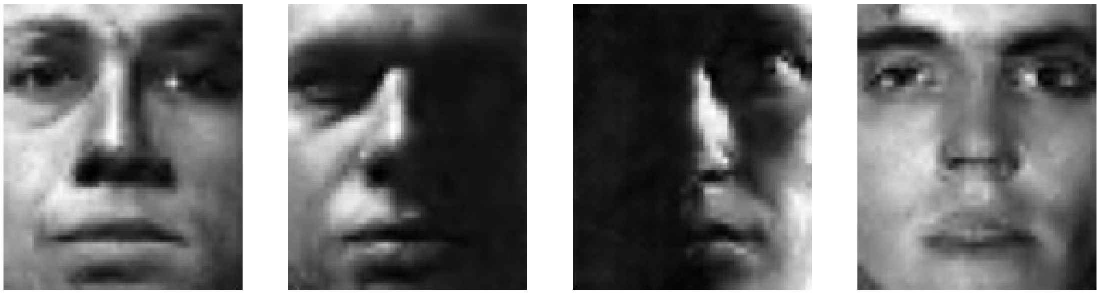
```
    D(G(z)): 0.0523 / 0.0276
[574/1000][20/42]    Loss_D: 0.0609  Loss_G: 12.0989 D(x): 0.9938
    D(G(z)): 0.0286 / 0.0011
[574/1000][40/42]    Loss_D: 0.0747  Loss_G: 12.6472 D(x): 0.9468
    D(G(z)): 0.0021 / 0.0011
[575/1000][0/42] Loss_D: 0.0659  Loss_G: 9.8358  D(x): 0.9672
    D(G(z)): 0.0055 / 0.0067
[575/1000][20/42]    Loss_D: 0.0055  Loss_G: 11.4985 D(x): 0.9995
    D(G(z)): 0.0049 / 0.0010
[575/1000][40/42]    Loss_D: 0.0414  Loss_G: 11.6264 D(x): 0.9696
    D(G(z)): 0.0067 / 0.0058
[576/1000][0/42] Loss_D: 0.0360  Loss_G: 11.7255 D(x): 0.9940
    D(G(z)): 0.0162 / 0.0090
[576/1000][20/42]    Loss_D: 0.1546  Loss_G: 10.7320 D(x): 0.9693
    D(G(z)): 0.0234 / 0.0030
[576/1000][40/42]    Loss_D: 0.0122  Loss_G: 11.7126 D(x): 0.9981
    D(G(z)): 0.0084 / 0.0136
[577/1000][0/42] Loss_D: 0.0174  Loss_G: 11.7108 D(x): 0.9995
    D(G(z)): 0.0141 / 0.0073
[577/1000][20/42]    Loss_D: 0.0431  Loss_G: 12.1099 D(x): 0.9746
    D(G(z)): 0.0078 / 0.0043
[577/1000][40/42]    Loss_D: 0.0269  Loss_G: 10.9492 D(x): 0.9802
    D(G(z)): 0.0044 / 0.0030
[578/1000][0/42] Loss_D: 0.0260  Loss_G: 9.9701  D(x): 0.9857
    D(G(z)): 0.0089 / 0.0090
[578/1000][20/42]    Loss_D: 0.0035  Loss_G: 10.1995 D(x): 0.9988
    D(G(z)): 0.0022 / 0.0011
[578/1000][40/42]    Loss_D: 0.2035  Loss_G: 8.4897  D(x): 0.9995
    D(G(z)): 0.0858 / 0.0089
[579/1000][0/42] Loss_D: 0.0055  Loss_G: 12.0453 D(x): 0.9976
    D(G(z)): 0.0030 / 0.0010
[579/1000][20/42]    Loss_D: 0.2078  Loss_G: 8.3109  D(x): 0.9996
    D(G(z)): 0.1099 / 0.0138
[579/1000][40/42]    Loss_D: 0.0507  Loss_G: 10.5192 D(x): 0.9646
    D(G(z)): 0.0050 / 0.0052
[580/1000][0/42] Loss_D: 0.0154  Loss_G: 9.9000  D(x): 0.9982
    D(G(z)): 0.0123 / 0.0036
[580/1000][20/42]    Loss_D: 0.0146  Loss_G: 11.9762 D(x): 0.9887
    D(G(z)): 0.0019 / 0.0028
[580/1000][40/42]    Loss_D: 0.0053  Loss_G: 9.5042  D(x): 0.9975
    D(G(z)): 0.0027 / 0.0020
```

```
[581/1000][0/42] Loss_D: 0.0144  Loss_G: 10.4742 D(x): 0.9993
      D(G(z)): 0.0123 / 0.0039
[581/1000][20/42]     Loss_D: 0.0076  Loss_G: 11.3095 D(x): 0.9930
      D(G(z)): 0.0002 / 0.0003
[581/1000][40/42]     Loss_D: 0.0130  Loss_G: 8.9600  D(x): 0.9992
      D(G(z)): 0.0114 / 0.0050
[582/1000][0/42] Loss_D: 0.0185  Loss_G: 8.6981  D(x): 0.9998
      D(G(z)): 0.0170 / 0.0070
[582/1000][20/42]     Loss_D: 0.0097  Loss_G: 12.9178 D(x): 0.9911
      D(G(z)): 0.0003 / 0.0002
[582/1000][40/42]     Loss_D: 0.0054  Loss_G: 10.6977 D(x): 0.9970
      D(G(z)): 0.0023 / 0.0020
[583/1000][0/42] Loss_D: 0.0524  Loss_G: 9.3176  D(x): 0.9994
      D(G(z)): 0.0356 / 0.0046
[583/1000][20/42]     Loss_D: 0.1471  Loss_G: 8.5689  D(x): 0.9777
      D(G(z)): 0.0039 / 0.0055
[583/1000][40/42]     Loss_D: 0.0066  Loss_G: 12.1934 D(x): 0.9950
      D(G(z)): 0.0015 / 0.0004
[584/1000][0/42] Loss_D: 0.0301  Loss_G: 12.4222 D(x): 0.9751
      D(G(z)): 0.0002 / 0.0002
[584/1000][20/42]     Loss_D: 0.0181  Loss_G: 11.2532 D(x): 0.9833
      D(G(z)): 0.0006 / 0.0006
[584/1000][40/42]     Loss_D: 0.0111  Loss_G: 7.9362  D(x): 0.9977
      D(G(z)): 0.0084 / 0.0087
[585/1000][0/42] Loss_D: 0.0243  Loss_G: 8.2328  D(x): 0.9998
      D(G(z)): 0.0213 / 0.0107
[585/1000][20/42]     Loss_D: 0.0007  Loss_G: 12.3702 D(x): 0.9995
      D(G(z)): 0.0001 / 0.0001
[585/1000][40/42]     Loss_D: 0.0747  Loss_G: 11.2747 D(x): 0.9616
      D(G(z)): 0.0010 / 0.0010
[586/1000][0/42] Loss_D: 0.0060  Loss_G: 11.5873 D(x): 0.9976
      D(G(z)): 0.0034 / 0.0034
[586/1000][20/42]     Loss_D: 0.0068  Loss_G: 11.2533 D(x): 0.9939
      D(G(z)): 0.0004 / 0.0007
[586/1000][40/42]     Loss_D: 0.0189  Loss_G: 10.0961 D(x): 0.9999
      D(G(z)): 0.0169 / 0.0040
[587/1000][0/42] Loss_D: 0.0060  Loss_G: 10.8954 D(x): 0.9966
      D(G(z)): 0.0025 / 0.0009
[587/1000][20/42]     Loss_D: 0.0041  Loss_G: 10.9571 D(x): 0.9967
      D(G(z)): 0.0007 / 0.0007
```

[587/1000][40/42]   Loss_D: 0.0047 Loss_G: 11.2530 D(x): 0.9981 D(G(z)): 0.0027 / 0.0027
[588/1000][0/42] Loss_D: 0.0038 Loss_G: 10.7091 D(x): 0.9971 D(G(z)): 0.0009 / 0.0007
[588/1000][20/42]   Loss_D: 0.0017 Loss_G: 12.2197 D(x): 0.9985 D(G(z)): 0.0002 / 0.0002
[588/1000][40/42]   Loss_D: 0.0030 Loss_G: 10.1246 D(x): 0.9991 D(G(z)): 0.0020 / 0.0016
[589/1000][0/42] Loss_D: 0.0057 Loss_G: 9.8510 D(x): 0.9964 D(G(z)): 0.0021 / 0.0016
[589/1000][20/42]   Loss_D: 0.0024 Loss_G: 9.9847 D(x): 0.9990 D(G(z)): 0.0014 / 0.0019
[589/1000][40/42]   Loss_D: 0.0025 Loss_G: 10.2448 D(x): 0.9988 D(G(z)): 0.0012 / 0.0010
[590/1000][0/42] Loss_D: 0.0044 Loss_G: 9.9672 D(x): 0.9968 D(G(z)): 0.0011 / 0.0011
[590/1000][20/42]   Loss_D: 0.0112 Loss_G: 9.5562 D(x): 0.9980 D(G(z)): 0.0082 / 0.0039
[590/1000][40/42]   Loss_D: 0.0020 Loss_G: 11.1790 D(x): 0.9989 D(G(z)): 0.0009 / 0.0006

[591/1000][0/42] Loss_D: 0.0018 Loss_G: 11.0630 D(x): 0.9993 D(G(z)): 0.0011 / 0.0008
[591/1000][20/42]   Loss_D: 0.0058 Loss_G: 10.7912 D(x): 0.9951 D(G(z)): 0.0008 / 0.0008
[591/1000][40/42]   Loss_D: 0.0084 Loss_G: 8.0106 D(x): 0.9984 D(G(z)): 0.0067 / 0.0050
[592/1000][0/42] Loss_D: 0.0131 Loss_G: 9.2007 D(x): 0.9971 D(G(z)): 0.0089 / 0.0050
[592/1000][20/42]   Loss_D: 0.0026 Loss_G: 10.7412 D(x): 0.9983 D(G(z)): 0.0009 / 0.0009
[592/1000][40/42]   Loss_D: 0.0112 Loss_G: 11.9645 D(x): 0.9946 D(G(z)): 0.0055 / 0.0015
[593/1000][0/42] Loss_D: 0.0053 Loss_G: 13.6397 D(x): 0.9952 D(G(z)): 0.0002 / 0.0002
[593/1000][20/42]   Loss_D: 0.0040 Loss_G: 10.8642 D(x): 0.9966 D(G(z)): 0.0006 / 0.0006
[593/1000][40/42]   Loss_D: 0.0042 Loss_G: 10.6909 D(x): 0.9976 D(G(z)): 0.0017 / 0.0016
[594/1000][0/42] Loss_D: 0.0042 Loss_G: 9.7668 D(x): 0.9976

```
      D(G(z)): 0.0018 / 0.0018
[594/1000][20/42]     Loss_D: 0.0031  Loss_G: 9.9530  D(x): 0.9984
      D(G(z)): 0.0015 / 0.0025
[594/1000][40/42]     Loss_D: 0.0073  Loss_G: 12.0865 D(x): 0.9943
      D(G(z)): 0.0012 / 0.0010
[595/1000][0/42] Loss_D: 0.0066  Loss_G: 11.0161 D(x): 0.9989
      D(G(z)): 0.0053 / 0.0039
[595/1000][20/42]     Loss_D: 0.0095  Loss_G: 9.9576  D(x): 0.9972
      D(G(z)): 0.0060 / 0.0039
[595/1000][40/42]     Loss_D: 0.0146  Loss_G: 10.0415 D(x): 0.9973
      D(G(z)): 0.0099 / 0.0040
[596/1000][0/42] Loss_D: 0.0063  Loss_G: 9.8746  D(x): 0.9970
      D(G(z)): 0.0032 / 0.0021
[596/1000][20/42]     Loss_D: 0.0014  Loss_G: 12.3390 D(x): 0.9990
      D(G(z)): 0.0003 / 0.0002
[596/1000][40/42]     Loss_D: 0.0082  Loss_G: 10.6662 D(x): 0.9931
      D(G(z)): 0.0011 / 0.0014
[597/1000][0/42] Loss_D: 0.0268  Loss_G: 9.1110  D(x): 0.9999
      D(G(z)): 0.0224 / 0.0124
[597/1000][20/42]     Loss_D: 0.0180  Loss_G: 9.4745  D(x): 0.9971
      D(G(z)): 0.0139 / 0.0111
[597/1000][40/42]     Loss_D: 0.2078  Loss_G: 13.1108 D(x): 0.9890
      D(G(z)): 0.0206 / 0.0155
[598/1000][0/42] Loss_D: 0.0621  Loss_G: 12.6420 D(x): 0.9945
      D(G(z)): 0.0194 / 0.0004
[598/1000][20/42]     Loss_D: 0.0149  Loss_G: 11.7467 D(x): 0.9973
      D(G(z)): 0.0103 / 0.0082
[598/1000][40/42]     Loss_D: 0.0029  Loss_G: 10.8996 D(x): 0.9999
      D(G(z)): 0.0027 / 0.0090
[599/1000][0/42] Loss_D: 0.0892  Loss_G: 9.1915  D(x): 0.9999
      D(G(z)): 0.0460 / 0.0238
[599/1000][20/42]     Loss_D: 0.0714  Loss_G: 12.0086 D(x): 0.9697
      D(G(z)): 0.0120 / 0.0040
[599/1000][40/42]     Loss_D: 0.0059  Loss_G: 13.5904 D(x): 0.9950
      D(G(z)): 0.0008 / 0.0007
[600/1000][0/42] Loss_D: 0.1140  Loss_G: 12.8283 D(x): 0.9253
      D(G(z)): 0.0002 / 0.0005
[600/1000][20/42]     Loss_D: 0.0664  Loss_G: 11.0441 D(x): 0.9988
      D(G(z)): 0.0241 / 0.0066
[600/1000][40/42]     Loss_D: 0.0139  Loss_G: 9.4973  D(x): 0.9909
      D(G(z)): 0.0036 / 0.0048
```



```
[601/1000][0/42]	Loss_D: 0.0149	Loss_G: 10.6516	D(x): 0.9882
	D(G(z)): 0.0021 / 0.0032
[601/1000][20/42]	Loss_D: 0.0254	Loss_G: 10.7745	D(x): 0.9972
	D(G(z)): 0.0193 / 0.0050
[601/1000][40/42]	Loss_D: 0.0197	Loss_G: 9.8774	D(x): 0.9999
	D(G(z)): 0.0161 / 0.0113
[602/1000][0/42]	Loss_D: 0.0320	Loss_G: 7.9990	D(x): 0.9990
	D(G(z)): 0.0258 / 0.0084
[602/1000][20/42]	Loss_D: 0.0070	Loss_G: 10.7177	D(x): 0.9978
	D(G(z)): 0.0045 / 0.0033
[602/1000][40/42]	Loss_D: 0.0519	Loss_G: 12.7820	D(x): 0.9967
	D(G(z)): 0.0208 / 0.0003
[603/1000][0/42]	Loss_D: 0.0369	Loss_G: 14.2056	D(x): 0.9736
	D(G(z)): 0.0001 / 0.0001
[603/1000][20/42]	Loss_D: 0.0094	Loss_G: 12.0682	D(x): 0.9982
	D(G(z)): 0.0069 / 0.0032
[603/1000][40/42]	Loss_D: 0.0165	Loss_G: 12.4739	D(x): 0.9894
	D(G(z)): 0.0048 / 0.0039
[604/1000][0/42]	Loss_D: 0.0247	Loss_G: 10.8942	D(x): 0.9990
	D(G(z)): 0.0148 / 0.0013
[604/1000][20/42]	Loss_D: 0.0156	Loss_G: 11.6198	D(x): 0.9877
	D(G(z)): 0.0024 / 0.0028
[604/1000][40/42]	Loss_D: 0.2161	Loss_G: 9.4337	D(x): 0.9972
	D(G(z)): 0.0854 / 0.0093
[605/1000][0/42]	Loss_D: 0.0020	Loss_G: 13.4714	D(x): 0.9984
	D(G(z)): 0.0005 / 0.0001
[605/1000][20/42]	Loss_D: 0.0096	Loss_G: 11.4014	D(x): 0.9958
	D(G(z)): 0.0049 / 0.0011
[605/1000][40/42]	Loss_D: 0.0598	Loss_G: 11.1016	D(x): 0.9809
	D(G(z)): 0.0179 / 0.0013
[606/1000][0/42]	Loss_D: 0.0135	Loss_G: 10.7282	D(x): 0.9891
	D(G(z)): 0.0020 / 0.0020
[606/1000][20/42]	Loss_D: 0.0148	Loss_G: 11.9376	D(x): 0.9881
	D(G(z)): 0.0012 / 0.0023
[606/1000][40/42]	Loss_D: 0.0058	Loss_G: 12.4981	D(x): 0.9972
	D(G(z)): 0.0028 / 0.0006
[607/1000][0/42]	Loss_D: 0.0261	Loss_G: 11.5740	D(x): 0.9814
	D(G(z)): 0.0053 / 0.0018
[607/1000][20/42]	Loss_D: 0.0229	Loss_G: 10.9985	D(x): 0.9966
	D(G(z)): 0.0180 / 0.0054
```

[607/1000][40/42] Loss_D: 0.0123 Loss_G: 12.6195 D(x): 0.9968
D(G(z)): 0.0084 / 0.0017
[608/1000][0/42] Loss_D: 0.0859 Loss_G: 13.1014 D(x): 0.9485
D(G(z)): 0.0010 / 0.0017
[608/1000][20/42] Loss_D: 0.0034 Loss_G: 10.6357 D(x): 0.9981
D(G(z)): 0.0015 / 0.0074
[608/1000][40/42] Loss_D: 0.0708 Loss_G: 10.3278 D(x): 0.9640
D(G(z)): 0.0137 / 0.0025
[609/1000][0/42] Loss_D: 0.0897 Loss_G: 8.8103 D(x): 0.9985
D(G(z)): 0.0497 / 0.0170
[609/1000][20/42] Loss_D: 0.0234 Loss_G: 11.9221 D(x): 0.9999
D(G(z)): 0.0198 / 0.0181
[609/1000][40/42] Loss_D: 0.0559 Loss_G: 9.2916 D(x): 0.9979
D(G(z)): 0.0306 / 0.0194
[610/1000][0/42] Loss_D: 0.0491 Loss_G: 9.6025 D(x): 0.9998
D(G(z)): 0.0320 / 0.0073
[610/1000][20/42] Loss_D: 0.0373 Loss_G: 13.4444 D(x): 0.9743
D(G(z)): 0.0016 / 0.0020
[610/1000][40/42] Loss_D: 0.0201 Loss_G: 10.9420 D(x): 0.9961
D(G(z)): 0.0140 / 0.0084

[611/1000][0/42] Loss_D: 0.0057 Loss_G: 10.9081 D(x): 0.9995
D(G(z)): 0.0049 / 0.0030
[611/1000][20/42] Loss_D: 0.0034 Loss_G: 12.1573 D(x): 0.9978
D(G(z)): 0.0012 / 0.0004
[611/1000][40/42] Loss_D: 0.0297 Loss_G: 9.6748 D(x): 0.9922
D(G(z)): 0.0156 / 0.0053
[612/1000][0/42] Loss_D: 0.0285 Loss_G: 10.4989 D(x): 0.9972
D(G(z)): 0.0218 / 0.0048
[612/1000][20/42] Loss_D: 0.0172 Loss_G: 10.8160 D(x): 0.9892
D(G(z)): 0.0040 / 0.0056
[612/1000][40/42] Loss_D: 0.0071 Loss_G: 9.9625 D(x): 0.9989
D(G(z)): 0.0058 / 0.0076
[613/1000][0/42] Loss_D: 0.0041 Loss_G: 10.1271 D(x): 0.9999
D(G(z)): 0.0039 / 0.0046
[613/1000][20/42] Loss_D: 0.0141 Loss_G: 10.2377 D(x): 0.9995
D(G(z)): 0.0119 / 0.0070
[613/1000][40/42] Loss_D: 0.0057 Loss_G: 8.7551 D(x): 0.9999
D(G(z)): 0.0055 / 0.0092
[614/1000][0/42] Loss_D: 0.1053 Loss_G: 8.5072 D(x): 0.9986

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    D(G(z)): 0.0632 / 0.0117
[614/1000][20/42]     Loss_D: 0.0202  Loss_G: 10.1460 D(x): 0.9946
    D(G(z)): 0.0118 / 0.0033
[614/1000][40/42]     Loss_D: 0.0256  Loss_G: 9.6670  D(x): 0.9868
    D(G(z)): 0.0083 / 0.0106
[615/1000][0/42] Loss_D: 0.0336  Loss_G: 9.1831  D(x): 0.9982
    D(G(z)): 0.0214 / 0.0132
[615/1000][20/42]     Loss_D: 0.0060  Loss_G: 11.4522 D(x): 0.9951
    D(G(z)): 0.0010 / 0.0009
[615/1000][40/42]     Loss_D: 0.0528  Loss_G: 9.1607  D(x): 0.9886
    D(G(z)): 0.0210 / 0.0054
[616/1000][0/42] Loss_D: 0.0130  Loss_G: 10.1922 D(x): 0.9907
    D(G(z)): 0.0020 / 0.0014
[616/1000][20/42]     Loss_D: 0.0414  Loss_G: 8.9657  D(x): 0.9990
    D(G(z)): 0.0306 / 0.0097
[616/1000][40/42]     Loss_D: 0.0022  Loss_G: 9.6459  D(x): 0.9985
    D(G(z)): 0.0007 / 0.0012
[617/1000][0/42] Loss_D: 0.0044  Loss_G: 9.8846  D(x): 0.9994
    D(G(z)): 0.0036 / 0.0047
[617/1000][20/42]     Loss_D: 0.0418  Loss_G: 11.2082 D(x): 0.9980
    D(G(z)): 0.0180 / 0.0008
[617/1000][40/42]     Loss_D: 0.0358  Loss_G: 9.8185  D(x): 0.9997
    D(G(z)): 0.0258 / 0.0129
[618/1000][0/42] Loss_D: 0.0116  Loss_G: 10.5115 D(x): 0.9970
    D(G(z)): 0.0080 / 0.0032
[618/1000][20/42]     Loss_D: 0.0240  Loss_G: 12.6348 D(x): 0.9996
    D(G(z)): 0.0178 / 0.0006
[618/1000][40/42]     Loss_D: 0.0101  Loss_G: 12.8304 D(x): 0.9914
    D(G(z)): 0.0003 / 0.0003
[619/1000][0/42] Loss_D: 0.0490  Loss_G: 12.5407 D(x): 0.9661
    D(G(z)): 0.0004 / 0.0008
[619/1000][20/42]     Loss_D: 0.0119  Loss_G: 10.8957 D(x): 0.9998
    D(G(z)): 0.0104 / 0.0045
[619/1000][40/42]     Loss_D: 0.0202  Loss_G: 11.2970 D(x): 0.9983
    D(G(z)): 0.0125 / 0.0019
[620/1000][0/42] Loss_D: 0.0049  Loss_G: 11.4452 D(x): 0.9964
    D(G(z)): 0.0012 / 0.0009
[620/1000][20/42]     Loss_D: 0.0200  Loss_G: 8.7459  D(x): 0.9999
    D(G(z)): 0.0182 / 0.0054
[620/1000][40/42]     Loss_D: 0.0144  Loss_G: 9.2229  D(x): 0.9889
    D(G(z)): 0.0013 / 0.0029
```

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[621/1000][0/42]	Loss_D: 0.0439	Loss_G: 8.2436	D(x): 0.9999
	D(G(z)): 0.0357 / 0.0122
[621/1000][20/42]	Loss_D: 0.0058	Loss_G: 12.3064	D(x): 0.9976
	D(G(z)): 0.0032 / 0.0014
[621/1000][40/42]	Loss_D: 0.0283	Loss_G: 11.5990	D(x): 0.9757
	D(G(z)): 0.0003 / 0.0002
[622/1000][0/42]	Loss_D: 0.0269	Loss_G: 11.2996	D(x): 0.9965
	D(G(z)): 0.0176 / 0.0045
[622/1000][20/42]	Loss_D: 0.0267	Loss_G: 12.0024	D(x): 0.9874
	D(G(z)): 0.0105 / 0.0010
[622/1000][40/42]	Loss_D: 0.0032	Loss_G: 11.7924	D(x): 0.9975
	D(G(z)): 0.0007 / 0.0011
[623/1000][0/42]	Loss_D: 0.0153	Loss_G: 9.8761	D(x): 0.9995
	D(G(z)): 0.0129 / 0.0066
[623/1000][20/42]	Loss_D: 0.2155	Loss_G: 12.1264	D(x): 0.9470
	D(G(z)): 0.0014 / 0.0017
[623/1000][40/42]	Loss_D: 0.3345	Loss_G: 10.5121	D(x): 0.8293
	D(G(z)): 0.0001 / 0.0011
[624/1000][0/42]	Loss_D: 0.1662	Loss_G: 9.8251	D(x): 0.9997
	D(G(z)): 0.1069 / 0.0571
[624/1000][20/42]	Loss_D: 0.0732	Loss_G: 12.4737	D(x): 0.9811
	D(G(z)): 0.0282 / 0.0007
[624/1000][40/42]	Loss_D: 0.0619	Loss_G: 10.3911	D(x): 0.9733
	D(G(z)): 0.0045 / 0.0057
[625/1000][0/42]	Loss_D: 0.2952	Loss_G: 11.3926	D(x): 0.9891
	D(G(z)): 0.1124 / 0.0108
[625/1000][20/42]	Loss_D: 0.2067	Loss_G: 14.4769	D(x): 0.9455
	D(G(z)): 0.0391 / 0.0054
[625/1000][40/42]	Loss_D: 0.3080	Loss_G: 10.4570	D(x): 0.9998
	D(G(z)): 0.0963 / 0.0127
[626/1000][0/42]	Loss_D: 0.0826	Loss_G: 12.7871	D(x): 0.9998
	D(G(z)): 0.0328 / 0.0023
[626/1000][20/42]	Loss_D: 0.0330	Loss_G: 15.9731	D(x): 0.9745
	D(G(z)): 0.0009 / 0.0001
[626/1000][40/42]	Loss_D: 0.0768	Loss_G: 11.5571	D(x): 0.9717
	D(G(z)): 0.0169 / 0.0014
[627/1000][0/42]	Loss_D: 0.0349	Loss_G: 11.7563	D(x): 0.9821
	D(G(z)): 0.0110 / 0.0017
[627/1000][20/42]	Loss_D: 0.0096	Loss_G: 9.9592	D(x): 0.9983
	D(G(z)): 0.0076 / 0.0067
```

[627/1000][40/42]	Loss_D: 0.0564	Loss_G: 10.3810	D(x): 0.9870
D(G(z)): 0.0195 / 0.0033
[628/1000][0/42]	Loss_D: 0.0124	Loss_G: 9.7647	D(x): 0.9998
D(G(z)): 0.0115 / 0.0095
[628/1000][20/42]	Loss_D: 0.0068	Loss_G: 10.8782	D(x): 0.9980
D(G(z)): 0.0046 / 0.0028
[628/1000][40/42]	Loss_D: 0.0327	Loss_G: 9.7349	D(x): 0.9999
D(G(z)): 0.0245 / 0.0211
[629/1000][0/42]	Loss_D: 0.0430	Loss_G: 10.3149	D(x): 0.9998
D(G(z)): 0.0234 / 0.0029
[629/1000][20/42]	Loss_D: 0.0014	Loss_G: 10.9257	D(x): 0.9991
D(G(z)): 0.0006 / 0.0005
[629/1000][40/42]	Loss_D: 0.0027	Loss_G: 9.7043	D(x): 0.9987
D(G(z)): 0.0014 / 0.0011
[630/1000][0/42]	Loss_D: 0.0104	Loss_G: 9.5212	D(x): 0.9977
D(G(z)): 0.0077 / 0.0040
[630/1000][20/42]	Loss_D: 0.0084	Loss_G: 10.6326	D(x): 0.9956
D(G(z)): 0.0035 / 0.0025
[630/1000][40/42]	Loss_D: 0.0109	Loss_G: 10.1440	D(x): 0.9913
D(G(z)): 0.0016 / 0.0020

[631/1000][0/42]	Loss_D: 0.0024	Loss_G: 10.6070	D(x): 0.9982
D(G(z)): 0.0006 / 0.0007
[631/1000][20/42]	Loss_D: 0.0011	Loss_G: 13.8510	D(x): 0.9995
D(G(z)): 0.0006 / 0.0003
[631/1000][40/42]	Loss_D: 0.0154	Loss_G: 10.1157	D(x): 0.9887
D(G(z)): 0.0020 / 0.0034
[632/1000][0/42]	Loss_D: 0.0348	Loss_G: 9.7106	D(x): 0.9994
D(G(z)): 0.0273 / 0.0060
[632/1000][20/42]	Loss_D: 0.0016	Loss_G: 9.4927	D(x): 0.9998
D(G(z)): 0.0014 / 0.0012
[632/1000][40/42]	Loss_D: 0.0034	Loss_G: 9.8607	D(x): 0.9998
D(G(z)): 0.0032 / 0.0024
[633/1000][0/42]	Loss_D: 0.0017	Loss_G: 12.9800	D(x): 0.9985
D(G(z)): 0.0002 / 0.0001
[633/1000][20/42]	Loss_D: 0.0128	Loss_G: 10.9167	D(x): 0.9890
D(G(z)): 0.0013 / 0.0012
[633/1000][40/42]	Loss_D: 0.0035	Loss_G: 10.7345	D(x): 0.9995
D(G(z)): 0.0028 / 0.0023
[634/1000][0/42]	Loss_D: 0.0109	Loss_G: 10.0037	D(x): 0.9922

```
      D(G(z)): 0.0023 / 0.0020
[634/1000][20/42]     Loss_D: 0.0033  Loss_G: 10.0803 D(x): 0.9985
      D(G(z)): 0.0018 / 0.0013
[634/1000][40/42]     Loss_D: 0.0038  Loss_G: 10.0883 D(x): 0.9997
      D(G(z)): 0.0035 / 0.0022
[635/1000][0/42] Loss_D: 0.0151  Loss_G: 9.6841  D(x): 0.9885
      D(G(z)): 0.0029 / 0.0029
[635/1000][20/42]     Loss_D: 0.0034  Loss_G: 10.6450 D(x): 0.9976
      D(G(z)): 0.0009 / 0.0009
[635/1000][40/42]     Loss_D: 0.0325  Loss_G: 12.0749 D(x): 0.9707
      D(G(z)): 0.0001 / 0.0001
[636/1000][0/42] Loss_D: 0.0025  Loss_G: 12.0636 D(x): 0.9981
      D(G(z)): 0.0005 / 0.0005
[636/1000][20/42]     Loss_D: 0.0164  Loss_G: 11.0034 D(x): 0.9871
      D(G(z)): 0.0020 / 0.0030
[636/1000][40/42]     Loss_D: 0.0041  Loss_G: 10.8076 D(x): 0.9968
      D(G(z)): 0.0009 / 0.0013
[637/1000][0/42] Loss_D: 0.0752  Loss_G: 8.6927  D(x): 0.9989
      D(G(z)): 0.0482 / 0.0060
[637/1000][20/42]     Loss_D: 0.0729  Loss_G: 10.0159 D(x): 0.9454
      D(G(z)): 0.0030 / 0.0094
[637/1000][40/42]     Loss_D: 0.0422  Loss_G: 10.2163 D(x): 0.9764
      D(G(z)): 0.0126 / 0.0070
[638/1000][0/42] Loss_D: 0.0027  Loss_G: 10.2484 D(x): 0.9982
      D(G(z)): 0.0008 / 0.0008
[638/1000][20/42]     Loss_D: 0.0172  Loss_G: 12.1799 D(x): 0.9994
      D(G(z)): 0.0126 / 0.0010
[638/1000][40/42]     Loss_D: 0.0039  Loss_G: 9.8525  D(x): 0.9980
      D(G(z)): 0.0018 / 0.0038
[639/1000][0/42] Loss_D: 0.0158  Loss_G: 11.3641 D(x): 0.9966
      D(G(z)): 0.0096 / 0.0033
[639/1000][20/42]     Loss_D: 0.0250  Loss_G: 13.8942 D(x): 0.9808
      D(G(z)): 0.0004 / 0.0003
[639/1000][40/42]     Loss_D: 0.0565  Loss_G: 9.0732  D(x): 0.9964
      D(G(z)): 0.0310 / 0.0071
[640/1000][0/42] Loss_D: 0.0216  Loss_G: 11.7978 D(x): 0.9962
      D(G(z)): 0.0119 / 0.0003
[640/1000][20/42]     Loss_D: 0.0036  Loss_G: 10.2946 D(x): 0.9987
      D(G(z)): 0.0023 / 0.0043
[640/1000][40/42]     Loss_D: 0.0146  Loss_G: 12.8977 D(x): 0.9940
      D(G(z)): 0.0072 / 0.0100
```

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[641/1000][0/42] Loss_D: 0.0933  Loss_G: 9.8137  D(x): 0.9998
     D(G(z)): 0.0279 / 0.0222
[641/1000][20/42]     Loss_D: 0.3533  Loss_G: 10.9545 D(x): 0.9965
     D(G(z)): 0.1107 / 0.0104
[641/1000][40/42]     Loss_D: 0.0247  Loss_G: 12.2833 D(x): 0.9967
     D(G(z)): 0.0179 / 0.0128
[642/1000][0/42] Loss_D: 0.0368  Loss_G: 11.7172 D(x): 0.9941
     D(G(z)): 0.0163 / 0.0015
[642/1000][20/42]     Loss_D: 0.0387  Loss_G: 9.5747  D(x): 0.9855
     D(G(z)): 0.0199 / 0.0089
[642/1000][40/42]     Loss_D: 0.0425  Loss_G: 10.9420 D(x): 0.9964
     D(G(z)): 0.0199 / 0.0014
[643/1000][0/42] Loss_D: 0.0174  Loss_G: 12.7990 D(x): 0.9983
     D(G(z)): 0.0129 / 0.0013
[643/1000][20/42]     Loss_D: 0.0046  Loss_G: 12.0485 D(x): 0.9971
     D(G(z)): 0.0016 / 0.0012
[643/1000][40/42]     Loss_D: 0.0022  Loss_G: 11.0914 D(x): 0.9990
     D(G(z)): 0.0012 / 0.0020
[644/1000][0/42] Loss_D: 0.0426  Loss_G: 10.1463 D(x): 0.9999
     D(G(z)): 0.0290 / 0.0156
[644/1000][20/42]     Loss_D: 0.0066  Loss_G: 10.2267 D(x): 0.9951
     D(G(z)): 0.0015 / 0.0042
[644/1000][40/42]     Loss_D: 0.0329  Loss_G: 13.9892 D(x): 0.9770
     D(G(z)): 0.0029 / 0.0017
[645/1000][0/42] Loss_D: 0.0373  Loss_G: 13.5007 D(x): 0.9746
     D(G(z)): 0.0004 / 0.0004
[645/1000][20/42]     Loss_D: 0.0224  Loss_G: 8.5845  D(x): 0.9999
     D(G(z)): 0.0186 / 0.0120
[645/1000][40/42]     Loss_D: 0.0493  Loss_G: 11.0600 D(x): 0.9987
     D(G(z)): 0.0341 / 0.0065
[646/1000][0/42] Loss_D: 0.0485  Loss_G: 11.8741 D(x): 0.9847
     D(G(z)): 0.0160 / 0.0088
[646/1000][20/42]     Loss_D: 0.1160  Loss_G: 12.4083 D(x): 0.9690
     D(G(z)): 0.0210 / 0.0005
[646/1000][40/42]     Loss_D: 0.0458  Loss_G: 13.3223 D(x): 0.9921
     D(G(z)): 0.0250 / 0.0017
[647/1000][0/42] Loss_D: 0.0044  Loss_G: 15.8524 D(x): 0.9988
     D(G(z)): 0.0030 / 0.0005
[647/1000][20/42]     Loss_D: 0.0137  Loss_G: 12.6863 D(x): 0.9929
     D(G(z)): 0.0059 / 0.0025
```

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[647/1000][40/42]	Loss_D: 0.0110	Loss_G: 11.1798	D(x): 0.9903
	D(G(z)): 0.0008 / 0.0010
[648/1000][0/42]	Loss_D: 0.0598	Loss_G: 11.1820	D(x): 0.9933
	D(G(z)): 0.0278 / 0.0021
[648/1000][20/42]	Loss_D: 0.0285	Loss_G: 9.3219	D(x): 0.9992
	D(G(z)): 0.0214 / 0.0083
[648/1000][40/42]	Loss_D: 0.0505	Loss_G: 9.9852	D(x): 0.9792
	D(G(z)): 0.0027 / 0.0020
[649/1000][0/42]	Loss_D: 0.0191	Loss_G: 10.1535	D(x): 0.9997
	D(G(z)): 0.0137 / 0.0047
[649/1000][20/42]	Loss_D: 0.2355	Loss_G: 10.8673	D(x): 0.8832
	D(G(z)): 0.0011 / 0.0037
[649/1000][40/42]	Loss_D: 0.0436	Loss_G: 14.0690	D(x): 0.9931
	D(G(z)): 0.0171 / 0.0001
[650/1000][0/42]	Loss_D: 0.0855	Loss_G: 15.8851	D(x): 0.9301
	D(G(z)): 0.0001 / 0.0000
[650/1000][20/42]	Loss_D: 0.0080	Loss_G: 11.6514	D(x): 0.9989
	D(G(z)): 0.0064 / 0.0039
[650/1000][40/42]	Loss_D: 0.0119	Loss_G: 7.5416	D(x): 0.9994
	D(G(z)): 0.0109 / 0.0084
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[651/1000][0/42]	Loss_D: 0.0208	Loss_G: 9.5448	D(x): 0.9998
	D(G(z)): 0.0166 / 0.0038
[651/1000][20/42]	Loss_D: 0.0283	Loss_G: 11.9101	D(x): 0.9799
	D(G(z)): 0.0032 / 0.0017
[651/1000][40/42]	Loss_D: 0.0057	Loss_G: 11.9972	D(x): 0.9955
	D(G(z)): 0.0011 / 0.0009
[652/1000][0/42]	Loss_D: 0.0021	Loss_G: 12.3062	D(x): 0.9981
	D(G(z)): 0.0002 / 0.0002
[652/1000][20/42]	Loss_D: 0.0023	Loss_G: 12.2233	D(x): 0.9979
	D(G(z)): 0.0001 / 0.0002
[652/1000][40/42]	Loss_D: 0.0044	Loss_G: 10.2657	D(x): 0.9992
	D(G(z)): 0.0035 / 0.0014
[653/1000][0/42]	Loss_D: 0.0024	Loss_G: 10.7624	D(x): 0.9987
	D(G(z)): 0.0011 / 0.0008
[653/1000][20/42]	Loss_D: 0.0060	Loss_G: 8.6583	D(x): 0.9999
	D(G(z)): 0.0057 / 0.0054
[653/1000][40/42]	Loss_D: 0.0034	Loss_G: 10.9915	D(x): 0.9983
	D(G(z)): 0.0016 / 0.0012
[654/1000][0/42]	Loss_D: 0.0028	Loss_G: 11.5468	D(x): 0.9976
```

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    D(G(z)): 0.0004 / 0.0003
[654/1000][20/42]     Loss_D: 0.0392  Loss_G: 10.1330 D(x): 0.9688
    D(G(z)): 0.0010 / 0.0016
[654/1000][40/42]     Loss_D: 0.0172  Loss_G: 9.4692  D(x): 0.9907
    D(G(z)): 0.0064 / 0.0026
[655/1000][0/42] Loss_D: 0.0017  Loss_G: 12.7048 D(x): 0.9992
    D(G(z)): 0.0009 / 0.0006
[655/1000][20/42]     Loss_D: 0.0152  Loss_G: 10.4759 D(x): 0.9902
    D(G(z)): 0.0039 / 0.0023
[655/1000][40/42]     Loss_D: 0.0626  Loss_G: 10.8286 D(x): 0.9998
    D(G(z)): 0.0203 / 0.0011
[656/1000][0/42] Loss_D: 0.0029  Loss_G: 11.5291 D(x): 0.9984
    D(G(z)): 0.0012 / 0.0006
[656/1000][20/42]     Loss_D: 0.0152  Loss_G: 12.5119 D(x): 0.9864
    D(G(z)): 0.0002 / 0.0002
[656/1000][40/42]     Loss_D: 0.0040  Loss_G: 10.9926 D(x): 0.9996
    D(G(z)): 0.0035 / 0.0031
[657/1000][0/42] Loss_D: 0.0337  Loss_G: 11.1986 D(x): 0.9759
    D(G(z)): 0.0042 / 0.0047
[657/1000][20/42]     Loss_D: 0.0183  Loss_G: 10.5263 D(x): 0.9991
    D(G(z)): 0.0126 / 0.0048
[657/1000][40/42]     Loss_D: 0.0067  Loss_G: 10.1484 D(x): 1.0000
    D(G(z)): 0.0065 / 0.0028
[658/1000][0/42] Loss_D: 0.0032  Loss_G: 11.3963 D(x): 0.9992
    D(G(z)): 0.0023 / 0.0012
[658/1000][20/42]     Loss_D: 0.0345  Loss_G: 10.1209 D(x): 0.9698
    D(G(z)): 0.0007 / 0.0016
[658/1000][40/42]     Loss_D: 0.0036  Loss_G: 10.1040 D(x): 0.9991
    D(G(z)): 0.0025 / 0.0036
[659/1000][0/42] Loss_D: 0.0141  Loss_G: 9.9854  D(x): 0.9997
    D(G(z)): 0.0111 / 0.0042
[659/1000][20/42]     Loss_D: 0.0034  Loss_G: 9.7942  D(x): 0.9993
    D(G(z)): 0.0027 / 0.0021
[659/1000][40/42]     Loss_D: 0.0048  Loss_G: 9.8514  D(x): 0.9999
    D(G(z)): 0.0045 / 0.0028
[660/1000][0/42] Loss_D: 0.0029  Loss_G: 9.4873  D(x): 0.9999
    D(G(z)): 0.0027 / 0.0016
[660/1000][20/42]     Loss_D: 0.0018  Loss_G: 10.7625 D(x): 0.9989
    D(G(z)): 0.0007 / 0.0005
[660/1000][40/42]     Loss_D: 0.0041  Loss_G: 11.4070 D(x): 0.9989
    D(G(z)): 0.0027 / 0.0012
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[661/1000][0/42] Loss_D: 0.0020  Loss_G: 11.7882 D(x): 0.9985
      D(G(z)): 0.0005 / 0.0004
[661/1000][20/42]     Loss_D: 0.0069  Loss_G: 10.0486 D(x): 0.9988
      D(G(z)): 0.0053 / 0.0018
[661/1000][40/42]     Loss_D: 0.0081  Loss_G: 10.9209 D(x): 0.9931
      D(G(z)): 0.0011 / 0.0010
[662/1000][0/42] Loss_D: 0.0037  Loss_G: 9.2137  D(x): 0.9994
      D(G(z)): 0.0030 / 0.0020
[662/1000][20/42]     Loss_D: 0.0016  Loss_G: 11.4230 D(x): 0.9995
      D(G(z)): 0.0011 / 0.0010
[662/1000][40/42]     Loss_D: 0.0075  Loss_G: 9.8422  D(x): 0.9955
      D(G(z)): 0.0027 / 0.0014
[663/1000][0/42] Loss_D: 0.0015  Loss_G: 11.5799 D(x): 0.9990
      D(G(z)): 0.0005 / 0.0005
[663/1000][20/42]     Loss_D: 0.0018  Loss_G: 10.4157 D(x): 0.9996
      D(G(z)): 0.0014 / 0.0013
[663/1000][40/42]     Loss_D: 0.0032  Loss_G: 11.2812 D(x): 0.9978
      D(G(z)): 0.0009 / 0.0010
[664/1000][0/42] Loss_D: 0.0021  Loss_G: 9.7892  D(x): 0.9998
      D(G(z)): 0.0019 / 0.0018
[664/1000][20/42]     Loss_D: 0.0019  Loss_G: 10.3917 D(x): 0.9988
      D(G(z)): 0.0007 / 0.0007
[664/1000][40/42]     Loss_D: 0.0057  Loss_G: 10.6783 D(x): 0.9951
      D(G(z)): 0.0006 / 0.0005
[665/1000][0/42] Loss_D: 0.0053  Loss_G: 11.2758 D(x): 0.9958
      D(G(z)): 0.0010 / 0.0008
[665/1000][20/42]     Loss_D: 0.0082  Loss_G: 10.0934 D(x): 0.9944
      D(G(z)): 0.0024 / 0.0017
[665/1000][40/42]     Loss_D: 0.0060  Loss_G: 10.9933 D(x): 0.9948
      D(G(z)): 0.0006 / 0.0004
[666/1000][0/42] Loss_D: 0.0057  Loss_G: 10.8838 D(x): 0.9969
      D(G(z)): 0.0025 / 0.0015
[666/1000][20/42]     Loss_D: 0.0031  Loss_G: 10.5453 D(x): 0.9990
      D(G(z)): 0.0020 / 0.0015
[666/1000][40/42]     Loss_D: 0.0024  Loss_G: 9.6769  D(x): 0.9995
      D(G(z)): 0.0019 / 0.0016
[667/1000][0/42] Loss_D: 0.0038  Loss_G: 9.8667  D(x): 0.9992
      D(G(z)): 0.0030 / 0.0027
[667/1000][20/42]     Loss_D: 0.0007  Loss_G: 11.6857 D(x): 0.9998
      D(G(z)): 0.0004 / 0.0003
```

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[667/1000][40/42]	Loss_D: 0.0037	Loss_G: 11.8459	D(x): 0.9981
	D(G(z)): 0.0018 / 0.0013
[668/1000][0/42]	Loss_D: 0.0138	Loss_G: 11.9098	D(x): 0.9890
	D(G(z)): 0.0008 / 0.0010
[668/1000][20/42]	Loss_D: 0.0030	Loss_G: 13.3658	D(x): 0.9973
	D(G(z)): 0.0003 / 0.0004
[668/1000][40/42]	Loss_D: 0.0238	Loss_G: 10.8099	D(x): 0.9905
	D(G(z)): 0.0103 / 0.0037
[669/1000][0/42]	Loss_D: 0.0043	Loss_G: 11.5030	D(x): 0.9987
	D(G(z)): 0.0029 / 0.0011
[669/1000][20/42]	Loss_D: 0.0057	Loss_G: 11.1473	D(x): 0.9993
	D(G(z)): 0.0049 / 0.0031
[669/1000][40/42]	Loss_D: 0.0051	Loss_G: 11.8507	D(x): 0.9964
	D(G(z)): 0.0013 / 0.0006
[670/1000][0/42]	Loss_D: 0.0063	Loss_G: 12.0594	D(x): 0.9945
	D(G(z)): 0.0006 / 0.0006
[670/1000][20/42]	Loss_D: 0.0026	Loss_G: 10.1794	D(x): 0.9997
	D(G(z)): 0.0023 / 0.0025
[670/1000][40/42]	Loss_D: 0.0172	Loss_G: 10.3554	D(x): 0.9999
	D(G(z)): 0.0136 / 0.0070
```

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[671/1000][0/42]	Loss_D: 0.0046	Loss_G: 11.7640	D(x): 0.9999
	D(G(z)): 0.0041 / 0.0008
[671/1000][20/42]	Loss_D: 0.0105	Loss_G: 11.1727	D(x): 0.9917
	D(G(z)): 0.0013 / 0.0007
[671/1000][40/42]	Loss_D: 0.0040	Loss_G: 12.3830	D(x): 0.9966
	D(G(z)): 0.0005 / 0.0004
[672/1000][0/42]	Loss_D: 0.0008	Loss_G: 12.8300	D(x): 0.9993
	D(G(z)): 0.0001 / 0.0002
[672/1000][20/42]	Loss_D: 0.0044	Loss_G: 10.1834	D(x): 0.9986
	D(G(z)): 0.0030 / 0.0019
[672/1000][40/42]	Loss_D: 0.0063	Loss_G: 8.5741	D(x): 0.9997
	D(G(z)): 0.0056 / 0.0047
[673/1000][0/42]	Loss_D: 0.0008	Loss_G: 10.7839	D(x): 0.9998
	D(G(z)): 0.0006 / 0.0006
[673/1000][20/42]	Loss_D: 0.0007	Loss_G: 11.1871	D(x): 0.9998
	D(G(z)): 0.0005 / 0.0007
[673/1000][40/42]	Loss_D: 0.0128	Loss_G: 11.4467	D(x): 0.9969
	D(G(z)): 0.0081 / 0.0018
[674/1000][0/42]	Loss_D: 0.0016	Loss_G: 12.5355	D(x): 0.9998
```

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    D(G(z)): 0.0014 / 0.0012
[674/1000][20/42]    Loss_D: 0.0008  Loss_G: 11.3281 D(x): 0.9999
    D(G(z)): 0.0007 / 0.0004
[674/1000][40/42]    Loss_D: 0.0416  Loss_G: 13.7615 D(x): 0.9996
    D(G(z)): 0.0305 / 0.0008
[675/1000][0/42]Loss_D: 0.0457  Loss_G: 14.3995 D(x): 0.9633
    D(G(z)): 0.0003 / 0.0002
[675/1000][20/42]    Loss_D: 0.1110  Loss_G: 12.2080 D(x): 0.9530
    D(G(z)): 0.0117 / 0.0094
[675/1000][40/42]    Loss_D: 0.0797  Loss_G: 10.8017 D(x): 0.9766
    D(G(z)): 0.0076 / 0.0090
[676/1000][0/42]Loss_D: 0.0892  Loss_G: 13.2471 D(x): 0.9736
    D(G(z)): 0.0334 / 0.0012
[676/1000][20/42]    Loss_D: 0.2494  Loss_G: 11.6184 D(x): 0.9864
    D(G(z)): 0.0563 / 0.0031
[676/1000][40/42]    Loss_D: 0.0815  Loss_G: 9.9837  D(x): 0.9773
    D(G(z)): 0.0295 / 0.0175
[677/1000][0/42]Loss_D: 0.0054  Loss_G: 14.2694 D(x): 0.9975
    D(G(z)): 0.0027 / 0.0008
[677/1000][20/42]    Loss_D: 0.0145  Loss_G: 13.7093 D(x): 0.9998
    D(G(z)): 0.0121 / 0.0052
[677/1000][40/42]    Loss_D: 0.1418  Loss_G: 17.9149 D(x): 0.9671
    D(G(z)): 0.0229 / 0.0001
[678/1000][0/42]Loss_D: 0.0560  Loss_G: 16.8466 D(x): 0.9598
    D(G(z)): 0.0003 / 0.0005
[678/1000][20/42]    Loss_D: 0.0151  Loss_G: 16.1005 D(x): 0.9982
    D(G(z)): 0.0100 / 0.0008
[678/1000][40/42]    Loss_D: 0.2278  Loss_G: 14.0515 D(x): 0.9616
    D(G(z)): 0.0412 / 0.0190
[679/1000][0/42]Loss_D: 0.0427  Loss_G: 14.9586 D(x): 0.9809
    D(G(z)): 0.0174 / 0.0030
[679/1000][20/42]    Loss_D: 0.0428  Loss_G: 11.2024 D(x): 0.9802
    D(G(z)): 0.0025 / 0.0036
[679/1000][40/42]    Loss_D: 0.0077  Loss_G: 14.7147 D(x): 0.9933
    D(G(z)): 0.0004 / 0.0001
[680/1000][0/42]Loss_D: 0.2445  Loss_G: 11.7791 D(x): 0.9814
    D(G(z)): 0.0518 / 0.0031
[680/1000][20/42]    Loss_D: 0.1023  Loss_G: 12.5511 D(x): 0.9998
    D(G(z)): 0.0403 / 0.0015
[680/1000][40/42]    Loss_D: 0.0118  Loss_G: 13.4347 D(x): 0.9916
    D(G(z)): 0.0017 / 0.0011
```

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[681/1000][0/42]Loss_D: 0.0331  Loss_G: 12.5409 D(x): 0.9940
     D(G(z)): 0.0200 / 0.0039
[681/1000][20/42]    Loss_D: 0.0408  Loss_G: 14.7187 D(x): 0.9754
     D(G(z)): 0.0009 / 0.0009
[681/1000][40/42]    Loss_D: 0.1003  Loss_G: 9.5443  D(x): 0.9944
     D(G(z)): 0.0666 / 0.0089
[682/1000][0/42]Loss_D: 0.0049  Loss_G: 13.4536 D(x): 0.9962
     D(G(z)): 0.0010 / 0.0004
[682/1000][20/42]    Loss_D: 0.0593  Loss_G: 11.6154 D(x): 0.9639
     D(G(z)): 0.0070 / 0.0052
[682/1000][40/42]    Loss_D: 0.0064  Loss_G: 12.2178 D(x): 0.9974
     D(G(z)): 0.0036 / 0.0042
[683/1000][0/42]Loss_D: 0.0090  Loss_G: 10.6710 D(x): 0.9994
     D(G(z)): 0.0077 / 0.0044
[683/1000][20/42]    Loss_D: 0.1013  Loss_G: 11.8926 D(x): 0.9484
     D(G(z)): 0.0011 / 0.0074
[683/1000][40/42]    Loss_D: 0.0034  Loss_G: 16.4893 D(x): 0.9982
     D(G(z)): 0.0015 / 0.0002
[684/1000][0/42]Loss_D: 0.0649  Loss_G: 16.6443 D(x): 0.9604
     D(G(z)): 0.0002 / 0.0002
[684/1000][20/42]    Loss_D: 0.2355  Loss_G: 13.1364 D(x): 0.9107
     D(G(z)): 0.0001 / 0.0003
[684/1000][40/42]    Loss_D: 0.0624  Loss_G: 16.4481 D(x): 0.9674
     D(G(z)): 0.0002 / 0.0001
[685/1000][0/42]Loss_D: 0.2242  Loss_G: 14.9148 D(x): 0.9514
     D(G(z)): 0.0241 / 0.0034
[685/1000][20/42]    Loss_D: 0.2149  Loss_G: 18.0606 D(x): 0.9600
     D(G(z)): 0.0241 / 0.0118
[685/1000][40/42]    Loss_D: 0.0641  Loss_G: 13.1644 D(x): 0.9624
     D(G(z)): 0.0146 / 0.0007
[686/1000][0/42]Loss_D: 0.0265  Loss_G: 14.9454 D(x): 0.9808
     D(G(z)): 0.0007 / 0.0004
[686/1000][20/42]    Loss_D: 0.0193  Loss_G: 13.5985 D(x): 0.9843
     D(G(z)): 0.0013 / 0.0004
[686/1000][40/42]    Loss_D: 0.0188  Loss_G: 14.4092 D(x): 0.9984
     D(G(z)): 0.0129 / 0.0017
[687/1000][0/42]Loss_D: 0.0857  Loss_G: 14.0404 D(x): 0.9447
     D(G(z)): 0.0002 / 0.0002
[687/1000][20/42]    Loss_D: 0.0486  Loss_G: 13.4244 D(x): 0.9791
     D(G(z)): 0.0008 / 0.0009
```

[687/1000][40/42]	Loss_D: 0.0071	Loss_G: 10.8886	D(x): 0.9973	D(G(z)): 0.0042 / 0.0018
[688/1000][0/42]	Loss_D: 0.0665	Loss_G: 10.9333	D(x): 0.9578	D(G(z)): 0.0106 / 0.0041
[688/1000][20/42]	Loss_D: 0.0113	Loss_G: 8.7187	D(x): 0.9994	D(G(z)): 0.0103 / 0.0071
[688/1000][40/42]	Loss_D: 0.0053	Loss_G: 12.2367	D(x): 0.9975	D(G(z)): 0.0027 / 0.0034
[689/1000][0/42]	Loss_D: 0.0268	Loss_G: 10.8255	D(x): 0.9875	D(G(z)): 0.0126 / 0.0083
[689/1000][20/42]	Loss_D: 0.0040	Loss_G: 11.6473	D(x): 0.9969	D(G(z)): 0.0008 / 0.0004
[689/1000][40/42]	Loss_D: 0.0343	Loss_G: 14.3499	D(x): 0.9816	D(G(z)): 0.0037 / 0.0008
[690/1000][0/42]	Loss_D: 0.0347	Loss_G: 14.8398	D(x): 0.9757	D(G(z)): 0.0001 / 0.0001
[690/1000][20/42]	Loss_D: 0.0320	Loss_G: 10.9711	D(x): 0.9756	D(G(z)): 0.0016 / 0.0014
[690/1000][40/42]	Loss_D: 0.0184	Loss_G: 12.2585	D(x): 0.9857	D(G(z)): 0.0016 / 0.0011

[691/1000][0/42]	Loss_D: 0.0273	Loss_G: 10.6494	D(x): 0.9921	D(G(z)): 0.0134 / 0.0018
[691/1000][20/42]	Loss_D: 0.0129	Loss_G: 10.6430	D(x): 0.9915	D(G(z)): 0.0039 / 0.0040
[691/1000][40/42]	Loss_D: 0.0181	Loss_G: 11.9975	D(x): 0.9858	D(G(z)): 0.0007 / 0.0006
[692/1000][0/42]	Loss_D: 0.0106	Loss_G: 11.4594	D(x): 0.9908	D(G(z)): 0.0005 / 0.0006
[692/1000][20/42]	Loss_D: 0.0044	Loss_G: 8.0774	D(x): 0.9999	D(G(z)): 0.0043 / 0.0052
[692/1000][40/42]	Loss_D: 0.0053	Loss_G: 10.6777	D(x): 0.9997	D(G(z)): 0.0049 / 0.0021
[693/1000][0/42]	Loss_D: 0.0158	Loss_G: 9.4982	D(x): 0.9981	D(G(z)): 0.0128 / 0.0026
[693/1000][20/42]	Loss_D: 0.0157	Loss_G: 8.9068	D(x): 0.9986	D(G(z)): 0.0125 / 0.0126
[693/1000][40/42]	Loss_D: 0.0058	Loss_G: 9.9219	D(x): 0.9995	D(G(z)): 0.0052 / 0.0022
[694/1000][0/42]	Loss_D: 0.0028	Loss_G: 11.0294	D(x): 0.9994

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      D(G(z)): 0.0022 / 0.0018
[694/1000][20/42]     Loss_D: 0.0094  Loss_G: 14.4436 D(x): 0.9910
      D(G(z)): 0.0000 / 0.0000
[694/1000][40/42]     Loss_D: 0.0176  Loss_G: 9.7212  D(x): 0.9862
      D(G(z)): 0.0025 / 0.0034
[695/1000][0/42] Loss_D: 0.0447  Loss_G: 8.3407  D(x): 0.9943
      D(G(z)): 0.0259 / 0.0101
[695/1000][20/42]     Loss_D: 0.0039  Loss_G: 10.2221 D(x): 0.9993
      D(G(z)): 0.0031 / 0.0027
[695/1000][40/42]     Loss_D: 0.0021  Loss_G: 10.7017 D(x): 0.9993
      D(G(z)): 0.0014 / 0.0013
[696/1000][0/42] Loss_D: 0.0058  Loss_G: 8.7751  D(x): 0.9985
      D(G(z)): 0.0042 / 0.0039
[696/1000][20/42]     Loss_D: 0.0026  Loss_G: 10.6536 D(x): 0.9989
      D(G(z)): 0.0015 / 0.0014
[696/1000][40/42]     Loss_D: 0.0134  Loss_G: 10.1717 D(x): 0.9896
      D(G(z)): 0.0026 / 0.0027
[697/1000][0/42] Loss_D: 0.0019  Loss_G: 10.7329 D(x): 0.9993
      D(G(z)): 0.0012 / 0.0012
[697/1000][20/42]     Loss_D: 0.0056  Loss_G: 10.6295 D(x): 0.9990
      D(G(z)): 0.0044 / 0.0017
[697/1000][40/42]     Loss_D: 0.0181  Loss_G: 10.4402 D(x): 0.9869
      D(G(z)): 0.0036 / 0.0022
[698/1000][0/42] Loss_D: 0.0330  Loss_G: 8.1801  D(x): 0.9992
      D(G(z)): 0.0223 / 0.0087
[698/1000][20/42]     Loss_D: 0.0087  Loss_G: 9.8100  D(x): 0.9983
      D(G(z)): 0.0067 / 0.0086
[698/1000][40/42]     Loss_D: 0.0059  Loss_G: 11.3198 D(x): 0.9999
      D(G(z)): 0.0053 / 0.0023
[699/1000][0/42] Loss_D: 0.0130  Loss_G: 11.0446 D(x): 0.9907
      D(G(z)): 0.0030 / 0.0022
[699/1000][20/42]     Loss_D: 0.0059  Loss_G: 10.6220 D(x): 0.9953
      D(G(z)): 0.0010 / 0.0009
[699/1000][40/42]     Loss_D: 0.0176  Loss_G: 10.8070 D(x): 0.9979
      D(G(z)): 0.0129 / 0.0059
[700/1000][0/42] Loss_D: 0.0016  Loss_G: 12.9724 D(x): 0.9985
      D(G(z)): 0.0001 / 0.0001
[700/1000][20/42]     Loss_D: 0.0014  Loss_G: 10.2090 D(x): 0.9996
      D(G(z)): 0.0010 / 0.0020
[700/1000][40/42]     Loss_D: 0.0037  Loss_G: 10.2043 D(x): 0.9985
      D(G(z)): 0.0022 / 0.0034
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[701/1000][0/42] Loss_D: 0.0073  Loss_G: 10.4462 D(x): 0.9994
     D(G(z)): 0.0064 / 0.0073
[701/1000][20/42]     Loss_D: 0.0509  Loss_G: 12.8456 D(x): 0.9565
     D(G(z)): 0.0001 / 0.0001
[701/1000][40/42]     Loss_D: 0.0224  Loss_G: 14.9513 D(x): 0.9805
     D(G(z)): 0.0001 / 0.0001
[702/1000][0/42] Loss_D: 0.1719  Loss_G: 14.4608 D(x): 0.8949
     D(G(z)): 0.0004 / 0.0024
[702/1000][20/42]     Loss_D: 0.0526  Loss_G: 10.9356 D(x): 0.9959
     D(G(z)): 0.0331 / 0.0081
[702/1000][40/42]     Loss_D: 0.0291  Loss_G: 11.8794 D(x): 0.9814
     D(G(z)): 0.0079 / 0.0016
[703/1000][0/42] Loss_D: 0.0076  Loss_G: 12.4557 D(x): 0.9956
     D(G(z)): 0.0029 / 0.0061
[703/1000][20/42]     Loss_D: 0.2916  Loss_G: 13.3961 D(x): 0.9322
     D(G(z)): 0.0382 / 0.0011
[703/1000][40/42]     Loss_D: 0.1916  Loss_G: 12.4875 D(x): 0.9242
     D(G(z)): 0.0089 / 0.0021
[704/1000][0/42] Loss_D: 0.0236  Loss_G: 10.3415 D(x): 0.9997
     D(G(z)): 0.0168 / 0.0151
[704/1000][20/42]     Loss_D: 0.0709  Loss_G: 13.3889 D(x): 0.9732
     D(G(z)): 0.0047 / 0.0029
[704/1000][40/42]     Loss_D: 0.0228  Loss_G: 12.8752 D(x): 0.9997
     D(G(z)): 0.0189 / 0.0014
[705/1000][0/42] Loss_D: 0.2225  Loss_G: 13.1852 D(x): 0.9822
     D(G(z)): 0.0207 / 0.0065
[705/1000][20/42]     Loss_D: 0.2446  Loss_G: 11.6054 D(x): 0.9556
     D(G(z)): 0.0292 / 0.0047
[705/1000][40/42]     Loss_D: 0.0036  Loss_G: 13.9998 D(x): 0.9979
     D(G(z)): 0.0014 / 0.0002
[706/1000][0/42] Loss_D: 0.0590  Loss_G: 19.1095 D(x): 0.9627
     D(G(z)): 0.0001 / 0.0000
[706/1000][20/42]     Loss_D: 0.1006  Loss_G: 10.7360 D(x): 0.9884
     D(G(z)): 0.0379 / 0.0768
[706/1000][40/42]     Loss_D: 0.0037  Loss_G: 10.2127 D(x): 0.9999
     D(G(z)): 0.0034 / 0.0084
[707/1000][0/42] Loss_D: 0.4205  Loss_G: 8.7065  D(x): 0.9999
     D(G(z)): 0.1387 / 0.0223
[707/1000][20/42]     Loss_D: 0.0490  Loss_G: 12.8398 D(x): 0.9675
     D(G(z)): 0.0021 / 0.0030
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[707/1000][40/42]	Loss_D: 0.0407	Loss_G: 12.0336	D(x): 0.9997
	D(G(z)): 0.0287 / 0.0008
[708/1000][0/42]	Loss_D: 0.0429	Loss_G: 16.7896	D(x): 0.9665
	D(G(z)): 0.0003 / 0.0000
[708/1000][20/42]	Loss_D: 0.0945	Loss_G: 10.6018	D(x): 0.9875
	D(G(z)): 0.0481 / 0.0055
[708/1000][40/42]	Loss_D: 0.0083	Loss_G: 14.2547	D(x): 0.9935
	D(G(z)): 0.0014 / 0.0003
[709/1000][0/42]	Loss_D: 0.0680	Loss_G: 14.9347	D(x): 0.9838
	D(G(z)): 0.0179 / 0.0024
[709/1000][20/42]	Loss_D: 0.0950	Loss_G: 9.6092	D(x): 0.9992
	D(G(z)): 0.0551 / 0.0060
[709/1000][40/42]	Loss_D: 0.0521	Loss_G: 12.5918	D(x): 0.9593
	D(G(z)): 0.0001 / 0.0002
[710/1000][0/42]	Loss_D: 0.0641	Loss_G: 10.3365	D(x): 0.9996
	D(G(z)): 0.0378 / 0.0137
[710/1000][20/42]	Loss_D: 0.0258	Loss_G: 10.3606	D(x): 0.9913
	D(G(z)): 0.0138 / 0.0053
[710/1000][40/42]	Loss_D: 0.0166	Loss_G: 7.8143	D(x): 1.0000
	D(G(z)): 0.0156 / 0.0077
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```
[711/1000][0/42]	Loss_D: 0.0082	Loss_G: 9.0421	D(x): 0.9988
	D(G(z)): 0.0068 / 0.0025
[711/1000][20/42]	Loss_D: 0.0297	Loss_G: 11.3426	D(x): 0.9817
	D(G(z)): 0.0043 / 0.0033
[711/1000][40/42]	Loss_D: 0.0068	Loss_G: 11.5977	D(x): 0.9969
	D(G(z)): 0.0034 / 0.0025
[712/1000][0/42]	Loss_D: 0.0096	Loss_G: 10.9296	D(x): 0.9928
	D(G(z)): 0.0022 / 0.0024
[712/1000][20/42]	Loss_D: 0.0212	Loss_G: 12.4351	D(x): 0.9818
	D(G(z)): 0.0005 / 0.0005
[712/1000][40/42]	Loss_D: 0.0068	Loss_G: 12.0716	D(x): 0.9939
	D(G(z)): 0.0005 / 0.0004
[713/1000][0/42]	Loss_D: 0.0018	Loss_G: 12.7338	D(x): 0.9984
	D(G(z)): 0.0002 / 0.0001
[713/1000][20/42]	Loss_D: 0.0372	Loss_G: 12.8118	D(x): 0.9691
	D(G(z)): 0.0020 / 0.0019
[713/1000][40/42]	Loss_D: 0.0099	Loss_G: 9.5743	D(x): 0.9988
	D(G(z)): 0.0083 / 0.0057
[714/1000][0/42]	Loss_D: 0.0023	Loss_G: 10.7253	D(x): 0.9994
```

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      D(G(z)): 0.0017 / 0.0019
[714/1000][20/42]     Loss_D: 0.0061  Loss_G: 9.9261  D(x): 0.9996
      D(G(z)): 0.0056 / 0.0048
[714/1000][40/42]     Loss_D: 0.0282  Loss_G: 11.2452 D(x): 0.9825
      D(G(z)): 0.0035 / 0.0022
[715/1000][0/42]Loss_D: 0.0158  Loss_G: 9.5181  D(x): 0.9967
      D(G(z)): 0.0112 / 0.0049
[715/1000][20/42]     Loss_D: 0.0252  Loss_G: 11.9885 D(x): 0.9853
      D(G(z)): 0.0066 / 0.0001
[715/1000][40/42]     Loss_D: 0.0327  Loss_G: 10.2332 D(x): 0.9809
      D(G(z)): 0.0011 / 0.0019
[716/1000][0/42]Loss_D: 0.0026  Loss_G: 10.8206 D(x): 0.9982
      D(G(z)): 0.0008 / 0.0008
[716/1000][20/42]     Loss_D: 0.0021  Loss_G: 12.6402 D(x): 0.9982
      D(G(z)): 0.0003 / 0.0003
[716/1000][40/42]     Loss_D: 0.0170  Loss_G: 10.6254 D(x): 0.9990
      D(G(z)): 0.0134 / 0.0036
[717/1000][0/42]Loss_D: 0.0024  Loss_G: 11.0738 D(x): 0.9980
      D(G(z)): 0.0004 / 0.0004
[717/1000][20/42]     Loss_D: 0.0368  Loss_G: 9.9582  D(x): 0.9986
      D(G(z)): 0.0233 / 0.0134
[717/1000][40/42]     Loss_D: 0.0133  Loss_G: 11.0651 D(x): 0.9999
      D(G(z)): 0.0113 / 0.0030
[718/1000][0/42]Loss_D: 0.0012  Loss_G: 11.4677 D(x): 0.9993
      D(G(z)): 0.0005 / 0.0004
[718/1000][20/42]     Loss_D: 0.0070  Loss_G: 12.6697 D(x): 0.9938
      D(G(z)): 0.0005 / 0.0005
[718/1000][40/42]     Loss_D: 0.0083  Loss_G: 11.2489 D(x): 0.9945
      D(G(z)): 0.0024 / 0.0016
[719/1000][0/42]Loss_D: 0.0018  Loss_G: 12.3424 D(x): 0.9987
      D(G(z)): 0.0005 / 0.0003
[719/1000][20/42]     Loss_D: 0.0034  Loss_G: 10.9795 D(x): 0.9986
      D(G(z)): 0.0019 / 0.0013
[719/1000][40/42]     Loss_D: 0.0486  Loss_G: 11.1482 D(x): 0.9857
      D(G(z)): 0.0205 / 0.0015
[720/1000][0/42]Loss_D: 0.0259  Loss_G: 10.8636 D(x): 0.9821
      D(G(z)): 0.0041 / 0.0023
[720/1000][20/42]     Loss_D: 0.0122  Loss_G: 9.7956  D(x): 0.9989
      D(G(z)): 0.0096 / 0.0044
[720/1000][40/42]     Loss_D: 0.0089  Loss_G: 12.7894 D(x): 0.9928
      D(G(z)): 0.0010 / 0.0009
```

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[721/1000][0/42] Loss_D: 0.0045  Loss_G: 10.7328 D(x): 0.9991
      D(G(z)): 0.0036 / 0.0029
[721/1000][20/42]     Loss_D: 0.0027  Loss_G: 9.9989  D(x): 0.9987
      D(G(z)): 0.0014 / 0.0016
[721/1000][40/42]     Loss_D: 0.0040  Loss_G: 10.4033 D(x): 0.9985
      D(G(z)): 0.0025 / 0.0016
[722/1000][0/42] Loss_D: 0.0015  Loss_G: 10.1617 D(x): 0.9993
      D(G(z)): 0.0008 / 0.0007
[722/1000][20/42]     Loss_D: 0.0114  Loss_G: 11.0491 D(x): 0.9997
      D(G(z)): 0.0088 / 0.0055
[722/1000][40/42]     Loss_D: 0.0194  Loss_G: 11.6418 D(x): 0.9900
      D(G(z)): 0.0070 / 0.0014
[723/1000][0/42] Loss_D: 0.0228  Loss_G: 10.8324 D(x): 0.9801
      D(G(z)): 0.0017 / 0.0013
[723/1000][20/42]     Loss_D: 0.0150  Loss_G: 12.6860 D(x): 0.9861
      D(G(z)): 0.0003 / 0.0004
[723/1000][40/42]     Loss_D: 0.0153  Loss_G: 8.8935  D(x): 0.9998
      D(G(z)): 0.0132 / 0.0069
[724/1000][0/42] Loss_D: 0.0072  Loss_G: 8.9559  D(x): 0.9999
      D(G(z)): 0.0069 / 0.0038
[724/1000][20/42]     Loss_D: 0.0667  Loss_G: 11.7681 D(x): 0.9503
      D(G(z)): 0.0002 / 0.0008
[724/1000][40/42]     Loss_D: 0.0582  Loss_G: 13.8095 D(x): 0.9968
      D(G(z)): 0.0273 / 0.0019
[725/1000][0/42] Loss_D: 0.2590  Loss_G: 11.2250 D(x): 0.9366
      D(G(z)): 0.0064 / 0.0070
[725/1000][20/42]     Loss_D: 0.0256  Loss_G: 12.0570 D(x): 0.9811
      D(G(z)): 0.0021 / 0.0030
[725/1000][40/42]     Loss_D: 0.0151  Loss_G: 13.4322 D(x): 0.9873
      D(G(z)): 0.0004 / 0.0003
[726/1000][0/42] Loss_D: 0.0342  Loss_G: 11.9062 D(x): 0.9808
      D(G(z)): 0.0003 / 0.0005
[726/1000][20/42]     Loss_D: 0.0114  Loss_G: 10.9949 D(x): 0.9936
      D(G(z)): 0.0045 / 0.0082
[726/1000][40/42]     Loss_D: 0.1655  Loss_G: 13.9282 D(x): 0.9608
      D(G(z)): 0.0006 / 0.0011
[727/1000][0/42] Loss_D: 0.0074  Loss_G: 12.3051 D(x): 0.9955
      D(G(z)): 0.0028 / 0.0047
[727/1000][20/42]     Loss_D: 0.0022  Loss_G: 10.4466 D(x): 1.0000
      D(G(z)): 0.0021 / 0.0022
```

```
[727/1000][40/42]	Loss_D: 0.0040	Loss_G: 12.3507	D(x): 0.9998
	D(G(z)): 0.0036 / 0.0020
[728/1000][0/42]	Loss_D: 0.0042	Loss_G: 11.9662	D(x): 0.9964
	D(G(z)): 0.0005 / 0.0003
[728/1000][20/42]	Loss_D: 0.0054	Loss_G: 10.0933	D(x): 0.9994
	D(G(z)): 0.0046 / 0.0020
[728/1000][40/42]	Loss_D: 0.0104	Loss_G: 9.1818	D(x): 0.9990
	D(G(z)): 0.0088 / 0.0055
[729/1000][0/42]	Loss_D: 0.0832	Loss_G: 11.4476	D(x): 0.9945
	D(G(z)): 0.0245 / 0.0019
[729/1000][20/42]	Loss_D: 0.0026	Loss_G: 11.9926	D(x): 0.9999
	D(G(z)): 0.0024 / 0.0014
[729/1000][40/42]	Loss_D: 0.0510	Loss_G: 8.9909	D(x): 0.9991
	D(G(z)): 0.0366 / 0.0106
[730/1000][0/42]	Loss_D: 0.0054	Loss_G: 10.9286	D(x): 1.0000
	D(G(z)): 0.0053 / 0.0011
[730/1000][20/42]	Loss_D: 0.0122	Loss_G: 13.1121	D(x): 0.9955
	D(G(z)): 0.0063 / 0.0021
[730/1000][40/42]	Loss_D: 0.0236	Loss_G: 9.6021	D(x): 0.9999
	D(G(z)): 0.0204 / 0.0096
```

```
[731/1000][0/42]	Loss_D: 0.0031	Loss_G: 10.2144	D(x): 0.9991
	D(G(z)): 0.0022 / 0.0011
[731/1000][20/42]	Loss_D: 0.0018	Loss_G: 12.3633	D(x): 0.9988
	D(G(z)): 0.0006 / 0.0002
[731/1000][40/42]	Loss_D: 0.0007	Loss_G: 11.0403	D(x): 0.9998
	D(G(z)): 0.0006 / 0.0012
[732/1000][0/42]	Loss_D: 0.0072	Loss_G: 9.8219	D(x): 0.9998
	D(G(z)): 0.0067 / 0.0048
[732/1000][20/42]	Loss_D: 0.1192	Loss_G: 13.0270	D(x): 0.9465
	D(G(z)): 0.0002 / 0.0003
[732/1000][40/42]	Loss_D: 0.2920	Loss_G: 8.3513	D(x): 0.9998
	D(G(z)): 0.0906 / 0.0222
[733/1000][0/42]	Loss_D: 0.0121	Loss_G: 13.8857	D(x): 0.9994
	D(G(z)): 0.0091 / 0.0003
[733/1000][20/42]	Loss_D: 0.0048	Loss_G: 10.9339	D(x): 0.9972
	D(G(z)): 0.0018 / 0.0041
[733/1000][40/42]	Loss_D: 0.0116	Loss_G: 13.4188	D(x): 0.9908
	D(G(z)): 0.0008 / 0.0005
[734/1000][0/42]	Loss_D: 0.0010	Loss_G: 10.8787	D(x): 1.0000
```

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    D(G(z)): 0.0009 / 0.0028
[734/1000][20/42]    Loss_D: 0.0366  Loss_G: 16.3194 D(x): 0.9747
    D(G(z)): 0.0001 / 0.0001
[734/1000][40/42]    Loss_D: 0.0235  Loss_G: 10.8004 D(x): 0.9996
    D(G(z)): 0.0154 / 0.0085
[735/1000][0/42] Loss_D: 0.1022  Loss_G: 9.8135  D(x): 0.9866
    D(G(z)): 0.0311 / 0.0074
[735/1000][20/42]    Loss_D: 0.0044  Loss_G: 11.2430 D(x): 0.9993
    D(G(z)): 0.0036 / 0.0050
[735/1000][40/42]    Loss_D: 0.2213  Loss_G: 9.6072  D(x): 0.9999
    D(G(z)): 0.0931 / 0.0139
[736/1000][0/42] Loss_D: 0.1296  Loss_G: 11.7841 D(x): 0.9984
    D(G(z)): 0.0723 / 0.0008
[736/1000][20/42]    Loss_D: 0.0717  Loss_G: 11.5146 D(x): 0.9858
    D(G(z)): 0.0318 / 0.0127
[736/1000][40/42]    Loss_D: 0.0119  Loss_G: 9.9373  D(x): 0.9997
    D(G(z)): 0.0107 / 0.0361
[737/1000][0/42] Loss_D: 0.2545  Loss_G: 8.0254  D(x): 1.0000
    D(G(z)): 0.1147 / 0.0271
[737/1000][20/42]    Loss_D: 0.1102  Loss_G: 11.0555 D(x): 0.9748
    D(G(z)): 0.0486 / 0.0059
[737/1000][40/42]    Loss_D: 0.0992  Loss_G: 11.5944 D(x): 0.9914
    D(G(z)): 0.0391 / 0.0014
[738/1000][0/42] Loss_D: 0.0196  Loss_G: 13.1120 D(x): 0.9985
    D(G(z)): 0.0163 / 0.0008
[738/1000][20/42]    Loss_D: 0.0069  Loss_G: 12.9441 D(x): 0.9952
    D(G(z)): 0.0020 / 0.0033
[738/1000][40/42]    Loss_D: 0.1149  Loss_G: 14.1638 D(x): 0.9472
    D(G(z)): 0.0140 / 0.0033
[739/1000][0/42] Loss_D: 0.0847  Loss_G: 12.9515 D(x): 0.9418
    D(G(z)): 0.0036 / 0.0010
[739/1000][20/42]    Loss_D: 0.0093  Loss_G: 12.3389 D(x): 0.9953
    D(G(z)): 0.0042 / 0.0017
[739/1000][40/42]    Loss_D: 0.0328  Loss_G: 12.7494 D(x): 0.9956
    D(G(z)): 0.0158 / 0.0039
[740/1000][0/42] Loss_D: 0.0213  Loss_G: 10.6598 D(x): 0.9876
    D(G(z)): 0.0069 / 0.0034
[740/1000][20/42]    Loss_D: 0.2239  Loss_G: 9.7992  D(x): 0.9992
    D(G(z)): 0.1327 / 0.0044
[740/1000][40/42]    Loss_D: 0.0093  Loss_G: 10.2131 D(x): 0.9961
    D(G(z)): 0.0050 / 0.0285
```

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[741/1000][0/42] Loss_D: 0.0090  Loss_G: 11.0623 D(x): 0.9994
      D(G(z)): 0.0080 / 0.0133
[741/1000][20/42]     Loss_D: 0.0311  Loss_G: 14.2120 D(x): 0.9809
      D(G(z)): 0.0056 / 0.0053
[741/1000][40/42]     Loss_D: 0.1164  Loss_G: 11.8290 D(x): 0.9730
      D(G(z)): 0.0021 / 0.0028
[742/1000][0/42] Loss_D: 0.0720  Loss_G: 10.4702 D(x): 0.9936
      D(G(z)): 0.0340 / 0.0165
[742/1000][20/42]     Loss_D: 0.0287  Loss_G: 10.8954 D(x): 0.9956
      D(G(z)): 0.0168 / 0.0082
[742/1000][40/42]     Loss_D: 0.0055  Loss_G: 14.2973 D(x): 0.9948
      D(G(z)): 0.0002 / 0.0001
[743/1000][0/42] Loss_D: 0.0086  Loss_G: 12.5306 D(x): 0.9948
      D(G(z)): 0.0031 / 0.0013
[743/1000][20/42]     Loss_D: 0.0214  Loss_G: 12.9369 D(x): 0.9820
      D(G(z)): 0.0002 / 0.0002
[743/1000][40/42]     Loss_D: 0.0423  Loss_G: 12.7053 D(x): 0.9851
      D(G(z)): 0.0155 / 0.0103
[744/1000][0/42] Loss_D: 0.0057  Loss_G: 12.3319 D(x): 0.9995
      D(G(z)): 0.0050 / 0.0031
[744/1000][20/42]     Loss_D: 0.0417  Loss_G: 9.8811  D(x): 0.9996
      D(G(z)): 0.0253 / 0.0075
[744/1000][40/42]     Loss_D: 0.0058  Loss_G: 12.9776 D(x): 0.9982
      D(G(z)): 0.0038 / 0.0024
[745/1000][0/42] Loss_D: 0.0225  Loss_G: 10.8328 D(x): 0.9865
      D(G(z)): 0.0064 / 0.0036
[745/1000][20/42]     Loss_D: 0.0212  Loss_G: 11.9064 D(x): 0.9859
      D(G(z)): 0.0005 / 0.0004
[745/1000][40/42]     Loss_D: 0.0021  Loss_G: 11.3771 D(x): 0.9985
      D(G(z)): 0.0006 / 0.0006
[746/1000][0/42] Loss_D: 0.0016  Loss_G: 11.8620 D(x): 0.9993
      D(G(z)): 0.0009 / 0.0009
[746/1000][20/42]     Loss_D: 0.0496  Loss_G: 14.4788 D(x): 0.9680
      D(G(z)): 0.0000 / 0.0000
[746/1000][40/42]     Loss_D: 0.1057  Loss_G: 11.6923 D(x): 0.9999
      D(G(z)): 0.0597 / 0.0039
[747/1000][0/42] Loss_D: 0.0027  Loss_G: 13.6327 D(x): 0.9977
      D(G(z)): 0.0003 / 0.0002
[747/1000][20/42]     Loss_D: 0.0327  Loss_G: 11.6625 D(x): 0.9746
      D(G(z)): 0.0002 / 0.0007
```

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[747/1000][40/42]	Loss_D: 0.0051	Loss_G: 9.8638	D(x): 0.9985
	D(G(z)): 0.0034 / 0.0036
[748/1000][0/42]	Loss_D: 0.0094	Loss_G: 8.8240	D(x): 0.9984
	D(G(z)): 0.0075 / 0.0061
[748/1000][20/42]	Loss_D: 0.0073	Loss_G: 11.9497	D(x): 0.9948
	D(G(z)): 0.0020 / 0.0022
[748/1000][40/42]	Loss_D: 0.0073	Loss_G: 12.7616	D(x): 0.9969
	D(G(z)): 0.0038 / 0.0018
[749/1000][0/42]	Loss_D: 0.0044	Loss_G: 13.5659	D(x): 0.9960
	D(G(z)): 0.0003 / 0.0003
[749/1000][20/42]	Loss_D: 0.0037	Loss_G: 9.6296	D(x): 0.9985
	D(G(z)): 0.0021 / 0.0011
[749/1000][40/42]	Loss_D: 0.0037	Loss_G: 12.1683	D(x): 0.9988
	D(G(z)): 0.0024 / 0.0017
[750/1000][0/42]	Loss_D: 0.1444	Loss_G: 9.6892	D(x): 0.9301
	D(G(z)): 0.0146 / 0.0108
[750/1000][20/42]	Loss_D: 0.0233	Loss_G: 10.2171	D(x): 0.9982
	D(G(z)): 0.0152 / 0.0086
[750/1000][40/42]	Loss_D: 0.0067	Loss_G: 11.1909	D(x): 0.9979
	D(G(z)): 0.0043 / 0.0038
```

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[751/1000][0/42]	Loss_D: 0.0025	Loss_G: 10.8934	D(x): 0.9998
	D(G(z)): 0.0023 / 0.0017
[751/1000][20/42]	Loss_D: 0.0039	Loss_G: 10.4735	D(x): 0.9979
	D(G(z)): 0.0018 / 0.0015
[751/1000][40/42]	Loss_D: 0.0087	Loss_G: 10.2510	D(x): 0.9986
	D(G(z)): 0.0068 / 0.0050
[752/1000][0/42]	Loss_D: 0.0076	Loss_G: 10.5683	D(x): 0.9976
	D(G(z)): 0.0049 / 0.0035
[752/1000][20/42]	Loss_D: 0.0065	Loss_G: 14.0030	D(x): 0.9938
	D(G(z)): 0.0001 / 0.0001
[752/1000][40/42]	Loss_D: 0.0026	Loss_G: 11.5401	D(x): 0.9980
	D(G(z)): 0.0006 / 0.0006
[753/1000][0/42]	Loss_D: 0.0036	Loss_G: 11.9327	D(x): 0.9974
	D(G(z)): 0.0010 / 0.0010
[753/1000][20/42]	Loss_D: 0.0027	Loss_G: 10.7154	D(x): 0.9991
	D(G(z)): 0.0018 / 0.0020
[753/1000][40/42]	Loss_D: 0.0256	Loss_G: 9.3152	D(x): 0.9987
	D(G(z)): 0.0169 / 0.0045
[754/1000][0/42]	Loss_D: 0.0559	Loss_G: 10.8834	D(x): 0.9991
```

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    D(G(z)): 0.0205 / 0.0035
[754/1000][20/42]    Loss_D: 0.0085  Loss_G: 11.2198 D(x): 0.9991
    D(G(z)): 0.0065 / 0.0017
[754/1000][40/42]    Loss_D: 0.0095  Loss_G: 11.7850 D(x): 0.9921
    D(G(z)): 0.0005 / 0.0004
[755/1000][0/42]Loss_D: 0.0062  Loss_G: 14.0574 D(x): 0.9941
    D(G(z)): 0.0001 / 0.0001
[755/1000][20/42]    Loss_D: 0.0379  Loss_G: 9.8208  D(x): 1.0000
    D(G(z)): 0.0278 / 0.0072
[755/1000][40/42]    Loss_D: 0.0950  Loss_G: 11.3940 D(x): 0.9990
    D(G(z)): 0.0207 / 0.0007
[756/1000][0/42]Loss_D: 0.0172  Loss_G: 14.1664 D(x): 0.9879
    D(G(z)): 0.0015 / 0.0006
[756/1000][20/42]    Loss_D: 0.0625  Loss_G: 13.4416 D(x): 0.9570
    D(G(z)): 0.0000 / 0.0001
[756/1000][40/42]    Loss_D: 0.0267  Loss_G: 12.0122 D(x): 0.9999
    D(G(z)): 0.0238 / 0.0071
[757/1000][0/42]Loss_D: 0.0375  Loss_G: 13.1712 D(x): 0.9694
    D(G(z)): 0.0016 / 0.0010
[757/1000][20/42]    Loss_D: 0.0178  Loss_G: 13.6122 D(x): 0.9931
    D(G(z)): 0.0082 / 0.0012
[757/1000][40/42]    Loss_D: 0.0078  Loss_G: 12.5620 D(x): 0.9984
    D(G(z)): 0.0059 / 0.0029
[758/1000][0/42]Loss_D: 0.0570  Loss_G: 11.9250 D(x): 0.9942
    D(G(z)): 0.0248 / 0.0034
[758/1000][20/42]    Loss_D: 0.0506  Loss_G: 14.3945 D(x): 0.9679
    D(G(z)): 0.0000 / 0.0001
[758/1000][40/42]    Loss_D: 0.0015  Loss_G: 10.7043 D(x): 0.9995
    D(G(z)): 0.0010 / 0.0008
[759/1000][0/42]Loss_D: 0.0079  Loss_G: 11.0243 D(x): 0.9933
    D(G(z)): 0.0007 / 0.0007
[759/1000][20/42]    Loss_D: 0.0027  Loss_G: 11.8455 D(x): 0.9985
    D(G(z)): 0.0011 / 0.0011
[759/1000][40/42]    Loss_D: 0.0154  Loss_G: 9.1107  D(x): 0.9941
    D(G(z)): 0.0085 / 0.0042
[760/1000][0/42]Loss_D: 0.0021  Loss_G: 12.2332 D(x): 0.9982
    D(G(z)): 0.0003 / 0.0002
[760/1000][20/42]    Loss_D: 0.0028  Loss_G: 12.5810 D(x): 0.9975
    D(G(z)): 0.0002 / 0.0002
[760/1000][40/42]    Loss_D: 0.0053  Loss_G: 10.9351 D(x): 0.9989
    D(G(z)): 0.0040 / 0.0030
```

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[761/1000][0/42]	Loss_D: 0.0026	Loss_G: 11.7359	D(x): 0.9980	D(G(z)): 0.0005 / 0.0005
[761/1000][20/42]	Loss_D: 0.0015	Loss_G: 11.3346	D(x): 0.9990	D(G(z)): 0.0005 / 0.0005
[761/1000][40/42]	Loss_D: 0.0008	Loss_G: 11.6504	D(x): 0.9995	D(G(z)): 0.0003 / 0.0003
[762/1000][0/42]	Loss_D: 0.0014	Loss_G: 12.7888	D(x): 0.9988	D(G(z)): 0.0002 / 0.0002
[762/1000][20/42]	Loss_D: 0.0059	Loss_G: 10.0620	D(x): 0.9985	D(G(z)): 0.0042 / 0.0018
[762/1000][40/42]	Loss_D: 0.0069	Loss_G: 11.3938	D(x): 0.9963	D(G(z)): 0.0029 / 0.0018
[763/1000][0/42]	Loss_D: 0.0044	Loss_G: 9.4767	D(x): 0.9998	D(G(z)): 0.0040 / 0.0035
[763/1000][20/42]	Loss_D: 0.0025	Loss_G: 10.0450	D(x): 0.9991	D(G(z)): 0.0016 / 0.0014
[763/1000][40/42]	Loss_D: 0.0009	Loss_G: 12.6842	D(x): 0.9994	D(G(z)): 0.0003 / 0.0003
[764/1000][0/42]	Loss_D: 0.0009	Loss_G: 12.1298	D(x): 0.9995	D(G(z)): 0.0004 / 0.0004
[764/1000][20/42]	Loss_D: 0.0026	Loss_G: 11.8660	D(x): 0.9979	D(G(z)): 0.0005 / 0.0004
[764/1000][40/42]	Loss_D: 0.0020	Loss_G: 12.1625	D(x): 0.9994	D(G(z)): 0.0014 / 0.0006
[765/1000][0/42]	Loss_D: 0.0052	Loss_G: 10.6617	D(x): 0.9963	D(G(z)): 0.0013 / 0.0009
[765/1000][20/42]	Loss_D: 0.0062	Loss_G: 13.2121	D(x): 0.9970	D(G(z)): 0.0031 / 0.0025
[765/1000][40/42]	Loss_D: 0.0019	Loss_G: 10.8477	D(x): 0.9992	D(G(z)): 0.0011 / 0.0010
[766/1000][0/42]	Loss_D: 0.0119	Loss_G: 12.4525	D(x): 0.9977	D(G(z)): 0.0080 / 0.0021
[766/1000][20/42]	Loss_D: 0.0087	Loss_G: 10.9760	D(x): 0.9995	D(G(z)): 0.0074 / 0.0011
[766/1000][40/42]	Loss_D: 0.0644	Loss_G: 12.2530	D(x): 0.9998	D(G(z)): 0.0322 / 0.0008
[767/1000][0/42]	Loss_D: 0.0023	Loss_G: 14.5543	D(x): 0.9987	D(G(z)): 0.0010 / 0.0005
[767/1000][20/42]	Loss_D: 0.0172	Loss_G: 10.9467	D(x): 0.9995	D(G(z)): 0.0152 / 0.0020
```

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[767/1000][40/42]    Loss_D: 0.0377  Loss_G: 17.1519 D(x): 0.9729
     D(G(z)): 0.0010 / 0.0005
[768/1000][0/42] Loss_D: 0.1786  Loss_G: 14.8859 D(x): 0.9037
     D(G(z)): 0.0075 / 0.0178
[768/1000][20/42]    Loss_D: 0.1089  Loss_G: 11.0379 D(x): 0.9999
     D(G(z)): 0.0473 / 0.0041
[768/1000][40/42]    Loss_D: 0.2728  Loss_G: 14.2047 D(x): 0.9100
     D(G(z)): 0.0055 / 0.0107
[769/1000][0/42] Loss_D: 0.0531  Loss_G: 12.5548 D(x): 0.9969
     D(G(z)): 0.0230 / 0.0083
[769/1000][20/42]    Loss_D: 0.1159  Loss_G: 11.8825 D(x): 1.0000
     D(G(z)): 0.0698 / 0.0009
[769/1000][40/42]    Loss_D: 0.0180  Loss_G: 11.2702 D(x): 0.9992
     D(G(z)): 0.0151 / 0.0058
[770/1000][0/42] Loss_D: 0.0023  Loss_G: 14.1868 D(x): 0.9982
     D(G(z)): 0.0004 / 0.0001
[770/1000][20/42]    Loss_D: 0.0152  Loss_G: 10.6443 D(x): 0.9992
     D(G(z)): 0.0127 / 0.0066
[770/1000][40/42]    Loss_D: 0.0069  Loss_G: 15.2611 D(x): 0.9938
     D(G(z)): 0.0004 / 0.0006
```

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[771/1000][0/42] Loss_D: 0.0024  Loss_G: 11.9834 D(x): 0.9979
     D(G(z)): 0.0003 / 0.0008
[771/1000][20/42]    Loss_D: 0.0144  Loss_G: 10.9437 D(x): 0.9982
     D(G(z)): 0.0110 / 0.0058
[771/1000][40/42]    Loss_D: 0.0041  Loss_G: 11.9911 D(x): 0.9979
     D(G(z)): 0.0019 / 0.0007
[772/1000][0/42] Loss_D: 0.0384  Loss_G: 10.7933 D(x): 0.9819
     D(G(z)): 0.0046 / 0.0030
[772/1000][20/42]    Loss_D: 0.0040  Loss_G: 12.4246 D(x): 0.9983
     D(G(z)): 0.0023 / 0.0018
[772/1000][40/42]    Loss_D: 0.0529  Loss_G: 15.8344 D(x): 0.9827
     D(G(z)): 0.0151 / 0.0005
[773/1000][0/42] Loss_D: 0.0717  Loss_G: 16.2648 D(x): 0.9630
     D(G(z)): 0.0005 / 0.0006
[773/1000][20/42]    Loss_D: 0.0661  Loss_G: 11.5336 D(x): 0.9987
     D(G(z)): 0.0357 / 0.0160
[773/1000][40/42]    Loss_D: 0.0563  Loss_G: 12.9078 D(x): 0.9987
     D(G(z)): 0.0299 / 0.0033
[774/1000][0/42] Loss_D: 0.0010  Loss_G: 13.3344 D(x): 0.9997
```

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    D(G(z)): 0.0008 / 0.0005
[774/1000][20/42]    Loss_D: 0.0073  Loss_G: 12.2355 D(x): 0.9985
    D(G(z)): 0.0055 / 0.0033
[774/1000][40/42]    Loss_D: 0.0198  Loss_G: 11.5758 D(x): 0.9874
    D(G(z)): 0.0009 / 0.0012
[775/1000][0/42] Loss_D: 0.0383  Loss_G: 9.1202  D(x): 0.9860
    D(G(z)): 0.0118 / 0.0103
[775/1000][20/42]    Loss_D: 0.0005  Loss_G: 13.6300 D(x): 0.9996
    D(G(z)): 0.0001 / 0.0000
[775/1000][40/42]    Loss_D: 0.0596  Loss_G: 11.8387 D(x): 1.0000
    D(G(z)): 0.0212 / 0.0016
[776/1000][0/42] Loss_D: 0.0782  Loss_G: 12.6197 D(x): 0.9832
    D(G(z)): 0.0200 / 0.0003
[776/1000][20/42]    Loss_D: 0.1289  Loss_G: 12.2236 D(x): 0.9760
    D(G(z)): 0.0194 / 0.0009
[776/1000][40/42]    Loss_D: 0.1076  Loss_G: 10.9980 D(x): 0.9999
    D(G(z)): 0.0662 / 0.0042
[777/1000][0/42] Loss_D: 0.0141  Loss_G: 13.4779 D(x): 0.9993
    D(G(z)): 0.0113 / 0.0021
[777/1000][20/42]    Loss_D: 0.1150  Loss_G: 11.8531 D(x): 0.9992
    D(G(z)): 0.0712 / 0.0039
[777/1000][40/42]    Loss_D: 0.1079  Loss_G: 12.8632 D(x): 0.9988
    D(G(z)): 0.0339 / 0.0015
[778/1000][0/42] Loss_D: 0.1059  Loss_G: 14.1256 D(x): 0.9559
    D(G(z)): 0.0006 / 0.0003
[778/1000][20/42]    Loss_D: 0.0608  Loss_G: 11.7169 D(x): 0.9993
    D(G(z)): 0.0241 / 0.0018
[778/1000][40/42]    Loss_D: 0.0836  Loss_G: 13.4807 D(x): 0.9971
    D(G(z)): 0.0387 / 0.0020
[779/1000][0/42] Loss_D: 0.0025  Loss_G: 15.8852 D(x): 0.9983
    D(G(z)): 0.0008 / 0.0004
[779/1000][20/42]    Loss_D: 0.0044  Loss_G: 11.9471 D(x): 0.9968
    D(G(z)): 0.0011 / 0.0008
[779/1000][40/42]    Loss_D: 0.0588  Loss_G: 11.8524 D(x): 0.9961
    D(G(z)): 0.0310 / 0.0038
[780/1000][0/42] Loss_D: 0.0175  Loss_G: 13.4416 D(x): 0.9881
    D(G(z)): 0.0039 / 0.0019
[780/1000][20/42]    Loss_D: 0.1050  Loss_G: 13.5882 D(x): 0.9653
    D(G(z)): 0.0120 / 0.0009
[780/1000][40/42]    Loss_D: 0.0026  Loss_G: 11.1450 D(x): 0.9991
    D(G(z)): 0.0017 / 0.0019
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[781/1000][0/42] Loss_D: 0.0076  Loss_G: 9.4622  D(x): 0.9984
      D(G(z)): 0.0056 / 0.0045
[781/1000][20/42]     Loss_D: 0.0316  Loss_G: 17.1311 D(x): 0.9724
      D(G(z)): 0.0000 / 0.0000
[781/1000][40/42]     Loss_D: 0.0025  Loss_G: 12.1169 D(x): 0.9994
      D(G(z)): 0.0019 / 0.0015
[782/1000][0/42] Loss_D: 0.0367  Loss_G: 11.5671 D(x): 0.9997
      D(G(z)): 0.0250 / 0.0026
[782/1000][20/42]     Loss_D: 0.0038  Loss_G: 12.5839 D(x): 0.9967
      D(G(z)): 0.0004 / 0.0005
[782/1000][40/42]     Loss_D: 0.0026  Loss_G: 11.2656 D(x): 0.9981
      D(G(z)): 0.0007 / 0.0005
[783/1000][0/42] Loss_D: 0.0058  Loss_G: 9.7214  D(x): 0.9977
      D(G(z)): 0.0035 / 0.0027
[783/1000][20/42]     Loss_D: 0.0240  Loss_G: 9.7179  D(x): 0.9984
      D(G(z)): 0.0205 / 0.0024
[783/1000][40/42]     Loss_D: 0.0045  Loss_G: 12.6821 D(x): 0.9970
      D(G(z)): 0.0014 / 0.0010
[784/1000][0/42] Loss_D: 0.0226  Loss_G: 11.1163 D(x): 0.9827
      D(G(z)): 0.0015 / 0.0023
[784/1000][20/42]     Loss_D: 0.0337  Loss_G: 12.5859 D(x): 0.9978
      D(G(z)): 0.0163 / 0.0010
[784/1000][40/42]     Loss_D: 0.0205  Loss_G: 11.4288 D(x): 0.9948
      D(G(z)): 0.0128 / 0.0037
[785/1000][0/42] Loss_D: 0.0012  Loss_G: 12.1855 D(x): 0.9997
      D(G(z)): 0.0009 / 0.0011
[785/1000][20/42]     Loss_D: 0.0015  Loss_G: 12.7375 D(x): 0.9996
      D(G(z)): 0.0010 / 0.0009
[785/1000][40/42]     Loss_D: 0.0025  Loss_G: 10.3230 D(x): 0.9994
      D(G(z)): 0.0019 / 0.0023
[786/1000][0/42] Loss_D: 0.0058  Loss_G: 12.2862 D(x): 0.9994
      D(G(z)): 0.0048 / 0.0034
[786/1000][20/42]     Loss_D: 0.0222  Loss_G: 10.4636 D(x): 0.9988
      D(G(z)): 0.0155 / 0.0040
[786/1000][40/42]     Loss_D: 0.0016  Loss_G: 14.1578 D(x): 0.9985
      D(G(z)): 0.0001 / 0.0001
[787/1000][0/42] Loss_D: 0.0113  Loss_G: 9.6009  D(x): 0.9920
      D(G(z)): 0.0030 / 0.0027
[787/1000][20/42]     Loss_D: 0.0006  Loss_G: 12.0211 D(x): 0.9997
      D(G(z)): 0.0003 / 0.0003
```

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[787/1000][40/42]	Loss_D: 0.0105	Loss_G: 13.5724	D(x): 0.9901
	D(G(z)): 0.0002 / 0.0005
[788/1000][0/42]	Loss_D: 0.0068	Loss_G: 11.4232	D(x): 0.9998
	D(G(z)): 0.0058 / 0.0071
[788/1000][20/42]	Loss_D: 0.0363	Loss_G: 12.3067	D(x): 0.9824
	D(G(z)): 0.0124 / 0.0011
[788/1000][40/42]	Loss_D: 0.0028	Loss_G: 10.6843	D(x): 0.9998
	D(G(z)): 0.0025 / 0.0027
[789/1000][0/42]	Loss_D: 0.0101	Loss_G: 9.7058	D(x): 0.9999
	D(G(z)): 0.0090 / 0.0071
[789/1000][20/42]	Loss_D: 0.0115	Loss_G: 10.5668	D(x): 0.9990
	D(G(z)): 0.0098 / 0.0041
[789/1000][40/42]	Loss_D: 0.0097	Loss_G: 9.6078	D(x): 0.9995
	D(G(z)): 0.0087 / 0.0043
[790/1000][0/42]	Loss_D: 0.0030	Loss_G: 10.1094	D(x): 0.9995
	D(G(z)): 0.0024 / 0.0021
[790/1000][20/42]	Loss_D: 0.0084	Loss_G: 11.7820	D(x): 0.9933
	D(G(z)): 0.0015 / 0.0019
[790/1000][40/42]	Loss_D: 0.0007	Loss_G: 12.0081	D(x): 0.9996
	D(G(z)): 0.0003 / 0.0002
```

```
[791/1000][0/42]	Loss_D: 0.0016	Loss_G: 11.3372	D(x): 0.9997
	D(G(z)): 0.0012 / 0.0010
[791/1000][20/42]	Loss_D: 0.0041	Loss_G: 11.1550	D(x): 0.9992
	D(G(z)): 0.0032 / 0.0017
[791/1000][40/42]	Loss_D: 0.0025	Loss_G: 11.7757	D(x): 0.9990
	D(G(z)): 0.0014 / 0.0005
[792/1000][0/42]	Loss_D: 0.0053	Loss_G: 10.5521	D(x): 0.9962
	D(G(z)): 0.0013 / 0.0012
[792/1000][20/42]	Loss_D: 0.0040	Loss_G: 11.5331	D(x): 0.9968
	D(G(z)): 0.0008 / 0.0007
[792/1000][40/42]	Loss_D: 0.0050	Loss_G: 13.4171	D(x): 0.9951
	D(G(z)): 0.0000 / 0.0000
[793/1000][0/42]	Loss_D: 0.0029	Loss_G: 11.7892	D(x): 0.9973
	D(G(z)): 0.0002 / 0.0002
[793/1000][20/42]	Loss_D: 0.0040	Loss_G: 10.0852	D(x): 0.9984
	D(G(z)): 0.0024 / 0.0023
[793/1000][40/42]	Loss_D: 0.0291	Loss_G: 11.2726	D(x): 0.9756
	D(G(z)): 0.0009 / 0.0011
[794/1000][0/42]	Loss_D: 0.0071	Loss_G: 11.3080	D(x): 0.9985
```

```
    D(G(z)): 0.0051 / 0.0033
[794/1000][20/42]    Loss_D: 0.0045  Loss_G: 10.9253 D(x): 0.9974
    D(G(z)): 0.0018 / 0.0013
[794/1000][40/42]    Loss_D: 0.0021  Loss_G: 13.1569 D(x): 0.9982
    D(G(z)): 0.0003 / 0.0003
[795/1000][0/42]Loss_D: 0.0021  Loss_G: 11.9427 D(x): 0.9988
    D(G(z)): 0.0009 / 0.0007
[795/1000][20/42]    Loss_D: 0.0026  Loss_G: 13.1422 D(x): 0.9975
    D(G(z)): 0.0001 / 0.0001
[795/1000][40/42]    Loss_D: 0.0038  Loss_G: 11.6543 D(x): 0.9978
    D(G(z)): 0.0015 / 0.0009
[796/1000][0/42]Loss_D: 0.0037  Loss_G: 16.0375 D(x): 0.9964
    D(G(z)): 0.0000 / 0.0000
[796/1000][20/42]    Loss_D: 0.0016  Loss_G: 10.6744 D(x): 0.9991
    D(G(z)): 0.0007 / 0.0006
[796/1000][40/42]    Loss_D: 0.0003  Loss_G: 11.8689 D(x): 0.9999
    D(G(z)): 0.0003 / 0.0003
[797/1000][0/42]Loss_D: 0.0017  Loss_G: 10.4248 D(x): 0.9997
    D(G(z)): 0.0014 / 0.0012
[797/1000][20/42]    Loss_D: 0.0021  Loss_G: 10.1665 D(x): 0.9997
    D(G(z)): 0.0018 / 0.0019
[797/1000][40/42]    Loss_D: 0.0014  Loss_G: 10.8364 D(x): 0.9997
    D(G(z)): 0.0012 / 0.0010
[798/1000][0/42]Loss_D: 0.0052  Loss_G: 10.9025 D(x): 0.9963
    D(G(z)): 0.0015 / 0.0014
[798/1000][20/42]    Loss_D: 0.0008  Loss_G: 11.3839 D(x): 0.9998
    D(G(z)): 0.0006 / 0.0006
[798/1000][40/42]    Loss_D: 0.0018  Loss_G: 10.0366 D(x): 0.9998
    D(G(z)): 0.0017 / 0.0017
[799/1000][0/42]Loss_D: 0.0033  Loss_G: 10.3526 D(x): 0.9997
    D(G(z)): 0.0029 / 0.0024
[799/1000][20/42]    Loss_D: 0.0013  Loss_G: 10.8324 D(x): 0.9992
    D(G(z)): 0.0005 / 0.0005
[799/1000][40/42]    Loss_D: 0.0042  Loss_G: 11.5375 D(x): 0.9980
    D(G(z)): 0.0021 / 0.0008
[800/1000][0/42]Loss_D: 0.0013  Loss_G: 12.2698 D(x): 0.9989
    D(G(z)): 0.0002 / 0.0002
[800/1000][20/42]    Loss_D: 0.0006  Loss_G: 12.3994 D(x): 0.9995
    D(G(z)): 0.0001 / 0.0001
[800/1000][40/42]    Loss_D: 0.0621  Loss_G: 11.6424 D(x): 0.9675
    D(G(z)): 0.0002 / 0.0007
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[801/1000][0/42] Loss_D: 0.0044  Loss_G: 10.8627 D(x): 0.9996
      D(G(z)): 0.0039 / 0.0117
[801/1000][20/42]     Loss_D: 0.0072  Loss_G: 8.3047  D(x): 0.9999
      D(G(z)): 0.0064 / 0.0228
[801/1000][40/42]     Loss_D: 0.0363  Loss_G: 15.2020 D(x): 0.9716
      D(G(z)): 0.0013 / 0.0010
[802/1000][0/42] Loss_D: 0.0603  Loss_G: 14.0455 D(x): 0.9604
      D(G(z)): 0.0042 / 0.0040
[802/1000][20/42]     Loss_D: 0.0152  Loss_G: 13.1437 D(x): 0.9879
      D(G(z)): 0.0006 / 0.0007
[802/1000][40/42]     Loss_D: 0.0101  Loss_G: 12.2179 D(x): 0.9945
      D(G(z)): 0.0040 / 0.0027
[803/1000][0/42] Loss_D: 0.0340  Loss_G: 14.8701 D(x): 0.9965
      D(G(z)): 0.0166 / 0.0002
[803/1000][20/42]     Loss_D: 0.6419  Loss_G: 11.5356 D(x): 0.9999
      D(G(z)): 0.1493 / 0.0004
[803/1000][40/42]     Loss_D: 0.0013  Loss_G: 11.0104 D(x): 0.9994
      D(G(z)): 0.0007 / 0.0016
[804/1000][0/42] Loss_D: 0.0103  Loss_G: 11.5065 D(x): 0.9996
      D(G(z)): 0.0096 / 0.0080
[804/1000][20/42]     Loss_D: 0.0703  Loss_G: 13.4633 D(x): 0.9996
      D(G(z)): 0.0213 / 0.0008
[804/1000][40/42]     Loss_D: 0.0465  Loss_G: 11.3645 D(x): 0.9874
      D(G(z)): 0.0262 / 0.0146
[805/1000][0/42] Loss_D: 0.1100  Loss_G: 13.5626 D(x): 0.9852
      D(G(z)): 0.0336 / 0.0026
[805/1000][20/42]     Loss_D: 0.0115  Loss_G: 18.0101 D(x): 0.9890
      D(G(z)): 0.0002 / 0.0001
[805/1000][40/42]     Loss_D: 0.1442  Loss_G: 14.4147 D(x): 0.9996
      D(G(z)): 0.0348 / 0.0122
[806/1000][0/42] Loss_D: 0.0960  Loss_G: 14.0631 D(x): 0.9846
      D(G(z)): 0.0219 / 0.0011
[806/1000][20/42]     Loss_D: 0.0181  Loss_G: 9.1242  D(x): 0.9995
      D(G(z)): 0.0143 / 0.0344
[806/1000][40/42]     Loss_D: 0.0569  Loss_G: 13.1967 D(x): 0.9963
      D(G(z)): 0.0284 / 0.0004
[807/1000][0/42] Loss_D: 0.0010  Loss_G: 17.3364 D(x): 0.9995
      D(G(z)): 0.0005 / 0.0003
[807/1000][20/42]     Loss_D: 0.2357  Loss_G: 14.0679 D(x): 0.9994
      D(G(z)): 0.0758 / 0.0027
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[807/1000][40/42] Loss_D: 0.1251 Loss_G: 16.7983 D(x): 0.9498 D(G(z)): 0.0010 / 0.0001
[808/1000][0/42] Loss_D: 0.0651 Loss_G: 17.8787 D(x): 0.9528 D(G(z)): 0.0000 / 0.0000
[808/1000][20/42] Loss_D: 0.0344 Loss_G: 14.9915 D(x): 0.9969 D(G(z)): 0.0240 / 0.0008
[808/1000][40/42] Loss_D: 0.0230 Loss_G: 17.5626 D(x): 0.9883 D(G(z)): 0.0078 / 0.0000
[809/1000][0/42] Loss_D: 0.0256 Loss_G: 18.9244 D(x): 0.9772 D(G(z)): 0.0001 / 0.0001
[809/1000][20/42] Loss_D: 0.0917 Loss_G: 13.5944 D(x): 0.9536 D(G(z)): 0.0020 / 0.0014
[809/1000][40/42] Loss_D: 0.0087 Loss_G: 12.9882 D(x): 0.9977 D(G(z)): 0.0059 / 0.0031
[810/1000][0/42] Loss_D: 0.0122 Loss_G: 12.6377 D(x): 0.9976 D(G(z)): 0.0093 / 0.0024
[810/1000][20/42] Loss_D: 0.0302 Loss_G: 13.5465 D(x): 0.9868 D(G(z)): 0.0108 / 0.0016
[810/1000][40/42] Loss_D: 0.0019 Loss_G: 11.3798 D(x): 0.9999 D(G(z)): 0.0018 / 0.0006

[811/1000][0/42] Loss_D: 0.0056 Loss_G: 14.4046 D(x): 0.9993 D(G(z)): 0.0046 / 0.0012
[811/1000][20/42] Loss_D: 0.0087 Loss_G: 11.7638 D(x): 0.9968 D(G(z)): 0.0049 / 0.0015
[811/1000][40/42] Loss_D: 0.0380 Loss_G: 10.4366 D(x): 0.9702 D(G(z)): 0.0007 / 0.0008
[812/1000][0/42] Loss_D: 0.0058 Loss_G: 9.8698 D(x): 0.9991 D(G(z)): 0.0047 / 0.0051
[812/1000][20/42] Loss_D: 0.0024 Loss_G: 14.2407 D(x): 0.9981 D(G(z)): 0.0004 / 0.0002
[812/1000][40/42] Loss_D: 0.2151 Loss_G: 7.8873 D(x): 1.0000 D(G(z)): 0.1189 / 0.0369
[813/1000][0/42] Loss_D: 0.1141 Loss_G: 12.3197 D(x): 0.9993 D(G(z)): 0.0468 / 0.0028
[813/1000][20/42] Loss_D: 0.0044 Loss_G: 9.3668 D(x): 1.0000 D(G(z)): 0.0042 / 0.0113
[813/1000][40/42] Loss_D: 0.0109 Loss_G: 11.6600 D(x): 0.9999 D(G(z)): 0.0092 / 0.0015
[814/1000][0/42] Loss_D: 0.0079 Loss_G: 13.0940 D(x): 0.9925

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      D(G(z)): 0.0002 / 0.0001
[814/1000][20/42]     Loss_D: 0.0375  Loss_G: 12.5022 D(x): 0.9994
      D(G(z)): 0.0205 / 0.0021
[814/1000][40/42]     Loss_D: 0.1727  Loss_G: 8.7794  D(x): 1.0000
      D(G(z)): 0.0788 / 0.0044
[815/1000][0/42]Loss_D: 0.0038  Loss_G: 14.0500 D(x): 0.9992
      D(G(z)): 0.0029 / 0.0003
[815/1000][20/42]     Loss_D: 0.0376  Loss_G: 9.9787  D(x): 0.9777
      D(G(z)): 0.0060 / 0.0051
[815/1000][40/42]     Loss_D: 0.0098  Loss_G: 12.6450 D(x): 0.9960
      D(G(z)): 0.0054 / 0.0006
[816/1000][0/42]Loss_D: 0.0062  Loss_G: 16.9249 D(x): 0.9942
      D(G(z)): 0.0001 / 0.0000
[816/1000][20/42]     Loss_D: 0.2465  Loss_G: 16.0518 D(x): 0.9193
      D(G(z)): 0.0017 / 0.0054
[816/1000][40/42]     Loss_D: 0.0936  Loss_G: 14.4594 D(x): 0.9787
      D(G(z)): 0.0076 / 0.0008
[817/1000][0/42]Loss_D: 0.0044  Loss_G: 15.0620 D(x): 0.9995
      D(G(z)): 0.0037 / 0.0020
[817/1000][20/42]     Loss_D: 0.1892  Loss_G: 16.4233 D(x): 0.9112
      D(G(z)): 0.0001 / 0.0002
[817/1000][40/42]     Loss_D: 0.0104  Loss_G: 13.1521 D(x): 0.9992
      D(G(z)): 0.0081 / 0.0012
[818/1000][0/42]Loss_D: 0.0285  Loss_G: 11.3372 D(x): 0.9805
      D(G(z)): 0.0037 / 0.0061
[818/1000][20/42]     Loss_D: 0.0164  Loss_G: 9.7637  D(x): 0.9990
      D(G(z)): 0.0140 / 0.0043
[818/1000][40/42]     Loss_D: 0.0024  Loss_G: 12.3585 D(x): 0.9997
      D(G(z)): 0.0021 / 0.0008
[819/1000][0/42]Loss_D: 0.0008  Loss_G: 12.3079 D(x): 0.9996
      D(G(z)): 0.0004 / 0.0002
[819/1000][20/42]     Loss_D: 0.0067  Loss_G: 12.3994 D(x): 0.9945
      D(G(z)): 0.0011 / 0.0008
[819/1000][40/42]     Loss_D: 0.0028  Loss_G: 12.6015 D(x): 0.9976
      D(G(z)): 0.0004 / 0.0004
[820/1000][0/42]Loss_D: 0.0030  Loss_G: 12.8508 D(x): 0.9975
      D(G(z)): 0.0005 / 0.0004
[820/1000][20/42]     Loss_D: 0.0071  Loss_G: 10.6452 D(x): 0.9946
      D(G(z)): 0.0014 / 0.0007
[820/1000][40/42]     Loss_D: 0.0019  Loss_G: 11.8496 D(x): 0.9982
      D(G(z)): 0.0001 / 0.0001
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[821/1000][0/42] Loss_D: 0.0032  Loss_G: 9.5655  D(x): 0.9997
      D(G(z)): 0.0028 / 0.0022
[821/1000][20/42]     Loss_D: 0.0018  Loss_G: 11.6779 D(x): 0.9988
      D(G(z)): 0.0006 / 0.0006
[821/1000][40/42]     Loss_D: 0.0019  Loss_G: 11.4384 D(x): 0.9994
      D(G(z)): 0.0013 / 0.0010
[822/1000][0/42] Loss_D: 0.0012  Loss_G: 10.8459 D(x): 0.9995
      D(G(z)): 0.0007 / 0.0006
[822/1000][20/42]     Loss_D: 0.0063  Loss_G: 11.3271 D(x): 0.9954
      D(G(z)): 0.0016 / 0.0015
[822/1000][40/42]     Loss_D: 0.0052  Loss_G: 9.0497  D(x): 0.9998
      D(G(z)): 0.0049 / 0.0047
[823/1000][0/42] Loss_D: 0.0063  Loss_G: 10.0956 D(x): 0.9999
      D(G(z)): 0.0059 / 0.0049
[823/1000][20/42]     Loss_D: 0.0021  Loss_G: 10.1835 D(x): 0.9990
      D(G(z)): 0.0011 / 0.0012
[823/1000][40/42]     Loss_D: 0.0067  Loss_G: 9.9622  D(x): 0.9986
      D(G(z)): 0.0051 / 0.0053
[824/1000][0/42] Loss_D: 0.0034  Loss_G: 10.2511 D(x): 0.9999
      D(G(z)): 0.0032 / 0.0022
[824/1000][20/42]     Loss_D: 0.0036  Loss_G: 10.2353 D(x): 0.9999
      D(G(z)): 0.0034 / 0.0021
[824/1000][40/42]     Loss_D: 0.0202  Loss_G: 11.1233 D(x): 0.9829
      D(G(z)): 0.0006 / 0.0006
[825/1000][0/42] Loss_D: 0.0168  Loss_G: 11.1158 D(x): 0.9863
      D(G(z)): 0.0013 / 0.0015
[825/1000][20/42]     Loss_D: 0.0031  Loss_G: 11.4431 D(x): 0.9980
      D(G(z)): 0.0011 / 0.0008
[825/1000][40/42]     Loss_D: 0.0043  Loss_G: 10.7351 D(x): 0.9980
      D(G(z)): 0.0022 / 0.0015
[826/1000][0/42] Loss_D: 0.0041  Loss_G: 12.4397 D(x): 0.9994
      D(G(z)): 0.0035 / 0.0021
[826/1000][20/42]     Loss_D: 0.0026  Loss_G: 10.7967 D(x): 0.9997
      D(G(z)): 0.0023 / 0.0037
[826/1000][40/42]     Loss_D: 0.0155  Loss_G: 10.5915 D(x): 0.9914
      D(G(z)): 0.0060 / 0.0039
[827/1000][0/42] Loss_D: 0.0030  Loss_G: 10.3368 D(x): 0.9992
      D(G(z)): 0.0022 / 0.0022
[827/1000][20/42]     Loss_D: 0.0178  Loss_G: 10.9135 D(x): 0.9836
      D(G(z)): 0.0005 / 0.0008
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[827/1000][40/42]	Loss_D: 0.0065	Loss_G: 10.1563	D(x): 0.9974
	D(G(z)): 0.0037 / 0.0029
[828/1000][0/42]	Loss_D: 0.0019	Loss_G: 10.5010	D(x): 0.9993
	D(G(z)): 0.0012 / 0.0014
[828/1000][20/42]	Loss_D: 0.0035	Loss_G: 12.6666	D(x): 0.9969
	D(G(z)): 0.0002 / 0.0004
[828/1000][40/42]	Loss_D: 0.0044	Loss_G: 12.7166	D(x): 0.9994
	D(G(z)): 0.0035 / 0.0011
[829/1000][0/42]	Loss_D: 0.0024	Loss_G: 11.2773	D(x): 0.9997
	D(G(z)): 0.0021 / 0.0008
[829/1000][20/42]	Loss_D: 0.0030	Loss_G: 12.0372	D(x): 0.9994
	D(G(z)): 0.0024 / 0.0013
[829/1000][40/42]	Loss_D: 0.0019	Loss_G: 11.9411	D(x): 0.9988
	D(G(z)): 0.0007 / 0.0005
[830/1000][0/42]	Loss_D: 0.0018	Loss_G: 11.5909	D(x): 1.0000
	D(G(z)): 0.0017 / 0.0013
[830/1000][20/42]	Loss_D: 0.0106	Loss_G: 13.0872	D(x): 0.9981
	D(G(z)): 0.0075 / 0.0013
[830/1000][40/42]	Loss_D: 0.0015	Loss_G: 11.4457	D(x): 0.9987
	D(G(z)): 0.0002 / 0.0003
```

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[831/1000][0/42]	Loss_D: 0.0064	Loss_G: 12.0610	D(x): 0.9947
	D(G(z)): 0.0008 / 0.0009
[831/1000][20/42]	Loss_D: 0.0087	Loss_G: 12.7457	D(x): 0.9930
	D(G(z)): 0.0015 / 0.0009
[831/1000][40/42]	Loss_D: 0.0351	Loss_G: 14.2388	D(x): 0.9699
	D(G(z)): 0.0000 / 0.0000
[832/1000][0/42]	Loss_D: 0.0186	Loss_G: 11.3530	D(x): 0.9858
	D(G(z)): 0.0020 / 0.0039
[832/1000][20/42]	Loss_D: 0.0044	Loss_G: 11.5928	D(x): 0.9985
	D(G(z)): 0.0028 / 0.0028
[832/1000][40/42]	Loss_D: 0.0032	Loss_G: 11.2524	D(x): 0.9997
	D(G(z)): 0.0028 / 0.0029
[833/1000][0/42]	Loss_D: 0.0341	Loss_G: 11.4268	D(x): 0.9787
	D(G(z)): 0.0012 / 0.0015
[833/1000][20/42]	Loss_D: 0.0116	Loss_G: 10.4044	D(x): 0.9935
	D(G(z)): 0.0038 / 0.0030
[833/1000][40/42]	Loss_D: 0.0009	Loss_G: 11.7529	D(x): 0.9996
	D(G(z)): 0.0005 / 0.0008
[834/1000][0/42]	Loss_D: 0.0131	Loss_G: 10.1618	D(x): 0.9998
```

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D(G(z)): 0.0110 / 0.0080
[834/1000][20/42]	Loss_D: 0.0220	Loss_G: 14.6551	D(x): 0.9809
	D(G(z)): 0.0002 / 0.0002
[834/1000][40/42]	Loss_D: 0.0704	Loss_G: 12.3786	D(x): 0.9562
	D(G(z)): 0.0002 / 0.0008
[835/1000][0/42]	Loss_D: 0.0719	Loss_G: 10.6817	D(x): 0.9990
	D(G(z)): 0.0244 / 0.0084
[835/1000][20/42]	Loss_D: 0.0580	Loss_G: 13.4127	D(x): 0.9789
	D(G(z)): 0.0058 / 0.0017
[835/1000][40/42]	Loss_D: 0.0488	Loss_G: 11.2441	D(x): 0.9990
	D(G(z)): 0.0287 / 0.0042
[836/1000][0/42]	Loss_D: 0.0651	Loss_G: 14.5273	D(x): 0.9998
	D(G(z)): 0.0211 / 0.0004
[836/1000][20/42]	Loss_D: 0.0193	Loss_G: 14.7277	D(x): 0.9914
	D(G(z)): 0.0085 / 0.0031
[836/1000][40/42]	Loss_D: 0.0391	Loss_G: 11.3548	D(x): 0.9861
	D(G(z)): 0.0193 / 0.0028
[837/1000][0/42]	Loss_D: 0.0091	Loss_G: 14.9682	D(x): 0.9919
	D(G(z)): 0.0003 / 0.0003
[837/1000][20/42]	Loss_D: 0.0160	Loss_G: 11.6899	D(x): 0.9951
	D(G(z)): 0.0099 / 0.0083
[837/1000][40/42]	Loss_D: 0.0029	Loss_G: 12.3117	D(x): 0.9996
	D(G(z)): 0.0024 / 0.0011
[838/1000][0/42]	Loss_D: 0.0034	Loss_G: 15.2039	D(x): 0.9971
	D(G(z)): 0.0005 / 0.0005
[838/1000][20/42]	Loss_D: 0.0227	Loss_G: 11.5278	D(x): 0.9843
	D(G(z)): 0.0053 / 0.0025
[838/1000][40/42]	Loss_D: 0.0034	Loss_G: 9.5088	D(x): 0.9999
	D(G(z)): 0.0032 / 0.0078
[839/1000][0/42]	Loss_D: 0.0844	Loss_G: 9.3616	D(x): 1.0000
	D(G(z)): 0.0640 / 0.0100
[839/1000][20/42]	Loss_D: 0.0082	Loss_G: 13.3720	D(x): 0.9932
	D(G(z)): 0.0008 / 0.0007
[839/1000][40/42]	Loss_D: 0.0055	Loss_G: 12.5820	D(x): 0.9984
	D(G(z)): 0.0038 / 0.0014
[840/1000][0/42]	Loss_D: 0.0350	Loss_G: 13.1123	D(x): 0.9741
	D(G(z)): 0.0006 / 0.0006
[840/1000][20/42]	Loss_D: 0.0873	Loss_G: 11.3677	D(x): 0.9685
	D(G(z)): 0.0169 / 0.0040
[840/1000][40/42]	Loss_D: 0.0030	Loss_G: 12.8406	D(x): 0.9993
	D(G(z)): 0.0022 / 0.0020
```

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[841/1000][0/42] Loss_D: 0.0356  Loss_G: 10.2175 D(x): 0.9953
      D(G(z)): 0.0244 / 0.0025
[841/1000][20/42]    Loss_D: 0.0010  Loss_G: 13.5411 D(x): 0.9991
      D(G(z)): 0.0001 / 0.0001
[841/1000][40/42]    Loss_D: 0.0069  Loss_G: 11.1148 D(x): 0.9999
      D(G(z)): 0.0061 / 0.0024
[842/1000][0/42] Loss_D: 0.0043  Loss_G: 11.3657 D(x): 0.9962
      D(G(z)): 0.0005 / 0.0004
[842/1000][20/42]    Loss_D: 0.0406  Loss_G: 10.4554 D(x): 0.9998
      D(G(z)): 0.0187 / 0.0034
[842/1000][40/42]    Loss_D: 0.0215  Loss_G: 9.5472  D(x): 0.9995
      D(G(z)): 0.0176 / 0.0093
[843/1000][0/42] Loss_D: 0.0366  Loss_G: 9.2532  D(x): 0.9993
      D(G(z)): 0.0285 / 0.0051
[843/1000][20/42]    Loss_D: 0.0187  Loss_G: 15.2969 D(x): 0.9923
      D(G(z)): 0.0090 / 0.0016
[843/1000][40/42]    Loss_D: 0.0143  Loss_G: 12.3955 D(x): 0.9965
      D(G(z)): 0.0099 / 0.0006
[844/1000][0/42] Loss_D: 0.0172  Loss_G: 12.4382 D(x): 0.9952
      D(G(z)): 0.0101 / 0.0019
[844/1000][20/42]    Loss_D: 0.0069  Loss_G: 14.0867 D(x): 0.9959
      D(G(z)): 0.0026 / 0.0009
[844/1000][40/42]    Loss_D: 0.0792  Loss_G: 14.7549 D(x): 0.9555
      D(G(z)): 0.0024 / 0.0026
[845/1000][0/42] Loss_D: 0.0136  Loss_G: 13.7988 D(x): 0.9974
      D(G(z)): 0.0099 / 0.0044
[845/1000][20/42]    Loss_D: 0.1614  Loss_G: 10.8962 D(x): 0.9542
      D(G(z)): 0.0020 / 0.0109
[845/1000][40/42]    Loss_D: 0.0496  Loss_G: 15.1424 D(x): 0.9741
      D(G(z)): 0.0107 / 0.0005
[846/1000][0/42] Loss_D: 0.0270  Loss_G: 13.7258 D(x): 0.9966
      D(G(z)): 0.0145 / 0.0029
[846/1000][20/42]    Loss_D: 0.7235  Loss_G: 11.1636 D(x): 0.7394
      D(G(z)): 0.0073 / 0.0167
[846/1000][40/42]    Loss_D: 0.0162  Loss_G: 14.8370 D(x): 0.9873
      D(G(z)): 0.0004 / 0.0090
[847/1000][0/42] Loss_D: 0.1783  Loss_G: 10.8124 D(x): 0.9996
      D(G(z)): 0.0675 / 0.0290
[847/1000][20/42]    Loss_D: 0.1717  Loss_G: 13.2251 D(x): 0.9810
      D(G(z)): 0.0787 / 0.0078
```

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[847/1000][40/42]     Loss_D: 0.0099  Loss_G: 13.0869 D(x): 0.9999
      D(G(z)): 0.0090 / 0.0078
[848/1000][0/42] Loss_D: 0.0797  Loss_G: 10.4254 D(x): 1.0000
      D(G(z)): 0.0452 / 0.0105
[848/1000][20/42]     Loss_D: 0.0437  Loss_G: 14.1537 D(x): 0.9774
      D(G(z)): 0.0080 / 0.0034
[848/1000][40/42]     Loss_D: 0.0461  Loss_G: 13.6852 D(x): 0.9670
      D(G(z)): 0.0004 / 0.0010
[849/1000][0/42] Loss_D: 0.0071  Loss_G: 13.6648 D(x): 0.9975
      D(G(z)): 0.0043 / 0.0033
[849/1000][20/42]     Loss_D: 0.0030  Loss_G: 13.1524 D(x): 0.9999
      D(G(z)): 0.0028 / 0.0003
[849/1000][40/42]     Loss_D: 0.0184  Loss_G: 13.4942 D(x): 0.9902
      D(G(z)): 0.0058 / 0.0015
[850/1000][0/42] Loss_D: 0.0070  Loss_G: 12.5901 D(x): 0.9972
      D(G(z)): 0.0038 / 0.0013
[850/1000][20/42]     Loss_D: 0.0302  Loss_G: 9.7015  D(x): 0.9856
      D(G(z)): 0.0119 / 0.0078
[850/1000][40/42]     Loss_D: 0.0042  Loss_G: 11.1990 D(x): 0.9976
      D(G(z)): 0.0018 / 0.0021
```

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[851/1000][0/42] Loss_D: 0.0106  Loss_G: 9.3150  D(x): 0.9994
      D(G(z)): 0.0094 / 0.0065
[851/1000][20/42]     Loss_D: 0.0051  Loss_G: 9.9339  D(x): 0.9990
      D(G(z)): 0.0039 / 0.0033
[851/1000][40/42]     Loss_D: 0.0124  Loss_G: 10.0978 D(x): 0.9988
      D(G(z)): 0.0095 / 0.0031
[852/1000][0/42] Loss_D: 0.0112  Loss_G: 11.9947 D(x): 0.9993
      D(G(z)): 0.0096 / 0.0035
[852/1000][20/42]     Loss_D: 0.0047  Loss_G: 13.5966 D(x): 0.9978
      D(G(z)): 0.0024 / 0.0013
[852/1000][40/42]     Loss_D: 0.0056  Loss_G: 12.0634 D(x): 0.9951
      D(G(z)): 0.0003 / 0.0003
[853/1000][0/42] Loss_D: 0.0039  Loss_G: 12.5231 D(x): 0.9972
      D(G(z)): 0.0011 / 0.0009
[853/1000][20/42]     Loss_D: 0.0040  Loss_G: 14.5749 D(x): 0.9966
      D(G(z)): 0.0004 / 0.0003
[853/1000][40/42]     Loss_D: 0.0238  Loss_G: 14.5937 D(x): 0.9819
      D(G(z)): 0.0028 / 0.0017
[854/1000][0/42] Loss_D: 0.0394  Loss_G: 13.6833 D(x): 0.9672
```

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    D(G(z)): 0.0007 / 0.0006
[854/1000][20/42]    Loss_D: 0.0053  Loss_G: 8.9286  D(x): 0.9974
    D(G(z)): 0.0027 / 0.0025
[854/1000][40/42]    Loss_D: 0.0056  Loss_G: 9.4133  D(x): 0.9996
    D(G(z)): 0.0049 / 0.0075
[855/1000][0/42] Loss_D: 0.0078  Loss_G: 8.7522  D(x): 0.9999
    D(G(z)): 0.0075 / 0.0081
[855/1000][20/42]    Loss_D: 0.0270  Loss_G: 11.6154 D(x): 0.9981
    D(G(z)): 0.0170 / 0.0010
[855/1000][40/42]    Loss_D: 0.0375  Loss_G: 13.4941 D(x): 0.9767
    D(G(z)): 0.0006 / 0.0005
[856/1000][0/42] Loss_D: 0.0009  Loss_G: 14.3749 D(x): 0.9996
    D(G(z)): 0.0006 / 0.0005
[856/1000][20/42]    Loss_D: 0.0032  Loss_G: 12.5811 D(x): 0.9984
    D(G(z)): 0.0015 / 0.0004
[856/1000][40/42]    Loss_D: 0.0013  Loss_G: 12.2079 D(x): 0.9992
    D(G(z)): 0.0005 / 0.0004
[857/1000][0/42] Loss_D: 0.0028  Loss_G: 11.4220 D(x): 0.9997
    D(G(z)): 0.0024 / 0.0017
[857/1000][20/42]    Loss_D: 0.0066  Loss_G: 11.4912 D(x): 0.9943
    D(G(z)): 0.0008 / 0.0008
[857/1000][40/42]    Loss_D: 0.0021  Loss_G: 10.3032 D(x): 0.9997
    D(G(z)): 0.0018 / 0.0017
[858/1000][0/42] Loss_D: 0.0016  Loss_G: 10.3695 D(x): 0.9999
    D(G(z)): 0.0014 / 0.0012
[858/1000][20/42]    Loss_D: 0.0061  Loss_G: 12.6289 D(x): 0.9956
    D(G(z)): 0.0014 / 0.0008
[858/1000][40/42]    Loss_D: 0.0023  Loss_G: 12.7930 D(x): 0.9991
    D(G(z)): 0.0014 / 0.0010
[859/1000][0/42] Loss_D: 0.0242  Loss_G: 13.8554 D(x): 0.9808
    D(G(z)): 0.0004 / 0.0005
[859/1000][20/42]    Loss_D: 0.0574  Loss_G: 12.4154 D(x): 0.9987
    D(G(z)): 0.0192 / 0.0093
[859/1000][40/42]    Loss_D: 0.0131  Loss_G: 10.2601 D(x): 0.9995
    D(G(z)): 0.0119 / 0.0078
[860/1000][0/42] Loss_D: 0.0007  Loss_G: 12.6178 D(x): 0.9999
    D(G(z)): 0.0006 / 0.0004
[860/1000][20/42]    Loss_D: 0.0057  Loss_G: 10.6054 D(x): 0.9990
    D(G(z)): 0.0046 / 0.0027
[860/1000][40/42]    Loss_D: 0.0035  Loss_G: 11.1707 D(x): 0.9970
    D(G(z)): 0.0006 / 0.0005
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[861/1000][0/42] Loss_D: 0.0036  Loss_G: 11.2700 D(x): 0.9968
      D(G(z)): 0.0004 / 0.0004
[861/1000][20/42]     Loss_D: 0.0230  Loss_G: 8.6100  D(x): 0.9836
      D(G(z)): 0.0031 / 0.0046
[861/1000][40/42]     Loss_D: 0.0017  Loss_G: 14.3048 D(x): 0.9987
      D(G(z)): 0.0004 / 0.0001
[862/1000][0/42] Loss_D: 0.0914  Loss_G: 13.1419 D(x): 0.9315
      D(G(z)): 0.0002 / 0.0004
[862/1000][20/42]     Loss_D: 0.0198  Loss_G: 10.3816 D(x): 0.9994
      D(G(z)): 0.0178 / 0.0075
[862/1000][40/42]     Loss_D: 0.0045  Loss_G: 10.8771 D(x): 0.9975
      D(G(z)): 0.0019 / 0.0013
[863/1000][0/42] Loss_D: 0.0037  Loss_G: 11.7331 D(x): 0.9997
      D(G(z)): 0.0032 / 0.0013
[863/1000][20/42]     Loss_D: 0.0023  Loss_G: 11.2531 D(x): 0.9999
      D(G(z)): 0.0022 / 0.0018
[863/1000][40/42]     Loss_D: 0.0018  Loss_G: 12.1902 D(x): 0.9987
      D(G(z)): 0.0005 / 0.0007
[864/1000][0/42] Loss_D: 0.0228  Loss_G: 9.9692  D(x): 0.9998
      D(G(z)): 0.0196 / 0.0075
[864/1000][20/42]     Loss_D: 0.0041  Loss_G: 15.2932 D(x): 0.9961
      D(G(z)): 0.0001 / 0.0002
[864/1000][40/42]     Loss_D: 0.0530  Loss_G: 9.7588  D(x): 0.9762
      D(G(z)): 0.0120 / 0.0065
[865/1000][0/42] Loss_D: 0.0018  Loss_G: 11.0418 D(x): 0.9992
      D(G(z)): 0.0010 / 0.0008
[865/1000][20/42]     Loss_D: 0.0032  Loss_G: 12.3275 D(x): 0.9986
      D(G(z)): 0.0017 / 0.0011
[865/1000][40/42]     Loss_D: 0.0011  Loss_G: 12.2212 D(x): 0.9992
      D(G(z)): 0.0002 / 0.0002
[866/1000][0/42] Loss_D: 0.0010  Loss_G: 12.1667 D(x): 0.9999
      D(G(z)): 0.0009 / 0.0009
[866/1000][20/42]     Loss_D: 0.0024  Loss_G: 11.6742 D(x): 0.9999
      D(G(z)): 0.0022 / 0.0028
[866/1000][40/42]     Loss_D: 0.0048  Loss_G: 10.7767 D(x): 1.0000
      D(G(z)): 0.0047 / 0.0029
[867/1000][0/42] Loss_D: 0.0047  Loss_G: 11.7519 D(x): 0.9996
      D(G(z)): 0.0042 / 0.0027
[867/1000][20/42]     Loss_D: 0.0016  Loss_G: 11.7332 D(x): 0.9997
      D(G(z)): 0.0013 / 0.0014
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[867/1000][40/42]	Loss_D: 0.0124	Loss_G: 10.1222	D(x): 0.9917
	D(G(z)): 0.0035 / 0.0016
[868/1000][0/42]	Loss_D: 0.0035	Loss_G: 10.5052	D(x): 0.9984
	D(G(z)): 0.0019 / 0.0021
[868/1000][20/42]	Loss_D: 0.0012	Loss_G: 11.4188	D(x): 0.9992
	D(G(z)): 0.0005 / 0.0004
[868/1000][40/42]	Loss_D: 0.0201	Loss_G: 10.7893	D(x): 0.9904
	D(G(z)): 0.0083 / 0.0012
[869/1000][0/42]	Loss_D: 0.0057	Loss_G: 11.0812	D(x): 0.9953
	D(G(z)): 0.0009 / 0.0008
[869/1000][20/42]	Loss_D: 0.0027	Loss_G: 11.2960	D(x): 0.9987
	D(G(z)): 0.0014 / 0.0021
[869/1000][40/42]	Loss_D: 0.0037	Loss_G: 12.7788	D(x): 0.9969
	D(G(z)): 0.0005 / 0.0007
[870/1000][0/42]	Loss_D: 0.0043	Loss_G: 11.7433	D(x): 0.9959
	D(G(z)): 0.0001 / 0.0002
[870/1000][20/42]	Loss_D: 0.0030	Loss_G: 10.9037	D(x): 0.9999
	D(G(z)): 0.0029 / 0.0011
[870/1000][40/42]	Loss_D: 0.0034	Loss_G: 12.9830	D(x): 0.9983
	D(G(z)): 0.0017 / 0.0016
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[871/1000][0/42]	Loss_D: 0.0038	Loss_G: 13.2502	D(x): 0.9989
	D(G(z)): 0.0027 / 0.0026
[871/1000][20/42]	Loss_D: 0.0009	Loss_G: 12.9543	D(x): 0.9997
	D(G(z)): 0.0006 / 0.0005
[871/1000][40/42]	Loss_D: 0.0018	Loss_G: 14.3300	D(x): 0.9990
	D(G(z)): 0.0008 / 0.0002
[872/1000][0/42]	Loss_D: 0.0794	Loss_G: 12.9581	D(x): 0.9536
	D(G(z)): 0.0002 / 0.0009
[872/1000][20/42]	Loss_D: 0.0036	Loss_G: 10.9476	D(x): 0.9975
	D(G(z)): 0.0010 / 0.0063
[872/1000][40/42]	Loss_D: 0.1000	Loss_G: 12.2477	D(x): 0.9991
	D(G(z)): 0.0419 / 0.0062
[873/1000][0/42]	Loss_D: 0.0172	Loss_G: 14.7587	D(x): 0.9861
	D(G(z)): 0.0002 / 0.0001
[873/1000][20/42]	Loss_D: 0.0014	Loss_G: 14.0049	D(x): 0.9998
	D(G(z)): 0.0011 / 0.0015
[873/1000][40/42]	Loss_D: 0.0585	Loss_G: 13.1026	D(x): 0.9570
	D(G(z)): 0.0004 / 0.0004
[874/1000][0/42]	Loss_D: 0.0008	Loss_G: 12.8730	D(x): 0.9994
```

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    D(G(z)): 0.0002 / 0.0003
[874/1000][20/42]    Loss_D: 0.0045  Loss_G: 9.5419  D(x): 0.9990
    D(G(z)): 0.0034 / 0.0055
[874/1000][40/42]    Loss_D: 0.0047  Loss_G: 13.3378 D(x): 0.9994
    D(G(z)): 0.0038 / 0.0010
[875/1000][0/42] Loss_D: 0.0038  Loss_G: 12.1648 D(x): 0.9984
    D(G(z)): 0.0021 / 0.0023
[875/1000][20/42]    Loss_D: 0.1008  Loss_G: 14.2844 D(x): 0.9779
    D(G(z)): 0.0001 / 0.0002
[875/1000][40/42]    Loss_D: 0.0260  Loss_G: 11.1251 D(x): 0.9999
    D(G(z)): 0.0164 / 0.0015
[876/1000][0/42] Loss_D: 0.0054  Loss_G: 11.3894 D(x): 0.9988
    D(G(z)): 0.0040 / 0.0014
[876/1000][20/42]    Loss_D: 0.0191  Loss_G: 12.9969 D(x): 0.9994
    D(G(z)): 0.0121 / 0.0001
[876/1000][40/42]    Loss_D: 0.0093  Loss_G: 10.8173 D(x): 0.9944
    D(G(z)): 0.0030 / 0.0040
[877/1000][0/42] Loss_D: 0.0320  Loss_G: 12.4177 D(x): 0.9996
    D(G(z)): 0.0192 / 0.0026
[877/1000][20/42]    Loss_D: 0.0024  Loss_G: 10.2237 D(x): 1.0000
    D(G(z)): 0.0024 / 0.0052
[877/1000][40/42]    Loss_D: 0.0062  Loss_G: 13.6913 D(x): 1.0000
    D(G(z)): 0.0059 / 0.0049
[878/1000][0/42] Loss_D: 0.0161  Loss_G: 14.2627 D(x): 0.9901
    D(G(z)): 0.0035 / 0.0042
[878/1000][20/42]    Loss_D: 0.0629  Loss_G: 17.1480 D(x): 0.9771
    D(G(z)): 0.0000 / 0.0001
[878/1000][40/42]    Loss_D: 0.0975  Loss_G: 14.2294 D(x): 0.9719
    D(G(z)): 0.0206 / 0.0042
[879/1000][0/42] Loss_D: 0.0133  Loss_G: 14.2645 D(x): 0.9985
    D(G(z)): 0.0111 / 0.0110
[879/1000][20/42]    Loss_D: 0.0773  Loss_G: 9.4608  D(x): 0.9998
    D(G(z)): 0.0458 / 0.0085
[879/1000][40/42]    Loss_D: 0.0598  Loss_G: 12.8687 D(x): 0.9778
    D(G(z)): 0.0145 / 0.0026
[880/1000][0/42] Loss_D: 0.0823  Loss_G: 11.6500 D(x): 0.9939
    D(G(z)): 0.0360 / 0.0064
[880/1000][20/42]    Loss_D: 0.0141  Loss_G: 20.7312 D(x): 0.9898
    D(G(z)): 0.0032 / 0.0028
[880/1000][40/42]    Loss_D: 0.0030  Loss_G: 10.3804 D(x): 0.9997
    D(G(z)): 0.0026 / 0.0317
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[881/1000][0/42] Loss_D: 0.6830 Loss_G: 12.9457 D(x): 1.0000
D(G(z)): 0.1759 / 0.0147
[881/1000][20/42] Loss_D: 0.0767 Loss_G: 17.7653 D(x): 0.9986
D(G(z)): 0.0198 / 0.0001
[881/1000][40/42] Loss_D: 0.3911 Loss_G: 13.8454 D(x): 0.8798
D(G(z)): 0.0136 / 0.0012
[882/1000][0/42] Loss_D: 0.0236 Loss_G: 12.5053 D(x): 0.9997
D(G(z)): 0.0193 / 0.0104
[882/1000][20/42] Loss_D: 0.0379 Loss_G: 14.5884 D(x): 0.9970
D(G(z)): 0.0224 / 0.0007
[882/1000][40/42] Loss_D: 0.0250 Loss_G: 12.3170 D(x): 0.9999
D(G(z)): 0.0197 / 0.0023
[883/1000][0/42] Loss_D: 0.1088 Loss_G: 13.0724 D(x): 0.9958
D(G(z)): 0.0597 / 0.0007
[883/1000][20/42] Loss_D: 0.0175 Loss_G: 15.6827 D(x): 0.9856
D(G(z)): 0.0020 / 0.0005
[883/1000][40/42] Loss_D: 0.0043 Loss_G: 14.9804 D(x): 0.9993
D(G(z)): 0.0034 / 0.0009
[884/1000][0/42] Loss_D: 0.1413 Loss_G: 14.7364 D(x): 0.9413
D(G(z)): 0.0023 / 0.0031
[884/1000][20/42] Loss_D: 0.0027 Loss_G: 13.3898 D(x): 0.9994
D(G(z)): 0.0021 / 0.0013
[884/1000][40/42] Loss_D: 0.0046 Loss_G: 12.8667 D(x): 0.9966
D(G(z)): 0.0011 / 0.0014
[885/1000][0/42] Loss_D: 0.0052 Loss_G: 13.0192 D(x): 0.9965
D(G(z)): 0.0016 / 0.0009
[885/1000][20/42] Loss_D: 0.0052 Loss_G: 15.0211 D(x): 0.9957
D(G(z)): 0.0007 / 0.0003
[885/1000][40/42] Loss_D: 0.0492 Loss_G: 12.3713 D(x): 0.9997
D(G(z)): 0.0248 / 0.0044
[886/1000][0/42] Loss_D: 0.0593 Loss_G: 10.6100 D(x): 0.9995
D(G(z)): 0.0236 / 0.0093
[886/1000][20/42] Loss_D: 0.0051 Loss_G: 11.5371 D(x): 0.9961
D(G(z)): 0.0009 / 0.0010
[886/1000][40/42] Loss_D: 0.0115 Loss_G: 18.1386 D(x): 0.9892
D(G(z)): 0.0000 / 0.0000
[887/1000][0/42] Loss_D: 0.0169 Loss_G: 18.0550 D(x): 0.9849
D(G(z)): 0.0000 / 0.0000
[887/1000][20/42] Loss_D: 0.0401 Loss_G: 14.2495 D(x): 0.9735
D(G(z)): 0.0000 / 0.0000

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[887/1000][40/42]	Loss_D: 0.0005	Loss_G: 11.7605	D(x): 0.9999
	D(G(z)): 0.0004 / 0.0003
[888/1000][0/42]	Loss_D: 0.0101	Loss_G: 11.6862	D(x): 0.9996
	D(G(z)): 0.0083 / 0.0025
[888/1000][20/42]	Loss_D: 0.0030	Loss_G: 11.9756	D(x): 0.9988
	D(G(z)): 0.0018 / 0.0013
[888/1000][40/42]	Loss_D: 0.0286	Loss_G: 14.3191	D(x): 0.9784
	D(G(z)): 0.0007 / 0.0008
[889/1000][0/42]	Loss_D: 0.0013	Loss_G: 13.3767	D(x): 0.9993
	D(G(z)): 0.0006 / 0.0009
[889/1000][20/42]	Loss_D: 0.0040	Loss_G: 11.0917	D(x): 0.9994
	D(G(z)): 0.0033 / 0.0018
[889/1000][40/42]	Loss_D: 0.0082	Loss_G: 10.7661	D(x): 0.9989
	D(G(z)): 0.0068 / 0.0047
[890/1000][0/42]	Loss_D: 0.0009	Loss_G: 12.8319	D(x): 0.9996
	D(G(z)): 0.0004 / 0.0004
[890/1000][20/42]	Loss_D: 0.0060	Loss_G: 9.9302	D(x): 0.9996
	D(G(z)): 0.0054 / 0.0039
[890/1000][40/42]	Loss_D: 0.0084	Loss_G: 10.9968	D(x): 0.9987
	D(G(z)): 0.0067 / 0.0027
```

```
[891/1000][0/42]	Loss_D: 0.0114	Loss_G: 12.2690	D(x): 0.9983
	D(G(z)): 0.0086 / 0.0028
[891/1000][20/42]	Loss_D: 0.0054	Loss_G: 11.4820	D(x): 0.9964
	D(G(z)): 0.0017 / 0.0008
[891/1000][40/42]	Loss_D: 0.0376	Loss_G: 12.5271	D(x): 0.9719
	D(G(z)): 0.0054 / 0.0032
[892/1000][0/42]	Loss_D: 0.0007	Loss_G: 12.7499	D(x): 0.9994
	D(G(z)): 0.0001 / 0.0001
[892/1000][20/42]	Loss_D: 0.0019	Loss_G: 11.6472	D(x): 0.9997
	D(G(z)): 0.0016 / 0.0016
[892/1000][40/42]	Loss_D: 0.0065	Loss_G: 10.6559	D(x): 0.9992
	D(G(z)): 0.0056 / 0.0054
[893/1000][0/42]	Loss_D: 0.0030	Loss_G: 11.0880	D(x): 0.9999
	D(G(z)): 0.0029 / 0.0021
[893/1000][20/42]	Loss_D: 0.0005	Loss_G: 12.8154	D(x): 0.9998
	D(G(z)): 0.0003 / 0.0003
[893/1000][40/42]	Loss_D: 0.0023	Loss_G: 11.3595	D(x): 0.9985
	D(G(z)): 0.0008 / 0.0008
[894/1000][0/42]	Loss_D: 0.0137	Loss_G: 10.2984	D(x): 0.9987
```

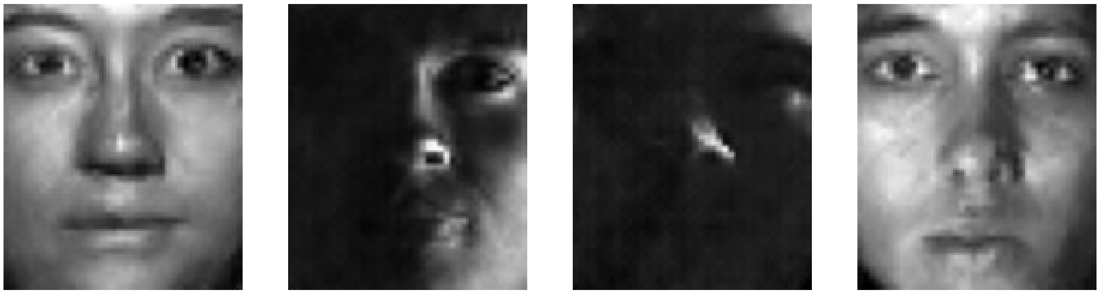
```
    D(G(z)): 0.0097 / 0.0023
[894/1000][20/42]    Loss_D: 0.0062  Loss_G: 11.3400 D(x): 0.9986
    D(G(z)): 0.0045 / 0.0027
[894/1000][40/42]    Loss_D: 0.0046  Loss_G: 11.6284 D(x): 0.9967
    D(G(z)): 0.0012 / 0.0012
[895/1000][0/42] Loss_D: 0.0056  Loss_G: 12.5741 D(x): 0.9947
    D(G(z)): 0.0001 / 0.0001
[895/1000][20/42]    Loss_D: 0.0030  Loss_G: 9.7701  D(x): 0.9985
    D(G(z)): 0.0015 / 0.0022
[895/1000][40/42]    Loss_D: 0.0020  Loss_G: 11.6211 D(x): 0.9982
    D(G(z)): 0.0001 / 0.0001
[896/1000][0/42] Loss_D: 0.0013  Loss_G: 12.2869 D(x): 0.9989
    D(G(z)): 0.0002 / 0.0002
[896/1000][20/42]    Loss_D: 0.0033  Loss_G: 10.8444 D(x): 0.9995
    D(G(z)): 0.0027 / 0.0022
[896/1000][40/42]    Loss_D: 0.0036  Loss_G: 10.2528 D(x): 0.9994
    D(G(z)): 0.0029 / 0.0018
[897/1000][0/42] Loss_D: 0.0019  Loss_G: 11.5531 D(x): 0.9999
    D(G(z)): 0.0017 / 0.0012
[897/1000][20/42]    Loss_D: 0.0024  Loss_G: 10.9546 D(x): 0.9988
    D(G(z)): 0.0012 / 0.0012
[897/1000][40/42]    Loss_D: 0.0039  Loss_G: 11.7252 D(x): 0.9990
    D(G(z)): 0.0027 / 0.0017
[898/1000][0/42] Loss_D: 0.0036  Loss_G: 11.3376 D(x): 0.9970
    D(G(z)): 0.0005 / 0.0005
[898/1000][20/42]    Loss_D: 0.0027  Loss_G: 9.4124  D(x): 0.9998
    D(G(z)): 0.0025 / 0.0021
[898/1000][40/42]    Loss_D: 0.0021  Loss_G: 14.7759 D(x): 0.9984
    D(G(z)): 0.0005 / 0.0005
[899/1000][0/42] Loss_D: 0.0081  Loss_G: 13.8236 D(x): 0.9931
    D(G(z)): 0.0005 / 0.0009
[899/1000][20/42]    Loss_D: 0.0052  Loss_G: 11.7260 D(x): 0.9996
    D(G(z)): 0.0047 / 0.0046
[899/1000][40/42]    Loss_D: 0.0016  Loss_G: 14.5986 D(x): 0.9986
    D(G(z)): 0.0001 / 0.0004
[900/1000][0/42] Loss_D: 0.0146  Loss_G: 10.2281 D(x): 0.9984
    D(G(z)): 0.0117 / 0.0127
[900/1000][20/42]    Loss_D: 0.0041  Loss_G: 12.0909 D(x): 0.9990
    D(G(z)): 0.0030 / 0.0021
[900/1000][40/42]    Loss_D: 0.0035  Loss_G: 14.3141 D(x): 0.9991
    D(G(z)): 0.0024 / 0.0007
```

```
[901/1000][0/42] Loss_D: 0.0021  Loss_G: 15.6489 D(x): 0.9986
     D(G(z)): 0.0006 / 0.0005
[901/1000][20/42]     Loss_D: 0.0058  Loss_G: 11.4579 D(x): 0.9949
     D(G(z)): 0.0006 / 0.0011
[901/1000][40/42]     Loss_D: 0.0069  Loss_G: 13.1015 D(x): 0.9968
     D(G(z)): 0.0036 / 0.0033
[902/1000][0/42] Loss_D: 0.0238  Loss_G: 11.6190 D(x): 0.9808
     D(G(z)): 0.0006 / 0.0015
[902/1000][20/42]     Loss_D: 0.0059  Loss_G: 15.0132 D(x): 0.9961
     D(G(z)): 0.0018 / 0.0006
[902/1000][40/42]     Loss_D: 0.0079  Loss_G: 12.5316 D(x): 0.9959
     D(G(z)): 0.0035 / 0.0057
[903/1000][0/42] Loss_D: 0.0269  Loss_G: 12.6399 D(x): 0.9883
     D(G(z)): 0.0121 / 0.0042
[903/1000][20/42]     Loss_D: 0.0019  Loss_G: 15.4072 D(x): 0.9994
     D(G(z)): 0.0013 / 0.0009
[903/1000][40/42]     Loss_D: 0.0137  Loss_G: 11.0810 D(x): 0.9971
     D(G(z)): 0.0101 / 0.0048
[904/1000][0/42] Loss_D: 0.0058  Loss_G: 10.5573 D(x): 0.9999
     D(G(z)): 0.0055 / 0.0064
[904/1000][20/42]     Loss_D: 0.0440  Loss_G: 9.0162  D(x): 0.9995
     D(G(z)): 0.0351 / 0.0063
[904/1000][40/42]     Loss_D: 0.0171  Loss_G: 14.0484 D(x): 0.9997
     D(G(z)): 0.0145 / 0.0026
[905/1000][0/42] Loss_D: 0.0018  Loss_G: 17.1223 D(x): 0.9987
     D(G(z)): 0.0005 / 0.0002
[905/1000][20/42]     Loss_D: 0.0748  Loss_G: 12.0066 D(x): 0.9957
     D(G(z)): 0.0323 / 0.0095
[905/1000][40/42]     Loss_D: 0.0393  Loss_G: 10.7669 D(x): 0.9874
     D(G(z)): 0.0176 / 0.0036
[906/1000][0/42] Loss_D: 0.0018  Loss_G: 12.0992 D(x): 0.9991
     D(G(z)): 0.0009 / 0.0006
[906/1000][20/42]     Loss_D: 0.0005  Loss_G: 14.4930 D(x): 0.9996
     D(G(z)): 0.0001 / 0.0002
[906/1000][40/42]     Loss_D: 0.0380  Loss_G: 11.3034 D(x): 0.9804
     D(G(z)): 0.0077 / 0.0021
[907/1000][0/42] Loss_D: 0.0032  Loss_G: 12.0392 D(x): 0.9987
     D(G(z)): 0.0019 / 0.0012
[907/1000][20/42]     Loss_D: 0.0043  Loss_G: 14.1366 D(x): 0.9960
     D(G(z)): 0.0001 / 0.0001
```

```
[907/1000][40/42]     Loss_D: 0.0014  Loss_G: 11.3072 D(x): 0.9996
      D(G(z)): 0.0010 / 0.0004
[908/1000][0/42] Loss_D: 0.0033  Loss_G: 13.8514 D(x): 0.9981
      D(G(z)): 0.0013 / 0.0005
[908/1000][20/42]     Loss_D: 0.0383  Loss_G: 9.7066  D(x): 0.9919
      D(G(z)): 0.0226 / 0.0080
[908/1000][40/42]     Loss_D: 0.0146  Loss_G: 11.6641 D(x): 0.9876
      D(G(z)): 0.0002 / 0.0002
[909/1000][0/42] Loss_D: 0.0014  Loss_G: 11.3909 D(x): 0.9996
      D(G(z)): 0.0010 / 0.0010
[909/1000][20/42]     Loss_D: 0.0038  Loss_G: 11.4937 D(x): 0.9999
      D(G(z)): 0.0036 / 0.0041
[909/1000][40/42]     Loss_D: 0.0262  Loss_G: 10.7061 D(x): 0.9986
      D(G(z)): 0.0189 / 0.0279
[910/1000][0/42] Loss_D: 0.0812  Loss_G: 13.4534 D(x): 0.9997
      D(G(z)): 0.0554 / 0.0040
[910/1000][20/42]     Loss_D: 0.1455  Loss_G: 12.8277 D(x): 0.9101
      D(G(z)): 0.0004 / 0.0011
[910/1000][40/42]     Loss_D: 0.0158  Loss_G: 14.8195 D(x): 0.9869
      D(G(z)): 0.0006 / 0.0003
```

```
[911/1000][0/42] Loss_D: 0.0142  Loss_G: 13.2801 D(x): 0.9890
      D(G(z)): 0.0010 / 0.0008
[911/1000][20/42]     Loss_D: 0.0012  Loss_G: 14.1922 D(x): 0.9997
      D(G(z)): 0.0009 / 0.0008
[911/1000][40/42]     Loss_D: 0.1161  Loss_G: 10.9448 D(x): 0.9900
      D(G(z)): 0.0359 / 0.0095
[912/1000][0/42] Loss_D: 0.0590  Loss_G: 12.5234 D(x): 0.9999
      D(G(z)): 0.0220 / 0.0003
[912/1000][20/42]     Loss_D: 0.0042  Loss_G: 13.1454 D(x): 0.9995
      D(G(z)): 0.0037 / 0.0067
[912/1000][40/42]     Loss_D: 0.0312  Loss_G: 13.9001 D(x): 0.9841
      D(G(z)): 0.0009 / 0.0008
[913/1000][0/42] Loss_D: 0.0094  Loss_G: 12.7810 D(x): 0.9997
      D(G(z)): 0.0086 / 0.0029
[913/1000][20/42]     Loss_D: 0.0105  Loss_G: 12.9397 D(x): 0.9909
      D(G(z)): 0.0001 / 0.0002
[913/1000][40/42]     Loss_D: 0.0031  Loss_G: 18.9367 D(x): 0.9976
      D(G(z)): 0.0007 / 0.0003
[914/1000][0/42] Loss_D: 0.0338  Loss_G: 16.6700 D(x): 0.9890
```

```
    D(G(z)): 0.0149 / 0.0023
[914/1000][20/42]     Loss_D: 0.0192  Loss_G: 13.0391 D(x): 0.9909
    D(G(z)): 0.0066 / 0.0120
[914/1000][40/42]     Loss_D: 0.0096  Loss_G: 11.9918 D(x): 0.9935
    D(G(z)): 0.0028 / 0.0019
[915/1000][0/42] Loss_D: 0.0655  Loss_G: 10.9320 D(x): 0.9801
    D(G(z)): 0.0037 / 0.0036
[915/1000][20/42]     Loss_D: 0.0042  Loss_G: 12.7892 D(x): 0.9978
    D(G(z)): 0.0019 / 0.0008
[915/1000][40/42]     Loss_D: 0.0959  Loss_G: 12.4113 D(x): 0.9568
    D(G(z)): 0.0055 / 0.0042
[916/1000][0/42] Loss_D: 0.0040  Loss_G: 11.5766 D(x): 0.9992
    D(G(z)): 0.0031 / 0.0026
[916/1000][20/42]     Loss_D: 0.0064  Loss_G: 11.5971 D(x): 0.9998
    D(G(z)): 0.0055 / 0.0017
[916/1000][40/42]     Loss_D: 0.0183  Loss_G: 10.4405 D(x): 0.9997
    D(G(z)): 0.0152 / 0.0022
[917/1000][0/42] Loss_D: 0.0033  Loss_G: 13.0674 D(x): 0.9974
    D(G(z)): 0.0006 / 0.0002
[917/1000][20/42]     Loss_D: 0.0029  Loss_G: 11.2473 D(x): 0.9995
    D(G(z)): 0.0023 / 0.0028
[917/1000][40/42]     Loss_D: 0.0006  Loss_G: 16.2501 D(x): 0.9997
    D(G(z)): 0.0003 / 0.0002
[918/1000][0/42] Loss_D: 0.0099  Loss_G: 14.4843 D(x): 0.9930
    D(G(z)): 0.0023 / 0.0006
[918/1000][20/42]     Loss_D: 0.0066  Loss_G: 11.5581 D(x): 0.9943
    D(G(z)): 0.0005 / 0.0004
[918/1000][40/42]     Loss_D: 0.0040  Loss_G: 10.1982 D(x): 0.9992
    D(G(z)): 0.0032 / 0.0021
[919/1000][0/42] Loss_D: 0.0015  Loss_G: 11.6615 D(x): 0.9997
    D(G(z)): 0.0012 / 0.0007
[919/1000][20/42]     Loss_D: 0.0154  Loss_G: 11.2159 D(x): 0.9910
    D(G(z)): 0.0037 / 0.0024
[919/1000][40/42]     Loss_D: 0.0018  Loss_G: 12.5557 D(x): 0.9984
    D(G(z)): 0.0002 / 0.0004
[920/1000][0/42] Loss_D: 0.0073  Loss_G: 12.5639 D(x): 0.9943
    D(G(z)): 0.0010 / 0.0016
[920/1000][20/42]     Loss_D: 0.0055  Loss_G: 13.8920 D(x): 0.9985
    D(G(z)): 0.0037 / 0.0095
[920/1000][40/42]     Loss_D: 0.0407  Loss_G: 13.9093 D(x): 0.9649
    D(G(z)): 0.0013 / 0.0003
```



```
[921/1000][0/42] Loss_D: 0.0009  Loss_G: 12.9524 D(x): 0.9998
     D(G(z)): 0.0007 / 0.0007
[921/1000][20/42]    Loss_D: 0.0870  Loss_G: 12.6663 D(x): 0.9771
     D(G(z)): 0.0179 / 0.0004
[921/1000][40/42]    Loss_D: 0.0156  Loss_G: 14.6024 D(x): 0.9885
     D(G(z)): 0.0026 / 0.0016
[922/1000][0/42] Loss_D: 0.0005  Loss_G: 12.8387 D(x): 0.9998
     D(G(z)): 0.0004 / 0.0006
[922/1000][20/42]    Loss_D: 0.0014  Loss_G: 11.7239 D(x): 0.9994
     D(G(z)): 0.0008 / 0.0014
[922/1000][40/42]    Loss_D: 0.0138  Loss_G: 13.2299 D(x): 0.9996
     D(G(z)): 0.0099 / 0.0009
[923/1000][0/42] Loss_D: 0.0043  Loss_G: 13.8335 D(x): 0.9997
     D(G(z)): 0.0038 / 0.0014
[923/1000][20/42]    Loss_D: 0.0058  Loss_G: 10.7126 D(x): 0.9974
     D(G(z)): 0.0030 / 0.0040
[923/1000][40/42]    Loss_D: 0.0751  Loss_G: 13.5121 D(x): 0.9987
     D(G(z)): 0.0441 / 0.0010
[924/1000][0/42] Loss_D: 0.0025  Loss_G: 16.8249 D(x): 0.9990
     D(G(z)): 0.0015 / 0.0002
[924/1000][20/42]    Loss_D: 0.0512  Loss_G: 11.8584 D(x): 0.9708
     D(G(z)): 0.0099 / 0.0153
[924/1000][40/42]    Loss_D: 0.0109  Loss_G: 13.1975 D(x): 0.9927
     D(G(z)): 0.0023 / 0.0020
[925/1000][0/42] Loss_D: 0.0405  Loss_G: 12.3644 D(x): 0.9801
     D(G(z)): 0.0097 / 0.0021
[925/1000][20/42]    Loss_D: 0.0121  Loss_G: 13.8119 D(x): 0.9892
     D(G(z)): 0.0003 / 0.0002
[925/1000][40/42]    Loss_D: 0.0013  Loss_G: 10.8752 D(x): 1.0000
     D(G(z)): 0.0013 / 0.0038
[926/1000][0/42] Loss_D: 0.0800  Loss_G: 10.7213 D(x): 1.0000
     D(G(z)): 0.0391 / 0.0031
[926/1000][20/42]    Loss_D: 0.0066  Loss_G: 10.7759 D(x): 0.9998
     D(G(z)): 0.0061 / 0.0169
[926/1000][40/42]    Loss_D: 0.0037  Loss_G: 11.4151 D(x): 0.9994
     D(G(z)): 0.0030 / 0.0013
[927/1000][0/42] Loss_D: 0.0699  Loss_G: 12.2874 D(x): 1.0000
     D(G(z)): 0.0342 / 0.0018
[927/1000][20/42]    Loss_D: 0.0291  Loss_G: 11.6301 D(x): 0.9994
     D(G(z)): 0.0207 / 0.0072
```

```
[927/1000][40/42]	Loss_D: 0.0014	Loss_G: 14.0845	D(x): 0.9992	D(G(z)): 0.0006 / 0.0001
[928/1000][0/42]	Loss_D: 0.0038	Loss_G: 12.2697	D(x): 0.9965	D(G(z)): 0.0003 / 0.0001
[928/1000][20/42]	Loss_D: 0.0130	Loss_G: 12.1755	D(x): 0.9996	D(G(z)): 0.0096 / 0.0008
[928/1000][40/42]	Loss_D: 0.0051	Loss_G: 11.4634	D(x): 0.9962	D(G(z)): 0.0011 / 0.0009
[929/1000][0/42]	Loss_D: 0.0017	Loss_G: 14.4996	D(x): 0.9988	D(G(z)): 0.0006 / 0.0005
[929/1000][20/42]	Loss_D: 0.0047	Loss_G: 13.2323	D(x): 0.9955	D(G(z)): 0.0001 / 0.0001
[929/1000][40/42]	Loss_D: 0.0019	Loss_G: 14.9199	D(x): 0.9981	D(G(z)): 0.0001 / 0.0001
[930/1000][0/42]	Loss_D: 0.0004	Loss_G: 11.7485	D(x): 0.9997	D(G(z)): 0.0001 / 0.0001
[930/1000][20/42]	Loss_D: 0.0059	Loss_G: 12.3572	D(x): 0.9944	D(G(z)): 0.0002 / 0.0002
[930/1000][40/42]	Loss_D: 0.0008	Loss_G: 11.1422	D(x): 0.9997	D(G(z)): 0.0005 / 0.0006
```

```
[931/1000][0/42]	Loss_D: 0.0231	Loss_G: 10.3681	D(x): 0.9993	D(G(z)): 0.0144 / 0.0012
[931/1000][20/42]	Loss_D: 0.0010	Loss_G: 12.4891	D(x): 0.9994	D(G(z)): 0.0004 / 0.0003
[931/1000][40/42]	Loss_D: 0.0031	Loss_G: 11.5254	D(x): 0.9982	D(G(z)): 0.0013 / 0.0012
[932/1000][0/42]	Loss_D: 0.0019	Loss_G: 12.8133	D(x): 0.9986	D(G(z)): 0.0005 / 0.0007
[932/1000][20/42]	Loss_D: 0.0043	Loss_G: 10.3017	D(x): 0.9980	D(G(z)): 0.0022 / 0.0022
[932/1000][40/42]	Loss_D: 0.0033	Loss_G: 11.7605	D(x): 0.9972	D(G(z)): 0.0005 / 0.0004
[933/1000][0/42]	Loss_D: 0.0027	Loss_G: 11.4370	D(x): 0.9978	D(G(z)): 0.0005 / 0.0004
[933/1000][20/42]	Loss_D: 0.0043	Loss_G: 12.4933	D(x): 0.9979	D(G(z)): 0.0021 / 0.0013
[933/1000][40/42]	Loss_D: 0.0028	Loss_G: 10.8255	D(x): 0.9996	D(G(z)): 0.0023 / 0.0037
[934/1000][0/42]	Loss_D: 0.0139	Loss_G: 10.6769	D(x): 1.0000
```

```
    D(G(z)): 0.0122 / 0.0082
[934/1000][20/42]    Loss_D: 0.0030  Loss_G: 12.6254 D(x): 0.9986
    D(G(z)): 0.0016 / 0.0012
[934/1000][40/42]    Loss_D: 0.0070  Loss_G: 10.8044 D(x): 0.9952
    D(G(z)): 0.0020 / 0.0022
[935/1000][0/42] Loss_D: 0.0014  Loss_G: 10.6047 D(x): 0.9999
    D(G(z)): 0.0013 / 0.0015
[935/1000][20/42]    Loss_D: 0.0020  Loss_G: 12.0298 D(x): 0.9999
    D(G(z)): 0.0018 / 0.0018
[935/1000][40/42]    Loss_D: 0.0015  Loss_G: 11.6203 D(x): 0.9994
    D(G(z)): 0.0009 / 0.0007
[936/1000][0/42] Loss_D: 0.0013  Loss_G: 12.4271 D(x): 0.9997
    D(G(z)): 0.0010 / 0.0008
[936/1000][20/42]    Loss_D: 0.0038  Loss_G: 13.3965 D(x): 0.9963
    D(G(z)): 0.0001 / 0.0001
[936/1000][40/42]    Loss_D: 0.0022  Loss_G: 9.6075  D(x): 0.9993
    D(G(z)): 0.0015 / 0.0270
[937/1000][0/42] Loss_D: 0.0201  Loss_G: 7.3602  D(x): 1.0000
    D(G(z)): 0.0184 / 0.0378
[937/1000][20/42]    Loss_D: 0.0060  Loss_G: 15.9611 D(x): 0.9955
    D(G(z)): 0.0009 / 0.0004
[937/1000][40/42]    Loss_D: 0.0360  Loss_G: 13.3532 D(x): 0.9813
    D(G(z)): 0.0003 / 0.0010
[938/1000][0/42] Loss_D: 0.0399  Loss_G: 12.4761 D(x): 0.9914
    D(G(z)): 0.0212 / 0.0038
[938/1000][20/42]    Loss_D: 0.3319  Loss_G: 10.9552 D(x): 1.0000
    D(G(z)): 0.1249 / 0.0054
[938/1000][40/42]    Loss_D: 0.0349  Loss_G: 13.6142 D(x): 0.9801
    D(G(z)): 0.0073 / 0.0055
[939/1000][0/42] Loss_D: 2.6396  Loss_G: 12.7672 D(x): 0.9694
    D(G(z)): 0.1173 / 0.0236
[939/1000][20/42]    Loss_D: 0.0786  Loss_G: 15.0897 D(x): 0.9997
    D(G(z)): 0.0442 / 0.0029
[939/1000][40/42]    Loss_D: 0.0045  Loss_G: 11.9688 D(x): 0.9981
    D(G(z)): 0.0025 / 0.0015
[940/1000][0/42] Loss_D: 0.0019  Loss_G: 12.0242 D(x): 0.9994
    D(G(z)): 0.0013 / 0.0021
[940/1000][20/42]    Loss_D: 0.0370  Loss_G: 14.5546 D(x): 0.9706
    D(G(z)): 0.0006 / 0.0010
[940/1000][40/42]    Loss_D: 0.0248  Loss_G: 13.8097 D(x): 0.9802
    D(G(z)): 0.0013 / 0.0013
```

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[941/1000][0/42] Loss_D: 0.0020  Loss_G: 12.5636 D(x): 0.9998
      D(G(z)): 0.0017 / 0.0021
[941/1000][20/42]     Loss_D: 0.0809  Loss_G: 13.3786 D(x): 0.9951
      D(G(z)): 0.0201 / 0.0031
[941/1000][40/42]     Loss_D: 0.0732  Loss_G: 12.9744 D(x): 0.9970
      D(G(z)): 0.0218 / 0.0010
[942/1000][0/42] Loss_D: 0.0431  Loss_G: 13.2877 D(x): 0.9728
      D(G(z)): 0.0060 / 0.0027
[942/1000][20/42]     Loss_D: 0.0035  Loss_G: 13.5517 D(x): 0.9986
      D(G(z)): 0.0021 / 0.0010
[942/1000][40/42]     Loss_D: 0.0013  Loss_G: 13.9000 D(x): 0.9997
      D(G(z)): 0.0009 / 0.0010
[943/1000][0/42] Loss_D: 0.0288  Loss_G: 13.4778 D(x): 0.9807
      D(G(z)): 0.0041 / 0.0044
[943/1000][20/42]     Loss_D: 0.0620  Loss_G: 12.8084 D(x): 0.9994
      D(G(z)): 0.0275 / 0.0015
[943/1000][40/42]     Loss_D: 0.0411  Loss_G: 12.6829 D(x): 0.9796
      D(G(z)): 0.0022 / 0.0007
[944/1000][0/42] Loss_D: 0.0237  Loss_G: 14.7210 D(x): 0.9780
      D(G(z)): 0.0001 / 0.0001
[944/1000][20/42]     Loss_D: 0.0115  Loss_G: 11.8256 D(x): 0.9929
      D(G(z)): 0.0038 / 0.0023
[944/1000][40/42]     Loss_D: 0.0349  Loss_G: 10.6781 D(x): 0.9783
      D(G(z)): 0.0012 / 0.0013
[945/1000][0/42] Loss_D: 0.0155  Loss_G: 10.5100 D(x): 0.9990
      D(G(z)): 0.0109 / 0.0043
[945/1000][20/42]     Loss_D: 0.0008  Loss_G: 14.2047 D(x): 0.9995
      D(G(z)): 0.0004 / 0.0002
[945/1000][40/42]     Loss_D: 0.0263  Loss_G: 16.2518 D(x): 0.9769
      D(G(z)): 0.0000 / 0.0000
[946/1000][0/42] Loss_D: 0.0079  Loss_G: 10.5545 D(x): 0.9983
      D(G(z)): 0.0057 / 0.0121
[946/1000][20/42]     Loss_D: 0.0241  Loss_G: 12.5071 D(x): 0.9999
      D(G(z)): 0.0166 / 0.0020
[946/1000][40/42]     Loss_D: 0.0061  Loss_G: 13.8343 D(x): 0.9945
      D(G(z)): 0.0002 / 0.0002
[947/1000][0/42] Loss_D: 0.0068  Loss_G: 13.5867 D(x): 0.9946
      D(G(z)): 0.0011 / 0.0010
[947/1000][20/42]     Loss_D: 0.0008  Loss_G: 13.0901 D(x): 0.9998
      D(G(z)): 0.0006 / 0.0004
```

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[947/1000][40/42]	Loss_D: 0.0021	Loss_G: 10.8863	D(x): 0.9997	D(G(z)): 0.0018 / 0.0012
[948/1000][0/42]	Loss_D: 0.0028	Loss_G: 10.4637	D(x): 0.9996	D(G(z)): 0.0023 / 0.0010
[948/1000][20/42]	Loss_D: 0.0030	Loss_G: 12.1321	D(x): 0.9999	D(G(z)): 0.0029 / 0.0009
[948/1000][40/42]	Loss_D: 0.0223	Loss_G: 9.2641	D(x): 0.9984	D(G(z)): 0.0185 / 0.0067
[949/1000][0/42]	Loss_D: 0.0032	Loss_G: 13.5089	D(x): 0.9993	D(G(z)): 0.0024 / 0.0016
[949/1000][20/42]	Loss_D: 0.0465	Loss_G: 12.9154	D(x): 0.9666	D(G(z)): 0.0007 / 0.0007
[949/1000][40/42]	Loss_D: 0.0039	Loss_G: 12.5814	D(x): 0.9991	D(G(z)): 0.0029 / 0.0017
[950/1000][0/42]	Loss_D: 0.0054	Loss_G: 12.9713	D(x): 0.9997	D(G(z)): 0.0047 / 0.0045
[950/1000][20/42]	Loss_D: 0.0097	Loss_G: 12.2961	D(x): 0.9922	D(G(z)): 0.0012 / 0.0007
[950/1000][40/42]	Loss_D: 0.0052	Loss_G: 10.0067	D(x): 0.9984	D(G(z)): 0.0034 / 0.0022
```

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[951/1000][0/42]	Loss_D: 0.0124	Loss_G: 10.9482	D(x): 0.9996	D(G(z)): 0.0097 / 0.0021
[951/1000][20/42]	Loss_D: 0.0049	Loss_G: 10.8887	D(x): 0.9998	D(G(z)): 0.0045 / 0.0018
[951/1000][40/42]	Loss_D: 0.0009	Loss_G: 13.8838	D(x): 0.9993	D(G(z)): 0.0002 / 0.0001
[952/1000][0/42]	Loss_D: 0.0131	Loss_G: 12.4156	D(x): 0.9877	D(G(z)): 0.0002 / 0.0002
[952/1000][20/42]	Loss_D: 0.0041	Loss_G: 12.7614	D(x): 0.9963	D(G(z)): 0.0004 / 0.0004
[952/1000][40/42]	Loss_D: 0.0014	Loss_G: 11.7538	D(x): 0.9992	D(G(z)): 0.0007 / 0.0032
[953/1000][0/42]	Loss_D: 0.0041	Loss_G: 8.7650	D(x): 0.9993	D(G(z)): 0.0034 / 0.0081
[953/1000][20/42]	Loss_D: 0.0074	Loss_G: 12.0997	D(x): 0.9946	D(G(z)): 0.0017 / 0.0023
[953/1000][40/42]	Loss_D: 0.0098	Loss_G: 11.1328	D(x): 0.9999	D(G(z)): 0.0089 / 0.0030
[954/1000][0/42]	Loss_D: 0.0008	Loss_G: 13.7571	D(x): 0.9995
```

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    D(G(z)): 0.0003 / 0.0001
[954/1000][20/42]    Loss_D: 0.0012  Loss_G: 13.0685 D(x): 0.9992
    D(G(z)): 0.0004 / 0.0003
[954/1000][40/42]    Loss_D: 0.0008  Loss_G: 12.7943 D(x): 0.9994
    D(G(z)): 0.0003 / 0.0002
[955/1000][0/42]Loss_D: 0.0142  Loss_G: 11.9465 D(x): 0.9992
    D(G(z)): 0.0104 / 0.0010
[955/1000][20/42]    Loss_D: 0.0082  Loss_G: 9.9857  D(x): 0.9962
    D(G(z)): 0.0041 / 0.0025
[955/1000][40/42]    Loss_D: 0.0491  Loss_G: 10.2437 D(x): 0.9975
    D(G(z)): 0.0275 / 0.0033
[956/1000][0/42]Loss_D: 0.0017  Loss_G: 12.1970 D(x): 0.9991
    D(G(z)): 0.0008 / 0.0004
[956/1000][20/42]    Loss_D: 0.0282  Loss_G: 12.7734 D(x): 0.9985
    D(G(z)): 0.0150 / 0.0004
[956/1000][40/42]    Loss_D: 0.0571  Loss_G: 11.0785 D(x): 0.9999
    D(G(z)): 0.0231 / 0.0029
[957/1000][0/42]Loss_D: 0.0364  Loss_G: 14.7857 D(x): 0.9985
    D(G(z)): 0.0177 / 0.0003
[957/1000][20/42]    Loss_D: 0.0006  Loss_G: 16.4749 D(x): 0.9994
    D(G(z)): 0.0000 / 0.0000
[957/1000][40/42]    Loss_D: 0.0007  Loss_G: 13.1709 D(x): 1.0000
    D(G(z)): 0.0006 / 0.0006
[958/1000][0/42]Loss_D: 0.0016  Loss_G: 14.0068 D(x): 0.9998
    D(G(z)): 0.0013 / 0.0023
[958/1000][20/42]    Loss_D: 0.0074  Loss_G: 12.5500 D(x): 0.9997
    D(G(z)): 0.0068 / 0.0052
[958/1000][40/42]    Loss_D: 0.0007  Loss_G: 13.1565 D(x): 0.9995
    D(G(z)): 0.0002 / 0.0003
[959/1000][0/42]Loss_D: 0.0134  Loss_G: 14.3159 D(x): 0.9999
    D(G(z)): 0.0115 / 0.0044
[959/1000][20/42]    Loss_D: 0.0324  Loss_G: 14.7216 D(x): 0.9733
    D(G(z)): 0.0001 / 0.0000
[959/1000][40/42]    Loss_D: 0.0069  Loss_G: 13.6665 D(x): 1.0000
    D(G(z)): 0.0066 / 0.0015
[960/1000][0/42]Loss_D: 0.0049  Loss_G: 15.0414 D(x): 0.9963
    D(G(z)): 0.0010 / 0.0004
[960/1000][20/42]    Loss_D: 0.0013  Loss_G: 14.7748 D(x): 0.9995
    D(G(z)): 0.0008 / 0.0002
[960/1000][40/42]    Loss_D: 0.0016  Loss_G: 11.0929 D(x): 0.9997
    D(G(z)): 0.0013 / 0.0007
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[961/1000][0/42] Loss_D: 0.0155  Loss_G: 12.1204 D(x): 0.9913
     D(G(z)): 0.0060 / 0.0022
[961/1000][20/42]     Loss_D: 0.0208  Loss_G: 15.2939 D(x): 0.9830
     D(G(z)): 0.0000 / 0.0000
[961/1000][40/42]     Loss_D: 0.0048  Loss_G: 11.5401 D(x): 0.9958
     D(G(z)): 0.0005 / 0.0014
[962/1000][0/42] Loss_D: 0.0038  Loss_G: 10.5841 D(x): 0.9990
     D(G(z)): 0.0027 / 0.0046
[962/1000][20/42]     Loss_D: 0.0318  Loss_G: 15.9364 D(x): 0.9723
     D(G(z)): 0.0001 / 0.0001
[962/1000][40/42]     Loss_D: 0.0077  Loss_G: 12.4409 D(x): 0.9981
     D(G(z)): 0.0051 / 0.0021
[963/1000][0/42] Loss_D: 0.0061  Loss_G: 12.6048 D(x): 0.9954
     D(G(z)): 0.0013 / 0.0013
[963/1000][20/42]     Loss_D: 0.0094  Loss_G: 13.4372 D(x): 0.9965
     D(G(z)): 0.0052 / 0.0043
[963/1000][40/42]     Loss_D: 0.1026  Loss_G: 8.0553  D(x): 0.9770
     D(G(z)): 0.0532 / 0.0163
[964/1000][0/42] Loss_D: 0.0182  Loss_G: 10.8067 D(x): 0.9991
     D(G(z)): 0.0159 / 0.0062
[964/1000][20/42]     Loss_D: 0.0006  Loss_G: 12.6450 D(x): 0.9996
     D(G(z)): 0.0002 / 0.0010
[964/1000][40/42]     Loss_D: 0.0600  Loss_G: 14.7804 D(x): 0.9739
     D(G(z)): 0.0005 / 0.0007
[965/1000][0/42] Loss_D: 0.0236  Loss_G: 12.5311 D(x): 0.9865
     D(G(z)): 0.0025 / 0.0060
[965/1000][20/42]     Loss_D: 0.0079  Loss_G: 15.5837 D(x): 0.9981
     D(G(z)): 0.0053 / 0.0004
[965/1000][40/42]     Loss_D: 0.0292  Loss_G: 14.1281 D(x): 0.9891
     D(G(z)): 0.0120 / 0.0010
[966/1000][0/42] Loss_D: 0.0024  Loss_G: 11.5567 D(x): 0.9998
     D(G(z)): 0.0022 / 0.0034
[966/1000][20/42]     Loss_D: 0.0041  Loss_G: 14.3084 D(x): 0.9996
     D(G(z)): 0.0035 / 0.0061
[966/1000][40/42]     Loss_D: 0.0034  Loss_G: 15.6045 D(x): 0.9970
     D(G(z)): 0.0004 / 0.0001
[967/1000][0/42] Loss_D: 0.0472  Loss_G: 15.1493 D(x): 0.9634
     D(G(z)): 0.0009 / 0.0007
[967/1000][20/42]     Loss_D: 0.1937  Loss_G: 13.8183 D(x): 0.8969
     D(G(z)): 0.0015 / 0.0015
```

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[967/1000][40/42]	Loss_D: 0.0190	Loss_G: 13.7433	D(x): 0.9946
	D(G(z)): 0.0102 / 0.0005
[968/1000][0/42]	Loss_D: 0.0099	Loss_G: 15.5960	D(x): 0.9965
	D(G(z)): 0.0054 / 0.0003
[968/1000][20/42]	Loss_D: 0.0775	Loss_G: 12.3137	D(x): 0.9987
	D(G(z)): 0.0202 / 0.0034
[968/1000][40/42]	Loss_D: 0.0347	Loss_G: 9.9856	D(x): 0.9999
	D(G(z)): 0.0302 / 0.0123
[969/1000][0/42]	Loss_D: 0.0122	Loss_G: 12.6657	D(x): 0.9997
	D(G(z)): 0.0109 / 0.0039
[969/1000][20/42]	Loss_D: 0.0101	Loss_G: 16.6446	D(x): 0.9909
	D(G(z)): 0.0002 / 0.0008
[969/1000][40/42]	Loss_D: 0.0918	Loss_G: 10.9262	D(x): 0.9999
	D(G(z)): 0.0234 / 0.0033
[970/1000][0/42]	Loss_D: 0.0610	Loss_G: 11.2610	D(x): 0.9908
	D(G(z)): 0.0371 / 0.0052
[970/1000][20/42]	Loss_D: 0.0037	Loss_G: 11.5485	D(x): 0.9976
	D(G(z)): 0.0012 / 0.0010
[970/1000][40/42]	Loss_D: 0.0176	Loss_G: 11.5870	D(x): 0.9913
	D(G(z)): 0.0060 / 0.0038
```

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[971/1000][0/42]	Loss_D: 0.0106	Loss_G: 11.8357	D(x): 0.9994
	D(G(z)): 0.0089 / 0.0040
[971/1000][20/42]	Loss_D: 0.0349	Loss_G: 11.6496	D(x): 0.9829
	D(G(z)): 0.0011 / 0.0011
[971/1000][40/42]	Loss_D: 0.0047	Loss_G: 13.3820	D(x): 0.9987
	D(G(z)): 0.0033 / 0.0027
[972/1000][0/42]	Loss_D: 0.0278	Loss_G: 14.6790	D(x): 0.9795
	D(G(z)): 0.0003 / 0.0003
[972/1000][20/42]	Loss_D: 0.0037	Loss_G: 12.2608	D(x): 0.9966
	D(G(z)): 0.0002 / 0.0003
[972/1000][40/42]	Loss_D: 0.0932	Loss_G: 15.3654	D(x): 0.9717
	D(G(z)): 0.0002 / 0.0001
[973/1000][0/42]	Loss_D: 0.0295	Loss_G: 12.1230	D(x): 0.9793
	D(G(z)): 0.0014 / 0.0013
[973/1000][20/42]	Loss_D: 0.0217	Loss_G: 12.2495	D(x): 0.9994
	D(G(z)): 0.0146 / 0.0007
[973/1000][40/42]	Loss_D: 0.0173	Loss_G: 12.2690	D(x): 0.9967
	D(G(z)): 0.0118 / 0.0036
[974/1000][0/42]	Loss_D: 0.0014	Loss_G: 14.5037	D(x): 0.9988
```

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    D(G(z)): 0.0001 / 0.0001
[974/1000][20/42]     Loss_D: 0.0048  Loss_G: 11.6736 D(x): 0.9988
    D(G(z)): 0.0035 / 0.0023
[974/1000][40/42]     Loss_D: 0.0033  Loss_G: 10.9899 D(x): 0.9970
    D(G(z)): 0.0003 / 0.0003
[975/1000][0/42] Loss_D: 0.0022  Loss_G: 12.8752 D(x): 0.9994
    D(G(z)): 0.0017 / 0.0014
[975/1000][20/42]     Loss_D: 0.0034  Loss_G: 11.1391 D(x): 0.9975
    D(G(z)): 0.0009 / 0.0012
[975/1000][40/42]     Loss_D: 0.0085  Loss_G: 8.6952  D(x): 0.9995
    D(G(z)): 0.0073 / 0.0072
[976/1000][0/42] Loss_D: 0.0178  Loss_G: 9.7263  D(x): 0.9999
    D(G(z)): 0.0121 / 0.0030
[976/1000][20/42]     Loss_D: 0.0428  Loss_G: 10.3775 D(x): 1.0000
    D(G(z)): 0.0283 / 0.0023
[976/1000][40/42]     Loss_D: 0.0008  Loss_G: 12.7912 D(x): 0.9995
    D(G(z)): 0.0003 / 0.0002
[977/1000][0/42] Loss_D: 0.0036  Loss_G: 13.2386 D(x): 0.9978
    D(G(z)): 0.0013 / 0.0014
[977/1000][20/42]     Loss_D: 0.0005  Loss_G: 15.3531 D(x): 0.9995
    D(G(z)): 0.0000 / 0.0000
[977/1000][40/42]     Loss_D: 0.0046  Loss_G: 14.8814 D(x): 0.9958
    D(G(z)): 0.0002 / 0.0001
[978/1000][0/42] Loss_D: 0.0009  Loss_G: 14.1164 D(x): 0.9996
    D(G(z)): 0.0006 / 0.0004
[978/1000][20/42]     Loss_D: 0.0175  Loss_G: 9.7759  D(x): 0.9999
    D(G(z)): 0.0157 / 0.0101
[978/1000][40/42]     Loss_D: 0.0009  Loss_G: 11.6315 D(x): 0.9999
    D(G(z)): 0.0008 / 0.0007
[979/1000][0/42] Loss_D: 0.0784  Loss_G: 11.6232 D(x): 0.9994
    D(G(z)): 0.0435 / 0.0019
[979/1000][20/42]     Loss_D: 0.0408  Loss_G: 14.1563 D(x): 0.9692
    D(G(z)): 0.0006 / 0.0005
[979/1000][40/42]     Loss_D: 0.0088  Loss_G: 11.2586 D(x): 0.9993
    D(G(z)): 0.0079 / 0.0023
[980/1000][0/42] Loss_D: 0.0017  Loss_G: 15.0523 D(x): 0.9990
    D(G(z)): 0.0006 / 0.0003
[980/1000][20/42]     Loss_D: 0.0086  Loss_G: 14.0476 D(x): 0.9921
    D(G(z)): 0.0001 / 0.0001
[980/1000][40/42]     Loss_D: 0.0056  Loss_G: 13.1943 D(x): 0.9950
    D(G(z)): 0.0001 / 0.0001
```

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[981/1000][0/42] Loss_D: 0.0397  Loss_G: 10.2986 D(x): 0.9998
    D(G(z)): 0.0233 / 0.0044
[981/1000][20/42]     Loss_D: 0.0073  Loss_G: 15.8575 D(x): 0.9931
    D(G(z)): 0.0001 / 0.0001
[981/1000][40/42]     Loss_D: 0.0012  Loss_G: 11.5712 D(x): 0.9992
    D(G(z)): 0.0004 / 0.0007
[982/1000][0/42] Loss_D: 0.0010  Loss_G: 12.4793 D(x): 0.9992
    D(G(z)): 0.0001 / 0.0002
[982/1000][20/42]     Loss_D: 0.0097  Loss_G: 12.9576 D(x): 0.9921
    D(G(z)): 0.0011 / 0.0010
[982/1000][40/42]     Loss_D: 0.0071  Loss_G: 14.4531 D(x): 0.9935
    D(G(z)): 0.0001 / 0.0001
[983/1000][0/42] Loss_D: 0.0193  Loss_G: 12.9724 D(x): 0.9849
    D(G(z)): 0.0005 / 0.0009
[983/1000][20/42]     Loss_D: 0.0023  Loss_G: 11.4564 D(x): 0.9996
    D(G(z)): 0.0018 / 0.0013
[983/1000][40/42]     Loss_D: 0.0189  Loss_G: 13.7422 D(x): 0.9827
    D(G(z)): 0.0003 / 0.0005
[984/1000][0/42] Loss_D: 0.0061  Loss_G: 11.8395 D(x): 0.9955
    D(G(z)): 0.0015 / 0.0024
[984/1000][20/42]     Loss_D: 0.0011  Loss_G: 12.2958 D(x): 0.9993
    D(G(z)): 0.0004 / 0.0005
[984/1000][40/42]     Loss_D: 0.0024  Loss_G: 12.9347 D(x): 0.9993
    D(G(z)): 0.0016 / 0.0010
[985/1000][0/42] Loss_D: 0.0241  Loss_G: 11.4734 D(x): 0.9881
    D(G(z)): 0.0094 / 0.0034
[985/1000][20/42]     Loss_D: 0.0138  Loss_G: 11.9442 D(x): 0.9989
    D(G(z)): 0.0112 / 0.0026
[985/1000][40/42]     Loss_D: 0.0005  Loss_G: 13.7306 D(x): 0.9996
    D(G(z)): 0.0001 / 0.0001
[986/1000][0/42] Loss_D: 0.0092  Loss_G: 12.5024 D(x): 0.9991
    D(G(z)): 0.0069 / 0.0013
[986/1000][20/42]     Loss_D: 0.0280  Loss_G: 16.4329 D(x): 0.9828
    D(G(z)): 0.0000 / 0.0000
[986/1000][40/42]     Loss_D: 0.0297  Loss_G: 14.2330 D(x): 0.9813
    D(G(z)): 0.0001 / 0.0000
[987/1000][0/42] Loss_D: 0.0086  Loss_G: 13.9699 D(x): 0.9917
    D(G(z)): 0.0001 / 0.0002
[987/1000][20/42]     Loss_D: 0.0105  Loss_G: 14.0986 D(x): 0.9988
    D(G(z)): 0.0075 / 0.0024
```

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[987/1000][40/42]	Loss_D: 0.0466	Loss_G: 12.8542	D(x): 0.9771	D(G(z)): 0.0137 / 0.0187
[988/1000][0/42]	Loss_D: 0.1377	Loss_G: 13.3536	D(x): 0.9936	D(G(z)): 0.0618 / 0.0049
[988/1000][20/42]	Loss_D: 0.0497	Loss_G: 13.9102	D(x): 0.9772	D(G(z)): 0.0135 / 0.0013
[988/1000][40/42]	Loss_D: 0.0163	Loss_G: 12.3452	D(x): 0.9999	D(G(z)): 0.0136 / 0.0040
[989/1000][0/42]	Loss_D: 0.1529	Loss_G: 13.1748	D(x): 0.9969	D(G(z)): 0.0236 / 0.0002
[989/1000][20/42]	Loss_D: 0.0498	Loss_G: 11.5027	D(x): 1.0000	D(G(z)): 0.0242 / 0.0031
[989/1000][40/42]	Loss_D: 0.4303	Loss_G: 9.7319	D(x): 0.9998	D(G(z)): 0.1572 / 0.0046
[990/1000][0/42]	Loss_D: 0.0032	Loss_G: 15.3935	D(x): 0.9988	D(G(z)): 0.0020 / 0.0002
[990/1000][20/42]	Loss_D: 0.0093	Loss_G: 13.1263	D(x): 0.9955	D(G(z)): 0.0044 / 0.0031
[990/1000][40/42]	Loss_D: 0.0115	Loss_G: 12.9851	D(x): 0.9903	D(G(z)): 0.0010 / 0.0008
```
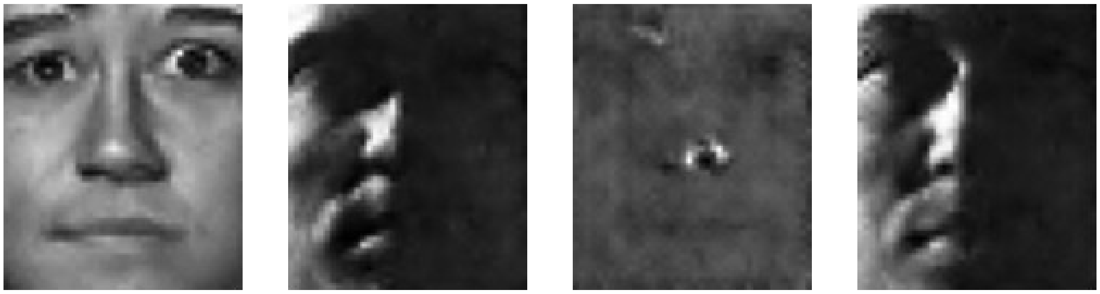

```
[991/1000][0/42]	Loss_D: 0.0702	Loss_G: 11.6212	D(x): 0.9761	D(G(z)): 0.0178 / 0.0017
[991/1000][20/42]	Loss_D: 0.0304	Loss_G: 10.1458	D(x): 0.9999	D(G(z)): 0.0225 / 0.0033
[991/1000][40/42]	Loss_D: 0.0056	Loss_G: 10.7881	D(x): 0.9999	D(G(z)): 0.0053 / 0.0033
[992/1000][0/42]	Loss_D: 0.0071	Loss_G: 11.4172	D(x): 0.9997	D(G(z)): 0.0063 / 0.0028
[992/1000][20/42]	Loss_D: 0.0012	Loss_G: 12.6930	D(x): 0.9995	D(G(z)): 0.0007 / 0.0004
[992/1000][40/42]	Loss_D: 0.0062	Loss_G: 15.6358	D(x): 0.9943	D(G(z)): 0.0000 / 0.0000
[993/1000][0/42]	Loss_D: 0.0596	Loss_G: 13.1681	D(x): 0.9921	D(G(z)): 0.0186 / 0.0003
[993/1000][20/42]	Loss_D: 0.0200	Loss_G: 10.2988	D(x): 1.0000	D(G(z)): 0.0183 / 0.0127
[993/1000][40/42]	Loss_D: 0.0683	Loss_G: 10.4707	D(x): 0.9999	D(G(z)): 0.0259 / 0.0028
[994/1000][0/42]	Loss_D: 0.0038	Loss_G: 13.2236	D(x): 0.9999
```

```
    D(G(z)): 0.0036 / 0.0015
[994/1000][20/42]    Loss_D: 0.2227  Loss_G: 12.1429 D(x): 0.8660
    D(G(z)): 0.0000 / 0.0003
[994/1000][40/42]    Loss_D: 0.0808  Loss_G: 14.6283 D(x): 0.9991
    D(G(z)): 0.0212 / 0.0005
[995/1000][0/42] Loss_D: 0.0309  Loss_G: 13.9486 D(x): 0.9845
    D(G(z)): 0.0026 / 0.0017
[995/1000][20/42]    Loss_D: 0.0212  Loss_G: 16.0337 D(x): 0.9805
    D(G(z)): 0.0000 / 0.0000
[995/1000][40/42]    Loss_D: 0.0018  Loss_G: 12.2015 D(x): 0.9994
    D(G(z)): 0.0013 / 0.0014
[996/1000][0/42] Loss_D: 0.0028  Loss_G: 12.0440 D(x): 0.9987
    D(G(z)): 0.0015 / 0.0023
[996/1000][20/42]    Loss_D: 0.0026  Loss_G: 11.7830 D(x): 0.9984
    D(G(z)): 0.0010 / 0.0008
[996/1000][40/42]    Loss_D: 0.0882  Loss_G: 10.6558 D(x): 0.9713
    D(G(z)): 0.0018 / 0.0013
[997/1000][0/42] Loss_D: 0.0032  Loss_G: 11.8331 D(x): 0.9981
    D(G(z)): 0.0013 / 0.0011
[997/1000][20/42]    Loss_D: 0.0246  Loss_G: 14.7601 D(x): 0.9793
    D(G(z)): 0.0002 / 0.0001
[997/1000][40/42]    Loss_D: 0.0503  Loss_G: 9.9693  D(x): 0.9998
    D(G(z)): 0.0197 / 0.0119
[998/1000][0/42] Loss_D: 0.0024  Loss_G: 12.5915 D(x): 1.0000
    D(G(z)): 0.0023 / 0.0014
[998/1000][20/42]    Loss_D: 0.0013  Loss_G: 12.6034 D(x): 0.9998
    D(G(z)): 0.0011 / 0.0011
[998/1000][40/42]    Loss_D: 0.0262  Loss_G: 14.8760 D(x): 0.9794
    D(G(z)): 0.0001 / 0.0001
[999/1000][0/42] Loss_D: 0.0012  Loss_G: 11.7525 D(x): 0.9993
    D(G(z)): 0.0006 / 0.0010
[999/1000][20/42]    Loss_D: 0.0026  Loss_G: 11.9659 D(x): 0.9992
    D(G(z)): 0.0018 / 0.0012
[999/1000][40/42]    Loss_D: 0.0211  Loss_G: 13.8039 D(x): 0.9813
    D(G(z)): 0.0001 / 0.0003
[1000/1000][0/42]    Loss_D: 0.0008  Loss_G: 14.9464 D(x): 0.9998
    D(G(z)): 0.0006 / 0.0007
[1000/1000][20/42]   Loss_D: 0.0051  Loss_G: 13.5170 D(x): 0.9951
    D(G(z)): 0.0001 / 0.0001
[1000/1000][40/42]   Loss_D: 0.0150  Loss_G: 7.5667  D(x): 0.9998
    D(G(z)): 0.0141 / 0.0937
```



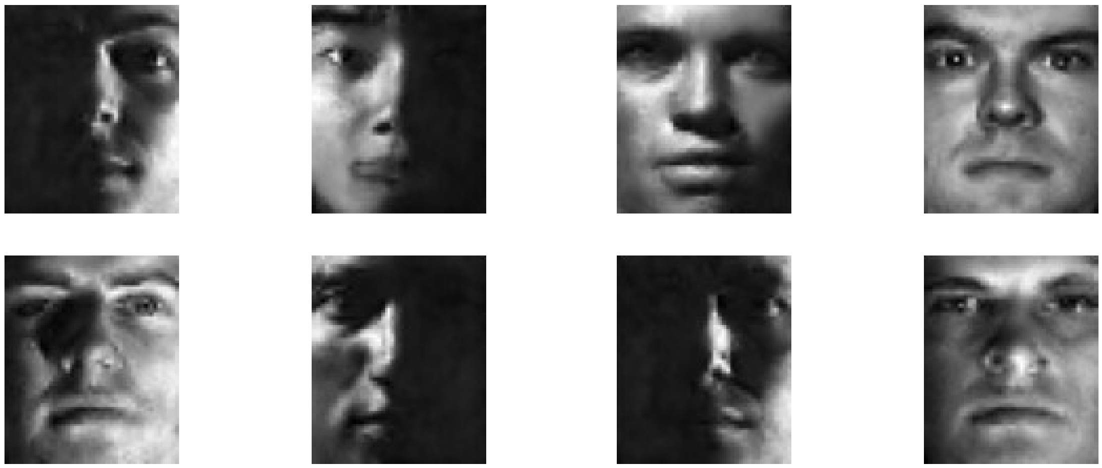
Save or load model tiles

```
torch.save(netG.state_dict(), os.path.join(ass_path,
'question_4_generator'))
torch.save(netD.state_dict(), os.path.join(ass_path,
'question_4_discriminator'))

# Run this tile in order to load the pretrained model for evaluation
netG.load_state_dict(torch.load(os.path.join(ass_path,
'question_4_generator'),
                                map_location=torch.device(device)))
netD.load_state_dict(torch.load(os.path.join(ass_path,
'question_4_discriminator'),
                                map_location=torch.device(device)))
```

```
<All keys matched successfully>
```

Generation of 8 random faces

```
z = torch.randn(25,nz,1,1,device=device)
images = netG(z)
figure = plt.figure(figsize=(10, 4))
cols, rows = 4, 2
for i in range(cols * rows):
    figure.add_subplot(rows, cols, i+1)
    plt.axis("off")
    plt.imshow(images[i,:].cpu().detach().squeeze()*127+127,
cmap="gray")
plt.show()
```



Interpolation between two random faces

```
nsamples = 7
z1 = torch.randn(1, nz, 1, 1, device=device)
z2 = torch.randn(1, nz, 1, 1, device=device)
z = torch.zeros(nsamples,nz,1,1,device=device)
for i in range(nsamples):
    w1 = i/(nsamples-1)
    w2 = 1-w1
    z[i,:,:,:] = w1*z1 + w2*z2
images = netG(z)

figure = plt.figure(figsize=(12, 4))
for i in range(nsamples):
    figure.add_subplot(1, nsamples, i+1)
    plt.axis("off")
    plt.imshow(images[i,:].squeeze().cpu().detach()*127+127,
cmap="gray")
plt.show()
```