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# **Pixyz Documentation**

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## Package Reference

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Pixyz is a library for developing deep generative models in a more concise, intuitive and extendable way!



# CHAPTER 1

---

## pixyz.distributions (Distribution API)

---

### 1.1 Distribution

```
class pixyz.distributions.distributions.Distribution(cond_var=[],      var='x',
                                                    name='p', dim=1)
```

Bases: torch.nn.modules.module.Module

Distribution class. In pixyz, all distributions are required to inherit this class.

**var** [list] Variables of this distribution.

**cond\_var** [list] Conditional variables of this distribution. In case that cond\_var is not empty, we must set the corresponding inputs in order to sample variables or estimate the log likelihood.

**dim** [int] Number of dimensions of this distribution. This might be ignored depending on the shape which is set in the sample method and on its parent distribution. Moreover, this is not consider when this class is inherited by DNNs. This is set to 1 by default.

**name** [str] Name of this distribution. This name is displayed in prob\_text and prob\_factorized\_text. This is set to “p” by default.

**distribution\_name**

**name**

**var**

**cond\_var**

**input\_var**

Normally, input\_var has same values as cond\_var.

**prob\_text**

**prob\_factorized\_text**

**get\_params** (params\_dict)

This method aims to get parameters of this distributions from constant parameters set in initialization and outputs of DNNs.

**params\_dict** [dict] Input parameters.

**output\_dict** [dict] Output parameters

```
>>> print(dist_1.prob_text, dist_1.distribution_name)
p(x) Normal
>>> dist_1.get_params()
{"loc": 0, "scale": 1}
>>> print(dist_2.prob_text, dist_2.distribution_name)
p(x|z) Normal
>>> dist_1.get_params({"z": 1})
{"loc": 0, "scale": 1}
```

**sample** (*x*={}, *shape*=None, *batch\_size*=1, *return\_all*=True, *reparam*=False)

Sample variables of this distribution. If *cond\_var* is not empty, we should set inputs as a dictionary format.

**x** [torch.Tensor, list, or dict] Input variables.

**shape** [tuple] Shape of samples. If set, *batch\_size* and *dim* are ignored.

**batch\_size** [int] Batch size of samples. This is set to 1 by default.

**return\_all** [bool] Choose whether the output contains input variables.

**reparam** [bool] Choose whether we sample variables with reparameterized trick.

**output** [dict] Samples of this distribution.

**log\_likelihood** (*x\_dict*)

Estimate the log likelihood of this distribution from inputs formatted by a dictionary.

**x\_dict** [dict] Input samples.

**log\_like** [torch.Tensor] Log-likelihood.

**forward** (\*args, \*\*kwargs)

When this class is inherited by DNNs, it is also intended that this method is overridden.

**sample\_mean** (*x*)

**replace\_var** (\*\**replace\_dict*)

**marginalize\_var** (*marginalize\_list*)

## 1.2 Exponential families

### 1.2.1 Normal

```
class pixyz.distributions.Normal(cond_var=[], var=['x'], name='p', dim=1, **kwargs)
Bases: pixyz.distributions.distributions.DistributionBase

distribution_name
sample_mean(x)
```

## 1.2.2 Bernoulli

```
class pixyz.distributions.Bernoulli(cond_var=[], var=['x'], name='p', dim=1, **kwargs)
    Bases: pixyz.distributions.distributions.DistributionBase
    distribution_name
    sample_mean(x)
```

## 1.2.3 RelaxedBernoulli

```
class pixyz.distributions.RelaxedBernoulli(temperature,      cond_var=[],      var=['x'],
                                              name='p', dim=1, **kwargs')
    Bases: pixyz.distributions.distributions.DistributionBase
    distribution_name
    log_likelihood(x)
        Estimate the log likelihood of this distribution from inputs formatted by a dictionary.
        x_dict [dict] Input samples.
        log_like [torch.Tensor] Log-likelihood.

    sample_mean(x)
```

## 1.2.4 FactorizedBernoulli

```
class pixyz.distributions.FactorizedBernoulli(cond_var=[],   var=['x'],   name='p',
                                                dim=1, **kwargs)
    Bases: pixyz.distributions.exponential_distributions.Bernoulli
    Generative Models of Visually Grounded Imagination
    distribution_name
```

## 1.2.5 Categorical

```
class pixyz.distributions.Categorical(one_hot=True, cond_var=[], var=['x'], name='p',
                                         dim=1, **kwargs)
    Bases: pixyz.distributions.distributions.DistributionBase
    distribution_name
    sample_mean(x)
```

## 1.2.6 RelaxedCategorical

```
class pixyz.distributions.RelaxedCategorical(temperature,     cond_var=[],     var=['x'],
                                               name='p', dim=1, **kwargs)
    Bases: pixyz.distributions.distributions.DistributionBase
    distribution_name
    log_likelihood(x)
        Estimate the log likelihood of this distribution from inputs formatted by a dictionary.
```

```
x_dict [dict] Input samples.  
log_like [torch.Tensor] Log-likelihood.  
sample_mean(x)
```

## 1.3 Special distributions

### 1.3.1 NormalPoE

```
class pixyz.distributions.NormalPoE(prior, dists=[], **kwargs)  
    Bases: torch.nn.modules.module.Module  
 $p(z|x, y) \propto p(z)p(z|x)p(z|y)$   
dists [list] Other distributions.  
prior [Distribution] Prior distribution.  
>>> poe = NormalPoE(c, [a, b])  
  
get_params(params, **kwargs)  
experts(loc, scale, eps=1e-08)  
sample(x=None, return_all=True, **kwargs)  
log_likelihood(x)  
sample_mean(x, **kwargs)
```

### 1.3.2 Deterministic

```
class pixyz.distributions.Deterministic(**kwargs)  
    Bases: pixyz.distributions.distributions.Distribution  
    Deterministic distribution (or degeneration distribution)  
distribution_name  
sample(x={}, return_all=True, **kwargs)  
    Sample variables of this distribution. If cond_var is not empty, we should set inputs as a dictionary format.  
x [torch.Tensor, list, or dict] Input variables.  
shape [tuple] Shape of samples. If set, batch_size and dim are ignored.  
batch_size [int] Batch size of samples. This is set to 1 by default.  
return_all [bool] Choose whether the output contains input variables.  
reparam [bool] Choose whether we sample variables with reparameterized trick.  
output [dict] Samples of this distribution.
```

### 1.3.3 DataDistribution

```
class pixyz.distributions.DataDistribution(var, name='p_data')
    Bases: pixyz.distributions.distributions.Distribution

    Data distribution. TODO: Fix this behavior if multiplied with other distributions

    distribution_name

    sample(x={}, **kwargs)
        Sample variables of this distribution. If cond_var is not empty, we should set inputs as a dictionary format.

        x [torch.Tensor, list, or dict] Input variables.

        shape [tuple] Shape of samples. If set, batch_size and dim are ignored.

        batch_size [int] Batch size of samples. This is set to 1 by default.

        return_all [bool] Choose whether the output contains input variables.

        reparam [bool] Choose whether we sample variables with reparameterized trick.

        output [dict] Samples of this distribution.

    input_var
        In DataDistribution, input_var is same as var.
```

### 1.3.4 CustomLikelihoodDistribution

```
class pixyz.distributions.CustomLikelihoodDistribution(var=['x'], likelihood=None,
                                                       **kwargs)
    Bases: pixyz.distributions.distributions.Distribution

    input_var
        In CustomLikelihoodDistribution, input_var is same as var.

    distribution_name

    log_likelihood(x_dict)
        Estimate the log likelihood of this distribution from inputs formatted by a dictionary.

        x_dict [dict] Input samples.

    log_like [torch.Tensor] Log-likelihood.
```

## 1.4 Flow-based

### 1.4.1 PlanarFlow

```
class pixyz.distributions.PlanarFlow(prior, dim, num_layers=1, var=[], **kwargs)
    Bases: pixyz.distributions.flows.Flow
```

## 1.4.2 RealNVP

```
class pixyz.distributions.RealNVP(prior, dim, num_multiscale_layers=2, var=[], image=False, name='p', **kwargs)
Bases: pixyz.distributions.distributions.Distribution

prob_text

forward(x, inverse=False, jacobian=False)
When this class is inherited by DNNs, it is also intended that this method is overridden.

sample(x={}, only_flow=False, return_all=True, **kwargs)
Sample variables of this distribution. If cond_var is not empty, we should set inputs as a dictionary format.
x [torch.Tensor, list, or dict] Input variables.

shape [tuple] Shape of samples. If set, batch_size and dim are ignored.

batch_size [int] Batch size of samples. This is set to 1 by default.

return_all [bool] Choose whether the output contains input variables.

reparam [bool] Choose whether we sample variables with reparameterized trick.

output [dict] Samples of this distribution.

sample_inv(x, return_all=True, **kwargs)

log_likelihood(x)
Estimate the log likelihood of this distribution from inputs formatted by a dictionary.
x_dict [dict] Input samples.

log_like [torch.Tensor] Log-likelihood.
```

## 1.5 Operators

### 1.5.1 ReplaceVarDistribution

```
class pixyz.distributions.distributions.ReplaceVarDistribution(a, replace_dict)
Bases: pixyz.distributions.distributions.Distribution

Replace names of variables in Distribution.

a [pixyz.Distribution (not pixyz.MultiplyDistribution)] Distribution.

replace_dict [dict] Dictionary.

forward(*args, **kwargs)
When this class is inherited by DNNs, it is also intended that this method is overridden.

get_params(params_dict)
This method aims to get parameters of this distributions from constant parameters set in initialization and outputs of DNNs.

params_dict [dict] Input parameters.

output_dict [dict] Output parameters
```

```
>>> print(dist_1.prob_text, dist_1.distribution_name)
p(x) Normal
>>> dist_1.get_params()
{"loc": 0, "scale": 1}
>>> print(dist_2.prob_text, dist_2.distribution_name)
p(x|z) Normal
>>> dist_1.get_params({"z": 1})
{"loc": 0, "scale": 1}
```

**sample** (*x={}*, *shape=None*, *batch\_size=1*, *return\_all=True*, *reparam=False*)

Sample variables of this distribution. If *cond\_var* is not empty, we should set inputs as a dictionary format.

**x** [torch.Tensor, list, or dict] Input variables.

**shape** [tuple] Shape of samples. If set, *batch\_size* and *dim* are ignored.

**batch\_size** [int] Batch size of samples. This is set to 1 by default.

**return\_all** [bool] Choose whether the output contains input variables.

**reparam** [bool] Choose whether we sample variables with reparameterized trick.

**output** [dict] Samples of this distribution.

**log\_likelihood** (*x*)

Estimate the log likelihood of this distribution from inputs formatted by a dictionary.

**x\_dict** [dict] Input samples.

**log\_like** [torch.Tensor] Log-likelihood.

**sample\_mean** (*x*)**input\_var**

Normally, *input\_var* has same values as *cond\_var*.

**distribution\_name**

## 1.5.2 MarginalizeVarDistribution

```
class pixyz.distributions.distributions.MarginalizeVarDistribution(a,
                                                               marginal-
                                                               ize_list)
```

Bases: *pixyz.distributions.distributions.Distribution*

Marginalize variables in Distribution.  $p(x) = \int p(x, z)dz$

**a** [pixyz.Distribution (not pixyz.DistributionBase)] Distribution.

**marginalize\_list** [list] Variables to marginalize.

**forward** (\*args, \*\*kwargs)

When this class is inherited by DNNs, it is also intended that this method is overrided.

**get\_params** (*params\_dict*)

This method aims to get parameters of this distributions from constant parameters set in initialization and outputs of DNNs.

**params\_dict** [dict] Input parameters.

**output\_dict** [dict] Output parameters

```
>>> print(dist_1.prob_text, dist_1.distribution_name)
p(x) Normal
>>> dist_1.get_params()
{"loc": 0, "scale": 1}
>>> print(dist_2.prob_text, dist_2.distribution_name)
p(x|z) Normal
>>> dist_1.get_params({"z": 1})
{"loc": 0, "scale": 1}
```

**sample** ( $x=\{\}$ ,  $shape=None$ ,  $batch\_size=1$ ,  $return\_all=True$ ,  $reparam=False$ )

Sample variables of this distribution. If  $cond\_var$  is not empty, we should set inputs as a dictionary format.

**x** [torch.Tensor, list, or dict] Input variables.

**shape** [tuple] Shape of samples. If set,  $batch\_size$  and  $dim$  are ignored.

**batch\_size** [int] Batch size of samples. This is set to 1 by default.

**return\_all** [bool] Choose whether the output contains input variables.

**reparam** [bool] Choose whether we sample variables with reparameterized trick.

**output** [dict] Samples of this distribution.

**log\_likelihood** ( $x$ )

Estimate the log likelihood of this distribution from inputs formatted by a dictionary.

**x\_dict** [dict] Input samples.

**log\_like** [torch.Tensor] Log-likelihood.

**sample\_mean** ( $x$ )

**input\_var**

Normally,  $input\_var$  has same values as  $cond\_var$ .

**distribution\_name**

**prob\_factorized\_text**

### 1.5.3 MultiplyDistribution

**class** pixyz.distributions.distributions.**MultiplyDistribution** ( $a, b$ )

Bases: *pixyz.distributions.distributions.Distribution*

Multiply by given distributions, e.g,  $p(x, y|z) = p(x|z, y)p(y|z)$ . In this class, it is checked if two distributions can be multiplied.

$p(x|z)p(z|y) \rightarrow$  Valid

$p(x|z)p(y|z) \rightarrow$  Valid

$p(x|z)p(y|a) \rightarrow$  Valid

$p(x|z)p(z|x) \rightarrow$  Invalid (recursive)

$p(x|z)p(x|y) \rightarrow$  Invalid (conflict)

**a** [pixyz.Distribution] Distribution.

**b** [pixyz.Distribution] Distribution.

```
>>> p_multi = MultipleDistribution([a, b])
>>> p_multi = a * b
```

**inh\_var**

**input\_var**

Normally, *input\_var* has same values as *cond\_var*.

**prob\_factorized\_text**

**sample** (*x*={}, *shape*=None, *batch\_size*=1, *return\_all*=True, *reparam*=False)

Sample variables of this distribution. If *cond\_var* is not empty, we should set inputs as a dictionary format.

**x** [torch.Tensor, list, or dict] Input variables.

**shape** [tuple] Shape of samples. If set, *batch\_size* and *dim* are ignored.

**batch\_size** [int] Batch size of samples. This is set to 1 by default.

**return\_all** [bool] Choose whether the output contains input variables.

**reparam** [bool] Choose whether we sample variables with reparameterized trick.

**output** [dict] Samples of this distribution.

**log\_likelihood** (*x*)

Estimate the log likelihood of this distribution from inputs formatted by a dictionary.

**x\_dict** [dict] Input samples.

**log\_like** [torch.Tensor] Log-likelihood.

## 1.6 Functions

`pixxyz.distributions.distributions.sum_samples(samples)`



# CHAPTER 2

---

## pixyz.losses (Loss API)

---

### 2.1 Loss

```
class pixyz.losses.losses.Loss(p1, p2=None, input_var=None)
Bases: object

    input_var
    loss_text
    mean()
    sum()
    estimate(x={}, **kwargs)
    train(x={}, **kwargs)
        Train the implicit (adversarial) loss function.
    test(x={}, **kwargs)
        Test the implicit (adversarial) loss function.
```

### 2.2 Negative expected value of log-likelihood (entropy)

#### 2.2.1 CrossEntropy

```
class pixyz.losses.CrossEntropy(p1, p2, input_var=None)
Bases: pixyz.losses.losses.Loss

Cross entropy, a.k.a., the negative expected value of log-likelihood (Monte Carlo approximation).
```

$$-\mathbb{E}_{q(x)}[\log p(x)] \approx -\frac{1}{L} \sum_{l=1}^L \log p(x_l),$$

where  $x_l \sim q(x)$ .

```
loss_text
estimate (x={})
```

## 2.2.2 Entropy

```
class pixyz.losses.Entropy (p1, input_var=None)
```

Bases: *pixyz.losses.Loss*

Entropy (Monte Carlo approximation).

$$-\mathbb{E}_{p(x)}[\log p(x)] \approx -\frac{1}{L} \sum_{l=1}^L \log p(x_l),$$

where  $x_l \sim p(x)$ .

**Note:** This class is a special case of the *CrossEntropy* class. You can get the same result with *CrossEntropy*.

```
loss_text
```

```
estimate (x={})
```

## 2.2.3 StochasticReconstructionLoss

```
class pixyz.losses.StochasticReconstructionLoss (encoder, decoder, input_var=None)
```

Bases: *pixyz.losses.Loss*

Reconstruction Loss (Monte Carlo approximation).

$$-\mathbb{E}_{q(z|x)}[\log p(x|z)] \approx -\frac{1}{L} \sum_{l=1}^L \log p(x|z_l),$$

where  $z_l \sim q(z|x)$ .

**Note:** This class is a special case of the *CrossEntropy* class. You can get the same result with *CrossEntropy*.

```
loss_text
```

```
estimate (x={})
```

## 2.3 Negative log-likelihood

### 2.3.1 NLL

```
class pixyz.losses.NLL (p, input_var=None)
```

Bases: *pixyz.losses.Loss*

Negative log-likelihood.

$$\log p(x)$$

```
loss_text
```

```
estimate (x={})
```

## 2.4 Lower bound

### 2.4.1 ELBO

```
class pixyz.losses.ELBO(p, approximate_dist, input_var=None)
Bases: pixyz.losses.losses.Loss
```

The evidence lower bound (Monte Carlo approximation).

$$\mathbb{E}_{q(z|x)}[\log \frac{p(x, z)}{q(z|x)}] \approx \frac{1}{L} \sum_{l=1}^L \log p(x, z_l),$$

where  $z_l \sim q(z|x)$ .

**loss\_text**

**estimate** (*x*={}, *batch\_size=None*)

## 2.5 Similarity

### 2.5.1 SimilarityLoss

```
class pixyz.losses.SimilarityLoss(p1, p2, input_var=None, var=['z'], margin=0)
Bases: pixyz.losses.losses.Loss
```

Learning Modality-Invariant Representations for Speech and Images (Leidai et. al.)

**estimate** (*x*)

### 2.5.2 MultiModalContrastivenessLoss

```
class pixyz.losses.MultiModalContrastivenessLoss(p1, p2, input_var=None, margin=0.5)
Bases: pixyz.losses.losses.Loss
```

Disentangling by Partitioning: A Representation Learning Framework for Multimodal Sensory Data

**estimate** (*x*)

## 2.6 Adversarial loss (GAN loss)

### 2.6.1 AdversarialJSDivergence

```
class pixyz.losses.AdversarialJSDivergence(p_data, p, discriminator, input_var=None,
optimizer=<class 'torch.optim.adam.Adam'>, optimizer_params={}, inverse_g_loss=True)
Bases: pixyz.losses.losses.Loss
```

Adversarial loss (Jensen-Shannon divergence).

$$\mathcal{L}_{adv} = 2JS[p_{data}(x) || p(x)] + const.$$

```
loss_text
estimate (x={}, discriminator=False)
d_loss (y1, y2, batch_size)
g_loss (y1, y2, batch_size)
train (train_x, **kwargs)
    Train the implicit (adversarial) loss function.

test (test_x, **kwargs)
    Test the implicit (adversarial) loss function.
```

## 2.6.2 AdversarialWassersteinDistance

```
class pixyz.losses.AdversarialWassersteinDistance (p_data,      p,      discriminator,
                                                clip_value=0.01, **kwargs)
Bases: pixyz.losses.adversarial_loss.AdversarialJSDivergence
Adversarial loss (Wasserstein Distance).

loss_text
d_loss (y1, y2, *args, **kwargs)
g_loss (y1, y2, *args, **kwargs)
train (train_x, **kwargs)
    Train the implicit (adversarial) loss function.
```

## 2.7 Loss for special purpose

### 2.7.1 Parameter

```
class pixyz.losses.losses.Parameter (input_var)
Bases: pixyz.losses.losses.Loss
estimate (x={}, **kwargs)
loss_text
```

## 2.8 Operators

### 2.8.1 LossOperator

```
class pixyz.losses.losses.LossOperator (loss1, loss2)
Bases: pixyz.losses.losses.Loss
loss_text
estimate (x={}, **kwargs)
train (x, **kwargs)
TODO: Fix
```

---

```
test (x, **kwargs)
    TODO: Fix
```

## 2.8.2 LossSelfOperator

```
class pixyz.losses.losses.LossSelfOperator (loss1)
    Bases: pixyz.losses.losses.Loss

    train (x={}, **kwargs)
        Train the implicit (adversarial) loss function.

    test (x={}, **kwargs)
        Test the implicit (adversarial) loss function.
```

## 2.8.3 AddLoss

```
class pixyz.losses.losses.AddLoss (loss1, loss2)
    Bases: pixyz.losses.losses.LossOperator

    loss_text
    estimate (x={}, **kwargs)
```

## 2.8.4 SubLoss

```
class pixyz.losses.losses.SubLoss (loss1, loss2)
    Bases: pixyz.losses.losses.LossOperator

    loss_text
    estimate (x={}, **kwargs)
```

## 2.8.5 MulLoss

```
class pixyz.losses.losses.MulLoss (loss1, loss2)
    Bases: pixyz.losses.losses.LossOperator

    loss_text
    estimate (x={}, **kwargs)
```

## 2.8.6 DivLoss

```
class pixyz.losses.losses.DivLoss (loss1, loss2)
    Bases: pixyz.losses.losses.LossOperator

    loss_text
    estimate (x={}, **kwargs)
```

## 2.8.7 NegLoss

```
class pixyz.losses.losses.NegLoss(lossI)
Bases: pixyz.losses.losses.LossSelfOperator

loss_text
estimate(x={}, **kwargs)
```

## 2.8.8 BatchMean

```
class pixyz.losses.losses.BatchMean(lossI)
Bases: pixyz.losses.losses.LossSelfOperator

Loss averaged over batch data.
```

$$\mathbb{E}_{p_{data}(x)}[\mathcal{L}(x)] \approx \frac{1}{N} \sum_{i=1}^N \mathcal{L}(x_i),$$

where  $x_i \sim p_{data}(x)$  and  $\mathcal{L}$  is a loss function.

```
loss_text
estimate(x={}, **kwargs)
```

## 2.8.9 BatchSum

```
class pixyz.losses.losses.BatchSum(lossI)
Bases: pixyz.losses.losses.LossSelfOperator

Loss summed over batch data.
```

$$\sum_{i=1}^N \mathcal{L}(x_i),$$

where  $x_i \sim p_{data}(x)$  and  $\mathcal{L}$  is a loss function.

```
loss_text
estimate(x={}, **kwargs)
```

# CHAPTER 3

---

## pixyz.models (Model API)

---

### 3.1 Model

```
class pixyz.models.Model(loss,      test_loss=None,      distributions=[],      optimizer=<class
                           'torch.optim.adam.Adam'>, optimizer_params={})
Bases: object

set_loss(loss, test_loss=None)
train(train_x={}, **kwargs)
test(test_x={}, **kwargs)
```

### 3.2 Pre-implementation models

#### 3.2.1 ML

```
class pixyz.models.ML(p, other_distributions=[], optimizer=<class 'torch.optim.adam.Adam'>, opti-
                      mizer_params={})
Bases: pixyz.models.model.Model

Maximum Likelihood (log-likelihood)

train(train_x={}, **kwargs)
test(test_x={}, **kwargs)
```

#### 3.2.2 VAE

```
class pixyz.models.VAE(encoder, decoder, other_distributions=[], regularizer=[], optimizer=<class
                        'torch.optim.adam.Adam'>, optimizer_params={})
Bases: pixyz.models.model.Model

Variational Autoencoder
```

[Kingma+ 2013] Auto-Encoding Variational Bayes

```
train (train_x={}, **kwargs)  
test (test_x={}, **kwargs)
```

### 3.2.3 VI

```
class pixyz.models.VI (p,      approximate_dist,      other_distributions=[],      optimizer=<class  
                           'torch.optim.adam.Adam'>, optimizer_params={})  
Bases: pixyz.models.model.Model
```

Variational Inference (Amortized inference)

```
train (train_x={}, **kwargs)  
test (test_x={}, **kwargs)
```

### 3.2.4 GAN

```
class pixyz.models.GAN (p_data, p, discriminator, optimizer=<class 'torch.optim.adam.Adam'>,  
                        optimizer_params={}, d_optimizer=<class 'torch.optim.adam.Adam'>,  
                        d_optimizer_params={})  
Bases: pixyz.models.model.Model
```

Generative Adversarial Network

```
train (train_x={}, adversarial_loss=True, **kwargs)  
test (test_x={}, adversarial_loss=True, **kwargs)
```

# CHAPTER 4

---

## pixyz.utils

---

```
pixyz.utils.set_epsilon(eps)
pixyz.utils.epsilon()
pixyz.utils.get_dict_values(dict, keys, return_dict=False)
pixyz.utils.delete_dict_values(dict, keys)
pixyz.utils.detach_dict(dict)
pixyz.utils.replace_dict_keys(dict, replace_list_dict)
pixyz.utils.tolist(a)
```



# CHAPTER 5

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## Python Module Index

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