experiments_8v3

June 9, 2023

source: https://medium.com/dataseries/convolutional-autoencoder-in-pytorch-on-mnist-dataset-d65145c132ac#63b2 source: https://stackoverflow.com/questions/37228371/visualize-mnist-dataset-using-opencv-or-matplotlib-pyplot

color source: https://matplotlib.org/stable/tutorials/colors/colors.html palette source: https://seaborn.pydata.org/tutorial/color_palettes.html

[ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, random_split
import torch.optim as optim
import torchvision
from torchvision import transforms

import matplotlib.pyplot as plt
import seaborn as sns

import pandas as pd
import numpy as np
from sklearn.metrics.pairwise import pairwise_kernels

import random
import tqdm
import time

from permutation_testing import *
from model import *

plt.rcParams['patch.edgecolor'] = 'none' # remove edges from histogram bars
```

[ ]:
```
# setting random seed
# https://pytorch.org/docs/stable/notes/randomness.html
torch.manual_seed(0)
np.random.seed(0)
random.seed(0)

torch.use_deterministic_algorithms(True)
```

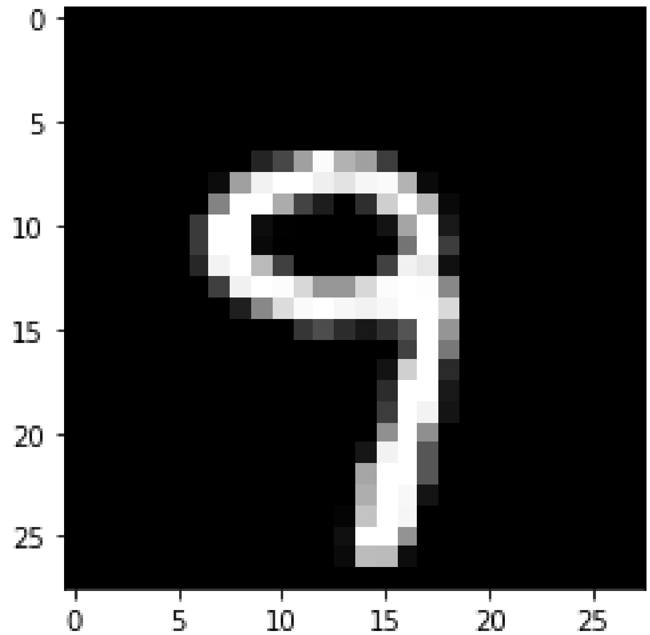
```
torch.backends.cudnn.deterministic = True

torch.backends.cudnn.benchmark = False
```

[ ]:
```
%load_ext autoreload
%autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

[ ]:
```
data_dir = 'dataset'
train_dataset = torchvision.datasets.MNIST(data_dir, train=True, download=True)
test_dataset  = torchvision.datasets.MNIST(data_dir, train=False, download=True)

train_transform = transforms.Compose([transforms.ToTensor(),])
test_transform = transforms.Compose([transforms.ToTensor(),])
train_dataset.transform = train_transform
test_dataset.transform = test_transform

m = len(train_dataset)
batch_size = 256

train_data, val_data = random_split(train_dataset, [int(0.8 * m), int(0.2 * m)])
train_loader = DataLoader(train_data, batch_size=batch_size)
val_loader = DataLoader(val_data, batch_size=batch_size)
test_loader = DataLoader(test_dataset, batch_size=batch_size,shuffle=False) #␣
 ↪dangit

for data in train_loader:
    print(data[0].shape)
    break

plt.imshow(data[0][0].squeeze(), cmap='gray')

print('Number of training samples:', len(train_dataset))
print('Number of test samples:', len(test_dataset))
```

```
torch.Size([256, 1, 28, 28])
Number of training samples: 60000
Number of test samples: 10000
```



0.0.1 keeping track of model weights

- 05232023a: epochs=50, lr=1e-3, d=4, inplace=T, ReLU
- 05302023a: epochs=50, lr=1e-3, d=4, inplace=F, ReLU
- 05302023b: epochs=50, lr=1e-3, d=4, inplace=F, ELU
- 06072023a: epochs=50, lr=1e-3, d=4, inplace=F, ELU; used deterministic things from PyTorch
  - epoch 50: train loss: 0.02580, val loss: 0.02636
- 06072023b: epochs=50, lr=1e-3, d=4, inplace=F, ELU; additionally used `torch.backends.cudnn.benchmark = False`
  - epoch 50: train loss: 0.02580, val loss: 0.02636
- 06072023c: same settings as 06072023b except d=6
  - epoch 50: train loss: 0.01868, val loss: 0.01931

[ ]:
```
device = torch.device("cuda") if torch.cuda.is_available() else torch.
 ↪device("cpu")
print(f'Selected device: {device}')

loss_fn = torch.nn.MSELoss()
lr = 0.001
num_epochs = 50
d = 6
```

```
Selected device: cpu
```

[ ]:

```
%%time

train = False
version = '06072023c' # NOTE: MAKE SURE TO UPDATE THIS EVERY TIME

encoder = Encoder(encoded_space_dim=d,fc2_input_dim=128)
decoder = Decoder(encoded_space_dim=d,fc2_input_dim=128)

if train:
    params_to_optimize = [
        {'params': encoder.parameters()},
        {'params': decoder.parameters()}
    ]

    optimizer = optim.Adam(params_to_optimize, lr=lr)
    print_every = 10

    encoder.to(device)
    decoder.to(device)
    plot_ae_outputs(encoder, decoder, test_dataset, device, n=10)
    losses = {'train_loss': [], 'val_loss': []}
    for epoch in range(num_epochs):
        train_loss = train_epoch(encoder,decoder,device, train_loader,loss_fn,␣
↪optimizer)
        val_loss = test_epoch(encoder, decoder, device, val_loader, loss_fn) #␣
↪better for this to be val_loader?
        print('EPOCH {}/{}: train loss: {:.5f}, val loss: {:.5f}'.format(epoch␣
↪+ 1, num_epochs, train_loss, val_loss))
        losses['train_loss'].append(train_loss)
        losses['val_loss'].append(val_loss)
        if (epoch + 1) % print_every == 0:
            plot_ae_outputs(encoder, decoder, test_dataset, device, n=10)
    # save the model
    torch.save(encoder.state_dict(), 'weights/encoder_weights_' + version + '.
↪pth')
    torch.save(decoder.state_dict(), 'weights/decoder_weights_' + version + '.
↪pth')
else:
    encoder.load_state_dict(torch.load('weights/encoder_weights_' + version + '.
↪pth'))
    decoder.load_state_dict(torch.load('weights/decoder_weights_' + version + '.
↪pth'))

encoder.eval(), decoder.eval()
```

```
CPU times: user 3.74 ms, sys: 1.36 ms, total: 5.09 ms
Wall time: 3.92 ms
```

[ ]:
```
(Encoder(
   (encoder_cnn): Sequential(
     (0): Conv2d(1, 8, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
     (1): ELU(alpha=1.0)
     (2): Conv2d(8, 16, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
     (3): ELU(alpha=1.0)
     (4): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2))
     (5): ELU(alpha=1.0)
   )
   (flatten): Flatten(start_dim=1, end_dim=-1)
   (encoder_lin): Sequential(
     (0): Linear(in_features=288, out_features=128, bias=True)
     (1): ELU(alpha=1.0)
     (2): Linear(in_features=128, out_features=6, bias=True)
   )
 ),
 Decoder(
   (decoder_lin): Sequential(
     (0): Linear(in_features=6, out_features=128, bias=True)
     (1): ELU(alpha=1.0)
     (2): Linear(in_features=128, out_features=288, bias=True)
     (3): ELU(alpha=1.0)
   )
   (unflatten): Unflatten(dim=1, unflattened_size=(32, 3, 3))
   (decoder_conv): Sequential(
     (0): ConvTranspose2d(32, 16, kernel_size=(3, 3), stride=(2, 2))
     (1): ELU(alpha=1.0)
     (2): ConvTranspose2d(16, 8, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), output_padding=(1, 1))
     (3): ELU(alpha=1.0)
     (4): ConvTranspose2d(8, 1, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), output_padding=(1, 1))
   )
 ))
```

[ ]:
```
test_error_on_classes = True
losses = {}
centers = {}
if test_error_on_classes:
    for label in data[1].unique():
        losses[label.item()] = 0
        centers[label.item()] = torch.zeros(6)
        num_digits = 0
        for ind, data in enumerate(test_loader):
            idx = data[1] == label.item()
            num_digits += idx.sum().item()
            original_images = data[0][idx]
```

```
            latent_representations = encoder(original_images)
            recon_images = decoder(latent_representations)

            losses[label.item()] += loss_fn(original_images, recon_images).
 ↪item()
            centers[label.item()] += latent_representations.mean(dim=0)

        losses[label.item()] /= num_digits
        losses[label.item()] = np.round(losses[label.item()], 7)

        centers[label.item()] /= num_digits
    pd.Series(losses).sort_values()
```

[ ]:
```
pd.Series(losses).sort_values(ascending=False) # 8 has the greatest␣
 ↪reconstruction error
```

[ ]:
```
8    0.001194
5    0.001158
2    0.001020
3    0.000971
6    0.000748
0    0.000733
4    0.000728
9    0.000646
7    0.000541
1    0.000144
dtype: float64
```

[ ]:
```
pairwise_center_distances = torch.zeros(10, 10)
for num1 in range(0, 10):
    for num2 in range(0, 10):
        pairwise_center_distances[num1, num2] = ((centers[num1] -␣
 ↪centers[num2]) ** 2).sum()
```

[ ]:
```
# see which digits have closest embeddings on average
torch.topk(pairwise_center_distances, k=2, dim=1, largest=False)
# so 8 and 3 are the digits with closest latent embeddings, on average
```

[ ]:
```
torch.return_types.topk(
values=tensor([[0.0000, 0.5765],
        [0.0000, 0.9230],
        [0.0000, 0.6556],
        [0.0000, 0.3532],
        [0.0000, 0.5178],
        [0.0000, 0.3877],
        [0.0000, 0.5765],
```

```
         [0.0000, 0.4212],
         [0.0000, 0.3532],
         [0.0000, 0.4212]], grad_fn=<TopkBackward0>),
indices=tensor([[0, 6],
         [1, 2],
         [2, 8],
         [3, 8],
         [4, 9],
         [5, 8],
         [6, 0],
         [7, 9],
         [8, 3],
         [9, 7]]))
```

0.1 Convenience Functions

```
[ ]: def p_val(simulated_stats, observed_stat):
         return (np.array([stat.item() for stat in simulated_stats]) > observed_stat.
      ↪item()).mean()#i
```

```
[ ]: def plot_permutation(
             simulated_stats,
             observed_stat,
             bins=50,
             filepath='',
             hist_color='tab:blue',
             line_color='tab.red'
         ):
         print('p_value:', p_val(simulated_stats, observed_stat))
         sns.displot([mmd.item() for mmd in simulated_stats], bins=bins,␣
      ↪color=hist_color)
         plt.axvline(observed_stat.item(), color=line_color)
         if filepath != '':
             print('Image saved to ' + str(filepath))
             plt.savefig(filepath + '.jpg', bbox_inches='tight')
         else:
             print('No image saved.')
         return
```

0.2 Creating X and Y samples

0.2.1 X = {images of 8's}, Y = {images of 3's}

```
[ ]: # generate x_batch, y_batch
     x_batch = []
     y_batch = []
     for ind, data in enumerate(test_loader): # filter batches based on digit
```

```
    if ind == 5:
        r_batch = data[0][(data[1] == 8) | (data[1] == 3)]
    elif 5 < ind and ind < 15:
        x_batch.append(data[0][data[1] == 8])
        y_batch.append(data[0][data[1] == 3])
    elif ind == 15:
        break
x_batch = torch.cat(x_batch, dim=0)
y_batch = torch.cat(y_batch, dim=0)
print('x_batch shape:', x_batch.shape)
print('y_batch shape:', y_batch.shape)
print('r_batch shape:', r_batch.shape)

n_perms = 250
```

```
x_batch shape: torch.Size([224, 1, 28, 28])
y_batch shape: torch.Size([237, 1, 28, 28])
r_batch shape: torch.Size([51, 1, 28, 28])
```

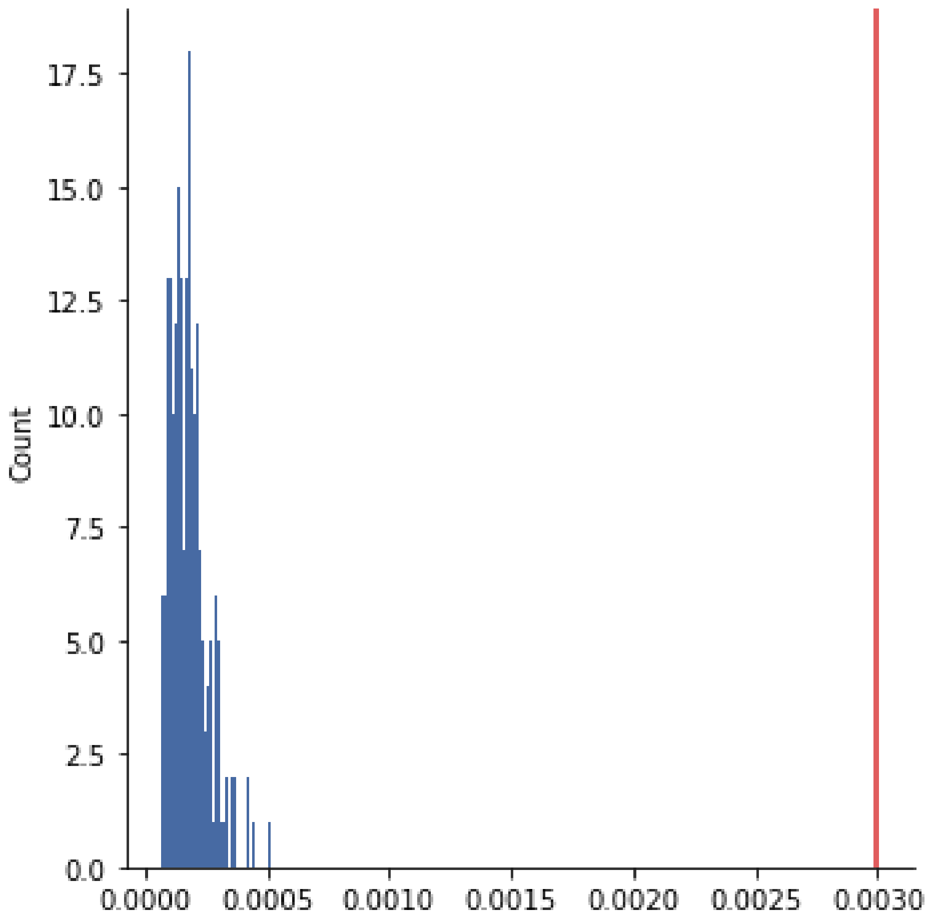
0.2.2 Statistics for Anisotropic Kernel

[ ]:
```
%%time

# anisotropic mmd

encoder.eval()
diff_anisotropic_stats = {}
for val in [-3, -2, -1, 0, 1, 2, 3]:
    start = time.time()
    observed_mmd_anisotropic8v3, simulated_mmds_anisotropic8v3 =␣
 ↪permutation_test_anisotropic_mmd(
        x_batch, y_batch, r_batch, encoder, n_perms=n_perms, sigma_squared=(2␣
 ↪** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_anisotropic8v3, observed_mmd_anisotropic8v3)
    diff_anisotropic_stats[val] = {'p': p, 'time': end - start}

    hist_color = '#093885'
    line_color = 'tab:red'
    filepath = 'images_latentdim6_8v3v8/diff_anisotropic_s' + str(val) + '_8v3'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_anisotropic8v3,
        observed_mmd_anisotropic8v3,
        hist_color = hist_color,
```

```
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

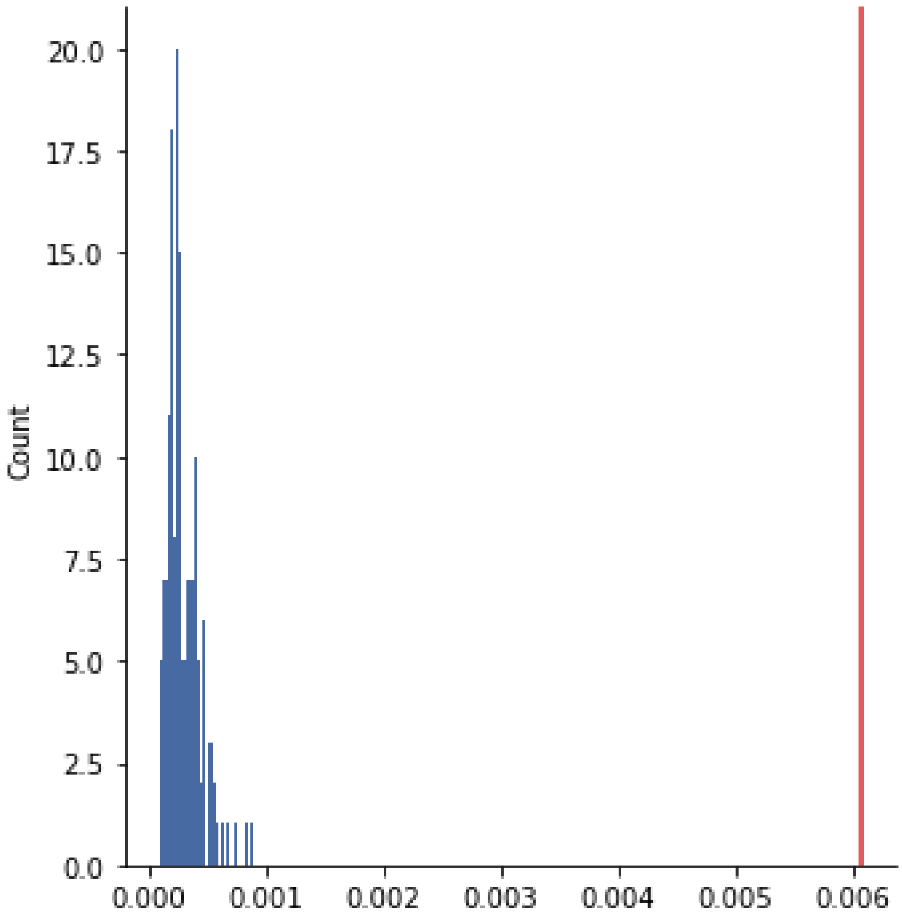
```
100%|      | 250/250 [00:14<00:00, 17.14it/s]
```

```
bandwidth: 0.125
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s-3_8v3
```

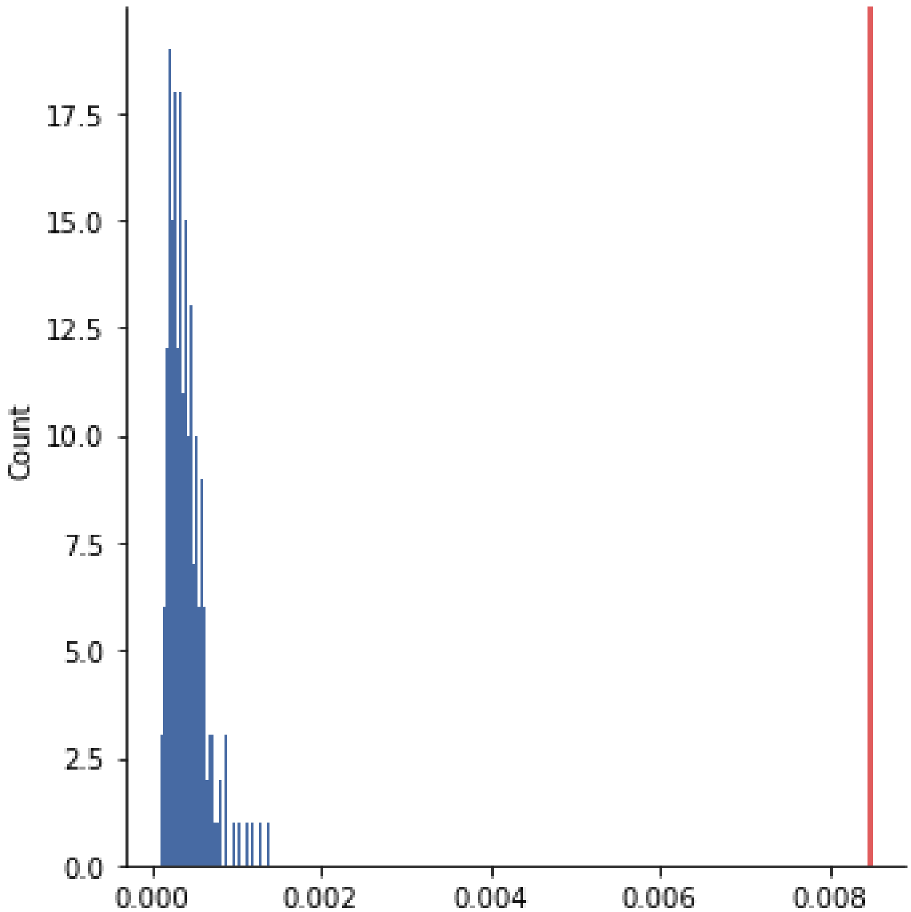



```
100%|      | 250/250 [00:16<00:00, 14.92it/s]
```

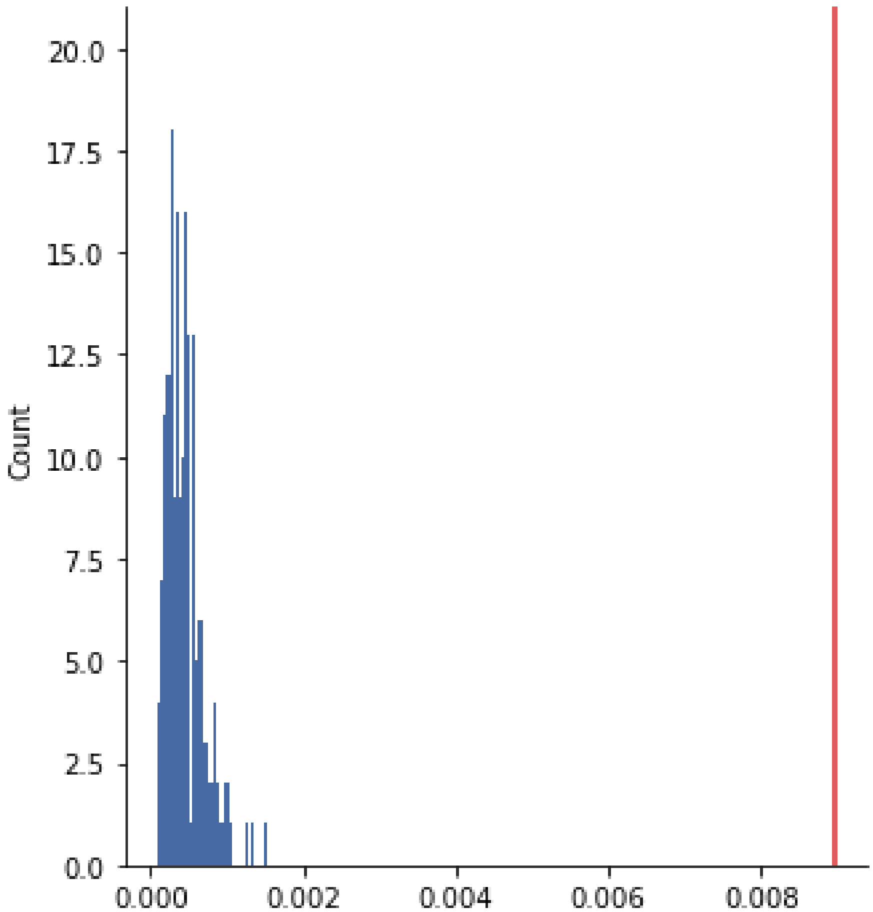
```
bandwidth: 0.25
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s-2_8v3
```



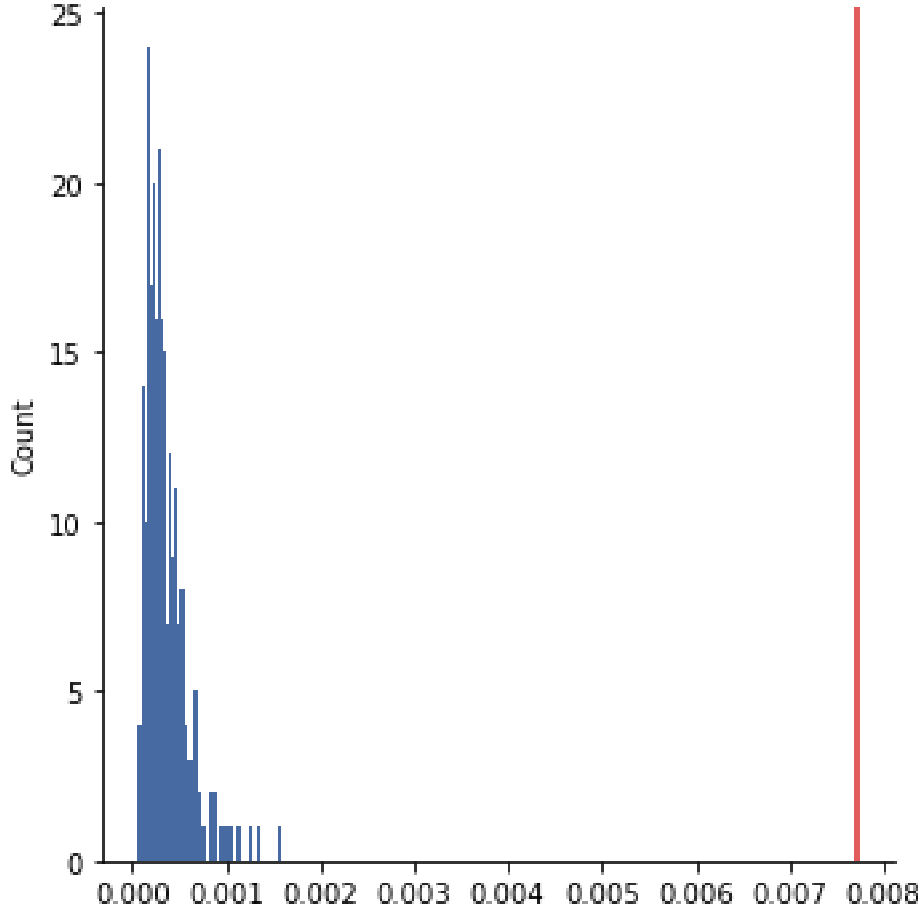

```
100%|          | 250/250 [00:13<00:00, 18.09it/s]

bandwidth: 0.5
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s-1_8v3
```



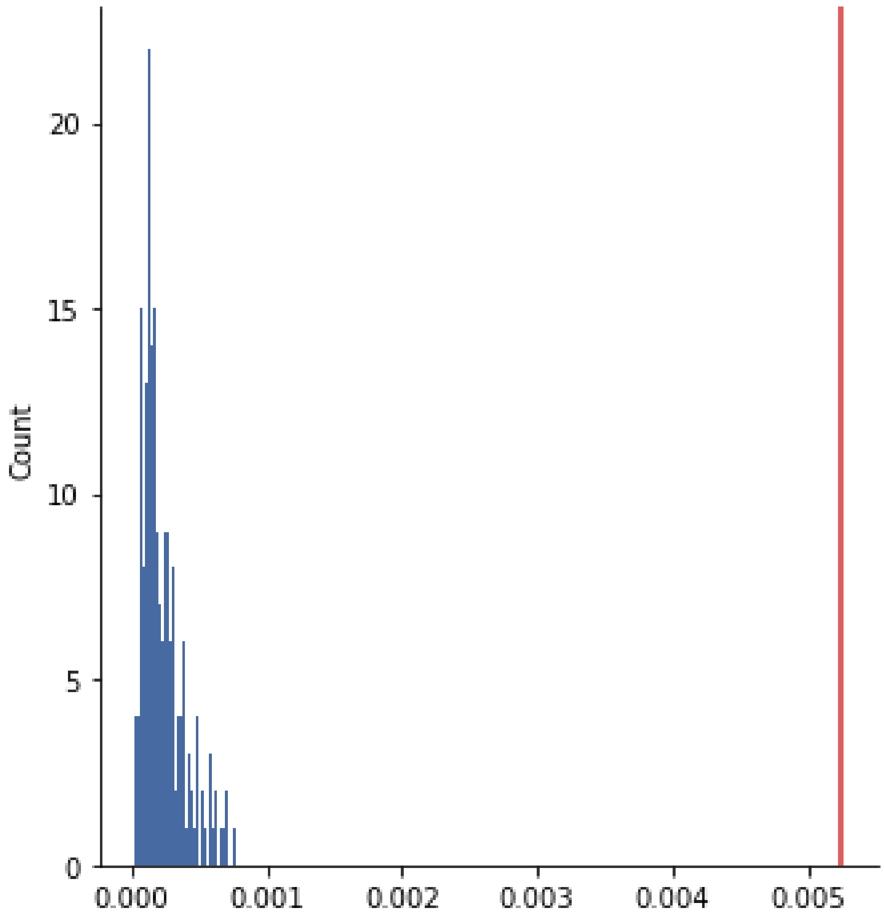

```
100%|      | 250/250 [00:14<00:00, 17.84it/s]

bandwidth: 1
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s0_8v3
```



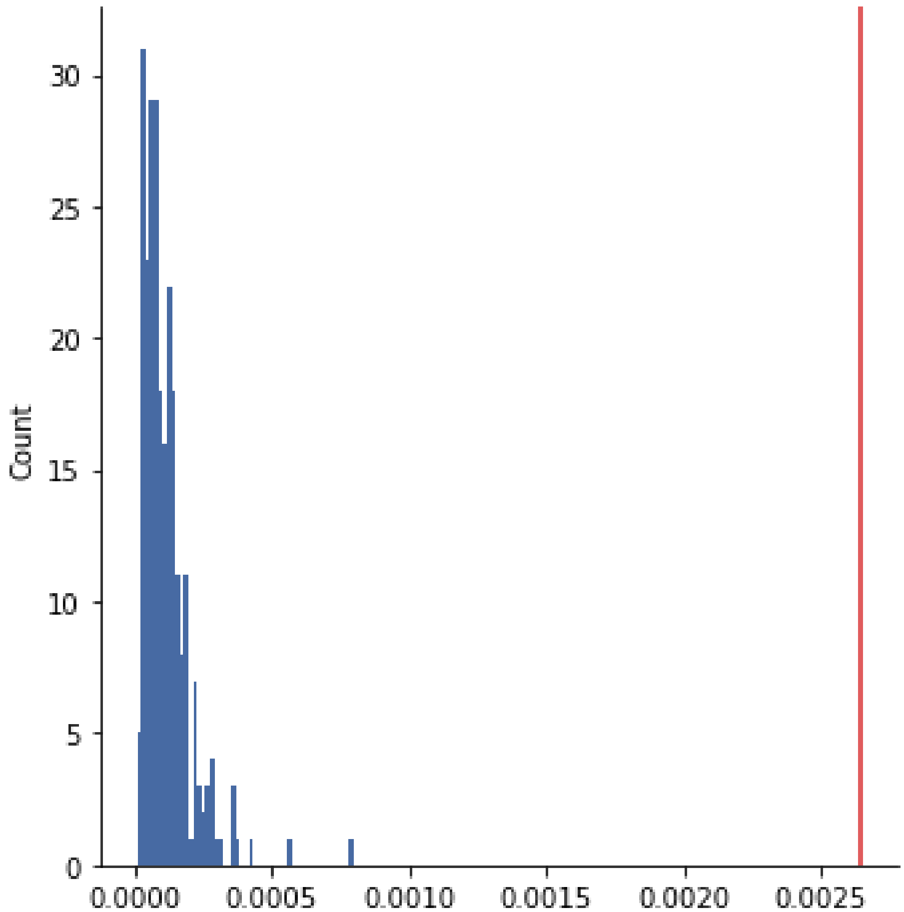

```
100%|      | 250/250 [00:14<00:00, 17.79it/s]

bandwidth: 2
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s1_8v3
```




```
100%|      | 250/250 [00:14<00:00, 17.25it/s]

bandwidth: 4
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s2_8v3
```




```
100%|      | 250/250 [00:13<00:00, 17.97it/s]

bandwidth: 8
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_anisotropic_s3_8v3
```




```
CPU times: user 2min 53s, sys: 6min 5s, total: 8min 58s
Wall time: 1min 55s
```

[ ]:
```
diff_anisotropic_stats
```

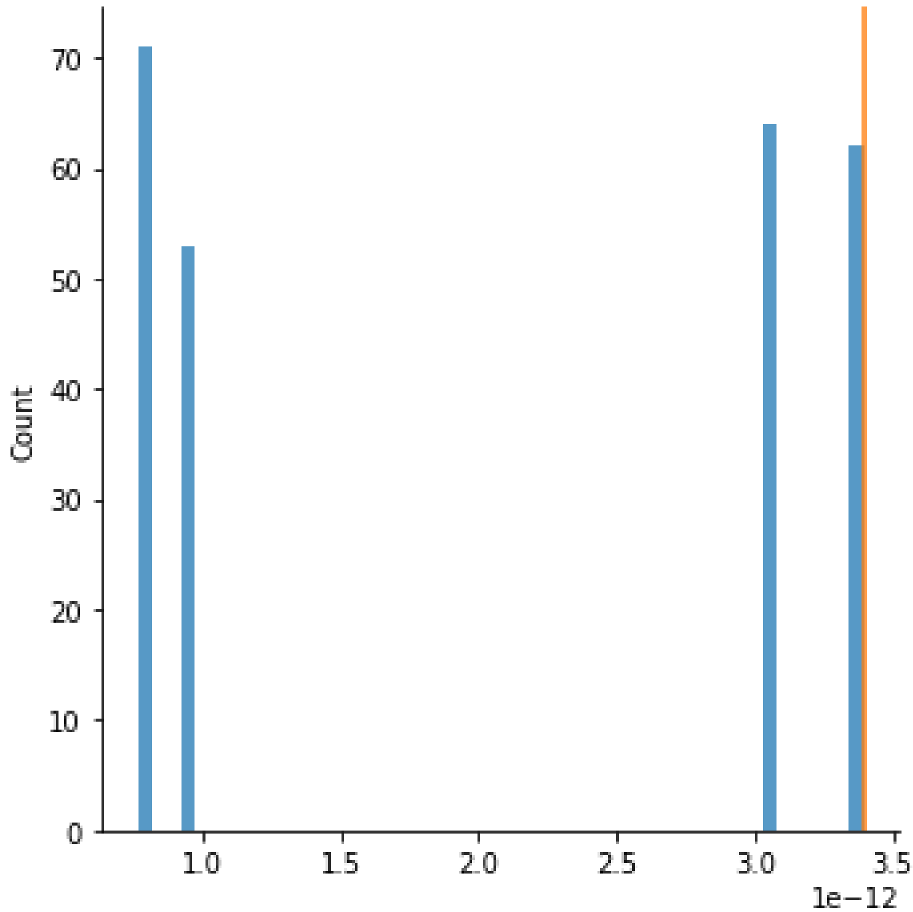
[ ]:
```
{-3: {'p': 0.0, 'time': 16.131669998168945},
 -2: {'p': 0.0, 'time': 19.450505018234253},
 -1: {'p': 0.0, 'time': 16.172513961791992},
 0: {'p': 0.0, 'time': 15.594956159591675},
 1: {'p': 0.0, 'time': 15.692456007003784},
 2: {'p': 0.0, 'time': 15.834607124328613},
 3: {'p': 0.0, 'time': 15.415678024291992}}
```

0.2.3 Statistics for Encoder Kernel

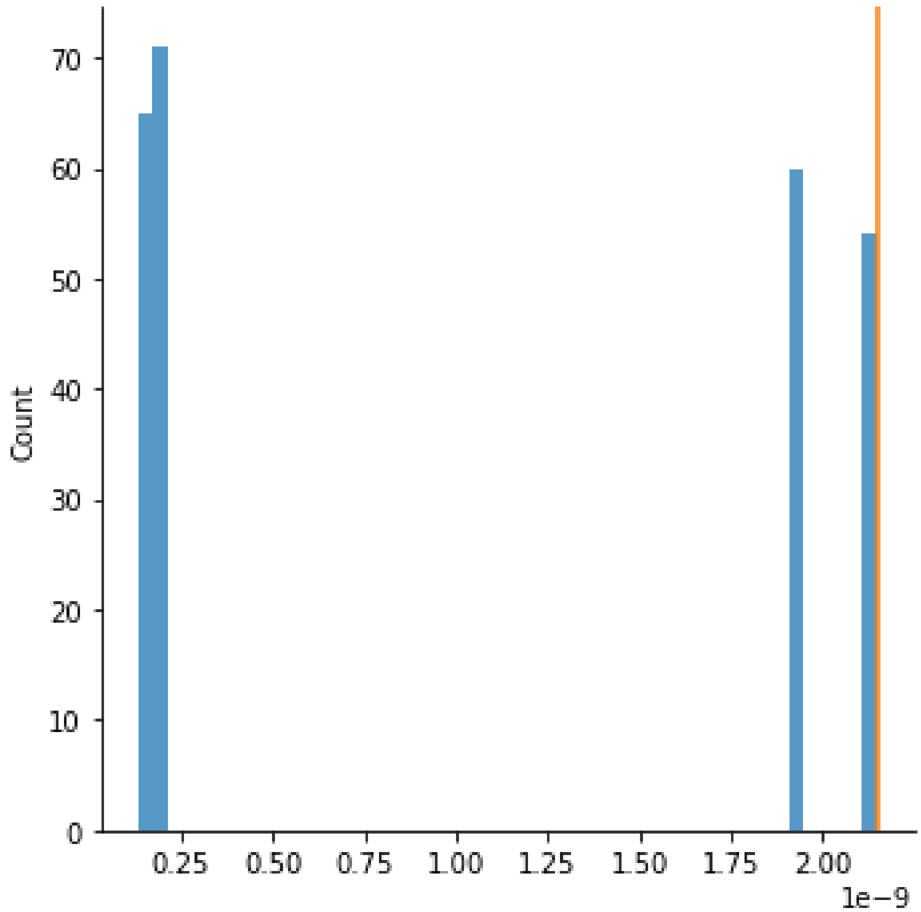
[ ]:
```
# encoder mmd
# suspect this is less robust to variance since this is not linear

encoder.eval()
```

```
diff_encoder_stats = {}
for val in [-3, -2, -1, 0, 1, 2, 3]:
    start = time.time()
    observed_mmd_encoder8v3, simulated_mmds_encoder8v3 =␣
↪permutation_test_encoder_mmd(
        x_batch, y_batch, r_batch, encoder, n_perms=n_perms, sigma_squared=(2␣
↪** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_encoder8v3, observed_mmd_encoder8v3)
    diff_encoder_stats[val] = {'p': p, 'time': end - start}

    hist_color = 'tab:blue'
    line_color = 'tab:orange'
    filepath = 'images_latentdim6_8v3v8/diff_encoder_s' + str(val) + '_8v3'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_encoder8v3,
        observed_mmd_encoder8v3,
        hist_color = hist_color,
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

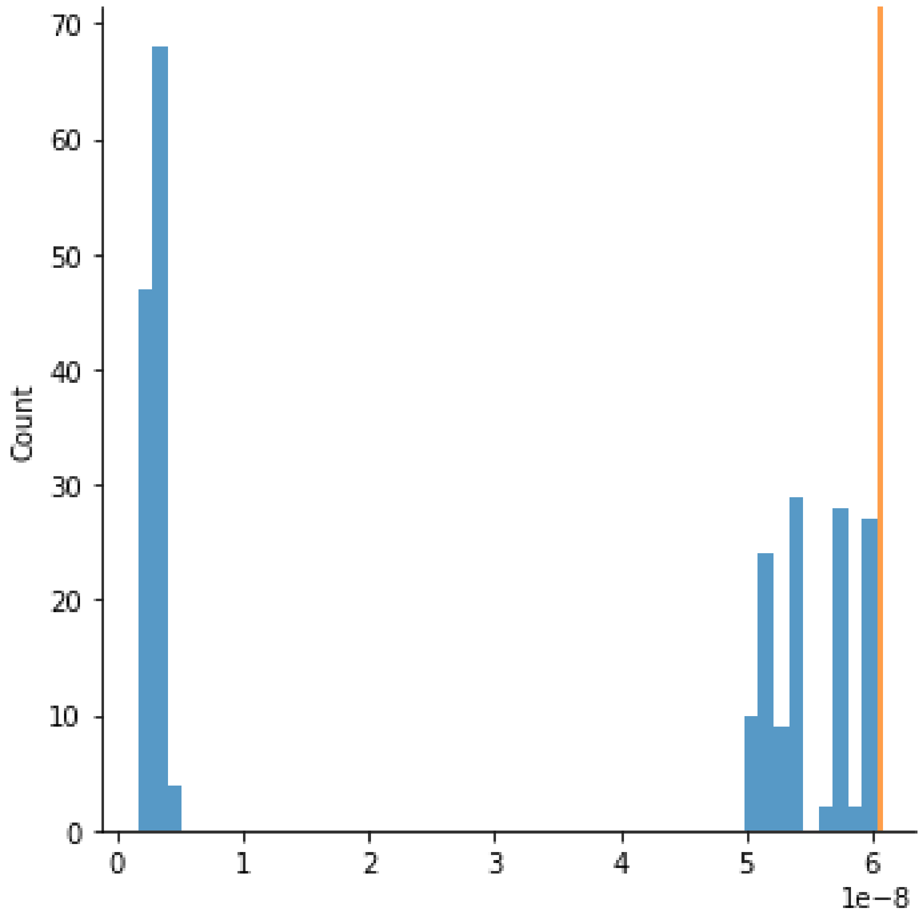
```
100%|          | 250/250 [00:26<00:00,  9.57it/s]

bandwidth: 0.125
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s-3_8v3
```



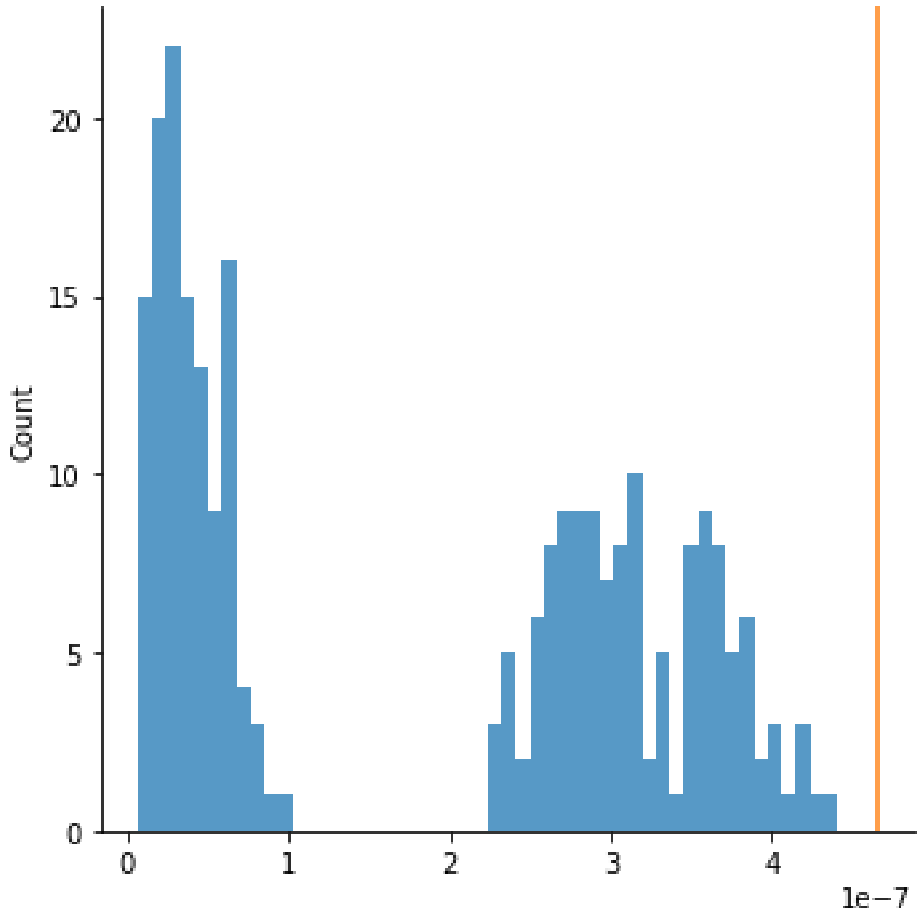

```
100%|      | 250/250 [00:26<00:00,  9.61it/s]

bandwidth: 0.25
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s-2_8v3
```



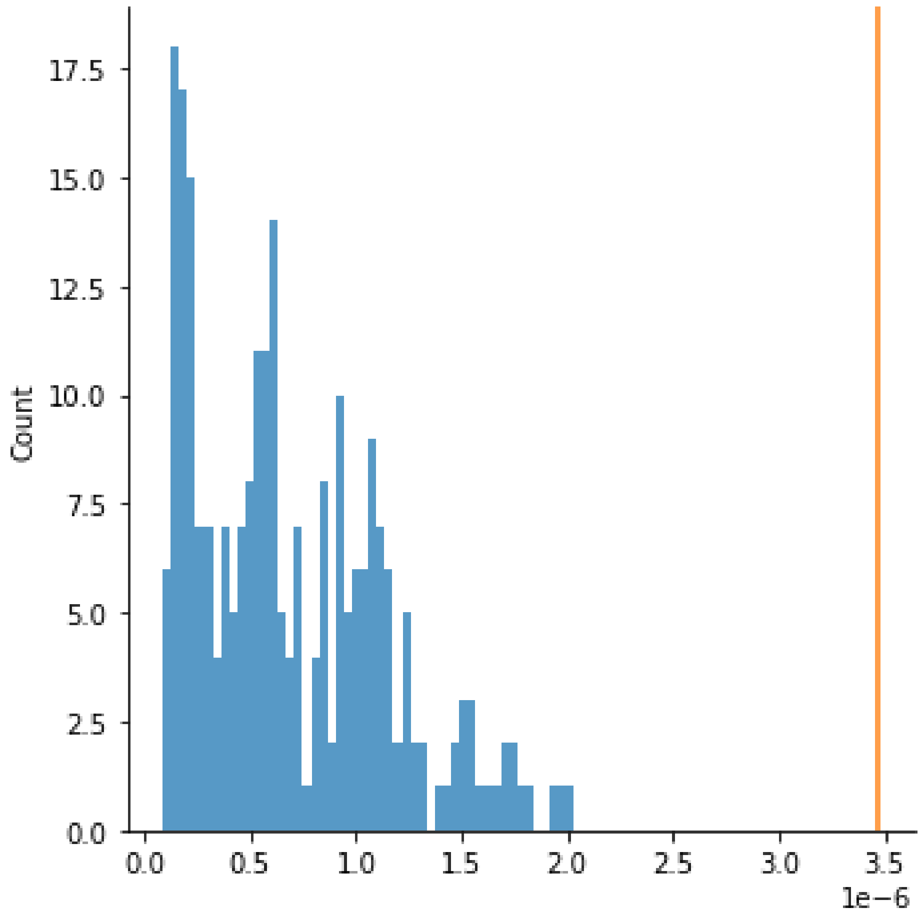

```
100%|      | 250/250 [00:25<00:00,  9.87it/s]

bandwidth: 0.5
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s-1_8v3
```



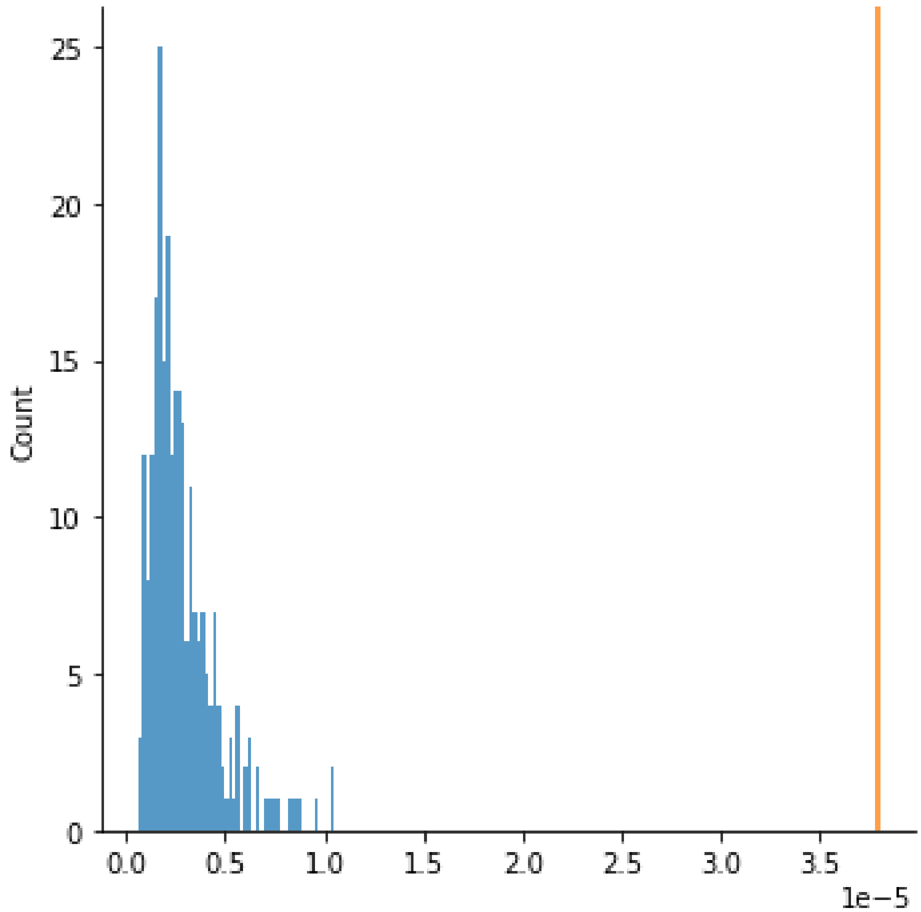

```
100%|      | 250/250 [00:25<00:00,  9.96it/s]

bandwidth: 1
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s0_8v3
```



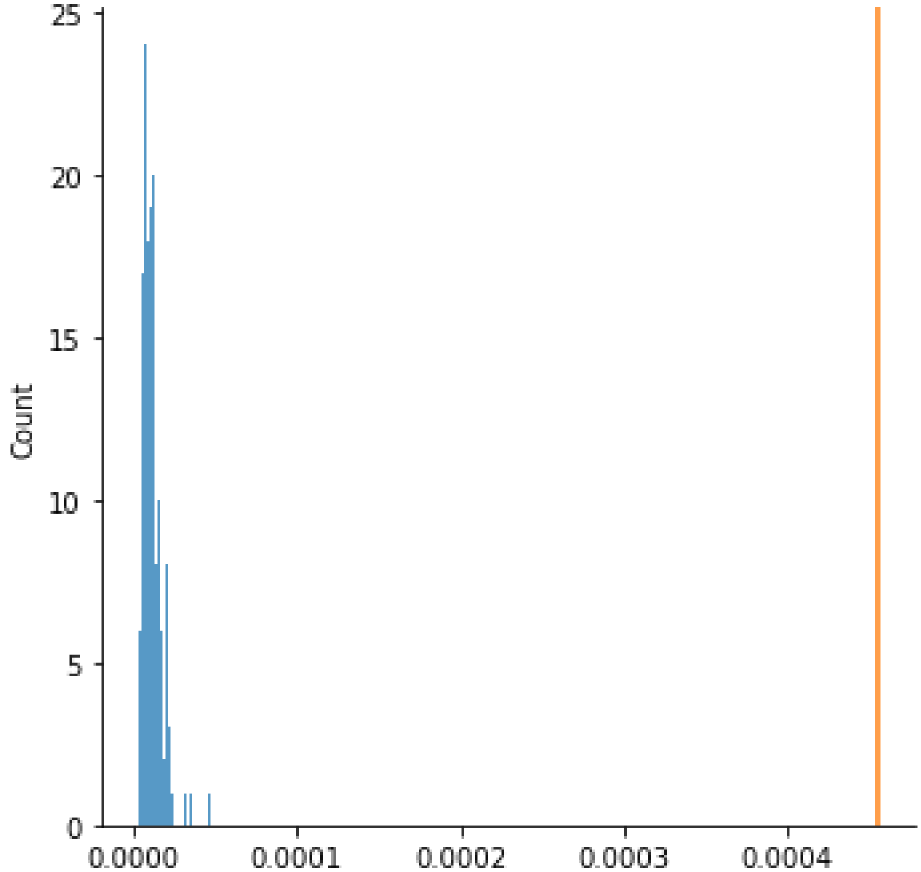

```
100%|      | 250/250 [00:25<00:00,  9.96it/s]
bandwidth: 2
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s1_8v3
```




```
100%|      | 250/250 [00:26<00:00,  9.57it/s]

bandwidth: 4
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s2_8v3
```




```
100%|      | 250/250 [00:25<00:00,  9.71it/s]

bandwidth: 8
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_encoder_s3_8v3
```



[ ]:
```
diff_encoder_stats
```

[ ]:
```
{-3: {'p': 0.0, 'time': 26.23369526863098},
 -2: {'p': 0.0, 'time': 29.212039947509766},
 -1: {'p': 0.0, 'time': 28.505435943603516},
 0: {'p': 0.0, 'time': 28.319178104400635},
 1: {'p': 0.0, 'time': 28.39599895477295},
 2: {'p': 0.0, 'time': 28.8230037689209},
 3: {'p': 0.0, 'time': 29.046234846115112}}
```

0.2.4 Statistics for Gaussian MMD

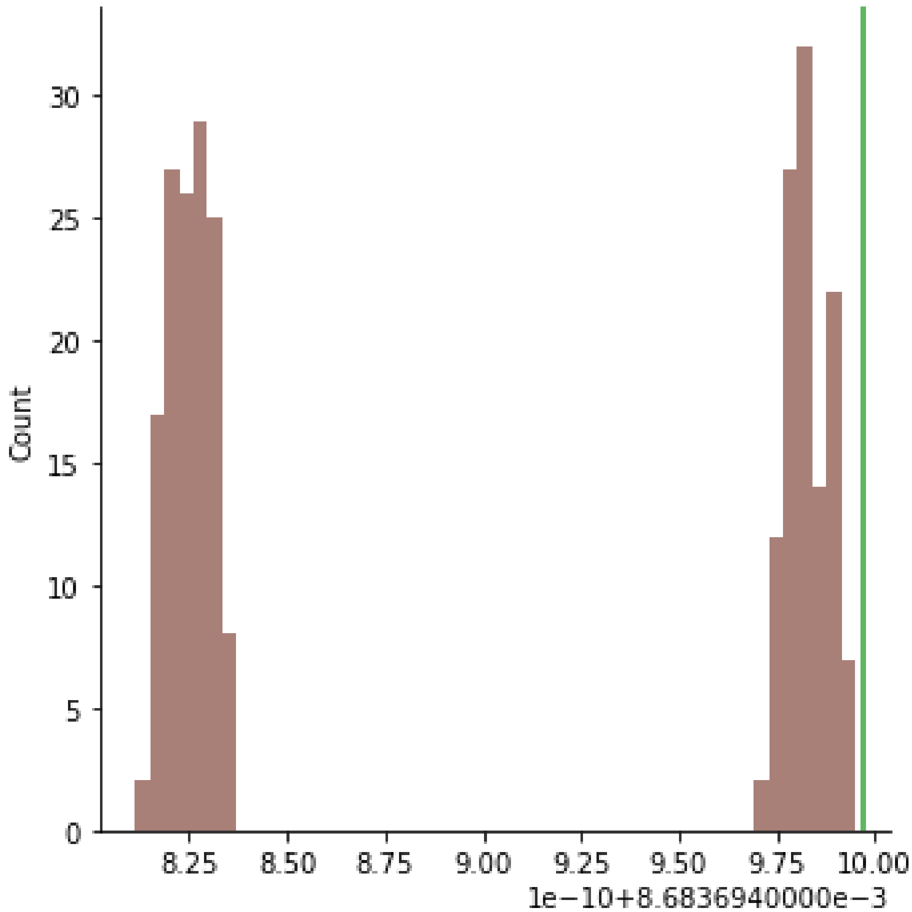
[ ]:
```
xy_batch = torch.cat([x_batch, y_batch], dim=0)
xy_batch_sample_mean = xy_batch.squeeze().flatten(start_dim=1).mean(dim=0)
xy_batch_sample_var = ((xy_batch.squeeze().flatten(start_dim=1) -␣
 ↪xy_batch_sample_mean) ** 2).sum()
xy_batch_sample_var /= (len(xy_batch ) - 1)
xy_batch_sample_var = xy_batch_sample_var.item()
print('xy_batch sample variance:', xy_batch_sample_var)
```

```
num_features = 28 * 28
print('number of features:', num_features)

scale_sigma_squared = 1 / (xy_batch_sample_var * num_features)
auto_sigma_squared = 1 / num_features
print('bandwidth selected by sklearn\'s scale method:', scale_sigma_squared)
print('bandwidth selected by sklearn\'s auto method:', auto_sigma_squared)
```

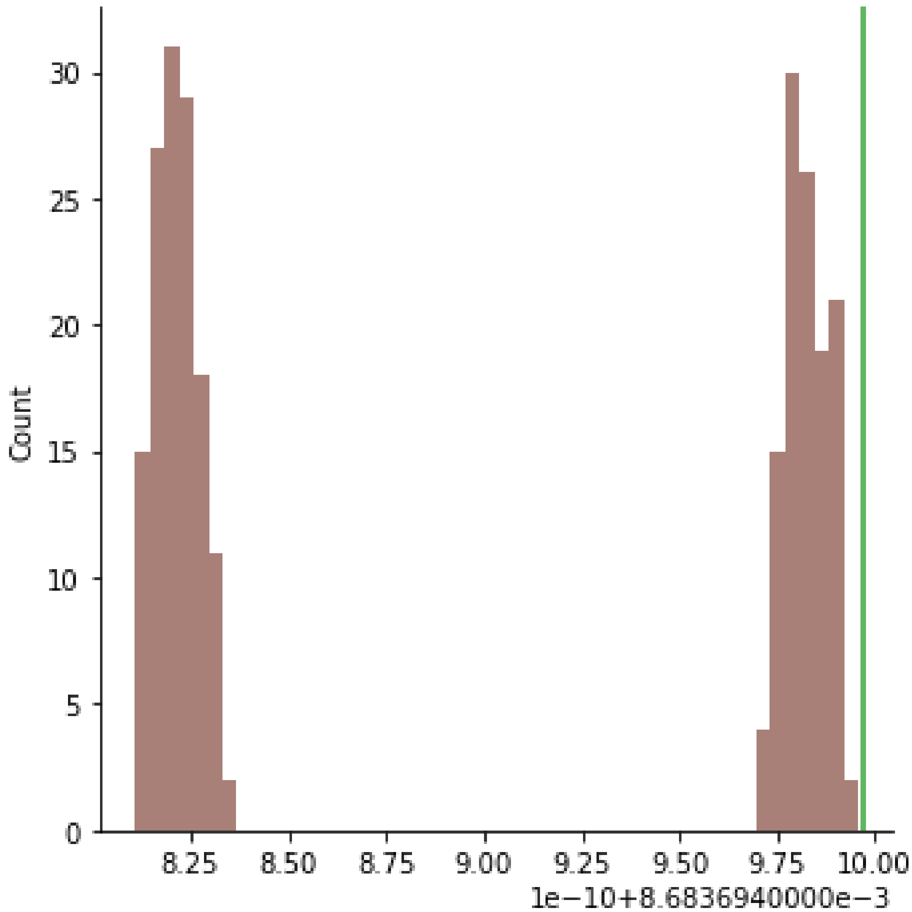
```
xy_batch sample variance: 44.21445846557617
number of features: 784
bandwidth selected by sklearn's scale method: 2.8848260237648284e-05
bandwidth selected by sklearn's auto method: 0.0012755102040816326
```

[ ]:
```
%%time

# gaussian mmd

diff_gaussian_stats = {}
for val in [scale_sigma_squared, auto_sigma_squared, -3, -2, -1, 0, 1, 2, 3]:
    start = time.time()
    observed_mmd_gaussian8v3, simulated_mmds_gaussian8v3 =␣
 ↪permutation_test_gaussian_mmd(
        x_batch, y_batch, n_perms=n_perms, sigma_squared=(2 ** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_gaussian8v3, observed_mmd_gaussian8v3)
    diff_gaussian_stats[val] = {'p': p, 'time': end - start}

    hist_color = 'tab:brown'
    line_color = 'tab:green'
    filepath = 'images_latentdim6_8v3v8/diff_gaussian_s' + str(val) + '_8v3'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_gaussian8v3,
        observed_mmd_gaussian8v3,
        hist_color = hist_color,
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

```
100%|          | 250/250 [00:05<00:00, 48.38it/s]

bandwidth: 1.0
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s2.8848260237648284e-05_8v3
```

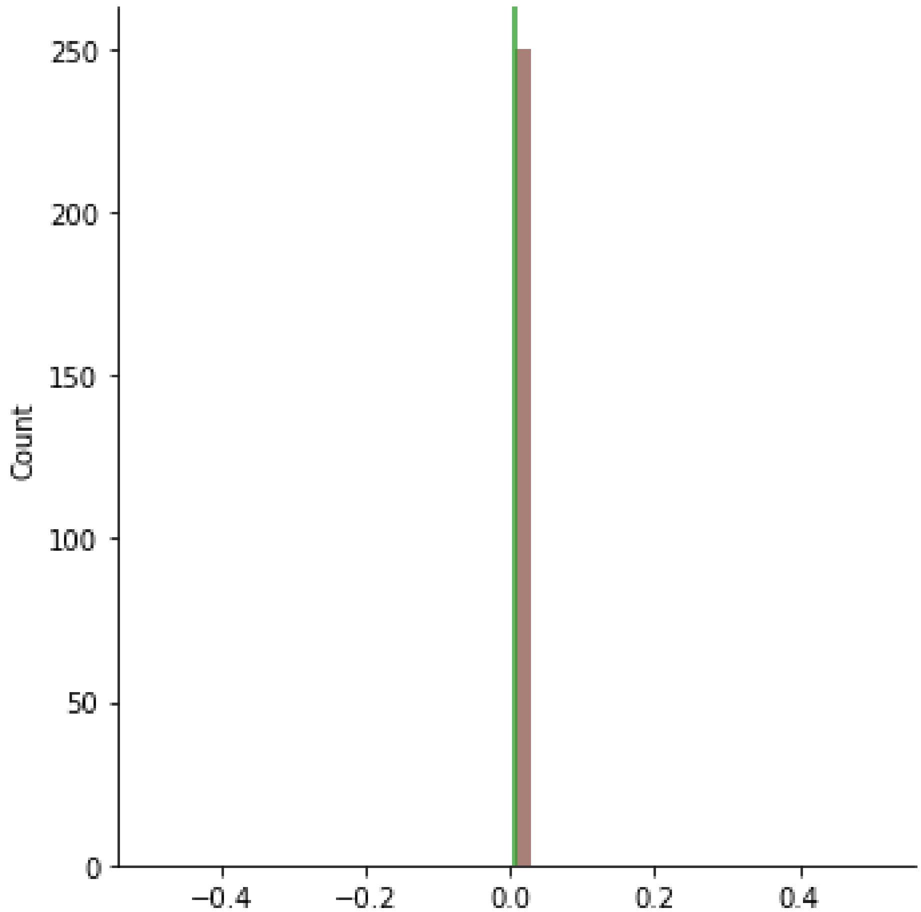



```
100%|          | 250/250 [00:03<00:00, 68.57it/s]

bandwidth: 1.001
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s0.0012755102040816326_8v3
```

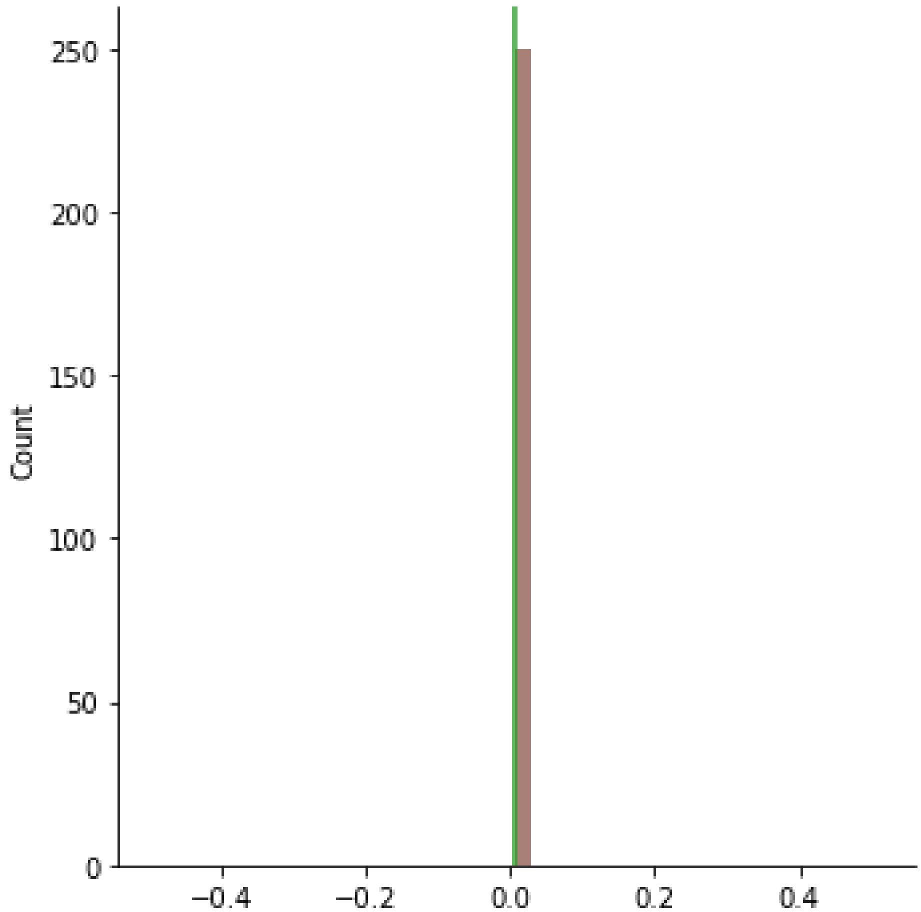



```
100%|      | 250/250 [00:03<00:00, 81.08it/s]
```

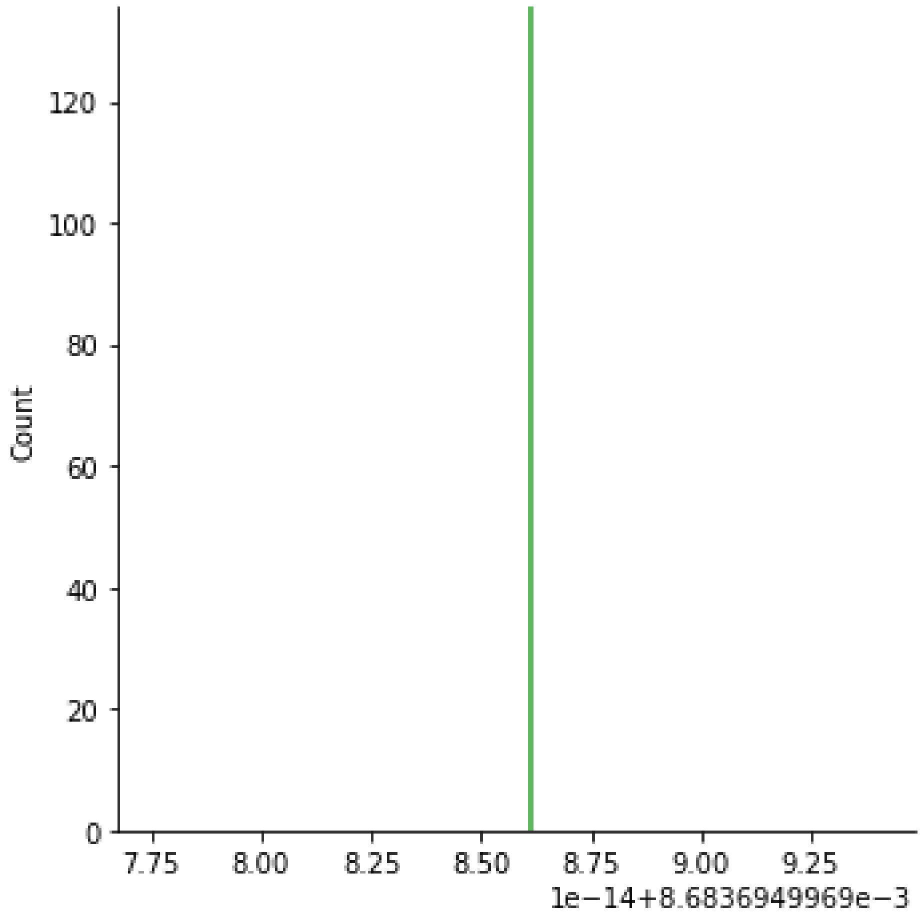
```
bandwidth: 0.125
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s-3_8v3
```



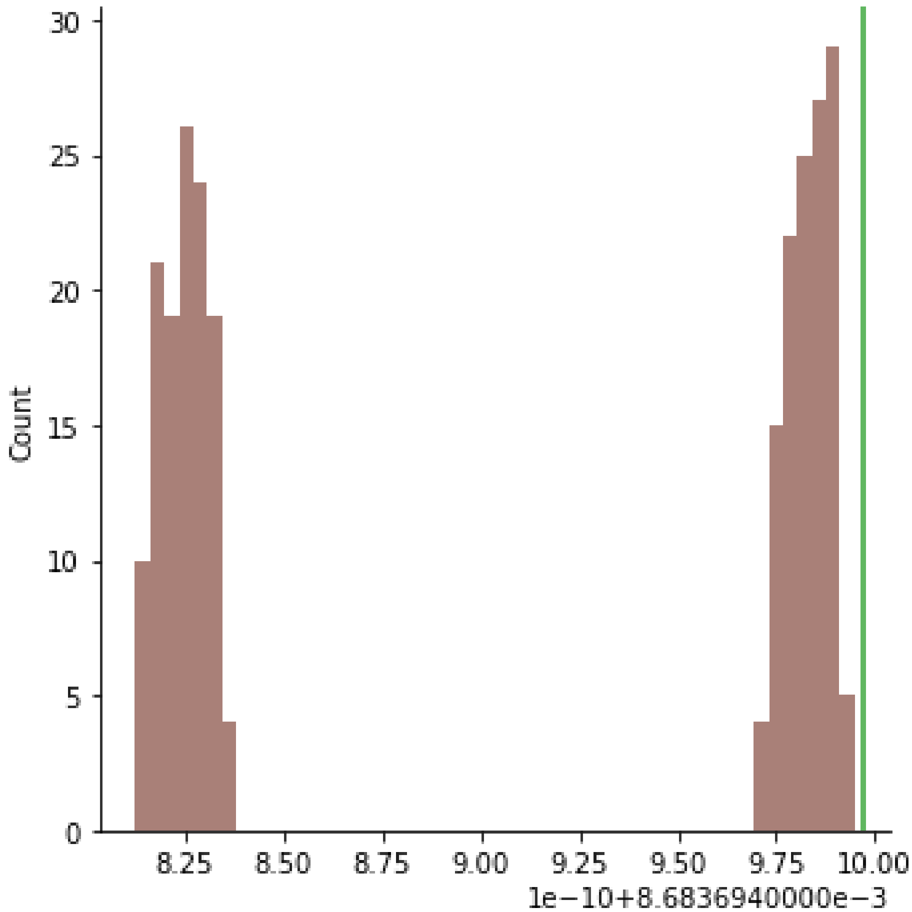

```
100%|      | 250/250 [00:02<00:00, 89.47it/s]

bandwidth: 0.25
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s-2_8v3
```



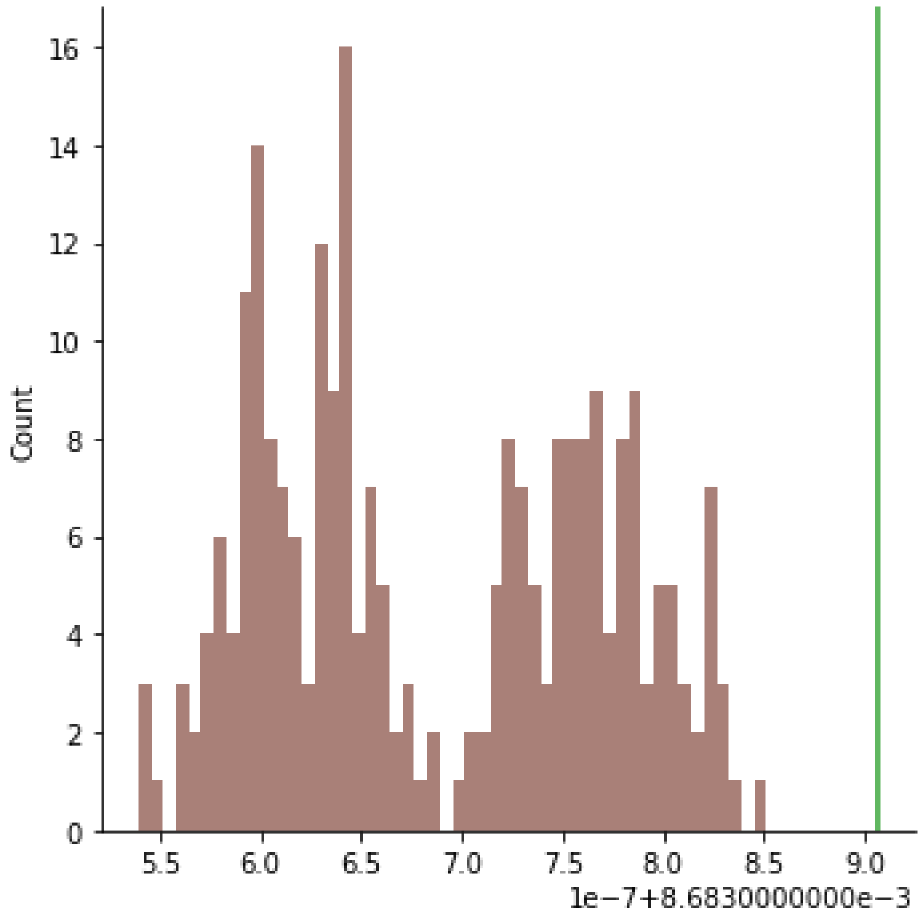

```
100%|      | 250/250 [00:03<00:00, 69.37it/s]

bandwidth: 0.5
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s-1_8v3
```



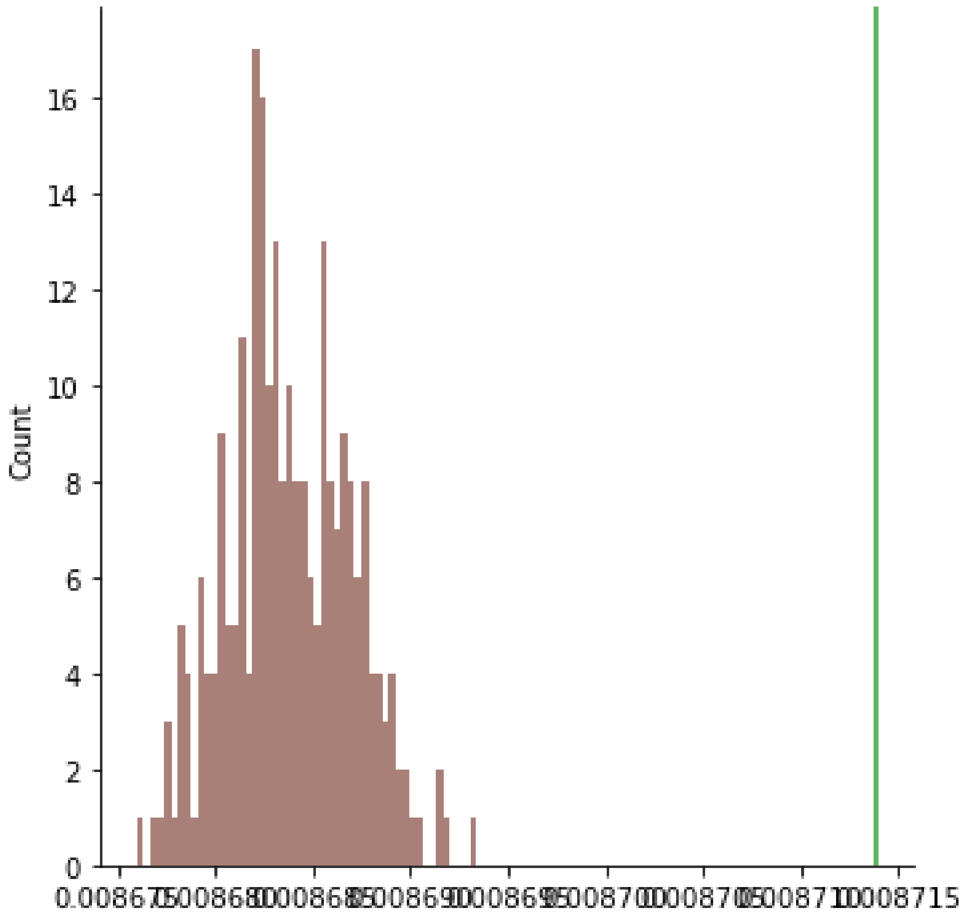

```
100%|          | 250/250 [00:03<00:00, 79.94it/s]

bandwidth: 1
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s0_8v3
```



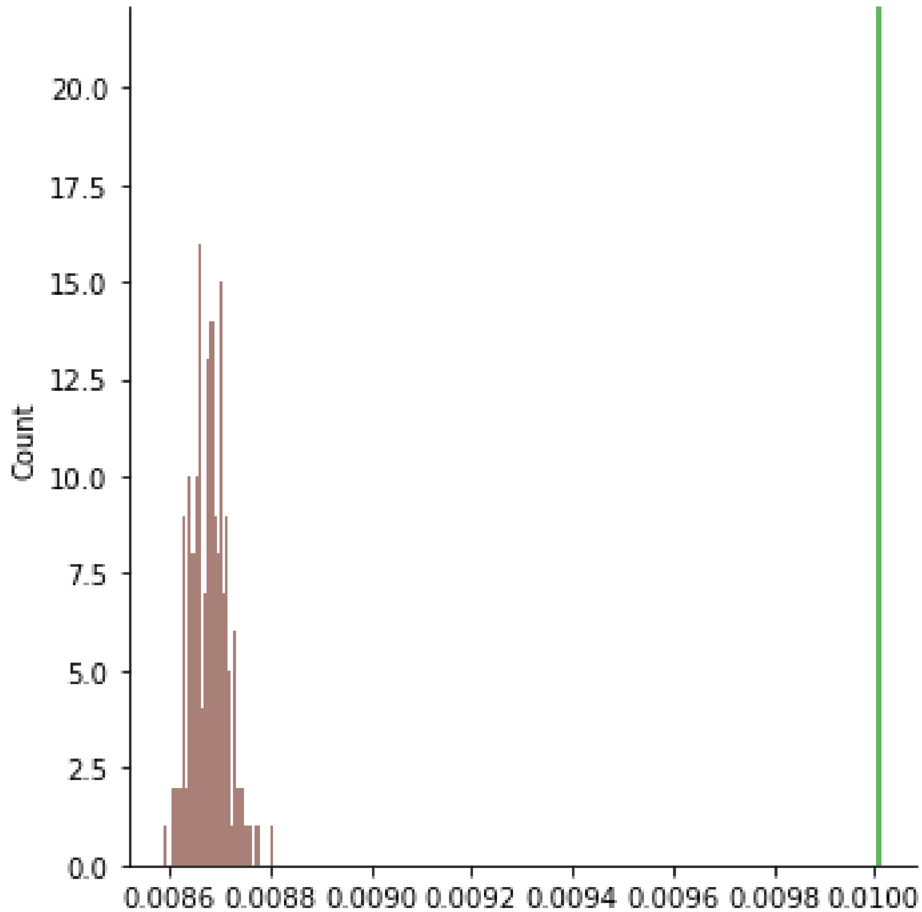

```
100%|          | 250/250 [00:02<00:00, 89.96it/s]

bandwidth: 2
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s1_8v3
```




```
100%|      | 250/250 [00:03<00:00, 66.38it/s]

bandwidth: 4
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s2_8v3
```




```
100%|      | 250/250 [00:03<00:00, 68.47it/s]

bandwidth: 8
p_value: 0.0
Image saved to images_latentdim6_8v3v8/diff_gaussian_s3_8v3
```




```
CPU times: user 2min 25s, sys: 59.6 s, total: 3min 25s
Wall time: 33 s
```

[ ]:
```
diff_gaussian_stats
```

[ ]:
```
{2.8848260237648284e-05: {'p': 0.0, 'time': 5.196414947509766},
 0.0012755102040816326: {'p': 0.0, 'time': 3.683488130569458},
 -3: {'p': 0.0, 'time': 3.092616319656372},
 -2: {'p': 0.0, 'time': 2.801586866378784},
 -1: {'p': 0.0, 'time': 3.6118781566619873},
 0: {'p': 0.0, 'time': 3.1359469890594482},
 1: {'p': 0.0, 'time': 2.788443088531494},
 2: {'p': 0.0, 'time': 3.7773919105529785},
 3: {'p': 0.0, 'time': 3.6625001430511475}}
```

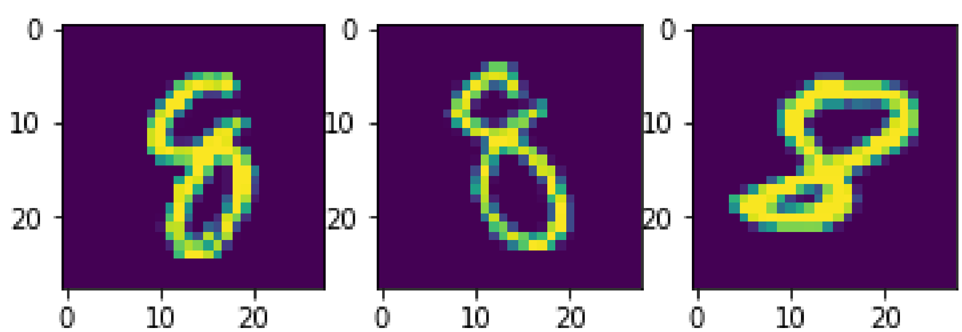
0.2.5 $X_1 = \{\text{images of 8's}\}$, $X_2 = \{\text{images of 8's}\}$

[ ]:
```
# testing when x1_batch and x2_batch are from the same distribution
x1_batch = []
x2_batch = []
r_batch = []
for ind, data in enumerate(test_loader): # filter batches based on digit
    if ind < 3:
        r_batch.append(data[0][data[1] == 8])
    elif 3 <= ind and ind % 2 == 0:
        x1_batch.append(data[0][data[1] == 8])
    elif 3 <= ind and ind % 2 == 1:
        x2_batch.append(data[0][data[1] == 8])
    if ind == 25: break
x1_batch = torch.cat(x1_batch, dim=0)
x2_batch = torch.cat(x2_batch, dim=0)
r_batch = torch.cat(r_batch, dim=0)
print('x1_batch shape:', x1_batch.shape)
print('x2_batch shape:', x2_batch.shape)
print('r_batch shape:', r_batch.shape)
```

```
x1_batch shape: torch.Size([299, 1, 28, 28])
x2_batch shape: torch.Size([289, 1, 28, 28])
r_batch shape: torch.Size([67, 1, 28, 28])
```

[ ]:
```
plt.subplot(1,3,1)
plt.imshow(x1_batch[0].squeeze())
plt.subplot(1,3,2)
plt.imshow(x2_batch[0].squeeze())
plt.subplot(1,3,3)
plt.imshow(r_batch[0].squeeze())
```

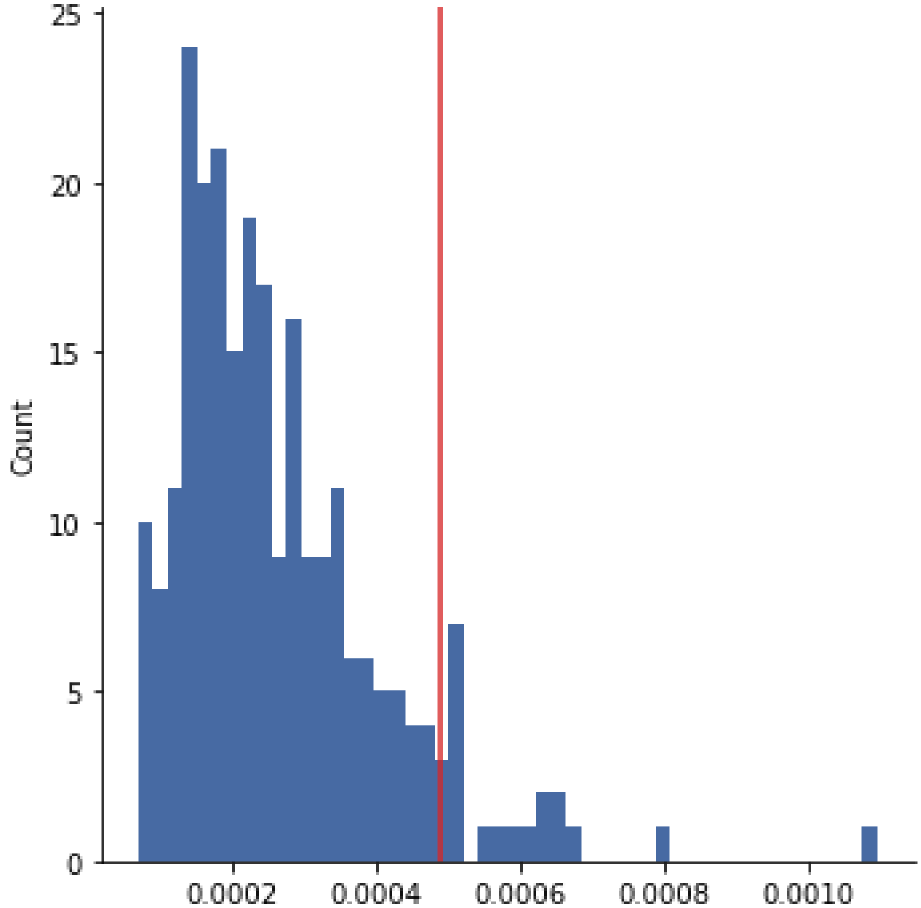
[ ]: <matplotlib.image.AxesImage at 0x2a8476a30>



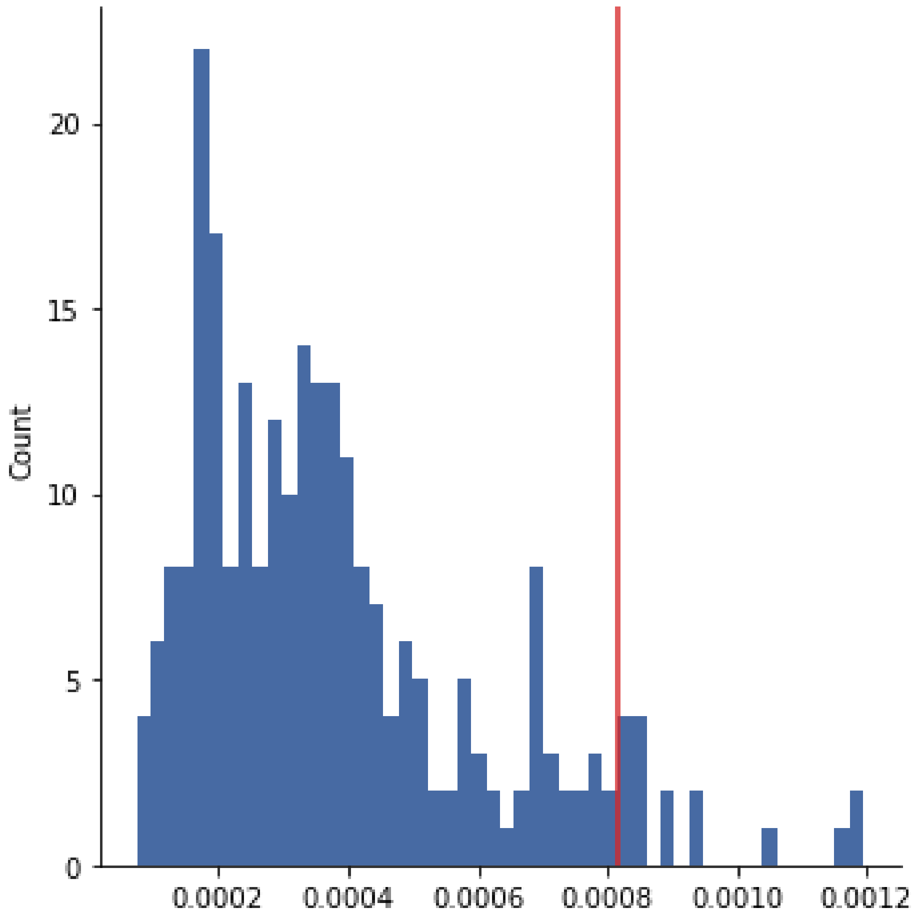
0.2.6 Statistics for Anisotropic Kernel

[ ]:
```
%%time

# anisotropic mmd
same_anisotropic_stats = {}
for val in [-3, -2, -1, 0, 1, 2, 3]:
    start = time.time()
    observed_mmd_anisotropic8v8, simulated_mmds_anisotropic8v8 =␣
 ↪permutation_test_anisotropic_mmd(
        x1_batch, x2_batch, r_batch, encoder, n_perms=n_perms, sigma_squared =␣
 ↪(2 ** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_anisotropic8v8, observed_mmd_anisotropic8v8)
    same_anisotropic_stats[val] = {'p': p, 'time': end - time}

    hist_color = '#093885'
    line_color = 'tab:red'
    filepath = 'images_latentdim6_8v3v8/same_anisotropic_s' + str(val) + '_8v8'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_anisotropic8v8,
        observed_mmd_anisotropic8v8,
        hist_color = hist_color,
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

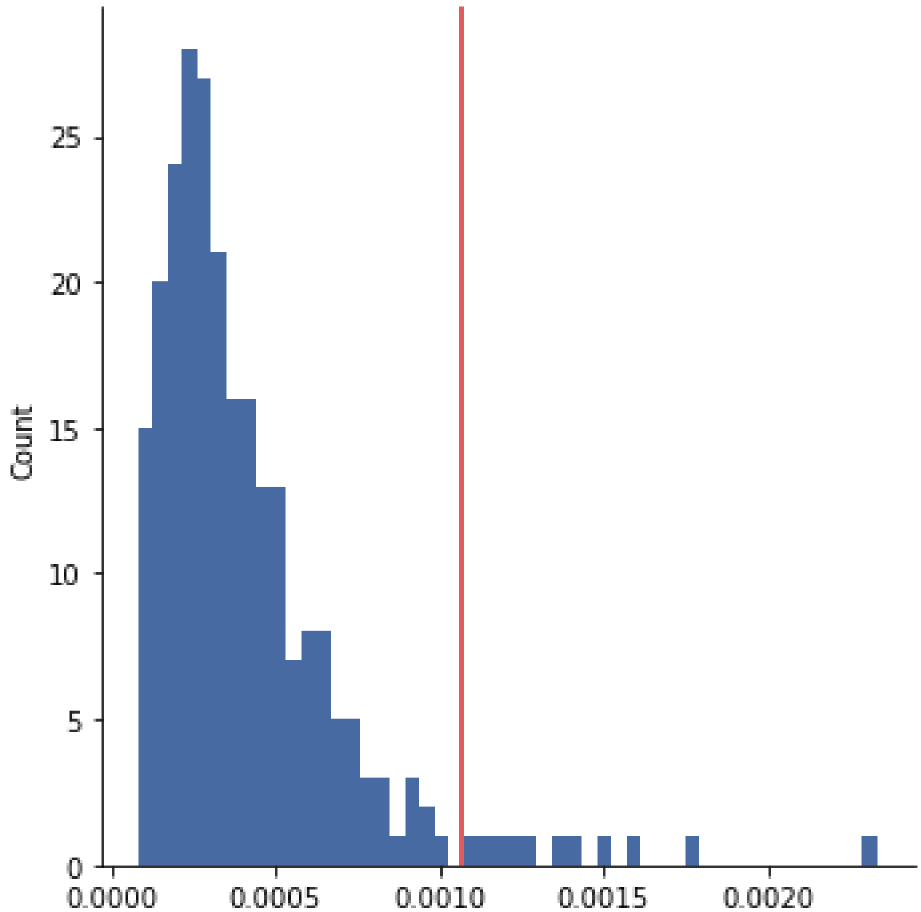
```
100%|          | 250/250 [00:18<00:00, 13.69it/s]

bandwidth: 0.125
p_value: 0.076
Image saved to images_latentdim6_8v3v8/same_anisotropic_s-3_8v8
```



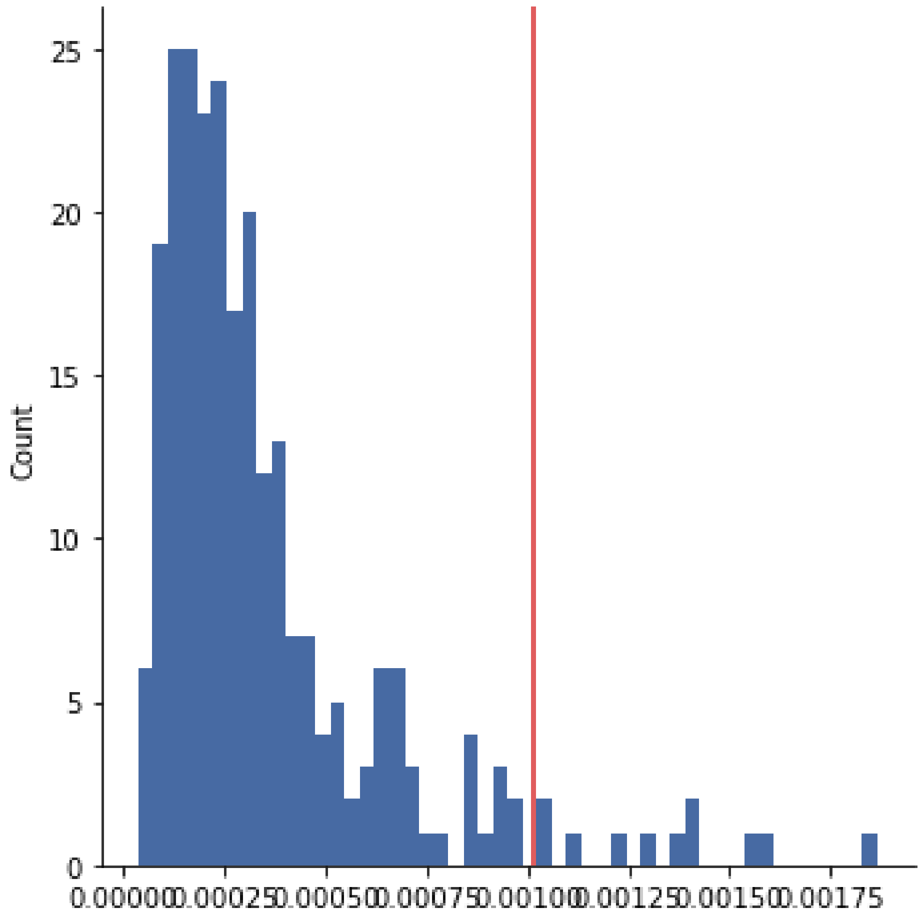

```
100%|      | 250/250 [00:19<00:00, 13.04it/s]

bandwidth: 0.25
p_value: 0.064
Image saved to images_latentdim6_8v3v8/same_anisotropic_s-2_8v8
```



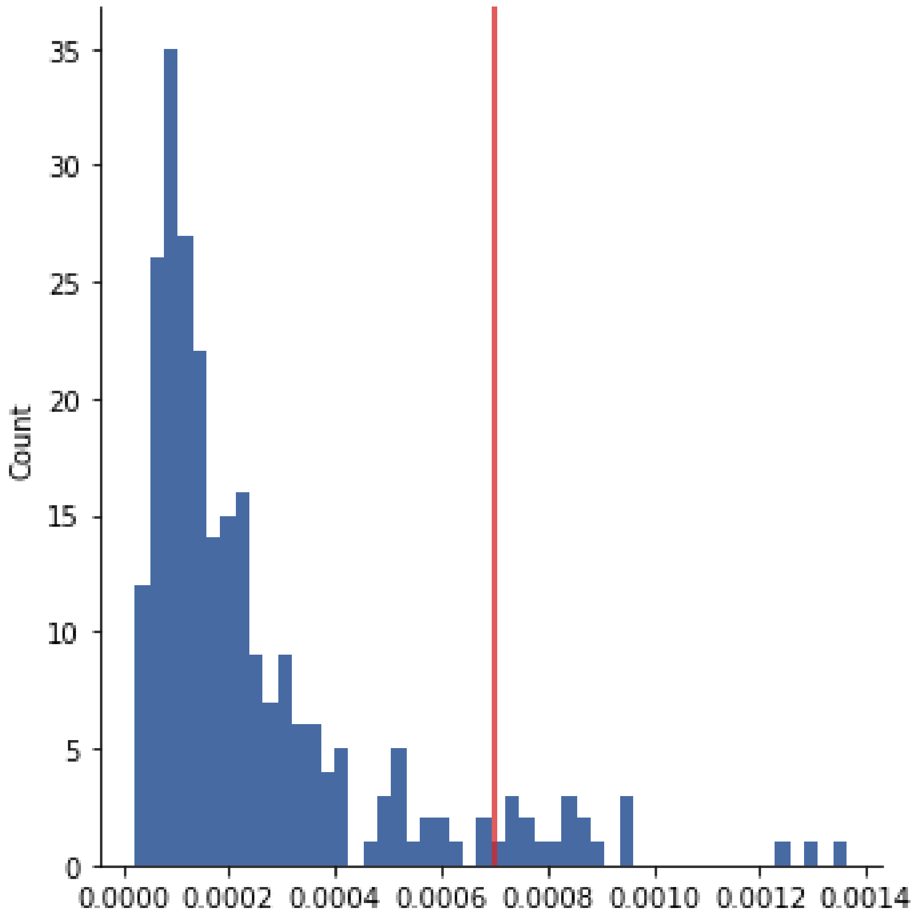

```
100%|      | 250/250 [00:21<00:00, 11.49it/s]

bandwidth: 0.5
p_value: 0.044
Image saved to images_latentdim6_8v3v8/same_anisotropic_s-1_8v8
```



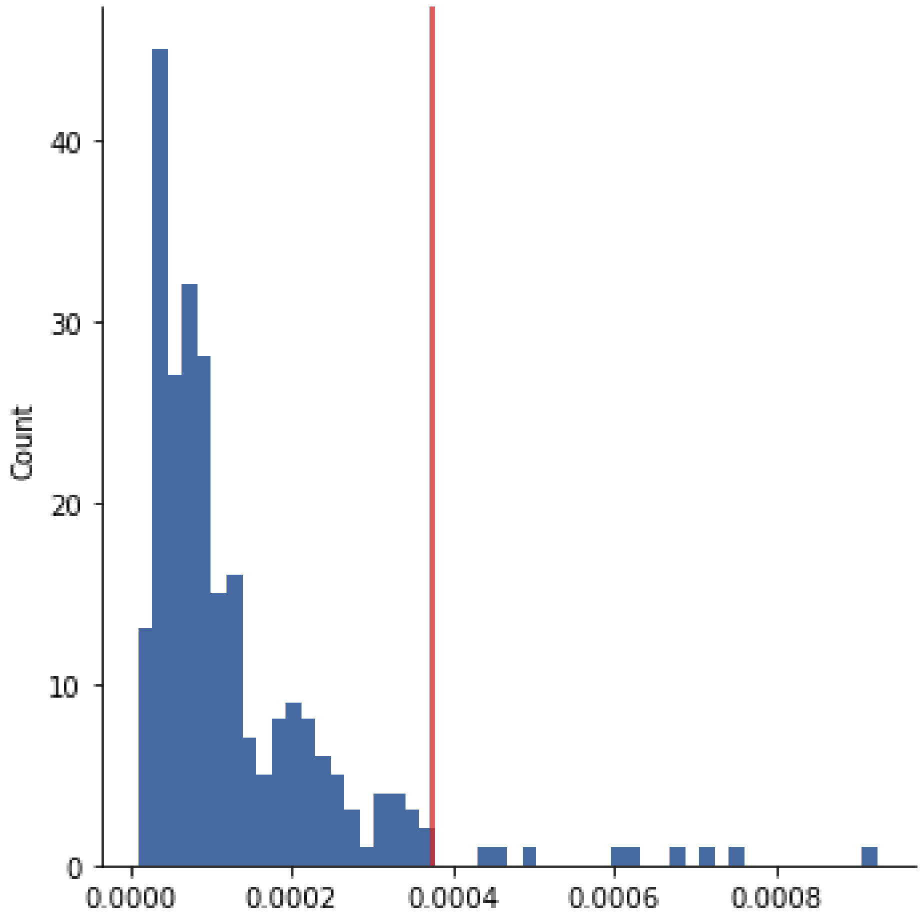

```
100%|      | 250/250 [00:19<00:00, 13.14it/s]

bandwidth: 1
p_value: 0.044
Image saved to images_latentdim6_8v3v8/same_anisotropic_s0_8v8
```



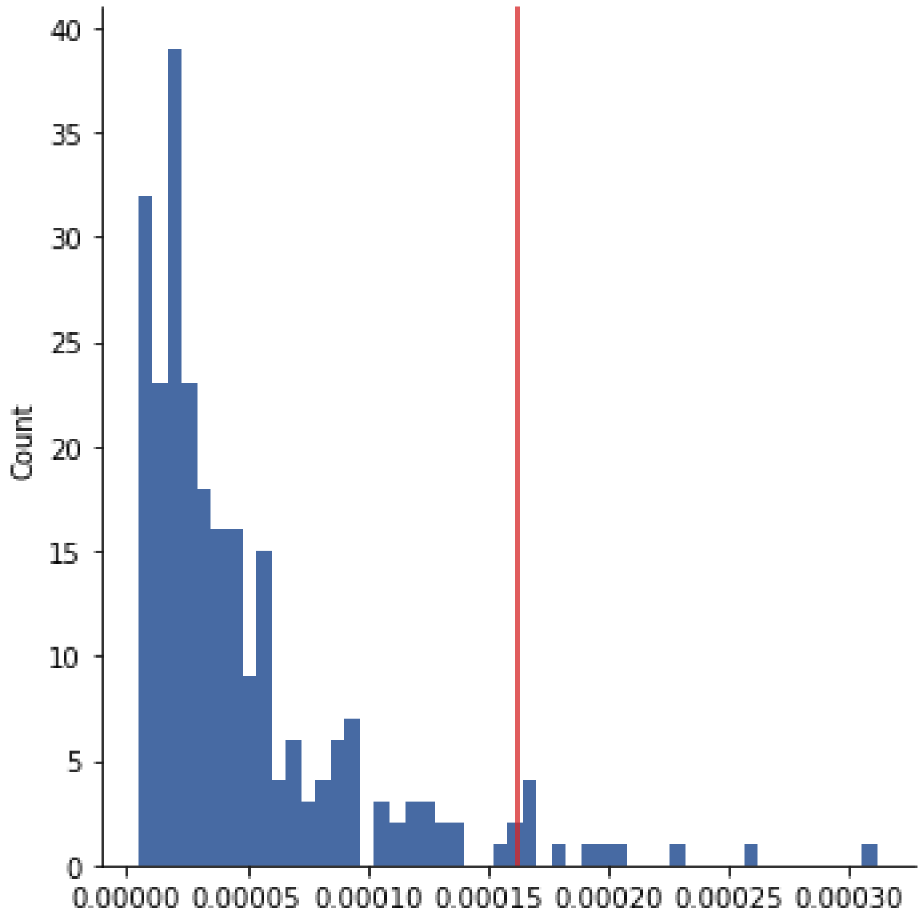

```
100%|      | 250/250 [00:17<00:00, 13.93it/s]

bandwidth: 2
p_value: 0.08
Image saved to images_latentdim6_8v3v8/same_anisotropic_s1_8v8
```




```
100%|          | 250/250 [00:19<00:00, 13.05it/s]

bandwidth: 4
p_value: 0.04
Image saved to images_latentdim6_8v3v8/same_anisotropic_s2_8v8
```




```
100%|      | 250/250 [00:19<00:00, 12.84it/s]

bandwidth: 8
p_value: 0.048
Image saved to images_latentdim6_8v3v8/same_anisotropic_s3_8v8
```




```
CPU times: user 4min 3s, sys: 8min 16s, total: 12min 19s
Wall time: 2min 32s
```

[ ]:
```
same_anisotropic_stats
```

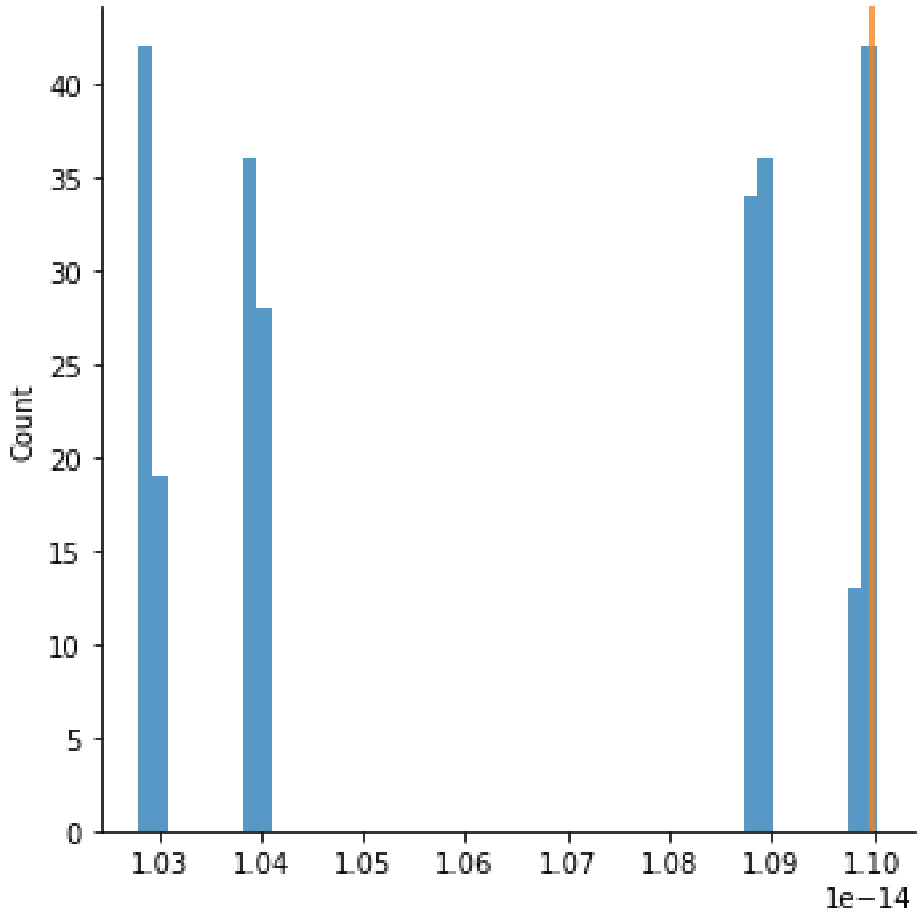
[ ]:
```
{-3: {'p': 0.076, 'time': <module 'time' (built-in)>},
 -2: {'p': 0.064, 'time': <module 'time' (built-in)>},
 -1: {'p': 0.044, 'time': <module 'time' (built-in)>},
 0: {'p': 0.044, 'time': <module 'time' (built-in)>},
 1: {'p': 0.08, 'time': <module 'time' (built-in)>},
 2: {'p': 0.04, 'time': <module 'time' (built-in)>},
 3: {'p': 0.048, 'time': <module 'time' (built-in)>}}
```

0.2.7 Statistics for Encoder Kernel

[ ]:
```
%%time

encoder.eval()
same_encoder_stats = {}
```

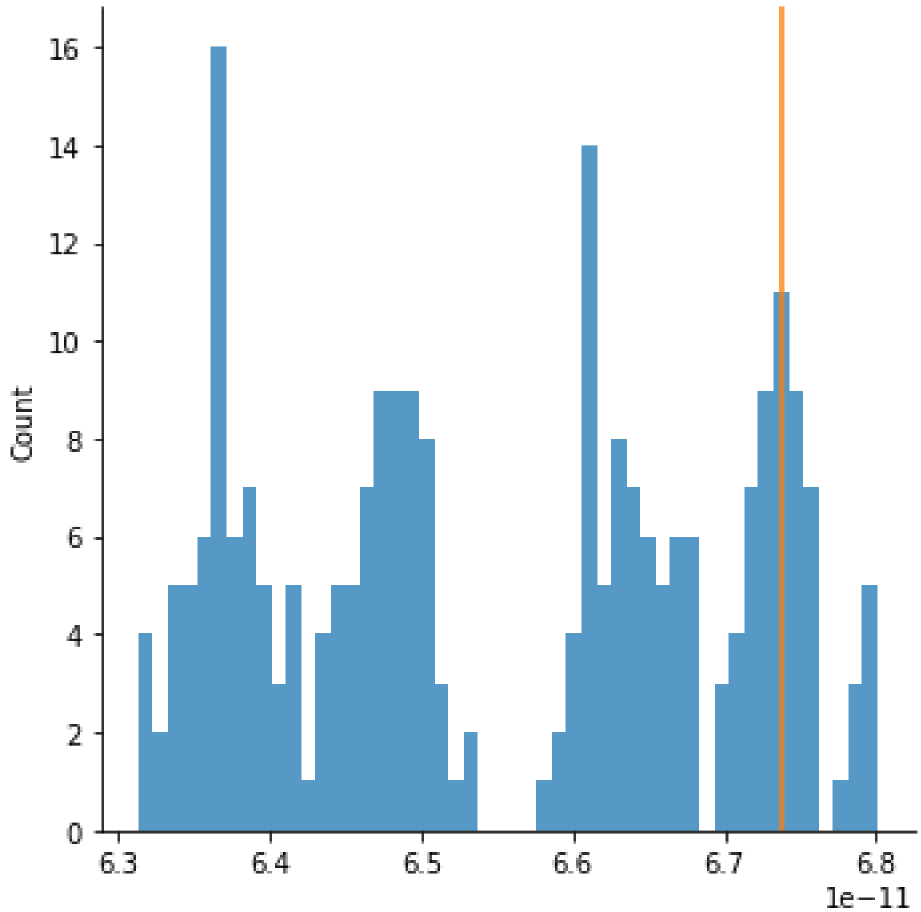
```python
for val in [-3, -2, -1, 0, 1, 2, 3]:
    start = time.time()
    observed_mmd_encoder8v8, simulated_mmds_encoder8v8 =␣
↪permutation_test_encoder_mmd(
        x1_batch, x2_batch, r_batch, encoder, n_perms=n_perms, sigma_squared=(2␣
↪** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_encoder8v8, observed_mmd_encoder8v8)
    same_encoder_stats[val] = {'p': p, 'time': end - start}

    hist_color = 'tab:blue'
    line_color = 'tab:orange'
    filepath = 'images_latentdim6_8v3v8/same_encoder_s' + str(val) + '_8v8'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_encoder8v8,
        observed_mmd_encoder8v8,
        hist_color = hist_color,
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

```
100%|      | 250/250 [00:34<00:00,  7.23it/s]

bandwidth: 0.125
p_value: 0.1
Image saved to images_latentdim6_8v3v8/same_encoder_s-3_8v8
```

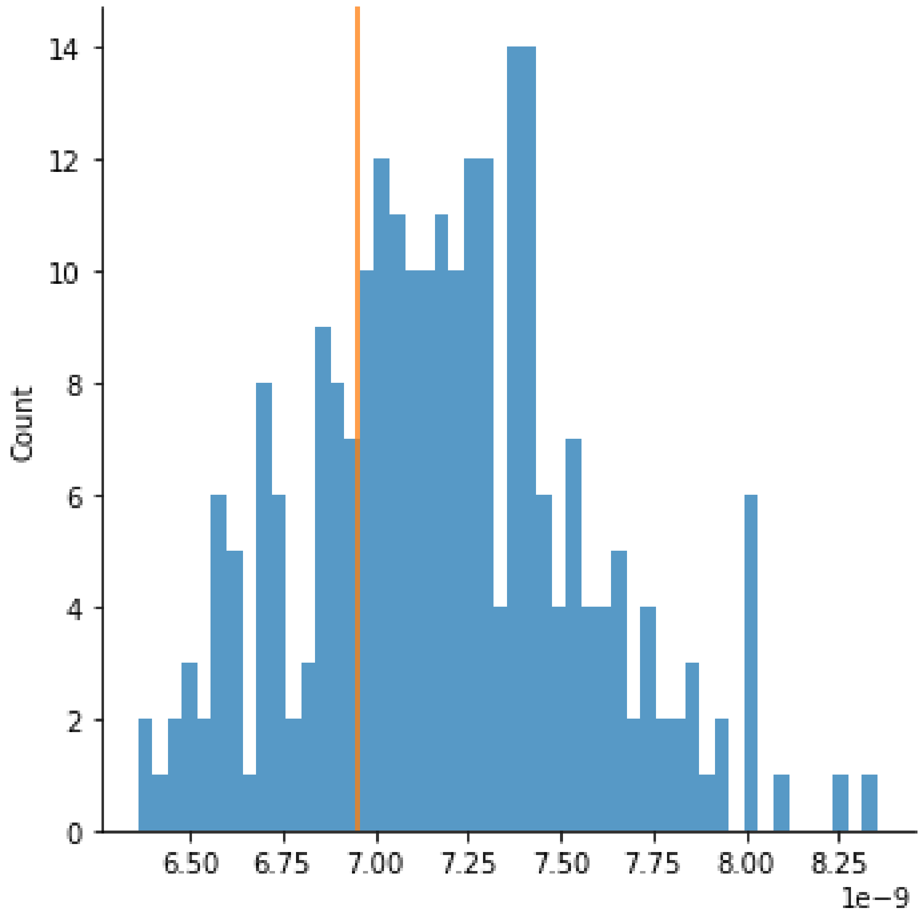



```
100%|      | 250/250 [00:34<00:00,  7.28it/s]
```

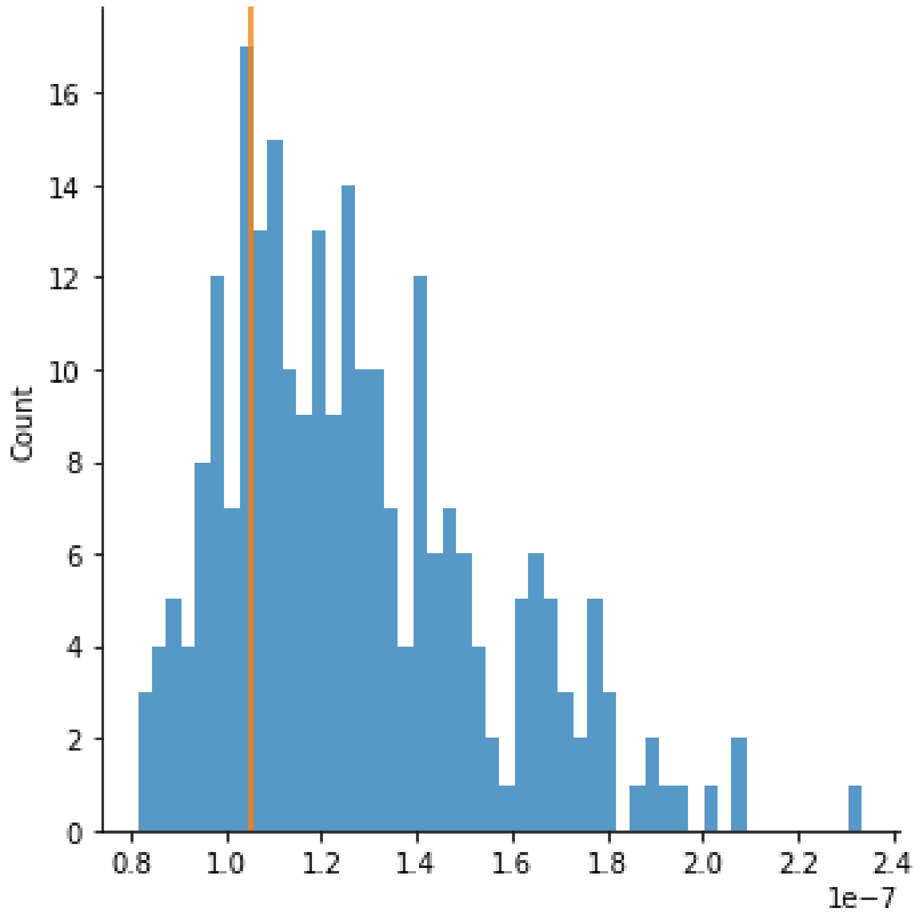
```
bandwidth: 0.25
p_value: 0.124
Image saved to images_latentdim6_8v3v8/same_encoder_s-2_8v8
```



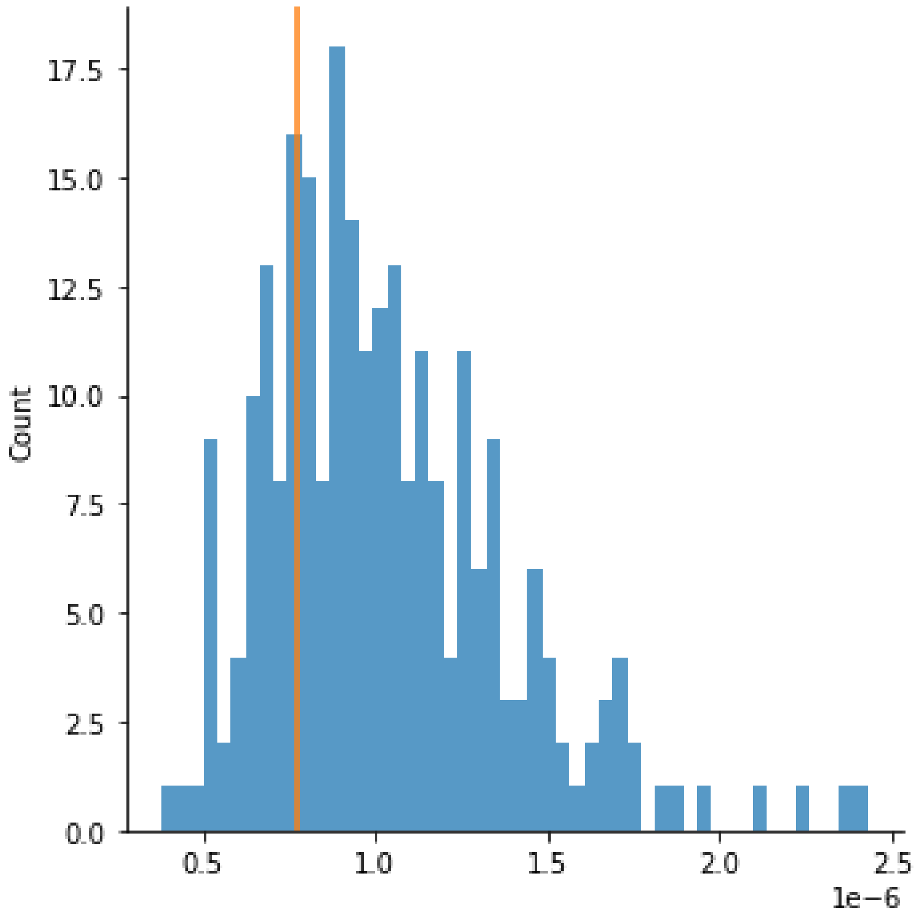

```
100%|      | 250/250 [00:36<00:00,  6.91it/s]

bandwidth: 0.5
p_value: 0.744
Image saved to images_latentdim6_8v3v8/same_encoder_s-1_8v8
```



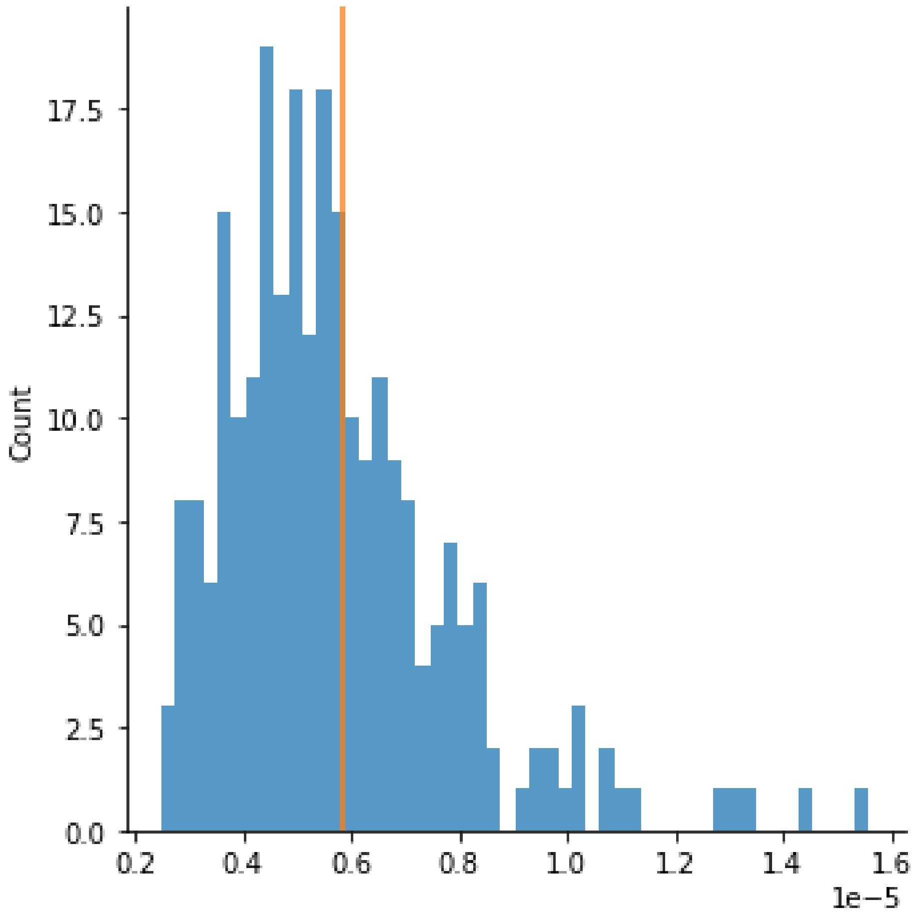

```
100%|      | 250/250 [00:32<00:00,  7.58it/s]

bandwidth: 1
p_value: 0.768
Image saved to images_latentdim6_8v3v8/same_encoder_s0_8v8
```



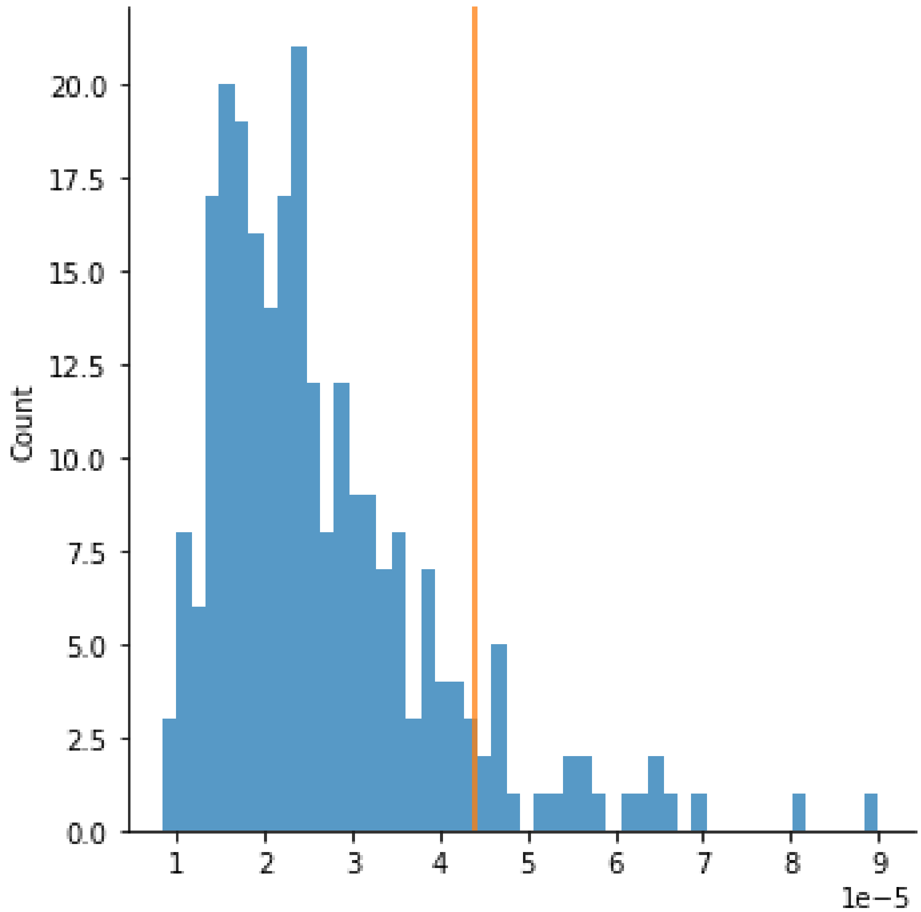

```
100%|      | 250/250 [00:32<00:00,  7.62it/s]

bandwidth: 2
p_value: 0.76
Image saved to images_latentdim6_8v3v8/same_encoder_s1_8v8
```




```
100%|      | 250/250 [00:33<00:00,  7.36it/s]

bandwidth: 4
p_value: 0.376
Image saved to images_latentdim6_8v3v8/same_encoder_s2_8v8
```




```
100%|      | 250/250 [00:34<00:00,  7.22it/s]

bandwidth: 8
p_value: 0.092
Image saved to images_latentdim6_8v3v8/same_encoder_s3_8v8
```




```
CPU times: user 5min 25s, sys: 14min 27s, total: 19min 52s
Wall time: 4min 28s
```

[ ]:
```
same_encoder_stats
```

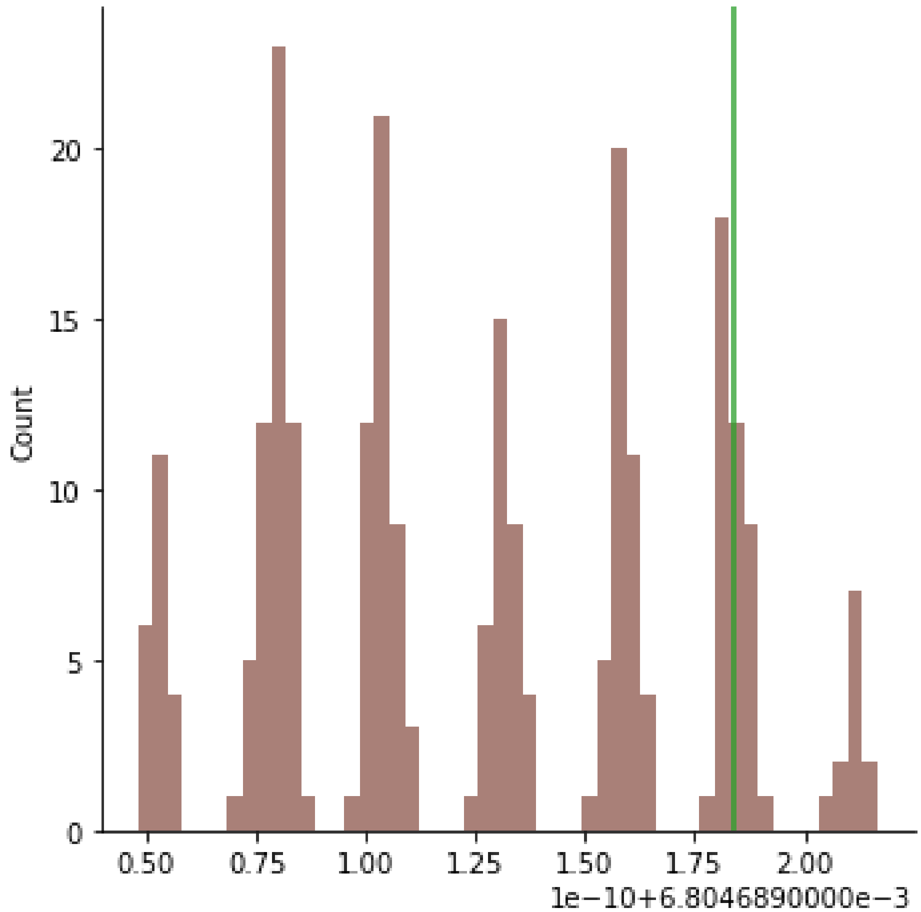
[ ]:
```
{-3: {'p': 0.1, 'time': 34.74849581718445},
 -2: {'p': 0.124, 'time': 39.05711221694946},
 -1: {'p': 0.744, 'time': 40.66038990020752},
 0: {'p': 0.768, 'time': 37.54035305976868},
 1: {'p': 0.76, 'time': 37.13159108161926},
 2: {'p': 0.376, 'time': 38.414994955062866},
 3: {'p': 0.092, 'time': 39.6552369594574}}
```

0.2.8 Statistics for Gaussian Kernel

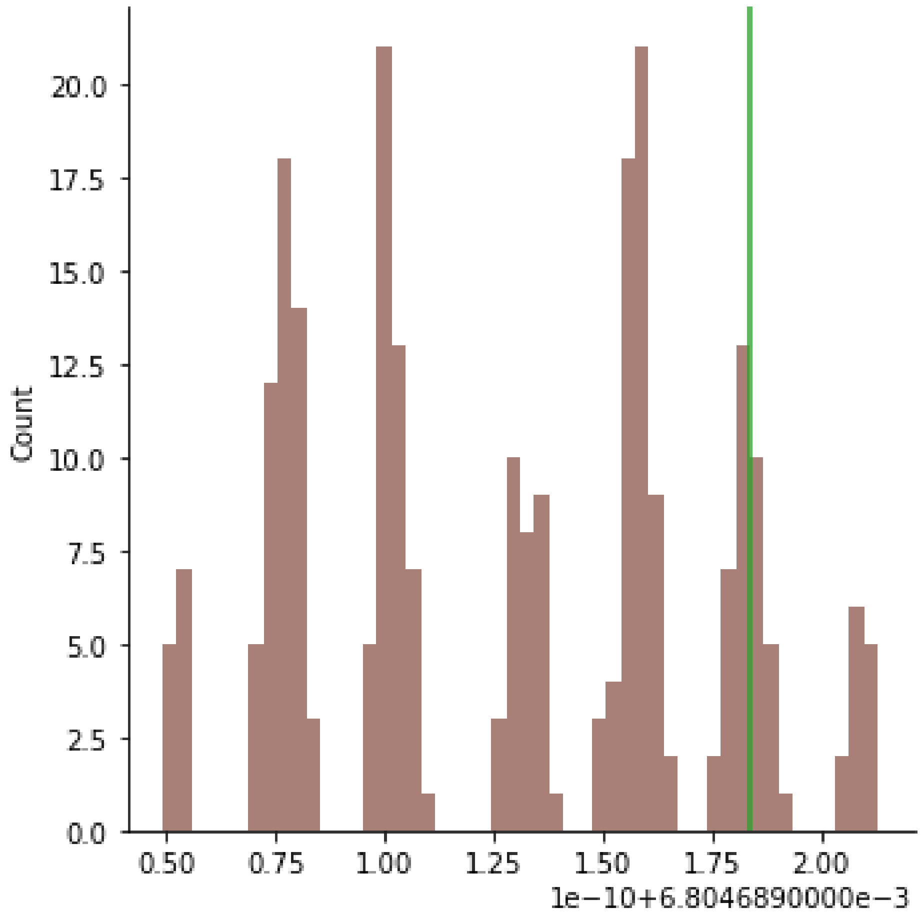
[ ]:
```
# gaussian mmd

same_gaussian_stats = {}
for val in [scale_sigma_squared, auto_sigma_squared, -3, -2, -1, 0, 1, 2, 3]:
```

```python
    start = time.time()
    observed_mmd_gaussian8v8, simulated_mmds_gaussian8v8 =␣
↪permutation_test_gaussian_mmd(
        x1_batch, x2_batch, n_perms=n_perms, sigma_squared=(2 ** val)
    )
    end = time.time()
    p = p_val(simulated_mmds_gaussian8v8, observed_mmd_gaussian8v8)
    same_gaussian_stats[val] = {'p': p, 'time': end - start}

    hist_color = 'tab:brown'
    line_color = 'tab:green'
    filepath = 'images_latentdim6_8v3v8/same_gaussian_s' + str(val) + '_8v8'

    print('bandwidth:', str(np.round(2 ** val, 3)))
    plot_permutation(
        simulated_mmds_gaussian8v8,
        observed_mmd_gaussian8v8,
        hist_color = hist_color,
        line_color = line_color,
        filepath = filepath
    )
    plt.show()
```

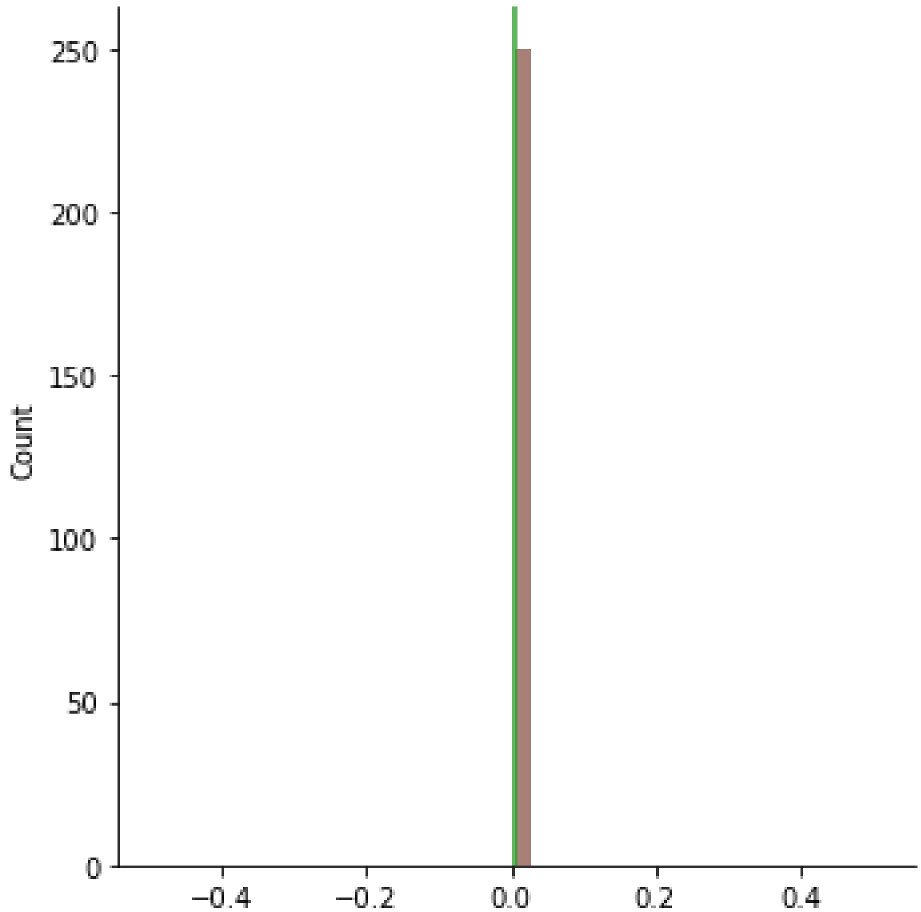
```
100%|      | 250/250 [00:04<00:00, 56.00it/s]

bandwidth: 1.0
p_value: 0.116
Image saved to images_latentdim6_8v3v8/same_gaussian_s2.8848260237648284e-05_8v8
```



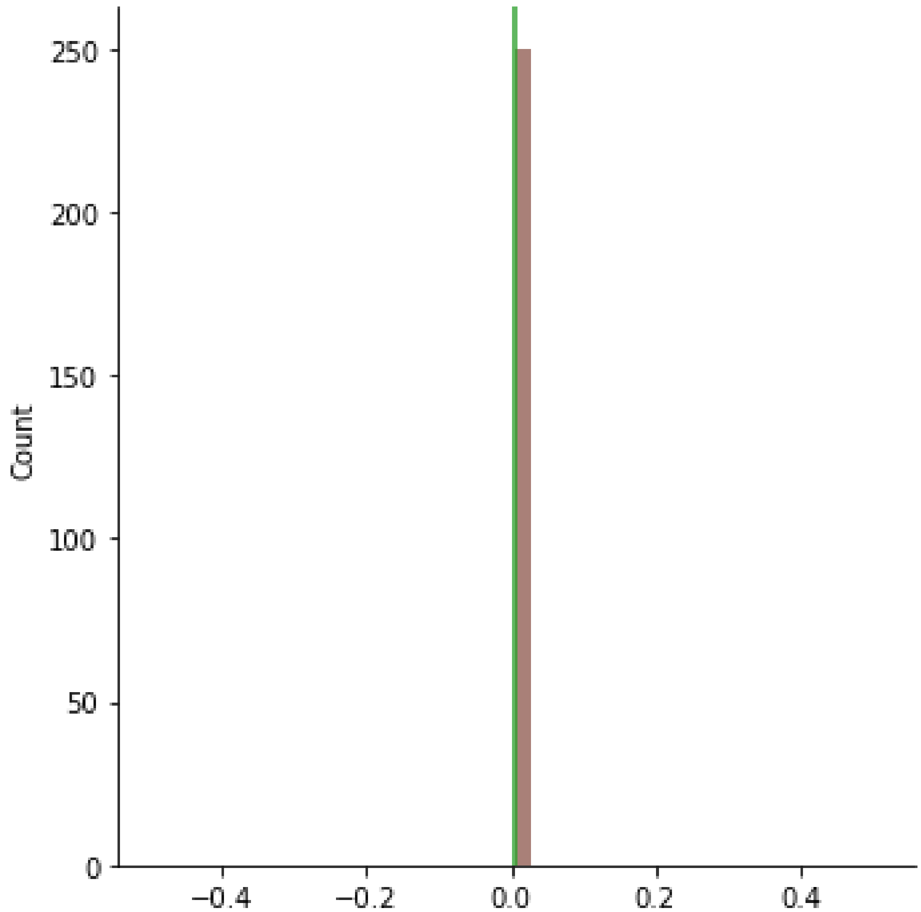

```
100%|          | 250/250 [00:04<00:00, 54.35it/s]

bandwidth: 1.001
p_value: 0.116
Image saved to images_latentdim6_8v3v8/same_gaussian_s0.0012755102040816326_8v8
```



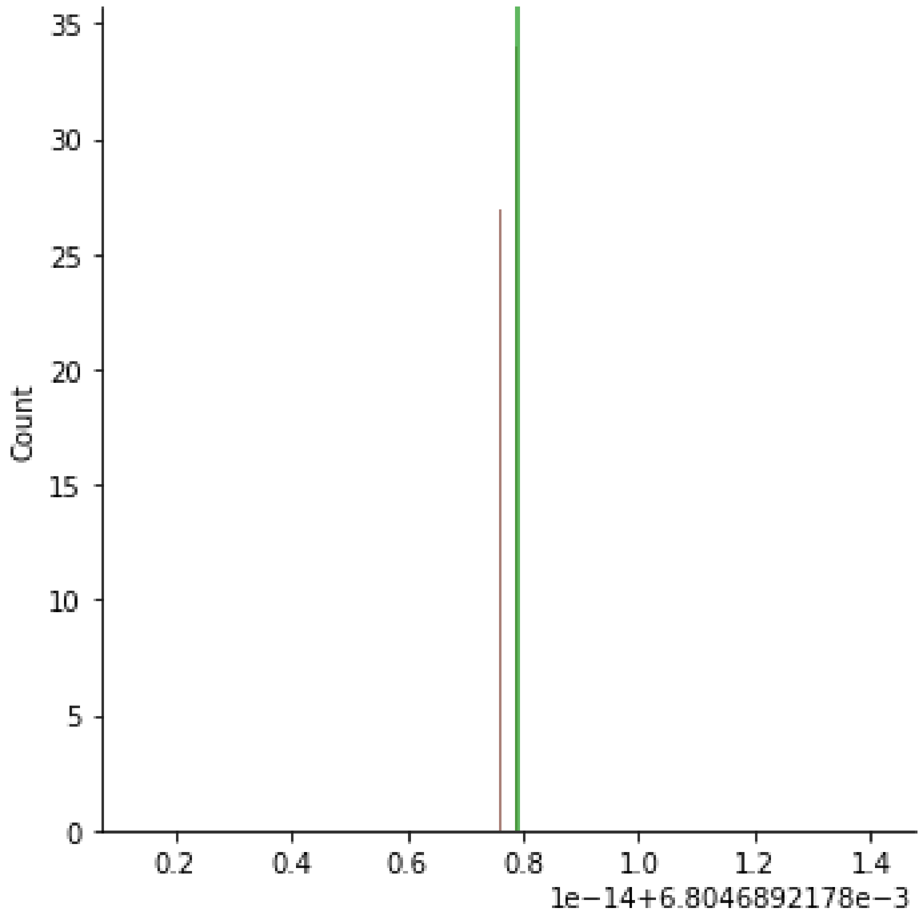

```
100%|          | 250/250 [00:05<00:00, 49.20it/s]

bandwidth: 0.125
p_value: 0.0
Image saved to images_latentdim6_8v3v8/same_gaussian_s-3_8v8
```



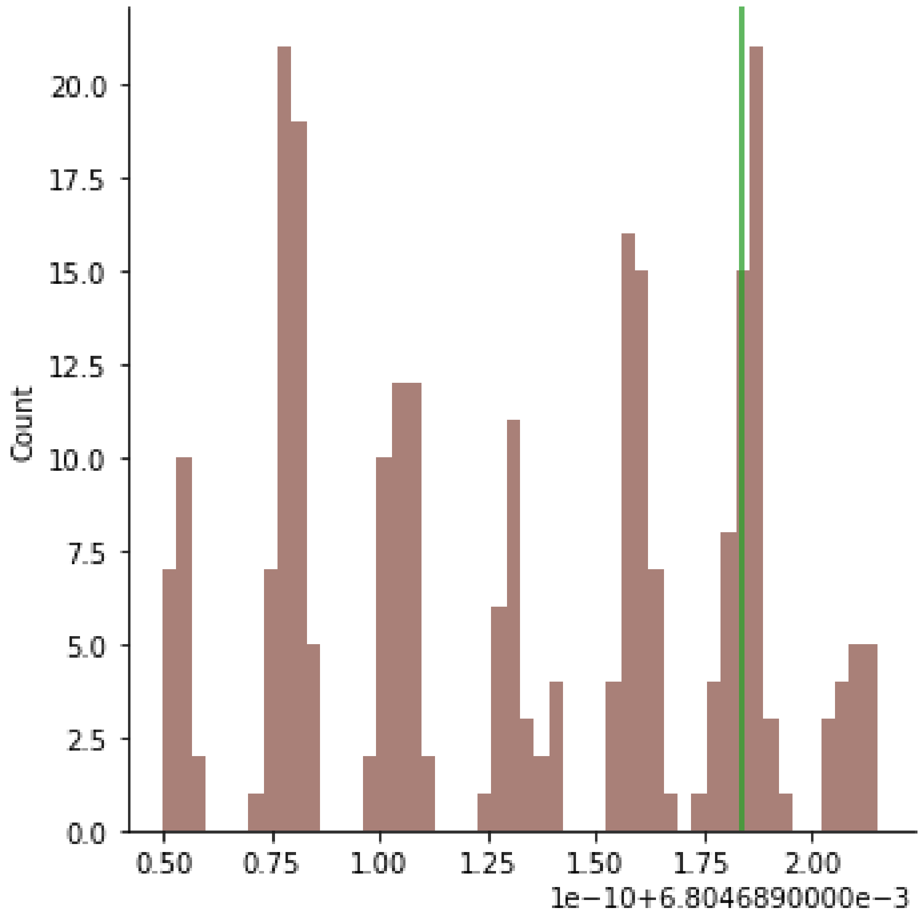

```
100%|      | 250/250 [00:03<00:00, 63.44it/s]

bandwidth: 0.25
p_value: 0.0
Image saved to images_latentdim6_8v3v8/same_gaussian_s-2_8v8
```



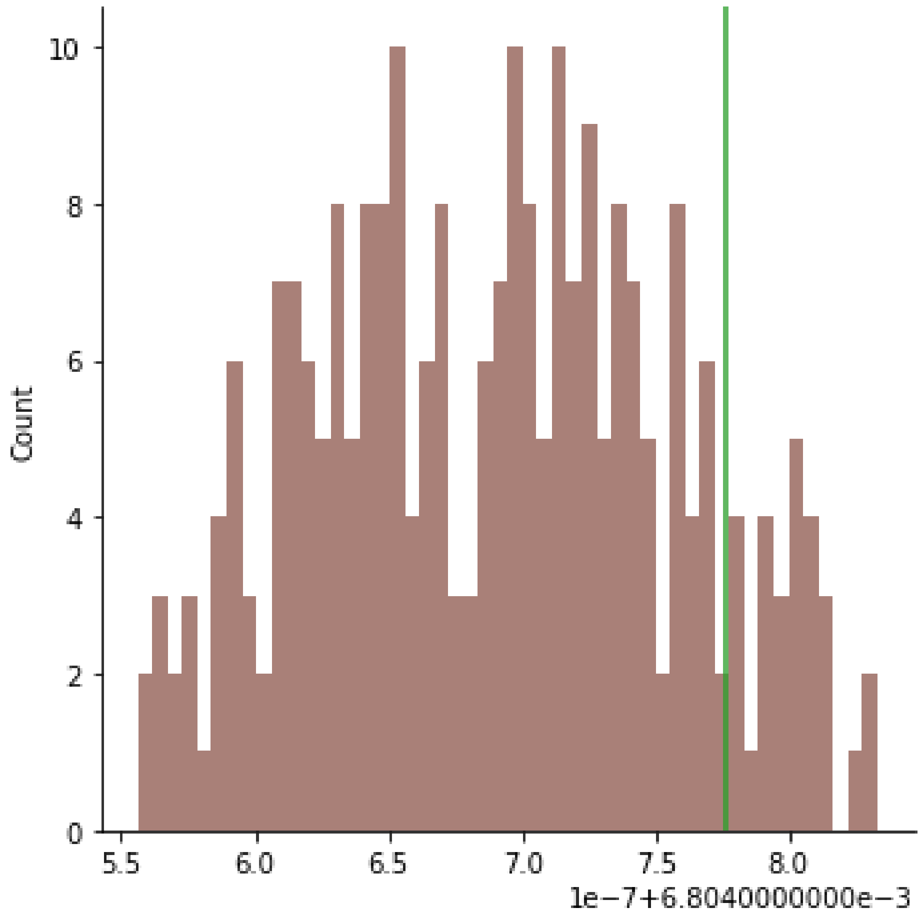

```
100%|          | 250/250 [00:03<00:00, 68.13it/s]

bandwidth: 0.5
p_value: 0.188
Image saved to images_latentdim6_8v3v8/same_gaussian_s-1_8v8
```



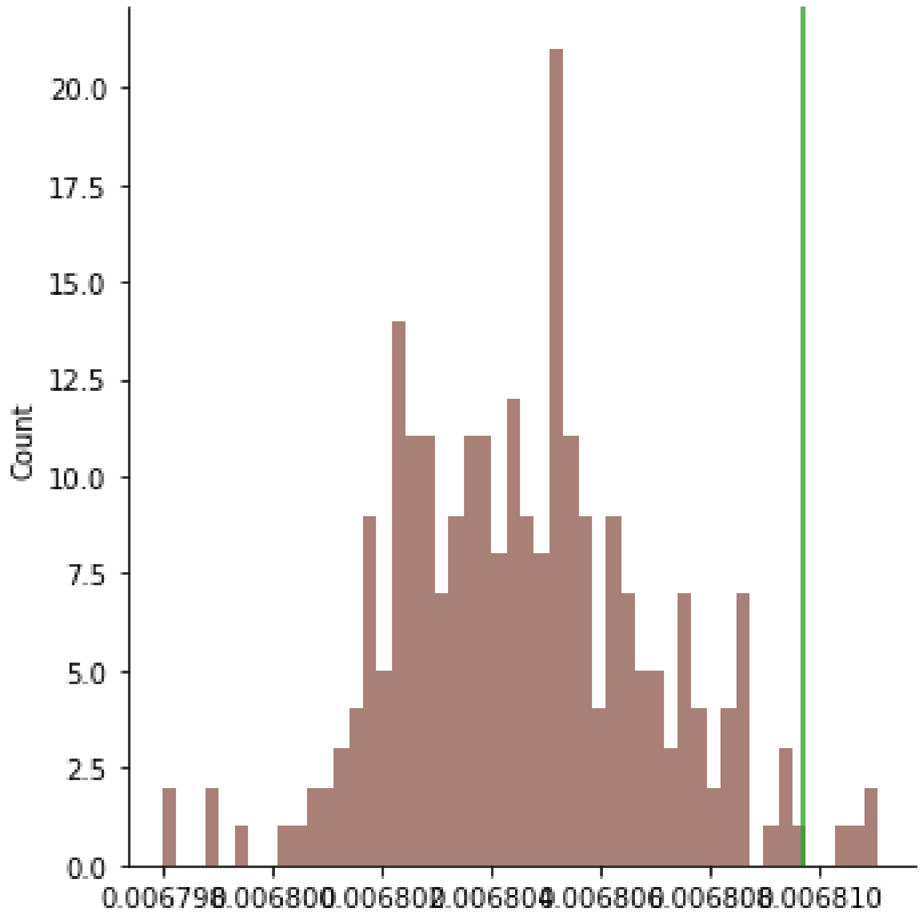

```
100%|      | 250/250 [00:03<00:00, 64.51it/s]

bandwidth: 1
p_value: 0.188
Image saved to images_latentdim6_8v3v8/same_gaussian_s0_8v8
```




```
100%|      | 250/250 [00:03<00:00, 80.19it/s]

bandwidth: 2
p_value: 0.112
Image saved to images_latentdim6_8v3v8/same_gaussian_s1_8v8
```

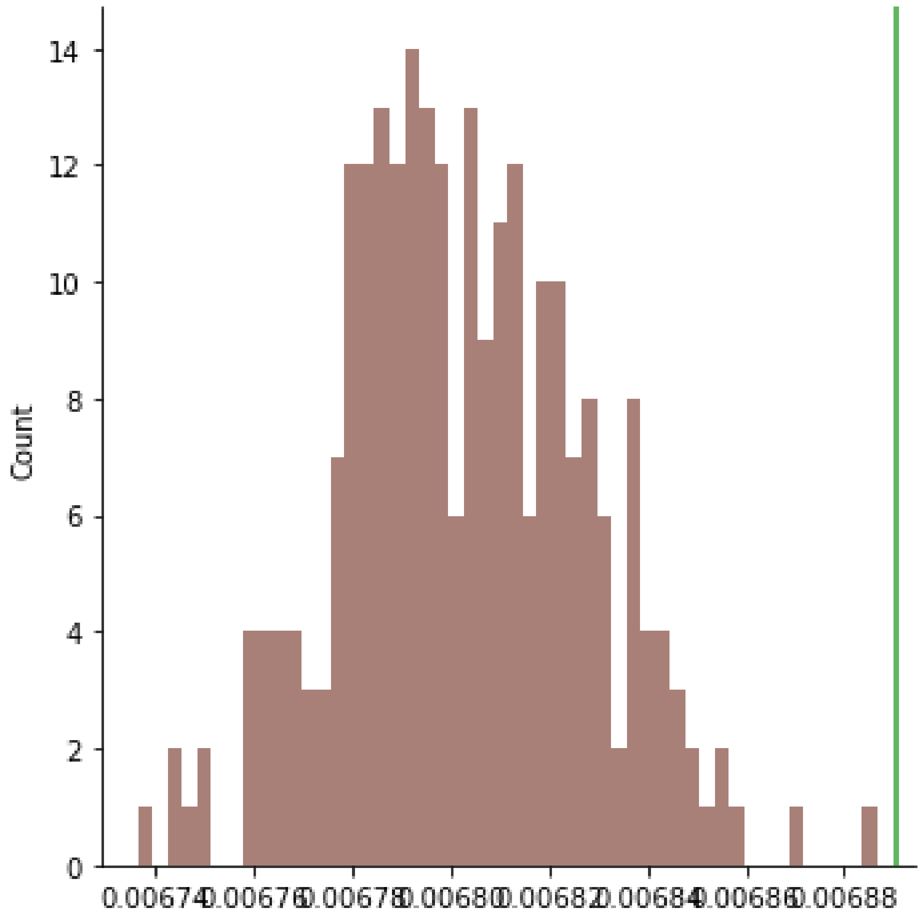



```
100%|          | 250/250 [00:03<00:00, 64.11it/s]

bandwidth: 4
p_value: 0.016
Image saved to images_latentdim6_8v3v8/same_gaussian_s2_8v8
```



100%| | 250/250 [00:03<00:00, 67.34it/s]

bandwidth: 8
p_value: 0.0
Image saved to images_latentdim6_8v3v8/same_gaussian_s3_8v8



[ ]:
```
same_gaussian_stats
```

[ ]:
```
{2.8848260237648284e-05: {'p': 0.116, 'time': 4.476850986480713},
 0.0012755102040816326: {'p': 0.116, 'time': 4.629081726074219},
 -3: {'p': 0.0, 'time': 5.093536138534546},
 -2: {'p': 0.0, 'time': 3.9547619819641113},
 -1: {'p': 0.188, 'time': 3.6981630325317383},
 0: {'p': 0.188, 'time': 3.8854548931121826},
 1: {'p': 0.112, 'time': 3.12951397895813},
 2: {'p': 0.016, 'time': 3.914917230606079},
 3: {'p': 0.0, 'time': 3.726551055908203}}
```