autoencoder

March 25, 2024

1 DeepFalcon

1.0.1 Common Task 1. Auto-encoder of the quark/gluon events

- Please train a variational auto-encoder to learn the representation based on three image channels (ECAL, HCAL and Tracks) for the dataset.
- Please show a side-by-side comparison of original and reconstructed events.

2 Genie

2.0.1 Common Task 1. Auto-encoder of the quark/gluon events

- Please train an auto-encoder to learn the representation based on three image channels (ECAL, HCAL and Tracks) for the dataset.
- Please show a side-by-side comparison of original and reconstructed events.

[ ]:
```python
import torch
import numpy as np
import h5py
import os
import matplotlib.pyplot as plt
import torch.nn as nn
import torch.nn.functional as F
from tqdm.autonotebook import tqdm
import torchvision
import random
import cv2
import matplotlib.colors as colors
```

```
/tmp/ipykernel_81769/1228640743.py:8: TqdmWarning: IProgress not found. Please
update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from tqdm.autonotebook import tqdm
```

2.1 SEEDING - For Reproducability

[ ]:
```
seed = 42
random.seed(seed)
np.random.seed(seed)
torch.backends.cudnn.benchmark = False
torch.backends.cudnn.deterministic = True

def seed_worker(worker_id):
    worker_seed = torch.initial_seed() % 2**32
    np.random.seed(worker_seed)
    random.seed(worker_seed)

g = torch.Generator()
g.manual_seed(seed)
```

[ ]:
```
<torch._C.Generator at 0x7f9f0e6f0b90>
```

2.2 Data Preprocessing and Data Visualisation

[ ]:
```
data_path = 'quark-gluon_data-set_n139306.hdf5'
```

[ ]:
```
class Quark_Gluon_Dataset(torch.utils.data.Dataset):
    def __init__(self,root_path,num_samples= 10000,transform=None):
        self.root_path = root_path
        self.transform = transform
        self.num_samples = num_samples
        self.f = h5py.File(self.root_path,'r')
        self.data_length = len(self.f['y'][:num_samples]) # subset of samples␣
 ↪due to limited computation

        self.X_jets = self.f['X_jets'][:num_samples]
        self.y = self.f['y'][:num_samples]

        if self.transform:
            self.X_jets = self.transform(torch.as_tensor(np.array(self.X_jets)).
 ↪permute(0,3,1,2)) # BxHxWxC ----> BxCxHxW

    def __getitem__(self,idx):
        X_jets = self.X_jets[idx]            # images
        # mass = f['m0'][:1000][idx]         # mass
        # momentum = f['pt'][:1000][idx]     # transverse momentum
        y = self.y[idx]                      # labels

        return torch.as_tensor(np.array(X_jets)),torch.as_tensor(np.array(y))

    def __len__(self):
```

```
        return self.data_length
```

[ ]:
```
transform = torchvision.transforms.Compose([torchvision.transforms.
 ↪Resize((128,128))])
data = Quark_Gluon_Dataset(data_path,transform=transform,num_samples=12000)
train_data,valid_data,test_data = torch.utils.data.
 ↪random_split(dataset=data,lengths=[0.7,0.2,0.1],generator=g)

batch_size = 256
train_dataloader = torch.utils.data.
 ↪DataLoader(dataset=train_data,batch_size=batch_size,num_workers=1,
                                         shuffle=True,␣
 ↪worker_init_fn=seed_worker,generator=g)
valid_dataloader = torch.utils.data.
 ↪DataLoader(dataset=valid_data,batch_size=batch_size,num_workers=1,
                                         shuffle=False,␣
 ↪worker_init_fn=seed_worker,generator=g)

test_dataloader = torch.utils.data.
 ↪DataLoader(dataset=test_data,batch_size=batch_size,num_workers=1,
                                         shuffle=False,␣
 ↪worker_init_fn=seed_worker,generator=g)
```

```
/home/pratyush/miniconda3/envs/clip/lib/python3.9/site-
packages/torchvision/transforms/functional.py:1603: UserWarning: The default
value of the antialias parameter of all the resizing transforms (Resize(),
RandomResizedCrop(), etc.) will change from None to True in v0.17, in order to
be consistent across the PIL and Tensor backends. To suppress this warning,
directly pass antialias=True (recommended, future default), antialias=None
(current default, which means False for Tensors and True for PIL), or
antialias=False (only works on Tensors - PIL will still use antialiasing). This
also applies if you are using the inference transforms from the models weights:
update the call to weights.transforms(antialias=True).
  warnings.warn(
```

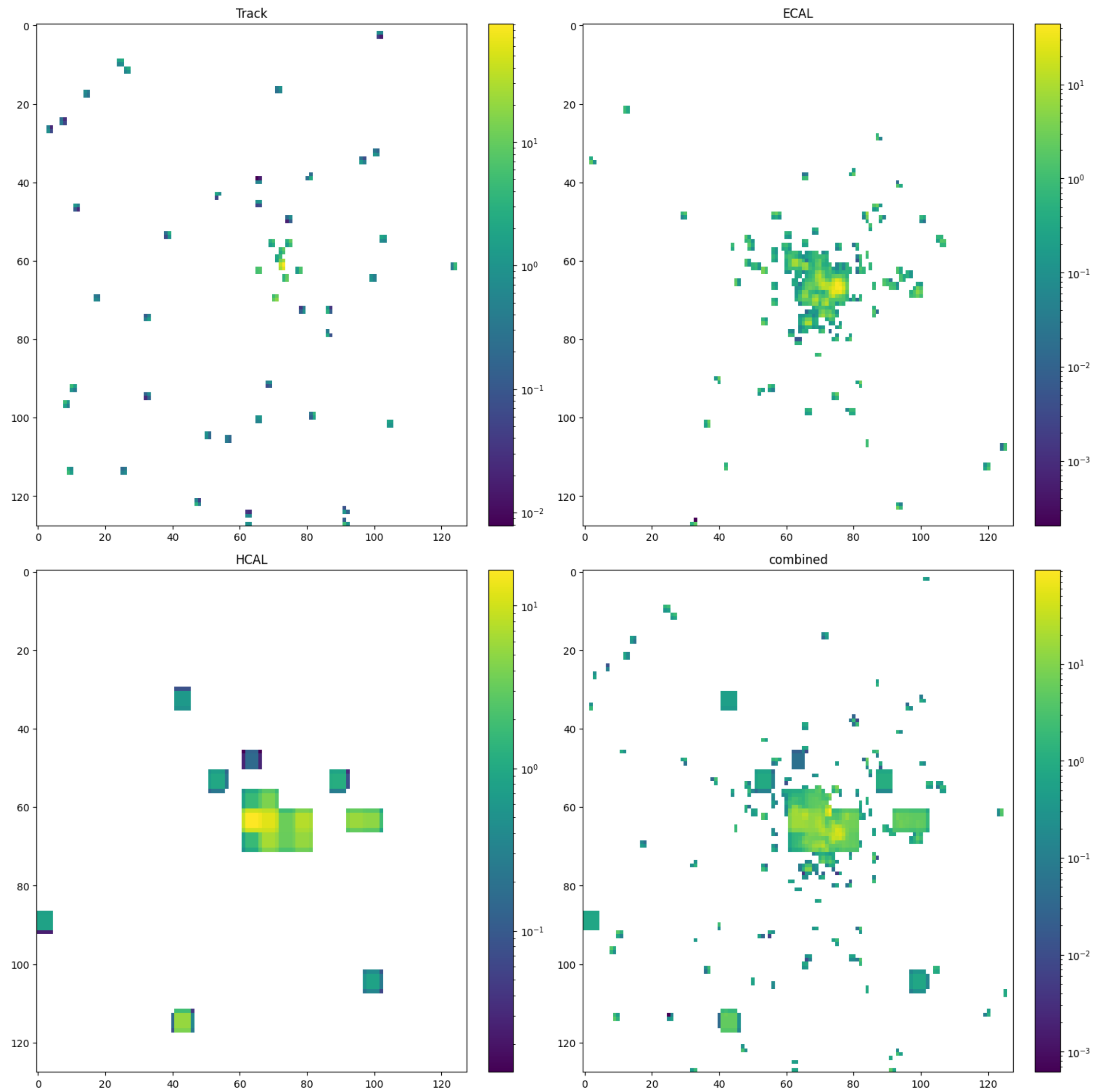
[ ]:
```
X_jets,y = next(iter(train_dataloader))
X_jets.shape
```

[ ]: `torch.Size([256, 3, 128, 128])`

2.2.1 VISUALISING A SAMPLE FROM TRAIN_DATA

[ ]:
```
i = 10

mean_track = torch.mean(X_jets[i][0,:,:])
std_track = torch.std(X_jets[i][0,:,:])
```

```
mean_ecal = torch.mean(X_jets[i][1,:,:])
std_ecal = torch.std(X_jets[i][1,:,:])

mean_hcal = torch.mean(X_jets[i][2,:,:])
std_hcal = torch.std(X_jets[i][2,:,:])

tracks = (X_jets[i][0,:,:] - mean_track) / std_track
ecal = (X_jets[i][1,:,:] - mean_ecal) / std_ecal
hcal = (X_jets[i][2,:,:] - mean_hcal) / std_hcal

combined = tracks + ecal + hcal

fig, axs = plt.subplots(2, 2, figsize=(15, 15), constrained_layout=True)

im_tracks = axs[0,0].imshow(tracks,aspect='auto', norm=colors.LogNorm())
axs[0,0].set_title('Track')
fig.colorbar(im_tracks, ax=axs[0,0])

im_ecal = axs[0,1].imshow(ecal,aspect='auto', norm=colors.LogNorm())
axs[0,1].set_title('ECAL')
fig.colorbar(im_ecal, ax=axs[0,1])

im_hcal = axs[1,0].imshow(hcal,  aspect='auto', norm=colors.LogNorm())
axs[1,0].set_title('HCAL')
fig.colorbar(im_hcal, ax=axs[1,0])

im_combined = axs[1,1].imshow(combined,aspect='auto', norm=colors.LogNorm())
axs[1,1].set_title('combined')
fig.colorbar(im_combined, ax=axs[1,1])

plt.show()
```



3 MODELS

3.1 1) AutoEncoder

```
[ ]: class AutoEncoder(nn.Module):
         def __init__(self,input_channels:int =3, base_channel_size:int = 32,␣
      ↪latent_dim:int = 1024, act_fn:object = nn.PReLU):

             super().__init__()
             c_hid = base_channel_size
             self.encoder_net = nn.Sequential(
```

```
            nn.Conv2d( input_channels, c_hid, kernel_size=3, padding=1,␣
↪stride=2,bias=False), #[B,3,128,128]---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
            nn.Conv2d(c_hid,c_hid,kernel_size=3,padding=1,bias=False),␣
↪#[B,c_hid,64,64] ---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
            nn.
↪Conv2d(c_hid,2*c_hid,kernel_size=3,padding=1,stride=2,bias=False) ,␣
↪#[B,c_hid,64,64] ---> [B,2*c_hid,32,32]
            act_fn(num_parameters = 2*c_hid),
            nn.Flatten(), #[B,2*c_hid,32,32] ---> [B,2*32*32*c_hid]
            )


        self.decoder_net = nn.Sequential(
            nn.
↪ConvTranspose2d(2*c_hid,2*c_hid,kernel_size=3,output_padding=1,padding=1,stride=2,bias=Fals
↪#[B,2*c_hid,32,32] --->[B,2*c_hid,64,64]
            act_fn(num_parameters = 2*c_hid),
            nn.Conv2d(2*c_hid,c_hid,kernel_size=3,padding=1,bias=False),␣
↪#[B,2*c_hid,64,64] ---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
            nn.
↪ConvTranspose2d(c_hid,input_channels,kernel_size=3,output_padding=1,padding=1,stride=2,bias
↪64.64] ---> [B,3,128,128]
            nn.Sigmoid()
            )
    def init_weights(self):
        for m in self.modules():
            if isinstance(m, nn.Conv2d) or isinstance(m, nn.ConvTranspose2d) or␣
↪isinstance(m, nn.Linear):
                init.xavier_uniform_(m.weight)
                if m.bias is not None:
                    init.constant_(m.bias, 0)

    def forward(self,x):
        x = self.encoder_net(x)
        x = x.reshape(x.shape[0],-1,32,32) #[B,2*32*32*c_hid] --->␣
↪[B,2*c_hid,32,32]
        x = self.decoder_net(x)
        return x
```

[ ]:

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model =  AutoEncoder(latent_dim=1024).to(device)
optimizer = torch.optim.Adam(model.parameters(),lr=1e-3)
def ae_loss(x,xhat):
```

```
    reconstruction_loss = F.binary_cross_entropy(xhat,x,reduction='sum')
    return reconstruction_loss
```

[ ]:
```
num_epochs = 50
for epoch in range(num_epochs):
    total_train_loss = 0
    total_valid_loss = 0


    model.train()
    for x_jets_train , labels in tqdm(train_dataloader,total =␣
↪len(train_dataloader)):
        x_jets_train = x_jets_train.to(device)

        optimizer.zero_grad()

        x_hat_train = model(x_jets_train)
        train_loss = ae_loss(x_jets_train,x_hat_train)

        train_loss.backward()
        optimizer.step()

        total_train_loss+=train_loss.item()

    avg_train_loss = total_train_loss / len(train_dataloader)

    model.eval()
    with torch.no_grad():
        for x_jets_valid , labels in tqdm(valid_dataloader,total =␣
↪len(valid_dataloader)):
            x_jets_valid = x_jets_valid.to(device)

            x_hat_valid = model(x_jets_valid)
            valid_loss = ae_loss(x_jets_valid,x_hat_valid)

            total_valid_loss += valid_loss.item()

    avg_valid_loss = total_valid_loss / len(valid_dataloader)

    torch.cuda.empty_cache()

    if (epoch+1)%5==0:
        print(f'epoch: {epoch+1}, train_loss: {avg_train_loss},valid_loss:␣
↪{avg_valid_loss}')
```

```
100%|          | 33/33 [00:02<00:00, 12.04it/s]
100%|          | 10/10 [00:00<00:00, 19.47it/s]
```

```
100%|          | 33/33 [00:02<00:00, 11.86it/s]
100%|          | 10/10 [00:00<00:00, 19.32it/s]
100%|          | 33/33 [00:02<00:00, 11.78it/s]
100%|          | 10/10 [00:00<00:00, 18.41it/s]
100%|          | 33/33 [00:02<00:00, 11.81it/s]
100%|          | 10/10 [00:00<00:00, 18.82it/s]
100%|          | 33/33 [00:02<00:00, 11.78it/s]
100%|          | 10/10 [00:00<00:00, 18.54it/s]

epoch: 5, train_loss: 1585353.5265151516,valid_loss: 1488996.35

100%|          | 33/33 [00:02<00:00, 11.79it/s]
100%|          | 10/10 [00:00<00:00, 17.49it/s]
100%|          | 33/33 [00:02<00:00, 11.50it/s]
100%|          | 10/10 [00:00<00:00, 18.47it/s]
100%|          | 33/33 [00:02<00:00, 11.69it/s]
100%|          | 10/10 [00:00<00:00, 18.25it/s]
100%|          | 33/33 [00:02<00:00, 11.56it/s]
100%|          | 10/10 [00:00<00:00, 19.47it/s]
100%|          | 33/33 [00:02<00:00, 11.85it/s]
100%|          | 10/10 [00:00<00:00, 19.41it/s]

epoch: 10, train_loss: 1440754.4621212122,valid_loss: 1375924.53125

100%|          | 33/33 [00:02<00:00, 11.76it/s]
100%|          | 10/10 [00:00<00:00, 17.83it/s]
100%|          | 33/33 [00:03<00:00, 10.64it/s]
100%|          | 10/10 [00:00<00:00, 19.71it/s]
100%|          | 33/33 [00:02<00:00, 11.83it/s]
100%|          | 10/10 [00:00<00:00, 19.27it/s]
100%|          | 33/33 [00:02<00:00, 11.68it/s]
100%|          | 10/10 [00:00<00:00, 17.61it/s]
100%|          | 33/33 [00:02<00:00, 11.49it/s]
100%|          | 10/10 [00:00<00:00, 17.63it/s]

epoch: 15, train_loss: 1401695.0151515151,valid_loss: 1342342.4375

100%|          | 33/33 [00:02<00:00, 11.57it/s]
100%|          | 10/10 [00:00<00:00, 18.55it/s]
100%|          | 33/33 [00:02<00:00, 11.54it/s]
100%|          | 10/10 [00:00<00:00, 17.48it/s]
100%|          | 33/33 [00:02<00:00, 11.59it/s]
100%|          | 10/10 [00:00<00:00, 18.97it/s]
100%|          | 33/33 [00:02<00:00, 11.62it/s]
100%|          | 10/10 [00:00<00:00, 18.05it/s]
100%|          | 33/33 [00:02<00:00, 11.53it/s]
100%|          | 10/10 [00:00<00:00, 18.34it/s]

epoch: 20, train_loss: 1384348.893939394,valid_loss: 1326917.375

100%|          | 33/33 [00:02<00:00, 11.46it/s]
100%|          | 10/10 [00:01<00:00,  5.13it/s]
```

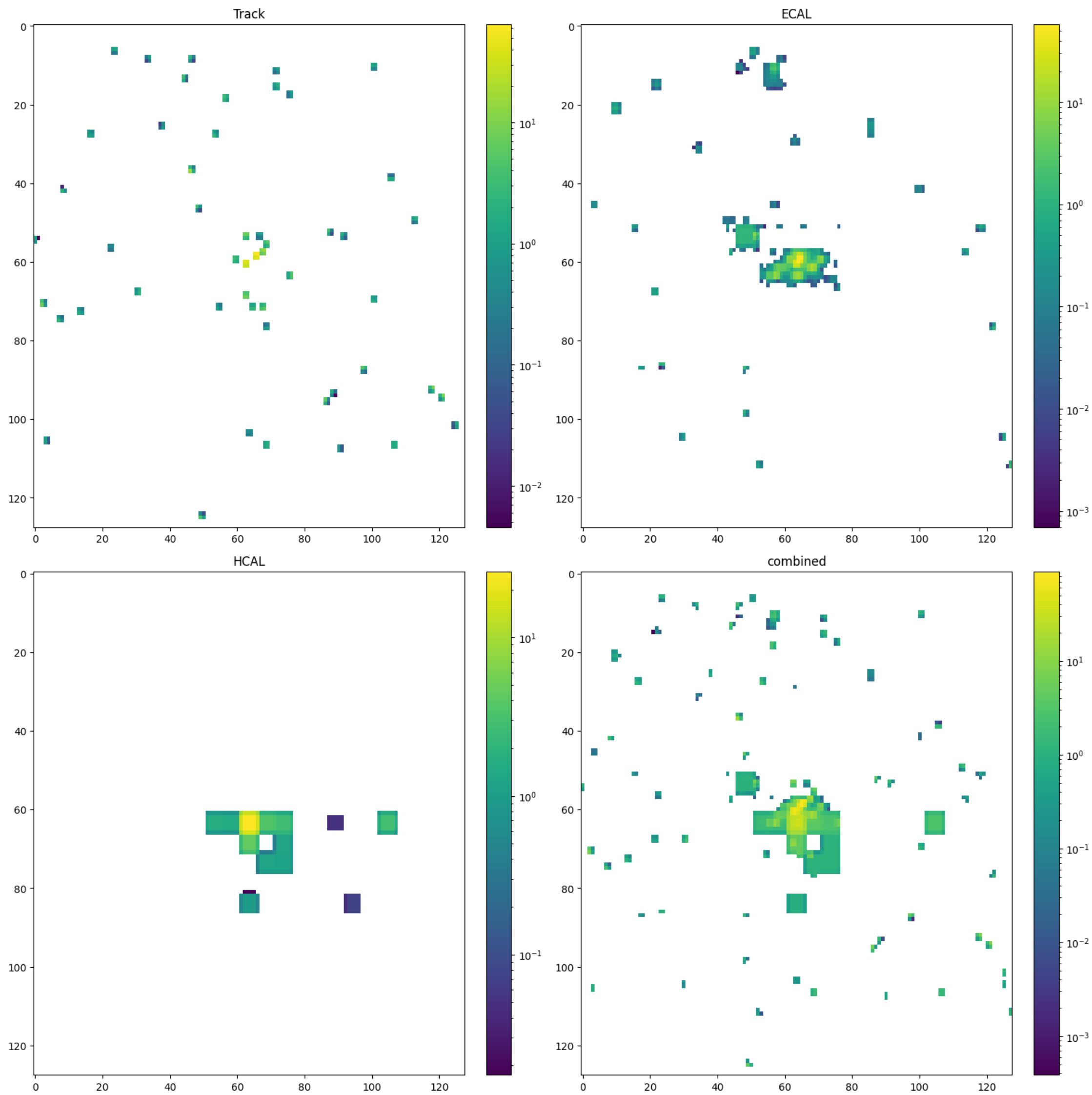
```
100%|     | 33/33 [00:05<00:00,  5.50it/s]
100%|     | 10/10 [00:00<00:00, 18.83it/s]
100%|     | 33/33 [00:02<00:00, 11.45it/s]
100%|     | 10/10 [00:00<00:00, 18.28it/s]
100%|     | 33/33 [00:02<00:00, 11.44it/s]
100%|     | 10/10 [00:00<00:00, 16.85it/s]
100%|     | 33/33 [00:02<00:00, 11.47it/s]
100%|     | 10/10 [00:00<00:00, 17.18it/s]

epoch: 25, train_loss: 1374793.253787879,valid_loss: 1318237.0375

100%|     | 33/33 [00:02<00:00, 11.42it/s]
100%|     | 10/10 [00:00<00:00, 18.12it/s]
100%|     | 33/33 [00:02<00:00, 11.41it/s]
100%|     | 10/10 [00:00<00:00, 17.79it/s]
100%|     | 33/33 [00:03<00:00, 10.97it/s]
100%|     | 10/10 [00:00<00:00, 16.83it/s]
100%|     | 33/33 [00:02<00:00, 11.33it/s]
100%|     | 10/10 [00:00<00:00, 17.68it/s]
100%|     | 33/33 [00:02<00:00, 11.03it/s]
100%|     | 10/10 [00:00<00:00, 16.23it/s]

epoch: 30, train_loss: 1368827.625,valid_loss: 1312752.79375

100%|     | 33/33 [00:03<00:00,  8.27it/s]
100%|     | 10/10 [00:02<00:00,  4.64it/s]
100%|     | 33/33 [00:06<00:00,  5.12it/s]
100%|     | 10/10 [00:02<00:00,  4.71it/s]
100%|     | 33/33 [00:03<00:00,  8.50it/s]
100%|     | 10/10 [00:00<00:00, 18.58it/s]
100%|     | 33/33 [00:02<00:00, 11.53it/s]
100%|     | 10/10 [00:00<00:00, 18.76it/s]
100%|     | 33/33 [00:02<00:00, 11.11it/s]
100%|     | 10/10 [00:00<00:00, 16.61it/s]

epoch: 35, train_loss: 1364794.3863636365,valid_loss: 1309009.225

100%|     | 33/33 [00:02<00:00, 11.41it/s]
100%|     | 10/10 [00:00<00:00, 18.35it/s]
100%|     | 33/33 [00:02<00:00, 11.25it/s]
100%|     | 10/10 [00:00<00:00, 18.12it/s]
100%|     | 33/33 [00:03<00:00, 10.70it/s]
100%|     | 10/10 [00:00<00:00, 18.30it/s]
100%|     | 33/33 [00:02<00:00, 11.14it/s]
100%|     | 10/10 [00:00<00:00, 18.11it/s]
100%|     | 33/33 [00:03<00:00, 10.80it/s]
100%|     | 10/10 [00:00<00:00, 17.22it/s]

epoch: 40, train_loss: 1361913.6590909092,valid_loss: 1306317.13125

100%|     | 33/33 [00:02<00:00, 11.06it/s]
100%|     | 10/10 [00:00<00:00, 17.85it/s]
```

```
100%|          | 33/33 [00:03<00:00,  8.74it/s]
100%|          | 10/10 [00:02<00:00,  4.76it/s]
100%|          | 33/33 [00:05<00:00,  5.63it/s]
100%|          | 10/10 [00:02<00:00,  4.86it/s]
100%|          | 33/33 [00:05<00:00,  5.54it/s]
100%|          | 10/10 [00:02<00:00,  4.86it/s]
100%|          | 33/33 [00:04<00:00,  6.71it/s]
100%|          | 10/10 [00:00<00:00, 17.26it/s]

epoch: 45, train_loss: 1359773.0681818181,valid_loss: 1304308.140625

100%|          | 33/33 [00:02<00:00, 11.54it/s]
100%|          | 10/10 [00:00<00:00, 17.33it/s]
100%|          | 33/33 [00:02<00:00, 11.26it/s]
100%|          | 10/10 [00:00<00:00, 17.86it/s]
100%|          | 33/33 [00:02<00:00, 11.35it/s]
100%|          | 10/10 [00:00<00:00, 17.84it/s]
100%|          | 33/33 [00:02<00:00, 11.16it/s]
100%|          | 10/10 [00:00<00:00, 18.82it/s]
100%|          | 33/33 [00:03<00:00, 10.99it/s]
100%|          | 10/10 [00:00<00:00, 16.68it/s]

epoch: 50, train_loss: 1358134.0454545454,valid_loss: 1302763.771875
```

[ ]:

```
test_X_jets, _ = next(iter(test_dataloader))

i = 10

mean_track = torch.mean(test_X_jets[i][0,:,:])
std_track = torch.std(test_X_jets[i][0,:,:])

mean_ecal = torch.mean(test_X_jets[i][1,:,:])
std_ecal = torch.std(test_X_jets[i][1,:,:])

mean_hcal = torch.mean(test_X_jets[i][2,:,:])
std_hcal = torch.std(test_X_jets[i][2,:,:])

tracks = (test_X_jets[i][0,:,:] - mean_track) / std_track
ecal = (test_X_jets[i][1,:,:] - mean_ecal) / std_ecal
hcal = (test_X_jets[i][2,:,:] - mean_hcal) / std_hcal

combined = tracks + ecal + hcal

fig, axs = plt.subplots(2, 2, figsize=(15, 15), constrained_layout=True)

im_tracks = axs[0,0].imshow(tracks,aspect='auto', norm=colors.LogNorm())
axs[0,0].set_title('Track')
```

```
fig.colorbar(im_tracks, ax=axs[0,0])

im_ecal = axs[0,1].imshow(ecal,aspect='auto', norm=colors.LogNorm())
axs[0,1].set_title('ECAL')
fig.colorbar(im_ecal, ax=axs[0,1])

im_hcal = axs[1,0].imshow(hcal,  aspect='auto', norm=colors.LogNorm())
axs[1,0].set_title('HCAL')
fig.colorbar(im_hcal, ax=axs[1,0])

im_combined = axs[1,1].imshow(combined,aspect='auto', norm=colors.LogNorm())
axs[1,1].set_title('combined')
fig.colorbar(im_combined, ax=axs[1,1])

plt.show()
```



[ ]:
```python
model.eval()
total_test_loss = 0
with torch.no_grad():
    for x_jets_test , labels in tqdm(test_dataloader,total =␣
 ↪len(test_dataloader)):
            x_jets_test = x_jets_test.to(device)

            x_hat_test = model(x_jets_test)
            test_loss = ae_loss(x_jets_test,x_hat_test)
            total_test_loss += test_loss.item()
    avg_test_loss = total_test_loss / len(test_dataloader)
    print(avg_test_loss)
```

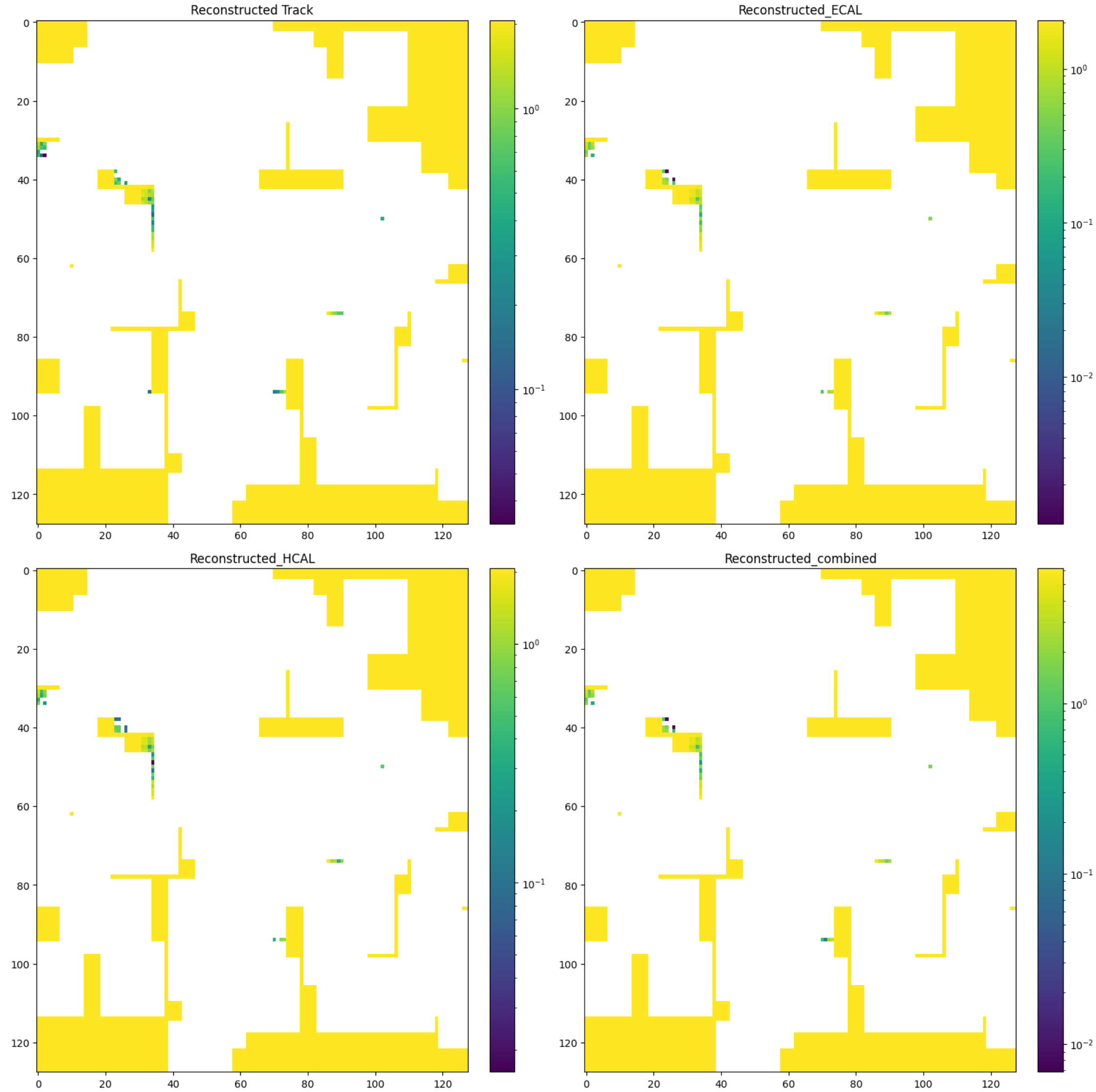
```
100%|      | 5/5 [00:00<00:00, 13.84it/s]
```

```
1292576.025
```

[ ]:
```python
model.eval()
with torch.inference_mode():
    test_img_pred = model(test_X_jets.to(device))
```

[ ]:
```python
i = 10

mean_track = torch.mean(test_img_pred[i][0,:,:])
std_track = torch.std(test_img_pred[i][0,:,:])

mean_ecal = torch.mean(test_img_pred[i][1,:,:])
std_ecal = torch.std(test_img_pred[i][1,:,:])

mean_hcal = torch.mean(test_img_pred[i][2,:,:])
std_hcal = torch.std(test_img_pred[i][2,:,:])

tracks = (test_img_pred[i][0,:,:] - mean_track) / std_track
ecal = (test_img_pred[i][1,:,:] - mean_ecal) / std_ecal
hcal = (test_img_pred[i][2,:,:] - mean_hcal) / std_hcal

combined = tracks + ecal + hcal

fig, axs = plt.subplots(2, 2, figsize=(15, 15), constrained_layout=True)

im_tracks = axs[0,0].imshow(tracks.detach().cpu(),aspect='auto', norm=colors.
 ↪LogNorm())
axs[0,0].set_title('Reconstructed Track')
fig.colorbar(im_tracks, ax=axs[0,0])
```

```python
im_ecal = axs[0,1].imshow(ecal.detach().cpu(),aspect='auto', norm=colors.LogNorm())
axs[0,1].set_title('Reconstructed_ECAL')
fig.colorbar(im_ecal, ax=axs[0,1])

im_hcal = axs[1,0].imshow(hcal.detach().cpu(),  aspect='auto', norm=colors.LogNorm())
axs[1,0].set_title('Reconstructed_HCAL')
fig.colorbar(im_hcal, ax=axs[1,0])

im_combined = axs[1,1].imshow(combined.detach().cpu(),aspect='auto', norm=colors.LogNorm())
axs[1,1].set_title('Reconstructed_combined')
fig.colorbar(im_combined, ax=axs[1,1])

plt.show()
```



3.2 2) Variational AutoEncoder

[ ]:
```
class VariationalAutoEncoder(nn.Module):
    def __init__(self,input_channels:int =3, base_channel_size:int = 32,␣
↪latent_dim:int = 1024, act_fn:object = nn.PReLU):

        super().__init__()
        c_hid = base_channel_size
        self.encoder_net = nn.Sequential(
            nn.Conv2d( input_channels, c_hid, kernel_size=3, padding=1,␣
↪stride=2,bias=False), #[B,3,128,128]---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
```

```
            nn.Conv2d(c_hid,c_hid,kernel_size=3,padding=1,bias=False),␣
↪#[B,c_hid,64,64] ---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
            nn.
↪Conv2d(c_hid,2*c_hid,kernel_size=3,padding=1,stride=2,bias=False) ,␣
↪#[B,c_hid,64,64] ---> [B,2*c_hid,32,32]
            act_fn(num_parameters = 2*c_hid),
            nn.Flatten(), #[B,2*c_hid,32,32] ---> [B,2*32*32*c_hid]
            )

        self.fc_mu = nn.Linear(2*32*32*c_hid,latent_dim)
        self.fc_logvar = nn.Linear(2*32*32*c_hid,latent_dim)

        self.linear = nn.Sequential(nn.
↪Linear(latent_dim,2*32*32*c_hid,bias=False),act_fn()) #[B,latent_dim] --->␣
↪[B,2*32*32*c_hid]

        self.decoder_net = nn.Sequential(
            nn.
↪ConvTranspose2d(2*c_hid,2*c_hid,kernel_size=3,output_padding=1,padding=1,stride=2,bias=Fals
↪#[B,2*c_hid,32,32] --->[B,2*c_hid,64,64]
            act_fn(num_parameters = 2*c_hid),
            nn.Conv2d(2*c_hid,c_hid,kernel_size=3,padding=1,bias=False),␣
↪#[B,2*c_hid,64,64] ---> [B,c_hid,64,64]
            act_fn(num_parameters = c_hid),
            nn.
↪ConvTranspose2d(c_hid,input_channels,kernel_size=3,output_padding=1,padding=1,stride=2,bias
↪64.64] ---> [B,3,128,128]
            nn.Sigmoid()
            )
    def init_weights(self):
        for m in self.modules():
            if isinstance(m, nn.Conv2d) or isinstance(m, nn.ConvTranspose2d) or␣
↪isinstance(m, nn.Linear):
                init.xavier_uniform_(m.weight)
                if m.bias is not None:
                    init.constant_(m.bias, 0)

    def reparametrize(self,mu,logvar):
        std = torch.exp(0.5*logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def forward(self,x):
        x = self.encoder_net(x)
        mu = self.fc_mu(x)
```

```
        logvar = self.fc_logvar(x)
        z = self.reparametrize(mu,logvar)
        x = self.linear(z)
        x = x.reshape(x.shape[0],-1,32,32) #[B,2*32*32*c_hid] --->␣
↪[B,2*c_hid,32,32]
        x = self.decoder_net(x)
        return x,mu,logvar
```

[ ]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = VariationalAutoEncoder(latent_dim=1024).to(device)
optimizer = torch.optim.Adam(model.parameters(),lr=1e-3)


def vae_loss (x,xhat,mu,logvar):
    # reconstruction_loss = F.mse_loss(xhat,x,reduction='sum')
    reconstruction_loss = F.binary_cross_entropy(xhat,x,reduction='sum')
    # reconstruction_loss = sigmoid_focal_loss(xhat,x,reduction='sum')
    kl_divergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
    # print(f'reconstruction_{reconstruction_loss}')
    # print(f'kl_divergence_{kl_divergence}')
    return reconstruction_loss + 1*kl_divergence
```

[ ]:
```
num_epochs = 50
for epoch in range(num_epochs):
    total_train_loss = 0
    total_valid_loss = 0


    model.train()
    for x_jets_train , labels in tqdm(train_dataloader,total =␣
↪len(train_dataloader)):
        x_jets_train = x_jets_train.to(device)

        optimizer.zero_grad()

        x_hat_train,mu_train,logvar_train = model(x_jets_train)
        train_loss = vae_loss(x_jets_train,x_hat_train,mu_train,logvar_train)

        train_loss.backward()
        optimizer.step()

        total_train_loss+=train_loss.item()

    avg_train_loss = total_train_loss / len(train_dataloader)

    model.eval()
    with torch.no_grad():
```

```
        for x_jets_valid , labels in tqdm(valid_dataloader,total =␣
↪len(valid_dataloader)):
            x_jets_valid = x_jets_valid.to(device)

            x_hat_valid,mu_valid,logvar_valid = model(x_jets_valid)
            valid_loss =␣
↪vae_loss(x_jets_valid,x_hat_valid,mu_valid,logvar_valid)

            total_valid_loss += valid_loss.item()

    avg_valid_loss = total_valid_loss / len(valid_dataloader)

    torch.cuda.empty_cache()

    if (epoch+1)%5 ==0:
        print(f'epoch: {epoch+1}, train_loss: {avg_train_loss},valid_loss:␣
↪{avg_valid_loss}')
```

```
100%|      | 33/33 [00:05<00:00,  6.34it/s]
100%|      | 10/10 [00:00<00:00, 17.47it/s]
100%|      | 33/33 [00:05<00:00,  6.36it/s]
100%|      | 10/10 [00:00<00:00, 16.36it/s]
100%|      | 33/33 [00:05<00:00,  6.29it/s]
100%|      | 10/10 [00:00<00:00, 16.34it/s]
100%|      | 33/33 [00:05<00:00,  6.29it/s]
100%|      | 10/10 [00:00<00:00, 16.08it/s]
100%|      | 33/33 [00:05<00:00,  6.25it/s]
100%|      | 10/10 [00:00<00:00, 15.78it/s]

epoch: 5, train_loss: 19826.513731060608,valid_loss: 17839.729541015626

100%|      | 33/33 [00:05<00:00,  6.24it/s]
100%|      | 10/10 [00:00<00:00, 16.01it/s]
100%|      | 33/33 [00:05<00:00,  6.23it/s]
100%|      | 10/10 [00:00<00:00, 16.07it/s]
100%|      | 33/33 [00:05<00:00,  6.19it/s]
100%|      | 10/10 [00:00<00:00, 15.63it/s]
100%|      | 33/33 [00:05<00:00,  5.87it/s]
100%|      | 10/10 [00:00<00:00, 15.84it/s]
100%|      | 33/33 [00:05<00:00,  6.15it/s]
100%|      | 10/10 [00:00<00:00, 15.71it/s]

epoch: 10, train_loss: 15995.38583096591,valid_loss: 13905.283154296874

100%|      | 33/33 [00:05<00:00,  6.17it/s]
100%|      | 10/10 [00:00<00:00, 15.32it/s]
100%|      | 33/33 [00:05<00:00,  6.06it/s]
100%|      | 10/10 [00:00<00:00, 16.34it/s]
100%|      | 33/33 [00:05<00:00,  6.04it/s]
```

```
100%|      | 10/10 [00:00<00:00, 15.10it/s]
100%|      | 33/33 [00:06<00:00,  5.40it/s]
100%|      | 10/10 [00:02<00:00,  4.72it/s]
100%|      | 33/33 [00:07<00:00,  4.51it/s]
100%|      | 10/10 [00:00<00:00, 11.22it/s]

epoch: 15, train_loss: 13386.508049242424,valid_loss: 11788.036962890625

100%|      | 33/33 [00:05<00:00,  6.00it/s]
100%|      | 10/10 [00:00<00:00, 15.59it/s]
100%|      | 33/33 [00:05<00:00,  5.97it/s]
100%|      | 10/10 [00:00<00:00, 15.62it/s]
100%|      | 33/33 [00:05<00:00,  5.88it/s]
100%|      | 10/10 [00:00<00:00, 14.17it/s]
100%|      | 33/33 [00:05<00:00,  5.89it/s]
100%|      | 10/10 [00:00<00:00, 15.05it/s]
100%|      | 33/33 [00:05<00:00,  5.85it/s]
100%|      | 10/10 [00:00<00:00, 15.35it/s]

epoch: 20, train_loss: 12091.1162109375,valid_loss: 10375.75732421875

100%|      | 33/33 [00:06<00:00,  4.75it/s]
100%|      | 10/10 [00:02<00:00,  4.75it/s]
100%|      | 33/33 [00:07<00:00,  4.55it/s]
100%|      | 10/10 [00:02<00:00,  4.81it/s]
100%|      | 33/33 [00:05<00:00,  5.54it/s]
100%|      | 10/10 [00:00<00:00, 15.84it/s]
100%|      | 33/33 [00:05<00:00,  5.82it/s]
100%|      | 10/10 [00:00<00:00, 15.03it/s]
100%|      | 33/33 [00:05<00:00,  5.79it/s]
100%|      | 10/10 [00:00<00:00, 15.28it/s]

epoch: 25, train_loss: 10825.706498579546,valid_loss: 9566.634545898438

100%|      | 33/33 [00:05<00:00,  5.73it/s]
100%|      | 10/10 [00:00<00:00, 14.94it/s]
100%|      | 33/33 [00:05<00:00,  5.55it/s]
100%|      | 10/10 [00:02<00:00,  4.74it/s]
100%|      | 33/33 [00:07<00:00,  4.57it/s]
100%|      | 10/10 [00:02<00:00,  4.71it/s]
100%|      | 33/33 [00:07<00:00,  4.56it/s]
100%|      | 10/10 [00:02<00:00,  4.70it/s]
100%|      | 33/33 [00:05<00:00,  5.63it/s]
100%|      | 10/10 [00:00<00:00, 14.83it/s]

epoch: 30, train_loss: 10061.13905658144,valid_loss: 8985.322705078124

100%|      | 33/33 [00:05<00:00,  5.87it/s]
100%|      | 10/10 [00:00<00:00, 14.70it/s]
100%|      | 33/33 [00:05<00:00,  5.71it/s]
100%|      | 10/10 [00:00<00:00, 15.54it/s]
100%|      | 33/33 [00:05<00:00,  5.76it/s]
```

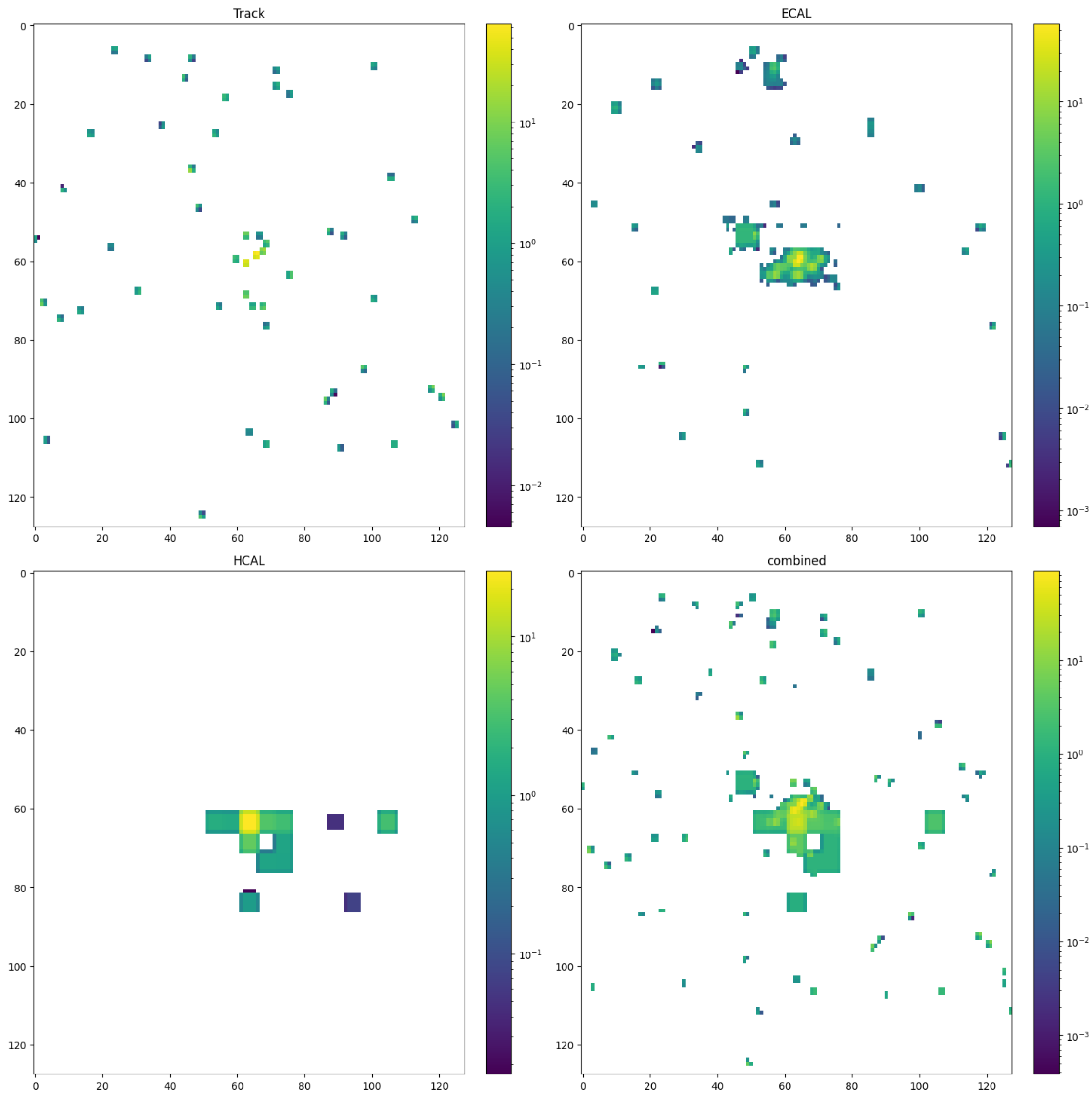
```
100%|     | 10/10 [00:00<00:00, 15.27it/s]
100%|     | 33/33 [00:05<00:00,  5.67it/s]
100%|     | 10/10 [00:00<00:00, 14.75it/s]
100%|     | 33/33 [00:06<00:00,  4.75it/s]
100%|     | 10/10 [00:02<00:00,  4.76it/s]

epoch: 35, train_loss: 9133.05918560606,valid_loss: 8291.2099609375

100%|     | 33/33 [00:07<00:00,  4.44it/s]
100%|     | 10/10 [00:02<00:00,  4.55it/s]
100%|     | 33/33 [00:06<00:00,  4.96it/s]
100%|     | 10/10 [00:00<00:00, 15.08it/s]
100%|     | 33/33 [00:05<00:00,  5.78it/s]
100%|     | 10/10 [00:00<00:00, 14.67it/s]
100%|     | 33/33 [00:05<00:00,  5.80it/s]
100%|     | 10/10 [00:00<00:00, 14.34it/s]
100%|     | 33/33 [00:05<00:00,  5.70it/s]
100%|     | 10/10 [00:00<00:00, 15.03it/s]

epoch: 40, train_loss: 8377.337550307766,valid_loss: 7675.403247070312

100%|     | 33/33 [00:05<00:00,  5.70it/s]
100%|     | 10/10 [00:00<00:00, 14.71it/s]
100%|     | 33/33 [00:06<00:00,  5.29it/s]
100%|     | 10/10 [00:02<00:00,  4.75it/s]
100%|     | 33/33 [00:07<00:00,  4.41it/s]
100%|     | 10/10 [00:02<00:00,  4.75it/s]
100%|     | 33/33 [00:07<00:00,  4.46it/s]
100%|     | 10/10 [00:02<00:00,  4.61it/s]
100%|     | 33/33 [00:06<00:00,  4.72it/s]
100%|     | 10/10 [00:00<00:00, 15.59it/s]

epoch: 45, train_loss: 7850.2333984375,valid_loss: 7231.53994140625

100%|     | 33/33 [00:05<00:00,  5.77it/s]
100%|     | 10/10 [00:00<00:00, 15.43it/s]
100%|     | 33/33 [00:05<00:00,  5.78it/s]
100%|     | 10/10 [00:00<00:00, 14.21it/s]
100%|     | 33/33 [00:05<00:00,  5.70it/s]
100%|     | 10/10 [00:00<00:00, 14.84it/s]
100%|     | 33/33 [00:05<00:00,  5.65it/s]
100%|     | 10/10 [00:00<00:00, 14.65it/s]
100%|     | 33/33 [00:06<00:00,  5.37it/s]
100%|     | 10/10 [00:02<00:00,  4.80it/s]

epoch: 50, train_loss: 7623.828554095644,valid_loss: 6950.908178710937
```

[ ]:

```
test_X_jets, _ = next(iter(test_dataloader))
```

[ ]:

```python
i = 10

mean_track = torch.mean(test_X_jets[i][0,:,:])
std_track = torch.std(test_X_jets[i][0,:,:])

mean_ecal = torch.mean(test_X_jets[i][1,:,:])
std_ecal = torch.std(test_X_jets[i][1,:,:])

mean_hcal = torch.mean(test_X_jets[i][2,:,:])
std_hcal = torch.std(test_X_jets[i][2,:,:])

tracks = (test_X_jets[i][0,:,:] - mean_track) / std_track
ecal = (test_X_jets[i][1,:,:] - mean_ecal) / std_ecal
hcal = (test_X_jets[i][2,:,:] - mean_hcal) / std_hcal

combined = tracks + ecal + hcal

fig, axs = plt.subplots(2, 2, figsize=(15, 15), constrained_layout=True)

im_tracks = axs[0,0].imshow(tracks,aspect='auto', norm=colors.LogNorm())
axs[0,0].set_title('Track')
fig.colorbar(im_tracks, ax=axs[0,0])

im_ecal = axs[0,1].imshow(ecal,aspect='auto', norm=colors.LogNorm())
axs[0,1].set_title('ECAL')
fig.colorbar(im_ecal, ax=axs[0,1])

im_hcal = axs[1,0].imshow(hcal,  aspect='auto', norm=colors.LogNorm())
axs[1,0].set_title('HCAL')
fig.colorbar(im_hcal, ax=axs[1,0])

im_combined = axs[1,1].imshow(combined,aspect='auto', norm=colors.LogNorm())
axs[1,1].set_title('combined')
fig.colorbar(im_combined, ax=axs[1,1])

plt.show()
```




```
[ ]: model.eval()
     total_test_loss = 0
     with torch.no_grad():
         for x_jets_test , labels in tqdm(test_dataloader,total =␣
      ↪len(test_dataloader)):
                 x_jets_test = x_jets_test.to(device)

                 x_hat_test,mu_test,logvar_test = model(x_jets_test)
                 test_loss = vae_loss(x_jets_test,x_hat_test,mu_test,logvar_test)
                 total_test_loss += test_loss.item()
         avg_test_loss = total_test_loss / len(test_dataloader)
         print(avg_test_loss)
```

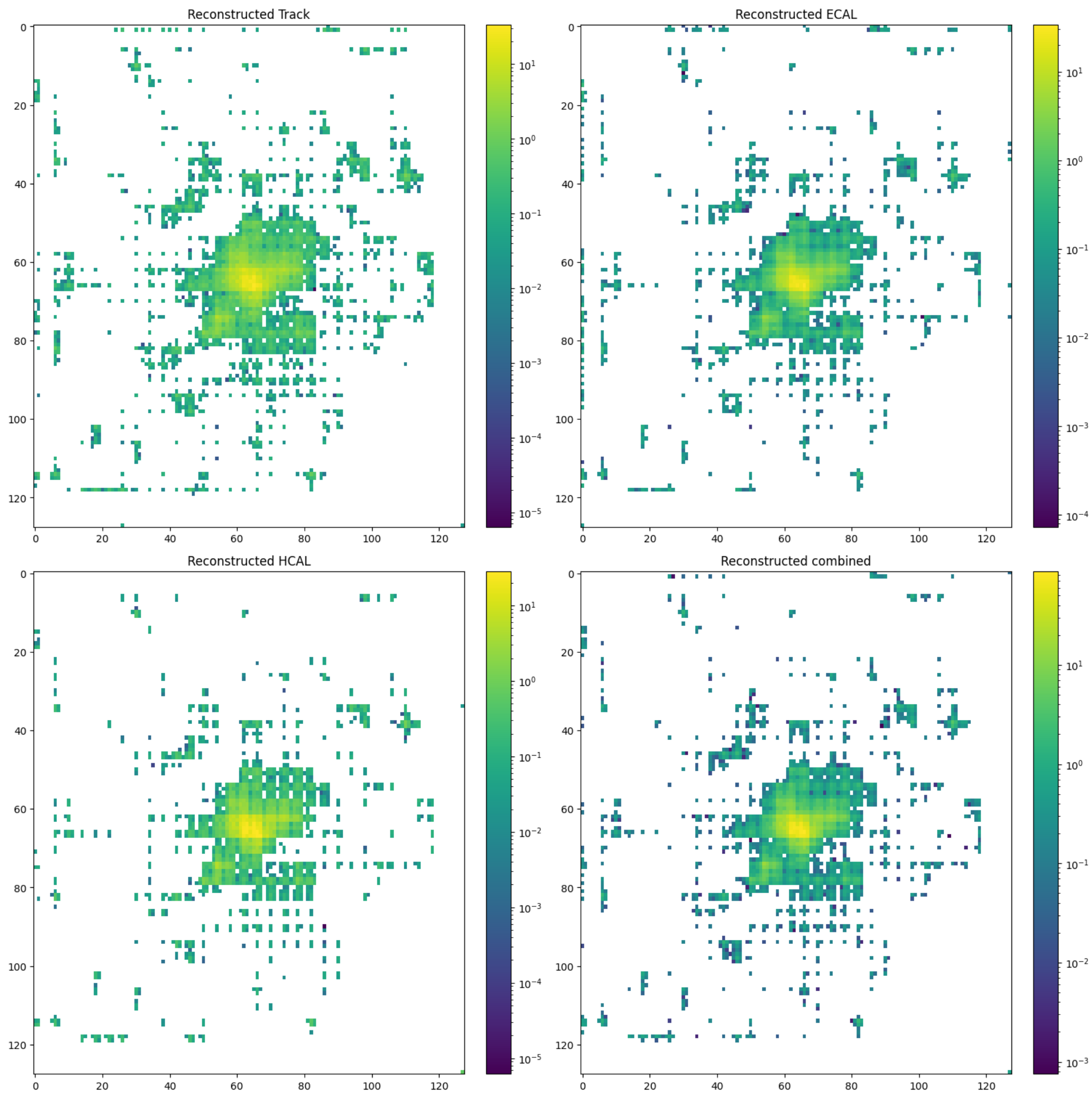
```
100%|          | 5/5 [00:01<00:00,  3.63it/s]
```

```
7080.3193359375
```

[ ]:
```
model.eval()
with torch.inference_mode():
    test_img_pred,mu_pred,logvar_pred = model(test_X_jets.to(device))
```

[ ]:
```
i = 10

mean_track = torch.mean(test_img_pred[i][0,:,:])
std_track = torch.std(test_img_pred[i][0,:,:])

mean_ecal = torch.mean(test_img_pred[i][1,:,:])
std_ecal = torch.std(test_img_pred[i][1,:,:])

mean_hcal = torch.mean(test_img_pred[i][2,:,:])
std_hcal = torch.std(test_img_pred[i][2,:,:])

tracks = (test_img_pred[i][0,:,:] - mean_track) / std_track
ecal = (test_img_pred[i][1,:,:] - mean_ecal) / std_ecal
hcal = (test_img_pred[i][2,:,:] - mean_hcal) / std_hcal

combined = tracks + ecal + hcal

fig, axs = plt.subplots(2, 2, figsize=(15, 15), constrained_layout=True)

im_tracks = axs[0,0].imshow(tracks.detach().cpu(),aspect='auto', norm=colors.
 ↪LogNorm())
axs[0,0].set_title('Reconstructed Track')
fig.colorbar(im_tracks, ax=axs[0,0])

im_ecal = axs[0,1].imshow(ecal.detach().cpu(),aspect='auto', norm=colors.
 ↪LogNorm())
axs[0,1].set_title('Reconstructed ECAL')
fig.colorbar(im_ecal, ax=axs[0,1])

im_hcal = axs[1,0].imshow(hcal.detach().cpu(),  aspect='auto', norm=colors.
 ↪LogNorm())
axs[1,0].set_title('Reconstructed HCAL')
fig.colorbar(im_hcal, ax=axs[1,0])

im_combined = axs[1,1].imshow(combined.detach().cpu(),aspect='auto',␣
 ↪norm=colors.LogNorm())
axs[1,1].set_title('Reconstructed combined')
fig.colorbar(im_combined, ax=axs[1,1])
```

```
plt.show()
```



3.3 DISCUSSION

- As the data doesn't contain normal RGB channels and instead has different channels like ECAL,HCAL,Tracks ,data preprocessing needs to be chosen carefully
- Model architecture might not be too complex to extract the patterns in the underlying data
- Since Images are highly structured data, the pixels are arranged in a meaningful way. If the way pixels are arranged changes then we lose the meaning , hence here convolutions may not work as we aren't dealing with our normal RGB channels image data.

- Instead working with other type of data like graphs (aka Graph Neural Networks) would give better results by extracting features in the graphical representation of the given images.