In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import torch
from tqdm import tqdm
import h5py

from matplotlib.colors import LogNorm
from scipy import stats
from dataload import load_json_config,process_data,load_data
```

In [2]:
```
import sys
sys.path.append('./')
from pytorch3dunet.unet3d.model import UNet3D,ResidualUNet3D
```

Load trained model

In [3]:
```
device='cpu'
ckp='checkpoint_model_29999.pth'
size=64
pad=16
config = load_json_config(custom_path='config.json')
```

In [4]:
```
model_b=ResidualUNet3D(in_channels=config["input_channels"],out_channels=cor
                f_maps=config["nchan"],num_levels=config["deep"],\
                conv_upscale=2,\
                upsample='deconv',\
                layer_order='cbr',\
                final_sigmoid=False, is_segmentation=False,dropout_prob=0.0)

model_z=ResidualUNet3D(in_channels=config["input_channels"],out_channels=cor
                f_maps=config["nchan"],num_levels=config["deep"],\
                conv_upscale=2,\
                upsample='deconv',\
                layer_order='cbr',\
                final_sigmoid=False, is_segmentation=False,dropout_prob=0.0)
```

In [5]:
```
checkpoint = torch.load(ckp, map_location='cpu')

model_state_dict = checkpoint['model_b']
if isinstance(model_b, torch.nn.DataParallel) or isinstance(model_b, torch.r
        # If the model is wrapped, we need to load the state_dict into model
    model_b.module.load_state_dict(model_state_dict)
else:
    # If the model is not wrapped, load the state_dict directly
    model_b.load_state_dict(model_state_dict)

model_state_dict = checkpoint['model_z']
if isinstance(model_z, torch.nn.DataParallel) or isinstance(model_z, torch.r
        # If the model is wrapped, we need to load the state_dict into model
    model_z.module.load_state_dict(model_state_dict)
else:
```

```
    # If the model is not wrapped, load the state_dict directly
    model_z.load_state_dict(model_state_dict)
```

Load data

try to load the data into one batch, and get a smooth prediction without using split and stitch with a pad zone.

In [6]:
```
bx,bx1,by,by1,bz,Zini,_,bscale=load_data(filename=config['filename'],hsize=c

dataset=torch.zeros((1,6,size*4,size*4,32),dtype=torch.float32)

dataset[0,0]=torch.tensor(bx[2*size:6*size,2*size:6*size],dtype=torch.float3
dataset[0,1]=torch.tensor(by[2*size:6*size,2*size:6*size],dtype=torch.float3
dataset[0,2]=torch.tensor(bz[2*size:6*size,2*size:6*size],dtype=torch.float3
dataset[0,3]=torch.tensor(Zini[2*size:6*size,2*size:6*size],dtype=torch.floa
dataset[0,4]=torch.tensor(bx1[2*size:6*size,2*size:6*size],dtype=torch.float
dataset[0,5]=torch.tensor(by1[2*size:6*size,2*size:6*size],dtype=torch.float
```

In [7]:
```
del bx, by, bz, Zini, bx1, by1
```

Load true $\vec{B}$ and Z

In [8]:
```
with h5py.File(config['filename'],'r') as f:
    Ztrue = f['tz3d'][:]
    Bxtrue = f['bx'][:]
    Bytrue = f['by'][:]
    Bztrue = f['bz'][:]
    bscale=np.nanmax(np.sqrt(f['bx'][:]**2 + f['by'][:]**2 + f['bz'][:]**2))

Ztrue=Ztrue[2*size:6*size,2*size:6*size]
Bxtrue=Bxtrue[2*size:6*size,2*size:6*size]/bscale
Bytrue=Bytrue[2*size:6*size,2*size:6*size]/bscale
Bztrue=Bztrue[2*size:6*size,2*size:6*size]/bscale
```

Apply model to data

In [9]:
```
pred_b=np.zeros((dataset.shape[0],3,dataset.shape[2],dataset.shape[3],datase
pred_z=np.zeros((dataset.shape[0],1,dataset.shape[2],dataset.shape[3],datase
```

In [10]:
```
with torch.no_grad():
    for ix in tqdm(range(dataset.shape[0])):
        pred_b[ix]=torch.tanh(model_b(dataset[ix].unsqueeze(0))).detach().nu
```

```
100%|██████████| 1/1 [00:16<00:00, 16.49s/it]
```

In [11]:
```
with torch.no_grad():
    for ix in tqdm(range(dataset.shape[0])):
        pred_z[ix]=torch.tanh(model_z(dataset[ix].unsqueeze(0))).detach().nu
```

```
100%|██████████| 1/1 [00:16<00:00, 16.41s/it]
```

Map the splited data back the original data shape.

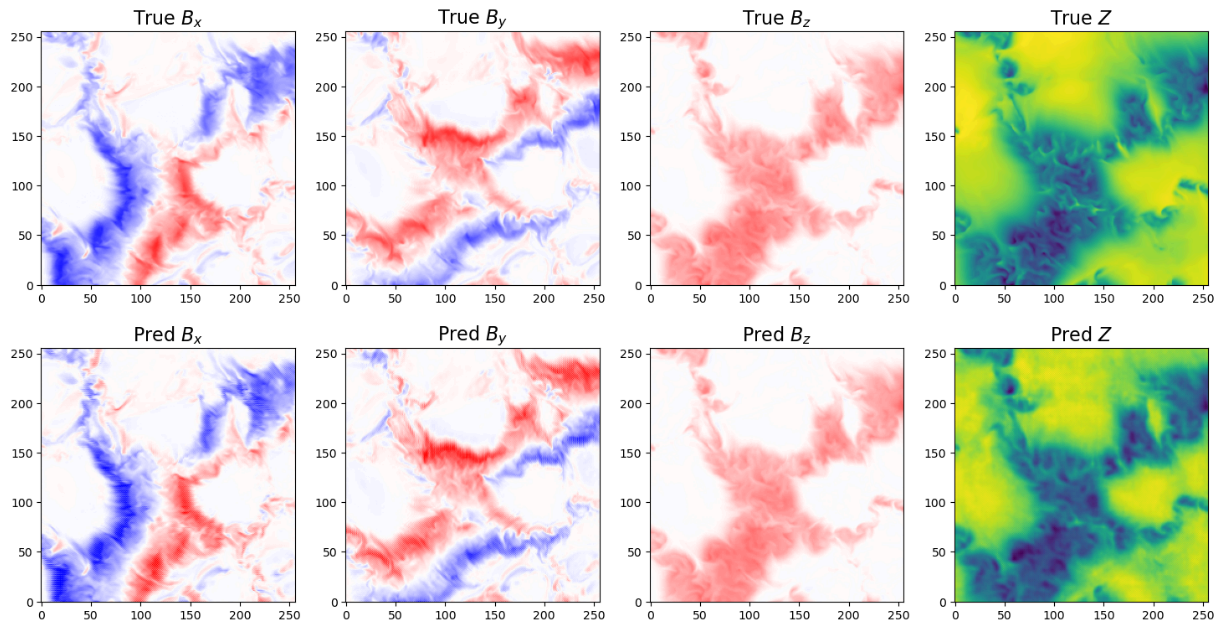
In [12]:
```
Bxp=pred_b[0,0]
Byp=pred_b[0,1]
Bzp=pred_b[0,2]
Zp=pred_z[0,0]
```

In [13]:
```
del pred_b
del pred_z
```

Visualization of $\vec{B}$ and Z, prediction vs. Truth on $\tau=1.6$ for each batch.

Bottom is prediction, top is true value.

In [14]:
```
fig,axs=plt.subplots(2,4,figsize=(18,9))
itau=16

axs[0,0].imshow(Bxtrue[...,itau].T,origin='lower',vmin=-0.3,vmax=0.3,cmap='b
axs[1,0].imshow(Bxp[...,itau].T,origin='lower',vmin=-0.3,vmax=0.3,cmap='bwr'


axs[0,1].imshow(Bytrue[...,itau].T,origin='lower',vmin=-0.3,vmax=0.3,cmap='b
axs[1,1].imshow(Byp[...,itau].T,origin='lower',vmin=-0.3,vmax=0.3,cmap='bwr'


axs[0,2].imshow(Bztrue[...,itau].T,origin='lower',vmin=-1,vmax=1,cmap='bwr')
axs[1,2].imshow(Bzp[...,itau].T,origin='lower',vmin=-1,vmax=1,cmap='bwr')

axs[0,3].imshow(Ztrue[...,itau].T,origin='lower')
axs[1,3].imshow(Zp[...,itau].T,origin='lower')

titlename=[r'True $B_x$',r'True $B_y$',r'True $B_z$',r'True $Z$',\
           r'Pred $B_x$',r'Pred $B_y$',r'Pred $B_z$',r'Pred $Z$']

axs=axs.flatten()
for ix in range(len(axs)):
    axs[ix].set_title(titlename[ix],fontsize=16)
```



Check the ambiguity result

In [15]:
```
tmp=Bxtrue+1j*Bytrue
phi_true=np.angle(tmp)

tmp= Bxp+1j*Byp
phi_pred=np.angle(tmp)
```

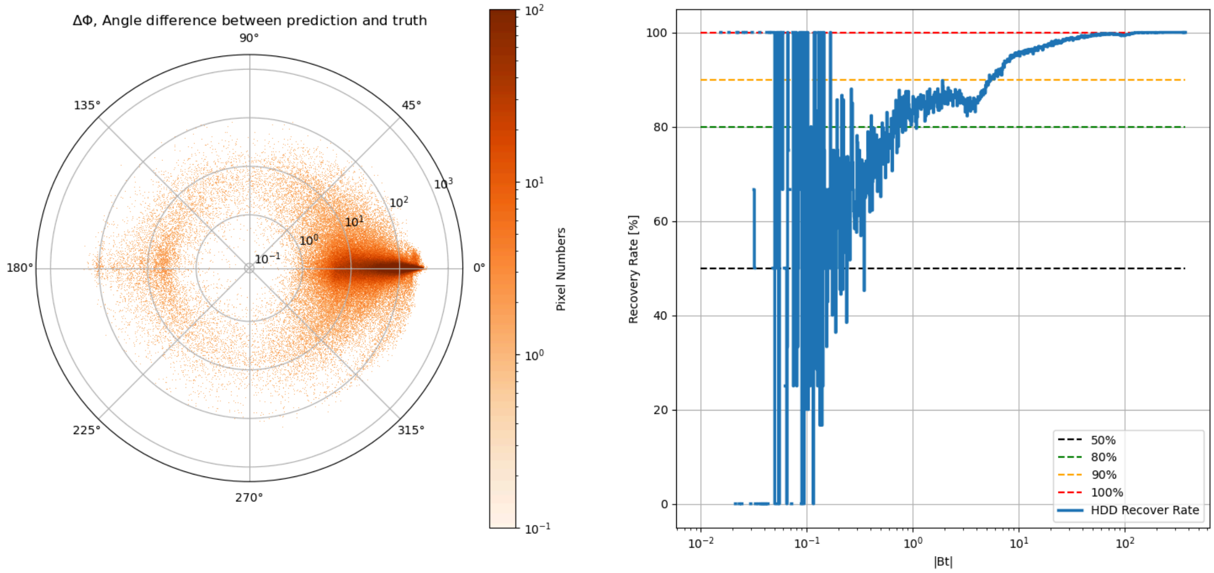
In [16]:
```
binsize=1024
phisize=2048
d_phi=np.mod(phi_true-phi_pred,2*np.pi)
babs=np.sqrt(Bxtrue**2+Bytrue**2)
minvalue=np.log10(babs.min())
maxvalue=np.log10(babs.max())
val=np.logspace(minvalue,maxvalue,binsize)
d_phi=np.mod(phi_true-phi_pred,2*np.pi)
bins=(val,np.linspace(0,2*np.pi,phisize))
depart,yedges,xedges=np.histogram2d(babs[:,:,:].flatten(),d_phi[:,:,:].flatt
accurate=1-np.sum(depart[:,phisize//4:3*phisize//4],axis=1)/np.sum(depart,ax
```

```
/var/folders/rr/2n3c73qx6r141zscx2v__r9w0000gn/T/ipykernel_36536/117300874.p
y:11: RuntimeWarning: invalid value encountered in divide
  accurate=1-np.sum(depart[:,phisize//4:3*phisize//4],axis=1)/np.sum(depart,
axis=1)
```

In [17]:
```
plt.figure(figsize=(18, 8))
ax = plt.subplot(121, polar=True)  # Create a polar subplot
c = ax.pcolormesh(xedges, yedges*bscale, depart, norm=LogNorm(vmax=1e2,vmin=
plt.colorbar(c, ax=ax,label='Pixel Numbers')  # Add a colorbar to show the c
ax.set_title(r'$\Delta\Phi$, Angle difference between prediction and truth')
plt.yscale('log')
plt.ylim([8e-2,2e3])

ax1 = plt.subplot(122)  # Create a polar subplot
xx=bscale*yedges
```

```
midpoints = bscale*(yedges[:-1] + yedges[1:]) / 2
ax1.plot([midpoints.min(),midpoints.max()],[50,50],'k--',label='50%')
ax1.plot([midpoints.min(),midpoints.max()],[80,80],linestyle='--',color='gre
ax1.plot([midpoints.min(),midpoints.max()],[90,90],linestyle='--',color='ora
ax1.plot([midpoints.min(),midpoints.max()],[100,100],linestyle='--',color='r
ax1.set_ylabel('Recovery Rate [%]')
ax1.step(midpoints, accurate*100, where='mid', linewidth=2.5,label='HDD Reco
ax1.grid()

ax1.legend()
ax1.set_xscale('log')
ax1.set_xlabel('|Bt|')
```

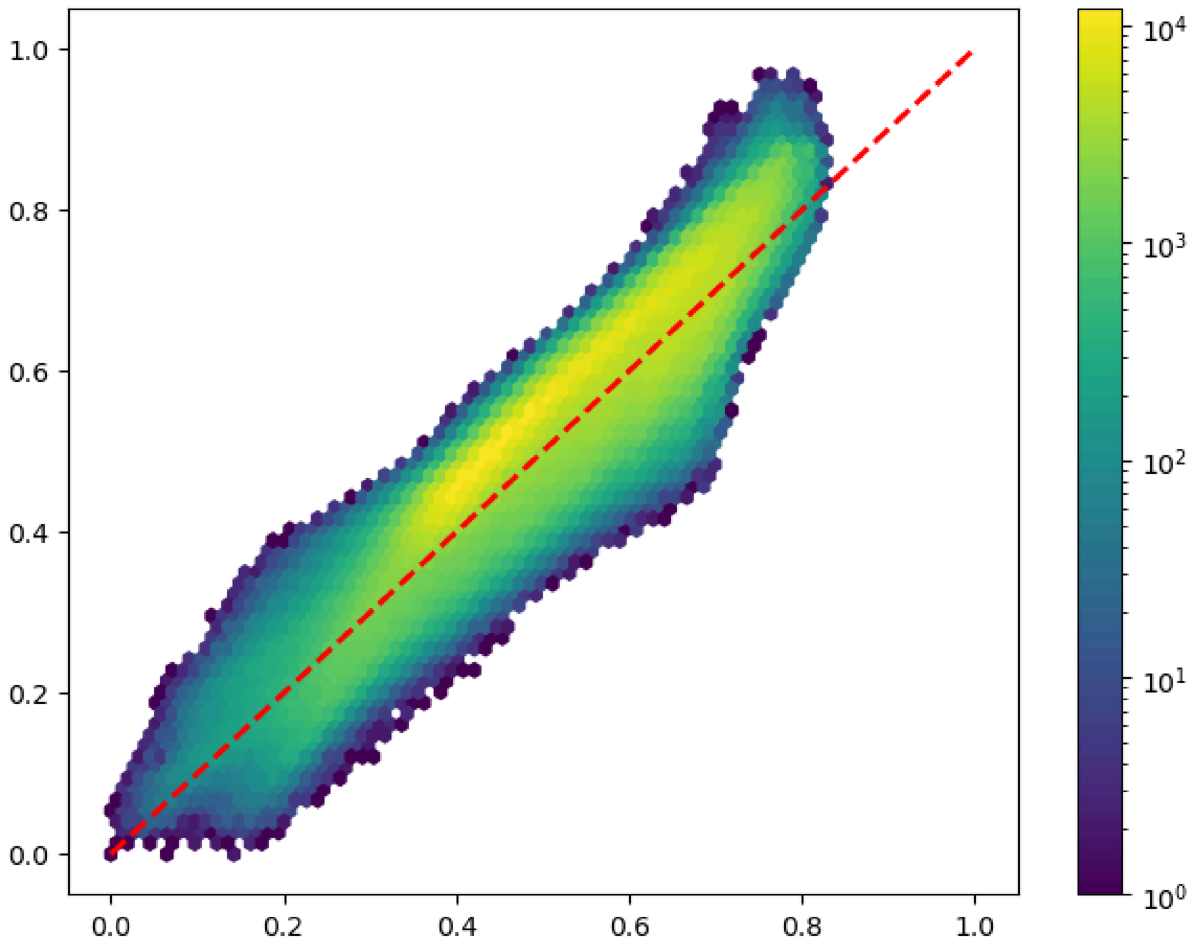
Out[17]: Text(0.5, 0, '|Bt|')



Check prediction of geometric height

In [18]:
```
fig=plt.figure(figsize=(8, 6))
ilayer=1

plt.hexbin(Zp[...,:].flatten()-Zp.min(),Ztrue[...,:].flatten()-Ztrue.min(),b
plt.plot([0,1],[0,1],'r--',linewidth=2,label='x=y line')

plt.colorbar()
```

Out[18]: <matplotlib.colorbar.Colorbar at 0x3ddeb3690>



In [ ]: