In [ ]:
```python
import numpy as np
import torch as torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import random
from scipy.stats import norm

import os
import pathlib

from Model import *
from utils import *

torch.autograd.set_detect_anomaly(True)
start_time=datetime.now().strftime('%B %d - %H:%M:%S')
```

In [ ]:
```python
#Global parameters
GlobalParams1=Params(param_type='k1',target_type='indicator',trick='clamp',loss_type='BCELoss',delta=0.01,w=1,lr=0.0001)
dB1 = SampleBMIncr(GlobalParams=GlobalParams1)
init_x1 =  Sample_Init(GlobalParams=GlobalParams1)
init_c1= torch.zeros_like(init_x1)

GlobalParams2=Params(param_type='k2',target_type='indicator',trick='clamp',loss_type='BCELoss',delta=0.01,w=1,lr=0.0001)
dB2 = SampleBMIncr(GlobalParams=GlobalParams2)   ## TODO: same dB?????
init_x2 =  Sample_Init(GlobalParams=GlobalParams2)
init_c2= torch.zeros_like(init_x2)

NT1=GlobalParams1.NT1
NT2=GlobalParams1.NT2
dt=GlobalParams1.dt
device=GlobalParams1.device
learning_rate = GlobalParams1.lr

#Forward Loss
forward_losses = []

#How many batches
MaxBatch= 750

#How many optimization steps per batch
OptimSteps= 25

#Train on a single batch?
single_batch = True
```

```
#Set up main models for y0 and z (z will be list of models)
v0_model_main1 = Network(scaler_type='sigmoid')
u0_model_main1 = Network(scaler_type='sigmoid')
y0_model_main1 = Network(scaler_type='sigmoid')

zv_models_main1 = [Network() for i in range(NT1)]
zu_models_main1 = [Network() for i in range(NT1)]
zy_models_main1 = [Network() for i in range(NT2)]
main_models1=Main_Models(GlobalParams=GlobalParams1)
main_models1.create(v0_model=v0_model_main1,
                    u0_model=u0_model_main1,
                    y0_model=y0_model_main1,
                    zv_models=zv_models_main1,
                    zu_models=zu_models_main1,
                    zy_models=zy_models_main1,
                    forward_loss=forward_losses,
                    dB=dB1,
                    init_x=init_x1,
                    init_c=init_c1)

v0_model_main2 = Network(scaler_type='sigmoid')
u0_model_main2 = Network(scaler_type='sigmoid')
y0_model_main2 = Network(scaler_type='sigmoid')

zv_models_main2 = [Network() for i in range(NT1)]
zu_models_main2 = [Network() for i in range(NT1)]
zy_models_main2 = [Network() for i in range(NT2)]
main_models2=Main_Models(GlobalParams=GlobalParams2)
main_models2.create(v0_model=v0_model_main2,
                    u0_model=u0_model_main2,
                    y0_model=y0_model_main2,
                    zv_models=zv_models_main2,
                    zu_models=zu_models_main2,
                    zy_models=zy_models_main2,
                    forward_loss=forward_losses,
                    dB=dB2,
                    init_x=init_x2,
                    init_c=init_c2)

pop1_dict={'dB':dB1,
           'init_x':init_x1 ,
           'init_c':init_c1 ,
           'GlobalParams':GlobalParams1,
           'main_models':main_models1}

pop2_dict={'dB':dB2,
           'init_x':init_x2 ,
           'init_c':init_c2 ,
           'GlobalParams':GlobalParams2,
           'main_models':main_models2}
```

In [ ]:

```
#Define optimization parameters
params=[]
params = list(main_models1.v0_model.parameters())+\
         list(main_models1.u0_model.parameters())+\
         list(main_models1.y0_model.parameters())+\
         list(main_models2.v0_model.parameters())+\
         list(main_models2.u0_model.parameters())+\
         list(main_models2.y0_model.parameters())
for i in range(NT1):
    params += list(main_models1.zv_models[i].parameters())
    params += list(main_models1.zu_models[i].parameters())
    params += list(main_models2.zv_models[i].parameters())
    params += list(main_models2.zu_models[i].parameters())

for i in range(NT2):
    params += list(main_models1.zy_models[i].parameters())
    params += list(main_models2.zy_models[i].parameters())

#Set up optimizer and scheduler
optimizer = optim.Adamax(params, lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=100, gamma=0.95)

for k in range(0,MaxBatch):

    print("Batch Number: ", k+1)
    sloss=0
    #optimize main network wrt the foward loss
    for l in range(0,OptimSteps):
        optimizer.zero_grad()
        loss = get_foward_loss(pop1_dict=pop1_dict, pop2_dict=pop2_dict)
        loss.backward()
        # torch.nn.utils.clip_grad_norm_(parameters=params,max_norm=0.7)
        optimizer.step()
        scheduler.step()
        nloss = loss.detach().numpy()
        sloss += nloss
        # print('OptimStep: '+ str(l+1))
        # print('forward_loss: ' + str(nloss))
    avgloss = sloss/OptimSteps
    print("Average Error Est: ", avgloss)
    forward_losses.append(avgloss)

    #Generate a new batch if using multiple batches
    if(not single_batch):

        dB1 = SampleBMIncr(GlobalParams=GlobalParams1)
        init_x1 =  Sample_Init(GlobalParams=GlobalParams1)
        init_c1= torch.zeros_like(init_x1)
        pop1_dict={'dB':dB1,
                'init_x':init_x1 ,
                'init_c':init_c1 ,
```

```
            'GlobalParams':GlobalParams1,
            'main_models':main_models1}

    dB2 = SampleBMIncr(GlobalParams=GlobalParams2)   ## TODO: same dB?????
    init_x2 =  Sample_Init(GlobalParams=GlobalParams2)
    init_c2= torch.zeros_like(init_x2)
    pop2_dict={'dB':dB2,
            'init_x':init_x2 ,
            'init_c':init_c2 ,
            'GlobalParams':GlobalParams2,
            'main_models':main_models2}
```

```
Batch Number:  511
Average Error Est:  1.6824539709091186
Batch Number:  512
Average Error Est:  1.6865029382705687
Batch Number:  513
Average Error Est:  1.684301724433899
Batch Number:  514
Average Error Est:  1.6838127660751343
Batch Number:  515
Average Error Est:  1.6852887630462647
Batch Number:  516
Average Error Est:  1.6869824409484864
Batch Number:  517
Average Error Est:  1.685720772743225
Batch Number:  518
Average Error Est:  1.683901653289795
Batch Number:  519
Average Error Est:  1.6836091184616089
Batch Number:  520
Average Error Est:  1.6861657094955445
Batch Number:  521
Average Error Est:  1.6839993810653686
Batch Number:  522
Average Error Est:  1.6859577989578247
Batch Number:  523
Average Error Est:  1.6876707649230958
Batch Number:  524
Average Error Est:  1.68301260471344
Batch Number:  525
Average Error Est:  1.6881186294555663
Batch Number:  526
Average Error Est:  1.6858909606933594
Batch Number:  527
Average Error Est:  1.6855929899215698
Batch Number:  528
Average Error Est:  1.6834970760345458
Batch Number:  529
Average Error Est:  1.6862510299682618
Batch Number:  530
Average Error Est:  1.6863108444213868
Batch Number:  531
Average Error Est:  1.6869402360916137
Batch Number:  532
Average Error Est:  1.6851856184005738
Batch Number:  533
Average Error Est:  1.6861200046539306
Batch Number:  534
Average Error Est:  1.6854363012313842
Batch Number:  535
Average Error Est:  1.6847105503082276
Batch Number:  536
```

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Average Error Est:  1.688040804862976
Batch Number:  537
Average Error Est:  1.6848394203186035
Batch Number:  538
Average Error Est:  1.6905893564224244
Batch Number:  539
Average Error Est:  1.6880903100967408
Batch Number:  540
Average Error Est:  1.687672996520996
Batch Number:  541
Average Error Est:  1.6845133590698242
Batch Number:  542
Average Error Est:  1.6838258123397827
Batch Number:  543
Average Error Est:  1.6850829601287842
Batch Number:  544
Average Error Est:  1.6830358219146728
Batch Number:  545
Average Error Est:  1.6877766895294188
Batch Number:  546
Average Error Est:  1.6819846439361572
Batch Number:  547
Average Error Est:  1.6824767303466797
Batch Number:  548
Average Error Est:  1.6843154907226563
Batch Number:  549
Average Error Est:  1.686055154800415
Batch Number:  550
Average Error Est:  1.6807348537445068
Batch Number:  551
Average Error Est:  1.6849817371368407
Batch Number:  552
Average Error Est:  1.6858178520202636
Batch Number:  553
Average Error Est:  1.6840467929840088
Batch Number:  554
Average Error Est:  1.6850014543533325
Batch Number:  555
Average Error Est:  1.6862866020202636
Batch Number:  556
Average Error Est:  1.6829587316513062
Batch Number:  557
Average Error Est:  1.685247507095337
Batch Number:  558
Average Error Est:  1.685205111503601
Batch Number:  559
Average Error Est:  1.6863167142868043
Batch Number:  560
Average Error Est:  1.6792222452163696
Batch Number:  561
Average Error Est:  1.6849729442596435
```

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Batch Number:  562
Average Error Est:  1.6844683408737182
Batch Number:  563
Average Error Est:  1.6848991107940674
Batch Number:  564
Average Error Est:  1.6826937770843506
Batch Number:  565
Average Error Est:  1.6852263975143433
Batch Number:  566
Average Error Est:  1.6875631046295165
Batch Number:  567
Average Error Est:  1.6825312852859498
Batch Number:  568
Average Error Est:  1.6866102266311644
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Batch Number:  570
Average Error Est:  1.6856303882598878
Batch Number:  571
Average Error Est:  1.6851705598831177
Batch Number:  572
Average Error Est:  1.683547887802124
Batch Number:  573
Average Error Est:  1.6831574487686156
Batch Number:  574
Average Error Est:  1.6853477668762207
Batch Number:  575
Average Error Est:  1.6859348106384278
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Batch Number:  578
Average Error Est:  1.6861838483810425
Batch Number:  579
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Batch Number:  580
Average Error Est:  1.6885153579711913
Batch Number:  581
Average Error Est:  1.686638717651367
Batch Number:  582
Average Error Est:  1.6861371278762818
Batch Number:  583
Average Error Est:  1.6896436023712158
Batch Number:  584
Average Error Est:  1.6871112537384034
Batch Number:  585
Average Error Est:  1.6829937982559204
Batch Number:  586
Average Error Est:  1.6810900783538818
Batch Number:  587
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Average Error Est:  1.6829934453964233
Batch Number:  588
Average Error Est:  1.6852147817611693
Batch Number:  589
Average Error Est:  1.6844466543197631
Batch Number:  590
Average Error Est:  1.683593430519104
Batch Number:  591
Average Error Est:  1.6839492893218995
Batch Number:  592
Average Error Est:  1.6814739608764648
Batch Number:  593
Average Error Est:  1.6864438915252686
Batch Number:  594
Average Error Est:  1.6801946020126344
Batch Number:  595
Average Error Est:  1.6818813848495484
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Average Error Est:  1.6812762880325318
Batch Number:  597
Average Error Est:  1.6839154386520385
Batch Number:  598
Average Error Est:  1.6851806926727295
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Batch Number:  600
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Batch Number:  602
Average Error Est:  1.6862303256988525
Batch Number:  603
Average Error Est:  1.6767702913284301
Batch Number:  604
Average Error Est:  1.6828896951675416
Batch Number:  605
Average Error Est:  1.6865469121932983
Batch Number:  606
Average Error Est:  1.6831800842285156
Batch Number:  607
Average Error Est:  1.6846273422241211
Batch Number:  608
Average Error Est:  1.685716052055359
Batch Number:  609
Average Error Est:  1.6838742208480835
Batch Number:  610
Average Error Est:  1.6888931846618653
Batch Number:  611
Average Error Est:  1.6852046060562134
Batch Number:  612
Average Error Est:  1.688194055557251
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Batch Number:  613
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Batch Number:  614
Average Error Est:  1.686228675842285
Batch Number:  615
Average Error Est:  1.6872141456604004
Batch Number:  616
Average Error Est:  1.6870223522186278
Batch Number:  617
Average Error Est:  1.6827640438079834
Batch Number:  618
Average Error Est:  1.6850918436050415
Batch Number:  619
Average Error Est:  1.6828772306442261
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Average Error Est:  1.688934144973755
Batch Number:  621
Average Error Est:  1.6815928649902343
Batch Number:  622
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Batch Number:  623
Average Error Est:  1.6860722732543945
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Average Error Est:  1.684215989112854
Batch Number:  626
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Average Error Est:  1.6812486410140992
Batch Number:  628
Average Error Est:  1.6839825057983397
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Average Error Est:  1.6797702169418336
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Average Error Est:  1.6853371858596802
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Average Error Est:  1.679506883621216
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Average Error Est:  1.6794397926330566
Batch Number:  634
Average Error Est:  1.6761370277404786
Batch Number:  635
Average Error Est:  1.674396014213562
Batch Number:  636
Average Error Est:  1.6776970100402833
Batch Number:  637
Average Error Est:  1.676101622581482
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Batch Number:  639
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Average Error Est:  1.685157494544983
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Average Error Est:  1.6840274810791016
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Average Error Est:  1.6913042497634887
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Average Error Est:  1.6896032285690308
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Batch Number:  664
Average Error Est:  1.6816156911849975
Batch Number:  665
Average Error Est:  1.6872336673736572
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Average Error Est:  1.682069149017334
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Average Error Est:  1.6856876087188721
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Batch Number:  686
Average Error Est:  1.6771343660354614
Batch Number:  687
Average Error Est:  1.6738365507125854
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Average Error Est:  1.6759105110168457
Batch Number:  689
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Average Error Est:  1.6743533945083617
Batch Number:  690
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Average Error Est:  1.6782470369338989
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Batch Number:  710
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Batch Number:  711
Average Error Est:  1.6752968072891234
Batch Number:  712
Average Error Est:  1.672436056137085
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Average Error Est:  1.6775158643722534
Batch Number:  714
Average Error Est:  1.6743745613098144
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Batch Number:  715
Average Error Est:  1.6760258150100709
Batch Number:  716
Average Error Est:  1.6756342649459839
Batch Number:  717
Average Error Est:  1.672943639755249
Batch Number:  718
Average Error Est:  1.676301393508911
Batch Number:  719
Average Error Est:  1.683203854560852
Batch Number:  720
Average Error Est:  1.6661761045455932
Batch Number:  721
Average Error Est:  1.6763416051864624
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Average Error Est:  1.6670189094543457
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Average Error Est:  1.6723020458221436
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Average Error Est:  1.6734485340118408
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Average Error Est:  1.673474612236023
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Batch Number:  729
Average Error Est:  1.670697979927063
Batch Number:  730
Average Error Est:  1.6634385442733766
Batch Number:  731
Average Error Est:  1.6711410522460937
Batch Number:  732
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Batch Number:  733
Average Error Est:  1.6678334045410157
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Average Error Est:  1.6719546031951904
Batch Number:  735
Average Error Est:  1.6749273538589478
Batch Number:  736
Average Error Est:  1.6755289697647096
Batch Number:  737
Average Error Est:  1.6755341100692749
Batch Number:  738
Average Error Est:  1.6819331073760986
Batch Number:  739
Average Error Est:  1.6775695896148681
Batch Number:  740
```

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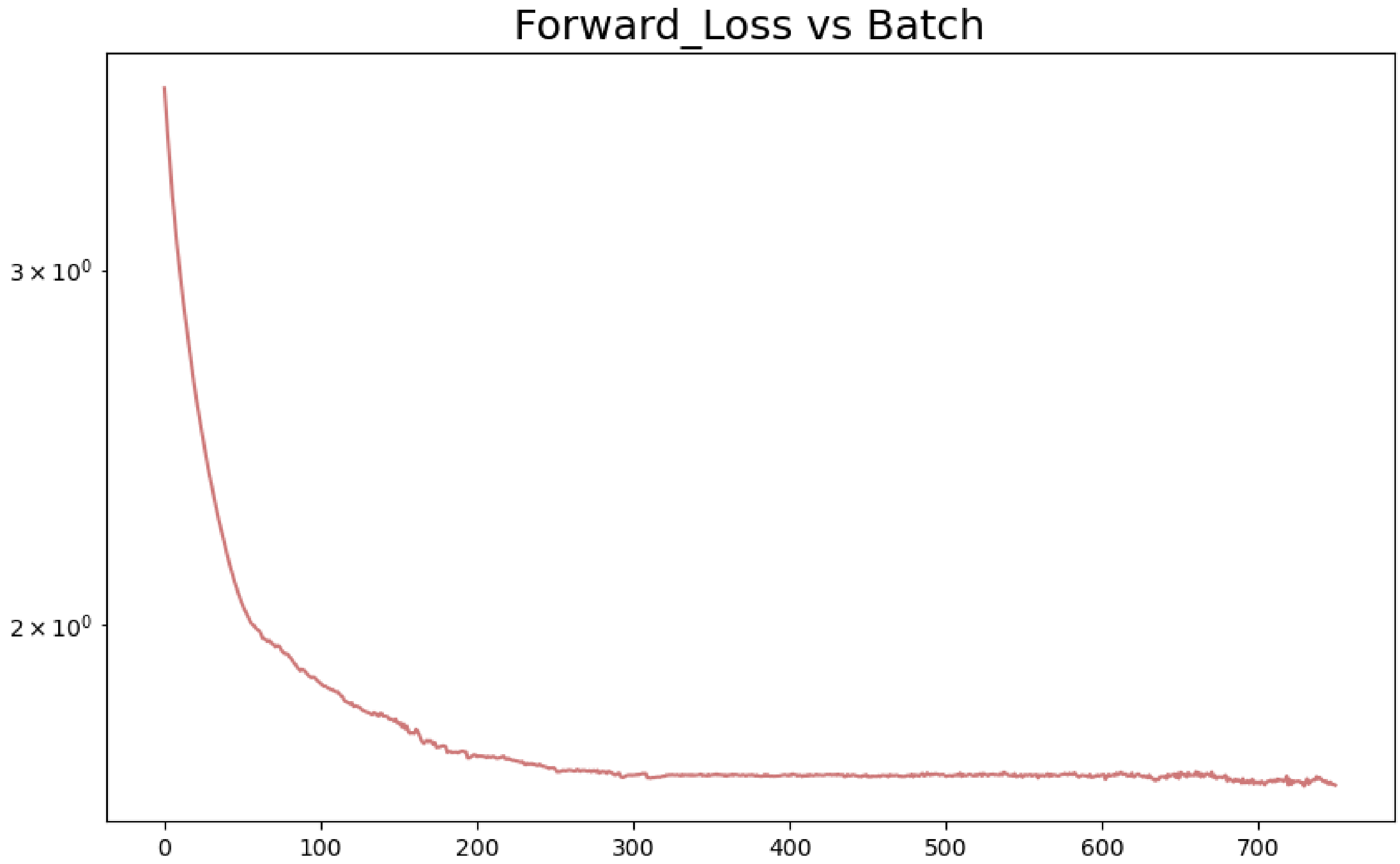
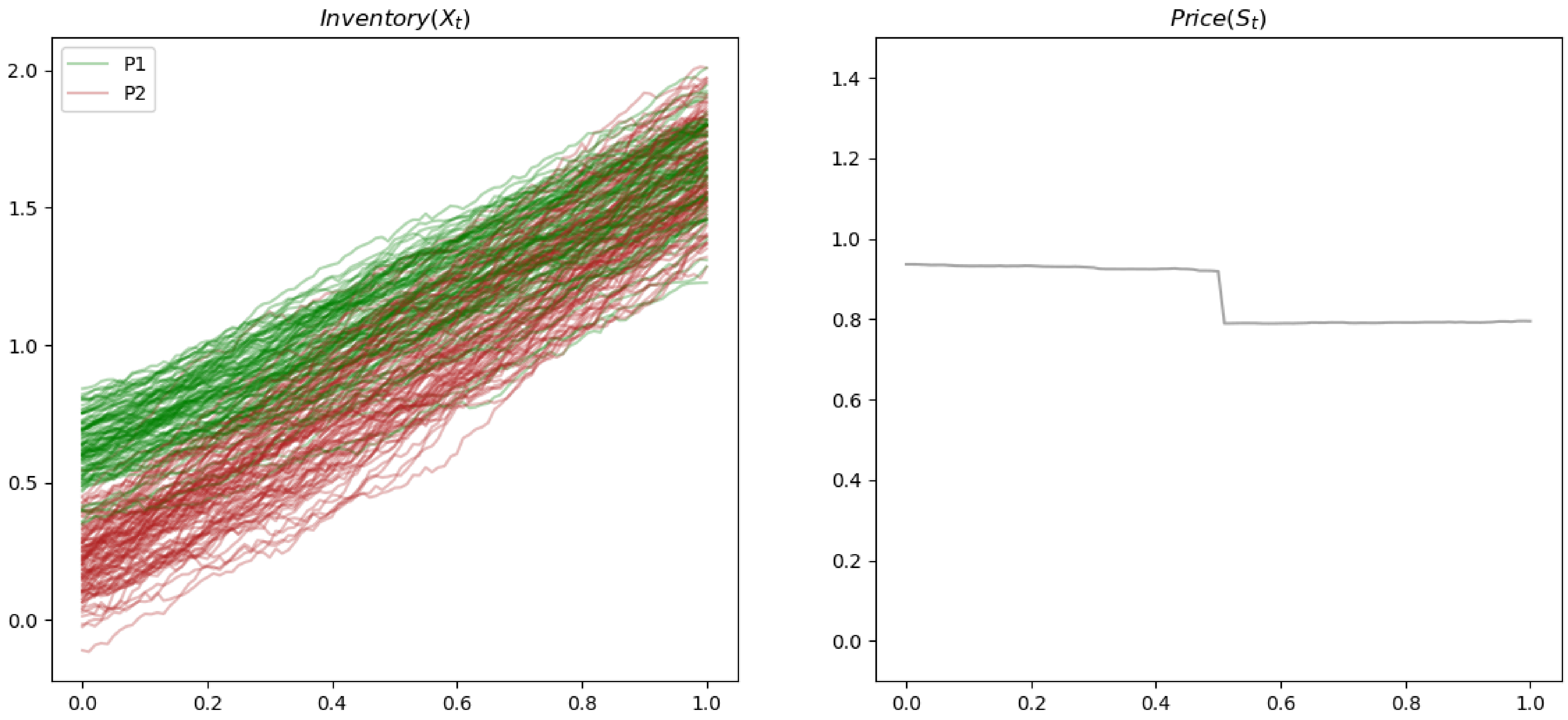
Average Error Est:  1.6803805255889892
Batch Number:  741
Average Error Est:  1.6775617504119873
Batch Number:  742
Average Error Est:  1.673789668083191
Batch Number:  743
Average Error Est:  1.6724073266983033
Batch Number:  744
Average Error Est:  1.6738758420944213
Batch Number:  745
Average Error Est:  1.6689344453811645
Batch Number:  746
Average Error Est:  1.667996597290039
Batch Number:  747
Average Error Est:  1.671448721885681
Batch Number:  748
Average Error Est:  1.6672642755508422
Batch Number:  749
Average Error Est:  1.667117977142334
Batch Number:  750
Average Error Est:  1.665627236366272
```

In [ ]:

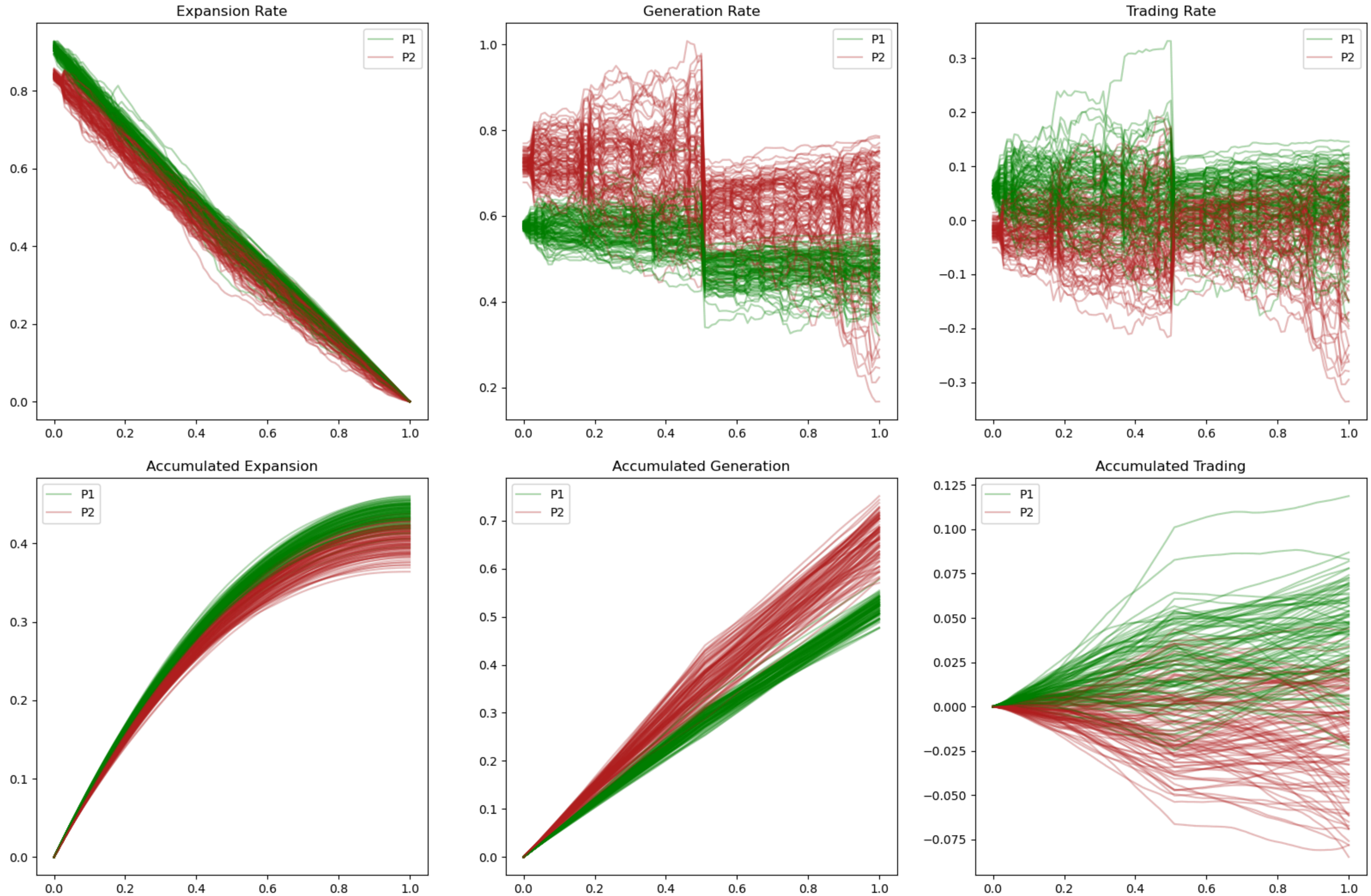
```
plot=plot_results(pop1_dict=pop1_dict, pop2_dict=pop2_dict, loss=forward_losses)
plot.FwdLoss(log=True)
plot.Inventory_And_Price()
plot.Decomposition_Inventory()
plot.Key_Processes()
plot.Terminal_Convergence()
```

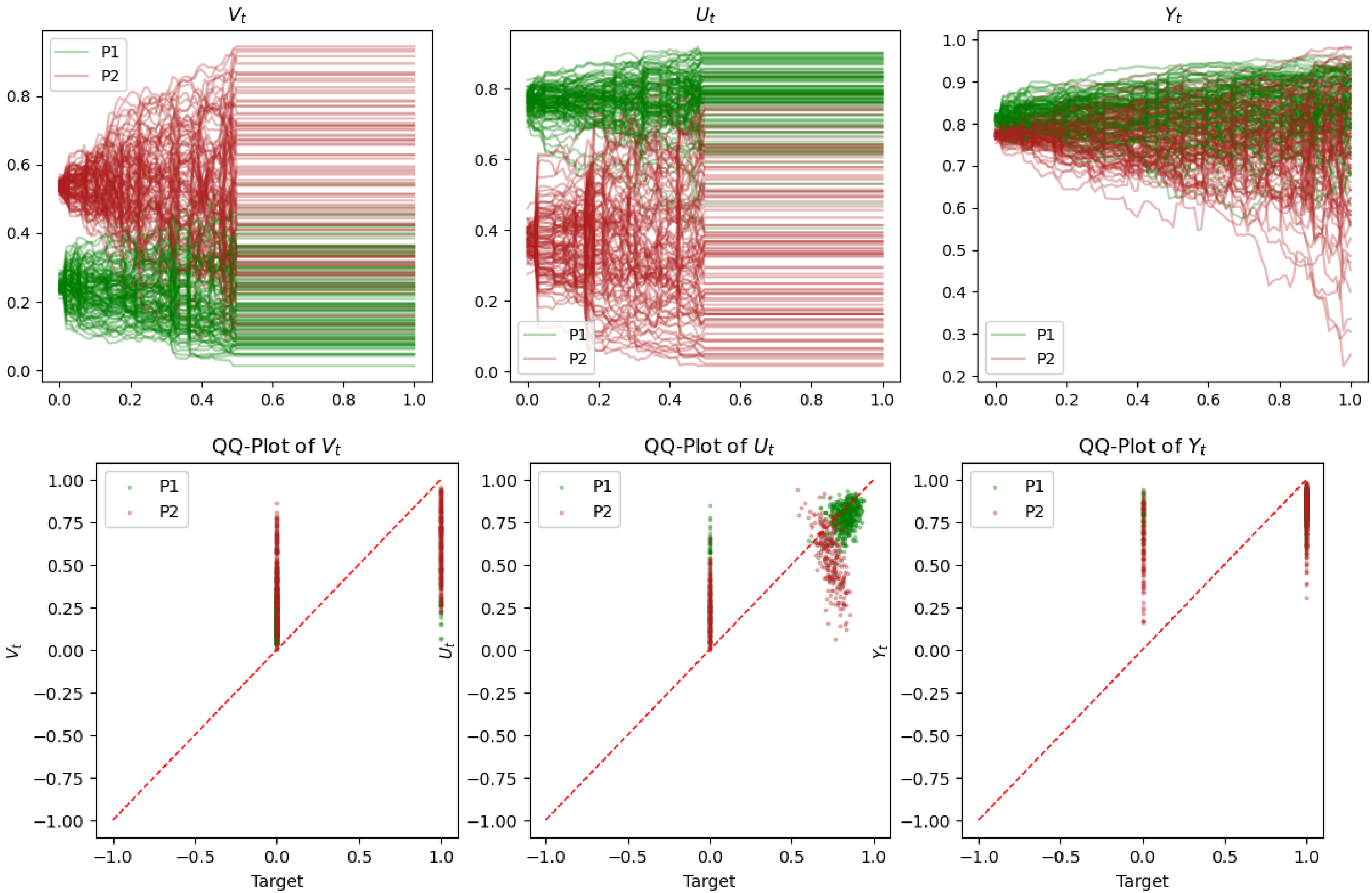


Forward_Loss vs Batch
3 × 10^0
2 × 10^0
0
100
200
300
400
500
600
700

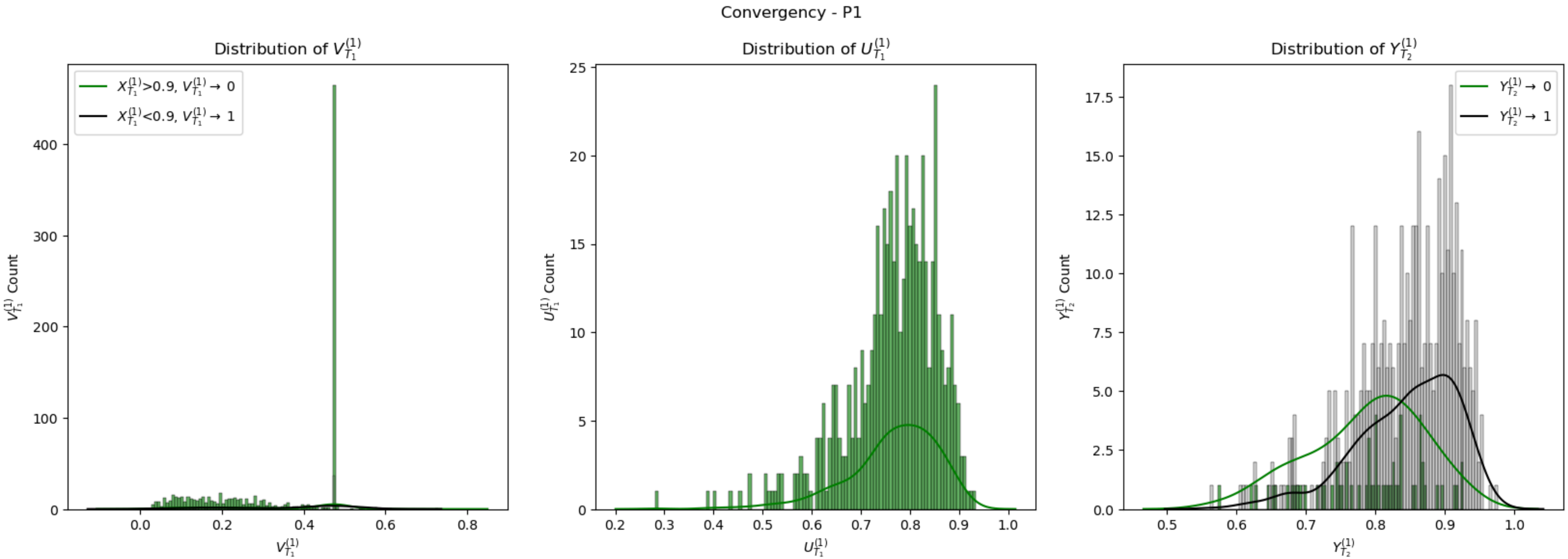


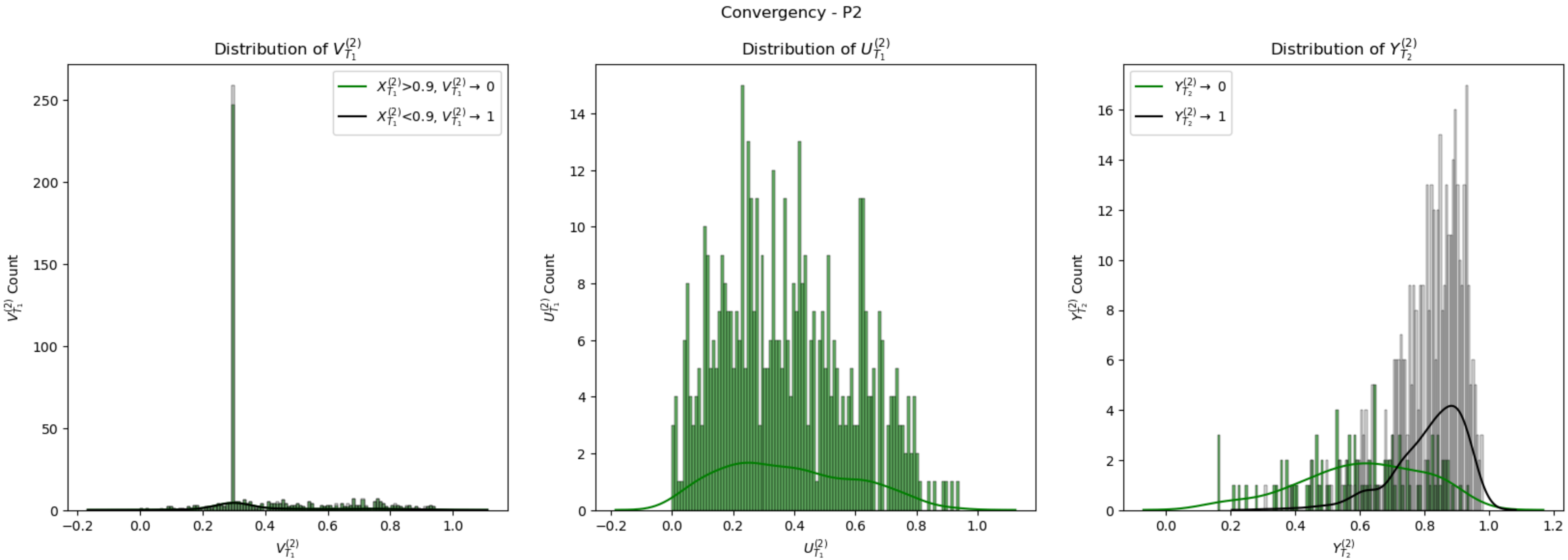
$Inventory(X_t)$
P1
P2
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0
$Price(S_t)$
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Expansion Rate
Generation Rate
Trading Rate
Accumulated Expansion
Accumulated Generation
Accumulated Trading
P1
P2



V_t
U_t
Y_t
P1
P2
QQ-Plot of V_t
QQ-Plot of U_t
QQ-Plot of Y_t
Target


Convergency - P1
Distribution of $V_{T_1}^{(1)}$
$X_{T_1}^{(1)}$>0.9, $V_{T_1}^{(1)} \to 0$
$X_{T_1}^{(1)}$<0.9, $V_{T_1}^{(1)} \to 1$
$V_{T_1}^{(1)}$ Count
$V_{T_1}^{(1)}$
Distribution of $U_{T_1}^{(1)}$
$U_{T_1}^{(1)}$ Count
$U_{T_1}^{(1)}$
Distribution of $Y_{T_2}^{(1)}$
$Y_{T_2}^{(1)} \to 0$
$Y_{T_2}^{(1)} \to 1$
$Y_{T_2}^{(1)}$ Count
$Y_{T_2}^{(1)}$


Convergency - P2
Distribution of $V_{T_1}^{(2)}$
$X_{T_1}^{(2)}$>0.9, $V_{T_1}^{(2)} \to 0$
$X_{T_1}^{(2)}$<0.9, $V_{T_1}^{(2)} \to 1$
$V_{T_1}^{(2)}$ Count
$V_{T_1}^{(2)}$
Distribution of $U_{T_1}^{(2)}$
$U_{T_1}^{(2)}$ Count
$U_{T_1}^{(2)}$
Distribution of $Y_{T_2}^{(2)}$
$Y_{T_2}^{(2)} \to 0$
$Y_{T_2}^{(2)} \to 1$
$Y_{T_2}^{(2)}$ Count
$Y_{T_2}^{(2)}$

Save The Models

In [ ]:
```
print(f"{len(main_models1.loss)} steps\nStarted @ {start_time}\nSaved @ {datetime.now().strftime('%B %d - %H:%M:%S')}")   ## to examine whether
dir_path=pathlib.Path(os.getcwd(),
                      'Results',
                      'Best Models Saved',
                      'sigmoid_ind_0.0001lr_750steps_BCE_1w')
dir_path.mkdir()
path1=pathlib.Path(dir_path,'pop1.pt')
path2=pathlib.Path(dir_path,'pop2.pt')
main_models1.save_entire_models(path=path1)
main_models2.save_entire_models(path=path2)
```

```
750 steps
Started @ August 07 - 14:20:05
Saved @ August 07 - 20:59:53
```

Load The Models

In [ ]:
```
# # GlobalParams1=Params(param_type='k1',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.03,K=0.9,lr=0.01)
# # GlobalParams2=Params(param_type='k2',target_type='indicator',trick='clamp',loss_type='MSELoss',delta=0.03,K=0.9,lr=0.01)
# models1=Main_Models(GlobalParams=GlobalParams1)
# models2=Main_Models(GlobalParams=GlobalParams2)
# path_dir=pathlib.Path(os.getcwd(),
#                       "Results",
#                       "Best Models Saved",
#                       'minmax_logit_0.01lr_300steps_BCELogits_1_dt')
# path1=pathlib.Path(path_dir,'pop1.pt')
# path2=pathlib.Path(path_dir,'pop2.pt')
# model_dict1=models1.load_entire_models(path=path1,overwrite=True)
# model_dict2=models2.load_entire_models(path=path2,overwrite=True)

# dB1=model_dict1['dB']
# init_x1=model_dict1['init_x']
# init_c1=model_dict1['init_c']
# pop1_dict= {'dB':dB1,
#             'init_x':init_x1,
#             'init_c':init_c1,
#             'GlobalParams':GlobalParams1,
#             'main_models':models1}

# dB2=model_dict2['dB']
# init_x2=model_dict2['init_x']
# init_c2=model_dict2['init_c']

# pop2_dict= {'dB':dB2,
#             'init_x':init_x2 ,
#             'init_c':init_c2 ,
```

```
#             'GlobalParams':GlobalParams2,
#             'main_models':models2}
# dt=GlobalParams1.dt
# NT1=GlobalParams1.NT1
# NT2=GlobalParams1.NT2
# NumTrain=GlobalParams1.NumTrain
# K=GlobalParams1.K
# loss=models1.loss

# plot=plot_results(pop1_dict=pop1_dict,pop2_dict=pop2_dict,loss=loss)
# plot.FwdLoss(log=True)
# plot.Inventory_And_Price()
# plot.Decomposition_Inventory()
# plot.Key_Processes()
# # plot.Terminal_Convergence()
```