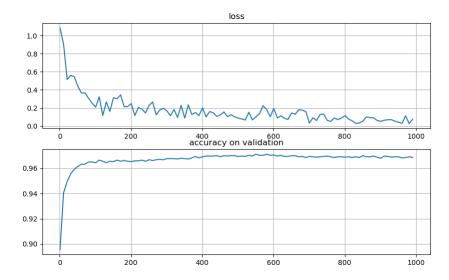
Train for multi-class classification

```
loss: 1.083643
loss: 0.903609
loss: 0.515120
                                                                                     10/ 1000]
20/ 1000]
30/ 1000]
                          loss:
                                           0.559094
                                                                                      40/ 10001
                          loss:
                                           0.546588
                                                                                      50/ 10001
                                                                                     60/ 1000]
70/ 1000]
80/ 1000]
                          loss:
                                           0.441140
                                          0.365204
0.366031
0.308687
                          loss:
                          loss:
                                                                                      90/
                                                                                                  10001
                          loss:
                                           0.253033
                                                                                   100/
                                                                                                 1000]
                          loss:
loss:
loss:
loss:
                                          0.210082
0.323321
0.117914
0.268384
                                                                                   110/ 1000]
120/ 1000]
130/ 1000]
140/ 1000]
                                          0.163159
0.314148
0.301961
0.345350
0.215941
0.215817
0.249675
                          loss:
                                                                                   150/ 1000]
                                                                                 150/ 1000]
160/ 1000]
170/ 1000]
180/ 1000]
190/ 1000]
200/ 1000]
                          loss:
                          loss:
loss:
loss:
                          loss:
                          loss:
                                          0.249675
0.115867
0.207075
0.189053
0.144920
0.229414
                                                                                 220/ 1000]
220/ 1000]
230/ 1000]
240/ 1000]
250/ 1000]
                          loss:
loss:
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loss:
                          loss:
                          loss:
                                           0.266092
0.123982
                                                                                  270/ 1000]
280/ 1000]
                          loss:
                                          0.123982
0.178462
0.196176
0.168153
0.114833
0.183321
                          loss:
                                                                                 290/ 1000]
300/ 1000]
310/ 1000]
                                                                                                1000]
1000]
1000]
                          loss:
                          loss:
                                                                                   320/
                          loss:
                                                                                  330/ 1000]
                                          0.095777
0.230289
0.088249
0.234299
                                                                                  340/ 1000]
350/ 1000]
360/ 1000]
370/ 1000]
                          loss.
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loss:
loss:
                                                                                 380/ 1000]
380/ 1000]
390/ 1000]
400/ 1000]
410/ 1000]
420/ 1000]
430/ 1000]
450/ 1000]
                                          0.128863
0.150503
0.116159
0.201118
0.101444
0.160854
                          loss:
                          loss:
loss:
loss:
                                          0.147623
0.107851
                          loss:
                          loss:
                          loss: 0.107851
loss: 0.123872
loss: 0.156791
loss: 0.105354
loss: 0.125542
loss: 0.102317
                                                                                 460/ 1000]
470/ 1000]
480/ 1000]
490/ 1000]
                                                                                   500/ 10001
                                          0.102317
0.088741
0.079975
0.066944
0.152889
0.068445
                                                                                 500/ 1000]
510/ 1000]
520/ 1000]
530/ 1000]
540/ 1000]
550/ 1000]
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loss:
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                          loss:
loss:
                                           0.103755
0.138058
                                                                                   560/ 1000]
570/ 1000]
                          loss:
loss:
loss:
loss:
                                          0.225921
0.183273
0.104766
0.195365
                                                                                 580/ 1000]
590/ 1000]
600/ 1000]
610/ 1000]
                                          0.195365
0.090388
0.112982
0.086784
0.073494
0.145628
0.131363
0.179785
                                                                                 610/ 1000]
620/ 1000]
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670/ 1000]
                          loss:
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loss:
                          loss:
                          loss:
                                                                                  680/
                                                                                                 10001
                          loss:
                                          0.176956
                                                                                  690/ 10001
                          loss: 0.160835
loss: 0.033706
loss: 0.092893
loss: 0.062387
                                                                                  700/ 1000]
710/ 1000]
720/ 1000]
730/ 1000]
                                          0.128669
0.133510
0.063594
0.052283
0.090075
0.072280
0.088315
                          loss:
                                                                                   740/ 1000]
750/ 1000]
                          loss:
                                                                                 750/ 1000]
760/ 1000]
770/ 1000]
780/ 1000]
790/ 1000]
800/ 1000]
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loss:
                          loss:
loss:
loss:
loss:
                                          0.116617
0.077982
0.058514
0.030378
                                                                                  810/ 1000]
820/ 1000]
830/ 1000]
840/ 1000]
                                          0.034574
0.056091
0.101805
0.093489
0.091548
0.063140
0.052897
                          loss:
                                                                                  850/ 1000]
                                                                                 850/ 1000]
860/ 1000]
870/ 1000]
880/ 1000]
900/ 1000]
910/ 1000]
                          loss:
                          loss:
loss:
loss:
                          loss:
                          loss:
                          loss:
                                           0.065542
                                                                                  920/ 10001
                          loss: 0.070062
loss: 0.071158
loss: 0.054972
loss: 0.043856
                                                                                 930/ 1000]
940/ 1000]
950/ 1000]
960/ 1000]
                          loss: 0.029621
loss: 0.113798
                                                                                  970/ 1000]
                                                                                  980/ 10001
                          loss: 0.028144
loss: 0.076223
                                                                       [ 990/ 1000]
[ 1000/ 1000]
In []:
    fig, (ax1, ax2) = plt.subplots(2,1,figsize=(10,6))
    ax1.set_title("loss")
    ax2.set_title("accuracy on validation")
    ax1.plot(range(1,n_epochs+1,10),loss_history)
    ax2.plot(range(1,n_epochs+1,10),val_accuracy)
    ax1.grid()
    ax2_orid()
```

ax2.grid()
plt.show()



Test for binary classification

Comparison with SVM

Test on multi-class classification

Neural Network

SVM

In []: clf.fit(X_train,gen_train).score(X_test,gen_test)

Saving the model

```
In [ ]: path = f"./checkpoints/multiclass_train_AID_df_34000_V2.pt"
torch.save(model.state_dict(),path)
```

Loading the model

```
In []: model = MultiClassClassifier(n_classes=len(GEN_T0_INT.keys()))
    model.load_state_dict(torch.load(path))

Out[]: <All keys matched successfully>

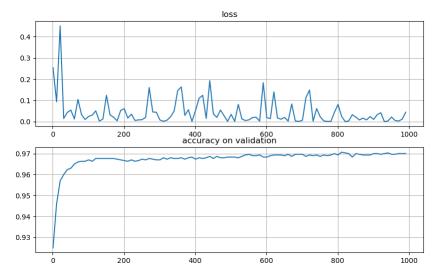
In []: model.eval().cuda(device)
    with torch.no_grad():
        for e in test_loader:
            pred = torch.argmax(model(e["features"].cuda(device)),dim=1)
            acc = torch.mean(torch.eq(e["generator"].cuda(device),pred).float()).item()
            print(acc)

0.9085294008255005
```

Test on OOD

Training a binary classifier

```
In [ ]: device = "cuda:0"
clf_binary = MultiClassClassifier(n_classes=2).to(device)
                 lr = 1e-3
batch_size = 128
n_epochs = 1000
                 loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(clf_binary.parameters(), lr=lr)
                 data = DeepFakeDatasetFastLoad(PATH_TO_DATA4 + "df_34000_V2.pt", remove_blacklisted_gen=True)
clf_binary.set_generators_maps(gen_to_int=GEN_TO_INT,int_to_gen=INT_TO_GEN)
                  \label{eq:rng} \begin{subarray}{ll} rng = torch.Generator().manual\_seed(SEED) \\ train\_data, test\_data, validation\_data = random\_split(data,[0.7,0.2,0.1],generator=rng) \\ \end{subarray}
                  train_loader = DataLoader(train_data,batch_size=batch_size,shuffle=True)
test_loader = DataLoader(test_data,batch_size=len(test_data),shuffle=True)
val_loader = DataLoader(validation_data,batch_size=len(validation_data),shuffle=True)
                 clf_binary.train()
pred = clf_binary(batch["features"].to(device))
loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))
                                   # backpropagation
                                  loss.backward()
optimizer.step()
optimizer.zero_grad()
                         loss, current = loss.item(), idx*batch_size + len(batch["features"])
if epoch%10 == 0 and epoch > 0:
    loss_history.append(loss)
    for v in val_loader:
        pred = torch.argmax(clf_binary(v["features"].to(device)),dim=1)
        val_accuracy.append(torch.mean(torch.eq(v["label"].to(device),pred).float()).item())
    print(f"loss: {loss:>7f}        [{epoch:>5d}/{n_epochs:>5d}]")
In [ ]:
    fig, (ax1, ax2) = plt.subplots(2,1,figsize=(10,6))
    ax1.set_title("loss")
    ax2.set_title("accuracy on validation")
    ax1.plot(range(1,n_epochs+1,10),loss_history)
    ax2.plot(range(1,n_epochs+1,10),val_accuracy)
                  ax1.grid()
                 ax2.grid()
plt.show()
```



In []: # path = f"./checkpoints/binary_epochs={n_epochs}_loss={loss}_filtered.pt"
torch.save(clf_binary.state_dict(),path)

Binary classifier Test VS MultiClass classifier

Test on AID TEST

Accuracy per class

```
binary_model=False)
                      accuracy_AID["multi"][g] = \
  model.get_model_accuracy_multiclass(
    d_AID[g]["features"],
    torch.ones_like(d_AID[g]["label"]) * GEN_TO_INT[g],
                      binary_model=False)
                       accuracy_AID_TEST["multi"][g] = \
  model.get_model_accuracy_multiclass(
    d_AID_TEST[g]["features"],
    torch.ones_like(d_AID_TEST[g]["label"]) * GEN_TO_INT[g],
           display("binary accuracy on test from AID:",accuracy_AID["binary"])
display("binary accuracy on AID_TEST: ",accuracy_AID_TEST["binary"])
display("multi-class accuracy on test from AID:",accuracy_AID["multi"])
display("multi-class accuracy on AID_TEST:",accuracy_AID_TEST["multi"])
```

Binary classifier

Performance of binary classifier on pair dataset

Train on 800 pairs and test on 200

```
In []: device = "cuda:1"
    model = MulticlassClassifier(n_classes=2,n_features=CLIP_FEATURE_DIM).to(device=device)
    model_double = MulticlassClassifier(n_classes=2,n_features=CLIP_FEATURE_DIM'2).to(device=device)
    model_train()
    model_train()
    model_double train()
    model_double train()
    model_double train()
    model_double_train()
    model_double_train()
    # model.load_state_dict(torch.load("./checkpoints/binary_epochs=1000_loss=0.02289319783449173.pt"))

lr = 1e-3
    batch_size = 64
    n_epochs = 1000

loss_fn = nn.CrossEntropyLoss()
    optimizerz = torch.optim.SGD(model_parameters(), lr=lr)
    optimizer2 = torch.optim.SGD(model_double_parameters(), lr=lr)
    optimizer3 = torch.optim.SGD(model_diff_parameters(), lr=lr)

rng = torch.Generator().manual_seed(SEED)

data = DoubleCLIP(load_from_disk=True,path_to_datset="/data4/saland/data/Double_CLIP_2000.pt")
    train_data, test_data = random_split(data,[0.2,0.8],generator=rng)
    train_loader = DataLoader(train_data,batch_size=64,shuffle=True)
    test_loader = DataLoader(train_data,batch_size=len(test_data))
```

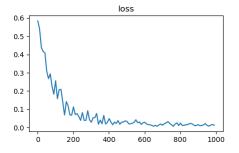
```
In []:
loss_history = []
for epoch in range(1,n_epochs+1):
    for idx, batch in enumerate(train_loader):
        # prediction and loss
        pred = model(batch("features"][:,:CLIP_FEATURE_DIM].to(device))
        loss = loss_fn(pred,batch("label"].type(torch.LongTensor).to(device))

        # backpropagation
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()

        loss, current = loss.item(), idx*batch_size + len(batch["features"])
        if epoch%10 == 0 and epoch > 0:
            loss_history.append(loss)
        print(f*loss: {loss>>7f}) [{epoch:>5d}/{n_epochs:>5d}]")
```

```
0.583756
0.539579
0.438721
                                                          10/ 1000]
20/ 1000]
30/ 1000]
loss:
loss:
loss:
loss:
                0.416519
                                                          40/
                                                                     10001
loss:
                0.408712
                                                          50/
                                                                     10001
                                                         60/ 1000]
70/ 1000]
80/ 1000]
loss:
                0.309370
               0.309370
0.267908
0.294130
0.225140
0.182545
loss:
loss:
                                                          90/
                                                                      10001
loss:
                                                       100/
                                                                      1000]
loss:
loss:
loss:
               0.256157
0.158156
0.207466
0.209256
                                                       110/
120/
130/
140/
                                                                     10001
                                                                    1000]
1000]
1000]
loss:
                0.140768
0.068818
                                                       150/ 1000]
                                                     150/ 1000]
160/ 1000]
170/ 1000]
180/ 1000]
190/ 1000]
200/ 1000]
loss:
loss:
loss:
loss:
                0.142247
0.119114
0.068986
loss:
                0.068263
0.112906
               0.071339
0.076113
0.060360
0.039138
0.081971
                                                     220/ 1000]
220/ 1000]
230/ 1000]
240/ 1000]
250/ 1000]
loss:
loss:
loss:
loss:
loss:
                0.039457
0.039661
                                                      270/ 1000]
280/ 1000]
loss:
               0.039661
0.092106
0.042148
0.029439
0.053061
0.054157
loss:
                                                     290/ 1000]
300/ 1000]
310/ 1000]
320/ 1000]
loss
loss:
loss:
                                                       330/ 1000]
loss:
loss:
loss:
               0.076776
0.018342
0.040988
0.020522
                                                      340/ 1000]
350/ 1000]
360/ 1000]
370/ 1000]
loss:
                0.066546
0.019537
                                                       380/ 1000]
                                                     380/ 1000]
390/ 1000]
400/ 1000]
410/ 1000]
420/ 1000]
430/ 1000]
440/ 1000]
               0.019537
0.027696
0.049153
0.030431
0.014990
0.030045
0.022594
loss:
loss:
loss:
loss:
loss:
               0.022594
0.038213
0.017799
0.029900
0.030164
0.036720
loss:
loss:
loss:
loss:
                                                      460/ 1000]
470/ 1000]
480/ 1000]
490/ 1000]
                                                       500/ 10001
loss:
               0.036720
0.034103
0.020227
0.020237
0.023274
0.028910
0.042629
0.025856
                                                     500/ 1000]
510/ 1000]
520/ 1000]
530/ 1000]
540/ 1000]
550/ 1000]
loss:
loss:
loss:
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loss:
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                                                       560/ 1000]
570/ 1000]
loss:
loss:
loss:
               0.030912
0.017213
0.026246
0.029192
                                                      580/ 1000]
590/ 1000]
600/ 1000]
610/ 1000]
               0.029192
0.019026
0.015804
0.011729
0.007162
0.012345
0.006837
0.015054
0.019335
loss:
                                                      620/ 1000]
                                                     620/ 1000]
630/ 1000]
640/ 1000]
650/ 1000]
660/ 1000]
670/ 1000]
loss:
loss:
loss:
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loss:
loss:
                                                      690/ 10001
loss:
loss:
loss:
               0.013034
0.019335
0.012731
0.021826
0.025399
                                                      700/ 1000]
710/ 1000]
720/ 1000]
730/ 1000]
loss:
               0.025399
0.032711
0.021752
0.015446
0.006741
0.019202
0.025521
0.011189
loss:
                                                       740/ 1000]
750/ 1000]
loss:
                                                     750/ 1000]
760/ 1000]
770/ 1000]
780/ 1000]
790/ 1000]
800/ 1000]
loss:
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loss:
               0.023951
0.011295
0.012027
0.015748
                                                      810/ 1000]
820/ 1000]
830/ 1000]
840/ 1000]
               0.015/48
0.015332
0.021128
0.022317
0.017479
0.010099
0.012004
0.015814
0.010053
loss:
                                                      850/ 1000]
                                                     850/ 1000]
860/ 1000]
870/ 1000]
880/ 1000]
900/ 1000]
910/ 1000]
loss:
loss:
loss:
loss:
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loss:
loss:
                                                      920/ 10001
loss:
loss:
loss:
loss:
               0.011627
0.015007
0.021446
0.011118
                                                      930/ 1000]
940/ 1000]
950/ 1000]
960/ 1000]
loss: 0.007925
loss: 0.013390
                                                      970/ 10001
                                                      980/ 10001
loss: 0.016757
loss: 0.012903
                                                       990/
                                              [ 1000/ 1000]
```

In []: fig= plt.figure(figsize=(5,3))
 plt.title("loss")
 plt.plot(range(1,n_epochs+1,10),loss_history)
 plt.show()



```
In [ ]: model.eval()
            with torch.no_grad()
                  for e in test_loader:
    print("n_train:",len(train_data))
    print("n_train:",len(test_data))
    acc = model.get_model_accuracy_binary(e["features"][:,:CLIP_FEATURE_DIM],e["label"],device,True)
            print(acc)
accuracy_768_features = acc
            n_train: 400
n test: 1600
            0.9906249642372131
            Train on concatenated version of CLIP features
In [ ]: fig= plt.figure(figsize=(5,3))
    plt.title("loss")
    plt.plot(range(1,n_epochs+1,10),loss_history)
    reference.
            plt.show()
             0.6
             0.5
             0.4
             0.3
             0.2
             0.1
             0.0
                                200
                                              400
                                                                        800
                                                                                    1000
In []: model.eval()
            mouel.eval()
with torth.no_grad():
    for e in test_loader:
        acc = model_double.get_model_accuracy_binary(e["features"],e["label"],device,True)
            print("n_train:",len(train_data))
print("n_test:",len(test_data))
print("Accuracy 768 CLIP features:
                                                                 ",accuracy_768_features)
            print("Accuracy double CLIP features:",acc)
           n_train: 400
n_test: 1600
            Accuracy 768 CLIP features: 0.9906249642372131
Accuracy double CLIP features: 0.9899999499320984
            Looking at the weights associated to each CLIP features (original and generated image)
In [ ]: torch.sum(torch.abs(model_double.fc1.weight[:768])).item()
Out[ ]: 10058.380859375
In [ ]: torch.sum(torch.abs(model_double.fc1.weight[:,768:])).item()
Out[]: 5020.86669921875
            Train on the difference between the 2 CLIP vectors
" pred = model_diff((batch["features"][:,:CLIP_FEATURE_DIM] - batch["features"][:,CLIP_FEATURE_DIM:]).to(device))
loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))
                        # backpropagation
                        loss.backward()
                        optimizer3.step()
optimizer3.zero_grad()
                  loss, current = loss.item(), idx*batch_size + len(batch["features"])
if epoch%10 == 0 and epoch > 0:
    loss_bistory.append(loss)
    print(f*loss: {loss:>7f} [{epoch:>5d}/{n_epochs:>5d}]")
In []: model.eval()
with torch.no_grad():
    for e in test_loader:
        acc_diff = model_diff.get_model_accuracy_binary((e["features"][:,:CLIP_FEATURE_DIM] - e["features"][:,CLIP_FEATURE_DIM:]),e["label"],device,True)
           n_train: 400
n_test: 1600
Accuracy 768 CLIP features: 0.9906249642372131
Accuracy double CLIP features: 0.989999499320984
Accuracy difference CLIP features: 0.9300000071525574
            Test on OOD of model trained on AID and fine-tuned on real/fake pairs
In [ ]: device = "cuda:1"
            uevite = Code.1
path_no_fine_tune = "checkpoints/binary_epochs=1000_loss=0.04426886886358261_filtered.pt"
model = MultiClassClassifier(n_classes=2).to(device)
model.load_state_dict(torch.load(path_no_fine_tune))
            model.eval()
```

(act): ReLU()

```
In [ ]: data_test = 00D("/data4/saland/data/ood.pt",
                                              load_preprocessed=True,
device=device,
remove_blacklisted_gen=True)
                acc = model.get_model_accuracy_binary(data_test.features,data_test.label,device,binary_model=True)
                print("accuracy of model on OOD before fine-tuning on real/fake pairs:",acc)
               In [ ]: torch.bincount(data_test.gen.int())
Out[ ]: tensor([100, 100, 100, 100, 100], device='cuda:1')
In [ ]: accuracy = {}
for gen in GEN_TO_INT_00D:
    mask = data_test.gen == GEN_TO_INT_00D[gen]
    accuracy[gen] = model.get_model_accuracy_binary(data_test.features[mask],data_test.label[mask],device=device, binary_model=True)
    display(accuracy)
               Insplay(acturacy)

{'null': 0.85999995470047,
'Lexica': 0.699999988079071,
'Ideogram': 0.7899999618530273,
'Leonardo': 0.8100000023841858,
'Copilot': 0.9799999594688416,
'img2lmg_SD1.5': nan,
'Photoshop_generativemagnification': nan,
'Photoshop_generativefill': nan}
                Fine-tuning on real/fake pairs
In [ ]: lr = 1e-3
    batch_size = 32
    n_epochs = 1000
    n_imgs = 100
               loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=lr)
               model.train()
rng = torch.Generator().manual_seed(SEED)
data = RealFakePairs(load_from_disk=True,path="/data4/saland/data/real_fake_pairs_1090.pt")
data_shuffled = shuffle_data(data,in_place=False,seed=SEED)
data_slice = select_slice(data_shuffled_n_imgs)
train_loader = DataLoader(data_slice,batch_size=batch_size,shuffle=True,generator=rng)
               shuffling features
shuffling label
 In [ ]: loss_history = []
                loss_instory = []
for epoch in range(1,n_epochs*1):
    for idx, batch in enumerate(train_loader):
        # prediction and loss
        pred = model((batch["features"]).to(device))
        loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))
                                # backpropagation
                               loss.backward()
                               optimizer.step()
optimizer.zero_grad()
                       loss, current = loss.item(), idx*batch_size + len(batch["features"])
if epoch%10 == 0 and epoch > 0:
    loss_history.append(loss)
    print(f"loss: {loss:>7f} [{epoch:>5d}/{n_epochs:>5d}]")
```

```
loss: 0.648602
loss: 0.568120
loss: 0.567317
                                                      10/ 1000]
20/ 1000]
30/ 1000]
                 loss:
                           0.617613
                                                       40/ 10001
                 loss:
                           0.420520
                                                       50/ 10001
                loss:
                           0.367580
                                                       60/ 1000]
                           0.376093
0.382430
                                                      70/
80/
                                                              1000]
1000]
                 loss:
                 loss:
                           0.233814
0.345064
                                                       90/
                                                               10001
                 loss:
                                                     100/ 1000]
                loss:
loss:
loss:
                           0.265198
0.183815
0.158704
0.241281
                                                     110/ 10001
                                                    120/ 1000]
120/ 1000]
130/ 1000]
140/ 1000]
                 loss:
                           0.223197
0.236249
                                                     150/ 1000]
                 loss:
                                                     160/ 10001
                loss:
loss:
loss:
                           0.166535
0.147699
0.159505
                                                    170/ 1000]
180/ 1000]
190/ 1000]
200/ 1000]
                 loss:
                           0.104365
0.119927
                                                    200/ 1000]
210/ 1000]
                 loss:
                          0.119927
0.132870
0.085604
0.102017
0.054877
0.060638
                                                    220/ 1000]
220/ 1000]
230/ 1000]
240/ 1000]
250/ 1000]
                loss:
loss:
loss:
loss:
                 loss:
                 loss:
                           0.076238
0.093681
                                                    270/ 10001
                 loss:
                                                    280/ 10001
                           0.093681
0.071183
0.049570
0.077595
0.142943
0.031797
                loss:
                                                    290/ 10001
                                                    300/
310/
                                                              1000]
1000]
                 loss:
                 loss:
                                                     320/
                                                              10001
                 loss:
                                                    330/ 1000]
                           0.053163
0.062460
0.073654
0.030702
                 loss.
                                                     340/ 10001
                                                    350/ 1000]
350/ 1000]
360/ 1000]
370/ 1000]
                loss:
loss:
loss:
                           0.031895
0.048693
0.028523
0.055153
                 loss:
                                                    380/ 1000]
390/ 1000]
                 loss:
                                                    400/ 1000]
400/ 1000]
410/ 1000]
420/ 1000]
430/ 1000]
440/ 1000]
                loss:
loss:
                           0.033133
0.034302
0.033053
0.037271
0.036634
                 loss:
                 loss:
                 loss:
                loss:
loss:
loss:
                           0.068536
0.038766
0.019831
0.055756
                                                    460/ 1000]
470/ 1000]
480/ 1000]
490/ 1000]
                                                              1000]
1000]
1000]
                 loss:
                 loss:
                           0.041419
                                                     500/ 10001
                 loss:
                           0.032802
                                                    510/ 10001
                           0.022648
0.015947
0.056358
0.051124
                                                    520/ 1000]
530/ 1000]
540/ 1000]
550/ 1000]
                 1055
                 loss:
                 loss:
                 loss:
                 loss:
                           0.027787
0.024908
                                                     560/ 1000]
                 loss:
                                                    570/ 1000]
                loss:
loss:
loss:
loss:
                           0.063908
0.015396
0.039129
0.011725
                                                    580/ 1000]
590/ 1000]
600/ 1000]
610/ 1000]
                           0.011/25
0.027839
0.046101
0.046641
0.052139
0.034220
0.027134
0.022907
0.010623
                 loss:
                                                    620/ 1000]
                loss:
loss:
loss:
                                                    630/ 1000]
640/ 1000]
650/ 1000]
660/ 1000]
                                                              1000]
                 loss:
                                                     670/
                 loss:
                                                    680/
                                                              10001
                 loss:
                                                    690/ 10001
                loss:
loss:
loss:
                           0.035484
0.013988
0.011439
0.008745
                                                    700/ 1000]
710/ 1000]
720/ 1000]
730/ 1000]
                 loss:
                 loss:
                           0.038446
0.011897
                                                     740/ 10001
                 loss:
                                                     750/ 10001
                           0.011897
0.009231
0.026995
0.009816
0.017916
0.027710
                                                    760/ 1000]
770/ 1000]
780/ 1000]
790/ 1000]
                loss:
                 loss:
                 loss:
                 loss:
                                                    800/ 1000]
                loss:
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loss:
                           0.007724
0.016254
0.015668
0.019503
                                                    810/ 1000]
820/ 1000]
830/ 1000]
840/ 1000]
                 loss:
                           0.005144
                                                    850/ 1000]
                                                    850/ 1000]
860/ 1000]
870/ 1000]
880/ 1000]
890/ 1000]
900/ 1000]
                 loss:
                           0.013432
0.014530
0.003654
0.039450
0.007473
0.012986
                loss:
loss:
loss:
                 loss:
                                                    900/ 1000]
910/ 1000]
                 loss:
                 loss:
                           0.015741
                                                    920/ 10001
                loss:
loss:
loss:
                           0.023200
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0.006802
0.011170
                                                    930/ 1000]
940/ 1000]
950/ 1000]
960/ 1000]
                 loss:
                 loss:
                           0.006867
0.008278
                                                    970/ 10001
                loss:
                                                    980/ 10001
                loss: 0.018037
loss: 0.019782
                                                     990/ 10001
                                              [ 990/ 1000]
[ 1000/ 1000]
In [ ]: model.eval()
acc = model.get_model_accuracy_binary(data_test.features,data_test.label,device,True)
print("accuracy of the model on OOD after fine-tuning:",acc)
                accuracy of the model on OOD after fine-tuning: 0.7520000338554382
In []: path_fine_tune = f"./checkpoints/binary_train_AID_fine_tune_pairs_loss={loss}.pt"
                    torch.save(model.state_dict(),path_fine_tun
In []: model_fine_tuned = MultiClassClassifier(n_classes=2).to(device)
    model_fine_tuned.load_state_dict(torch.load("./checkpoints/binary_train_AID_fine_tune_pairs_loss=0.000141876342240721.pt"))
    model_fine_tuned.eval()
               model_fine_tuned.eval()
acc = model_fine_tuned.get_model_accuracy_binary(data_test.features,data_test.label,device,True)
print("accuracy of the model on 00D after fine-tuning (from checkpoint):",acc)
                accuracy of the model on OOD after fine-tuning (from checkpoint): 0.800000011920929
data_test.gen,
                                                                                              data_test.gen,
device,
True,
GEN_TO_INT_OOD)
```

```
Out[]: {'null': 0.939999976158142,
    'Lexica': 0.6200000047683716,
    'Ideogram': 0.759999904632568,
    'Leonardo': 0.75,
    'Copilot': 0.9599999500055847,
    'img2img_515': nan,
    'Photoshop_generativemagnification': nan,
    'Photoshop_generativefill': nan}

Test sur long caption avec et sans fine-tune

In []: path_fine_tune = "./checkpoints/binary_train_AID_fine_tune_pairs_loss=0.000141876342240721.pt"
    model = MultiClassClassifier(n_classes=2).to(device)
    model_fine_tuned = MultiClassClassifier(n_classes=2).to(device)
    model_fine_tuned = MultiClassClassifier(n_classes=2).to(device)
    model_fine_tuned.load_state_dict(torch.load(path_fine_tune))

    model_eval()
    model_eval()
    model_fine_tuned.eval()
    long_caption = LongCaption(path="/data4/saland/data/LongCaption.pt", load_from_disk=True)
```

long_caption.label,
device=device,
binary_model=True))

Binary accuracy on long caption images: 0.8497109413146973
Fine-tune accuracy on long caption images: 0.8323699235916138

binary_model=True))

binary train on 2k real and 2k fake

```
In []: device = "cuda:0"
    model = MulticlassClassifier(n_classes=2).to(device)
    model.train()
    lr = 1e-3
    batch_size = 32
    n_epochs = 1000
    n_imgs = 1000

    loss_fn = nn.CrossEntropyLoss()
    optimizer = torch.optim.SGD(model.parameters(), lr=lr)

    model.train()
    rng = torch.Generator().manual_seed(SEED)
    data = FlickAndPairs(path="/data4/saland/data/flickr_and_pairs_DinoV2.pt",load_from_disk=True)
    train_loader = DataLoader(data,batch_size=batch_size,shuffle=True,generator=rng)
```

```
loss: 0.502425
loss: 0.271259
loss: 0.216291
                                                          10/ 1000]
20/ 1000]
30/ 1000]
                  loss:
                             0.204625
                                                           40/ 10001
                  loss:
                             0.148112
                                                           50/ 10001
                                                          60/ 1000]
70/ 1000]
80/ 1000]
                  loss:
                             0.041347
                  loss:
                  loss:
                             0.039667
0.022802
                                                                   10001
                  loss:
                                                         100/ 1000]
                  loss:
loss:
loss:
loss:
                             0.044861
0.023949
0.026538
0.027375
                                                        110/ 1000]
120/ 1000]
130/ 1000]
140/ 1000]
                                                        140/ 1000]
150/ 1000]
160/ 1000]
170/ 1000]
180/ 1000]
200/ 1000]
210/ 1000]
                  loss:
                             0.017287
0.023578
                  loss:
                             0.023578
0.025720
0.018888
0.017412
0.021926
0.014409
                  loss:
loss:
loss:
                  loss:
                  loss:
                  loss: 0.0114409
loss: 0.011642
loss: 0.008274
loss: 0.013666
loss: 0.012596
loss: 0.008794
                                                        220/ 1000]
220/ 1000]
230/ 1000]
240/ 1000]
250/ 1000]
                  loss:
                             0.010618
                                                        270/ 1000]
280/ 1000]
                  loss:
                             0.005700
                             0.005700
0.005616
0.007401
0.005720
0.008593
0.006102
                  loss:
                                                        290/ 1000]
300/ 1000]
310/ 1000]
                                                        300/ 1000]
310/ 1000]
320/ 1000]
                  loss:
                  loss:
                                                        330/ 1000]
                  loss:
                             0.006715
0.006789
0.003347
0.005897
                                                        340/ 1000]
350/ 1000]
360/ 1000]
370/ 1000]
                  loss.
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loss:
loss:
                            0.00589/
0.006217
0.004787
0.002686
0.004223
0.003616
0.003971
0.005222
0.004513
                  loss:
                                                        380/ 1000]
390/ 1000]
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400/ 1000]
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                  loss:
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                            0.004513
0.004684
0.004796
0.001684
0.001545
0.002868
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                                                        460/ 1000]
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490/ 1000]
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                  loss:
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                  loss:
                             0.004363
                             0.003061
0.003216
0.003732
0.003420
                  1055
                  loss:
                  loss:
                  loss:
                  loss:
                             0.003265
0.003799
                                                        560/ 1000]
570/ 1000]
                  loss:
                  loss:
loss:
loss:
loss:
                             0.002587
0.001751
0.002847
0.002927
                                                        580/ 1000]
590/ 1000]
600/ 1000]
610/ 1000]
                             0.002927

0.002885

0.002998

0.001743

0.003599

0.002107

0.002721

0.002432
                                                        620/ 1000]
630/ 1000]
640/ 1000]
650/ 1000]
660/ 1000]
                  loss:
                  loss:
loss:
loss:
                                                        670/ 1000]
                  loss:
                  loss:
                                                        680/ 10001
                             0.002017
                  loss:
                                                        690/ 10001
                  loss: 0.002379
loss: 0.001127
loss: 0.001688
loss: 0.002390
                                                        700/ 1000]
710/ 1000]
720/ 1000]
730/ 1000]
                            0.002390
0.002208
0.001799
0.001913
0.002023
0.002446
0.001294
0.001492
                  loss:
                                                         740/ 1000]
                  loss:
                                                         750/ 10001
                                                        760/ 1000]
770/ 1000]
780/ 1000]
790/ 1000]
                  loss:
                  loss:
                  loss:
                                                        800/ 1000]
                  loss:
                  loss: 0.001349
loss: 0.001153
loss: 0.001820
loss: 0.001981
                                                        810/ 1000]
820/ 1000]
830/ 1000]
840/ 1000]
                  loss: 0.001981
loss: 0.001939
loss: 0.001696
loss: 0.001516
loss: 0.001661
loss: 0.001613
                                                        850/ 1000]
850/ 1000]
860/ 1000]
870/ 1000]
880/ 1000]
900/ 1000]
910/ 1000]
                  loss:
                             0.001137
                                                        920/ 10001
                  loss: 0.001084
loss: 0.001947
loss: 0.001247
loss: 0.001719
                                                        930/ 1000]
940/ 1000]
950/ 1000]
960/ 1000]
                  loss: 0.001191
loss: 0.001666
                                                        970/ 10001
                                                        980/ 10001
                  loss: 0.001745 [ 990/ 1000]
loss: 0.001453 [ 1000/ 1000]
In [ ]: torch.save(model.state dict(),"./checkpoints/binary train real2k fake1999 dinoV2.pt")
binary_model=True)
                filtering: 0%|
0.28200000524520874
                                                                 Out[]:
```

```
In []: device = "cpu"
model = MultiClassClassifier(n_classes=2).to(device)
               model.load_state_dict(torch.load("./checkpoints/binary_train_real2k_fake1999.pt"))
model.eval()
              rng = torch.Generator().manual_seed(SEED)
              data = TestMeta(path="/data4/saland/data/test_meta.pt",load_from_disk=True)
train_data, test_data = random_split(data, [0.8, 0.2],generator=rng)
              train_loader = DataLoader(train_data, batch_size=64,shuffle=True,generator=rng)
test_loader = DataLoader(test_data,batch_size=len(test_data))
              Accuracy on meta test before fine tuning
for e in test_loader:
                    e in test_loader:
for i, features in enumerate(e["features"]):
    gen = e["gen_original_name"][i]
    label = e["label"][i]
    d[gen]["features"] = torch.cat((d[gen]["features"], features.unsqueeze(0)),dim=0)
    d[gen]["label"] = torch.cat((d[gen]["label"],label.unsqueeze(0)),dim=0)
               acc = {}
for gen in d:
                    device = device)
             display(acc)
              fine-tuning
 In [ ]: lr = 1e-3
              batch_size = 64
n_epochs = 200
              loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=lr)
              model.train()
Out[]: MultiClassClassifier(
                  (fc1): Linear(in_features=768, out_features=512, bias=True)
(fc2): Linear(in_features=512, out_features=2, bias=True)
(act): ReLU()
In [ ]: loss_history = []
for epoch in range(1,n_epochs+1):
    for idx, batch in enumerate(train_loader):
    # prediction and loss
    pred = model((batch["features"]).to(device))
    loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))
                            # backpropagation
                           loss.backward()
optimizer.step()
optimizer.zero_grad()
                    loss, current = loss.item(), idx*batch_size + len(batch["features"])
if epoch%10 == 0 and epoch > 0:
    loss_bnistory.append(loss)
    print(f*loss: {loss:>7f} [{epoch:>5d}/{n_epochs:>5d}]")
               loss: 0.041811
                                              10/ 2001
              loss: 0.222908
loss: 0.012555
loss: 0.120002
loss: 0.015896
                                              20/
30/
40/
50/
                                                      200]
200]
200]
200]
              loss: 0.015896
loss: 0.020531
loss: 0.045851
loss: 0.045070
loss: 0.032931
loss: 0.005113
loss: 0.052948
loss: 0.27596
                                              60/
                                                      2001
                                              70/
80/
                                                       2001
                                                      200]
200]
200]
                                             110/
                                                       200]
                                             120/
                                                       2001
              loss: 0.52/596
loss: 0.073503
loss: 0.001805
loss: 0.019284
loss: 0.090728
loss: 0.013563
                                            130/
140/
150/
160/
170/
                                                       2001
                                                      200]
200]
200]
                                                      2001
              loss: 0.025673
loss: 0.094159
loss: 0.106813
                                             180/
                                                      2001
                                             190/
                                                       2001
                                            200/
```

Accuracy on Test Meta after fine-tuning

Train FlickrAndPairs CLIP + DINOV2 -> fine tune test meta CLIP + DINO V2

```
In []: fp_clip = FlickrAndPairs(path="/data4/saland/data/flickr_and_pairs.pt",load_from_disk=True)
    fp_dino = FlickrAndPairs(path="/data4/saland/data/flickr_and_pairs_DinoV2.pt",load_from_disk=True)
    train_data = SimpleDataset(torch.cat((fp_clip.features, fp_dino.features), dim=1), fp_clip.label)

tm_clip = TestMeta(path="/data4/saland/data/test_meta_pti",load_from_disk=True)
    tm_dino = TestMeta(path="/data4/saland/data/test_meta_DinoV2.pt",load_from_disk=True)
    ft_data = SimpleDataset(torch.cat((tm_clip.features, tm_dino.features), dim=1), tm_clip.label)
```

```
In []:
    device = "cuda:0"
    model = MulticlassClassifier(n_features=CLIP_FEATURE_DIM+DINO_FEATURE_DIM,n_classes=2).to(device)

lr = 1e-3
    batch_size = 64
    n_epochs = 1000

loss_fn = nn.CrossEntropyLoss()
    optimizer = torch.optim.SGD(model.parameters(), lr=lr)
    rng = torch.Generator().manual_seed(SEED)

model.train()

train_loader = DataLoader(train_data,batch_size=batch_size, generator=rng)

for epoch in range(1.n_epochs=1):
    for idx, batch in enumerate(train_loader):
        # prediction and loss
        pred model((batch)*features*]).to(device))
        loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))

# backpropagation
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()

loss, current = loss.item(), idx*batch_size + len(batch["features"])
        if epoch%i0 == 0 and epoch > 0:
              loss_history.append(loss)
              print(f*feloss: {loss.item}), idx*batch_size + len(batch["features"])
        if epoch%i0 == 0 and epoch > 0:
              loss_history.append(loss)
              print(f*feloss: {loss.item}), idx*batch_size + len(batch["features"])
```

```
0.278704
0.157806
0.106904
                                                            10/ 1000]
20/ 1000]
30/ 1000]
loss:
loss:
loss:
loss:
                 0.079469
                                                            40/
                                                                        10001
loss:
                 0.061921
                                                            50/
                                                                        10001
                                                           60/ 1000]
70/ 1000]
80/ 1000]
loss:
                 0.049769
                0.049769
0.041108
0.034674
0.029796
0.025970
loss:
loss:
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                                                                         1000]
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loss:
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                 0.015098
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0.010048
0.009359
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loss:
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                0.004564
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0.004191
0.004023
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                0.003866
0.003719
0.003582
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0.003215
0.003107
0.003004
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                0.003004
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loss:
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550/ 1000]
loss:
                 0.002496
                0.002496
0.002426
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0.002296
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0.002177
0.002121
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                                                         560/ 1000]
570/ 1000]
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loss:
                0.002068
0.002018
0.001969
0.001922
                                                       580/ 1000]
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               0.001922
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loss:
                                                        620/ 1000]
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                0.001577
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                                                         700/ 1000]
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                0.001485
0.001427
0.001402
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760/ 1000]
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loss: 0.000967
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```

```
In [ ]: device = "cuda:0"
    model = MultiClassClassifier(n_features=CLIP_FEATURE_DIM+DINO_FEATURE_DIM,n_classes=2).to(device)
    model.load_state_dict(torch.load("../model/checkpoints/binary_train_real2k_fake1999_clip_dino.pt"))
                   lr = 1e-3
batch_size = 64
n_epochs = 200
                    loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=lr)
rng = torch.Generator().manual_seed(SEED)
                    model.train()
                    train_loader = DataLoader(ft_data,batch_size=batch_size, generator=rng)
                    for epoch in range(1,n_epochs+1):
    for idx, batch in enumerate(train_loader):
                                       # prediction and loss
pred = model((batch["features"]).to(device))
loss = loss_fn(pred,batch["label"].type(torch.LongTensor).to(device))
                                       # backpropagation
loss.backward()
                                       optimizer.step()
optimizer.zero_grad()
                              loss, current = loss.item(), idx*batch_size + len(batch["features"])
if epoch%10 == 0 and epoch > 0:
    loss_bistory.append(loss)
    print(f*loss: {loss:>7f} [{epoch:>5d}/{n_epochs:>5d}]")
                   print(f
loss: 0.002120
loss: 0.003366
loss: 0.003721
loss: 0.003721
loss: 0.003728
loss: 0.003728
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loss: 0.003508
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loss: 0.002271
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In \ [\ ]: \ torch.save(model.state_dict(),"../model/checkpoints/binary_train_real_fake_2k\_fine_tune_meta_test\_clip_dino.pt")
```