## **Report of Anomaly Detection HW4**

Name: 高煒軒

Student ID: 112062646

# Implementation & explanation

## Problem 1:



### Problem 2:

```
(smoothing: True): dataset = avenue, auc = 0.694730936234571 aver_result: [0.6181524418357716] (smoothing: True): dataset = avenue, auc = 0.6318882585921665 aver_result: [0.5418812810853003] (smoothing: True): dataset = avenue, auc = 0.6634296815054975 aver_result: [0.5743266656891045]
```

我認為 binary classification 的任務可能過於簡單,使得 modle 難以從

temporal permutation 中學習到有用的資訊。

#### Modified code

修改 dataset 的 code  $\cdot$  使其若有作 temporal permutation 則將 label 設為 1 否 則為 0  $\circ$ 

```
Video Anomaly Dataset.
===> Modify the temporal permutation for change prediction as a binary classification (0 : normal) / (1 : abnormal).
def getitem (self, idx):
   temproal_flag = idx % 2 == 0
record = self.objects_list[idx]
    label = 0
    if self.test_stage:
       perm = np.arange(self.frame_num)
       if random.random() < 0.5:
           perm = np.arange(self.frame_num)
           perm = np.random.permutation(self.frame_num)
           if np.any(perm != np.arange(self.frame_num)):
               label = 1
   obj = self.get_object(record["video_name"],
                         record["frame"], record["object"])
   if not temproal_flag and not self.test_stage:
       if random.random() < 0.0001:</pre>
           spatial_perm = np.arange(9)
           spatial_perm = np.random.permutation(9)
       spatial_perm = np.arange(9)
   obj = self.jigsaw(obj, border=2, patch_size=20,
                     permuation=spatial_perm, dropout=False)
    obj = torch.from_numpy(obj)
```

並且在 main.py 中,將 temp\_loss 改為使用 nn.BCEWithLogitsLoss 計算

```
criterion = nn.CrossEntropyLoss(reduction='mean')
temp_criterion = nn.BCEWithLogitsLoss(reduction='mean')
optimizer = optim.Adam(params=net.parameters(), lr=1e-4)
```

```
temp_logits, spat_logits = net(obj)
# temp_logits = temp_logits[t_flag].view(-1, args.sample_num)
temp_logits = temp_logits[t_flag].view(-1)
spat_logits = spat_logits[~t_flag].view(-1, 9)

temp_loss = temp_criterion(temp_logits, temp_labels.float())
spat_loss = criterion(spat_logits, spat_labels)

loss = temp_loss + spat_loss
```

### Problem 3:

```
(smoothing: True): dataset = avenue, auc = 0.677991901253842 aver_result: [0.6243217356891717] (smoothing: True): dataset = avenue, auc = 0.6074922272438982 aver_result: [0.504837138566415] (smoothing: True): dataset = avenue, auc = 0.6490599511236678 aver_result: [0.5491909099300794]
```

#### ■ Modified code

使用一個 list(此處命名為 all\_perm)記錄所有可能的 permutation · 並根據 temporal permutation 的結果返回 list 中對應的 index 作為 multiclass predction 的 label。

## Additional information of Problem 3:

在此次作業的 problem3 中我觀察到一些有趣的現象,以此為記錄。

1. Temporal permutation 的機率:

在我上述的 Modified code 中 Temporal permutation 的機率同 Problem 2,

而我另外測試了將機率設為 0.0001。做法為直接將 dataset 繼承原

#### dataset

但是最終實驗的結果顯示兩種機率設定並沒有對 performance 造成太大的

#### 影響

```
(smoothing: True): dataset = avenue, auc = 0.6483190444721401 aver_result: [0.6052123423789282] (smoothing: True): dataset = avenue, auc = 0.5848984552063051 aver_result: [0.4965623012310326] (smoothing: True): dataset = avenue, auc = 0.6369814651368049 aver_result: [0.5393306739944885]
```

2. Anomaly score 的設定:

上述的 Problem3 實驗結果是根據 pdf,將 anomaly score 設為

1 – probability of Permutation #1,如下

```
temp_probs = F.softmax(temp_logits, -1)
# diag2 = torch.diagonal(temp_probs, offset=0, dim1=-2, dim2=-1)
scores2 = 1 - temp_probs[:, 0].cpu().numpy()
```

但是我在實驗過程中曾經誤將 anomaly score 設定如下

```
temp_probs = F.softmax(temp_logits, -1)
# diag2 = torch.diagonal(temp_probs, offset=0, dim1=-2, dim2=-1)
scores2 = temp_probs[:, 0].cpu().numpy()
```

而這樣的設定卻反而獲得了比原 problem3 更加的結果,甚至接近原

#### problem 1 的結果

```
(smoothing: True): dataset = avenue, auc´= 0.6677167833873694 aver_result: [0.6019024598874825]
(smoothing: True): dataset = avenue, auc = 0.8864652033335255 aver_result: [0.8697488969686828]
(smoothing: True): dataset = avenue, auc = 0.7774326176336227 aver_result: [0.7353518981718512]
```