PoseCVAE: Anomalous Human Activity Detection

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[1]Denotes equal contribution

Datasets

- There are three publicly available datasets:

CUHK Avenue[1]	**ShanghaiTech**[2]	**IITB-Corridor**[3]
16 training videos	330 training videos	208 training videos
21 test videos	107 test videos	150 test videos
Short-term anomaly	Multi-camera	Close to real world

Table: Available Datasets

- Since we are concerned only with human anomaly, we will be working on subsets of above datasets i.e., HR-Avenue, HR-ShanghaiTech and HR-IITB Corridor (**proposed by us**)

Preprocessing Pipeline: Trajectory Extraction

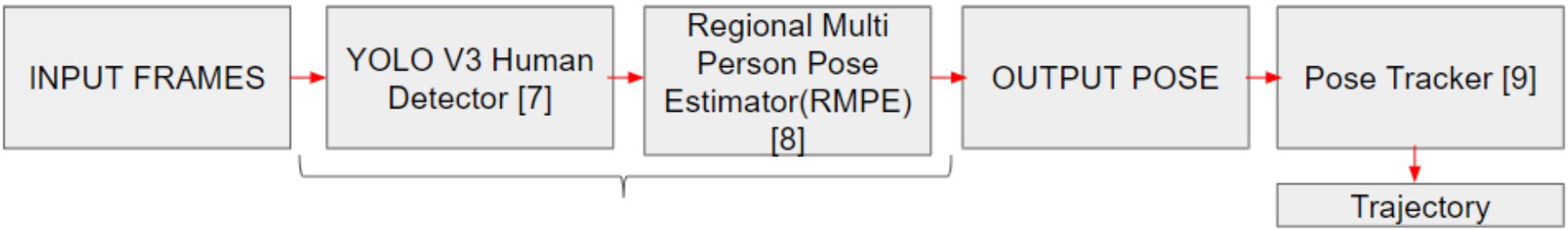


Figure: Trajectory Extraction Pipeline

- Used a network with combined detection and pose estimator
- Pose detector output is 17 keypoints i.e. (x,y) coordinates

Preprocessing Pipeline: Normalization

- Keypoints obtained from pose estimator are not normalized
- This causes increase in error due to closer entities
- To correct depth effect we propose bounding box normalization as shown:

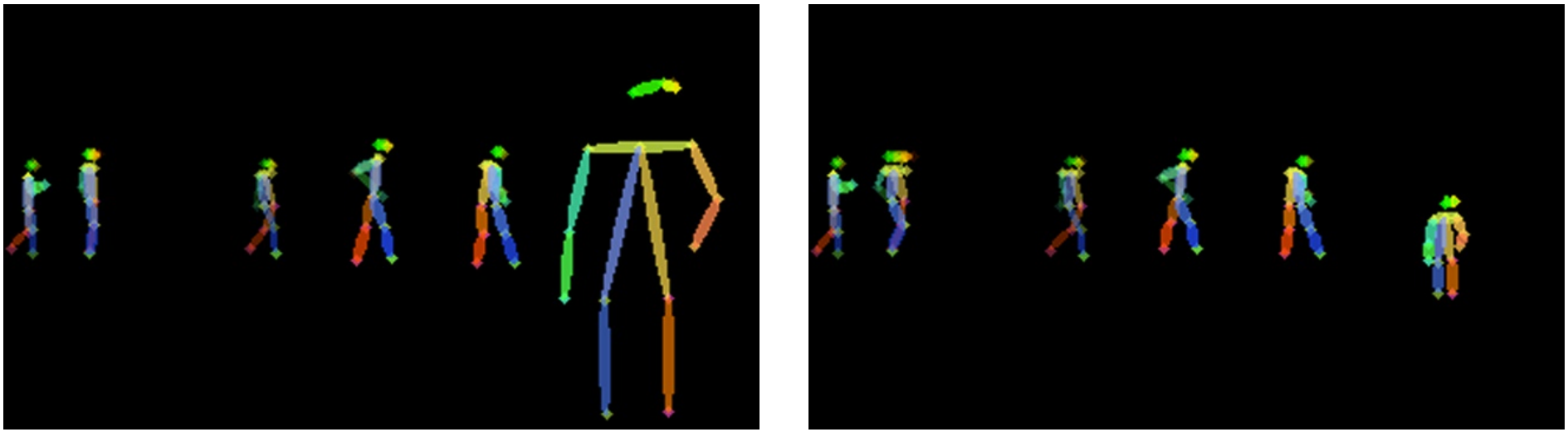


Figure: Left: Without Normalization Right: With Normalization

Preprocessing Pipeline: Data Augmentation

- It's better to take small tracks of person instead of long corrupted tracks
  - The output of Pose tracker is affected by illumination, depth, occlusion
  - Tracking in multi person environment is difficult due to overlapping trajectories
- We use sliding window to divide trajectories into multiple tracks
- This helps in data augmentation as well

PoseCVAE: High Level Flow

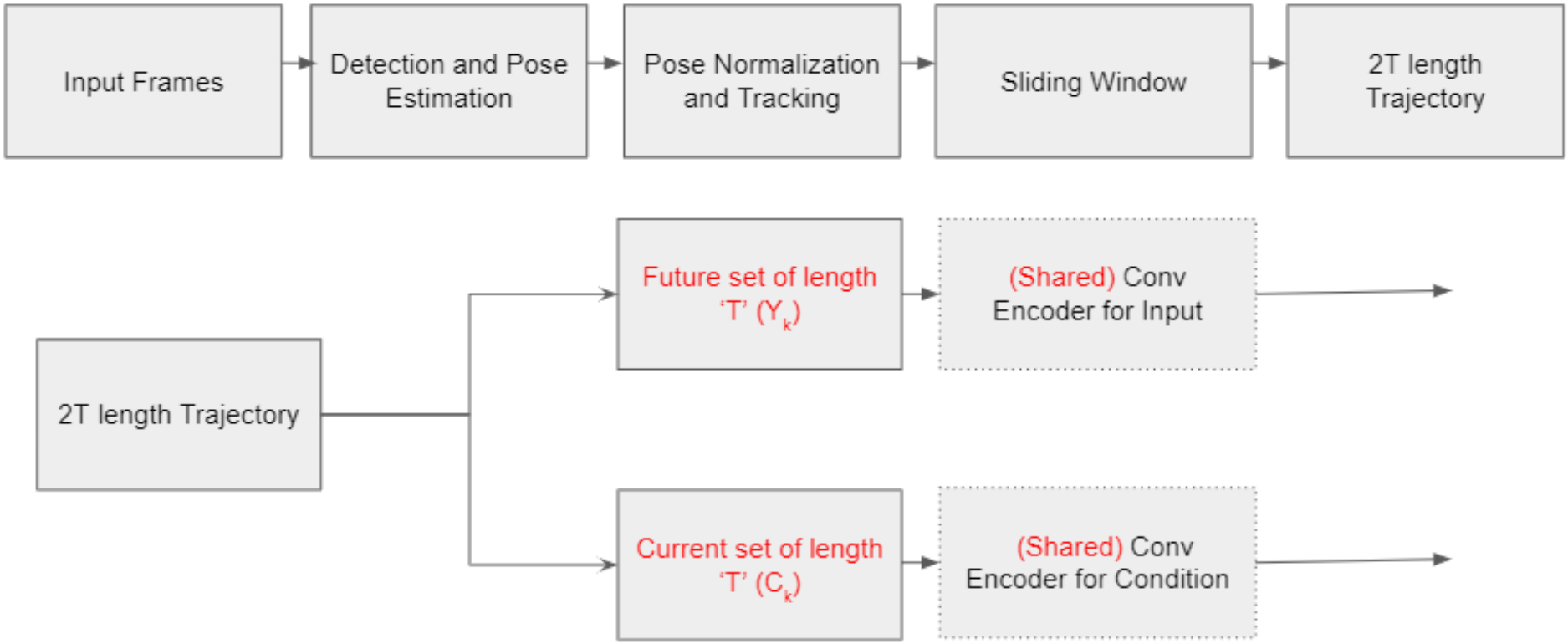


Figure: High Level Flow Diagram

PoseCVAE: Architecture

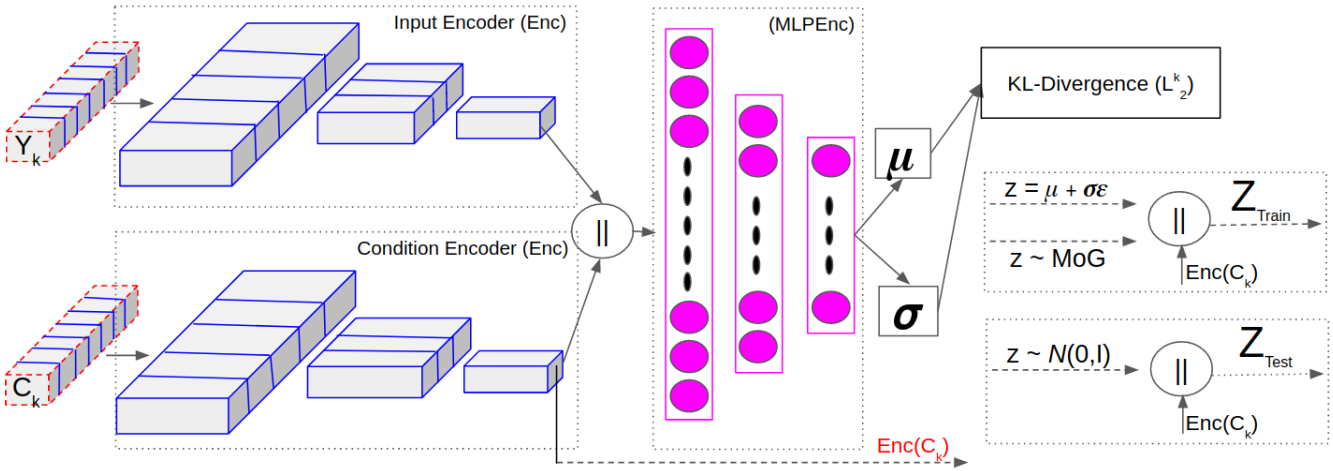


Figure: Encoder

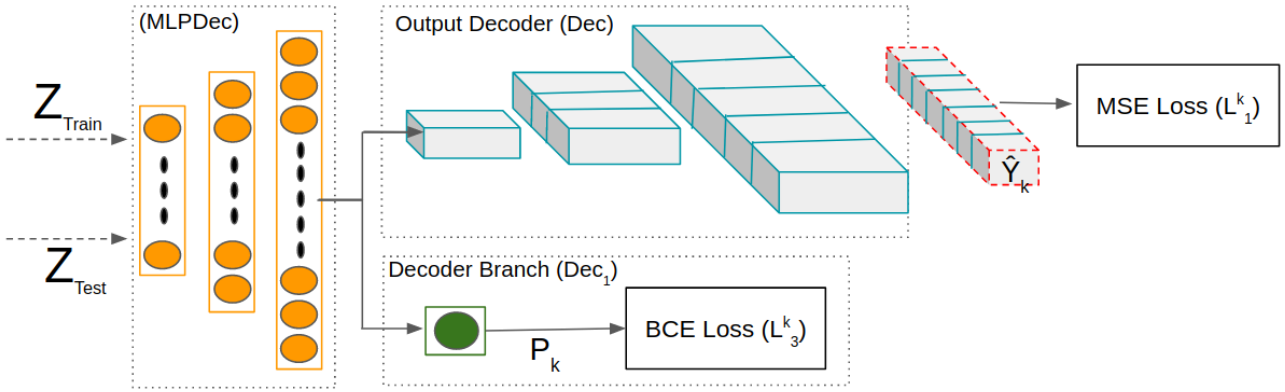


Figure: Decoder

Imitating Abnormal Pose Trajectory in the Latent Space

- To maximise the separation between normal and abnormal classes, we split a decoder branch (Dec_1) which gives class probability, P_k as output
- Normal Class is labelled '0', Abnormal class is labelled '1'
- Different possibilities for the concatenated latent vector:

$$Z_{normal} \equiv z \sim \mathcal{Q}(.) \mid\mid Enc(C_k) \tag{1}$$

$$Z_{abnormal} \equiv z \sim \mathcal{N}(0, I) \mid\mid Enc(C'_k) \tag{2}$$

$$\tilde{Z}_{abnormal} \equiv z \sim MoG \mid\mid Enc(C_k) \tag{3}$$

- The output of the classifier branch is mapped as follows:

$$Dec_1(MLPDec(Z_{normal})) \rightarrow 0 \tag{4}$$

$$Dec_1(MLPDec(\tilde{Z}_{abnormal})) \rightarrow 1 \tag{5}$$

Loss Function

Used combination of three loss functions during training:

- Reconstruction Loss: Maximising the conditional expectation translates into minimising MSE:

$$L_1^k(Y_k, \hat{Y}_k) = \left|\left|\hat{Y}_k - Y_k\right|\right|_2^2 \tag{6}$$

- KL divergence Loss: Minimise the KLD to maximise the conditional likelihood:

$$L_2^k(\mu, \sigma) = \mathcal{KL}[\mathcal{N}(\mu(Y_k, C_k), \sigma(Y_k, C_k)) \,||\, \mathcal{N}(0, I)] \tag{7}$$

- BCE loss: **To make normal and abnormal latent samples more distinguishable:**

$$L_3^k(y_k, P_k) = -(y_k \log P_k + (1 - y_k) \log(1 - P_k)) \tag{8}$$

Training Strategy

- Input: future trajectory to be predicted, length = 'T'
- Condition: past trajectory of length 'T'
- Aim: learn conditional posterior and reconstruct the input given the condition

We train in 3 stages:

- Stage 1: Self Supervised Learning (Pre-training the Conv. Encoder and decoder)
  - Objective: Reconstruct the given trajectories
- Stage 2: Unsupervised Learning (Training the PoseCVAE)
  - Objective: Reconstruct the given trajectory given the past trajectory and minimise the KLD (Maximising the conditional likelihood)
- **Stage 3: Unsupervised with OoD sample generation and minimise BCE** (Fine-tuning the PoseCVAE framework)
  - Objective: For normal latent points: Minimise the KLD, MSE and BCE, for abnormal latent points: Minimise the MSE and BCE

Inference: Obtaining the Frame-level Anomaly Score

- Input: Noise randomly sampled from standard normal
- Condition: past trajectory, length = 'T'
- Output: future trajectory, length = 'T'
- Obtain the corresponding squared difference between prediction and GT
- Average it to obtain the final squared difference for a given time instant $(T+1)$ and a given person (k), $\delta_k(T+1)$
- Obtain $\delta_k(i) \forall\, i \,\epsilon\, T_k, \forall k$. Here T_k is the entire track of person 'k'
- Frame-level anomaly score, $\Delta(t_0)$, at $t = t_0$, is obtained as shown:

$$\Delta(t_0) = \max_{j \in \mathcal{S}(t_0)} \delta_j(t_0) \tag{9}$$

Here $S(t_0)$ refers to the set of all person IDs that appear in the video at $t = t_0$

Results: Visualisation

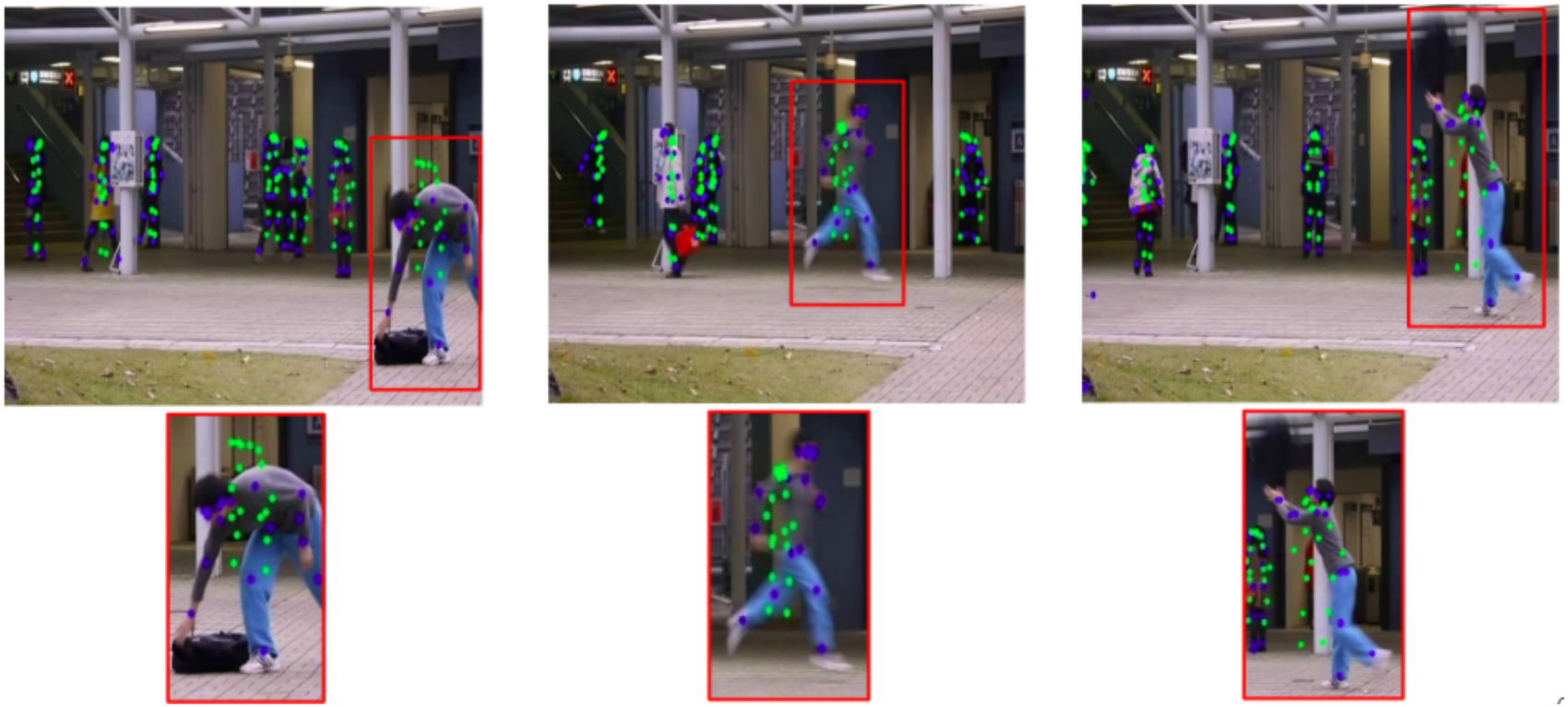


Figure: Green skeleton is from the predicted trajectory and Blue one is from the ground truth. Notice the greater dissimilarity between the two skeletons for abnormal motion/ poses.

Results: Frame-level Anomaly Score Plot

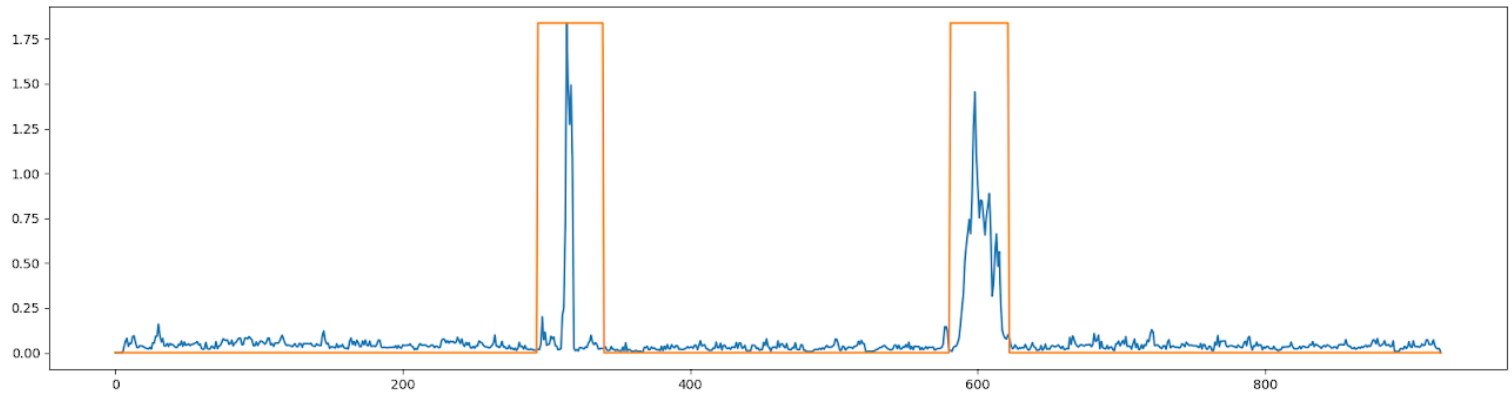


Figure: Frame-level anomaly score plot, Video 3 from the test set, HR-Avenue (HR version of Avenue Dataset[1]). Notice the frame-level anomaly score is lower for normal frames and shoots up for abnormal frames.

Results: AUC Score

	HR-Avenue	HR-ShanghaiTech	HR-IITB
Hasan *et al.* [4]	84.80	69.80	-
Liu *et al.* [2]	86.20	72.70	-
Luo *et al.* [5]	-	-	-
Morais *et al.* [6]	86.30	75.40	68.07
Rodrigues *et al.* [3]*	88.33	**77.04**	-
Ours	**87.78**	75.86	**70.60**

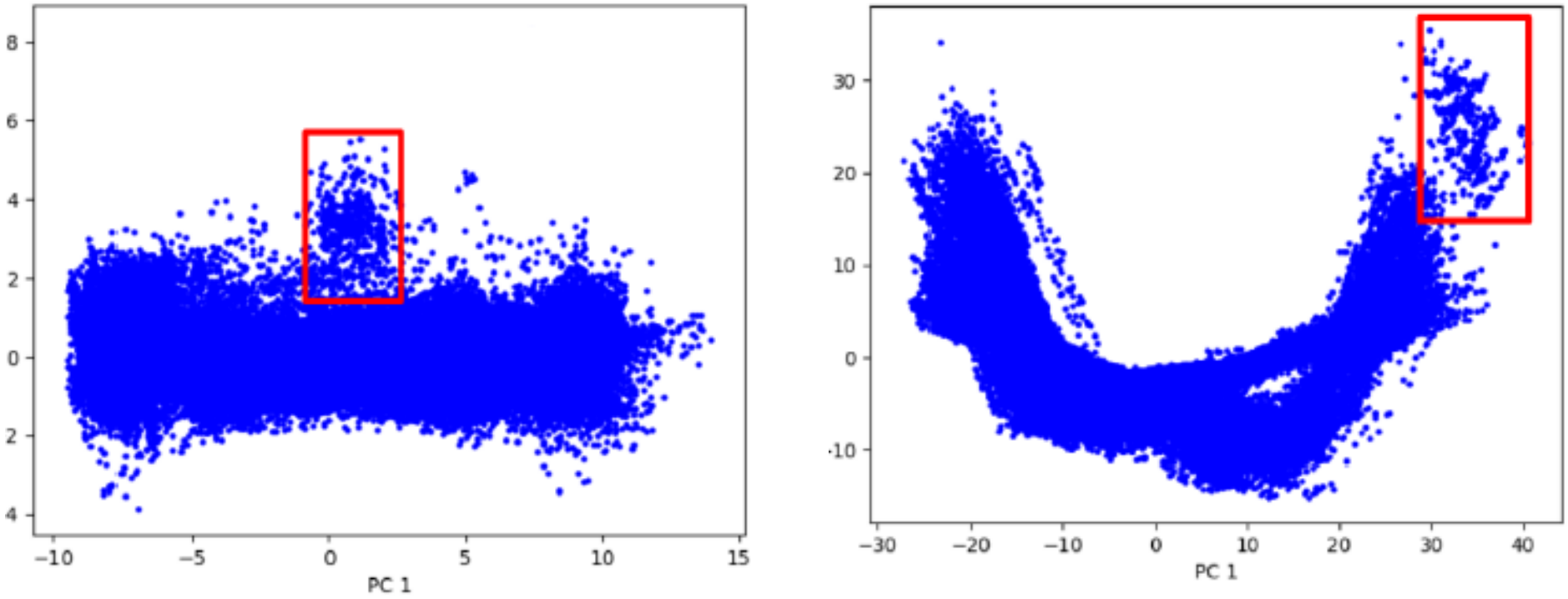
	Avenue	ShanghaiTech	IITB Corridor
Hasan *et al.* [4]	70.20	69.80	-
Liu *et al.* [2]	**84.90**	72.80	64.65
Luo *et al.* [5]	81.71	-	68.00
Morais *et al.* [6]	-	73.40	64.27
Rodrigues *et al.* [3]*	82.85	**76.03**	67.12
Ours	82.10	74.90	**67.43**

Results: Comparison with the SOTA

	T	Predictions/Iteration	AUC
Rodrigues *et al.*[3] **(Multi-timescale)**	3 only	2	72.05%
	3 & 5	4	73.39%
	3,5 & 13	6	75.65%
	3,5,13 & 25	8	77.04%
Ours **(One-timescale)**	7	**1**	75.86%

Table: Frame-level AUC score comparison between [3] and Our method on HR-ShanghaiTech for different timescales

Ablation Study: Effect of Multistage Training



(a) Trained without Stage 3

(b) Trained with Stage 3

Figure: Latent space representation of the test set trajectories obtained from PoseCVAE post- training completion. Notice the increase in the separation between the normal and abnormal trajectory classes after introduction of stage 3 in the training strategy.

Shortcomings: Videos in which we do not perform well

- We do not perform well on Video 25 and Video 32 of HR-Avenue
- We achieve AUC scores of $\approx 36\%$ and $\approx 44\%$ respectively on both of the videos
- If we calculate the AUC score excluding the two videos, we get an overall AUC score of 90.87% (Current: 87.78%)

Reason: Both these videos, the anomaly is due to the person roaming in a restricted area.

- **We accept this as a shortcoming of our framework as we capture only pose based information and discard locality during pre-processing**

HR-IITB Corridor Dataset

We remove all the object driven anomalies from the original IITB-Corridor dataset proposed in [3]

- Test split: 150 videos, Train split: 208 videos
- Activities grouped into different categories such as: Fighting, Chasing, Cycling, Loitering, Sudden Running, Protests, Carrying Objects, Bag Exchange, Playing with a ball and Hiding
- We construct the HR-IITB dataset as shown:
  - Included Videos from IITB-Corridor: Fighting, Chasing, Cycling, Loitering, Sudden Running and Protests. A total of 78 videos
  - Removed Videos from IITB-Corridor: Carrying Objects, Bag Exchange, Playing with a ball and Hiding. A total of 72 videos

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The End