2021 ICCV OCTOBER 11-17 VIRTUAL

A Hybrid Video Anomaly Detection Framework via Memory-Augmented Flow Reconstruction and Flow-Guided Frame Prediction





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Video Anomaly Detection

- Motivation
  - Surveillance cameras are widely used.
  - VAD is an essential task to save human labor.

Airport

Bank

School

Video Anomaly Detection

- Goal: to identify unexpected behaviours in a video.

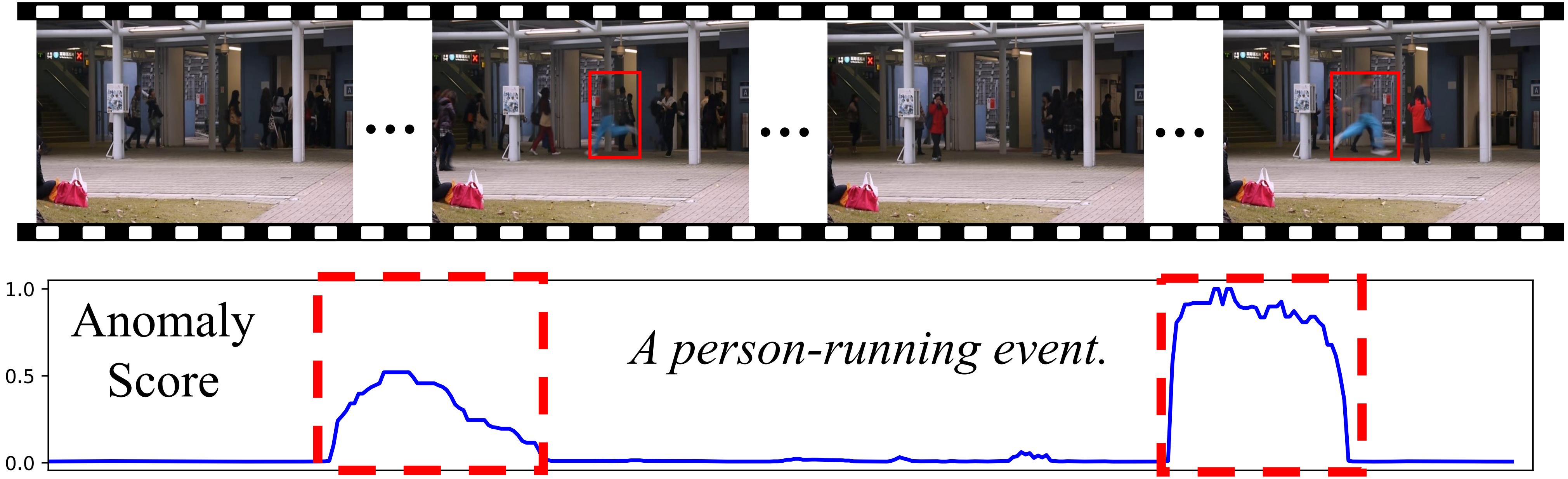
Ped2[1] test video #04

Avenue[2] test video #04

[1] http://www.svcl.ucsd.edu/projects/anomaly/dataset.html
[2] http://www.cse.cuhk.edu.hk/leojia/projects/detectabnormal/dataset.html

Video Anomaly Detection

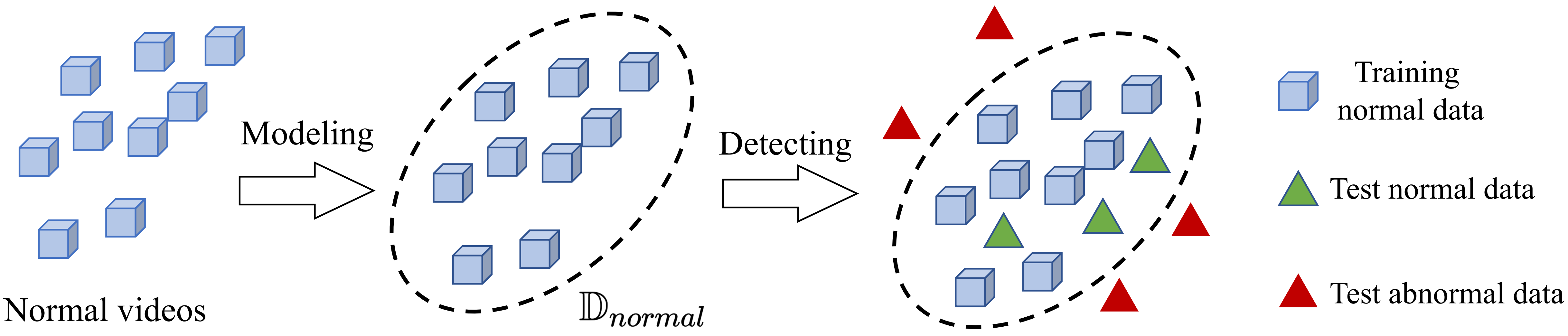
- Goal: to identify unexpected behaviours in a video.



- Useful but challenging task.

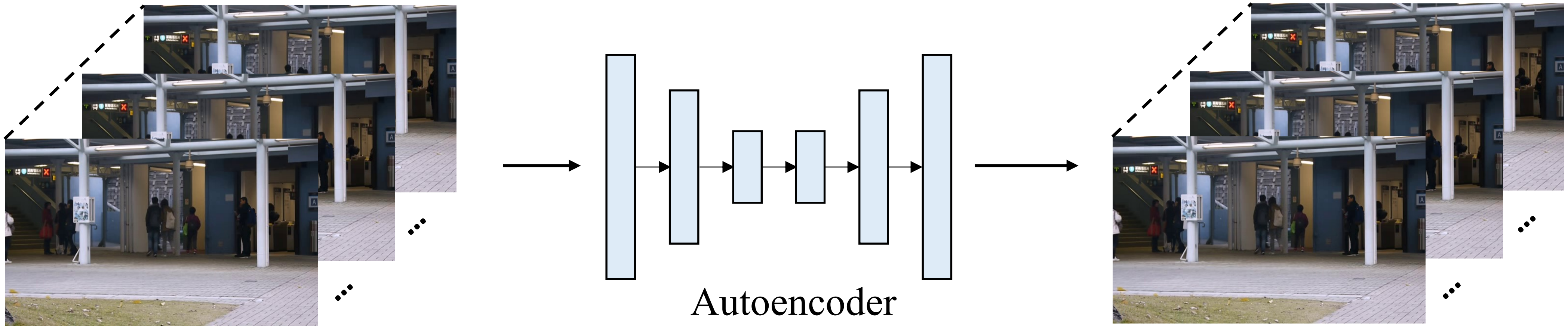
Video Anomaly Detection

- Challenges
  - Anomaly rarely happens.
  - What is anomaly?
- Solution



Related work

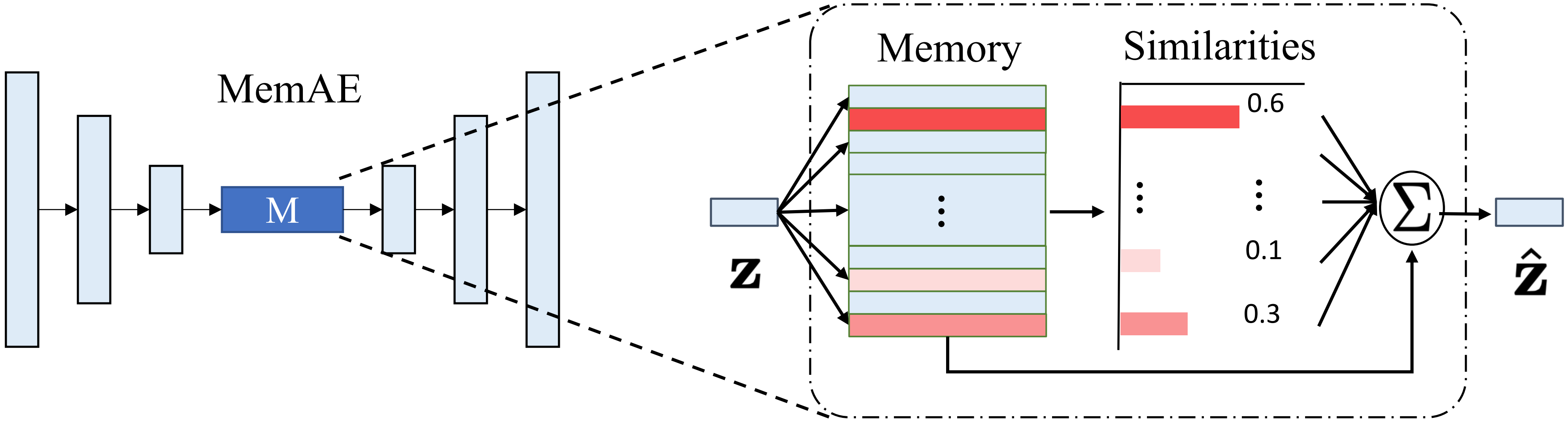
- Reconstruction-based method
  - Train AE with L1 or L2 loss.



  - Assume the anomalies lead to larger reconstruction errors.

Related work

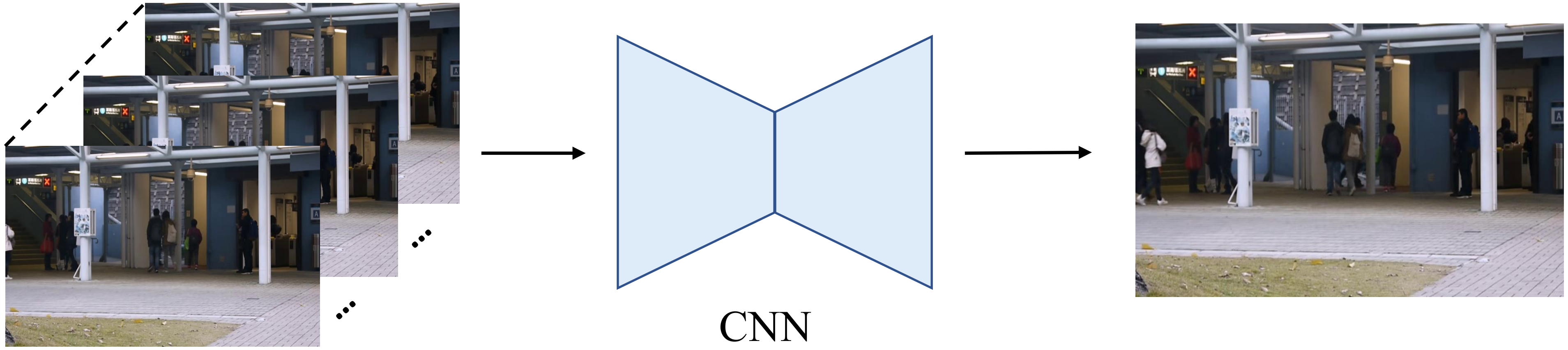
- Reconstruction-based method
  - Memory-augmented AE to mitigate the ``over-generalization`` problem.



$$\hat{\mathbf{z}} = \mathbf{wM} = \sum_{i=1}^{N} w_i \mathbf{m}_i \qquad w_i = \frac{\exp(d(\mathbf{z}, \mathbf{m}_i))}{\sum_{j=1}^{N} \exp(d(\mathbf{z}, \mathbf{m}_j))}$$

Related work

- Prediction-based method
  - Take the temporal information into consideration [Liu. et al, 2018].



$I_1, I_2, \ldots, I_t$ $\qquad$ I_{t+1}

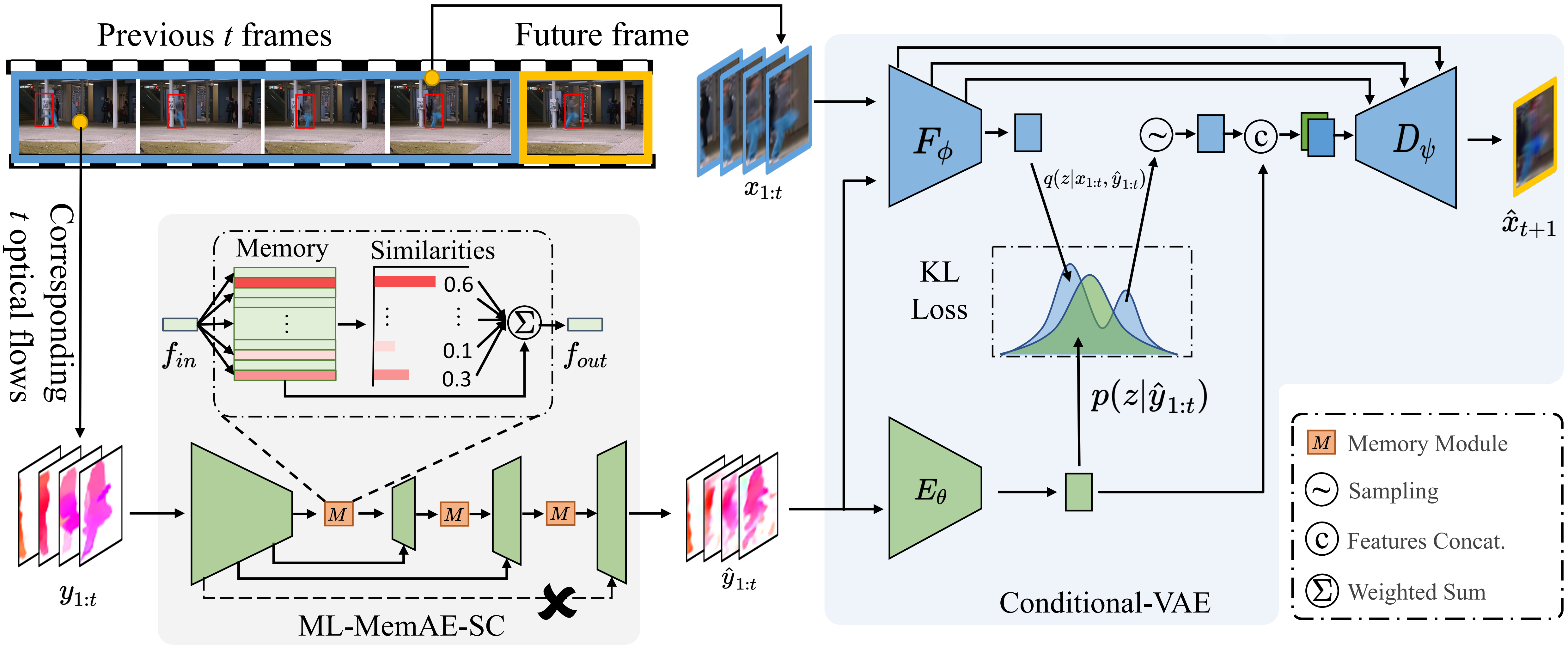
$$\mathcal{L} = ||\hat{I}_{t+1} - I_{t+1}||_2^2$$

[Future Frame Pred.] W. Liu et.al, CVPR, 2018

Our approach

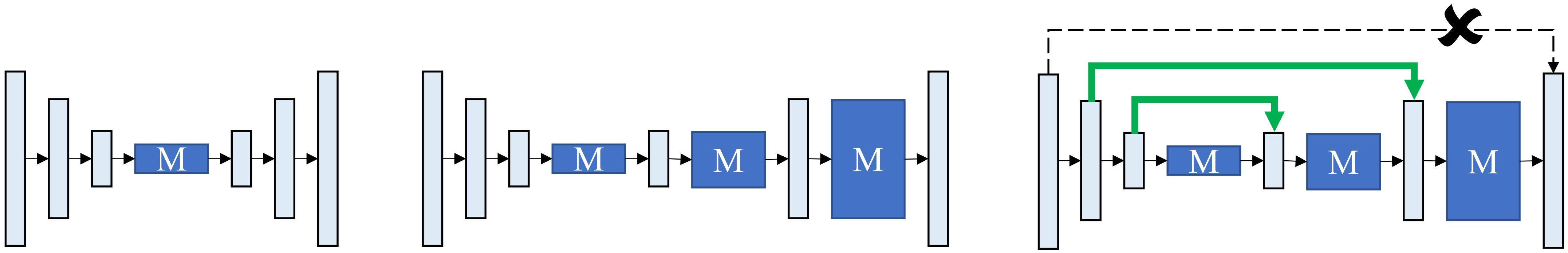
- Insight
  - Previous work rarely exploits the **consistency between flows and frames**.
  - For an abnormal event, what if we manipulate the flows beforehand, and try to **produce a poor prediction?**
  - Propose to **reconstruct the flows first**, then using the reconstructed flows as condition to predict future frame.

HF²-VAD pipeline



ML-MemAE-SC

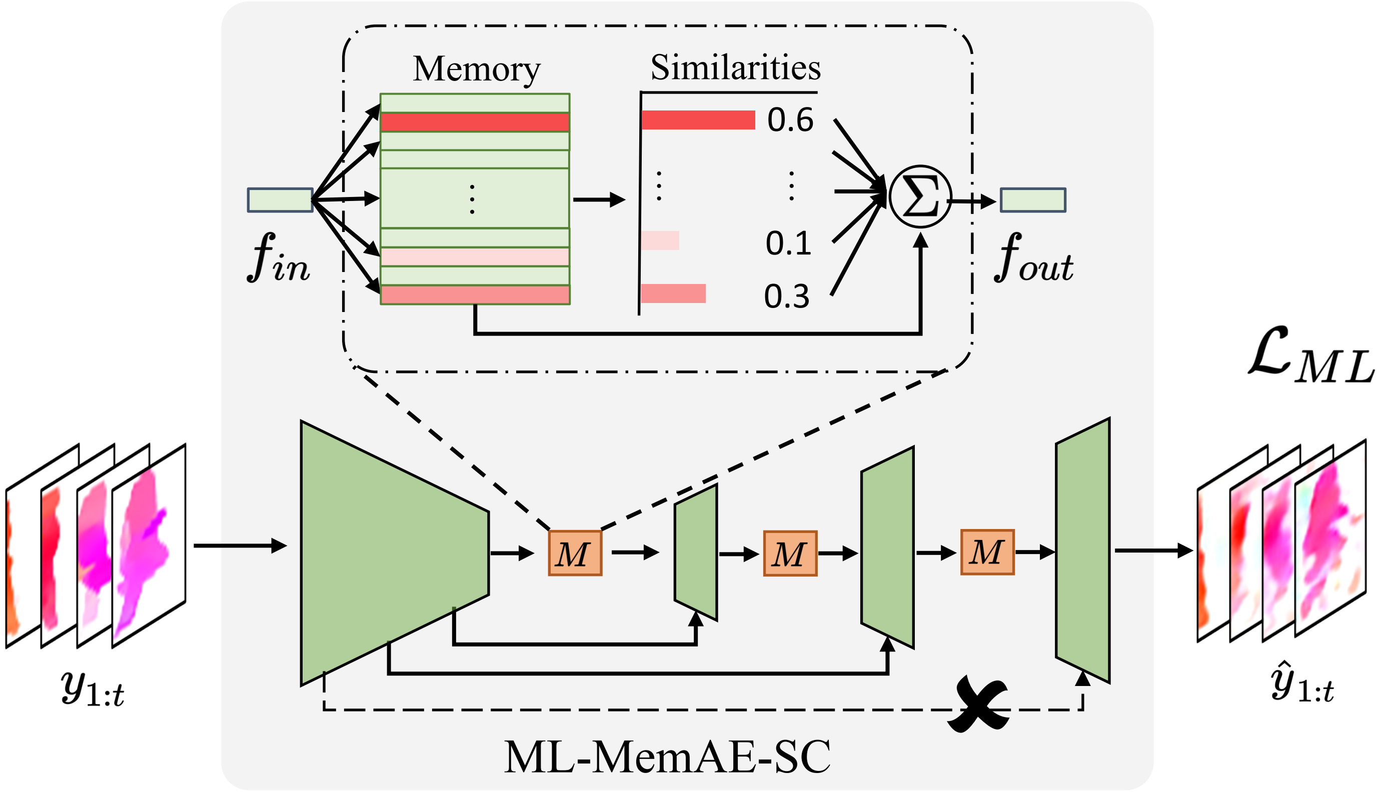
- Observations
  - Memory only in bottleneck cannot remember all normal patters.
  - AE with multi-level memories (ML-MemAE) leads to degradation.
  - Skip connection helps.



(a) MemAE (b) ML-MemAE (c) ML-MemAE-SC

ML-MemAE-SC

- Flow reconstruction objective



$$\mathcal{L}_{\text{recon}} = \|y_{1:t} - \hat{y}_{1:t}\|_2^2$$

$$\mathcal{L}_{\text{ent}} = \sum_{i=1}^{M} \sum_{k=1}^{N} -\hat{w}_{i,k} \log(\hat{w}_{i,k})$$

$$\mathcal{L}_{ML-\text{MemAE-SC}} = \lambda_{\text{recon}} \mathcal{L}_{\text{recon}} + \lambda_{\text{ent}} \mathcal{L}_{\text{ent}}$$

CVE for prediction

- Formulation
  - Let $x_{1:t}$ and x_{t+1} be the previous and future frame, $y_{1:t}$ be the reconstructed flows, z be the hidden variables that control the content information:

$$\log p(x_{t+1} \mid y_{1:t}) \geq \mathbb{E}_q \log \frac{p(x_{t+1} \mid z, y_{1:t}) p(z \mid y_{1:t})}{q(z \mid x_{t+1}, y_{1:t})} \quad \text{(Evidence Lower Bound)}$$

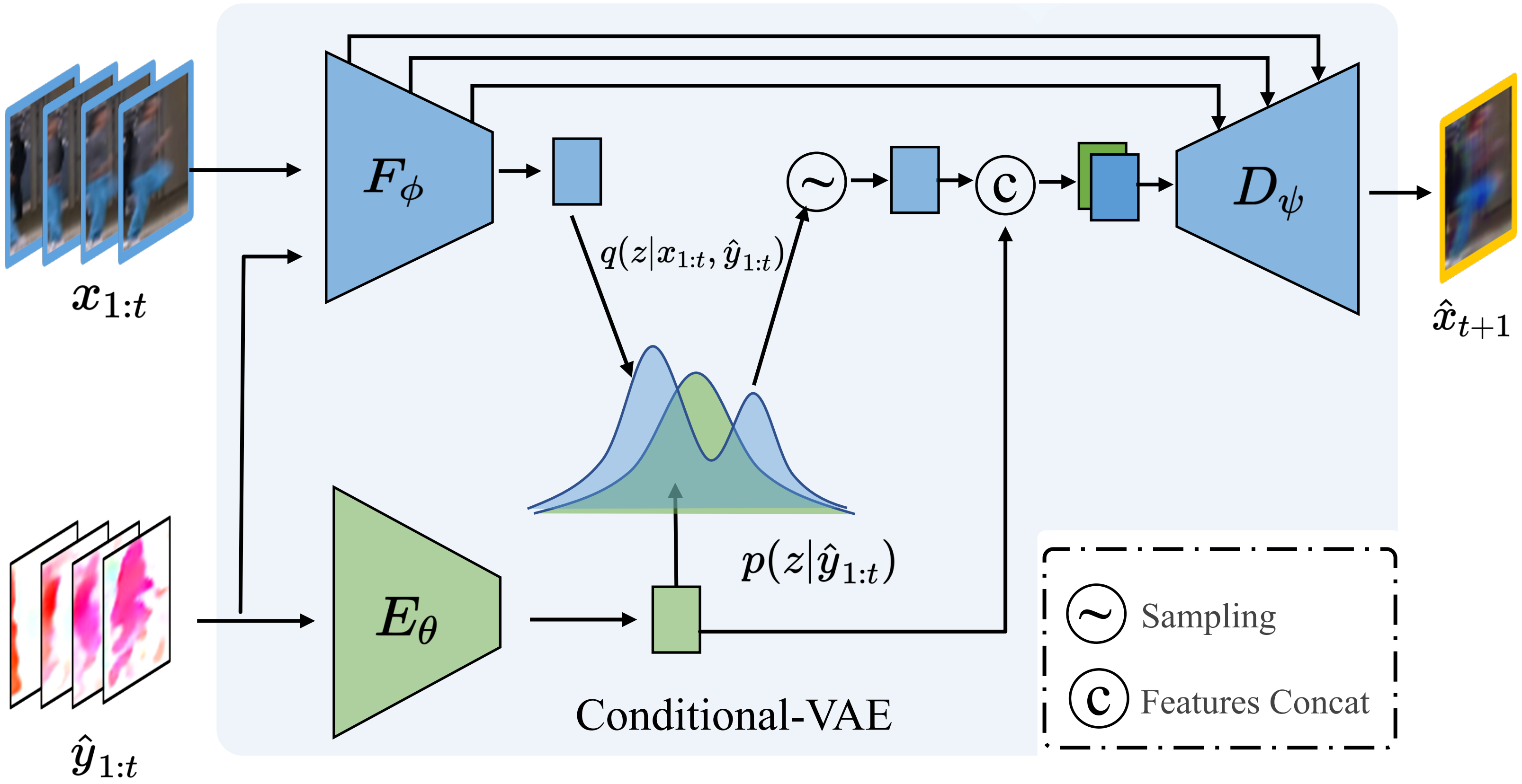
$$\approx \mathbb{E}_q \log \frac{p(x_{t+1} \mid z, y_{1:t}) p(z \mid y_{1:t})}{q(z \mid x_{1:t}, y_{1:t})} \quad \text{(Short Duration Assumption)}$$

$$= -KL[q(z \mid x_{1:t}, y_{1:t}) \| p(z \mid y_{1:t})] + \mathbb{E}_q[\log p(x_{t+1} \mid z, y_{1:t})]$$

  - Resort the conditional Variational Autoencoder (CVAE).

CVE for prediction

- Frame prediction objective



$$\mathcal{L}_{CVAE} = KL[q(z \mid x_{1:t}, y_{1:t}) || p(z \mid y_{1:t})] + \|x_{t+1} - \hat{x}_{t+1}\|_2^2$$

$$\mathcal{L}_{gd}(X, \hat{X}) = \sum_{i,j} \left| |X_{i,j} - X_{i-1,j}| - |\hat{X}_{i,j} - \hat{X}_{i-1,j}| \right| \left| |X_{i,j} - X_{i,j-1}| - |\hat{X}_{i,j} - \hat{X}_{i,j-1}| \right|$$

$$\mathcal{L} = \lambda_{CVAE} L_{CVAE} + \lambda_{gd} \mathcal{L}_{gd}(\hat{x}_{t+1}, x_{t+1})$$

Anomaly detecting

- At test time, the anomaly score is composed of two parts:
  - Reconstruction error $S_r = \|\hat{y}_{1:t} - y_{1:t}\|_2^2$
  - Prediction error $S_p = \|\hat{x}_{t+1} - x_{t+1}\|_2^2$
- Frame-level anomaly score

$$S_{O_i} = w_r \cdot S_r + w_p \cdot S_p \qquad S = max\{S_{O_1}, S_{O_2}, \ldots S_{O_N}\}$$

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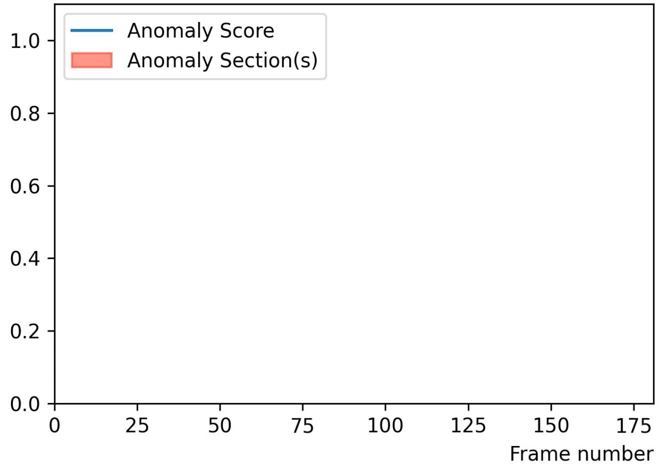
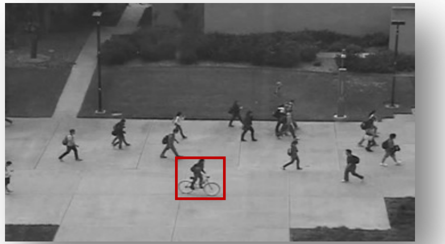


Experimental results

- Datasets

a) UCSD Ped2



b) CUHK Avenue

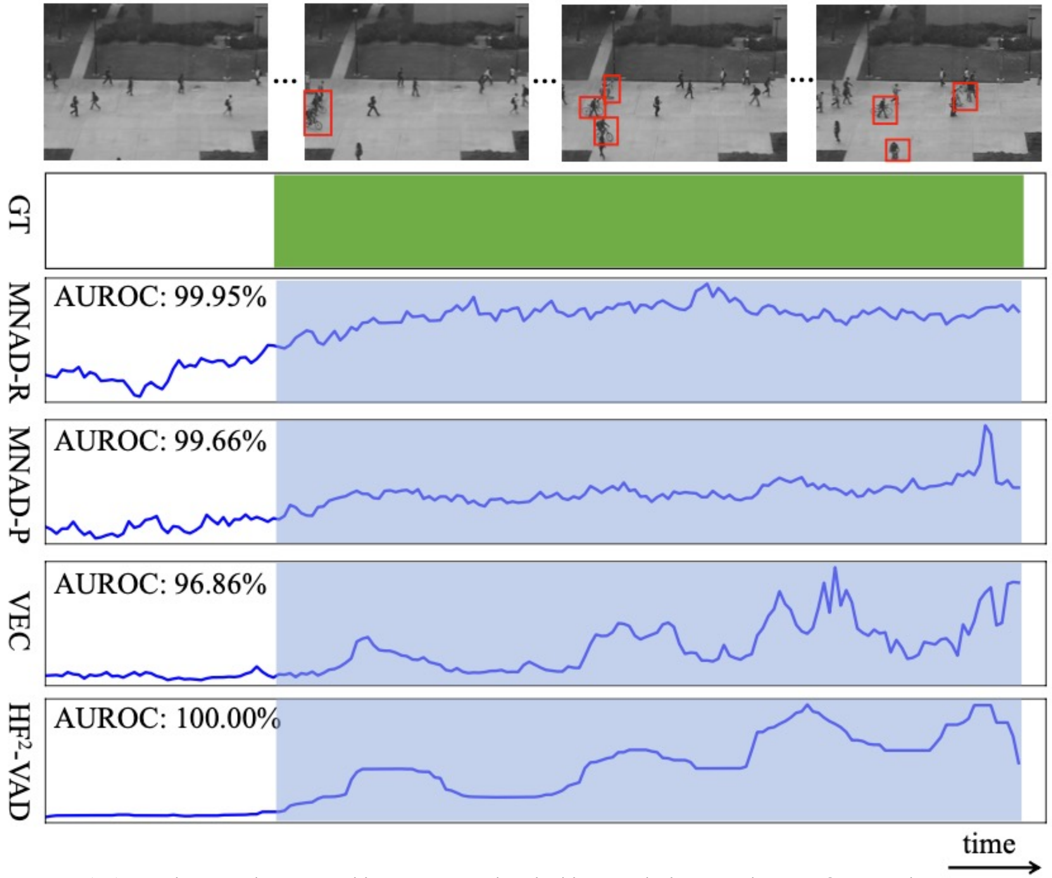
c) ShanghaiTech

- Quantitative results

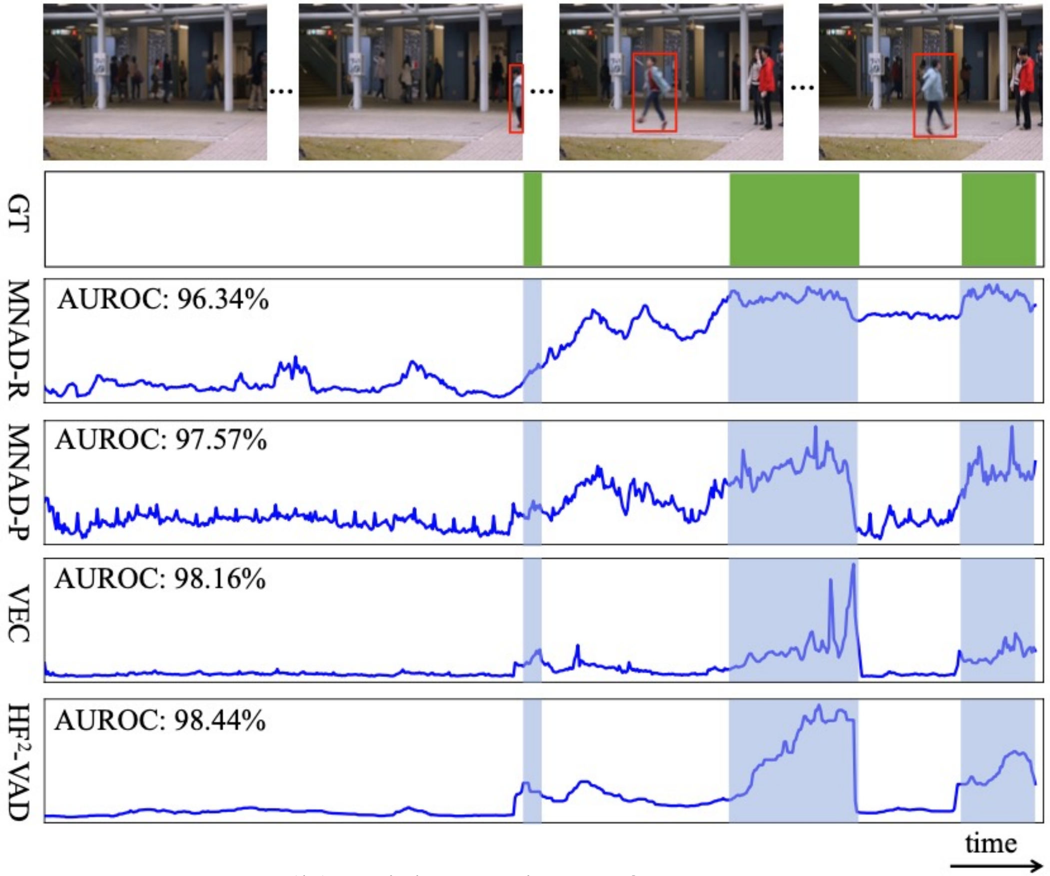
	Method	UCSD Ped2	CUHK Avenue	SHTech
Recon.	Conv-AE [11]	90.0	70.2	-
	ConvLSTM-AE [32]	88.1	77.0	-
	GMFC-VAE [7]	92.2	83.4	-
	MemAE [8]	94.1	83.3	71.2
	MNAD-R [39]	90.2	82.8	69.8
Pred.	Frame-Pred. [26]	95.4	85.1	72.8
	Conv-VRNN [31]	96.1	85.8	-
	MNAD-P [39]	97.0	88.5	70.5
	VEC [50]	97.3	90.2	74.8
Hybrid	ST-AE [53]	91.2	80.9	-
	AMC [37]	96.2	86.9	-
	AnoPCN [49]	96.8	86.2	73.6
	HF^2-VAD w/o FP	98.8	86.8	73.1
	HF^2-VAD w/o FR	94.5	90.2	76.0
	HF^2-VAD	**99.3**	**91.1**	**76.2**

Experimental results

- Qualitative results



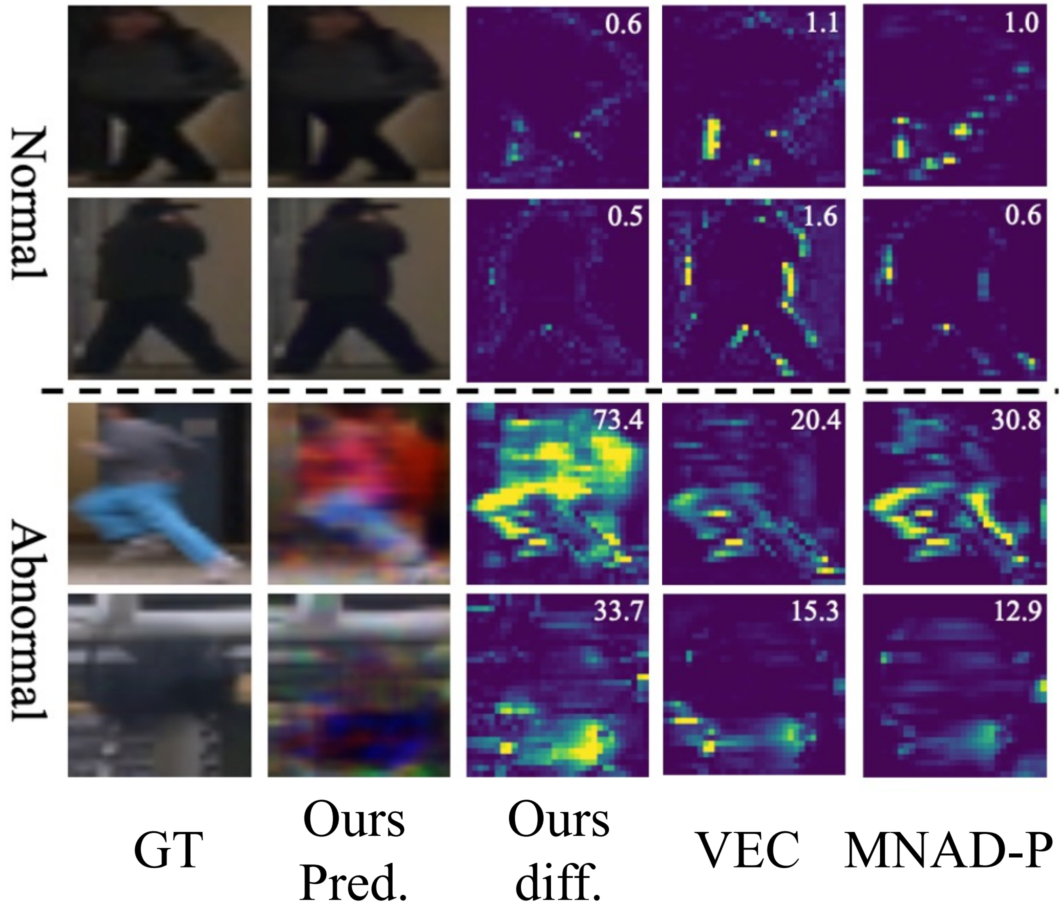
(a) Skateboarding and riding bicycle of Ped2.



(b) Kid running of Avenue.

Experimental results

• Visualization



• Ablation study

Table 2. Ablation study results on UCSD Ped2 [35] dataset. The anomaly detection performance is reported in terms of AUROC ↑ (%). Number in bold indicates the best result.

	Memory-augmented Reconstruction Models			Prediction Models		AUROC
				VAE	CVAE	
Flow	✓					96.27
		✓				97.75
			✓			98.81
Frame				✓		89.96
					✓	94.48
Hybrid	✓				✓	96.91
		✓			✓	98.28
			✓		✓	**99.31**

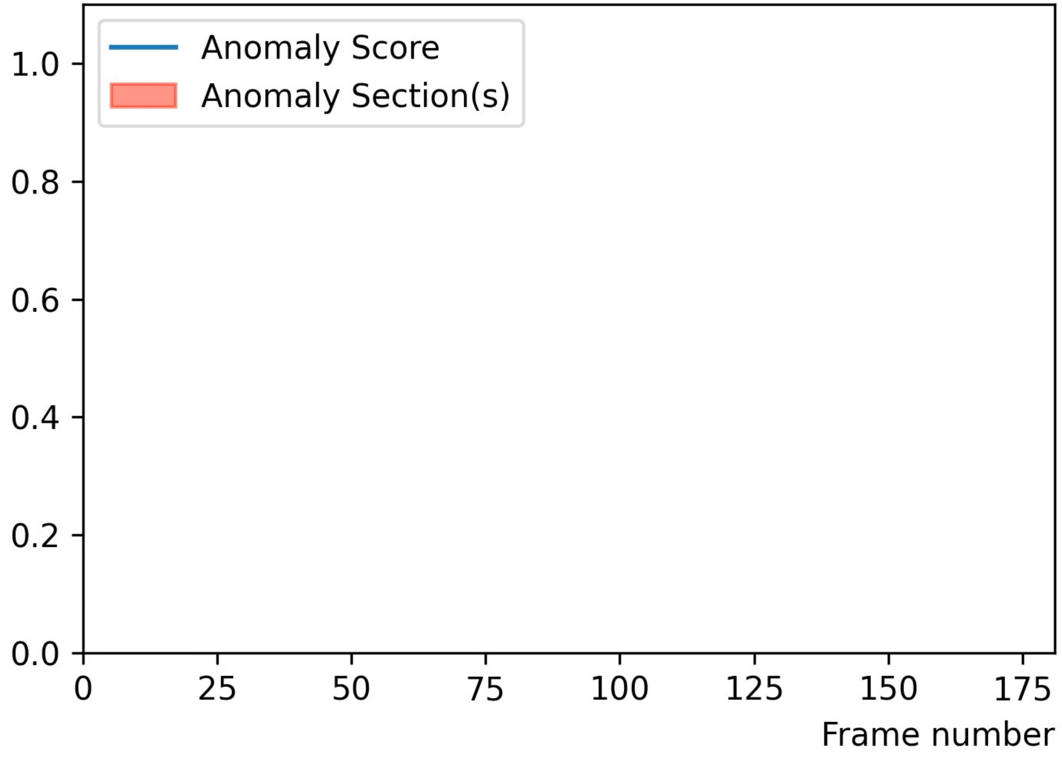
[VEC] G. Yu et.al, ACM-MM, 2020
[MNAD-P] H Park et.al, CVPR, 2020

Video anomaly detection demo

- On Ped2 dataset

Ped2 Test Video 04

Abnormal events: unusual lorry and bicycle.

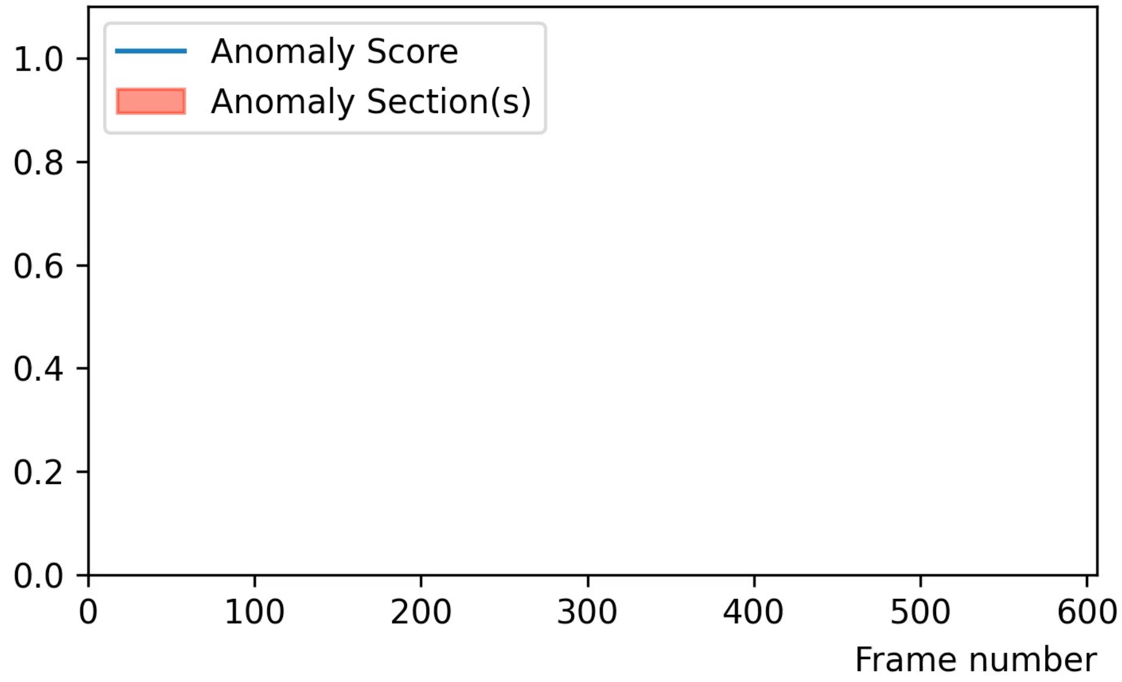


Video anomaly detection demo

- On Avenue dataset

Avenue Test Video 07

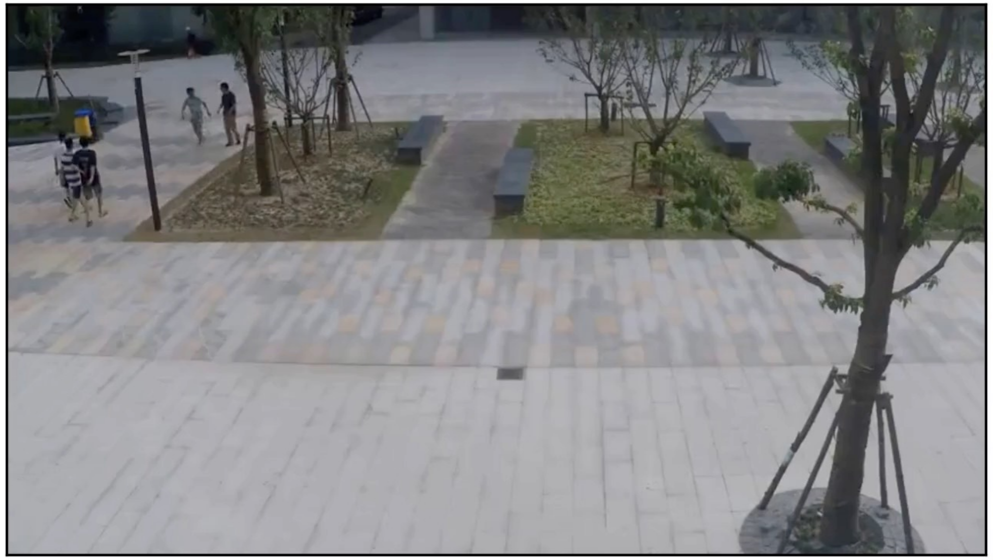
Abnormal event: kid running.



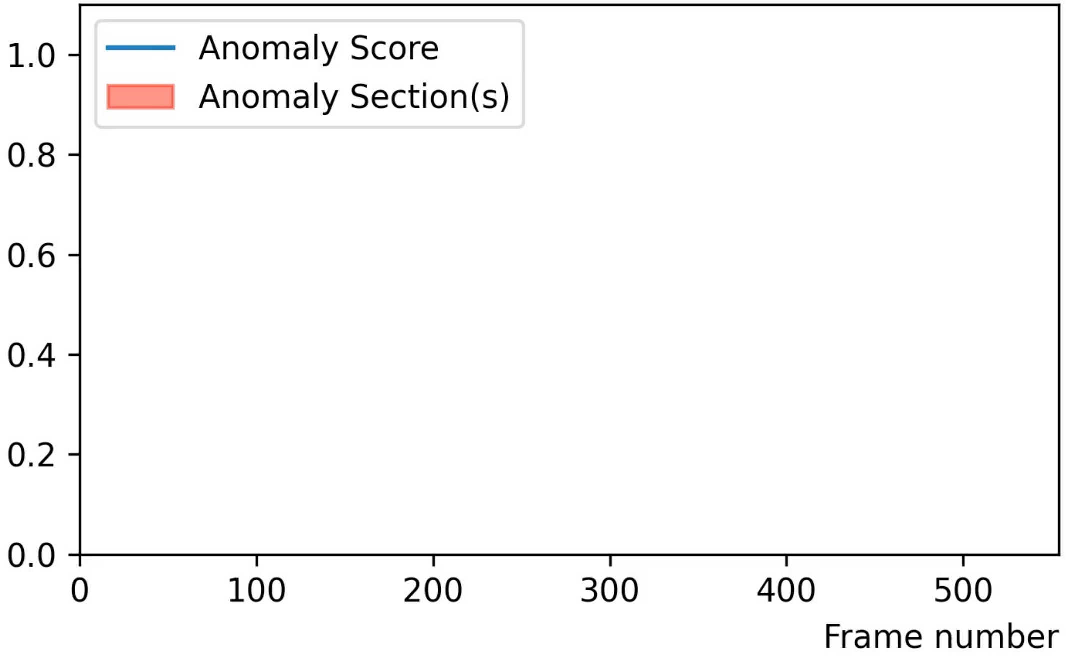
Video anomaly detection demo

- On ShanghaiTech dataset

ShanghaiTech Test Video 04_0001



Abnormal events: chasing and jumping.



Conclusion

- Design the Multi-Level Memory Autoencoder with Skip Connections (ML-MemAE-SC) for flow reconstruction.
- Propose to model the consistency between flows and frames by leveraging the conditional Variational Autoencoder (CVAE).
- Design a novel *hybrid* framework in a combination of *flow* reconstruction and flow-guided *frame* prediction, named as *HF*^{2}*-VAD*.

Project QR Code

https://github.com/LiUzHiAn/hf2vad

Thank you!