

Video Surveillance anomaly detection using Autoencoders

Ernesto Cruz-Esquivel | Advisor: Zobeida Guzman-Zavaleta
Universidad de las Americas Puebla, Mexico



Introduction

- Video surveillance monitors scenes to detect **critical events**, like accidents or crimes
- Such anomalies are deviations from the usual or the considered normal and are **context dependent**
- Current video anomaly detection methods use a **high amount of computational resources**

The **main purpose** of this research is to propose an architecture based on Autoencoders **balancing the time-accuracy tradeoff** in comparison with expensive related methods. The improvement of **spatiotemporal feature extraction for video data** is a priority.

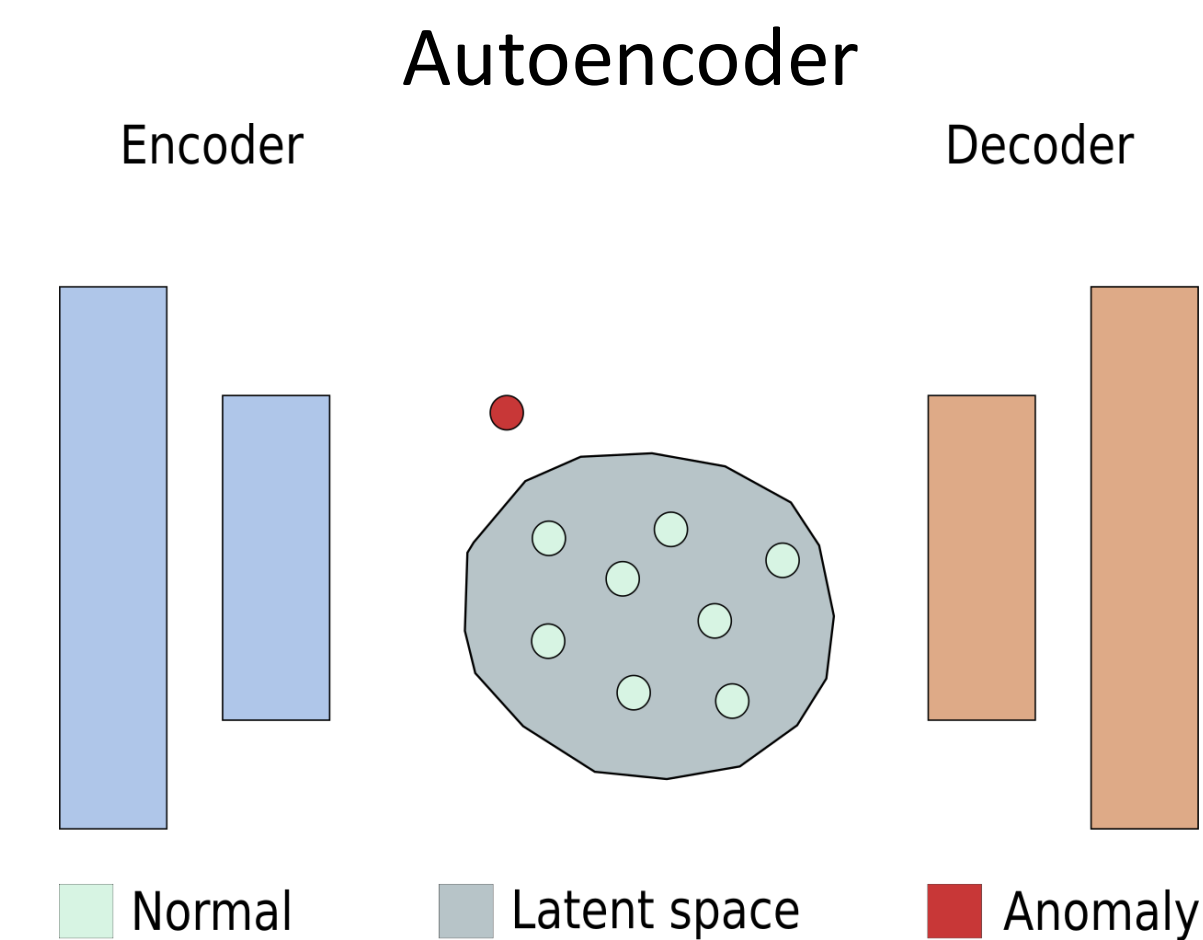


Fig. 1 Anomaly detection using Autoencoders

Autoencoder **trained** using only **normal data**. Trained autoencoder cannot **encode or decode anomalies**.

Acknowledgments

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Contact Info:

Ernesto Cruz Esquivel – ernesto.cruzel@udlap.mx

Initial proposal

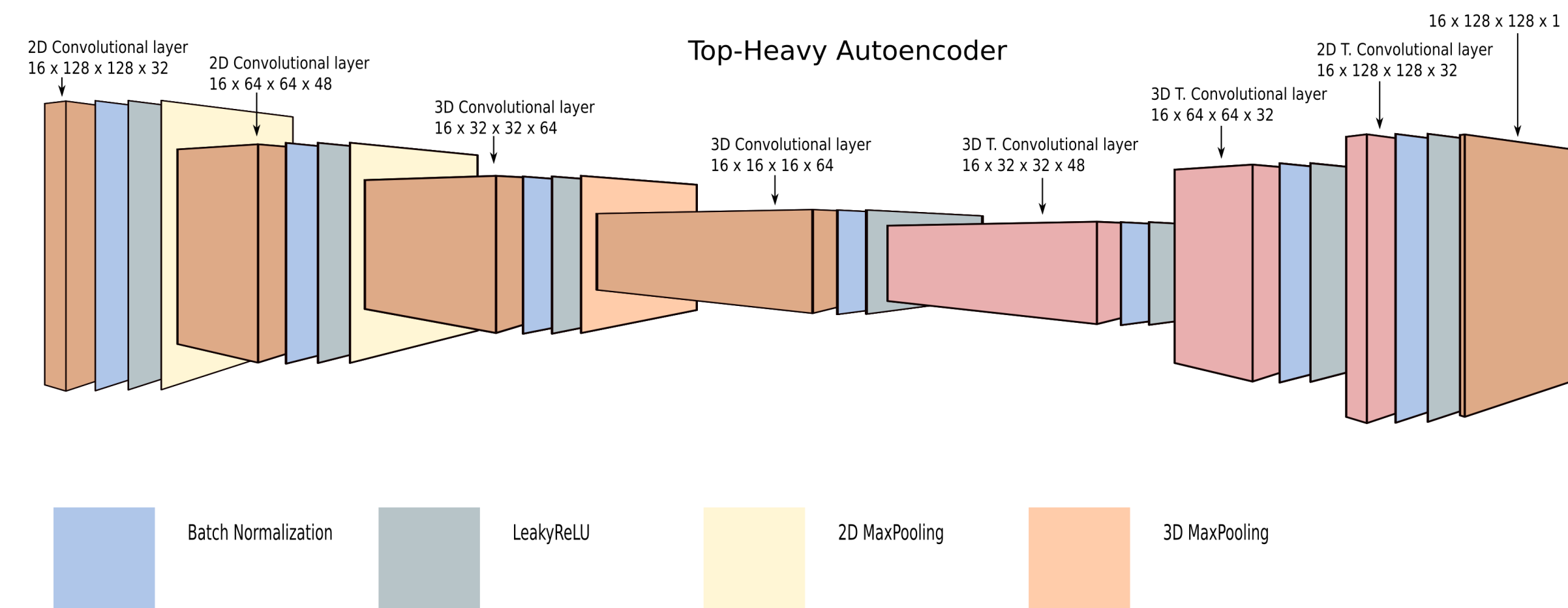


Fig. 2 Top-Heavy Autoencoder combines 2D and 3D convolutional layers and it was used for the tested models.

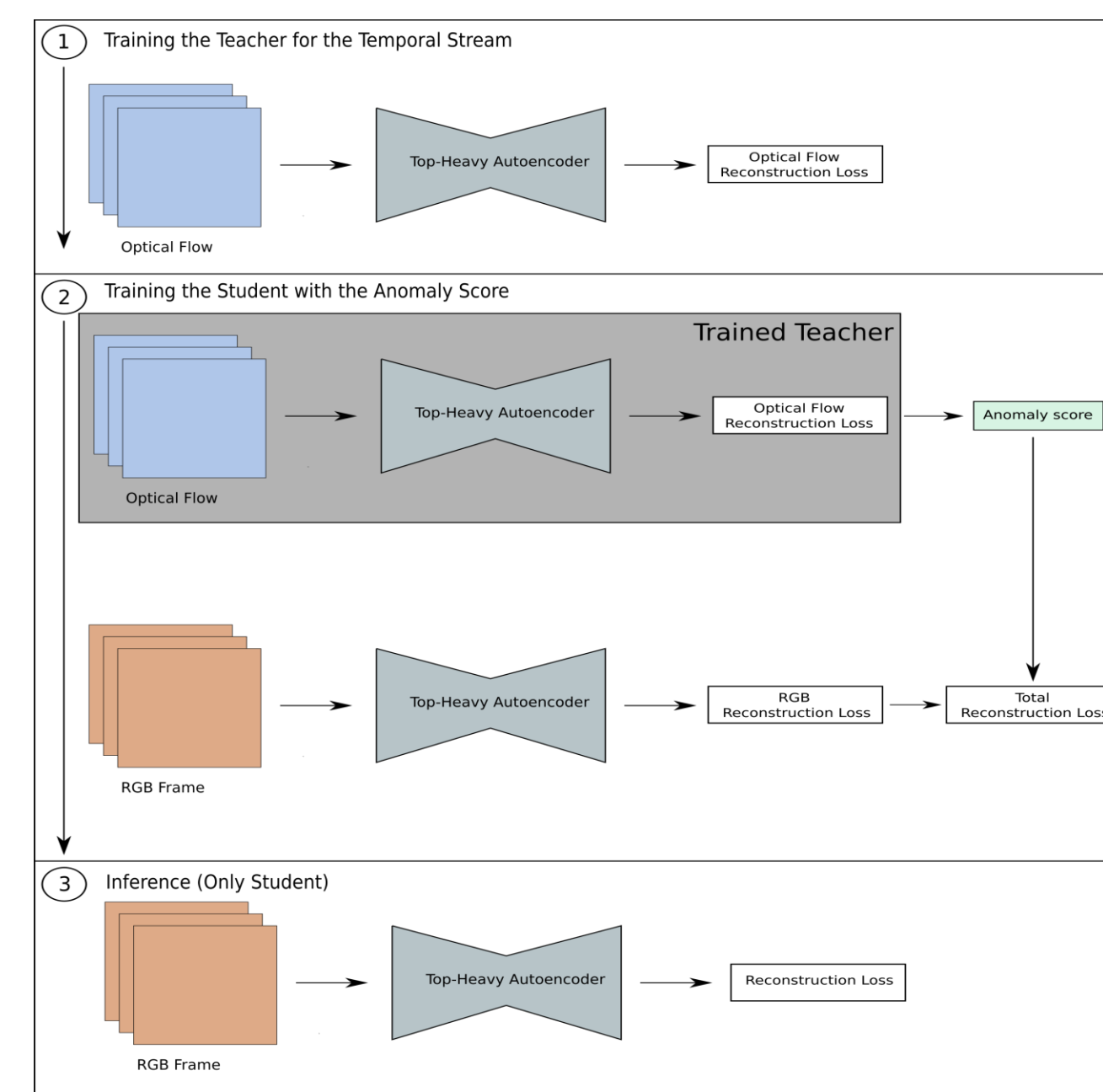


Fig. 3 Anomaly score distillation pipeline

Anomaly score distillation

- Extract **spatiotemporal features** using a single network
- $s(\theta, x^{(i)}) = [L_t(x^{(i)}) - L_s(x^{(i)}; \theta)]^2$
Temporal reconstruction loss L_t , Spatial reconstruction loss L_s , Training parameters θ , Dataset $x^{(i)}$
- Anomaly score increases when there exists a **difference between the spatial and temporal reconstruction loss**

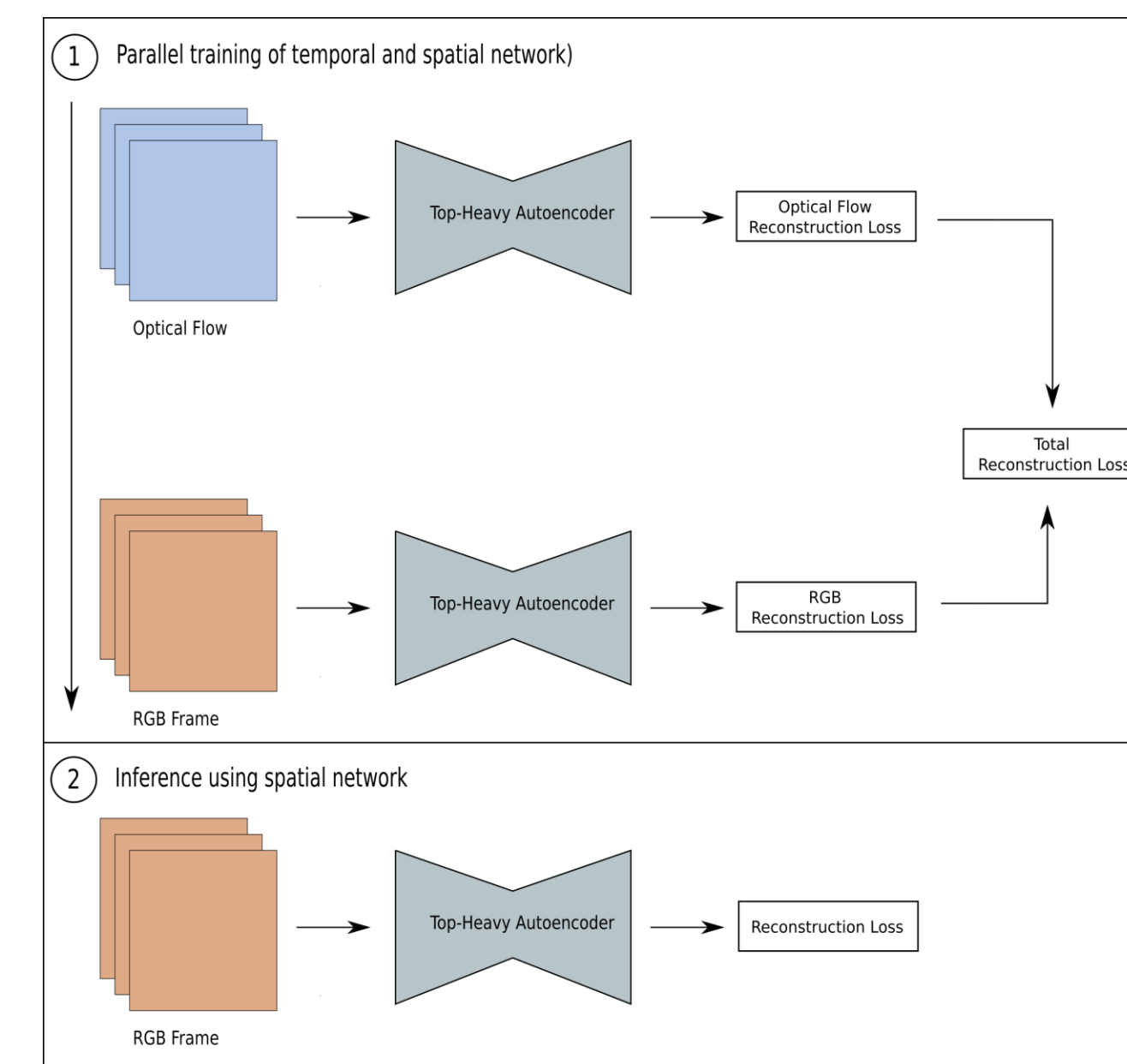


Fig. 4 Joint spatiotemporal training pipeline

Joint spatiotemporal training

- Extract **spatiotemporal features** using a single network
- $L(\theta_1, \theta_2) = L_s(\theta_1) + [L_s(\theta_1) * L_t(\theta_2)]$
Temporal reconstruction loss L_t , Spatial reconstruction loss L_s , Spatial training parameters θ_1 , Temporal training parameters θ_2
- Parallel training of the **temporal and spatial stream**

Results

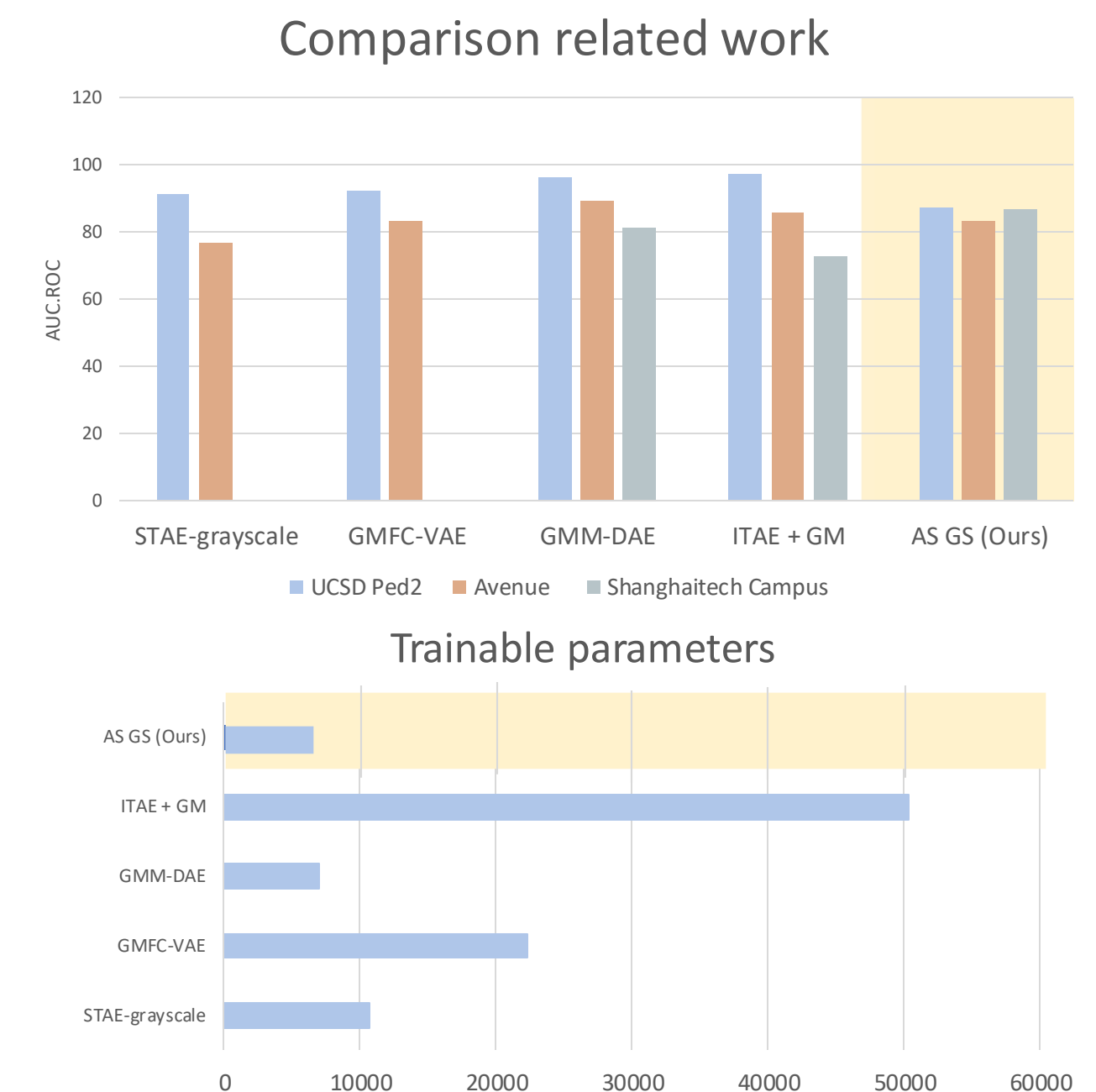


Fig. 5 Comparison against related work of AUC-ROC and trainable parameters. Our work highlighted in yellow background.

- Results of **ShanghaiTech Campus** are the best of related work
- The least quantity of **trainable parameters**

Conclusions

- Top-Heavy Autoencoder** uses only the **57%** of the trainable parameters compared to the 3D autoencoder with an average absolute difference of the **AUC-ROC** between both models of **1.2**
- The **AUC-ROC** difference between **Anomaly Score** and **Joint spatiotemporal** training methods has an average of **1.12**
- The results show a slight improvement in **temporal features extraction** and the extraction of more defining temporal features must be addressed for future work.

References

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