



Learning Traffic Anomalies from Generative Models on Real-Time Observations

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Traffic Anomaly Detection Setup

- Detection of traffic anomalies → crucial for:
 - Effective urban traffic management
 - Congestion mitigation
 - Responding to and preventing accidents
- Real-time, minute-by-minute observations from **42 traffic cameras** across Gothenburg, Sweden
- Preprocessing → **Flow** metric representing vehicle density: number of detected vehicles / maximum vehicle capacity

$$\text{flow} = \frac{\text{number of detected vehicles}}{\text{maximum vehicle capacity}}$$



STGAN Framework

Capturing Spatiotemporal Features

- Results with Spatiotemporal Graph Convolutional Adversarial Network (**STGAN**)
- STGAN combines:
 - **Graph Neural Networks (GNNs)**
 - **Long Short-Term Memory (LSTM)**
- To capture complex spatial and temporal dependencies in traffic data

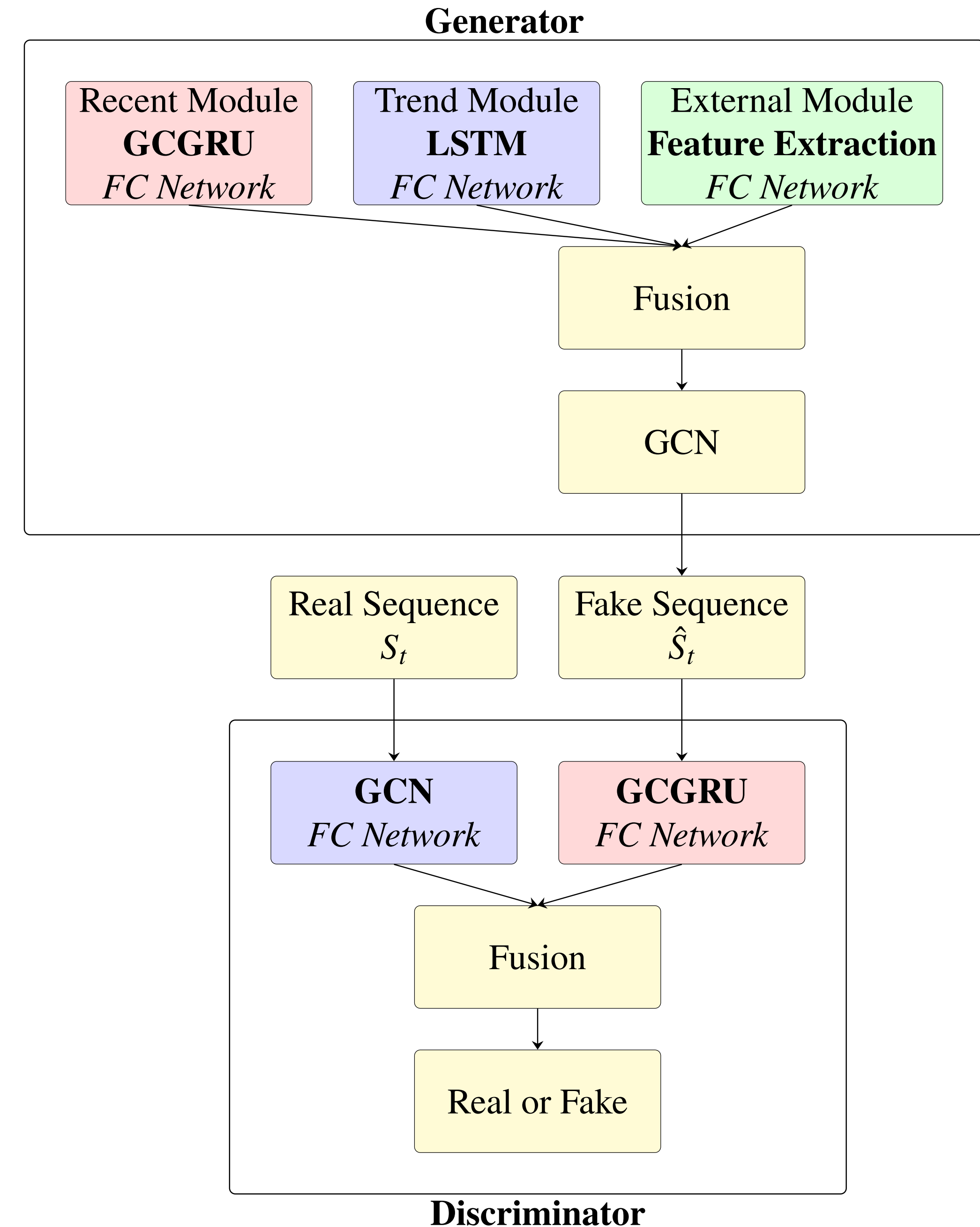
STGAN Framework

Generator and Discriminator

- Traffic network: weighted graph $G = (V, E, \mathbf{W})$

$$\mathbf{W}_{ij} = \begin{cases} \exp\left(-\frac{\text{dist}(v_i, v_j)^2}{\sigma^2}\right), & \text{if } (i, j) \text{ adjacent} \\ 0, & \text{otherwise} \end{cases}$$

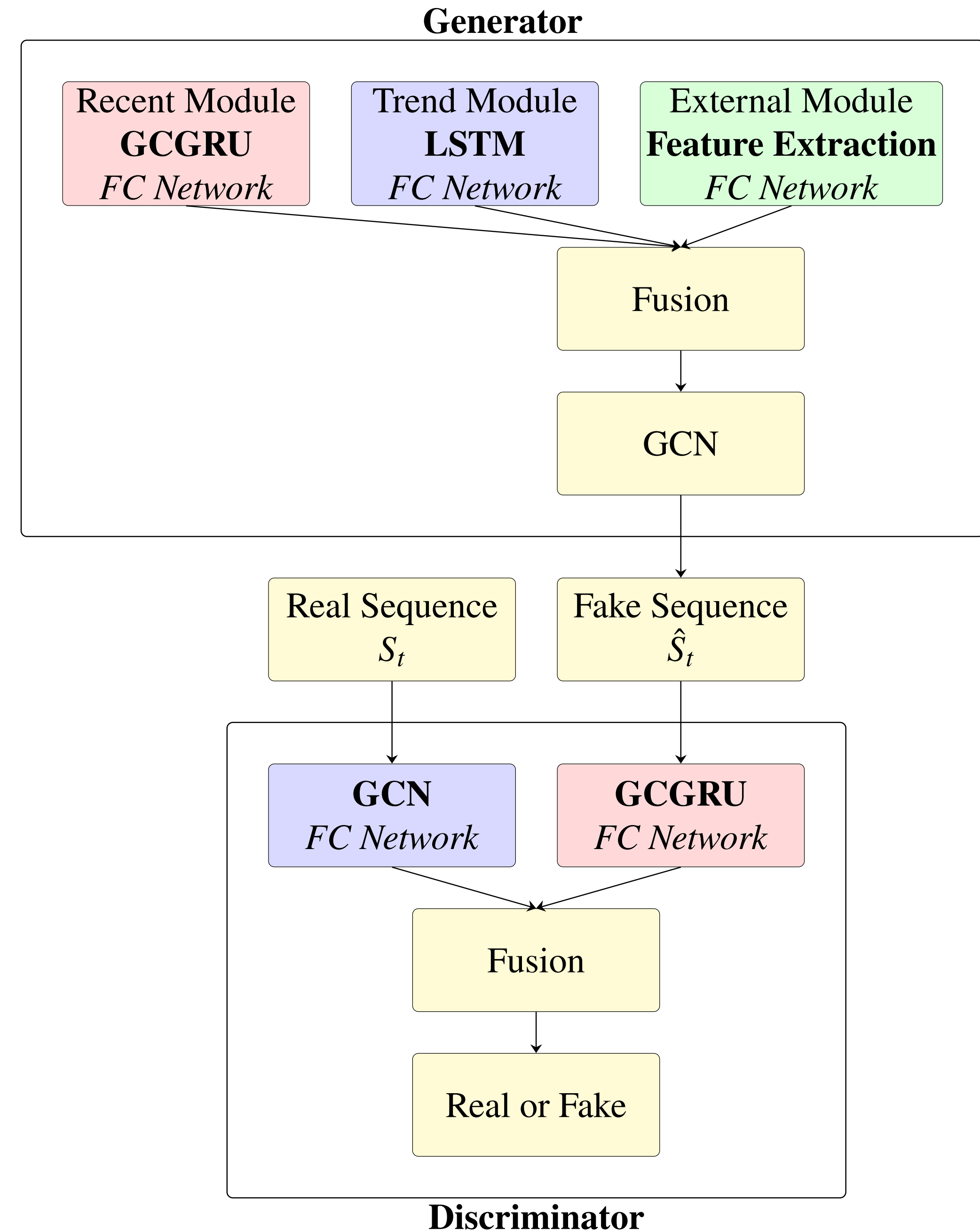
- Spatiotemporal Generator:** Generates predicted sequences of traffic data
- Spatiotemporal Discriminator:** Distinguishes between real and generated sequences



STGAN Framework

Generator Modules

- **Recent Module:** Captures short-term spatiotemporal dependencies using a Graph Convolutional Gated Recurrent Unit (**GCGRU**)
- **Trend Module:** Learns long-term temporal patterns using an LSTM network
- **External Module:** Incorporates external factors (e.g., time of day, day of the week) using a fully connected layer
- These inputs are fused and passed through a Graph Convolutional Networks (**GCN**) to model spatial dependencies, generating a fake sequence
- The discriminator, using GCGRU and GCN modules, evaluates the generated sequence against real sequences



STGAN Framework

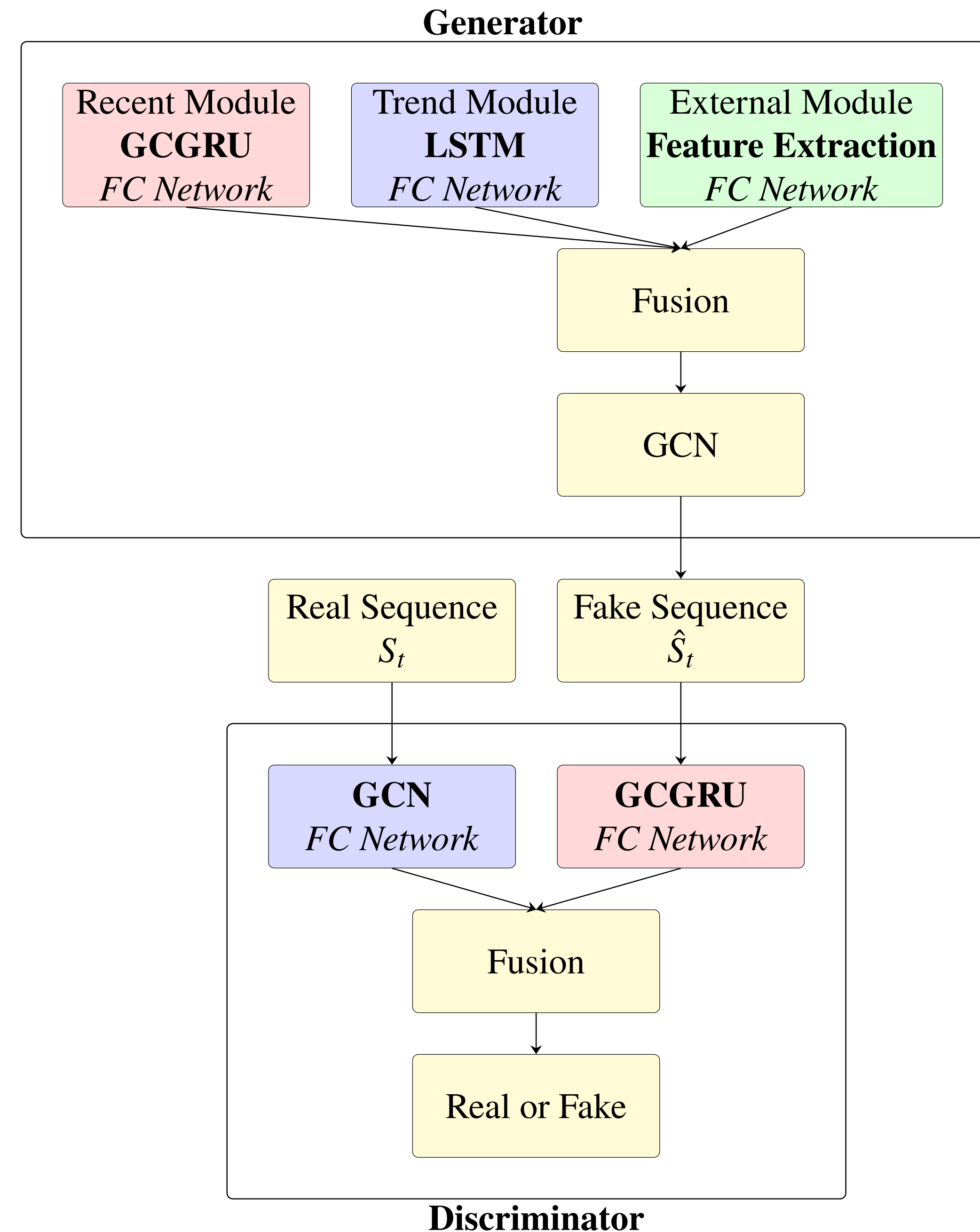
Anomaly Scores

- Anomalies are detected by comparing the **generated data** to the **real data** and assessing the discriminator's confidence
- Anomaly score:** combine discriminator error and generator error

$$s_G(v, t) = \|G_\theta(v, t) - \mathbf{X}_{v,t}\|^2$$

$$s_D(v, t) = D_\phi(\mathbf{S}_{v,t}) - D_\phi(\hat{\mathbf{S}}_{v,t})$$

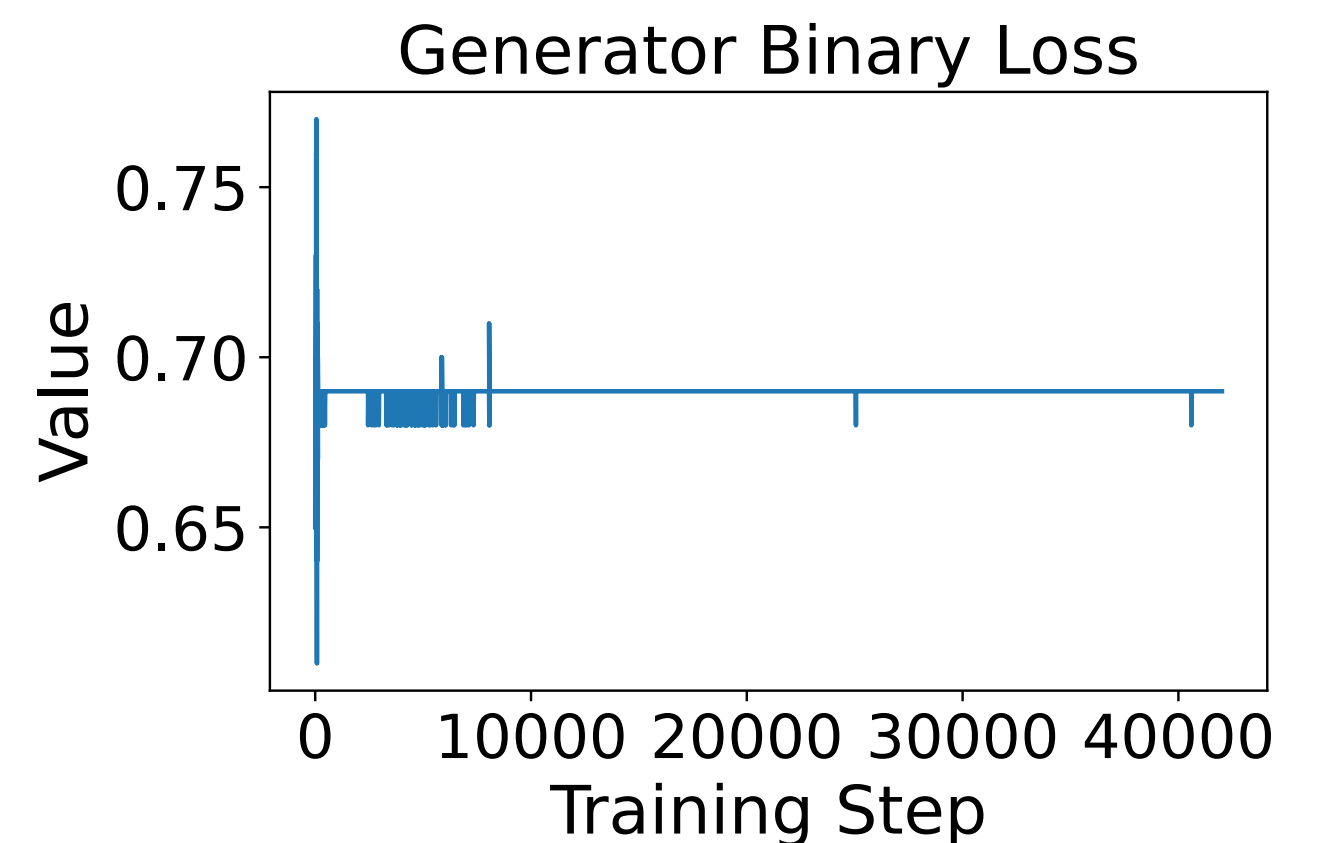
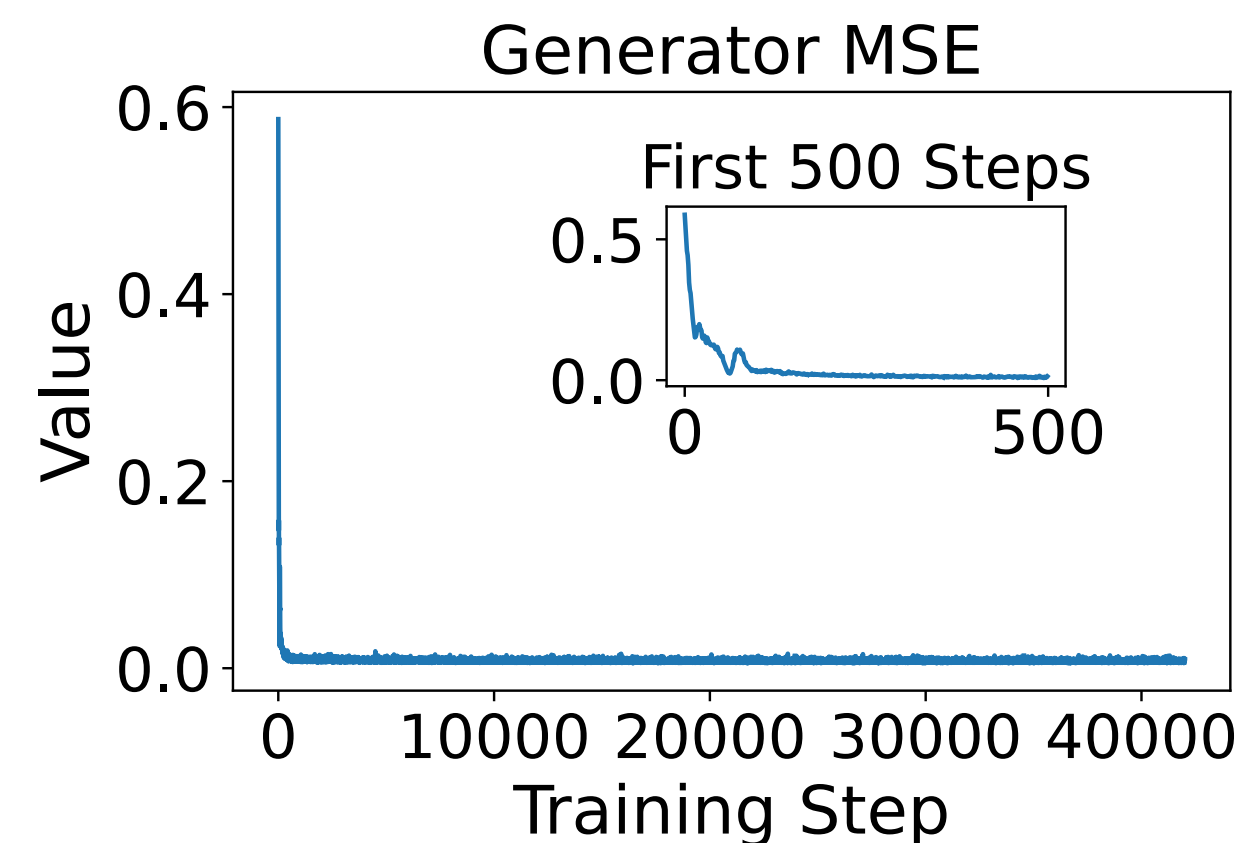
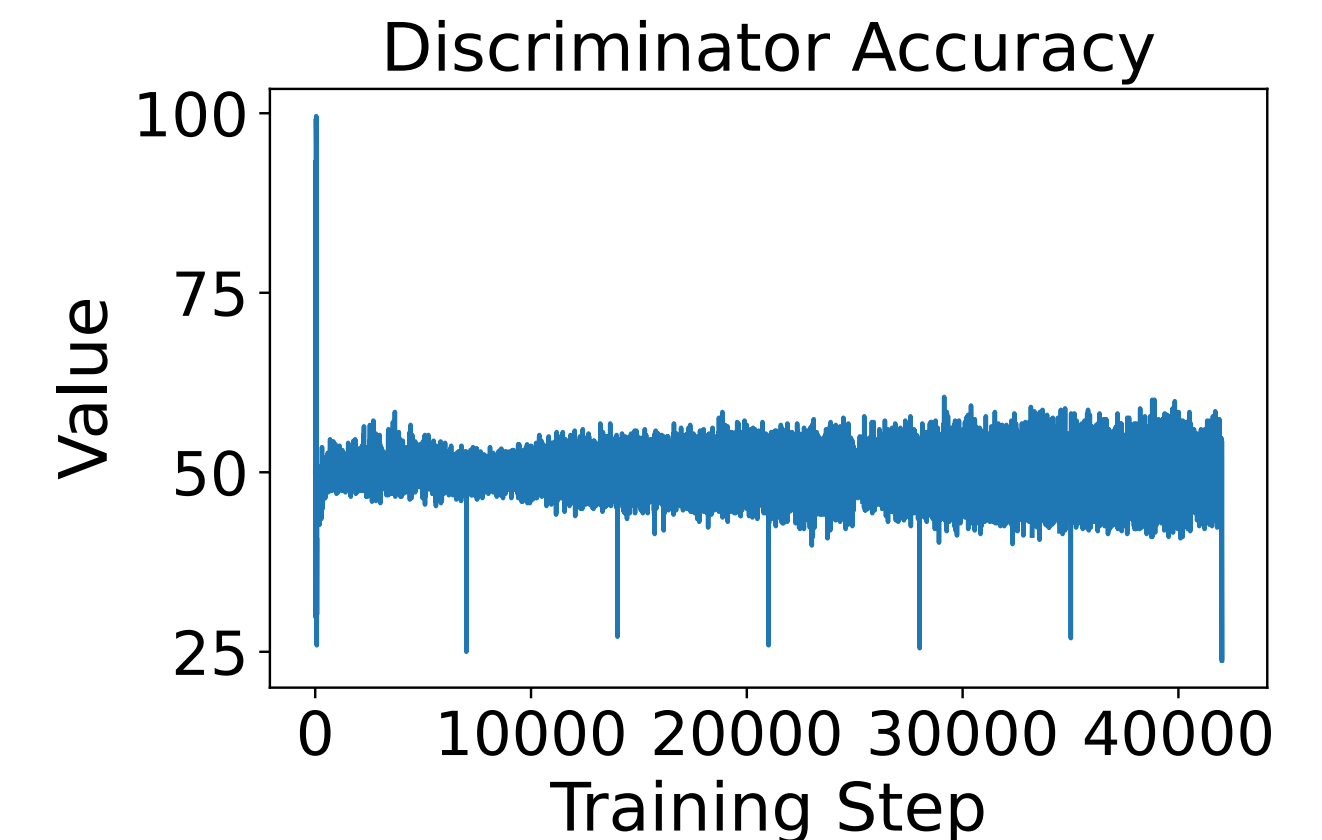
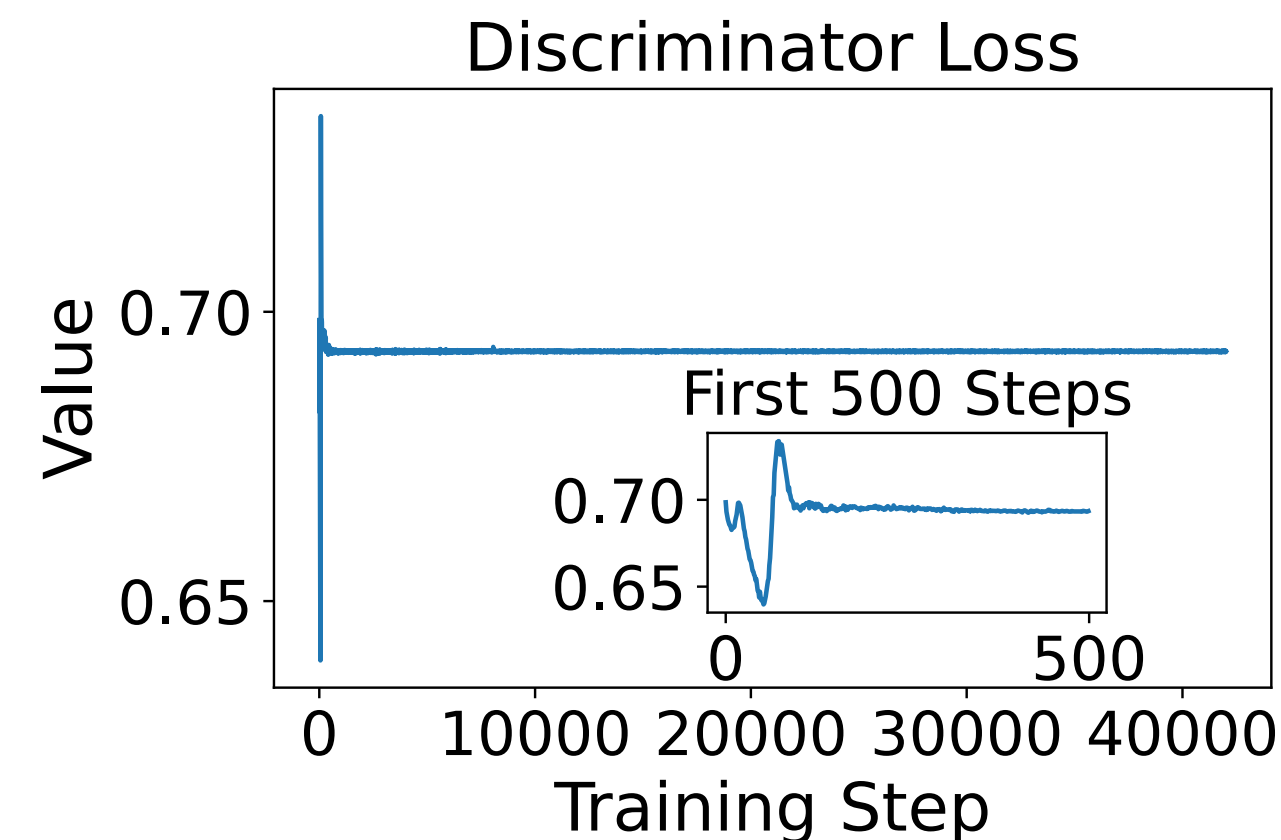
$$\text{score}(v, t) = s_G(v, t) + \lambda s_D(v, t)$$



Training Process

STGAN Framework

- Preprocessing:
 - 5-minute **smoothing** of the data
 - **Patch** missing minutes (forward fill)
 - **Truncate** times $< 4:53$ am and $> 9:00$ pm
 - Calculation of node **distances**, node subgraphs and **time feature** (weekday, hour)
- **Training**: April to November 2020
- **Validation**: November 14–23, 2020
- Repo: github.com/fginas/traffic-anomaly-detection



Traffic Anomaly Detection

Evaluation

- Calculate the anomaly scores of all the data in the test set
- Label **top K%** anomaly scores as **anomalies**

lower K $\leftrightarrow$ fewer false positives $\leftrightarrow$ higher precision

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

- Evaluating AD in **real-world scenarios** remains an open **challenge**
- **Manually** verify anomalies using unprocessed photos

Traffic Anomaly Detection

Results

- Model effectively detects traffic anomalies
- **Camera signal cut/restart** → Signals due to problems with the functioning of the camera
- **Visual artifacts** → Anomalies triggered due to the visual quality of the input
- **Extreme weather conditions** → Anomalies due to developments in the weather

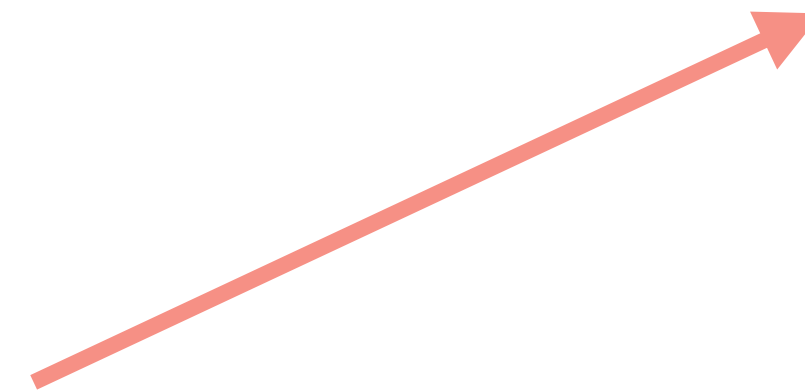
Anomaly Type	Number of Anomalies
Camera signal cut/restart	71
Visual artifacts	2
Extreme weather conditions	2
True positives	75
False positives	6
Total	81

Identified anomalies and anomaly types for K=0.1%

Traffic Anomaly Detection

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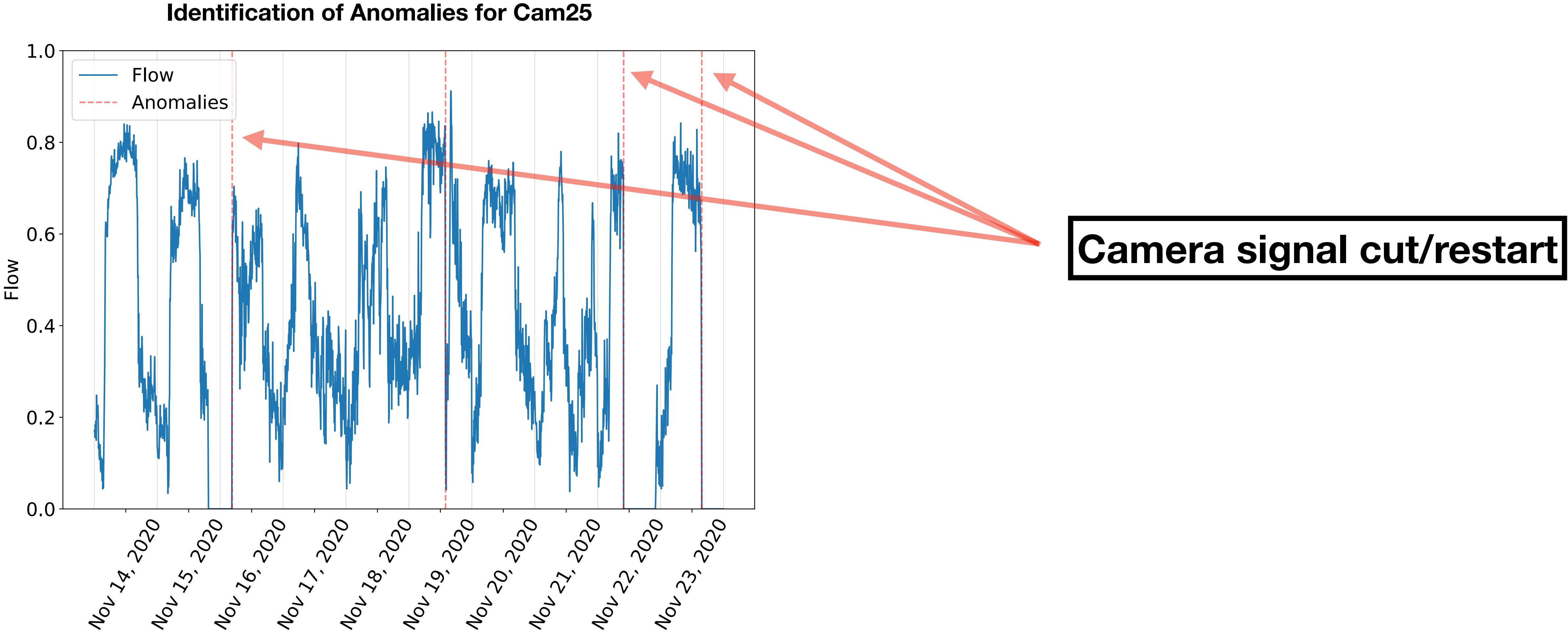
Dry roads



Wet roads: water creates visual artifacts

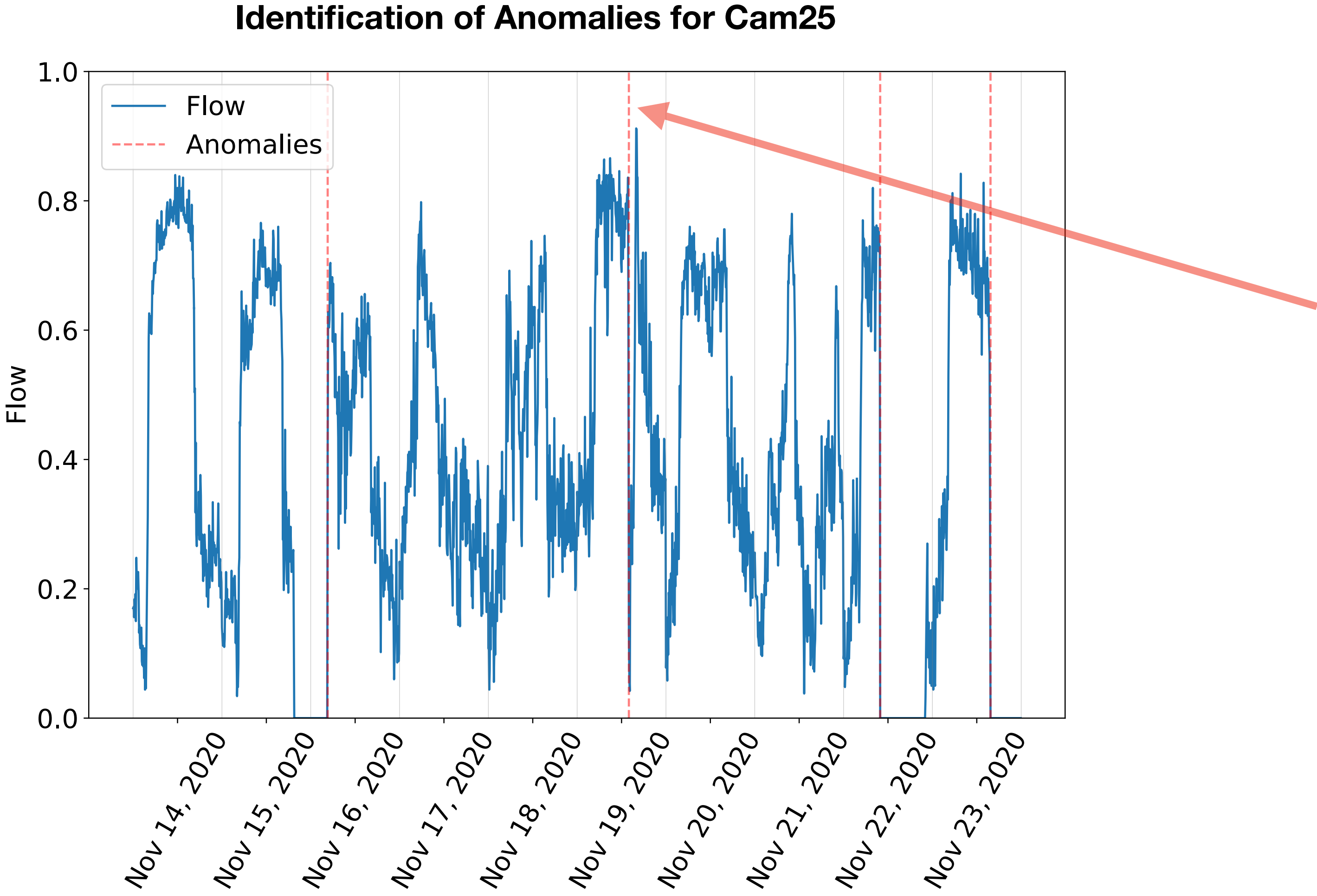
Traffic Anomaly Detection

Results



Traffic Anomaly Detection

Results



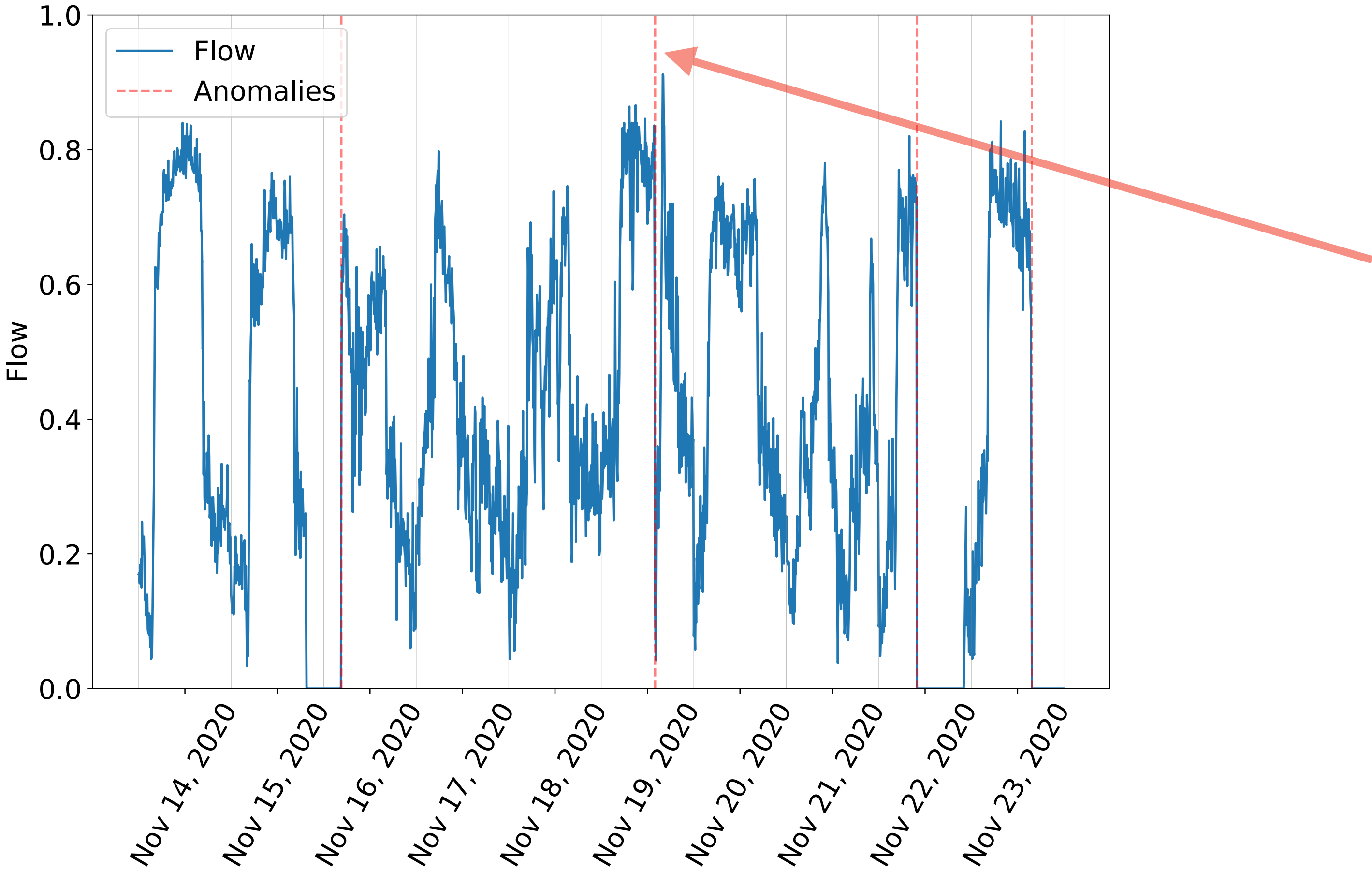
Nov. 19, 2020, Cam14, 14:10



Nov. 19, 2020, Cam14, 14:20

Traffic Anomaly Detection Results

Identification of Anomalies for Cam25



Nov. 19, 2020, Cam25, 14:15



Nov. 19, 2020, Cam25, 14:18

Conclusion

arXiv:2502.01391

Traffic Anomaly Detection

- Presented the **STGAN** Framework
- Combining **GCNs** and **LSTMs**
- Successfully **identified** spatial and temporal features
- Flagged traffic anomalies due to **extreme weather**

Future Work

- Enhancing model robustness against visual artifacts
- Optimizing hyperparameter selection for different urban contexts

Thank you!

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