Research Track | Systems and Infrastructure for Web, Mobile, and WoT

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Supervised Fine-Tuning for Unsupervised KPI Anomaly Detection for Mobile Web Systems

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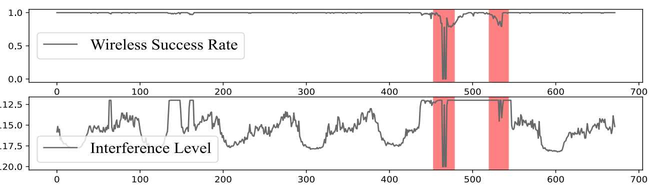
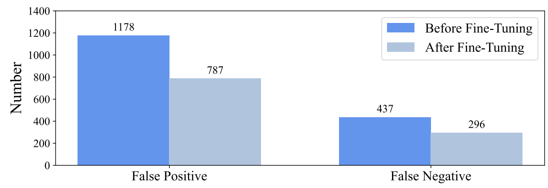
Background



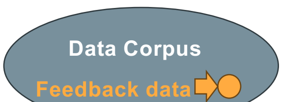
- A Wireless Base Station (WBS), also known as a cell tower or cellular tower, is a fundamental component of mobile web systems.
- To maintain high service quality, operators from Internet Service Providers (ISPs) constantly monitor the operational status of WBSes and deploy multivariate time series (MTS) **anomaly detection** methods
- **Feedback data** serve as crucial sources for improving the anomaly detection performance.
- **However, for unsupervised KPI anomaly detection, feedback data are not effectively used to improve anomaly detection performance.**

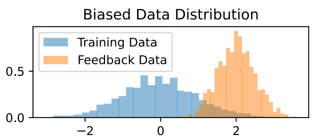
Motivation



- **Feedback** derived from real-world applications of an multivariate time series anomaly detection method **significantly contributes to the enhancement of the method**.
- The reliable operation of WBSes is crucial for ISPs, hence, the **impact of false negatives** on WBSes is particularly severe.
- The **proportion of false negative and false positive feedback** on the MTS anomaly detection methods is imbalanced.

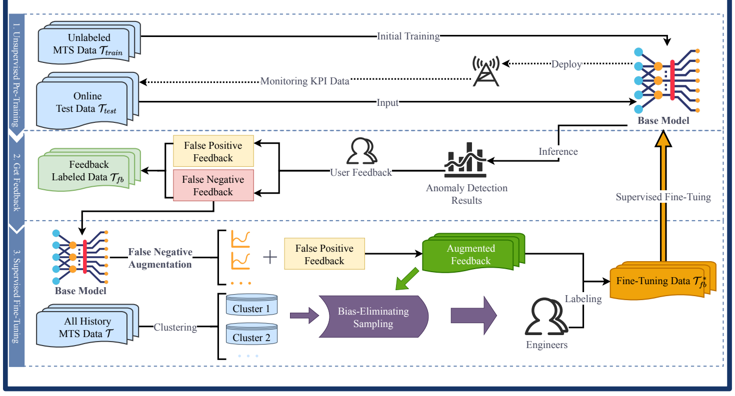
Challenge





- **Scarce data:** It is difficult for MTS anomaly detection methods to learn effectively from the scarce data of false negative feedback, which operators are seriously concerned.
- **Biased data distribution:** The distribution of the feedback data collected after deploying an MTS anomaly detection method can differ significantly from that of the training.

Our Approach: *AnoTuner*



Methodology

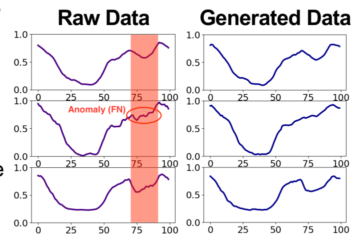
Label Aware ELBO

$$\mathcal{L}(x,c) = -\mathbb{E}_{z\sim q_\phi(z|x,c)}[\log p_\theta(x|z,c,y=0)] + \mathbb{E}_{z\sim q_\phi(z|x,c)}[\log p_\theta(x|z,c,y=1)] - \int (2y-1)q_\phi(z|x,c)\log\frac{q_\phi(z|x,c)}{p_\theta(z|c)}dz$$

- Categorization based on feedback
- Where $y=0$, our objective is to minimize the reconstruction error, thereby approximating the distributions
- For $y=1$, our goal is to amplify the reconstruction error, ensuring that the distributions diverge significantly.

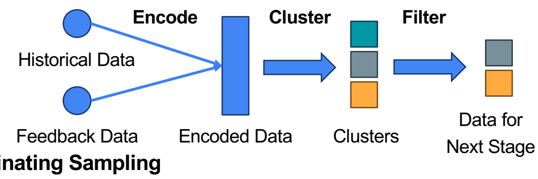
False Negative Augmentation

- A deep learning-based conditional generation for MTS.
- Generate data similar to the false negative feedback data.
- Enhance the fine-tuning performance the anomaly detection model



Two-Stage Active Learning

- **Step 1 Cluster-Based Filter**
- Identify data from the historical data that differs from the existing feedback data.

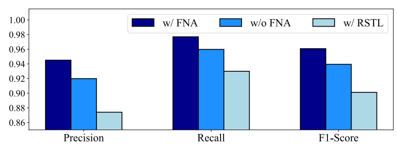


- **Step 2 Bias-Eliminating Sampling**
- Judiciously sample from the data selected in the first stage, thereby **reducing the distribution bias** in the final dataset used for fine-tuning.

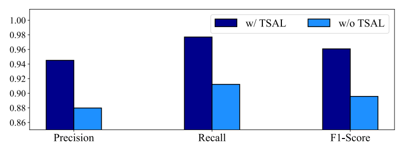
Evaluation

- Compared to SOTA models, *AnoTuner* utilizes feedback better.

Method	w/o fine-tuing			FP+FN fine-tuing		
	P	*R*	*F1*	*P*	*R*	*F1*
LSTM-NDT	0.8234	0.8926	0.8566	0.8269	0.8690	0.8474
OmniAnomaly	0.8964	0.9064	0.9014	0.7293	0.7044	0.7167
Interfusion	0.8923	0.8786	0.8854	0.9159	0.8187	0.8646
AnomalyTrans	**0.9170**	0.9129	0.9149	0.8735	0.8955	0.8841
ACVAE	0.9158	0.8856	0.9005	0.9222	0.8964	0.9091
AnoTuner	0.8922	**0.9411**	**0.9160**	**0.9451**	**0.9770**	**0.9608**

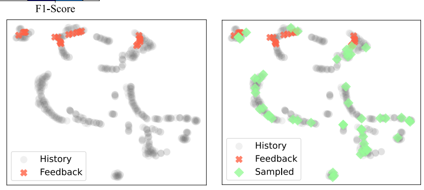


- High-quality data generated by False Negative Augmentation effectively enhance performance.



- TSAL effectively improves the effect of anomaly detection.
- The mechanism effectively solves the problem of biased feedback.

- After *TSAL* The distribution of the dataset used for fine-tuning significantly **resembles the distribution of the entire dataset.**



Conclusion

- Proposed *AnoTuner*, a **supervised anomaly tuner for unsupervised KPI anomaly detection**.
- Introduced *Label Aware ELBO loss* and *False Negative Augmentation* to **effectively learn patterns from scarce false negative data**.
- Developed *Two-Stage Active Learning* to **counter bias caused by discrepancy** between distributions of feedback data and training data.
- Demonstrated *AnoTuner* 's effectiveness on a real-world dataset from a top-tier global ISP, **even with limited feedback data (0.74% of test set).**