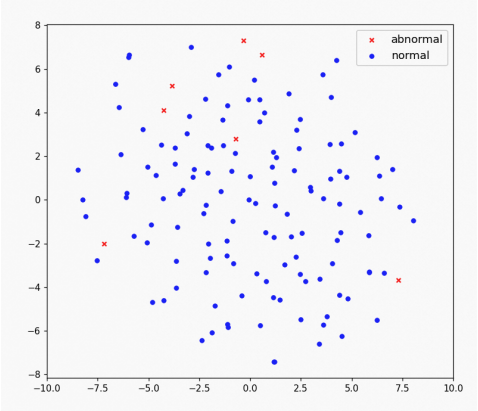
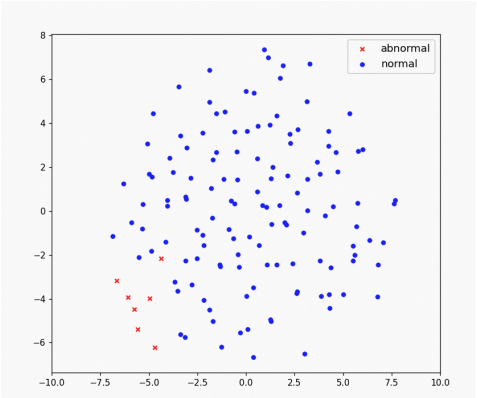
Case Studies

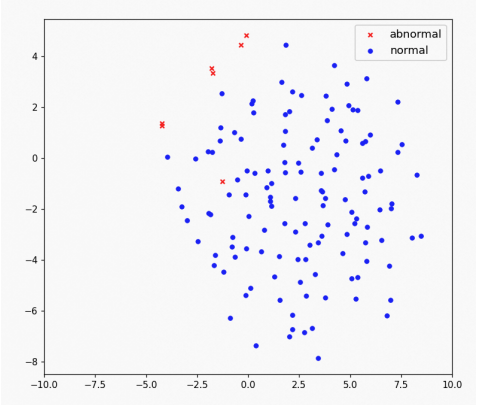
Density-Aware Graph Neural network



(a) Representations without GNN



(b) Representations with Adaptive GNN (No Density Information)



(c) Representations with Density-Aware GNN

Figure 1: A t-SNE Plot of the Subsequence Representations. Blue Dots denote normal samples, and red crosses denote abnormal samples. Results in (a) are without GNN, results in (b) use adjacency matrix corresponding to Theorem 4.1 and results in (c) correspond to Theorem 4.2. The normal representations of adapive GNN output has more concentration compared to model without GNN, and the proposed DAGNN can generate more compact normal representations which we call noise removal. Besides, the anomalies are relatively distant to the normal samples with DAGNN. The results are consistent with Theorem 4.1 and 4.2. Thus, representations corresponding to normal and abnormal samples using DAGNN are more discriminative which eventually facilitates the detection ability.

length Selection Mechanism

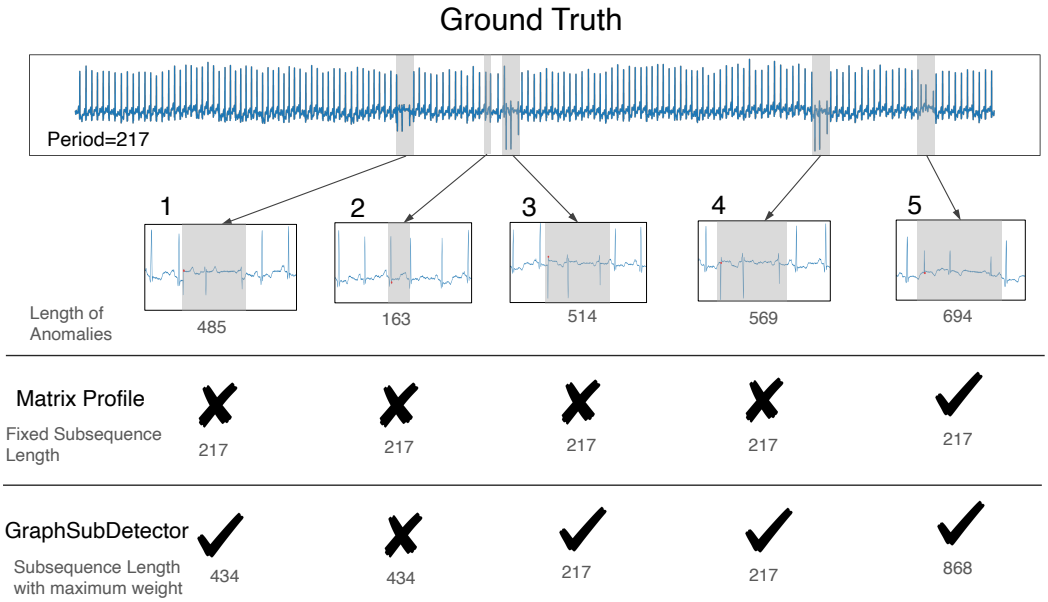


Figure 2: The Length Selection Mechanism Selects Appropriate Subsequence Length for Better Detection. We extend Figure 5 in the paper by adding subsequence length set or learnt in the models. In Matrix Profile, we set a fixed length of period length, which can hardly account for anomalies of different types and length. In GraphSubDetector, we mark the length with maximum weight learnt by selection mechanism. The case shows that this mechanism can adaptively learn different subsequence length for better anomaly detection.