**PROBLEM**

Time Series Anomaly Detection

- **Anomalies** are patterns that do not conform to expected behavior.
- Time series anomalies are **range based**, i.e., they occur over a period of time.
- Detecting and mitigating anomalies can be safety critical.

**Application Diversity**

- Applications of anomaly detection are numerous and diverse.

**Point-based vs. Range-based Anomalies**

- Prior work: Classical model, Numenta model, Activity recognition metrics
- Lack of support for partial detection and flexible time bias

**How to Measure Accuracy?**

### SOLUTION

**Range-based Precision and Recall**

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$, $R_i$</td>
<td>set of real anomaly ranges, the $i^{th}$ real anomaly range</td>
</tr>
<tr>
<td>$\hat{R}$, $\hat{R}_i$</td>
<td>set of predicted anomaly ranges, the $i^{th}$ predicted anomaly range</td>
</tr>
<tr>
<td>$N$, $N_i$</td>
<td>number of all points, number of real anomaly ranges, number of predicted anomaly ranges</td>
</tr>
<tr>
<td>$\omega()$</td>
<td>overlap cardinality function, overlap size function, positional bias function</td>
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</tbody>
</table>

\[
\text{Recall}(R) = \frac{\sum_i \text{Recall}(R_i, P)}{N} \\
\text{Recall}(R_i, P) = \alpha \times \text{Existence}(R_i, P) + (1 - \alpha) \times \text{Overlap}(R_i, P)
\]

\[
\text{Existence}(R_i, P) = \begin{cases} 
1, & \text{if } \sum_j |R_i \cap P_j| \geq 2 \\
0, & \text{otherwise}
\end{cases}
\]

\[
\text{Overlap}(R_i, P) = \text{CardinalityFactor}(R_i, P) \times \left( \sum_j \omega(R_i, R_j, P) \right)
\]

\[
\text{Precision}(R) = \frac{\sum_i \text{Precision}(R_i, P)}{N} \\
\text{Precision}(R_i, P) = \frac{\text{CardinalityFactor}(R_i, P) \times \left( \sum_j \omega(R_i, R_j, P) \right)}{N_i}
\]

**CUSTOMIZATION EXAMPLES**

### RESULTS

**Comparison to Classical Model**

- Our model: subsumes the classical point-based model, when:
  - all ranges are represented as unit-size ranges, and
  - $\alpha = 0$, $\gamma() = 1$, $\delta()$ is as below, and $\delta(\cdot) = \text{Flat}$.

- Our model **subsumes** the classical model.
- is sensitive to positional bias.
- Results are similar for Precision and F-Score.

**Comparison to Numenta Model**

- Our model can:
  - mimic Numenta by setting $\delta() = \text{Front-end}$.
  - catch additional intricacies.
- Results are similar for all Numenta app profiles.

**Future Directions**

- New training strategies for range-based anomaly detection
- Exploring use in other time series classification tasks and applications

**More Information**

Watch: https://www.youtube.com/watch?v=K5fdUBiQP4
Read: https://arxiv.org/abs/1803.03639
Use: https://github.com/IntelLabs/TSAD-Evaluator