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Anomaly Detection in Complex Data Streams

Researchers at Stanford have developed a machine learning method for identifying anomalies in complex data streams. Anomalies, such as faults in assembly lines, defects in manufacturing processes, and equipment in need of maintenance, reduce the yield rate and increase the cost of manufacturing. Existing methods for detecting anomalies rely either on expert human knowledge or costly labeled datasets. The Stanford technology aims to discover these faults with high accuracy while requiring no labeling and minimal human intervention and labor. The new method is based on a novel training structure in which multiple machine learning models are trained simultaneously to maximize the outputs' covariance (or associated statistical metrics). By training multiple models—taking different data streams as inputs—to maximize the covariance of the network outputs, the models learn to cluster the input data and identify anomalous conditions.

Stage of Development
Proof of concept. A prototype algorithm has been demonstrated on data from the SLAC linear accelerator, manufacturing milling processes, and various synthetic benchmarks.

Applications

- Identifying faulty components on assembly lines
- Manufacturing, e.g., automotive and semiconductor industries
- Equipment maintenance and fault prevention
- Big data companies

Advantages

- Unsupervised learning from unlabeled datasets
- Minimal human intervention and labor
- Ability to process high-dimensional input data
- Accuracy and robustness to noise and data corruption

Publications

- Humble, R., Zhang, Z., O'shea, F. Et al. "Coincident Learning for Unsupervised Anomaly Detection." *arXiv* (2023)

Patents

- Published Application: 20230409422

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