Paranom: A Parallel Anomaly Dataset Generator

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ABSTRACT
In this paper, we present Paranom, a parallel anomaly dataset generator. We discuss its design and provide brief experimental results demonstrating its usefulness in improving the classification correctness of LSTM-AD, a state-of-the-art anomaly detection model.

1 INTRODUCTION
A dataset, a collection of data usually manipulated as a single unit, is necessary for many machine learning (ML) techniques [11]. In the context of deep learning, it has been shown that the larger and richer the dataset, the greater the potential accuracy of the model that can be built from it [7]. Because of this, possessing a large, high-quality dataset is usually a first step in building an ML model.

Contrarily, the practical development of ML models usually requires various sizes of data, beginning with a few items for initial model construction and up to billions of items for model deployment. In early development, small, yet rich, datasets can be useful because they enable rapid model tuning and topological changes without suffering significant performance penalties (e.g., days or weeks in training time). In practice, this means many ML models are generated iteratively by training and re-training on a growing dataset. If such manipulation is performed manually, it increases engineering overhead and the potential for data manipulation errors.

Anomaly detection, the process of identifying outliers in a specific domain [2, 6], adds even more complexity to the dataset problem for at least two reasons. First, anomalies by definition are infrequent and therefore building an accurate anomaly detection model can be challenging due to the scarcity of anomalous data [6]. Second, anomalies tend to be continuous events, which means data presented for them must usually be in a periodic, or time-series, ordered form [4, 9]. For these reasons, and the growing importance of streaming systems, building large, rich, and meaningful datasets for anomaly detection is an open and increasingly important problem [4, 12].

In this paper, we present Paranom, a parallel anomaly dataset generator. We make the following technical contributions:

1. A brief overview of Paranom’s technical design.
2. An illustration of how Paranom’s synthetic data can be used with LSTM-AD [10], a state-of-the-art anomaly detection model, improving its accuracy over using only real data.

2 PARANOM’S DESIGN
In this section we discuss Paranom’s data uniqueness, data generation, data stochasticism, and parallel run-time execution model.

2.1 Data Uniqueness
In synthetic data generation, data uniqueness cannot always be guaranteed. To illustrate this, consider an example where a user requests unique anomalous data, providing two possible discrete values: 0 and 1. Once both entries have been generated, it is impossible for any system to fulfill a third unique anomalous data point request.

To help manage this, Paranom provides two uniqueness controls for data generation: hard and soft. We define hard uniqueness as a data property that must be met. If hard uniqueness is requested, and, after a user-specified number of tries Paranom has unsuccessfully generated a unique datum, Paranom will terminate execution. We define soft uniqueness as a data property that might be met, but, after a user-specified number of tries, it has not been met, Paranom will continue execution using its last generated datum entry.

Because anomalous data may be scarce, duplication of any of its already small number of data points may result in model overfitting [5]. To address this, Paranom provides two data uniqueness controls: one for normal data and one for anomalous data. This enables a user to generate soft unique non-anomalous data and hard unique anomalous data, or vice-versa, as needed.

2.2 Data Generation
Paranom supports the following two ways of data generation. 1

Stochastic Variables. These variables support controlled randomization, where developers define them with a specified range of stochasticism for both the anomalous and non-anomalous values they will generate. Paranom then handles all value generation.

Callback Variables. If a developer requires full control over value generation, she can define a callback variable, which requires the construction of two callback functions for each variable, one for anomalous data generation and one for non-anomalous. At runtime, the appropriate callback function will be invoked for value generation for each variable at each unique discrete timestamp.

1Due to limited space, we have omitted code examples.
2.3 Data Stochasticism
Paranom provides seedable randomization, which (if needed) can ensure repeatable stochasticism in dataset generation. This can be useful for iterative ML training from small to large datasets, where the previously seen data is guaranteed to remain unchanged as the dataset grows in size. Paranom also provides controls for the anomalous and non-anomalous data that will be randomly present in a dataset. In addition to providing controls for the absolute number of data points, Paranom also provides controls for the stochastic frequency of anomalous and non-anomalous data.

2.4 Parallel Run-Time Execution
To ameliorate the performance overhead of possibly generating billions of entries for a dataset, Paranom was designed with the goal of being perfectly parallel, where there is no multithreaded synchronization used in the generation of its data (see Figure 1) [8]. Although Paranom’s data generation is perfectly parallel, user level synchronization can be used, if needed, within the user-defined callback variables. This can be useful in generating unique data and sequentially dependent time-series data, among other things.

3 EXPERIMENTAL EVALUATION
In this section, we describe how we used Paranom to improve the accuracy of LSTM-AD, a state-of-the-art anomaly detection ML model by Malhotra et al., compared to using only real data for a space shuttle valve sensor anomaly [10].

Experimental Setup. We trained two LSTM-AD models in TensorFlow [1]. One used only real space shuttle data. The other used portions of the real non-anomalous data in conjunction with anomalous data solely generated by Paranomas described below.

Similarities. Both models were constrained to the same training data size (i.e., 10,000 data points) and tested against the same real test data. All aspects of the LSTM-AD model (e.g., topology, activations, etc.), as well as the training iterations, were identical in both settings.

Differences. The model trained using Paranom’s generated training data did not use any of the real-world anomalous training data. Instead, we created a Paranom callback variable that would generate anomalous data uniquely different from the real-world non-anomalous data with a stochastically chosen value range. We then had Paranom inject synthetic anomalies with a 1% frequency and a variable anomaly duration range similar to its real anomalous events.

Results. The differences between the original training data and our Paranom generated data can be seen in Figures 2 and 3, respectively. Figure 2 shows the original data used to train LSTM-AD, including six real anomalies (denoted by red ovals). It also shows the LSTM-AD predictions against the test data after being trained against the original data. Figure 3 shows our Paranom generated training data, which includes Paranom’s synthetically generated stochastic anomalies. Once trained against the real training data and Paranom’s training data, we tested both LSTM-AD models against the original testing data. The original model identified two of the six anomalies. The Paranom model identified five of the six anomalies. The Paranom model identified five of the six anomalies.

As can be seen in Figure 4, the Paranom LSTM-AD model had improved accuracy, recall, $F_1$, and $F_{0.1}$ score when compared to the model trained against only real data. The only LSTM-AD result that was not improved was precision. This is because the Paranom LSTM-AD model introduced some false positives.

![Figure 2: Visualization of original LSTM-AD space shuttle training, testing and prediction data (red ovals are anomalies).](image)

![Figure 3: Visualization of Paranom LSTM-AD space shuttle training, testing and prediction data (red ovals are anomalies).](image)

![Figure 4: The performance results of LSTM-AD when using its original training data versus using Paranom’s training data.](image)

4 CONCLUSION
In this paper, we briefly presented Paranom’s design and parallel execution model. We provided an empirical illustration showing the benefit of using Paranom’s synthetically created data to improve the robustness of LSTM-AD, a state-of-the-art anomaly detection ML model, by an order of magnitude for recall and $F_1$ using Paranom’s data over using only real data.
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