# Leveraging Spark and Docker for Scalable, Reproducible Analysis of Railroad Defects

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## ABSTRACT

The resiliency of railroad networks depends on the ability of railroad engineers to identify and mitigate track and rail defects. As railroads modernize their defect identification measures, the volume and velocity of defect data substantially increases, necessitating adoption of techniques for "Big Data" analytics. We present a study of railroad defect prediction built atop Apache Spark and Docker–increasingly common substrates for predictive analytics on large data sets.

## 1. INTRODUCTION

According to the United States Federal Railroad Administration Office of Safety Analysis, track defects are the second leading cause of accidents on railways in the United States. In light of the economic significance of railway accidents [1], there is a pressing need in the railroad engineering community to adopt data-driven scalable data analysis tools from the greater "Big Data" ecosystem. [3] Track maintenance–i.e., identifying and repairing defects–is one of the primary factors that affect the service life of a rail track, but due to the severe safety implications of undeftected or unrepaired defects, the ability to predict common defects is highly desirable.

In this work, we present a case study centered on the analysis of two railroad defect data sets obtained from railroad engineering researchers in the University of Delaware Department of Civil Engineering. Hereafter we will refer to these datasets as the `rail_defects` data set and the `track_geometry_defects` data set. Respectively, these data sets describe defects in the rails themselves, such as voids or internal changes in crystalline structure, and misalignment of track components, such as one rail tilting away from the other. We investigate the feasibility of predicting the type of a defect based on associated data such as geographic region, mean gross tonnage (MGT) the track is subject to, and rail type. In the rest of this paper, we outline the construction of our analysis platform, present some initial results on

classification accuracy, and propose extensions to our work.

## 2. METHODOLOGY

The data sets under consideration present familiar, but nevertheless nontrivial challenges. The `rail_defects` data set consists of 26,432 20-dimensional points, and the `track_geometry_defects` data set consists of 25,421 41-dimensional points. Both data sets contain mixed numerical and categorical data, and each data set's points are each labeled with a class label indicating the kind of defect the point refers to. Due to the variety of data types and due to missing data, careful preprocessing is necessary prior to any analysis. In this section we descibe our preprocessing stages, and justify our selection of analyses.

In light of the properties of the `rail_defects` and `track_geometry_defects` data sets, we initially focus on obtaining accurate predictions from multilabel classification models. We argue that studying the accuracy of standard multilabel classifiers against our static data sets is a crucial first step towards models that can predict likely defects for a particular section of railroad.

## 3. PLATFORM

With a view towards coping with larger data sets than those currently under consideration, we implement our analysis plaform using the MapReduce framework Apache Spark. Spark provides improved performance for the data transformation tasks we perform during preprocessing relative to other MapReduce frameworks [2], and offers convenient Python bindings. Moreover, Spark comes packaged with a full-fledged paralllel machine learning library–MLLib–whose classifier implementations we use. In order to guarantee portability and reproducibiliy of our analyses, we package our code, data, and environment as a Docker container.

We present a block diagram of our platform's high-level design in Figure 1

## 4. EVALUATION

To evaluate our classifier's performance, we examine the overall accuracy rate of the classifier and its associated confusion matrix. When we train the classifier on training data drawn uniformly at random from the

## 5. CONCLUSIONS AND CONTINUING WORK

We identified the potential of acheiving better classification accuracy by training classifiers on subsets of data from
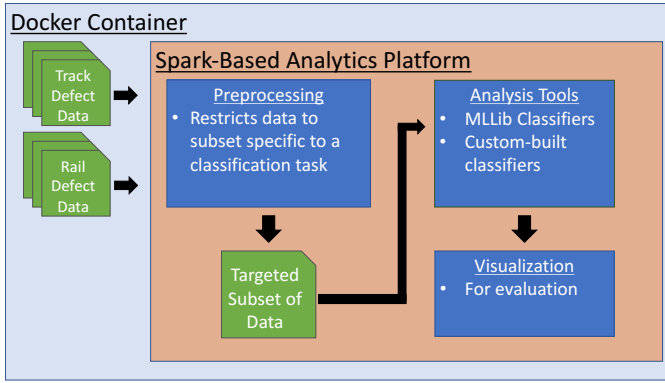
**Figure 1: Block Diagram of Analytics Platform**

regions that have similar distributions of defects. We propose adding a preprocessing stage to our platform that partitions the data by subdivision, computes the distribution of defects for each subdivision, and then groups subdivisions based on a similarity metric for distributions.

Currently we use a simple similarity metric–the Chi-squared distance–and group subdivision based on a fixed similarity threshold. We plan to refine our similarity metric, use it to explore the efficacy of clustering techniques for grouping subdivisions, and evaluate the usefulness of the grouping by training and testing defect type classifiers on each such group.

Similarity metric: $S(D_1, D_2) = \sum_{i=0}^{N} \frac{(x_i - y_i)^2}{sdfdsfdsf}$

## 6. REFERENCES

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