Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations

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Abstract. A company operating in a commercial maritime port often experiences clients filing insurance claims on damaged shipping containers. In this work, multiple classifiers have been trained on synthesized data, to predict such insurance claims. The results show that Random Forests outperform other classifiers on typical machine learning metrics. Further, insights into the importance of various features in this prediction are discussed, and their deviation from expert opinions. This information facilitates selective information collation to predict container claims, and to rank data sources by relevance. To our knowledge, this is the first publication to investigate the factors associated with container damage and claims, as opposed to ship damage or other related problems.

1 Introduction

Commercial maritime ports require high operational throughput, highlighting the importance of optimizing intensive workflows such as those induced by filing a claim on a damaged shipping container. To handle such a claim, port officials collate and analyze multimodal data including visual inspection logs cargo manifests environmental data, which is a time-consuming process [1, 2]. Operational time aside, human predictive accuracy reduces with human cognitive biases [3], data volume and complexity, and prediction specificity [4] and volume [5].

Fast and accurate automated data processing is computationally expensive, due to noisy and incomplete data. Predicting container claims affords restricting data collation to smaller subsets, reducing computational requirements.

To our knowledge, this is the first publication to investigate container damage causes using Machine Learning (ML) techniques, which constrains the scope of the current knowledge against which to compare the presented methodologies. Accurate container damage predictions enable discussing the dynamic selection between data sources and algorithms used to process the data therefrom. This may be used in a decision support system integrated into a terminal OS to realize container damage causes and alleviate data collation and analysis bottlenecks.

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The remainder of the paper is structured as follows: Sec. 2 reports a survey of related work, while our methodologies are outlined in Sec. 3, the results of which are presented and discussed in Sec. 4. Finally, Sec. 5 concludes this work with some directions in which it can be expanded.

2 Related Work

Related publications incorporating ML solutions and features involving ports, ships, personnel, weather, and geography are used to guide this study.

Surveys of Taiwanese domain experts [6] reveal a taxonomy of risks posed to refrigerated containers in their port-to-port travel, while Canadian experts (discussed in Sec. 3) maintain that quay crane operator errors are most relevant human error sources. A study of the determining factors of consignors' port choice shows positive correlation with port proximity due to decreased en route damage probability [7]. Operational conditions such as weather and human factors are the primary travel risk factors [8,9]. Further, terminal-side accident reports are confidential, hence unavailable. Yet, probability distributions modeling operational capabilities of personnel and equipment were used in this study.

A case study of a Seattle-bound ship [10] discusses mathematical constructs used in simulation software [11], whose features guide this work. Yet, no ML methodologies were used to compute feature importance. Ship characteristics extracted from a source like [12] may be correlated with maritime accidents using an ML approach. [13]. Mined features and probability densities of environmental have been used in a custom discrete event simulator, to determine oil tanker loading times and port storage capacity [14]. Few publications use ML techniques to discover the causes of shipping container damage. One study compared the efficacy of decision trees in predicting the total loss and damage to a ship [15], supporting the use of a binary classification tree.

3 Methodology

3.1 Data

To predict container damage, container voyage data is required. A trained prediction model may be applied to real-world scenarios in order to learn which data sources and feature/information extraction techniques are best suited for a given scenario. As robust, accurate algorithms typically require more computational power, it is favorable to use them only when absolutely necessary. Determining which data sources to use at a given time, and when to switch between algorithms is out of the scope of this paper and left as future work.

The synthesis of the container damage prediction data set (of 1.6M records) is discussed in this section. Each attribute in this data set was captured in a survey completed by industry experts in Canada.[3] The survey results revealed how

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[3] The survey (named Bottlenecks in Port Operations) was distributed by a Google Forms link in July 2017, after receiving the necessary approval from the Research Ethics Board of the University of Ottawa

strongly each attribute and correlated with container damage claims. Attribute values were accordingly weighted on a $(0, 3]$ scale to capture their correlation with container damage. The value of each attribute was modeled to contribute some amount of damage to be sustained by the container, which increased the probability of it being claimed. The generation of attribute values and their contributed damage to the container are discussed below.

Data Synthesis Each shipping container was assigned to one of 46 known tracks in Jan. - Mar. 2014 and Douglas Sea Scale (DSS) [16] measures were computed from environmental data [17]. The average damage contribution of sea state (modeled as the modified sigmoid function $(2(1 + e^{7-DSS}))^{-1}$) weighted at 1 is the damage sustained by the container.

The containers were probabilistically assigned to shipping lines (SLs) and trucking companies using roulette wheel selection [18], weighted by annual cargo throughput [19, 20]. The error probability per shipping line (L) was computed based on fleet size ($FS(L)$), annual throughput ($T(L)$) and market share ($MS(L)$), weighted at 3, as described by Eq (1), capturing the notion that shipping lines with higher FS, T, and MS are less likely to cause shipping container damage.

$$P(Error|L) = \begin{cases} 0 & c(L) > \frac{2}{3}C \\ 0.5 & c(L) < \frac{1}{3}C \\ \frac{3 \times c(L) - 1}{2} & \text{otherwise} \end{cases}, \begin{aligned} & C = max(\{c(L)|L \in SLs\}) \\ & c(L) = 0.3 \times FS(L) + 0.35 \times T(L) \\ & \quad + 0.35 \times MS(L) \end{aligned}$$

(1)

Finally, the container's recipient correlates positively with damage claims, which were modeled as having a claim probability and a claim amount, respectively distributed in $\mathcal{U}([0, 0.5])$ and $\mathcal{U}([0, 10^8])$, weighted at 1. The remaining features (cargo value, fragility, sensitivity, mass distribution, packing and loading seasons, etc) and their correlated error probabilities are listed in Table 1.

Table 1. Container Features and Error Probabilities

Feature Name	Feature Weight	Feature Distribution	Error Probability
Cargo Value (v)	3	$\mathcal{N}\left(\mu = \frac{10^5}{2}, \sigma^2 = 10^{10}\right)$	$P(Error|v) = \begin{cases} 0 & v \leq V/3 \\ 0.5 & v \geq V/3 \\ 1.5 \times \frac{v}{V} - 0.5 & \text{otherwise} \end{cases}$
Cargo Sensitivity (s)		$\mathcal{U}(\{0, 1\})$	$P(Error|s) = 0.5 \times s$
Weight Balance (d)		$\mathcal{U}(0, 20.4)$	$P(Error|d) = 0.5 \times \frac{d}{20.4}$
Quay Crane Operator(g)		$\mathcal{U}(0, 0.1)$	$P(Error|g) = g^{-1}$
Packing/Loading Season(s)	1	$\mathcal{U}(\{\text{fall, winter, spring, summer}\})$	$P(Error|s) = \begin{cases} 0.5 & s \in \{\text{fall, spring}\} \\ 0 & \text{otherwise} \end{cases}$
Time in Storage Yard(t)		$\mathcal{U}(0, 364)$	$P(Error|t) = \frac{366}{365-t}$
Cargo Fragility (f)	0.01	$\mathcal{U}(\{0, 1\})$	$P(Error|f) = 0.01 \times f$
Container Weight (w)		$w = \begin{cases} 55 & \text{with probability 0.2} \\ 275x_{0.2 \leq x \leq 0.4} & \text{with probability 0.2} \\ 110 & \text{with probability 0.6} \end{cases}$	$P(Error|w) = 2 \times \left(\frac{w}{110} - 0.25\right)^2$

Classifiers were trained on this 15-dimensional data describing the above features, to learn which features accurately predict container claims. This allows for the proactive gathering and collation of the terminal-side data, to present to port officials upon the incidence of a claim (as mentioned in Sec. 1).

3.2 Experimental Setup

Table 1 lists the CI methods used from [21], along with their 95% Confidence Intervals performance metrics. These were trained by 10x10 fold cross validation, with training data drawn from the synthesized 1.6M records. This was then run 30 times, accounting for 100 data points per run, shown in Figure 1.
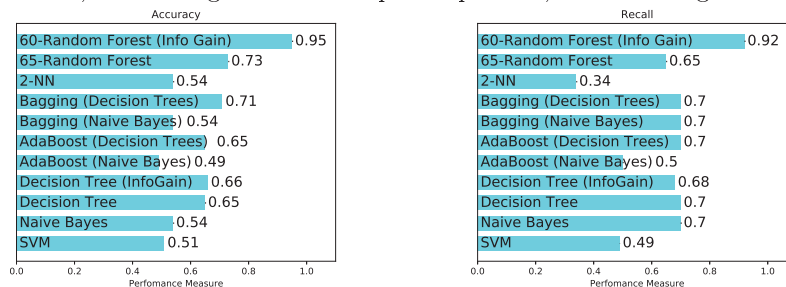

Accuracy

Classifier	Value
60-Random Forest (Info Gain)	0.95
65-Random Forest	0.73
2-NN	0.54
Bagging (Decision Trees)	0.71
Bagging (Naive Bayes)	0.54
AdaBoost (Decision Trees)	0.65
AdaBoost (Naive Bayes)	0.49
Decision Tree (InfoGain)	0.66
Decision Tree	0.65
Naive Bayes	0.54
SVM	0.51

Recall

Classifier	Value
60-Random Forest (Info Gain)	0.92
65-Random Forest	0.65
2-NN	0.34
Bagging (Decision Trees)	0.7
Bagging (Naive Bayes)	0.7
AdaBoost (Decision Trees)	0.7
AdaBoost (Naive Bayes)	0.5
Decision Tree (InfoGain)	0.68
Decision Tree	0.7
Naive Bayes	0.7
SVM	0.49

Fig. 1. Performance Metrics of Various Classifiers

4 Results and Discussion

Human reviewers remain the post-data-collation bottleneck. Since investigations are triggered by incoming claims, false negatives are less favorable. It is therefore important to compare the accuracy of classifiers that have equivalent AUC (shown in Fig 1). The superior performance of Random Forests (significantly better than random chance) suggests that other such nonlinear and ensemble methods may be applicable. Analysis of trained decision trees and Random Forests reveals relative feature importances (see Fig. 2), showing that the amount of time a container spends in the storage yard is the most revealing feature in predicting container damage claims. While a container's cargo value was expected to be an important feature, the quay crane operator, shipping line, and time spent in the storage yard yield the highest container claims predictability, counter to expert opinion.[4]

Analyzing the most important features shows that cargo value, hazardousness, longevity, sensitivity, mass distribution, storage time, and exposure to rough seas correlate strongly positively with filed claims, while calm sea states have strong negative correlation. Container packing and loading seasons correlate weakly with container claims with 25% support and 13% confidence in the relevant association rules. Logistics companies are also weak features (18% support, 11% confidence).

Cargo Fragility is found to very weakly correlate with container damage claims (Pearson R coefficient of 3.7×10^{-4} and 50% support, 50% confidence for relevant association rules), again counter to expert opinion. This could be due to proper container packing compensates for cargo fragility, while quay crane operator error dominates in human error (with 8% support and 4% confidence).

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[4] The survey results showed that cargo value, hazardous and/or sensitive cargo were the most important attributes in predicting insurance claims
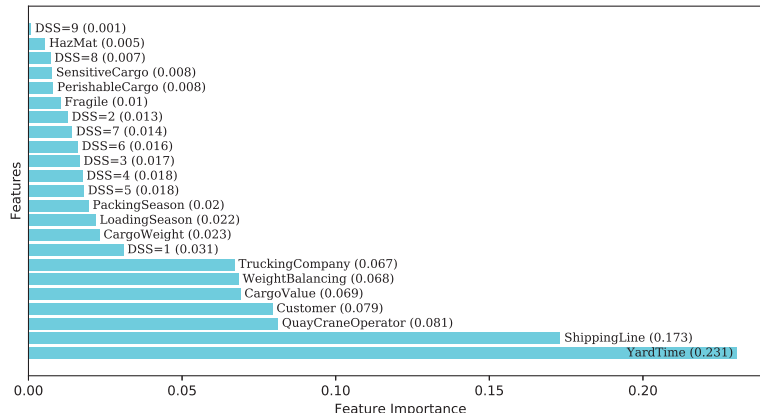
Fig. 2. Relative Feature Importances

As expected, rough sea conditions correlate with more insurance claims. Additionally, the amount of time a container spends in the storage yard positively correlates with container damage claims, counter to the survey results. This may be due to increased in-yard storage density decreasing the performance of container moving equipment [2].

5 Conclusions and Future Work

Future directions of this study include identifying and fusing alternative data sources (e.g., sources of weather, commercial cargo values, etc), enabling pertinence based data source ranking, to dynamically switch between them. This would save computational costs without compromising prediction accuracy.

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[5] Each GPC node runs Intel's Xeon E5540 8-core CPU at 2.53 GHz, with 16GB RAM; each P7 node runs an IBM Power 755 server with four 8-core 3.3GHz Power7 CPUs and 128GB RAM. Detailed specifications can be found at https://www.scinethpc.ca/

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