Customs Import Declaration Datasets

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ABSTRACT

Given the huge volume of cross-border flows, effective controlling of trades becomes more crucial in customs administrations. However, limited accessibility of the customs datasets hinders the progress of open research and lots of member countries have not benefited from the recent progress. In this paper, we introduce an import declarations dataset to facilitate the collaboration between the domain experts in customs administrations and data science researchers. The dataset contains 54,000 artificially generated trades with 21 key attributes and it is synthesized with CTGAN while maintaining correlated attributes. Synthetic data has several advantages. First, releasing the dataset is free from restrictions that do not allow disclosing the import data even if its anonymized. Second, the fabrication step minimizes the possible identity risk which may exist in trade statistics. Lastly, the published data follow a similar distribution to the source data so that it can be used in various downstream tasks. With the provision of data and its generation process, we open baseline codes for fraud detection tasks, as we empirically show that more advanced algorithms can better detect frauds.

CCS CONCEPTS

• **Social and professional topics → Taxation**; • **Applied computing → E-government**.

KEYWORDS

Import Declarations, Synthetic Data, Tabular Data, Customs Fraud Detection, Correlation Analysis

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1 INTRODUCTION

Customs clearance is the process of getting permission from the customs administrations to either move goods out of a country (export) or bring goods into the country (import). The customs declarant handles the customs formalities of the goods and declares it to the customs office, and the permission is given only when

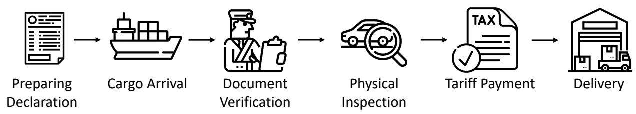

Figure 1: Import clearance process.

the declaration is legitimate. If the shipment exceeds the threshold value ($150 in Korea), the customs impose tariffs on the item. Once the tariff is collected, they allow the goods to be taken out.

Given the enthusiasm around the use of data and the possibilities offered by artificial intelligence [9], the adoption of new technology is relatively slow in customs community. The major reason is the lack of publicly available data. Disclosure of import declaration data outside customs is strictly prohibited because of its sensitivity. Only authorized departments or institutions could conduct research internally, and there is no visible community effort taking place.

This lead us to design a synthetic data that can be open to public. The dataset contained in this paper includes 54,000 artificially generated trades with 21 key attributes. By using tabular synthesizer with post-processing technique, we maintain the distribution and correlation in the synthetic dataset are similar to those of source dataset. Empirical results on fraud detection demonstrate the potency of the data. Meanwhile, the data is used for competition in three universities to develop algorithms that can be applied to the actual work process. We conclude the paper by discussing possible scenarios to use the data and summarizing necessary thoughts on the data synthesis. The data and code can be found in https://github.com/Seondong/Customs-Declaration-Datasets/tree/en.

2 DATA DESCRIPTION

2.1 Data Schema

The tabular form dataset consists 54,000 import declarations, where each row describes the report of a single goods. Among 62 attributes in the import declaration form,[1] the data includes 21 representative attributes without overlapped or less important attributes. The first 19 values are prepared in the declaration stage of the customs clearance, while the rest two attributes are labeled after the inspection. *Fraud* indicates whether the inspected result of the actual imported goods conflict with its declaration. *Critical fraud* is the case that may threaten the public safety or stability of society, such as copyright infringement, drug smuggling, false declaration of the origin of goods. Categorical attributes and their values follow the handbook provided by KCS, which contains trade codes used for filling out import and export declaration in Korea.[2] Detailed data descriptions and example values are shown in Table 1.

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[1]Import declaration format and explanation: https://bit.ly/import-declaration-form
[2]https://www.data.go.kr/data/3040477/fileData.do

Table 1: Data description

Attribute	Value	Explanation
Date	2020-01-01	Date when the declaration is reported
Office ID	13	Customs office that receives the declaration (e.g., Seoul regional customs)
Process Type	B	Type of the declaration process (e.g., Paperless declaration)
Import Type	11	Code for import type (e.g., OEM import, E-commerce)
Import Use	21	Code for import use (e.g., Raw materials for domestic consumption, from a bonded factory)
Payment Type	11	Distinguish tariff payment type (e.g., Usance credit payable at sight)
Mode of Transport	10	Nine modes of transport (e.g., maritime, rail, air)
Declarant ID	L77JJEG	Person who declares the item
Importer ID	HQ0W7JA	Consumer who imports the item
Seller ID	PBP2MYI	Overseas business partner which supplies goods to Korea
Courier ID	MWIDNS	Delivery service provider (e.g., DHL, FedEx)
HS10 Code	0901210010	10-digit product code (e.g., 090121xxxx = Coffee, Roasted, Not Decaffeinated)
Country of Departure	JP	Country from which a shipment has or is scheduled to depart
Country of Origin	JP	Country of manufacture, production or design, or where an article or product comes from
Country of Origin Indicator	B	Way of indicating the country of origin (e.g., B = Mark on package)
Tax Rate	8.0	Tax rate of the item (%)
Tax Type	A	Tax types (e.g., FTA Preferential rate)
Net Mass	1262.0	Mass without any packaging (kg)
Item Price	1437418.0	Assessed value of an item (KRW)
Fraud	1	Any fraudulent attempt to reduce the customs duty? (0/1)
Critical Fraud	1	Critical case which may threaten the public safety (0/1)

2.2 Data Reliability

We conduct statistical tests between the source data and the synthetic dataset to show whether two data comes from the same distribution. The Chi-Squared test compare the distributions of two categorical attributes, the value indicates the probability of the two attributes are sampled from the same distribution. The Two-Sample Kolmogovrov-Smirnov test is used to compare cumulative distribution functions of two continuous variables, the value denotes the similarity. We used synthetic data evaluation functions built in the Synthetic Data Vault library [10]. Both metrics compare individual attribute from the source data with the corresponding one at from the synthetic data, and report the averaged final score ranging from 0 to 1. As shown in the Table 2, our synthetic dataset is quite indistinguishable from the source dataset.

In addition, we compare the distribution of each attribute in two datasets. Figure 2 show the distribution of representative attributes (*Import Type, Country of Departure, Country of Origin Indicator, Critical Fraud*) in the dataset is analogous to that of the source dataset. Figure 3 illustrates that the correlation between the attributes in the synthetic data is similar to that of the source data. Figure 4 shows representative features in the downstream fraud detection task performed on each datasets by using the XGBoost model [1]. The tendency of feature importance score is analogous in both datasets. *Impoter ID, Item Price, Net Mass, Declarant ID*, and *HS10 Code* were considered important with high score.

Table 2: Statistical test results indicate that the synthetic data and the source data come from similar distribution.

Metric	Score
Chi-Squared Test	0.705
Two-Sample Kolmogovrov-Smirnov test	0.783

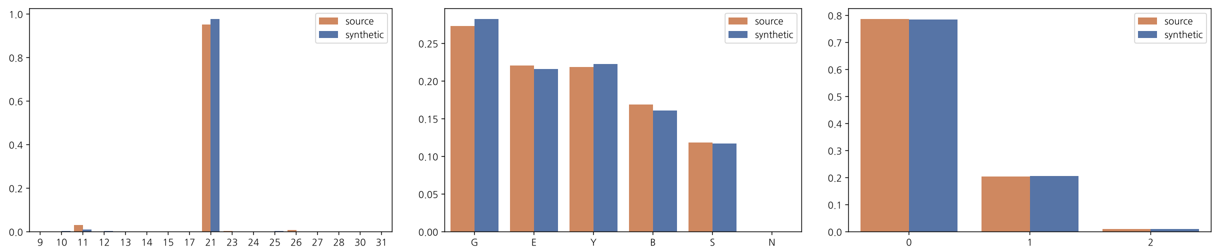
3 DATA GENERATION

3.1 Preprocessing

Among 24.7 million customs declarations reported for 18 months between January 1, 2020 and June 30, 2021, we used the inspected (i.e., labeled) part of the declarations to synthesize our data. Inspected items account for a fairly small percentage of the total, but they are more accurate, all validated by field officers. We call it as the source data throughout the paper. Identifiable information such as importer name in the source data are anonymized into *Importer ID*. The price of goods traded between vendors (i.e., *Item Price*) can be problematic when fully disclosed, so we add some Gaussian noise to the average price of each category of item.

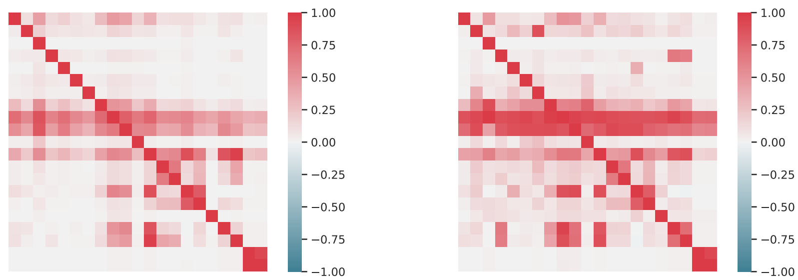
3.2 Generating Data with CTGAN

We used conditional tabular GAN (CTGAN) [13] from the Synthetic Data Vault library to generate the data. CTGAN is a specialized for tabular data and it uses conditional techniques to handle imbalanced discrete variables and multi-modal continuous variables. Compared to other tabular generative models such as TGAN [14] or TVAE [13], CTGAN showed the most realistic output to our dataset, preserving the relationship between columns. The data generation process can



(a) Import Type **(b) Country of Origin Indicator** **(c) Critical Fraud**

Figure 2: Representative feature distributions are similar between synthetic data and source data.



(a) Feature correlation in synthetic data **(b) Feature correlation in source data**

Figure 3: Feature correlation in synthetic data and in source data are also similar to each other.

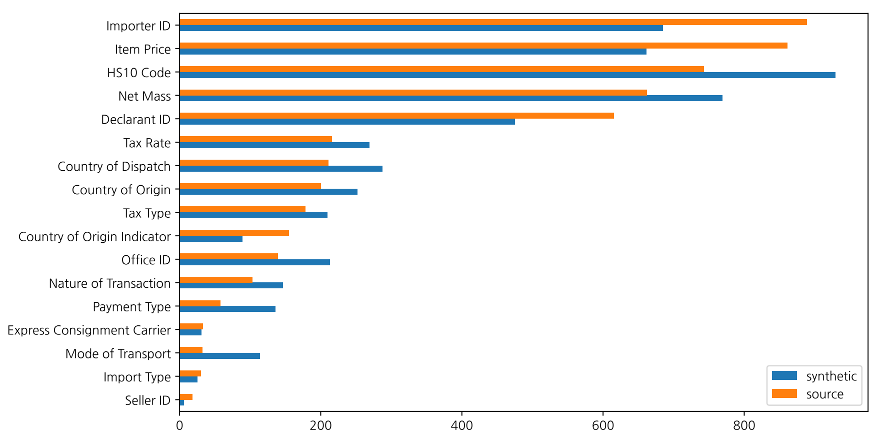


Figure 4: Important features for fraud detection task are also similar between the two datasets.

be done in serial or in parallel manner. Users with limited resources can split the data in chronological order, train the CTGAN model on each split, synthesize samples from each model, and aggregate the result. For each split, the model is trained for 100 epochs.

3.3 Maintaining Correlated Attributes

One of the important features of tabular data is correlation among attributes. To generate an realistic import declaration data, correlated attributes and their values should be maintained during the generation process. Although CTGAN is a tabular-specific generative model, the generated output often show distorted relation between attributes that have clear and strict relevancy. For example, attributes *HS10 Code—Country of Departure—Country of Origin—Tax Rate—Tax Type* are highly correlated to each other based on customs valuation policies. The correlation must be preserved also in the synthetic data. To maintain these obvious dependencies, we aggregate those attribute values and save it temporarily before running the CTGAN model. After running the model, the value is splitted to get the original format. In other case, *Item Price* attribute is dependent to the item and unit price. To maintain this property, *Item Price* is reconstructed after the data generation step, by the multiplication of *Net Mass* and the unit price of the each item.

4 APPLICATION— FRAUD DETECTION

In this section, we introduce how our dataset can be used as a benchmark for customs fraud detection problem.

4.1 Background

Smuggling drugs and weapons or fraudulent transactions such as tax dodging are fatal threats to society and public safety and customs administrations tries preventing those risks by inspecting suspicious items. But due to high amount of trade volume and limited budget, customs offices have to decide which item to inspect. Therefore, establishing a smart customs selection, or fraud detection system is a key to facilitate the clearance process [4–6, 8]. By predicting which item is likely-fraud, the inspection level of each item can be determined. The most suspicious items are subjected to physical inspection requiring human labor, so the smarter the algorithm, the more efficiently customs can operate its workforce.

4.2 Using the Data

For fraud detection problem, we can use the data by setting *Fraud* column as the target label. Then the aim is to develop a model to find the patterns behind the features on predicting the label. Data is split into three pieces. We assign the first 12-month of data into training set, and the following three months into validation set, and the last three months into test set. Categorical variables are label-encoded and numerical variable are min-max scaled. We used various models including Logistic Regression, Decision Tree, Random Forest, AdaBoost in scikit-learn [11] and gradient boosting decision tree (GBDT) models such as LightGBM [3], CatBoost [12], XGBoost [1]. We set the model to predict each record's fraud score ranging from 0 to 1. Among test records, we considered that n% of items with the highest score are inspected. Model performance is evaluated by the precision@n%, representing how much inspected items are actually fraud.[3]

4.3 Performance Comparison

Table 3 shows the performance trend of applying various fraud detection algorithms on synthetic and source data. Given that customs administration inspect a limited quantity of goods, we considered two inspection rates – 5% and 10%. In both datasets, precision on 5% setting is higher than that of 10%, and the performance of GBDT models such as CatBoost, XGBoost, and LightGBM is higher than the other models. Interestingly, the performance gain by applying an advanced model is distinguishable in synthetic data with a low inspection rate setting. From these reasonable results, we conclude that the synthetic data can be used as an open benchmark to develop advanced fraud detection algorithms.

[3]The amount of workforce available for physical inspection is usually fixed, so it is difficult to change n. Therefore, precision@n% is a more suitable metric than AUC or f-score.

Table 3: The fraud detection performance in the synthesized data follow a similar trend to the real data.

	Synthetic data		Source data	
Model | Precision	n = 5%	n = 10%	n = 5%	n = 10%
Logistic Regression	0.2870	0.2657	0.2320	0.2237
AdaBoost	0.3722	0.3363	0.5280	0.5047
Decision Tree	0.3722	0.3520	0.5440	0.4993
Random Forest	0.4215	0.3980	0.5520	0.5220
CatBoost	0.5874	0.5000	0.5813	0.5206
XGBoost	0.5942	0.5067	0.5760	0.5113
LightGBM	0.7220	0.5897	0.5493	0.5220

5 DISCUSSION

Area of research: In addition to the problem of selecting suspicious items, this import declaration data can be used for various data science problems in customs such as HS code classification [7], trade pattern analysis between key players such as importers, declarants, and offices. Together with these efforts, we expect to see user-friendly support in customs e-clearance systems.

Distribution of data: For the convenience of users, we create the data for items that were inspected thus labeled. However, this is not true in practice. According to each country's inspection standards, large portion of goods are cleared without going through any physical inspection, especially in developed countries with low fraud rate. This partially-labeled scenario can be simulated through post-processing such as erasing the labels of some data.

Degree of fabrication: There are some concern that data anonymization is not a sufficient condition to mitigate the potential risk of releasing the data. Adversaries may catch the patterns between the key players and disrupt the trade order even if the declarant code, product classification code, and extraction country code are anonymized. That was the main reason of synthesizing the data.

Generative model: Recently, a diffusion model has been discussed as an alternative way of generating artificial data in the computer vision domain [2]. If a diffusion model specialized for tabular data is released, it can be used to synthesize the data.

6 CONCLUSION

We present the customs import declaration data produced as part of sharing challenging data science problem in customs administration and facilitate the collaboration between customs and data science communities. With careful fabrication strategy, the generated data is fairly similar to the actual data, and can be used as a benchmark for downstream tasks such as fraud detection and product classification.

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