PRIMAFF Review No.100(2021.3),pp12-13

Predicting Substandard Fertilizer Using Machine Learning

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Visual inspection does not reveal the quality of fertilizer. Under such incomplete and asymmetric information, Nobel Prize-winning economist George A. Akerlof demonstrated that low-quality products would drive good ones out of the market. This prediction appears to be correct for fertilizer markets. Fertilizers with insufficient nutrition contents are frequently reported in developing countries (Bold et al. 2017) and were also reported a century ago in Japan (Takahashi 2017). To guarantee the quality of fertilizers, the Japanese government enacted a set of fertilizer regulations (the *Fertilizer Regulation Act*) in 1901, including licensing manufacture and sales, the attachment of labels containing ingredients and nutrition information, on-the-spot inspection, and a penalty system. However, substandard fertilizers are still in use today. Approximately 20% of inspected fertilizers violate labeling formats, advertised nutrient content, and/or tolerance limits of banned substances. We developed a methodology to detect substandard fertilizers using machine learning in order to improve inspection efficiency.

1. Method

Machine learning is a general term for a diverse set of statistical algorithms used to make predictions. Our goal is to determine whether the fertilizer meet the standard by analyzing various features of manufacturers and products. Researchers must choose independent (feature) variables somewhat subjectively when there are many possible candidate variables, but machine learning techniques employ more objective selection procedures based on prediction performance. In addition to conventional logistic regressions, we used the random forest (RF) and LASSO algorithms.

The model's output is either positive or negative. In this study, fertilizers that do not meet regulatory requirements are classified as positive (substandard), while others are classified as negative. Several metrics can be used to evaluate model performance, but we will focus on two metrics listed below. The first metric is *precision*, which is defined as a fraction of correct predictions among all positive predictions (TP/PM in Table 1), while the second metric—*recall* is defined as a fraction of fertilizers that are correctly predicted as positive among all substandard fertilizers (TP/P0).

Table 1. Confusion matrix

		Predicted condition		Total
		Negative	Positive	
Actual condition	Negative	TN (True Negative)	FP (False Positive)	N0
	Positive	FN (False Negative)	TP (True Positive)	P0
Total		NM	PM	

Source: Created by the author.

2. Results

The dataset includes about 3,000 inspection results from December 2015 to February 2020. During this period, 21% of inspected fertilizers were found to be positive. To avoid overfitting, the model parameters were identified using a random sample of 2/3 of the observations (training dataset), and prediction performance was evaluated using the remaining 1/3 observations (test dataset).

Figure 1 shows the results of the three models. We generated 99 results for each model by increasing the probability threshold of a positive and negative split from 1% to 99%. If the predicted probability is greater than this threshold, the fertilizer is classified as positive. In most regions, RF achieves higher precision and recall rates than the other two models, meaning that RF outperforms the other two models.

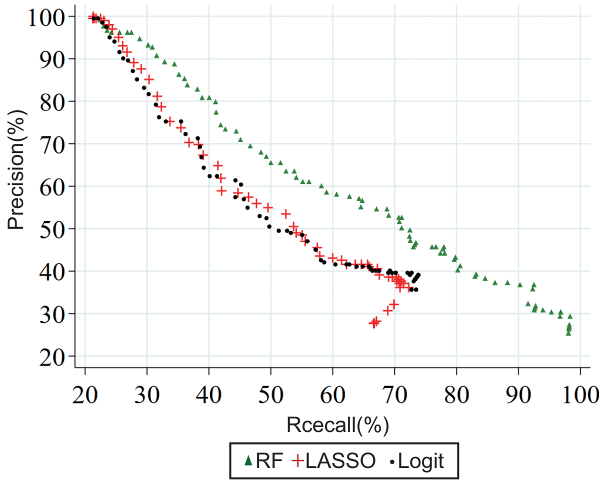

Figure 1. Model performance
Source: Created by the author.

Table 2. Confusion matrix (random forest with 41precision)

		Predicted condition		Total
		Negative	Positive	
Actual condition	Negative	523	223	746
	Positive	46	156	202
Total		569	379	948

Source: Author's calculations.

Table 2 shows an example of a confusion matrix derived from the RF model. This model classifies 40% (379/948) of all observations in the test dataset as positive, and 41% (156/379) of these predictions are correct. This is a precision concept. Furthermore, 77% (156/202) of actual

Original; Japanese
Translated and published in Jul. 2021

substandard fertilizers are classified as positive. It is a recall. In contrast, the remaining 23% are incorrectly classified as negative (false negative).

3. Application to Inspection System

To improve inspection efficiency, we used RF models. Consider a simple audit rule that inspects all available fertilizers sequentially. If the authority inspects I items per year out of N registered items, all inspections will take N/I years to complete. Our goal is to shorten this period, herein referred as the "inspection cycle."

Next, we divided inspection resources I into positive and negative classes predicted using RF models. To avoid false negatives, the negative class is also inspected. We discovered that when the probability threshold and resource allocations are optimized, the inspection cycle is reduced by 16%. Under this optimal audit rules, 33% of inspection resources I are allocated to the positive class, while the remainder is allocated to the negative class. Compared to the benchmark, the inspection cycle for the negative class is slightly longer (+24%), while it is nearly half the length for the positive class. As a result, the average inspection cycle is reduced by 16% when weighted by the number of substandard fertilizers. It should be noted that the size of N and I do not affect these results.

We also discovered that more complex inspection algorithms based on predicted probability and/or production volumes could cut the inspection cycle by more than half.

【References】

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Original; Japanese
Translated and published in Jul. 2021