Intelligent Causal Analysis System for Wafer Quality Control using Sparse Modeling

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Introduction

In semiconductor factories, it is critical to deal with variance of quality indicators timely and precisely. Quality experts can analyze causes of its variance using advanced statistical methods or tools, but doing so is typically time and cost consuming. Although there have been some attempts to realize automatic causal analysis, it remains difficulties because (i)there are often too many causal candidates and (ii)exhibit high correlations among them.

We propose a new intelligent causal analysis system using sparse modeling. Sparse modeling is a state-of-the-art modeling technique that overcomes the difficulty (i). In addition, we propose a technique that overcomes the difficulty (ii). To our knowledge, this is the first research that demonstrates the effectiveness of sparse modeling for automatic causal analysis based on primary production line data. Our method is widely applicable to many other fields.

Proposed Method

We consider the goal of causal analysis for a specific quality indicator to be extraction of causal variables and construction of a linear regression model that explains the behavior of the quality indicator. In practice, sample sizes are small relative to the number of causal candidates, so ordinary linear regression cannot be applied. However, one of the most representative sparse modeling methods, "Lasso" [1], is applicable. Lasso solves $\min_{\beta}\|y - X\beta\|_2^2 + \lambda\|\beta\|_1$, where n is the number of samples, p is the number of variables, $X \in \mathbb{R}^{n\times p}$ are variables of causal candidates, $y \in \mathbb{R}^n$ is an objective quality indicator, $\beta \in \mathbb{R}^p$ are regression coefficients, and λ is a regularization parameter. The Lasso solution $\hat{\beta}$ is sparse, meaning it has few nonzero coefficients. Therefore, Lasso automatically selects effective variables and resolves the difficulty arising from a large number of causal candidates.

However, the problem of strong correlation between causal candidates remains. In cases of strongly correlated variables, Lasso selects only one and discards the others. As a result, we may miss true causal variables. To overcome this problem, we extract the remaining variables that are correlated to the Lasso variables, yielding a comprehensive extraction of causal candidates.

The following summarizes the overall procedure.

(1) Input all variables of causal candidates.
(2) Construct a linear regression model using Lasso.
(3) Extract variables correlated with Lasso variables.
(4) Check the validity of the model. Repeat procedures (1)–(3) after reconstructing input data according to validity.

Results

We experimentally applied the proposed method to a wafer quality indicator, using 303 samples and 23,600 variables. We first used Lasso. We found that 0.75 was the largest value of the regularization parameter such that the error was within one standard error of the minimum (Fig. 1), and 27 variables were selected (Fig. 2), which is far less than the number of candidates. We then computed the correlation between Lasso variables and remainders, and extracted those with values exceeding a threshold.

To evaluate the accuracy of causal variable selection, we performed comparisons with variables extracted by quality experts. Since traditional linear regression cannot be used, the experts used ANOVA, p-values, several graphs and their expert knowledge. As a result, we found that our method covered more than 90% of variables extracted by quality experts.

These results can be visualized as a network diagram (Fig. 3), where nodes represent extracted causal variables and edges represent relations among them. Lasso variables are connected to a central wafer quality indicator, and similar variables are connected to Lasso variables. We can intuitively see the relations among variables.

Since our framework executes automatically and is easy to interpret, it drastically reduces analysis times. In our trial, the time required for analysis was reduced from 7 days to 1 day. The proposed method thus timely extracts causes.

Conclusion

We proposed a new framework for automatic causal analysis. We experimentally applied the method to a wafer quality indicator, thereby demonstrating the effectiveness of the method.

References

[1] Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 267-288.

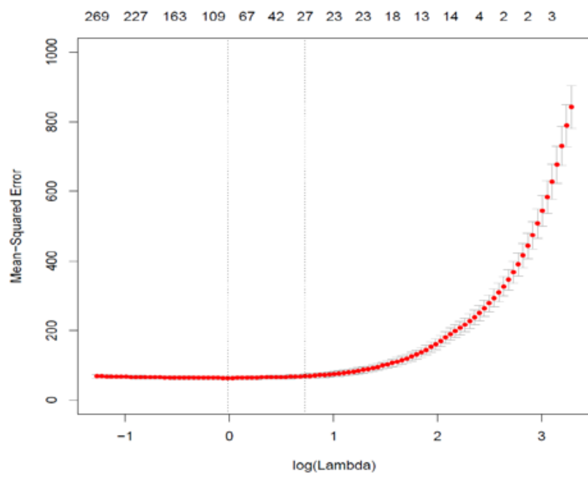

Figure 1: Mean squared error and the regularization parameter

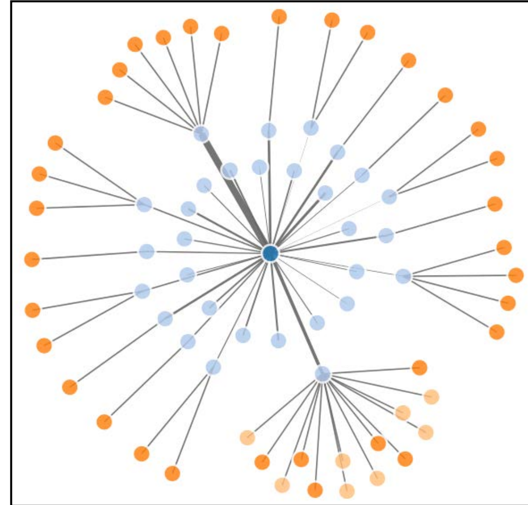

Figure 3: Network diagram of causal variables

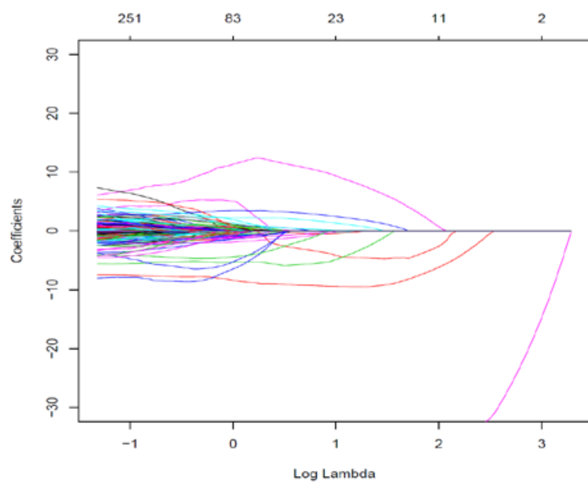

Figure 2: Coefficients and the regularization parameter