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# An investigation on hybrid feature selection based on impurity and LIME feature importance

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***Abstract***

With respect to explainable artificial intelligence, feature importance is a key indicator for understanding the prediction criteria of a model. This paper presents the experimental results of performing feature selection based on feature importance and comparing model performance for each constructed feature subset. To this end, the ranking for each feature is determined by combining impurity and LIME feature importance on a random forest regressor model trained on the sales dataset. Next, the process of constructing a feature subset from which week features are removed according to the feature importance ranking through the recursive feature elimination method and measuring its performance is repeated.

***Keywords*****:** eXplainable Artificial Intelligence, feature selection, model-agnostic explanation, LIME

## 1. Introduction

eXplainable Artificial Intelligence (XAI) is being studied to understand the operation process and prediction results of machine learning models deployed and operating in the field. In particular, feature importance is used as an informative indicator not only when interpreting the output of the model, but also in the feature selection process before model training. Optimizing feature selection yields opportunities that reduce training time and memory consumption while preserving the performance of the model as much as possible.

In this paper, we present experimental results to investigate the effectiveness of a hybrid feature selection combining two types of feature importance; the first is impurity-based feature importance, and the second type is feature importance derived from Local-Interpretable Model-agnostic Explanations (LIME [1]), a well-adopted XAI technique for the local explanation. To this end, the ranking for each feature is determined by combining two types of feature importance on a random forest regressor model trained on the sales dataset. Next, the process of constructing a feature subset from which week features are removed according to the feature importance ranking through the recursive feature elimination method and measuring its performance is repeated.

## 2. Feature Importance Measures

### 2.1 Impurity-based Feature Importance

When training a tree-based model, it is possible to compute how much each feature decreases the impurity. Therefore, the feature that decreases the impurity more is the more important one.

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### 2.2 LIME Feature Importance

LIME [1] is an XAI method to understand the instance-level prediction results created by a black-box machine learning model. As LIME focuses on local explanations, an explanation model that approximates the original model linearly is trained centered on the selected instance which needs to be explained. LIME creates an explanation model that balances local fidelity and interpretability as a trade-off behavior.

## 3. Experimental Result

To investigate the effectiveness of the hybrid feature selection method, we exploit a Rossmann store sales dataset [2] and conduct a feature extraction task. The feature set for the experiment includes the following:

- StoreType: different store models (a, b, c, d)
- Assortment: describes an assortment level
- CompetitionDistance: distance in meters to the nearest competitor store
- CompetitionOpenElapsedDays: the elapsed days since the competitor store opened
- Promo: indicates whether a store is running a promo on that day
- Promo2ElapsedDays: the elapsed days since the store started participating in the promotion

Table 1 represents the ranking of features derived by combining impurity and LIME feature importance. As the trained model is of a random forest, the impurity decrease from each feature is the average across trees.

**Table 1.** Feature importance and ranking results

| feature | impurity | LIME | ranking |
|---|---|---|---|
| Promo | 0.1367(2) | 855.8936(1) | 1 |
| DayOfWeek_1 | 0.0335(5) | 222.7965(2) | 2 |
| Competition OpenElapsedDays | 0.1302(3) | 68.0728(7) | 3 |
| Promo2 ElapsedDays | 0.0413(4) | 74.8060(6) | 3 |
| Competition Distance | 0.3928(1) | 54.9832(10) | 5 |
| Month_12 | 0.0223(7) | 108.2533(4) | 5 |
| Assortment_c | 0.0112(14) | 117.1192(3) | 7 |
| Assortment_a | 0.0107(15) | 102.2983(5) | 8 |
| PromoInterval_ Mar,Jun,Sept,Dec | 0.0157(11) | 59.3330(9) | 8 |
| PromoInterval_0 | 0.0206(8) | 20.9589(17) | 10 |

Based on the feature importance results, we conduct measuring model performance in terms of accuracy (mean absolute error) and computation time. To construct a feature subset, we use the recursive feature elimination as a feature selection method and Fig. 1 shows the results of the performance evaluation.

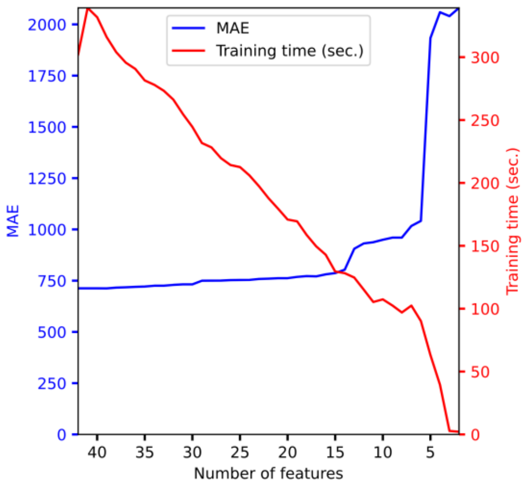


**Fig. 1.** MAE and training time by the number of features

The experimental result suggests that even if the feature size is reduced by more than half through the hybrid feature selection (e.g., 42→15), the adverse effect on MAE is acceptable (e.g., 712→786), while training time can be significantly decreased (e.g., 302 sec. →129 sec.).

## 4. Conclusions

In this paper, we investigated the effectiveness of hybrid feature selection based on impurity and LIME feature importance that yields decreased computation time while preserving model accuracy at an acceptable level.

## References

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