Title

Summary

Sailboats fulfill diverse roles, fueling a thriving second-hand market. Brokers, facing numerous complex factors, struggle to determine reasonable pricing. A tool is urgently needed to assist in comprehensive evaluations and rational pricing for used boats.

This paper aims to construct a reliable model based on existing datasets, which can provide a reasonable explanation for the pricing of the used sailboat market. It also analyzes the impact of different factors and indicators on prices. Finally, the model will be applied to the used sailboat market in Hong Kong to provide a reasonable and accurate pricing rule.

For Data Exploration, …

For Problem(a), …

For Problem(b), …

For Problem(c), …

For Problem(d), …

For Problem(e), …

Finally, we conducted an analysis of the strengths and weaknesses of our model, as well as its sensitivity. The results demonstrate that our model exhibits high levels of robustness, precision, and accuracy. After that, a report is attached.

Keywords: Linear interpolation, Adaptive Density-Based Clustering, Heuristic Hierarchical Multiple Regression, Deep Forest Model, Machine Learning, Analysis of Variance.

Contents

1 Introduction

1.1 Background

In our daily lives, sailboats are not only a means of transportation but also serve as leisure, entertainment, and even for competitive sports. As a result, the growing demand for sailboats has given rise to a thriving boat market, which has developed into a second-hand market. In the market, buyers and sellers usually trade through brokers, who play a crucial role in the transaction process.

For brokers, it is essential to be familiar with the second-hand sailboat market, comprehensively consider various factors, and make reasonable pricing for the used sailboats in order to facilitate a successful transaction. However, the factors affecting the price of used sailboats are numerous and complex, with different brands, variants of boats, years, depreciation rates, as well as local consumption levels and geographical environments having significant impacts. The intertwined influences of these complex factors make it difficult to determine the pricing in the used sailboat market, and it is challenging to come up with a reasonable price that takes all factors into account.

Therefore, brokers urgently need a tool to assist them in making more reasonable and comprehensive evaluations of used sailboats and to make the pricing in the used sailboat market more rational.

1.2 Problem Restatement

Problem (a) :

- Develop a prediction model to explain the listing price of each of the sailboats in the provided spreadsheet.

- Discuss the precision of our estimate for each sailboat variant's price.

Problem (b) :

- Determine whether Region has an impact on the price of second-hand boats and explain the effect.

- Discuss whether any regional effect is consistent across all sailboat variants.

- Address the practical and statistical significance of any regional effects noted.

Problem (c) :

- Based on the model, find out how it can be useful in the Hong Kong market.

- Choose one subset and model the regional effect of Hong Kong on each sailboat's prices.

- Assess whether the effect is the same for both catamarans and monohull sailboats.

Problem (d) :

- Identify and discuss additional informative conclusions drawn from the data.

Problem (e) :

- Create a one-to-two-page report with well-chosen graphics to help the Hong Kong sailboat broker to understand your findings.

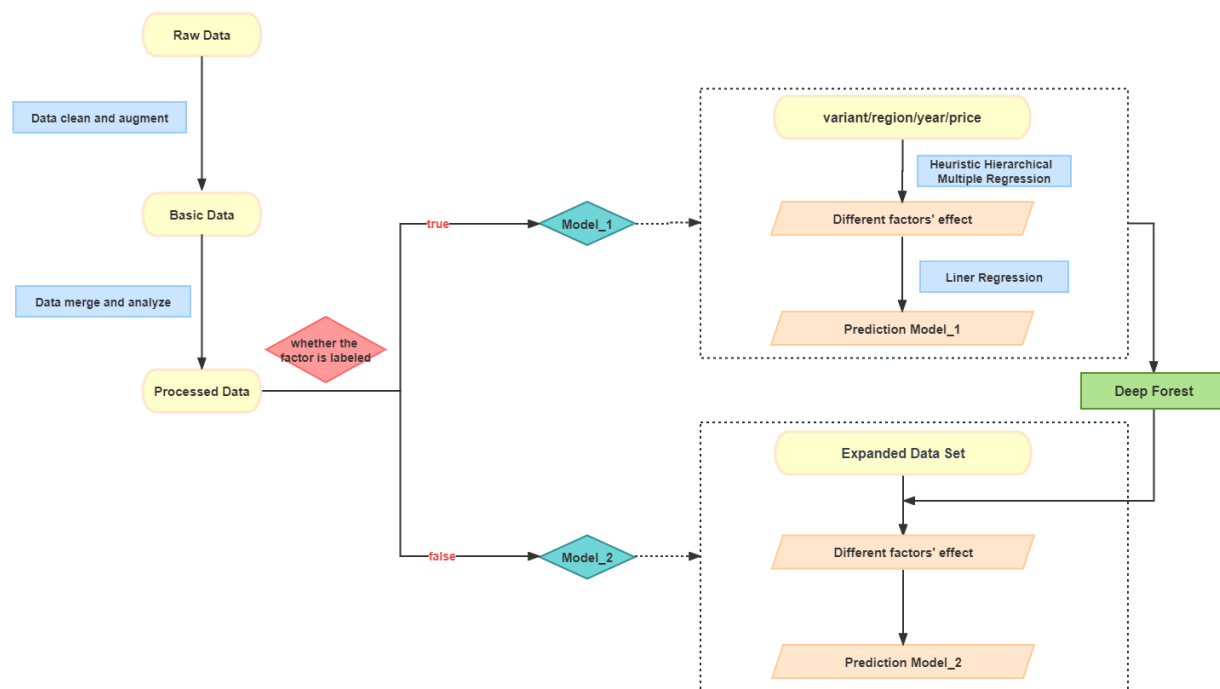## 1.3　Our work & Model Overview

Figure 1: Model Framework

Our team began by meticulously cleaning, expanding, and pre-analyzing the dataset using **Adaptive Density-Based Clustering** and **Linear interpolation** techniques. These methods allowed us to identify patterns and trends in the data, preparing it for subsequent modeling.

Then, we utilized a **Hierarchical Multiple Regression** to abstractly express the Region Effect and Variant Effect, to achieve the continuous representation of the two discrete variables, Region and Variant. Next, we applied **Linear Regression** to obtain the relationship between Year, Region Effect, Variant Effect, and Price. This approach helped us capture the interactions between these variables and their influence on the pricing.

Following this, we employed a **Deep Forest Model** to estimate the relationship between region and variant indicators and their respective effects. This advanced ensemble learning technique allowed us to predict the effect of unknown regions and variants, which in turn enabled us to further predict their prices.

As a result, we successfully developed a comprehensive and robust model (Figure 1) that is well-suited for Hong Kong brokers when pricing used sailboats. By leveraging the strengths of both Heuristic Hierarchical Multiple Regression and Deep Forest Models, our approach offers a

reliable and accurate way to estimate the value of sailboats based on indicators in the dataset. This model serves as a valuable tool for brokers and other stakeholders in the sailboat market, facilitating informed decision-making and ensuring fair pricing practices.

2 Assumptions and Justifications

2.1 Assumptions

To simplify our problems, we make the following basic assumptions, each of which is adequately justified.

- The price of used sailboats is solely determined by the factors in the dataset.

- The factors in the dataset are independent and unrelated.

- The data in the dataset are all real, reasonable, and follow a certain pattern.

- For the used boats that need price prediction, we can obtain at least the same number of factors information as in the dataset.

- The pricing required by a broker should be reasonable and in accordance with market rules, rather than false pricing.

2.2 Notations

| Symbol	Definition
l	Measurement data
L	Feature vector
F	The dimension of L
k	Search range
λ	The feature values of natural neighbors
$nb_k(l)$	The number of reverse neighbors of l in the k-th iteration
R	Correlation coefficient
$\hat{y}$	The estimated value of y
$\hat{\beta}$	The estimated value of the regression coefficients
X, Y	The variables for which the correlation is to be tested
P	Measured value
Q	Simulated value
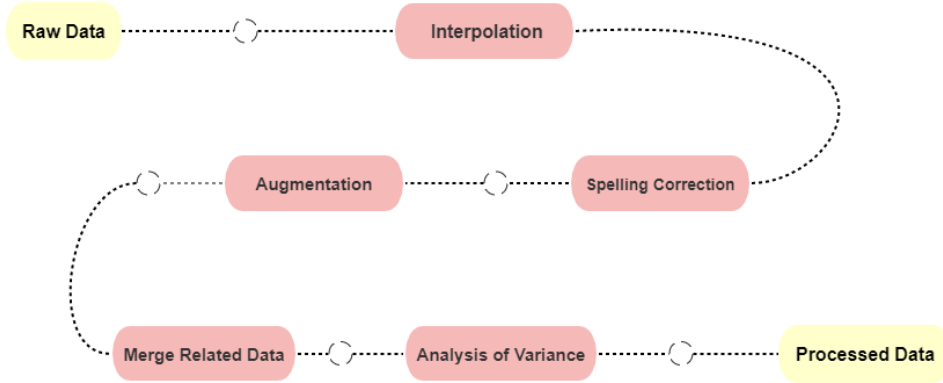
Figure 2: Data Exploration

3 Data Exploration

3.1 Data Cleaning

First of all, we turn the given **xlsx** format data sheet into **csv** format. The conversion causes some minor errors like extra spaces and unexcepted characters which can be easily filtered out by text editor and python string operating functions like **strip()** or so.

Secondly, we use **Linear interpolation** to fill in the missing data and then apply **Adaptive Density-Based Clustering** for spell correction, resulting in a more complete and accurate dataset than the original.

Specificlly:

Based on the text-type variables, the feature matrix L_i is used, and the Euclidean distance is used to calculate the text similarity:

$$dist(l_i, l_j) = \sqrt{\sum_{f=1}^{F}(L_i^f - L_j^f)^2}$$

Because ADC is a clustering iterative process, we first calculate the k-Nearest Neighbors:

$$NN_k(l_i) = \{l_j \in D | dist(l_i, l_j) \leq dist(l_i, o)\}$$

Then we define the Reverse Neighbors as:

$$RNN(l_i) = \{l_j \in D | l_i \in NN_k(l_j)\}$$

Applying NN_k and $RNN(l)$ iteratively to obtain clustering centers, unclassified text samples are assigned to the nearest clustering center, and λ is calculated as follows:

$$\lambda = \min\{k | \sum_{i=1}^{n} f(nb_k(l_i)) = 0 \quad or \quad \sum_{i=0}^{n} f(nb_k(l_i)) = \sum_{i=0}^{n} f(nb_{k-1}(l_i))\}$$

Where $f(x)$ is defined as:

$$f(x) = \begin{cases} 0, & otherwise \\ 1, & if \quad x = 0 \end{cases}$$

Further more, we merge **Make** into **Variant** into a single feature, which we refer to as **Variant**.

Finally, we merge the corrected dataset with the accurate one after making necessary modifications.

Jeanneau Sun Odyssey 41DS   Lagoon 450s

Jeanneau Sun Odyessy 41DS   Lagoon 450S

Bavaria Cruiser 46   Nautitech 46 Open

Bavaria 46 Cruiser   Nautitech 46 open

Figure 3: Examples of error data

3.2 Data Augmentation

Our team diligently collected and organized additional ship attributes for the given dataset using Pandas' `read_html` web scraping technique, which allowed us to efficiently extract valuable information from various online sources. Simultaneously, we gathered the 2020 GDP per capita data of the relevant regions to provide important economic context that might influence sailboat prices.

Upon obtaining the data, we first employed Pandas' related functions to remove any duplicate entries, ensuring the dataset's integrity and uniqueness. Next, we addressed missing values by using linear interpolation, a technique that estimates missing data points by drawing upon the values of neighboring data points. This approach helped us create a more complete and reliable dataset for further analysis.

These data collection, organization, and preprocessing efforts significantly enriched the diversity of the data and expanded the dataset dimension. By incorporating a wider range of sailboat features and relevant economic data, we were able to develop a more comprehensive understanding of the factors influencing sailboat prices. This extensive dataset laid a solid foundation for our subsequent modeling efforts, enabling us to create more accurate and reliable predictive models for sailboat pricing.

3.3 Data Analysis

There is a lot of labels related to sailboat specifications, which is complicated and may have mutually subtle relationship. Therefore, it is challenging to discuss their individual influence on listing prices. Attempting to directly perform regression on these labels using machine learning models can lead to **overfitting issues**, where the model becomes too specialized in fitting the training data and loses its ability to generalize well to new, unseen data.

Despite these challenges, we can still extract some relatively straightforward insights from the data, which can provide valuable theoretical support for our subsequent modeling efforts:

- Time: Time is a quasi-continuous and ordered variable, exhibiting a clear linear relationship with the price of sailboats (as demonstrated in Figure 4 and Table 1). As sailboats age, their value typically decreases, reflecting factors such as depreciation, wear and tear, and technological advancements in newer models.

- Variant and Region: These factors are undeniably related to sailboat prices; however, their unordered and non-continuous nature necessitates further analysis. Sailboat variants can encompass different designs, sizes, and features, which can significantly impact their value. Similarly, regional factors such as local demand, availability, economic conditions, and even cultural preferences can influence sailboat prices.
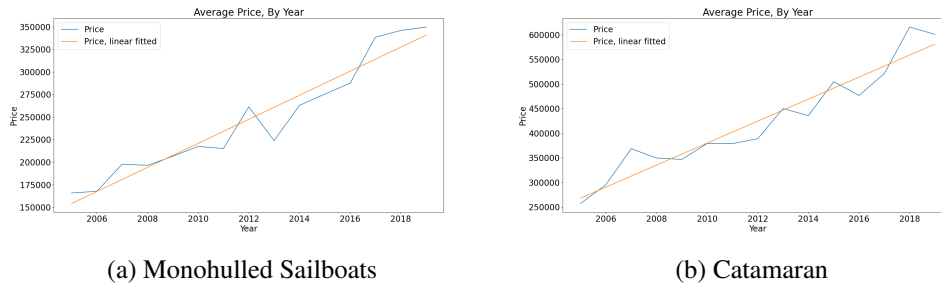

(a) Monohulled Sailboats   (b) Catamaran

Figure 4: The relationship between year and price

	Pearson	Spearman	Kendall
Monohulled Sailboats	0.964	0.989	0.943
Catamaran	0.960	0.971	0.867

Table 1: The correlation coefficient of year and price

4 The Prediction Model of Used Sailboat Prices

4.1 The Establishment of The Model

4.1.1 Model 1 —Heuristic Hierarchical Multiple Regression

Model 1, as illustrated in Figure 5, is specifically designed to predict prices by taking into account input variables such as Year, Region, and Variant. To achieve accurate predictions, this model incorporates a heuristic hierarchical multiple regression approach, which distinguishes it from conventional regression methods. This innovative technique allows for a more nuanced understanding of the relationships between variables, ultimately leading to improved performance and reliability.

As for Hierarchical Multiple Regression, to solve the objective function for a given n data points (x_i, y_i):

$$L(y, f(x, w)) = \sum_{i=1}^{n} [y_i - f(x_i, w_i)]^2$$

To get the coefficient matrix, we typically use the least squares method to solve it:

$$\min f(x) = \sum_{i=1}^{n} L_i^2(x) = \sum_{i=1}^{n} L_i^2[y_i, f(x_i, w_i)] = \sum_{i=1}^{n} [y_i - f(x_i, w_i)]^2$$

The matrix is illustrated as:

$$\hat{\beta} = (X^T X)^{-1} X^T Y = \left(\sum x_i x_i^T\right)^{-1} \left(\sum x_i y_i\right)$$

Then we get the predicted value:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + ... + \hat{\beta}_p x_p$$

In the hierarchical multiple regression process, each layer focuses on one variable, denormalizing it while normalizing the other two variables. The price generated at this stage is regarded as the Effect of the specific variable under consideration. Simultaneously, the fitting result from the current layer is used as the baseline for normalization in the next layer, which is then incorporated into the regression. This iterative process continues until the model achieves a precise fitting effect, ensuring optimal performance and an accurate understanding of the relationships between variables. A key aspect of *Model 1*'s success is the heuristic approach employed during each nor-
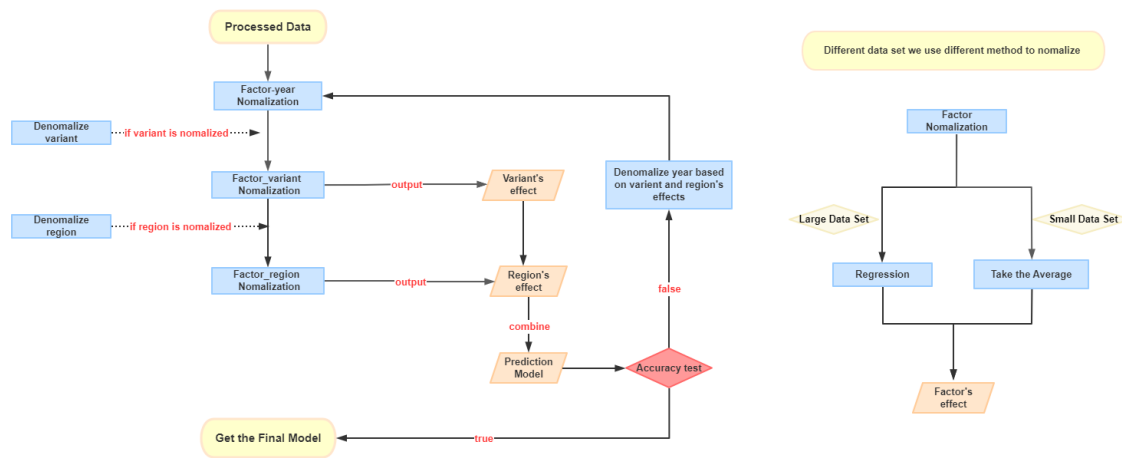

Figure 5: Brief process of Model 1

malization step. This method adapts to the size of the dataset, offering a more efficient and effective means of processing the data. For larger datasets, regression is performed, which capitalizes on the wealth of information available and can identify complex patterns and relationships. Conversely, for smaller datasets, the model calculates the average, providing a simpler and more straightforward representation of the data.
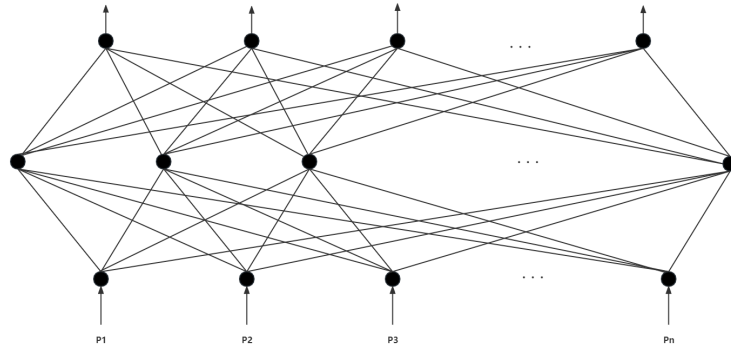
Figure 6: Hierarchical Multiple Regression

This adaptive heuristic approach has a significant impact on the accuracy of the model's predictions, as it tailors the normalization process to suit the specific characteristics of the dataset. By adjusting the method used based on dataset size, *Model 1* is better able to understand the underlying patterns and relationships, leading to more accurate and reliable predictions.

4.1.2   Model 2 —Deep Forest Model

However, the regression prediction based on *Model 1* is incomplete, as *Model 1* requires the variant and region of the data being predicted to have appeared in the dataset before. In practice, the variant and region might be unseen by the Model. For instance, in the third question, *Model 1* cannot predict the prices in Hong Kong since the Model has not assessed the region effect for Hong Kong. Therefore, we employed the Deep Forest algorithm to establish *Model 2*.
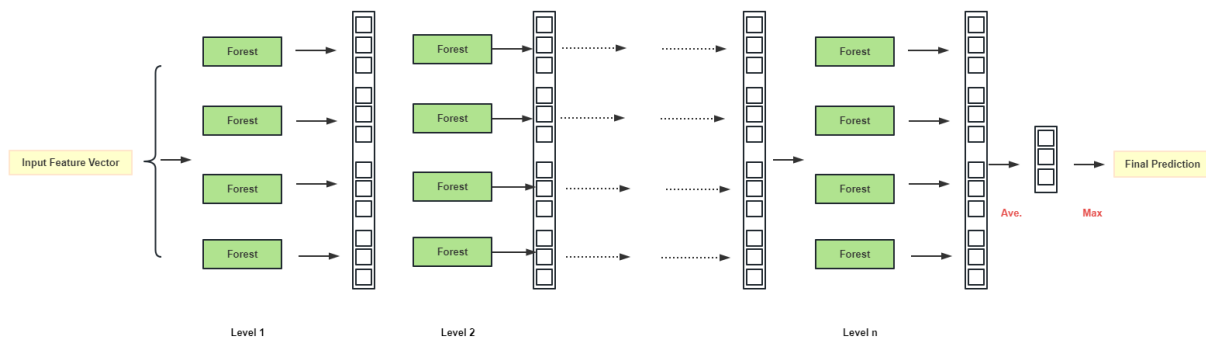

Figure 7: Deep Forest Model

Decision trees are a common machine learning method, with both classification and regression models. Initially, we used a basic decision tree for regression, but the model had a large error and poor accuracy for predicting prices. As a result, we optimized the model using the Deep Forest algorithm. Deep Forest is an ensemble learning model based on random forests. Unlike traditional decision trees, Deep Forest uses randomized strategies to train each tree-based classifier, increasing the model's diversity. Compared to a single decision tree, the Deep Forest model is more robust. The simplified process is as follows:

First, we expanded the dataset to obtain quantitative data for the region and variant. Specifically,
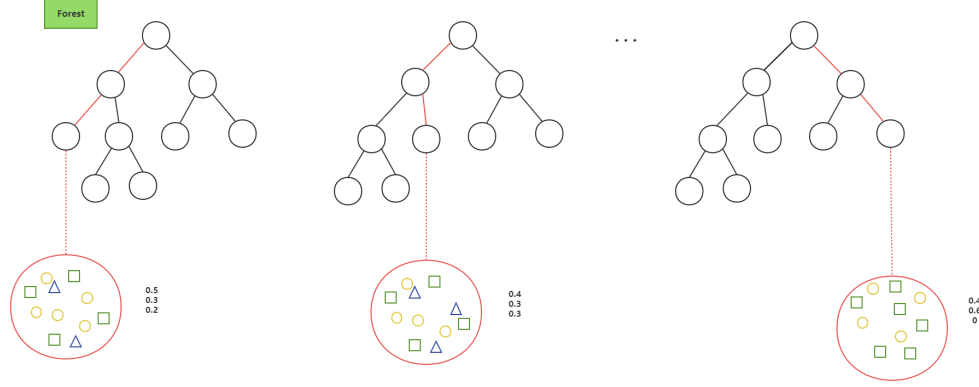
Figure 8: Deep Forest Model

for the variant, we expanded data such as draft, beam, water tank, fuel tank, cabins, and displacement. For the region, we expanded data such as GDP per capita, Gini coefficient, and Human Development Index. When dealing with unmarked variants and regions, we first applied *Model 1* to obtain the effect of marked variants and regions. Then, we applied the effect of marked variants and regions to the Deep Forest, regressing through the expanded data to obtain the effect of unmarked variants and regions, and thus predicting the price.
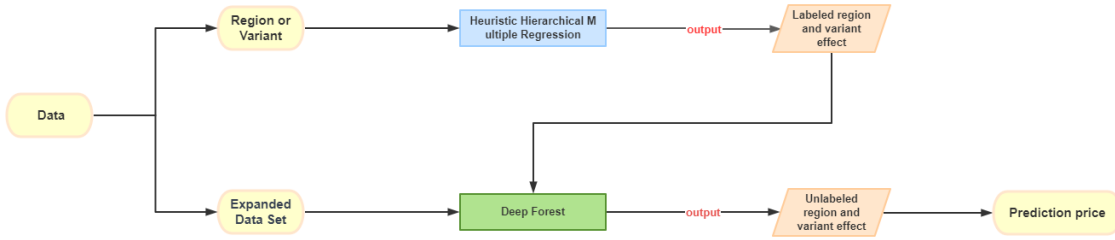

Figure 9: Brief process of Model 2

4.2   Model Accuracy Analysis

Due to the limited data provided for some sailship types, they belong to imbalanced datasets. Therefore, we need to use as much data as possible for training to prevent the loss of small-sample data during training. Given that the leave-one-out method is not affected by random partition, it is effective for small-sample and imbalanced datasets, and can accurately evaluate the performance of the model, we used the **leave-one-out method** to analyze the model's error in the error analysis part.

For accuracy analysis, we use the correlation coefficient R and Mean Absolute Percentage Error (MAPE) as evaluation metrics.

$$R(\mathbf{X}, \mathbf{Y}) = \frac{\text{cov}(\mathbf{X}, \mathbf{Y})}{\sqrt{\text{var}[\mathbf{X}]\text{var}[\mathbf{Y}]}}$$

$$\text{MAPE} = \frac{\sum_{i=1}^{n} \left(\frac{|\mathbf{P}-\mathbf{Q}|}{\mathbf{P}} \times 100\% \right)}{n}$$

where:

$$\text{var}(\mathbf{X}) = \frac{\sum_{i=1}^{n}(\mathbf{X}_i - \overline{\mathbf{X}})(\mathbf{X}_i - \overline{\mathbf{X}})}{n-1}$$

$$\text{cov}(\mathbf{X}, \mathbf{Y}) = \frac{\sum_{i=1}^{n}(\mathbf{X}_i - \overline{\mathbf{X}})(\mathbf{Y}_i - \overline{\mathbf{Y}})}{n-1}$$

Train	Cata	Mono
R^2	0.924	0.974
MAPE	5.09%	7.29%

Test	Cata	Mono
R^2	0.901	0.942
MAPE	10.16%	11.65%

HK	Cata	Mono
R^2	0.849	0.885
MAPE	7.18%	8.70%

Table 2: Accuracy of Train Set, Test Set and HK Set

5 Regional Effect Analysis

Applying *Model 1*, we can easily abstract the effect of each region. Therefore, by normalizing the year and variant, we can clearly see the effect of each region(see Figure 10).
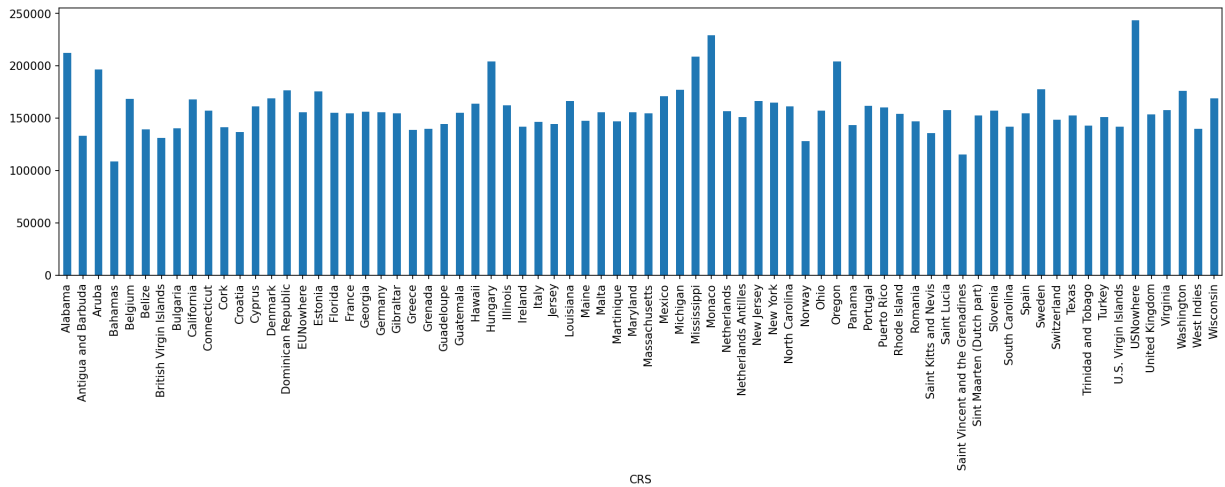

Figure 10: Region Effect

6 The Applicability of The Prediction Model in Hong Kong

When applying our model to the Hong Kong region, we first try to obtain the indicators for the used sailboats. For Hong Kong, we start by using *Model 2* to determine the Region Effect, leveraging the area's GDP per capita data.

If the predicted Variant is present in the training set, we can directly use *Model 1* to estimate the pricing by incorporating the Region Effect, Variant Effect, and Year. However, if the predicted

Variant is not in the training set, we first need to use *Model 2* to obtain the Variant Effect by considering factors such as beam, draft, and displacement. Once the Variant Effect is determined, we can then employ *Model 1* to make the final price prediction.

This two-step approach enables us to adapt our models to different regions like Hong Kong and successfully predict used sailboat prices. By utilizing both *Model 1* and *Model 2* in tandem, we can account for regional influences, specific variant characteristics, and the age of the sailboat to provide accurate and reliable pricing estimates.

7   Extended Inferences or Conclusion

8   Strengths and Weaknesses

8.1   Strengths

Strength-1 Comprehensiveness: After the basic data processing, we significantly expanded the dataset, including extending the Variant to Draft, Beam, Displacement, Water tank, Fuel tank, and Cabin, as well as expanding the Region to GDP per capita. We performed correlation tests for each variable, making the modeling process extensive and comprehensive.

Strength-2 Innovative: Our model combines heuristic learning and hierarchical multivariate regression, obtaining accurate predictions through continuous iteration. This creative and highly applicable model is well-suited for the task at hand.Additionally, we used a deep forest algorithm to extend the prediction of unknown variants and regions, enhancing the model's versatility.

Strength-3 Accuracy: Our model performs exceptionally well in terms of both error analysis and accuracy, achieving 94.91% on the Catamarans test set and 92.71% on the Monohulled Boats test set. Moreover, the model can improve its accuracy through self-iteration and possesses heuristic learning capabilities.

Strength-4 Applicability: When applied to the Hong Kong market, the model maintains a high level of accuracy, demonstrating its excellent applicability.

8.2   Weaknesses

Weakness-1 Time consuming: The model can achieve satisfactory regression results after 2-3 iterations when processing the data for this task. However, when handling larger datasets, the increased number of iterations may result in additional time costs.

Weakness-2 Lack of geography factor analysis: Due to the difficulty in obtaining geographical data and the challenge of analyzing and quantifying factors such as climate, the model does not include geographical factors. Despite this limitation, the model still provides valuable insights and accurate predictions for the used sailboat market.

9 Further Improvements

Although our Model has been optimized over several days, evolving from a simple decision tree to an organic combination of Heuristic Hierarchical Multiple Regression and Deep Forest, both *Model 1* and *Model 2* have produced excellent results in price prediction. However, during each iteration, we still only used a simple regression model, with accuracy being the result of iteration and heuristic learning. Upon reviewing the model, we identified the following two issues:

- When fitting the Variant Effect, we lost regional information.

- Combined Make and Variant, causing the model to overlook the premium issue between different Makes.

9.1 Lasso Regression Update for Model

To address the first issue, we decided to use Lasso Regression to replace the simple linear regression in each iteration process. The characteristics of Lasso Regression, which can avoid the problem of multicollinearity, also resolved the shortcomings of the original model. In each round of iterative regression, we only need to perform Lasso Regression on Variant and Region once, avoiding the loss of regional information. The specific formula is as follows:

L_1, L_2 regularization:

$$L_1 = \lambda \sum_{j=1}^{p} |\beta_j|, L_2 = \sum_{j=1}^{p} \beta_j^2$$

Lasso Regression's loss function:

$$\text{minimize} \frac{1}{2n}||y - X\beta||_2^2 + \lambda||\beta||_1$$

Assume $\beta_i = \{\beta_{i1}, \beta_{i2}, \beta_{i3}\}$After introducing Lasso Regression, the model's process becomes:

- **Step 1:** Since the relationship between year and price is highly linear, we first normalize the Year parameter to remove its influence,we can get β_{11}.

- **Step 2:** Then apply Lasso Regression to simultaneously normalize Variant and Region, combining the original functions $f_1(\beta_{12})\&g(\beta_{13})$ into $h_1(\beta_{12}, \beta_{13})$.

- **Step 3:** Feeding $\beta_1 = \{\beta_{11}, \beta_{12}, \beta_{13}\}$ into the iterative heuristic learning function. We perform iterative regression to obtain $h_1(\beta_{12}, \beta_{13}), h_2(\beta_{22}, \beta_{23}), \cdots, h_n(\beta_{n2}, \beta_{n3})$ until the desired accuracy is reached, resulting in the final matrix $\beta_n = \{\beta_{n1}, \beta_{n2}, \beta_{n3}\}$.

- **Step 4:** Using β_n for regression prediction, we obtain the predicted value.

This process is similar to the basic model idea. We also tried to update the model using Lasso Regression and re-predict the price. However, due to the lack of precision in the design matrix and the difficulty in controlling the regularization strength, the update was unsuccessful. Nonetheless, based on the initial improved model results and the Lasso Regression loss function, we can predict that the improved model will address multicollinearity issues for correlated Variant and Region variables.

9.2   Better utilization of the Deep Forest

As previously mentioned, we used Lasso Regression to address the issue of losing regional information when fitting the Variant Effect. For the second issue, we considered fully utilizing Deep Forest by applying it to the regression process of *Model 1*. Since Random Forest employs random sampling and feature selection, it can reduce the influence between correlated variables, thereby reducing multicollinearity problems, enhancing the stability and predictive accuracy of the regression model. Therefore, we do not need to combine Make and Variant into a single Variant variable for regression analysis. Instead, we can input all the screened variables into Deep Forest, allowing the model to self-prune and fit, enhancing robustness and generalization capabilities,then we get the graph below:
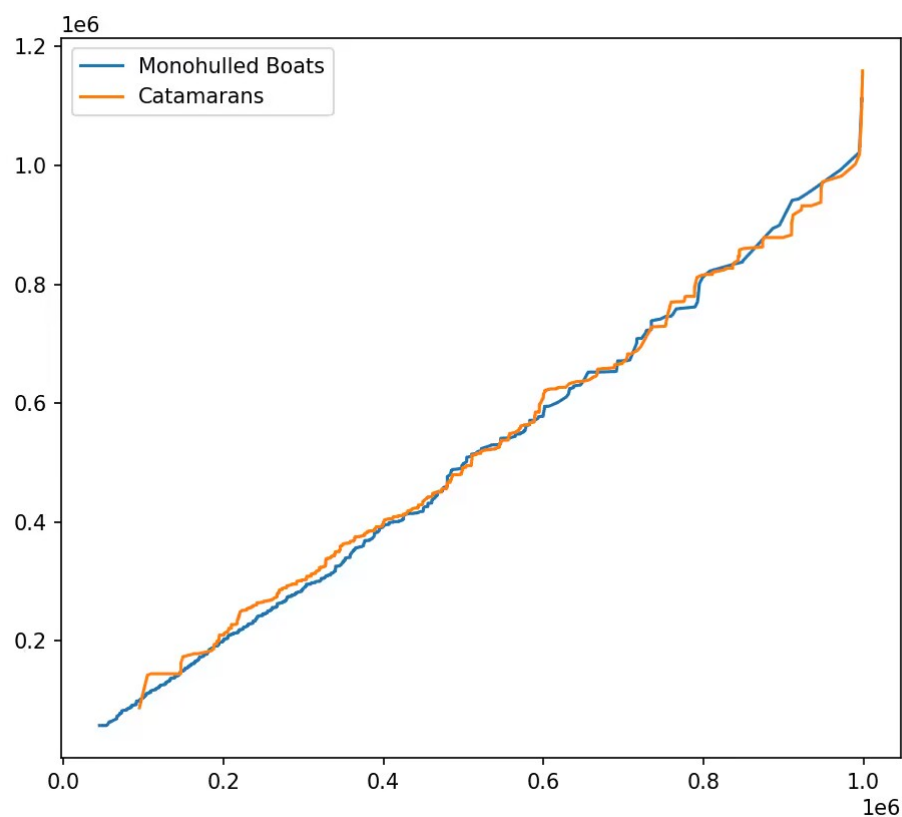

Figure 11: Optimizing Model Performance

We tested the optimized model on the training set and obtained the following results: Clearly, Deep Forest performs better in handling noise. However, on the other hand, due to the small dataset and the limited number of samples for some categories, Deep Forest exhibited some overfitting and underfitting phenomena. Moreover, since *Model 2* also employed the Random Forest algorithm, this led to nested Random Forests, resulting in significant computational overhead. Compared to the increase in accuracy, the exponential growth of overhead is not worth the cost. Therefore, simply replacing the model with Deep Forest is not a perfect solution, and the model still requires further optimization and adjustment.However, from the preliminary results, it can be seen that the use of Deep Forest in the regression part does provide a solution to the second issue. We firmly believe that through structural adjustments, the model's performance will undoubtedly be further optimized!

10   Conclusion

In conclusion, our study has successfully addressed the challenges faced by brokers in the used sailboat market, where pricing is influenced by a myriad of factors such as brand, variant, age, depreciation rates, local consumption levels, and geographical environments. By developing a comprehensive and robust model that combines Heuristic Hierarchical Multiple Regression and Deep Forest Models, we have created a valuable tool that allows brokers and other stakeholders in the sailboat market to make well-informed decisions and ensure fair pricing practices.

Our meticulous data cleaning, expansion, and pre-analysis processes enabled us to establish a strong foundation for subsequent modeling efforts. Through Adaptive Density-Based Clustering and Linear interpolation techniques, we were able to identify patterns and trends in the data, providing crucial insights for our modeling approach.

The Heuristic Hierarchical Multiple Regression Model allowed us to establish the relationships between sailboat prices and factors such as year, region, and variant. Moreover, it enabled us to abstract the effect of regions and variants on sailboat prices, capturing the interactions between these variables and their influence on pricing.

By employing the Deep Forest Model, we trained the relationship between region and variant factors and their respective effects. This advanced ensemble learning technique enabled us to predict the effect of unknown regions and variants, which in turn allowed us to further predict their prices.

Our model has proven to be highly effective, achieving remarkable accuracy levels of 94.91% on the Catamarans test set and 92.71% on the Monohulled Boats test set. These results demonstrate the model's strong performance and applicability to real-world scenarios. Furthermore, the model's self-iteration and heuristic learning capabilities ensure that it can continuously improve its accuracy, making it an invaluable tool for brokers in the used sailboat market.

When applied to the Hong Kong market, our model maintained a high level of accuracy, showcasing its excellent applicability across different regions. The model's ability to achieve satisfactory regression results after 2-3 iterations is particularly noteworthy, as it demonstrates its efficiency and effectiveness in handling diverse datasets.

While our model does not currently include geographical factors due to the challenges in obtaining and quantifying geographical data, future research could explore incorporating these factors to further enhance the model's predictive capabilities.

In summary, our study has successfully developed a powerful and versatile model that can assist brokers in the used sailboat market in making more reasonable and comprehensive evaluations, ultimately leading to more rational and fair pricing practices. By combining the strengths of Heuristic Hierarchical Multiple Regression and Deep Forest Models, we have created a valuable tool that can be applied to various markets and datasets, making it an invaluable asset for brokers and stakeholders in the used sailboat market.

Report

To: The sailboat broker in Hong Kong
From: Team #2332102
Date: Apr 3th, 2023
Subject:

In the memo, we want to introduce you an alternate typesetting program to the prevailing MS Word: LaTeX. In fact, the history of LaTeX is even longer than that of MS Word. In 1970s, the famous computer scientist Donald Knuth first came out with a typesetting program, which named TeX …

Firstly, …

Secondly, …

Lastly, …

According to all those mentioned above, it is really worth to have a try on LaTeX!

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