Problem Chosen	2023 MCM/ICM Summary Sheet	Team Control Number
Y		2330733

summary

The value of a sailboat is determined by time and its attributes. In order to help brokers better understand the sailing market, we searched for more data about sailing ships and countries, and finally trained a mathematical model to explain the impact of various data on sailing prices.

First, we performed data cleaning on the given data table to remove a small number of missing sailboat types. Then, in order to train the mathematical model, we looked for the attributes of different sailboats and substituted them for the sailboat manufacturer and sailboat model as data input. Then, to explore whether the region has an impact on the price of sailing boats, in order to distinguish different regions, we looked for several data that may have an impact on the price, such as the per capita GDP of each region, luxury consumption and so on. These data are then entered into the mathematical model instead of the regions. Finally, we changed the year list to use time to better train the mathematical model, since the sailboats were built in similar years. In the end, we combined these new data categories as inputs to our mathematical models, experimenting with MLP, linear regression, decision trees, random forests, etc., and finally came up with our best model random forest regression.

After training the model, we did a test of accuracy. Although the relationship between used boat prices and the market is very complex, we still find that the accuracy of the training set is over 95 percent, and the accuracy of the test set is close to 90 percent. In the end, we used the trained model to analyze different problems. Most of the results were in line with our expectations, but there were some surprises. Finally, we present these results through a combination of images and texts.

We ended up writing a report for the Hong Kong sailing broker and sharing our findings with him.

Keywords: Second-hand sailboat price; Data Collection; Random Forest Regression

Contents

1 Abstract

The purpose of this paper is to develop a model of the influence of second-hand sailing prices. We first need to develop a forecast model. In addition to the data given in the title, we also collect other sailing data and regional economic data that may be related to sailing prices. Then, after combining all the data, they trained a model to predict the price of used sailboats. After the accuracy of the model reaches the standard, the influence of the region on the second-hand price will be studied, and then the influence will be transferred to the Hong Kong market to explore whether the model is applicable to the Hong Kong market. Finally write a one to two page report for Hong Kong sailing brokers.

For task1, based on all the data, we trained three models, MLP, logistic regression and random forest regression, to predict the price of used sailboats. By comparing the accuracy, we found that random forest regression has the highest accuracy among the three models, so we chose it as our final model. We evaluated the accuracy of the model. It is found that the accuracy of the model can reach 95 percent in the training set and close to 90 percent in the test set. We then examined the weight of each attribute in the sailing price forecast, and finally visualized the data.

For task2, study the effect of region on second-hand sailboat prices and whether there is a regional effect that is consistent across all sailboat variants. Through the single factor variance influence analysis model, we find that the region has a certain influence on the second-hand sailboat price. In order to study the regional effect affecting the price of second-hand sailing boats, we collected a variety of data related to the region, and finally found that there are only one kinds of data closely related to the price, namely the proportion of tourism industry. Finally, we classified and summarized the data, counted the characteristics of different regions, and visualized them.

For task3, we discussed the influence of regional factors on the model, made preparations for applying the model to the Hong Kong market, collected the selling price of sailing boats in Hong Kong, and studied the influence of Hong Kong on sailing prices

For task4, we also found some data that did not accord with the prediction of the

model. Panama, for example, has three times as much tourism as France. The model predicts that similar sailboats should cost significantly more in Panama than in France. But the figures show that sailboats cost significantly less in Panama than in France. After searching for information, we finally found the reason.

2 Basic Introduction

2.1 Background

A sailboat is a wind-driven boat, often used for recreation and competition. As the love of water activities grows, so does the demand for sailing boats in the market. However, for those who want to buy a sailboat, it is not easy to choose a sailboat that suits their needs, where price, age and attributes are the key considerations.

The price of sailing boats is one of the most important factors for buyers. The price of a sailboat fluctuates more than other large items due to factors such as size, design, materials, age and usage. Used sailboats generally cost much less than brand new sailboats. The age of the boat is also a key consideration for buyers. The older the ship, the more wear and tear on the hull and equipment, the more repairs and replacement equipment will be required. Although age has an effect on the price, it is not enough to consider age as the actual condition of the buyer varies from ship to ship. In addition to price and age, the attributes of the boat are also considered by buyers. Different sailboats have different performance and characteristics, such as size, speed, stability, maneuverability, equipment and facilities. Calculate, to choose a suitable sailing boat.

2.2 Problem Restatement

We believe that the price of a second-hand sailboat is related to its market time and its attributes. First, we need to build an evaluation model to evaluate the price of a sailboat. The evaluation is required to fit almost all kinds of sailing ships in the world with high accuracy and guiding significance. After adding more attributes of sailboats, these attributes should be scientifically analyzed, and those attributes which have obvious effect on price should be selected for detailed consideration and further discussion. For the selected Hong Kong market, considering that Hong Kong sailboats are not included in the original sample data, we need to propose an achievable and reasonable target, study the geographical and ship characteristics of this market, and

make an objective and accurate assessment of the price of sailboats in Hong Kong market. The results are then compared with the prices of sailboats in other markets to verify the correctness of the model.

After that, we will provide targeted policies and reports based on our model and comprehensive considerations to help brokers get the right assessment of sailing prices in the Hong Kong market. We also need scientific models to assess the effectiveness of policies.

3 Assumptions and Notations

3.1 Assumptions and justifications

In order to achieve the discussion of used sailboat prices, we have taken a thorough consideration and need appropriate assumptions for better simplification and understanding. The assumptions are as follows.

1. **Suppose that the data related to regional factors are per capita GDP, luxury consumption power and so on.**

2. **Suppose that other characteristics of sailboats are related to the price of sailboats.**

3. **Suppose that the year of production has nothing to do with weather and other data, and only represents how long the sailboat has been in use.**

4. **External shocks such as COVID-19 and the financial tsunami are not taken into account.**

5. **The data we collect is accurate.**

   Our data is collected from sailboatdata.com and other sailboat data websites.

6. **Suppose that the influence effect of Hong Kong on the price of sailing ships is little compared with that of Europe and America.**

3.2 Notations

The key notations used in this paper are listed in Table1.

Table1 : Notation

Notations	Statement
LWL	Load waterline length
Beam	Maximum ship width
Draft	The Vertical depth of a ship in the water
Displacement	The volume it occupies in the water
MAPE	Mean absolute percentage error
R-Squared	Determination coefficient

4 Data Processing

4.1 Get Information about Sailboat by Make and Variant

The original data provided for this project only has Length as basic parameters of sailboats. So it is necessary for us to find more information by Make and Variant of sailboats. In the project, we use crawler tools to get more information which may influence list prices of sailboats, such as LWL, Beam, Draft, Displacement and Sail Area. These data reflects the size of sailboats, which may be the most important factor to decide the list prices of them. The sources of this information are some vessel trading platforms[1] and other official websites for the maker of sailboats and the final table is like figure 1.

4.2 Get Economic Data by Region

Except basic parameters of sailboats, the economic data of the region which Sailboats were listed for sale is also very significant. As a commodity, the listing price of a sailboat is affected by regional demand. Since we are dealing with small sailboats in this project, their main role should be as a vehicle for recreational activities in tourism. For example, experience the pleasure of sailing and the beauty of nature by sailing on a lake or coastline. Thus, we can infer that the development degree of regional tourism will affect the demand for sailboats and further affect the listing price of sailboats. In addition, regional GDP can reflect the local economic level and purchasing power level, which may also affect the listing price of sailboats.

[1]Source: https://www.boattrader.com/, https://www.nadaguides.com/boats

monohulled sailboats type	LWL (ft)	Beam (ft)	Draft (ft)	Displacement (lbs)	Sail Area (sq ft)
Alubat Ovni 395	37.24	12.63	3.94	22,046	824
Bavaria 38 Cruiser	36.06	12.99	6.07	15,432	721
Bavaria 39 Cruiser	37.07	13.02	6.23	19,621	776
Bavaria 42 Match	41.01	13.12	8.86	18,298	902
Bavaria 42 Cruiser	40.35	13.33	6.92	19,290	915
Bavaria Cruiser 46	44.13	14.43	6.56	27,113	1,087
Bavaria 50 Cruiser	46.56	14.76	6.73	31,747	1,119
Bavaria 49 Cruiser	45.28	14.75	7.38	29,542	1,055
Beneteau First 40.7	39.37	12.33	7.54	16,415	850
Beneteau Cyclades 39.3	37.73	12.86	6.07	18,079	721
Beneteau Oceanis 423	38.68	12.83	5.25	19,621	835
Beneteau Cyclades 43.3	41.01	13.85	6.56	21,164	1,012
Beneteau Oceanis Clipper 423	38.68	12.83	5.25	19,621	835
Beneteau Oceanis 43	39.33	13.42	5.75	19,621	883
Beneteau First 44.7	42.85	13.06	8.2	23,810	1,002
Beneteau Oceanis Clipper 473	43.83	14.6	6.75	28,660	1,011
Beneteau Oceanis 473	44.92	14.42	6.75	27,557	1,019

Figure 1: Supplementary Data for Monohulled Sailboats

City/Region	DP（houdred millions USD)	GDP per capita (USD)	Tourism GDP	Proportion of tourism GDP
Martinique	22.7	21981	0.8	0.035242291
Guadeloupe	18.5	24191	1.1	0.059459459
Florida	1000	47682	97.3	0.0973
Mexico	1150	9293	23.4	0.020347826
Panama	66.8	16466	4.2	0.062874251
Croatia	57.8	13647	13.5	0.233564014
Grenada	0.8	7189	0.1	0.125
Spain	1394	29352	82.3	0.059038737
Turkey	851	10361	34.1	0.040070505
Georgia	16.4	4346	1.8	0.109756098
Dominican Republic	84.7	7827	7.2	0.085005903
U.S. Virgin Islands	3.6	35313	0.8	0.222222222
United Kingdom	2622	39959	106.1	0.040465294
Greece	209	18694	37.7	0.180382775
Italy	2001	33259	58.4	0.029185407

Figure 2: Supplementary Data for Regions

5 Task1: Model for Sailboat Listing Price Prediction

5.1 Definition of Predictive Accuracy of Model

MAPE is mean absolute percentage error. Its range is [0,+∞). A MAPE of 0% indicates a perfect model, and a MAPE greater than 100% indicates a poor model.

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{1}$$

R-Squared is determination coefficient. Where, the numerator represents the sum of square variances of the real value and the predicted value, which is similar to the mean square variance MSE. The denominator part represents the sum of the square variance of the true value and the mean value, which is similar to the variance Var.

The model is judged according to the value of R-Squared, whose value range is [0,1]. If the result is 0, the model fitting effect is poor. If the result is 1, the model is error-free.

Generally speaking, the larger R-Squared is, the better model fitting effect will be. R-Squared reflects the approximate accuracy, because with the increase of the number of samples, R-Square will inevitably increase, so it is impossible to quantify the accuracy, but only approximate.

$$\mathrm{R-Squared} = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2} \tag{2}$$

Among them, $\hat{y_i}$ as predicted, y_i as the real value, n is the number of samples in the test set. When the smaller the value of the MAPE or the greater the value of R-Squared, the prediction of sailing on value and the actual sailing on the smaller the error between the observed value, further illustrate the performance of the prediction model is used, the better.

5.2 Problem Analysis and Model Selection

Because we need to predict the listing prices of sailboats, the problem in this project is a regression problem. So in the beginning we try to use linear regression and Multilayer Perceptron(MLP). However, the result of both two models is unsatisfactory. According to the data in the figure, it can be found that the error on the test set is much larger than that on the training set, indicating that the two models are seriously overfitting as shown in the figure 3 below.

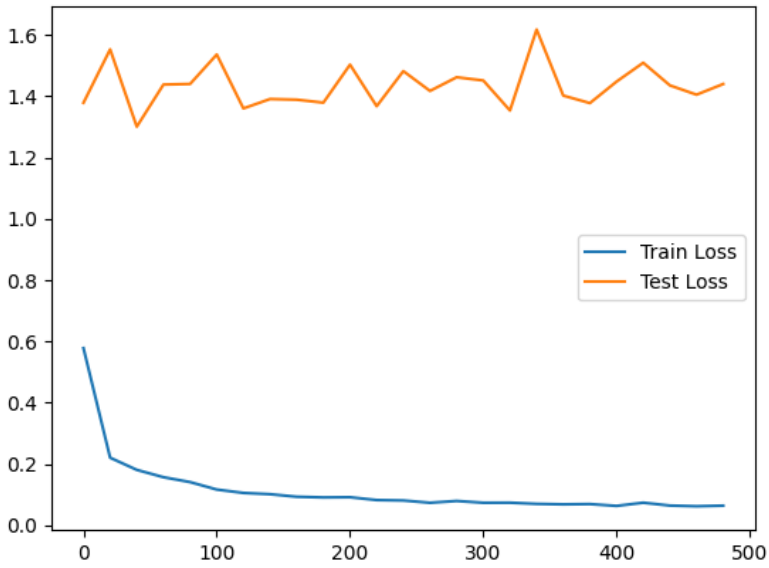

Figure 3: MLP Loss

This may be due to some data augmentation in our data processing, such as LWL, Beam, Draft and Displacement. However, we cannot guarantee that every data item will have a strong linear or other form of relationship with the listing price of the sailboat. Given time constraints, it's also unlikely that we'll be able to fill in much more data for each example. This leads to the fact that these two models do not learn the correct law, but instead learn random perturbations.

Therefore, in the case of limited data sets, we choose some models with simple structures, high generalization, and not easy to overfit. So we have tried Random Forest Regression, LGBM Regression, XGBOOST Regression and finally selected Random Forest Regression.

5.3 Model Establishment and Result

5.3.1 Model Introduction

We take random forest regression as our final model because of its ability to handle large datasets with high dimensionality, deal with missing data, and reduce overfitting. Random forest regression is a machine learning algorithm that belongs to the family of ensemble methods. It is a supervised learning technique that is commonly used for regression tasks. The algorithm builds a forest of decision trees and uses the majority

vote of the individual trees to predict the output value.

In a random forest regression model, a large number of decision trees are created using bootstrap sampling and random feature selection. The bootstrap sampling involves taking random samples from the training data with replacement, which results in multiple subsets of data. These subsets are used to train different decision trees, and the final prediction is made by averaging the output of all the individual trees just like the figure 4.

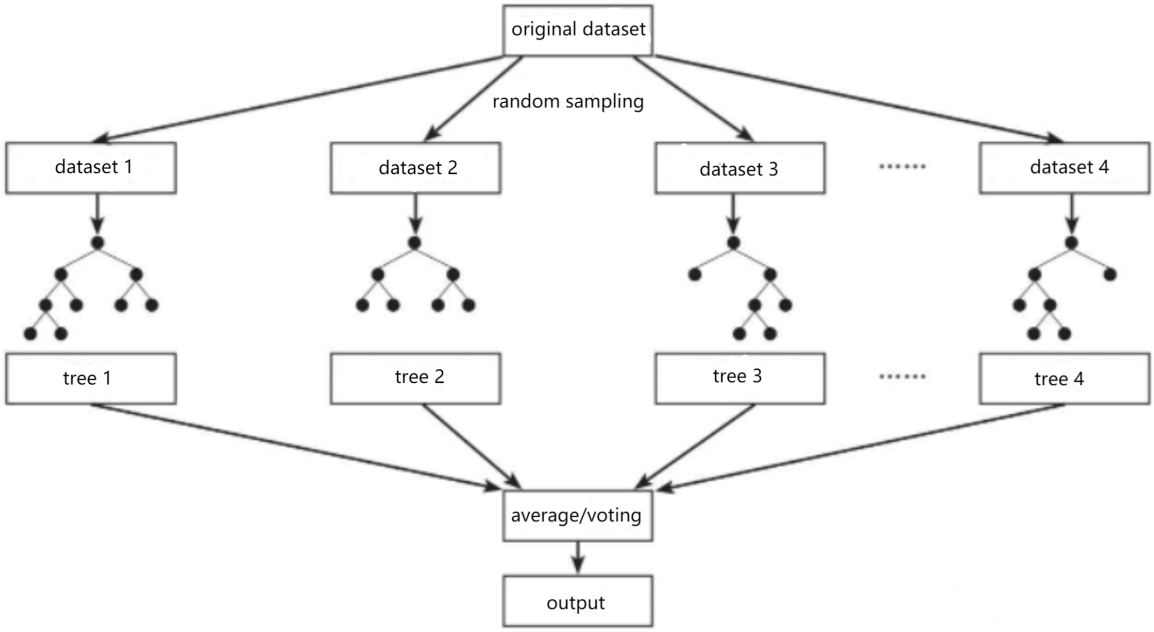

Figure 4: Random Forest Regression

In addition to bootstrap sampling, random forest regression also uses a technique called feature bagging. This involves selecting a subset of features from the original dataset at random and only using those features to train the individual decision trees. This helps to reduce overfitting and improves the accuracy of the model.

The final prediction from the random forest regression model is the average of the predictions made by all the individual decision trees. This approach results in a more accurate and robust model than a single decision tree or other regression models.

Finally, we tested the trained random forest regression, and found that the accuracy of the training set could reach 95 percent, and the accuracy of the test set could also approach 90 percent, which is valuable in the actual complex market environment.

5.3.2 Prediction Result

We calculate the MAPE and R-Squared values of different models for monomers and catamarans. When the MAPE is smaller or the R-Squared value is larger, the prediction accuracy of the model is better. As can be seen from the following two graphs, random forest regression has the best prediction effect in the four regression models, and the prediction effect of catamarans is better than that of monomers. The MAPE values of each model are figure 5 below.

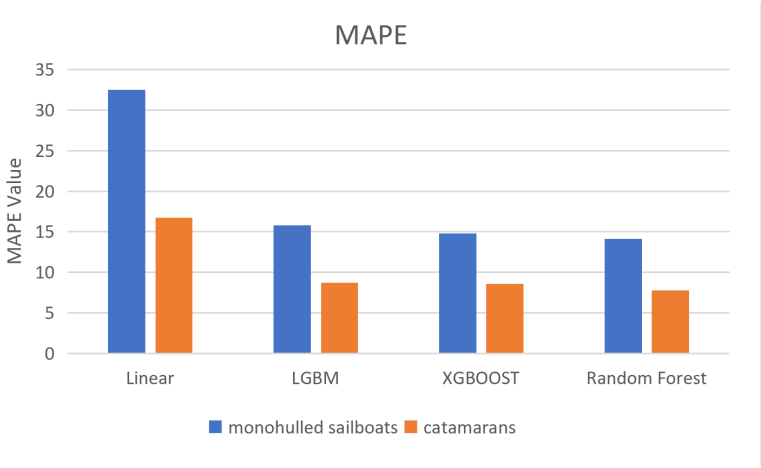

Figure 5: MAPE

The R-Squared values of each model are figure 6 below.

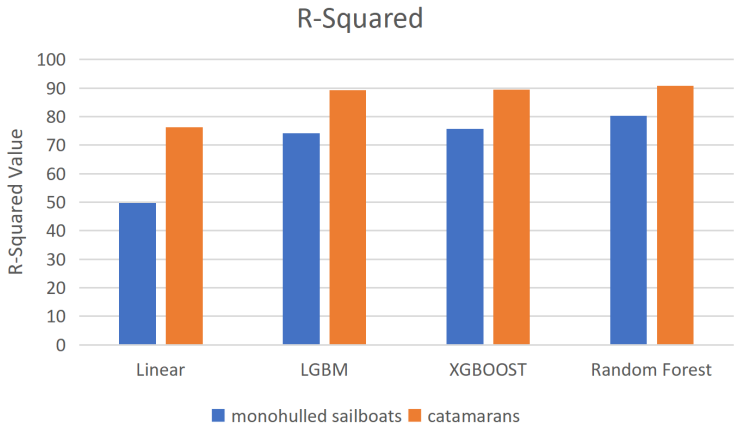

Figure 6: R-Squared Score

We compared the predicted results of monohulled sailboats and catamarans with the real price. It is found that both of them have better prediction effect. The average

price error for monohulled sailboats was 1.931 percent, while the average price error for catamarans was slightly smaller at 0.592 percent. So the model predicts better results for catamarans. The data is shown as figure 7 and figure 8 below.

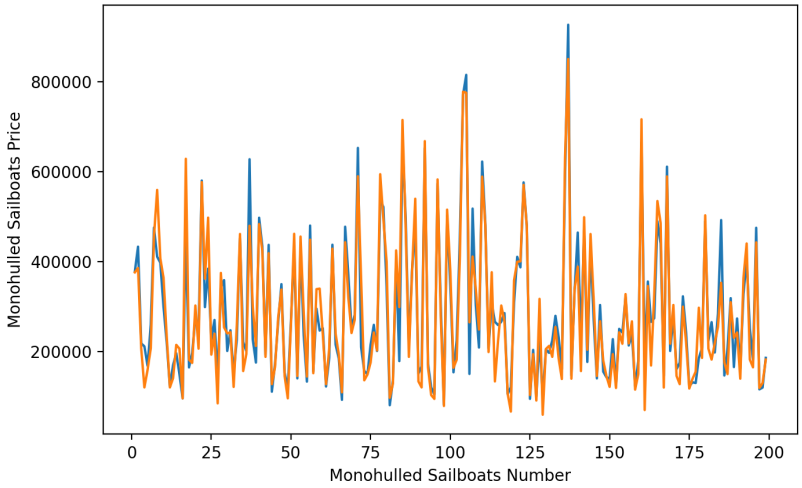

Figure 7: Price Comparison of Monohulled Sailboats

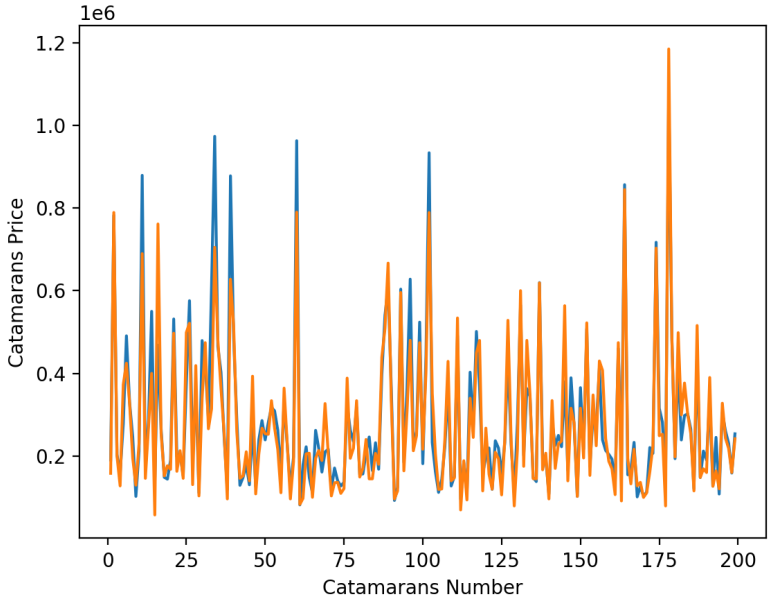

Figure 8: Price Comparison of Catamarans

6 Task2: Explain Impact of Region on Listing Price

6.1 General Analysis on Region Consistency

With the result of variance analysis, region factor has limited impact on listing price.

Table2 : Normality Test on Listing Price

Median	Mean	Standard Deviation	S-W Test	K-S Test
245000	303432	198302	0.837	0.119

First, as shown in Table 2, S-W test shows that the original values in the listing price coincident with normal distribution.

Table3: Part of ANOVA Result

Variable	Samples	Mean	Standard Deviation
France	269	357858	218812
Croatia	589	248236	166768
Greece	539	307541	203120
Italy	407	284602	182404
Netherlands	47	362460	238203
Spain	286	296881	168291
Florida	143	373738	231996
Illinois	5	192560	157985
Mexico	27	355666	272480

From the result of ANOVA, F is 3.073 and P is 0.000***. It shows that the difference between each regions is significant.

6.2 Analysis of Specific Factors

With the conclusion that regional differences indeed have an impact on the listing price of the two types of sailboats, we want to explore which economic factors affect the listing price of sailboats, and to what extent the impact is relative to the attributes of sailboats.

6.2.1 SHAP

At this section, we use SHapley Additive exPlanation(SHAP) as a method for post-hoc model interpretation. SHAP is a ”model interpretation” package developed in Python that can interpret the output of any machine learning model. Inspired by cooperative game theory, SHAP constructs an additive explanatory model in which all features are considered ”contributors”. For each predicted sample, the model generates a predicted value, and SHAP value is the value assigned to each feature in the sample. The schematic diagram of SHAP is as follows.

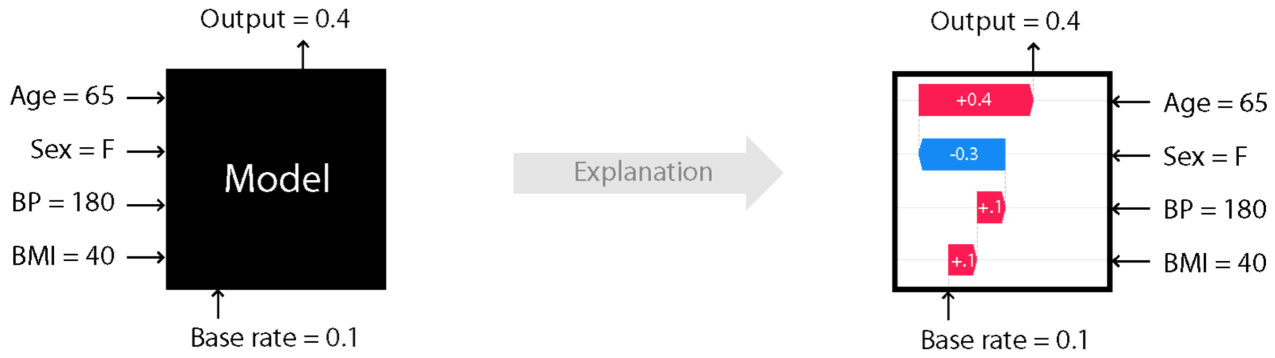

Figure 9: SHAP

Suppose the ith sample is x_i, the ith sample's JTH feature is x_{ij}, the model's predicted value for the sample is y_i, and the baseline of the entire model (usually the mean value of the target variable of all samples) is y_{base}, then SHAP value obeys the following equation:

$$y_i = y_{base} + f(x_{i1}) + f(x_{i2}) + ... + f(x_{ik}) \tag{3}$$

Where $f(x_{ij})$ is the SHAP value of x_{ij}. Intuitively, f(xi,1) is the contribution of the first feature in the ith sample to the final predicted value y_i, when $f(xi, 1) > 0$, indicating that the feature improves the predicted value and has a positive effect; Otherwise, it indicates that this feature reduces the predicted value and has a counter-effect.

6.2.2 Comparison between monohulled sailboats and catamarans

At first, we try to find out which features influenced the listing prices most. By SHAP, we get figures like figure 10 and 11. For the monohulled sailboats, Displacement is the most important factor, and followed by Year, Beam and Length. As for catamarans, Year, Sail Area and Length are more important factors. Tourism's radio

of GDP does affect the listing price of a sailboat, but it is less important than the basic attributes of the boat itself. Moreover, the influence of the ratio of regional tourism to total GDP on the two types of sailboat prices is far greater than that of regional GDP.

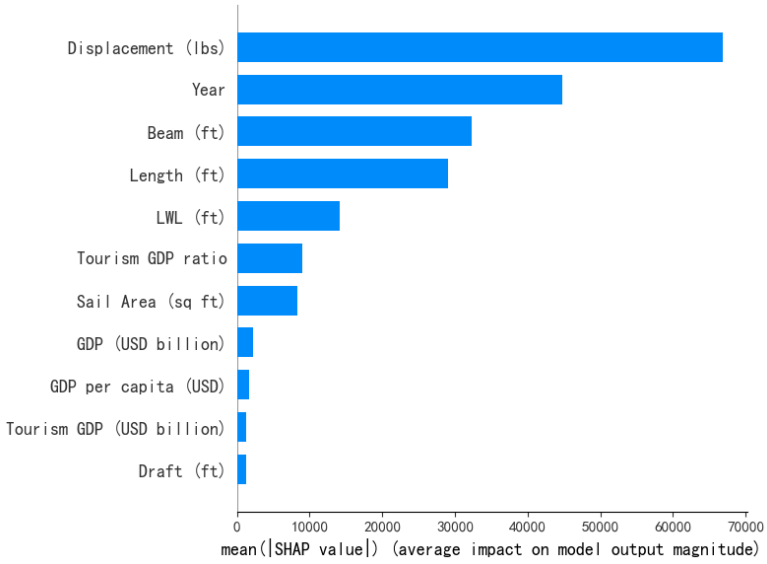

Figure 10: Importance for Different Feature of Monohulled Sailboats

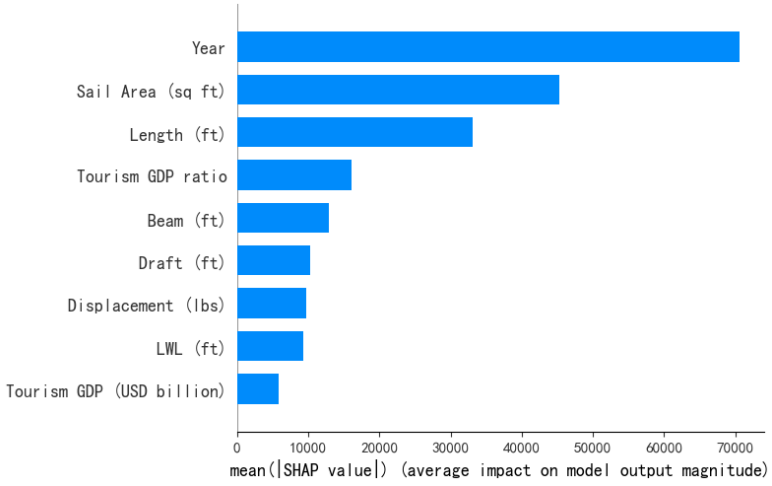

Figure 11: Importance for Different Feature of Catamarans

Next, we further investigate what specific effects these factors will have on sailboat listing prices. By SHAP, we get figures like figure 12 and 13. In these figures, the closer the color to red, the higher the listing price. The impact of the attributes of the sailboat on its listing price is consistent with our expectation. For the two different sailboats, there is a trend that the larger the size, the larger the production year, and the higher the listing price.

However, the influence of regional economy on the listing price of sailboats is very interesting. For the two types of sailboats, the price of sailboats is higher in regions with relatively high tourism development, so there is a certain regional consistency. We looked at some information to try to explain reasons.

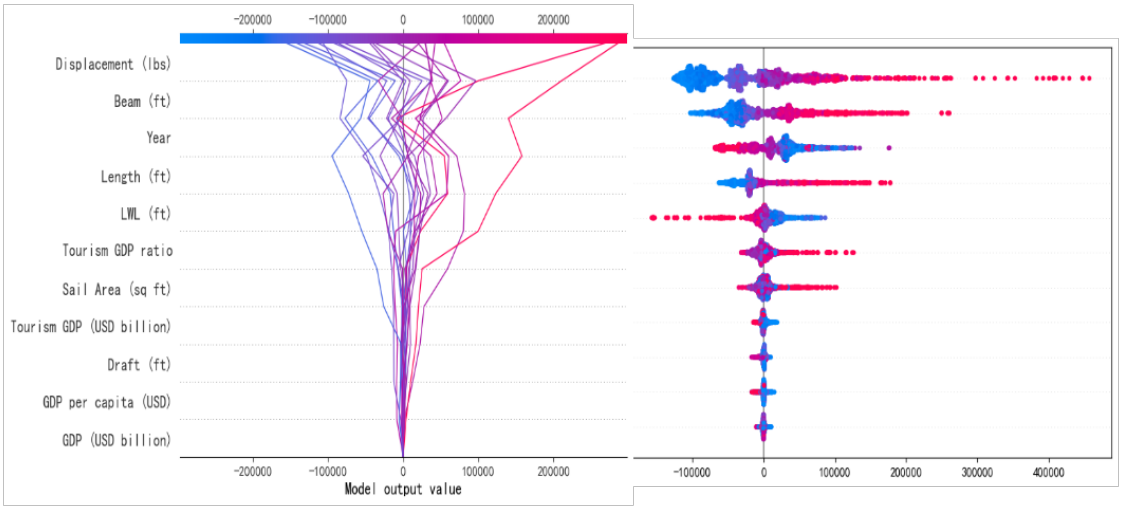

Figure 12: Influence for Different Features of Monohulled Sailboats

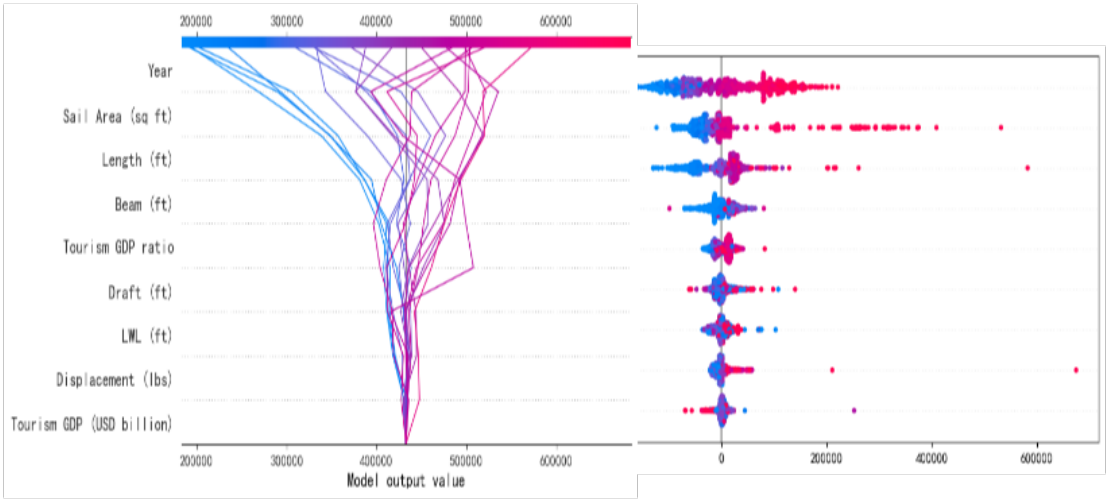

Figure 13: Influence for Different Features of Catamarans

One study found a positive correlation between the listing price of small sailboats and the degree of tourism in Florida's tourist hotspots. Tourism has increased demand for small sailboats in the area, so sailboat sellers and rental companies have increased

listing prices accordingly.

7 Task3: Regional Effect Analysis of Listing Price of Hong Kong Sailboat

Hong Kong has a GDP of 362 billion dollar, cargo throughput of 3.5 million tons, average GDP of 48,111 dollars and tourism GDP of 34.8 billion dollars. We can use these data in our prediction.

7.1 Prediction of Hong Kong sailboat price

From online websites, we found that current sale price of some sailboats in Hong Kong[2]. Use the boat data and the region data in our module as input, we can have the predicted price. These predictions includes monohulled sailboats and catamarans.

Table4: Prediction of Monohulled Sailboats in Hong Kong

Variant	Predicted Price	Actual Price
Beneteau Oceanis 38	179,388	165,000
Beneteau Sense 38	195,396	220,000

Table5: Prediction of Catamarans in Hong Kong

Variant	Predicted Price	Actual Price
Fountaine Pajot Saona 47	811,669	1,161,333
Lagoon 450	585,006	560,000
Lagoon 450	585,006	650,000

7.2 Analyses of Prediction

In Hong Kong, The total GDP is quite high, so the main regional effect would be the higher GDP. In both Monohulled Sailboats and Catamarans, higher GDP in Hong Kong leads to significantly higher listing price.

[2]Source: https://www.yachtworld.com/boats-for-sale/type-sail/region-asia/country-hong-kong/?year=-2020

8 Task4: Other Discovery

In the process of exploring the influence of different characteristics on the listing price of sailboats in Task2, we come to the conclusion that the development degree of regional tourism is an influencing factor. However, in some specific examples, counterexamples to this rule appear. For example, Panama has a bigger share of tourism in its GDP than France, but the listing price for a sailboat of the same model and year is lower. The data is shown in figure 14.

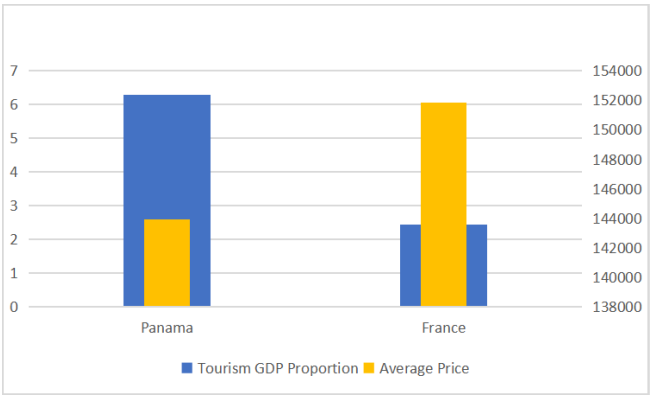

Figure 14: Comparison about Panama and France tourism gdp radio and Centurion 40s

This abnormal phenomenon attracted our attention. After searching for some relevant materials, we found the possible cause. A study in Panama found no significant relationship between the listing price of small sailboats and the level of tourism there. This is because the local shipping and transportation industry is relatively developed, the sales market is large, and the competition of shipbuilding industry is more intense, which makes the listing price of second-hand sailboats low. In addition, sailboat manufacturers can also reduce production costs through cheaper transportation costs, thus making the listing price of sailboats more competitive.

On this basis, we put forward the assumption that the regional shipping level will also affect the listing price of sailboats, and the larger the shipping volume, the lower the sailboat price tends to be. Data statistics shown in figure 15 also confirm our conjecture.

Of course, we should also note that the relationship between listing price and a single factor is not fixed. It is affected by many factors, and the specific situation needs to be analyzed according to different regions and market conditions.

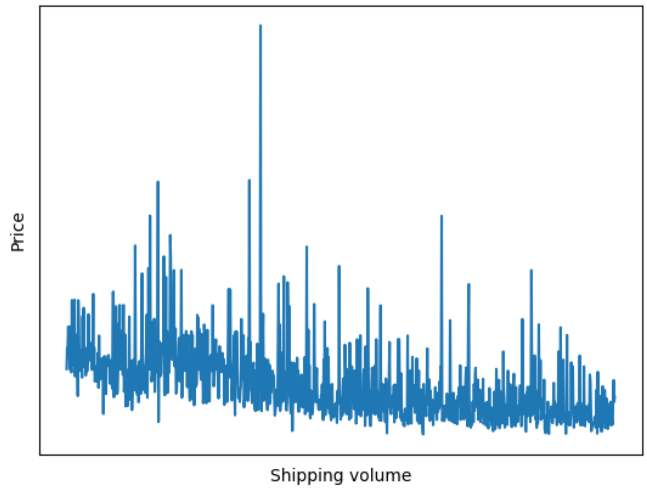

Figure 15: Price changes with volume

9 Task5: A Report for Hong Kong Sailboat Broker

Dear Sir/Madam:

It is our pleasure to share with you the results of our research on listing prices of single and catmaran sailboats in Hong Kong.

Firstly, we obtained a mathematical model based on the provided data and some supplementary data. By inputting the boat make, model, year of production and some economic data about Hong Kong to this model, you can get a relatively accurate forecast of the listing price of a sailboat. Just like figure 16.

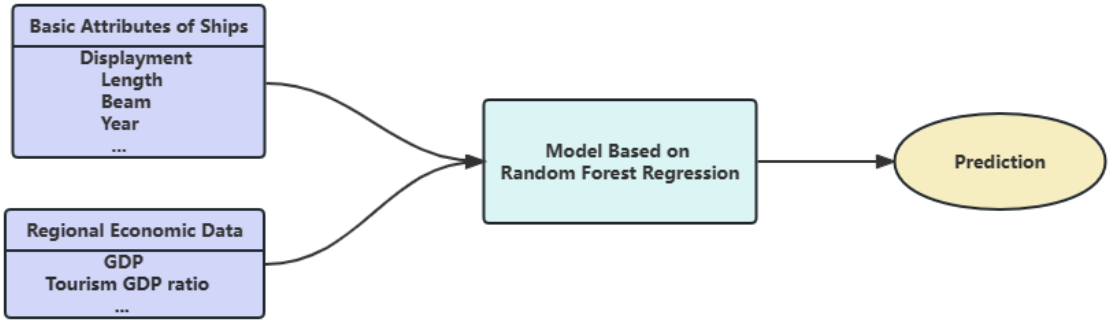

Figure 16: Model for Prediction

After that, we performed a visual analysis of this mathematical model. We find that the most important factors affecting listing price differ between monohull and

catamaran sailboats which is shown in figure 17. For example, The main factors affecting the listing price of single sailboats are displacement, year of production and length of sailboat in turn, while year of production and sail area have a greater impact on catamaran sailboats. However, there is also some regional consistency between them. For monohull sailboat and catamaran sailboat, the basic attributes of the ship itself have more influence than the regional economic factors. Among the regional economic factors, tourism GDP radio has a greater impact than GDP.

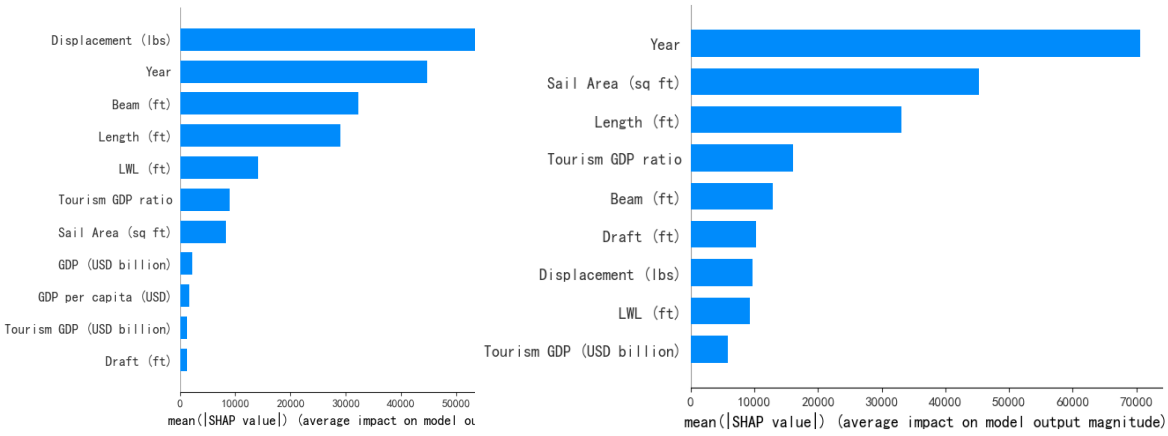

Figure 17: The influence of different factors on the price of monohull and catamaran

Later, further research showed that the listing prices of the two types of sailboats were mainly related to two kinds of regional economic data: the proportion of tourism in GDP and shipping traffic. Developed tourism has more demand for small sailboats in the area, so sailboat sellers and rental companies have increased listing prices accordingly. While a developed shipping industry will intensify competition and lower listing prices. Through the analysis of the data, we found that compared with North America, the Caribbean and Europe, the proportion of tourism in Hong Kong is not too high, which is shown in figure 18. This means that the listing price of Hong Kong sailboats will not be excessively inflated by the tourism boom. Similarly, the relatively developed shipping level indicates that the size of the ship market in Hong Kong will not be too small, as figure 19, so if necessary, the listing price of sailing ships can be appropriately adjusted to increase its competitiveness.

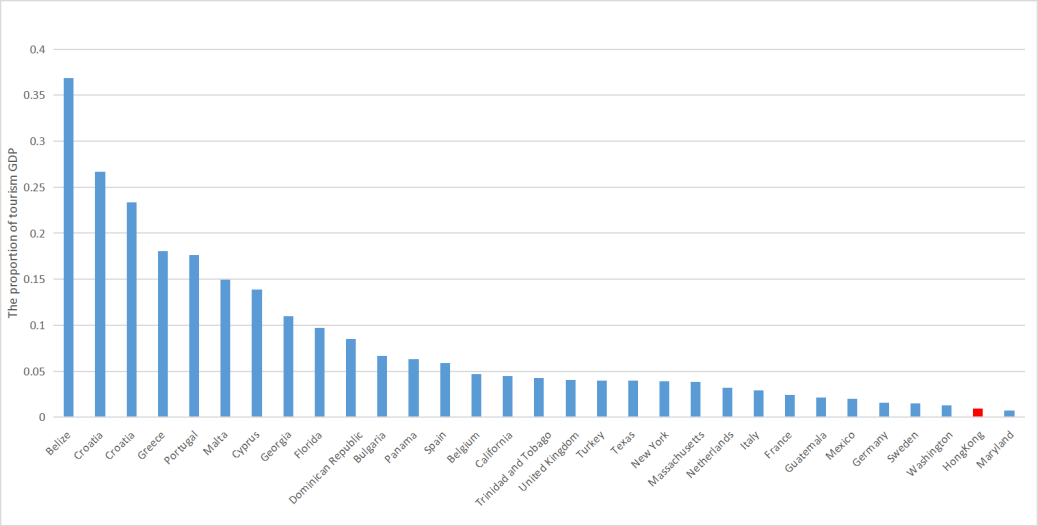

Figure 18: The proportion of tourism GDP

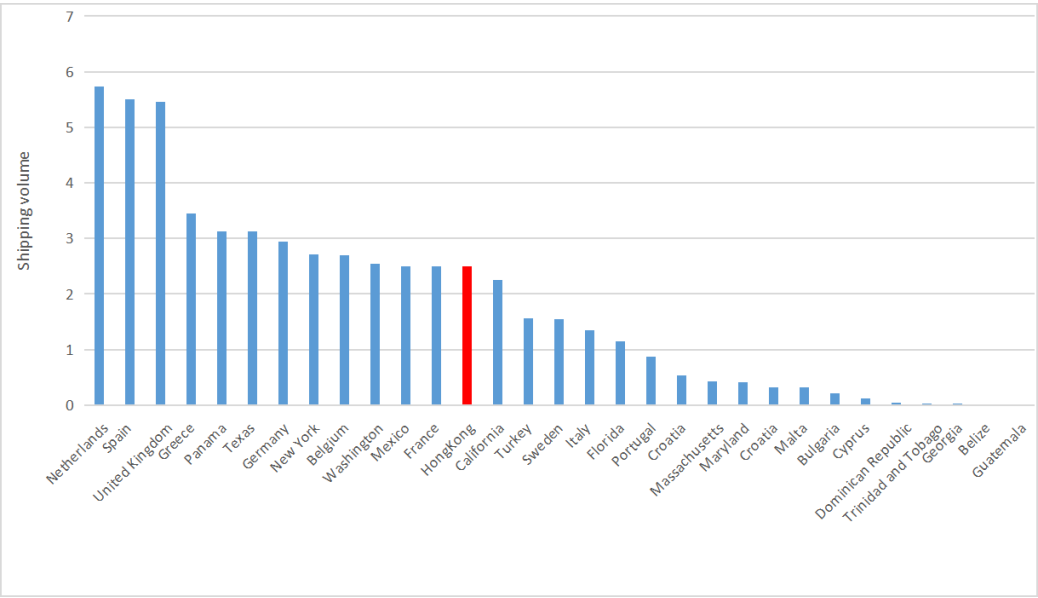

Figure 19: Shipping Volume

Finally, due to the high level of local consumption and the high demand for entertainment and leisure, compared with other countries or regions, there are differences in the listing prices of sailing boats in Hong Kong, which need to be compared and analyzed according to specific circumstances.

10 References

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