Evaluating Democracy Satisfaction in Different Countries

1 Introduction

One of the core missions of Asian Barometer Survey is to strengthen intellectual and institutional capacity for research on democracy. This research is going to put their mission into practice. In the dataset released, for those variables which are considered important, we found that most of them can be considered either directly or indirectly related to reflecting the society status of a country. Thus, we plan to make this research more lean to investigate what people think about their government. In this study, we will use the q098, which is the democracy satisfaction as our outcome of our model. As we tend to believe that how a government leans on democracy can really affect its people and the entire society, we plan to conduct our research to examine the acknowledgement.

Based on that, we have surveyed some materials for further making our topic more concrete. The previous studies on the Asian Barometer Survey focus on one specific country, for instance, the democratic satisfaction in China (Zhai, 2019). We decided to analyze all the countries from the Asian Barometer Survey and provide an overview of satisfaction in different countries. Therefore, in this research we will base on the characteristics of the people and the society to predict how people think democracy is functioning in their country. In another word, we want to leverage the survey data to analyze how people in different regions are satisfied with the democracy in their country.

2 Exploratory Data Analysis

The merged data consists of all the survey results from wave 1, which results in 22 million entries. There are a lot of missing values in the dataset, including responses with 'not sure' and 'no answer'. The data has to be completed with no missing values in order to fit a regression model, and thus we have to impute the data. Some columns, like parties the respondent voted for last year, have more than 60% missing values. We remove those columns from our predictors to ensure the validity of the data as their imputed data will be less accurate. We also acknowledge that most of the predictor variables are categorical. Thus, the KNN imputation is invalid as euclidean distances cannot be calculated. As an alternative, we use a simple imputation method, which is filling the missing values with the mode of each question.

The survey population itself is unbalanced as we had more than 10 million data points from Mainland China. In order to balance the dataset and shorten runtime, we used bootstrapping with replacement to resample 80 thousand entries from the imputed dataset, with 10 thousand entries from each country. We then did Exploratory Data Analysis plots on the sampled dataset. We want to examine how each predictor affects our outcome response, which is the satisfactory score in different regions. First, we look at the distribution of satisfactory scores across different countries. We can see that country 8, which is Thailand, the responses from the samples have been satisfied with their democracy. On the contrary, in country 6, which is the Philippines, there are less moderate responses and more responses toward dissatisfaction. It seems like country is having an effect on democracy satisfaction.

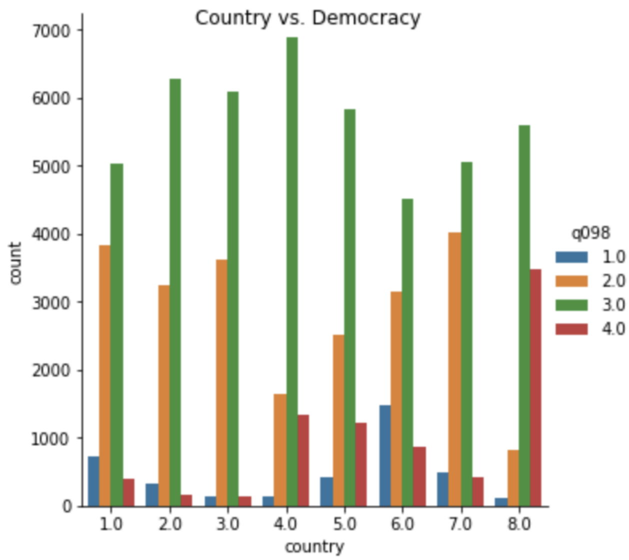

Figure 1: Democracy Satisfaction Distribution By Country

We also examined country versus democracy satisfaction by each different predictors. For instance, the distributions of democracy satisfaction are different from the economic condition comparison levels. We later proved that this is one of the important predictors.

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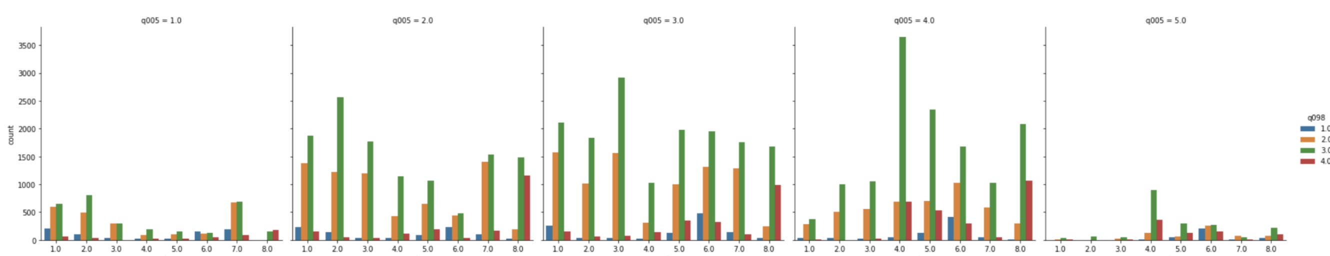

Figure 2: Democracy Satisfaction Distribution v.s Country by Current Economy Comparison

3 Proposed Methodology

This is a classification problem, so we have two options of classification models in our blueprint, which are ordinal regression using probit function and random forest. To remove those features that do not have a significant effect on the prediction of output, we conducted a feature importance test. We preferred to use the backward elimination algorithm as it is the fastest method. The feature importance test claims that no feature should be dropped, so we will include all of them in our model. We then split the training and testing datasets in the ratio of 7 to 3.

There are two link functions for ordinal regression modeling. Since logit function is used for interpreting odds ratio, we decide to use probit function in our ordinal regression. Both the training and testing accuracy of the probit model is low and makes the model unable to make predictions on new data, so we will move onto implementing the random forest model (Appendix 1).

4 Analysis

We first fitted a baseline random forest model using the RandomForestClassifier from the sklearn library. For this baseline, we did not specify on any of the model parameters and used default values. The training and testing accuracy (Appendix 2) look way too good to be true. We have definitely experienced overfitting issues here due to the fact that the default tree is too deep. So, in the next step, we will need to tune the parameters and trim the decision trees' depth and number of leaves in the random forest models.

To tune the random forest model, we planned to use the randomized search cross validation method to find the best set of parameters that can create a model with the lowest RMSE. The method fits 3-fold cross validation for each of 50 candidate groups of parameters, totalling 150 different random forest models, and generates the best combination of parameters (Appendix 3).

Here is our final model's training and testing accuracy:

Training Accuracy	Testing Accuracy
0.96	0.93

True\Predicted	Pred Class 1	Class 2	Class 3	Class 4
True Class 1	887	81	154	3
Class 2	0	6193	652	12
Class 3	0	58	13475	20
Class 4	0	30	567	1868

The decrease in accuracy is expected as the baseline model's depth is shrunk and its leaves are trimmed. This is a good sign because we have spent effort to eliminate the overfitting problem. We are confident that this model has great predictive power and generalizability. We computed the RMSE, which is 0.0846, showing that the loss of our model is not significant at all.

Last but not least, we saved the predicted classes of q098 of the test dataset and combined the X_test and y_pred into one dataset. We visualized the predicted mean democracy satisfaction score by region and visualized it on a world map using Excel. In Japan, Taiwan, South Korea, and Singapore, the public are slightly less satisfied with their current democracy situation than the public in mainland China and Thailand. The result is a bit counter-intuitive, but we hypothesize that people living in the more democratic countries actually care more about democracy and individual rights than the people living in countries that have highly centralized governments.

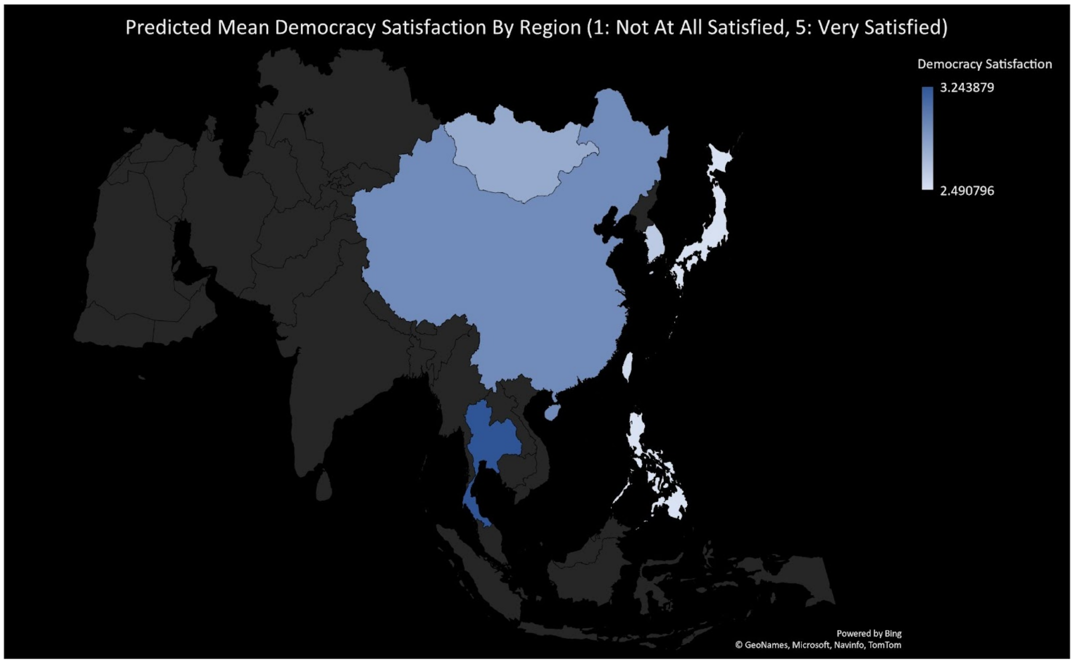

Figure 3: Average Predicted Democracy Satisfaction

5 Conclusion

The result in the analysis section is a bit counter-intuitive. However, we hypothesize that people living in the more democratic countries actually care more about democracy and individual rights than the people living in countries that have highly centralized governments. In other words, people who care less about democracy might end up getting lazy and choosing the same option repeatedly. For example, the proportion of choosing "fairly satisfied" is super high in China for our response variable q098.

Even though the prediction accuracy of our final model could be considered satisfying, we do acknowledge that there is still room for improving our first model, the ordinal regression using probit function. For example, there could be several potential interactions with the "country" variable, e.g., the "courts" variable, people's trust on the courts, might vary in different countries. What's more, the country variable can also be treated as a group variable, and we can build a hierarchical model for this issue to further improve its performance.

As for the random forest model that we picked as our final model, its predicting power, versatility, and generalizability meet our expectation, however, fitting and tuning the model have long runtimes, so we can think about speeding up the process in the future.

Appendix 1: Additional Graphs

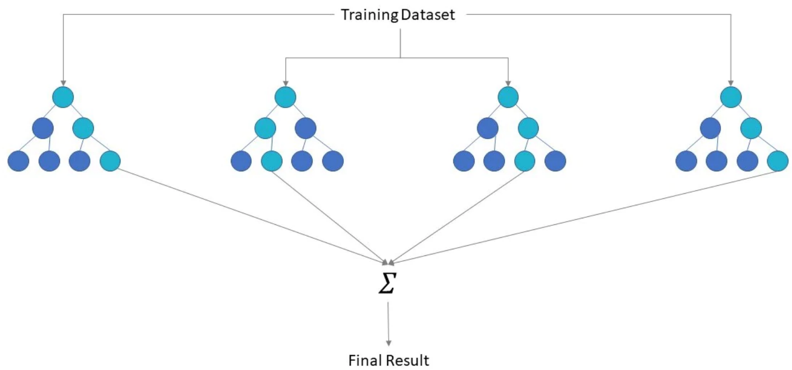

Figure 1: Visualizing Random Forest Process

Appendix 2: High-Level Diagram of a Random Forest Classifier

Training Accuracy	Testing Accuracy
0.99	0.99

True\Predicted	Pred Class 1	Class 2	Class 3	Class 4
True Class 1	1121	2	2	0
Class 2	0	6785	71	1
Class 3	0	16	13526	11
Class 4	0	0	60	2405

Appendix 3: Randomized search cross validation

Parameters	Proposed Parameter Values	Randomized Search CV Output
n_estimators	100 - 500	500
min_samples_split	2 - 10	10
min_samples_leaf	0 - 10	10
max_features	auto, sqrt	sqrt
max_depth	10 - 100	90
bootstrap	True/ False	False

Appendix 3: References Zhai, Y. (2019). Popular conceptions of democracy and democratic satisfaction in China. International Political Science Review, 40(2), 246-262. https://doi.org/10.1177/0192512
Random Forest. (2020). IBM. https://www.ibm.com/cloud/learn/random-forest