

MET CS 699 Data Mining Project On Final Report of the Asian American Quality of Life

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1. Statement of Data Mining Goal

The U.S. Census defines Asian Americans as individuals having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent (U.S. Office of Management and Budget, 1997). Currently, in the U.S, 18.64 million Asian Americans represent 7% of the nation's overall population in 2021. The number is projected to surpass 46 million by 2060. (Pew Research)

Asian American community is a unique community that is diverse in culture, yet shares many similarities within. As Asian American population exponentially grows from minority to majority, we wish to better understand the current social and health state of the community.

Our goal in this project is to predict Asian Americans' satisfaction level with their overall "Quality of life", which is also our class attribute, based on different attributes. There are many attributes such as housing, salary, family ties, religion, and ethnicity which would help us better understand what are the driving forces of Asian Americans' quality of life.

2. Detailed description of the dataset

Our team's dataset was the Final Report of the Asian American Quality of Life (AAQoL), a compiled individual survey which was conducted on Asian American population in the city of Austin, Texas.

Survey questions were divided into answers to 7 different sections: Demographic, Immigration and Acculturation, Health, Special Interest, Social and Community Resources, Life in the City of Austin. The original dataset consists of 231 columns and 2,609 tuples of Asian Americans' survey results, including attributes like Age, Gender, Ethnicity, Marital Status, Education Status, Household Size, Religion, Employment Status, Income, English Level, Family Connection, Transportation Modes, and more. Each 2,609 unique survey represents an individual's information, which can be used for attributes determining the quality of life. Considering the design of the survey, the dataset mainly consisted of nominal and ordinal data.

The full list of attributes and the corresponding descriptions are in the link below. https://data.austintexas.gov/City-Government/Final-Report-of-the-Asian-American-Quality-of-Life/hc5t-p62z

3. Brief description of data mining tool(s) used

Various tools were used for different purposes throughout the project. Once the data has been extracted from the source, our team used R for the Data Preprocessing task. We have dropped unnecessary attributes, such as the 'Other' sections, where surveyors would input character values for further explanation. R was used to detect any missing values, noisy data, and inconsistencies between variables. Outlier detection has been conducted using R as well. Finally, once all cleaning and prepping have been completed, we split the data into training and testing with R.

For attribute selection tasks, we utilized Weka. Weka provides easy access to various attribute selection methods. For model building and testing, performance analysis and visualization, we used Weka.

4. Brief description of classification algorithms you used.

We built 5 different models to predict our class attribute(Quality of life): Naive Bayes, SimpleLogistic, Bagging, ClassificationViaRegression, RandomForest

 Naive Bayes is a Bayesian classification model with the assumption that attributes are related to each other. This model attempts to calculate the probability of class membership. This is a simple but powerful model comparable performance with decision trees and selected neural networks.

$$P(\mathbf{X}|C_i) = \prod_{k=1}^{n} P(x_k | C_i) = P(x_1 | C_i) \times P(x_2 | C_i) \times ... \times P(x_n | C_i)$$

- **SimpleLogistic** is a classifier for building linear logistic regression models. LogitBoost with simple regression functions as base learners is used for fitting the logistic models. The optimal number of LogitBoost iterations to perform is cross-validated, which leads to automatic attribute selection.
- Bagging or bootstrap aggregating model averages the prediction over a collection of classifiers. This model is an ensemble method and provides significantly better accuracy than a single classifier derived from the dataset.
- ClassificationViaRegression is a class for doing classification using regression methods. Class is binarized and one regression model is built for each class value.

$$f(\mathbf{x};\hat{\mathbf{w}}) = w_0 + \mathbf{x}^T\hat{\mathbf{w}}_1,$$
 to classify any new (test) example \mathbf{x} according to label = 1 if $f(\mathbf{x};\mathbf{w}) > 0.5$, and label = 0 otherwise

• Random Forest model is also an ensemble method that builds multiple trees, and each tree classifies a given sample. This model is usually less susceptible to errors and outliers, handles unbalanced data well, and overfitting is not an issue.

Because only a subset of attributes is considered at each node, it is faster than most models.

5. Brief description of attribute selection methods you used.

We used 5 different attribute selection methods: CfsSubset, Correlation, WrapperSubset, OneR, InfoGain

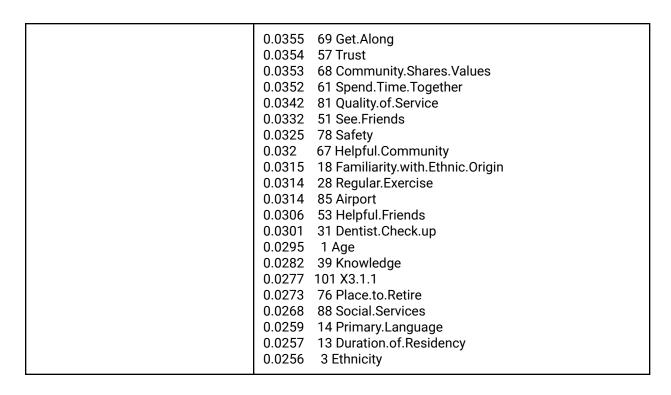
- Correlation-based Feature Selection (CFS) subset is an algorithm that couples this evaluation formula with an appropriate correlation measure and a heuristic search strategy (Waikato).
- **Correlation** evaluates the worth of an attribute by measuring the correlation (Pearson's) between it and the class. Nominal attributes are considered on a value by value basis by treating each value as an indicator. An overall correlation for a nominal attribute is arrived at via a weighted average.
- WrapperSubset method wraps a classifier in a cross-validation loop: it searches
 through the attribute space and uses the classifier to find a good attribute set.
 Searching can be forwards, backwards, or bidirectional, starting from any subset.
 Cross validation is used to estimate the accuracy of the learning scheme for a
 set of attributes.
- 1R or One Rule is a simple, robust and efficient classification algorithm that generates one rule for each predictor. The goal is to make rules based on a single attribute. The algorithm chooses the minimum-error attribute as the rule.
- **InfoGain** Evaluates the worth of an attribute by measuring the information gain with respect to the class. In other words, this method measures how each feature contributes in decreasing the overall entropy.
- 6. The set of attributes selected by each attribute selection method.

| Attribute selection method | Set of attributes selected |
|----------------------------|---|
| CFS Subset Evaluator | 11,15,23,24,28,31,35,37,38,51,95,106,120 : 13 |
| | Achieving.Ends.Meet English.Speaking Present.Mental.Health Present.Oral.Health Regular.Exercise Dentist.Check.up Satisfaction Satisfied.With.Life.1 |

| | Satisfied.With.Life.2 See.Friends Library.Internet.Acess Satisfaction.With.Housing. Public.Meeting |
|----------------------------|--|
| Correlation Ranking Filter | 106,38,11,37,13,35,23,72,74,24,15,22,55,54,62,28,45,80,71,14,73, 50,56,49,59,92,120,17,16,5,77,53,123,61,33,58,57,78,1,82,20,51,6 0,85,46,10,31,18,93,101 : 50 0.1536 106 Satisfaction.With.Housing. 0.1416 38 Satisfied.With.Life.2 0.139 11 Achieving.Ends.Meet 0.1358 37 Satisfied.With.Life.1 |
| | 0.1349 13 Duration.of.Residency 0.1283 35 Satisfaction 0.1275 23 Present.Mental.Health 0.1191 72 Place.to.Live 0.1145 74 Place.to.Work 0.1118 24 Present.Oral.Health 0.1084 15 English.Speaking 0.1058 22 Present.Health |
| | 0.1053 55 Similar.Values 0.1049 54 Family.Respect 0.1023 62 Feel.Close 0.102 28 Regular.Exercise 0.1012 45 Advanced.Directives 0.1006 80 Qualtiy.of.Life 0.1 71 Residency 0.0963 14 Primary.Language |
| | 0.0954 73 Raising.Children 0.0951 50 Helpful.Family 0.095 56 Successful.Family 0.0946 49 Close.Family 0.0942 59 Family.Pride 0.094 92 EMS.Classes 0.0932 120 Public.Meeting |
| | 0.0913 17 Familiarity.with.America 0.0884 16 English.Difficulties 0.0861 5 Education.Completed 0.0848 77 Arts.and.Culture 0.0817 53 Helpful.Friends 0.0816 123 City.Election 0.0814 61 Spend.Time.Together |
| | 0.0813 33 Dental.Insurance 0.0813 58 Loyalty 0.0799 57 Trust 0.0799 78 Safety 0.0789 1 Age 0.0777 82 Parks.and.Recs |
| | 0.0765 20 Belonging 0.0755 51 See.Friends 0.0743 60 Expression |

| Wrapper Subset Evaluator | 0.0735 85 Airport 0.0732 46 Have.an.Advanced.Directive 0.0731 10 Income 0.0695 31 Dentist.Check.up 0.0688 18 Familiarity.with.Ethnic.Origin 0.0683 93 Fire.Alarm 0.0679 101 X3.1.1 23,38,59,95,97,122,123:7 Present.Mental.Health Satisfied.With.Life.2 Family.Pride Library.Internet.Acess |
|--------------------------|---|
| | Citizenship.Class Contact.City.Official City.Election |
| OneR feature evaluator | 38,37,23,22,106,24,17,35,80,81,120,78,71,125,121,126,49,50,45,4 1,86,19,87,65,83,46,13,59,62,61,27,26,42,14,18,8,10,28,57,43,11,4 4,54,33,48,29,51,53,21,64:50 |
| | 58.8657 38 Satisfied.With.Life.2 58.0183 37 Satisfied.With.Life.1 56.0626 23 Present.Mental.Health 55.2803 22 Present.Health 54.8892 106 Satisfaction.With.Housing. 54.5632 24 Present.Oral.Health 52.9335 17 Familiarity.with.America 52.5424 35 Satisfaction 52.5424 80 Qualtiy.of.Life 52.2164 81 Quality.of.Service 51.6949 120 Public.Meeting 51.369 78 Safety 51.2386 71 Residency 51.1734 125 Informed 50.9778 121 Council.Meeting 50.9778 121 Council.Meeting 50.9778 126 City.Effort.Satisfaction 50.9126 49 Close.Family 50.8475 50 Helpful.Family 50.717 45 Advanced.Directives 50.6519 41 Prevention 50.6519 49 Identify.Ethnically 50.5215 65 Religious.Importance 50.5215 83 Libraries 50.5215 46 Have.an.Advanced.Directive 50.4563 13 Duration.of.Residency |

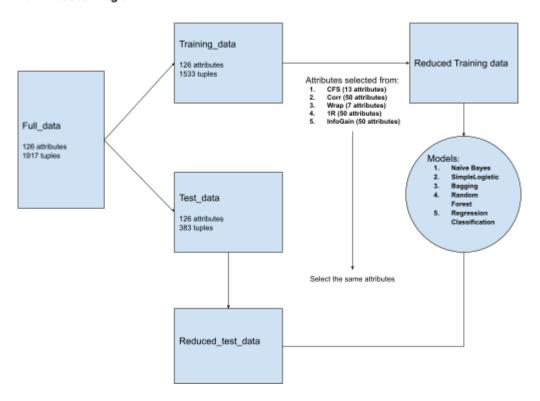
| | T |
|---------------------------------|---|
| | 50.3911 26 Smoking 50.3911 42 AgingAD. 50.3911 14 Primary.Language 50.3911 18 Familiarity.with.Ethnic.Origin 50.3911 8 Retired 50.3911 10 Income 50.3911 28 Regular.Exercise 50.3911 57 Trust 50.3911 43 CureAD. 50.3911 14 Achieving.Ends.Meet 50.3911 54 Family.Respect 50.3911 33 Dental.Insurance 50.3911 48 See.Family 50.3911 29 Healthy.Diet 50.3911 53 Helpful.Friends 50.3911 53 Helpful.Friends 50.3911 64 Religious.Attendance |
| Information Gain Ranking Filter | 37,38,23,24,22,15,17,106,10,11,34,16,74,80,59,56,72,35,55,62,75,54,58,60,77,70,33,73,82,69,57,68,61,81,51,78,67,18,28,85,53,31,1,39,101,76,88,14,13,3:50 0.2846 |



7. Detailed description of data mining procedure.

Our team followed a full testing process of the selected models, described in the Diagram below.

Full Process Diagram



7.1 Data Preprocessing

- Step1. Checking for Missing Value
 We removed NA values on the surveyor's demographic information.
- Step2. Encoding categorical data
 The "No.One" column is categorical data with 2 levels, "living with no one" and
 "0", we encoded it into "1", "0".
- Step3. Checking for Inconsistent data
 We removed inconsistent data of "household size" and "living with no one".
- Step4. Checking for Outliers
 6 people over the age of 80 are detected as outliers. 2 Surveyors with duration of residency over 50 years are detected as outliers. We decided against excluding age as a factor of outlier detection and removed outliers detected with Duration of Residency.
- Step5. Data Reduction
 Because this is survey data, many entries are not subject to mining. These surveyor inputs are unnecessary, and therefore dropped.
- **Step6**. Reformatting the class attribute We reformatted the class attribute "Quality of life" to factors with wider bin size.
- Step7. Splitting the dataset into the training and test set
- **Step8**. Data formatting and export

```
tib3
# Checking for Outliers
summary(tib3)
boxplot(tib3$Duration.of.Residency)
hist(tib3$Duration.of.Residency, xlab = "Duration.of.Residency", main
= "Histogram of Residency Duration")
                                                      Histogram of Residency Duration
   8
                                             200
  20
                                                0
                                                              40
                                                          Duration.of.Residency
boxplot(tib3$Age)
hist(tib3$Age, xlab = "Age", main = "Histogram of Age")
 100
                                                      Histogram of Age
 8
                                          200
                                          150
                                          100
 40
boxplot(tib3$Household.Size)
```

```
hist(tib3$Household.Size, xlab = "Household Size", main = "Histogram"
of Household Size")
                                                  Histogram of Household Size
                                          20
                                         200
                                         400
                                          200
                                                      Household Size
# Removing Outliers detected with Duration of Residency. Based on the
technique covered in class.
Q1 <- quantile(tib3$Duration.of.Residency, .25, na.rm = T)
Q3 <- quantile(tib3$Duration.of.Residency, .75, na.rm = T)
IQR <- IQR(tib3$Duration.of.Residency, na.rm = T)</pre>
tib4 <- subset(tib3, tib3$Duration.of.Residency > (Q1 - 1.5*IQR) &
tib3$Duration.of.Residency < (Q3 + 1.5*IQR))</pre>
dim(tib3)
dim(tib4)
##### Data Reduction #####
# Dimensionality Reduction
tib5 <- tib4[-c(8:14, 19:20, 47:56, 69, 71, 73:81, 85:88, 195:209)]
colnames(tib4[c(8:14, 19:20, 47:56, 69, 71, 73:81, 85:88, 195:209)])
# Column Unemployed and Disabled are 0.
tib5 < - tib5[-c(14, 15)]
tib6 <- na.omit(tib5)</pre>
summary(tib6)
# reformatting the class attribute to factors with wider bin size
```

```
tib7 <- tib6
QoL factor <- cut(as.numeric(tib6$Quality.of.Life), breaks = c(0, 3,
4, 6, 8, 10), labels = 1:5)
tib7$Quality.of.Life <- QoL factor
#Creating the training set and test set separately
library(caTools)
set.seed(123)
split = sample.split(tib6$Quality.of.Life, SplitRatio = 0.8) # returns
true if observation goes to the Training set and false if observation
goes to the test set.
training set = subset(tib6, split == TRUE)
test set = subset(tib6, split == FALSE)
training set
Test set
# Exporting to csv for further mining process
write.csv(tib7, "full set.csv")
write.csv(test set, "test set.csv")
write.csv(training set, "training set.csv")
```

7.2 Attribute Selection

With the training and test dataset generated, our team then moved to the attribute selection process. In this process, as our Process Diagram shows, we ran all 5 attribute selections in Weka on the training set generated. Each training set with selected attributes were separately saved.

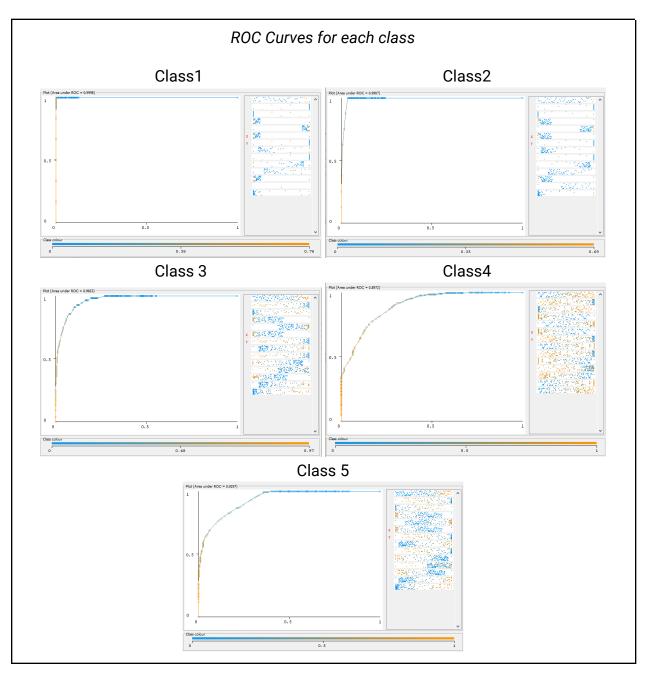
7.3 Model Generation

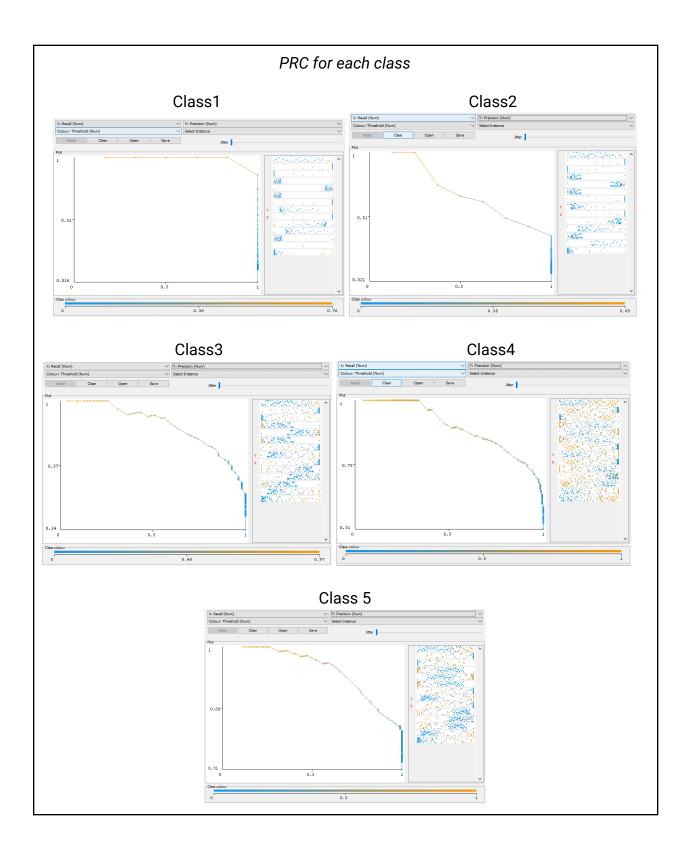
With the reduced training dataset of selected attributes, our team started generating 5 models selected from above 5 classification methods. Once the model was generated with each of the 5 reduced training dataset, we tested out models with a corresponding test dataset with the same attributes.

8. Data mining result and evaluation:

Conclusion: According to the performances of 25 classification models below, we concluded that using **WrapperSubset** attribute selection method and **RandomForest** classification algorithm generates the best model. (*Accuracy = 78.0679%, ROC Area = 0.921, PRC Area = 0.874*) PRC Area has been used to evaluate the performance along with ROC Area, given that the dataset is unbalanced.

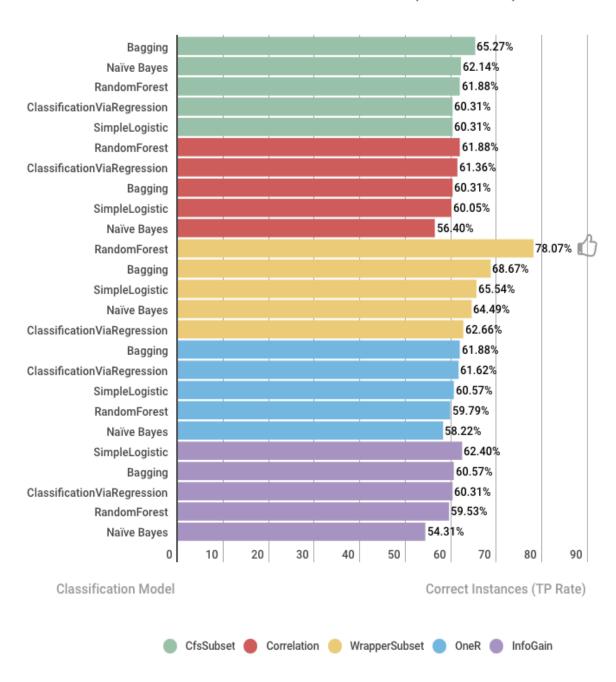
As we can see in the Curves below, for each class, the predicted class has been mostly accurate, especially for the lower ratings for quality of life.





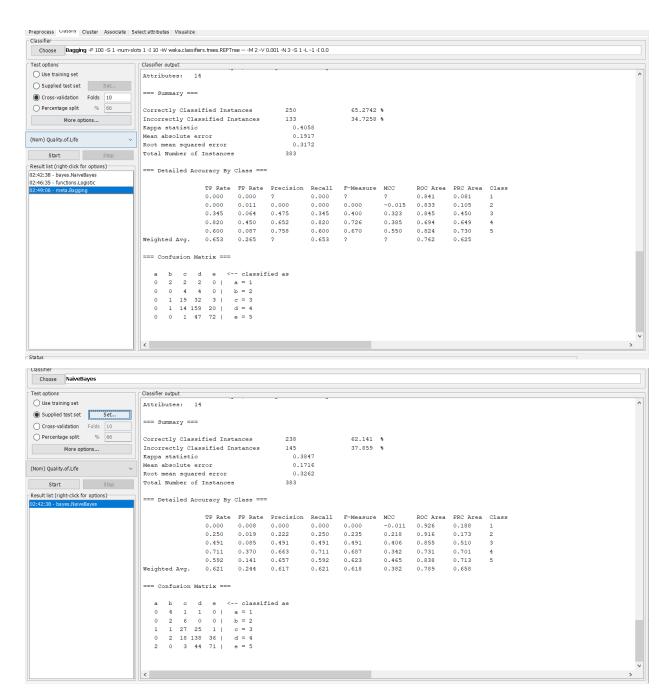
One of the reasons the Random Forest model performs best is because of the unbalanced nature of the dataset. Random forest tries to minimize the overall error rate, so when we have an unbalanced data set, the larger class will get a low error rate while the smaller class will have a larger error rate. Random Forest model builds multiple decision trees and merges them together to get a more accurate and stable prediction. It is also worth noting that the Random Forest model works with subsets of data, and thus works well with high dimensional data.

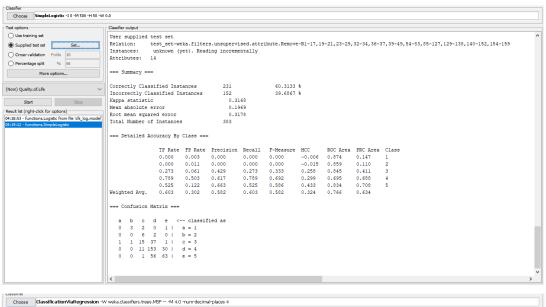
Performances of 25 classification models (test dataset)

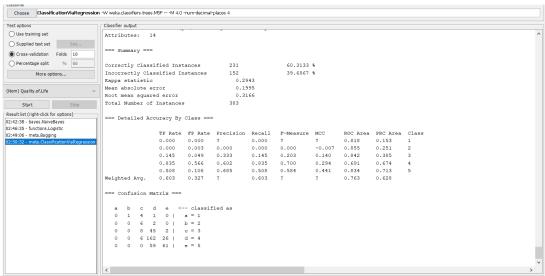


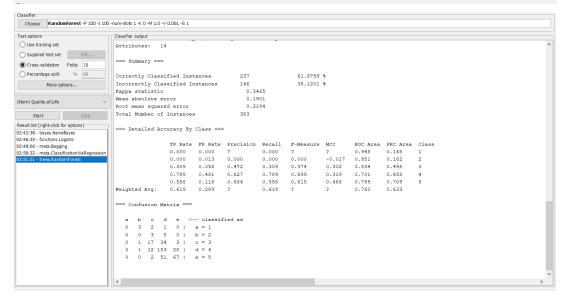
8.1 Results of testing models on reduced test datasets:

Reduced test dataset1: CfsSubset

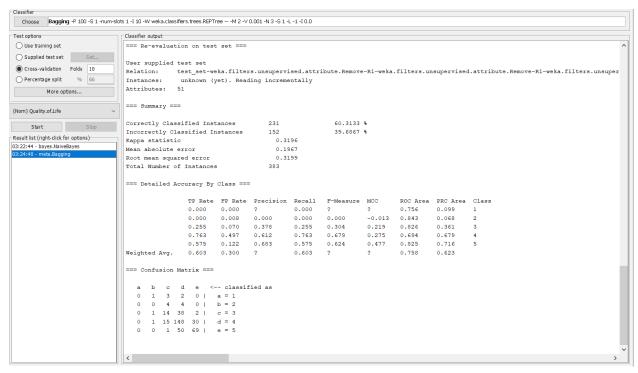


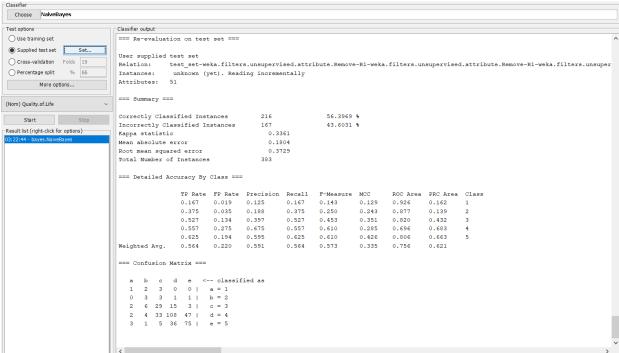


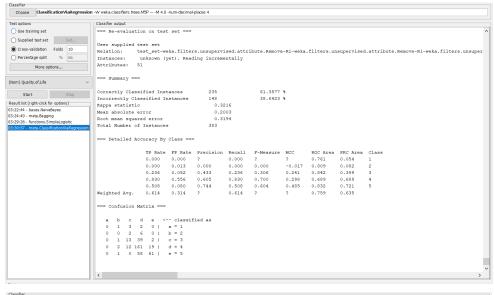


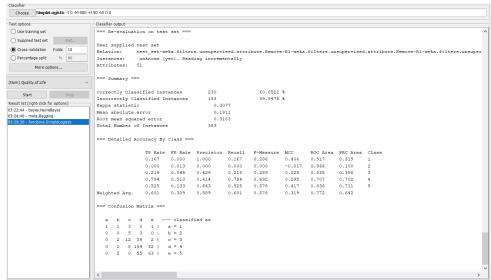


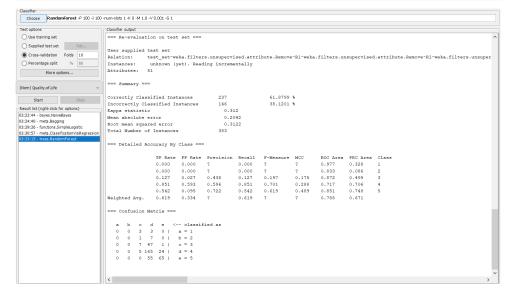
Reduced test dataset2: Correlation



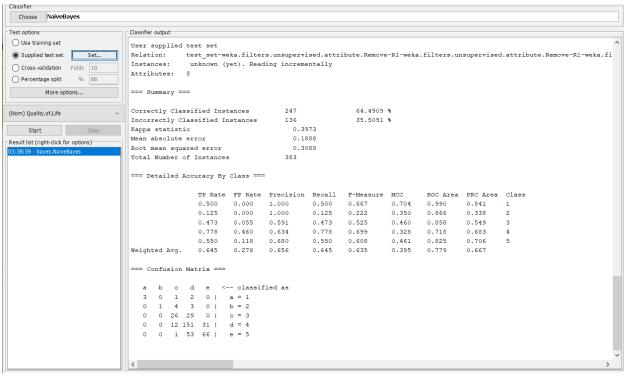


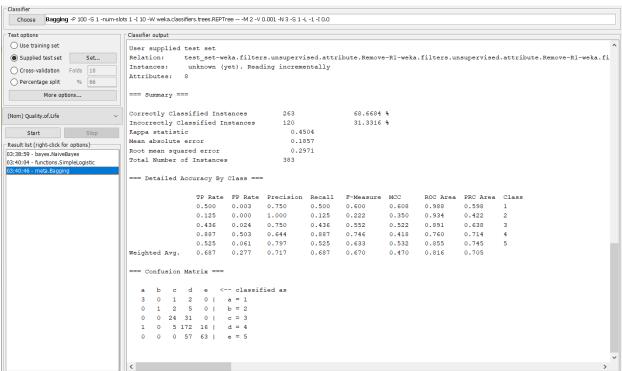


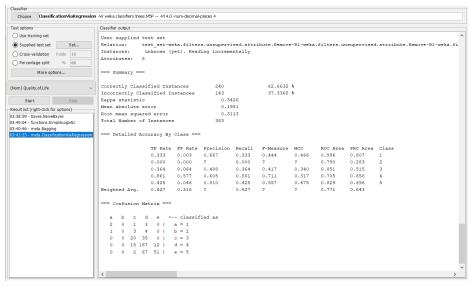


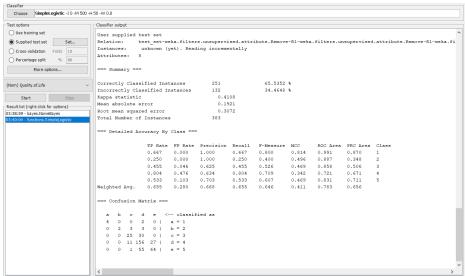


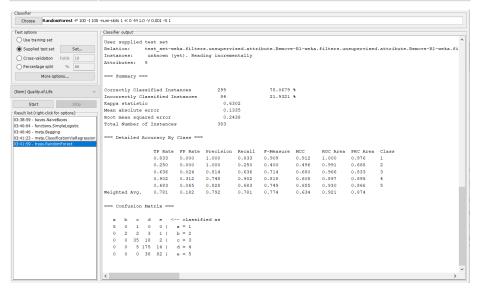
Reduced test dataset3: WrapperSubset



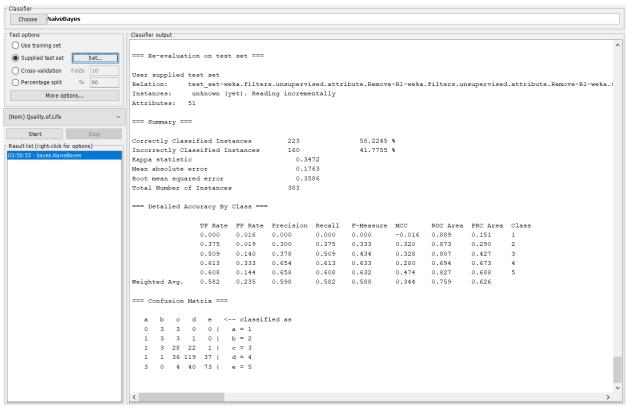


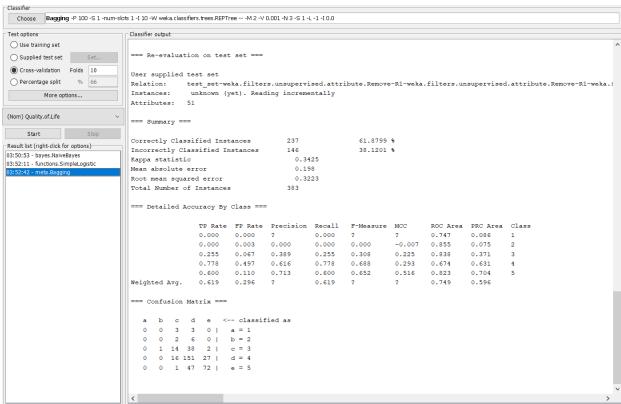


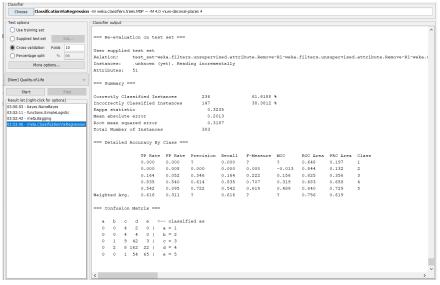


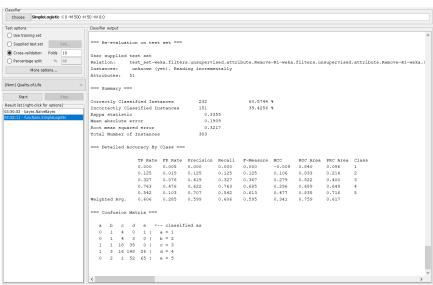


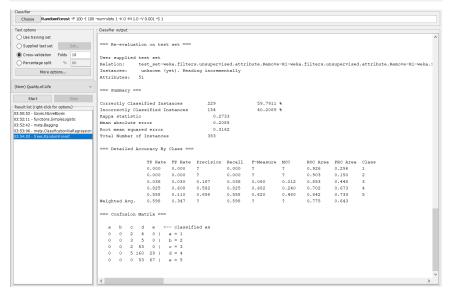
Reduced test dataset4: OneR



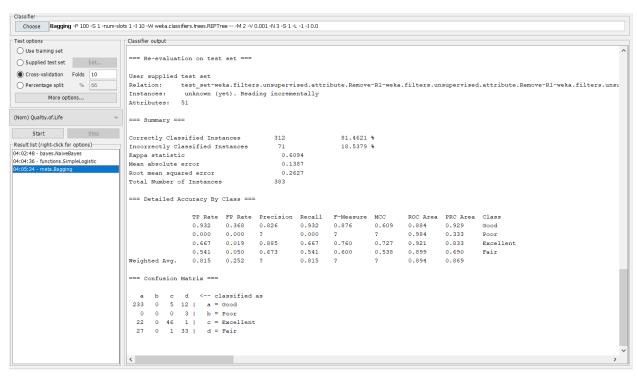


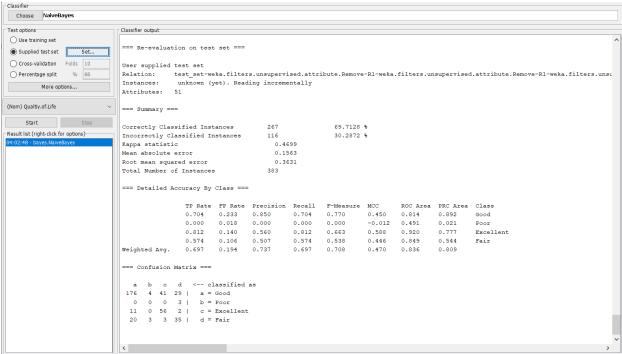


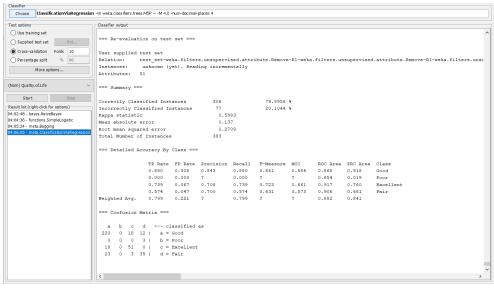


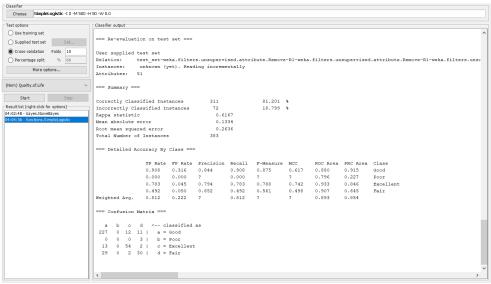


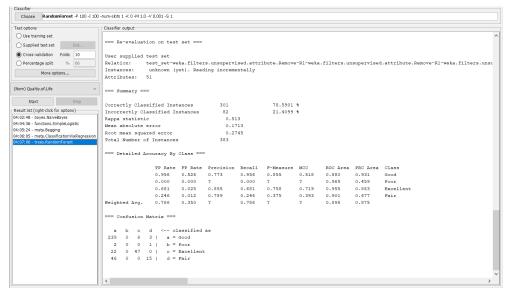
Reduced test dataset5: InfoGain





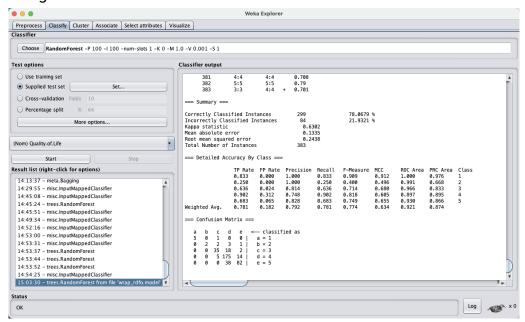




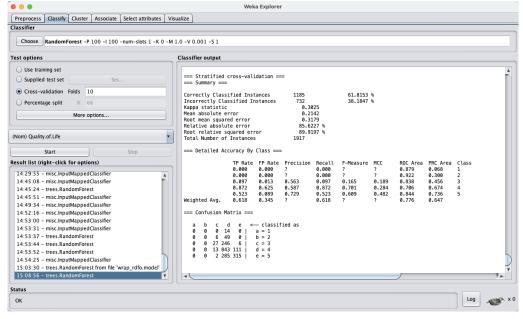


8.2 Comparison of the performances of the best model with the model that was built using the same classification algorithm from the dataset with all attributes.

The best model (using WrapperSubset attribute selection method with 8 attributes selected and Random Forest classification algorithm) performed (*Accuracy = 78.0679%, ROC Area = 0.921, PRC Area = 0.874*) better than the model with all attributes (*Accuracy = 61.8153%, ROC Area = 0.776, PRC Area = 0.647*). The TP rate of the best model is 16.2526% higher than another one.



Best model with 8 attributes



The model with all attributes (121 attributes)

9. Discussion and conclusion, including what you learned from this project.

9.1 Methods to increase performance

To increase the performance of our classifier models, several methods have been proven to be useful in our project:

- Removing inconsistent data and any outliers
- Reducing dataset
- Encoding the class attribute
 Encoding the class attribute "Quality of life" from "1-10" to "1-5" roughly increased 20% of the model accuracy.

9.2 Findings of the testing results

- Generally, the datasets with attributes selected using WrapperSubset method generated better performance, 5%-20% higher accuracy than other four attribute selection methods (CfsSubset, Correlation, OneR, InfoGain);
- Random Forest algorithm generates the best TP rate for Correlation and WrapperSubset test sets.
- Compared to other attributes selection methods, WrapperSubset selected the least number of attributes (only 8 attributes), so we conclude that less attributes contributes to better performance.
- Apart from the Random Forest classification algorithm, the bagging algorithm performs better than most other classification models. For test sets of CfsSubset and OneR, bagging generates the highest True Positive rates.

9.3 Suggestions for the future steps

- Based on the selected attributes using WrapperSubset, attributes including
 Present mental health, Satisfaction with life, Family pride, Library internet access,
 Citizenship class, Contact city official or not, City election, we found that people
 caring more about the city life and participating in local political activities seems
 to be important factors in quality of life. Contrary to what we believed, mental
 health and state were a bigger factor in quality of life than physical health or
 condition. These findings should be taken into account for future study.
- For the dataset(after preprocessing) using Correlation attribute selection method, we found that attributes like Satisfaction.With.Housing(ρ = 0.1536), Satisfied.With.Life.2(ρ = 0.1416), Achieving.Ends.Meet(ρ = 0.139), Satisfied.With.Life.1(ρ = 0.1358), Duration.of.Residency(ρ = 0.1349) have weakly relationship with the class attribute "Quality of life." To better understand what factors influence Asian Americans' quality of life, further research can be taken

on exploring its correlation with peoples' satisfaction with housing, achieving ends meet or not, and duration of the residency.

^{*} We do all the work of this project together while Philip contributes a little bit more on R and the first half of this report, and Min contributes a little bit more Weka and the second half of the report.