Team #101

Report of Datathon 2020

The data provided contains different types of business settlements in different zip code regions with their sales/revenue/receipts in different ranges and the corresponding number of settlements to each revenue range. In order to determine a list of zip code that is prioritized, we analyzed the marketing potential of each regions. The market potential is under the assumption that people live in a zip code region will spend their money on the business in the same region. Therefore, if there is a lower settlement’s revenue to resident’s income rate, then there is a higher market potential. However, if the market potential is too low, then probably people live in that region does not have a great desire on consuming, so the best choices of business are regions with the middle 50% of market potential. Since the dataset does not provide all the information we need, we use outside resources of number of people in different income range in zip code to help determine market potential. We use the median of each range to multiply the number of population in that range and sum together to get the total income of each zip code region, and perform similar approach on the business’ sale to get total sale in each zip code region and then merge the two datasets together to calculate variable marketPotential. Then we output the list of zip code region that is the middle 50% of marketPotential. There are 41 states included in the middle 50% of marketPotential, which reveals that the opportunities of business are not concentrated in a specific state or region, instead, it is widespread around the US. The top three states that have the most zip code regions inside are Texas, New York, and California. The result of that actually matches our impression of there are lots of opportunities inside these states. Further analysis shows that the number of population and settlements and market potential are highly correlated. Which makes sense since more population will generate more income, and the same for the number of business. We also find that the sales will decrease with a high marketPotential, which suggest that the regions with high marketPotential is saturated. We also want to use Random Forest to classify the zip code regions so business can find out which region is a better choice and which features have significantly influences. To build the Random Forest model, we add several variables that are relative to taxes from another outside dataframe. Since we do have lots of variables, we perform the ANOVA test first to remove the variables that are not significant to zip code at all to have a better performance on later model. Surprisingly, the variable about state and local income taxes amount does not have an important effect on the zip code region. After cleaning there are 16 independent features. Because the dataset is too large to run on our computer, we randomly sample out 50% of data to build and test the model. We split the sampled subset into train, validation and test dataset, each contains 20%, 20%, and 60% of the sampled dataset respectively. The output of the random forest shows an accuracy rate of

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which is lower than our expectation, but it may because the zip codes are all unique, so it is hard for the model to classify data into categories that are not in the training dataset. The Random Forest model also produce a list of the significance of variables. From the result list, we can find out that the variables

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are important to identify the zip code region.