Meetfresh Store Location Recommendation System

- Need Finding, Model Construction, and Business Value

Audiences: project supervisors and site recommendation system users

1 Introduction

1.1 Meet Fresh Business Background

Meet Fresh is a dessert franchise chain store. The chain specializes in fresh Taiwanese desserts, including taro balls and grass jelly. So far, it has 35 stores in the US. Most of them are located in big cities like New York City, Boston and Los Angeles. The major consumers are Asian, especially from China. Compared with other chain stores like Starbucks, Meet fresh has great potential in expanding its business.

1.2 Project Background

In order to facilitate the growth of the business, we provide a solution to this: a recommendation system on locations. This system is based on the zip code: each zip code will be given a score measuring the suitability of opening a store. However, Meet Fresh has only 26 stores in the US, which puts a big challenge on building the recommendation system. Given the similarity between the Meet fresh and the bubble tea stores, we generalize the recommendation system to the bubble tea store. In this project, we use the information of geography, population, Big Malls, SuperMarket, Starbucks, McDonald and schools to train our recommendation system by using the techniques including linear regression, random forest, decision tree, neutral network, Xgboost and SVM. We will present the performance of various models and evaluate the best model.

2 Discovery summary

In order to understand the business pain point and develop recommender system ideas, we conduct need-finding for MeetFresh products, from the aspect of naturalistic observation, participant observation, and user interview. The need-finding process is centered around understanding shop owner's concerns, customers' purchase habits, decision making process, and their personalized opinions about MeetFresh. The sessions below give a high-level summary of the need-finding exercise and the results. Detailed transcripts are included in the appendix.

2.1 Naturalistic observation

We observed in-store and online food ordering processes, the data are recorded and collected during the observation. After data analyzation and comparison between two ordering methods, we got following insights:

a. There are less items from online platforms but most of the items can still be ordered online. For an order with two items, over 1/3 of the price comes from service fee, delivery fee and tips.
b. The features customers care about the most are flavor, wait time and quality control. While customers ordered in store pay more attention to store environment and service, those ordered online care more about packaging and if there is any order missing or incorrect.
c. About 70% of customers are Asian whose age is between 15-30. 70% of orders are walk in, 30% are picked up.

2.2 Participant observation

Each of the group members recorded the experience and decision making process we had ordering food (drinks) from MeetFresh. The data collected in the activity are used to learn more about MeetFresh business and to try to find the unmet needs. The distance from the store, health concerns and food portion size are the largest barriers stopping customers from placing orders in MeetFresh.

2.3 User interview (business owner + customer)

User interview section is divided into two parts, customer interviews and business interviews. Aside from understanding customer's purchase behavior in participant observation and naturalistic observation, we want to further understand the reasons for customer behaviors and their thinking patterns, so we need to reach a more in-depth understanding through customer interviews. On the other hand, listening from one side is far from enough. We are aware that the business side (staff in stores) also makes up an important part of our understanding of MeetFresh's business pain-point. In this case, we incorporated business interviews with a MeetFresh store manager and a bubble tea shop owner to perfect the interview dynamic. Insights we got from the interviews are:

a. Meet Fresh's bubble tea only contributes 20% of income. over 70% contributed by desserts.
b. One mentioned that it might encourage customers to order more if MF can have "sweet-level indicator" for each of the products.
c. If MF provides a membership program and she gets credits (that can be used as money) when she buys products, she would like to go to the stores more often.

3 Brainstorming summary

With the unmet needs found and collected from the previous section, we start brainstorming on how some of these problems can be solved. This section shows the brainstorming plans and results of possible directions to improving Meetfresh business and creating recommendation-system-related products that generate business value in the sweet food industry.

3.1 Brainstorming plan

a. Each group member needs to come up with at least 10 ideas
b. The ideas can be subject to help the customer or the business.

c. Think about what the customers really need and what they may not be aware of.
d. Think about what the customers really want from the experience.
e. Think about aspects of the business other than the product.
f. Think about problems that the business may face that are not directly associated with sales or profits.
g. Think about the problems that the business may have in the past, present, or future.
h. Think about what can be improved in the current business model.
i. Think about what data can be used to solve the problems.

3.2 Brainstorming execution

Each member had his/her own individual brainstorming sessions and each had provided at least 10 ideas. A group brainstorming session was used to compare and compile ideas. A summary of the brainstorming sessions is provided below:

a. Analyze the customers' comments on social media, use the NLP technique to extract the complaints and trends. Generate report for the business owner.
b. Introduce new products based on popularity and trends in the area.
c. Recommend new presentations and designs of the products
d. Recommend potential investors and people who may be interested in joining the franchise
e. Recommend locations for new stores based on factors such as population, demographics, income level, etc.
f. Recommend for inventory stockings based on sales, cost, and availability of supplies.

3.3 Selection Criteria

a. Addressing crucial needs of users. The "users" can come from a wide rage, including customers of Meetfresh, business owners of Meetfresh, or opportunity seekers who are willing to open a new Meetfresh store.

b. Bringing business value. The essential goal of the project is to bring potential value to the business development of Meetfresh. The more value we make from the project, the more impact we can make on the growth of Meetfresh.
c. Generalizability. Our aim is not limited to merely finishing a project for Meetfresh. We look beyond and want to make real contributions to the industry. The generalizability of our model/product/website decides how far we can go and how much bigger contribution we can make to this world.

4 Low fidelity prototyping

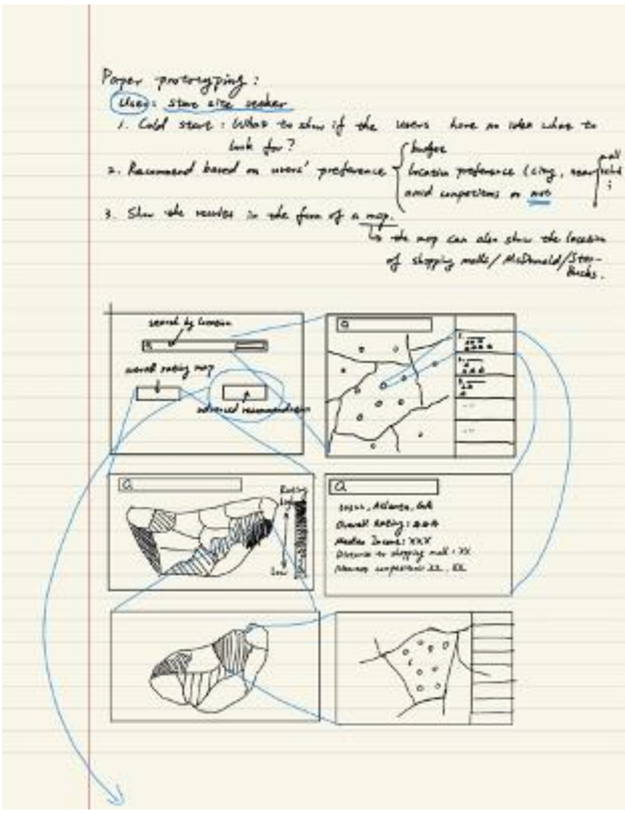
Low-fidelity prototyping is a quick and easy way to translate high-level design concepts into tangible and testable artifacts. It is very important for efficiently finding the right direction of the solution. The first and most important role of Low-fidelity prototypes is to check and test functionality of the product.

The prototypes come from the view of the shop owner. During the investigation of the MeetFresh (MF), we find the shops are only limited to some places. Many people need to drive a long distance to try it and this restricts the promotion of the business. We also find some cases failing to run a MF. The MF is a franchise store and this means we can recommend the location of the shop. Given the similarity to other dessert stores, we expand our horizon to all dessert shops. We think this is a high practical value business idea. In the following, we will describe how this prototype works.

4.1 Verbal prototype

This prototype is web-based. It provides the key information to help the people of interest choose their ideal shop location. When considering opening a store, the first thing is the market. We need to know people's preferenc e for dessert, how many and how much people will spend on dessert, when and how to eat dessert, the popularity among different ages and so on. After this, the next step will be the analysis of the location. A good location should have convenient transportation like the subway (metro) and large parking lot. Big stores, shopping malls, big companies and schools are also good indications of how many people live surround and visit. We can also learn from how McDonald or Starbucks choose their store locations. The next part is the cost estimation. The prototype should also provide the manpower cost, rent, tax and if possible, the estimated revenue. In order to have an intuitive feeling, the prototype will provide good visualizations of the information above. Finally, the prototype can also generate a report and final score (how ideal is the location) on the selected location.

4.2 Paper prototype



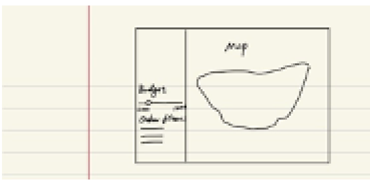


Figure. x paper prototype of site selection

After making sure of the overall input, output and processes of the recommendation in our system (based on the persona, timelines, etc. shown above). We started designing interfaces where we can more easily show our thoughts on the methods of how we are going to collect information from users and implement the models. Figure x. is the paper prototype we created. The landing page is shown on the top left corner. We have two different choices on the main page: overall rating map and advanced recommendation. Overall rating map corresponds to the popularity based cold start model we have and this function is designed for those who have little idea about how their dessert shop would be like and those who are interested in the information in a big picture. While users input the address of the area they are interested in and click the other button 'advanced recommendation', the website will lead them to another page collecting detailed information from them and provide them a more personalized recommendation result.

5 Evaluation: user interviews on the design

We collected feedback from our potential users using this paper prototype and got many valuable suggestions. Some of the examples of the suggestion include (but not limited): 1. adding the button before each of the filters provides users more flexibility. This would also allow us to collect statistical data about the features users think highly of and make adjustments on the positions how these filters should be displayed. 2. Advanced recommendation results (recommended zip code and corresponding locations) should be shown in the largest area possible based on the distance filter information input. The rating points can be added to the results so it would be easier for the users to compare. Detailed information should be given after a specific area is clicked by the user. 3. Useful features that could be helpful for site selection are also discussed in the process of collecting feedback.

We made changes based on these suggestions and updated the prototype. We created website demo designs to better show the prototype ideas and the details of these updates will be shown in the subsection below.

1) +-

6 Final product solution design before the technical development

6.1 Product functions

The main function of our product is to provide site selection services for new MeetFresh stores, as brand expansion is essential for any franchise businesses. This product presents huge business needs, because it will help MeetFresh expand their dessert businesses by opening new store locations, and at the same time, help individuals who are interested in franchising find sites for new stores. Site selection is a difficult task in the food business as it requires tons of research and considerations. Market research, industry analysis, demographic survey, and competitor analysis are all needed to determine an appropriate site. The product provides the full package and takes all the metrics into consideration to help users determine the optimal solution for new site selection.

One of the two main features of the product is to provide an overview of all the potential locations in the USA with rating scores based on the suitability of the sites. This is helpful for users who have no location preference and are just looking to see any available sites in the USA. The other feature is the Advanced Recommendation, where users are required to provide inputs to the system, and the potential sites are filtered to choices that fit the users' preference. Then users will also see an overview map which includes population statistics information about the region which they query.

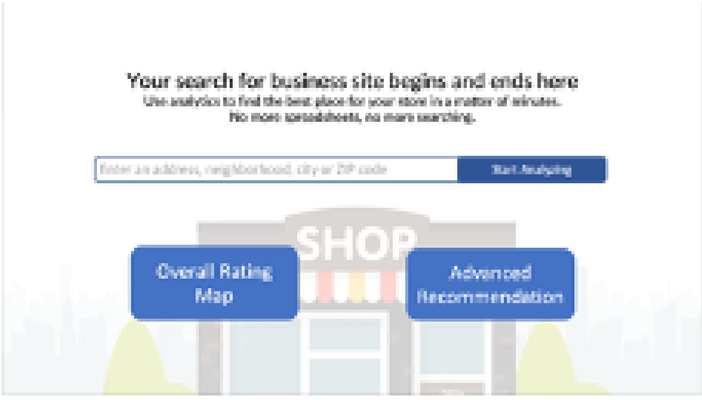
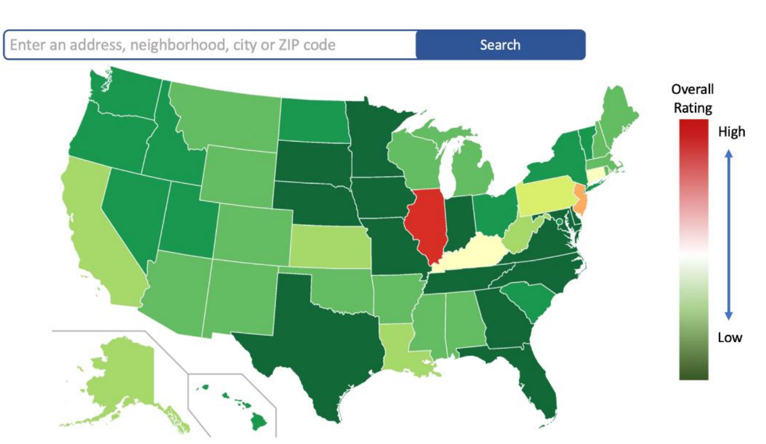


Figure x. Two main features



Figure

The main input required from the users are the location preferences. It can be a region, a state, or a city, then the recommender takes the input and will generate ratings on all the zip codes within the input region, higher rating will mean opening a store in the particular zip code region is recommended. The decision made by the recommender is supported by machine learning models that run on data associated with the demographics, markets, income levels, etc. of all the zip codes. After users select their interested area, they can use a filter module to narrow down their demand, such as budget, business type, distance from home or other customized filter. Then we will run our back end processing model that assigns weight for each feature according to users' preferences to generate a list and rank the matched location. Each location not only contains basic statistics information, but also creates image comparison with nearby areas.

6.2 Product deployment

The final form of the product will be a website. We would use the website to collect the information from customers (their locations, features they are interested…) and also to present the recommendation result and details of the recommended area (shown in Fig.??). The deployment of the product can be separated into two main parts: model deployment and website deployment. The performance of the model will be monitored and the models and the parameters in the models will be updated based on the collected user data.

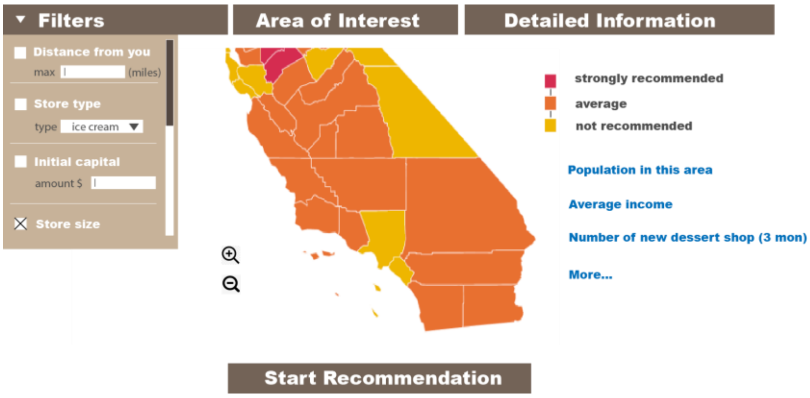


Figure 1. User input (location and important features)

Figure 2. Recommendation result: recommended locations and local details

Different from the data collected directly from the users, in our system the data we collected are used to describe the local circumstances, which is expected to be stable and does not need to be updated frequently. We decided to deploy the database and the model locally on our server. The data will be updated either once every quarter (common renew cycle length of the demographic data) regularly or when significant changes are observed. The model will also be trained locally and they will be retrained only when the data are updated or the performance of the model (evaluated based on the customers' feedback/ matrices) needs to be approved.

After the model is trained and tuned to reach the standard, Flask is utilized to deploy the model to a web service. However inconsistency is usually the problem if the code is run locally, which can be attributed to a lack of consistent environment that runs the software across different machines. Ideally, our code itself should be independent of the underlying machine/OS that runs it. Containerization of our web-server will help us to solve the problem mentioned above. We use docker to containerize the flask service and run our web-service on a cloud virtual machine.

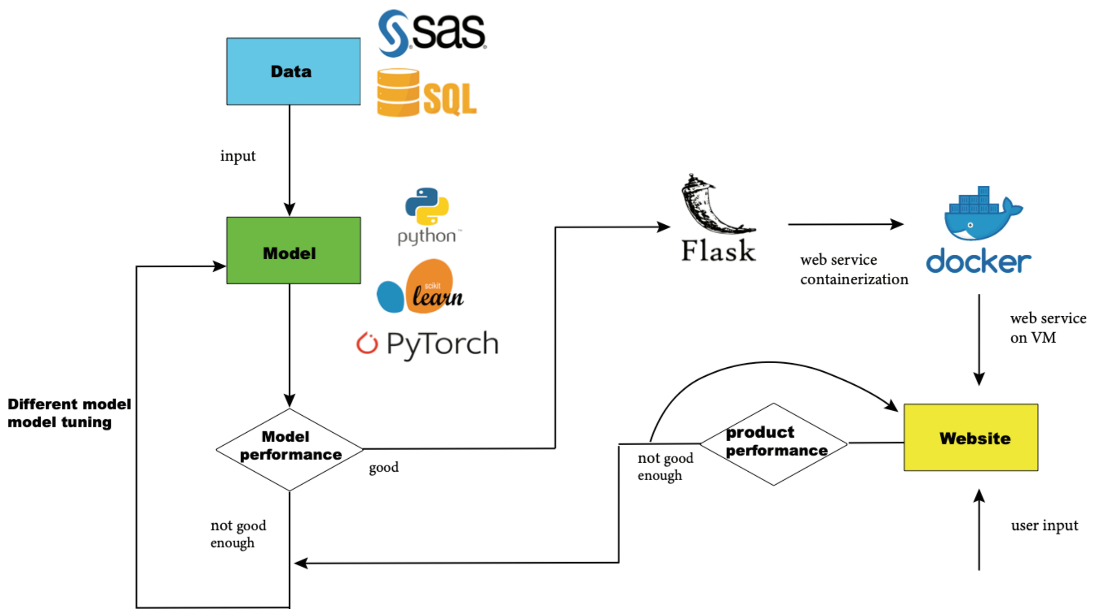


Figure 3. Product implementation details

7 Product technical solution design

7.1 Data Collection and data cleaning

7.1.1 Data source

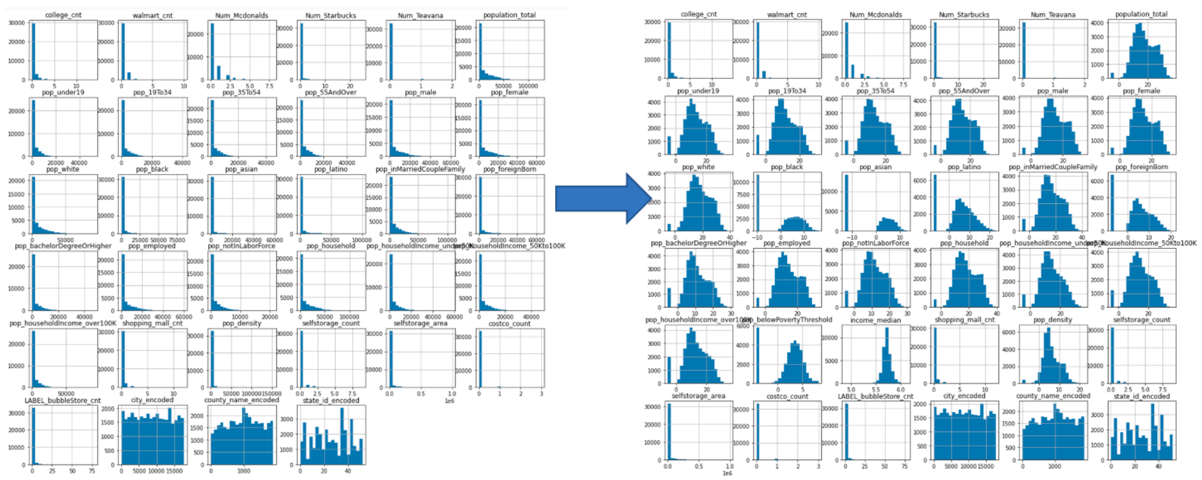
We collected data that covers four aspects of ***general information*** about zip codes in the US, including demographic data [1], traffic data[3-22], important functional location data[25,26], and tax rate data [add reference]. Demographic data includes important information of individuals and households within each zip code area in the US, including median income, race segmenta tion, education level, employment status, age segmentation, etc. Traffic data includes bus stop count, and traffic count in each zip code area. Important functional location data contains the count of colleges, high schools, walmart, costco, big shopping mall, McDonald, Starbuck, and Teavana within each zip code area. Tax rate data covers the state level tax rate information. In addition, we filtered bubble tea store information from google review, and derived the number of bubble tea stores in each zip code area.

7.1.2. Missing value handling and data preprocessing

The combined general information data originally possesses 867 rows of missing data out of 33788 rows. We impute the missing data by the median value of each city. After imputing the missing value, we adjusted the skewness of some variables with Box-Cox transformation [2], whose formula is written as:

$$\psi(y, \lambda) = \begin{cases} y^{\lambda}, & \lambda \neq 0, \\ \log y, & \lambda = 0. \end{cases}$$

Fig. X shows the distributions of variables before and after the skewness adjustment.

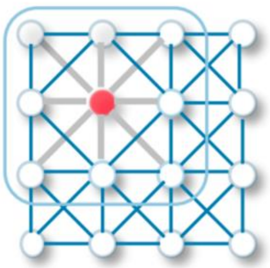


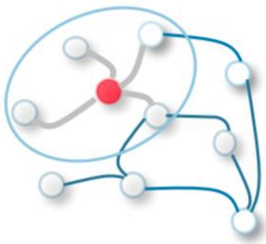
Afterwards, we normalized the data by each variable to ensure unbiased training data for downstream tasks.

7.1.3 Data Aggregation

Based on the zip code level database, we conducted a series of exploratory data analysis, and discovered that people living in adjacent zip codes could have statistically different general information, even though they share similar access to the bubble tea stores in the area. In this case, it is necessary to smooth the general information of adjacent zip codes by data aggregation in order to perform a more unbiased recommendation task. We borrowed ideas from convolutional graph neural networks when conducting zip code level information aggregation.

We consider zips within 8 miles of a center zip as the center zip’s **first neighborhood**, and zips within 16 miles of a center zip as the center zip’s **second neighborhood**. In information aggregation of a center node k, we assign equal weights 1 for all neighbors of the center zip k, and assign weight 4 for k. We then normalize the weights and get the weighted sum of the values of k and its neighbors for every variable. We call this data the **first-aggregated data**. Then using the first-aggregated data, we repeat the above step to derive the **second-aggregated data**.





7.2 Methods

7.2.1 Input and Output

We set the number of tea shops in the area where each zip code address is located and take it as a predicted object and drop columns which are relevant with zip code, city, county and state information, then select the rest o f columns but predict values as training objects. We trained and tested our model on both first-aggregated data and second-aggregated data.

7.2.2 Introduce Algorithms

Model 1. Linear Regression Model. [Panchal.2020]

Linear regression is a very simple approach for supervised learning. It's a useful tool for predicting a quantitative response. It has been around for quite a long time and is the topic of innumerable textbooks. Though it may seem too simple when compared to advanced models, it still works widely as a statistical learning method.

Although simple, linear regression can work as a great benchmark when we are training our statistical learning model. And beyond linear regression, we can have many generalizations and extensions which make simple linear regression powerful.

Model 2. Ridge Regression Model. [Panchal.2020]

The simplest way to understand ridge regression is based on adding weight constraint to the simple linear regression. Where MSE is the loss function of simple linear regression.

Ridge is also called $L2$ regularization because the regularization term is the $L2$ norm of the weight vector.

Model 3. Lasso Regression Model. [Panchal.2020]

Least Absolute Shrinkage and Selection Operator Regression (LASSO) is $L1$ regularization of simple linear model. Similar to Ridge regression, in LASSO we add $L1$ weight constraint to the loss function rather than $L2$ in Ridg

e. Unfortunately, LASSO does not have a closed-form formula solution. It can only be solved via numerical optimization methods.

Model 4. Random Forest Regression Model. [Panchal.2020]

Random Forest (RF) is an extended variant of Bagging. On the basis of constructing Bagging integration with RF decision tree-based learner, random attribute selection is further introduced in the training process of decision tree. Specifically, the traditional decision tree selects an optimal attribute from the attribute set of the current node (assuming that there are D attributes) when selecting partition attributes. The initial performance of random forest is often relatively poor, especially when there is only one base learner in the integration. It's easy to understand, because the performance of individual learners in random forests tends to decrease by introducing attribute perturbation. However, with the increase of the number of individual learners, the random forest usually converges to a lower generalization error. It is worth mentioning that the training efficiency of random forest is often better than that of Bagging, because Bagging uses a "deterministic" decision tree in the process of building individual decision trees, and all the attributes of nodes should be examined when selecting partition attributes, while the "random" decision tree used by random forest only needs to examine a subset of attributes.

7.2.3 Metrics

We chose the best regression model according to our evaluation metrics which included R-squared, mean absolute error (MAE), mean squared error (MSE), root of mean squared error (RMSE) and 5 fold cross validation score from 5 regression models. We picked the model which has the highest R-squared score and lowest rmse in the test dataset.

8 Solution development and results

8.1 Model Selection

Model 1. Linear Regression Model.

Linear Regression Model

```
reg = LinearRegression()
steps = [('Linear_Regression_regression',reg)]
pipeline = Pipeline(steps)
pipeline.fit(X_train, Y_train)
reg_pred = pipeline.predict(X_test)
pipeline.score(X_test, Y_test)
```

Figure 1. Linear Regression Model Code

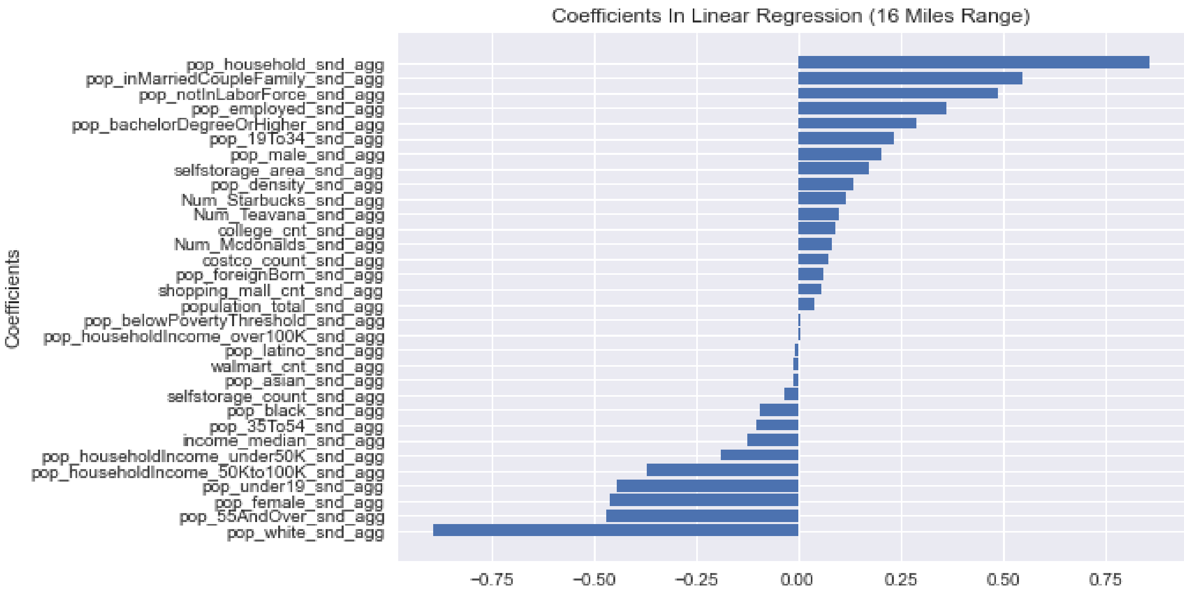


Figure 2. Line Chart about Linear Regression Model Coefficients

	Coefficient
pop_household_snd_agg	0.855648
pop_inMarriedCoupleFamily_snd_agg	0.547080
pop_notInLaborForce_snd_agg	0.488253
pop_employed_snd_agg	0.360843
pop_bachelorDegreeOrHigher_snd_agg	0.290035

Figure 3. Top 5 Important Features in Linear Regression Model

According to the line chart, we can see that Household and Married Couple Family are most relevant features with the predicted object. After we hyperparameter the model, the evaluation metrics outcome shows below.

Model 2. Ridge Regression Model.

```
from sklearn.linear_model import Ridge
rng=Ridge(alpha=0.001)
steps = [('Ridge_regression',rng)]
pipeline = Pipeline(steps)
pipeline.fit(X_train, Y_train)
rng_pred = pipeline.predict(X_test)
pipeline.score(X_test, Y_test)
```

Figure 5. Ridge Regression Model Code

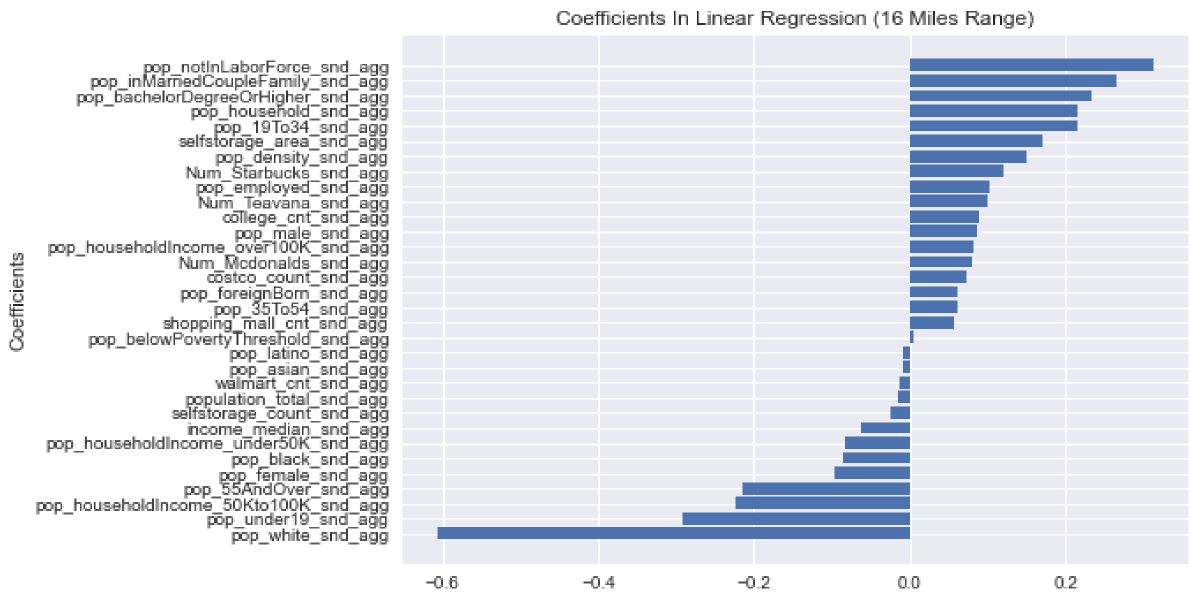


Figure 6. Line Chart about Ridge Regression Model Coefficients

	Coefficient
pop_notInLaborForce_snd_agg	0.311946
pop_inMarriedCoupleFamily_snd_agg	0.264127
pop_bachelorDegreeOrHigher_snd_agg	0.234132
pop_household_snd_agg	0.215676
pop_19To34_snd_agg	0.215269

Figure 7. Top 5 Important Features in Ridge Regression Model

According to the line chart, we can see that not In Labor Force and Married Couple Family are most relevant features with the predict object. After we hyperparameter the model, the evaluation metrics outcome shows below.

Model 3. Lasso Regression Model.

```python
from sklearn.linear_model import Lasso
lasso= Lasso(alpha=0.001)
steps = [('Lasso_regression',lasso)]
pipeline = Pipeline(steps)
pipeline.fit(X_train, Y_train)
lasso_pred = pipeline.predict(X_test)
pipeline.score(X_test, Y_test)
```

Figure 9. Lasso Regression Model Code

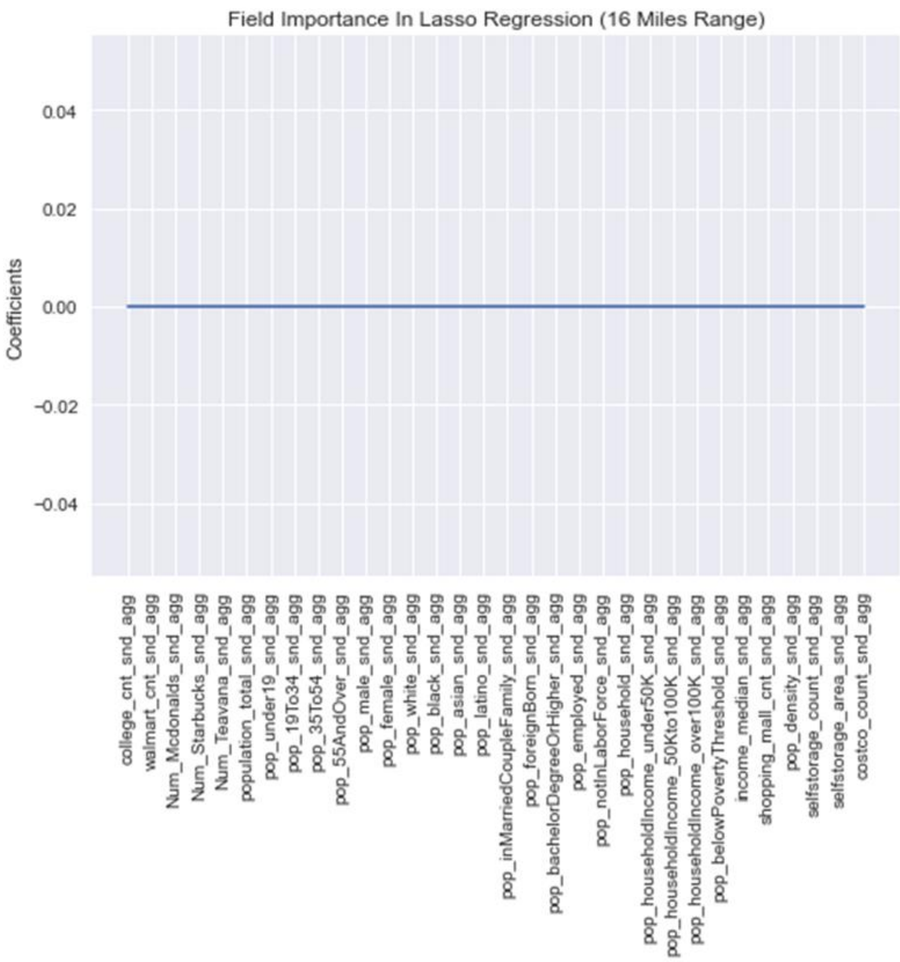


Figure 10. Line Chart about Lasso Regression Model Coefficients

	Coefficient
college_cnt_snd_agg	0.0
walmart_cnt_snd_agg	0.0
selfstorage_area_snd_agg	0.0
selfstorage_count_snd_agg	0.0
pop_density_snd_agg	0.0

Figure 11. Top 5 Important Features in Lasso Regression Model

According to the line chart, we can see that all features are shrined to 0 because of the model hard to distinguish which feature is important from scaling data. After we hyperparameter the model, the evaluation metrics outcome shows below.

Model 4. Random Forest Regression Model.

```
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor(bootstrap=True, max_features='auto', min_samples_leaf = 4, min_samples_split=2, n_estimators=80,max_depth = 20 )
steps = [('Random_Forest_Regressor',rfr)]
pipeline = Pipeline(steps)
pipeline.fit(X_train, Y_train)
rfr_pred = pipeline.predict(X_test)
pipeline.score(X_test, Y_test)

Tree_features = pd.DataFrame(rfr.feature_importances_, Names, columns=['Importance'])


Tree_features.sort_values(by=['Importance'],ascending=False)
```

Figure 13. Random Forest Regression Model Code

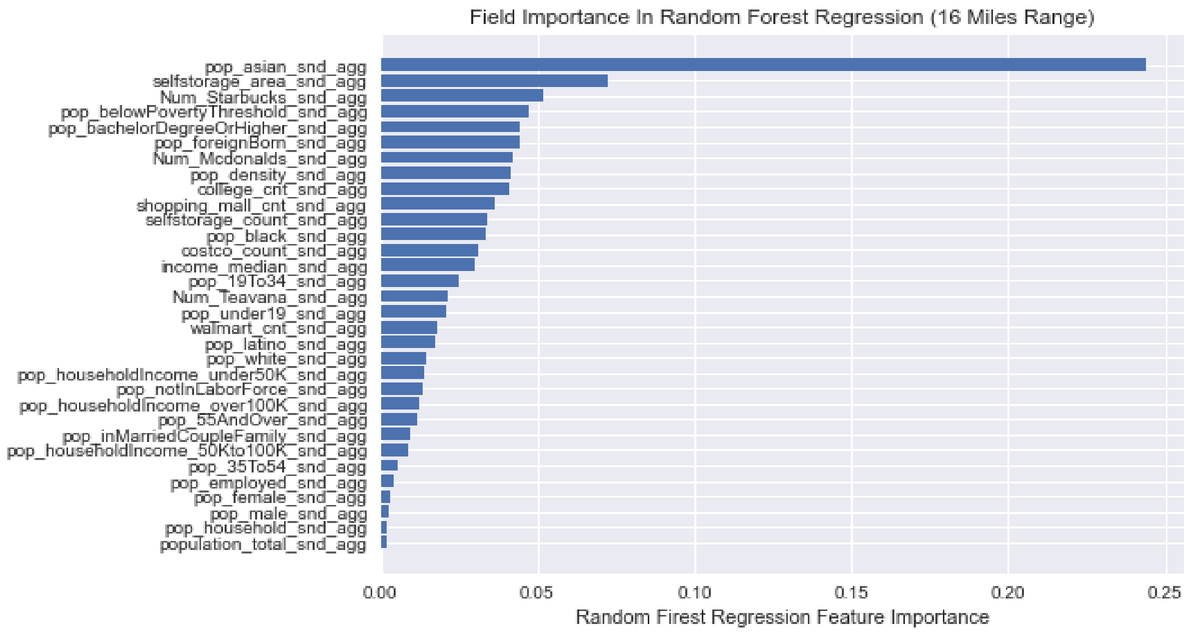


Figure 14. Line Chart about Random Forest Regression Model Field Importance

	Importance
pop_asian_snd_agg	0.244054
selfstorage_area_snd_agg	0.072926
Num_Starbucks_snd_agg	0.051787
pop_belowPovertyThreshold_snd_agg	0.046291
pop_foreignBorn_snd_agg	0.044208

Figure 15. Top 5 Important Features in Random Forest Regression Model

According to the line chart, we can see that Asian and self-storage areas are most relevant with the predicted object. The evaluation metrics outcome shows below.

Model 5. XGBoost Regression Model.

```
import xgboost as xgb
xgb2 = xgb.XGBRegressor(objective ='reg:linear', colsample_bytree = 0.1, learning_rate = 0.1,
                max_depth = 20, alpha = 0.1, n_estimators = 200,verbosity = 0,subsample = 1,min_child_weight=3 )
steps = [('XGboost_Regressor',xgb2)]
pipeline = Pipeline(steps)
pipeline.fit(X_train, Y_train)
xgb_pred = pipeline.predict(X_test)
pipeline.score(X_test, Y_test)
```

Figure 17. XGBoost Regression Model Code

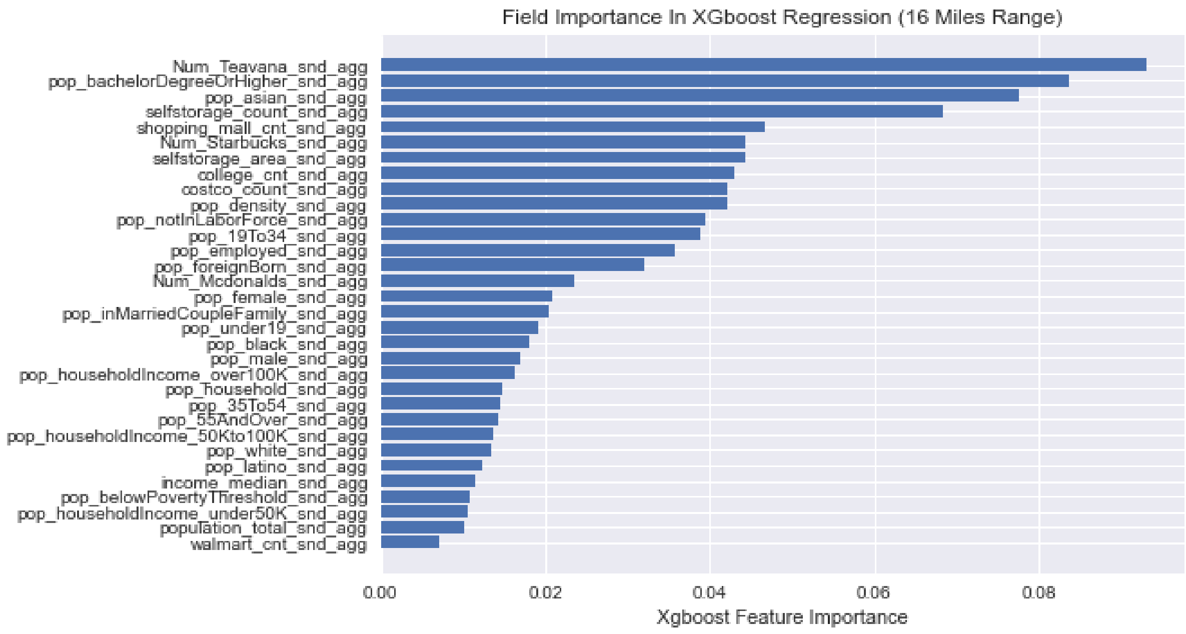


Figure 18. Line Chart about XGBoost Regression Model Field Importance

	Importance
Num_Teavana_snd_agg	0.093034
pop_bachelorDegreeOrHigher_snd_agg	0.083737
pop_asian_snd_agg	0.077566
selfstorage_count_snd_agg	0.068467
shopping_mall_cnt_snd_agg	0.046798

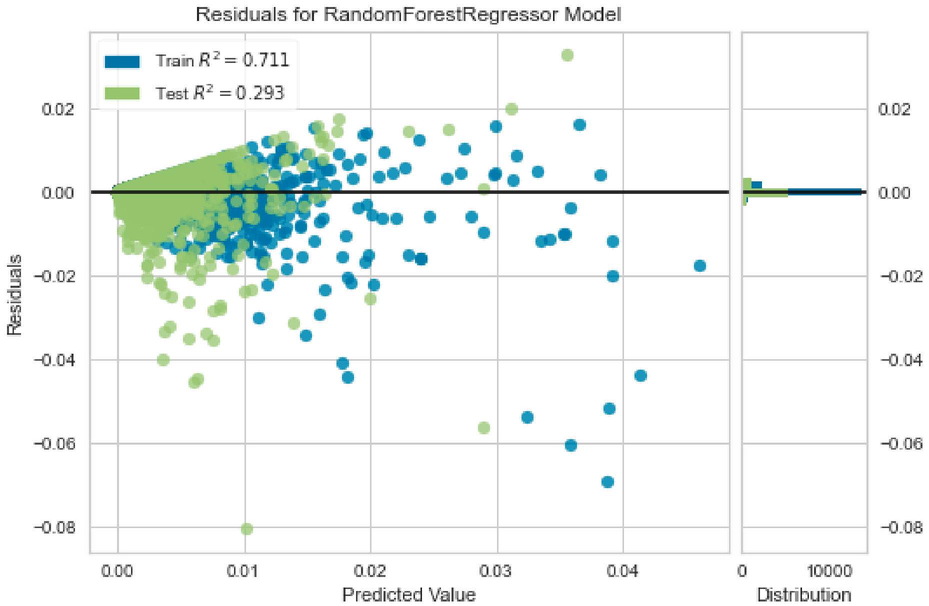
Figure 19. Top 5 Important Features in Random Forest Regression Mode l

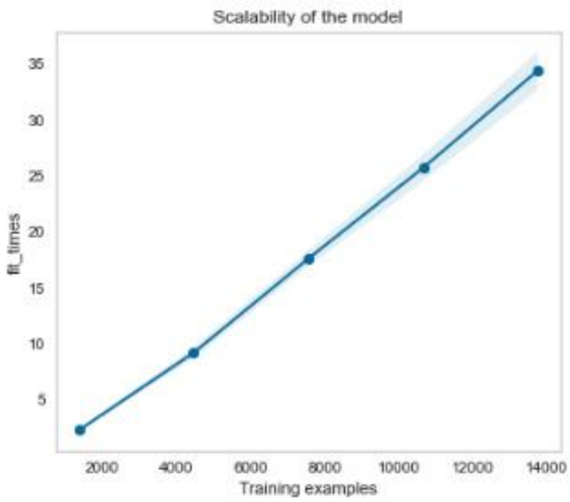
According to the line chart, we can see that Teavana and bachelor degree or higher are most relevant with the predicted object. The evaluation metrics outcome shows below:

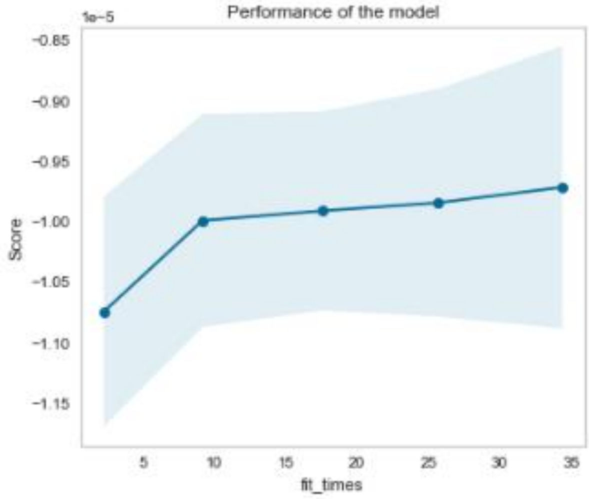
	1st Agg MSE	1st Agg RMSE	1st Agg R2	1st Agg MAE	2nd Agg MSE	2nd Agg RMSE	2nd Agg R2	2nd Agg MAE
RF	6.36E-06	2.52E-03	3.66E-01	9.54E-04	4.58E-06	2.14E-03	3.89E-01	8.02E-04
XGB	6.60E-06	2.57E-03	3.41E-01	9.79E-04	4.88E-06	2.21E-03	3.49E-01	8.60E-04
Linear	7.41E-06	2.72E-03	2.60E-01	1.12E-03	5.51E-06	2.35E-03	2.65E-01	9.73E-04
Lasso	1.00E-05	3.17E-03	-3.68E-04	1.36E-03	7.50E-06	2.74E-03	-2.96E-04	1.19E-03
Ridge	7.43E-06	2.73E-03	2.59E-01	1.10E-03	5.53E-06	2.35E-03	2.62E-01	9.58E-04
KNN	9.30E-06	3.05E-03	2.16E-01	9.30E-06	5.78E-06	2.41E-03	2.27E-01	8.93E-04
DT	9.61E-06	3.05E-03	2.16E-01	9.30E-06	5.78E-06	2.41E-03	2.27E-01	8.93E-04
MLP	1.42E-05	3.76E-03	-1.96E-01	1.82E-03	8.86E-06	2.98E-03	-1.83E-01	1.46E-03

Figure 21. Evaluation Matrix for All Models

Based on each model evaluation results, we can see that the random forest regression model has the highest R-squared and lowest RMSE score. Thus, we decided to choose the random forest regression model for further predictition.

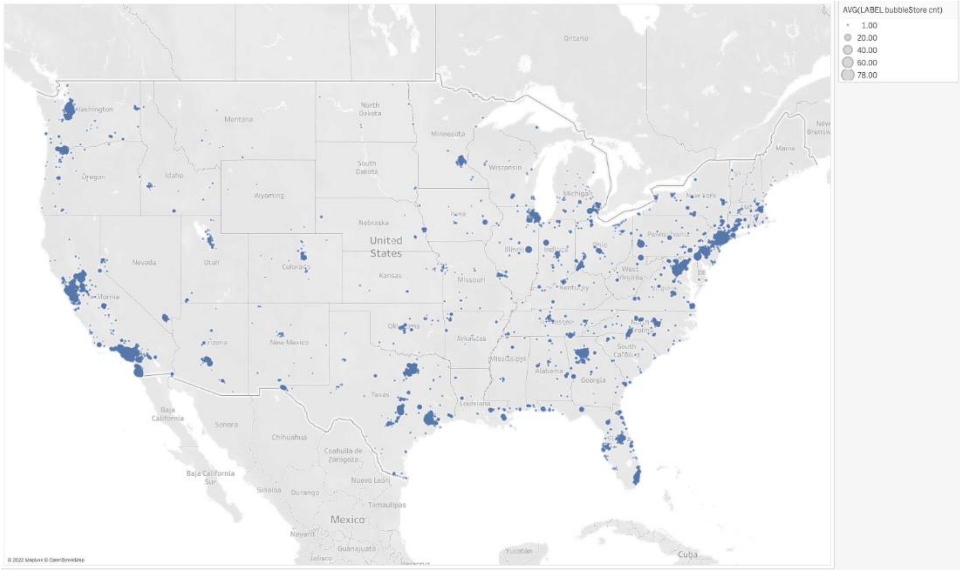




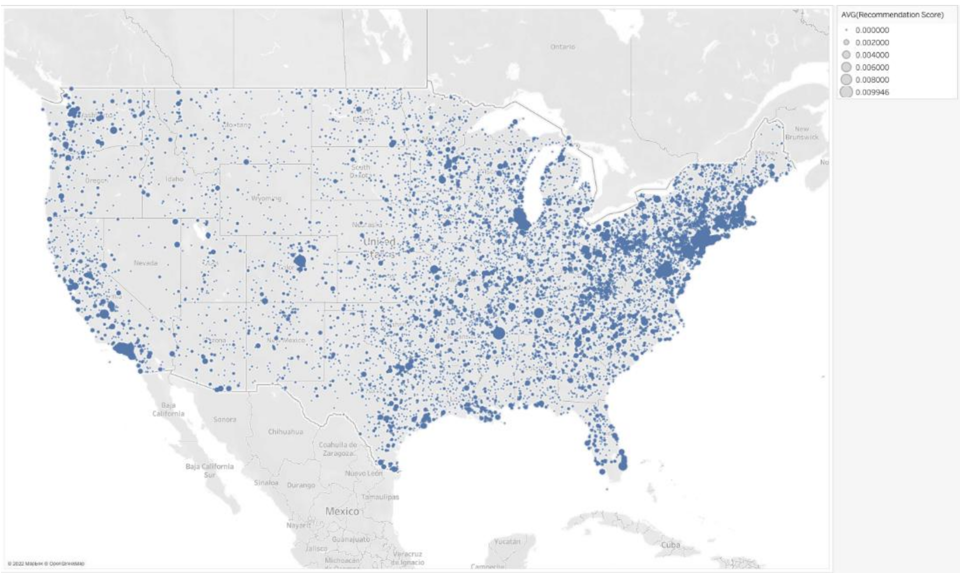


8.2 Recommendation Results

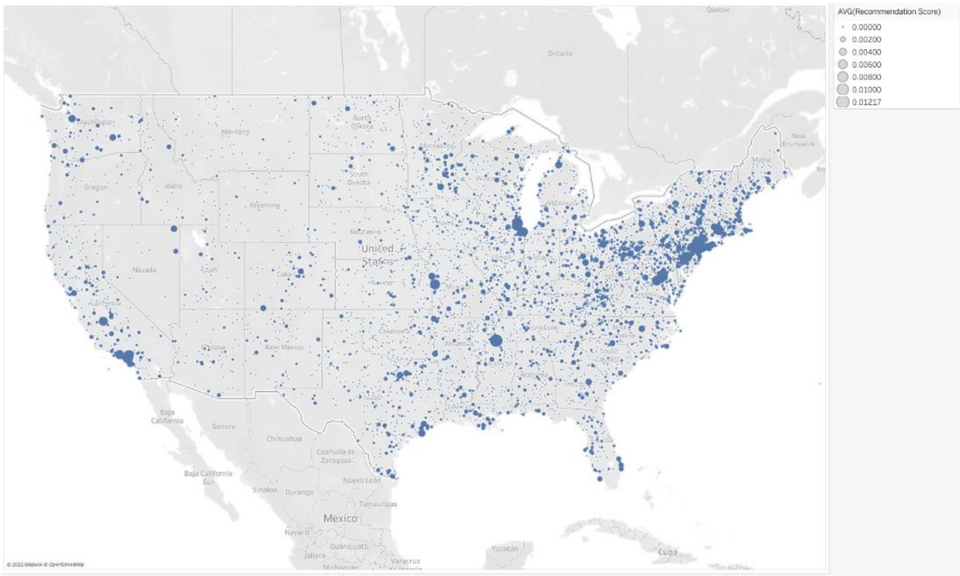
Based on the original training data (shown below),



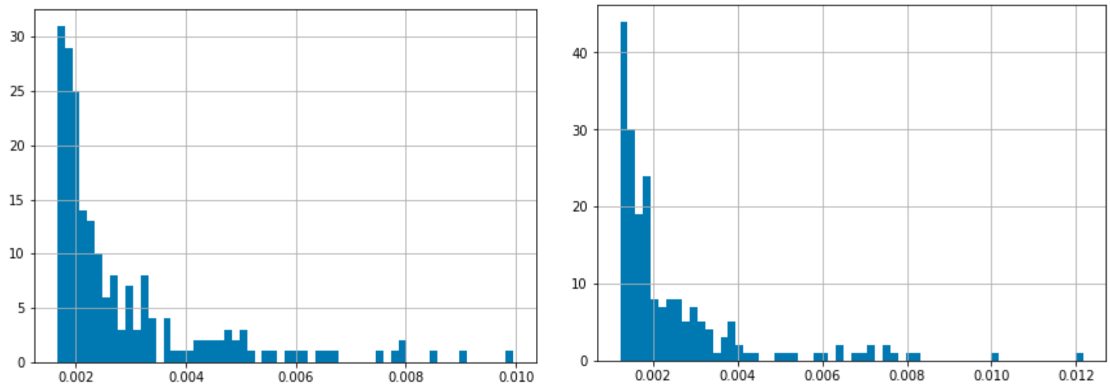
we generated recommendation scores for the rest of the zips in the US, with the first aggregation data:



and the second aggregation data:

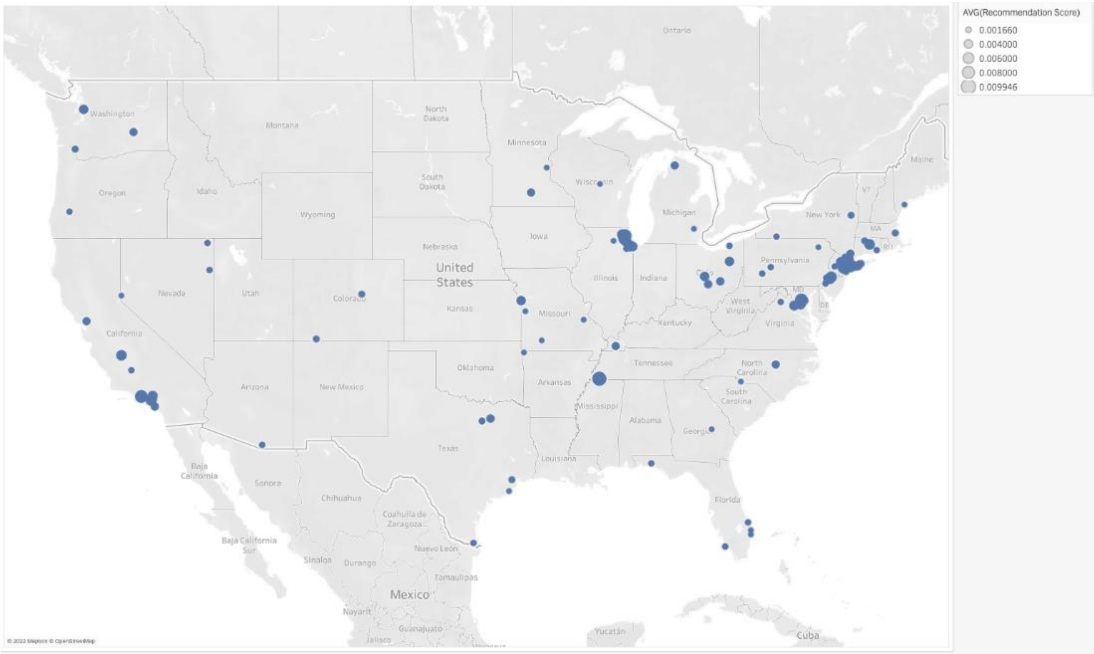


Below are the histograms of the recommendation scores of 200 most recommended zips with the first and the second aggregation data:

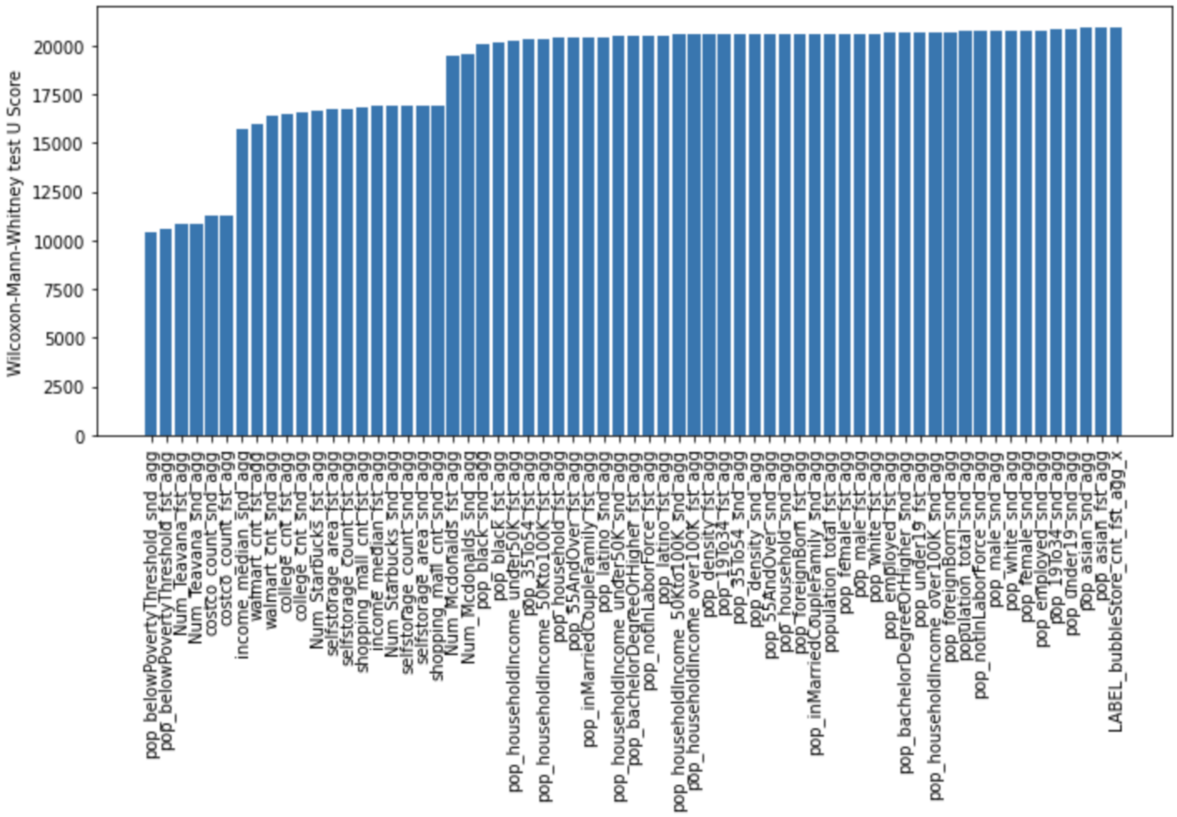


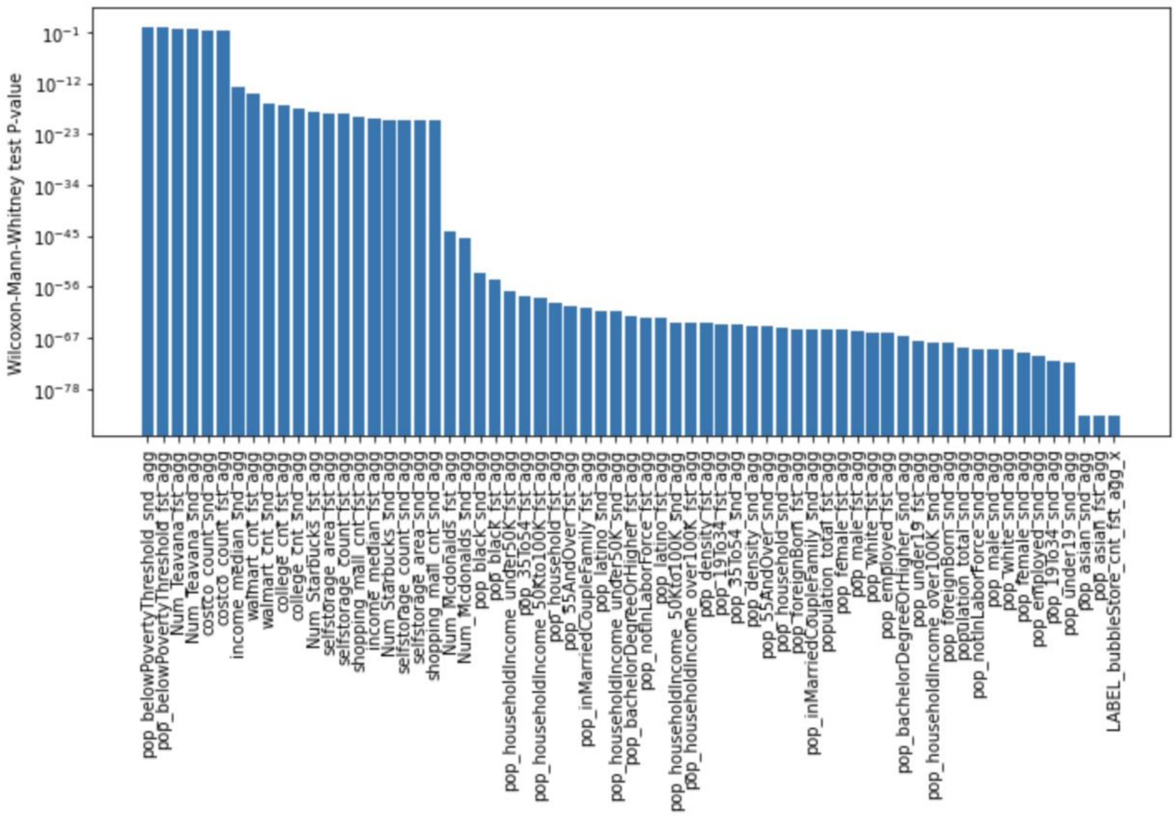
From the histograms, we notice that some zips have extraordinarily high scores, meaning that our model is doing a good job differentiating zips that are suitable for opening a bubble tea store from those that are not.

Below is a visualization of the intersection of the most recommended 200 zips with the first aggregation data and the second aggregation data. We observe that most of the recommended zips are located in the west and the east coast, while the east coast has a bigger number of recommended sites.



In order to understand the amount of difference between the 200 most recommended zips and the 200 least recommended zips, we conducted the Wilcoxon-Mann-Whitney test to compare the distributions of general information of the two groups. The reason we chose to use the Wilcoxon-Mann-Whitney test is capable of comparing skewed variables, which is suitable in our case considering that most of the variables are skewed. The two figures below demonstrates the U score of Wilcoxon-Mann-Whitney test between the two groups. The bigger the U scores are, the more difference there is between two skewed distributions.

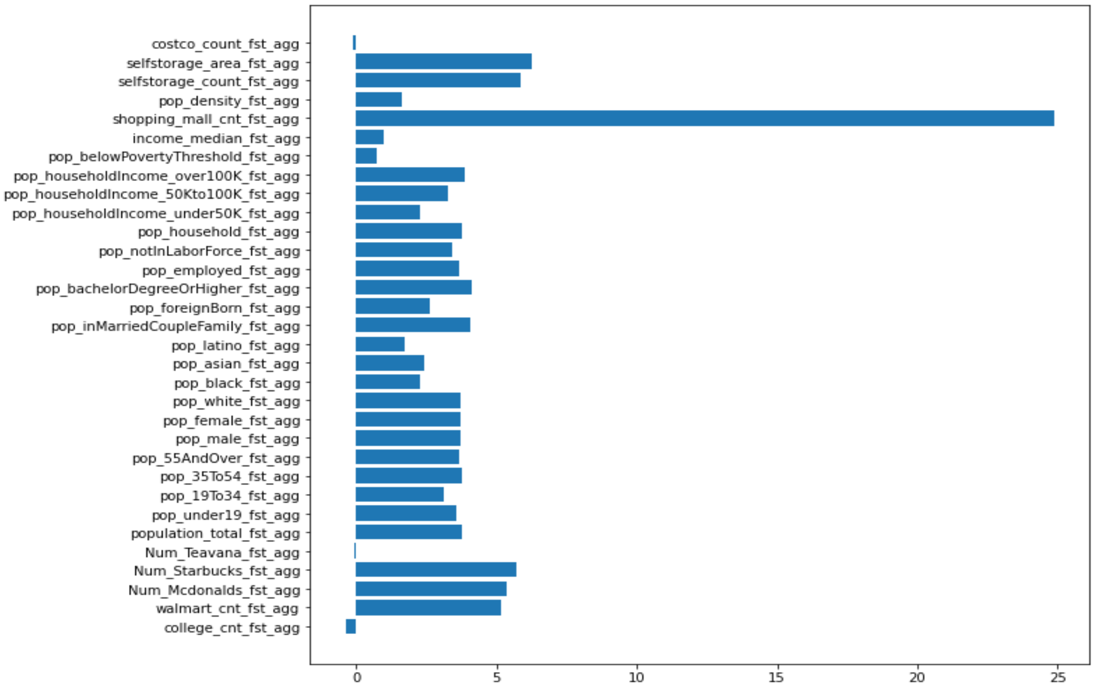


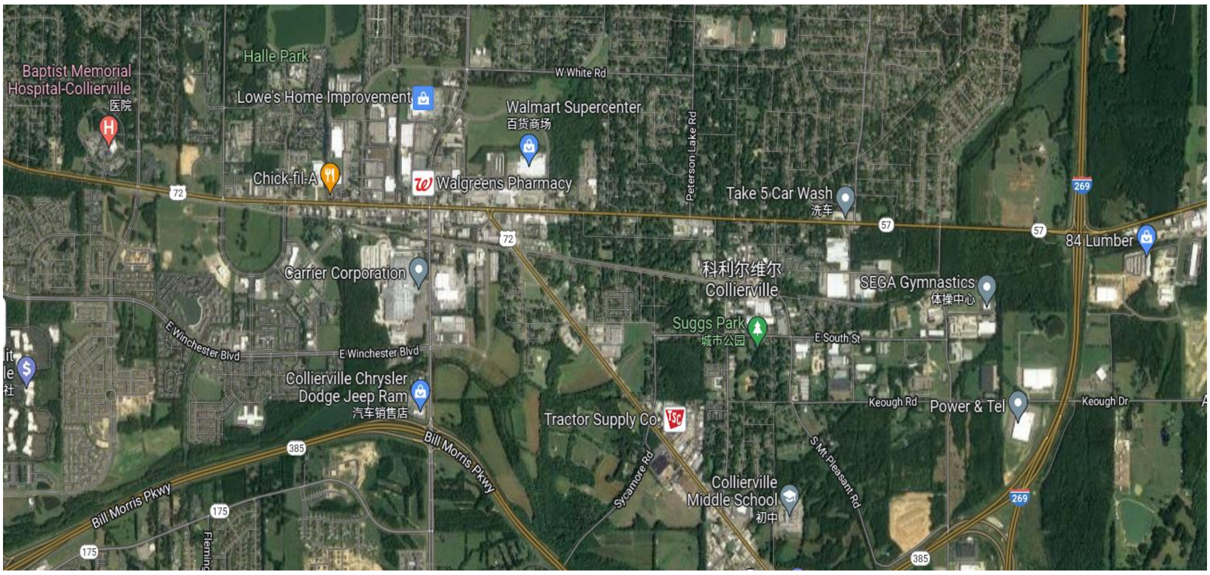


Based on the test results, we conclude that the majority of the variables of the two groups are statistically different, supported by relatively small p-values. “Asian percentage” is the variable that differs the most between the two groups.

8.3 Case Study

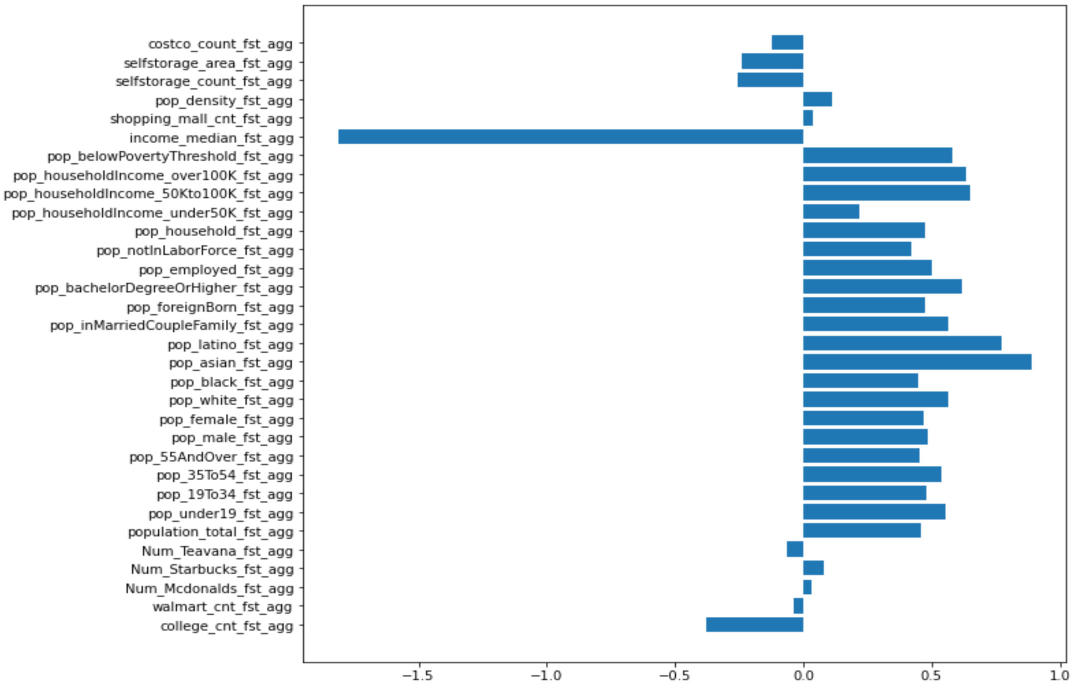
We check the solution by selecting the best, median and worst zip codes and see if they make sense. The first zip code (38017) is the best one, which has the highest prediction value according to the model:

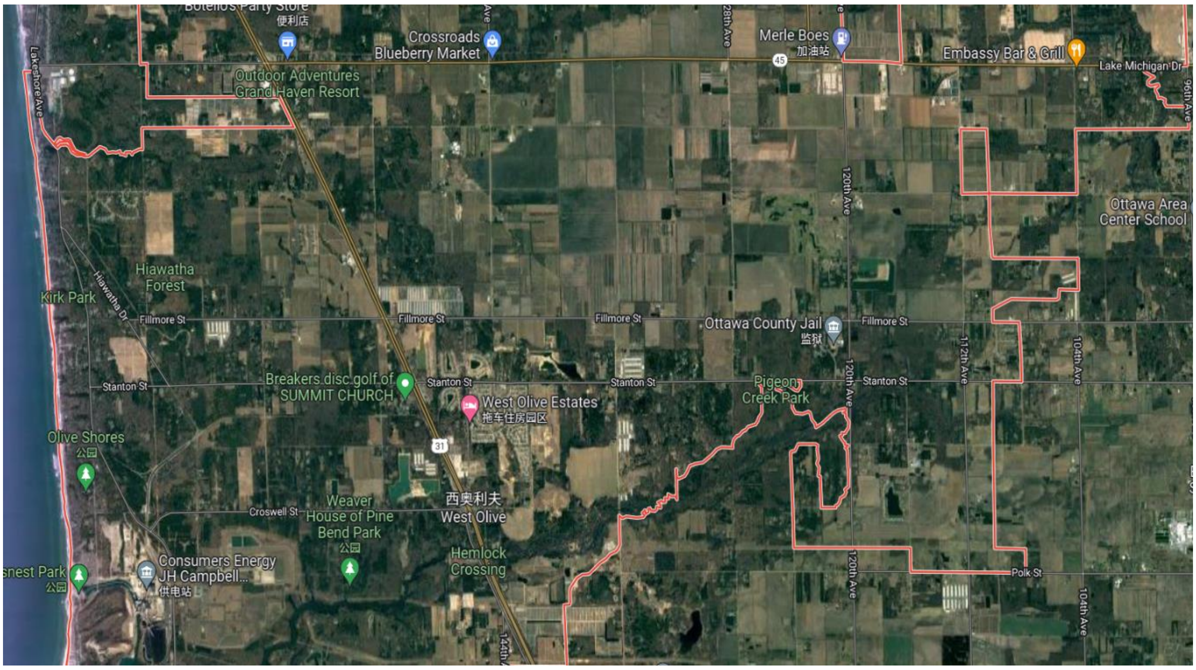




The top picture shows the difference compared with the mean value (in standard deviation) and the bottom picture shows the surroundings (by google map). This place has more markets and a higher population. It looks like downtown. For me, it is a good place to open a bubble tea shop.

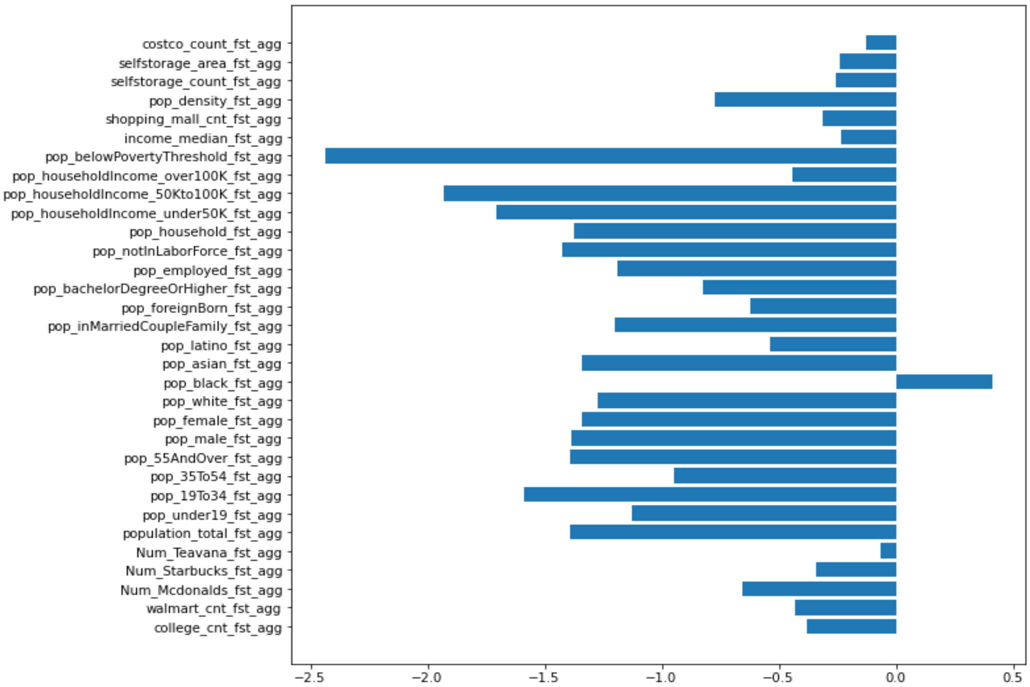
The second zip code example is 49460, which is the median.

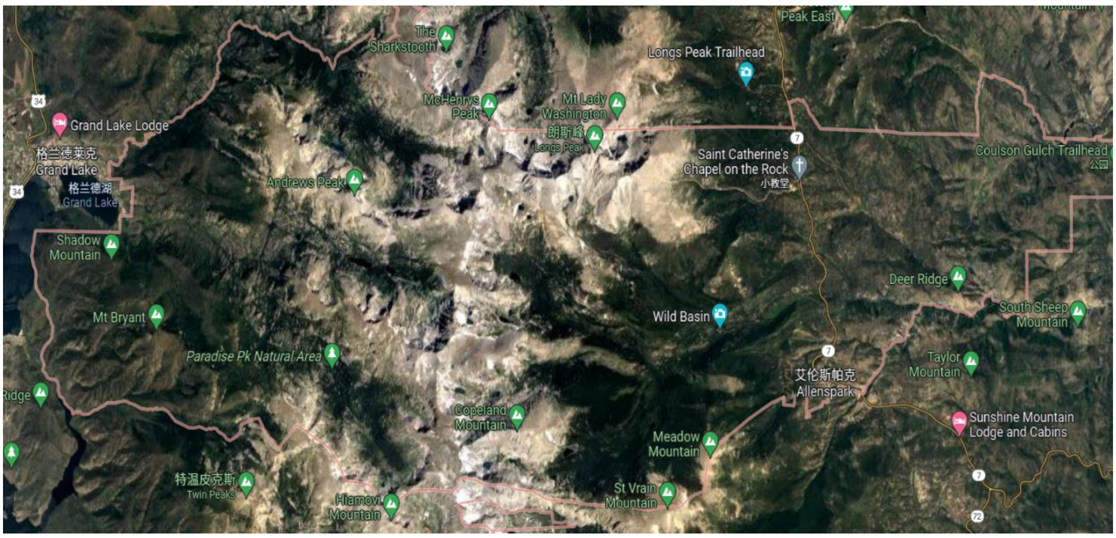




From the top histogram, this place has lower median income. The bottom picture shows a Jail around, which indicates a poor area. This zip code is not a good choice for opening a bubble tea store.

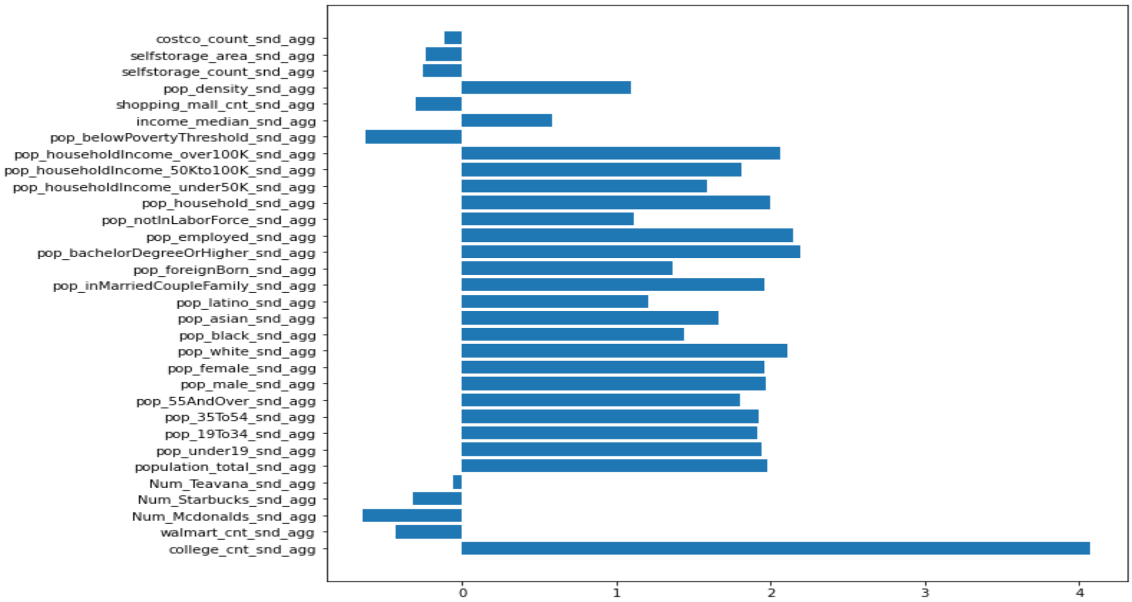
The next zip code is 80510, a bad recommendation suggested by the model. Most features are lower than the mean value, especially the population . By the google map, we see this place is wilderness. It may be a good place for hiking or camping, of course, not a idea area for opening bubble tea shops (I think no one would like open a store in wilderness).

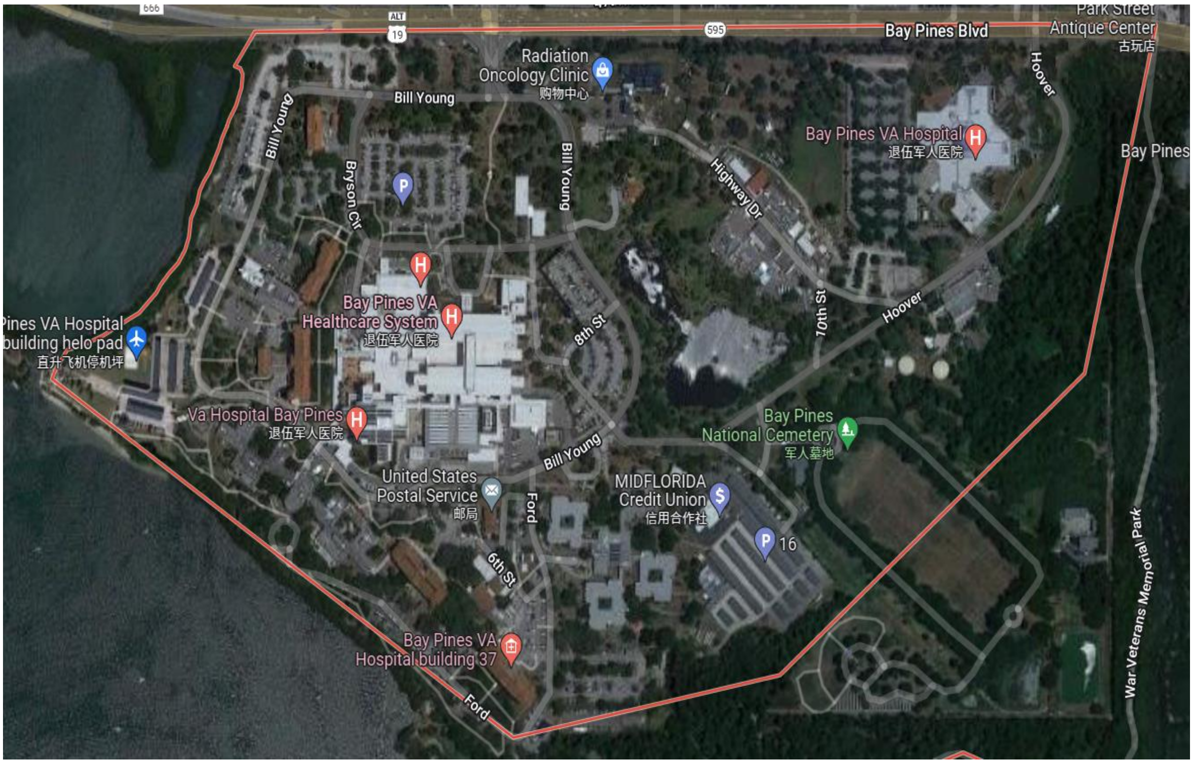




The last zip code is 33747. The model suggests this area is not a good place for opening the store. From the histogram below, this place has a large population, high media income, low poverty and more colleges and schools. One strange thing is that the number of Starbucks, McDonalds or markets is low. By checking the google map, this place seems like a controlled area: an area providing special services for veterans.

In all, the model does a good job. The recommended or not recommended areas make sense.





9 Summary

9.1How good is the model

– Does your tech solution fits the original product solution design? Did you change anything due to technical difficulty? Justification.

All in all, according to the prediction result, we were satisfied that our model fit our original product solution design. However, we cut several practical functions due to the shortage of relevant data, such as business space rental for each zip-code; bubble tea shop financial data, those belonging to sensitive data which are hard to collect then cause the limitation of our predict model.

9.2 What kind of business value will your final solution likely bring?

The goal of our product is to help normal citizens gain professional location selecting services with lower cost. Compared with big firms, small busi nesses usually do not have enough budget and time to afford professional consulting services. Our services can help users save time from location filtering via our back end database and model. Thus, our user would have more time focusing on field research to gather other details which they were concerned about.

9.3 Next steps

The product can be potentially optimized in (but not limited by) the following different ways:

a. The product can be expanded to many other businesses like general restaurants, bars, clothing shops etc. New customers will be obtained not only because the range of the businesses that can be recommended gets wider but also because the comprehensive data collected in the process will also help us to improve the performance of the model.
b. Cooperating with real estate companies and land agents to get data and resources from the supplier side. On the one hand, we can provide a more accurate recommendation on the potential locations of a new bubble tea shop (in a specific building or plaza), which will also make it easier for the potential shop owners to find a suitable store. On the other hand, our product will also be a platform to attract people who are interested in renting or buying the stores and can be a suitable place for the real estate companies to promote and recommend their products.
c. The functions involved in the product, design of the website layout and some of the parameters in the model (for example the weight of the features used to generate final recommendation level of an area) can be adjusted based on the results of the targeting metrics monitored during the usage of the customers.
d. We hope to add store information of each region, such as store area, rent, permitted business scope and so on, to the final site selection

recommendation results. This information is valuable to users but difficult to collect and process, so in order to improve the commercial value of our products, we will further develop our products and models in this direction.

9.4 Final thoughts

Although all kinds of business knowledge we have learned emphasize the importance of site selection, in our actual development process, most of the key information given in books are difficult to find suitable indicators to quantify, and some solutions are only applicable to large enterprises rather than small businesses. Especially for ordinary people who want to open milk tea, professional consulting services are too expensive and time-consuming, but some key information is difficult for individuals to obtain and process, such as the statistics of regional traffic and store business.
Therefore, we set out to help this kind of people reduce their difficulty in opening stores, and reduce their learning costs through the knowledge of data processing and modeling that we have learned, so that they can have more time to develop their own businesses instead of spending a lot of time looking for answers to problems that others have already solved.

Acknowledgment

This report and the research behind it would not have been possible without the exceptional support of my supervisor, Tara Su and Emma. Their enthusiasm, knowledge and exacting attention to detail have been an inspiration and kept my work on track from my first encounter with this Meetfresh’s data science project. I am also grateful for the selfless help and the insightful comments offered by my colleagues, especially Tu Xue, Guanyuan Shuai, Jingxuan Li, and Vivian Chan.

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Annex

Discovery Report

Group 2 Need Finding for MeetFresh Project

Binglin Li, Shuai Zhang, Hongwen Song, Liankun Zou, Dengcheng Ji

Abstract

In order to understand the business pain point and develop recommender system ideas, we conduct need-finding for MeetFresh products, from the aspect of naturalistic observation, participant observation, and user interview. The need-finding process is cente

red around understanding customers' purchase habits, decision making process, and their personalized opinions about MeetFresh. The sessions below give a high-level summary of the need-finding exercise and the results. Detailed transcripts are included in the appendix.

I. Need finding exercise 1: Naturalistic observation

1.1 In-store food ordering process:

The Meet Fresh store I walked in located at Boston University community. This store' s dining area around 20 square meters with simple decoration, running by 5 staffs: 3 working in front desk, 2 working in back kitchen. Order processes as same as other fast-food stores. Waiting about 5 minutes got my product which is Hot Grass Jelly Signature, it cost $ 10.36 included tax, tasty but only one fix size that weight 20oz is oversize for me. If I want to order Meet Fresh again, I would enjoy their Signature Series as Breakfast or Brunch rather than afternoon desert.

1.2 Online food ordering process:

We did naturalistic observations on three different apps (Doordash, Ubereats, HungryPanda) and compared the user interfaces, items available, price and delivery time. We also ordered the same two items (Icy grass jelly signature, taro tofu pudding) from each of these apps and included the information of the ordering experience in this section.

The basic components of the user interfaces of these apps are similar but there are still noticeable differences that affected our ordering experiences. The information about the popular restaurants can be easily found in all these apps. While Doordash shows the previous order to the top part of the page, Ubereats and HungryPandas choose to put more discount related information on the home page. When we clicked into the MeetFresh page, one thing special about HungryPanda is that we are able to see all the categories including the recommended items at the same time without sliding the page. This saved us time on both finding the items and making decisions (ordering time: 5 minutes for HungryPanda, 7-8 minutes for Doordash and Ubereat). As for the ratings and customers' review, although the ratings can be seethe related information are available on Doordash and HungryPanda.

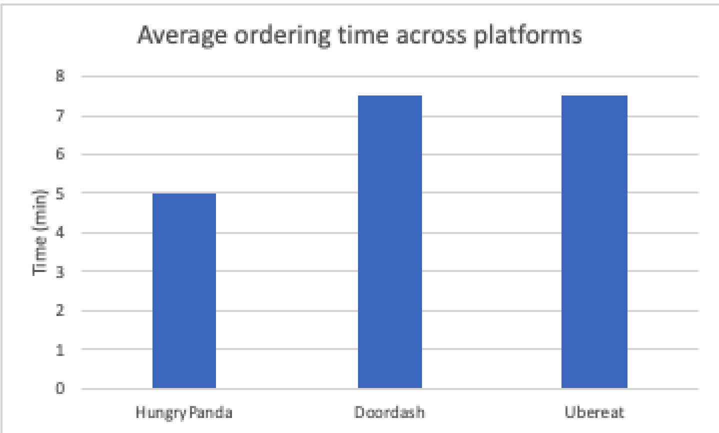

Figure 1. Average ordering time across platforms

Items listed in these apps are the same and they are also utilizing a similar way to classify the items into different categories. The recommended items are similar in Ubereats and HungryPanda and most of them are grass jelly signatures and taro ball signit ures. However, in Doordash, half of the featured items recommended are milk tea and herbal tea products. Compared to the menu in store, there are some items not available online (e.g. fruit flavor shaved ice, egg wafles)

The prices of the items are the same in different apps ($ 15.5). The extra fee mainly comes from delivery fee, service fee, tax and tip. The total payment on the Doordash is 25.68 for these two items ($4.99 delivery fee for a 4-mile distance, $3 service fee, $1.02 tax $2.33 discount and $3.5 dasher tip), which is more than 65% higher than the price of the desserts themselves. Ubereats charged $25.84 in total ($4.4 tax & service fee, $0.49 delivery fee, $2 CA driver benefits, $0.45 temporary fuel surcharge, $3 tip). HungryPanda, as an app focusing on delivery Asian food to Chinese users living in US, charges the least among these apps ($22.2, including $2.75 tax & service fee, $2.49 delivery fee and $1.46 tips). Comparing the payment amount among these apps, we found that the ratios of the tax and service fee are similar while delivery fee and suggested tips vary from each other. Lowest tip suggested in these apps are: $3.5 from Doordash , $3 from Ubereat and $1.46 from HungryPanda separately and this shows the cultural difference for different users.

Figure 2. Price breakdown across platforms

We also observed the delivery time from these apps. It took the staff 10-15 minutes to finish preparing the dessert (2 items we mentioned above) and another 20-30 minutes for delivery (4 miles distance). The dessert are all well packaged, there is no leakin g or missing order. The shaved ice in icy grass jelly signature is slightly melt but the quality is good overall.

1.3 Customers' feedback:

100 reviews from Yelp, Doordash and HungryPanda are collected an d comapared. The reasons for picking these three platforms are 1. plenty of customer reviews 2. More people leaving comments on Yelp are customers dinning in store and reviews from Doordash an d HungryPanda are good supplements showing the opinions of custo mers ordering online. We collected 50 reviews from Yelp and 50 r eviews from the other two apps and the results are shown below:

For customers who dine in stores, the most posted and discussed products are icy grass jelly signature, taro ball signature, egg waffles and shaved ice. Grass jelly signatures and waffles are also the products with highest ratio of positive comments. For those who like MeetFresh, the most common reasons are: 1. short waiting time (5) 2. flavor (14) 3. consistent quality (6) 4. nice store environment (9) 5. friendly staff (3) The most frequent complaints are 1. bad service (5) 2. flavor (2) 3. texture (2) 4. price (2) 5. long wait time (2)

Figure 3. In-store customer reviews (positive)

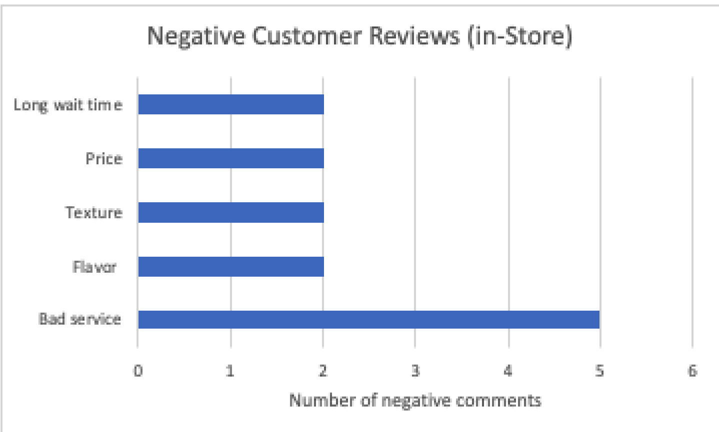

Figure 4. In-store customer reviews (negative)

Other than the features talked above, people ordering online also care about packaging, delivery time, whether they are getting the right order and if the quality of the dessert is the same as those in store. The most mentioned advantages of MeetFresh from Doordash and HungryPanda are: 1. Flavor (20) 2. packaging (7) 3. fast delivery (5) 4. consistent quality compared to those in store (4) 5. quantity of dessert (2). The negative comments are mostly about 1. wrong/missing order/ingredient (6) 2. spoon or straw not provided (2) 3. melting (2) 4. Price (2).

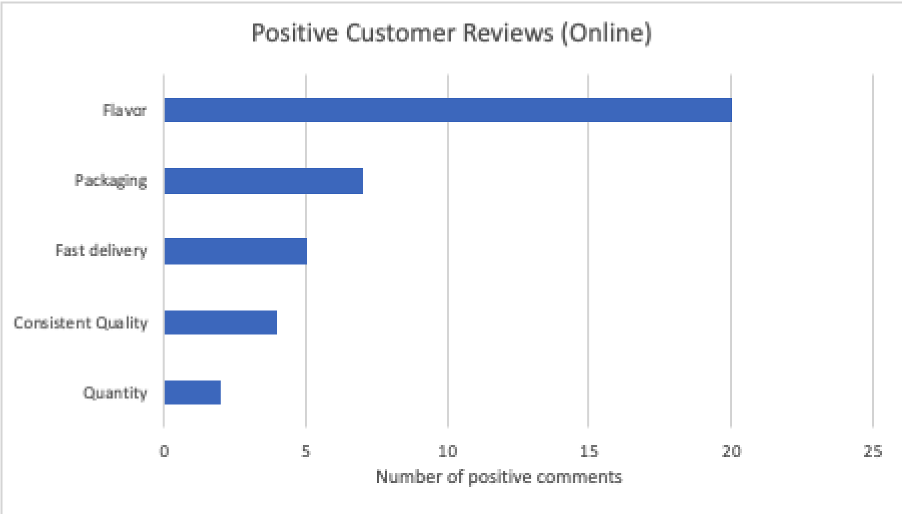

Figure 5. Online customer reviews (positive)

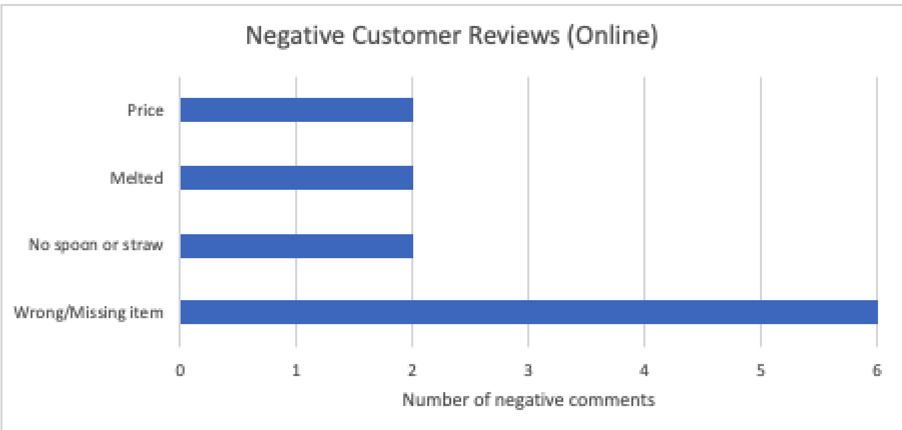

Figure 5. Online customer reviews (negative)

II. Need finding exercise 2: participant observation

In this situation, I' m the one who got the recommendation of MeetFresh from friends and want a try. The four environments I tested are morning in bed, after lunch, after exercise and after dinner.

Morning in the bed

What is my major purpose?

At this time, I' m thirsty and hungry and want a warm healthy breakfast with high in fiber and rich in protein to evoke my brain and body.

What do I need to achieve the purpose?

Order the breakfast online or prepare it myself.

What specific tasks I do? What are the subtasks?

My high-level task is to quickly check the uber eat and check if some good breakfast is available. Or get up and prepare the breakfast.

What' s my thoughts and complaint?

The breakfast in the Uber eat is not health to me. Besides, the price is high (including the delivery fee). I also try to check the MeetFresh: the store is not open util 12:00PM.

What hacks did I use to help achieve the goal?

Prepare the breakfast myself.

After Lunch

After lunch, the temperature is high, and I want some coo l dessert to cool me down. Ice cream is fine, but I want to try MeetFresh. Open the App “Uber Eat” and search for Mee tFresh. No result. Open MeetFresh app and choose the clos est store (87miles ! So far away !). No Online order is avai lable, and you need to call them to order. I still want to s ee what they have. There are many categories. On the top i s the signature series. I'm attracted by the icy grass jell y first (I tasted the grassy jelly when I was a child and li ke it). The picture looks fine to me, and the signs blow sh ows the ingredients and something like vegetarian, glute n free. The price ($8) is a little expensive for me. There a re a lot of extra toppings, choice of sugar as well as the i ce level. These looks good to me. Besides the signature se ries, there are a lot other choices. I don't know which one to check. The last category is the tea: a lot of types and I'm lost. I may have a try if the store is nearby.

After the exercise

I work out a lot and feel so thirsty and want something fresh. I have several choices:

Coke: No (The original taste has a lot of sugar. For the diet, I don’ t like the taste)

Energy Drink: fine, I don’ t really like its taste.

Ice cream: No. I don’ t this can quench my thirst.

MeetFresh: I think this may be the better choice, but it is too far away.

Finally, I drink a cup of milk and a lot water

After dinner

Study and relax. No desire for food

Summary

The nearest store in my place is too far away. The online order platform is not convenient. The food is not so healthy. If more protein is added, it will be better. For the choice, I made the decision based on the food I ate. I think MeetFresh is a good c hoice after the exercise.

III. Need finding exercise 3: User Interview (Customer + Business)

Our third need-finding exercise was user interviews, which are d ivided into two parts, customer interviews and business intervie ws. Aside from understanding customer’s purchase behavior in pa rticipant observation and naturalistic observation, we want to f urther understand the reasons of customer behaviors and their th inking pattern, so we need to reach a more in-depth understandin g through customer interview. On the other hand, listening from one side is far from enough. We are aware that the business side (staff in stores) also makes up an important part of our underst anding of MeetFresh’s business pain-point. In this case, we inc orporated business interviews to perfect the interview dynamic.

3.1 Customer Interview:

We reached out to 10 MeetFresh (MF) customers (with age ranging from 21 to 33), refined the interview scripts together, and conducted the customer interview. The detailed transcripts are available in the appendix.

Firstly, we received some positive feedback from the interviewees, especially when talking about the competitors of MF. Most of them don’t think MF has too many competitors, especially when talking about Taro Balls.

Secondly, almost all of them mentioned a pain-point when ordering online - the expensive extra fee. “I can only order MeetFrash from Chowbus, yet it costs too much with the extra fee”, said a 22-year-old college student. In this case, most of them prefer to order in store. What’s more, because many MF products come with ice, they will only order such products in store, so that the ice would not melt half way of delivery. Besides, if customers realize online ordering would take over 30 min to get their products, they would look for other stores.

Thirdly, when talking about the factors that prevent them from making more MF orders, one thing that is constantly mentioned is health issues. Most of them think eating MF is not healthy, so they try not to eat too often. If customers do care about their health, nutritional facts are a critical index determining their purchasing will. One mentioned that it might encourage him to order more if MF can have “sweet-level indicator” for each of th

e products. They don’t know that MF has its own website, and they don’t have intention to use them because they think “ordering food that can only be picked up” is a useless function.
What’s more, we also collected interesting information about customers’ purchase behaviors. If making orders in store, most interviewees tend to try new products, products with ice, or shareable products; if making orders from online platforms, most of them would be more conservative, only ordering classis products, products with no ice, and more likely to order an extra milk tea (so that the order price reaches the delivery lower limit). Most of the interviewees enjoy MF with friends, and they tend to buy MF if their friends are buying. The taste of the product is the most important factor that most customers take into consideration when deciding whether to buy a product. For some female customers, if a product’s appearance is appealing enough, she would like to try it, even if this product contains ingredients that she does not like. In this case, appearance does matter, especially when women make up the majority of the customer group. Some young customers (age < 25) mentioned that they are not satisfied with MF because MF barely has new products every year, and not having much tending/new products is the main factor that makes her not buying MF actively. These young customers also mentioned that they expect MF to provide more “solid” desserts, such as cakes. Some customers think the size of MF bowl is too large that leads them into a dilemma - if they eat the bowl before meal, th

eir belly has no space for other food; but if after a meal, thei r belly has no space for MF bowls. One suggested that if MF provides a membership program and she gets credits (that can be used as money) when she buys products, she would like to go to the stores more often.

3.2 Business Interview

The first business interviewee is Meet Fresh store manager, who worked in this business about 5 years. Compare with the bubble tea, Meet Fresh deserts usually take 5 more minutes for processing, bubble tea only need 2 minutes maximum. Because of their own producing policies. Customers must receive the product in fresh, which means they hard to do some preparation works before the busy hours (7pm-10pm). These policies in one hand grantee the quality of the product, in other hand cause stores have not much space to arrange flexible calendar deal with the producing pressure during busy hours. About 70% of customers choosing to walk in to enjoy their desserts, usually with friends, and most of couple shar one dessert rather than purchasing two, because the average weight of the dessert is 20oz. In general, deserts contribute 80 % of the sales; 70% of consumers are Asian whose age between 15 to 30; 30% of customer would customize their desserts.

The second interviewee is a shareholder in a bubble shop, he also has 5 years experiences in restaurant and bubble tea business. In bubble shop business, walk in and online ordering is 50: 50, customers walk in to order usually with company. He mentioned that Online ordering platforms take 20%- 30% of commission per order. So, they increase the price to erase the affection from platform’s commission. He also used his shop as a example to illustrate the revenue spending: 30% pay staff salary, 30% of material purchasing, 20% store rental + incidents, 20% gross profit.

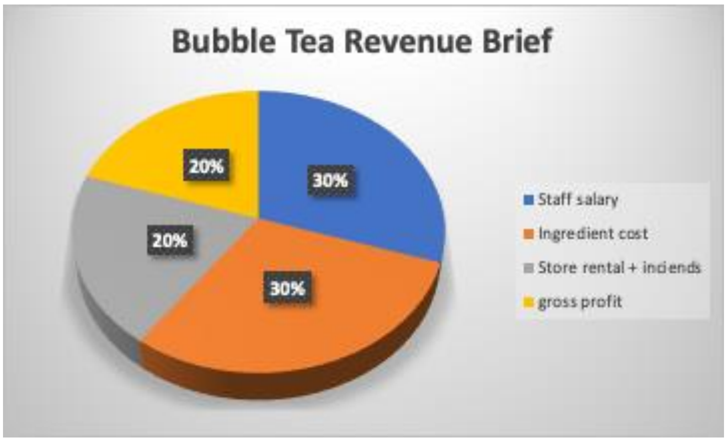

Figure 6. Revenue Spending

IV. Insights

1. There are less items from online platforms but most of the items can still be ordered online. For an order with two items, over 1/3 of the price comes from service fee, delivery fee and tips.
2. The features customers care about the most are flavor, wait time and quality control. While customers ordered in store pay more attention to store environment and service, those ordered online care more about packaging and if there is any order missing or incorrect.

3. It’ s important to consider the attitudes of the custome rs toward this type of food, some people are getting it just for fun, not necessity, and they may not eat it oft en, so they probably will not be concerned with the impa ct of the food on their health. Seems like this type of customer would only focus on the flavor, this is a notab le point when creating the recommendation system.
4. Most of customers have concerns about health, and this i s one of the main reasons that prevents them from buying MF.
5. One mentioned that it might encourage customers to order more if MF can have “sweet-level indicator” for each o f the products.
6. If MF provides a membership program and she gets credits (that can be used as money) when she buys products, she would like to go to the stores more often.
7. Meet Fresh’ s bubble tea only contributes 20% of income. over 70% contributed by desserts.

Figure 7. Item Sales

8. Preparing a dessert usually costs 5 more mins, bubble tea only takes 1-2 mins.
9. About 70% of customers are Asian whose age is between 15-30.
10. 70% of orders are walk in, 30% are picked up.

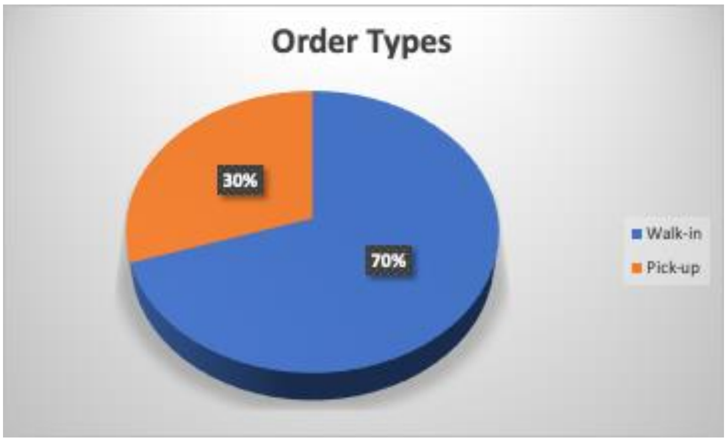

Figure 7. Order Types

11. Couples usually share 1 dessert rather than 2. Because dessert weighs 20oz.
12. Busy hours: 7pm-10pm (business hours: 1pm - 10pm)

V. Appendix

Transcripts

Customer interview questions:

1. How do you feel about the online platforms?
2. Tips for Chowbus, too expensive?
3. Time taken while ordering?Convenient?

4. Do you know that Meetfresh has its own app?
5. Do you have trouble choosing what items to order?
6. How do you usually have Meetfresh? (in the store, delivery, or something else?)
7. Would you order different items in store and online? why?
8. What triggers your thought of wanting to order from there?
9. Rank the aspects of an item that satisfy you: lower price, better flavor, more in quantity, something new, aesthetics, lots of side items.
10. If an item has ingredients you don’t like, but aesthetically appealing, would you still order it?
11. How often do you order Meetfresh products?
12. One thing you don’t like about Meetfresh?
13. Do you have experience when you wanted to order desserts but didn’t at the end? Why did you give up? What are the alternatives you would choose to do when you really want some dessert but cannot get it right away? (Try to cook desserts by yourself, imitate MeetFresh products, or purchase alternative desserts from wholesale)
14. Describe your last experience deciding to order desserts from other stores rather than Meetfresh. What is the main reason for that?

15. What is the scenario when you want to order MeetFresh’s products? (At rest or while studying or working)
16. Would you tend to buy more products if you know the products are at a discount?
17. Would you rather go alone or with friends?

Business interview questions：

1. What’s the pain point that the business is currently facing?
2. What do you think could be a potential way to increase revenue?
3. While ordering, customers buy only one item or buy a combo?
4. What items would you rather sell more? less? Why?
5. Do you have any preparation before busy hours? If so, what are the preparations? For example, make popular products in advance. How much time does it take to do the preparation?
6. What changes and challenges do you see as we are in the era of online ordering?
7. What would you recommend to a new customer? How would you make the recommendation?
8. How much percentage of customers need your commendation?
9. What is your major customer group? Student, office worker, or others?

10. Do people from different age, cultural groups have different order behavior?
11. Does weather influence the sales?

Customer Interview:

Customer 1

Profile:

- Age: 22
- Gender: Female
- Student
- Frequency: Once per month

What platform do you usually use to make the order?

- In US, use Chowbus. In China, in store and 美团.

How do you feel about the overall experience while making the order on Chowbus?

- Too expensive
- Too much extra fee comparing to ordering in store

Do you ever order in the store? If so, how much percent of your orders?

- 30% in the US.

Do you know any other competitors of MeetFresh in the US?

- Not many. I consider all other sweet stores as its competitor?

What makes you choose MeetFresh rather than other competitors?

- Location, mood, physical condition (eat cold or warm).
- MeetFresh’s quality

- Familiarity makes it a safe option, especially when making online orders.

How do you choose a certain product? Why do you specifically like it?

- I always choose the same product. 芋圆4号，珍珠换薏米，有时加芋头（取决于钱包和肚子）。Partially because there are not many options.
- I have tried many types of the products in China, so I have found the one I love.
- 有时会点饮料，取决于是否到运费要求的线。其他情况不会加饮料，因为点两个产品就太多了。

What drink would you have?

- 小芋圆奶茶。
- 一直选这个，因为没有太多选择，并且比冬瓜茶好喝，比较合胃口。

It seems that you pick the same product all the time. Do you think this is common amongst your friends?

- I think most of us do choose the same products all the time.
- Different people usually have their own preference. 喜欢芋圆就一直选芋圆相关的产品，喜欢仙草就一直点仙草相关的产品。

是什么阻碍你更频繁购买？

- Chowbus is too expensive
- Too much waiting time. 等到的时候已经不想吃了

- 热量比较高。为健康考虑。

Customer 2

Profile:

- Age: 28
- Gender: Male
- Student
- Frequency: Once per year (6 times in total)

How do you make orders in the US?

- In store only, because online ordering is too expensive.

Do you know MeetFresh has its own app? Its own website?

- I don't know that they have an app, but I do know they have a website.

But I do not use its website because even though I can make online orders from the website, I still need to pick it up from the stores, so why not just order in store?

How did you choose a certain product? What is the decision making process?

- 如果我今天想吃芋圆，我就在芋圆的分类下看。考虑到美国的甜品一般都比较甜，我会尽量在看起来不那么甜的产品中挑选。比如"黑糖**XX**"看起来就比较甜，"红茶**XX**"看起来就不太甜。**【MeetFresh需要更明确的甜度指导】**

If MeetFresh provided a "sweetness level indicator" for its products, would it make you easier for you in the decision making process?

- Absolutely. I will even buy its product more often if they have this kind of indicator.

Why did you choose MeetFresh against other competitors?

- **MeetFresh doesn't have many competitors for me.** 在我想吃芋圆的时候，我只能想到鲜芋仙。在同类产品中竞争力很强。

Can you name your favorite product?

- 芒果芋圆。

Do you order other products at Meetfresh?

- 不，我一般只点一份就够吃了。我知道他们家还有奶茶产品，但是奶茶的替代品太多了，我不会特别想点鲜芋仙的产品。

What are the top factors that make you want to buy sweet products?

- 第一是口味，第二是有新款 (不会吃腻)

如果价格相差不大，你会更想在店里吃还是叫鲜芋仙外卖？

- 叫外卖。但是冰沙产品不会点，因为会化。如果是芋圆产品的话，我不介意等待时间稍微长一点。

你身边的人一般会如果购买鲜芋仙产品？

- **Chowbus**。

Customer 3

Profile:

- Age: 21
- Gender: Female
- Student
- Frequency: Once a month (6 times in total)

This user had experience in eating MeetFresh in both China and the US. This interview majorly focuses on her relevant experience in the US. She had MeetFresh about 5 times in the US. She usually orders it in companion with food from other stores. If she order from the store, she would prefer the bowl with 芋圆; if ordering online, she would have the milk tea because she thinks the bowl would be tasteless as the ice would be melted by the time of delivery. She buys MF’s (MeetFresh) product mainly because she wants to eat 芋圆. She does not know that MF has its own website and app, but she will not use the two platforms after learning about these two platforms, because she thinks “in store pickup” makes these two platforms useless. It usually takes her 3 minutes to make the order, and she does not find much inconvenience in this process. She tends to order the same bowl product all the time, but tends to try different milk tea products. Among all the factors, she thinks “delicious” is most important to her while deciding whether to buy a sweet product. **However, it’s worth noting that, if a product’s appearance is appealing enough, she would like to try it, even if this product contains ingredients that she does not like.** So the appearance does matter for her. She usually goes into the store with her friends and makes the order together. Her friends have similar purchase behavior as hers. She does not have experience of entering the store but then decided to leave. She does not think there are any competitors of MF. If there are discounts, she tends to buy more items and save for later. She thinks it would be great if MF can make the delivered bowls more delicious or provide larger sizes.

Customer 4

Profile:

- Age: 22
- Gender: Female
- Student
- Frequency: Once a year (3 times in total)

This user has experience of eating MF in both the US and China. She usually eats in the store because she does not like the ice to melt when ordering online, and she usually comes with a bunch of friends. The motivation of going to MF is usually because she passes by the store with friends. She doesn't know that MF has a website and app for ordering. She said she should buy more if the website and app provide credits for her purchases. **In this case, she thinks that if MF provides a membership program and she gets credits (that can be used as money), she would like to go to the stores more often.** When choosing a product, she usually relates to the products that she tried before. She is not a complete sweet-lover, so she doesn't eat MF so often, but she tends to buy MF if her friends want to buy it. The most important factors that she considers when choosing a product are "delicious" and ingredients she likes. **Interestingly, just like the second interviewee, she thought the appearance of the desserts is very** important, she doesn’t mind trying desserts that are good-looking but containing ingredients that she dislikes. She thinks that the appearance of dessert would make her relate to the taste of the product. What she is not satisfied with MF is that MF barely has new products every year, which makes her not wanting to try more. She doesn’t buy the milk tea product of MF because she thinks there are too many competitors in the field of milk tea. She thinks that not having much tending/new products is the main factor that makes her not buying MF actively. She mentions three main competitors of MF at Las vegas, including Mongo Mongo, 杏记甜品, and 微信上卖的私人甜品, she buys MongoMongo more because MongoMongo has cakes and some other products that MF doesn’t have. On the other hand, If she wants to eat 仙草 or 芋圆, she would definitely go to MF. If MF has a discount, she will not likely be influenced.

Customer 5

Profile:

- Age: 25
- Gender: Male
- Student
- Frequency:twice per month (24 times in total)

Have you bought Meetfresh before?

- Yes, I have.

Do you like Meetfresh? Why?

- Yes, I like Meetfresh because they have more options to customize that allow me to enjoy more grass jelly than ever before, the other shops can't do that.

How do you place your order? Online or in store?

- In store only, because online ordering has worse taste and I don't like to wait so long.

Would you rather go alone or with friends?

- Usually with friends.

When you know the nutritional fact of the product, would you continue shopping?

- I would not continue shopping if it is bad for my health.

Do you have experience when you wanted to order desserts but didn't at the end? Why did you give up?

- Yes , I have, because I place the order too late or too far to pick up.

What are the alternatives you would choose to do when you really want some dessert but cannot get it right away? (Try to cook desserts by yourself, imitate MeetFresh products, or purchase alternative desserts from wholesale)

- I tried to make bubble tea for myself, it worked, however it is not tasty compared with the shop products.

Would you tend to buy more products if you know the products are at a discount?

- If the shop closed where I live, I would.

What is the scenario when you want to order MeetFresh’s products? (At rest or while studying or working)

- It depends, I usually want to order MeetFresh between 10 am - 3pm.

Customer 6

Profile:

- Age: 32
- Gender: Female
- Accoutant
- Frequency:twice per month

Have you bought Meetfresh before?

- Yes, I have.

Do you like Meetfresh? Why?

- Yes, I like it because it’s authentic asian sweets, it made me feel like I’m visiting an Asian country.

How do you place your order? Online or in store?

- In store, I like eating them fresh

Would you rather go alone or with friends?

- Sometimes with friends sometimes alone

When you know the nutritional fact of the product, would you continue shopping?

- Yes, I don’t eat them that often, it’s more for a recreational purpose, I don’t think it will impact my heath that much.

Do you have experience when you wanted to order desserts but didn’t at the end? Why did you give up?

- Yes, I gave up because of guilt, because I know that these things are not healthy.

What are the alternatives you would choose to do when you really want some dessert but cannot get it right away? (Try to cook desserts by yourself, imitate MeetFresh products, or purchase alternative desserts from wholesale)

- Buy them from supermarkets

Would you tend to buy more products if you know the products are at a discount?

- Not really, when I order them it will be in my mind that these things are not healthy. I would intentionally not ordering too much.

What is the scenario when you want to order MeetFresh’s products? (At rest or while studying or working)

- Only on the weekends.

Customer 7

Profile:

- Age: 22
- Gender: Male
- Student

How do you like your experience ordering MeetFresh via Doordash?

- It is convenient. However, I am not able to see the reviews from customers for most of the items, there are also many products without pictures.

How often do you have MeetFresh?

- I used to have Meetfresh once every several days.

Is the frequency changing now?

- Twice a year.

What is the reason for that?

- The menu haven’t been changed over years and it is now a bit more expensive than I expected.

Is there any ingredients that you don’t like?

- Most of the ingredients taste good

What’s your overall impression about MeetFresh?

- There is little sparkle

One thing you don’t like about MeetFresh?

- It shouldn’t cost so much.

Describe your last experience deciding to order desserts from other stores rather than Meetfresh. What is the main reason for that?

- My friends and I are more into popular dessert that we have never tried before.

What new items would you recommend Meetfresh to have?

- More snacks (buns, bread, cakes). It would be nice to have a combo

What are the alternatives you would choose to do when you really want some dessert but cannot get it right away?

- Dessert from wholesale

Customer 8

Profile:

- Age: 26
- Gender: Male
- Student

How often do you have dessert an how often do you have Meetfresh?

- I have dessert almost everyday but most of them are bought from wholesales. MeetFresh is not one of my favorate, I order MeetFresh once every two months.

What are the most important features you would consider when you order dessert?

- Flavor (freshness and quality control) > price > delivery time

If an item has ingredient you don’t like, but aesthetically appealing, would you still order it?

- Probably.

One thing you don’t like about MeetFresh?

- I can’t think of many scenarios to order it. The products are being too sweet as a proper meal but the taro balls give the feeling of fullness and that’s why I don’t usually want to have MeetFresh as dessert. I can’t finish the dessert at all.

What is your overall impression over MeetFresh products?

- They have fancy ‘porridge’. I seldomly try their milk tea, I would rather choose a well known milk tea brand.

How do you feel about the online platforms?

- I personally enjoy ordering online. (Hungry panda). It usually takes me 5 minutes to finish order and 30-40 minutes for the delivery, which is acceptable.

Do you know MeetFresh has their own app?

- I don’t.

Would you order different items in store and online? Why?

- I prefer to order items that I can share with friends in store, also I do not order items with shaved ice just in case they would melt on their way. When ordering online, I would choose classic items.

Describe your last experience deciding to oder desserts from other stores rather than MeetFresh. What is the main reason for that?

- I would like to have something light and refreshing after a big meal.

Customer 9

Profile:

- Age: 33
- Gender: Female

- Director of a start up company

How often do you order MeetFresh?

- Once a month.

What is the scenario when you want to order MeetFresh’s products?

- Sometimes I don’t feel like to eat a lot. I would order MeetFresh as replacement. But for most of cases, I order MeetFresh with friends together.

What are your favorite items? (She has no trouble choosing what to order)

- Winter melon tea and tofu pudding.

One thing you don’t like about MeetFresh?

- Too far from where I live.

What are the differences you have noticed when ordering in store and ordering online?

- There are some items non-available when I ordered online. The desserts look less appealing when they are delivered.

Would you tend to buy more products if you know the products are at a discount?

- Only if they are the products I like.

Rank the aspects that are important to you?

- Flavor > something new > if they are healthy > aesthetics

Customer 10

Profile

- Age: 23
- Gender: Male
- Education: college student

Have you ever tasted MeetFresh?

- No. But heard of

From your friends’ recommendation?

- My friends said they tried it. He said he want to eat MeetFresh.

It sounds something like the milk tea store.

- I don’t have the habit of drinking milk tea or eat dessert in the afternoon

Do you want to try it?

- If the time is available, I will go with my friends. But I will not take the initiative to eat

Do your friends also have the same idea as you?

- I’m not sure. But I know some of my friends really like it.

Business Interview:

First Business interview:

Profile:

- Age: 27
- Gender: Male
- MeetFresh store manager
- Store Opened Date: 01/15/2022

While ordering, customers buy only one item or buy a combo?

- 50 to 50

What items would you rather sell more? less? Why?

- We have no preference to sell our product, because HQ had already optimized the product.

Do you have any preparation before busy hours? If so, what are the preparations? For example, make popular products in advance. How much time does it take to do the preparation?

- Due to the product’s nature, it must be fresh. So, it is hard to do some preparation work before the busy hour. Apart from that, each bowl needs 5 min to cook, a bubble tea only needs 1 min to process, it is a pain spot in our business.

What changes and challenges do you see as we are in the era of online ordering?

- Sales are increasing, the proportion of walk in and online order is 7: 3.

How much percentage of customers need your recommendation?

- Only 10% of customers need our recommendation, and we usually suggest the best seller products.

What is your major customer group? Student, office worker, or others?

- Usually is Asian youth, but 20% of customers’ age over 40.

Do people from different age, cultural groups have it differently?

- No, there is no significant difference when they place the order.

Does weather influence the sales?

- It does, bad weather would increase the proportion of online orders, but decrease sales by 20 % in general.

If there is a technology that can meet the individual needs of customers, will you use existing products to find new customers or develop new products to meet the needs of different customers?

- We don't have enough flexibility to adjust the menu, HQ has strict policy about this part. But personally, I prefer to develop new products to fulfill different demands from all customers.

While waiting for my order, I found several couples sharing one bowl of your product. So, when couples order, do they usually share a bowl?

- Sharp observation, and yes, most couples share one bowl of our product, because our product has 20 oz for each bowl, no competitor can offer this volume with the same price. It becomes one of our advantages.

Second Business interview:

Profile:

- Age: 26
- Gender: Male

- Bubble Tea store shareholder
- Store Opened Date: 11/12/2021

While ordering, customers buy only one item or buy a combo?

- It depends, no accurate number.

Do you have any preparation before busy hours? If so, what are the preparations? For example, make popular products in advance. How much time does it take to do the preparation?

- Yes, we usually take 3 hours for preparation work before the busy hour, if we have a discount event on the next day, we will prepare one day earlier.

What changes and challenges do you see as we are in the era of online ordering?

- Sales are increasing 40% in general, the proportion of walk in and online order is 4: 6.

How much percentage of customers need your recommendation?

- Only 5% of customers need our recommendation, our customers usually do a lot of research via Google or Yelp before they order it

What is your major customer group? Student, office worker, or others?

- Usually it is youth, about 70% of customers' age over between 15 - 30.

Do people from different age, cultural groups have it differently?

- Yes, Vietnam and Indian customers really enjoy our Thai tea Latte.

Does weather influence the sales?

- It does, bad weather would kill the business of the day, we have better sales performance in summer compared with other seasons.

If there is a technology that can meet the individual needs of customers, will you use existing products to find new customers or develop new products to meet the needs of different customers?

- I **prefer to develop new products to fulfill different demands from all customers.** Because it is difficult to predict customers' favorite flavor.

Brainstorming, Prototyping, and Evaluation Report

Brainstorming, Low Fidelity Prototyping, and Evaluation

Binglin Li, Olivia Song, Shuai Zhang, Liankun Zou, Dengcheng Ji

Abstract

This report documents the brainstorming results of possible directions to improving Meetfresh business and creating recommendation-system-related products that generate business value in the sweet food industry. After the brainstorming, 2 ideas were selected, including one customer-side idea (product recommendation) and one business-owner-side idea (store site selection). Verbal prototype, paper prototype, and wireframe prototype were used to represent the solutions. With three rigorous selection criteria, the tradeoff and suitability for users were analyzed accordingly.

Brainstorming Plan

1. Each member needs to come up with at least 10 ideas.
2. The ideas can be subject to help the customer or the business.
3. Think about what the customers really need and what they may not be aware of.
4. Think about what the customers really want from the experience.
5. Think about aspects of the business other than the product.
6. Think about problems that the business may face that are not directly associated with sales or profits.
7. Think about the problems that the business may have in the past, present, or future.
8. Think about what can be improved in the current business model.
9. Think about what data can be used to solve the problems.

Brainstorming Execution

Each member had his/her own individual brainstorming sessions and each had provided at least 10 ideas. A group brainstorming session was used to compare and compile ideas. A summary of the brainstorming sessions is provided below:

1. Customer Side
    a. Create customizable items using customers' input data as recipes. The recipes can then be used to recommend new or existing customers based on their popularity.
    b. Recommend based on what other customers have ordered before.
    c. Recommend based on the most popular items, new items, etc.
    d. Recommend based on items with similar texture, ingredient, taste, etc.
    e. Recommend based on lifestyles of customers.
    f. Recommend based on what the customers' friends have ordered.
    g. Recommend based on the health concerns of the customer.
    h. Recommend items for group ordering.
    i. Recommend side items for deals.

j. Use of graphics (pictures, texts, layout…) to make the items more appealing.

2. Business Side

   a. Analyze the customers' comments on social media, use the NLP technique to extract the complaints and trends. Generate report for the business owner.
   b. Introduce new products based on popularity and trends in the area.
   c. Recommend new presentations and designs of the products
   d. Recommend potential investors and people who may be interested in joining the franchise
   e. Recommend locations for new stores based on factors such as population, demographics, income level, etc.
   f. Recommend for inventory stockings based on sales, cost, and availability of supplies.

Selection Criteria

The selection criteria we used were:

1. Addressing crucial needs of users. The "users" can come from a wide rage, including customers of Meetfresh, business owner of Meetfresh, or opportunity seekers who are willing to open a new Meetfresh store.
2. Bringing business value. The essential goal of the project is to bring potential value to business development of Meetfresh. The more value we make from the project, the more impact we can make on the growth of Meetfresh.
3. Generalizability. Our aim is not limited to merely finishing a project for Meetfresh. We look beyond and want to make real contributions to the industry. The generalizability of our model/product/website decides how far we can go and how much bigger contribution we can make to this world.

Based on the brainstorming results and our idea selection criteria, we picked two promising directions that need low-fidelity prototyping - product recommendation and store site selection.

Prototype 1: Product recommendation

The first idea we want to develop is to create a recommendation system for customized dessert. We found customers often spend too much time studying or simply give up DIY because they are not familiar with the optional ingredients. We intend to split the whole DIY process and divide it into three parts: main material 1, main material 2 and auxiliary materials. The main ingredient determines the taste of the whole dessert. If customers are unfamiliar with the optional main ingredients, they can click the exclamation mark next to the main ingredient name to learn more about it, or recommend the usual choices of customers' friends or nearby residents according to our recommendation algorithm. The same is true for the choice of accessories.

Besides, when customers finish their DIY dessert, they can record the current recipe in the form of QR code and store it in their accounts. If their friends want to try his works, they only need to send the QR code instead of giving specific instructions by phone or social media. Merchants can analyze customers' taste preferences according to the QR code formula stored in customers' accounts, so as to optimize and expand the quality and diversity of ingredients. You can also publish KOI's own co-branded formula QR code by cooperating with KOL (Key Opinion Leader). Thereby increasing sales and expanding customer base through fan effect. During this process, our recommendation system can collect more user behavior data and taste preferences, so that new users can see the popularity of different ingredients during DIY, recommend interesting or popular formulas related to specific ingredients.

Prototype 2: Site Selection

This prototype comes from the view of the shop owner. During the investigation of the MeetFresh (MF), we find the shops are only limited to some places. Many people need to drive a long distance to try it and this restrict the promotion of the business. We also find some cases failing to run a MF. The MF is a franchise store and this means we can recommend the location of the shop! Given the similarity to other dessert stores, we expand our horizon to all dessert shops. We think this is a high practical vale business idea. In the following, we will describe how this prototype works.

Verbal prototype

This prototype is web-based. It provides the key information to help the people of interest choose their ideal shop location. When considering opening a store, the first thing is the market. We need to know people’s preference for dessert, how many and how much people will spend on dessert, when and how to eat dessert, the popularity among different ages and so on. After this, the next step will be the analysis of the location. A good location should have convenient transportation like the subway(metro) and large parking lot. Big stores, shopping malls, big companies and schools are also good indications of how many people live surround and visit. We can also learn from how the McDonald or Starbucks choose their store locations. The next part is the cost estimation. The prototype should also provide the man power cost, rent, tax and if possible, the estimated revenue. In order to have an intuitive feeling, the prototype will provide good visualizations of the information above. Finally, the prototype can also generate a report and final score (how ideal is the location) on the selected location.

Paper prototype

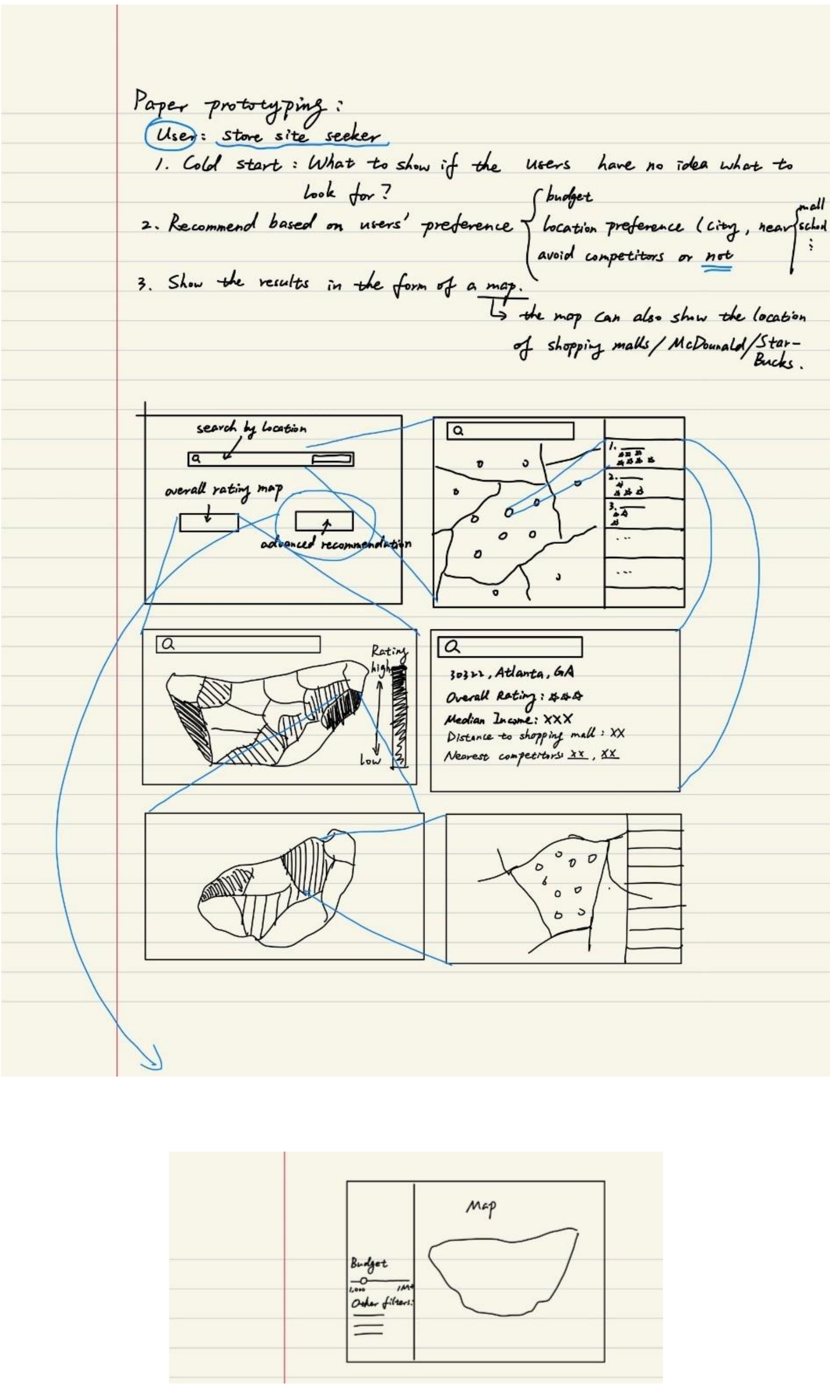

Figure. 1 paper prototype of site selection

After making sure of the overall input, output and processes of the recommendation in our system (based on the persona, timelines, etc. shown above). We started designing interfaces where we can more easily show our thoughts on the methods of how we are going to collect information from users and implement the models. Figure 1. is the paper prototype we created. The landing page is shown on the top left corner. We have two different choices on the main page: overall rating map and advanced recommendation. Overall rating map corresponds to the popularity based cold start model we have and this function is designed for those who have little idea about how their dessert shop would be like and those who are interested in the information in a big picture. While users input the address of the area they are interested in and click the other button ‘advanced recommendation’, the website will lead them to another page collecting detailed information from them and provide them a more personalized recommendation result.

We then collected feedback from our potential users using this paper prototype and got many valuable suggestions. Some of the examples of the suggestion include (but not limited): 1. adding the button before each of the filter providing users more flexibility. This would also allow us to collect statistical data about the features users think highly of and make adjustments on the positions how these filters should be displayed. 2. Advanced recommendation results (recommended zipcode and corresponding locations) should be shown in the largest area possible based on the distance filter information input. The rating points can be added to the results so it would be easier for the users to compare. Detailed information should be given after a specific area is clicked by the user. 3. Useful features that could be helpful for site selection are also discussed in the process of collecting feedback. We made changes based on these suggestions and updated the prototype. We created website demo designs to better show the prototype ideas and the details of these updates will be shown in the subsection below.

Wireframe Prototype

Main page

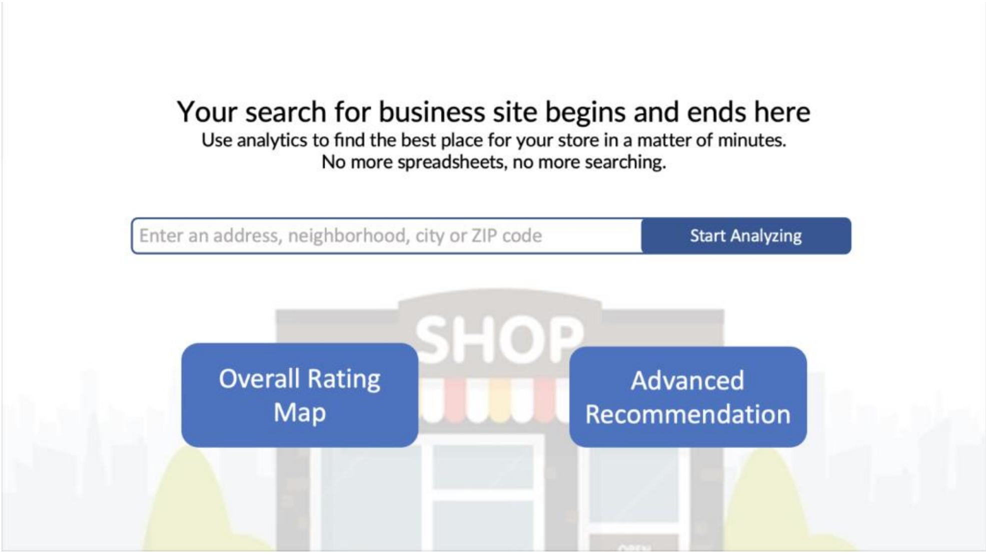

Figure 2. main page design

We provided background information on how this website can help people at the top of the main page. 'Overall rating map' and 'advanced recommendation' are the two main functions provided on the website. We can either generate a quick result with our cold start model to show the users or lead them to the page collecting data from them (see figure 4 in information input section) after they clicking 'advanced recommendation' button. The location information will be collected for advanced recommendation. Users can either input the address of the area they are interested in or we will track their IP address and set the location by default.

Overall rating map page

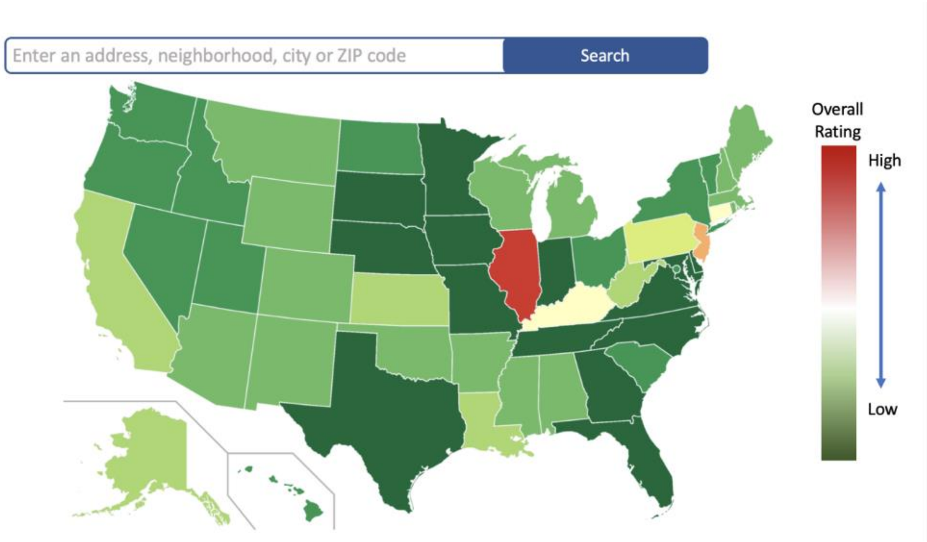

Figure 3. overall rating map page

We will build up a cold start model based on the population, economy, local flavor preference (whether they are dessert lover, etc.) information and give an overall rating countrywide. A more detailed rating map will be shown when people click a specific state.

Information input

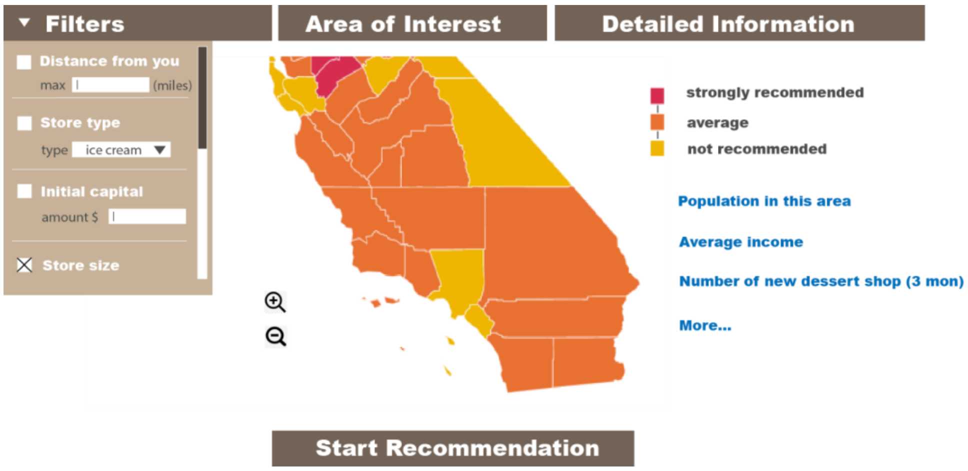

Figure 4. information input page

When users want a more personalized, accurate recommendation. This page will guide the users to select and input detailed information on the features they are interested in. We have a box on the left of each filter and users can anti-select the features they don’t care about or they don’t have too much information on. The middle part of this page shows an area of interest map based on the location information collected from the main page. Users can change the area of interest by updating the information in filter if the area shown is not are they are thinking about opening a shop in. Detailed information that could be helpful for the users to know the basic information on the area is listed on the right-hand side. After finishing filter input and viewing the information, users can click ‘start recommendation’ at bottom for detailed recommendation results.

Advanced recommendation results and detailed information

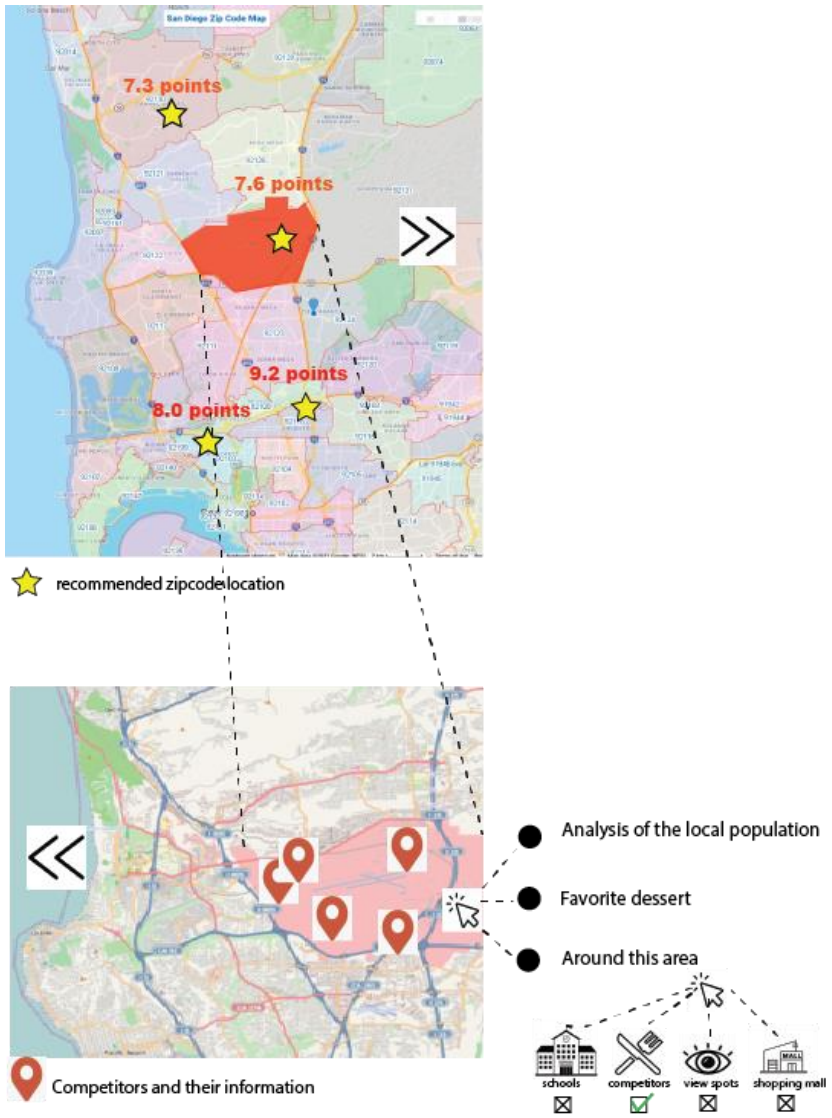

Figure 5. advanced recommendation results

Figure 5 shows the results of advanced recommendation. The granularity of the location will be zipcode area. We will provide 3-5 zipcode and label their locations and ratings based on the filter information collected. The figure above in figure 5 shows the first part of the recommendation results. When users click on one specific area, another page will show up (bottom figure in figure 5) and a zoomed in map is shown on the page providing more details of the area. The choices of information that would be helpful for the potential shop owners will pop up when placing the mouse cursor on the area. One of the information listed in the figure is ‘around this area’, which will show the location of schools, shopping malls, competing dessert shops and view sights in the area. Like what we did for filter selection, users can focus on some of this information by selecting or anti-selecting. For example, we have competitors selected (box below the icon) and the distribution of the competing stores can be seen on the map. People might repeat this process by going back to the upper result page and selecting another area for further details. The arrow buttons on the website will allow them to do so easily.

Results

The second prototype (store site selection) gained more positive feedback from the prototyping step. It satisfied the three criteria: Addressing crucial needs of users (business owner), bringing crucial business value, and have the generalizability to be extend to various types of store site selection (not limited to dessert store, but could also be shopping mall, restaurant, etc.). After many iterations of prototyping in different forms (including verbal, paper, and wireframe), we derived a more sophisticated overview about the prospect of the site selection idea, made clear of the major functionalities that need to be achieved, and started the initial data collection step (see Appendix A). Now we are ready to continue our journey to t he next step - data collection, model construction, and high-fidelity prototyping.

Appendix A - Datasets

- Demographics
- Traffic (bus stops, parking space, etc) - Dengcheng
  - Chicago "L" - https://data.cityofchicago.org/Transportation/CTA-System-Information-List-of-L-Stops/8pix-ypme
  - NYC subway - https://data.cityofnewyork.us/Transportation/Subway-Stations/arq3-7z49
  - Washinton DC Metro: https://data.imap.maryland.gov/datasets/120913815e11405c9c8996b63a65087d/explore?location=38.943072%2C-77.091050%2C10.99&showTable=true
  - Miami Dade:
    - https://www.miamidade.gov/transit/WebServices/Transit_XML_Data_Feeds.pdf
    - https://www.miamidade.gov/transit/WebServices/TrainStations/?StationID=
  - LA Metro: https://developer.metro.net/gis-data/
  - Massachusetts Bay Transporation Aurhority:
    - https://mbta-massdot.opendata.arcgis.com/datasets/MassDOT::rapid-transit-stops/explore?location=42.186112%2C-71.042550%2C9.39&showTable=true
- Location:
  - Big store (Costco) - Dengcheng
  - shopping mall - Dengcheng
  - **school(区分公立和私立) - Dengcheng**
    - https://nces.ed.gov/programs/edge/Geographic/SchoolLocations

- 写字楼（中高层建筑，7楼以上，企业，公司规模）**liankun (company list $500)**
    - Starbucks (bing) : https://www.kaggle.com/datasets/azhal23/starbucks-store-loacation-dashboard?resource=download
    - McDonald location (bing) : https://www.kaggle.com/datasets/ben1989/mcdonalds-locations
    - Dessert stores (Bing) : https://towardsdatascience.com/yelp-reviews-analysis-for-bubble-tea-shops-f23094d3d32d
- Competitor distribution (number of competitors near a location)
- **Local people's preference （行业报告）Liankun (market report $1000)**
- **Real estate related information （房价）Liankun (scrape)**
- Economic development direction (GDP and median wage going up or down?) (Bing)
- Tax rate (Bing) : https://taxfoundation.org/publications/state-corporate-income-tax-rates-and-brackets/

Appendix B - Brainstorm ideas

- Use the location, weather, time, and local temperature to recommend.
- Deploy the MeetFresh to more platforms
- For the new users, free try some signature samples
- Analysis the feedback from the comments, use the NLP technique to extract the pain point and trend. Use this information to update the system. Generate report to stakeholder
- Accumulate the MeetFresh Information from the social median. Use the CV and NLP to analysis. Use this information to update the recommendation system. Generate report to stakeholder

- Analysis the other popular desserts (Not Meetfresh) and provide the new ideas (including taste, ingredient and appearance) for the new product development.
- For the new user, the big pain point is the “cold start taste”. Try to use the some words and picture which can indicate the taste the dessert.
- In the customized menu, come up different pictures and descriptions when choosing different ingredients.
- Cooperate with the fit app and recommend after the exercise.
- Content based recommendations
- Customer based recommendations (gender, race)
- Friends recommendation (refer bonus)
- Customize the size of the dessert
- Recommend membership
- Voice base recommendation.
- Weekly, monthly plan
- Personalized combo
- Accept customer’s expectations and develop new dessert
- Recommend the food with similar texture, taste, ingredient … (e.g. pudding --> grass jelly)
- Change the recommended items based on the feedbacks from online and offline customers
- Platforms and new customers for advertisements
- Recommend to those whose friends had meetfresh before
- A series of different ways to describe the items (pictures, text, the features that are important to the customers, the layout preference...) and use different combination of these pictures and text to attract customers.
- Recommend items based on user’s habits (drinks with caffeine/ refreshing dessert in work time...)

- New desserts that are popular in the area.
- Other desserts customers ordered together with
- Potential investors that might be interested in opening a new meet fresh store
- Cities and positions that would be suitable for opening new store (dessert preference, Asian population, average income, community nearby). Some revenue and rating info needed.
- Staff based on their text on their social media (personality)
- Music, decoration in the store (how long customers are willing to stay in store)
- Sort by popularity or number of sales or rating
- Filter for wanted / unwanted ingredients
- Filter for texture and taste (sticky or refreshing, cold or hot, solid or liquid, sweet or not)
- Picture-based recommendation (products that look like the ones that you tried before)
- Filter based on level of healthiness or Calorie
- Filter for food that does not cause your allergy
- Recommend based on demographic info (gender, age, occupation, etc.)
- Rating prediction (LSTM based, incorporating both short-term trend and long-term memory)
- **Maintaining the balance – how to recommend the best product for different customers while also keeping the sales ratio to be steady.** 因为要考虑到库存问题.
- Group recommendation - What to recommend when a company wants to buy 100 bowls for its employees?
- “Your friend Amy bought this.” Keeping records of purchase history and link to social media.

- Explicitly Categorize: Asian’ s favorite, California’ s favorite, etc → can be tags.
- Recommendation for the side - Do you want a cup of milk tea in companion?
- Collecting data based on search logs
- Ingredient’ s illustration tag.
- Webpage for customized dessert.
- Interactive webpages include materials and ingredients’ images.
- Encoding DIY dessert via QR code.
- QR code can be share to other consumer and can be decoded by store to processing.
- Analysis DIY dessert and expand ingredients’ categories for various flavor demanding.
- Categorized customers’ DIY desert with different features, such as low calories, sweet, party supply etc.
- Hold DIY dessert race to attract new customer from social media and develop new products basing champion recipe.
- Develop dessert package for customers far from store according to their purchase record.
- Create discussion broad allow Meet Fresh fans talking about their DIY desserts.
- Recommend for ingredient suppliers based on location and customer base
- Recommend for inventory stockings based on sales, cost and availability of suppliers
- Recommend for working procedures based on item popularity
- Recommend for the elimination of nonprofitable items or hard to make item
- Recommend for work station arrangement for more lean processing of orders

- Recommend for replacement ingredients for the ones that is hard to come by
- Recommend for replacement ingredients to attract foreign customers
- Recommend for trending flavors or presentation
- Recommend for extra items to make a deal combo