Classification of take-out orderers by Expectation Maximization Algorithm.

- Topic: Research on UCAS students' online take-out ordering
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Introduction

With the fast development of the mobile Internet, more and more people are using online take-out food platforms to order food. According to the report of Institute of Frontier Industry Research in 2016, the whole market of online take-out selling will reach at 118 billion yuan per year at the end of 2017. Meanwhile, the fast-growing Big Data technology and the Mobile Internet technology have exerted a more and more powerful impact on traditional food markets (iiMedia Research, 2016). The growth trend of the O2O food market is unstoppable and it is easy to predict that the market will grow even faster in the following few years (iiMedia Research, 2017). Above all, it is obvious that buying online take-out food is becoming a natural part of urban citizens' life.(How relevant is this sentence here?)

Among all the people who buy take-out online, students are the very first group of people who use online platform for take-out as soon as they are launched, and also an unignoreable group of people who buy food online (TrustData, 2017). TrustData found a strong relationship between the number of take-out orders and the number of universities, which also suggests that students consumed a large number of online take-out(citation information needed). However, among all the exist studies, no math model of university students' take-out ordering pattern has been developed. Despite many reports focusing on the whole market of take-out, none of them is detailed enough to show the buying pattern on campus. There have also been reports made by other universities' students which are based on rather casual questionnaires and guesses (reference needed), which is not enough to reveal the whole pattern of campus online take-out buying.

Our research is focused on the data obtained from UCAS's Yuquan campus. With the help of data analysis algorithm offered by Weka, it is easier to find out the pattern of online take-out buying and the relationships between all these factors. After the analysis of the results of xxx questionnaires, the result clearly shows that (Add our result here when we finished analysis), which will benefit (......).

Methods

1. Questionnaire design

For the purpose of the research, we adopt the method of online questionnaire. The object of the survey is all the undergraduates in the Yuquanlu campus of University of Chinese Academy of Sciences(hereinafter referred to as UCAS).

We have posted our online questionnaire on all the major social platforms at school. It is convenient to count the data through the backstage when the number of samples are large enough.

The main contents of the questionnaire include the following aspects:

1.1 Consumption situation on online ordering

1. Online ordering frequency: the options were set to as follows: "never", "no more than three times a month", "several times a week", "almost once a day", "two or three times a day".
2. Online ordering time: the options were set to as follows: "mostly on weekends", "mostly on weekdays", "whenever I want".
3. Online ordering platform: the options included the three most commonly used takeout platforms.
4. Online ordering price range: the options were set to as follows: "<15 rmb/share", "15-25 rmb/share", "25-50rmb/share", ">50 rmb/share".

Take the eleme app as an example, the starting discount price of most stores is set at approximately 20-30 rmb, the preferential larger can reach 15 rmb, there may be a part of classmate hoping to reach the most affordable prices; for most of the students, in order to use the red envelopes, each consumer has to reach more than 35 rmb, the final cost will be more than 25 yuan. So we set up the price range above.

1.2 Influence factors on online ordering

1. The main factors considered in online ordering: we considered the subjective needs of the consumers and the quality of the store's service as two major aspects and provided several possible options, an "Other-Specify" is also included.

2. The main reasons for choosing online ordering: we provided following possible options: "terrible food in canteen", "terrible food in canteen", "crowded canteen", "coupons ", "recommend by others", "Several people together has a discount", "missed the meal time", "want to have a big meal", "do not want to go out", "too much money",an "Other-Specify" is also included.

1.3 Other views on takeout

In this part, we investigated the degree of concern about the hygiene of takeout, the degree of parents' support for child ordering online and students' general evaluations of takeout. We also added a fill - in question to investigate what causes the students to give up their takeout, hoping to provide more information for the later analysis.

2. Preliminary studies

3. Pre-process

4. Basic analyzation

5. Applying the Expectation Maximization Algorithm

After collecting and pre-processing the data, we are going to analyze the influence factors through the EM algorithm to explore some possible relationships between the various factors. Expectation–Maximization (EM) algorithm is an iterative method to find maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables.

> 岳佳. (2007). 基于EM算法的模型聚类的研究及应用. (Doctoral dissertation, 江南大学).

The EM Algorithm ,as the name suggests, is an algorithm used for getting the classification of a known data set which have the max expectation(Do, C. B., & Batzoglou, S. (2008)). In this experiment, we used the EM algorithm included in Weka (Waikato Environment for Knowledge Analysis) by the University of Waikato.

(Do, C. B., & Batzoglou, S. (2008). What is the expectation maximization algorithm?. Nature biotechnology, 26(8), 897.)

At the very begining, we apply the EM algorithm directly to the pre-processed data, the first test uses the following parameters:

```
weka.clusterers.EM -I 100 -N -1 -X 10 -max -1 -ll-cv 1.0E-6 -ll-iter 1.0E-6 -M 1.0E-6 -K 10 -num-slots 1 -S 100
```

The results are listed as follow.

```
EM
Number of clusters selected by cross validation: 2
Number of iterations performed: 14
                               Cluster
Attribute                            0       1
                                (0.56)  (0.44)
===============================================
WHERE-ELM
  yes                          29.1075 35.8925
  no                            17.871   1.129
  [total]                      46.9785 37.0215
WHERE-BD
  yes                           9.6428 16.3572
  no                           37.3356 20.6644
  [total]                      46.9785 37.0215
```

The result includes a large sum of data, which is quite hard to find some significant results in it. However, the EM algorithm did succeed in part the raw data into two different sets with similar size. For most of the attributes int the result list, the difference is not obvious. However, for some of the binary attributes, the classification martix showed that the 2 sets generated by this algorithm have huge difference in those properities. We picked out these attributes as following:

```
att picked out by EM

WHY-TOGETHER
  no                    28.7305 32.2695
  yes                   17.9241  5.0759
  [total]               46.6546 37.3454
WHY-OUTOFLUNCHTIME
  yes                   29.7774 12.2226
  no                    16.8772 25.1228
  [total]               46.6546 37.3454
FREQUENCY
  c                     15.7128 29.2872
  b                     28.9297  1.0703
  d                      1.0111  6.9889
  e                      1.0024  1.9976
  a                      2.9985  1.0015
  [total]               49.6546 40.3454
AT_TIME
  c                     19.2888 27.7112
  a                     25.4579  9.5421
  b                      2.9078  1.0922
  [total]               47.6546 38.3454
WHY-AWFULCANTEEN
  no                    25.9073  5.0927
  yes                   20.7473 32.2527
  [total]               46.6546 37.3454
WHY-CROWDEDCANTEEN
  no                    35.1047 10.8953
  yes                   11.5498 26.4502
  [total]               46.6546 37.3454

......
```

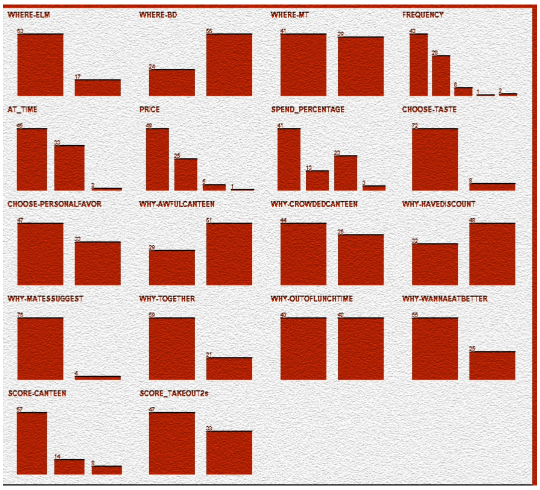
All the attributes listed above had obvious difference in the two groups, and this was only the basic result generated by the EM algorithm with the initial parameters.

6. Improve the Algorithm

Although we could already see the difference in the two groups, there were still vast improvement space for it.

In the first classification, we take 25 factors into consideration. However, according to the result, only some of them shows great differences in the two sets, which showed they had no significant contribution for the classification. Therefore, doing further process of these attributes should be able to improve the outcome greatly.

For some of the other attributes, the choices gathered together in single choices.



(Pre-processed data, 1-1)

For instance, in attributes like WHY-MATESUGGEST (which asked if the responder choose to order out-take because of ohter peoples' suggest), is greatly imbalanced. As the graph suggests, few participants order out-take because others' suggest. In this situation, this attribute can be deleted in the next EM test, for it can hardly provide any useful informations for classification, so according to the principle of EM. , deleting them will not harm the general result. Also, if left untouched, these imbalance attrtbute will introduce more Randomness into the result of EM. Attributes with similar conditions are:

```
WHY-IAMRICH
CHOOSE-ELSE
WHERE-ELSE
WHY-MATESSUGGEST
WHY-TASTE
CHOOSE-SERVICE
WHY-NOOUTDOOR
```

These attributes were removed before the next turn of EM began.

Not only the common pattern will make blur of the results, but also one question with many different options can also add up to the difficulty of data analize. In order to avoid this, we choosed to merge the options of such questions.

Take the score for canteen attribute for instance. In the questionnaire, the question asking participants to make a score foe the canteen was designed as a Likek scale (Likert summated rating scale) in order to make out te difference between the slight difference in attitudes towards the canteen. Unfortunately, the design also made the result too complexed so that the algorithm could not use this key to do classify works correctly, for the algorithm does not know the relationship between "dislike" and "hate". The algorithm considered these 2 options as totally different emotions while in fact they are only representation of different level of negative emotions. Therefore, merge such options together as negative attitude can greatly improve the outcome of the algorithm.

> 林东方. (2012). 基于EM算法的不完全测量数据的处理方法研究. (Doctoral dissertation, 中南大学).

Attributes with merged options are listed below.

```
SCORE-CANTEEN
  neutral               33.9477 26.0523
  positive               10.721   5.279
  negative               2.9859  7.0141
  [total]               47.6546 38.3454
SCORE_TAKEOUT2s
  neutral               29.6341 19.3659
  positive              17.0205 17.9795
  [total]               46.6546 37.3454
```

At the same time, we also did the same thing for the special points in "PRICE", "AT-TIME", "FREQUENCY" and "SPEND-PERCENTAGE". For these salient points are limited in number so that they can be sort into adjecant classes, hence we can get a better result.

Apply EM algorithm again to the adjusted data, we get the result as following:

```
=== Clustering model (full training set) ===


EM
==

Number of clusters selected by cross validation: 2
Number of iterations performed: 20


                       Cluster
Attribute                    0       1
```

```
                        (0.58)  (0.42)
=======================================
WHERE-ELM
  yes                   30.3819 34.6181
  no                    17.6323  1.3677
  [total]               48.0142 35.9858
WHERE-BD
  yes                    9.4627 16.5373
  no                    38.5514 19.4486
  [total]               48.0142 35.9858
WHERE-MT
  no                    17.1953 25.8047
  yes                   30.8189 10.1811
  [total]               48.0142 35.9858
FREQUENCY
  c                     17.1175 27.8825
  b                     28.8838  1.1162
  d                      1.0127  6.9873
  e                      1.0013  1.9987
  a                      2.9989  1.0011
  [total]               51.0142 38.9858
AT_TIME
  c                     20.3408 26.6592
  a                     25.7288  9.2712
  b                      2.9446  1.0554
  [total]               49.0142 36.9858
PRICE
  b                      27.734  23.266
  c                     16.2951 10.7049
  a                      3.9873  3.0127
  d                      1.9979  1.0021
  [total]               50.0142 37.9858
SPEND_PERCENTAGE
  a                     40.0709  2.9291
  c                      1.7132 13.2868
  b                      6.2307 18.7693
  d                      1.9994  3.0006
  [total]               50.0142 37.9858
CHOOSE-PRICE
  yes                   35.7326 31.2674
  no                    12.2816  4.7184
  [total]               48.0142 35.9858
CHOOSE-PERSONALFAVOR
  yes                   27.6935 21.3065
  no                    20.3207 14.6793
  [total]               48.0142 35.9858
WHY-AWFULCANTEEN
  no                     26.908   4.092
  yes                   21.1061 31.8939
  [total]               48.0142 35.9858
WHY-CROWDEDCANTEEN
  no                    36.4262  9.5738
  yes                    11.588  26.412
  [total]               48.0142 35.9858
WHY-HAVEDISCOUNT
  yes                    18.976  15.024
  no                    29.0382 20.9618
  [total]               48.0142 35.9858
WHY-TOGETHER
  no                    29.8723 31.1277
  yes                   18.1419  4.8581
  [total]               48.0142 35.9858
WHY-OUTOFLUNCHTIME
  yes                   30.1958 11.8042
  no                    17.8183 24.1817
```

```
  [total]               48.0142 35.9858
WHY-WANNAEATBETTER
  no                    31.5739 25.4261
  yes                   16.4403 10.5597
  [total]               48.0142 35.9858
SCORE-CANTEEN
  neutral               35.1152 24.8848
  positive              10.8694  5.1306
  negative               3.0295  6.9705
  [total]               49.0142 36.9858
SCORE_TAKEOUT2s
  neutral               30.8225 18.1775
  positive              17.1917 17.8083
  [total]               48.0142 35.9858


Time taken to build model (full training data) : 0.48 seconds

=== Model and evaluation on training set ===

Clustered Instances

0      45 ( 56%)
1      35 ( 44%)


Log likelihood: -11.44594
```

7. Verifing of the final result by EM.

Result

Combine the result of the EM algorithm and the result of the interview, we can devide the out-take orderers in UCAS roughly into two groups. Generally, the first group can be described as a group of people who have negative attitude towards the canteen, most of them evaluate the out-taken as high level, and enjoy ordering out-take together with their roommates. Meanwhile, most of them also believes the canteen is too crowded some times.

The other group of people share different characteristic with the first group of people. While half of them claim that they choose out-take because the canteen is too awful(which is far less then the first group, in which almost all the people believes that the awful canteen is the reason for them to order out-take), they order out-take mainly because of they missed the time for lunch or dinner. These people order out-take mainly at the weekends, and they are less likely to share out-take with their friends.

To sum up, the first group of people can be defined as those who do not like the school canteen so that they choose to take out-take, while another group, which is similar in size with the first group, mainly because they want food out of the meal time and dinner time.

Therefore, some suggestions ...

Discussion

References