NOVA IMS
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Market Basket Analysis

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INDEX

1. INTRODUCTION 1
2. BUSINESS UNDERSTANDING 1
2.1. Background..1
2.2. Business Objectives 1
2.3. Business Success criteria 1
2.4. Situation assessment..1
2.5. Determine Data Mining goals...2
3. PREDICTIVE ANALYTICS PROCESS 2
3.1. Data understanding..2
3.2. Data preparation 4
3.2.1. Coherence / Discrepancy Verification (Data cleaning) 4
3.2.2. Feature engineering 4
3.3. Modeling...4
3.3.1. Customer segmentation with K-means..4
3.3.2. Apriori Algorithm and Association Rules...5
3.3.3. Modelling Evaluation...5
4. RESULTS EVALUATION 6
4.1.1. Market Basket Analysis for Delivery purchases 6
4.1.2. Market Basket Analysis for Dine-in (Friends cluster) 6
4.1.3. Market Basket Analysis for Dine-in (Party cluster) 7
5. DEPLOYMENT AND MAINTENANCE PLANS 8
5.1. Deployment for Delivery: 8
5.2. Deployment for Dine-In:..8
6. CONCLUSIONS 9
6.1. Considerations for model improvement 9
7. REFERENCES...10
APPENDIX: RFM ANALYSIS FOR DELIVERY CUSTOMERS 10

1. INTRODUCTION

In the restaurant business, new competitors with disruptive changes in the business are constantly appearing, creating a big pressure in the restaurants that already exist. Due to the evolution of the digital transformation of business models and the available data, it is possible to support this kind of decisions on data-driven strategies. In this report, a Restaurant Market Basket Analysis is developed to discovery patterns across time in the restaurant's sales data to better understand customers' patterns of consumption and preferences (AspireSystems, n.d.). Prior, a customer segmentation was performed to associate those patterns to the restaurant's customer's profiles.

2. BUSINESS UNDERSTANDING

2.1. BACKGROUND

One of the first Restaurant brands created by the C company is having difficulties in maintaining their profit margin and continuous growth due to increasing competition and customers' changes inhabits. Therefore, the sales data of this restaurant were provided to our consultancy group in order to revert this situation.

2.2. BUSINESS OBJECTIVES

The actual Business Case aims to better understand customers' patterns of consumption and preferences of a Restaurant owned by company C. By doing a Market Basket Analysis, it will be possible to identify set of products that customers are interested in purchasing at the same time, as well as, increase customer retention and fulfil customers' needs.

The main goal is to provide a new set of menus, products and offers, that match the actual customers' consumption preferences. This new strategy path aims to increase the restaurant's revenues by taking advantage of its 2018's sales data.

2.3. BUSINESS SUCCESS CRITERIA

In order to develop success criteria of any project, it is crucial to have a comprehensive understanding of the business processes, financial statements and strategic goals. However, with the provided information, the success criteria were defined as such:

- Increase revenues by having a better targeting of sold products per customer segments and creating products combinations based on Market Bastet Analysis.
- Reduce costs, which leads to exclude infrequent dishes from the menu.

2.4. SITUATION ASSESSMENT

In order to efficiently perform this analysis, we used mainly Python 3 deploying results via Jupiter Notebook, it is advisable to rely on this version and platform to explore the work done by our consultancy group. Given some data discrepancies found on the dataset, it is possible that the presented results are slightly biased. At the end of this report some suggestions are made. Doing some improvements in how the data is extracted, is possible to get more precise results just by re-running the model or, if necessary, do small adaptations (in case new variables are added).

2.5. DETERMINE DATA MINING GOALS

With the provided dataset, might be possible to create separation among different invoices, identifying stronger rules and understanding who is being targeted on the different suggestions we intend to deploy. In this technical context, it is aimed to concretize the following goals:

Clustering (customers'/invoices' segmentation) - Get a proper segmentation, getting groups as far apart as possible with group members as close as possible (ensured with a high silhouette score, which measures how similar are the members of each cluster). Deciding the best lower number of clusters is possible by plotting the sum of squared errors and choosing the first point where the variation starts to be insignificant by increasing the number of clusters.

Market Basket Analysis – Perform Apriori Algorithm to find association rules. All this rules must be strong, matching the following metrics: a lift higher than 1.2, guaranteeing that the sets do are dependent and there is some likeliness that customers will get the consequent product(s); A support higher than 5%, to ensure the rule frequency of occurrence. At last, a confidence of 0.5 so it's possible to guarantee that the consequents happen after the antecedents', at least in 50% of the invoices.

3. PREDICTIVE ANALYTICS PROCESS

3.1. DATA UNDERSTANDING

Due to the natural differences of the services, an individual analysis was made for Dine-In and Delivery purchases and for instance, to explore significant differences among those types of customers. Based on that, the following descriptive analysis was developed to get the most important insights:

Looking at **DocNumber**, there are 11,035 invoices on the provided datasets, which represents € 804,939.24 on sales. The 58.65% of the invoices are from Dine-In and the rest 41.35% are from Deliveries.

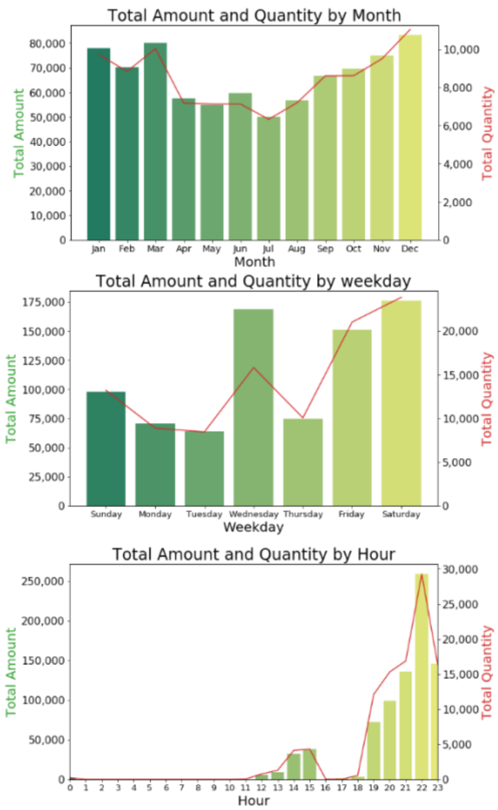

Figure 1. Sales aggregated by time.

Dine-In or Deliveries: Deliveries are sparse along 13 cities, all those deliveries represent € 242,730.57 which is the 27% of the 2018 sales, which indicates the importance of deliveries for the business. The cities with more deliveries are: Egkomi (31%), Strobolos (22%), Lakatemeia (14%) and Leykosia (13%), the rest of the cities share the 20% of the deliveries sales. Nevertheless, customers tend to spend more while eating in the restaurant, the average spent per invoice for deliveries is € 6.78, against € 11.87 of eating in the restaurant.

As sales (**Total Amount**) are related to quantity variable, the visualizations display in figure 1 shows patterns of purchases over time granularity. Sales tend to decrease between April and August, being December the month with higher sales, mainly for Christmas Eve and New Year's Eve sales.

Considering the days of the week, the best days for sales are Saturdays, Wednesdays and Fridays, in this order, registering 62% of the total sales. High sales on Fridays and Saturdays can be explained due to the free time of customers during the weekend, but sales on Wednesday probably can be attributed to a restaurant promotion.

Sales along the hours reflect 4 different consumption ranges: from 11 to 14 hours (lunchtime), the lowest sales are registered, from 14 to 17 hours high sales with low number of invoices and high pax are registered (events). From 18 to 00 hours is the time range with more revenues (dinner time), both for dine-in and delivery services, being 22 hour the most demanding time of the day.

The **Pax** variable shows the number of people per table, its distribution is skewed right, meaning that most of the purchases are done for less than 3 customers per table, however there are purchases with pax of 200 customers that suggest events with big groups.

About **Products**, he most sold products are Spring Roll, Mineral Water, Egg fried rice and Buffet Sushi. Considering sales amount, the products with most revenues are Buffet Sushi, Sweet Sour Chicken ¼ Duck and Spring Roll. By other hand, the most ordered products through delivery service are: Salt pepper squid, Sweet sour chicken, Buffet sushi, Curry, Mineral water and Egg fried rice. A separated top 10 for Delivery and Dine-In most sold items is shown on Figure 2, displaying differences on the preferences for each segment.

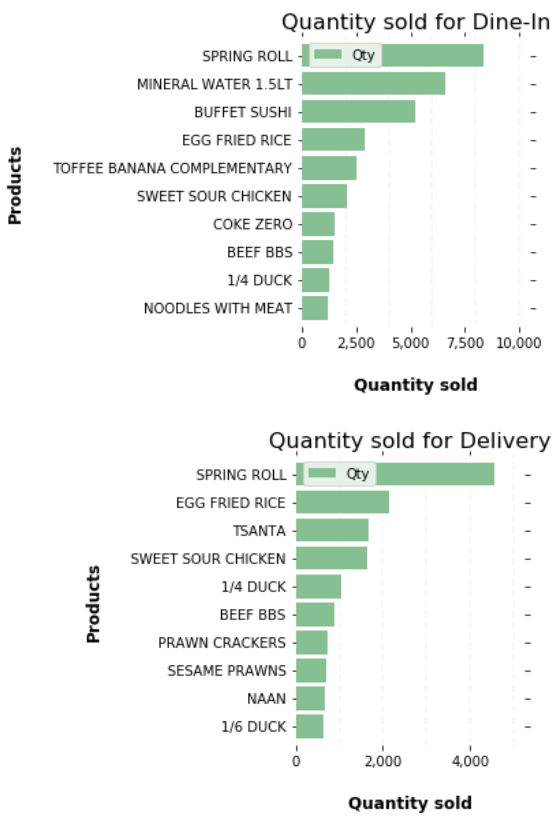

Figure 2. Top items for Dine-In and Delivery

In contrast, there were products that were almost not ordered, present in less than 12 invoices (1 invoice per month). Beverages and extras were excluded as they can be stored and not necessarily represent extra costs. However, this analysis was also done for these products and is possible to find details on the notebook. The products and respective count of invoices were the following: New Sushi: Classic Rolls Veg (1), Chasing the Dragon (4), Classic Rolls Cucumber. Rice: Chow Mein Beef (2), Chow Mein Chicken (5). Desserts: Toffee Apple Ice-cream (8), Lychees (4), Sorbet (6), Ice-cream (12), Poached Pears (6) and Sorbet IND (1).

3.2. Data preparation

3.2.1. Coherence / Discrepancy Verification (Data cleaning)

In this section all the values for the variables are verified, considering what each variable is measuring. In order to obtain perform a proper discrepancy verification, the dataset was kept split into Delivery and Dine-In, because in the Dine in dataset the variables related to customer's were mostly nulls, they were not used. This verification is done firstly with the aid of the variable's summary statistics, conforming some variables did not have discrepancies. The ones with incorrect values were examined one by one:

- **Customer city:** Since this is a categorical variable, the veracity of its values was tested by examining all the distinct cities. Two different cities were represented at least twice, under different spellings, this was corrected by changing the wrong spelling. However, one of the cases was slightly more serious, since despite having three different spellings of the same city none of these was correct – the city was Lakatamia.
- **Customer Since:** considering this data is from 2018, there can be no customers that have joined the restaurant since. However, there are 41 records where the date of creation of the customer is 2019. Since these records represent such a small percentage of the data they were simply dropped.

3.2.2. Feature engineering

3.2.2.1. Creating new calculated features

- **CustomerSinceYear**: A variable regarding the year of CustomerSince value, since the information about the month, day or hour are not needed. The year of each registration is enough to differentiate among old and new customers.
- **CustomerCity:** This variable, in the Delivery dataset, was transformed into severeval dummy variables regarding each city. Cities with very low transactions were grouped into 'Other'. This transformation was done so the k-means could be applied.

3.2.2.2. Import external data source to complement the analysis

External data sources like Weather in Cyprus for the year 2018 (*Τύμβου Weather*, n.d.), and Holidays in Cyprus (*Holidays Cyprus 2018*, n.d.)were added to the dataset to enrich the analysis. Rarely, these additional datasets do not add too much value to the analysis, just a few findings were obtained: 1) Temperature, as main weather measure, does not affected sales, only during summer months there was a reduction of sales, but it should be misleading to ensure that temperature reduces sales, since other factors as vacations can be involved. 2) Only three Holidays presented a considerably higher amount of sales, those were Valentines' Day, Christmas' Eve and New Year's Eve.

3.3. Modeling

3.3.1. Customer segmentation with K-means

The main goal of these Business Case is to perform a Market Basket Analysis and provide to the company valuable insights about frequently purchases, nevertheless to reach a more detailed analysis, a Customer Segmentation was performed prior the Market Basket Analysis, in order to find patterns consumptions and execute a Market Basket Analysis over each segment.

It is important to note that the clustering is done on the invoice numbers (one per purchase) and not over customers data. K-means clustering was performed over the two separated mentioned datasets, Delivery and Dine-In.

For the Delivery, two additional variables were considered, the year they became customers and their cities (the variable was transformed into a dummy variable, as mentioned in the feature engineering section). Initially, when interpreting the clusters, it was noticed that the variable Quantity remained with the same one for all clusters, for this reason, a second clustering execution was made excluding this variable. However, results were not very favorable, since no clear clusters were found on Delivery dataset, hence, this dataset was considered as a unique customer segment.

For the **Dine-in** dataset, the resulting clusters were the following:

- **First cluster (Friends):** This cluster has in average three customers per table and spends around the average total amount of €76. Normally they order only one or two dishes per person.
- **Second cluster (Party):** In this cluster the number of people per table is higher, averaging five people. Also has a high total amount spent, 117€. In average, they order around or two items per person.

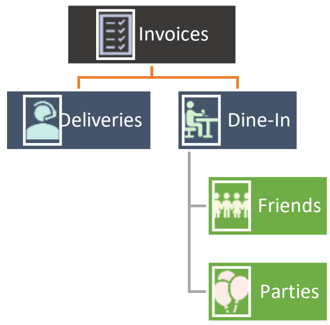

Figure 3. Customers segments

Two clusters, **Friends** and **Parties**, were found for Dine-In services, and Market Basket Analysis was evaluated for both green clusters and **Deliveries**, as illustrated in Figure 3.

3.3.2. Apriori Algorithm and Association Rules

In order to find close relationships between purchased products together in transactions, a Market Basket Analysis is performed trough Apriori algorithm, consequently the evaluation of the association rules obtained by this model is presented in this section.

3.3.3. Modelling Evaluation

For associations rules, only strong rules were selected, like (Gordon, 2013) and (Han et al., 2011) have demonstrated. To ensure this, rules must satisfy both a minimum support 5% threshold and a minimum confidence threshold of 50%. For lift, a minimum threshold of 1.2 was set to prevent rules about independent items. Subsequently, rules were sorted all the resulting rules decently by lift, support and confidence, in that specific order, and selected only the top rules for each segment to guarantee to keep only the most valuables association rules.

4. RESULTS EVALUATION

4.1.1. Market Basket Analysis for Delivery purchases

For Deliveries analysis, the dataset had 4,563 invoices, nevertheless, only 3,670 invoices (80%) has registered delivery charges, the 20% rest was not charged, probably by delays on delivery or promotions. These deliveries rules are presented according to the total revenue generated by the items contained on the rules.

1. Rules about SWEET SOUR CHICKEN:

These rules have the lowest lift values of all rules (1.53), which is not bad, there still being complementary items. Even so, the sold items for these rules had generated (74% of delivery's revenue), which implies that a quick deployment over these rules can generate more revenues fast.

2. Rules about SPRING ROLL:

These rules have generated (39% of delivery's revenues), they are complementary to point one, since the SWEET-SOUR CHICKEN and EGG FRIED RICE are repeated, however, these rules has SPRING ROLL as antecedents.

3. Other rules:

These rules have generated (19% of delivery's revenues), these rules have a lift value above 4, which implies a high correlation between the products presented on each rule. It is important to mention that the confident value for rule 3.2 is 100% which means there is a high probability of customers asking for NOODLES without meat and with EGG FRIED RICE.

In general, for delivery orders, there are no beverages involved on rules. Sweet Sour Chicken and Egg Fried Rice are the most requested products and usually they are ordered together.

4.1.2. Market Basket Analysis for Dine-in (Friends cluster)

For Friends cluster, characterized by customers who usually have a meal in groups of 3, asking 1 or 2 similar products and spending in average a total amount of €76, the rules were the following:

1. Rules about NOODLES WITH MEAT and NO MEAT and MINERAL WATER 1.5LT:

All have a lift of 5, it means that when customers buy Noodles with meat and Mineral water is 5 times more likely that they ask for no meat. When customers ask for no meat 100% of the times, they ask for noodles with meat. And given the low difference among the antecedents' support (no meat – 12.4% and no meat + water – 11.5%) can be concluded that most of the times this combination (noodles with meat + no meat) happens with Mineral Water.

2. Rules about SWEET SOUR CHICKEN, EGG FRIED RICE, SPRING ROLL and MINERAL WATER:

Two of those rules, 2.1 (EGG FRIED RICE and SPRING ROLL → SWEET SOUR CHICKEN) and 2.2 (EGG FRIED RICE and SPRING ROLL and MINERAL WATER 1.5LT → SWEET SOUR CHICKEN) are very similar, having all the same values in the different measures: a lift of 1.58, support of 12% and a confidence of 57%. Although, looking for the rule 2.1 antecedent's support (20%) is close to the 2.2 rule's antecedent support (19%), even having an extra antecedent. Said that, water is a huge tendency to accompany this set of items.

Other rule that must be pointed out, with a lift of 1.54, is 2.3 (SWEET SOUR CHICKEN and MINERAL WATER 1.5LT → EGG FRIED RICE). 68% of people who buys Sweet Sour Chicken and Water ends up buying Egg Fried Rice. Both antecedents and consequents have a high support value (34% and 44%), being a lot purchased individually and together, having also the highest support together (23%).

Also, 55% of the customers who bought Egg Fried Rice also bought Sweet Sour Chicken (2.4). These items have high supports, occurring much individually (supports of 44% and 36%) and together (support of 25%), however having less occurrences of Sweet-Sour Chicken individually, therefore this value could be increased.

3. Rules about NOODLES WITH MEAT and SPRING ROLL and MINERAL WATER 1.5LT:

Given the antecedents supports, it's possible to observe that Water and noodles (with support of 18%) occur almost the same amount of times in the database than noodles with meat alone (support of 19%). Looking to the consequents' support it's also possible to observe that Spring roll happens jointly with the water (34%) almost the same amount of times than alone (36%). At least 54% of people that purchase noodles with meat purchase spring rolls.

4. Rules about BEEF BBS, EGG DRIED RICE and MINERAL WATER 1.5LT:

Looking for those two rules is possible to observe (given the antecedents' support) that the Beef alone happens in the data base (22%) almost the same amount of times that beef and water together (20%). It's also possible to observe that 67% of the times that people buy beef BBS and Water, people buy the egg fried rice.

4.1.3. Market Basket Analysis for Dine-in (Party cluster)

For the Party cluster, which is characterized by spending a high average total, probably because they're normally a large group (around 5 people), the rules were:

1. Rules about SPRING ROLL, NOODLES WITH MEAT, NO MEAT, SWEET SOUR CHICKEN, EGG FRIED RICE, MINERAL WATER 1.5LT:

There are 4 rules with this exact combination. The lift for these rules around 7, indicating a great link between the products. Considering the support, the 7 products occurs together 5% of the times. The confidence is highest when 'no meat, egg fried rice and, sweet sour chicken' are the antecedents, indicating that if you order these three items you are 85% likely to buy spring rolls, mineral water 1.5lt and, noodles with meat.

2. Rules about SPRING ROLL, NOODLES WITH MEAT, NO MEAT, SWEET SOUR CHICKEN, EGG FRIED RICE:

Two rules included this exact combination. Just like the rule above, they have a lift around 7 and support around 5%. They have a higher confidence, 0.6, when spring rolls, noodles with meat and sweet-sour chicken are antecedents.

3. Rules about SPRING ROLL, NOODLES WITH MEAT, NO MEAT, SWEET SOUR CHICKEN, MINERAL WATER 1.5LT:

There is only one combination supporting this rule. Although it is very similar to first rule, expect instead with no egg fried rice. It has a lift of 6.6, and a support of 6%. The confidence indicates that a client from this cluster is 85% more likely to purchase spring roll, noodles with meat and mineral water 1.5lt, if he purchases no meat, sweet sour chicken.

4. Rules about SPRING ROLL, NOODLES WITH MEAT, NO MEAT, TOFFEE BANANA COMPLEMENTARY, MINERAL WATER 1.5LT:

There is only one combination of this rule. It has a lift of 6.7, a support of 6% and a confidence of 85%.

5. DEPLOYMENT AND MAINTENANCE PLANS

New product: We notice throughout the market basket analysis a pattern of customers asking for 'Noodles with meat' with 'no meat': 60% of times people ask noodles, people ask for no meat. This shows that the restaurant has a lot of clients that either don't eat or don't enjoy the meat provided. Since 'no meat' is a special request no deduction of the price is made, despite being the most expensive ingredient. For this reason, a new product, ('**Regular Noodles**'), that has all the ingredients 'Noodles with meat' has, expect for the meat. Ideally, this product would be slightly cheaper than the previous.

5.1. DEPLOYMENT FOR DELIVERY:

Nowadays, the whole delivery business has changed due to digital transformations. For instance, the first recommendation is to make the company a Restaurant partner on the top digital platforms for food service rating, like TripAdvisor. Secondly, to avoid having a complex own website that handles with deliveries, to evade the maintenance and daily operation of this system. Instead, become Partner on deliveries services platforms that operates on Cyprus like Bolt Food and Uber eats (SimilarWeb, n.d.). The benefits of redirect the business to this path are several: mainly the network effect of customers sharing their experience on platforms, which rises the probabilities of being recommended by customers, and saving money by not having delivery personal. Based on associations rules, it is suggested to publish on digital platforms the following menu combinations for delivery:

Menu 1: Sweet Sour Chicken and Egg Fried Rice
- **Cross-selling**: ¼ Duck; Tsanta; Spring rolls;

Menu 2: Noodles without meat and Egg Fried Rice

Menu 3: Jira Pulao, ¼ Duck and Naan.

5.2. DEPLOYMENT FOR DINE-IN:

As this is the set of the business that generates bigger revenues (73% of revenues), these customers should have the highest attention, implementing at first this suggested solutions. The distinction done, considering the two profiles mentioned on the analysis, has only the purpose to distinguish the usual targets of the suggestions, adapting them across the profile's characteristics. Noted with 'P1' are the menus that should be considered by the company to be created for 3 or 4 people, with 'P2' for 5 or 6 people, if matches the restaurant's interests. Options not noted, are consumption patterns regarding both profiles.

New offers: Here were found several main combinations, that sometimes are combined with other products. This way, based on associations rules, it is suggested the following menu combinations for dine-in and cross-selling options:

Menu 1: "Regular Noodles" and Mineral Water 1.5L.

- **Cross-selling:** Spring roll**;** Egg fried rice; Toffee banana complementary;

Menu 2 (P1): Noodles with meat, Spring Roll and Mineral Water 1.5L.

Menu 3 (P1): Egg Fried Rice, Sweet Sour Chicken and Mineral Water 1.5L.

- **Cross-selling:** Spring Roll;

Menu 4 (P1): Beef BBS, Egg Fried Rice and Mineral Water 1.5LT.

Menu 5 (P2): **"**Regular Noodles", Sweet sour chicken, Egg fried rice and Mineral Water 1.5L.

- **Cross-selling:** Spring Roll;

6. CONCLUSIONS

Summarizing the presented work, it is possible to conclude:

- There are major differences among delivery and dine-in customers based on products choices and consumption patterns. Given the tendencies found in each subset, a different approach was proposed for each of them.
- Many products in both categories, food and beverage, have a low number of orders. This leads to unnecessary costs. In this analysis was also detected a majorly asked combination of an existing products and hold, which implies that new products are needed.
- Many consumption tendencies were found, in each group. As said delivery and dine-in are totally different, however both groups in dine in share several of the found patterns together.

If Company C follows the stated suggestions, revenues may increase. By taking out unnecessary products that are currently being offered, creating new menus based on found association rules, and including products that aligns with customers' preferences; costs may be reduced, customer retention increased, and consequently revenue will increase as well.

6.1. CONSIDERATIONS FOR MODEL IMPROVEMENT

For Dine-in customers it is possible to have zero customers at the table, however, these records should not be eliminated, because they can be takeout customer. Ideally a new column with three values (0-Dine in, 1- Delivery and 2-Takeout) should be created.

The quality of the results is impacted on the data that is offered. For this reason, misspelled data should be avoided, mainly cities and dishes names. To avoid imputation errors, fields with value option (city, products etc.) should be created.

In addition, the more data about the customers the more accurate the analysis will be. Although, data there is a lot of data about the transactions made, there is no demographics information, therefore it would be interesting to create 'fidelity cards', to match their behavior with their profiles. This information would allow, for example, the possible creation of new menus.

7. REFERENCES

AspireSystems. (n.d.). *Restaurant Menu Engineering with Market Basket Analysis*. Retrieved March 22, 2020, from https://blog.aspiresys.com/digital/big-data-analytics/menu-engineering-market-basket-analysis/

Gordon. (2013). For Marketing, Sales, and Customer Relationship Management. In *Journal of Chemical Information and Modeling* (Vol. 53, Issue 9). https://doi.org/10.1017/CBO9781107415324.004

Han, J., Kamber, M., & Pei, J. (2011). *Data Mining. Concepts and Techniques, 3rd Edition (The Morgan Kaufmann Series in Data Management Systems)*.

Holidays Cyprus 2018. (n.d.). Retrieved March 22, 2020, from https://www.timeanddate.com/holidays/cyprus/2018

SimilarWeb. (n.d.). *The Most Popular iPhone Food & Drink Apps in CY according to App Store*. Retrieved March 21, 2020, from https://www.similarweb.com/apps/top/apple/store-rank/cy/food-and-drink/top-free/iphone

Τύμβου Weather. (n.d.). Retrieved March 22, 2020, from https://www.wunderground.com/history/monthly/cy/τύμβου/LCEN

APPENDIX: RFM ANALYSIS FOR DELIVERY CUSTOMERS

As an extra analysis was decided to include an RFM analysis for customer's in the Delivery dataset. For Dine In customers there weren't all the needed variables on disposal (Customer ID was missing).

It is easier to sell more to customers that already purchased something and showed interest to the company's product, than finding new customers. With RFM analysis is possible to quantify customer behavior and decide the best way to target them with specific marketing campaigns, increasing response rates. This is done by evaluating the customer's recency, frequency and monetary.

After calculating such variables for each customer, in order to further perform K-means, given this algorithm's sensibility outliers were also extracted. At the end, was possible to conclude that the restaurant's customers could be divided in 3 segments:

Best Customers (Keepers): Customers that in averaged haven't returned for some time, but have ordered more frequently, spending higher Monetary values in total. (890 customers)

- These are the ones that require more attention. They should feel special, keeping their interest in coming more times, with special promotions per example.

Newer Customers (Promising): Customers that have ordered more recently, but a smaller number of times, had spent consequently lower monetary values. (776 customers)

- These are the most recent clients, however, should be incentivized to reorder and spend higher monetary values.

Old Customers (Reactivate them): Customers that haven't ordered for a long time (almost a year), with also small number of orders spending the lowest monetary value. (472 customers)

- a good suggestion for these customers would be to get them to know the new menu options for delivery and try to reactivate them.