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Multiple Product Affinity Makes Much More Sense

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ABSTRACT

Retailers proactively seek a data-driven approach to tailor communications or provide customized product recommendations to increase sales and enhance customer loyalty. Product affinity models are often employed to achieve these goals. Often the clustering algorithm assigns customers to groups when the likelihood of purchasing the product type is the highest and the likelihood meets certain minimum and absolute requirements. This does a good job of identifying customers who purchase largely from one product type. However, customers who regularly purchase multiple product types (could be up to 30% of the total universe) are often thrown into a catchall group without a tailored recommendation. This paper addresses how to make a recommendation for this important group of customers with a multiple product affinity model developed in SAS® using macros. An innovative assignment algorithm is used to tease apart the catchall group and place customers in appropriate multiple product affinity groups using the retailer's transactional data. This is accomplished using a clustering algorithm and nonparametric tree model for model building. The assignment of customers to product affinity groups is done using SAS® macros, provided in the appendix.

INTRODUCTION

Imagine customers shopping for clothes. Some of them only look at the casual skirts and hair accessories, some show interest in buying jeans for men, some always shop this brand for business dresses and suits, and some are window shopping. This is a typical mix of customers for a given retail environment. Often direct mail and email are used to get customers into the store, and store associates help convert visitors to buyers, recommending additional products for purchase. Ideally there would be some follow up communication timed for future purchase. This communication cycle could be optimized if the direct mail and email pieces were tailored to customer preferences.

With the prosperous e-commerce growth, information technology engineers and marketing scientist have tried to copy the retail service model to develop and implement automated systems which provide customized recommendation to increase sales and build customer loyalty with the personal touch. Two kinds of product recommendation systems are commonly employed - collaborative filtering (Breese, Heckerman, and Kadie, 1998) and content-based filtering (Jafarkarimi, Sim and Saadatdoost, 2012).

In general, collaborative filtering approaches are based on consumer behavior whereas content-based filtering approaches are based on product qualities. The collaborative filtering approach builds a model based on the user's past behavior or numerical ratings given to items as well as similar information from other users to predict purchasing likelihood. (Melville and Sindhwani, 2010) The content-based filtering approach utilizes a series of discrete characteristics of an item in order to recommend additional items for a buyer (Mooney and Roy, 1999).

Market research studies show that personalized marketing significantly improve retailers' traffic, conversations, customers' retention and loyalty (SAP report, 2013).Naturally, retailers are eager to adopt personalized marketing. An automated product recommendation strategy can enhance customer relationship management, inform direct marketing strategies, and create a more pleasant shopping experience for the customer. As e-mail is so cost efficient, it has replaced direct-mail as the major mass marketing communication tool for retailers. However, promotional e-mail campaigns generally have a lower response rate than direct mail campaigns. Understanding customers' enthusiasm helps to tailor marketing messages. By understanding what draws a customer to shop at the brand, the retailer can better craft messages and personalized visuals via not only e-mail, but direct mail and mobile messaging.

In this scenario, product affinity models have been widely adopted in retail industry to serve as a targeting

segmentation method (Baer and Chakraborty, 2013). Using collaborative filtering ideas, the methodology segments customers based on their likelihood to purchase from product affinity group who consists of products that tend to be purchased together. Ideally, each customer would be associated with a product affinity group and this information would be used by marketers to customize marketing communications, e.g. product-oriented contents and visuals. One major issue with this method is that not all customers can be segmented (Baer and Chakraborty, 2013). In practice, there are 10% to 30% of customers (cross buyers) who have such a diverse product purchase history that they cannot be classified with only one product affinity group. One standard approach is to treat these customers as “like it all” buyers and give them the same general “who buy it all” message. Though this strategy seems reasonable, in practice the members in this group are often very different from each other. This is because those customers cross-shop different products or product categories. Recall our scenario with the clothing buyers – a “like it all” buyer who buys accessories, skinny jeans and casual skirts can be quite different from a buyer who buys blouses, business suits and skirts. In our experience, customers who cross shop generate more sales than customers shopping only one product category. These are high value customers for the retailer. Well-crafted communication with these customers can greatly enhance the customer's brand experience. Irrelevant messaging, however, can train the customer to ignore emails from the brand and can even increase the email opt-out rate. This is the last thing marketers want to see.

To meet this challenge, a rule-based segmentation is proposed which flexibly segments customers using fuzzy product groups. A customer can be associated with minimum of one product group all the way up to being associated with all the product groups. This solution retains the strategy for customers primarily shopping from one product group, while adding useful targeting segmentation for the multiple group buyers. It decreases the number of general targeted customers and increases the recommendation quality for the customer base as a whole.

First Generation Product Affinity Segmentation

Segmentation divides a big group into several subsets or segments where each of the segments is homogeneous within the segment and heterogeneous with other segments. “A segmentation basis is defined as a set of variables or characteristics used to assign potential customers to homogeneous group.” (Wedel & Kamakura, 2000). By definition, the variables can be any meaningful attributes that provide useful separation of the population. Simple customer segmentation could be based on discrete attributes, such as gender or education, based on continuous attributes, such as income or age, or based on more complex concepts, such as social status which may involve income, occupation, age, vehicle type, and residence-style/house value. The same ideas discussed above when grouping customers by purchasing behavior can also apply when we look at grouping customers by the customer's inherent characteristics.

Product affinity is generally a two stage process leveraging transactional data and using collaborative filtering. It begins with that products are clustered into affinity groups based on the likelihood to be bought together. Modelers use transactional history to discover the purchase patterns and which products are naturally bought together using a disjoint clustering method such as k-means. In SAS, the procedures employed can be Proc Fastclus or Proc Cluster with appropriate options. Usually, for marketing convenience purpose, the total numbers of patterns are limited to 6 to 10 list of products that tend to be bought together form a product affinity group. Once the product affinity groups are formed, frequency purchase percentage tables for each customer are derived. And they are used for customer segment assignment.

For example, customer A of retailer R with six product affinity groups has a row of frequency of purchase from each of the six groups attributes to represent his/her product preferences and interest. A row of 20%, 0%, 0%, 22%, 0%, 58% indicates this customer purchased 20% quantity of his/her total purchase at a given of time from product affinity group 1, 22% from product group 4, 58% from product affinity group 6 and none for the rest. We refer to this list of percentages as the percentage attribute list of a customer. Note that the clusters are mutually exclusive. The next step is to assign customer membership to an affinity group.

By leveraging the percentage attributes, we use two criteria to process the rule-based segmentation: minimum threshold and absolute threshold. In the formula, we call them MT and AT.

We assign a customer to a product affinity group segment based on the customers' proclivity to purchase these products. The minimum threshold ensures a general interest level in that type of product and the absolute threshold informs us that the customer likes that product group more than the next preferred group. If the difference in frequency in percentage between the top two groups is less than the absolute threshold, we treat the preference to both groups are not different, or identical.

Below is the product affinity segmentation assignment rule of the first generation:

$$FGPA(X_i) = \begin{cases} k_i = \max(k_{1,} k_{2,} \ldots k_{n,}) \ and \ k_i > MT \ and \ (\max(k_{1,} k_{2,} \ldots k_{n,}) - \text{second} \max(k_{1,} k_{2,} \ldots k_{n,})) > AT & \boldsymbol{S_n} \\ & \boldsymbol{Like\ it\ All\ Buyers} \end{cases}$$

Formula 1.

Formula 1 shows us that X_i is an arbitrary customer with a product affinity preference on n product affinity groups listed as $K_{1,} K_{2,} K_{3,} through\ K_n$. The k represents the propensity likelihood to buy from a product affinity group in percentage and n represents the total number of product affinity groups the retailer has. The S represents the single product affinity group segment if a customer satisfied assignment rule to be assigned to. Customers who fail to satisfy rules are put to "like it all" buyer pool.

Practically, we like to set the minimum threshold to be as twice as big as the even distribution percentage with groups number from 6 to 10. For example, if there are 10 groups, an even distribution would be 10%, so the minimum threshold could be set at around 20%. In the example for retailer R, the minimum threshold chosen would be 34%. On the other hand, the absolute threshold criteria are designed to quantify how much difference of preference in percentage we can say that a customer favors products from one group to another. In another words, if someone holds preference difference to a given number of product affinity, compare a pair of them, two by two, we say the customers has equal preference to the groups. Quick rule, we can set absolute threshold at to one third to half of the even distribution percentage. As an example, for six to ten product groups, we may require a top frequency to be more than 5% higher than the next highest frequency in order to say that the customer has a clear preference for products in the top group. In general, depends on retailer's business and customer nature, the threshold criteria reply on researcher's experience and choice.

Product Affinity Segmentation Application

For retailers, email is the most common channel to have sent people into stores, followed by direct mail and coupons. It is reported that over 75% of customers make purchase in a retail store. Also, considering that as of 2015, most retailers are still struggling of email click through rate while half of email is now open from a mobile device. It is extremely in this era to accurately catch a customer's attention and make it last longer. Success retailers manage customer relationship by knowing them, getting their attention, building trust, tailoring message and conveying benefits to make a deal happen. Product affinity segmentation can be the foundation for a retailer's marketing strategies in many areas, such as web product recommendation, co-purchase promotion, direct-mail and opt-in email advertising programs. Today, customers shop much different than before. They research, discuss, compare, buy and share. In any point of the shopping scenario wheel could be a touchpoint to deliver a message to make product on influences and purchase decisions. The better we do our job on segmentation methodology, the more efficient we target our best customers to achieve the "to buy" and "buy more" goals.

The "Buy It All" Customer Market Targeting Challenge

In the first generation product affinity segmentation, the "like it all" segment, by industry, usually fall in the range between 10% and 30%, in most cases, 20% or more. The size is big considering that an even distribution probability for a retailer with 6 segments is 17%. According to our case analyses on this

particular segment, they are not any less necessary to approach compare to others who are clearly segmented and may even be very value incremental in terms of profitability, loyalty and shopping propensity. How did this happen? Intuitively, it makes sense that those customers cross shop are advocates of brand so in observation, their liking to products of a brand is more diverse and this could result by more trips taken.

Let's dive into the problem more with a concrete example. Recall our retailer R case. Let's take a look at the segmentation with given minimum threshold 34% and absolute threshold to be 5%.

Customer	Preference by Quantity Purchase Percentage From Product Affinity Group							Segment
	PAG1	PAG2	PAG3	PAG4	PAG5	PAG6	Total	
A	20	0	0	22	0	58	100	PAG 6
B	0	0	0	0	48	52	100	Like-it-all
C	0	33	35	32	0	0	100	Like-it-all
D	0	33	0	32	0	35	100	Like-it-all
E	17	17	17	17	17	15	100	Like-it-all
F	12	40	12	12	12	12	100	PAG 2

Table 1.

In this setup, customer A is successfully assigned to product affinity group segment 6 as not only the top favorite group preference is over 34% but also, by passing the 5% absolute threshold, the favorite group is 38% more preferable than its second favorite segment. Following the same rule, F goes to segment 2. As customer B, C and D don't see develop a single product group buying pattern, they are the "like it all" buyers. However, take a closer look. From the preference table, we observe that B likes products from class 5 and 6, C likes product class 2, 3, 4 and D likes product class 2, 4, 5 and finally, E, is a genuine like it all buyer.

By leveraging product affinity segmentation, we'd like to link customer to their favorite products to create tailored marketing messages and visualization. In this case, the "like it all" buyers lose the opportunity to be personalization because they are viewed identical with preference spread across all product groups.

The goal is to optimize marketing communication quantity by creating product customized messages. Do we want to change our threshold setup in order to increase the segmented customers by taking the risk that; it may lead to suspicious and less insightful segmentation? As marketing segmentation is known the first building block of strategies, a solution not only makes business sense and but also ca be robustly modeled. In this paper, we're proposing to use a fuzzy match assignment approach to deal with the issue. The methodology can naturally describe customers' preference taking out the restriction of segmenting based on single product affinity group.

Fuzzy Match Product Affinity Segmentation Methodology

This model segments customers by individual's product preference using their transaction history. By this segmentation rule setup, a customer is assigned, or classified into a segment when rule conditions met. Those who carried attributes which cannot satisfy rule conditions are put into "like it all or others" segment. The fundamental concept of doing fuzzy match is to segment by explicitly considering customers' preference without the assumption of dominant one group product affinity.

In this model, we have three parameters: minimum threshold, absolute threshold and non-zero class difference adjustment factor which is expressed by parameter AF. Each customer has n preference product attributes as input.

1. Assign to a single product group pattern product affinity segment if formula 1 condition met.

2. For those who failed to obtain a single product group buyer pattern, assign them to a m-fuzzy (m<=n= total number of product affinity groups available) segment ***S*** if the minimum top ***M*** is grater then top (M+1) by absolute threshold or larger and

a. For a customer's top M favorite product affinity groups, compare the M groups two by two, has preference frequency percentage difference less than the absolute threshold or

b. For a customer, has only M product affinity groups purchase records (M non zero preference frequency percentages available), compare all of the preference percentage two by two, the difference is within 35% multiply by the even distribution probability of 100% by M.

The full segmentation rule is illustrated below in formula 2.

$$FGPA(X_i) = \begin{cases} k_i = \max(k_1, k_2, \dots k_n) \textit{ and } k_i > MT \textit{ and } (\max(k_1, k_2, \dots k_n) - \text{second} \max(k_1, k_2, \dots k_n)) > AT & \boldsymbol{S_n} \\ \textit{else if } \text{non zero}(K) > M \textit{ and } (k_{top\ m} - k_{top\ (m+1)}) > AT \textit{ and } abs(any\ two\ (k_a - k_b)) \leq AT, \quad where\ a, b \in top\ m & \boldsymbol{S_{top\ M}} \\ \qquad \textit{else if } \text{non zero}(K) = M \textit{ and } abs(any\ two(k_a - k_b)) \leq \left(\frac{\boldsymbol{AF}}{\boldsymbol{M}}\right), where\ a, b \in top\ m \quad \boldsymbol{S_{top\ M}} & \\ else & \boldsymbol{Like\ it\ All\ Buyers\ and\ others} \end{cases}$$

Formula 2.

The AF is a non-zero class difference adjustment factor. This factor is created for comparison fairness. This adjustment increases the absolute threshold tolerance due to limited purchase history from fewer product affinity groups.

Consider a customer, only bought 2 out of a total of 6 product affinity groups a retailer has with the preference percentage 55% and 45% has an obvious fuzzy two purchasing pattern. However, the successful assignment wouldn't happen without the b. criteria. The number of 35%, in our case is determined based on the number of absolute threshold.

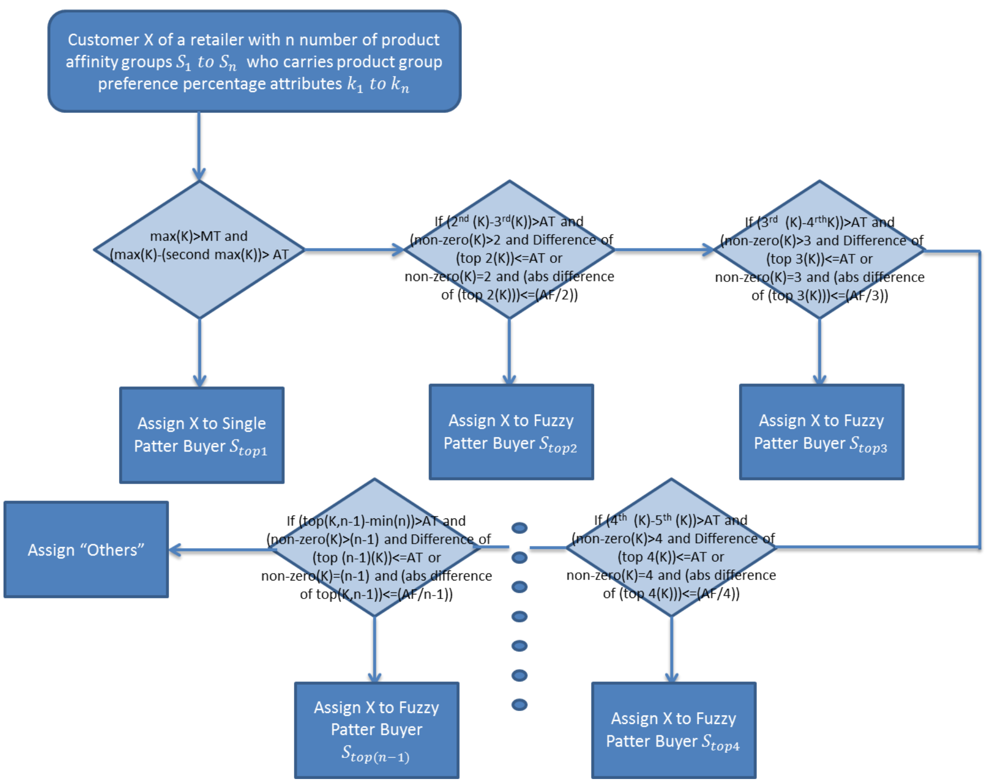

Figure 1.

Based on the new rule, we re-segmented our retailer R customers and assigned them into to new segments as shown in table 2.

Customer	Preference by Quantity Purchase Percentage From Product Affinity Group							Segment
	PAG1	PAG2	PAG3	PAG4	PAG5	PAG6	Total	
A	20	0	0	22	0	58	100	PAG 6
B	0	0	0	0	48	52	100	PAG 56
C	0	33	35	32	0	0	100	PAG 234
D	0	33	0	32	0	35	100	PAG 246
E	17	17	17	17	17	15	100	PAG 123456
F	12	40	12	12	12	12	100	PAG 2

Table 2.

In the new segmentation, “like it all” buyers are turned to different cross product group buyers and are successfully differentiated. In the following of the paper, we will illustrate the insightful fuzzy match product affinity segmentation solution and its value to retail marketing by providing a comprehensive retail application example.

Retail Example and Demonstration

We use customers from a hard good retailer brand which owns stores in many cities in the US. The brand sells furnishing products, home goods, lighting products, decoration items, women accessories and fragrances. In the next few sections, we will talk about the two segmentation methods SAS macros and apply on them on datasets, evaluate the performance and compare the results.

The data is collected from Point-of-Sale (POS) from 561,802 customers who shopped during June 2010 and May 2011. From the transactional data, we can mine the customers’ first-purchase-date, purchased item department, purchased item spend and purchased item quantity.

a. Product Affinity Group Creation

After data cleanse, we use item purchased quantity frequency percentage as our variables for product affinity model building. k-means, a disjoint clustering method and a hierarchy clustering method are employed to from product affinity groups. We obtained a list of 8 procut classes and each of them consists with product departments which contains products highly likelihood be purchased togather. Proc Fastclus, Proc Varclus and Proc Cluster procedures can serve for the purpose. Generally, we use the first two procedures to produce initial disjoint clusters and follow by that, take Proc Cluster hierarchy output, by the tree map distance information, to validate k-means clusters results and do business adjustment. For instance, if it is observed that two products are supposed to be grouped together, in the marketing perspective, like shampoo and conditioner, however, falling apart into neighbor segments with a relative short similarity distance overall. With such case, we can consider moving the products together to one segment for marketing convenience.
Below is one example code for create product affinity groups using proc varclus.

```
proc varclus data=input_dataset. maxclusters=5 centroid hierarchy;
      var cat1 - cat100;
run;
```

For most of retail brands, we usually use product categories or department such relative big units as our clustering variables as items may go out fast and the available quantity is difficult to control. In below, the table lists the final 8 product affinity groups obtained and their number of departments made with.

Product Affinity Group Name	Number of Product categories
Product Affinity Group 1	7
Product Affinity Group 2	2
Product Affinity Group 3	4

Product Affinity Group 4	5
Product Affinity Group 5	6
Product Affinity Group 6	5
Product Affinity Group 7	7
Product Affinity Group 8	2
Total	38

Table 3.

b. Single Product Affinity Group Segmentation Result

The SAS macro %***classify_sing*** lists below can be used to generate single product affinity group segmentation.

```
%macro classify_sing(dsnin,dsnout,item_cnt);
data &dsnout.;
%let perc1=0.17;
%let perc2=0.08;
%let vblist=k1,k2,k3,k4,k5,k6,k7,k8;
%put &vblist.;
      set &dsnin.;
        length group $12;
      *single category;
      array ks {*} k1-k8;
*one category;
do i=1 to 8;
select;*one category; when (
      ks(i)>&perc1.*2 and ks(i)>(largest(2,&vblist.)+&perc2.))
group=cat('grp',i);otherwise;end;
end;
keep cust_id group &item_cnt. k1-k8;
data &dsnout.; set &dsnout.; run;
%mend classify_sing;
%classify_sing(Input_dataset,Output_dataset,product_quantity);
```

The three macro augments are input, output and calculation base, in this case, is the quantity of product purchased. Table 4 is an example out what an inout dataset should look like. rts is the pronoun of preference probability and all of them should sum up to 1.

cust_id	rts1	rts2	rts3	rts4	rts5	rts6	rts7	rts8	Quantity
11	0.5	0	0	0.22	0	0.58	0	0	16
22	0	0	0	0	0.48	0.52	0	0	12
33	0	0.33	0.35	0.32	0	0	0	0	8
44	0.18	0.22	0.08	0.16	0.16		0.133	0.067	72

Table 4

In this assignment rule, macro variable &perc1. is half of the minimum threshold requirement equals to even distribution probability. Macro variable &perc2. is the absolute threshold requirement which is half of the even distribution probability. The absolute threshold is set big in range because for hard goods retailers, customers usually have a longer shopping gap window; this is to tolerant higher preference variation. On the other hand, if for a grocer or women apparel retailer, it is not surprised that we see the number set as low as one third of even distribution probability. Again, two threshold requirement number selections very much rely on different retailers' nature. This is the moment when data science needs the art or business intuition.

Table 5 is the output example obtaining from running the fuzzy match SAS macro.

cust_id	rts1	rts2	rts3	rts4	rts5	rts6	Quantity	Segment
1	0	0	0	0	0.48	0.52	10	PAG 56
2	0	0.33	0.35	0.32	0	0	20	PAG 234
3	0	0.33	0	0.32	0	0.35	48	PAG 246
4	0.17	0.17	0.17	0.17	0.17	0.15	16	PAG 123456
5	0.12	0.4	0.12	0.12	0.12	0.12	20	PAG 2

Table 5.

One obtain the result, we'd like to see how customer quality differentiates by segments. The results by segments are presented in below in table 6.

Product Affinity Group	Customer Count	Customer Count in %	Average Dollar Spend	Item Quantity Purchased	Trips	Tenure in Month
Group 1	49,183	9%	$154	8	3	64
Group 2	27,654	5%	$271	3	2	61
Group 3	38,741	7%	$97	4	2	63
Group 4	28,422	5%	$56	6	2	66
Group 5	107,922	19%	$79	10	4	65
Group 6	34,886	6%	$237	6	3	63
Group 7	135,488	24%	$121	12	4	65
Group 8	60,899	11%	$94	10	4	66
Like It All	**78,607**	**14%**	**$212**	**12**	**6**	**68**
Total	561,802	15%	$135	9	4	65

Table 6.

Summary of our findings:

- 14% of buyers are like-it-all buyers which makes the 3rd largest segments for this brand
- Each of the buyers contributes $212 annual spend in average which is also the 3rd highest
- This segment has an average of top 1 item purchase quantity and top 1 number of trips
- The like it all buyers have the longest tenure overall

Given those facts, we definitely think to target "like it all" with a general marketing solution not to seem a good idea. Actually, although the size of this segment in this example seem not too bad compare to the retail 10% to 30% range, it is still significantly big.

c. Fuzzy Match Product Affinity Group Segmentation

Now, let's use Fuzzy Match Product Affinity Approach to segment customers. The SAS Macro is appended in the appendix due to content space efficiency. In this case, three arguments are still input-dataset, output-dataset and the calculation base.

```
%classify(Input_dataset,Output_dataset,product_quantity);
```

In this macro, &perc3. Is the non zero class adjustment factor which is fixed at 35%. Minimum threshold is 34% and absolute threshold is 8%. In table 5, among the 14% "like it all" buyers, 81% of them can be fuzzy two product affinity segmented. This indicates the majority of the customers are either single product affinity buying pattern buyers or fuzzy two pattern buyers who majorly cross from two product affinity class.

Fuzzy Matched	Count	Percentage
2 Product Affinity Group Fuzzy	63,712	81.05%
3 Product Affinity Group Fuzzy	9,688	12.32%
4 Product Affinity Group Fuzzy	1,401	1.78%
5 Product Affinity Group Fuzzy	146	0.19%
6 Product Affinity Group Fuzzy	15	0.02%
7 Product Affinity Group Fuzzy	2	0.00%
Multi Group	3,643	4.63%
Total	78,607	100%

Table 7.

Table 5 shows us that the new rule successfully assigned 93% of the "like it all" into a fuzzy 2 or fuzzy 3 segment while 81% of them are fuzzy 2 segments. Notice, though the SAS macro is hard coded for 8 product groups(which is a common number a retailer can pick to set affinity groups), users would be able to use it for product affinity groups with any numbers of 8 or less.

In the following table, we can examine the customer quality by spend, item quantity, trips and customer average tenure in month by single or cross shopping pattern. We only focus on the three fuzzy and less product affinity segments as the rest of segments are less significant in quantity. Here are our findings:

- Fuzzy two pattern buyers have longer brand tenure, more in spend, item quantity and trips over single pattern buyers
- Fuzzy three pattern buyers, compared to fuzzy two, have longer tenure, more in spend and trips.
- Customers' tenure with the brand and diversity of preference are positive correlated.
- 1% of customers are un-classifiable by not meeting the segmentation rule.

Product Affinity Group	Customer Count	Customer Count in %	Tenure in Month	Average Dollar Spend	Item Quantity Purchased	Trips
Single Product Affinity Group Segment	**483,134**	**86.6%**	**64.57**	**$123**	**9**	**3**
2 Fuzzy Product Affinity Group Segment	**63,712**	**11.4%**	**67.22**	**$189**	**11**	**5**
3 Fuzzy Product Affinity Group Segment	9,749	1.7%	68.34	$202	10	6
4 Fuzzy Product Affinity Group Segment	1,401	0.3%	69.99	$219	9	6
5 Fuzzy Product Affinity Group Segment	146	0.0%	68.91	$220	9	7
6 Fuzzy Product Affinity Group Segment	15	0.0%	79.42	$362	10	8
7 Fuzzy Product Affinity Group Segment	2	0.0%	72.53	$203	8	8
8 Fuzzy Product Affinity Group Segment and Others	3,643	0.7%	78	$638	32	15

Table 8.

Customers with longer brand tenure are likely to contribute more in sales, gradually establish diverse product interest. In our case, single and fuzzy two segments make up 98% of total customers. For business purpose, the number of customers who are supposed to receive a general tailored message would significantly decrease from 14% to 2%.

In this case, we also observed a segment of 0.7% made of customers who are either real "like it all" buyers with evenly preference on all 8 groups or for some reason, the rule exception from high fuzzy segments. This segment has outstanding metrics and they can be special targeted like the idea for the first generation "like it all". One challenge for marketing segmentation is that there will always be exception unless a hard-segmentation method is applied. However, a 0.7% is fairly small and in reality, this segment can be suggested to combine with high (grater than 4 or 5) fuzzy segment.
Overall, employing the fuzzy match product affinity segmentation, in this way, 11.4% extra customers, with better performance metrics, can now be product relevant marketing targetable.

CONCLUSION

This paper presents a fuzzy match rule based segmentation which divides customers using the natural link between them and the products they are attracted to. It is always encouraged to use the same methodology to try on more marketing challenges using other affinity attributes, such as coupon affinity, marketing program affinity and so on.

Retailers can take the advantage of knowing customers' product preference to market, target and sell. An individual's product affinity information can be applied in email tagline, direct mail text, letter content and visualization to increase direct email click-through rate, direct mail response rate, product recommendation conversions and decrease advertising program opt-out rate.

Fuzzy match product affinity segmentation model is especially recommended for retailers because it provides a convenient way to generate insightful and robust solution for a given period of time. The model is suggested to be updated quarterly or it can be updated as frequent as real time to a brand's best interests. Beyond customer level interaction, it also captures the cross-purchase patterns among shoppers about product groups to optimize customers' experience with the brand. For example, co-purchased product groups can be identified and the information can be applied for store placement and even bundle program ideation. Overall, this method optimizes customer segmentation quality by affinity and preferences determined by historical transaction data.

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APPENDIX

1. The Fuzzy Match SAS Macro

```
%macro classify(dsnin,dsnout,item_cnt);
data &dsnout.;
%let perc1=0.17;
%let perc2=0.08;
%let perc3=0.35;
%let vblist=rt1,rt2,rt3,rt4,rt5,rt6,rt7,rt8;
%put &vblist.;
      set &dsnin.;
         length group $12;
      *single category;
      array rts {*} rt1-rt8;
*one category;
do i=1 to 8;
       select;*one category; when (
          rts(i)>&perc1.*2 and rts(i)>(largest(2,&vblist.)+&perc2.))
group=cat('grp',i);otherwise;end;
       do j=i+1 to 8;
               select; *two category; when (
             (abs(rts(i)-rts(j))<=&perc2. and
min(rts(i),rts(j))>largest(3,&vblist.)) or
                        (min(rts(i),rts(j))>largest(2,&vblist.)>0 and
min(rts(i),rts(j))>largest(3,&vblist.)=0 and abs(rts(i)-
rts(j))<=&perc3.*0.5)
             ) group=cat('grp',i,j);otherwise;end;
               do k=j+1 to 8;
                       select; *three category; when (
                (abs(rts(i)-rts(j))<=&perc2. and abs(rts(i)-
rts(k))<=&perc2. and abs(rts(j)-rts(k))<=&perc2. and

min(rts(i),rts(j),rts(k))>largest(4,&vblist.)) or

(min(rts(i),rts(j),rts(k))>largest(4,&vblist.)=0 and abs(rts(i)-
rts(j))<=&perc3.*0.33 and abs(rts(j)-rts(k))<=&perc3.*0.33 and
abs(rts(i)-rts(k))<=&perc3.*0.33)
                 ) group=cat('grp',i,j,k);otherwise;end;
                       do l=k+1 to 8;
                               select; *four category; when (
                               (abs(rts(i)-rts(j))<=&perc2. and
abs(rts(i)-rts(k))<=&perc2. and abs(rts(i)-rts(l))<=&perc2. and
                                        abs(rts(j)-rts(k))<=&perc2. and
abs(rts(j)-rts(l))<=&perc2. and
                                        abs(rts(k)-rts(l))<=&perc2. and

min(rts(i),rts(j),rts(k),rts(l))>largest(5,&vblist.) ) or

(min(rts(i),rts(j),rts(k),rts(l))>largest(5,&vblist.)=0 and abs(rts(i)-
rts(j))<=&perc3.*0.25 and abs(rts(j)-rts(k))<=&perc3.*0.25 and
abs(rts(k)-rts(l))<=&perc3.*0.25 and abs(rts(i)-rts(l))<=&perc3.*0.25)
                    ) group=cat('grp',i,j,k,l);otherwise;end;
                 do m=l+1 to 8;
                               *five category;
                               select; when (
                          (abs(rts(i)-rts(j))<=&perc2. and abs(rts(i)-
rts(k))<=&perc2. and abs(rts(i)-rts(l))<=&perc2. and abs(rts(i)-
rts(m))<=&perc2. and
                                                 abs(rts(j)-
rts(k))<=&perc2. and abs(rts(j)-rts(l))<=&perc2. and abs(rts(j)-
rts(m))<=&perc2. and
                                                 abs(rts(k)-
rts(l))<=&perc2. and abs(rts(k)-rts(m))<=&perc2. and
                                                 abs(rts(l)-
rts(m))<=&perc2. and

min(rts(i),rts(j),rts(k),rts(l),rts(m))>largest(6,&vblist.) ) or

(min(rts(i),rts(j),rts(k),rts(l),rts(m))>largest(6,&vblist.)=0 and
abs(rts(i)-rts(j))<=&perc3.*0.20 and abs(rts(j)-rts(k))<=&perc3.*0.20
and abs(rts(k)-rts(l))<=&perc3.*0.20 and abs(rts(l)-
rts(m))<=&perc3.*0.20) and abs(rts(i)-rts(m))<=&perc3.*0.20)
                          group=cat('grp',i,j,k,l,m);otherwise;end;
                                       do n=m+1 to 8;
                                       *six category;
                                       select; when (
                               (abs(rts(i)-rts(j))<=&perc2. and
abs(rts(i)-rts(k))<=&perc2. and abs(rts(i)-rts(l))<=&perc2. and
abs(rts(i)-rts(m))<=&perc2. and abs(rts(i)-rts(n))<=&perc2. and
                                                        abs(rts(j)-
rts(k))<=&perc2. and abs(rts(j)-rts(l))<=&perc2. and abs(rts(j)-
rts(m))<=&perc2. and abs(rts(j)-rts(n))<=&perc2. and
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                                                        abs(rts(k)-
rts(l))<=&perc2. and abs(rts(k)-rts(m))<=&perc2. and abs(rts(k)-
rts(n))<=&perc2. and
                                                        abs(rts(l)-
rts(m))<=&perc2. and abs(rts(l)-rts(n))<=&perc2. and
                                                        abs(rts(m)-
rts(n))<=&perc2. and

min(rts(i),rts(j),rts(k),rts(l),rts(m),rts(n))>largest(7,&vblist.) ) or

(min(rts(i),rts(j),rts(k),rts(l),rts(m),rts(n))>largest(7,&vblist.)=0
and abs(rts(i)-rts(j))<=&perc3.*0.17 and abs(rts(j)-
rts(k))<=&perc3.*0.17 and abs(rts(k)-rts(l))<=&perc3.*0.17 and
abs(rts(l)-rts(m))<=&perc3.*0.17 and abs(rts(m)-rts(n))<=&perc3.*0.17
and abs(rts(i)-rts(n))<=&perc3.*0.17)
                             )
group=cat('grp',i,j,k,l,m,n);otherwise;end;
                          do o=n+1 to 8;
                                             *seven category;
                                                       select; when (
                              (abs(rts(i)-rts(j))<=&perc2. and
abs(rts(i)-rts(k))<=&perc2. and abs(rts(i)-rts(l))<=&perc2. and
abs(rts(i)-rts(m))<=&perc2. and abs(rts(i)-rts(n))<=&perc2. and
abs(rts(i)-rts(o))<=&perc2. and
                                                               abs(rts(j)-
rts(k))<=&perc2. and abs(rts(j)-rts(l))<=&perc2. and abs(rts(j)-
rts(m))<=&perc2. and abs(rts(j)-rts(n))<=&perc2. and abs(rts(j)-
rts(o))<=&perc2. and
                                                               abs(rts(k)-
rts(l))<=&perc2. and abs(rts(k)-rts(m))<=&perc2. and abs(rts(k)-
rts(n))<=&perc2. and abs(rts(k)-rts(o))<=&perc2. and
                                                               abs(rts(l)-
rts(m))<=&perc2. and abs(rts(l)-rts(n))<=&perc2. and abs(rts(l)-
rts(o))<=&perc2. and
                                                               abs(rts(m)-
rts(n))<=&perc2. and abs(rts(m)-rts(o))<=&perc2. and
                                                               abs(rts(n)-
rts(o))<=&perc2. and

min(rts(i),rts(j),rts(k),rts(l),rts(m),rts(n),rts(o))>smallest(1,&vblist
.)) or

(min(rts(i),rts(j),rts(k),rts(l),rts(m),rts(n),rts(o))>smallest(1,&vblis
t.)=0 and abs(rts(i)-rts(j))<=&perc3.*0.14 and abs(rts(j)-
rts(k))<=&perc3.*0.14 and abs(rts(k)-rts(l))<=&perc3.*0.14 and
abs(rts(l)-rts(m))<=&perc3.*0.14 and abs(rts(m)-rts(n))<=&perc3.*0.14
and abs(rts(i)-rts(n))<=&perc3.*0.14)
                                 )
group=cat('grp',i,j,k,l,m,n,o);otherwise;end;
           *multi-category;
         *otherwise group='undefined';
                                             end;
                                      end;
                              end;
                      end;
              end;
      end;
end;
keep cust_key group &item_cnt. rt1-rt8;
data &dsnout.;
set &dsnout.;
run;
%mend classify;
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