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Research Article

Comparing Customer Segmentation With CLV Using Data Mining and Statistics: A Case Study

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Abstract

Customer segmentation is an essential activity for marketing executives. To penetrate to target market, they should analyze their clients very well. Undoubtfully customer lifetime value (CLV) is a compact calculation method to understand customer behaviors and their values. Various models are presented for CLV interpretation in literature. Two of them are statistical hypothesis tests and k-means. This case study provides the comparison these methods for a B2B IT company. The methodology can easily be used for similar purposes in other organizations. The successful clusters are obtained by k-means application.

Keywords: B2B Marketing, Customer Segmentation, Customer Lifetime Value, CLV, k-means

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1. Introduction

All organizations have limited resources while arranging marketing activities. Usually it is hard to know the optimal expenditures to maximize the sales and profitability. Therefore the academicians and practitioners study to obtain easy-to-use frameworks and models to guide for budgeting marketing costs. The customer needs and requests have become crucial with the start of customer centric marketing concept since 1960s (Kotler, 2002). One of the main goals of this marketing concept is to present products in conformance with the quality vision and statements of your target market audience (Aksoy, Keiningham and Bejou, 2008). In different words, the firms should maximize customer value (Baş, Tolon and Aktepe 2015) with the product dimensions of the service, price and placement. Customer retention is as important as customer acquisition. Loyal clients tend to more profitable purchases than new ones (Mani et al., 1999). The satisfied and long-life clients increase brand value. Their 'word

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of mouth' activities provide to expand market share. In fact, customer lifetime value (CLV) has been a popular research topic for 30 years. It is a financial measurement of current customers' profits for the organization. Lifetime value is a net present value of future purchases of the customer through entire relationship with the firm. The marketing managers and other decision makers can order their clients with applying CLV analysis. Several science people have been performed CLV focused researches to generate straightforward models to apply in industry (Cox, 1972; Rosset et al., 2003; Dwyer, 1989; Berger and Nasr, 1998; Hwang et al., 2004). The researches have been resulted with similar basic formulas to calculate this value for each customer. The academicians have also discovered Recency, Frequency and Monetary (RFM) analysis as an alternative to CLV for customer grouping requirements. There have been some studies applying RFM with data mining approaches for 20 years. The data set is obtained from each customer's acquisitions by acquiring the last purchase date, the time frame between purchases and the sale prices of them (Liu and Shih, 2005; Gupta et al., 2006; Paauwe et al., 2007; Khajvand et al., 2011). These data can easily be collected and exported from Customer Relationship Management (CRM) tools. The RFM based studies has been expanding in literature with the becoming widespread of CRM applications.

The marketing departments want to plan their sources for more willing customers to buy in a short time frame than others. They need solutions to filter these customers. Customer grouping or clustering analyses are commonly applied for this purpose. Some statistical tests (Venkatesan and Kumar, 2004; Yapraklı and Keser, 2008; Chen and Chen, 2014) and data mining (Liu and Shih, 2005; Haenlein et al., 2007; Glady et al., 2009) approaches are used to analyze CLV or RFM data for segmenting the customers. However, the good part of these researches is performed in consumer markets, mostly telecommunication and banking (Hwang et al., 2004; Haenlein et al., 2007; Kim et al., 2006; Kahreh et al., 2014). The few of them arranged for IT (information technologies) industry but again for B2C market (Zhang, Liang and Wang, 2016). The sample case studies for B2B IT sector are so rare that this limitation is mentioned in some articles (Berger et al., 2006; Kumar, 2010).

We present a case study to take into account this situation. Our study provides an overview of IT firm's products, which are selling to its B2B customers, and evaluate the results of different customer segmentation methods. In conclusion part, we compare and suggest the best practicable and confident approaches for the company to meet the B2B IT industry marketing requirements. The paper is organized as follows: first, the literature review; second, research methodology used in the study is described; third, discussion by comparing the obtained results from different methods; and finally, the conclusions, limitations and implications of the study are discussed.

2. Literature Review

Cox (1972) presented the framework of statistical analysis for years ago. His approach related with regression models and life tables was suitable for hazard detection for banking and telecommunications industries. And also, it is the beginning point of Mani et al. (1999)'s LTV (Lifetime Value) model. The classical statistical and neural network data mining approaches were described as the alternatives for customer lifetime estimation. Rosset et al. (2002) provided CLV models for the decision support of telecommunications marketing activities based upon Cox's study by using length of service and churn probability data. Dwyer (1989) provided the heuristics of two alternative LTV estimation models, named as customer retention model and customer migration model, with two case studies. They were consisted of only several basic parameters of each account records. Therefore, they were a good starting point for modern-day customer lifetime value concept, however they were not easily understandable and applicable in practice for industry.

Keane and Wang (1995) applied LTV analysis in practice for the marketing decisions of newspaper publishing business. The regional customer segments could be ranked according their LTVs. This study was the one of the first LTV applications for a business model. Gloy et al. (1997) performed a CLV (Customer Lifetime Value) application for rural petroleum industry. They analyzed the company's customer segments' CLVs on a product specific basis. This analysis was starting with the product mix representation of the company.

Berger and Nasr (1998) defined some straightforward formulas for CLV calculation of various situations. These formulas were well accepted by lots of practitioners and academicians, and have been used until today. Hoekstra and Huizingh (1999) provided a survey study to analyze the usage areas of the LTV concept, and reveal required fundamentals of LTV analysis for marketing purposes. They emphasized that the marketing managers were needed to have empirical models of LTV computations to perform them easily and cost-efficiently. Berger and Nasr (2001) presented a research regarding with a general approaches to apply for the allocation decisions of promotion budget in different market conditions. The main components of this approach were the managers' customer acquisition and retention rate expectation/estimations and its cornerstone was the use of decision calculus concept. Hwang et al. (2004) suggested a CLV model for customer segmentation. This model evaluated the customers from three perspectives: past contribution, potential value and churn rate based customer loyalty. The model was tried in a wireless telecommunication company. Berger et al. (2006) presented a conceptual framework of shareholder value. It was shown as the evolution of CLV. It was a theoretical study. Venkatesan and Kumar (2004) recommended a framework for measurement and usage of CLV. They calculated CLV with a formula that was composed of customers' income and cost items. They explained the generation of allocation rules to budget appropriate marketing resources after CLV calculation. They tested their theories by hypothesis tests, statistically. Yapraklı and Keser (2008) performed a field research for the factors, which affect the CLV in public practice accounting business, which is a B2B market. They analyzed 749 customers' data of 10 companies. The results show that the customers, which are located in town and are interactive longer time have higher CLV. Blattberg et al. (2009) gave four empirical generalizations, which have positive affects on CLV in their literature review. They provided suggestive finding for the firms to increase CLV in their qualitative study. Benoit and Poel (2009) suggested quantile regression rather than linear regression for CLV segmentation to manage customer portfolio. They performed their study with demographical customer, CLV, recency and frequency variables. Çalhan et al. (2012) explained CLV, customer equity and customer value in their conceptual study. He recommended analyzing CLV in different industries with primary datasets for future work. Kumar (2010) showed the CLV usage for marketing communication with a new framework. He segmented the customers in 4 groups according to their CLVs. The B2B and B2C companies can determine their marketing and communication channel and activities, which are the best fitted with the related customer type. Chen and Chen (2014) presented the relationships of brand image, satisfaction and CLV in education industry. They were positive impact by seen a statistical hypothesis test analysis using SPSS and AMOS. The study performed by the parameter values obtained by a survey of these three dimensions. Kahreh (2014) provided a case study to segment banking customers based on CLV formula. They compared 4-year customer and average CLV data of 6 customer groups.

Liu and Shih (2005) grouped customers into 8 segments by using weighted normalized RFM data for recommendation systems. They made correlation analysis by determining weights of RFM, and k-means analysis for clustering. Therefore, it was a hybrid analysis model, which contained statistical and data mining analyses. The precision, recall and F1 metric were used for comparison of weighted RFM, k-NN, CF and non-clustering methods. They stated that the suggested methodologies had been given better result for loyal customers. They suggested a new framework for recommendation systems that were used all of these methods and additionally with association rules and correlation. Kim et al. (2006) provided a case study related on a wireless telecommunication company. They suggested a framework for customer segmentation by using different CRM parameters to mine low loyal customers. The CLV segmentation gave some decision rules of low level loyalty with decision tree method. Gupta et al. (2006) presented a study of the explanations of current models and the perspectives for future. They stated that CLV model usage was resulted with higher success rates than RFM models. They did not recommend Pareto/NBD model for contractual business or noncontractual but with fixed events business. They recommended covariation models for B2B applications that these analyses were frequently performed in companies, which were fulfilling cross-selling and up-selling. They defended that computer science models (data mining methods) were known little for now, but it was necessary to search for future.

Haenlein et al. (2007) applied machine learning regression model CART in a retail banking context. They segmented CLV based on their several demographical customer metrics. They obtained 22 segments with a regression tree and they converted transition matrix for age parameter, which is an output of markov chain analysis. The CART with markov chain model was successful, because it did not require any new data for banks and it was easy to use. Therefore, this model can be used for other industries, but the transition matrix has some limited points related with assumptions of customer behaviors. Paauwe et al. (2007) researched rich data of the customers in an e-commerce Internet retailer for CLV analysis. They used decision tree (CART) and markov chain method together (named DTMC) like Haenlein et al. But there is a difference, they analyzed RFM data rather than customer based banking parameters. They obtained 5 segments on the tree and markov matrices for different scenarios. At the end they generated transitions probabilities for 7 different customer states. These results provide to estimate the perspective of the customer behavior. It means that this analysis is giving a chance to the marketers to change customer behavior in a positive manner. Glady et al. (2009) performed churner/less loyal customer analysis with banking data. They applied Pareto/NBD, linear regression, decision tree, neural network, AdaCost and cost-sensitive tree methods. They gave the comparison of the results of these models. It was seen that Pareto/Dependent model, AdaCost and cost-sensitive tree had given the best solution with the parameters, the number of customer transactions and the profit. They indicated that the socio demographic dependency and cross-selling effects could be studied for future work. Yılmaz and Büyüklü (2009) performed a study to find the best data mining method to analyze 73.449 customers' shopping data by using Clementine tool in her thesis study. The logistic regression method was the best one for their CLV analysis. Khajvand et al. (2011) performed a case study based on CRISP methodology to segment the customers of a health and beauty company which had being produced over 100 products. They applied k-means clustering to RFM data with 7000 CRM records. They obtained 4 clusters which have different average CLVs.

Chan et al. (2010) gave the value creation process of customers and the firm. He recommended markov chain model for CLV calculation by using iThink tool. This tool uses several brand and user experience data. Cheng et al. (2012) researched CLV computation with stepwise model. First, they used regression analysis to find the factor(s), which provided higher CLV. Second, they predicted churn probability and average service time by using decision tree and neural network. Finally, they calculated CLV by markov chain analysis. The customer behavior approach was only for one variable in markov chain analysis. The authors suggest Petrinet or system dynamic simulations model for analysis with multiple variables for future work. Clempner and Poznyak (2014) generated a new method named local-optimal policy approach for CLV computation. Its inspiration was from markov chain analysis and linear programming.

Gupta and Lehmann (2006) searched CLV and firm value relation for new generation marketing. They explained the approaches of CLV analysis based marketing activities and their benefits for firm valuation. They gave some examples from popular platform firms such as Netflix, Amazon, E-Bay etc. They stated the limitations of CLV analysis as ignorance of customer network and word-of-mouth. They mentioned that it had been hard to use for R&D critic businesses. Nenonen and Storbacka (2016) recommended shareholder value analysis with customer asset management beyond CLV for B2B industries. Because they argue that CLV is insufficient for these industries. They presented a conceptual framework that consisted of 11 ways to increase economic profit in a B2B company. After that they were performing three case studies with different three firms. Finally, they suggest portfolio or segment-level analysis rather than customer level analysis (CLV).

It is seen that few researches are available performed for B2B technology/engineering industry companies. There are different models and calculation methods for CLV. But Berger's formulas (Berger and Nasr, 1998) and RFM are the most popular ones that are still commonly used for customer segmentation. Also, markov chain probability model are popular in last decade, but it still has limitations to give sufficient information about customer behavior transitions.

3. Methodology

In our study we aim to solve a problem of a company that produces IT technologies for B2B market and has 150 employees. The company has over 30 products and its marketing department wants to segment their customers to vary their value propositions for their customer segments, which have higher lifetime value. The organization only has cost, discount and RFM data of their customers. It does not have a CRM to keep the customers' any other data, which can be variable for statistical regression tests or machine learning methods. Any product does not have any periodical purchase event chain, the purchases occur rare (in an average frequency more than 2 years) and totally random.

First of all, it was needed to define product mix like the study of Gloy et al. 1997. Because of the customer audience and target market are different of each product. The products are grouped into 5 groups according to their functional concepts as in the diagram below.

Table 1. Product Mix of Company

Company Product Mix				
Category A	**Category B**	**Category C**	**Category D**	**Category E**
Product Family A.1	Product Family B.1	Product Family C.1	Product Family D.1	Product Family E.1
Product Family A.2	Product Family B.2	Product Family C.2	Product Family D.2	Product Family E.2
Product Family A.3	Product Family B.3		Product Family D.3	Product Family E.3
Product Family A.4	Product Family B.4			Product Family E.4
Product Family A.5	Product Family B.5			
Product Family A.6	Product Family B.6			
Product Family A.7	Product Family B.7			
Product Family A.8	Product Family B.8			
Product Family A.9	Product Family B.9			
	Product Family B.10			

Each product category in Table 1 has product families varying according to the target customers. Current customer numbers are so low for some product families. Therefore, these products are removed from our study and we focused on the product family B.5, which can be purchased more than one in a year.

There were 523 records from 212 customers. The 76 of these customers bought more than one time from the company. Therefore, we included only those 76 customers in the segmentation process. The customer purchase data were kept for 3 years from the beginning of related product's lifecycle, the first sale in the Turkish market. In this market there is not a chance to sell the same product to same customer's same office more than one without any governmental necessity, but you can try to make up-sells and cross-sells. These strategies were required to be strong and competitive in the market by the product's and market's nature. Thus, the cross-sell and up-sell transaction data were included in the analysis.

The CLV of each customer was calculated by Berger et al. (1998)'s formula in Figure 1. Then, we clustered the customers by two ways, statistical data resolution and k-means machine learning.

Figure 1. CLV Formula (Berger et al., 1998)

Case 2b. In this case, sales/transactions occur less frequently than once a year. In cases of durables, replacements often occur only every few years. Let q be the length of a cycle or the number of years between two consecutive sales. For example, if a car is leased every 3 years, then $q = 3$. Then,

$$CLV = \{GC' * \sum_{i=0}^{n/q} [(r')^i/(1+d)^{iq}]\} - \{M' * \sum_{i=1}^{n} [(r')^{(i-1)/q}/(1+d)^{i-0.5}]\} \quad (3)$$

We assume in this case that promotion costs are approximated to occur at the middle of each year of the cycle, and again, sales and the corresponding cost of sales occur once per purchase cycle, with the first transaction taking place at the time of the acquisition/determination of CLV. Cash flows are illustrated as follows (note that the number of purchase cycles equals n/q):

```
Now
I—*—x—*—x . . .
  Year 1  Year 2
  x—*—I—*—x—*—x . . . x—*—I . . .
    Year q  Year q +1
                     I—*—x—*—x . . . x—*—I
                                        Year n
```

where the I, the beginning of purchase cycles, denotes cash flows (both inflows and outflows) pertaining to sales transactions, i.e., GC. On the other hand, the * shows the approximate timing of promotional expenses (assumed to be the middle of each year). One may relax the assumptions concerning the timing of cash flows without major changes in the model. The value of r' pertains to a full cycle.

3.1. Statistical Data Resolution

CLV based customer data were diverged to three groups in Table 2 by analyzing descriptive statistics after outlier values detection and remove. Excel XLSTAT plug-in's data resolution analysis was used for this purpose.

Table 2. CLVs Based Segmentation by Descriptive Statistics

CLV Based Groups			CLV Change Rate Based Groups		
Group 1 (Cold Customer)	3624,716904	21526,77973	**Group 1 (Cold Customer)**	-46%	-9%
Group 2 (Warm Customer)	21527,77973	39429,84255	**Group 2 (Warm Customer)**	-8%	30%
Group 3 (Hot Customer)	39430,84255	57332,90537	**Group 3 (Hot Customer)**	-31%	68%

The hypothesis below was tested with Kruskall Wallis to understand that these groups were statistically significant.

H_0: The groups are from same population.

H_1: The groups are not from same population.

3.2. K-means machine learning

CLV based customer data were clustered in Table 4 by Excel XLSTAT plug-in's k-means machine learning analysis.

4. Results

4.1. Statistical Data Resolution

The CLV based groups were not from same population with 95% confidence, we rejected H_0 according to Table 3. It means that the groups are meaningful as customer segments.

Table 3. Kruskall Wallis Hypothesis Test Result

Summary statistics:

Variable	Observations	Obs. with Missing Data	Obs. without Missing Data	Min.	Max.	Mean	Std. Deviation
Var1	74	0	74	3624,717	57330,905	14640,608	12469,718

Summary statistics (Subsamples):

Variable	Categories	Counts	Frequencies	%
Groups1	WARM	11	11	14,865
	HOT	1	1	1,351
	COLD	62	62	83,784

Summary statistics (Data / Subsamples):

Variable	Observations	Obs. with missing data	Obs. without missing data	Min.	Max.	Mean	Std. Deviation
Var1 | WARM	11	0	11	23420,814	57330,905	39881,680	11243,305
Var1 | HOT	1	0	1	39577,170	39577,170	39577,170	0,000
Var1 | COLD	62	0	62	3624,717	21497,574	9760,151	4008,400

Kruskal-Wallis test / Two-tailed test (Var1):

K (Observed value)	29,788
K (Critical value)	5,991
DF	2
p-value (one-tailed)	< 0,0001
alpha	0,05

4.2. K-means machine learning

It was seen that the difference between class was 99,15% and it within class was 0,85%. These results in Table 5 showed that we had perfect clusters, which were heterogeneous in a high rate.

Table 4. CLVs Based Segmentation with K-Means

Result by Class:

Class	1	2	3	4	5
Objects	10	38	10	17	1
Sum of Weights	10	38	10	17	1
Whithin-class Variance	86610974,727	3267474,868	12865284,651	2209319,557	0,000
Minimum Distance to Centroid	3087,607	119,697	185,542	26,687	0,000
Avarage Distance to Centroid	7881,503	1169,605	2543,275	1082,198	0,000
Maximum Distance to Centroid	14666,129	8227,126	8008,861	3576,622	0,000
	Customer 1	Customer 2	Customer 8	Customer 11	Customer 39
	Customer 9	Customer 3	Customer 16	Customer 13	
	Customer 31	Customer 4	Customer 19	Customer 17	
	Customer 35	Customer 5	Customer 25	Customer 22	
	Customer 38	Customer 6	Customer 27	Customer 26	
	Customer 40	Customer 7	Customer 29	Customer 28	
	Customer 46	Customer 10	Customer 32	Customer 30	
	Customer 47	Customer 12	Customer 44	Customer 33	
	Customer 61	Customer 14	Customer 49	Customer 41	
	Customer 68	Customer 15	Customer 66	Customer 42	
		Customer 18		Customer 43	
		Customer 20		Customer 51	
		Customer 21		Customer 52	
		Customer 23		Customer 56	
		Customer 24		Customer 58	
		Customer 34		Customer 65	
		Customer 36		Customer 76	
		Customer 37			
		Customer 45			
		Customer 48			
		Customer 50			
		Customer 53			
		Customer 54			
		Customer 55			
		Customer 57			
		Customer 59			
		Customer 60			
		Customer 62			
		Customer 63			
		Customer 64			
		Customer 67			
		Customer 69			
		Customer 70			
		Customer 71			
		Customer 72			
		Customer 73			
		Customer 74			
		Customer 75			

Table 5. K-Means Performance Parameters

	Absolute	Percent
Within-class	14810310,104	0,85%
Between-class	1735478546,204	99,15%
Total	1750288856,309	100,00%

5. Discussion and Conclusion

Gloy et al. (1997) determined on the product families that would be focused to CLV analysis, after obtaining product mix of the company. Likewise, we focused on the product families of which purchase order transaction data were sufficient in our study.

Both statistical and data mining methods were applied for CLV analysis in literature. The best-known and frequently used ones of these methods are the CLV calculation formulas of Berger and Nasr (1998), RFM (recency-frequency-monetary) data used ones, statistical hypothesis tests, Pareto analysis, k-means, CART decision tree machine learning approaches and markov chain matrix. Therefore, we preferred to apply Berger and Nasr's (1998) CLV formula, statistical hypothesis test and k-means in our model.

Mani et al. (1999) analyzed CLV with regression analysis and neural networks methods. And they mentioned that neural networks provided more detailed information with their comparison. Statistical data grouping, Kruskall-Wallis hypothesis test and k-means data mining methods are applied in our paper. Mani et al. (1999) explained that the result of the data mining k-means clustering method was more successful than the result of statistical data resolution and hypothesis test, similar to our study.

Hwang et al. (2004) analyzed churn for disloyal customers. Kim et al. (2006) performed a similar analysis by applying decision tree. It is seen that churn and LOS (length of service) models are usually applied in B2C service provider organizations such as telecommunication and banking, especially. However, these models are not suitable for B2B markets, which make production.

Liu and Shih (2005) used k-means clustering data mining method in CLV based models to recommend products to their customers by their websites such as Amazon. Khajvand et al. (2011) applied k-means in their CLV models developed to define marketing strategies based on each customer segment.

Yapraklı and Keser (2008), Chen and Chen (2014), and Zhang et al. (2016) tested hypotheses for CLV analyses. Therefore, we compare the results of hypothesis test and k-means machine learning method in our study to understand the more applicable model for CLV analysis.

Benoit and Poel (2009) performed regression analysis with available large amount of data from finance sector for their statistical regression models. In our study, we could not use regression analysis because we had only customer purchase order transaction data, not any other variable data such as gender, age, credit card numbers, etc.

The organizations want to diverge their customers in groups to allocate them optimal marketing activity resources. Customer lifetime value is a commonly used measure to achieve an accurate segmentation. There are lots of CLV based segmentation models and frameworks for practitioners in literature. However, little of them are adaptable for B2B industries. The main reason is relatively limited number of customers in comparison with consumer markets. In our case study, the IT company has been producing more than 30 different model products. It was meaningful to evaluate and segment the related customers among related product families. Therefore, the product mix table defined for the first task. The product family that has sufficient transaction record data was chosen for the segmentation analysis. The customers of the chosen product family were included in the CLV analysis. Incident customer based CLV was calculated. For statistical analysis, Excel's data resolution method was used and they were categorized in three groups. The hypothesis test was performed and tested the confidence of our grouping. For data mining analysis, k-means clustering method was used and they were categorized in five groups/clusters. And clusters' performance was viewed. It is seen that data mining clustering is more successful than statistical method. Because you do not need outlier analysis, you can include all data to analysis and you can have homogeneous segments easily. To use CLV analysis for your organization's marketing purposes, first you should calculate it for each of your customers. There are different calculation approaches, but we applied an approved and validated one, which had been used for years. It was Berger's formulation. This formula is suitable for equal or less than one sell within a year. Before this calculation, your previous step should be specifying your corporations' market segments by documenting product mix. You should evaluate your each market segments among them one by one. To make it easy, you should have sufficient data in the market segments for analyses. CRM data can help you. We can use two different methods for CLV analysis based customer segmentation. They are statistical data resolution and hypothesis tests versus machine learning k-means clustering. Statistical analysis show us the customer segments and their significancy in a roughly manner. For a more granular segmentation we need data mining. CLV measurement, analysis and customer segmentation provide us an easier decision making basics while we dedicate our resources for sales. We can give our priority to hot customers to maximize our sales. We used Excel XSTAT for our analyses. Since, we wanted to use a common tool, access of which is easy for our analyses. We did not have various data of different case studies. Therefore our data is not sufficient to generate a mathematical model for the CLV calculation and clustering. Additional case studies can be arranged to create a framework for future work.

The studies performed in last years show that portfolio/segment level analyses are more useful than customer level ones. This is because they can be good choice to evaluate the companies' valuation performance. In our research we make an induction approach, obtaining segments by analyzing customer based CLV. To include other customer variables such as sociodemographic attributes is another future work. Thus, we can detect association rules and correlations between these factors and CLV in each segment.

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