Cloud Computing Market Segmentation

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Abstract: The topics of cloud pricing models and resources management have been receiving enormous attention recently. However, very few studies have considered the importance of cloud market segmentation. Moreover, there is no a better, practical and quantifiable solution for a cloud service providers (CSP) to segment cloud market. We propose a novel solution that combines both hierarchical clustering and time series forecasting on the basis of the classical theory of market segmentation. In comparison with some traditional approaches, such as nested, analytic, Delphi, and strategy-based approaches, our method is much more effective, flexible, measurable and practical for CSPs to implement their cloud market strategies by rolling out different pricing models. Our tested results and empirical analysis show that our solution can efficiently segment cloud markets and also predict the market demands. Our primary goal is to offer a new solution so that CSPs can tail its limited cloud resources for its targeted market or cloud customers.

1 INTRODUCTION

The issue of cloud pricing models, revenue, and resources management (cloud economics) is one of the most critical topics in the cloud computing (Buyya, 2002; Wang, 2012) because it does not only become increasingly important for many CSPs to implement their cloud business strategy but also allow them to innovate their business processes and models(Weinman, 2012; Berman, 2012). However, previous studies only focus on finding an optimal solution from a pure CSP perspective (internal rationality) and often ignore market impacts (external rationality). In this study, we concentrate on the problem of cloud market segmentation, especially for business to business (B2B) market by taking into account both CSP's resources and market factors(McDonald, 2012).

The B2B cloud market segmentation is believed to be a complex problem for many CSPs (Shapiro, 1984). It is challenging because it involves many disciplines such as managerial decision, market theory, cloud computing, and microeconomics. Moreover, it is often very subjective and arbitrarily.

We restrict in our current study to B2B because the B2B market is more significant than business to consumers (B2C) and consumer to consumer (C2C) according to US Census Bureau. Statista reported (global-ecommerce, 2017) the size of the Global B2B e-commerce market ($7.7 Trillion) is about 235% larger than B2C ($2.3 Trillion) in 2017. The cloud is a type of e-commerce as it shares the characteristic of online access (NIST, 2011). Although the size of the B2B market is considerable large and it is crucial for CSP's business strategy and pricing, as of now to the best our knowledge, no work has been done on this topic. Yet, many CSPs urgently need to understand how to serve their targeted customers well for the limited resources. Hence, our goal is to find a better solution to segment cloud market.

To motivate the problem, we consider the following scenario. Suppose a local Internet Service Provider (ISP) has decided to expand its hosting business into the B2B cloud market with a limited investment budget. The CEO asks the management team to formulate a business strategy with different pricing models to grow both the cloud business revenue and profit. One of the most straightforward solutions is the "one-size fits all" or uniform pricing. It means that the ISP can set up a markup price for its desired profit margin while the customers have to decide either "take or leave it" regardless of what the customer's needs are. The subsequent question is

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would this business strategy work. If not, what is an alternative solution that can be pursued?

An intuitive answer could be to deliver the cloud services or product with personalized pricing to suit each customer's need. However, it is impracticable for a CSP to offer personalized service and price because of the limited budget or resources. Fortunately, many individual customers have similar requirements, and their usage patterns may have some common characteristics, such as a size of computing (CPUs) and memory. It means that we can group these customers' demands. This idea leads to the group pricing, which is also called as market segmentation. The original concept of the market segmentation was introduced by (Smith, 1956). He defined the term of the segmentation at a strategic level, which "is based upon developments on the demand side of the market and represents a rational and more precise adjustment of product and marketing effort to consumer or user requirements." He argued that good market segmentation will lead to a successful business strategy.

As a matter of fact, the uniform pricing and the personalized pricing are two extreme ends of the group pricing (Figure.1). Belleflamme et al. (Belleflamme, 2015) stated: "the better the information about consumers, the finer the partition of the consumers into groups and the larger the possibilities for firms to extract consumer surplus."

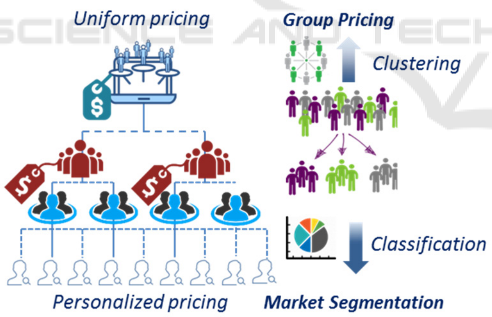

Figure 1: Uniform, Group, and Personalized Pricing.

Therefore, the goal of the segmentation process is to extract the customer information, such as usage patterns or behaviors and then to develop various pricing models and service configurations to meet their needs. In fact, (Yankelovich, 2006) argued the good market segmentation should meet the following criteria:

1. Align with the company's strategy;
2. Specify where the revenue and profit come from;
3. Articulate cloud customers' business values, attitudes, and beliefs, which are closely associated with the product or service (such as cloud instance) offerings;
4. Focus on actual business customers' behaviors;
5. Make sense to the firm's senior executive team and the broad;
6. Flexible and quickly accommodate or anticipate changes in markets or consumer behaviors.

Based on these criteria, we develop a novel solution that allows CSPs to identify the B2B cloud market segment quickly. In comparison with other traditional methods, such as analytical(Wind, 1978), strategy-based(Verhallen,1998), nested (Shapiro, 1984), survey, and Delphi methods(Best, 1974), it is much more tangible, flexible, agile, and cost-effective for a CSP to roll out different cloud pricing models for its cloud business strategy. It also enables CSP to respond to the ever-changing environment of the cloud market rapidly. The inputs and outputs of the process are illustrated in Figure 2.

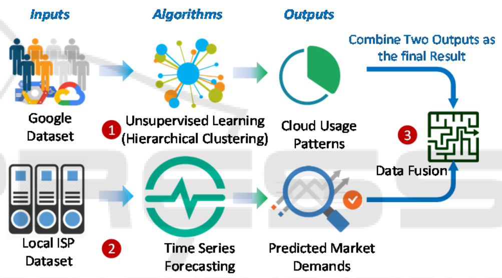

Figure 2: The Solution Process of Cloud Market Segmentation.

The solution is summarized in three steps: 1) We use hierarchical clustering to segment cloud market; 2) We apply time series forecasting (TS) for the sales volume prediction; 3) We combine both results for each market segment. We use both Google's and the local hosting service datasets in our analysis to demonstrate our methodology. The final results are expected in Table 1.

Table 1: The Expected Results of Segmentation.

Cloud Market Segmentation	Segment1		Segment k	Total
Demand (Sales Quantity)	q_1	...	q_k	$\sum_{i=1}^{k} q_i = Q_T$
The proportion of Each Segment	$p_1 = q_1/Q_T$	...	$p_k = q_k/Q_T$	$\sum_{i=1}^{k} p_1 = 1$
Market Segment's Charectretsics	Memory Pattern	...	Memory, CPU, Network	k

By doing so, we make three contributions:

1. We demonstrate how to use hierarchical clustering (HC) algorithms to identify the

optimal number of cloud market segments and extract (or assess) various cloud usage patterns.
2. We use TS forecasting to predict the local B2B market demand for virtual machines (VMs).
3. Finally, we combine both results into the final cloud market segmentation table so that a local CSP can leverage it further to build different cloud price models for its targeted market.

The rest of the paper is organized as follows, In Section 2 we provide a brief literature review of market segmentation. In Section 3 we describe the details of our solution of market segmentation, such as fundamental principles of the experimental methods, and some assumptions that we made. In Section 4, we illustrate how to use the HC to segment cloud market and find the appropriate number of segments. In Section 5, we present how to forecast the quantity of VMs demands and then combine both results. In Section 6, we analyze and discuss our empirical results. Section 7 provides the summary of this paper with conclusions.

2 RELATED WORK

Since (Smith, 1956) first cast the term of market segment, the topic has been studied in great detail in term of its theory, methodology (Wedel, 1998), concept, foundation, and process (McDonald, 2012). Along with the consumer market, the B2B market theory (Wind, 1974) has also been developed due to its growing momentum and substantial market size and values. Due to the targeted value proposition of the B2B cloud market, namely product, price, place, and promotion (or Kotler's four Ps), the related work consists of theory, analytic approach, and cloud pricing in term of the market segmentation.

According to (Wedel, 1998), the essence of the market segmentation is "a theoretical marketing concept involving artificial groupings of consumers constructed to help managers design and target their strategies." In practice, it is an iterative process to assign a set of variables (e.g., four Ps) to many potential customers that help a firm to form homogenous groups. Under the Wedel's concept, (Thomas, 2012) gave a further clarification of the B2B market segmentation, which is "a dynamic business decision process driven by an (economic) theory of how market functions." In practice, it is a set of decision process and activities that can be divided into two different approaches: One is the top-down approach, which is the process of splitting customers into different segments. Another is bottom-up one, which is to agglomerate each customer into different groups (Claycamp, 2000). claimed that although the top-down approach is a simple and appealing, it is very challenging to implement because the splitting process is mainly to drive the potential value of customer surplus. Claycamp exhibited that market segmentation is ultimately a bottom-up process of aggregation in theory. However, the bottom-up approach is also facing challenges in practice because some parameters are very hard to estimate, such as marginal response or managerial requirements (Laughlin, 1991). One of the solutions is to propose some controllable marketing variables in identifying marketing stimuli, which is down to only one "P" (Promotion). It is like an analytic approach.

Ralph (Oliva, 2012), indicated the B2B market "segmentation is an analytic discovery process for dividing a large group of customers or prospects into smaller groups." Similarly, Seufert (Freemium, 2014) presented an analytic approach to segment user groups for the freemium pricing model. Their approach focused on the core value of the business. If we compare the core value with the hedonic value analysis (Pakes, 2003), we can draw an analogy between Irwin Gross' core value, cost, and prices with the hedonic function (Equation 1).

$$p_j = \sum_{l=0}^{L} p_l + mc_j + \frac{Q_j}{|\partial Q_j/\partial p|} \tag{1}$$

where p_j is the price of the cloud VM instance "j." mc_j is the marginal cost, Q_j is a quantity, $|\partial Q_j/\partial p|$ is the partial derivative of the quantity taken in term of a price, and $Q_j / |\partial Q_j/\partial p|$ is a markup price, and p_l is the CSP's purchasing price from other vendors. Here, a potential value lost is defined by consumer surplus (CS_i) (Belleflamme, 2015). The core value is the economic driving force (Figure. 3)

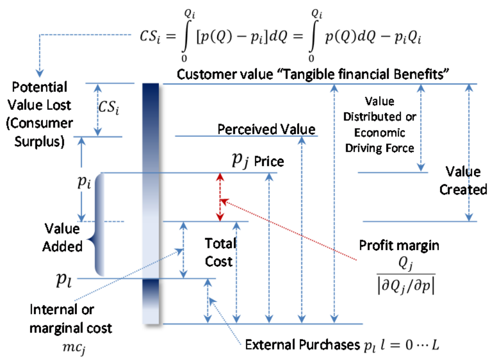

Figure 3: Analytic Method of The B2B Market Segmentation.

However, Richard (Plank, 1985) criticized the analytic approaches because many methods are complicated to translate their analytic results into a business strategy. In order to improve the analytic approach, Theo (Verhallen, 1998). proposed a strategy-based approach, which is to identify unobservable characteristics (e.g., firm's goals, objectives, strategy types, and long-term plans) in contrast to observable traits (business size, location, and four Ps). Furthermore, in relation to different input variables, Benson (Shapiro, 1984) proposed the nested- approach, which is to nest from demographics, operating, purchasing, and situational variables to personal characteristics but the author indicated their approach could not be generalized. Alternatively, (Best, 1974) offered an expert solution that can become a prior probability of input variables for market segmentation process.

In contrast to the above methods, Balakrishna's (Balakrishna, 1980) focuses on a solution based on how to better use the industrial market concept for the B2B market segmentation. It is more like a generalized solution for the B2B market. Although these solutions are very persuasive, the main issue remains unsolved, which these solutions are unquantifiable for CSPs to implement their cloud business strategy by rolling out different cloud price models. As a consequence, many recent studies directly focus on cloud pricing models for CSPs to maximize its revenue.

As early as in 2002, (Buyya, 2002) proposed economic models or pricing schemes to regulate the grid computing resources, which can be considered as one of the prototypes of cloud pricing model. (Javadi, 2011) developed a statistical model for Amazon Web Service (AWS) spot instance prices in public cloud environments. Although the model is valid, the spot instance is not desirable for the mainstream of B2B cloud resources because many B2B applications require the mission-critical cloud infrastructure to support its business.

Similarly, Hong (Xu, 2013) proposed the alpha-fair utility function to quantify the applications' needs for cloud users in term of cloud resource allocation. Although the study is beneficial for a theoretical exploration, the model assumptions require further consolidation because the alpha-fairness utility function is mainly applied to the issue of traffic congestion of communication networks (Hande, 2010) rather than cloud services. Practically, different cloud applications (such as web hosting, database, data storage, virtual desk infrastructure, and so forth) will have different requirements, which lead to different market segments. As respect to the word of segmentation, (Wang, 2012) investigate this problem from an aspect of segmenting cloud capacity, which is to formulate an optimal capacity segmentation strategy for revenue maximization to satisfy the random market demand.

Overall, we can see that there is a gap, which is how to find a quantifiable solution to segment the B2B cloud market so that CSPs can build various optimal price models for its targeted market or customers in connection with both internal costs and external market demand. Our solution provides the answer for this gap.

3 PREPARATION TESTS

As (Claycamp, 2000) stated in their theoretical study, the clustering analysis is one of the practical solutions for the market segmentation. However, there are many clustering methods of clustering methods, such as categorical (hard vs. soft), structure (flat vs. hierarchical), data type (model-based vs. cost-based), and regime methods (parametric vs. nonparametric). The question is which one is the right method for our problem.

A good strategy is to explore the datasets in our hands. The first dataset is Google's cloud trace (cluster-data, 2011) which consists of large cloud clusters for more than 12,500 VMs. It has six dimensions: timestamp, job ID, Task ID, and job type, normalized task cores, and normalized task memory. However, Google has obfuscated some information of the dataset, in which "certain values have been mapped onto a sorted series" for confidential reasons. Fortunately, the encryption schemes will not impact market segmentation because we are looking for underlying customer usage patterns.

The second dataset is collected by one of the leading Australia telco firms for its hosting business. The dataset has sales records of web servers for its business customers between 2003 and 2009. The idea of the first experiment is to estimate the number of cloud market segments and the proportion of each segment. The Google's dataset would unveil the cloud usage patterns. We assume that both global and local cloud customers have the same usage pattern in this case. The 2nd experiment is to forecast the local B2B market demand because the local B2B market demand is closely associated with a robust B2B relationship (Narayandas, 2005).

3.1 Proposed Method of Segmenting

On the base of the good criteria for segmenting market (Yankelovich, 2006) and the dimensions of Google's dataset, we propose HC method. The reasons are as follows:

1. We do not know the exact number of cloud market segments in advance.
2. Referring to the Claycamp's theory, it has to be an agglomerative process of fusion clustering, which is a bottom-up process of clustering.
3. Furthermore, it would be preferable to leverage HC because we can form a dendrogram (a tree diagram) that allows us to choose the dendrogram at any desired level. This analytic feature allows CSPs to segment the B2B market at any granularity level so that a CSP can explore opportunities of any niche market.

However, all methods have its disadvantages. One of the primary difficulties of HC is too sensitive to the number of clusters. One solution to solve this problem is to use Ward's algorithm to minimize the variance of Sum Square of Errors (SSE) by consideration of all possible methods. Our overall strategy of the 1st experiment is illustrated in Figure. 4. The essence of the clustering algorithms is to calculate dissimilarity that is measured by the Euclidean distance of data points. For the Ward's algorithm, the equations of SSE are as follows:

$$\Delta_{C_a \cup C_b} = SSE_{C_a \cup C_b} - (SSE_{C_a} + SSE_{C_b}) = \frac{n_a n_b}{n_a + n_b}(\mu_a + \mu_b)^2 \quad (2)$$

$$where\ SSE_{C_a} = \sum_{i=1}^{n_a}(a_i + \mu_a)^2,\ SSE_{C_b} = \sum_{i=1}^{n_b}(b_i + \mu_b)^2,$$

$$and\ SSE_{C_a \cup C_b} = \sum_{i=1}^{n_c = n_a + n_b}(c_i + \mu_c)^2 \quad (3)$$

where $\Delta_{C_a \cup C_b}$ is the cost function to combine two clusters C_a and C_b that have the number of observations n_a and n_b respectively. a_i, b_i, and c_i are the ith observations in the cluster C_a and C_b, and the merged cluster $C_a \cup C_b$. Likewise, μ_a, μ_b, and μ_c are the centroid of these clusters. To update the Euclidean distance, we can use Lance-Williams dissimilarity update formula (Murtagh, 2012).

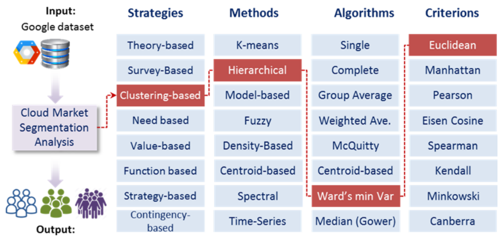

Figure 4: The Map of Hierarchical Clustering Method.

3.2 Proposed Method of Predicting

The idea of the second test is to predict or forecast the B2B market demand in the next 12 months so that we can build cloud infrastructure capacity to meet the local B2B cloud market demand. Several techniques can be applied for prediction, such as linear and multiple regression, random forest, decision tree, ANN, and time series forecast.

In this study, we adopt the TS forecast model to predict the total volume of VM sales. The reasons are. 1.) TS forecasting is simple. It would be easier to be presented. 2.) We can estimate each sales volume for every month or year so that it would be convenient for cloud capacity planning. 3.) The forecasting result will tell the confidence interval. 4.) It can be updated very quickly.

4 CLOUD MARKET SEGMENTS

We test the Google's dataset first and see whether the dataset has the meaningful patterns or not. This process is called "clustering tendency evaluation." The reason to check the clustering tendency of the data is that a hierarchical clustering method can impose patterns or clusters onto a randomly distributed dataset even if there are no such definable or extractable clusters within the dataset.

(Wang,2010) and Kotagiri (Lawson, 1990) did some studies regarding of clustering tendency assessment. There are many techniques available for cluster tendency evaluation. One of the methods is Hopkins statistic (Brain,1954) null hypothesis test. Hopkins' test can be expressed using the following equation:

$$H = \frac{\sum_{i=1}^{n} P_i^2}{\sum_{i=1}^{n} I_i^2 + \sum_{i=1}^{n} P_i^2} \quad (4)$$

where I_i square is the distance between an observation x_i and its nearest neighbor x_j (x_i, $x_j \in D$

= dataset). P_i square is the distance between a random y_i and its nearest neighbor y_j (y_i, $y_j \in D_r$ = random dataset). The null hypothesis test shows that if H value is equal or close to 0.5, the tested dataset D has no meaningful clusters so that we accept the null hypothesis. Otherwise, we reject the null hypothesis. Based on the above Hopkins' equation, we calculate the Hopkins' index. It is equal to 0.064, which is approaching zero. We also use R command "fviz_dist" (display dissimilarity matrix) to visualize the Google's dataset with a comparison of a randomly generated dataset (Figure 5, on the left)

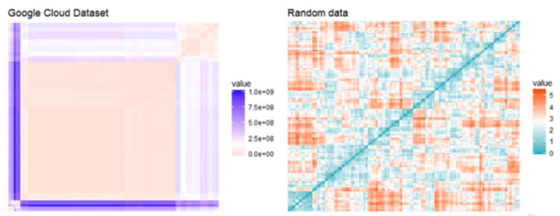

Figure 5: Assessing Clustering Tendency of Google's Dataset.

The pink color indicates I_i square = 0 and the purple color means I_i square = 1. In contrast, the right diagram of Figure5 shows that both values are randomly distributed across the dissimilarity matrix. Hopkins null hypothesis test result tells us Google's dataset has clustering tendency.

4.1 Extract Cloud Usage Patterns

For R system, the bottom-up and top-down is known as Agglomerative Nesting (or AGNES) and Divisive Analysis (or DIANA) respectively. The linkage algorithm is "Ward' because we want to minimize the SSE variance. If we temporarily assume the number of segments is four (McDonald,2012) suggested the number is between 5-10 and others suggestion is between 4 and 5(Thomas J. 2016)), we can plot out the dendrogram or segment (Figure. 6).

We can also cut the cluster dendrogram into seven segments by moving the vertical distance height around to height distance 10. Consequently, the cluster 1 and 4 are split further, and 2 and 3 remain the same (Figure.6). The number of clusters seems to be decided arbitrarily. Now, the issue is how we chose an optimal number of clusters, "k."

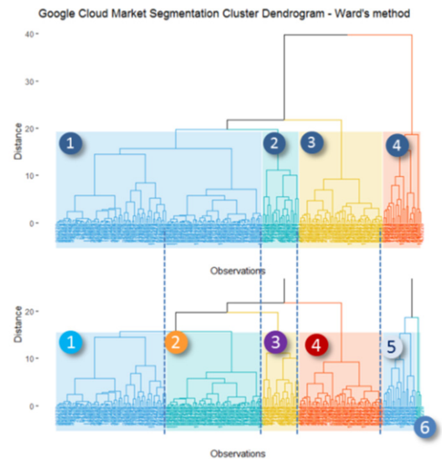

Figure 6:The Result of Cloud Market Segmentation.

4.2 Deciding Optimal Number

This is a challenging question. If the number is predetermined, we can adopt other algorithms to do the clustering, such as k-means. However, this number is unknown. Fortunately, many existing schemes can help us to estimate this number, such as Dark Block Extraction (DBE) (Wang, 2009), hierarchical, partitioning, direct, statistical testing, density mode seeking, clumping, grid-based clustering, etc. R has more than 30 methods or indices to decide this optimal number (Charrad, 2014) developed "NbClust" package to decide the number of clustering. Our analysis of Google data shows the optimal number "k" is four (Figure. 7).

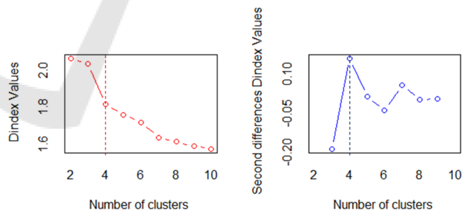

Figure 7: Optimal Number of Test Result by NbClust Package.

The index shown in Figure7 is the Dindex graphic to determine the optimal number of clusters. Dindex is to measure clustering gain on intra-cluster inertia, which is the degree of homogeneity between the data points in a cluster. The equation of Dindex can be presented as follows:

$$w(P^q) = \frac{1}{q}\sum_{k=1}^{q}\frac{1}{n_k}\sum_{x_i \in C_k} d(x_i, c_k) \qquad (5)$$

$$gain = w(P^{q-1}) - w(P^q) \quad (6)$$

where P^q is the "q" number of partitions by imposing "k" number of clusters, "d" is the distance and "c_k" is the center of a cluster, "n_k" is the number of data points in a cluster. "x_i" is any data point within a cluster. The clustering gain on intra-cluster inertia should be minimized. Ultimately, the Dindex is to measure "the degree of homogeneity of the data in a cluster." (Charrad, 2014)

5 DEMAND PREDICTION

Ralph (Oliva,2012) suggested any B2B market strategy has to focus on the object of Key Account Market (KAM). In this case, ISP has to predict own local cloud market demand so that ISP can achieve a realistic sales forecast. This target can be either arbitrarily or rational. If an executive team requires a making- sense sales target, the forecast demand has to come from a local dataset.

For the local ISP firm, the natural extension of the cloud business is its existing web hosting business. We can leverage the previous sales records to estimate the cloud market demand. Our second dataset has 3,192 data points (Windows servers only) over 67 months (between Aug-2003 and Feb-2009). We plot these data points monthly (Figure.8).

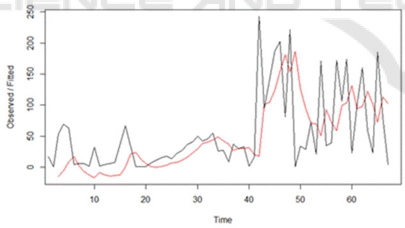

Figure 8: Local Hosting ServiceMonthly Dataset.

The red line in Figure 8 is to smooth the observation data points. As we can see it, the sales volume is quite low in the first 40 months but the movement of the next 27 months was very volatile.

There are many different methods to estimate or predict the future sales volume, such as logistic regression, support vector machine (SVM), decision trees or Classification and Regression Tree (CART), random forests, and time series (TS). In comparison, TS (Shumway, 2011) would be a better tool to estimate the sales volume because the dataset is collected in a time series. Moreover, it can give us the monthly and yearly forecasting quantity or VM sales. The result will be valuable for the cloud capacity planning and budgeting.

Although the seasonal component is not apparent, we still set the "gamma" value equals to "False" to remove the seasonal components in the TS model. We then use "forecast" package of R to plot the next 12 months (Figure.9, up) and eight years trends (Figure.9, bottom). We can see there is a downward trend in sales volume for the monthly but upward trend for the yearly forecasts.

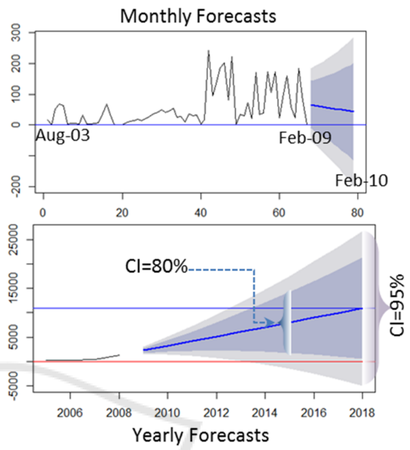

Figure 9: VM Sales Prediction Results.

Now, the issue "Is the TS a valid model for the forecasting?" We can plot the model residual to visualize the errors trend. If we find any pattern in the residual plot, it means the model is inadequate for prediction. Otherwise, we can say it is a good TS model. Based on Figure 10, we can see the residuals are moving around zero.

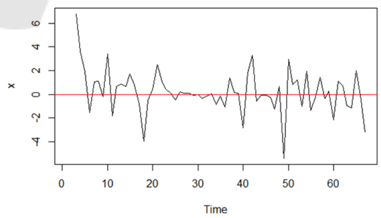

Figure 10: Residuals of TS model Sales Volume.

We can also use both histogram plot and Auto Correction Function (ACF) function (Figure. 11) to valid the TS model. The histogram plot (left of Figure11) shows a normal distribution and the ACF plot (right of Figure. 11) shows there is only one line that exceeds the boundary limit lines. So, we can conclude the TS model is valid.

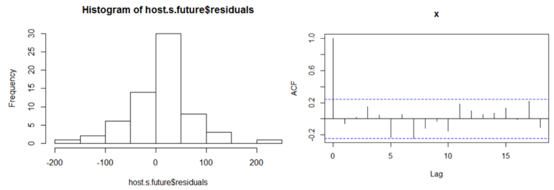

Figure 11: TS Residuals Histogram and ACF plot.

If we adopt recent Gartner's reports to assume the average market share of Windows server is around 36.56%, we can estimate the final result of total VM quantity is 6,250 in 2009 (2,285 for Windows servers) or market demand in next 10 years as noted in Table 2.

Table 2: VM Sales Yearly Forecast.

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Win. Servers	2,285	3,241	4,197	5,153	6,109	7,065	8,021	8,977	9,933	10,889
All VMs Qty.	6,250	8,865	11,480	14,095	16,710	19,324	21,939	24,554	27169	29,784

Per our proposed solution in Table 1, we can combine two test results for the final market segmentation is shown in Table 3.

Table 3: The Final Result of Market Segmentation.

Segment	Seg. 1	Seg. 2	Seg. 3	Seg. 4
Job Priority	2	1	0	3
Cores	1	1	23	11
Memory	6	5	6	99
%	10.05%	56.46%	22.97%	10.53%
Sales Vol.	593	3329	1354	620
Possible Workload	Static	Dynamic	High Availability	Backend

6 ANALYSIS AND DISCUSSION

Our three-step process solution shows how to segment the B2B cloud market for the ISP to expand its existing business from hosting to the cloud. The novel idea of our solution is that it can practically extract the cloud customer usage patterns from a cloud trace dataset. The job priority (as shown in Table 3) means the scheduling constraints on some jobs. The most substantial proportion of cloud usage (or workload) is the segment 2, which the most of customers were using only one core and lower amount memory. It is not surprising that Google indicates users often overestimate their resource consumption. In contrast, the lower priority jobs (or backend data processing workloads) consume the most significant amount of memory capacity (Segment 4). Although the top priority job of segment 3 consumes a lot of computing power (23 cores), the memory usage is relatively less.

Based on the limited parameters shown above Table 3, we can probably guess what type of workload is most likely even though Google data did not provide this information. Segment 1 is more like static web hosting workload; Segment 2 would be dynamic (because of job priority ranking is high than static one). Segment 3 is more like Highly Availability workload, such as customer relationship management(CRM) applications, and segment 4 is more like backend workloads, such as database backup or business analytics. One of the insights from Table 3 is the cloud infrastructure, or a server farm should be tailored into 12 units per cloud server cluster. A memory configuration should be built in 6 GB per slot.

For the HC algorithm, it is essential to indicate that one of the influencing factors for the optimal number of the market segment is "seed," However, it does not only impact on the clustering method but also other methods that require setting "seed." In this study, we assume there are no differences regarding of usage patterns between B2C and B2B for the Google's dataset. By using HC algorithm, we can meet the good market segment criteria (Yankelovich, 2006) 3, 4 and 6. However, HC algorithm alone is not enough because the input dataset comes from a global dataset. It only provides information about the customer behaviors.

The total demand estimation has to come from a local B2B dataset for business strategy. Typically, the sales' target often becomes Key Performance Index (KPI) for senior management. It is desirable to use TS model for the local market demand because the B2B cloud market is often built upon the long-term B2B relationship. Furthermore, the purchasing decision is made by a group of people rather than a single individual. The TS can deliver both monthly and yearly sales forecasts. By adopting TS model, we can satisfy the criteria (Yankelovich, 2006) of good market segmentation 1, 2, and 5. In comparison with other solutions (Table 4), our solution has the following advantages:

Table 4: Segmentation Solutions Comparison.

Different Methods for Market Segmentation	Customers' Business Values	Focus Usage pattern	Flexible	Align with business strategy	Specify revenue and profit	Make sense
Analytic Method	√		√		√	√
Nested Method	√	√				√
Strategy-Based			√	√		
Delphi Method		√		√		√
HC + TS	√	√	√	√	√	√

- The solution is practicable and quantifiable, which has the input variables (Table 3) for the process of the B2B cloud market segmentation.
- The solution can quickly be updated for the rapidly changing environment of the cloud market, such as customer behaviors shift, the internal investment budge variation, and the cloud technology eruption.
- It can assist senior executives for a managerial decision to test different local niche markets that many global CSPs might not have a local B2B relationship.
- The solution allows CSP to develop pricing model based on both the market and customer-value, which it emphasizes on both the external rationality rather than internal rationality.

In contrast, the analytic method cannot extract usage patterns, and the nested approach has to be case-by-case. The strategy-based method is often quite challenging to be translated into a practical solution. Survey and Delphi methods often take too long to be accomplished and often it is indirect.

To the best our knowledge, it is the first kind of study on B2B cloud market segment. Many existing and incoming CSPs require this kind of knowledge to assist their cloud business investment strategy in term of budgeting and resource capacity planning. Market segmentation helps CSPs to find a better pricing strategy for maximizing their profits.

7 CONCLUSIONS

This paper demonstrates how to combine both Hieratical Clustering (HC) and Time Series (TS) forecast to segment the cloud market and predict market demands. In summary, we show HC + TS is a better method to understand the market potential. It is also very practical for any CSP to implement its cloud market strategy by rolling out different pricing models for various market segments. Our approach allows CSPs to tailor their limited cloud resources for the targeted customers. Moreover, CSPs can optimize their cloud pricing beyond the reach of the traditional cost-based cloud pricing. It leads to opportunities for the CSP to maximize the revenue and profits based on the various cloud customers' utility and surplus. The details of how to define the customer surplus or cloud customer utility functions and how to establish and optimize different cloud pricing models are our future works. We will explore these two topics in future studies.

REFERENCES

Buyya R, et al., 2002, Economic models for resource management and scheduling in Grid computing. Concurrency and Computation, pp1507.

Weinman J., 2012, loudonomics, The Business Value Of Cloud Computing, *Hoboken, N.J. : Wiley, pp20*

Wang W., et al., 2012, Towards Optimal Capacity Segmentation with Hybrid Cloud Pricing. *2012 IEEE 32Nd International Conference On Distributed Computing Systems, Distributed Computing Systems (ICDCS), pp425*

Berman S, et al., July 2012, How cloud computing enables process and business model innovation. *Strategy & Leadership.40(4), pp27-35*

http://www.businessinsider.com/visa-partners-with-banks-for-cross-border-b2b-payments-2017-11/?r=AU&IR=T (Business Insider, 2017)

Smith, R., 1956, “Product Differentiation and Market Segmentation as Alternative Marketing Strategies.” *Journal of Marketing, vol. 21, no. 1, pp. 3–8.*

Belleflamme, P & Peitz, M, 2015, Industrial Organization, *Cambridge: Cambridge Univ. Press, pp.195*

Yankelovich, D., & Meer, D., 2006, Rediscovering Market Segmentation, *Harvard Business Review, Vol. 84, Issue 2, pp.122-131*

Claycamp, J. & William, M., 2000, “A Theory of Market Segmentation.” *Journal of Marketing Research, vol. 5, no. 4, 1968, pp. 388–394.*

Wedel, M, & Kamakura, WA, 1998, Market segmentation: conceptual and methodological foundations / Michel Wedel, Wagner A. Kamakura, *Boston: Kluwer Academic.*

McDonald, M, & Dunbar, I., 2012, Market Segmentation. how to do it and how to profit from it, Chichester: John Wiley & Sons.

Wind, Y, & Cardozo, R,1974, Industrial Market Segmentation,' Industrial Marketing Management, vol. 3, no. 3, pp. 153-165.

Kotler P. Feb-1964, Marketing Mix Decisions for New Products. *Journal of Marketing Research (JMR) 1(1): pp. 43-49.*

Ariel Pakes, A., 2003, A Reconsideration of Hedonic Price Indexes with an Application to PC's. *The American Economic Review;(5):pp1578*

Abramson D & Buyya R, Giddy J., Jan-2002, A computational economy for grid computing and its implementation in the Nimrod-G resource broker. *Future Generation Computer Systems. 1; pp18*

Javadi, B. et al., 2011, Statistical Modeling of Spot Instance Prices in Public Cloud Environments. *2011 Fourth IEEE International Conference On Utility And Cloud Computing, Utility And Cloud Computing (UCC), pp219*

Hong X & Baochun L, 2013, A study of pricing for cloud resources, *SIGMETRICS Perform. Eval Rev, 40(4): pp.3–12*

Hande, P. et al., 2010, Pricing under Constraints in Access Networks: Revenue Maximization and Congestion Management. *Proceedings IEEE INFOCOM* https://github.com/google/cluster-data/blob/master/TraceVersion1.md, (cluster-data 2011)

https://hbr.org/2005/09/building-loyalty-in-business-markets (Narayandas, D., HBR, 2005)

Wang L, & Ramamohanarao K., 2010, iVAT, and aVAT: Enhanced Visual Analysis for Cluster Tendency Assessment. *Lecutre Notes in Computer Science:16*

Lawson, R G, Jurs, P C, Feb-1990, *Journal of Chemical Information & Computer Sciences., Vol. 30 Issue 1, p36-41.*

Brain H, J. G. S., 1954, A New Method for determining the Type of Distribution of Plant Individuals. *Annals Of Botany;(70):pp.213*

https://www.decisionanalyst.com/whitepapers/marketsegmentation/ , (Thomas J. 2016)

Liang Wang, & Ramamohanarao K, 2009, Automatically Determining the Number of Clusters in Unlabeled Data Sets. *IEEE Transactions on Knowledge and Data Engineering, 3) pp.335.*

https://www.jstatsoft.org/article/view/v061i06 (Charrad, M., 2014)

Shapiro B, Bonoma T.1984, How to segment industrial markets. Harvard Business Review.62(3): pp.104-110

Shumway R, Stoffer D. 2011, Time Series Analysis And Its Applications: With R Examples, *New York: Springer*

Kuo R, et al., 2016, An application of a metaheuristic algorithm-based clustering ensemble method to APP customer segmentation. *Neurocomputing September 12; 205: pp.116-129*

Wind Y, et al., Jul-1978, Market-based Guideline for Design of Industrial Products, *Journal of Marketing. ;42(3): pp. 27-37.*

Verhallen T, et al., Jul-1998, Strategy-Based Segmentation of Industrial Markets. *Industrial Marketing Management;27(4): pp.305-313.*

Best R.,1974, An Experiment in Delphi Estimation in Marketing Decision Making. *Journal of Marketing Research (JMR) November;11(4): pp. 448-452*

McDonald M & Dunbar I., 2012, Market Segmentation.: How To Do It And How To Profit From It, *Chichester: John Wiley & Sons, pp.255*

Seufert E. Freemium, 2014, Economics: Leveraging Analytics And User Segmentation To Drive Revenue, Waltham, *Massachusetts: Morgan Kaufmann.*

Laughlin J, Taylor C., 1991, An approach to industrial market segmentation. *Industrial Marketing Management, pp127*

Plank R. A, May-1985, Critical Review of Industrial Market Segmentation. *Industrial Marketing Management; 14(2):pp79-91*

Balakrishna G. Feb-1980, Better Used the industrial Marketing Concept. *Industrial Marketing Management, 9(1): pp71-76*

https://www.shopify.com/enterprise/global-ecommerce-statistics, (Global e-commerce ,2017)

https://www.nist.gov/news-events/news/2011/10/final-version-nist-cloud-computing-definition-published (NIST, 2011)

Murtagh F & Contreras P., 2012, Algorithms for hierarchical clustering: an overview, II. *Wiley Interdisciplinary Reviews-Data Mining And Knowledge Discovery, 2 1, p86-p97, 12p.*

https://en.wikipedia.org/wiki/Usage_share_of_operating_systems (StatCounter, 2018)

Shin, K, 2013,'The Executor of Integrated Marketing Communications Strategy: Marcom Manager's Working Model'

Oliva, R. A., 2012, a High-Level overview: a value perspective on the price of Business to Business market, *Handbook of B2B Marketing. Cheltenham, Gloucestershire: Edward Elgar Publishing, pp.15-40*

Thomas, R. J., 2012, B2B market segmentation, Handbook of B2B marketing, *Cheltenham, Glouces - tershire: Edward Elgar Publishing, pp.182-207.*