On the Effects of User Ratings on the Profitability of Cloud Services

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***Abstract*—In todays cloud market, providers are taking advantage of consumer reviews and ratings as a new marketing tool to establish their credibility. However, to achieve higher ratings, they need to enhance their service quality which comes with an additional cost. In this paper, we model this conflicting situation as a Stackelberg game between a typical service provider and multiple service users in a cloud environment. The strategy of the service provider is to adjust the price and IT capacity by predicting the users ratings as well as their demands variation in response to his given price, quality and rating. The game is solved through a backward induction procedure using Lagrange function and Kuhn-Tucker conditions. To evaluate the proposed model, we performed experiments on three real world service providers who have low, medium and high average of users' ratings, obtained from the Trust Feedback Dataset in the Cloud Armor project. The results show that improvement in ratings is mostly profitable for highly rated providers. The surprising point is that providers having low ratings do not get much benefit from increasing their average ratings, meanwhile, they can perform well when they lower the service price.**

***Keywords*-Stackelberg game, cloud service, provider profit, user satisfaction, rating prediction, service pricing.**

I. Introduction

Cloud computing has emerged as a significant promising computing paradigm by facilitating customers access to computing services without owning any computing resources. The large number of services inevitably incurs the competition among service providers that offer similar functionality [1]. Survival for new and less famous cloud providers in this competition is more challenging, unless they provide high quality services and gain good reputation. Today's on-line market made it easy for providers to establish their own credibility.

On-line rating systems have attracted users' attentions as an evaluation factor of providers' operational premises and their actual performance. Rating platforms enable users to share their experience and interests with other users in a timely fashion. Reviews and ratings, known as digitized word-of-mouth, play an important role in the future customers decision making. Theses ratings reflect users satisfaction in today's commercial world and can affect the providers revenue largely [2].

High rating comes with a price for service providers, since rating represents users' benefits and not necessarily providers' profit. The main issue arises due to the fact that each participating party in the cloud has its own interest. Users want to purchase elastic and high-quality services with minimum price. However, from the provider's perspective, higher quality means more cost and minimum price means low profit. Moreover, the service price has a large effect on users willingness to order, and quality influences users' ratings that represent their satisfaction as a reference for future users. Planning a suitable pricing strategy in early stages of the service development life cycle is highly significant since pricing may give special requirements to the architectural design, such as scalability and customizability [3]. The problem with the existing revenue maximization strategies in the domain of cloud computing is that they do not consider the impact of the users' preferences and priorities over the price and QoS trade-off on their demands. This may result in considerable losses for providers in terms of the gained revenue and for users in terms of the quality of service. Further, it can lead to poor cloud scalability failing providers to scale up or scale down their resources on time, and to support their long-term and strategic needs. Failing to meet the expected users' demands for cloud services can result in deficiency or large up-front investments in infrastructure. To address these issues, this paper models the conflicting interests and selfish actions of the participants as a Stackelberg game. The strategy of the service provider as a leader is to maximize his profit and, at the same time, satisfy the users' needs to maintain his good reputation. Meanwhile, the service users as followers seek for less costly and high quality services to optimize their own utility.

Contributions: The novelty of this paper lies in the theoretical and empirical research conducted to study the impact of on-line customers' ratings and demand variations on the revenue of infrastructure cloud service providers. The main contributions can be summarized as follows:

- Assessing the profitability of user ratings on cloud providers' income in a competitive on-line rating system. To the best of our knowledge, our work is the first that presents a comprehensive study on the users' ratings on the providers' profit in a cloud environment.
- Enabling providers to identify influential parameters on users demands and capturing the variations of users' demands in response to the changes of each parameter to enable scalability of cloud services and avoid under

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and over resources provisioning.
- Maximizing the providers' profit through a Stackelberg game model while adjusting the services' price and capacity based on the underlining users' demand.
- Maintaining users' satisfaction and incentivizing them to provide good ratings for the providers.

The rest of the paper is: a brief review of related literature in Section2, Structure and game formulation in Section 3, methods of rating prediction in Section 4 and obtaining the game equilibrium and best responses in Section 5;at the end simulating results of the game is presented. For empirical evaluation, the model is implemented using a real world dataset obtained from the Cloud Armor project[1], on three service providers with low, medium and high rating.

II. Related work

Game theory is widely applied where the interactions of players have to be taken into account. This cannot be designed with the classical optimization theory, since the players' actions affect the other players. Game theory has been successfully applied to address resource allocation and Quality of Service (QoS) issues [4]. In cloud computing it is mainly utilized to deal with resource allocation and pricing issues [5]. As an example, a two stage provisioning Stackelberg game is offered by Di Valerio et al. [6] for Software as a Service (SaaS) providers who use cloud facilities provided by an Infrastructure as a Service (IaaS) provider. First, the SaaS providers determine the number of required instances, then the SaaS providers compete by bidding for the spot instances.

The perspective of the user and provider is considered by Al Daoud et al. [7], who propose a policy to maximize the cloud providers revenue and users utilities. The authors focus on the pricing problem and proved the existence of a Nash equilibrium. A very similar approach is taken by Hadji et al. [8]. A Stackelberg game is designed to consider constrained pricing with limited resources offered by an IaaS provider and the optimal user demands. However, price is the only utility factor considered for both the user and provider in existing research; and the importance of QoS or ratings as well as the trade-off relation between price and QoS are yet to be investigated. It is worth mentioning that none of the above discussed research has utilized real world datasets for demonstration of their game applicability in real life.

A recent survey conducted by BrightLocal in November 2016, acknowledged that 84% of people trust on-line ratings and reviews as much as personal recommendations, and 58% of consumers say that the star rating of a business is the most important decisive factor[2]. Yet, there have been few works exploring the user ratings effect on business owners profit [2], that can be found mainly in marketing and economic literatures. For instance, empirical studies showed that improving book review ratings on Amazon.com and BarnesandNoble.com tends to increase their sales [2]. In the cloud service literature, Wang et al. [9] proposed a reputation measurement approach based on feedback ratings to obtain the trust vector of each cloud service. Their model generates a reputation score for cloud services and is limited to the users who already used the service in the past, but does not support future users. To the best of our knowledge, this work is the first that models cloud services profitability while considering future users ratings, where unlike classic economic models, the main challenge is how to consider the elasticity feature of cloud services along with QoS factors.

[1] http://cs.adelaide.edu.au/∼cloudarmor/ds.html

[2] www.brightlocal.com/learn/local-consumer-review-survey/

Table I
Notations used in service provider-user Stackelberg game

Decision variables	
x_{ik}	Demand size of user i for service k
ϕ	IT capacity/process rate of the service provider
P_k	Price per unit of service k
Input parameters	
$i = 1, 2, ...n \in N$	Index of n users in the set N
B_i	User i Budget
R_{ik}	Rating utility of service k from user i
r_{ik}	Service rating of user i for service k
$\bar{r}_k$	Average of n users' ratings for service k
$\bar{r}_i$	Average ratings of all the services given by user i
$\hat{r}_{ik}$	Predicted rating of user i for service k
α_i	Price elasticity for user i
β_i	Rating elasticity for user i
γ_i	Amount of service elasticity for user i
l	User's arrival rate
k, j	Services (offered by two different providers)
μ	Constant scale of user demand
ϕ	IT capacity/process rate of service provider
Q_k	Quality of service k stated in SLA
C_{0k}/C_k	Fixed cost/marginal cost of service k
$\lambda, \lambda_1, \lambda_2$	Lagrange multipliers

III. Cloud service provider-user Stackelberg game

We model the cloud service market interactions between a service provider and the service users as a Stackelberg game, where the service provider is the leader and the service users are the followers. The users observe the price and ratings to adjust their demand accordingly. In quest of the users demands, the service provider makes decision on his pricing strategy and optimal capacity. In the provider objective model, the provider tries to comply with Service Level Agreement (SLA) to obtain and maintain his good rating, otherwise poor quality affects users rating and future users demand. We assumed there is no limitation for provider capacity, so he can increase his capacity as the demand grows. The proposed model considers different parameters, which are provided in Table 1.

The cloud service delivery requires provisioning an estimated amount of the required cloud resources to satisfy customers' demands. A precise estimation will benefit cloud providers with a balanced capacity and reduced cost.

This challenging task of estimation depends on several factors including the number of consumers, variation of their demand, and their expected QoS [10]. Elasticity capabilities of cloud resources enable providers to scale their capacities and to configure provisioned resources to take into account the user demand behavior and specified QoS requirements for each user. In order to capture demand elasticities and variations specific for each user, which are fundamental aspects in cloud environments, we define the user demand using the Cobb-Douglas function that models well these elasticity aspects [11]. The Cobb-Douglas demand function is continuous, convex or concave, and has constant elasticities in relation with each input parameter. In real world situations, a user demand depends on service price and perceived quality. The user will have the opportunity to check the provider rating that represents the actual user satisfaction level of the service quality. Therefore, in addition to the amount of service and the service price, the user rating is considered influential in our user demand function. We define the user demand function as follows:

$$D_i(x_{ik}, P_k, r_{ik}) = \mu \ x_{ik}^{\gamma_i} \ P_k^{-\alpha_i} \ r_{ik}^{\beta_i} \tag{1}$$

where α_i, β_i and γ_i, $i = 1, 2, ..., n$ are elasticities of the service price P_k, rating r_{ik} and size x_{ik} respectively. Different market users, having different requirements and satisfaction levels, do not react evenly to the same price or rating. It is the combination of these factors that produces different values of α_i, β_i and γ_i. These values are independent of the specific values of P_k, r_{ik} and x_{ik}, which is an inherent property of the Cobb-Douglas function. User demand has a negative relation with service price, and positive relation with service rating. The user (i.e., a typical follower) aims to maximize his payoff:

$$\begin{aligned} \text{maximize} \quad & UP(x_{ik}) = D_i(x_{ik}, P_k, r_{ik}) - P_k \\ \text{subject to} \quad & P_k x_{ik} \leq B_i \\ & x_{ik} \geq 0, \forall i \in N \end{aligned} \tag{2}$$

The user's objective is to maximize the demand size x_{ik} within his budget B_i while minimizing the cost P_k. Users' ratings that reflect their satisfaction level enhance their total utility encoded in the demand function. Service provider predicts the new user rating based on the given previous ratings that is influenced by the actual service quality. The user can only decide on the size of the demand, and price should be obtained through the provider's utility function.

As the cloud service provider needs to maintain his reputation through the user ratings, he is responsible to process users requests on time. Thus, it is important to consider service processing rate that represents IT capacity of the service provider, denoted as ϕ. A large processing rate requires a higher IT capacity, meaning a higher cost for ϕ that includes fixed cost of C_0 and marginal cost of C_k. Thus, the total cost for capacity ϕ is $C_{0k} + C_k\phi$.

Following previous literature in cloud computing [12], we model arrival of customers as a Poisson process with mean arrival rate l. The average delay for a customer in an M/M/1 queue can be defined as $\frac{1}{\phi - l}$. The provider is willing to optimize his profit by maximizing the price and ratings given by the users, and minimizing the costs. Thus, the provider (i.e., the leader) optimization problem is:

$$\begin{aligned} \text{maximize} \quad & PP(P_k, \phi) = \sum_{i=1}^{n} (P_k - \ \phi \ C_k) \ D(x_{ik}^*, P_k, r_{ik}) \\ & + \ \sum_{i=1}^{n} R_{ik} - C_{0k} \\ \text{subject to} \quad & \frac{1}{\phi \ - \ l} \leq Q_k \\ & \phi > 0, P_k > 0, \forall i \in N \end{aligned} \tag{3}$$

x_{ik}^* is the outcome of the optimization problem Eq.2, which corresponds to the best user's response in terms of demand size to the offered service price and quality. The provider can only maintain his high records of ratings, if he offers a service quality not less than what is stated in SLA. Thus, based on the defined constraint, the average delay should not be more than Q_k stated in SLA.

The user ratings do not always enhance the utility of the provider. When the provider receives a low rating, it may have a negative effect on his payoff. To reflect that, we assign to R_{ik} a negative sign when the user rating is less than the average user ratings as follows:

$$R_{ik} : = \begin{cases} +R_{ik} & \text{if } \hat{r}_{ik} \geq \bar{r}_k \\ -R_{ik} & \text{if } \hat{r}_{ik} < \bar{r}_k \end{cases} \tag{4}$$

$\hat{r}_{ik}$ is the predicted rating of user i which will be calculated in the next section.

IV. User rating prediction

Each service has a history of user rating values that can be used for future user ratings for other services. In this paper, we predict the rating value of service k using a set of similar services to service k that have been rated by the users. The similar service neighbors are identified using the Pearson Correlation Coefficient (PCC) measure. PCC is a common method of similarity computation in recommender systems that measures the extent to which two variables linearly relate with each other. Therefore, the similarity among two services k and j with the same functionality consumed by user i is computed as follows:

$$Sim(k, j) = \frac{\sum_{i \in N} (r_{ik} - \bar{r}_k)(r_{ij} - \bar{r}_j)}{\sqrt{\sum_{i \in N} (r_{ik} - \bar{r}_k)^2} \sqrt{\sum_{i \in N} (r_{ij} - \bar{r}_j)^2}} \tag{5}$$

where $\bar{r}_k$ and $\bar{r}_j$ represent the average rating values of service k and j consumed by n users. After calculating the similarity values, it is important to select neighbors that are really similar to the service. Therefore, the similar neighbor set S for service k is defined as follows:

$$S(k) = \{j | j \in T_K, Sim(j,k) > 0, j \neq k\} \tag{6}$$

T_K represents a set of the Top-K similar services to service k. The identified similar service set is utilized for rating predictions. Based on the user experience of the similar service set, the missing rating value of service k for user i would be:

$$\hat{r}_{ik} = \bar{r}_i + \frac{\sum_{j \in S(k)} Sim(k,j)(r_{ij} - \bar{r}_j)}{\sum_{j \in S(k)} Sim(k,j)} \tag{7}$$

Predicted rating of service k from user i will be placed as an input for the defined function of R_{ik} in Eq.4 to compute the final utility for the service provider. For convenience, we use r_{ik} to designate $\hat{r}_{ik}$ or r_{ik} in the rest of the paper.

V. Stackelberg game equilibrium

We solve the equilibrium point of the above defined Stackelberg game by a backward induction procedure. Therefore, the followers' (users) problem has to be solved first to obtain the response function of these users. The leader's (provider) decision problem is then computed considering all possible reactions of his followers in order to maximize his net profit. For every possible provider's action, every user's optimal reaction shall be determined by considering the providers decisions as its input parameters. At last, the provider identifies his optimal decision that leads to his optimal payoff, by assuming that the users are rational and make the optimal response to his decisions. The best response functions are discussed in the following sections.

A. *User best response*

The user has to adjust the size of his demand according to his budget for a given price. In our model, increasing the budget is not allowed for the user. By definition, the Cobb-Douglas function $D_i(x_{ik}, P_k, r_{ik})$ is an increasing and concave function of r_{ik}, so we have a positive first derivative and a negative second derivative,

$$\frac{\partial D_i(x_{ik}, P_k, r_{ik})}{\partial r_{ik}} = \beta_i \mu P_k^{-\alpha_i} r_{ik}^{\beta_i - 1} x_{ik}^{\gamma_i} > 0 \tag{8}$$

$$\frac{\partial^2 D_i(x_{ik}, P_k, r_{ik})}{\partial r_{ik}^2} = \beta_i(\beta_i - 1)\mu P_k^{-\alpha_i} r_{ik}^{\beta_i - 2} x_{ik}^{\gamma_i} < 0 \tag{9}$$

Considering the above equations, we have $0 < \beta_i < 1$. We can get the same range for γ_i, $0 < \gamma_i < 1$, since the function is increasing and concave in x_{ik}, and $\alpha_i > 0$.
As the objective function in Eq.2 is continuous and concave in x_{ik}, we obtain the solution using Lagrange multipliers, λ_1 and λ_2, with Kuhn-Tucker conditions. So, we will have a new objective function:

$$L_{up} = D_i(x_{ik}, P_k, r_{ik}) - P_k - \lambda_1(x_{ik}P_k - B_i) + \lambda_2 x_{ik} \tag{10}$$

with the following conditions:

$$\lambda_1(x_{ik}P_k - B_i) = 0 \tag{11}$$

$$\lambda_2 x_{ik} = 0 \tag{12}$$

$$\lambda_1, \lambda_2, x_{ik} \geq 0$$

The only coupling point between users is x_{ik}, so we take the derivative with respect to x_{ik}.

$$\frac{\partial L_{UP}\ (x_{ik})}{\partial x_{ik}} = \frac{\partial D_i\ (x_{ik})}{\partial x_{ik}} - \lambda 1 P_k + \lambda_2 = 0 \tag{13}$$

We have two cases: 1) $x_{ik} = 0$: regardless of the value of λ_1, λ_2, this means that the user is not demanding any services, so his utility will be zero. 2) $x_{ik} > 0$: from slackness complementary condition in Eq.12 we can conclude that $\lambda_2 = 0$; so we have:

$$\gamma_i \mu x_{ik}^{\gamma_i - 1} P_k^{-\alpha_i} r_{ik}^{\beta_i} - \lambda_1 P_k = 0 \tag{14}$$

$$x_{ik} = \left(\frac{\lambda_1 P_k^{\alpha_i + 1}}{r_{ik}^{\beta_i} \gamma_i \mu}\right)^{\frac{1}{\gamma_i - 1}} \tag{15}$$

By substituting x_{ik} from Eq.15 in Eq.11 we obtain λ_1:

$$\lambda_1\left[\left(\frac{\lambda_1 P_k^{\alpha_i + 1}}{r_{ik}^{\beta_i} \gamma_i \mu}\right)^{\frac{1}{\gamma_i - 1}} P_k - B_i\right] = 0 \tag{16}$$

$$\lambda_1^{\frac{1}{\gamma_i - 1}} = \frac{B_i r_{ik}^{\beta_i} \gamma_i \mu}{P_k^{\frac{\alpha_i + 1}{\gamma_i - 1} + 1}} \tag{17}$$

The final response x_{ik} from user i is attained by replacing Eq.17 in Eq.15.

$$x_{ik}^* = \frac{B_i (r_{ik}^{\beta_i} \gamma_i \mu)^{\frac{\gamma_i - 2}{\gamma_i - 1}}}{P_k} \tag{18}$$

The above obtained x_{ik}^* is optimal where Eq.11 slacks and $\lambda_1 > 0$. However, we claim that it is reasonable to consider slackness rather than binding, since having $\lambda_1 = 0$ is an extreme case where the user cares only about the price and does not consider the previous ratings or quality.

B. *Cloud service provider best response*

In the case of having a non zero demand for the service provider and close values of price and cost, the provider can only survive when he receives a high rating that can cover his sacrificed price loss. But, if his rating is low and he cannot set a high price, he will eventually suffer from a loss and leave the market. Using Lagrange multiplier λ, we model the objective optimization in Eq.3 as follows:

$$L_{PP}(P_k, \phi, \lambda) = PP(P_k, \phi) - \lambda\left(\frac{1}{\phi - l} - Q_k\right) \tag{19}$$

The Kuhn-Tucker condition for our model is:

$$\frac{\partial PP(P_k, \phi)}{\partial \phi} - \lambda \frac{\partial(\frac{1}{\phi - l} - Q_k)}{\partial \phi} = 0 \tag{20}$$

$$\frac{\partial PP(P_k,\phi)}{\partial P_k}=0 \tag{21}$$

$$\lambda(\frac{1}{\phi-l}-Q_k)=0 \tag{22}$$

where $\lambda \geq 0, P_k, \phi > 0$. To find the optimal capacity ϕ, we first assume that Eq.22 binds and $\lambda > 0$. Referring to Eq.20 we have:

$$C_k D_i(x^*_{ik}, P_k, r_{ik}) - \lambda(\frac{-1}{(\phi-l)^2}=0$$
$$\lambda = -C_k D_i(x^*_{ik}, P_k, r_{ik})(\phi-l)^2 \tag{23}$$

Knowing that $C_k > 0$ and $D_i(x^*_{ik}, P_k, r_{ik}) > 0$, we obtain a negative λ in Eq.23 that contradicts with the defined constraint $\lambda \geq 0$. Therefore, $\lambda = 0$ and Eq.22 slacks which means the service provider should not provide the capacity equal to satisfaction of his promised quality, it has to be more. Any assigned capacity can be optimal as long as the following condition holds:

$$\phi^* = \frac{1}{Q_k}+l+\epsilon \tag{24}$$

ϵ represents a very small amount. By solving Eq.21 we can get the optimal price as follows:

$$\frac{\partial[(P_k-\phi C_k)D_i(x^*_{ik}, P_k, r_{ik})]}{\partial P_k} =$$
$$(-\frac{\alpha_i}{\gamma_i-1})B_i r_{ik}^{\beta_i(\frac{-\gamma_i+1}{\gamma_i-1})}\gamma_i^{\frac{-\gamma_i+1}{\gamma_i-1}}P_k^{\frac{-\alpha_i}{\gamma_i-1}-1}-$$
$$\phi C_k(\frac{-\alpha_i}{\gamma_i-1}-1)B_i r_{ik}^{\beta_i(\frac{-\gamma_i+1}{\gamma_i-1})}\gamma_i^{\frac{-\gamma_i+1}{\gamma_i-1}}P_k^{\frac{-\alpha_i}{\gamma_i-1}-2}=0$$

$$P^*_k = \phi C_k(\frac{\alpha_i+\gamma_i}{\alpha_i+\gamma_i-1}) \tag{25}$$

Obtaining optimal response points enables us to develop an equilibrium algorithm to solve our proposed Stackelberg game. According to Algorithm 1, the utility of predicted rating is calculated for the service provider, then the user demand is calculated and the final provider payoff is obtained.

Algorithm 1 PP/UP Stackelberg Game

procedure INPUT: Set $i = 1, 2, ..., n$; $\alpha_i > 0$; $0 < \gamma_i, \beta_i < 1$; Get $C_k, C_{0k}, r_{ik}, \bar{r}_k$ for service k.
  $TotalR, sum1, sum2 \leftarrow 0$
  for each $i \in N$ **do**
    Predict the rating ▷ use Eq.7
    if $r_{ik} \geq \bar{r}_k$ **then**
      $R_{ik} \leftarrow r_{ik}$
    else
      $R_{ik} \leftarrow -r_{ik}$
    end if
    $TotalR \leftarrow R_{ik} + TotalR$
    Obtain the optimal P_k ▷ use Eq.25
    Calculate x_{ik} ▷ use Eq.18
    Calculate D_i ▷ use Eq.1
    Obtain the optimal ϕ ▷ use Eq.24
    $UP_i \leftarrow D_i - P_k$
    $sum1 \leftarrow sum1 + P_k * D_i$
    $sum2 \leftarrow sum2 + \phi * C_k * D_i$
  end for
  $PP \leftarrow sum1 - sum2 + TotalR - C_{0k}$
end procedure

VI. SIMULATION RESULTS AND ANALYSIS

In order to evaluate our proposed Stackelberg game, we performed our experiments on three real life cases. We chose HostGator, Carbonite, and AceHost as our Stackelberg leaders. They all are actual IaaS providers who offer cloud backup and hosting services to business and individual users. The intuition behind selecting these three providers was their difference in average rating values that make each of them in high, middle, and low class of ratings. This section provides the simulation of users' demands and assesses how the users react to changes in the price, rating, and volume of each service. It helps investigate how the profit obtained by service providers in each rating class varies when the user sensitivities towards the service volume, rating and price change.

A. Experiment setup

As the main purpose of this experiment is to demonstrate the reliability of the proposed Stackelberg game and its solution algorithm, we have to set meaningful data and reasonable game parameters. To do so, we obtained real world data and investigated some properties of the Cobb-Douglas function originally used in supply chain practices [13]. We simulated 300 cloud service users for each of the providers using real customer ratings from the Trust Feedback Dataset, provided by Noor et. al. [14] in the Cloud Armor project, with respect to speed and response time. HostGator has a very good record of user ratings with an average of "4.72". Afterwards, Carbonite has an average record of user ratings "2.58", while AceHost has low record of user ratings "1.83".

Considering the fact that users usually rate the price according to their budgets, we scaled up the daily budget of users based on their ratings given to the service price factor. To obtain the process rate, we referred to the providers promised quality in the SLA statements. For example, Carbonite promises the minimum speed of 2 mbps, and from this value we computed the process rate ϕ for a day with l= 5 requests per second that gives a reasonable response time of 0.01. We set the constant scale of μ to 1 consistently with previous literature [15]. Since there is no information available about the providers' cost, we assume that they are renting their cloud infrastructure from Google, so the margin cost is obtained from Google Cloud Storage that is $C_k = 0.026$ monthly.

B. Rating prediction

Through the dataset, we tried to find similar services that had ratings for the same quality factor. We identified 14 well-known service providers such as Go Daddy, Dropbox, and Dream host including the previously three nominated service providers who offer similar services. The rating prediction was conducted with a Mean Absolute Error of 1.209, and Root Mean Square Error of 1.478.

C. Pricing strategies

Service provider has to set the optimal price based on the predicted user demand response given the offered price. Considering possible users reactions towards the given price can help service provider as a leader to choose the best pricing strategy. This reactions towards changes in demand related parameters are to be analyzed with the defined elasticities that represents users sensitivities by changing each parameter. As an example, $\beta_i = \frac{\partial D_i(x_{ik},P_k,r_{ik})}{\partial r_{ik}} \frac{r_{ik}}{D_i(x_{ik},P_k,r_{ik})}$ indicates that one percentage change in r_{ik} brings a β_i percentage change in $D_i(x_{ik}, P_k, r_{ik})$. Figure 1 depicts the best pricing strategies that a service providers can adopt. It is not surprising that user rating sensitivity does not affect the optimal service pricing, as it was found earlier in Eq.25. Meanwhile, price reduction towards size sensitivity has to be much less than what it has to be against price sensitivity. Since the optimal pricing strategies of all the three providers are similar and only differ in price reduction scale, we only provide the figure for AceHost. From these pricing strategies, we need to investigate how the users react in their demands and how these strategies will ultimately enhance the provider's profit.

D. Sensitivity analysis of rating

Let us consider the rating elasticity parameter β. What a service provider in our Stackelberg game needs to know is how users will respond to ratings improvement, and how this response ultimately affects the provider's profit. In order to illustrate variations of demands within the user population, box plots are provided. Figure 2 shows that users' demands of all three providers rise with increase of β, but not in the same distribution. The quartiles and median of the HostGator service demand are increasing along with the growth of β. For Carbonite, the quartiles are increasing but the median remains almost unchanged. This shows less users have increased their demands. However, those who enlarged their demands, had more variation than the users of HostGator, whose variation is going up more than 120,000. AceHost has a different situation. The majority of users' demands are unchanged, while some had increased in even more amount compared to the other two providers (more than 150,000).

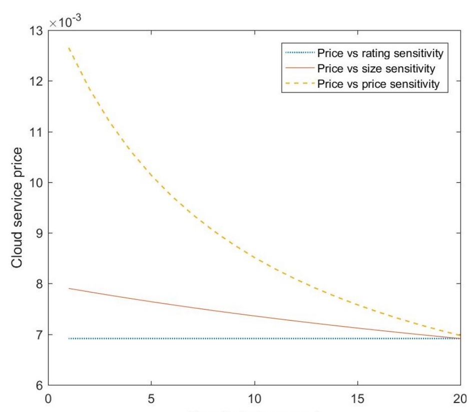


Figure 1. Pricing strategies (AceHost)

The effect of these changes are reflected in Figure 3a, where the profits of the three providers are compared. Since the process rate and marginal cost of HostGator are high, at first Carbonite is better off. But after increasing β, HostGator outperforms Carbonite. As it was expected for AceHost, the profit has a slight improvement when β is increased.

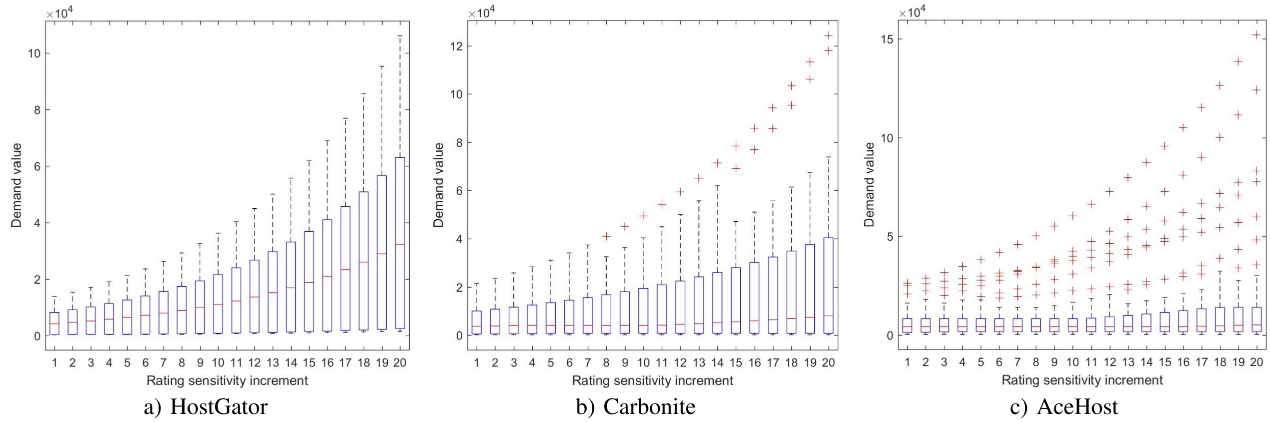
By analyzing these results, we can conclude that users who become customers of HostGator, mainly care about quality and rating. So when the provider increases his rating, he will see a dramatic increase of profit but not early. Carbonite has almost the same situation but less intense, so this provider can witness the increase of profit at slower pace. Meanwhile, the users of AceHost are not much sensitive towards rating. Therefore, rising the rating has a minor effect on AceHost profit.

E. Sensitivity analysis of service volume

To estimate the volume of service that users obtain, we analyzed γ. According to Figure 4, variation of user demand distribution for service volume is almost the same as ratings. However, very few users have lowered their demand when they met their budget limits. Figure 3b shows the three providers' profit gained at a milder slope in comparison with rating increment. This is due to the fact that only few customers lowered their demands, specially HostGator' customers who should pay more money. Yet, HostGator and Carbonite have similar trend of gaining the profit out of size increment.

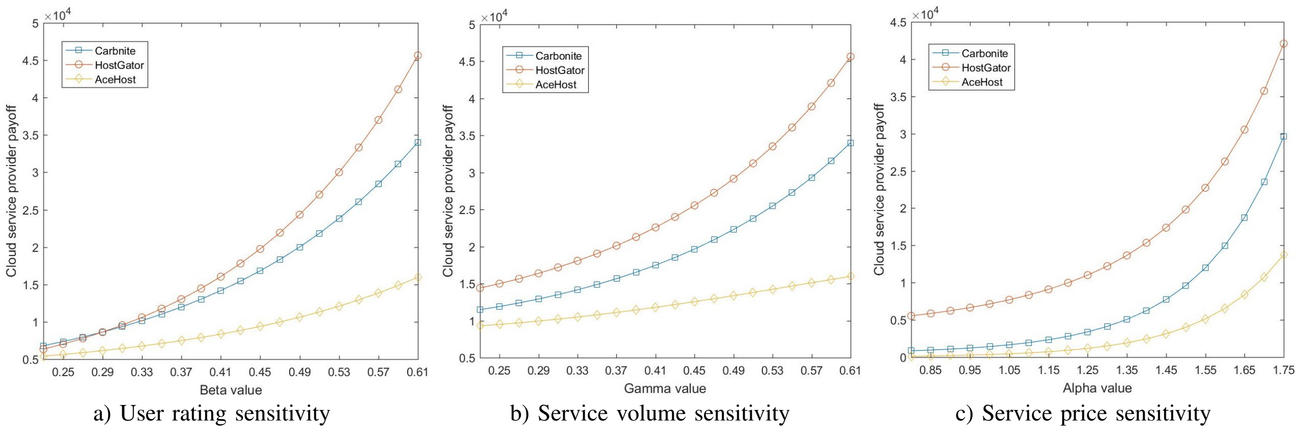
F. Sensitivity analysis of price

Users react differently towards the decrease of price. As α goes up, the price goes down. The change of price has to be greater than the other parameters to enhance the user demands. Figure 5 depicts the fact that users have a late reaction towards the decrease of price, but when they start to boost their demand, it goes up very fast. Consequently, the three providers' profits are more curvy with variation of price than the other parameters, as presented in Figure 3c. Like the case of the other two parameters, AceHost received less increment but most intense in variation. HostGator, Carbonite and AceHost behave similarly at the beginning, but Carbonite profit speeds up over scaling the price reduction. This shows that medium rated providers with



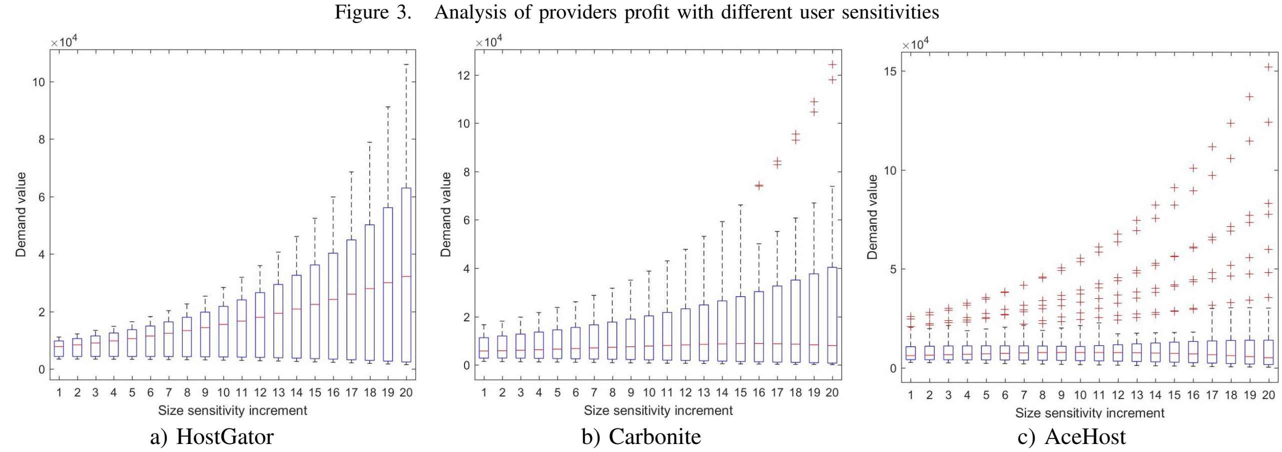
a) HostGator b) Carbonite c) AceHost

Figure 2. Demand variation with rating elasticity (20 different values of β [0.25-0.61]



a) User rating sensitivity b) Service volume sensitivity c) Service price sensitivity

Figure 3. Analysis of providers profit with different user sensitivities



a) HostGator b) Carbonite c) AceHost

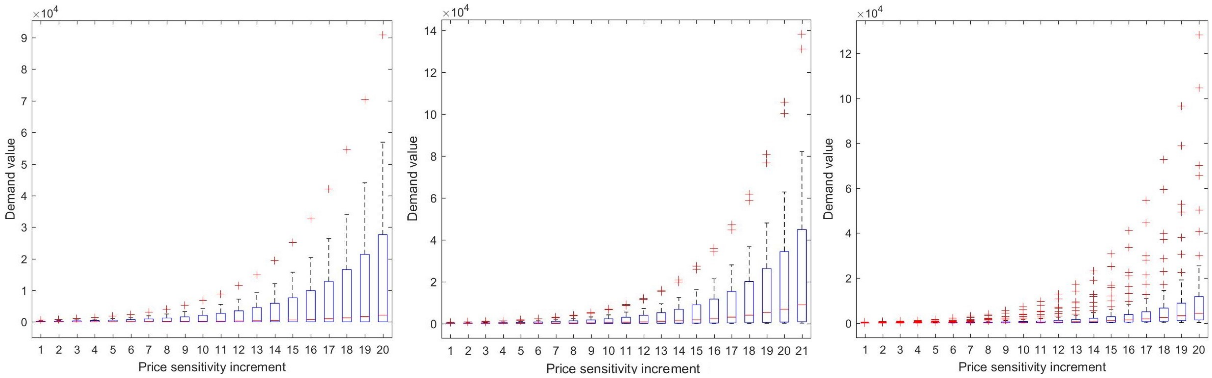
Figure 4. Demand variation with size elasticity (20 different values of γ [0.25-0.61]

medium cost and price have better opportunity to gain user satisfaction by cutting the service price.

In summary, it can be inferred that users react to small changes of rating and service size, meanwhile price deduction has to be large to affect considerably the users demand. For providers with higher capacity and higher rating values, the slope of profit increment will be higher than those with less capacity and lower rating values. Although providers with high capacity and rating obtain higher profits, providers with low capacity and low rating may receive some unexpected demand growth by enlarging the service size, improving the rating values, or reducing the price.

VII. Conclusion

This paper introduced a Stackelberg game model between a typical IaaS provider and the users to optimize the profit of the service provider who operates within an on-line rating platform. The theoretically obtained results confirmed



a) HostGator b) Carbonite c) AceHost

Figure 5. Demand variation with price elasticity (20 different values of α [0.85-0.75]

by the game simulation on a real world dataset showed that rating improvement is mostly influential for high rated providers who compete with high quality providers and attracted the users who prioritize quality in their decision making. Improving the ratings of a low rated provider does not increase his profit as much as it does for a medium and high rated provider. Meanwhile, an average rated provider takes the most advantage out of the price reduction, that can be related to his medium cost and process rate. Lowering the price boosted almost all the users demands greatly, but only when it is reduced in large scale. In a nutshell, providers with higher capacity, rating and also cost can make more profit when the user demands increase. The main competitive advantage of high rated providers is their service quality that becomes most profitable by enhancing their ratings. Providers with lower capacity, cost and rating may see some unexpected increase of demand from some customers, but in total they will have less demand and less profit. Yet their main advantage is lower cost that attracts low budget customers with continuing their price reduction. Finally, as the competition among providers is not considered in this paper, we intend, as future work, to design a dynamic game that models this competition over time.

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