Assisting Seller Pricing Strategy Selection for Electronic Auctions

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Abstract

This research examines sellers' pricing strategy oriented to bidders' risk preferences, within the context of an electronic auction. A business model is then proposed to predict the probability of potential bidders' risk preference, which sellers can consider to set pricing strategy to maximize their profits. A tailored intelligent auction registry engine is constructed based upon an initial version of our business model. Because the eXtensible Markup Language (XML)-based Simple Object Access Protocol (SOAP) is utilized to support interactions with other resources, our engine is decoupled from the underlying technology choices; therefore, it can be deployed to different platforms.

1. Introduction

The last two decades have witnessed the rapid emergence and spawn of electronic commerce (e-commerce) that seamlessly integrates business with computer science, especially information technologies [7], as well as web technologies to conduct business online [12]. Among the various types of e-commerce, the online auction, also called electronic auction or Internet auction, has been gaining enormous academic and industrial momentum [17] because it moves an important commerce form to the web [16].

As McAfee defined formally, an auction is "a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants" [10]. Electronic auctions, which refer to the auctions conducted via the Internet, differ from traditional auctions in several significant ways. First, the average time limit is longer than spot auctions, as electronic auctions can last from several hours to several days. For instance, eBay sellers can choose the closing day as of one, two, three, five, or ten days [4]. Second, electronic bidders may participate in a common auction via the Internet at different times and different places. Third, normally online bidders join in auctions anonymously; as a result, it is very unlikely that bidders can bid as a group. Therefore, the individual bidders can be ideally viewed as independent. Fourth, electronic auctions need to serve a scalable and growing Internet population. Fifth, bidders may obtain more information during the bid as they can surf online or do some research on the object at the same time as they bid actions. Sixth, as computers and software are involved in electronic auctions in addition to human beings, the issues of security and consistency need to be addressed. Due to these obvious differences, the mature research results on traditional auctions deserve to be reexamined in the context of electronic auctions. Meanwhile, computing technologies should be utilized to facilitate electronic auctions.

Following traditional auctions, there are different types of taxonomy [9,10,17] regarding online auctions. One popular categorization divides online auctions into two categories, namely, single-sided auctions and double-sided auctions. Double-sided auctions refer to auctions that permit multiple sellers and buyers to conduct selling and buying at the same time. Studied mainly theoretically, single-sided auctions refer to auctions that contain one uniform seller or one uniform buyer. Another taxonomy categorizes auctions into English and Dutch auctions. English auctioneers start at a high price and incrementally increase the price; and Dutch auctioneers start at a low price and incrementally decrease the price. Yet another taxonomy categorizes auctions into sealed auctions and outcry auctions, based upon whether bids are sealed or public. Sealed auctions can be in turn divided into first-price sealed auctions and second-price sealed auctions. In both first-price and second-price sealed auctions, each bidder independently submits a single bid, and the object is granted to the bidder who makes the highest bid. The only difference is that, in a first-price sealed auction, the winner pays the highest bidding price; while in a second-price sealed auction, the winner pays the second highest bidding price. These taxonomies overlap each other.

During the past two decades, a variety of popular web sites has been established to support electronic auction activities, such as eBay [4], onSale [13], AuctionNet [1], NETIS auction web [2], etc. In addition, a number of experimental auction systems serving research purposes are also observed, such as AuctionBot [17] and eMIDIATOR [14]. Among these prolific efforts, different web sites adopt various strategies to attract sellers and gain a reputation. For instance, some web sites provide comprehensive Graphical User Interface (GUI) features to sellers to set up auctions, such as AuctionNet [1]; some sites allow sellers to configure selling strategies, such as

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AuctionBot [17]. More and more web sites intend to support more types of auctions such as eBay [4]. For example, eBay supports single-sided auctions, sealed-bid auctions, and English auctions [4]. However, in the literature, existing web sites typically rely on sellers themselves to make decisions on selling strategies, rather than providing explicit facilities to assist sellers to select the most appropriate selling strategies to obtain the most profit.

This on-going research aims to explore the possibility of web sites to provide intelligent facilities to help sellers decide selling strategies, based upon economic principles and dynamically collected historical information. We expect that our work will interest web site management interested in attracting more sellers and consequently earning more profits. Due to the page limitation, in this paper, we report only our research results on single-sided sealed electronic auctions. A prototype is also established to implement the intelligent support. The remainder of the paper is organized as follows. Section 2 introduces the related work. Section 3 proves that different sealed auction-oriented selling strategies have different effects under different situations. Section 4 discusses the corresponding algorithm to help sellers make decisions. Section 5 describes the implementation of our prototype. Section 6 makes conclusions and discusses future work.

2. Related work

Much research has been conducted in the field of electronic auctions. A rich body of literature focuses on establishing efficient negotiation protocols in order to automate electronic auctions by customers and merchants [3]. Kikuchi [8] proposes a new protocol for multiple distributed auctioneers to find the highest price and the set of winners; Hirakiuchi [6] proposes a group of signatures and the identity escrow-based, anonymous sealed-bid auction protocol. Subramanian [16] proposes a secure electronic auction protocol to favour security, privacy, anonymity, atomicity, and low overhead. Other researchers construct electronic auction systems to explore various online auction frameworks. Among them, AuctionBot [17] is an experimental Internet auction server established at the University of Michigan. AuctionBot provides a list of predefined auction types for sellers to choose from. Sellers can also customize related parameters. After an auction is set up, the system will enforce the multilateral distributive negotiation protocols. Panzieri and Shrivastava [11] replicate auction servers to achieve data integrity, responsiveness, and scalability.

There are other popular web sites established to support electronic auction activities, such as eBay [4], onSale [13], AuctionNet [1], NETIS auction web [2], etc. Different web sites adopt various strategies to attract sellers and gain a reputation. For instance, some web sites provide comprehensive Graphical User Interface (GUI) features to sellers to set up auctions, such as AuctionNet [1]; some sites allow sellers to configure selling strategies, such as AuctionBot [17]. More and more web sites intend to support more types of auctions such as eBay[4]. For example, eBay supports single-sided auctions, sealed-bid auctions, and English auctions [4]. However, these web sites typically rely on sellers themselves to make decisions on selling strategies, rather than providing explicit facility to assist sellers to select the most appropriate selling strategies to obtain the most profit. Compared to the existing web sites, in our work, web sites act as intelligent experts to help sellers decide selling strategies, based upon economical principles and dynamically collected historical information. In addition, web sites collect statistical information from each auction activity for future strategic decision-making.

3. How pricing works during auctions

In order for web sites to assist sellers to make decisions, we first need to prove that different selling strategies have different effects on different situations in electronic auctions. Due to the page limitation, this paper will focus on single-sided sealed electronic auctions only, where there is only one uniform seller and all bids are sealed. Our research results on other types of electronic auctions will be presented in other papers. In this section we will first formally define the auction problem with assumptions; then we will conduct the proof. The structure of a single-sided sealed electronic auction problem can be defined by the following four essential aspects. First, there are multiple buyers called "bidders" competing for a common object, and no entry fee is needed. Second, there is only one seller in the auction, and the seller bears no cost in selling objects. Third, only the seller knows the true value of the bidding object. Fourth, only the winner needs to pay for the bid object, while others pay nothing. To facilitate our discussion, in this paper we simplify the auction problem with four further assumptions as follows:

1. All bidders are independent and there is no assembly.
2. Each bidder knows his/her own values for the bid objects, but not others'.
3. Bidders always adopt (symmetric) Nash equilibrium [5] strategy in auctions
4. The seller is aware of the bidders' strategy [5].

Here we introduce some notations that will be utilized to discuss auction problems throughout the paper.

Notations:
1. There are **I** bidders, i={1,2,…,I}, where I is a finite natural number, and it is unexpected.
2. **X** represents a set of alternative pricing methods.

3. Θ_i[1] represents the type of bidder i, where $i \in I$.

Θ_i = (θ_{i1}, θ_{i2}, …, θ_{in}), is a set of non-negative real numbers R. **θ_i** is uniformly distributed, i.e. **$\theta_i \sim U[0, V]$**.

4. A utility function over each bidder is used to represent his/her own preference. Bidder i's utility function, depending on his/her own type, can be donated as:

$u_i: X \times \Theta_i \rightarrow R$

5. Every bidder i is an expected utility maximizer, which means:

$$u_i = \underset{u_i}{\text{argmax}}\ E\ u_i(\theta_i)$$

Now we will examine the seller's expected profits with respect to two different types of preferences that a bidder may fall into: risk neutral, and non-risk neutral. A bidder is considered to be risk neutral to a bidding object if he/she is indifferent to bidding for it. Otherwise, a bidder is considered non-risk neutral if he/she either refuses (risk-averse) or happily accepts (risk-seeking) the bidding object.

3.1 Risk Neutral/ Linear Utility

In economics, risk neutral preference yields linear utility functions. Suppose linear utility: **$u_i = \theta_i - P_i$**, where **θ_i** is the private type or value that bidder i assigns to the object; and P_i is the bid price that bidder i asks, in other words, the payment if i wins the object.

$u_i(j, P_1, P_2, ..., P_I, \theta_i) = \theta_i - P_i$, if j=i (if i wins the bid, she will get the value of $\theta_i - P_i$), and

$u_i = 0$, otherwise. (bidders who do not win the bid do not need to pay anything)

We will discuss a seller's expected profits in the two types of pricing mechanisms: first-price sealed-bid auction and second-price sealed-bid auction.

1) First-price Sealed-bid Auction:

A Nash equilibrium strategy for every bidder is $\delta_i(\theta_i)$[2] = $\frac{I-1}{I}\theta_i$ [5]. Therefore the seller's expected revenue is:

$$E\pi_1 = \frac{I}{I-1} E\,[\,\max\{\theta_1, \theta_2, \ldots, \theta_I\}]$$

$$= \frac{I}{I-1}\int_0^v uIf(u)[F(u)](I-1)du$$

$$= \frac{I}{I-1}\int_0^v uIf(u)[F(u)](I-1)du$$

$$= \frac{I-1}{I+1}V \qquad (1)$$

2) Second-Price Sealed-bid auction:

Since $\sigma_i(\theta_i) = \theta_i$ is a dominant strategy for all bidders [5], the seller's expected revenue is the same as in the first-price sealed-bid auction.

$$E\pi_2 = E[\,2^{nd}\text{ highest }\{\theta_1, ..., \theta_I\}\,]$$

$$= \int_0^{\bar{V}} u \cdot I(I-1)\cdot f(u)[1-F(u)](F(u))^{I-2}du$$

$$= I(I-1)\int_0^{\bar{V}} u \cdot \frac{1}{\bar{V}}(1-\frac{u}{\bar{V}})(\frac{u}{\bar{V}})^{I-2}du$$

$$= \frac{I-1}{I+1}\bar{V}\,. \qquad (2)$$

It can be seen that (1) and (2) are the same, i.e. $E\pi_1 = E\pi_2$.

As a result, if we assume that bidders are risk neutral (their utility functions are linear), the first-price or second-price do not matter to the seller's profit. However, the linearity assumption is a weak assumption. As it is released, different results may be exhibited, as we will discuss in the next section.

3.2 Non-risk Neutral/Non-linear Utility Function

Suppose bidders' utility function is $(\theta_i - P_i)^\alpha$, $\alpha \in (0,1)\cup(1,\infty)$. When α is in (0,1), bidders are risk-averse; when α is greater than 1, bidders are risk-seeking. Similar to our discussion in the previous section, we will discuss a seller's expected profits in a first-price sealed-bid auction and a second-price sealed-bid auction, respectively.

1) First-price Sealed-bid Auction:

The bidders' Nash equilibrium strategy is: $\sigma_i(\theta_i) = \frac{I-1}{I-1+\alpha}\theta_i$ [5]. The seller's expected revenue is:

$$E(\pi_1') = \frac{I-1}{I-1+\alpha}\Pr(\text{i wins})E(\text{surplus} \mid \text{i wins})$$

[1] The term *type* here refers to the real number a bidder assigns to a subjectively valued object.

[2] Since bid price is the decision rule for each bidder to get the maximized expected utility, it is the same as the decision rule. Hence, we alternatively use "b," bid price, or "δ," decision rule, to represent the strategy for each bidder.

$$= \frac{I-1}{I-1+\alpha} \Pr(\theta_i \ge \theta_j) \mathrm{E(u)}$$

$$= \frac{I-1}{I-1+\alpha} \int_0^1 [F(u)]^{I-1} u \cdot f(u) I du$$

$$= \frac{(I-1)I}{(I+1)(I-1+\alpha)}. \quad (3)$$

2) Second-Price Sealed-bid auction:

The bidders' dominant strategy is similar to our previous discussion, which is: $\sigma_i(\theta_i) = \theta_i$ [5]. Accordingly, the seller's expected profits are:

$\mathrm{E}(\pi_2')$

= Pr (i wins, $\overline{\theta}_j$ is the second highest value) $\cdot$ E(u|i wins, $\overline{\theta}_j$ is the second highest value)

$= I(I-1) \Pr(\theta_i \ge \overline{\theta}_j, \overline{\theta}_j \ge \theta_k, i \ne j \ne k) \cdot \mathrm{E(u)}$

$= I(I-1) \int_0^1 [1-F(u)] \cdot [F(u)]^{I-2} u \cdot f(u) I du$

$$= \frac{I-1}{I+1}. \quad (4)$$

We can see that $E\pi_1' \neq E\pi_2'$. When α is in (0,1), $E\pi_1' > E\pi_2'$; when α is greater than 1, $E\pi_1' < E\pi_2'$. In either way, the expected profits for the seller under two different pricing methods are different.

In summary, we have proved that for single-sided sealed-bit electronic auctions, the seller's expected profits adopting different pricing methods vary in accordance with the bidders' risk preferences. When bidders are risk neutral, the seller can expect the same profits via first/second pricing. However, when bidders are non-risk neutral, from the risk-averse bidders, the seller expects higher profits by adopting first pricing; but from the risk-seeking bidders, the seller expects higher profits by adopting second pricing.

4. Pricing selection algorithm

In the previous section, we have proved that, in order for a seller to gain higher profits, different pricing strategies need to be adopted in accordance with different bidders' risk preferences. The technical difficulty then becomes how to find out bidders' risk preferences for a given bid object. In other words, a seller needs to predict bidders' risk preferences so that the most appropriate pricing strategy can be implemented. Research has revealed that bidders' risk preferences can be decided by the bid object's set of properties, such as its bidders' mean household income, its price range, its durabilitybid, its functionsbid, and its personalitybid [10]. For example, a luxury item, e.g. a Starbucks Barista Espresso machine that costs \$300, should be considered as a risk-lover's choice. As an ordinary coffee maker's price ranges from \$6-\$300, the Espresso machine should be considered a luxury item in this category of commodity. Since the machine can make not only ordinary coffee, but also latte and cappuccino, it should be considered as serving not only a universal function but also special functions. Furthermore, the machine is a Starbucks-recommended coffee maker; therefore, it possesses personal stylishness. As a result, the Espresso machine is normally purchased by customers with a household income of more than \$100,000 and the customers are generally risk seekers.

Therefore, we propose that the probability of bidder's risk preference represented as a function of a set of parameters, as is shown below:

$Y = f(X_1, X_2, X_3, X_4, X_5, \ldots)$

or

$Y = A_1 * X_1 + A_2 * X_2 + A_3 * X_3 + A_4 * X_4 + A_5 * X_5 \ldots + \varepsilon$ (5)

X_1 denotes the mean household income of potential bidders; X_2 denotes the durability of the bid object; X_3 denotes the price range of the bid object; X_4 denotes the function of the bid object, whether it is for universal or special usage; X_5 denotes the personality or style of the bid object. ε is an error term, which is a measure of the accuracy of predictions that can be made with a regression equation. More parameters can be added if more features should be included to calculate the bidders' risk preference for a given bid object.

If the value of the function Y is greater than 0.5, the risk preference of the potential bidders for this object is considered to be risk seeking; if Y is equal to 0.5, their risk preference is considered to be risk neutral; and if Y is less than 0.5, it is considered to be risk averse.

As shown in formula (5), different parameters contribute differently to the risk preference. The weight of each element, including the sign and magnitude, however, is not concluded by any published literature; therefore, only empirical data can be used to deduce each weight. To date, in order to simplify the discussion, our current work proposes an adjusted formula as shown below:

$Y = 1/6 * HI/50000 + 1/6 * PR/RA - 1/6 * DU/5 + \varepsilon$ (6)

In this simplified formula (6), we assume that only three properties of a given bid object contribute to its risk preference of its bidders, namely, the mean household income of potential customers, its price, and its durability. We assume that the three properties weigh equally in absolute value to the risk preference, but the first two have positive effects while the last one has a negative effect. *HI* denotes the mean household income of the potential group of customers. Without losing generalization, 50,000$ is used as an average household income as comparison. *PR* denotes the price of the object, while *RA* denotes the highest price of the same category of commodity. *DU* denotes the durability of the object. Without losing generalization, 5 years is used as an average length of durability. For example, let's use a Starbucks Barista Espresso machine as before. We assume that the mean household income of customers is $70,000. The information can be gathered from stores that sell this type of machine. The price is $300, and the price range of an ordinary coffee maker is $6-$300. The duration of this type of machine is 4 years. According to our formula, the calculated risk preference of the machine is:

$$Y = 1/6 * 70000/50000 + 1/6 * 300/296 - 1/6 * 4/5$$
$$= 0.533$$

Consequently, the risk preference of the customer is considered to be risk-seeking. As a result, based upon our discussion in the previous section, a second-price sealed-bid auction should be suggested to the seller whenever an online auction is conducted.

Therefore, a price selection algorithm is summarized as illustrated in Figure 1. First, the name and the category of the bid object need to be collected. The category may contain hierarchical information. For example, a Starbucks Barista Espresso machine belongs to "Home / kitchen & housewares / coffee makers." Second, the durability of the object needs to be obtained in years. As we discussed, without losing generalization, a five-year period is used to be compared. For example, the durability of the coffee machine is four years. Third, the seller needs to state whether the object has special functions, or is just for general purposes. For example, an Espresso machine can make cappuccino and latte in addition to ordinary coffee. Fourth, a seller needs to state whether the object has personal style. For example, a Starbucks Barista Espresso machine is fashionable. Fifth, the mean household income of the buyers of the object needs to be collected, either from corresponding stores that sell the same type of objects, or from the historical information. For example, queries from a store that sells the same type of Starbucks Barista Espresso machines may provide the information that the average household income of the customers who purchase the machine is $70,000. With all the information gathered, the formula (5) or (6) can be applied to get the expected probability of the potential bidders' risk preference. In practice, it might be difficult to judge the result to be 0.5. Thus, we might set up a threshold, say 0.005. Therefore, if the result falls between (0.495, 0.505), it is considered to be equal to 0.5. If the result is equal to 0.5, there is no difference between the two pricing strategies; therefore, either one can be suggested. If the result is greater than 0.505, the second-pricing sealed-bid algorithm is suggested; if the result is less than 0.495, the first-pricing sealed-bid algorithm is suggested. In future research, when we can regress (5) based upon the data we collect, all parameters can be re-estimated, and the weight of each parameter will be tested under the theory of statistics.

1. Get object name and category;
2. Get durability of the object;
3. Get whether the object has special functions;
4. Get whether the object has personal style;
5. Check the mean household income of the object buyers;
6. Use the formula (5)/(6) to calculate the risk preference of the object;
7. If the result is greater than 0.505, the second pricing is suggested;
   If the result is less than 0.495, the first pricing is suggested;
   If the result falls between 0.495 and 0.505, either strategy is suggested.

Figure 1. Pricing strategy selection algorithm

5. Intelligent pricing recommendation agent

In this section, we present our Intelligent Auction Registry (IAR) engine that is a prototype to help auction sellers make right pricing decisions. Figure 2 illustrates the architecture and the components of our IAR engine. Four components fulfill three roles in the IAR engine, namely, auction editor, intelligent auction registry, statistical manager, and SOAP translator. Two repositories are also included in the engine: rules repository and history repository. In order to help sellers better describe the bidder objects they want to register, the auction editor provides a user interface to prompt sellers to input object name, select a suitable object category, and provide durability, function, and style information. The rule repository stores both the auction selling price selection algorithm and corresponding information, such as the parameters needed.

The intelligent auction registry component has the following three functionalities. First, it receives the information of bid objects from the auction editor. Second, it queries the history repository for the mean household income of the corresponding potential customers. Third, it may communicate to other outside components, e.g. stores, via the Internet for the mean household income of the potential customers, if the corresponding information cannot be found in the history repository. IAR then is able to provide pricing strategy suggestions to the seller. In

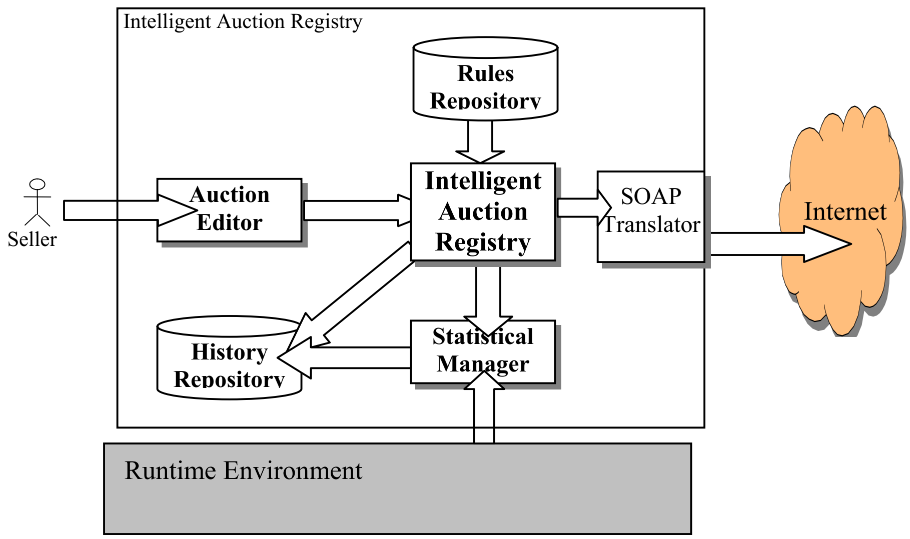

Figure 2. Intelligent auction registry engine

order to decouple our engine from the underlying technology choices and make it easier to communicate with other third-party resources, the eXtensible Markup Language (XML)-based [18] Simple Object Access Protocol (SOAP) [15] is utilized to support the interaction with the outside world, as shown in Figure 2. A SOAP translator is part of our IAR engine. Because all queries are transmitted via XML, a universal format for structured documents and data definitions on the web [18], our engine can be deployed to different platforms.

After the auction is performed, the statistical manager gathers information from the runtime environment and stores it in the history repository for future usages. The types of statistical data that needed to be built and maintained in order to provide the probability and timing data for the agent's decision process are bid object, object category, and mean household income of the bidders. These data can be in turn utilized to further verify the pricing selection algorithm (5) and (6).

The system has been under development since early 2003. The agent, including much of the data-collecting capability described in this paper, is in place. The principle elements of the Intelligent Auction Registry agent are complete, including a highly adaptable search engine designed to support bid evaluation in this environment.

6. Conclusions and future work

This research examines seller's pricing strategy oriented to bidders' risk preferences, within the context of an electronic auction. A business model is then proposed to predict the probability of potential bidders' risk preference, which the sellers can consider to set pricing strategy to maximize their profits. This research gains some insights into the possibility the web sites can provide intelligent facilities to help sellers decide selling strategies, based upon economic principles and dynamically collected historical information. This paper reports our research result on single-sided sealed electronic auctions: by adopting different pricing methods in accordance with the bidders' risk preferences, the seller can expect different profits. When bidders are risk-neutral, the seller can expect the same profits via first/second pricing. However, when bidders are non-risk neutral, the seller expects higher profits by adopting first pricing over second pricing when bidders are risk averse; and expects higher profits by adopting second pricing when bidders are risk seeking. Through this study, we suggest that website management may design different pricing for different kinds of auction objects to let sellers get more profits, which may be a way to attract more sellers online. Based upon our study, a tailored intelligent auction registry engine is constructed.

However, current research focuses on single-sided sealed-bid auctions only, which is a subset of possible types of on-line auctions. In addition, further investigations are needed to examine the business model that estimates the possibility of potential bidder's risk preference, which is denoted by formula (5) and (6).

Current efforts include a user interface that will present risk information and allow a user to interact with and override agent recommendations, and use the search engine interactively. Additional study is needed to develop detailed strategies for other types of electronic auctions than sealed auctions, and to relax some of the assumptions used in this analysis, such as single-bid object.

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