An Alternative Approach in Analyzing the Impacts of Online Feedback System: A Bayesian Inference Model

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Abstract

Previous studies present the mixed results on online reputation mechanism. In this study, we have found that an approach based on Bayesian statistics can explain most results of previous studies which are conflicting with each others. With this model, we explain why negative ratings have more significant marginal impacts on sellers' reputation than positive ones do. Furthermore, we even show why the feedbacks with a few negative ratings may increase the value of the item and final prices by confirming buyers' prior beliefs on the sellers' reputation much more than those without negative ratings.
Also, we explain why there are not many negative ratings. Even though some studies suggest this because of generosity of users, our model shows that the reason is that the existence of FS itself prevents bad sellers from participating to the market as a signal itself. Even further, we show how this extreme tendency of positive ratings gets even stronger as markets evolve.
Finally, to validate our analytical results, we examine the previous studies and see what factors affect the outcomes of their analyses.

Keywords:

Online feedback system, Bayesian approach, Signaling

1. Introduction

As Electronic Commerce (EC) widely opens to public, it has been one of the most bustling domains of the Internet. Anyone who wants to trade with others can freely participate in this market as a seller or a buyer with a pseudonym. In most online dealings the buyers are unable to observe sellers' product or service quality at the time they just purchase them. It seems like purchasing a lottery [26]. In this way, a buyer needs to experience hidden information for products or services before he or she buy, but these actions are not likely to be realized in this market. Eventually these uncertainties bring about severe information asymmetry such a lemon problem among the participants. [1]

Recently most of online marketplaces have introduced innovative tools such feedback systems (FS), escrow service, and money-back guarantee that alleviate this given unfairness between a seller and a buyer [4]. Especially the FS, including consumers' ratings and comments, has become the most prevalent device for building trust on online market.[11] Furthermore in large volumes of studies, FS has been regarded not only as a proxy in experiencing product quality[12], but also as an enormous megaphone in promoting products sales [29]. In this context it is clear that a seller's cumulative reputation play an important role as a quality indicator [25] and as a promotion tool
In our research, we look at the Feedback Systems as a signaling for mitigating information asymmetric. Applying Bayesian statistical inference, we explain how FS act as a signal. From our model we find the existence of FS itself can be a trustful signal of unobservable seller's reputation; it prevents bad sellers from participating. Moreover we show the maturity of FS can make the bad participants hard to join the market. With this statistical estimation, finally, we explain the mixed results of impacts from FS shown in previous studies

2. Literature reviews

2.1 FS Mechanism

Previous studies present the mixed results on online FS mechanism. It is mainly because different studies have each of their distinctive purpose on feedback profile [11]. These various results are largely divided by two issues. First, feedback profiles seem to affect both the probability of sale and final bidding price [6, 7, 8, 22]. Second, the impact of feedback profiles is more highly affected by negative and recently posted ratings [14, 15, 18]. In our study we mainly explain the latter phenomenon rather than the former ones, which are relatively supported by much research.

2.2 Signaling

In Michael Spence's study [26], a signal is defined as an alterable indicator and therefore potentially it influence by signal senders who have more information. There are large volumes of literatures on quality signaling, covering a wide variety of signals. Especially, the problems for the reputation of retailers or sellers, and the quality of products have been researched actively [21, 31]. In this context, recent studies argue that the FS mechanism is emerging as a promising alternative tool for promoting trust and as a quality indicator [3, 10]. Most of these studies on FS are deeply related to the effect of FS process in providing the information. However our study is to concentrate more on the existence of FS itself.

2.3 Bayesian approach

Bayesian framework has been widely introduced to explain how reputation mechanism is working [13, 17, 19]. In general Bayesian updating model [19], individual reputation is continually renewable by informed party. Unlike these studies, we are focusing on providing alternative approaches on several impacts of FS with applying Bayesian statistical inference.

3. MODEL

We have two significant assumptions. First a seller's reputation, or a personal profile provided by FS, is fully correspondent to the quality of goods which he or she sells. *Reputation* means a concept that arises in repeated game settings when there is uncertainty about some property of one or more players in the mind of other players. [30] Usually quality of goods imply deliver time, quality of good itself, money back guarantee and something related to the quality.[25] Many studies show that quality is equivalent to reputation. In this study we assume that quality of goods is dependent on reputation.

The second assumption is that a buyer's profile is insignificant while a seller's reputation rating is significant on a final price and probability of sales. Even though online auctions like eBay allow reciprocal ratings, we only focus our interest on sellers' reputation. In online markets, a buyer has more fraud risk than a seller. Usually buyers pay beforehand, so there have more possibilities to defraud by seller-sellers who may deliver less quality goods than advertised ones. Eventually a buyer's reputation seems less important than a seller's one [11].

3.1 The process of FS Mechanism

There are sequential feedbacks between buyers and sellers. At the first time buyers can not discern which sellers are good or not. In this way, sellers decide sequentially whether to try to effort for quality. Each type of sellers choose an optimal effort for FS, and then each of them pays a different cost for FS with reflecting current his or her own reputation in the market. Secondly a buyer observes the relationship between a real product and an advertised product. This stage is occurred after purchasing products or services. With this evaluation, a buyer's probabilistic belief for sellers' reputation is updated. In this stage, buyers determine which seller is reputable or not. Also they determine how much reward they pay to sellers (in this study a buyer only posts a positive or a negative rating). The amount of reward is dependant on seller's reputation. This reward can contain money for goods and reliability for a seller. In the end of this session, each type of seller receives a reward equivalent to his or her reputation level from the buyer's evaluation. Finally from the reward, the seller determines whether to make more efforts for quality of goods in the next session. These all feedback stages are repeated infinitely.

3.2 A Bayesian inference

Let us suppose that there are just two distinctive types of sellers and buyers who are facing them, and a market intermediary, which is providing a seller's reputation to buyers and controlling them. Good types of sellers, T_H, have good reputations and provide high quality of goods, while bad type of sellers, T_L, have bad reputations and provide low quality of goods. There is no way to tell in advance which seller will be of the good or bad type before real purchasing. From the buyers' sequential feedbacks based on FS mechanism, these two types of sellers are distinctively divided. We introduce Bayesian statistical inference to explain the posterior beliefs after successive buyers' feedbacks based on prior beliefs on the average sellers' quality in the market

A seller's trust on quality, q_0, is distributed according to the Beta Distribution that is,

$$q_0 \ : \ Beta(\alpha_0, \beta_0) \tag{1}$$

α_0 is the number of T_H, and β_0 is the number of T_L. In other words these are interpreted as the number of good transactions and the number of bad transactions respectively in total dealings with buyers.

$$E[q_0] = \frac{\alpha_0}{\alpha_0 + \beta_0} \tag{2}$$

$E[q_0]$ means the expect quality of the market, that is a buyer's prior beliefs in the market which has no device, such a FS Mechanism, to distinguish T_H from T_L. External events, or binary feedbacks, can be expressed as the likelihood function, $L(q_0)$, of sampling distribution following Binomial distribution.

$$L(q_0) : \ Binomial(n, p) \tag{3}$$

The expected value of this external event is:

$$E[q_0] = ngp. \tag{4}$$

Like Bernoulli's trials, Binary feedbacks have distinctive two events: a positive rating and a negative rating- usually probability of events, p, is close to 0.5. The number of buyers' feedback, n, is the sum of the positive ratings, α_n, and negative ratings, β_n. From equation (2) and (4), we can estimate the posterior beliefs for average quality of market. The estimated acquired average quality of market is distributed as:

$$q_n \ : \ Beta(\alpha_n + \alpha_0,\ n - \alpha_n + \beta_0) \tag{5}$$

$$E[q_n] = \frac{\alpha_0 + \alpha_n}{\alpha_0 + \beta_0 + n} = \frac{\alpha_0 + \alpha_n}{\alpha_0 + \beta_0 + \alpha_n + \beta_n} \tag{6}$$

$$= \frac{n}{n + \alpha_0} g \frac{\alpha_n}{n} + \frac{\alpha + \beta}{n + \alpha + \beta} g \frac{\alpha}{\alpha + \beta} \tag{7}$$

We adopt the equation (6) to estimate a buyer's posterior belief for average quality of the market. As indicated equation (7) a Bayesian Inference property is showing that the expected quality of market, $E[q_0]$, is more affected by external events, $L(q_0)$, as the number of feedbacks increase.

4. A market without FS

Proposition 1

In a market which has no devices for alleviating quality uncertainty of goods, the reputable sellers will not stay in the market and leave.

Like a traditional secondhand car market, an online market does not reveal quality of goods before real purchasing. We introduce Akelof's the lemon principles [1] to describe a market which has uncertainty of seller's quality for goods. Having no indicator for recognizing a seller's quality, buyers make their decision based only on the average quality of sellers-the average quality of market In general a seller is eager to earn profits depend on his or her quality. In other words a seller's Willingness-to-get(WTG) is defined as:

$$WTG(q_0) = q_0 g w - c_f, \quad q_0 : u(0,1) \tag{8}$$

A seller's initial quality, q_0, is normally distributed from 0 to 1, w is unit revenue for q, and C_f means an initial fixed cost such a raw material cost or transaction cost. However in the market a seller's expected revenue is dependant on average quality of market. The average quality of market, a buyer's prior beliefs on market quality, is shown as an expected value of Beta distribution.

$$E[q_0] = \frac{\alpha_0}{\alpha_0 + \beta_0} = \lambda_0^M, \quad \lambda_0^M : u(0,1) \tag{9}$$

An average quality of sellers in a market, λ_0^M, is normally distribute from 0 to 1 . An overall sellers' profit, π_0, can be shown:

$$\pi_0 = \lambda_0^M g w - c_f \tag{10}$$

Thus sellers who have better reputations than average reputations of market are out of market.

$$WTG(q_n) = q_n \vartheta g w - c_f > \pi_n = \lambda_n^M g w - c_f \tag{11}$$

θ is a quality coefficient to measure the difference between q_n and λ_n^M.

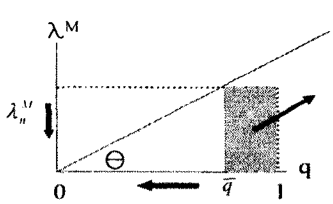

Figure 1

Figure 1 indicates that equation (11). The shaded areas, including the people who have higher reputations than average sellers' reputations in market, are out of market, because the sellers make a loss if they participate in this market. Consequently buyers' prior beliefs is determined by existing sellers who have quality between 0 and $\bar{q}$. Continually the average quality of markets would decrease, if there are no measures against it. The quality uncertainty in a market, eventually, drives all reputable sellers out except the low reputable sellers who have quality near to 0. Simply when $q_n > \lambda_n^M$, it lead to market failure as shown in equation (12)

$$\lim_{n\to\infty} q_n = 0, \ \lim_{n\to\infty} \lambda_n^M = 0 \tag{12}$$

Clearly because, in this one shot game, there is no accumulation of feedbacks, a seller's best choice is not to make an effort to increase his reputation profile. Furthermore, we found that the larger θ, the more TL are out.

5. A Market with FS in Two-Stage Game

5.1 A period for Introducing FS

Proposition 2

The existence of FS itself as a signaling prevents bad sellers from participating in the market.

When a seller participate in a market which has FS, he or she is likely to feel burden to be trustful. In the market a seller put efforts, or costs, into quality to make a profit while a traditional market without FS require any other costs except transaction costs. Unlike Kim [16] who considers self-quality assurance with endogenous variables such a maintenance level of used car in lemon market, we introduce an exogenous variable, C_r, to avoid a lemon problem. That is, a seller who will join future transactions revealing information of personal reputation, expects that his or her Willingness-To-Get is changed, while a buyer's expected quality of overall quality, λ_n^M , is remained.

$$WTG(q_n^r) = q_n \vartheta g w - c_r \tag{13}$$

If C_r exceeds revenue based on average quality of market, $W(\lambda^M)$, no one participates in the market. The optimal initial cost for FS:

$$0 < c_r^* < w(\lambda^M) \tag{14}$$

Thus, when $WTG(q_n^r) = q_n \vartheta g w - c_r \leq 0$, low quality sellers, T_L, who cannot afford to pay C_r are out of market. Only reputable sellers, T_H, participate in the market if

$$WTG(q_n^r) < \pi_n \tag{15}$$

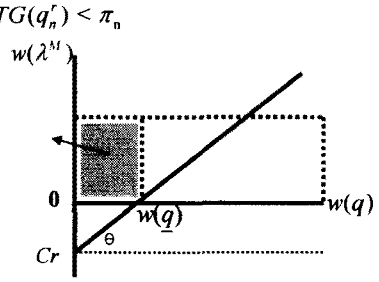

Figure 2

Sellers in shaded area on Figure 2 decide to slip out of the market. Even though they pay C_r they are doomed to deficit. The elimination of a group of T_L makes overall market quality increase.

Simply the number of T_L who cannot afford to pay C_r can be shown as β_c^M . $0 \le \beta_c^M \le \beta_0^M$ That is, a buyer's initial belief for quality, λ_0^M changes into:

$$\lambda_0'^M = \frac{\alpha^M{}_0}{\alpha_0^M + \beta^M{}_0 - \beta^M{}_c} \tag{16}$$

From the difference between a buyer's beliefs for quality after adopting FS, $\lambda_0'^M$ and a buyer's prior beliefs for quality, λ_0^M , we find that there exists a quality increase after advent of FS.

$$\Delta E[q^M{}_0] = [\frac{\alpha^M{}_0}{\alpha^M{}_0 + \beta^M{}_0 - \beta^M{}_c} - \frac{\alpha^M{}_0}{\alpha^M{}_0 + \beta^M{}_0}]$$
$$= \frac{\alpha^M{}_0 g \beta^M{}_c}{(\alpha^M{}_0 + \beta^M{}_0)(\alpha^M{}_0 + \beta^M{}_0 - \beta^M{}_c)} > 0 \tag{17}$$

Equation (17) shows amount of increasing buyer's belief for quality. As shown Figure 2 the increase of C_r makes more T_L be out.

Additionally we find that the increase of C_r makes more T_L be out.

$$w(\underline{q}) = \frac{c_r}{\theta} \tag{18}$$

The maturity of FS can represent the amount of C_r. That is, markets which established FS long before are likely to have higher level of FS. We will prove that phenomenon next section 6. The sellers who survive in first game are already paid C_r to get better reputation, so some of higher reputable sellers, T_H are not out of market because they know their reputations will be higher than now. From this reason they have a commitment on their action [17, 20]

Several studies show that vast majority of ratings and comments from buyers are extremely positive. Resnick and Zeckhauser[22] mentioned this phenomenon as a 'high courtesy equilibrium' mainly come from reciprocal ratings; a buyer fear tit for tat from sellers. Also Dellarocas [9] described it as a 'culture of praise' that a market encourage positive feedback-"most of buyers feel a moral obligation to follow the prevailing social norms and be nice and relatively forgiving to their trading partners."

Unlike these studies that present extremely positive ratings and comments are mainly come from buyers' psychological issues such a generosity, our model presents the rare negative ratings on sellers' transactions are mainly come from existence of FS itself. In addition our finding is supported by the evidence on the cheat.com, a Korean online fraud accusation web site. We investigate 572 accusations for online fraud during Jan. 1 to Jan 20. Only 20 events are occurred in markets which have FS such auction.com, G-market, but other 552 events are occurred by markets without FS such some online communities and personal-owned shops.

5.2 A Period for Separating

After filtering bad reputable sellers, β_c^M , out of the market, sellers who pay C_r should continually determine to use FS whether to exert efforts, C_v for quality to accumulate positive feedbacks from buyers at every transact. The FS mechanism requires continuous efforts to keep their reputations. [10] In this processes, some sellers who do not effort to get positive ratings abandon continually selling their goods because of losses. Our model finds a separating equilibrium.

Proposition 3

There exists a separating equilibrium when

$$w(\lambda_n^I) - \alpha_n^I g c_v \ \ge \ w(\lambda_0^I) \tag{19}$$

Only when the profits, left-hand side of equation (19), of sellers who use FS is larger than each of their initial profits, right-hand side of equation (19) from buyers prior beliefs for quality, T_H are remained. From the equation (16), furthermore, initial sellers' profits have to satisfy that condition:

$$\lambda_0^I = \frac{\alpha_0^I}{\alpha_0^I + \beta_0^I} > \frac{\beta_c^M}{\alpha_0^M + \beta_0^M} \tag{20}$$

A seller's initial reputation should larger than markets' lowest reputation, the right-hand side of equation (20). The T_L who pay C_v do not stay when he or she become a loss though he get higher reputation. This is because of C_v, cost for exerting higher efforts. After sellers come to the market with FS, they should pay attention to continually provide quality goods because their feedback profiles are accumulated. In this dynamic the sellers who do not effort to providing quality goods are out. As a result, when $\alpha_n^I > \beta_n^I$, a seller can earn a profit-he decides to remain in the market but when $\alpha_n^I \le \beta_n^I$, a seller make a loss-she leaves the market

6. Maturity of FS

The maturity of FS can be explained by successive of separating between sellers. The maturity of FS mechanism makes sellers do efforts to get higher reputations. Ideally all sellers can reveal their productivity in this market. Back to the 1[St] stage of game, the market which has highly matured FS can bring about more vast initial costs for entry. It can make low reputable sellers hard to transact in a market.

$$E[\lambda_0'^M] = \frac{\alpha_0^M}{\alpha^M{}_0 + \beta_0^M - \beta_c^M}$$
$$E[\lambda_1'^M] = \frac{\alpha_0^M + 1 g E(\lambda_0'^M)}{\alpha^M{}_0 + \beta_0^M - \beta_c^M + 1} \tag{21}$$
$$E[\lambda_2'^M] = \frac{\alpha_0^M + 1 g E(\lambda_0'^M) + 1 g E(\lambda_1'^M)}{\alpha^M{}_0 + \beta_0^M - \beta_c^M + 1 + 1}$$

M

$$E[\lambda_n'^M] = \frac{\alpha_0^M + \sum_{i=1}^{n} E(\lambda_i'^M)}{\alpha^M{}_0 + \beta_0^M + \beta_c^M + n}$$

$$E[\lambda_{n\to\infty}'^M] = 1$$

Equation (21) shows a process of self-evolution in a market with FS. A market has a probability of increasing overall quality of market, $E[\lambda_n'^M]$, at every separating. This probability affects next overall quality of market. Eventually a buyer's belief on quality of goods in the market turns into a conviction for quality. Our finding reflects the actual state on the market with FS like eBay. To explain our model, we examined 3 leading online markets: eBay, the world largest online auction founded in 1995, initially invented a FS. Auction.com, now owned by eBay, is the largest online auction in Korea. Mple.com is the emerging second largest online auction in Korea. We collected sellers' feedback profiles on a MP3 player, made by Samsung, in each of markets. Although there are other factors for affecting the average seller's feedback profile, we only consider the average seller's reputation according to the timing of introducing FS in a market.

Table 1 – Comparison of FS Maturity (March 23, 2007)

Market	Start-up	Intro. FS	# of sellers	Average Reputation
eBay.com	1995	1996	6	98.61
Auction.com	1998	1998	8	93.5
Mple.com	2006	2006	10	83.5

As we shown Table 1, the average reputation on a specific MP3 player is deeply correlated when a market introduced FS. Average seller's reputation on eBay has the nearest to 100. This figure is significantly higher than those of other markets.

7. Mixed Results and Bayesian Approach

Even though mixed results are showing different impacts of FS, there exist some agreements on significant impacts. First, negative feedback in a seller's reputation profile will be affected more profoundly than positive feedback [14, 18, 27]. According to the Bayesian inference we adopted, this result is explained.

$$\frac{\partial \dfrac{\alpha_0+\sum\alpha_i}{\alpha_0+\beta_0+n}}{\partial\alpha}>0 \qquad \frac{\partial^2 \dfrac{\alpha_0+\sum\alpha_i}{\alpha_0+\beta_0+n}}{\partial\alpha^2}<0 \tag{22}$$

$$\frac{\partial \dfrac{\alpha_0+\sum\alpha_i}{\alpha_0+\beta_0+n}}{\partial\beta}<0 \qquad \frac{\partial^2 \dfrac{\alpha_0+\sum\alpha_i}{\alpha_0+\beta_0+n}}{\partial\beta^2}>0 \tag{23}$$

From equation (18) and (19) we find that the impact of positive feedback marginally decrease, but that of negative one marginally increase. Thus, the marginal impact of negative rating is larger than that of positive one. Also the argument that recently posted negative ratings have greater influences on a seller's reputation [5] is supported. This phenomenon is exampled in Table2. With checking variations of reputations, $\Delta\lambda$, and uncertainties, $\Delta\sigma$, we examine transitions of buyers' beliefs and uncertainties for sellers' quality. A buyer's uncertainty for a seller's quality is estimated as:

$$\sigma(\lambda_n') = \frac{(\alpha_n' + \alpha_0')(n - \alpha_n' + \beta_0')}{(n + \alpha_0' + \beta_0')^2 (n + \alpha_0' + \beta_0' + 1)} \tag{24}$$

Table 2-The marginal impacts of feedbacks

	Distribution	λ	Δλ	σ	$\Delta\sigma$
$E(q_0)$	$B(\alpha_0, \beta_0)$	0.6	0	0.06859	0
$E(q_1)$	*B(1, 0)*	0.6078	+0.008	0.06770	-0.00089
	B(0, 1)	0.5882	-0.0118	0.06824	-0.00035
$E(q_{10})$	*B(10, 0)*	0.6667	0	0.06035	0
$E(q_{11})$	*B(11, 0)*	0.6721	+0.005	0.05962	-0.00073
	B(10, 1)	0.6557	-0.0111	0.06034	-0.00001
$E(q_{100})$	*B(100, 0)*	0.8667	0	0.02766	0
	B(101, 0)	0.8675	+0.0008	0.02749	-0.00017
$E(q_{101})$	*B(100, 1)*	0.8609	-0.0058	0.02806	+0.00038
$E(q_{110})$	*B(110, 0)*	0.8750	+0.0083	0.02606	-0.0016
$E(q_{110})$	*B(100, 10)*	0.8125	-0.0542	0.03162	+0.00396

Table2 show the reputation of a seller, whose initial score is 0.6, is more affected by negative ratings. When he gets more positive ratings, his quality uncertainty from buyers is significantly reduced.

Furthermore, there is a unique phenomenon that the existence of one or few negatives ratings can reduce the uncertainty. Some study empirically show that a few negative ratings may increase the value of the item and final prices by confirming buyers' prior beliefs on the sellers' reputation much more than those without negative ratings. [6, 7, 9, 15].

Table 3-The impacts of few negative ratings

	Distribution	λ	Δλ	σ	$\Delta\sigma$
$E(q_0)$	$B(\alpha_0, \beta_0)$	0.2857	0	0.05361	0
$E(q_1)$	*B(1, 0)*	0.2957	+0.01	0.05378	-0.00017
	B(0, 1)	0.2816	-0.0041	0.05301	-0.0006
$E(q_{10})$	*B(10, 0)*	0.375	0	0.05379	0
$E(q_{11})$	*B(11, 0)*	0.3827	+0.0077	0.05367	-0.00012
	B(10, 1)	0.3703	-0.0047	0.05332	-0.00047
$E(q_{100})$	*B(100, 0)*	0.7058	0	0.03484	0
	B(101, 0)	0.7076	+0.0018	0.03453	-0.00031
$E(q_{101})$	*B(100, 1)*	0.7017	-0.0041	0.03488	+0.00004
$E(q_{110})$	*B(110, 0)*	0.7222	+0.0164	0.03329	-0.00155
$E(q_{110})$	*B(100, 10)*	0.6667	-0.0392	0.03503	+0.00019

From Table 3 we find an alternative perspective on such a unique phenomenon. When a bad reputable seller, whose initial score is 0.2857, comes into a market, his quality uncertainty from buyers is increased even though he gets positive ratings. Thus few negative ratings can positively affect a buyer's uncertainty on quality.

8. Conclusion

By applying Bayesian statistics' approach, we come to a conclusion that the mechanism of Feedback System can guarantee the trust among the anonymous participants in online market. Initially, the FS prevents bad sellers from participating to the market as a signaling itself. Then reputable sellers try to be remained in the market with efforts to reveal their good quality products or services, while bad reputation sellers cannot pretend to be a good sellers. Finally, as the FS in a market becomes more matured, not only sellers can reveal their true quality but also buyers can reduce the uncertainty of quality. Additionally, we suggest alternative perspectives on mixed results of the FS impacts

There are further studies possible in the future. First, Meta analysis of empirical studies in the past would be helpful in validating our model. Furthermore, the impact of the combination of FS with other factors or moderating effects will be able to be examined. As one of our further studies, we are now working on a meta analysis of FS from the empirical studies in the past.

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