Bid Sniping on eBay by Andy Chou

Introduction:

Ebay, the world's foremost leading online auction site has become a major institution over the Internet. This worldwide leader in Internet innovation started with a humble beginning. eBay was founded by Pierre Omidyar in September 1995 inside his living room in San Jose. At the time, it was meant to be a small personal site to sell used items utilizing a simple ascending bidding system. Little did Omidyar know that his system of online auctioning would revolutionize the world by blending in the convention of auctions with the technology of the Internet to increase the efficiency of day to day "sales." Over eighty million people visit eBay.com with over two hundred million individual auctions. This combination generates over four billion dollars in transactions each year, representing an unprecedented amount of economic activity online through auctions.

Since online auctions is still a relatively new concept, extensive studies and theories have not been conjectured until recently. Due to this limitation, eBay consumers had to rely on logic, and trial and errors in the first years of eBay. Gradually, different bidding techniques were developed to induce competition between bidders and introduced an entirely new way and method of purchasing online goods. This bidding system is still new a territory to the study of the Internet because it is one of the newest trends to appear, in online sales. Instead of strict prices and amounts that dictate the consumer attitude toward purchasing, the procedure of buying and selling to a self-imposed price brings about an entirely new way to understand the rationality behind internet sales and auctions on sites like eBay.

This paper will focus on the behavior and rationality of eBay bidders. It will examine if the seller's "reputation", measured by seller's feedback, has a positive correlation to buyer's willingness to bid on an item as well as the price of the item. Furthermore, this paper will also take a look at whether the length of the days the seller puts an item for sale has any correlation to the final price bidders are willing to pay.

It has been widely agreed that in second price auctions the dominant strategy is to have bidders simply bid their true reservation price (Ockenfels and Roth 2002). This paper will also scrutinize why this is not true and why it is actually better to not reveal

one's true value until the end. This paper will go into length about the bidding techniques such as sniping and bid shading. The paper will address what they are, and how rational the consumers are in incorporating them as part of their strategy when bidding on auction sales. Ockenfels and Roth (2002) attest that the phenomena of late bidding on eBay does not **always** result from irrational behavior, and can instead occur at equilibrium.

Method for Seller Reputation Experiment:

In order to test the correlation between seller rating and bidders, one would need a large sample size of data to get consistent result. Due to limitations of not being able to design a computer program to extract this information, I have decided to use the data collected by David Lucking-Reiley and Daniel Reeves from their paper "The Determinants of Price in Online Auctions." The authors used a program written in Perl to extract information from a specific category of eBay auction. In this experiment, "Coins and Stamps" auction category on eBay was used. The program would go into the completed auction section for the day and save up all the links, then use the links to find the completed auctions of two days ago, then three days, four days and so on. By using this method, the program is able to easily obtain three months of completed transactions, or roughly 20000 sets of unique links. The authors then used the same program to extract out relevant data for the experiment from the links. This includes a user feedback rating (User feedback rating is calculated as the number of positive unique feedbacks – number of negative unique feedbacks), the color of star next to the rating (The color of star changes to indicate larger and larger ratings), the number of positive feedbacks and the number of negative feedbacks. Finally, anyone with the rating of minus four or lower will be banned from auctioning on eBay.

A glaring problem with this enormous set of data is that with so many different kinds of coins and different conditions, it is impossible to obtain a consistent, controlled set of data for analysis. The authors took this into account and used SQL to sort through data to find the one type of coin that was auctioned the most during the three months span. The program was able to find 461 auctions with U.S Indian Head pennies minted from 1859-1909 with graded condition of 60-66 out of 100 point scale. The authors then

were able to go to a website to find out the book value of the coins to use as control. This set of data would be used for analysis for this experiment to see buyer's willingness to bid on the item as well as the correlation between the final price of the item to user's ratings.

The authors used the same set of 461 auctions to test the correlation between the length of days seller designated the auction to be to the final price bidders are willing to pay. The data is divided up into four different sets: auctions of three days or less, auctions between three to five days, auctions between five to seven days, and auctions between seven days to maximum allowed of ten days. Since there were more than forty sets of data for each of the four sets, this setup is more than feasible. Thus the data is also set for analysis for the experiment to see the length of days affecting the final price of the item being sold.

Method for Snipe Bidding and Shading Price Experiment:

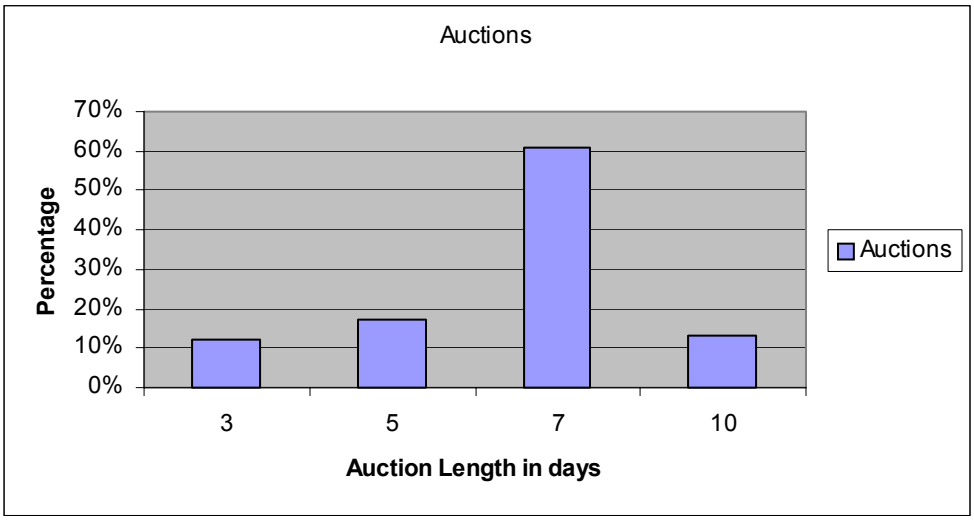
Snipe bidding is a common strategy now in Internet auctions. Don't be too happy next time you see a pair of NBA finals tickets for only $50. Chances are the price is going to jump astronomically before it's all said and done. The strategy of bidding one or two minutes before the auction is over is known as snipe bidding. Bid shading is the act of hiding what the true value of the item is to you until the very end when you submit one last bid for the item. At first glance, this seems rather irrational since this strategy seems unorthodox compared to traditional bidding strategies of bidding your true value since there weren't any optimum strategies before in auctions where it is best for bidders to wait until very last minute before submitting their true bid value. I will use the resources available to me to dig deeper into this and see how rational snipe bidding and bid shading really is.

In order to perform the experiment on why sniping and bid shading are rational strategies in eBay auctions, I have used the experiment done in the paper An Experimental Analysis of Ending Rules in Internet Auctions (Ockenfels and Roth 2002). The experiment tests the situation of eBay1. In eBay1, there are two bidding stages, early and late stage. In the early stage, the bidders are allowed to bid simultaneously back and

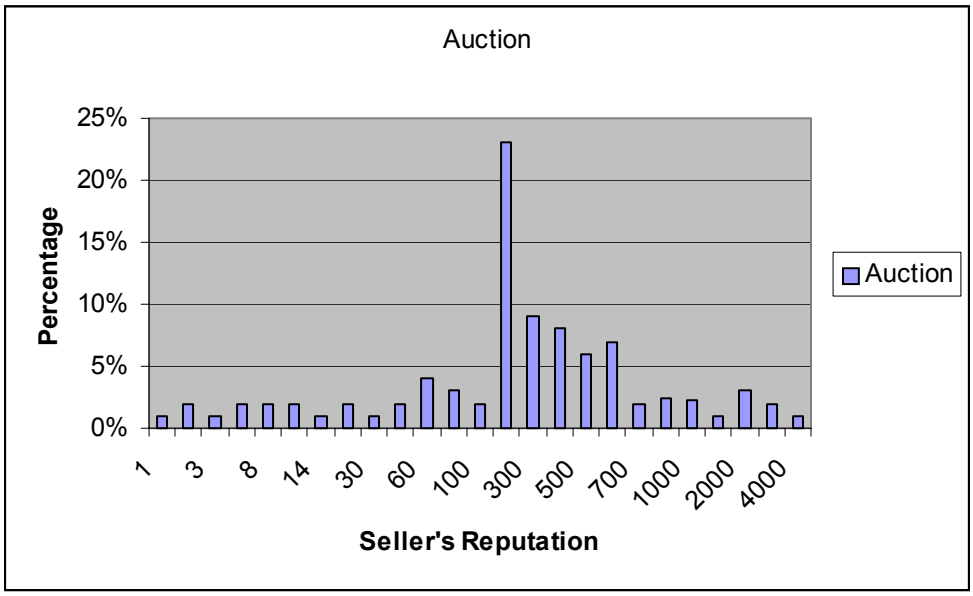
forth, nonstop. At the end of each round, the high bidder as well as the current high price will be made available to everyone. Early stage ends when there are no more bids. In late stage, the bidders are allowed one chance each to simultaneously submit one last bid for the item. This study was conducted in eight groups of six bidders for eBay1. Within each group the authors randomly re-matched pairs of two bidders for a total of 18 auctions per bidder. This experiment was conducted to simulate how user behavior changes after going through multiple trials of auctions with one another.

Data For Seller Reputation on Bidder Behavior:

The chart below is displays the average auction length. The data is from the original set of 20000 data collected so it is not the filtered out data. The chart shows that most of the auctions on eBay are seven days in length, while only around 12% are maximum length of ten days.



The graph below shows the average percentage of the auction seller's reputation. Again, the pool is from the original data that the computer program collected of around 20000 sets of data. The graph groups the auctions by the rating of the seller. This chart shows that more than 20% of the sellers have a rating of between 200 to 400. The chart also shows that more than 50% of the sellers in the auction are in between 200 to 800 rating. The rating is reflected based on the seller's cumulative positive feedback minus its cumulative negative feedback.

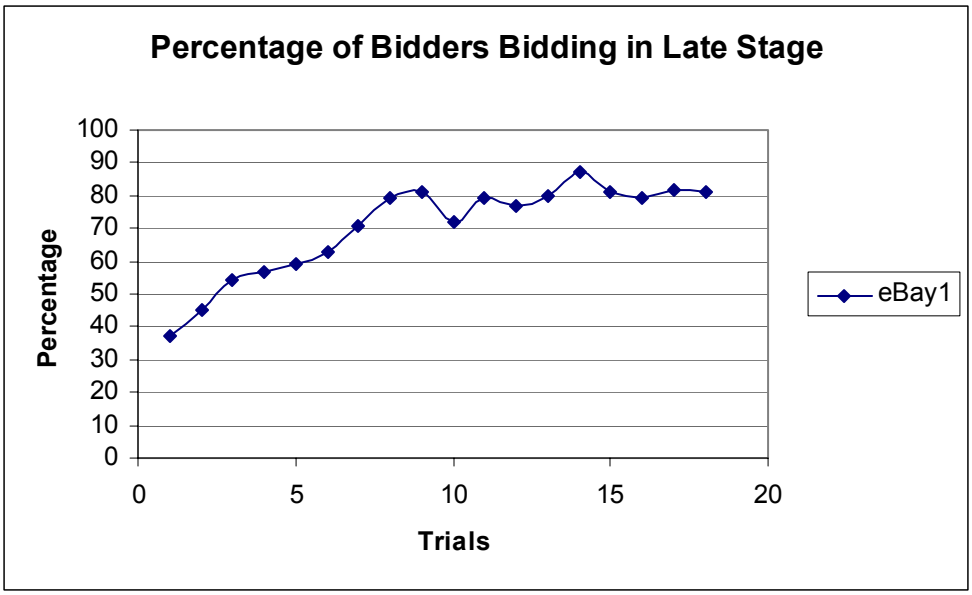


The table below shows the regression results of the 461 samples of the eBay coin auctions from July to September. The reason we use this much smaller sample is because it has tangible variables to compare to (coin date and its rated condition). A regression model is often used to perform statistical analysis in order to get a more linear graph set in order to find patterns better. The dependent variable in the following table is ln(PRICE) while it is compared to the correlation of an extra positive rating, negative rating, as well as auctions that are five days long, seven days long, and ten days long.

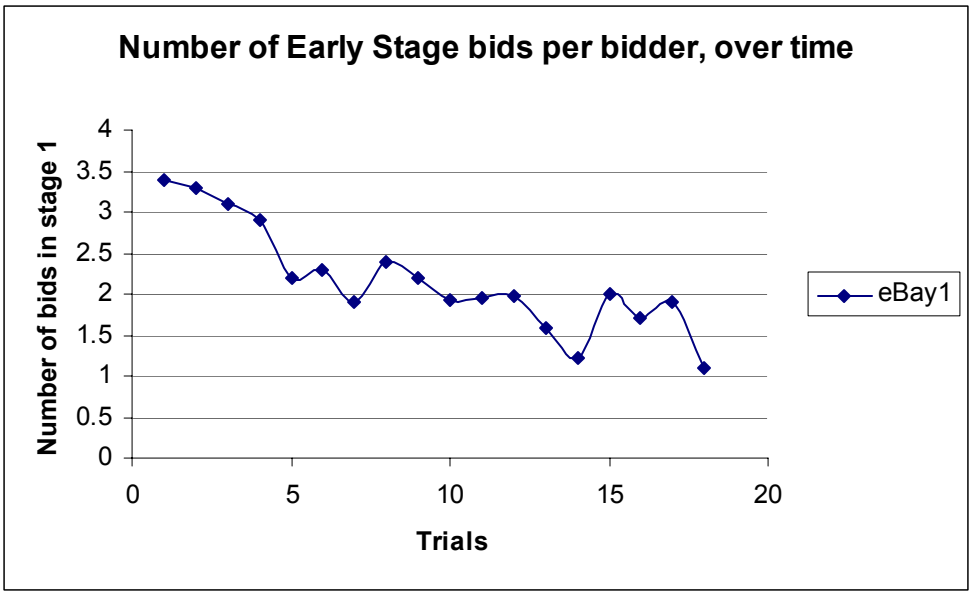
ln (POS +1)	0.0384
ln (NEG +1)	-0.1104
DAYS 5	-0.0148
DAYS 7	0.2188
DAYS 10	0.3544

Data For Snipe Bidding and Shade Pricing:

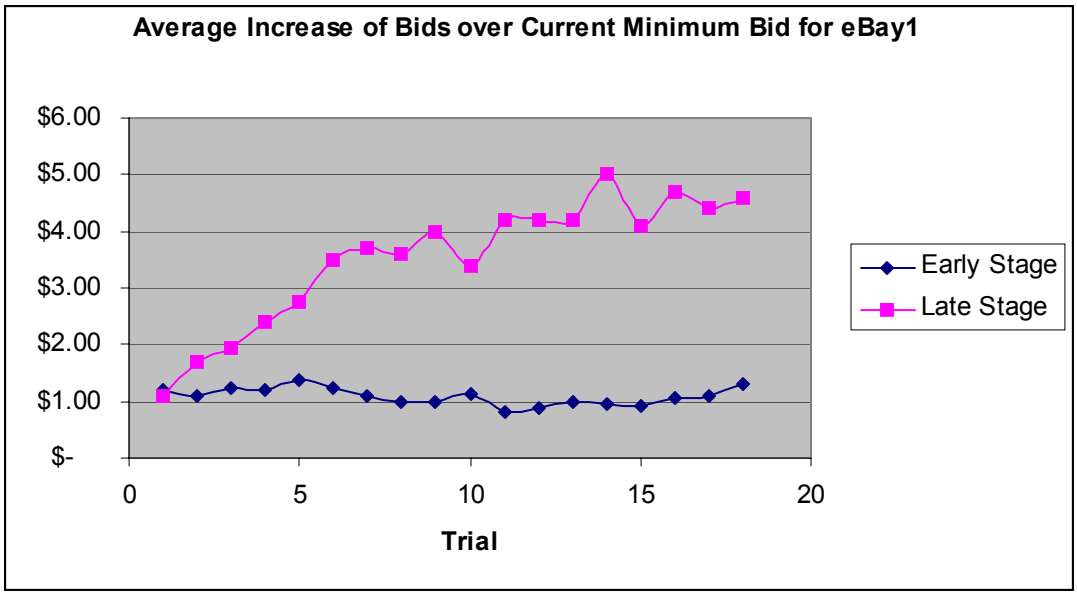
The graph below shows the percentage of bidders bidding in late stage, which also means the probability of bidders bidding at last minute, or snipe bidding. The data shows that in trial 1 of eBay1, there were only about 37% of bidders making one last bid after early stage is over. Majority of the bidders bid their true value in the early stage and stopped once it is over their private value of the item. However, as the graph depicts, the percentage gradually increased with each additional auction. By trial 18, more than 80% of bidders are submitting a late stage bid. This shows that the bidders must have learned something from the experience to have to have changed their tactic in the auction.



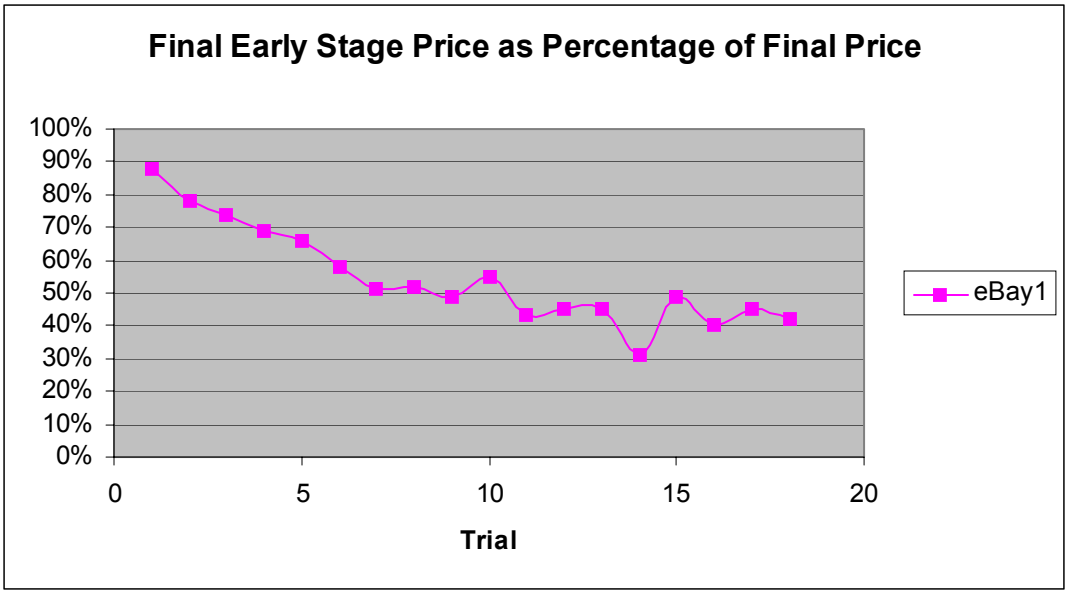
The graph below shows the average number of early stage bids per bidder, over time. The data shows that in the first trial, about each bidder bid around 3.4 times before stopping in the early stage. However, bidder behavior gradually changed over time as the average number of early bids decreased consistently as the trials went on. By trial 18, each bidder only submits a little over one bid for the early stage. Combining the first graph and this graph shows that bidders on average each puts out a price and generally shades until late stage to really conduct "serious" bidding.



The graph below shows the increase of bids for early stage compared to late stage over the course of 18 trials. This is to show how much bidders shade in the early stage in order to concentrate on late stage bidding for eBay. The graph shows that in trial 1, there isn't really much of a difference in terms of increase over bid for early stage and late stage. But while early stage increase of bid remained relatively constant, late stage increase over minimum bid jumped dramatically. By trial 18, bidders are bidding about four times the amount over the minimum bid.



The graph below shows the final early stage price as a percentage of the final price when the transaction is done. Again, the data shows that in the first few trials, most of the people bid their private value of the product. However, by trial 18 bidders only bid about forty percent of the final price at the end of early stage. This goes to show that early stage is not a good predictor of the final price, and in fact, from the graphs above, you can see that bidders actually seem to try to bid as little as possible in the early stages.



Analysis of Length of Auction and User Reputation:

From the graphs and dataset, there really isn't a strong correlation between the seller's rating and buyer's willingness to bid on the item. Instead, we see from the linear regression that with each percent increase in positive feedback for the seller, he/she will be able to obtain a 0.03% increase in auction price. However, there is a stronger correlation between negative feedback and price of the auction. With each percent increase in seller's negative feedback, there is a 0.11% drop in auction price on average! The sample size of 461 is big enough to form a consistent basis for this experiment. From my personal experience shopping on eBay (I have 12 positive and 0 negative feedbacks), negative feedback is always the first thing I look for. To me, it is where you are able to glean into the seller's reputation and see what type of seller he is. Having a

negative feedback often translates into me not bidding on the item at all, no matter how low the price is. Ebay users would rather spend a little extra money and get more assurance that they are getting a quality product. I was surprised to see such a strong correlation between the longevity of auction and final price of an item. Apparently, between zero to five days, there is no significant increase in final auction price. The auctions that are set for seven days, however, are able to get an additional 22% return on final price and auctions that last ten days get a whopping 35% more return than standard five days auctions. The rationality to this is that given extra time, more bidders would attempt to put in a new high bid. Since the high bids can only go higher and not lower and that the fixed deadline for auction is longer, it is most likely that the longer an auction is held, the more competition it will induce. I knew that there is a positive correlation between time and final price, but I thought the market would be saturated enough by fifth day in any time-period auction that it wouldn't have a dramatic difference. Also, Ockenfel and Roth's experiment showed that the early stage period does not really matter and that average bidder only submit an average of one bid in early stage. This means that the number of days an auction is should not be a factor influencing the outcome of final price because people should just wait and bid at the very end of an auction.

Regardless, studies of experiment (Melnik and Alm) show that the seller's reputation is an important consideration in buyer's willingness to bid on an auction item. Melnik and Alm's empirical results show that a seller with a better reputation can expect to receive a higher price for an auction's good. Although, their same studies have shown that this impact is smaller than expected. This affect is confirmed through the experiment from David Lucking-Reiley and Daniel Reeves.

Analysis of Snipe Bidding and Shade Pricing:

The data and graphs all point to the fact that bidders learn and make adjustments as they gain experience in bidding. Through the trials, there was gradual decrease in number of early stage bids and a gradual increase in the percentage of late bids submitted as well as the late stage bid price. The bidders adapted the strategies of shading price until end and snipe bidding are not necessarily irrational. In David Lucking Reiley's

paper "Secret Reserve Price Auctions"(December 2000), he mentioned that one of the reasons why bidding late became a dominant strategy is to avoid unnecessary bidding war. A bidding war between bidders wanting the item would raise the expected final price, often to the point where it exceeds the winner's private value. This is known as winner's curse, where the winner is paying more than everyone else. By delaying the bidding until late stage as shown in the experiment can keep the final price down. This means that the expected profit for the bidders would increase as result. Roth and Ockenfel (Experimental Analysis Ending Rules in Auctions, 2002) pointed out that sniping may also be a best response to incremental bidding. An incremental bidder starts with a bid below his value and is then prepared to raise his bid when he is outbid. Snipe bidding would take care of this problem as it would not give incremental bidder any opportunity to respond to being outbid. To take this a step further, by snipe bidding at the very end, a bidder might even win the auction against an incremental bidder even when his private value is higher. By not revealing the true value, other bidders have no clue how much you value the price until when the auction is over.

Conclusion:

The two experiments in this paper are intended to show user behavior in eBay auctions. The focus is on late bidding behavior among eBay bidders. The experiments confirmed the rationality of many strategies bidders and sellers use in today's eBay auctions. In the coin experiment, the data shows a weak correlation between the actual rating of seller and final price sold. Instead, it seems that the bidders focus more on the positive and negative feedback on the seller. Negative feedback particularly has a strong correlation with the final price of the item sold. The coin experiment also demonstrated that there is a strong, positive correlation between the length of the auction and the final price sold. From the data, items auctioned between zero to five days do not have an increase on the final price. Items auctioned for seven days, however, sees an average of 22% increase in its final price than if it was for five days. If you auction an item for the

maximum time allowed of ten days, you get an average of more than 35% increase. This effect is due to the fixed deadline being extended, so there is a greater chance of people bidding before the late stage.

The late bidding experiment demonstrates one of the most important concepts about human behavior in auctions, that we all learn and develop strategies with experience. The experiment allows users to go through 18 trials in order to get experience and learn from mistakes. The trend shows that bids gradually decrease in early stage, instead putting more emphasis on late stage bidding. This is to counter incremental bidders that tries to outbid other bidders every time he gets outbid. Another reason that makes late bidding rational is to drive the final price down. This is obvious since it is more profitable for all bidders if the final price of the item sold is lower.

Online auction is such a dynamic system that has revolutionized business and increased efficiency in the ways trading with one another. This is a field that still has much untapped potential and something worth studying on.

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