An Analysis of Paperclip Arbitrage

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Abstract. While bartering is arguably the world's oldest form of trade there are still many instances where it surprises us. One such case is the remarkable story of Kyle MacDonald who, by means of a sequence of bartering exchanges between July 2005 and July 2006, managed to trade a small red paperclip for a full sized house in the town of Kipling Saskatchewan. Although there are many factors to consider in this achievement, his feat raises basic questions about the nature of the trades made and to what extent they are repeatable by others. Furthermore, it raises issues as to whether such events could occur in Agent–based Electronic Environments – and under what conditions. In this paper we provide an intuitive model for the type of trading environment experienced Kyle and study its consequences. In particular the work is focused on understanding whether such trading phenomena require altruistic agents to be present in the environment and under what conditions agents can reach their individual goals. Results cover both the case of a single "Kyle like" goal driven agent and what happens when multiple such agents are present in an environment.

1 Introduction

Although the motivation for making trades amongst the participants in Kyle's story [9] is unknown, some of them may have been motivated by altruism (In this case a willingness to accept something of lower value for them in an exchange in order to help Kyle on his way) or other peripheral secondary in–direct benefits (such as a desire to participate in an interesting experiment). However, it is likely that the majority of participants were probably making trades in which they at least sought significant value (if not full value) – Kyle was deliberately seeking out potential exchange partners who valued his current item the most. Further, while the motivations of the original participants are unknown, a key question in such scenarios is – "Would such a general mechanism work if there were no altruists at all?" – i.e. if all participants were purely self–interested. Scenarios where self–interested agents barter/exchange resources in order to increase their individual welfare are ubiquitous: examples include The trueque club [1] and most normal bartering situations [2]. The work presented in this paper studies the *bartering dynamics* of a population of agents that follows a similar pattern to that found in Kyle MacDonald's story.

The paper develops a simple agent population model based on active and passive agents with ranges of personal value distributions for the items they own and uses a simple trading mechanisms to show that scenarios such as Kyle's story are indeed possible for goal–driven agents without relying altruistic behavior given that a number of conditions hold. The work characterizes these conditions and goes on to study the emerging dynamics which occur as increasing numbers of agents become active and as agents apply more sophisticated search techniques to the problem.

2 Formal definition

The model developed for the scenario is relatively simplistic, but captures the main elements of Kyle's trading environment. See Section 9 for comments on extensions and modifications. The model consists on the following components:

- A population of agents in which each agent plays one of these two roles:
  - *Goal driven agents* (GDA): These agents try to reach a dream (i.e. an item with a value that seems infinite to them and is also very high on the general market value ranking). The initial property of this type of agent is considered low in the general market ranking. This agent is looking for rich/beneficial trading encounters in order to move upwards in market value.
  - *Passive agents* (PA): These agents have an item and do not seek any new concrete item, however they know a good deal when they see one. In case a GDA tries to trade with a PA, the PA only accepts it if it is beneficial – i.e. its own satisfaction is increased by the trade.
- A list of items: This list follows a strict order in function of a general *market value* (MV). MV is the value fixed and determined by buyers and sellers in an open market.
- Each agent has a *personal value* (PV) for each item in the market (and hence for each item they own). This PV differs for each agent in the market with a statistical deviation (which may be positive or negative) – in other words an agent may value certain items at above or below general MV. $MV_i(g_j)$ and $PV_i(g_j)$ represent the MV and PV respectively of the agent$_i$ with respect to the item g_j.
- Each agent is connected to the rest of the members in the market.
- A set of ranges: A range contains multiple items with the same MV and a range of possible PV restricted to two values [-σ, +σ] related to this MV. Without this clustering the cost to finding all possible ways can be too expensive

  For example figure 1 shows the paths from μ_1 at μ_4 by means of exchanges are:
  - To exchange x_1 by x_2 ($1 \Leftrightarrow 2$) and afterwards x_2 by x_3 ($2 \Leftrightarrow 3$) and finally x_3 by x_4 ($3 \Leftrightarrow 4$),
    $\mathrm{P}(\mathrm{A}_1) = \mathrm{P}((\mu_2(x_2) - \mu_2(x_1)) < 0) \cap \mathrm{P}((\mu_3(x_3) - \mu_3(x_2)) < 0) \cap \mathrm{P}((\mu_4(x_4) - \mu_4(x_3)) < 0)$
  - To exchange x_1 by x_2 ($1 \Leftrightarrow 2$) and afterwards x_2 by x_4 ($2 \Leftrightarrow 4$),
    $\mathrm{P}(\mathrm{A}_2) = \mathrm{P}((\mu_2(x_2) - \mu_2(x_1)) < 0) \cap \mathrm{P}((\mu_4(x_4) - \mu_4(x_2)) < 0)$

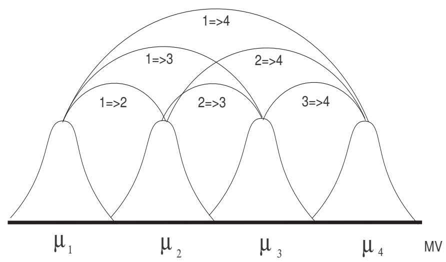

Fig. 1. All paths from node 1 to node 4 showing the $MV = \mu$.

- To exchange x_1 by x_3 ($1 \Leftrightarrow 3$) and afterwards x_3 by x_4 ($3 \Leftrightarrow 4$), $\mathrm{P(A_3)} = \mathrm{P}((\mu_3(x_3)$ - $\mu_3(x_1))$ <0) $\cap$ P(($\mu_4(x_4)$ - $\mu_4(x_3)$) <0)
- To exchange x_1 by x_4 ($1 \Leftrightarrow 4$) directly $\mathrm{P(A_4)} = \mathrm{P}((\mu_4(x_4)$ - $\mu_4(x_1))$ <0)

This goal cannot be reached via another path – each one of these sequences of exchanges is named an *event*. The objective is to calculate the probability of all of these events (i.e. P($A_0 \cup \ldots \cup A_n$)). From the basic properties of probabilities (see Eq. 1).

$$\{P(A \cup B) = P(A) + P(B) - P(A \cap B)\}. \tag{1}$$

Extending to n events:

$$\begin{aligned} P(A_0 \cup A_1 \cup \ldots \cup A_{n-1} \cup A_n) = & \quad P(A_0) + \ldots + P(A_n) \\ & -(P(A_0 \cap A_n) + \ldots + (P(A_{n-1} \cap A_n)) \\ & +(P(A_0 \cap A_1 \cap A_2) + \ldots + P(A_{n-2} \cap A_{n-1} \cap A_n)) \\ & -/+\ldots-/++P(A_0 \cap \ldots \cap A_n). \end{aligned}$$

To simplify the formulation of the union of n events, let E_α (α = 1, 2, ..., n) is Eq. 2:

$$\{P(\bigcup_{\alpha=1}^{n})E_\alpha = \sum_{\alpha=1}^{n} P(E_\alpha) - \sum_{\beta>\alpha=1}^{n} P(E_\alpha \cap E_\beta) + \ldots + (-1)^{n-1} P(E_1 \cap \ldots \cap E_n)\}. \tag{2}$$

Given that the events are independent then Eq. 3:

$$\{P(\bigcup_{\alpha=1}^{n})E_\alpha = \sum_{\alpha=1}^{n} P(E_\alpha) - \sum_{\beta>\alpha=1}^{n} P(E_\alpha) P(E_\beta) + \ldots + (-1)^{n-1} P(E_1) \ldots P(E_n)\}. \tag{3}$$

Where n is the quantity of different events and $\mathrm{P}(E_\alpha)$ is the probability that the event E_α happens. Unfortunately, the cost to finding all simple paths in a graph is too expensive. The only way to find the complete solution is to enumerate all permutations with $2, 3, \ldots N$ elements (N being the number of vertices in the graph), starting with S and ending with T (source and target node) and checking such permutation specifies a path in the graph. This is a NP–complete, since the problem of finding the longest simple path between two nodes is NP–complete. Having considered the high cost of dealing with the all paths it is necessary to establish a manageable abstraction. In our case, to collect the items in ranges. Exchanges are only permitted between items that belong to neighbor ranges (in fact they could be allowed across ranges – but as explained below it is improbably that trades to jump multiple ranges would be available). In a market it is usual to have many items to exchange. For this reason, there are multiple ways to start with item g_A and reach the item g_Z. When GDAs reach an interchange with an item from the range above, GDAs pass to the next range. As the distance increases between MVs it becomes more difficult for a GDA to pass to the next range.

2.1 The exchange process

Agents are *individually rational*, thus trades are a *non–zero–sum activity* since each party must consider the item s/he is receiving as being at least fractionally more valuable to him/her than the item s/he is giving up. In barter–exchange markets, agents seek to swap their items with one another, in order to improve their own utilities. The exchange may look unequal to a third party, but the third party might have different PVs than the two participants in the exchange, as it only knows the MV of the items in the exchange [3].

The exchange strategy: An exchange between two agents GDA and PA is accepted iff there exist two items g_i, g_j that are in neighboring ranges such as:

$$\{PV_{PA}(g_i) > PV_{PA}(g_j) \textit{ and } MV_{GDA}(g_j) > MV_{GDA}(g_i)\}. \tag{4}$$

Nevertheless, the equation 4 is not enough to assure that the item obtained in the exchange that GDA gets is one of the items that part in the chain of items to get the desired item. The equation only states that the trade is profitable for both sides and therefore that it could be made.

3 Experiments

3.1 Experimental configuration

Bringing together descriptions of the problem from the previous sections, the high level properties of the model are the following:

– Initially, items are randomly assigned to agents. One item per agent.
– The market is composed of five thousand agents.

- The number of ranges is fifty. Each range is composed of one hundred items. In range$_1$ there are the items with smaller value (e.g. paper–clips) and in the range$_{50}$ the items with the higher value (e.g. houses).
- *GDAs* know there are the rest of the agents and it can communicate with them (i.e. the system is fully connected).
- Items have a unique MV but each agent (PA or GDA) has its PV.
- Trades are conducted by means of bartering.
- *GDAs* only take local decisions.
- *GDAs* only trade when the interchange is immediately beneficial according to general MV. The *PAs* only trade when the interchange is immediately beneficial according to its PV.
- The PV of the items follows a $\sim \mathcal{N}(\mu, \sigma)$. Then, μ_i - μ_{i+1} represents the distance between ranges or between cluster of items with the same MV and σ represents the variation of PV. These two parameters are fixed for all the items in the simulations. Let, $X \sim \mathcal{N}(\mu_i, \sigma_i)$ and $Y \sim \mathcal{N}(\mu_{i+1}, \sigma_{i+1})$. Then $\exists$ an profitable exchange for PA with the item x_{i+1} iff the PV of the item x_i is greater than the PV of the item x_{i+1}. This is equivalent to $\exists$ an exchange iff $\mu_{i+1}(x_i) > \mu_{i+1}(x_{i+1})$. Finally, it is possible to turn this into equation 5.

$$\{P(\mu_{i+1}(x_i) > \mu_{i+1}(x_{i+1})) = P(\mu_{i+1}(x_i) - \mu_{i+1}(x_{i+1}) \leq 0)\}. \qquad (5)$$

- In each of our graphs, each data point is an average of ten simulations, and we provide statistical significance results to support our main conclusions.
- A *blocking situation* is when a GDA wants some item from a range but no one in this range wants to trade. This is because the agents in the ranges are *GDAs* or the item offered is not good enough for the *PAs* in the next range.
- A steady state is achieved when the *GDAs* reach the desired item or when *GDAs* stay in a blocking situation or when the simulation deadline pass fifty steps.

4 One GDA

The most basic form of the systems to be explored is that in which there is only a single GDA looking for a desired item which has the highest value in the market.

The probability of turning an item from range$_x$ into an item of range$_{x+1}$ depends on the quantity of items per range, the quantity of ranges, the range of PV and the distance between ranges associated to MVs.

When the quantity of items per range is near to zero, P(success) will be zero. At the other extreme, when the quantity of items per range tends to infinity, P(success) tends to be one. Figure 2 a) shows the effect of the quantity of items per range. The only two parameters modified are: the quantity of items per range and the distance between ranges. The rest of the parameters are fixed. Simulations are related to the case where the distance between the lower range and the higher range is equal to fifty (i.e. fifty hops are necessary to transform a paperclip into a house) and the range of PV is equal to five. The figure shows that as there are more items per range there are more probabilities that the GDA will reach the last range and thus more access to the most valuable items. Also the figure shows that in some configurations (for example – with few items per range as 10 items x range), the probability of reaching the last range is near to zero. And in other configurations, for example with 1,000 items x range and a distance between ranges equals to 2, this probability is high but not 1 – in this case 0.82.

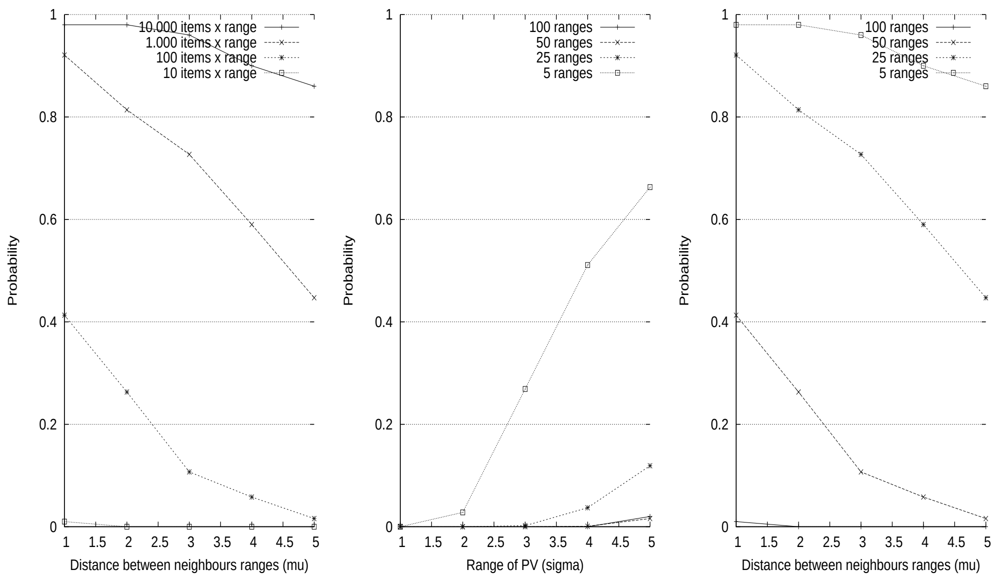

Fig. 2. Results related to the parameters in the simulator a) items per range b) variations of PV and c) distance between ranges

Figure 2 b) shows different variations of PV from 1 to 5 when the quantity of items per range is one hundred. Increasing the value of PV the probability of reaching the last range increases. The distance between ranges is fixed to five and the quantity of items per range is equal to 1,000. Reducing the variation of PV the probability of reaching the last range is reduced.

Finally, figure 2 c) shows the effect of the distance between ranges combined with the quantity of ranges. The probability of reaching the last range decreases as distances between ranges increase or the quantity of ranges increases. The variation of PV is fixed to five and the quantity of items per range is equal to 1,000. As the number of ranges to cross over is lower, it is easier to reach the last range. It could be noted that as the distance decreases between ranges it becomes easier to get an item from the last range.

The statement from this section show GDA can turn an item from the initial range to the last range with a high probability of success under many configurations such as with a distance between ranges from 0 to 2, with more than 1,000 items per range with a $\sigma > 4$ and where the number of ranges are those included between 25 and 50 ranges. The probability of reaching the last range is close to one. Furthermore, this probability is completely independent of altruism. Because, by definition, neither GDAs nor PAs accept any detrimental trade.

To turning back on Kyle's feat where the scenario seems more favorable. Due to that its real scenario where the quantity of Internet users is upper to 1,000 million with limitless number of items to interchange and each one with his/her PV, the probability that by means of twenty trades up Kyle can get his objective is high.

5 Multiple *GDAs*

Once proven that an isolated GDA can reach an item from the last range under some configurations, the next step is to balance the quantity of PAs and GDAs, to check the behavior of the market with other distribution populations. Therefore, the strategy is to increase the percentage of GDAs in the market in order to reveal the dynamics that appears in front of the variation of populations.

The set of experiments uses configurations with a percentage ranged from 0, 0.02 , 2, 10, 20, 30, 40, 50, 60, 70, 80, 90 to 100 % GDAs. Other parameters are set as follows: the variation of PV is equal to five, the distance is equal to five (i.e. difference between two consecutive MV). These parameters are chosen from the previous section because they form a fruitful environment trades with one GDA can be made. These results are presented in figure 3 where the quantity of crossed ranges or jumps is shown with respect to the percentage of GDAs. The solid line is related to the maximum sum jumps. This value captures starting from a random distribution of the GDAs in the different ranges, how many crossed ranges should be crossed to become this initial situation in a situation where all the $GDAs$ have the best available items. On the other hand, the dotted line is related to the sum jumps that were obtained by simulations.

Focusing on this latter value, the figure shows that when the percentage is reduced (i.e. less than 2 %) the value of jumps in our simulator and the maximum value expected is equal. The best results with respect to the quantity of crossed jumps are achieved when the balance of GDAs is around 10 %. The reason is because many GDAs are making jumps but not enough to decrease the opportunities to make exchanges from the rest of GDAs in the market. Under other configurations this property is not applicable. As the quantity of GDAs increases in the market the sum of jumps go down slightly. At first glance, more GDAs in the market should implies that more jumps could be done, the problem is that the opportunities of jumps decreases, ending up with the opposite of the expected value.

As the number of GDAs increases, it is more difficult to make trades between agents. The reasons are:

- As great the distribution of GDAs is less probably to have an encounter with a PA.
- Once a PA makes a trade the following events occur:
  - The PA increases its PV.
  - The PA moves downwards by one range.

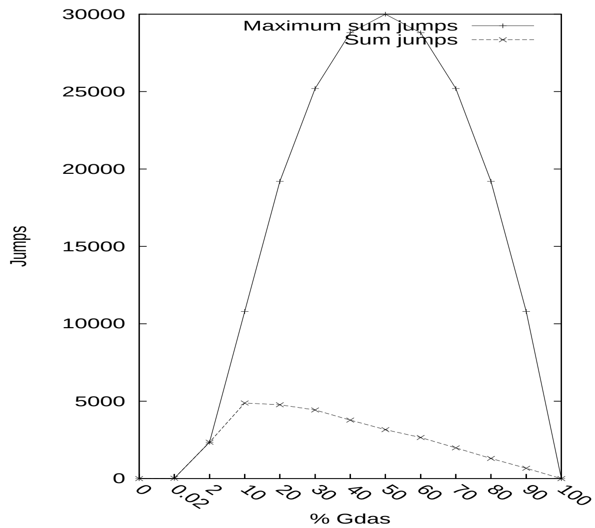

Fig. 3. The mean range value decreases as quantity of GDAs increases.

Unsurprisingly, GDAs with an item near to the last range (i.e. rich agents) tends to obtain better results than GDAs with an item far from the last range.

- To be far from the last range implies more jumps between ranges. The probability decreases when more jumps need be made to reach the last range.
- GDAs share a common goal. They try to move upwards and the competition amongst GDAs increases. The displacement of GDAs in the ranges of the market takes place, from an initial uniform distribution in the initial step to an n–shape once the simulation runs. In this last figure we can observe how GDAs are gathered in the upper ranges making the swap more competitive between these ranges
- GDAs near to the last range trade with PAs that allow to get upper ranges. Once these PAs have made a trade it will be more difficult for the next GDAs to offer an useful item.

At a large–scale way the inclusion of GDAs turn a fruitful market into one without opportunities. With lower levels of GDAs (i.e. less than 10 %) the GDAs can turn into best ranges. But once passed 10 %, the opportunities to improve decrease and changes to get the desired item disappear quickly.

These results show a decreasing refund in contrast of when the market has an isolate GDA that the competition among GDAs reduces the chances to reach the desired item.

6 Using backtracking

The Kyle's experiment can be seen as a *path finding problems* such problems are focused on finding an efficient, and possibly optimal path is from some initial state to some final state. The aim for any GDA is to reach the desired item in the last range. In a single search process when it is not possible to progress, the process ends. But this does not mean that other paths will not be possible (i.e. another exchanges could carry on to satisfy the GDA). In order to look for other paths a classical backtracking algorithm been applied [13]. Until now, the searching process works without backtracking (BT), this means once the search process arrives at a range where it is not possible to advance the process ends (i.e. monotonically) as it is showed in algorithm monotonic search. However, the BT algorithm [4] tries to overcome this situation by looking for new paths (i.e. non–monotonic search). In order to apply BT is necessary to include downward exchanges. Two types of exchanges are considered:

– Upward exchanges: An exchange between an GDA with an item from range$_x$ and PA with an item from range$_{x+1}$.
– Downward exchanges: An exchange between an GDA with an item from range$_{x+1}$ and PA with an item from range$_x$. This type of exchange will be done when a GDA makes a backtrack (BT).

Figure 4 shows the necessary requirements to be able to exchange an item in downward and upward form.

In the worst case the classical BT has an exponential cost. In order to reduce this cost the space search has been restricted. Therefore, our objective in this section will be to compare and contrast results using BT and without BT.

Figure 5 shows the mean range obtained when the GDAs work with BT limiting the search to k=2 and without BT. The parameters remain as in the previous configuration. Except for the range of PV that turns his value from 5 into 2. With this change, opportunities to pass from a range to the upper range are reduced. This allows to advise the benefits or not of BT.

BT algorithm reaches the maximum ranges when the percentage of GDAs is lower than 0.5 %. From 0.5 % to 2 % the BT algorithm gets best results than when the agents are not working with BT. However in this range the BT algorithm does not reach the maximum ranges, the reason is due to the destructive nature of the search. From the rest of scenarios the BT algorithm worse the results.

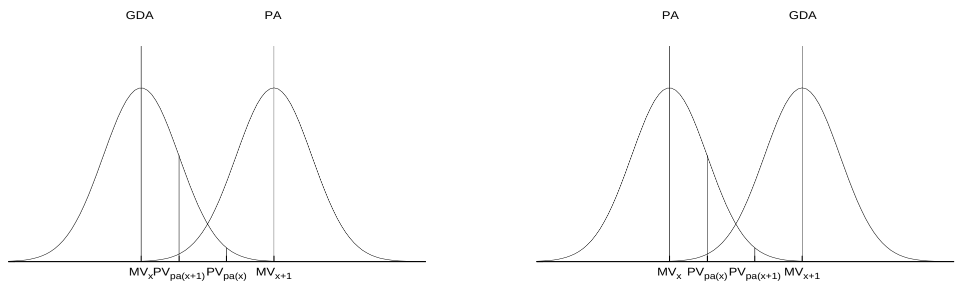

Fig. 4. a) Upward exchange. The GDA is increasing its MV and the PA is decreasing its MV but it is increasing its PV and b) Downward exchange. The GDA is decreasing its MV and the PA is increasing its MV and PV.

Surprisingly, the BT algorithm does not improve the performance. The main reason is because the search process is destructive (i.e. making upward and downward exchanges the environment changes), in terms of changes the state of the market. The PAs become more demanding with each exchange (i.e. reducing the marginal utility). In the initial exchanges PAs have a wide range of values to exchanges (i.e. from $PV_{pa(x)}$ to $MV_{x+1} + \sigma$) where the PA will accept an exchange. But during the simulations the PAs exchanges its item by means of upward and downward exchanges and the range of items interesting from the PA decreases. Following with results from figure 5, with 0.5 % GDAs and BT around 890 exchanges are made in front of 297 without BT. Obviously, BT increases the quantity of trades because the search process in instead of stopping how in the original approach, BT looks for other exchanges. However, when the market has 1 % GDAs the trades are 2,484 with BT with respect to 477 without BT. The growth of trades is not supported by the market affecting to the performance.

The effect of an individual or few individuals in a population is insignificant because although the trades are reducing, the marginal utility from some PAs others PAs are available in the population to deal. But when the quantity of GDA is high, the destructive process eliminates the possible benefit that the BT algorithm provides. Therefore, the results show that when the quantity of GDAs is limited, the BT gets better results. But once the market is plenty of GDAs differences between working and not working with BT are negligible.

7 Discussion and Analysis of Results

In the modeled market, there are sequences of trades that turn an item from range$_x$ into an item of the highest range. However, a number of conditions need to be met in order for GDAs to be able to make these trades and in particular the following parameters are of relevance:

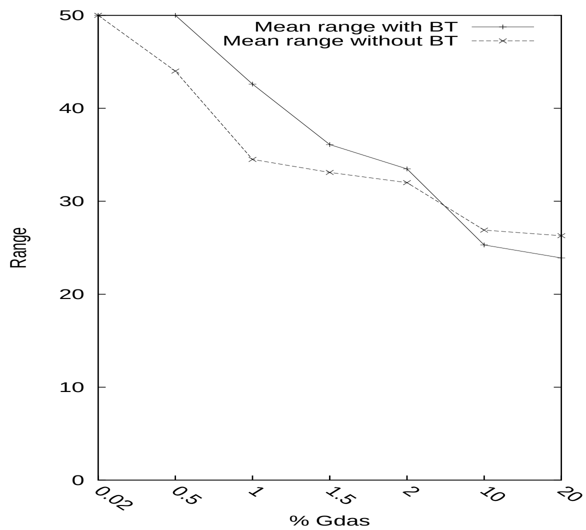

Fig. 5. The mean range with BT and without BT.

- The distance between MVs. As this distance increases it is more difficult to change an item – with increasing gaps between valuations.
- The variance of PV. The greater the variance in the PV, the greater the probability that a PAs will be interested in to interchanging items – since some outliers will have very high valuations.
- The quantity of items per range. A market where the quantity of items is great will increase the possible chains to reach the target item.
- The quantity of ranges. The fewer the ranges the easier it is for GDAs to have access to the last range where the desired item resides (in fact this parameter varies with the distance between ranges).
- The quantity of GDAs in the market. More GDAs there are, the more competition there is since many GDA may be trying to get the best items in the market. On the other hand, the quantity of PAs increases the opportunities to trade up by the GDAs.

- Finding a profitable exchange for a buyer–seller (i.e. a double coincidence of wants) depends most importantly on how many members are shaping the market. Thus, when the number of agents and items increases, chances for GDAs increase. In the model GDAs start with an item belonging to a range and aims for an item from the last range.

Social mobility is the degree where an individuals social status can change within a society throughout the course of their life through a system of stratification (i.e. levels based on wealth or power). Subsequently, it is also the degree towards where individual's or group's descendants move up and down the class system. In the model, class is related to the range that the item's agent belongs.

For example, societies which use slavery are an example of low social mobility because, for the slaved individuals, upward mobility is practically nonexistent. Only rich individuals have opportunities to improve.

In this paper, we have explored the behavior of population of selfish agents. The most significant findings are:

- Under some conditions in the market it can be shown with certainty that a GDA reaches the desired item, even when all the agents in the market are selfish.
- As greater numbers of GDAs enter the market, the more difficult it is to reach the desired items – however that this change is non-linear in the growth of the number of GDAs.
- As more rich is an agent (i.e. more close to the last range) more opportunities, as far as possible, to reach the last range.

BT mechanisms improves the performance when the quantity of GDAs is reduced but with many GDAs BT does not improve the results.

8 Related Work

The allocation of scarce resources is a matter of concern in Computer Science and Economics. A survey of multi–agent approaches to resource allocation can be found in ([5], [10]) and a survey of economic models for resource management in distributed systems in [6]. A further area of relevance is negotiation in which a population of agents communicate with one another in order to reach an agreement on resource allocation. [7]

The one red paperclip is a classic example of arbitrage ([11], [12]) – where value is extracted by playing on the asymmetries of PAs valuations. Betting exchanges have many similarities to the Kyle's experiment. Betfair[1], Betdaq[2] and other similar betting exchanges have huge turn over now and many billions of pounds are matched each month on these markets. In betting exchanges an arbitrageur exploits existing price discrepancies when bookmakers' prices differ enough that they allow to back all outcomes and still make a profit. In paperclip exchanges a GDA exploits PV discrepancies. The $GDAs$ take advantage from the personal valuation differential between agents. Other similarity is that sports arbitrage are more accessible to everyday people because of the internet as in the Kyle's experiment a large-scale market benefit. But there are still barriers which stop everyone from being successful in both scenarios. Both scenarios take capital, time, organization and energy to make profits.

Furthermore, bartering has been used in commercial applications such as: SwapAce[3] and Worldwide Barter Board[4] or SwapTree[5]. These systems are innovative online marketplaces where individuals or communities trade and interact

[1] Betfair in http://www.betfair.com
[2] Betdaq in http://www.betdaq.com
[3] SwapAce in http://www.swapace.com
[4] Worldwide Barter Board in http://www.worldwidebarterboard.com
[5] SwapTree in http://www.swaptree.com

with each other - which may potentially exhibit similar dynamics to those studies in this paper. In particular participants are not motivated by pure market value – but by value to them at a particular point in time.

Kyle's and other similar experiences show alternative economic visions to normal electronic transaction which are anonymous and money oriented, by relying on personal encounters which are mediated by useful trades for both parts of the negotiation. This is a more basic trading approach but opens new opportunities for exchanging and negotiation studies in large–scale social context.

9 Conclusions and Future Work

Returning to Kyle's story and reviewing the results of section 4 we can see that Kyle's feat is possible. Considering that its real surroundings where the quantity of Internet users is upper to 1,000 million with limitless number of items to interchange, the probability that by means of twenty trades Kyle can get his objective is high. On the contrary in section 5, where there are many GDAs in the market, it becomes clear that it is not necessarily possible to repeat the Kyle's behavior over and over again. As the number of GDAs grows, not only do the number of paths of trades to the top decrease but further, many paths become unavailable since GDAs compete to use them. Therefore a man trading up from paper clip to house differ from men trading up from paper clips to houses. The scarce resources should be allocated amongst the population of GDAs. Increasing the quantity of GDAs is increasing the competition and limiting the trade up opportunities.

With respect to the backtracking, the first idea once have been added backtracking is that the performance should improve. However, this is not true. To work in a dynamic market where a great quantity of population follows the same objective eliminates many paths that allow to improve the GDA population.

A feature to emphasize is that in our model no one follows an altruistic behavior. In the trading process, every agent can improve their initial satisfaction or they prefer not to trade. The GDA has a different perception of value, they only care about MV and reaching the last range. Therefore, the results show that under balances where the quantity of PAs is great than GDAs it is possible that these GDAs reach the desired item. On the contrary, when the quantity of GDAs is great in the population, all of them do not reach the desired item.

Future research includes other modeling choices, such as:

– Non–linear value ranges: Instead of ranges with the same quantity of items the market will have ranges with a quantity of items depending on its value. For example, as more MV less items in a range.
– Opportunistic GDA: The new GDA can predict future price movements for stocks and commodities through observing and analyzing past and current market trends (i.e. the economic benefits of speculation).
– Looking up process and cost: To establish some balance or mechanism to obtain the best balance between the cost to discover good trading and the benefit obtained with the trade.

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