On the Optimal Minimum Global Selection of Service Providers by Isolated Consumer Decision

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Abstract. *Complex phenomena can be studied by breaking them into smaller components and understanding the interactions between its parts. In this article, we propose a multi agent system that simulates the behavior of consumers and providers of services in an environment of concurrency. Each agent has its own preferences and makes his decision without communicating with the others. The isolate decision of each agent leads to a global emergent behavior where the minimum amount of providers that satisfy global demand is selected; potentially leaving unattended providers. The results provide useful insights for the resource allocation domain and suggest that the model developed may be useful in a wide range of problems involving multi agent self-organization.*

1. Introduction

The resource provider and consumer problem can be modeled in a way to resemble the well known bars and customers model. This metaphor is used in this paper as a means to achieve a clearer picture of the model, without loss of generality.

The capacity of a certain bar contributes directly for the amount of profit the company is able to make. However, there is a limitation in the number of customers that will actually go into the bar. In order to estimate the size of the target audience, one has to consider the competing bars and customer preferences.

In this paper, we present a novel approach to capacity planning. Using a simulation model, it is possible to predict the occupancy of the bars in a given area. The model is based on the idea that people will usually avoid entering an empty place, if they have the option of choosing another that has a considerable number of people[1]. It is important to note, however, that a very crowded place is also a bad thing. If the number of people in the bar is greater than what the manager is expecting, it is likely that the waiting time for orders will be high, and the service will not be good.

We assume that each customer makes his choice alone (ignoring the fact that there may be groups of friends). Each one leaves his house at a certain time (given by a probability

[1] This can happen for a number of reasons, like the fact that an empty place is usually interpreted as an indicative of poor quality or that people willing to find a date will prefer the bar with more people inside.

distribution) and examines several different bars until choosing to enter one. After entering a bar, the person can stay and consume or decide at any time to leave and go to a different one. For example, a person could have entered the bar when there were lots of people in it, and after some time, the place started to get empty. In this case, the subject is likely to leave the bar and choose another one.

The decision of a customer regarding going to a bar was treated in the classical El farol bar article [2]. In that paper, it is observed a convergence of the occupancy of the bar at 0.6 of capacity, despite differences in the customer evaluation function. In our approach, a convergence is also observed, yet different in nature, as will be presented in section 3.

Now let's see the problem from the point of view of the bar owner. Suppose a bar is always fully occupied. If the owner wants do improve his profit, he has at least three choices: increase his margin (with possible negative impact on quality), increase the capacity of the bar, or open a new one. If, on the other hand, the bar is not generating enough profit, the owner could try to change its size, reduce price, or change the product mix, for example. In either case, he must think of the impact each of this changes would have on his customers. We will show that our model can be of help in predicting the best decision.

This paper is organized as follows: Section 2 describes the model in detail, showing the equations that give the probability of an individual entering or leaving a bar. Section 3 shows the simulation results in the case where all bars are equal. Section 4 introduces new features in the model, with the results shown in section 5. Finally, we show the contributions and future work in section 6.

2. The Model

We assume the customer agents will choose a region that groups a number of bars of similar kind. That is, in a given city, there is a number of bars that have the same customer profile, as well as the same sort of offerings. Similar bars group themselves in clusters. From this situation, the bar agent is given a choice of varying the offer it makes to the consumers, but restrained by the mood of the bar cluster it is into (see [3]).

As we are interested in modeling the instant choice of the consumer, the consumer agent will have no memory of its previous visits to the bar cluster nor from previous visits to any single bar. The consumer is then present in a region of bars, and has to choose which one he will enter. Two factors affect the consumer choice, namely the current occupancy of the bar and a proxy for the attractiveness of each bar.

We constructed a multi-agent system where there are two different kinds of agents acting together, the customer agent and the bar owner agent (bar agent). The bar agent has no active role in the simulation, as his choices requires time and cannot be made implanted within one night time. At each time step of the simulations, each customer agent is presented with an opportunity to change his status. A customer agent inside a bar can decide to stay or to leave, and an exploring agent can choose to enter any bar.

The choice of the bar agent is limited to the reciprocal aspects of customer choice, that is, bar capacity and bar attractiveness. The bar attractiveness, in conjunction with the consumer interests can be as complex as we choose them to be. In the simulation, however, they were modeled as a single parameter relative to the bar and generalized to all consumers. As all consumers have no difference in the choices they make i.e. only their count (not influenced by any individual consumer characteristic) in a given bar influences other consumer agents. All consumers are considered to be exactly equal for the purposes at this point.

The simulation is run for the period of one night only, so the bar agent has no choice to change its characteristics within the simulation. The bar can raise its attractiveness, increasing the chance of higher occupancy, but this also increases the cost of maintaining the bar, and can have a negative effect in total profit. The bar agent can increase or lower the bar capacity, influencing in the customer choices, but with nontrivial effects in the bar profit.

A model that fits these constraints is presented in [1] and considers how individual cockroaches form groups that lead to the optimum benefit of each individual without any communication among them. Each individual cockroach can be either exploring the environment or resting inside a shelter. For any given exploring cockroach the probability it will join shelter i (Ri) is given by equation 1.

$$R_i = \mu\left(1 - \frac{x_i}{S}\right) \quad (1) \qquad Q_i = \frac{\theta}{1 + \rho\left(\frac{x_i}{S}\right)^n} \quad (2) \qquad \frac{1}{B(a,b)} x^{a-1}(1-x)^{b-1} \quad (3)$$

In equation 1, μ represents the kinetic constant for a cockroach to leave its exploring state and enter a shelter; x_i is the current occupancy and S is the total shelter capacity. The chance of a cockroach entering a shelter is maximum when the shelter is empty and decreases linearly with the occupancy.

The other influence in the individual cockroach is its chance of leaving a shelter once it is inside. It is given by equation 2.

Parameter θ represents shelter quality; ρ is related to total carrying capacity of shelter; x_i and S have the same meaning as in equation 1 and n represents the level of social interaction among cockroaches. When n is equal to 1, there is no social interaction and all shelters tend to hold the same number of cockroaches at the end of experiment.

The correspondence we explore is then from cockroaches to customers and shelters to bars. We used θ and ρ constant among all bars. In the simulations described in section 3 we used constant values of μ and S equal for all bars.

All simulations were run over a period of 100,000 time steps, where each customer agent chooses to act in each time step.

The rate of customer entrance in the simulation affects its final result. If the customers keep coming into the simulation up to its end, there is not enough time for the bars occupancy to converge and the results are misleading[2]. We chose a beta distribution over the first third of the total number of events with a = 3 and b = 5, as show in equation 3.

[2] Besides, this is not a reasonable assumption, as people tend to concentrate on the beginning of the night to leave home and celebrate.

In the simulation where all agents begin to search for bars at time = 0, the final result is identical to the one obtained with distributed activation. The dynamic of bar occupancy, however, is altered and the results to bar owners are misguiding. It was therefore abandoned in our simulations.

3. Results

The parameters used were μ=0.001; θ=0.01; n=*2*; ρ=1667 (see [1]). Every result presented here was averaged over 30 runs. The number of bar agents was picked from the interval [2, 10], and the number of customer agents was in the interval [20, 1.2*T], where T is the sum of the capacity of all bars, unless otherwise stated.

3.1. Bar occupancy over time

The first set of tests was performed to observe the evolution of bar attendance over time. In these simulations, there are 50 customer agents and 3 bar agents. Each bar has a capacity of 40 customers. Figure 1 shows the results of 2 individual simulations. Note that it is not relevant what individual bar is related to each line, since the bars are all equal.

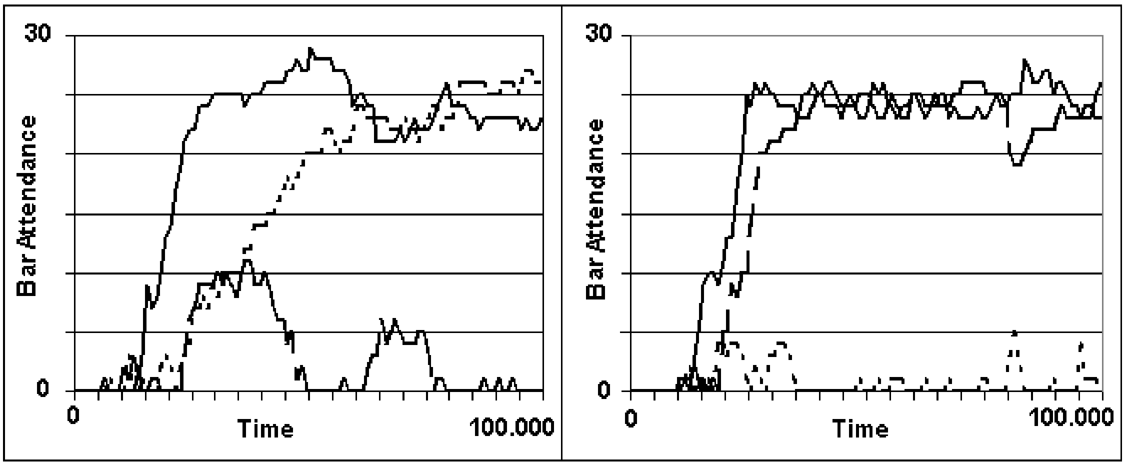

Figure 1 - Bar occupancy over time. The graphics show two simulation results with 50 customer agents and 3 bar agents. Each line represents one bar, and y axis is the number of customers that were in the bar at each time step.

In the case shown on the left corner of Figure 1, when the agents start activating, we can see the growing occupancy of bar 1. When bar 1 is about 2/3 full, and the number of activated agents continues to increase, they start to enter bars 2 and 3. However, the total number of agents is not enough to fill 3 bars, so the best global solution is to use only 2. Indeed, in time 40.000, the agents start to migrate from bar 3 to bar 2. Finally, the system reaches a stable state with bars 1 and 2 occupied and bar 3 empty. It is important to note that the customer agents do not know the total number of customers or bars. Still, they are able to reach a global solution that fits 2 constraints: (i) use the minimum necessary number of bars and (ii) distribute themselves evenly between the chosen bars. Up to this point, our model shows results similar to those in [1].

3.2. Bar occupancy *versus* total number of customers

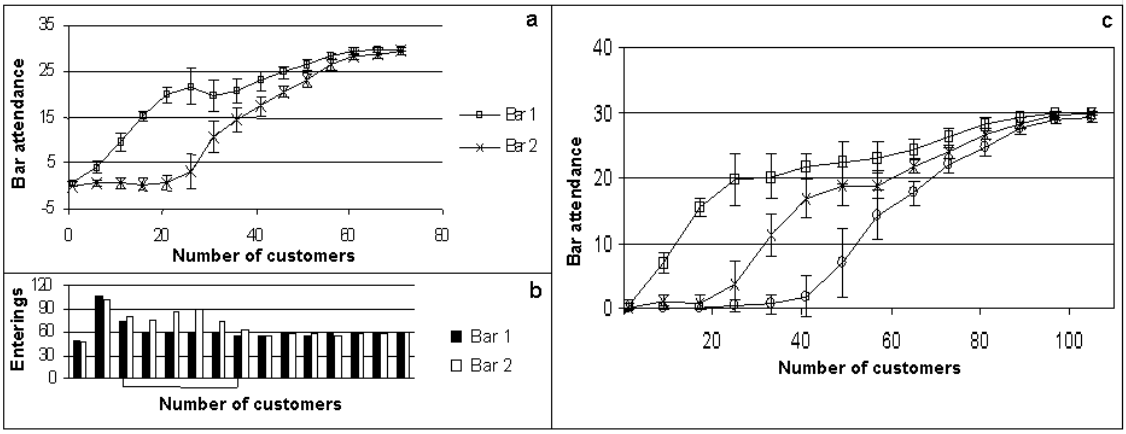

Figure 2 - Bar attendance X Number of customers. a) Average final bar occupancy with 2 bars, as the number of customer increases. Each point in this plot corresponds to the average result of 30 simulations. Vertical lines show standard deviation. b) Vertical bars show the number of times some customer entered the bar at each time interval. c) Average final bar occupancy with 3 bars.

The next step is to investigate the relation between the total number of agents and the number of bars occupied. To do so, we ran several simulations changing these parameters and observing the results. An important preprocessing step on the data in this case is to sort the bars (without loss of generality) according to their final occupancy, in order to differentiate between the occupied and empty bars. This happens because, as the bars are undistinguishable for the customers, only the number of empty bars is constant in the simulations, but any specific bar will be randomly empty or with the same amount of customers as other bars.

Figure 2a shows the final occupancy of two bars (y axis) as the number of customer (x axis) is changed. The standard deviation is represented as vertical lines over the points in the graphic. The bottom plot represents the number of customer entrances in the bar in each time interval. Notice that the number of customer entering the bar is approximately the same over time, except for the region indicated by the line below the bars in figure 2b, between 10 and 35 customers. Both bars have a capacity of 30 customers. When the number of customer agents is small (0-20), there is always only one bar chosen as the populated bar. As the number of agents increase, however, the second bar starts to be populated as well.

The point in Figure 2a where the occupancy of the second bar starts to increase shows some distinct features. At first, the standard deviation is very high. This happens because it is the frontier between the two regions with distinct behaviors: occupying one bar (when the number of agents < 20) or occupying both. On some executions, the agents would gather in one bar, while on others they were divided in two. Also worth of note is that the bars with smaller occupancy have a higher number of entries. Customers will go into the bar, but won't stay long, since the probability to leave is higher (see equation 2).

With more than 2 bars, the results are similar. Figure 2c shows what happens with 3. We can see that when the number of customers exceeds 20, they start to occupy two bars, and when it reaches 60 (2/3 of the total capacity), all three bars are occupied.

3.3. Analyzing the number of enterings

We now turn to the point of analysing how many times a bar has been visited by customers. We call this the total number of entries of the bar.

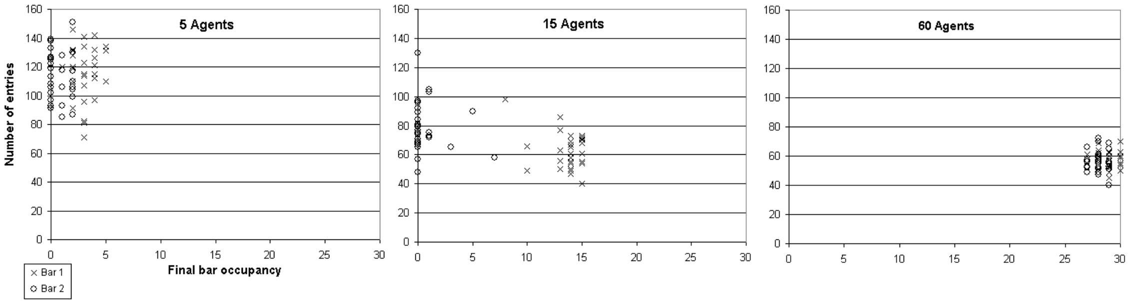

Figure 3 - Final bar occupancy and total number of entries. Each plot shows 30 simulation results, with bar 1 represented as crosses and bar 2 as circles. Left plot shows low bar occupancy (x axis) and a high number of bar entries (y axis). Center plot ilustrates the case where only one bar is occupied. With more agents on the simulation, the bar occupancy increases and the number of enterings decreases, as shown on the right plot.

Figure 3 shows two scatter plots representing the total number of entries in a bar (y axis) and the final occupancy of the bar (x axis). Bar 1 is represented as crosses and bar 2 as circles. Each plot shows the result of 30 runs.

With 5 agents on the simulation, none of the bars can be fully occupied. The number of entrances is high for both bars, indicating that the system is in an unstable state. When there are 15 agents, it can be seen that one of the bars is almost always empty, while the other shows an average occupation close to the total number of customers. Moreover, the number of visits is higher for the empty bar. As we increase the number of agents, the clusters representing the two bars start to merge into one, showing that both bars are occupied, and the total number of entrances is low. In fact, when the number of agents is 60, both bars are indistinguishable.

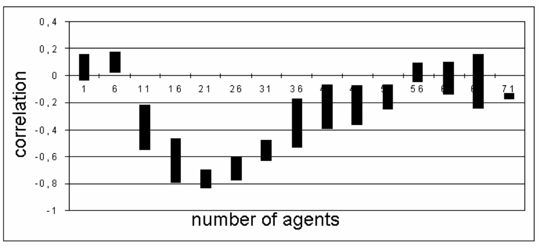

Figure 4 - Correlation between number of agents in the bar and number of bar entries. Each bar shows the minimum and maximum correlation, grouped by 5 agents.

An interesting aspect of the dynamic of bar occupation reveals itself when the number of customers in a bar is compared with the number of entrances in the bar. The less occupied bars have a higher rate of entrance than the more occupied ones. Figure 4 presents a graph of the number of agents in a bar and the correlation between this number of agents and the number of entries. As presented in subsection 3.2, when the total number of agents is close to 20, there is a higher variance on the bar occupancy. This fact is reflected in figure 4, where the correlation is (negative) strongest precisely close to 20 agents.

4. Extending the Model

The results presented so far show that the cockroach model can lead to the optimal selection of bars in an autonomous way. However, it lacks the capacity to accomodate distinct individual behaviours. In order to include the individual preferences of each agent, the model had to be extended. We considered the following effects:

- There are different kinds of bars, and the agents may like ones better than others;
- The agents also have characteristics and preferences about other agents' characteristics, seeking agents with certain profiles that match those preferences. They may also dislike other certain agents' characteristics.

The characteristics of the bars are modeled by a feature vector ω. Each position in the vector corresponds to a certain feature, and is equal to +1 if the bar has that feature, and -1 otherwise.

The agents have one feature vector and two preferences vectors. The agent's feature vector φ is similar to the bar feature vector. The agent's bar preferences vector λ^B describes the types of bar the agent prefers. It has the same dimensionality as ω. The values in this vector are in the range [-1, 1], where -1 means that the agent does not like bars with that feature, +1 means he likes, and 0 means the feature does not influence agent's choice. The agent's agent-preferences vector λ^A defines the characteristics of other agents that the agent likes (or not) to be with. Its values are also in the range [-1, 1].

Every time an agent visits a bar, it makes an evaluation, given by equation 4:

$$e = \frac{P_B \dfrac{(\vec{\lambda}^B \cdot \vec{\omega})}{\sum \left|\lambda_i^B\right|} + P_A \dfrac{\sum_{i \in X} \vec{\lambda}^A \cdot \vec{\varphi}_i}{n \sum \left|\lambda_i^A\right|}}{P_B + P_A} \quad (4)$$

Where X is the set of all agents currently in bar b, n is the number of agents in bar b, $\sum|\lambda_i|$ denotes the sum of the absolute value of all components of the vector λ, and P_B and P_A are constants that set the relative weight of bar evaluation and agent evaluation.

Note that e will always lie in the interval [-1, +1]. If $e>0$, the bar suits the agent's preferences, so its probability of entering it will be higher, as shown in equation 5:

$$R_i = (P_E e + 1)\mu\left(1 - \frac{x_i}{S}\right) \quad (5)$$

The probability Q_i of leaving the bar is also affected by the evaluation, but in the inverse proportion:

$$Q_i = (-P_E e + 1)\frac{\theta}{1+\rho\left(\frac{x_i}{S}\right)^n} \quad (6)$$

P_E is the weight that defines the amount of influence the evaluation has on the probability of entering or leaving the bar. For example, if $P_E=0.1$, a maximum evaluation of a bar (e=1) will increase R (and decrease Q_i) by 10%. When the evaluation is 0, the probabilities are unchanged. Negative values of *e* decrease entering and increase leaving probabilities.

5. Further Results

To test the new model, we simulated a scenario with 130 agents and 8 bars. The bars have a capacity of 40 and are of two kinds, B (bars 0-3) and R (bars 4-7). There are 70 agents that like bars like B, and 60 that like bars like R. The customers also have another attribute for which 50 have type A, 20 are B and the ohers are neither A or B. Half the agents are male and the oher half, female.

The inclusion of agents' preferences into the model preserved the global emerging pattern previously presented (using an optimal number of bars to accommodate all agents) while having great impact in the agents distribution into the bars. The choice of the bar by the agents is directly influenced by agent choice and the weight of its choice.

Figure 5 presents the distribution two agents (averaged over 30 runs) into the eight available bars and the influence of the Agent Evaluation. The two agents were chosen because they have an opposite preference vector for bars. The first agent prefers the bars [1-4] while the second prefers the bars [5-8].

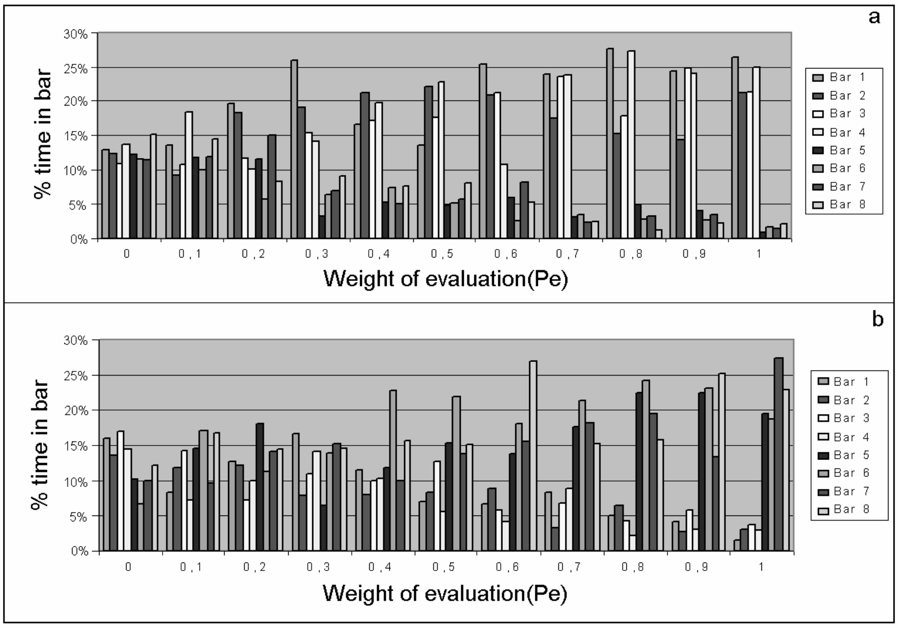

Figure 5 – Bar attendance by agents 10(a) and 120(b). X axis is the P_E parameter (equation 6), and the vertical bars represent the time in each bar.

For small values of weight of agent choice, the amount of time the agent spends in each bar does not present any particular trend. As the weight increases, a clear pattern emerges, with a clear (opposite) preference in each agent.

In fact, there is a strong correlation (+0,91) between the weight of agent choice and the standard deviation in the bars occupancy, evaluated over all agents. The weight of choice also has a strong negative correlation (-0,78) with the number of entrances in each bar, as with a higher weight, the agent tend to enter only the bar it prefers and once inside, have smaller incentive to leave thus reducing total transit.

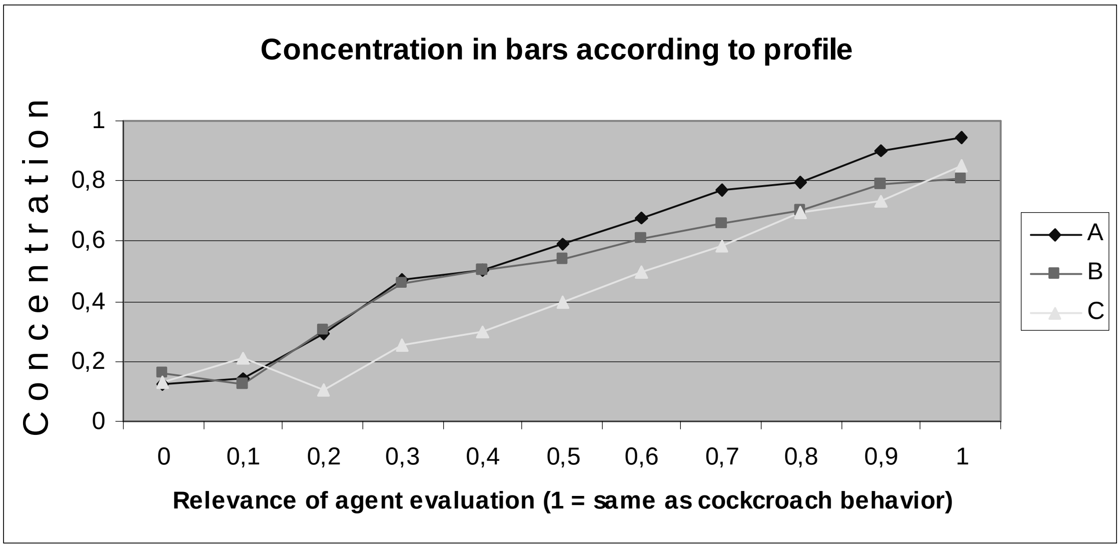

Figure 6 – Concentration in bars

If the agents are divided in three groups, with different preferences, their distribution into the bars that best fit their preference is presented in figure 6. As the agent evaluation weight increases, the agents tend to concentrate in the bars that match their preferences.

6. Conclusions and future work

In this paper, we present a model that predicts which bars will be occupied, given the bar sizes, attractiveness, total number of customers and the characteristics of agents inside the bars. We extend the research presented in [1], by investigating in detail the evolution of occupancy over time, with a more adaptable basis that can be simulated to any desired number of agents, while preserving the global emergent behavior.

The individual agent choice related to other agents and bars characteristics produced a stark modification in the consumer behavior, providing the basic algorithm with means to be used in a number of situations where individual agents cannot communicate, yet they profit from the formation of groups with matching characteristics. It is important to note that the model provides agents with opportunities to visit new providers, even when a satisfying provider has been found, alleviating the problem of local maxima.

The proposed model reflects important aspects of consumer behavior. Directions for future research include implementing an autonomous bar agent with a learning algorithm that will provide the bar agent with resources to adapt its bar according to customer behavior. Also, influence of consumer agent memory of the bars visited before will be evaluated.

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