# Smart Environment for Smarter Agents in E-markets

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**Abstract**

In this paper, we report on experiments with a software multi-agent electronic market where intelligent behaviors are due to both agents internal capabilities and advanced mechanisms in the environment. Our aim is to demonstrate how the environment can be a degree of freedom in the design of intelligent systems.

## Introduction

The environment has played a substantial role in designing intelligent systems, for example with the blackboard and tuple-space mechanisms. Its explicit design is even considered as *essential* (Russell & Norvig Edition 2003; Weyns *et al.* 2005). Still, the environment in software settings remains most often reduced to the underlying computing infrastructure (operating system and computer hardware). Agent systems usually assume the environment as an implicit part of the system, and concentrate on the 'important' part, *i.e.* the agent.

The purpose of this paper is to set forth that the environment is a *degree of freedom* that can be advantageously exploited in the design of intelligent software systems. To this end, we developed a multi-agent system (MAS) for electronic markets where agents are kept simple, but the environment is endowed with advanced functionalities to support agents. We report in this paper on our results relative to the contribution of the environment to the system.

## E-Market model

The electronic market of our experiments is a MAS where agents feature rational trading behaviors. The market is open, so that agents can enter and exit at any time. Agents in the market can have two roles, either buyer or seller, and they interact with each other to trade items. Agents outside the market cannot interact with agents inside; they have to enter the market first. As simplifying hypothesis, we suppose agents are honest, but this is not a limitation as our purpose is to compare different implementations of the system under the same hypothesis. We detail hereafter the interaction, agent, and environment models involved in the market.



### Interaction types

Interactions in the market have three complementary types: Standard, overhearing, and tag interactions. Standard interactions are usual message-passing techniques following the Contract-Net Protocol to trade items (Smith 1980).

Overhearing is an indirect interaction type that lets agents hear conversations among others (Kaminka, Pynadath, & Tambe 2002). In our experiments, overhearing is enacted and enforced by the environment that diffuses messages among all agents trading the same items in the market, thus increasing the potential relevance of overheard messages.

Tag interactions model a feature of complex adaptive systems (Holland 1996). Tags are markers on agents that can be observed by others for reasoning (Platon, Sabouret, & Honiden 2005). In the market place, buyer tags indicate the items in which the agent is interested. Seller tags are the type of items they trade, the current price, and their stock. The environment notifies agents trading the same items of any tag change event. On notification, agents can reason and react accordingly. Typically, seller agents can notice the presence of buyer agents and initiate sells, instead of waiting for requests as done in most systems.

### Agent models

Buyer and seller agents are state machines endowed with a strategy (Chavez & Maes 1996), a rule-based reasoning model, and tags to annotate the agent (as detailed in the previous part). Compared to advanced agent models such as (Kakas *et al.* 2004), our model is voluntarily simple.

Buyers states simulate an employee life cycle where agents in turn earn money, enter the market, buy, and exit the market. Their strategy in the market is to buy as much as possible at the lowest available price. They exit the market after a timeout (need for working) or when they lack money. Rules define their behavior in negotiation.

Sellers states are similar to buyers. They in turn produce, enter the market, sell, and exit. Their strategy is to sell as much as possible while maximizing their profit. They exit the market after a timeout or when their stock empties. Rules define their behavior in negotiation and facing opportunities from overheard messages or tag notifications.

## Environment model

The environment focuses on agent interaction enactment and regulation. The environment enacts overhearing and tag interactions, as presented in the interaction section. Overheard and tag messages are diffused according to the agent trading items so as to increase the potential information relevance to receiving agents.

In addition, the regulation provided by the environment is the application of a set of rules. In the case of our electronic market, the only rule is to enforce a level of honesty. The environment prevents agents to set prices out of the market price range. Sellers can attempt to expose a price for advertising their items. If the price is out of the market range, the environment is responsible for changing the value to the closest allowed one.

## Experiments and Results

Our experiments compare an electronic market with only standard interactions (baseline system) to the same market extended with overhearing and tag interactions. The criteria of comparison is the number of failed deals in the market, *i.e.* when agents fail to contract.

This criteria allowed us to appreciate some characteristics of the two systems in several configurations. The number of agents varied from 4 to 20 of each type with different ratios of buyers and sellers, and simulation lengths varied from 4 seconds to one hour. Each configuration of the two systems ran up to 100 times to provide mean and standard deviation values for the aforementioned criteria. The main results from our experiments are shown on Fig. 1 in five configurations.

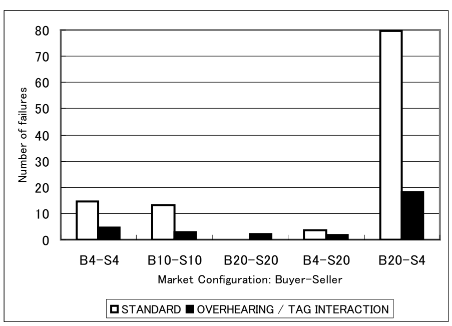


Figure 1: Number of failed deals per configuration

The result from Fig. 1 is that the system augmented with the environment outperforms the one with standard interactions only. The number of failures is always significantly inferior with the environment, except for the configuration with 20 buyers and 20 sellers (B20-S20). One interpretation for the general result is that overhearing and tag interactions introduce more opportunities for agents to interact with and match other agents in trading potential offers. In the B20-S20 case, both systems have low failure rates and the standard deviations are similar. However, such a configuration features as many buyers as sellers, in 'large' amount. It means the probability for agents to contract is much higher than in the other configurations, so that the difference between the two systems becomes insignificant. A similar result holds for B4-S20, which is in addition a rare case in practice. The largest difference is in the case B20-S4, which is the more realistic in a real market.

In contrast with Fig. 1, the analysis of the simulation logs showed that seller agents earn less and buyer agents consume less when interacting through the environment. This result can be explained with the computational cost of overhearing and tag interactions that require sending more messages and events in the market.

## Conclusion

Our experiments show in a simple case that the environment contributes significantly to the agent performance in trading items. The environment does not replace the agent, but it completes it and 'makes it smarter'. The environment is therefore an exploitable degree of freedom in the design of intelligent software systems. Further work aims at exploring more complex settings where the environment could contribute to advanced agent architectures, and identifying a methodology on how to design the appropriate environment for a given application.

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