Technical Report

Assessing the Impact of Informedness on a Consultant's Profit

Eugen Staab and Martin Caminada

Faculty of Sciences, Technology and Communication
University of Luxembourg
6, rue R. Coudenhove-Kalergi
1359 Luxembourg
Luxembourg

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Eugen Staab and Martin Caminada
University of Luxembourg
{eugen.staab,martin.caminada}@uni.lu

Abstract

We study the notion of informedness in a client-consultant setting. Using a software simulator, we examine the extent to which it pays off for consultants to provide their clients with advice that is well-informed, or with advice that is merely meant to appear to be well-informed. The latter strategy is beneficial in that it costs less resources to keep up-to-date, but carries the risk of a decreased reputation if the clients discover the low level of informedness of the consultant. Our experimental results indicate that under different circumstances, different strategies yield the optimal results (net profit) for the consultants.

Keywords: well-informedness, argumentation, social simulation.

1 Introduction

When purchasing information, one wants to be sure of the quality of the information in question. However, if one is not an expert oneself in the relevant domain, assessing the quality of information can be difficult. For the sellers of information (which we will simply refer to as "the consultants") this provides an incentive for dishonesty. After all, gaining real expertise costs significant efforts as well as time and money. However, if the consumer of information (which we will refer to as "the client") has difficulties assessing the quality of the provided information, then why not pretend to have a higher level of expertise than one actually has? As long as the chance that the client detects this dishonesty is low, a consultant can charge the same price for his advice, yet spend less resources on maintaining up-to-date of the state of the art. Moreover, the more consultants decide to take it easy, the less likely it is that the clients will find out about it. This is because once a critical mass of consultants gives ill-informed advice, it becomes more and more difficult for the clients to obtain the kind of well-informed advice that they need in order to detect the ill-informedness of the other advice. This implies that once a critical mass of low expertise consultants has become established, the incentive for consultants to take it easy will increase, since the chance of discovery has decreased.

The issue of low quality information has been studied in [8, 5]. What is new, however, is that we have now developed a software simulator that is able to assess the pay-off for the consultants of either a strategy of hard work or a strategy of taking it easy when it comes to staying up to date with the state of the art. In particular, we are able to provide qualitative insight on which strategy yields the most profitable results under which circumstances.

2 Argumentation and Informedness

The aim of this section is to examine how argumentation can play a role to examine the concept of informedness, which can be seen as background theory for the remaining, more practical part of this paper.

In standard epistemic logic (S5), informedness is basically a binary phenomenon. One either has knowledge about a proposition p or one does not. It is, however, also possible to provide a more subtle account of the extent to which one is informed about the validity of proposition p. Suppose Alex thinks that Hortis Bank is on the brink of bankruptcy because it has massively invested in mortgage backed securities. Bob also thinks that Hortis is on the brink of bankruptcy because of the mortgage backed securities. Bob has also read an interview in which the finance minister promises that the state will support Hortis if needed. However, Bob also knows that the liabilities of Hortis are so big that not even the state will be able to provide significant help to avert bankruptcy. From the perspective of formal argumentation [7], Bob has three arguments at his disposal.
A: Hortis Bank is on the brink of bankruptcy, because of the mortgage backed securities.
B: The state will save Hortis, because the finance minister promised so.
C: Not even the state has the financial means to save Hortis.
Here, argument B attacks A, and argument C attacks B (see eq. 1). In most approaches to formal argumentation, arguments A and C would be accepted and argument B would be rejected.

$$A \longleftarrow B \longleftarrow C \tag{1}$$

Assume that Alex has only argument A to his disposal. Then it seems to regard Bob as more informed with respect to proposition p ("Hortis Bank is on the brink of bankruptcy") since he has a better knowledge of the facts relevant for this proposition and is also in a better position to defend it in the face of criticism.

The most feasible way to determine whether someone is informed on some given issue is to evaluate whether he is up to date with the relevant arguments and is able to defend his position in the face of criticism. One can say that agent X is more informed than agent Y if it has to its disposal a larger set of relevant arguments.

We will now provide a more formal account of how the concept of informedness could be described using formal argumentation. An *argumentation framework* [7] is a pair (Ar, att) where Ar is a set of arguments and att is a binary relation on Ar. An argumentation framework can be represented as a directed graph. For instance, the argumentation framework $(\{A, B, C\}, \{(C, B), (B, A)\})$ is represented in eq. 1.

Arguments can be seen as defeasible derivations of a particular statement. These defeasible derivations can then be attacked by statements of other defeasible derivations, hence the attack relationship. Given an argumentation framework, an interesting question is what is the set (or sets) of arguments that can collectively be accepted. Although this question has traditionally been studied in terms of the various fixpoints of the characteristic function [7], it is equally well possible to use the approach of argument labelings [2, 4, 6]. The idea is that each argument gets exactly one label (accepted, rejected, or abstained), such that the result satisfies the following constraints.

1. If an argument is labeled accepted then all arguments that attack it must be labeled rejected.

2. If an argument is labeled rejected then there must be at least one argument that attacks it and is labeled accepted.

3. If an argument is labeled abstained then it must not be the case that all arguments that attack it are labeled rejected, and it must not be the case that there is an argument that attacks it and is labeled accepted.

A labeling is called complete iff it satisfies each of the above three constraints. As an example, the argumentation framework of eq. 1 has exactly one complete labeling, in which A and C are labeled accepted and B is labeled rejected. In general, an argumentation framework has one or more complete labelings. Furthermore, the arguments labeled accepted in a complete labeling form a complete extension in the sense of [7]. Other standard argumentation concepts, like preferred, grounded and stable extensions can also be expressed in terms of labelings [2].

In essence, one can see a complete labeling as a reasonable position one can take in the presence of the imperfect and conflicting information expressed in the argumentation framework. An interesting question is whether an argument *can* be accepted (that is, whether the argument is labeled accepted in at least one complete labeling) and whether an argument *has to be* accepted (that is, whether the argument is labeled accepted in each complete labeling). These two questions can be answered using formal discussion games [9, 11, 1, 6]. For instance, in the argumentation framework of eq. 1, a possible discussion would go as follows.
Proponent: Argument A has to be accepted.
Opponent: But perhaps A's attacker B does not have to be rejected.
Proponent: B has to be rejected because B's attacker C has to be accepted.
The precise rules which such discussions have to follow are described in [9, 11, 1, 6]. We say that argument A can be *defended* iff the proponent has a winning strategy for A. We say that argument A can be *denied* iff the opponent has a winning strategy against A.

If informedness is defined as justified belief, and justified is being interpreted as defensible in a rational discussion, then formal discussion games can serve as a way to examine whether an agent is informed with respect to proposition p, even in cases where one cannot directly determine the truth or falsity of p in the objective world. An agent is informed on p iff it has an argument for p that it is able to defend in the face of criticism.

The dialectical approach to knowledge also allows for the distinction of various grades of informedness. That is, an agent X can be perceived to be at least as informed as agent Y w.r.t. argument A iff either X and Y originally disagreed on the status of A but combining their information the position of X is confirmed, or X and Y originally agreed on the status of A and in every case where Y is able to maintain its position in the presence of criticism from agent Z, X is also able to maintain its position in the presence of the same criticism.

When $AF_1 = (Ar_1, att_1)$ and $AF_2 = (Ar_2, att_2)$ are argumentation frameworks, we write $AF_1 \sqcup AF_2$ as a shorthand for $(Ar_1 \cup Ar_2, att_1 \cup att_2)$, and $AF_1 \sqsubseteq AF_2$ as a shorthand for $Ar_1 \subseteq Ar_2 \wedge att_1 \subseteq att_2$. Formally, agent X is at least as knowledgeable about argument A as agent Y iff:

1. A can be defended using AF_X (that is, if X assumes the role of the proponent of A then it has a winning strategy using the argumentation framework of X), A can be denied using AF_Y (that is, if Y assumes the role of the opponent than it has a winning strategy using the argumentation framework of Y), but A can be defended using $AF_X \sqcup AF_Y$, or

2. A can be denied using AF_X, A can be defended using AF_Y, but A can be denied $AF_X \sqcup AF_Y$, or
3. A can be defended using AF_X and can be defended using AF_Y, and for each AF_Z such that A can be defended using $AF_Y \sqcup AF_Z$ it holds that A can also be defended using $AF_X \sqcup AF_Z$,
4. A can be denied using AF_X and can be denied using AF_Y, and for each AF_Z such that A can be denied using $AF_Y \sqcup AF_Z$ it holds that A can be denied using $AF_X \sqcup AF_Z$.

Naturally, it follows that if $AF_Y \sqsubseteq AF_X$ then X is at least as informed w.r.t. each argument in AF_Y as Y.

In the example mentioned earlier (eq. 1) Alex has access only to argument A, and Bob has access to arguments A, B and C. Suppose a third person (Charles) has access only to arguments A and B. Then we say that Bob is more informed than Alex w.r.t. argument A because Bob can maintain his position on A (accepted) while facing criticism from Charles, where Alex cannot. A more controversial consequence is that Charles is also more informed than Alex w.r.t. argument A, even though from the global perspective, Charles has the "wrong" position on argument A (rejected instead of accepted). This is compensated by the fact that Bob, in his turn, is more informed than Charles w.r.t. argument A. As an analogy, it would be fair to consider Newton as more informed than his predecessors, even though his work has later been attacked by more advanced theories.

3 Simulation

We developed a software-simulator in order to better understand the impact of a consultant's informedness on his profit. The simulator has the objective to reveal when it pays off for a consultant to be *ill-informed*, i.e. less well-informed as is the state of the art. If ill-informedness is more profitable for a consultant than being well-informed, the spread of outdated and possibly wrong facts or arguments is preprogrammed. Of course, such a situation would be harmful to our society, and so a study of its causes seems to be important.

In the following, we describe the simulator (Sect. 3.1), show results (Sect. 3.2) and discuss these (Sect. 3.3).

3.1 The Simulator

In the first part of this section, we describe the client-consultant scenario that we aim to simulate. We then detail the considered argumentation framework. Two different strategies of the consultants concerning the acquisition of newly available information are defined afterwards, one representing well-informed consultants and the other representing ill-informed consultants. Finally, we specify the procedure of how clients select their consultants.

3.1.1 Client-Consultant Scenario

The scenario is basically defined by a set of clients, a set of consultants, and a finite number of rounds in each of which the clients seek advice from the consultants. In each round, consultants acquire new information, either from other sources (researchers, analysts, etc.), or do investigations on their own. We model this acquisition of information simply as fixed costs per piece of information; in our case, this information comes in the form of arguments as we will see later. The more clients request a certain consultant's advice, the lower his price for a consultation can be. Note that this actually explains why the intermediary role of consultants exists.

Clients are free to choose their consultant, and so select in each round the consultant that they think is currently the most appropriate one. In our simulations, this selection is based on price and reputation of the consultants as it will be detailed later.

3.1.2 Argumentation Framework

We consider the following argumentation structure consisting of N_{arg} many arguments:

$$A_1 \longleftarrow A_2 \longleftarrow \ldots \longleftarrow A_{N_{\text{arg}}} \,. \tag{2}$$

Here, any argument A_i (for $1 < i \leq N_{\text{arg}}$) defeats its predecessor argument A_{i-1}. If N_{arg} is even, then all arguments A_i where i is even, are "in", and all other arguments are "out". If N_{arg} is odd, it is the other way around.

At the beginning of a simulation, only argument A_1 is known to the consultants and only this argument is known in the whole society, i.e. it represents the "state of the art". To model the discovery/emergence of new information, we make a certain number of new arguments available to the consultants in each round. This represents the evolution of the state of the art. The number of new arguments per round will be fixed for a simulation and is denoted by ΔN_{arg}. We assume that the consultants extend their already known chain of arguments with new arguments always in a seamless manner, i.e. without gaps. This assumption was made in order to be in line with argument games (such as described in [9, 11, 1]) where each uttered argument is a reaction to a previously uttered argument, thus satisfying the property of *relevance* [3].

For a better understanding, the following shows the structure of the chain of arguments at any round of the simulation ($k \leq i$ must hold):

$$\overbrace{\underbrace{A_1 \longleftarrow \ldots \longleftarrow A_k}_{\text{known to certain consult.}} \longleftarrow \ldots \longleftarrow A_i}^{\text{``state of the art''}} \longleftarrow \overbrace{A_{i+1} \longleftarrow \ldots \longleftarrow A_{i+\Delta N_{\text{arg}}}}^{\text{becoming available next round}} \longleftarrow \ldots \longleftarrow A_{N_{\text{arg}}} \,. \tag{3}$$

Consultants generally want to provide the least amount of information needed for a consultation, because this way they can give more consultations. However, consultants generally want to give good advice at the same time, to increase their reputation. We assume that consultants believe that the latest argument they know is the most justified one, because it is closest to the current state of the art. As a consequence, in order to give good advice, they only consult arguments that are compliant to the latest argument they possess, i.e. arguments whose index has the same parity as the latest argument they know. To provide the least amount of information at the same time, a rational consultant acts as follows: he provides the client with *two* arguments, if the latest argument known to the client is of the same parity as the latest argument known to the consultant, and with *one* argument otherwise. The latest argument known to the client is updated accordingly.

To keep things simple, the cost of an argument is set to a constant c_{arg}. So, to get the knowledge about argument A_{10}, the consultant has an overall expense of $10 \cdot c_{\text{arg}}$ (recall that arguments can only be acquired in a row). We write n_{arg} to denote the total number of arguments acquired by a specific consultant (where $n_{\text{arg}} \leq N_{\text{arg}}$). Thus, we model the expenses E of a consultant as:

$$E = n_{\text{arg}} \cdot c_{\text{arg}} \; . \tag{4}$$

3.1.3 Strategies of the Consultants

We consider two types of consultants that deal differently with newly available arguments:

well-informed (*wi*): *wi*-consultants buy arguments as soon as these become available, since they want to be always up-to-date.

ill-informed (*ii*): *ii*-consultants only buy arguments as to appear knowledgeable to the clients. That is, as soon as they notice that a client is as informed as they are, or even better informed, they buy a number of new arguments such that they know one argument more than this client.

Clearly, *ii*-consultants can offer their consultations at a lower price. However, the reputation of a consultant decreases with each consultation where the client turns out to be as informed as the consultant – and this happens more often to *ii*-consultants.

The turnover of a consultant is defined by the sum of prices the consultant was paid. Let S be the multiset enumerating all prices paid by clients up to a certain round. So, S represents the consultations where the consultant actually was better informed than the client, and thus was paid. Then the turnover T up to this point is defined as:

$$T = \sum_{p \in S} p \; . \tag{5}$$

Finally, the profit P of a consultant up to a certain round is the difference between his turnover and his expenses so far:

$$P = T - E \; . \tag{6}$$

3.1.4 Selection of a Consultant

In our simulations, clients rate consultants according to two criteria: the consultant i's current reputation r_i and price p_i. The two criteria are explained in more detail later in this section. For now, it suffices to know that they are normalized to $[0, 1]$. To make both parameters "positive", the price p_i will be expressed in the form of *cheapness* c_i, i.e., $c_i = 1 - p_i$. This way, both a *high* cheapness and a *high* reputation characterize a good consultant. A parameter $\alpha \in [0, 1]$ defines which of the two criteria a client thinks is more important. Consequently, a client chooses consultant i with a probability proportional to:

$$P_i := \alpha \cdot c_i + (1 - \alpha) \cdot r_i \; . \tag{7}$$

A high α favors the choice of cheaper consultants, while a low α favors the choice of more reputable consultants.

Price Let δ be the *profit margin* of a consultant, with $\delta \in [0, \infty)$; then $\delta = 0.5$ for example represents a typical profit margin of 50%. Using a certain profit margin, a consultant i computes his current price ${p'}_i$:

$$ {p''}_i = (1 + \delta) \frac{E}{|S|} \ . \tag{8} $$

Here, $\frac{E}{|S|}$ is a simple estimate to provide cost recovery, where E models the expenses (see eq. 4), and $|S|$ is the number of successful consultations so far (see eq. 5). Still, no client would choose a consultant that is more expensive than the acquisition of the information itself. Hence, we limit the price to the cost of the two arguments that a consultant advises at most $(2 \cdot c_{\text{arg}})$.

Finally, we normalize the prices of all consultants to $[0, 1]$:

$$ p_i = \frac{{p'}_i - \min_j \left({p'}_j\right)}{\max_j \left({p'}_j\right) - \min_j \left({p'}_j\right)} \ . \tag{9} $$

Reputation In our simulator, clients use a *reputation system* [10] to share their experience about consultants. This allows clients to better estimate the trustworthiness of the consultants and thus to better select their future consultants. We assume perfect conditions for the reputation system, since this will make it even harder for *ii*-consultants to hold their ground. These perfect conditions consist of:

- *honest reporting* of the clients,
- all clients have the same idea of how to fuse the experiences with consultants, and so a global reputation score can be computed, and
- *total information sharing*, i.e., every client shares his experience with every other client.

The reputation system should be as simple as possible, and the only requirement we have is that it measures a consultant's performance relatively to the performance of other consultants. We consider two different reputation systems. A very basic system (R1), and a more sophisticated one (R2).

Reputation System R1 In the reputation system R1, a client is satisfied with a consultation if the consultant is better informed than the client. This is motivated by the fact that clients cannot question the correctness of the consultants arguments since they are less well informed. So, any consultation where the consultant is better informed than the client counts as a positive experience with that consultant. Consultations where this is not the case count as negative experiences. The clients share their experience and maintain for each consultant i a global counter n_i^+ of positive experiences, and a global counter n_i^- of negative experiences. Then an intermediate reputation score is computed as follows:

$$ {r'}_i = n_i^+ - n_i^- \ . \tag{10} $$

To bring these scores into $[0, 1]$, we normalize the intermediate values of all consultants and get the final global reputation score r_i:

$$ r_i = \frac{{r'}_i - \min_j \left({r'}_j\right)}{\max_j \left({r'}_j\right) - \min_j \left({r'}_j\right)} \ . \tag{11} $$

This basic reputation score has the desired property: the overall performance of a consultant is measured relatively to the performance of other consultants.

Reputation System R2 In this reputation system, a client reactively decides about positive and negative experiences. Each client assumes that the latest argument he was advised on by a consultant is correct. Then for all consultants i that advised him with a conflicting argument in the past (i.e., where the parity of the argument's index is different), each client increases the global value n_i^-, and for all consultants that advised a compatible argument, n_i^+ is increased. As in R1, if the consultant is not more informed than the client, n_i^- is additionally increased. Given n_i^+ and n_i^-, the computation of r_i is the same as in R1.

3.2 Results

On the following pages we show simulation results to compare the profit of *wi*-consultants and *ii*-consultants for different parameters. We conducted the experiments by computing the mean and standard deviation of the consultants' profit over 2^8 simulation runs. Each simulation consisted of 2^7 rounds. We used 2^{10} clients and 2^7 consultants.

We varied the following parameters:

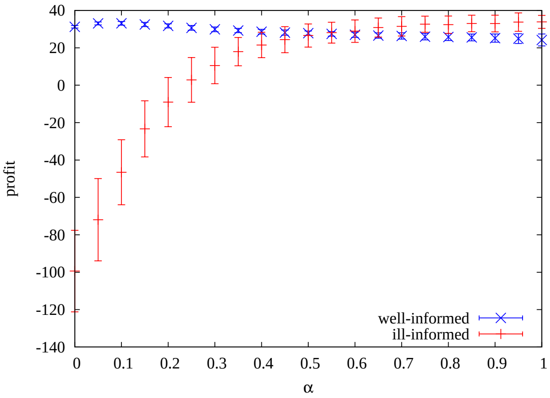
- the number of arguments becoming available each round ($\Delta N_{\text{arg}} \in \{2, 3, 4(, 5)\}$),
- the fraction of *ii*-consultants ($f_{ii} \in \{0.1, 0.5, 0.9\}$),
- the profit margin ($\delta \in \{0.1, 0.5\}$), and
- the factor α that regulates the importance of price and reputation in the clients' consultant selection process ($\alpha \in [0, 1]$, shown on the x-axis).

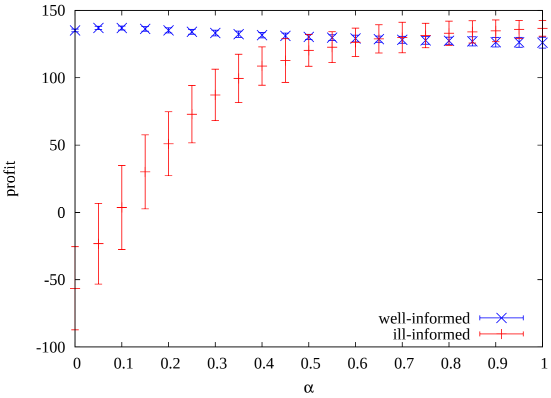
The figures on the left depict simulations with $\delta = 0.1$, those on the right depict simulations with $\delta = 0.5$. Furthermore, we conducted all experiments for the two different reputation systems R1 and R2. At the end of this section, we provide an analysis of the shown results.

(Note: For making it easier to compare the different figures, we start on the next page.)

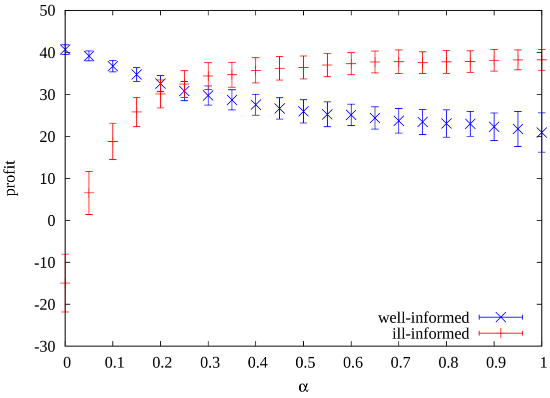
3.2.1 Using R1

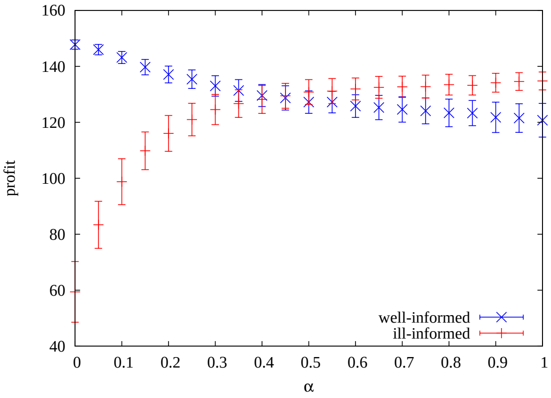
- Information rate $\Delta N_{\text{arg}} = 2$:
  - Fraction of ii-consultants $f_{ii} = 0.1$:



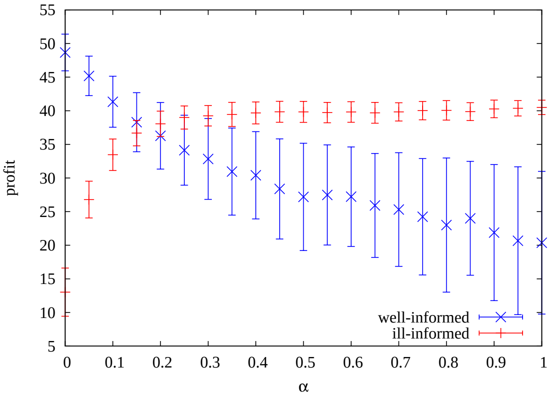


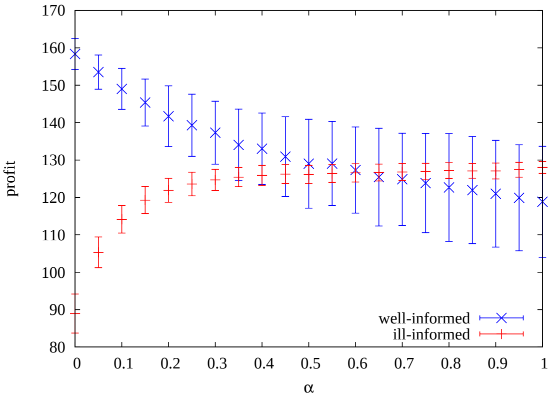
  - Fraction of ii-consultants $f_{ii} = 0.5$



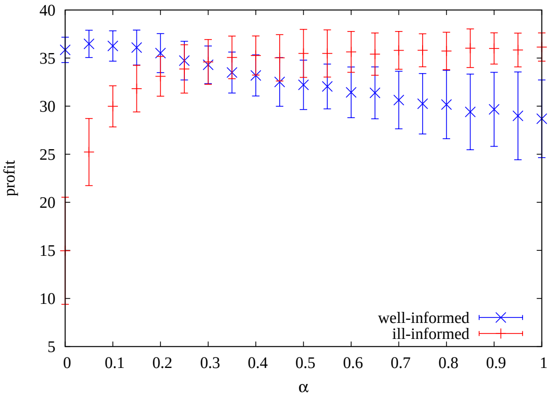


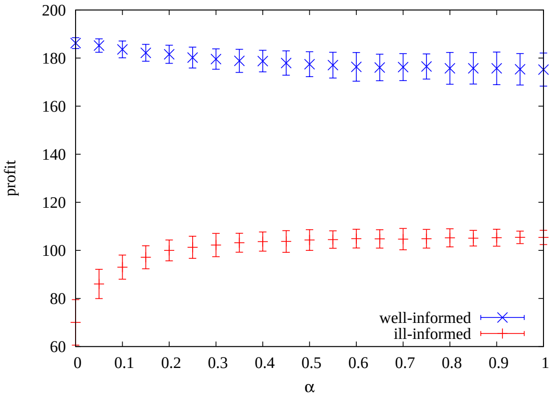
  - Fraction of ii-consultants $f_{ii} = 0.9$



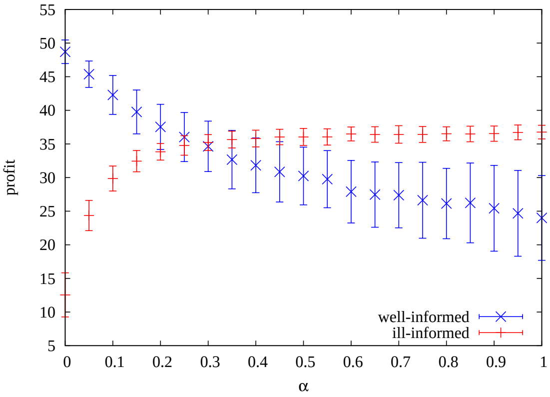


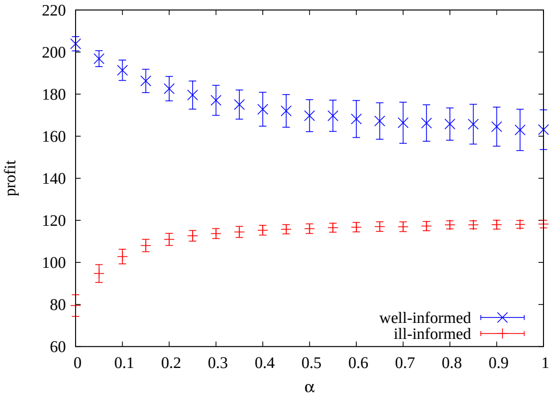
- Information rate $\Delta N_{\text{arg}} = 3$:
  - Fraction of ii-consultants $f_{ii} = 0.1$:



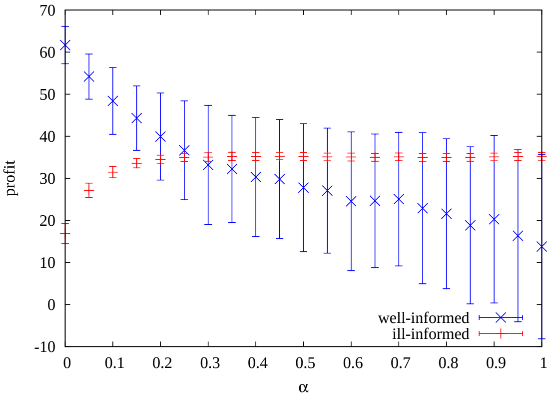


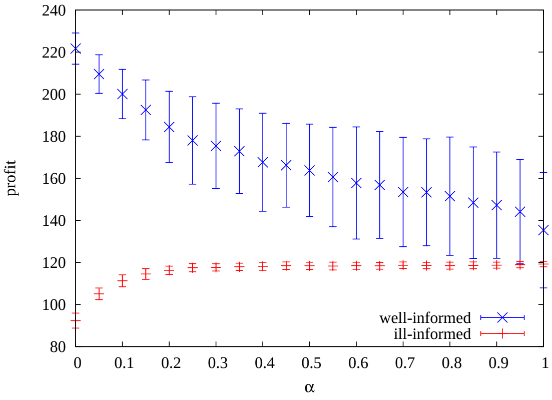
  - Fraction of ii-consultants $f_{ii} = 0.5$



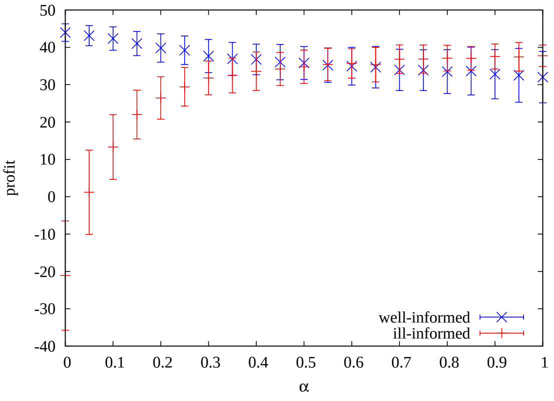


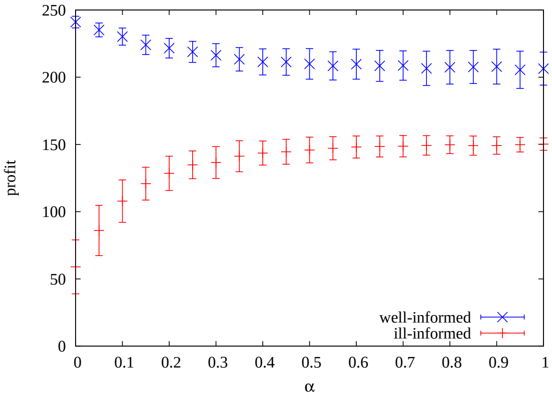
  - Fraction of ii-consultants $f_{ii} = 0.9$



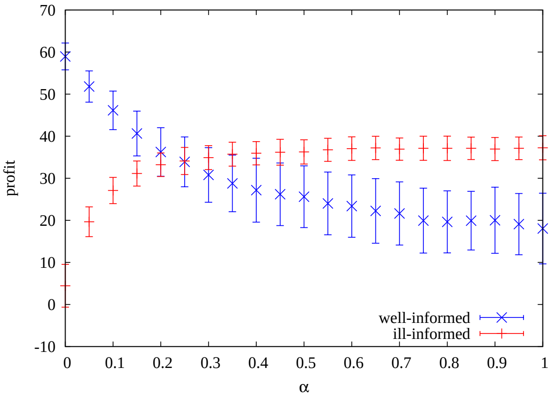


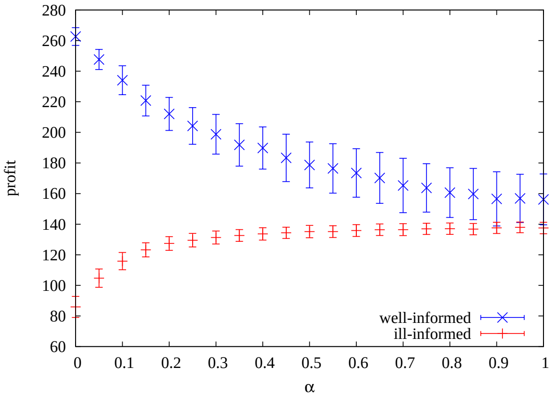
- Information rate $\Delta N_{\text{arg}} = 4$:
  - Fraction of ii-consultants $f_{ii} = 0.1$:



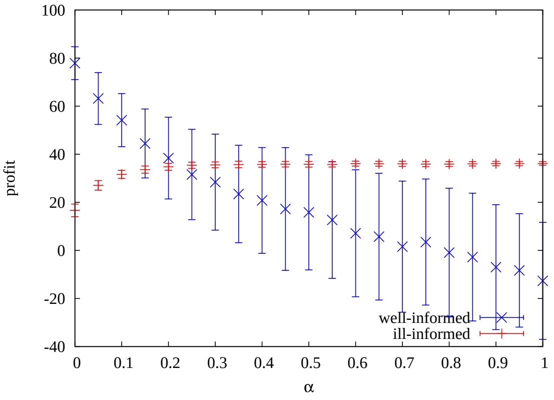


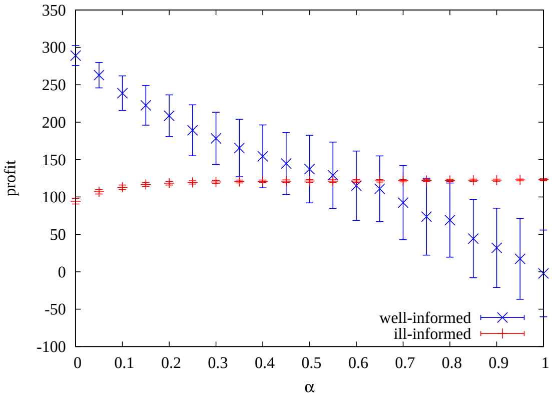
  - Fraction of ii-consultants $f_{ii} = 0.5$





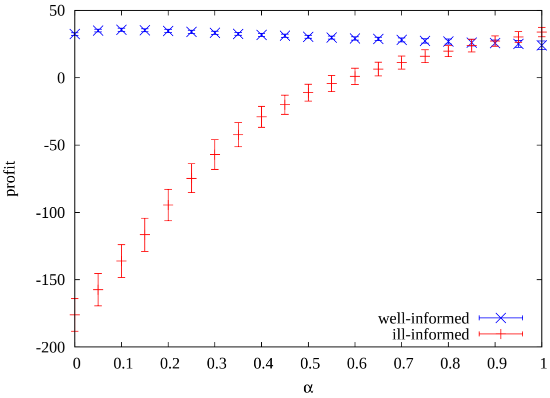
  - Fraction of ii-consultants $f_{ii} = 0.9$

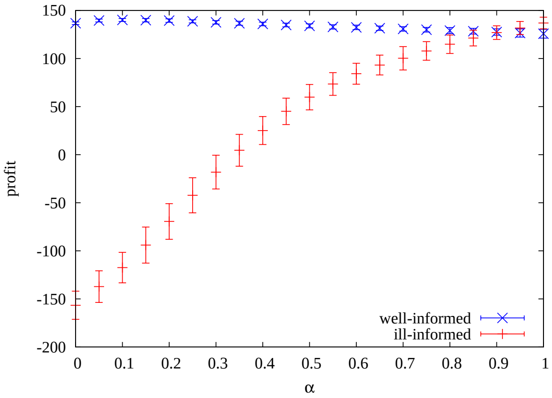




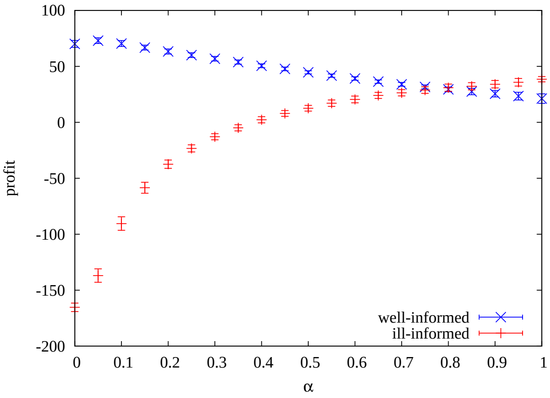
3.2.2 Using R2

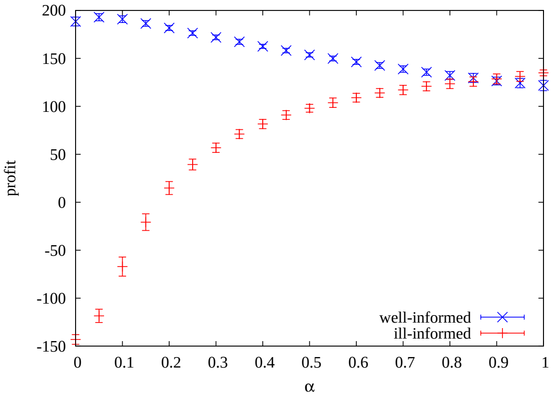
- Information rate $\Delta N_{\text{arg}} = 2$:
  - Fraction of ii-consultants $f_{ii} = 0.1$:



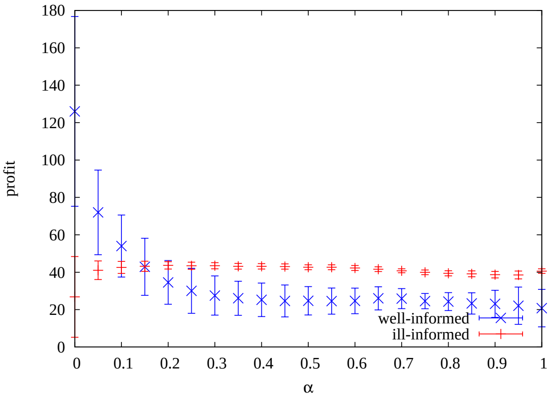


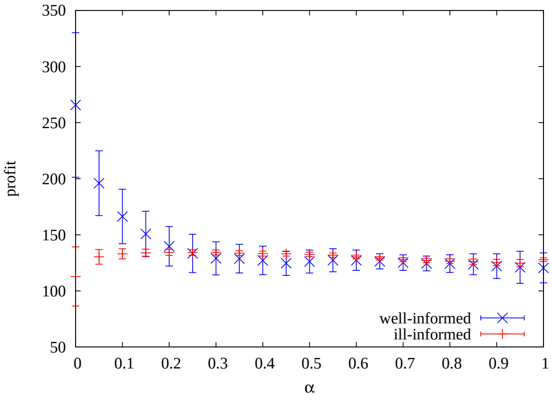
  - Fraction of ii-consultants $f_{ii} = 0.5$



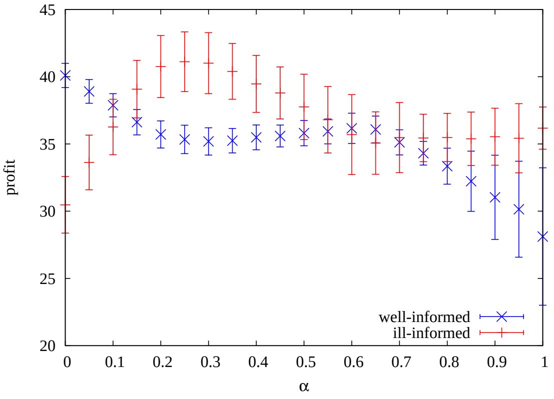


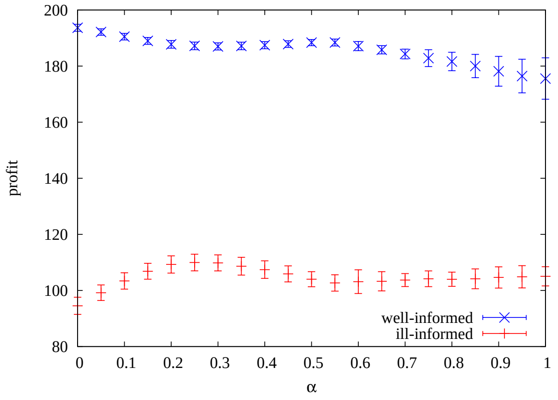
  - Fraction of ii-consultants $f_{ii} = 0.9$



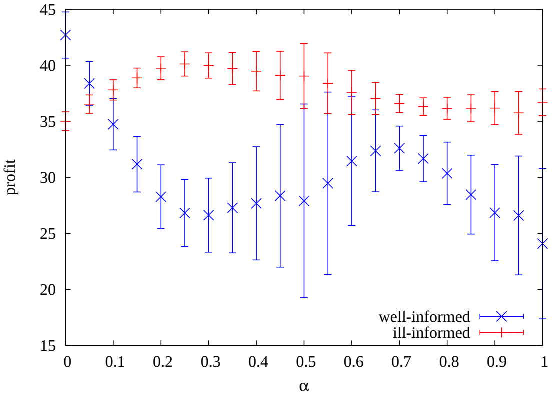


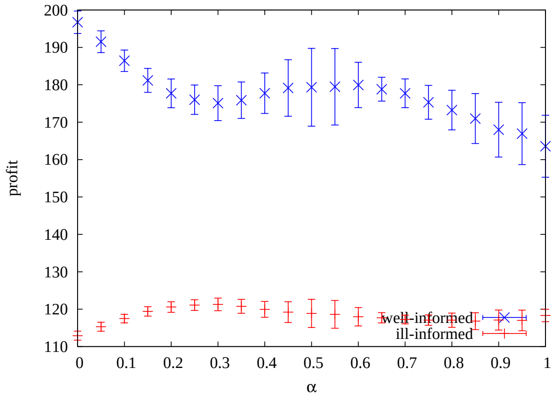
- Information rate $\Delta N_{\text{arg}} = 3$:
  - Fraction of ii-consultants $f_{ii} = 0.1$:



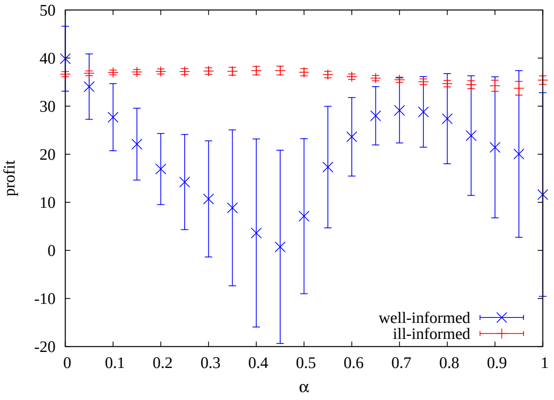


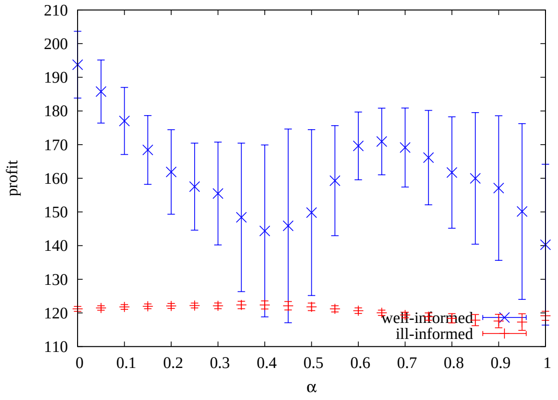
  - Fraction of ii-consultants $f_{ii} = 0.5$



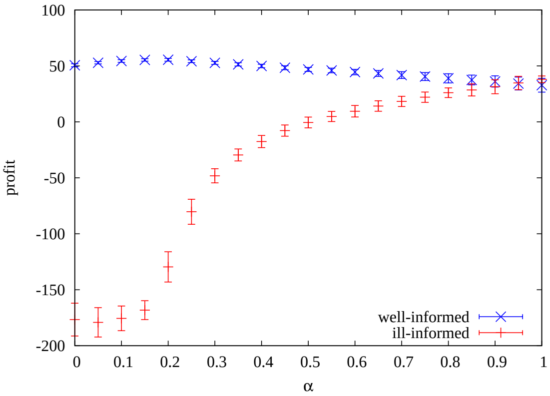


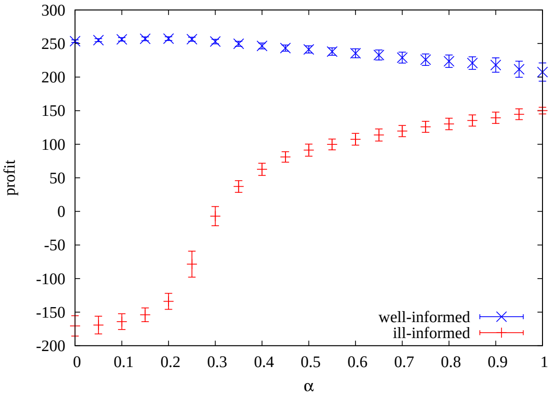
  - Fraction of ii-consultants $f_{ii} = 0.9$



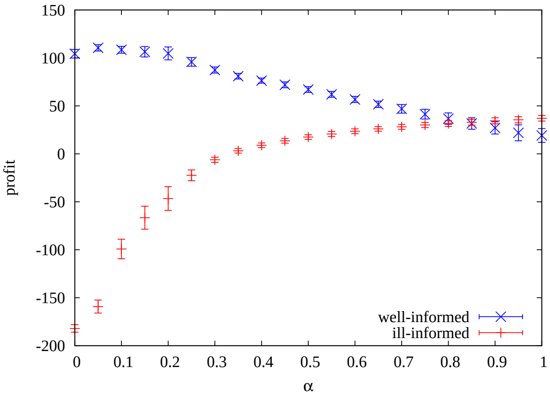


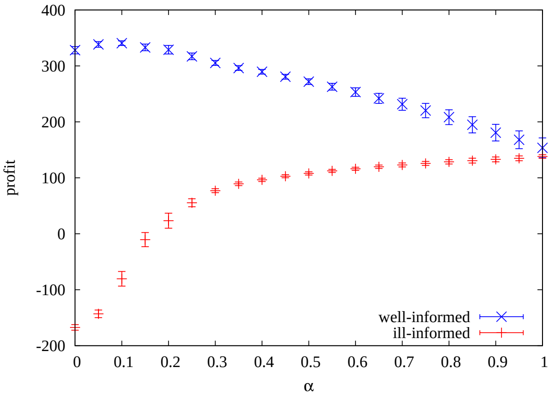
- Information rate $\Delta N_{\mathrm{arg}} = 4$:
  - Fraction of *ii*-consultants $f_{ii} = 0.1$:



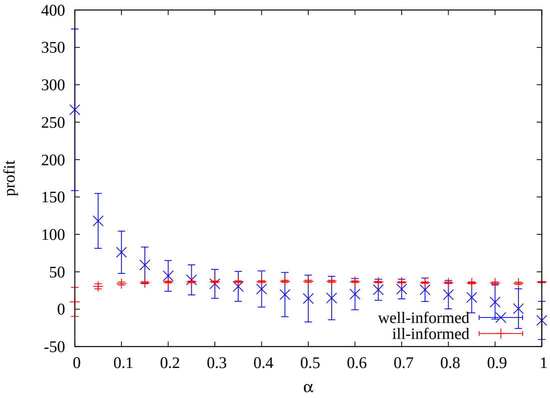


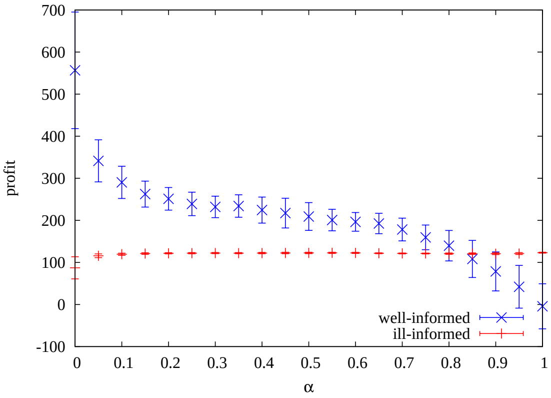
  - Fraction of *ii*-consultants $f_{ii} = 0.5$



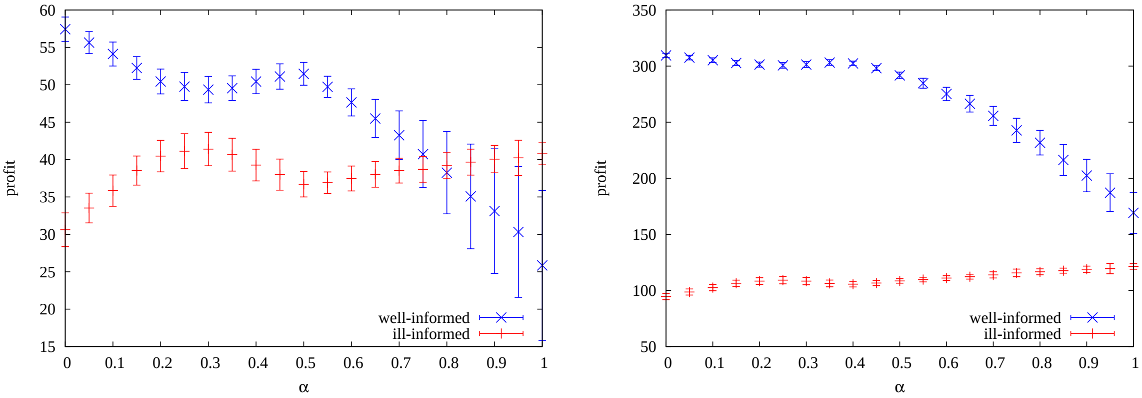


  - Fraction of *ii*-consultants $f_{ii} = 0.9$

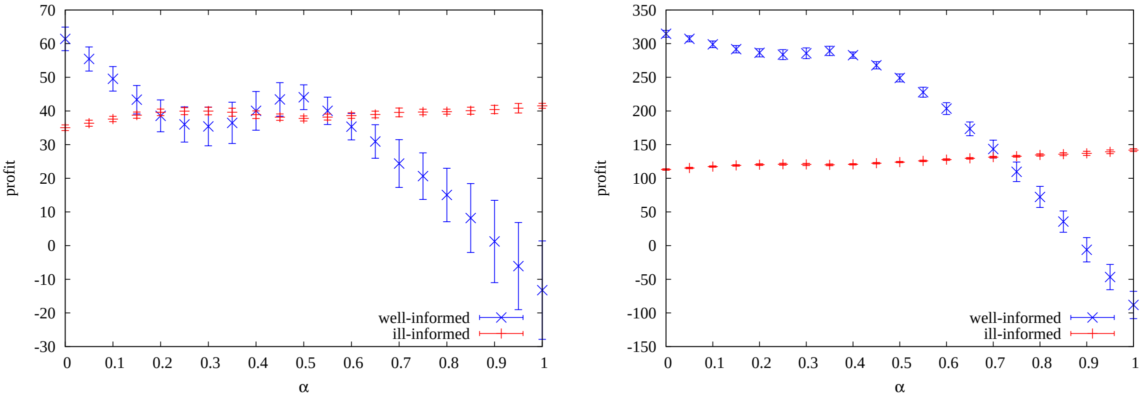




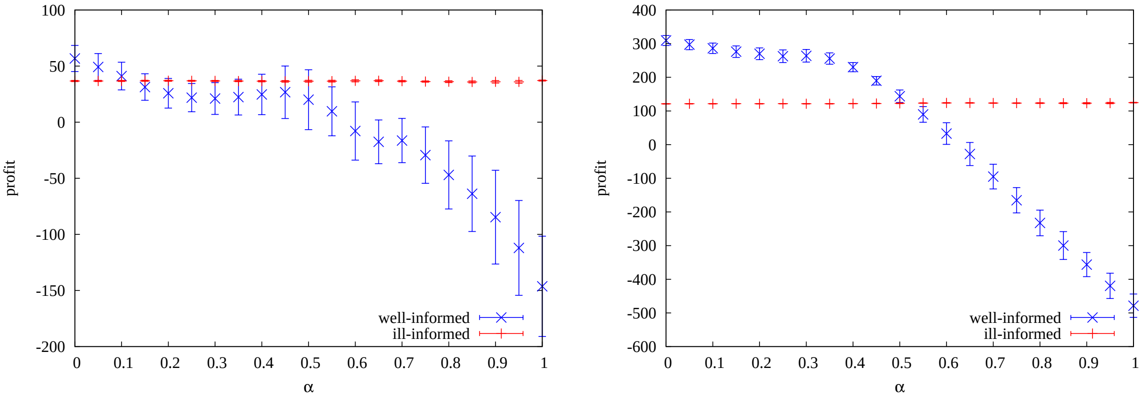
- Information rate $\Delta N_{\mathrm{arg}} = 5$:
  - Fraction of *ii*-consultants $f_{ii} = 0.1$:



  - Fraction of *ii*-consultants $f_{ii} = 0.5$



  - Fraction of *ii*-consultants $f_{ii} = 0.9$



3.3 Analysis

First of all, it is evident that in some scenarios *ii*-consultants have a higher profit than *wi*-consultants. We can conclude that under certain circumstances it is more profitable for a consultant to follow the *ii*-strategy than being well-informed. Some more detailed observations about the results are described in the following.

3.3.1 Using R1

One can see that if reputation is used as the only criterion for selection ($\alpha = 0$), *wi*-consultants are always better off. As the price of the consultants gets more important, the profit of *ii*-consultants generally increases, whereas the profit of *wi*-consultants decreases. In most settings the *wi*-consultants' profit decreases so much that at some point it falls below the profit of the *ii*-consultants. Besides, *ii*-consultants seem to generally benefit from a low profit margin (δ).

An increasing fraction of *ii*-consultants causes the curves of both *ii*-consultants and *wi*-consultants to have a lower slope value (have a look at the values on the y-axis to verify that). As a result, the point where the two curves intersect moves to the left, i.e. the *ii*-strategy becomes more effective.

A varying ΔN_{arg} impacts also the slope of the curves, as well as their distance. Consider for instance the variation of ΔN_{arg} for otherwise fixed parameters: R1, $f_{ii} = 0.5$ and $\delta = 0.5$ (figures on the right side). For $\Delta N_{\text{arg}} = 2$, the *ii*-strategy is the better strategy for $\alpha \geq 0.45$; for a ΔN_{arg} of 3 or 4, the *wi*-strategy is always better – for 3 very distinct, and less distinct for 4.

3.3.2 Using R2

The same observations as for R1 can also be made for R2. The main difference lies in the shape of the curves. In particular, the shape of the lines depends on the parity of ΔN_{arg}. This can be explained as follows. If an even number of new arguments gets available each round, *wi*-consultants will always advice even arguments; however, if $DeltaN_{\text{arg}}$ is odd, they switch each round between advising even and odd arguments. Since clients retrospectively judge consultants in R2, they will find in the odd case that *wi*-consultants contradict each other over time, which will never be the case in the even case. So, in the even case, clients will decrease the reputation of a *wi*-consultant only if their most recent consultant was ill-informed and consulted an odd argument. This explains also why the profit of *wi*-consultants is much higher and the profit of *ii*-consultants is much lower in the even cases (also in comparison to R1).

Apart from these specific shapes, in the same way as for R1 we can observe that the *ii*-strategy yields in many settings higher profits.

4 Conclusion & Future Work

Our simulations suggest that at least four factors have an impact on the profitability of being ill-informed:

- the clients' balancing act of choosing a consultant according to his reputation or his price (α),

- the fraction of ill-informed consultants in the set of consultants (f_{ii}),
- the speed with which new information enters the system and becomes available to consultants (ΔN_{arg}), and
- the profit margin of the consultants (δ).

In our simulations, a high α and a high f_{ii} made it generally less profitable for consultants to be well-informed. The observation that an increasing fractions of *ii*-consultants increases their payoff, raises the problem of consultants that follow the crowd, even if this means to stay ill-informed.

The simulated model in this work is certainly simplifying the complexity of reality. There are many ways for making it more realistic. For instance, the price computation given by eq. 8 is purely reactive; it does not exploit the fact that a lower prices would attract more clients and so could be used in a proactive manner. Still, since all consultants computed their price in the same way, it is not clear whether a more complex approach would make the *ii*-strategy less profitable. This is subject to future research. Also, our consultants pursued two basic strategies (acquiring all arguments becoming available, and acquiring only as needed); this can be extended to more sophisticated strategies, e.g. to be a *wi*-consultant for a certain time to boost the reputation, and then become *ii*-consultant. Furthermore, the impact of publicity campaigns is completely ignored and would be an interesting continuation of our research.

References

[1] M. Caminada. *For the sake of the Argument. Explorations into argument-based reasoning.* Doctoral dissertation, Free University Amsterdam, 2004.

[2] M. Caminada. On the issue of reinstatement in argumentation. In M. Fischer, W. van der Hoek, B. Konev, and A. Lisitsa, editors, *Proceedings of the 10th European Conference on Logics in Artificial Intelligence (JELIA 2006)*, volume 4160 of *LNAI*, pages 111–123. Springer Verlag, 2006.

[3] M. Caminada. Semi-stable semantics. In P. Dunne and T. Bench-Capon, editors, *Proceedings of the 1st International Conference on Computational Models of Argument (COMMA 2006)*, pages 121–130. IOS Press, 2006.

[4] M. Caminada. An algorithm for computing semi-stable semantics. In *Proceedings of the 9th European Conference on Symbolic and Quantitative Approaches to Reasoning with Uncertainty (ECSQARU 2007)*, volume 4724 of *LNAI*, pages 222–234. Springer Verlag, 2007.

[5] M. Caminada. Truth, lies and bullshit; distinguishing classes of dishonesty. In *Proceedings of the Social Simulation Workshop at the International Joint Conference on Artificial Intelligence (SS@IJCAI)*, 2009.

[6] M. Caminada and Y. Wu. An argument game of stable semantics. *Logic Journal of IGPL*, 17(1):77–90, 2009.

[7] P. M. Dung. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77:321–357, 1995.

[8] H. G. Frankfurt. *On Bullshit.* Princeton University Press, 2005.

[9] H. Prakken and G. Sartor. Argument-based extended logic programming with defeasible priorities. *Journal of Applied Non-Classical Logics*, 7:25–75, 1997.

[10] P. Resnick, K. Kuwabara, R. Zeckhauser, and E. Friedman. Reputation systems. *Commun. ACM*, 43(12):45–48, 2000.

[11] G. A. W. Vreeswijk and H. Prakken. Credulous and sceptical argument games for preferred semantics. In *Proceedings of the 7th European Workshop on Logic for Artificial Intelligence (JELIA 2000)*, volume 1919 of *LNAI*, pages 239–253. Springer Verlag, 2000.