Social Behavior Bias and Knowledge Management Optimization

Yaniv Altshuler[1], Alex "Sandy" Pentland[2], Goren Gordon[2]

(1) Athena Wisdom
yaniv@athenawisdom.com

(2) MIT Media Lab
{pentland,ggordon}@media.mit.edu

Abstract. Individuals can manage and process novel information only to some degree. For instance, it was recently shown that when performing a perceptual novel task, there is a cost to high information flow. Hence, there is a balance between too little information (i.e. not getting enough to finish the task), and too much information (i.e. a processing constraint). In other words, actions are selected so as to have a high yet stable amount of novel information on the environment. Combining these new findings to a formal mathematical description of efficiency of novel information processing results in an inverted U-shape, wherein too little information is not effective to solving a problem, yet too much information is also detrimental as it requires more processing power than available. The optimal place to be is at a specific point, such that novel information is managed at a high signal-to-noise ratio. However, in an information flooded economic environment, it has been shown that humans are rather poor at managing information overload, which results in far from optimal performance. In this work we speculate that this is due to the fact that they are actually trying to maximize the wrong thing, e.g. maximizing monetary gains, while completely disregarding information management principles that underlie their decision-making. In other words, people do not internalize the fact that too much information is sometimes detrimental, since it confounds the decision-making process. Thus, in a social decision-making environment, when information flows from one individual to another, people may "misuse" the abundance of information they receive. Using the model of individual novelty management, and the empirical statistical nature of investors' inclination to information, we have derived the social network information flow dynamics and have shown that the "spread" of people's position along the inverted U-shape of efficient information management leads to an unstable and inefficient macro-scale dynamics of the network's performance. This was in turn validated through a global inverted U-shape, observed in the macro-scale network performance. We suggest that changing the distribution of people's position along the information management axis can have drastic effects on the network performance. Two basic manipulations can be considered from a physical system analogy: (i) changing the "temperature" of the system, i.e. either raising it to create a more diverse spread or lowering it to make a more homogenous network; (ii) by lowering the system's temperature one can then tune the distribution center to be more in the optimal efficient information management regime.

Keywords: Behavioral Modeling, Social Networks, Social Physics, Information Flow, Information Management

1. Introduction

In the Information Age, getting the correct amount and type of information is essential. In many scenarios, the decision-making process is driven by information, even though the goal is not information-specific, e.g. investment gains. Moreover, recent platforms enable the social connectivity among participants to be the source of information flow, i.e. information flows from one agent to another, thus influencing not only the individual performance but also the global performance (see for example [29]). Thus, there are several levels in which one can analyze and evaluate the information flow and its effect on the efficiency and productivity of the system. For example, one approach may rely on the individual agent perspective and analyzing the decision making process from a psychological point of view [30]. Another can take a systems approach and analyze the interconnectivity in a given network and the flow of information in it [31,32], or observing the data from a more statistically oriented approach [33].

In our work we have taken a neuro-social-physics integrated approach in which new understanding of neuroscience and the underlying neurophysiological mechanisms of decision making, as well as their mathematical modelling can be analyzed and inform a larger-scale social network information flow characteristics. The analysis follows a statistical physics approach such that the individual decision making agents are akin to atoms and their interaction, which results in the network, is akin to an ensemble, e.g. gas. The first step in our approach is presented in this paper, wherein we projected recent results and models on how biological agents, humans [36] and animals [34], process information in an information-oriented task, onto a social trading platform (called "eToro", serving over 3 million financial investors worldwide [29]). The models enable the unique possibility to have a specific quantifiable prediction on performance of individuals in a social trading platform, where information is key to efficiency.

More specifically, we show that a basic underlying principle of biological decision-making agents is novelty management, i.e. the trade-off between too little and too much information. Two complementary studies have presented mathematical models, validated in experiments in humans [36] and rodents [35] that stress the importance of a processing cost to information. In other words, these neuroscience-based models attempt to explain and predict that too little and too much information is detrimental to the decision making process.

These models predict that in an information-rich environment there will be an inverted-U relation between the amount of information an individual agent receives and its efficiency in that system, in other words too little or too much information reduces the efficiency, generating a unique sweet-spot. We have analyzed data from a social trading platform, eToro [29], where over 3 million financial investors participate in a `collaborative decision making process', manifested through the fact that each individual agent makes a decision based on information sources available in the system – the previous investment decisions of the other participants. We show that our prediction holds, i.e. the revenues of an individual agent is related to the number of information sources in an inverted-U manner. We thus establish a unique relation between neuroscience findings and individual agents' performance in a social interaction scenario.

The rest of the paper is organized as follows: Section 2 discusses related works in this field, whereas Section 3 presents the data used for this research and the results obtained from analyzing it. Section 4 contains concluding remarks and discussion regarding future work.

2. Related Work

We live in the "big data" era. Many of our daily activities, and specifically those that has to do with our social or financial behaviors, are heavily influenced by information we obtain from our surroundings through various media channels, and through direct or indirect interactions with our peers [31,32]. The sudden influx of data is transforming social sciences at an unprecedented pace [27,28]. Various recent works have shown how large communities can be modeled as "swarms", allowing interactions meta-data to be used as the sole (or major) data source for the generation of accurate predictions regarding dominating crowd behaviors and trends [19-25]. In many cases these predictions are dominated by the topological properties of the network formed by these interactions [26].

Recent studies have already illustrated the potential that extensive behavioral data sets (e.g., Google trends, Wikipedia usage patterns, and financial news developments) could offer us a better understanding of collective human behavior in financial markets [1-4]. In this work we focus on economic decision under risk, a key subject of behavior economics [5]. Successful behavior economic theories acknowledge the complexity of human economic behavior and introduce models that are well grounded in psychological research. For example, prospect theory is viewed as the best available descriptive model of how people evaluate risk [6-11]. Prospect theory states that people make decisions based on the potential value of losses and gains rather than the final outcome, and that people evaluate these losses and gains using certain heuristics.

Despite the fact that prospect theory offers many remarkable insights and has been studied for more than three decades, there exist very few large-scale empirical research and most of the previous studies have been undertaken with micro-panel data [12-18]. Moreover, there are relatively few well-known and broadly accepted applications of prospect theory in economics and finance [11]. The emergence of online social trading platforms and the availability of burgeoning volume of financial transaction data of individuals help us explore the empirical aspect of prospect theory to an unprecedented large-scale. Moreover, analyzing the trading behavior at the individual level offers an excellent opportunity to develop pragmatic financial applications of prospect theory.

There have been several psychological studies showing the merit and sources of an inverted-U shape of virtues and attributes. These have been claimed to be sources of wellbeing in the sense that "too much of a good thing" is not necessarily good [39,41]. However, these studies have not presented a neuroscience-based mathematical model that can serve as the basis of a comprehensive framework for individual and social interactions.

Recent studies in neuroscience have enabled the development of rich models that attempt to explain complex behaviors of biological agents in information-oriented tasks. The first study was done with rodents who explored new arenas for the first time [40]. This exploration task resulted in very structured yet complex behavioral patterns. The rodents explored the new environment in a growing dimensional complexity, first exploring the zero-dimension entrance to the arena, then the one-dimension wall and only then the two-dimensional open-space. These exploration excursions were intermittent with retreats, in which the rodents went back to their home cage. A new model was presented that accounted for this complex behavior from a single principle of novelty management [34]. It was shown that information-seeking animals maximized their novelty signal-to-noise ratio, i.e. they aimed for a stable flow of information. Too little information led to low exploration, whereas too much information led to unstable flow.

The rodents in the study displayed different degrees of exploration, which could be accounted for by the variability in the model parameters [34]. Nevertheless, they all exhibited optimality, in terms of maximizing the novelty signal-to-noise ratio. Humans, however, have been shown to be sub-optimal in purely information tasks, compared to rodents [37]. In other words, while rodents have evolved to optimize this SNR and thus do not exhibit in their natural behavior the full spectrum of information flows, and hence sub-optimality, we predict that humans will do so. Namely, we speculate that through their constant attempts to increase revenues, human participants will advocate various strategies for the rate and diversity of their information acquisition, thus resulting in an explicit observable inverted-U shape of information-efficiency curve.

In a different study with human participants, a perceptual task was designed to test the behavior of people with new senses, i.e. artificial whiskers on their fingers [36]. The behavior they exhibited spontaneously in this information-seeking task showed a convergent exploration behavior, similar to those exhibited in rodents. A Bayesian perception optimal-control model suggested that there is a processing cost to too much information, which then leads to a stable information flow. This study suggests that humans follow the same principles as the exploring mice.

3. Data Collection and Results

The financial transaction data used in this work was received from an online social financial trading platform for foreign exchanges, equity indices and commodities, called *eToro* [29]. This trading platform allows traders to take both long and short positions, with a minimal bid of a few dollars as well as leverage up to 400 times. The most important feature of social trading platform is that each trader automatically has a complete access to all trades executed in the platform by additional investors. Investors can then set their accounts to copy one or more trades made by any other investors, in which case the social trading platform will automatically execute the trade(s). Accordingly, there are three types of trades: (i) Single (or non-social) trade: Investor A places a normal trade by himself or herself; (ii) Copy trade: Investor A places exactly the same trade as investor B's single trade; (iii) Mirror trade: Investor A automatically executes Investor B's every single trade, i.e., Investor A follows investor B's exact trading activities (and implicitly – investment decisions). Both (ii) and (iii) are hereafter referred to as social trading, and can be regarded as decision making that is based on information received through the social (investing) medium. There are approximately 3 million registered accounts in this online social trading platform. Our data are composed of over 40 million trades during years 2011 to 2014.

Based on the signal-to-noise (SNR) optimality in decision making processes in mice, we conjecture that a formal mathematical description of the efficiency of novel information acquisition and processing in human decision makers will also result in an inverted U-shape. In other words, that with human decision making as well, too little information is not effective to solving a problem, yet too much information is also detrimental as it requires more processing power than available. The optimal place to be is at a specific point, such that novel information is *managed* at a high signal-to-noise ratio.

As mentioned in previous sections, whereas mice were evolutionary “calibrated” to behave according to this optimal SNR, in an information flooded economic environment, human investors have been shown to perform poorly at managing information overload, which results in far from optimal performance ([37] and many others). We believe that this is due to the fact that human financial investors are constantly trying to maximize the wrong element of their decision making process, e.g. maximizing monetary gains (instead of information sources), and disregarding the basic information management principles that govern their decision-making. In other words, people do not internalize the fact that too much information is sometimes detrimental, since it confounds the decision-making process. Hence, while rodents appear to be (almost-) always on the top of the inverted U-shape, we have discovered that humans appear to be distributed along it, with some people getting too little information, while other too much. This is shown in Figure 1, illustrating the dependency of the average return of investment on the number of information resources, demonstrating an inverted-U pattern.

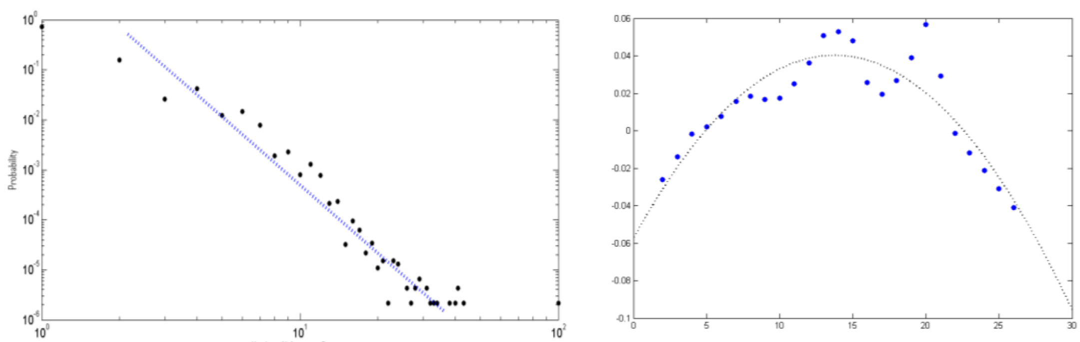

Figure 1: *The Figure depicts the average financial transaction gains as a function of the amount of information sources used. The data was provided by a leading social-trading platform, representing over 3 million investors, for a period of 2 years. Power low of the information sources distribution (left), and the mean gain as a function of the number of information sources (right).*

Thus, in a social decision-making environment, when information flows from one individual to another, people may “misuse” the abundance of information they receive. Using the model of individual novelty management [34], and the empirical statistical nature of investors’ inclination to information, we have derived the social network information flow dynamics and have shown that the “spread” of people’s position along the inverted U-shape of efficient information management leads to an unstable and inefficient macro-scale dynamics of the network's performance. This was in turn validated through a global inverted U-shape, observed in the macro-scale network performance [38].

5. Conclusions

In this paper we have conjectured that human financial investors behave similarly to rodents, with respect to their inability to process unlimited amounts of data sources, and subsequently – the existence of an optimal signal-to-noise ratio with respect to the number of different information sources they handle during their decision making process. We have further predicted that while rodents were evolved to maintain an optimal number of information sources, human, while trying to maximize financial gains, will stray from this optimal configuration (usually by acquiring and handling a larger number of information sources). We have shown that if such behavior indeed exists, it will be manifested through an observable inverted-U ratio between the average financial gain and the number of information sources used in order to obtain it.

We have tested our hypothesis using a highly detailed large financial trading database, containing the complete financial trades of 3 million financial investors. We have demonstrated the existence of the predicted inverted-U ratio, validating our assumption regarding the strong dependency of decision making (in finance at least) by the number of information sources used, the existence of an optimum for it, and the inability of human investors to maintain it.

We suggest that changing the distribution of people's position along the information management axis can have drastic effects on the network performance. Two basic manipulations can be considered from a physical system analogy: (i) changing the "temperature" of the system, i.e. either raising it to create a more diverse spread or lowering it to make a more homogenous network; (ii) by lowering the system's temperature one can then tune the distribution center to be more in the optimal efficient information management regime.

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