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Modeling signal-based decisions in online search environments: A non-recursive forward-looking approach

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ABSTRACT

Consider a rational decision maker (DM) who must acquire a finite amount of information sequentially online from a set of products. The DM receives signals on the distribution of the product characteristics. Each time an observation is acquired, DMs redefine the probability of improving upon the products observed. The resulting information acquisition process depends on the values of the characteristics observed, the number and potential realizations of the remaining observations, and the type of signal received. We construct two functions determining the information acquisition behavior of DMs and illustrate numerically the importance of the characteristic on which signals are issued.

1. Introduction

1.1. Motivation

The elimination of the uncertainty faced in most real-life decisions and its transformation into risk constitutes one of the main incentives for the design of information acquisition algorithms [13,43,44]. Consider the search problem faced by a decision maker (DM) who must sequentially acquire information on a set of products whose main characteristics are grouped into two differentiated categories. The acquisition of information by rational DMs constitutes a fundamental subject of analysis in a wide array of disciplines, ranging from consumer behavior and economics to psychology, management and operations research. Each discipline provides its own approach to the problem involving a DM who must generally decide when to stop gathering information based on the last observation acquired and some simplifying (martingale-based) assumptions regarding the value of the potential expected realizations [8].

The standard framework of analysis that both the management and operations research literature build upon considers the introduction of a new technology to the market [35–37,41,58]. The algorithms designed in these papers determine the information acquisition incentives of the DMs and their stopping rules based on the expected value of the next characteristic realized and the information acquisition costs faced by the DM [31,54,58]. The use of standard dynamic programming techniques to illustrate the existence of information acquisition thresholds requires imposing several formal restrictions on the corresponding return functions.

In these models, three important constraints are generally imposed on the algorithms that determine the information acquisition behavior of the DMs, namely,

1. The DM seldom considers recalling previous partially observed products (Shepherd and Levesque [53] are an exception).

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2. The information acquisition incentives of the DM do not depend on the number or the potential realizations of the observations remaining to be acquired.
3. The DM does not consider the set of potential improvements that may be realized relative to the products observed previously.

A similar intuition applies to the technology acceptance models based on the subjective perception of the DM when observing different characteristics of a given product [10,23,59]. At the same time, the previous models do not consider the strategic quality inherent to the process of information transmission [9,28,29,47]. In other words, the operations research literature generally overlooks the strategic implications that different signaling strategies regarding the value of unknown technological characteristics have for the information acquisition and choice behavior of the DM.

An important exception is given by the game theoretical branch of the operations research literature [50]. This research area concentrates on the strategic incentives driving the diffusion of technology but does not consider the information acquisition process of the DM when defining his technology adoption decisions. This line of research has been further developed by the economics and the consumer choice literature, which have both formally and empirically described the strategic effect that signals have on the information acquisition and choice incentives of the DM [8,40].

The potential applications of these algorithmic structures lie within the decision support and the consumer choice literature. As in the corresponding theoretical settings, the applications of these information acquisition models rely on simplifying assumptions that allow for the use of dynamic programming techniques to obtain optimal sequential choice policies. These simplifications range from heuristic mechanisms that limit the number of alternatives evaluated by the DM [19] and the elimination of recall [34] to the absence of optimal information acquisition thresholds or analysis of their behavior [5,49,62].

1.2. Contribution

The current paper studies the information acquisition behavior of a rational DM who is sequentially gathering $n \in N$ observations from a set of products whose attributes have been grouped into two differentiated categories. This simplification is applied in several disciplines, which concentrate on a small number of characteristic categories when describing the products available to the DMs. For example:

- consumer choice analysts utilize quality and preference [30],
- economists consider performance and cheapness [38], and
- operations researchers concentrate on variety and quality [6].

The defining quality of our paper relies on the formalization of the information acquisition process of the DM, which will be defined for each observation available on the following criteria:

- the values of all the characteristics observed previously,
- the number and potential realizations of all the remaining observations, and
- all possible combinations of the potential realizations of the remaining observations and the characteristics observed.

These criteria together prevent the use of standard dynamic programming techniques in the design of the information acquisition algorithm. In particular, the information acquisition incentives of DMs will be based on:

- the number of observations that remain to be acquired,
- the potential values of these observations, and
- the subjective probability that these values allow the DM to observe a product that delivers a higher utility than the best among the ones observed.

These incentives must be redefined each time an observation is acquired, as suggested, for example, by Saad and Russo [51].

Given the value of the realizations observed and the number of observations remaining to be acquired, the information acquisition behavior of the DM will be determined by the following:

- a continuation function describing the utility that the DM expects to obtain from continuing to acquire information on a partially observed product, and
- a starting function defining the expected utility the DM expects to obtain from starting to check the characteristics of a new product.

Fig. 1 illustrates the possibility spaces that must be considered by the DM when defining his information acquisition process. The variable x_i ($i = 1, 2$) represents the first and the second characteristic of the initial product; x_i^n refers to a new second product, while x_i^{n+1} refers to a new third product. Fig. 1a describes the two-observation scenario, where the spaces of potential realizations to be considered by the DM are bidimensional. Fig. 1b shows that in the three-observation setting, the DM must consider one three-dimensional space versus the union of three different three-dimensional spaces. Similarly, in the case with four observations, the DM will have to consider the union of two four-dimensional spaces (when continuing) versus the union of eight different four-dimensional spaces (when starting). This figure highlights the non-recursivity of the information acquisition process analyzed in the current paper.

Fig. 1 also illustrates the increase in the dimensionality of the problem faced by the DM as he considers acquiring additional observations. More precisely, the setting that would result from considering more than three observations cannot be analyzed directly. We synthesize the information acquisition incentives of the DM within two real-valued functions that determine the expected utility derived from the potential use given to the remaining observations. That is, we simplify a problem requiring the analysis of a multiple-dimensional continuous environment into a two-dimensional one, which makes it tractable and allows for a verifiable analysis of the behavior of the DM.

Moreover, firms will be allowed to issue signals on the characteristics defining their products, thus prompting the DM to update his expected search utilities following both Bayesian and subjective learning rules. Each time an observation is acquired, the DM has to modify the probability of improving upon the products already observed with the remaining observations available and also account for the distributional implications derived from the signal.

We will illustrate how the characteristic on which the signals are issued plays a fundamental role in determining the information acquisition incentives of the DM. This will be the case *even if the signals are considered reliable by the DM and indicate improvement in one of the characteristics of the product*. In particular, issuing signals on the second characteristic may have the opposite effect of that intended by the firm.

Given the number of observations that are expected to be acquired by the DM, our model allows firms to forecast the information acquisition behavior of the DM as well as the probability of having their products inspected and considered for purchase. This possibility introduces an important strategic component, particularly in the formalization of online search