An Ontology-based Data-driven Architecture for Analyzing Cognitive Biases in Decision-making

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Abstract

Decision-making is an old process that continues to be studied a lot. Both individuals and organizations need to improve their way of making decisions as much as possible to succeed in their choices. Despite seeming very rational, a decision is commonly influenced by cognitive biases, which are still unknown by most decision-makers. Prospect Theory and its derivations in Behavioral Economics address this issue, being important actors in identifying the biases we are subject to. In previous works, an ontology of decision-making encompassing value and risk was the starting point to define how intuitive and rational decision-making takes place and enabled the creation of a history of decision-making scenarios. This, in turn, becomes a valuable asset towards identifying recurrent situations subject to cognitive biases, so as to better understand which are the most influential features. This work proposes an ontology-based data-driven architecture for identifying and analyzing the most influential features of cognitive biases in decision-making scenarios involving monetary losses, using Machine Learning.

Keywords

cognitive bias, ontology, decision-making, machine learning

1. Introduction

Every individual or organization needs to make decisions daily. In certain contexts, a decision can have its impact amplified, for example, a CEO's decision on whether to continue or stop a large company project. Therefore, the study of decision-making becomes essential for its improvement, in view of the many factors that influence them, such as the domain in which the decision is being taken, technical knowledge, external factors, etc. Several theories about decision-making were formulated, emphasizing the decision-maker as the main element, and assisting him in all stages of the decision-making process. Several devices have been created to combine theory and practice in favor of the development of these methodologies. This research proposes an ontology-based data-driven architecture to identify which features influence cognitive biases during decision-making, particularly involving monetary losses.

One of the most critical issues that have been addressed in the literature during decision-making is the influence of biases. Whether due to a personal belief or an external influence, biases can influence decision-making at all stages and may be due to several factors, such as the existence of incorrect data or selection of a non-representative subset of data for analysis, inadequate instrumentation, or even the cognitive strategy unconsciously applied by a decision maker to select the alternative to be chosen (the so-called cognitive biases). Whether due to the extensive experience or the high technical quality of the decision maker (among other aspects), all human decision-makers are subject to cognitive "traps", when the brain searches (often unconsciously) for the most feasible and quick alternative that satisfies a presented set of constraints; therefore, cognitive biases are usually very present during a decision-making process. Although the field of behavioral economics (BE) has much to offer in identifying

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human biases in decision-making, it is difficult to find precise definitions and models of biases adapted to specific business problems [1].

An ontology was proposed [2] [3] that organizes and relates all relevant concepts to precisely characterize intuitive decision-making, and which served as the basis for designing a relational scheme of a database (DB) to store a history of decisions taken. In addition to the ontology and the DB, the authors developed a method and a computational tool to support the method capable of identifying cognitive biases (Risk Seeking type) during intuitive decision-making, applying rational decision theories (Expected Utility Theory and Expected Value Theory), Prospect Theory and the definitions of risk aversion and risk seeking cognitive biases [3]. Such a proposal, however, is limited to the scope of individual decision-making and to only one type of cognitive bias, not considering the history of decisions already taken as part of the knowledge needed to help automatically identify cognitive biases and their most influential features.

The proposed architecture encompasses a repository of historical data on decision-making, a cognitive bias detection tool for risk-seeking/risk-averse decisions, and a module for learning cognitive bias patterns through machine learning. Together, these components make it possible for decision-makers to know their risk preferences, considering the history of decisions taken previously within the same context. An application example in the domain of monetary decision-making is described.

2. Cognitive Biases during Decision-Making

In a business context, the most recognized school that studies decision-making is based on the theory of bounded rationality[5]. Economic decision-making is considered rational when it maximizes this expected utility. The idea of an economic man is summed up by the logic that the perfect decision-maker makes decisions with complete knowledge of all aspects included in the situation, has infinite information processing abilities, and does not consider aspects of human psychology.

According to Simon[5], decision-makers' rationality was limited and not perfect. That is, instead of maximizing utility, they accommodate the circumstances and make the best decision they can in each situation. This research created a phase model for decision-making containing four stages: intelligence, design, choice, and revision. Bounded rationality theory explains that decision-makers use heuristics or ground rules instead of optimization processes, increasing the risk of biased decisions.

As claimed by[6], cognitive biases are a challenge for evolutionary psychology, and logic and precision factors are compared with the resolution of a specific problem, that is, the proficiency and specificity that the cognitive trait can bring to identify a design flaw or a good use of psychic resources. The authors typify cognitive biases into three categories: (i) Heuristics, (ii) Error management, and (iii) Artifact. The first is the most known and studied, it deals with the limited processing of information by our brain, associating it with evolutionary restrictions. The second deals with cases in which, as there is no specific solution to a problem, a known bias is used, but which can reduce the error in relation to other methods.

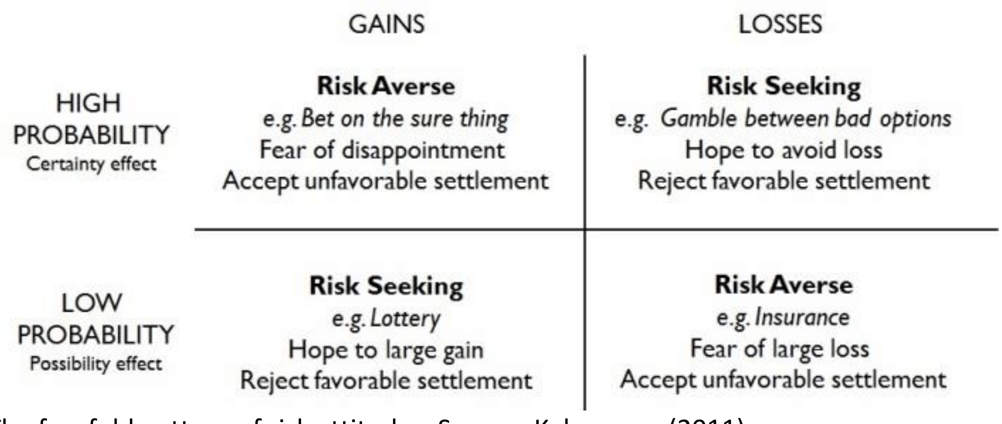

Figure 1: The fourfold pattern of risk attitudes. Source: Kahneman (2011)

The third is a product of placing humans in unnatural environments or the application of inappropriate normative standards, being treated as apparent research strategies. Due to space limitations, only a subset of the biases related to the utility curve treated by [7] will be treated in this research. These biases compose the Prospect Theory in scenarios of high risk of losses, showed in Figure 1.

That contrary to the domain of gains (Figure 1), in the domain of losses, risk-seeking behavior is observed when there are high probabilities of occurrence of this loss. If an individual already knows that there is a high chance of losing, he starts to want to avoid this scenario, being willing to take more risks. In the domain of earnings, the logic is reversed, because when there are great chances of accumulating some value, risk is avoided [8].

3. Automatic Bias Identification (ABI) approach

[9][2] argues for the importance of understanding the nature of decisions and the decision-making process to provide better support for decision-making. They propose the Core Ontology of Decision Making.

[2] extends the existing ontology to include intuitive decision-making according to Cumulative Prospect Theory (CPT) and introduces concepts such as intuition, reference point, cognitive bias, loss aversion, gain, loss, risk aversion, risk-seeking, attribution of psychological value and psychological value. The ontology (Figure) considers decisions under risk and uncertainty for intuitive and rational decision-making and incorporated the concepts of value and preference for Go/Kill decisions. It served as a basis for codifying a logical scheme of a database for an information system to support cognitively-biased decision-makers.

In Figure 2, the decision maker is an Agent (more specifically, a ValueBeholder), and his choice about a decision is made in a deliberative or intuitive way. If it is intuitive, it will be subject to cognitive biases (such as loss aversion). The authors differentiate the rational value from the psychological value. Rational value is determined based on objective criteria and is used to choose alternatives, while psychological value considers how people assign values to gains and losses in relation to a reference point. Cognitive biases, such as loss aversion, influence psychological value attribution.

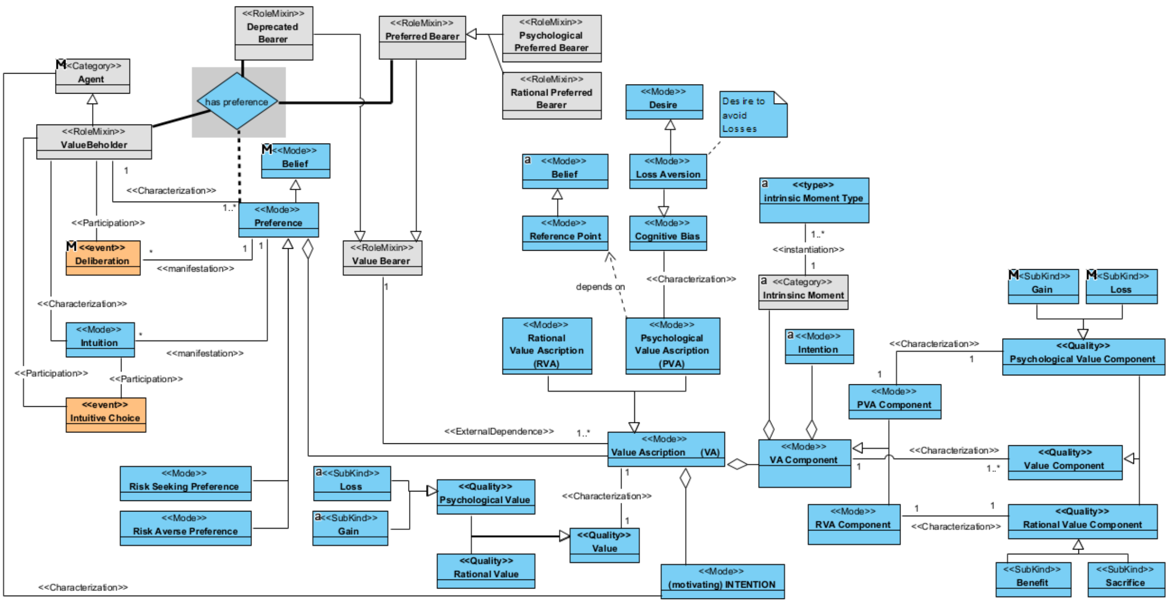

Figure 2: Deliberation, Intuition, Value and Preference in the Intuitive Decision Ontology. Source: Ramos (2021).

The decision-making process is described based on rational deliberation or intuitive choice, considering the agent's preferences in relation to value carriers. The resulting decision may have

[2] Available at https://ceur-ws.org/Vol-2728/paper1.pdf

implications for how the agent evaluates the consequences and influences future decisions. The author also developed the Automatic Bias Identification (ABI) Tool, which identifies the risk-seeking bias in situations of uncertainty but is applied to isolated decisions. The categorization of decisions taken (in biased or unbiased decisions) allows storing a history of all decisions taken in the organization, including a description of the problem in which the decision is contextualized, the alternatives considered, each one with its risk probabilities and possible monetary impact, and the alternative selected by the decision maker.

4. An Architecture for Bias Identification

An architecture is proposed to complement the work of Ramos [2] in that, in addition to addressing the problem and the bias that ABI addresses, implements a machine learning model capable of identifying the user's value and risk preferences for different and subsequent decisions. The research question for this ecosystem is: "*Under which circumstances does cognitive bias contribute to making more valuable decisions?*". A learning model of cognitive biases through data will be developed to evaluate the impact of decisions on gains and losses for each decision-maker. All components of this architecture can be seen in Figure 3 and will be explained in more detail below.

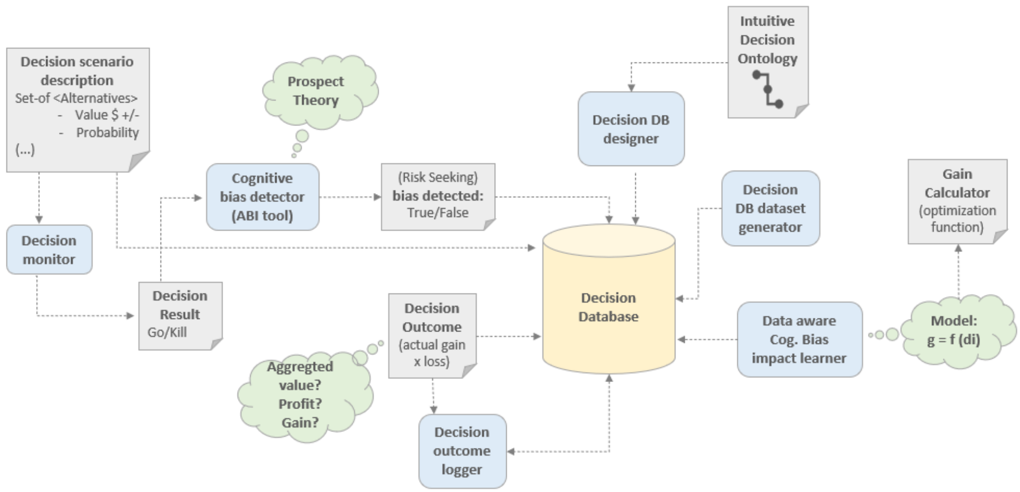

Figure 3: Proposed architecture for automatic detection and analysis of cognitive biases. Source: The authors

Historically, data has always been an essential resource for decision-making. With recent technological advances, the exponential growth in the amount of data available has brought a challenge to organizations on how to extract useful knowledge from this data. In this context, data mining processes (Data Mining) emerged as an approach to extract strategic knowledge from large data collections, applying Machine Learning techniques and algorithms. More recently,[10] defined Machine Learning as the discipline that uses algorithms and procedures to identify patterns, trends, or clusters, and from that extract valuable information to analyze data in an automated way.

All these definitions, methodologies, and techniques have been incorporated into the recent (and still growing) area of knowledge of Data Science [11]. Despite many recent terminological changes in this topic and related areas, Data Mining is essentially a process that encompasses the understanding of the problem and definition of the question to be investigated, the collection and preparation of data, the automatic discovery of patterns from the data, evaluation of the models built with a view to the research question, and then implementation and use of this model in real scenarios. The Intuitive Decision Ontology represents the intuitive and rational decision-making ontology proposed by Ramos [2], being fundamental for architecture. Through this work, it is possible to identify and explain the cognitive biases of risk-seeking according to the theory of Behavioral Economics [7][8]. This contribution was also used in the logical scheme to model the database, to be accessed by a computational decision support application.

The central idea of the architecture is, from the ontology exposed in the previous section, to derive an ecosystem with its defined logical relations, facilitating the implementation and adaptation for similar cases. The proposed architecture extends the work of Ramos [2] to consider the decisions taken historically and their respective categorizations (with or without cognitive bias) and implement a data-oriented approach that automatically identifies the user's value and risk preferences, for new different and later decisions. The bias classification made by the ABI Tool is boolean and categorically assesses whether or not there is incurrence of bias, therefore database plays a fundamental role in recording all occurrences and providing inputs for the analysis of the entire ecosystem. The outputs of the architecture are the results of machine learning algorithms and the classification of bias during decision making. Other developments are analyzes and constructions based on these results.

Regarding the rectangles in blue represent the computational modules, gray documents represent input and output data that is later stored in the database (yellow cylinder). Balloons represent the theory or rationale behind the components to which they are related.

In reference to the architecture's modules, they are: Decision Monitor, ABI Tool, Decision Outcome Logger, Decision DB Designer, Dataset Generator for Decision DB, and Data Aware Cognitive Bias Impact Learner. The first three are related to real-time monitoring, classification of the decision as to its bias, and recording of this occurrence. The theoretical basis for the ABI Tool is the Prospect Theory, which provides the foundations for defining a bias. The Decision DB Designer encodes the ontology-based conceptual model into a relational database model so that data related to past decision scenarios can be accessed, stored, and transformed quickly and securely into computational parameters.

The Dataset generator for Decision DB and the Data Aware Cognitive Bias Impact Learner are the major contribution components of this work. Together they act in the data-driven part to extract patterns from the datasets about the behavior of the decision-maker. The Dataset Generator generates simulated data or collects data publicly available. The decision maker's interactions with this architecture take place through the monitor and the ABI tool, responsible for warning during the decision whether or not he is biased. The result of the user's choice can be stored later. The Cognitive Bias Impact Learner receives this data and applies machine learning algorithms to understand the features that contributed to biased decisions. This individual utility of the decision maker will be modeled to his perception of how he can achieve his goals.

At last, the documents in gray that represent inputs and products of system interactions are Decision scenario description, Decision Result, Bias detected, Decision Outcome, Intuitive Decision Ontology, and Gain Calculator. The first four are related to the process of describing the proposed scenario, the result of the decision, the result of identifying (or not) the cognitive bias, and what the decision produced in the scenario. All this information is stored in the database and is available for the system to query and for the data science model to use.

5. Preliminary Results

An example scenario was built using the Choice Prediction Competition 18 (CPC 18) database (Figure 4), a large source of decisions taken by Israeli university students on 30 different problems involving monetary values and probabilities of their occurrence [12]. CPC consists of an experiment with real decision data for a gamble, with the objective of inferring unprecedented decisions of individuals based on previous decisions and predicting the average aggregate rate of choice of each option in each game. Through these data, it would be possible to explore all decision quadrants of The Fourfold Pattern [8], but in the first phase of the research only the losses domain will be explored for a match with the ABI Tool bias classifier. The CPC was used as a framework for structuring a possible decision-making scenario, complemented by a set of data (Table 1) provided as benchmark for recording the decision-making results. From this, a dataset was built by adapting the CPC experiment to the data structure provided by the ontology [2].

Table 1: View from Decision Database adapted for CPC-18. Source: The authors

Colums	1	2	3	4	5	6	7	8	9	10	n
SubjID	60004	60004	60004	60004	60004	61026	61026	61026	61026	61036	...
Gender	F	F	F	F	F	M	M	M	M	F	...
Age	23	23	23	23	23	33	33	33	33	30	...
GameID	151	153	156	162	163	154	159	175	177	157	...
HighValue	27	39	-1	39	25	65	20	-2	42	33	...
pHighValue	0.8	0.4	1	0.6	1	0.2	0.95	0.8	0.4	0.5	...
LowValue	-37	6	-1	14	25	2	16	-25	-9	14	...
LotShape	R-skew	Symm	-	-	-	Symm	-	Symm	Symm	-	...
LotNum	7	5	1	1	1	5	1	9	5	1	...
Option	A	A	A	A	A	B	B	B	B	B	...
Amb	0	0	0	0	0	1	0	0	1	0	...
Corr	0	1	0	0	0	0	0	0	0	0	...
Order	2	27	20	30	26	23	2	21	15	15	...
Trial	1	1	1	1	1	1	1	1	1	1	...
Button	L	R	L	R	L	R	L	R	R	L	...
Choice	1	1	0	0	1	0	1	0	0	1	...
Payoff	-37	6	0	24	25	16	20	-4	41	33	...
Forgone	20	15	-1	39	12	67	14	-4	41	16	...
RT	10467	12906	12508	2910	8557	5172	8566	7055	9085	7615	...
Fb	0	0	0	0	0	0	0	0	0	0	...
block	1	1	1	1	1	1	1	1	1	1	...

This dataset identified which game choices were subject to risk-seeking biases by the students who participated in the CPC. Machine Learning was applied to this dataset, for automatic learning the recurring characteristics involved in the biased choices. To exemplify this step, the XGBoost algorithm [13] was specially applied. XGBoost follows an ensemble approach in which several simple models are trained to produce a more robust final model. The algorithm builds decision trees for each iteration, where the models are no longer trained independently but sequentially, based on adjusting the previously trained models [13]. From a total of 1500 choices in the dataset, the learned model correctly predicted 267 biased choices (TP = 267) and 760 unbiased choices (TN = 760), missed 469 biased choices (FN = 469) and incorrectly predicted 4 unbiased choices (FN = 4). This led to a model precision of 68% and recall of 18%. The preliminary result shows that the model was able to characterize unbiased choices better than biased ones. Further analysis will be performed with additional techniques, to better understand the most influential characteristics for biased choices.

6. Discussion and Next Steps

Despite their growing importance and impact on business decision-making, there are few applications of cognitive biases in the literature, and they generally only address the specific problem for which they were established, even though they track various types of cognitive biases. It is important to note that the greater the generalization and scope, the more difficult it becomes to detect many biases precisely. The proposed architecture establishes how all the steps involved (from the conception of a possible problem to be addressed to the inferences based on the data) can interact and complement each other, giving greater robustness to the analysis and directing the possible developments. Other possible applications are reinforcement learning techniques and inverse reinforcement, where it is possible for the model to learn the utility function present in its training sample, or even what actions are necessary to ensure that the decision maker's needs are met [14].

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