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Data stream solution for decision-making processes: a general and adaptive system for decision support

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ABSTRACT

With the rise of new data generation processes and availability rates, new challenges appear linked with the information and pattern extraction for decisional processes. In these contexts, decision support systems (DSS) need to incrementally integrate the data flows to provide readable, understandable and meaningful conclusions. This research presents a novel adaptive DSS that offers updated and explainable knowledge for decision makers, especially in uncertain decision scenarios. Also, this work explores applications of this technology in some social fields, aiming to analyse the potential contribution of machine learning, combined with adaptive decision systems, in society.

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KEYWORDS
Decision support system; DSS; data streams; adaptive; tool

Introduction

The context of decision-making in organisations has improved significantly with the rise of new technologies during the last decades. The use of DSS was extended thanks to the generalisation of data that could be stored and then used to lead the decision-making process (Gorry & Morton, 1971). A DSS is formed by several components such as a database, a model, a user interface and a decision-maker (Sprague & Watson, 1979). Historically, DSS focused on structured problems, approachable through classic mathematical models. However, over time, the focus has shifted towards semi-structured and unstructured problems, reflecting real-world situations where decisions often involve uncertainty and complexity.

Concurrently, the increase of the use of technology is allowing systems to generate an important amount of data that is gathered to be used to make decisions. Some of this data cannot be understood as a set of constant relations, but instead as a data stream with variable frequencies and patterns (Babcock et al., 2002). These data streams can be seen as continuous, time varying flow of data that could lead to inaccuracies in a traditional decision system (Mollá, Heavin, et al., 2022). To address this, there is a growing trend towards adaptive systems that can use this streaming data effectively for real-time decision-making. The improvement in the data generation and collection processes, allow new adaptive

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systems to be generated and run using this continuous data to lead decisions. This approach has become increasingly relevant in the management of data streams, where the phenomenon of concept drift – changes in data distribution over time – poses unique challenges.

Traditional batch models fall short in continuously changing data systems as they lack the rapid responsiveness needed for concept drift events. The adoption of new adaptive models leveraging these data streams introduces new opportunities in DSS design and application, particularly beneficial in environments of uncertainty and variability (Lu et al., 2020). Mollá, Heavin, et al. (2022) highlight instances where adaptive models enhance DSS, demonstrating their value in varied scenarios such as the COVID-19 pandemic, transportation crises, and fluctuating economic and political situations like post-Brexit EU, providing substantial advantages for decision-makers and public officials.

In this work, we propose a new experimentation on adaptive continuous systems using decision rules to represent the information modelled and provide it in a highly interpretable structure. Specifically, we present a decision tool implemented as a website solution that allows users to interact with the updated knowledge extracted from their data streams. The proposed system attempts to add value by providing an updated continuous solution that models data streams, representing the decision rules in a highly informative way and contributing to access relevant information that might be difficult to extract by a non-technical user after a machine learning process.

Moreover, the use of descriptive modelling methods is crucial for detecting and highlighting possible data biases. The use of readable structure such as the decision rules, guarantees the understanding of the recommended decisions or conclusions, allowing the decision-maker to detect unfairness or biases that might appear in data. This focus on transparency is especially pertinent in contexts like health care or social aid, as well retail or e-commerce.

This article is structured as follows: Section 2 presents the adaptive DSS, the problems that might arise within this context as well as some examples of scenarios in which this technology might be specially enriching. Section 3 is dedicated to the description of the adaptive tool. Section 4 presents the discussion of the presented solution, their added value to the proposed scenarios, as well as the main conclusions that could be derived from the research.

Adaptive decision support systems

Adaptive DSS (ADSS) most relevant theoretical and formal approaches were proposed in the 90s decade. Fazlollahi et al. (1997) propose an architecture of adaptive DSS from the perspective of the decision-maker. A little later, Chuang and Yadav (1998) proposed a comprehensive conceptual model of ADSS from a research methodology that unifies the existing approaches to date. From the 2000s onwards, the ADSS started to expand more generally, especially in the corporation and business context. There are some relevant examples such as the one of Papazoglou et al. (2000) especially oriented to the opportunities of integrating value chains. Also, we can find some relevant works such Krishen et al. (2011) analysing changing typical scenarios of e-commerce, or that of Osuszek and Stanek (2015) from the comprehensive perspective of BPM (business process management).

ADSS with learning capabilities emerged especially around the 2010s. From this period, some works combined ADSS with Machine learning capabilities (Piramuthu & Shaw, 2008). Also starting in the 2010s, the ADSS have a greater presence in other productive contexts. For example, in agronomy, Wijffels et al. (2011) propose a generic framework for automated support of complex land use planning and allocation. In a context dependent on changing climatic conditions, ADSS earns some importance in some agronomic contexts (Kašpar et al., 2018).

Recently, rulers and public managers began to put their interest in incorporating adaptive systems to the management of public service and care problems in favour of a well-being society, increasingly more aged. The work proposed by Davies et al. (2023) addresses, from a solid methodological approach, the adaptation of medical care for patients with dementia in hospitals based on their evolution. In other fields such as e-governance, adaptive systems deal with very dynamic situations derived from rapid social changes. Sundberg and Gidlund (2017) transfer the main concepts of decision theory to the field of e-governance while Melaku (2023) addresses the security problems inherent to this field. In the social field, it is common for data to change rapidly since it comes from highly uncertain scenarios. Therefore, the application of classical static models provides predictions whose accuracy degrades rapidly. In these cases, the incorporation of adaptive predictive models is offered as a very appropriate solution in the field of decision-making.

Definition of the adaptive DSS tool

Premises of the tool

To acquire the potential enrichment of adaptive systems to the DSS context, we design and implement a solution based on Incremental Decision Rules Algorithm (IDRA), an adaptive decision rule algorithm presented by Mollá, Rabasa, et al. (2022). IDRA prioritised explainable and concrete knowledge over time, to provide better accuracy levels and help understanding the conclusions or recommendations made by the ADSS. The main objectives of the tool are to integrate continuous intelligence in a DSS, providing updated and adaptive recommendations, as well as to assure readable and understandable knowledge that could prevent unfair automatised actions by using classification rules that make the chosen variables and the relationship between them explicit in the decision-making. While it does not guarantee fairness, it is a step towards accountability, as users can acknowledge which and how variables contribute to the outcome within a confidence level. The adaptive tool presented in this paper is a website solution developed in Bubble.io that, based on the interactions between the user (decision-maker) and the system, can generate updated understandable responses relying on a Python core and a database. This solution can use several types of data streams and, therefore, it can be applied to multiple scenarios. It is relevant to highlight that the decisional contexts in which we expect this tool to run are not so fast as commonly seen in the data stream analysis. Thus, the use of a highly informative and accurate engine that is slower than other methods yet quick enough for a decisional context is justified for an ADSS (Mollá, Heavin, et al., 2022).

Limitations of the work

The present work proposes the integration of an incremental solution (IDRA) in a decision-making tool in order to explore the application of new methods to ADSS. This work aims to discuss the uses, advantages and weaknesses of the mentioned approach but it is limited to a proof of concept. The database and algorithm logics underneath the adaptive system are mentioned but not described in detail due to the commercial interests of the company that co-financed the work (Registered in the US Copyright Office, registration number TXu 2-407-991).

Database

In data stream analysis, the database is not treated as a constant static number of instances. On the contrary, the data streams form a continuous flow of information, and this can be used by an ADSS to provide updated responses based on last data. The streams arriving to our system are temporarily stored in a database connected both to a learning module and to the web interface. The learning engine integrates the new data arriving providing an updated model that will interact with the decision-maker through the website.

The design of the relational database is based on the different table categories that define the components used by the system to model the learning process. In this sense, we can differentiate four categories of table: (1) those related with the data management, (2) those related with the analysis restrictions, (3) those related to the results generated and (4) those related to the user management. The tables associated with data management (1) compile and structure the data streams that arrive to the system in a way that could be quickly retrieved and integrated into the model. The tables related with the analysis restrictions (2), gather the parameters defined by the user for all the cases of study. For each analysis, the database gathers information such as the explicative variables, the objective value, the evaluation window size, etc. These tables compile the information needed by the learning module to generate the knowledge base, as well as to retrieve each analysis when an update is required. The tables related with the generated outcome (3), store the updated learning results derived from all launched analysis. These tables store the rule sets generated with the relevance metrics for each rule. Finally, the tables related with the user management (4) gather the user information, the permissions granted and the institution information. This information is used to guarantee the authorised access to the data. This database is designed to work as a link between the learning model and the user interface. Thus, after any action given in the model module or the web application, the partial results or gathered information are integrated in the database, allowing the other module to access.

Model

The learning model is the core module that provides the base of knowledge integrated in the ADSS. In this case, the selected model is IDRA presented by Mollá, Rabasa, et al. (2022). A high-level flowchart of the method is presented in Figure 1. Based on Machine Learning mechanisms for modelling (predict) categorical target variables (classification techniques), IDRA uses decision rules in order to provide the knowledge in a readable and explainable structure. Also, this methodology has proved to perform more accurately than

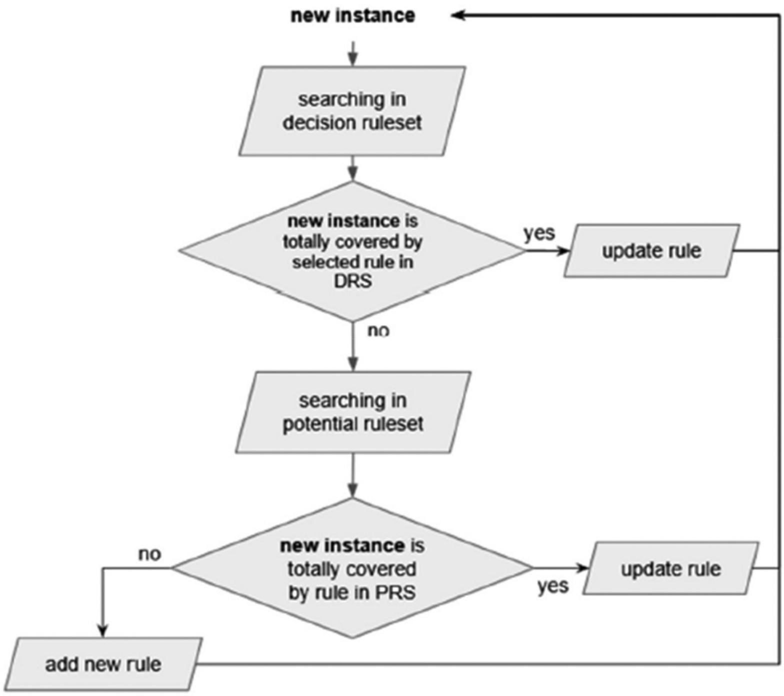

Figure 1. High level flowchart of IDRA (Mollá, Rabasa, et al., 2022).

the reference very-fast adaptive solution (Mollá, Rabasa, et al., 2022) in exchange for higher time rates. The reported times stayed at acceptable rates for decision-making, reporting significant benefits for this context. In addition, IDRA tends to build concrete decision rules to improve accuracy levels, as well as to help explain observed situations in detail, giving the opportunity to better understand specific conclusions or recommendations made by the ADSS or cases of study.

As mentioned previously, the presented tool relies on different modules that cover all the expected functionalities. The communication of the results of the IDRA and the web application in Bubble.io is made through the relational database. However, we need an event that launches the algorithm code when, for example, a new analysis is defined in the application (Figure 3), or new data arrives to the system (Figure 2). Thus, we rely on a Flask REST application in Python that manages the required endpoints. These endpoints deal with the appropriate actions depending on the event. In the illustrated examples, a first rule set needs to be built based on the analysis parametrised by the user (Figure 3) and the set of rules need to be updated after the arrival of new data (Figure 2). The endpoints manage the corresponding actions linked to each situation, generating a first base of knowledge when a new analysis is settled, or recovering and updating an existing one when the data stream provides new instances to the database.

User interface

The user interface was designed and implemented through a Bubble.io web application, a no-code development platform. The application is structured to facilitate data analysis

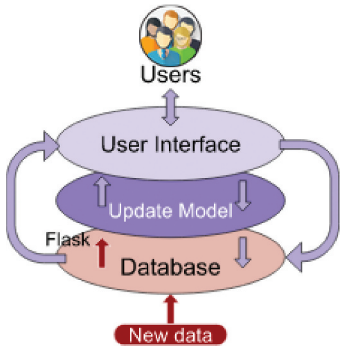

Figure 2. Communications and actions in the model module when new data arrives.

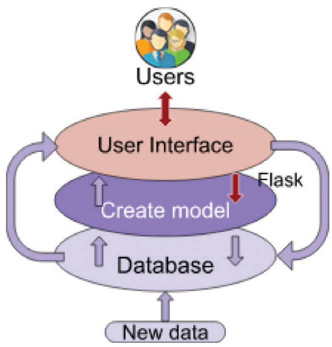

Figure 3. Communications and actions in the model module when a new analysis is parametrized.

and manipulation through a series of interactive dashboards and interfaces. Data is primarily handled through an external SQL plugin (API SQL Database Connector) and an internal Bubble database. This structure ensures seamless integration of new data, updating the model to interact effectively with users through the web interface. The application is divided into three main functions or modules: dashboard, analysis and datasets. The tool integration of dashboard functionality, dataset handling, and analysis features encompasses from data collection to decision-making. Annex I provides detail over the user interface and tool design, and it will be addressed along this section.

Dashboard. The primary interface of the application is the dashboard. It serves as a launchpad, displaying a real-time overview of the most recent analysis and datasets. It includes features for initiating new analysis and exploring more detailed views of the existing ones. When a user accesses the dashboard, a workflow fetches and displays relevant information through clickable elements.

Datasets. The two dataset screens serve as key components in data management. They list and provide detailed views of individual datasets, highlighting their characteristics and associated categories. The presentation of the datasets is organised through dynamic tables that show small samples of the contained data that the system is receiving for a data stream. When initiated, the dataset view screen launches an API call to the database with the selected data stream. The design of this interface reflects the adaptive nature of the tool, capable of handling and working with continuous data flows.

Analysis. The analysis screens are the core of the visual tool, designed to launch, visualise and edit analysis, aiming to provide insights to the decision-making process. In this sense, users can select descriptive and objective variables for their analysis and set up relevant analytical parameters, such as the evaluation window, the algorithm version and related criteria (see Annex I - Figure A1). It also dynamically fetches metrics relevant to each selected or created analysis such as rules applied (support) and classification outcomes (confidences for all classes). Users can also modify an existing analysis, which is relevant for dynamic data environments where parameter importance may change over time. The interface also focuses on filter selection and graphical representation of support and confidence metrics. This feature allows users to understand the classifications made by the model, reflecting the importance of explainability in modern DSS.

Decision-maker

The updated information provided by the adaptive system could be used as a base to guide the conclusions of decision makers. The visual response to study cases, allow the decision process to be led in an easy and affordable way for not technical profiles (see Annex I - Figure A2). Nonetheless, high-tech specialists could also profit from the knowledge modelled by checking the whole rule set (see Annex I - Figure A3).

Discussion & conclusions

The need to guarantee a transparent decision-making process, lead us to design more explainable and understandable models to be integrated in DSS. In this sense, the use of decision rules favours the readability of the generated bases of knowledge and allows users to comprehend the conclusions or recommendations made by the system.

The presented application can be used to analyse different data streams, and/or different aspects of the same data stream, maintaining the same result representation. The application allows to parametrise different study cases through the same interface. As an example, in the annex, Figures A1–A3 illustrate the definition of a use case shown in Table 1, the analysis configuration menu (Figure A1), an specific employer case

Table 1. Challenges and contributions to adaptive situations in different application fields.

Field	Adaptive challenge	Adaptive contribution
Healthcare	Real-time monitoring of levels in chronic or intensive care patients	Timely responses to treatment changes or medical interventions
Financial markets	Market fluctuations and economic trends	Risk management and updated advice
Retail and e-commerce	Changes in consumer behaviour and market trends	Dynamic pricing and inventory management
Environmental management	Drifts in climate patterns or pollution levels	Resource allocation and emergency responses
Social aid	Migratory emergencies or global pandemics	Resource allocation
Human resources management	In current work contexts, high turnover of professionals	Talent retention

classification (Figure A2), and the full classification rule systems to predict income based on the employee's profile (Figure A3) on changing circumstances.

The use of ADSS in uncertain or changing scenarios could lead to significant improvements in the accuracy of the suggested actions. The adaptation capability enriches a system since the decisions are made based on adjusted models that integrate concept drifts. The use of relevant adjusted knowledge is highly valuable for managemental processes, as well as for decisional systems (Kaklauskas, 2015).

Providing an adaptive logic to DSS enriches the decision-making process in many unexplored ways. Table 1 shows some of the possible challenges that could be faced by an ADSS in relevant contexts, and the contributions that could be made using this technology. In the field of healthcare, an ADSS can manage continuous patient data streams for real-time monitoring and adaptive treatment plans. Specifically, in managing chronic diseases or intensive care units, ADSS can quickly adjust to changing patient conditions, providing timely insights for medical interventions with relevant contributions. Within the financial markets, an ADSS can react to market fluctuations and evolving economic trends, where it can provide financial institutions with up-to-date advice on investments and risk management, responding quickly to market concept drifts. Also, for retail and e-commerce, an adaptive system can readjust to consumer behaviour changes and market trends, which includes dynamic pricing, inventory management, and personalised customer recommendations. In environment monitoring, ADSS can remodel after changes in climate patterns or pollution levels, assisting in making informed decisions about resource allocation and emergency responses, among other applications.

Thus, providing an incremental logic to a BI solution could report multiple benefits in the strategic plans of different sectors, considering the adaptive and dynamic nature of DSS, as highlighted above. This approach offers substantial advantages across various sectors. For companies, it enables a more nuanced control over risks associated with certain actions and decisions. For instance, a business can make informed decisions about when to disinvest in declining products or projects, thus avoiding potential financial losses. This is relevant in fast-paced market environments where the cost of inaction or delayed action can be substantial. Similarly, for public institutions and social organisations, the ability to monitor and analyse data flows with an incremental logic provides significant benefits. This capability is essential for resource allocation, especially in times of crises such as migratory emergencies due to wars or climate disasters, as well as global pandemics. By identifying and responding to evolving patterns in real-time, these organisations can optimise their responses and resource distribution, ensuring that they are addressing the most pressing needs effectively. Therefore, the proposed tool can enable organisations to not only react to current conditions but also anticipate and prepare for future changes, with transparency and explainability. This proactive approach in decision-making is invaluable in navigating the complexities and uncertainties inherent in multiple sectors, from business to public services.

Disclosure statement

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Ana Bossler is a data scientist that combines academic and industrial experience. She is also a Master student in Computational Statistics and Data Science at Miguel Hernández University of Elche in Spain. She holds an interdisciplinary profile with a degree in Law and Economics, as well as multiple experiences in business field and data analytics.

Alejandro Rabasa is a PhD and specialist in Data Science. He has experience in multiple technology transfer projects for decision support systems in decision-making environments in the public sphere (Hospitals, Tourism CV, Security, Social Services, etc.). Specifically, in the area of decision-making in social and socio-health policies, he has led the vulnerability segmentation project for the Red Cross in the Valencian Community and five annual Agreements with the Valencia Regional Government to study the public system of social centres. He is also part of the team of experts "Data Sciences in the fight against SARS-CoV-2" that has been conducting continuous analysis and reports of the pandemic for the Presidency of the Generalitat Valenciana, since March 2020. This group has been in charge of the analysis of citizen behaviour and emotional and economic impact of confinement.

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Annex I: User interface and tool screens

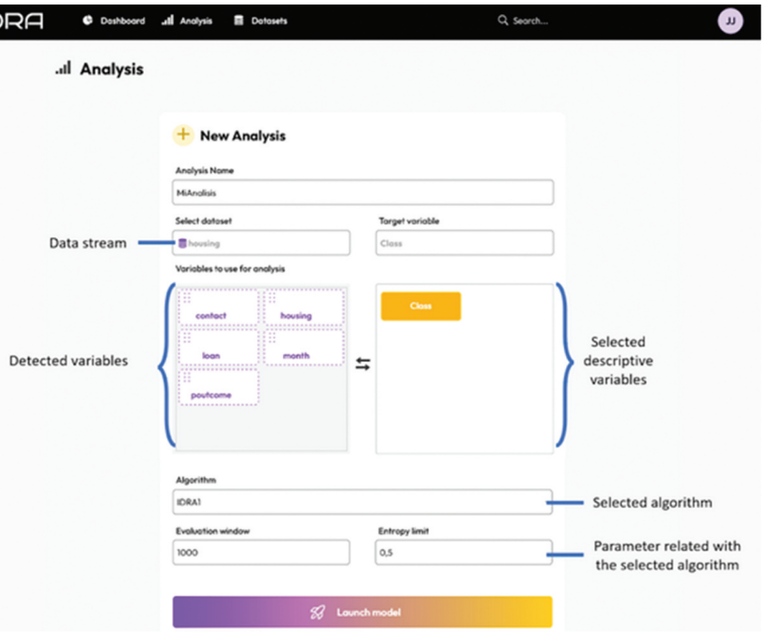

Figure A1. Definition of a new analysis in the presented tool.

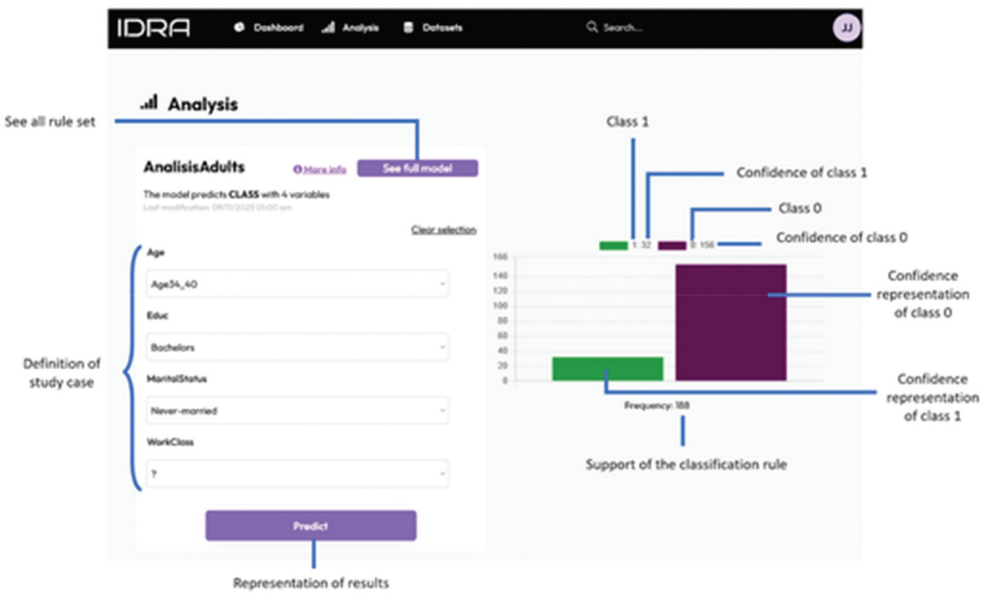

Figure A2. Study case screen.

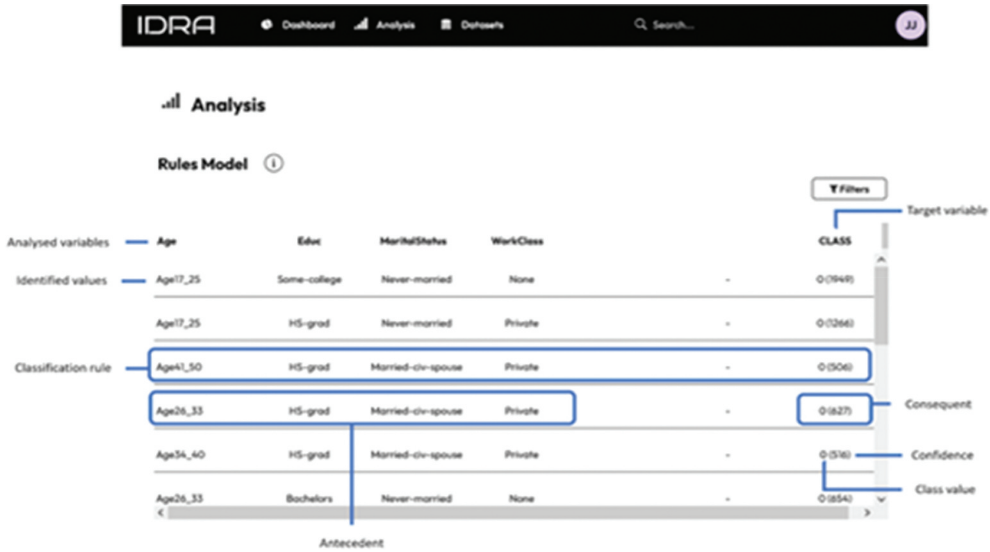

Figure A3. Full model screen.