UTILIZING ALGORITHMS FOR DECISION MINING DISCOVERY

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Abstract Organizations are executing operational decisions in fast changing environments, which increases the necessity for managing these decisions adequately. Information systems store information about such decisions in decision- and event logs that could be used for analyzing decisions. This study aims to find relevant algorithms that could be used to mine decisions from such decision- and event logs, which is called decision mining. By conducting a literature review, together with interviews conducted with experts with a scientific background as well as participants with a commercial background, relevant classifier algorithms and requirements for mining decisions are identified and mapped to find algorithms that could be used for the discovery of decisions. Five of the twelve algorithms identified have a lot of potential to use for decision mining, with small adaptations, while six out of the twelve do have potential but the required adaptation would demand too many alterations to their core design. One of the twelve was not suitable for the discovery of decisions.

Keywords: decision management, decision mining, algorithms, knowledge discovery.

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.4.2022.21
ISBN 978-961-286-616-7

1 Introduction

Organizations are executing decisions in fast changing, sometimes unexpected, environments (Smirnov et al., 2009). This increases the necessity to manage these operational, high-volume, decisions, which is referred to as decision management. Decision management consists of a set of tools and techniques that allows businesses to create, validate, execute, monitor and improve decisions(Flexrule, 2021; Smit & Zoet, 2018; Von Halle & Goldberg, 2010; Zoet, 2014) and aims to improve the intelligence of business operations by developing and improving fast, consistent and precise decisions. In the past decade, decisions and underlying business logic are increasingly seen and managed separately from other aspects of an information system (Smit & Zoet, 2018; Zoet, 2014). This is in line with the separation of concerns that argues that componentization reduces complexity and enhances comprehensibility (Parnas, 1972). Separation of concerns has become a best practice in information technology architecture over the years (van der Aalst & Basten, 1997; Versendaal, 1991; Weske, 2012).

Due to the separation of concerns, many information systems store relevant process or decision data separately in some structured way (van der Aalst et al., 2012; Von Halle, 2001). For example, Business Process Management Systems register the start and completion of events, and ERP systems event log all transactions and mutations. Van der Aalst (2005) used these outputs, which are called event logs, for process mining. Process mining uses machine learning and data mining techniques to discover, conform and enhance business processes within organizations (van der Aalst & Weijters, 2005). Process mining aims to make unexpressed knowledge explicit and to facilitate a better understanding of the process (van der Aalst et al., 2012). One of the techniques used within process mining is Decision Point analysis. This technique aims to "detect data dependencies that affect the routing of a case" (Rozinat & Aalst, 2006). Decision Point analysis mines 'sequencing patterns' from a process viewpoint but leaves out the derivation patterns within decisions as it is focused on a single decision point. Therefore we consider such analysis techniques to operate from a process focused viewpoint (De Smedt, Vanden Broucke, et al., 2017; Leewis et al., 2020). However, in practice, decisions are often dependent on each other's output, which makes a Decision Point analysis less suitable for analyzing how decisions are related to each other and their implementation in the underlying business logic.

Recent studies show the need for the decision focused viewpoint (De Smedt, Vanden Broucke, et al., 2017; Leewis et al., 2020). Decision mining is a rather novel technique, which is defined as: "*the method of extracting and analyzing decision logs with the aim to extract information from such decision logs for the creation of business rules, to check compliance to business rules and regulations, and to present performance information*" (Leewis et al., 2020). Previous studies indicate that the decision focused viewpoint is necessary to advance in decision mining (De Smedt, Vanden Broucke, et al., 2017; Leewis et al., 2020). While various techniques are presented for decision mining from a process viewpoint (De Leoni & van der Aalst, 2013; Mannhardt et al., 2016; Rozinat & Aalst, 2006), only a few techniques are proposed for decision mining from a decision viewpoint. De Smedt et al., (2017) and Leewis et al., (2020) proposed examples of four algorithms for the discovery of decisions, all of which are classification algorithms as these algorithms are based on pattern recognition (Duda et al., 2001). Therefore, in this study, we focus on classification algorithms, with a focus on pattern recognition, only. Further, we try to identify requirements for decision mining techniques and map these to available algorithms found in the body of knowledge. This leads to the following research question we aim to answer in this paper: *Which classification algorithms are applicable for decision mining to discover decisions from structured data*? We do this by identifying requirements for the selection of appropriate classification algorithms through six semi-structured expert interviews. Based on the results, the body of knowledge is analyzed on the applicability of available algorithms resulting in the presentation of an overview of applicable algorithms for decision mining.

The remainder of the paper is structured as follows: The next section consists of a background and related works on decision mining and its ongoing evolution. This is followed by the research method. Next, the data collection & analysis is discussed. Then, the results are presented. Lastly, the conclusion and discussion are presented, together with future research directions.

2 Background & Related Work

Decision management manages the decisions and underlying decision logic for an organization. A decision is defined as: "The act of determining an output value from a number of input values, using decision logic defining how the output is determined from the inputs." Furthermore, decision logic is defined as: "a collection of business rules, business decision tables, or executable analytic models to make individual business decisions". There are multiple ways for an organization to discover decisions and the underlying decision logic (Etikala & Vanthienen, 2021). The most common way is to acquire knowledge from domain experts and manually model the gained information to decisions and the underlying decision logic. However, many other sources exist to gather decisions and the underlying business logic such as event logs, text documents, and decision logs (Etikala & Vanthienen, 2021). These sources can be used to automatically discover the decisions and underlying decision logic, which minimizes the cost and time spent on manual modeling with the help of domain experts. The automatic retrieval of decisions and decision logic from event logs, decision logs, or case data is referred to as decision mining.

Decision mining aims to extract and analyze decision logs to discover, check the conformance of, and improve decisions and decision logic (Leewis et al., 2020). De Smedt et al. (2017) created a decision mining quadrant with four types of decision mining identified in literature. The first two types are the Data-First approach and Control flow first approach. They both focus on data attributes of single instances, or the sequential parts of the instances (De Smedt, Vanden Broucke, et al., 2017), see for example the work of van der Aa (2016) and Petrusel (2010). The output of these approaches is usually represented in Petri net models and focuses on sequences. The third type of decision mining is decision-annotated process mining. In this type, control flow data is used to determine the structure of the process as a first step. The second step is to use the instance attributes to define where data had impact on the workflow. This approach uses fixed decision points in an event log instead of looking for decision points throughout the model. The fourth and last type of decision mining is Decision-aware control flow, which focuses on the decision itself first, instead of the process. De Smedt et al (2017) argues that there is a gap in knowledge on the fourth type, because the focus on mining decisions is usually fixed on using event log data only.

The mining of decisions is done by using algorithms. An algorithm is a set of steps that are followed in order to solve a (mathematical) problem or to complete a computer process (Merriam-Webster, 2021). Within data mining, classification algorithms are used to place data into preset categories, which is a form of pattern recognition (Duda et al., 2001). There are different types of classification algorithms, e.g., Decision trees, K-Nearest Neighbor, Random Forest, Support Vector

Machines, Bayesian Classifier, and Artificial Neural Networks (Aggarwal & Zhai, 2012; Wu et al., 2008). All algorithms have several subtypes and specific implementations of algorithms are available. De Smedt et al (2017) already proposed five classification algorithms for decision mining with a decision focused viewpoint, namely: 1) decision trees, 2) neural networks, 3) support vector machines, 4) random forest, and 5) time series analysis. However, no further explanation is provided about the suitability of these algorithms. Therefore, we argue that the body of knowledge would benefit from further exploration about the suitability of these classification algorithms for decision mining with a decision focused viewpoint.

To be able to conduct proper algorithm selection for a given problem and its context we need to use appropriate requirements. The concept of requirements is very broad, and many types exist with each their distinct differences, looking at the software engineering domain on itself, e.g., functional requirements, non-functional requirements, and constraints (Sommerville & Sawyer, 1997). Adding to this, requirements and their elicitation, formulation and management has been researched in detail in the past decades (Cziharz, 2015; Lucassen et al., 2016; Zowghi & Coulin, 2005). To narrow the selection in favor of feasibility of this study, we choose to identify functional requirements and non-functional requirements with regards to the algorithm selection in this study. Therefore, both types are addressed in the interview protocol used in the empirical phase of this study. To ensure the results in this study are properly interpreted we provide a definition of both requirement types. A functional requirement is defined as "a function that a system (...) must be able to perform" (IEEE, 1990). A non-functional requirement is defined as "describe the nonbehavioral aspects of a system, capturing the properties and constraints under which a system must operate" (Antón, 1997). We utilize these requirement types due to two reasons. The first reason is that both requirement types, as well as their combination, represent the concept of quality very well (Chung & do Prado Leite, 2009; Glinz, 2007). The second reason is that both types are very recognizable to IS/IT practitioners and are in use for over two decades as well as being researched extensively in the past (Glinz, 2007).

3 Research Method

The goal of this study is to explore currently available classification algorithms and analyze their usefulness with regards to decision mining. To select an appropriate research method, the maturity of the research field must be taken into account. Based on the work of Edmonson and McManus (2007), research field maturity can be defined along a continuum of nascent, intermediate, and mature archetypes. Given the fact that the separation of the 'decision management' concern is considered and researched only in the last few years compared to other concerns such as processes, user interfaces, and databases, one could say that the research field maturity of decision management is nascent. This is further acknowledged in other recent studies focusing on decision mining (De Smedt, vanden Broucke, et al., 2017; Leewis et al., 2020). Therefore, our research method should focus on establishing new constructs and underlying relationships by using qualitative research methods that are more appropriate for gathering data via open-ended inquiry (Edmondson & Mcmanus, 2007).

To answer the research question, the study is divided into three research phases. The first phase comprises the identification of classification type algorithms that can mine decisions from structured data, in the body of knowledge through a literature search. The second phase comprises the empirical part of this study in which six experts from the field are interviewed using a semi-structured approach in order to establish which classification algorithms are usable for decision mining. We use interviews as a method and not literature because, as addressed earlier in this paper, the current body of knowledge almost solely focuses on decision mining from a process perspective (i.e., decision point analysis). The third phase comprises the evaluation of the identified classification algorithms against the identified requirements, to establish which classification algorithms are useful for decision mining.

4 Data Collection & Analysis

The data collection for this study is separated into three phases: 1) the identification of the classification algorithms, 2) the semi-structured interviews for requirements gathering, and 3) the evaluation of the classification algorithms against the requirements.

4.1 Phase one: identification of classification algorithms

To identify classification algorithms we conducted a scoping review (Paré et al., 2015). To ground our scoping review we address the search strategy and steps to extract relevant algorithms. The first step comprised the query identification. To identify relevant queries we looked at the scope and goal of this study, which in this case is identifying classification algorithms that could extract decisions. Based on this goal the following search term was used using google scholar: " 'classification algorithm' AND 'decision OR rules' AND 'data mining' ". We used Google scholar as the main search database due to the fact that it has a higher coverage compared to other search engines (Amara & Landry, 2012; Franceschet, 2010; Harzing & Alakangas, 2016; Wildgaard, 2015). The exclusion criteria used for the scoping review were: 1) the source must be written in English to be included, 2) the source must be available via the internet to be included, and 3) the algorithm has to have an output regarding a decision, e.g., a rule.

4.2 Phase two: semi-structured interviews for requirements gathering

Data collection for this phase was conducted between September 2019 and January 2022. We interviewed six experts on algorithms and/or decision mining. Four have an international scientific background and two have an commercial background. Of the four scientists, three are full professors and one is an assistant professor at a university. The two participants from the commercial sector have the following roles: 1) assistant manager at a data & analytics department and 2) managing data scientist. During the interviews, an interview protocol was used to help understand what the requirements are. The interview protocol consisted of the following questions: 1) What is decision mining?, 2) Which algorithms for decision discovery do you know and which do you already apply?, 3) What are the main considerations to take into account when developing algorithms for the discovery of decisions?, and 4) What are the most important requirements for such an algorithm?

All interviews were fully transcribed. Thematic coding was used to analyze the semi-structured interview transcriptions. A coding scheme was created before the analysis. The following attributes were coded: 1) Functional requirements, 2) Non-functional requirements, 3) Rationale, and 4) Algorithms.

4.3 Phase three: evaluation of classification algorithms against requirements

For the evaluation phase, two rounds were organized and multiple research team members independently evaluated the results of the previous two phases, in order to improve the validity and reliability of the results of phase three. In the first round, three research team members independently evaluated the identified algorithms against the identified requirements. They evaluated the core mechanisms of the algorithms and not the potential the algorithm has with modifications. In the second round, one of the members of the first round together with a research team member that has not participated in the first round needed to reach consensus whether a requirement has been met by the identified algorithm, based on the results of the first evaluation round. We do this to decrease the chance of interpretation error or bias occurring that could have affected the results, thus establishing high inter-rater reliability (Armstrong et al., 1997).

5 Results

The scoping review and interviews resulted in twelve relevant classifier algorithms that could potentially be used for decision mining. The identified algorithms are described in table 1.

Table 1: Found classifier algorithms

C4.5	The C4.5 algorithm is an improvement of ID3 algorithm developed by Quilan Ross. It can handle attributes with different costs, can handle training data with missing attribute values and can both handle continuous and discrete attributes (Salzberg, 1994).
CART	CART is an abbreviation for classification and regression trees and was introduced in 1984 by Breiman. It can build both classifications as well as regression trees. It is based on the same algorithm as C4.5, but it is unique due to the fact that it also uses regression analysis (Kumar, 2011).
J48	J48 is a java implementation of the C4.5 algorithm and is a classification algorithm that generates decision trees based on rules (Franco et al., 2019). The J48 algorithm has additional features compared to C4.5, including decision tree pruning derivation and the derivation of rules.

Artificial Neural Network	Neural networks provide models of data relationships through interconnected neurons that accept inputs, apply weighting, and feed the output to another neuron. It is an iterative process where different 'layers' of neurons are passed to deliver the desired outcome. A neural network can model data that has nonlinear relationships between variables and it can also handle interactions between variables (Wang, 1994).
Naïve Bayes classifier	A naive bayes classifier assumes that a particular feature is independent of any other feature. It does not take into account any possible correlations between other features and thus does say that each feature contributes independently to the probability of an outcome (Domingos & Pazzani, 1997).
K-means algorithm	K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data. The goal of this algorithm is to find groups (clusters) in the data. Data points are clustered based on feature similarity (Krishna & Narasimha Murty, 1999).
Apriori algorithm	Apriori is the first algorithm that was used for frequent itemset mining. It is used to find frequent association rules from datasets (Agrawal & Srikant, 1994; Wu et al., 2008).
Trace clustering	the event log is split into homogeneous subsets and for each subset a process model is created (Song et al., 2009).
Random Forest	A random forest constructs multiple decision trees and the output of a random forest is the class selected by most trees (Tin Kam Ho, 1995). They are mostly used for predictions as their accuracy is generally higher than decision trees.
Fuzzy decision tree miner	A fuzzy decision tree miner deals with uncertainty by permitting a gradual assessment of the membership of elements in relation to a set (Rokach & Maimon, 2007). This means that it can distinguish different values from an attribute. For example, the time of day can have the values morning, evening and night.
Adaboost	AdaBoost is an ensemble learning method that was initially created to increase the efficiency of binary classifiers. AdaBoost uses an iterative approach to learn from the mistakes of weak classifiers, and turn them into strong ones (Schapire, 2013).
Support Vector Machines	Support Vector Machines are supervised learning models that analyze data for classification and regression analysis (Farhat, 1992).

The interviews were coded using the coding scheme presented earlier, which resulted in seven requirements for decision mining discovery. Six of the requirements are functional requirements and one is non-functional, see table 2.

Table 2: Requirements for decision mining

ID	Requirement	Type	Example coding
1	An algorithm must design rules from an event- or decision log	FR	"That's one form and then there are forms where the two come together a bit more where from a data log you not only solve, let's say one classification problem, but also try to include the hierarchy of decision"
2	An algorithm must extract one or more decisions from an event- or decision log	FR	"Not just a classification with some variables and then one set of outcomes, but a full decision structure with the top decision and some sub-decisions with information items. Also the rules must be included such that a whole DMN model can be generated."
3	The algorithm must use structured data	FR	"Because nobody writes anything structured on there. That's just documents, all very difficult..."
4	An algorithm must find a derivation pattern to create a decision model	FR	"So looking purely at the data and trying to fully derive that model."
5	An algorithm must find multiple decisions in the dataset	FR	"Often, if you use a larger event log, you may have trouble to find multiple rules in the dataset ..."
6	The output of an algorithm must be explainable and comprehensible by Subject Matter Experts	NFR	"When it comes to properly understanding why a business rule is a business rule, then you have a very different kind of use of an algorithm. Then, transparency is very important,"
7	A 'black box' algorithm must have a comprehensible decision visualization (e.g., Decision Model and Notation)	FR	"... that those algorithms have is that they are usually black boxes, [...]. If you take a neural network, and you cannot really understand which rules are made for the output."

The algorithms, with the explanation and the requirements, were mapped by three experts, see table 3. Each requirement is mapped to an algorithm with one of the following codes. "Y" fulfilled the requirement completely, "N" does not fulfill the requirement, "P" does fulfill the requirement in part. "P*", does partly fulfill the requirement but could be easily adapted to fulfill it completely, and NA if the requirement does not apply to the algorithm, e.g., a transparent algorithm is never a black box.

Table 3: Mapping of algorithms against requirements

Algorithm / Requirement ID	1	2	3	4	5	6	7
Fuzzy decision tree miner	**Y**	**Y**	**Y**	**P***	**Y**	**Y**	**NA**
C4.5	**Y**	**Y**	**Y**	**P***	**Y**	**Y**	**NA**
CART	**Y**	**Y**	**Y**	**P***	**Y**	**Y**	**NA**
J48	**Y**	**Y**	**Y**	**P***	**Y**	**Y**	**NA**
Apriori algorithm	**Y**	**Y**	**Y**	**P***	**Y**	**Y**	**NA**
Random Forest	**N**	**Y**	**Y**	**P***	**N**	**Y**	**NA**
Adaboost	**N**	**Y**	**Y**	**P***	**N**	**Y**	**NA**
Naive Bayes classifier	**Y**	**Y**	**Y**	**P***	**Y**	**N**	**NA**
k-means algorithm	**N**	**Y**	**Y**	**P***	**N**	**N**	**NA**
Artificial Neural Network	**N**	**Y**	**N**	**P***	**Y**	**N**	**N**
Support Vector Machine	**N**	**Y**	**Y**	**P***	**N**	**N**	**N**
Trace clustering	**N**	**N**	**Y**	**N**	**N**	**Y**	**NA**

6 Conclusion

The goal of this research was to answer the following research question: *Which classification algorithms are applicable for decision mining to discover decisions from structured data*? We collected relevant algorithms from a literature review and conducted interviews to find functional and non-functional requirements. The algorithms and requirements were mapped by experts. This research shows that all found classifier algorithms are suitable. However, none of them are directly applicable to be used for the discovery of decisions for decision mining. Five of the twelve algorithms have a lot of potential due to the fact that only one part has to be adapted. The part that has to be adapted is the discovery of derivation patterns between decisions. The five algorithms are C4.5, CART, J48, Fuzzy decision miner, and apriori algorithm. These algorithms can mine indivudal decisions, but cannot find the relations between decisions. C4.5, CART, and J48 show the same answers for the requirements. This is explainable as they are all based on the ID3 algorithm. Some algorithms show potential, but a lot of work has to be done. For example, the Random Forest algorithm, as this algorithm has to change its core mechanics to be able to output rules. The advantage of a random forest is using multiple decision trees for predicting an outcome, which could not be used for decision mining as the main focus for decision mining discovery is extracting rules from event- and decision logs. The only algorithm that has no potential is trace clustering. Trace clustering is based on finding sequences, while decisions primarily are focused on derivation patterns.

7 Discussion & Future Work

In this study, we identified twelve classifier algorithms that could be used for discovering decisions. However, like every study, this study has limitations that should be discussed.

The first limitation is that we solely included publicly available algorithms, which limits the selection in a way that algorithms from the commercial domain are not included. These algorithms are often integrated within commercial software or when available separately, not entirely documented to be analyzed like required in this study. Although, to our best knowledge, we think that we included a selection of algorithms that are well known and documented. Of course, it could be the case that potentially relevant (commercial) algorithms for decision mining are not included and our overview is not generalizable. Future research could therefore take into account how suitable algorithms from the commercial domain rank up in terms of suitability for decision mining against the selection of algorithms analyzed and discussed in this study.

The second limitation concerns the focus of the study towards algorithms that support the 'discovery' of decisions. Decision mining also comprises the 'conformance' and 'improvement' of decisions, which are not included in this study. This is because the goal of 'conformance' (checking discrepancies between the decision log and the decision model) and 'improvement' (extending or improving the decision model based on the decision logs) of decisions is different than that of 'discovery' of decisions, thus classification type algorithms are not suitable.

Additionally, only data and process mining algorithms were included in this study, which is in line with earlier research on the relevancy of such algorithms for decision mining (de Jong et al., 2021). Future research should focus on similar explorations such as done in this study for the 'conformance' and 'improvement' of decisions.

The third limitation entails the research methods used in this study. Although we used a rigorous approach to identify and select algorithms in the first phase, it could be the case that newer and less known classification algorithms were unintentionally left out during the selection. Concerning the second phase one could argue that a limited selection of experts was utilized to derive a set of requirements for the selection of appropriate algorithms as well as that the abstraction of the requirements could be set-up differently. Currently, not many decision-mining researchers and experts could be identified, which is in line with the low maturity of the research field of decision mining. Additionally, the outcomes of the semi-structured interviews are in line with the body of knowledge on decision mining. For the third phase we used a research team to determine the scores for each requirement, until consensus was reached, which mitigates personal bias of individual research team members. Future research should focus on including more participants for both the second and third phase so that the generalizability of the results can be increased.

Acknowledgements

We would like to thank Gerrit van de Bunt for helping with preparing and executing the literature review and for constructing the interview protocol. We would also like to thank the participants of the interviews. We also would like to thank Sam Leewis and John van Meerten for participating in the mapping of the algorithms.

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