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Prescriptive analytics: Literature review and research challenges

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ABSTRACT

Business analytics aims to enable organizations to make quicker, better, and more intelligent decisions with the aim to create business value. To date, the major focus in the academic and industrial realms is on descriptive and predictive analytics. Nevertheless, prescriptive analytics, which seeks to find the best course of action for the future, has been increasingly gathering the research interest. Prescriptive analytics is often considered as the next step towards increasing data analytics maturity and leading to optimized decision making ahead of time for business performance improvement. This paper investigates the existing literature pertaining to prescriptive analytics and prominent methods for its implementation, provides clarity on the research field of prescriptive analytics, synthesizes the literature review in order to identify the existing research challenges, and outlines directions for future research.

1. Introduction

Business analytics refers to the extensive use of data, acquired by diverse sources, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions to proper stakeholders (Davenport & Harris, 2007; Soltanpoor & Sellis, 2016). To do this, business analytics utilizes methods from the data science, operational research, machine learning and information systems fields (Mortenson, Doherty, & Robinson, 2015). In this sense, business analytics deal not only with descriptive models but also with models capable of providing meaningful insights and supporting decisions about business performance. To this end, business analytics has evolved beyond a simple raw data analysis on large datasets with the aim to provide organizations a competitive advantage (Mikalef, Pappas, Krogstie, & Giannakos, 2018; Vidgen, Shaw, & Grant, 2017).

Business analytics is categorized to three main stages characterized by different levels of difficulty, value, and intelligence (Akerkar, 2013; Krumeich, Werth, & Loos, 2016; Šikšnys & Pedersen, 2016): (i) descriptive analytics, answering the questions "What has happened?", "Why did it happen?", but also "What is happening now?" (mainly in a streaming context); (ii) predictive analytics, answering the questions "What will happen?" and "Why will it happen?" in the future; (iii) prescriptive analytics, answering the questions "What should I do?" and "Why should I do it?".

Currently, the vast majority of business analytics efforts are spent on descriptive analytics and predictive analytics with typical methodologies including data mining, machine learning, artificial intelligence and simulation (den Hertog & Postek, 2016; Habeeb et al., 2018; Larose & Larose, 2015). Note that there is an extension to descriptive analytics named "diagnostic analytics" which is related to the question "Why did it happen?" (Soltanpoor & Sellis, 2016). It helps organizations grasp the reasons of the events that happened in the past and understand relationships among different kinds of data (Soltanpoor & Sellis, 2016). However, similarly to other research works (Krumeich et al., 2016; Šikšnys & Pedersen, 2016), we consider it as part of descriptive analytics. The reason for this is to ensure consistency among the three stages of analytics so that each one answers the questions "What?" and "Why?". As far as descriptive analytics is concerned, there is a distinction between the past ("What has happened?") and the present ("What is happening now?").

Compared to descriptive and predictive, prescriptive analytics is still less mature (Gartner, 2017). Recently, however, prescriptive analytics has been increasingly gathering research interest (Larson & Chang, 2016). It has been considered as the next step towards increasing data analytics maturity and leading to optimized decision making, ahead of time, for business performance improvement (den Hertog & Postek, 2016; Gartner, 2017). New Information and Communication Technologies (ICT) such as the Internet of Things (IoT),

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real-time streaming and sensor-driven business operations have bolstered prescriptive analytics and have provided businesses with accurate prescriptions facilitating reliable and effective decision making. ICT advancements are also challenging the operational research community toward the development of methods and algorithms that can take advancement of available technologies and work in synergy with prescriptive analytics, helping business know which solution is best suited for a given business problem.

Although, there are several literature review papers about descriptive (Batrinca & Treleaven, 2015; Duan & Xiong, 2015; Sun, Wu, Liang, & Liu, 2013; Tsai, Lai, Chao, & Vasilakos, 2015) and predictive analytics (Lu et al., 2017; Mishra & Silakari, 2012), to the best of our knowledge this paper is the first that targets a systematic literature review on prescriptive analytics. The objectives of our work are: (i) to investigate the existing literature regarding prescriptive analytics and prominent methods for its implementation; (ii) to provide clarity on the research field of prescriptive analytics; (iii) to synthesize the literature review in order to identify the existing research challenges; (iv) to outline directions for future research.

The rest of the paper is organized as follows: Section 2 provides a synthesis of background related to business analytics with a focus on prescriptive analytics. Section 3 presents the methodology that we followed for the literature review, while Section 4 describes the analysis of the reviewed papers. Section 5 outlines directions for future research work, while Section 6 concludes the paper.

2. Towards prescriptive analytics

Prescriptive analytics, which is the focus of the current literature review, is the most sophisticated type of business analytics and can bring the greatest intelligence and value to businesses (Šikšnys & Pedersen, 2016). It aims at suggesting (prescribing) the best decision options in order to take advantage of the predicted future utilizing large amounts of data (Šikšnys & Pedersen, 2016). To do this, it incorporates the predictive analytics output and utilizes artificial intelligence, optimization algorithms and expert systems in a probabilistic context in order to provide adaptive, automated, constrained, time-dependent and optimal decisions (Basu, 2013; Engel, Etzion, & Feldman, 2012; Gartner, 2017).

Prescriptive analytics has two levels of human intervention: decision support, e.g. providing recommendations; decision automation, e.g. implementing the prescribed action (Gartner, 2017). The effectiveness of the prescriptions depends on how well these models incorporate a combination of structured and unstructured data, represent the domain under study and capture impacts of decisions being analyzed (Basu, 2013; Šikšnys & Pedersen, 2016).

The business value of the three stages of business analytics with respect to time is depicted in Fig. 1. Beginning from the left side, descriptive analytics aims to determine what is happening now by gathering and analyzing parameters related to the root causes of the event to be eliminated or mitigated. Descriptive analytics is able to detect patterns that indicate a potential problem or a future opportunity for the business. On this basis, predictive analytics is able to predict whether an event will happen, when it is about to happen as well as the reason why it will happen. As shown in Fig. 1, predictive analytics has proved to contribute significantly to the business value. However, this is closely related to the decisions that are taken and the actions that are implemented. In case of human decisions, it is very much depending on their knowledge and experience.

Full exploitation of predictive analytics can be achieved in conjunction with prescriptive analytics for optimized decision making ahead of time. However, even in this case, it is not possible to achieve the maximum potential of predictive analytics since there is a time interval until the decision. Therefore, there is an inevitably lost business value between the event prediction and the proactive decision. The time scale of this interval may vary depending on the computational environment, e.g., real-time vs. offline, and the application domain. In any case, the minimization of this interval is of outmost importance.

As shown in Fig. 1, prescriptive analytics generate proactive decisions on the basis of the predictive analytics outcomes. Between the decision and the implementation of the action, there is a time interval for the preparation of the action. Moreover, it should be noted that an action may be better to be implemented at a specific time before the predicted event occurrence when the expected utility/ loss is optimized. When the event actually occurs, descriptive analytics is applied in order to derive insights about what happened and why it happened. In this case, descriptive analytics may be applied in a different timescale. In this sense, it may deal with near real-time reactive actions or with more long-term actions. Therefore, a timely detection of the current state of a business and a timely prediction of emerging events are crucial in terms of potential loss of business value.

3. Literature review methodology

In this Section, we outline the methodology of the literature review which is based on Tranfield, Denyer, and Smart (2003). This methodology has been widely used in literature reviews for big data analytics, operational research and management science (Barbosa, Vicente, Ladeira, & Oliveira, 2018; Howick & Ackermann, 2011; Nguyen, Li, Spiegler, Ieromonachou, & Lin, 2018; Seifert, Seifert, & Protopappa-Sieke, 2013), while similar methodologies have been followed in other domains (Duan, Edwards, & Dwivedi, 2019; Ismagilova, Hughes, Dwivedi, & Raman, 2019; Koivisto & Hamari, 2019; Senyo, Liu, & Effah, 2019; Tamilmani, Rana, Prakasam, & Dwivedi, 2019).

We searched the literature using the query term "prescriptive analytics". Although the query was quite generic, the limited amount of research works on this field made it sufficient for our literature review. We searched in the following scientific databases: ACM, ArXiv, Emerald, IEEE, ScienceDirect and SpringerLink. We limited our search space to include only journals, books and conferences publications. We exclude any grey literature like white papers and blog posts because their quality may vary and can affect the validity of our results.

More specifically, we follow the procedure described below:

- *We select the papers* to be reviewed according to the criteria of the literature review methodology (Section 3).

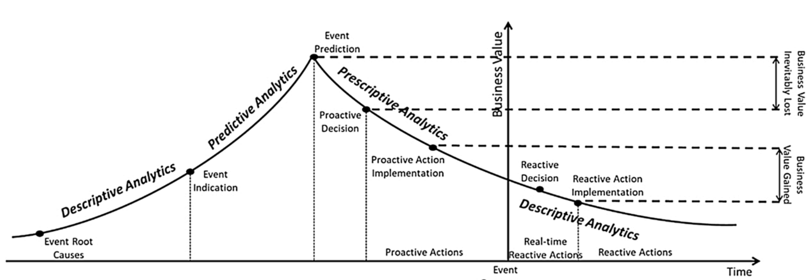

Fig. 1. The business value of analytics with respect to time (Source: Adapted from (Krumeich et al., 2016)).

- Since prescriptive analytics takes as input the outcome of predictive analytics algorithms, the vast majority of the reviewed research works include methods for predictive analytics as well. Therefore, *we separate the methods used for predictive analytics and the methods used for prescriptive analytics for each reviewed paper* (Section 4.1).
- *We classify the identified methods* for predictive analytics and the ones for prescriptive analytics in 7 categories: Probabilistic Models, Machine Learning/Data Mining, Statistical Analysis, Mathematical Programming, Evolutionary Computation, Simulation, Logic-based Models (Section 4.1).
- Since most of the reviewed research works utilize combinations of methods (instead of a single method), *we identify the categories of methods and their combinations* in the literature for both predictive and prescriptive analytics (Section 4.1). Then, we focused on the methods that are used for performing prescriptive analytics.
- *We also classify the reviewed papers per application domain* in order to show the application domains that have gathered the most and the least interest, as well as the categories of methods that have been used (Section 4.1).
- *For each category of methods and for each identified combination, we extensively discuss how they have been used in the context of prescriptive analytics* in the related papers, the problems that they solved, while we identified the key contributions. We also distinguished promising methods and approaches (Section 4.2).
- Based on the literature review, *we conclude in a synthesis, in which we also discuss the existing research challenges and potential directions for future research* (Section 5).

The identification and selection of documents is conducted in three phases in order to filter out the relevant documents. The number of papers identified in each phase is shown in Table 1. For the first phase, we queried the scientific databases to find papers that contain the query in their full record, including the full text of the publication, without any other constraints. The first phase of our search resulted in 917 papers. We found that there is almost an exponential growth of the use of the term "prescriptive analytics" in publications throughout the last years. This trend outlines an increasing research interest and contributes to the argumentation of the need for a literature review on prescriptive analytics.

Since the first phase of the search includes works that do not necessarily contribute to the field of prescriptive analytics, we conducted a second phase in order to search for research works with the query term in their metadata, i.e. title, abstract, keywords or other metadata of their record. The second phase resulted in 99 papers, as shown in Table 1. However, several papers refer the term "prescriptive analytics" without contributing to the field. For example, in many cases, it exists in introductory paragraphs (as background information) about business analytics.

Therefore, the third phase of our search aimed at examining more in-depth the content of these papers. To this end, it is conducted according to the following inclusion criteria: (i) The papers contribute to the field of prescriptive analytics; (ii) the publication date is between January 2010 and January 2019; (iii) the publication type is scientific journal, conference or book chapter. The third phase resulted in 56 papers, consisting of 19 journal articles, 36 conference papers and 1 book chapter.

Table 1
The three phases of search.

Source	Number of papers		
	First phase	Second phase	Third phase
ACM	15	11	6
ArXiv	5	5	4
Emerald	42	1	0
IEEE	260	40	17
ScienceDirect	186	23	8
SpringerLink	409	20	21
TOTAL	**917**	**99**	**56**

Table 2
The distribution of the third phase's papers throughout the years.

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Papers	1	0	0	2	8	7	9	12	15	2

The distribution of the number of papers with respect to years is shown in Table 2. This trend shows that there is also an increasing trend in publications contributing to the research field of prescriptive analytics. It should be noted that no journal or conference gathers specifically research works on prescriptive analytics. The publications examined exist in several different journals and conference proceedings from various research fields.

4. Analysis of reviewed papers

As we mentioned in Sections 1 and 2, prescriptive analytics takes as input the outcome of predictive analytics algorithms. For this reason, the vast majority of the reviewed research works include methods for predictive analytics as well, with the aim to provide the required input to prescriptive analytics. In this Section, we present the methods that we have identified in the reviewed papers for both predictive and prescriptive analytics.

4.1. Categories of methods for predictive analytics and prescriptive analytics

Fig. 2 depicts the classification of the methods for predictive analytics that we have identified in the reviewed papers. We classified these methods in three categories: Probabilistic Models, Machine Learning/Data Mining and Statistical Analysis. Fig. 3 depicts the classification of the methods for prescriptive analytics that we have identified in the reviewed papers. We classified these methods in six categories: Probabilistic Models, Machine Learning/Data Mining, Mathematical Programming, Evolutionary Computation, Simulation and Logic-based Models.

Since the boundaries among these categories are not always clear, we provide the following definitions according to which we classified the methods for predictive and prescriptive analytics that we found in the literature.

- Probabilistic models

A probabilistic model quantifies the uncertainty by integrating first-principle knowledge with data in order to capture the dynamics in a distribution over model predictions for state transitions between samples in a batch run (Martinez, Cristaldi, & Grau, 2009; Martínez, Cristaldi, & Grau, 2013). In this sense, this category includes models that represent uncertain causal relationships (i.e. between causes and effects). In predictive and prescriptive analytics, probabilistic models are used to calculate the likelihood of certain events occurring Instead of monitoring actual data in search of events and data points that conform to a set of rules defined by historical analysis.

- Machine learning/data mining

Machine learning refers to algorithms that rely on models and inference based upon data processing without using explicit instructions (Nasrabadi, 2007). Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task. It has been considered as a subset of artificial intelligence. Data mining is the process of discovering patterns in large data sets with

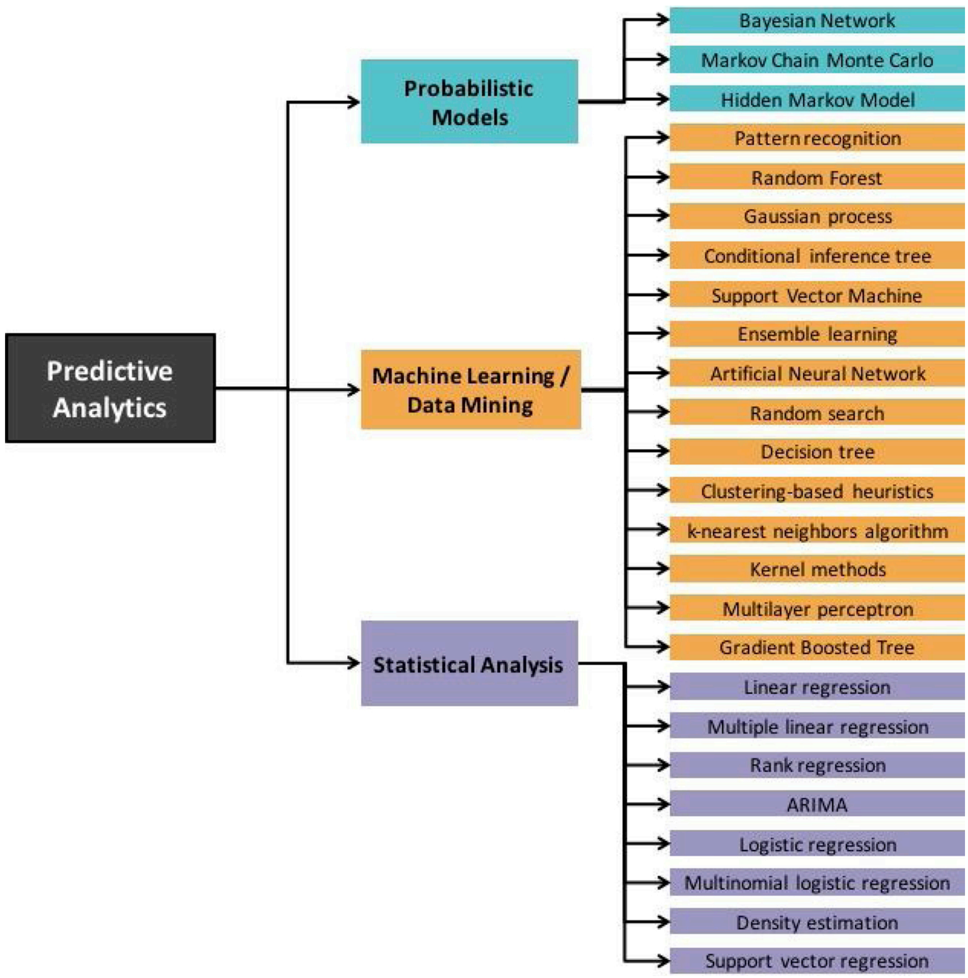

Fig. 2. Classification of the methods for predictive analytics.

the aim to extract information and transform it into a comprehensible structure for further use (Chakrabarti et al., 2006). It involves analysis, database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating (Chakrabarti et al., 2006). Since machine learning and data mining are terms that are closely interrelated (Chakrabarti et al., 2006), we treat them as one category of methods. Essentially, using machine learning and data mining techniques, we can build algorithms to extract data and see important hidden information from them. In predictive analytics, we seek information that can predict future outcome from data based on previous patterns while in prescriptive analytics we seek information that can help in finding the best course of action for a given situation.

- Statistical analysis

Statistical analysis is a branch of mathematics dealing with data collection, organization, analysis, interpretation and presentation (Dodge, 2006; Romijn, 2014). Statistical analysis deals with all aspects of data, including the planning of data collection in terms of the design of surveys and experiments studies, and solves problems related to a statistical population or a statistical model process (Romijn, 2014). In predictive analytics, statistical analysis is used to extract information from data and using it to predict trends and behavior patterns.

- Mathematical programming

Mathematical programming deals with the optimal allocation of limited resources among competing activities, under a set of constraints imposed by the nature of the problem being studied. In broad terms, mathematical programming can be defined as a mathematical representation aimed at programming or planning the best possible allocation of scarce resources. It is considered to be a branch of mathematics, management science and operational research that aims at enabling better decisions by arriving at optimal or near-optimal solutions to complex decision-making problems (Chong & Zak, 2008).

- Evolutionary computation

In computer science, evolutionary computation is a family of algorithms for global optimization inspired by biological evolution, and the subfield of artificial intelligence and soft computing studying these algorithms (Bäck, Fogel, & Michalewicz, 1997). In technical terms, they are a family of population-based trial and error problem solvers with a metaheuristic or stochastic optimization character. An initial set of candidate solutions is generated and iteratively updated. Each new generation is produced by stochastically removing less desired solutions, and introducing small random changes. In the context of prescriptive analytics, evolutionary computation is used for solving complex problems in data-rich environments in which exact solutions cannot be derived.

- Simulation

Simulation is referred to the process of modelling a real-life or

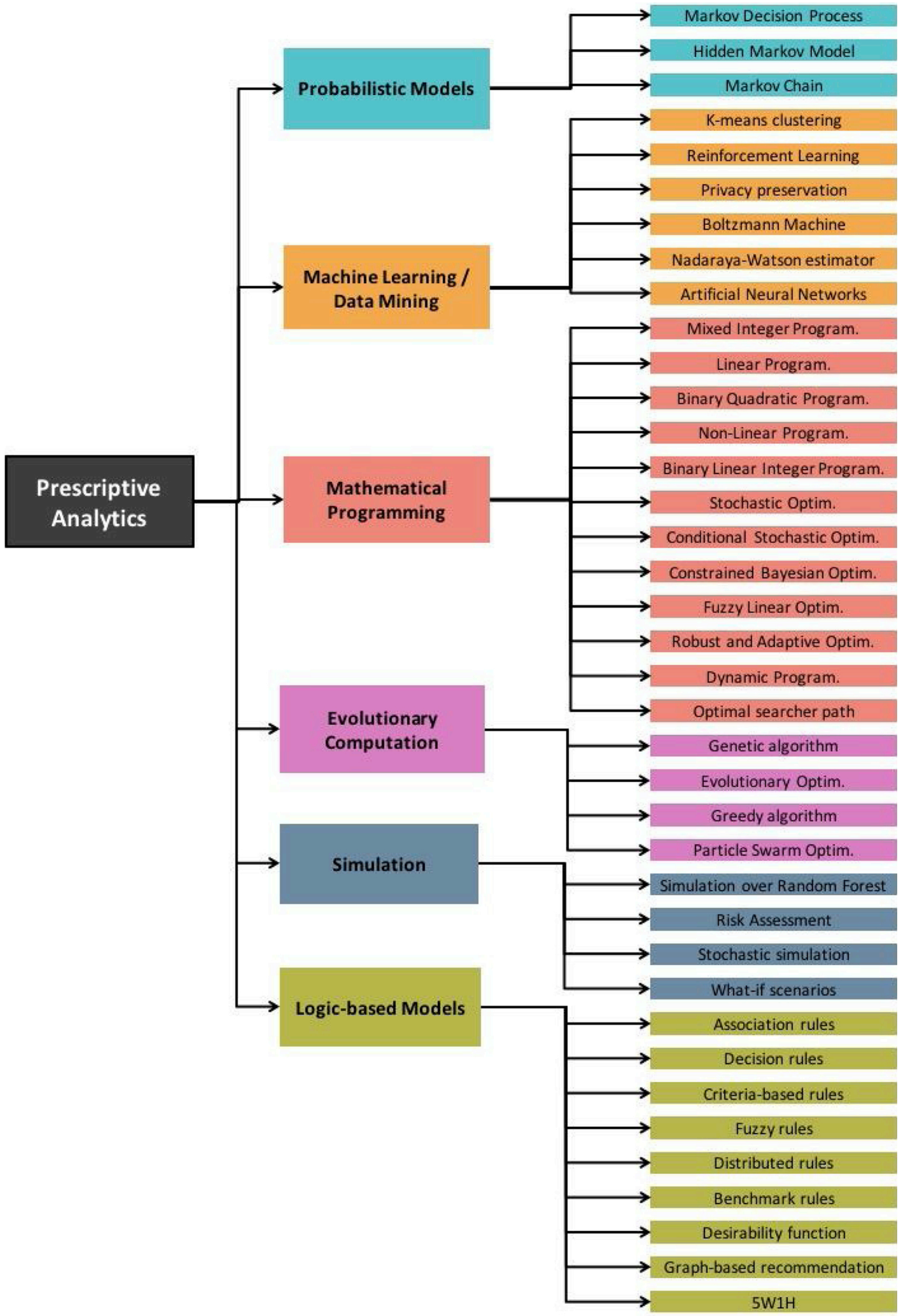

Fig. 3. Classification of the methods for prescriptive analytics.

hypothetical situation on a computer so that it can be studied to see how the system works (Jerry, 2005). By changing variables in mathematical models along with expert knowledge, predictions about the behaviour of the system can be generated and decisions can be facilitated. Simulation is used in prescriptive analytics in order to improve the effectiveness of decisions made by humans or by decision logic embedded in applications. In this respect, simulation is useful because it can be used to test new ideas about business decisions and actions to mitigate risk pertaining to a process or system, or how modifications will affect an existing process or system. Simulation is often used in prescriptive analytics applications related to safety of infrastructure as well as safety, quality, and design of products.

- Logic-based models

Logic-based models are hypothesized descriptions of the chain of causes and effects leading to an outcome of interest. In the context of the information systems, they may include rule-based systems, representation of expert knowledge and elicitation of domain knowledge for supporting proactive decision making in prescriptive analytics applications.

Most of the reviewed research works utilize combinations of methods in order to provide a solution for the problem under examination, while the same methods may be used for addressing different research challenges. To this end, Fig. 4 illustrates a Venn diagram

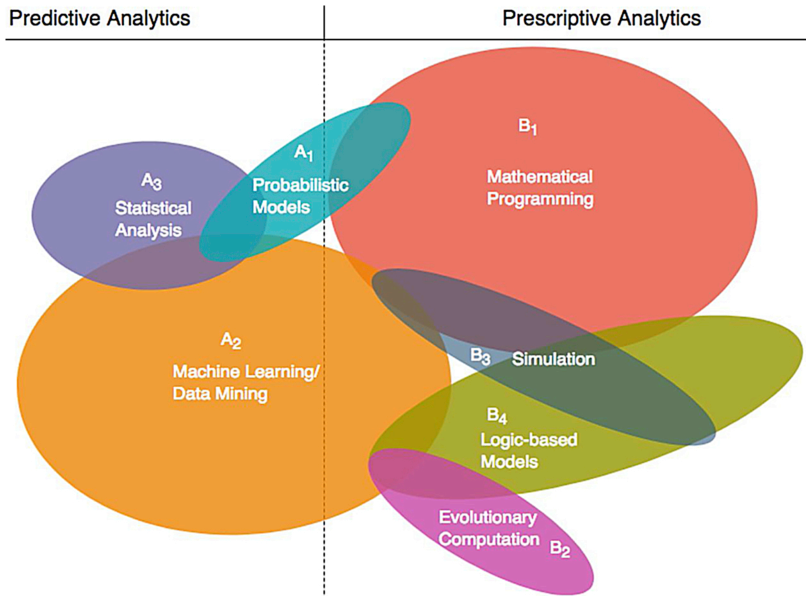

Fig. 4. Venn diagram for the representation of the methods used in literature.

Table 3
Classification of papers according to predictive analytics categories of methods.

A. Predictive Analytics			
	Categories of methods	References	Count
A1	Probabilistic Models	Ayhan et al., 2018	1
A2	Machine Learning/Data Mining	Anderson, 2017; Aref et al., 2015; Bertsimas & Kallus, 2014; Bertsimas & Van Parys, 2017; Christ et al., 2016; de Aguiar, Greve, & Costa, 2017; Dey et al., 2019; Giurgiu et al., 2017; Gröger et al., 2014; Harikumar et al., 2018b; Huang et al., 2018; Ito & Fujimaki, 2017; Jank et al., 2018; Kawas et al., 2013; Laude, 2018; Lo & Pachamanova, 2015; Mendes et al., 2014; Schwartz, York, Nowakowski-Sims, & Ramos-Hernandez, 2017; Srinivas & Ravindran, 2018; Stein, Meller, & Flath, 2018; Thammaboosadee & Wongpitak, 2018; von Bischhoffshausen et al., 2015	22
A3	Statistical Analysis	Baur et al., 2014; Ceravolo & Zavatarelli, 2015; Du et al., 2016; Matyas et al., 2017	4
A2∩A3	Machine Learning/Data Mining *AND* Statistical Analysis	Goyal et al., 2016; Hupfeld, Maccioni, Sesemann, & Ravazzolo, 2016	2
A1∩A3	Probabilistic Models *AND* Statistical Analysis	Shroff et al., 2014	1
A1∩A2∩A3	Probabilistic Models *AND* Machine Learning/Data Mining *AND* Statistical Analysis	Wang et al., 2018	1

which depicts the categories of methods and their combinations that have been identified in the literature for both predictive and prescriptive analytics. Each circle refers to a category of methods, while the size of each circle represents the amount of research works belonging to this specific category. The intersections of the circles illustrate the combinations of the categories. Fig. 4 is separated into two parts: Predictive Analytics and Prescriptive Analytics. Tables 3 and 4 show the associated references for each circle and for each intersection of circles for predictive and prescriptive analytics respectively. Moreover, Table 5 presents the categories of methods used per application domain.

4.2. Analysis of research works and discussion

In this section, we further discuss the methods that have been used in the literature, with an emphasis on the methods used for prescriptive analytics, which is the focus of our work.

4.2.1. Mathematical programming

As it can be seen in Fig. 4 and in Table 4, Mathematical Programming has been widely used in the context of prescriptive analytics. Particularly, the vast majority of the reviewed papers deal with optimization methods and algorithms. Optimization methods have gathered the research interest in the context of prescriptive analytics in order to derive optimal solutions based on several objectives. The objective most often considered is the operational cost to be minimized (Achenbach & Spinler, 2018).

Arguably, linear programming and its extensions are the most used optimization methods in prescriptive analytics. Linear programming is a technique for the optimization of a linear objective function, subject to linear equality and linear inequality constraints (Sierksma & Zwols, 2015). Specifically, the linear integer programming model has been used in the context of prescriptive analytics for finding a feasible combination of environmental alternatives that minimizes the emissions of transport fleets (Wu & Yang, 2017) and for planning sales force assignments on the basis of predictions about the sales impact (von Bischhoffshausen, Paatsch, Reuter, Satzger, & Fromm, 2015). Linear integer programming has also been used in the context of information systems for redesigning the enterprise software stack centered around a unified declarative programming model in order to support mathematical optimization (Aref et al., 2015). Linear integer programming has been also used for capacity planning in stadiums for sports events (Ghoniem, Ali, Al-Salem, & Khallouli, 2017) as well as for optimally determining hotel room prices to be published in the tour operator's brochure (Baur, Klein, & Steinhardt, 2014).

Mixed integer linear programming differs from linear integer

Table 4
Classification of papers according to prescriptive analytics categories of methods.

B. Prescriptive Analytics			
	Categories of methods	References	Count
A1	Probabilistic Models	–	0
A2	Machine Learning/Data Mining	Revathy & Mukesh, 2018	1
B1	Mathematical Programming	Aref et al., 2015; Baur et al., 2014; Berk et al., 2019; Bertsimas & Kallus, 2014; Bertsimas & Van Parys, 2017; Chalamalla, Ilyas, Ouzzani, & Papotti, 2014; Dey et al., 2019; Ghoniem et al., 2017; Goyal et al., 2016; Harikumar et al., 2018a, 2018b; Huang et al., 2018; Ito & Fujimaki, 2017; Kawas et al., 2013; Lo & Pachamanova, 2015; von Bischhoffshausen et al., 2015; Wu & Yang, 2017	17
B2	Evolutionary Computation	Dey et al., 2019	1
B3	Simulation	Giurgiu et al., 2017; Jank et al., 2018; Wang et al., 2018	3
B4	Logic-based Models	Ceravolo & Zavatarelli, 2015; Cho et al., 2015; Du et al., 2016; Du et al., 2018; Gröger et al., 2014; Lee et al., 2014; Matyas et al., 2017; Ramannavar & Sidnal, 2018; Song et al., 2013, 2014; Srinivas & Ravindran, 2018	11
A1∩B1	Probabilistic Models ***AND*** Mathematical Programming	Ayhan et al., 2018; Jiang et al., 2010	2
A2∩B4	Machine Learning/Data Mining ***AND*** Logic-based Models	Gröger et al., 2014; Mendes et al., 2014	2
A2∩B2	Machine Learning/Data Mining ***AND*** Evolutionary Computation	Thammaboosadee & Wongpitak, 2018	1
B1∩B3	Mathematical Programming ***AND*** Simulation	Hupfeld et al., 2016; Stein et al., 2018	2
B3∩B4	Simulation ***AND*** Logic-based Models	Srinivas & Ravindran, 2018	1
A2∩B2∩B4	Machine Learning/Data Mining ***AND*** Evolutionary Computation ***AND*** Logic-based Models	Laude, 2018	1
A2∩B1∩B4	Mathematical Programming ***AND*** Machine Learning/ Data Mining ***AND*** Logic-based Models	Ghosh et al., 2016	1
A2∩B1∩B3	Machine Learning/Data Mining ***AND*** Mathematical Programming ***AND*** Simulation	Shroff et al., 2014	1

Table 5
Classification of papers based on application domains for prescriptive analytics methods.

Application domain	Count	Categories	References
Manufacturing	12	B1	Anderson, 2017; Goyal et al., 2016
		B2	Dey et al., 2019
		B4	Ceravolo & Zavatarelli, 2015; Gröger et al., 2014; Matyas et al., 2017
		A2∩B2	Thammaboosadee & Wongpitak, 2018
		B1∩B3	Brodsky et al., 2017; Krumeich et al., 2016; Stein et al., 2018
		B1∩B4	Ringsquandl et al., 2016
		A2∩B1∩B3	Shroff et al., 2014
Sales/ Marketing	14	B1	Aref et al., 2015; Baur et al., 2014; Bertsimas & Kallus, 2014; Bertsimas & Van Parys, 2017; Hong et al., 2015; Huang et al., 2018; Ito & Fujimaki, 2017; Kawas et al., 2013; Lo & Pachamanova, 2015; von Bischhoffshausen et al., 2015
		B3	Jank et al., 2018
		B4	Du et al., 2018
		B1∩B3	Hupfeld et al., 2016
		A2∩B1∩B3	Shroff et al., 2014
Education/Research	7	B1	Harikumar et al., 2018a
		B4	Cho et al., 2015; Du et al., 2016; Lee et al., 2014; Song et al., 2013, 2014
Health/Social Policy	6	A2	Schwartz et al., 2017
		B1	Harikumar et al., 2018a, 2018b
		B4	Srinivas & Ravindran, 2018
		A2∩B4	de Aguiar et al., 2017; Osmani, Forti, Mayora, & Conforti, 2017
Human Resources	3	B1	Berk et al., 2019
		B4	Ramannavar & Sidnal, 2018
		A1∩B1	Jiang et al., 2010
Transport	3	B1	Achenbach & Spinler, 2018; Wu & Yang, 2017
		A1∩B1	Ayhan et al., 2018
Business Strategy	3	B3	Wang et al., 2018
		B4	Ghosh et al., 2016
Data Engineering/ Information Systems	3	A2	Revathy & Mukesh, 2018
		B1	Chalamalla et al., 2014
		B3	Giurgiu et al., 2017
Capacity Planning	1	B1	Ghoniem et al., 2017
Social Media	1	B4	Mendes et al., 2014
Agriculture	1	A2∩B2∩ B4	Laude, 2018

programming in that only some of the variables are constrained to be integers, while other variables are allowed to be non-integers and hence is suitable in prescriptive analytics applications such as allocating sales teams to sales opportunities with the aim to maximize business revenue and profit (Kawas, Squillante, Subramanian, & Varshney, 2013). In this case, the prescriptive analytics algorithm incorporates predictions derived from mining historical selling data in order to capture the behavioral relationship between the size and composition of the sales team and the revenue earned for different types of clients and opportunities subjected to the business constraints.

Binary linear programming has been applied in cases when all of the variables are binary such when recommending products or services to customers (Lo & Pachamanova, 2015). In this research work, the problem was formulated as a multiple treatment optimization model with binary decision variables.

Non-linear programming, i.e. when some of the constraints or the objective function is non-linear, was used by Goyal et al. (2016) in the context of asset health management. More specifically, the authors proposed a method based on mixed integer non-linear programming for scheduling and planning preventive, proactive and corrective maintenance in an electrical network considering budgetary constraints. On the other hand, Ito and Fujimaki (2017) proposed a prescriptive analytics model based on binary quadratic non-linear programming for deriving the optimal price strategy, i.e. the one which maximizes the future profit on the basis of a customer-centric pricing approach. The problem was solved by a combination of semi-definite programming relaxation and rounding techniques (fast approximation algorithm). Finally, Huang, Bergman, and Gopal (2018) addressed the problem of selecting expansion locations for retailers selling add-on products whose demand is dependent on the demand of another base product. They concluded in a non-linear binary quadratic optimization problem affected by the non-linear predictive model.

A traditional technique for decision making under uncertainty is stochastic optimization (Birge & Louveaux, 2011). Stochastic optimization refers to a collection of methods for minimizing or maximizing an objective function when randomness is present. In this sense, it focuses on decision making under uncertainty (Bertsimas & Kallus, 2014; Kawas et al., 2013). Bertsimas and Kallus (2014) defined prescriptive analytics from an operational research point of view as a conditional stochastic optimization problem given imperfect observations, where the joint probability distributions that specify the problem are unknown. However, stochastic optimization has been difficult to implement in practice (Berk, Bertsimas, Weinstein, & Yan, 2019). Multi-period problems suffer from the curse of dimensionality; although optimal solutions can be computed using the Bellman equations, these equations grow exponentially in size with the dimension of the state space (Berk et al., 2019). Moreover, the required probability distributions are difficult to estimate without copious amounts of data, which could be a barrier for companies just beginning forays into predictive and prescriptive analytics.

Adaptive robust optimization has started to be used in the literature for solving prescriptive analytics problems. Adaptive robust optimization is an improved version of the static robust optimization in which instead of assigning probability distribution to handle uncertainty, it treats uncertainty as a function of ellipsoid, polyhedron, or any other ways that might best serve a specific case of interest. Adaptive robust optimization is inspired by the statistical bootstrap and deals with optimization problems in which a certain measure of robustness is sought against uncertainty that can be represented as deterministic variability in the value of the parameters of the problem itself and/or its solution. Furthermore, the characterization of the uncertainty sets can be data-driven and is often interpretable (Bertsimas, Brown, & Caramanis, 2011). Therefore, Bertsimas and Van Parys (2017) proposed a generic robust and adaptive optimization solution. Further, Berk et al. (2019) got involved with the optimization component of the human resources planning problem in order to model the forecasting uncertainty within the optimization problem. Their aim was to dynamically make hiring decisions that maximize profit while remaining as flexible as possible

Finally, an increasingly emerging optimization method is Bayesian optimization. Bayesian optimization is a technique for efficiently optimizing multiple continuous parameters with computationally expensive function evaluations. Typically, this process begins by evaluating a small number of randomly selected function values, and fitting a Gaussian process regression model to the results (Letham, Karrer, Ottoni, & Bakshy, 2019). It is able to solve a variety of optimization problems where traditional numerical methods and global optimizers are insufficient (Gardner, Kusner, Xu, Weinberger, & Cunningham, 2014). Harikumar et al. (2018a) exploited this technique in combination with constraint programming, i.e. Constrained Bayesian Optimization, for solving a nested global optimization problem aiming at guarantying the privacy of the data. Further, Harikumar et al. (2018b) proposed a promising method for prescriptive analytics aiming at finding the minimum change that should be made in order to move from an undesirable state to a desirable state. In this sense, the proposed prescriptive analytics method is generic and thus, capable of being applied in different application domains and problems. The authors compared their results with the Improved Stochastic Ranking Evolution Strategy Genetic Algorithm and concluded that the latter failed to converge in the case of expensive function evaluation but converges faster in the absence of it.

4.2.2. Evolutionary computation

For problems that are too complicated to get the optimal solution with mathematical programming, evolutionary computation methods can be used for providing approximate solutions efficiently (Duan & Xiong, 2015). Evolutionary computation methods have been established as optimization tools since they have been proved to be powerful global optimizers. Evolutionary approaches such as genetic algorithms have been studied as a prescriptive analytics tool by Dey, Gupta, Pathak, Kela, and Datta (2019). Their work proposes a genetic algorithm for performing the search of the composition of the steel to achieve a target property, based on the prediction of steel features similar to strength, ductility and hardness.

4.2.3. Simulation

Another important category of methods for prescriptive analytics is Simulation. Giurgiu et al. (2017) applied simulation over the random forest model for prescribing the required improvement actions to servers by using the information available from the incident tickets. In addition, stochastic simulation was exploited by Jank, Dölle, and Schuh (2018) in order to maximize the benefits of a company's product portfolio in accordance with the corporate objectives. On the other hand, Wang, Cheng, and Deng (2018) proposed a method based on stochastic simulation over a Bayesian Belief Network in order to conduct fact-based decision making based on KPIs in a data-driven way. In this way, they moved beyond expert-oriented or multi-criteria decision making.

4.2.4. Machine learning/data mining

Machine Learning/Data Mining algorithms have been widely used in predictive analytics during the last years. However, their exploitation in the context of prescriptive analytics is rather scarce. We found that only one paper relies solely on machine learning and data mining algorithms (Revathy & Mukesh, 2018). The authors present an approach based on k-means clustering in order to address the problem of adaptive data placement across distributed nodes in a secure way by considering the sensitivity and security of the underlying data. Moreover, Shroff et al. (2014) proposed a framework based upon reinforcement learning, i.e. learning the behavior of an agent through trial-and-error interactions within a dynamic environment, integrated with simulation and optimization in an online learning scenario.

4.2.5. Logic-based models

Logic-based Models, especially rule-based systems, have been used in the prescriptive analytics literature for incorporating the expert knowledge into the prescriptive analytics models. Ceravolo and Zavatarelli (2015) developed a knowledge acquisition process as an investigation over the process executions. The prescriptive knowledge base evaluates the achievement of the business rules or the objectives associated to a process and identifies unexpected patterns. Matyas, Nemeth, Kovacs, and Glawar (2017) proposed a procedural approach for realizing prescriptive maintenance planning. The approach is based on rules represented by mathematical functions for each machine component, taking into account the prognoses of the wear reserve for machine components, condition based monitoring and variations in product quality.

Ramannavar and Sidnal (2018) proposed a distributed architecture which integrates advanced analytics to map a job to resumes utilizing semantic technologies. For a given job description, every resume is ranked according to two measures, coverage and comprehensibility, denoting the number of concepts from a predefined class and the number of sections and subsections covered in a resume, respectively. Du, Plaisant, Spring, and Shneiderman (2016) focused on the presentation and explanation of recommendations of temporal event sequences using a prescriptive analytics interface. They developed the EventAction system, which identifies similar records, estimates the current record's potential outcomes based on the outcome distribution of the similar archived records and recommends actions by summarizing the activities of those who achieved the desired outcome. This approach was applied in an education scenario as well as in a digital marketing scenario (Du, Malik, Koh, & Theocharous, 2018). In the latter, the authors evaluated the effectiveness of their tool in helping marketers prescribing personalized marketing interventions. Further, prescriptive analytics have been utilized the 5W1H (What to do, with whom, where, how/when) methodology embedded in an information system for the purpose of providing recommendations and advice on research directions to researchers (Cho, Song, Weber, Jung, & Lee, 2015; Lee, Cho, Gim, Jeong, & Jung, 2014; Song et al., 2013, 2014).

4.2.6. Combinations of categories

As seen in Fig. 4 and Table 4, there are various combinations of the aforementioned categories of methods in order to perform prescriptive analytics. Shroff et al. (2014) proposed a framework that combines Mathematical Programming, Simulation and Machine Learning/ Data Mining. This framework is based upon reinforcement learning, i.e. learning the behavior of an agent through trial-and-error interactions within a dynamic environment, integrated with simulation and optimization in an online learning scenario. Srinivas and Ravindran (2018) proposed a method which combines the categories of Mathematical Programming and Logic-based Models. More specifically, they proposed a prescriptive analytics model which involves scheduling rules evaluated using simulation. Simulation models are used to generate the schedule and determine the weighted score of the generated schedule. In this way, they achieve to improve the performance of an appointment system with respect to patient satisfaction and resource utilization.

Thammaboosadee and Wongpitak (2018) combined Evolutionary Computation and Machine Learning/ Data Mining, and particularly k-means clustering, in order to allocate electrical equipment's parts taking into consideration the customer behavior and the company policy. Moreover, Laude (2018) focused on the application of prescriptive analytics for automated agriculture systems. For this, they defined a prescriptive analytics engine as the aggregation of several actionable insights to generate a set of trigger events, consisting of any combination of ensemble methods, particle swarm optimization and fuzzy linear programming or fuzzy rule-based systems.

Gröger, Schwarz, and Mitschang (2014) combined methods of Machine Learning/ Data Mining and Logic-based Models, and specifically data mining techniques and rules derived from decision trees, in order to perform recommendation-based business process optimization on top of a holistic process warehouse. They also presented a case study in the manufacturing domain. It was shown that the proposed recommendation-based business process optimization approach moves beyond pattern-based optimization, recommendation-based process mining, and risk-based decision support. This research work provides a significant contribution since it exploits prescriptive analytics methods in order to transform analysis results into concrete improvement actions without leaving this step completely up to the subjective judgment of the user. Another contribution is that it integrates process data and operational data, while it is able to perform a proactive improvement during process execution.

On the other hand, Mendes et al. (2014) investigated how the word choice in Twitter messages contributes to their propagation and proposed an approach for prescribing changes to the tweet wording in order to get more retweets. To do this, they used generalized linear models, i.e. a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution, embedded in a rule-based system. An advantage of generalized linear models is that they are transparent and friendly for user interaction since the weights can be displayed as knobs or sliders on an interface, giving the users the freedom to disagree with our model's suggestions.

Ghosh, Gupta, Chattopadhyay, Banerjee, and Dasgupta (2016) combined methods from the Mathematical Programming, Machine Learning/ Data Mining and Logic-based Models in order to define, monitor, rank and classify a set of KPIs measuring the operational efficiency of business process outsourcing service providers. To do this, they used the Kemeny rank aggregation method in order to generate an aggregate ranked list that minimizes the number of pair-wise disagreements between client pairs between the individual rank lists. They combined it with integer linear optimization and rule-based systems.

Jiang, Jensen, Cao, and Kumar (2010) combined Mathematical Programming and Probabilistic Models in order to build business intelligence applications having predictive and prescriptive analytics capabilities. Ayhan, Costas, and Samet (2018) developed a prescriptive analytics method for the long-range aircraft conflict detection and resolution problem. Their proposed approach learns from descriptive patterns of historical trajectories and pertinent weather observations and builds a Hidden Markov Model using a variant of the Viterbi algorithm. The system avoids the airspace volume in which the conflict is detected and generates a new optimal trajectory that is conflict-free.

5. Synthesis, challenges and future directions

Based on our literature review, there is a clear trend towards prescriptive analytics models capable of being executed in a real-time, streaming computational environment in the context of IoT. In addition, the wide availability of big data from heterogeneous data sources paves the way for minimizing human judgement, that suffers from subjectivity and for exploiting the information that can be derived from data processing. In this way, the prescriptive analytics models will be able to be built and updated dynamically as soon as new data are acquired. Therefore, there is the need for generic prescriptive analytics models and systems capable of fulfilling the aforementioned requirements.

Further, there is a trend of applying artificial intelligence methods and tools to prescriptive analytics (Lee, Davari, Singh, & Pandhare, 2018). Up to now, the full potential of these capabilities has been investigated only conceptually (Anderson, 2017; Bertsimas & Van Parys, 2017; Giurgiu et al., 2017; Nechifor, Puiu, Tarnauca, & Moldoveanu, 2015; Shroff et al., 2014; Soltanpoor & Sellis, 2016). Although descriptive and predictive analytics have evolved during the last years towards these directions in order to be applicable to data-rich environments, prescriptive analytics is still at its dawn. For example, our survey revealed only sparse advanced techniques for uncertainty handling of streaming data that are useful for prescriptive analytics. In order to contribute to further advancements in prescriptive analytics, in the following we synthesize the challenges derived from the literature review and we outline potential directions for future research.

5.1. Offline vs. real-time processing approaches

According to our literature review, real-time processing has not been well exploited in prescriptive analytics research, since 64% of the reviewed papers deal with offline prescriptive analytics models. However, the emergence of IoT in modern enterprises has led to an increasing demand for real-time systems. Apart from the technical challenges that exist in developing scalable and efficient sensor-driven information systems (Biegler, Yang, & Fischer, 2015; Yaqoob et al., 2016), there is also the need for recursive algorithms for prescriptive analytics, which are able to process data with time-varying characteristics and thus, to solve large-scale problems. Recursion deals with solving a problem that depends on solving smaller instances of the same problem.

Proposition 1. *The development of real-time, sensor-driven information systems and recursive algorithms can promote the application of prescriptive analytics in large-scale problems.*

The computational challenges are even higher when predictive and prescriptive algorithms need to be developed for distributed platforms (Biegler et al., 2015), i.e. platforms with components that are located in different networked computers, communicating and coordinating their actions by passing messages to each other (Tanenbaum & Van Steen, 2007). According to our literature review, there is only one paper (Hong et al., 2015) that proposes an implementation of a prescriptive analytics approach in a distributed parallel computing platform. Prescriptive analytics can significantly benefit from distributed computing for processing large amounts of unstructured, semi-structured and structured big data.

Proposition 2. *Prescriptive analytics can benefit from distributed computing for processing large amounts of data.*

Various research communities have independently arrived at stream processing as a programming model for efficient and parallel computing (Hirzel, Soulé, Schneider, Gedik, & Grimm, 2014). In this context, Complex Event Processing (CEP) technologies can play a significant role. CEP tracks and processes streams of information (data) about things that happen (events) by combining multiple sources with the aim to infer events or patterns that reveal meaningful events, such as opportunities or threats, and to react to them (Bates, 2012; Etzion, Niblett, & Luckham, 2011; Luckham, 2011; Schmerken, 2008).

Proposition 3. *Stream processing and Complex Event Processing can enable the development of prescriptive analytics in a real-time environment.*

5.2. Deterministic vs. probabilistic approaches

The uncertainty that is handled by prescriptive analytics approaches, methods and algorithms has three main sources: (i) the uncertainty of the prediction, which is estimated by a prediction evaluation method in predictive analytics algorithms; (ii) the uncertainty of the quality of data; and, (iii) the subjectivity in human judgement when building the prescriptive analytics model. Although uncertainty is considered a crucial aspect of prescriptive analytics by 76% of the reviewed papers, it is usually limited to data cleaning techniques for tackling issues of incomplete data. In this sense, the prescriptive analytics model that represents the decision making process is considered deterministic.

Although prediction evaluation algorithms have gathered recent research attention, it is not clear how to go from a good prediction to a good decision (Bertsimas & Kallus, 2014), since prescriptive analytics algorithms incorporate additional uncertainty sources in information processing. Currently, dealing with incomplete and noisy data, elicitation and modelling of expert knowledge and uncertainty in decision making process are three fields that are developed in parallel to prescriptive analytics research without clear connections among them. This fact becomes even more important when analyzing real-time data and there is the need for timely decisions in day-to-day business operations.

Proposition 4. *It is necessary to address the uncertainty introduced by the predictions, the incomplete and noisy data and the subjectivity in human judgement.*

Due to the uncertain nature of prescriptive analytics, most of the problems can be represented in a probabilistic structure. Probabilistic graphical models, and especially Bayesian Networks, have been considered a powerful tool for representing the graphical structure among the random variables in terms of the conditional dependencies (Gudivada, Irfan, Fathi, & Rao, 2016) and thus, they can enhance prescriptive analytics models.

On the other hand, Markov Decision Processes (MDP), which have been used for proactive decision making by representing the decision making process instead of the physical process itself (Bousdekis, Papageorgiou, Magoutas, Apostolou, & Mentzas, 2018), can be utilized in prescriptive analytics for handling uncertainty. MDP is a discrete time stochastic control process which provides a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker (Meyn, 2008). MDPs are useful for studying optimization problems solved via dynamic programming and reinforcement learning. In general, in comparison to physical models (e.g. simulation of the physical process of a manufacturing equipment), probabilistic generative models enable also inference using statistical predictive models to ease the search for optimal parameter settings (Shroff et al., 2014).

Proposition 5. *Due to the uncertain nature of prescriptive analytics, most of the problems can be represented in a probabilistic structure.*

Moreover, during the last years, there have been some attempts for coupling probabilistic logic and uncertainty into CEP engines in order to react to predictions about future events before they occur (Cugola, Margara, Matteucci, & Tamburrelli, 2015; Engel et al., 2012; Lee & Jung, 2017; Mousheimish, Taher, & Zeitouni, 2016; Wang, Cao, & Zhang, 2013). Still, there is very limited work on how to integrate the probabilistic results pertaining to event predictions within CEP systems (Christ, Krumeich, & Kempa-Liehr, 2016). Therefore, similarly to the approaches using CEP for detecting important patterns and situations and reacting to them, prescriptive analytics can significantly benefit from these advancements in order to utilize CEP for prescribing appropriate actions in a proactive way, on the basis of predictions. In this direction, machine learning can be coupled to CEP in order to enrich the knowledge base beyond the knowledge of the domain experts.

Proposition 6. *Prescriptive analytics can benefit from coupling probabilistic logic with CEP engines for prescribing actions in a proactive way.*

5.3. Domain knowledge vs. data-driven models

While the use of big data adds significant value to business throughout the entire value chain, the integration of big data analytics to the decision-making process remains a challenge (Akter et al., 2019). In this sense, prescriptive analytics has the potential to play a crucial role towards this direction. According to our literature review, 82% of existing research on prescriptive analytics relies on models that have been developed solely or mainly on the basis of expert knowledge. However, such models depend on human subjectivity and are cumbersome to develop because there are several challenges associated with expert knowledge elicitation.

Although there is an increasing trend towards the use of the availability of data for model development, this is currently an underexplored area. The emergence of big data applications paves the way for the development of prescriptive analytics models less dependent on domain expert knowledge and based more upon data analytics. Although there have been a lot of descriptive and predictive algorithms utilizing data mining, machine learning and artificial intelligence (Larson & Chang, 2016; Tsai et al., 2015), prescriptive analytics has not gathered the same attention yet. In most reviewed papers, prescriptive analytics relies on an optimization problem with an objective function created by the expert.

Proposition 7. *Prescriptive analytics models have the potential to become less dependent on domain expert knowledge and more dependent upon big data analytics.*

Further research is also needed towards the direction of combining the "learned knowledge" of machine learning and data mining methods with the "engineered knowledge" elicited from domain experts. To this end, the combined use of machine learning and knowledge engineering can complement each other's strengths and mitigate their weaknesses, since explicitly represented application knowledge could assist data-driven machine-learning approaches to converge faster on sparse data and to be more robust against noise.

Proposition 8. *Further research is needed towards the direction of combining the "learned knowledge" of machine learning and data mining methods with the "engineered knowledge" elicited from domain experts.*

As already mentioned, apart from the aforementioned methods and algorithms, we have also identified in the literature some conceptual approaches which pave the way for the development of more advanced prescriptive analytics models. In all conceptual approaches, the full potential of big data to prescriptive analytics is outlined with the aim to reduce the input by the domain expert in a way that the human has a more supervisory role in the data analytics lifecycle. To this end, stochastic simulation and business rules (Soltanpoor & Sellis, 2016), CEP (Krumeich et al., 2016), autonomic networking (Nechifor et al., 2015) and graph-based analytics (Ringsquandl, Lamparter, & Lepratti, 2016) in a stream processing computational environment have been considered as key enablers for the further development of prescriptive analytics in various application domains. In addition, there are several attempts for designing conceptual architectures addressing real-time data analytics with a particular focus on prescriptive analytics (Brodsky et al., 2017; Deshpande, 2019; Pospieszny, 2017; Tan, Ang, Lu, Gan, & Corral, 2016).

With the advancements in big data technologies, artificial intelligence has become an important element of digital systems, because, among others, they make a profound impact on human decision making (Duan et al., 2019). As a result, there is an increasing demand for information embedding artificial intelligence and machine learning algorithms for decision making (Duan et al., 2019). In this way, there will be the possibility to develop generic, domain-agnostic, data-driven methodologies and algorithms for performing prescriptive analytics.

Proposition 9. *There is the need for generic prescriptive analytics methods and algorithms utilizing artificial intelligence and machine learning.*

Some prominent machine learning methods that have been utilized effectively in decision making problems in different contexts are: Artificial Neural Networks (Domingos, Burguillo, & Lenaerts, 2017), Bayesian Networks (Said, Shahzad, Zamai, Hubac, & Tollenaere, 2016), topic models (Roberts et al., 2014), fuzzy sets (Pal & Ceglarek, 2013), Markov models (Bousdekis et al., 2018). In addition, constraint programming is a promising approach to this direction. Constraint programming is a programming paradigm wherein relations between variables are stated in the form of constraints (Ceberio & Kreinovich, 2016). Constraints differ from the common primitives of imperative programming languages in that they do not specify a step or sequence of steps to execute, but rather the properties of a solution to be found (Ceberio & Kreinovich, 2016).

Proposition 10. *Constraint programming is a promising approach for building prescriptive models.*

5.4. Static vs. dynamic prescriptive models

Since change is an indispensable aspect of modern real-world applications, dynamic, flexible and adaptive response to changes plays a key role in organizations' success. Although adaptation mechanisms providing feedback to descriptive and predictive algorithms are a well-studied area, their application to prescriptive analytics is rarely investigated. However, adaptation of prescriptive analytics is of outmost importance, especially in today's complex and dynamic business environment with lots and heterogeneous data and information sources. A dynamic prescriptive model refers to the adaptation of the model in order to be valid when new requirements arise or when new knowledge is gained, e.g., new types of constraints have to be added or there is a change in problem environment.

Adaptation of prescriptive analytics can be defined in terms of amended decisions, changed recommendations or new courses of actions (Soltanpoor & Sellis, 2016). Such feedback mechanisms need to track the suggested recommendations as well as unprecedented events occurrence in system's lifetime (Soltanpoor & Sellis, 2016). Although adaptation of predictive analytics has been identified as an important factor for their reliability, implementations in algorithms are presented only in 29% of the reviewed papers, while implementations in information systems are non-existent. Even in the aforementioned papers, the capabilities of the adaptation mechanisms are limited.

Notable approaches aiming at exploiting the full potential of data-rich environments are those by Nechifor et al. (2015) and Soltanpoor and Sellis (2016), albeit still at a conceptual level. The remaining relevant publications investigate extensions to domain-specific, user-defined prescriptive models in order to derive some values that were previously estimated by the user. The significance of a closed-loop feeding the recommendations back into a process control system was identified by Gröger et al. (2014), while an attempt to tackle it is the Prescriptive Information Fusion framework which incorporates adaptive closed-loop prescriptive analytics approaches (Shroff et al., 2014).

Proposition 11. *Adaptation mechanisms for prescriptive analytics are of outmost importance in dynamic environments.*

Adaptation mechanisms aiming to improve performance and reliability of prescriptive analytics become even more important in a real-time/ streaming computational environment and especially when the decision is implemented automatically. However, the direction of decision automation has not been explored yet. We found only one paper (Nechifor et al., 2015) with a conceptual approach that deals with decision automation. A major challenge in this area is the fact that the uncertainty and the probabilistic nature of prescriptive analytics may result in implementing inappropriate actions. Moreover, very complex application domains are not mature to address decision automation. For example, the automatic reproduction of an inappropriate video has incomparably lower risk than the automatic inappropriate reconfiguration of an industrial machine. In the first case, the negative impact will probably be the instant disturbance of the user, while, in the second case, it will probably be a failure which can lead to high costs, but also to accidents and environmental pollution.

Proposition 12. *Prescriptive analytics can enable decision automation, provided that the challenges of uncertainty, dynamicity and complexity are faced effectively.*

6. Conclusions

Business analytics is an evolving area which gathers the interest of both researchers and practitioners. With the increasing availability of large amounts of data within organizations, many research works aim to contribute to the business analytics field in order to enable organizations gain meaningful insights about their performance. In this paper, we investigated the literature on prescriptive analytics, analyzed the results, identified the existing research gaps and outlined directions for future research, depicted in Table 6 in the form of research propositions. Our review has shown that prescriptive analytics is a critical

Table 6
A summary of research propositions.

Challenges	Propositions
Offline vs. real-time processing	**Proposition 1:** *The development of real-time, sensor-driven information systems and recursive algorithms can promote the application of prescriptive analytics in large-scale problems.* **Proposition 2:** *Prescriptive analytics can benefit from distributed computing for processing large amounts of data.* **Proposition 3:** *Stream processing and Complex Event Processing can enable the development of prescriptive analytics in a real-time environment.*
Deterministic vs. probabilistic	**Proposition 4:** *It is necessary to address the uncertainty introduced by the predictions, the incomplete and noisy data and the subjectivity in human judgement.* **Proposition 5:** *Due to the uncertain nature of prescriptive analytics, most of the problems can be represented in a probabilistic structure.* **Proposition 6:** *Prescriptive analytics can benefit from coupling probabilistic logic with CEP engines for prescribing actions in a proactive way.*
Domain knowledge vs. data-driven models	**Proposition 7:** *Prescriptive analytics models have the potential to become less dependent on domain expert knowledge and more dependent upon big data analytics.* **Proposition 8:** *Further research is needed towards the direction of combining the "learned knowledge" of machine learning and data mining methods with the "engineered knowledge" elicited from domain experts.* **Proposition 9:** *There is the need for generic prescriptive analytics methods and algorithms utilizing artificial intelligence and machine learning.* **Proposition 10:** *Constraint programming is a promising approach for building prescriptive models.*
Static vs. dynamic prescriptive models	**Proposition 11:** *Adaptation mechanisms for prescriptive analytics are of outmost importance in dynamic environments.* **Proposition 12:** *Prescriptive analytics can enable decision automation, provided that the challenges of uncertainty, dynamicity and complexity are faced effectively.*

advancement in analytics. It can improve decision making and process effectiveness by helping analysts get closer to tying outcomes to specific situations. Currently, prescriptive analytics appears to have attracted attention in a rather restricted range of application domains.

The review presented herein is limited to works explicitly scoped as prescriptive analytics. It does not deal with works from different research fields that can potentially contribute to the field of prescriptive analytics. There is a plethora of advancements in areas such as optimization, simulation, machine learning, recommender systems and uncertain decision making, which should be examined from the view of prescriptive analytics and assessed in the context of the challenges that prescriptive analytics problems present, as well as the opportunities provided by recent advancements in information technology.

Prescriptive analytics is expected to become much more common and understood by a wide variety of managers. Capturing business value from data requires action quickly on real-time events, or the value disappears. But taking intelligent actions quickly requires more than a prediction; it requires knowing exactly what to do and when to do it. Our review has shown that prescriptive analytics fills this critical gap for business analytics. With recent advancements in event processing technology as well as distributed, pervasive computing infrastructures, we expect that next generation prescriptive analytics systems will exploit sophisticated features such as distributed processing and data management and will embed scalable operational research and machine learning algorithms to facilitate actionability. Through distributed processing and data management and in conjunction with advanced algorithms, next generation analytics systems will be able not only to identify risks and potential problems in business situations, but also recommend mitigating actions, effectively delivering clear, definitive, real-time decision support to business users.

Declarations of interest

None.

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