Supervised Descriptive Rule Discovery: A Survey of the State-of-the-Art

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Abstract

The supervised descriptive rule discovery concept groups a set of data mining techniques whose objective is to describe data with respect to a property of interest. Among the techniques within this concept are the subgroup discovery, emerging patterns and contrast sets.

This contribution presents the supervised descriptive rule discovery concept within the data mining literature. Specifically, it is important to remark the main difference with respect to other existing techniques within classification or description. In addition, a a survey of the state-of-the-art about the different techniques within supervised descriptive rule discovery throughout the literature can be observed. The paper allows to the experts to analyse the compatibilities between terms and heuristics of the different data mining tasks within this concept.

1. Introduction

The knowledge discovery in databases (KDD) is a computational process for discovering knowledge in data through the use of different methodologies, technologies and systems (Fayyad et al., 1996). Within the KDD process there are two areas differentiated perfectly: predictive data mining and descriptive data mining. Former attempts to make predictions about unknown objects with respect to a class whereas the descriptive searches for relationships between data. In general, the predictive data mining process employs the supervised learning because it is necessary to have a property of interest in order to predict it. However, the descriptive data mining process is based on unsupervised learning because it is not necessary this class.

The supervised descriptive rule discovery (SDRD) concept was presented in (Kralj-Novak et al., 2009b). Its main proposal is the search for interesting descriptions in data with respect to a property or class of interest. Essentially, SDRD describes labelled data, i.e. it combines the descriptive data mining with supervised learning. The most representative techniques within SDRD are Subgroup Discovery (SD) (Herrera et al., 2011, Carmona et al., 2014), Emerging Patterns (EPs) (Dong and Li, 1999) and Contrast Sets (CSs) (Bay and Pazzani, 2001). These techniques have defined by different

These techniques have been studied and analysed at different stages by different authors. However, their main goals are very similar and it is primarily the terminology that differs as well as the quality measures used in order to analyse a given problem. This contribution presents a perfect positioning of the SDRD concept and a state-of-the-art for the different techniques grouped on the SDRD.

The paper is organised as follows: the definitions and main properties are outlined for SD are presented in Section 3, for EPs in Section 4 and for CSs in Section 5. Finally, Section 6 presents the compatibilities between the different concepts and terms within the SDRD, and Section 7 shows the main heuristics employed within the SDRD.

2. Supervised descriptive rule discovery

In data mining there are two main approaches used in order to analyse data: supervised learning (labelled data) and unsupervised learning (unlabelled data). Together with these approaches we further distinguish between predictive and descriptive induction, whereby predictive data mining methods are usually supervised (induce models from labelled data), and descriptive data mining methods are typically unsupervised (induce interesting association in unlabelled data).

The SDRD concept was introduced by Kralj-Novak et al. (Kralj-Novak et al., 2009b). It describes the group of rule based techniques used in order to obtain descriptive knowledge with respect to labelled data. All techniques represented in this concept have as their objective the understanding of underlying phenomena instead of the classification of new instances.

An illustrative example for an SDRD model:

> *A medical center wants to know in what circumstances a patient may suffer a certain type of cancer; the intention is not to predict cancer, but to understand the risk factors that lead to this.*

In Fig. 1 examples of the predictive supervised, descriptive unsupervised and SDRD tasks are presented in order to show the main differences and properties of the tasks included in the SDRD concept:

- Fig. 1(a) represents graphically the model obtained by a predictive algorithm based on the extraction of rules for classification. As can be observed, six rules (areas between dotted lines) divide the space into different areas that allow analysis of the problem in an easy way. In this way, the model is able to classify new instances of the problem with good values of precision.

- The model presented in Fig. 1(b) is an unsupervised descriptive model, e.g. clustering that groups unlabelled instances in different areas (circles). As can be observed, the model obtains three groups of instances with a soft overlapping between the lower and the remaining groups, with a simple and single interpretation for each group.

- On the other hand, Fig. 1(c) presents an SDRD model, where two rules (circles) for each value of the target variable are obtained. Rules are usually represented in a similar way to Fig. 1(a). Another important property is that the knowledge for each rule is considered as individual knowledge instead of rules dependant on one another. There is a possibility of overlapping between rules, as can be observed in the rules for the blue target value.

3. Subgroup discovery

The SD was introduced by Kloesgen (Kloesgen, 1996) and Wrobel (Wrobel, 1997). Its objective is to discover interesting relationships between different objects in a set with respect to a property of interest. The patterns extracted are normally represented through rules (Gamberger and Lavrac, 2002), such as:

$$R = Class \leftarrow Cond$$

where *Cond* is a conjunction of attribute-value pairs and *Class* the property of interest. These patterns were called subgroups by Siebes (Siebes, 1995).

There is no consensus within SD about the use of a concrete quality measure, however the weighted accuracy relative (*WRAcc*) is the one most employed in the literature. This quality measure was defined as (Lavrac et al., 1999):

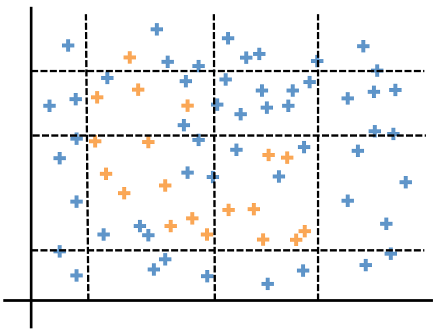
$$\begin{aligned} &WRAcc(Class \leftarrow Cond) = \\ &p(Cond) \cdot (p(Class|Cond) - p(Class)) \end{aligned} \tag{1}$$

where a balance between generality, precision and gain accuracy is considered.

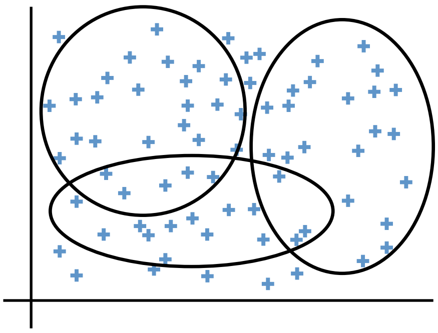
From the inception of the SD concept in 1996 there has been a wide application, especially in the last decades with the appearance of different approaches and applications in real-world problems. In fact, in (Herrera et al., 2011) a complete review of SD, its algorithms and applications was presented in order to show the community its importance; and recently, some reviews one focused on evolutionary algorithms (Carmona et al., 2014), another focused on exhaustive algorithms (Atzmueller, 2015), and in a empirical evaluation (Helal, 2016), have been presented.

In summary, SD algorithms can be classified according to the search algorithm employed in order to obtain rules, such as:

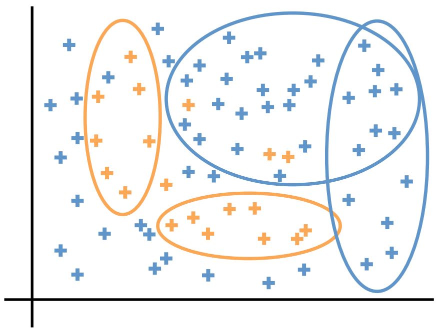
1. *Heuristic algorithms*: Within this group can be found CN2-SD (Lavrac et al., 2004), which is one of the exponent within SD, and the pioneering approaches EXPLORA (Kloesgen, 1996) and MIDOS (Wrobel, 1997). On the other hand, there are a large number of approaches based on soft computing techniques such as NMEEFSD (Carmona et al., 2010a), amongst others (Carmona et al., 2015, del Jesus et al., 2007a,b, Luna et al., 2013, Pachón et al., In Press, Rodríguez et al., 2012). Recently, a new evolutionary fuzzy system for big data environments has been presented in (Pulgar-Rubio et al., 2017) or for example, SDIGA (del Jesus et al., 2007b), MESDIF (del Jesus et al., 2007a), FuGePSD (Carmona et al., 2015), G3P (Luna et al., 2013), EDER-SD (Rodríguez et al., 2012), or GAR-SD (Pachón et al., In Press)



(a) Classification model



(b) Clustering model



(c) Supervised Descriptive Rule Model

Figure 1: Representation of data mining techniques with different types of induction

amongst others. Recently, a new evolutionary fuzzy system for big data environments called MEFASD-BD has been presented in (Pulgar-Rubio et al., 2017).

2. *Exhaustive algorithms*: In this group the most relevant algorithms are the Apriori-SD (Kavsek and Lavrac, 2006) and the SD-Map (Atzmueller and Puppe, 2006), although there are other interesting approaches such as Merge-SD (Grosskreutz and Rueping, 2009), CG (Zimmerman and de Raedt, 2009) or GP-Growth (Lemmerich et al., 2012). In addition, within this group, there are some algorithms that are able to work with numerical target variables such as SD-Map$*$ (Atzmueller and Lemmerich, 2009) and NumBSD (Lemmerich et al., 2016).

In the pioneering papers of SD, a wide applicability of the algorithms to different real-world problems such as medicine or bioinformatics was presented (Herrera et al., 2011). In fact, the interesting properties of SD have continued demonstrating its ability to obtain novelty knowledge in such disparate areas as educational data mining (Carmona et al., 2010b, 2011, Poitras et al., 2016a), bioinformatics and medicine (Carmona et al., 2015, Lavrac and Kralj-Novak, 2013, Liu et al., 2015, Poitras et al., 2016b), industry and technology (Almeida and Soares, 2013, Carmona et al., 2013, Jin et al., 2014, Konijn et al., 2013) or commerce (Brito et al., 2015, Carmona et al., 2012, Gamberger et al., 2013, Rodríguez et al., 2012, 2013), for example.

4. Emerging patterns

The EPs were defined by Dong and Li (Dong and Li, 1999, 2005) as itemsets whose support increases significantly from one dataset (D_1) to another (D_2) in order to discover trends in data, time or differentiating between features. In this way, a pattern is emerging if it has a growth rate (GR) higher than one and it is defined as (Dong and Li, 1999):

$$GR(x) = \begin{cases} 0, & IF\ Supp_{D_1}(x) = Supp_{D_2}(x) = 0, \\ \infty, & IF\ Supp_{D_2}(x) = 0 \wedge \\ & \quad Supp_{D_1}(x) \neq 0, \\ \dfrac{Supp_{D_1}(x)}{Supp_{D_2}(x)}, & another\ case \end{cases} \tag{2}$$

where $Supp_{D_1}(x)$ is the support for the pattern x in the first dataset and $Supp_{D_2}(x)$ is the support with respect to the second dataset, i.e. $Supp_{D_1}(x) = \dfrac{count_{D_1}(x)}{|D_1|}$ and $Supp_{D_2}(x) = \dfrac{count_{D_2}(x)}{|D_2|}$.

These patterns can be associated to datasets with classes and they are usually represented as pairs with a variable (Var) and a value ($value$) for this variable. Pairs are connected through conjunctions such as (Dong and Li, 1999):

$$x = \{Var_1 = value_1\}, \ldots, \{Var_n = value_n\}$$

The search space is related directly to the complexity of the dataset and in this way the number of EPs obtained by one algorithm could become huge. Throughout the literature there have been attempts to filter the number of patterns extracted with the use of different concepts or filtering operators such as jumping EPs (Dong et al., 1999a), essential EPs (Fan and Ramamohanarao, 2002), strong EPs (Fan and Ramamohanarao, 2006), maximal EPs (Wang et al., 2005) or noisy EPs (Fan and Ramamohanarao, 2006), negative EPs (Terlecki and Walczak, 2007), chi EPs (Fan and Ramamohanarao, 2004), shared EPs (Chen and Zhang, 2013), fuzzy EPs (García-Borroto et al., 2011), or disjunctive EPs (Vimieriro and Moscato, 2014), amongst others.

These concepts have been joined with different search strategies in order to obtain efficient EPs. In summary, the algorithms for extracting EPs can be grouped into:

- *Algorithms based on borders*: A border defines a pair of minimal and maximal patterns $< L, R >$ in order to represent all the patterns within this border (Dong and Li, 1999). Each element of L is a subset of some element in R and each element of R is a superset of some element in L. The pioneering algorithms of EPs employ this concept in order to discover all the EPs of a problem, for example, DeEPs (Li et al., 2004), CAEP(Dong et al., 1999b), BCEP (Ramamohanarao and Fan, 2007) and JEPC algorithm (Ramamohanarao et al., 2001).

- *Algorithms based on trees:* These algorithms employ this type of structure in order to optimise the complexity related to the search space with the border concept. Within this group there are two different subtypes: trees used to mine association rules such as Strong-JEP (Fan and Ramamohanarao, 2006), Tree-based JEP (Bailey et al., 2002), Top-k minimals JEP (Terlecki and Walczak, 2008), DCGP-Tree (Liu et al., 2014), or DFP-SEPSF (Alvai and Hashemi, 2015). On the other hand, there is another group of algorithms based on decision trees such as Fuzzy-EP (García-Borroto et al., 2011) and LCMine (García-Borroto et al., 2010).

- *Evolutionary approaches:* Only one preliminary proposal has been presented in (García-Vico et al., 2016), the EvAEP algorithm which is an evolutionary fuzzy system for extracting EPs.

A complete review of these strategies is presented in (García-Borroto et al., 2014). As can be observed, the use of EPs is mainly focused on the classification task because this type of methodology has a very interesting differentiating character in spite of the fact that the EP concept was defined for descriptive problems. In recent years, there has been increasing interest in the analysis of real-world problems based on EPs from a predictive point of view such as streaming data (Akhriza et al., 2015, Alavi and Hashemi, 2014, Park et al., 2010, Yu et al., 2015, 2012), sequential data (Barreto and Antunes, 2014, Desai and Ganatra, 2015, Nofong et al., 2014), technology (Acosta-Mendoza et al., 2016, Ding et al., 2010, Gu et al., 2011a,b, Kobylinski and Walczak, 2010, Li and Zhou, 2016, Yu et al., 2014a,b) and bioinformatics (Asses et al., 2012, Chen and Chen, 2011, Gardiner and Gillet, 2015, Loglisci et al., 2015, Métivier et al., 2015, Sherhod et al., 2013, 2012, Tzanis et al., 2011), amongst others.

5. Contrast sets

The CS technique was defined by Bay and Pazzani (Bay and Pazzani, 2001) as finding patterns as conjunctions of attributes and values that differ meaningfully in their distributions across groups (G_1, G_2, ..., G_i). It is important to remark that the groups must be exclusive among them, i.e. the instances can only belong to one group.

A pattern (x) is considered as CS if there is a significant difference of support (DS) between the support of the groups (Bay and Pazzani, 2001):

$$\begin{array}{l} \exists_{ij} \ where \ P(x = True \mid G_i) \ \neq \ P(x = True \mid G_j) \\ DS(x) = max_{ij} \ |Sup(x, G_i) - Sup(x, G_j)| \ \geq \ \delta \end{array} \quad (3)$$

where $Sup(x, G_i)$ is the support for the pattern x in the i^{th} group and $Sup(x, G_j)$ for the j^{th} group. The δ value is the minimum threshold (minimum difference needed) in order to consider a pattern as contrast. The 0.10 value is usually employed.

The CSs are represented as conjunctions of pairs variable-value ($Var = value$) such as (Bay and Pazzani, 2001):

$$x = \{Var_1 = value_1\} \wedge \ldots \wedge \{Var_n = value_n\}$$

CSs have traditionally been the least extensive task within SDRD. Nonetheless, there is a large number of algorithms throughout the literature (Boettcher, 2011). With respect to the algorithms presented, they can be classified into:

- *Algorithms based on trees:* Within this group are the more well-known in CSs such as STUCCO (Bay and Pazzani, 2001), CIGAR (Hilderman and Peckham, 2005, 2007) and Magnum-Opus (Webb et al., 2003). In (Webb, 2007) different concepts were presented in order to improve the quality of the patterns extracted in these algorithms such as productivity or the importance of avoiding false discoveries. Other approaches with tree structures are (Morita et al., 2009, Simeon and Hilderman, 2007, 2011a,b, Simeon et al., 2012, Zhu et al., 2015).

- *Approaches based on association rules:* The most relevant algorithm within this group is the algorithm RCS (Azevedo, 2010). It employs statistical tests and a pruning procedure based on preservation of support in order to obtain the most significant patterns.

The search for CSs in real-world problems has not been extended in the literature and it has been focused mainly on medicine (Kralj-Novak et al., 2009a, Li and Yang, 2007, Reps et al., 2015), enterprises (Wei et al., 2013) and social studies (Magalhaes and Azevedo, 2015). However, it is very important to note the existing relations between CS and other very close (although relatively novel) concepts, such as change mining (Liu et al., 2001), discriminative patterns (Fang et al., 2012, He et al., 2017, Kameya and Sato, 2012), correlated pattern (Morishita and Sese, 2000), closed sets (Garriga et al., 2008) and collaborative patterns (Zhu et al., 2011), amongst others.

6. Compatibilities of concepts and terms for supervised descriptive rule discovery tasks

All of these different techniques grouped by SDRD concept were developed in different communities, each developing their own terminology. However, CSs, EPs and SD show that terms used in different communities are compatible, according to the their definitions. These compatibilities were defined in (Kralj-Novak et al., 2009b):

Specifically, Table 1 provides a dictionary of equivalent terms from CSs, EPs and SD, in a unifying terminology of classification rule learning, and in particular of concept learning (considering class C_i as the concept

Table 1: Table of synonyms from different communities, showing the compatibility of terms

Contrast Sets	Emerging Patterns	Subgroup Discovery	Rule Learning
contrast set	itemset	subgroup description	rule condition
groups $G_1, \dots, G_n$	datasets D_1 and D_2	class/property C	class/concept C_i
attribute value pair	item	binary feature	condition
examples in groups	transactions in datasets	examples	examples of $C_1, \dots, C_n$
examples for which the CS is true	transactions containing the itemset	subgroup of instances	covered examples
support of CS on G_i and G_j	support of EP in D_1 and D_2	true/false positive rate	true/false positive rate

to be learned from the positive examples of this concept, and the negative examples formed of examples of all other classes).

Once, we have established the compatibility among the terminologies, now it is provided the similarities between the definitions of these techniques. As we have defined previously:

- **CSs**. Let $A_1, A2, \dots, A_k$ be a set of k variables called attributes. Each A_i can take values from the set $\{v_{i1}, v_{i2}, \dots, v_{im}\}$. Given a set of user defined groups $G_1, G_2, \dots, G_n$ of data instances, a contrast set is a conjunction of attribute-value pairs, defining a pattern that best discriminates the instances of different user-defined groups. A special case of contrast set mining considers only two contrasting groups (G_1 and G_2). In such cases, we wish to find characteristics of one group discriminating it from the other and vice versa.

- **SD**. A subgroup is described as conjunctions of features. Given the property of interest C, and the population of examples of C and $\overline{C}$, the SD aims at finding population subgroups that are as large as possible and have the most unusual statistical (distributional) characteristics with respect to the property of interest C.

- **EPs**. Let $I = \{i_1, i_2, \dots, i_N\}$ be a set of items (equivalent to a binary feature in SD, and an individual attribute-value pair in CSs). A transaction is a subset T of I. A dataset is a set D of transactions. A subset X of I is called an itemset. Transaction T contains an itemset X in a dataset D, if $X \subseteq T$. For two data sets D_1 and D_2, EPs aims at discovering itemsets whose support increases significantly from one data set to another.

Instead of the definitions appear different we can observe that the goals of these descriptive data mining techniques are similar: *to search for discriminating characteristics, emerging trends and/or subgroup descriptions between different values of a class property*. In this way, there is a compatibility between concepts as can be observed in Table 2.

The knowledge is represented through patterns (x) or rules (R) and in general they are described through pairs attribute-value and a class or target variable. In summary, the rule R can be formally defined as:

$$R : Cond \ \rightarrow \ Class$$

$Cond$ is the conjunction of features (attribute-value pairs), and $Class$ is a value for the variable of interest or class. This $Class$ is represented through G_1, D_1 and C, i.e. the positive examples (P) of the problem, and G_2, D_2 and $\overline{C}$ represents the negative examples (N).

7. Heuristics in supervised descriptive rule discovery tasks

The main quality measures used throughout the literature for the different techniques within the SDRD employ different nomenclatures and it is necessary to homogenize them in order to analyse in a better way. However, most measures are derived by analysing the covering properties of the rule and the class in the rule consequent considered as positive. This relationship can be depicted by a confusion matrix as can be observed in Table 3.

Table 3: Confusion matrix for a rule

	Predicted condition		
True condition	Positive	Negative	
Positive	$p = tp$	$\overline{p} = fn$	$p + \overline{p} = P$
Negative	$n = fp$	$\overline{n} = tn$	$n + \overline{n} = N$
	$p + n$	$\overline{p} + \overline{n}$	$P + N = T$

Table 2: Compatibility of definitions

	CSs	EPs	SD	SDRD
Knowledge	pattern (x)	pattern (x)	subgroup (R)	rule (R)
Cond	itemsets	itemsets	pairs att-val	pairs att-val
Class	$G_1, \ldots, G_i$	D_1, D_2	$C, \overline{C}$	P, N

The confusion matrix for a rule represents the following information:

- p number of examples correctly covered,
- $\overline{p}$ number of examples for the class not covered,
- n number of examples incorrectly covered,
- $\overline{n}$ number of examples not covered for the non-class,
- $p + n$ number of examples covered for the rule,
- $\overline{p} + \overline{n}$ number of examples not covered for the rule, and
- $P = p + \overline{p}$ number of examples for the positive class. Examples containing a concrete value for the target variable are considered.
- $N = n + \overline{n}$ number of examples for the negative class. Examples for the remaining values of the target variable are included.
- $T = P + N$ number of examples for the whole dataset.

Next, the original quality measures presented in the pioneering papers for each approach are shown:

- Contrast Sets:

$$DS(x) = max_{ij} \ |Sup(x, G_i) - Sup(x, G_j)| \ \geq \ \delta \tag{4}$$

- Emerging Patterns:

$$GR(x) = \frac{supp_{D1}(x)}{supp_{D2}(x)} \tag{5}$$

- Subgroup Discovery:

$$WRAcc(Class \leftarrow Cond) = p(Cond) \cdot (p(Class|Cond) - p(Class)) \tag{6}$$

As can be observed, there are different nomenclatures for each one but nevertheless they employ very close concepts. Next, we present the quality measures modified with the use of the matrix presented in Table 3:

- Contrast Sets:

$$\begin{aligned} DS(R) &= |Sup(R, PIS) - Sup(R, NIS)| \ \geq \ \delta \\ DS(R) &= \left|\frac{p}{P} - \frac{n}{N}\right| \ \geq \ \delta \end{aligned} \tag{7}$$

- Emerging Patterns:

$$\begin{aligned} GR(R) &= \frac{Sup(R, PIS)}{Sup(R, NIS)} \\ GR(R) &= \frac{\frac{p}{P}}{\frac{n}{N}} > 1 \end{aligned} \tag{8}$$

- Subgroup Discovery:

$$\begin{aligned} WRAcc(R) &= p(Cond) \cdot (p(Class \cdot Cond) - p(Class)) \\ WRAcc(R) &= \frac{p+n}{P+N}\left(\frac{p}{p+n} - \frac{P}{P+N}\right) \end{aligned} \tag{9}$$

These equations present some interesting assertions regarding the possible future study and analysis of the different techniques from different point of view:

1. The GR and the DS are directly related because when the DS is positive the GR is upper than one. In this way, we could confirm that a CSs is emerging, but an EPs is contrasting rule only when the differences between the positives rate and negative rate is upper than α.
2. The $WRAcc$ is a more complicated quality measure but it is interesting to see that the value of this measure is positive when the accuracy of the rule is upper than the percentage of the examples of the class.

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