Mining Surgical Meta-actions Effects with Variable Diagnoses' Number

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Abstract. Commonly, information systems are organized by the use of tables that are composed of a fixed number of columns representing the information system's attributes. However, in a typical hospital scenario, patients may have a variable number of diagnoses and this data is recorded in the patients' medical records in a random order. Treatments are prescribed based on these diagnoses, which makes it harder to mine meta-actions from healthcare datasets. In such scenario, the patients are not necessarily followed for a specific disease, but are treated for what they are diagnosed for. This makes it even more complex to prescribe personalized treatments since patients react differently to treatments based on their state (diagnoses). In this work, we present a method to extract personalized meta-actions from surgical datasets with variable number of diagnoses. We used the Florida State Inpatient Databases (SID), which is a part of the Healthcare Cost and Utilization Project (HCUP) [1] to demonstrate how to extract meta-actions and evaluate them.

Keywords: Meta-actions, Actionable rules, Surgical treatments.

1 Introduction

Meta-actions are a higher level concept used to model a generalization of action rules [2]. They are actions taken by deciders to trigger transitions in some flexible attributes' values. Those transitions will eventually cascade to a change in values of some decision feature to model an action rule. In other words, action rules are specialized meta-actions that are associated with a decision attribute value transition. Meta-actions are commonly used to acquire knowledge about possible transitions in the information system and their causes. This knowledge is used to trigger action rules.

Meta-actions are commonly used in the healthcare, business, and social media domains. In the healthcare arena, meta-actions represent treatments prescribed by doctors to their patients. In this paper, we are mining meta-actions' effects to discover surgical treatment effects on patients.

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Meta-actions were first introduced in [3] as role models to mine actionable patterns, then formally defined by Raś et. al and used to discover action rules based on tree classifiers in [4]. They were also used to personalize action rules based on patients side effects in [5]. In these papers, the authors assumed that meta-action effects and their side effects are known. In addition, meta-actions were mined in [6] for action rules personalization and reduction based on a utility function; however, they were mined from traditional information systems with a fixed number of attributes. There are multiple techniques to mine action rules [7,8,9] and actionable patterns [10]; however, mining meta-actions directly from information systems with variable number of attributes was not studied in earlier work. In this paper, we present a meta-actions mining technique for datasets with variable number of attributes, and we apply this work for non-traditionally structured (varied number of attributes for objects in the system) healthcare dataset models.

2 Preliminaries

Data is commonly represented statically in an information system. In this section, we will present the static data model and define the action model.

2.1 Static Representation

In this section, we give a brief description of how static data is represented and stored in information systems. We also describe the state of an object in the context of information systems.

Definition 1 (Information System). *By information system [11] we mean a triple of the form $S = (X, A, V)$ where:*

1. *X is a nonempty, finite set of objects.*
2. *A is a nonempty, finite set of attributes of the form $a : X \to 2^{V_a}$, which is a function for any $a \in A$, where V_a is called the domain of a.*
3. *V is a finite set of attribute values such as: $V = \bigcup\{V_a : a \in A\}$.*

If $a(x)$ is a singleton set, then $a(x)$ is written without parentheses (for instance, $\{v\}$ will be replaced by v). Table 1 represents an information system S with a set of objects $X = \{x_1, x_2, x_3, x_4, x_5\}$, a set of attributes $A = \{a, b, c, d\}$, and a set of attribute values $V = \{a_1, a_2, b_1, b_2, b_3, c_1, c_2, c_3, d_1, d_2\}$.

In practice, data is not commonly well organized, and information systems may not only have multivalued attributes but also missing data and/or variable number of attributes. To simplify the concept of objects with variable number of attributes and attributes with several values, we introduce the notion of object state and we define it as follows:

Definition 2 (Object State). *An object state of $x \in X$ is defined by the set of attributes A_x that the object x is characterized by, and their respective values $A(x) = \bigcup\{a(x) : a \in A_x\}$*

Table 1. Information System Example

	a	b	c	d
x_1	a_1	b_2	c_2	d_1
x_2	a_2	b_2	c_2	d_2
x_3	a_2	b_1	c_3	d_1
x_4	a_1	b_3	c_1	d_2
x_5	a_2	b_1	c_1	d_1

2.2 Actions Representation

In this section, we will define a few concepts that will help us represent actionable data with regards to an information system. Those concepts will be used in the following section to define meta-action effects and their extraction.

Definition 3 (Stable Attributes). *Stable attributes are object properties that we do not have control over in the context of an information system. In other words, actions recommending changes of these attributes will fail. For example, a birth date is a stable attribute.*

This type of attribute is not used to model actions since their values do not change. They are commonly used to cluster the dataset.

Definition 4 (Flexible Attributes). *Flexible attributes are object properties that can transition from one value to another triggering a change in the object state. For instance, salary and benefits are flexible attributes since they can change values.*

Flexible attributes are the only possible attributes that can inform us about the possible changes an object may go through. However, to model possible actions, values transition of attribute, we need another concept which is defined as:

Definition 5 (Atomic Action Terms). *Atomic action term, also called elementary action term in S, is an expression that defines a change of state for a distinct attribute in S.*

For example, $(a, v_1 \to v_2)$ is an atomic action term which defines a change of value for the attribute a in A from v_1 to v_2, where $v_1, v_2 \in V_a$. In the case when there is no change, we omit the right arrow sign, so for example, (a, v_1) means that the value of attribute a in A remains v_1, where $v_1 \in V_a$. We use atomic action terms to model a single attribute value transition; however, to model transitions for several attributes, we use Action Terms defined as:

Definition 6 (Action Terms). *Action terms are defined as the smallest collection of expressions for an information system S such that:*

- *If t is an atomic action term in S, then t is an action term in S.*
- *If t_1, t_2 are action terms in S and $\wedge$ is a 2-argument functor called composition, then $t_1 \wedge t_2$ is a candidate action term in S.*
- *If t is a candidate action term in S and for any two atomic action terms $(a, v_1 \to v_2), (b, w_1 \to w_2)$ contained in t we have $a \neq b$, then t is an action term in S.*

3 Meta-actions

In order to move objects from their current population state to a more desirable population state, deciders need to acquire knowledge on how to perform the necessary changes in objects' state. For instance, moving a patient from the sick population state to the healthy population state requires the practitioner to use a treatment such as a surgery. This actionable knowledge is represented by meta-actions that are defined as follows:

Definition 7 (Meta-actions). *Meta-actions associated with an information system S are defined as higher level concepts used to model certain generalizations of actions rules [3]. Meta-actions, when executed, trigger changes in values of some flexible attributes in S.*

Let us define $\mathbf{M}(S)$ as a set of meta-actions associated with an information system S. Let $a \in A$, $x \in X$, and $M \subset \mathbf{M}(S)$, then, applying the meta-actions in the set M on an object x will result in $M(a(x)) = a(y)$, where object x is converted to object y by applying all meta-actions in M to x. Similarly, $M(A(x)) = A(y)$, where $A(y) = \{a(y) : a \in A\}$ for $y \in X$, and object x is converted to object y by applying all meta-actions in M to x for all $a \in A$.

The changes in flexible attributes, triggered by meta-actions, are commonly represented by action terms for the respective attributes, and reported by an influence matrix presented in [3]. However, when an information system contains multivalued attributes where each attribute takes a set of values at any given object state and transitions to another set of values in a different object state, it is better to represent the transitions between the attribute initial set of values and another set of values by action sets that are defined as:

Definition 8 (Action Set). *An action set in an information system S is an expression that defines a change of state for a distinct attribute that takes several values (multivalued attribute) at any object state.*

For example, $\{a_1, a_2, a_3\} \rightarrow \{a_1, a_4\}$ is an action set that defines a change of values for attribute $a \in A$ from the set $\{a_1, a_2, a_3\}$ to the set $\{a_1, a_4\}$ where $\{a_1, a_2, a_3, a_4\} \subseteq V_a$. Action sets are used to model meta-action effects for information systems with multivalued attributes. In addition, action sets' usefulness is best captured by the set intersection that models neutral action sets and set minus that models positive action sets between the two states involved. In the previous example, neutral and positive action sets are respectively computed as follows: $\{a_1, a_2, a_3\} \rightarrow [\{a_1, a_2, a_3\} \cap \{a_1, a_4\}]$ and $\{a_1, a_2, a_3\} \rightarrow [\{a_1, a_2, a_3\} \setminus \{a_1, a_4\}]$.

In this paper, we are studying surgical meta-action effects that trigger a change in the patients' state. The patients are in an initial state where the meta-actions are applied and move to a new posterior state. We use the set minus (positive action set) between two patients' states to observe the diagnoses that disappeared as a positive effect of applying meta-actions in the initial state.

Furthermore, we use set intersection (neutral action set) to observe the diagnoses that remain the same; in other words, meta-actions applied had a neutral effect on these diagnoses. This type of information concerning meta-actions is represented by an ontology (personalized) [12]. For instance, the example shown in Figure 1 models a meta-action composed of positive action sets which are labeled *positive* and neutral action sets which are labeled *neutral*. In addition, *positive* and *neutral* are composed of action sets respectively labeled $\underline{As_n}$ and $\overline{As_n}$, which in turn are composed of diagnoses labeled Dx_n.

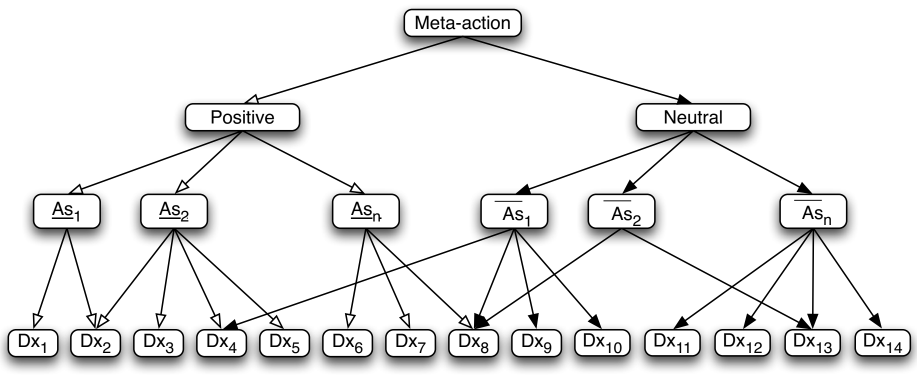

Fig. 1. Ontology Representation of a Meta-action

4 Meta-action Extraction

Meta-actions effects in the context of healthcare represent the patient's state transition from an initial state to a different state. Those effects are mined from large datasets for each patient separately then merged together based on their common subsets to form state transition patterns. In other words, each patient's state is extracted from a uniquely identified transaction and patients' visit transactions are clustered by the patients' identifier. In this paper, each state transaction for a patient represents a doctor consultation (patient visit to the doctor).

For each patient cluster, each transactions should be ordered based on temporal sequential order. Every two consecutive patient's transactions will be paired for every meta-action based on a temporal precedence relationship. The resulting pairwise partition will model the effects of the meta-actions taken.

Given real life data representation in an information system, we defined two methods to extract meta-actions effects. The first methods was defined in [6] and is used to extract meta-actions effects from traditional informations systems. In this method, since each attribute has a different meaning and a single value at any given object state in the information system, meta-actions effects are represented with action terms and saved in an influence matrix to be used by practitioners. The second method is defined in this section and used to extract meta-actions effects from information systems with variable number of attributes and multivalued attributes. This method is best suited for the surgical meta-actions mining problem since patients are diagnosed with several diagnoses at any consultation and have a different number of diagnoses.

4.1 Extracting Meta-actions with Variable Number of Attributes

Let us assume that $\mathbf{M}(S)$, where $S = (X, A, V)$, is a set of meta-actions associated with an information system S. In addition, we define the set $T = \{v_{i,j} : j \in J_i,\ x_i \in X\}$ of ordered transactions, patient visits, such that $v_{i,j} = [(x_i, A(x_i)_j)]$. The set $A(x_i)_j$ is defined as the set of attribute values $\{a(x_i) : a \in A\}$ of the object x_i for the visit uniquely represented by the visit identifier j. Each visit represents the current state of the object (patient) when recorded with respect to a temporal order based on j for all $v_{i,j} \in T$. For any particular visit, the patient state is characterized by a set of diagnoses. Each diagnosis is seen as an attribute, and each visit may have a different number of diagnoses.

For each patient's two consecutive visits $(v_{i,j}, v_{i,j+1})$, where meta-actions were applied at visit j, we can extract an action set. Let us define the set $P(S)$ of patient's two consecutive visits as $P(S) = \{(v_{i,j}, v_{i,j+1}) :\ x_i \in X, j \in J_i\}$. The corresponding action sets are: $\{(A(x_i)_j \rightarrow A(x_i)_{j+1}) :\ x_i \in X, j \in J_i\}$. We also define neutral action sets noted as $\overline{AS}$, and positive action sets noted as $\underline{AS}$. These action sets are: $\{(A(x_i)_j \rightarrow (A(x_i)_j \cap A(x_i)_{j+1})) :\ x_i \in X, j \in J_i\}$ and $\{(A(x_i)_j \rightarrow (A(x_i)_j \setminus A(x_i)_{j+1})) :\ x_i \in X, j \in J_i\}$ correspondingly, where $A(x_i)_j$ represents the set of diagnoses for a patient x_i at visit j.

The action sets resulting from the application of meta-actions represent the actionable knowledge needed by practitioners. However, patients do not have the same preconditions and do not react similarly to the same meta-actions. In other words, some patients might be partially affected by the meta-actions and might have other side effects not intended by the practitioners. For this reason, we need to extract the historical patterns in action sets. Let us assume that $\overline{as}_{i,j} = A(x_i)_j \cap A(x_i)_{j+1}$ and $\underline{as}_{i,j} = A(x_i)_j \setminus A(x_i)_{j+1}$, for any $x_i \in X$ and $j \in J_i$. Now, we define some properties for both the neutral and positive action sets extracted as follows:

1. $(\forall W)[W \subset \overline{as} \Rightarrow \overline{W} \in \overline{AS}]$
2. $(\forall W)[W \subset \underline{as} \Rightarrow \underline{W} \in \underline{AS}]$
3. $(\forall x_i \in X)(\forall j \in J_i)[\overline{as}_{i,j} \cup \underline{as}_{i,j} \subseteq A(x_i)_j]$
4. $(\forall x_i \in X)(\forall j \in J_i)[\overline{as}_{i,j} \cap \underline{as}_{i,j} = \emptyset]$

From the property number 1 and 2, given that any subset of an action set is an action set of the same meta-action, we can extract all action sets present in any pair of patient's visits using power sets. Let us define $\overline{P_{i,j}}$ as the power set of neutral action set $\overline{as_{i,j}}$ such that $\overline{P_{i,j}} \in \overline{AS}$. Similarly, we can define the set $\underline{P_{i,j}}$ as power set of positive action set $\underline{as_{i,j}}$ such that $\underline{P_{i,j}} \in \underline{AS}$. Hence, we can have all possible action sets composing a meta-action using power sets.

4.2 Meta-actions and Action Set Evaluation

To evaluate these actions set patterns, we need to compute their frequency of occurrence for all patients. A good measure of frequency is the support and it is seen here as the likelihood of the occurrence for a specific action set (set of diagnoses disappearing or remaining). The likelihood $Like(\overline{as})$ of a neutral action set $\overline{as}$ is defined as follows:

$$Like(\overline{as}) = card(\{(v_{i,j}, v_{i,j+1}) \in P(S) : \ \overline{as} \in \overline{P_{i,j}}\}) \tag{1}$$

The likelihood $Like(\underline{as})$ of a positive action set $\underline{as}$ is defined as follows:

$$Like(\underline{as}) = card(\{(v_{i,j}, v_{i,j+1}) \in P(S) : \ \underline{as} \in \underline{P_{i,j}}\}) \tag{2}$$

The likelihood support of action sets measures the likelihood of attributes being affected by the meta-actions applied, but it does not give a sense of how confident is the action set. A more sophisticated way to evaluate action sets is by computing their likelihood confidence. The intuition behind the action set confidence lies in the normalization of the action set with regards to the patient's precondition. The likelihood confidence of a neutral action set $\overline{as}$ is computed as follows:

$$ActionConf(\overline{as}) = \frac{Like(\overline{as})}{card(\{v_{i,j} : \ \overline{as} \subseteq A(x_i)_j, \ \forall x_i \in X\})} \tag{3}$$

The likelihood confidence of a positive action set $\underline{as}$ is computed as follows:

$$ActionConf(\underline{as}) = \frac{Like(\underline{as})}{card(\{v_{i,j} : \ \underline{as} \subseteq A(x_i)_j, \ \forall x_i \in X\})} \tag{4}$$

Depending on the objects' states, some of the action sets in AS may not be triggered by meta-actions. To be more precise, for a given meta-action m, only objects $x_l \in X$ that satisfy the following condition will be affected:

$(\exists (v_{i,j}, v_{i,j+1}) \in P(S))(\exists v_{l,k} \in T)[A(x_l)_k \cap A(x_i)_j \neq \emptyset]$

Given the action sets composing a meta-action m, we can define the global confidence of m as the weighted sum of its action sets likelihood confidences where the weights represent action sets likelihood support. The intuition behind the meta-action confidence is in defining how efficient is the application of a meta-action for any patient's precondition. The meta-action confidence $MetaConf(m)$ is computed for both neutral and positive action sets as follows:

$$MetaConf(m) = \frac{\sum_{i=1}^{n} Like(as_i) \cdot ActionConf(as_i)}{\sum_{i=1}^{n} Like(as_i)} \tag{5}$$

where n is the number of action sets in m.

5 Experiments

5.1 Dataset Description

In this paper, we used the Florida State Inpatient Databases (SID) that is part of the Healthcare Cost and Utilization Project (HCUP) [1]. The Florida SID dataset contains records from several hospitals in the Florida State. It contains over 2.5 million visit discharges from over 1.5 million patients. The dataset is composed of five tables, namely: AHAL, CHGH, GRPS, SEVERITY, and CORE. The main table used in this paper is the *Core* table. The *Core* table contains over 280 attributes; however, many of those attributes are repeated with different codification schemes. In the following experiments, we used the Clinical Classifications Software (CCS) that consists of over 260 diagnosis categories, and 231 procedure categories. In our experiments, we used fewer attributes that are described in this section. Each record in the Core table represents a visit discharge. A patient may have several visits in the table. One of the most important attributes of this table is the $VisitLink$ attribute, which describes the patient's ID. Another important attribute is the Key, which is the primary key of the table that identifies unique visits for the patients and links to the other tables. As mentioned earlier, a $VisitLink$ might map to multiple Key in the database. This table reports up to 31 diagnoses per discharge as it has 31 diagnosis columns. However, patients' diagnoses are stored in a random order in this table. For example, if a particular patient visits the hospital twice with heart failure, the first visit discharge may report a heart failure diagnosis at diagnosis column number 10, and the second visit discharge may report a heart failure diagnosis at diagnosis column number 22. It is worth mentioning that it is often the case where patients examination returns less than 31 diagnoses. The *Core* table also contains 31 columns describing up to 31 procedures that the patient went through. Even though a patient might go through several procedures in a given visit, the primary procedure that occurred at the visit discharge is assumed to be the first procedure column. The *Core* table also contains an attribute called $DaysToEvent$, which describes the number of days that passed between the admission to the hospital and the procedure day. This field is anonymized in order to hide the patients' identity. There are several demographic data that are reported in this table as well such as: race and gender. Table 2 maps the *Core* table features to concepts described in this paper.

Table 2. Mapping Between Attributes and Concepts

Attributes	**Concepts**
VisitLink	Patient Identifier
DaysToEvent	Temporal visit ordering
DXCCSn	n^{th} Diagnosis, flexible attributes
PRCCSn	n^{th} Procedure, meta-actions
Race, Age Range, Gender,..	Stable attributes

5.2 Evaluation

We used our technique to extract meta-actions effects on the Florida SID dataset for several meta-actions. In this paper, we reported the confidence $ActionConf(as)$ and likelihood $Like(as)$ of few action sets for four different meta-actions. You can note from Table 3 that the positive action sets $ActionConf$ is very high, which means that patients' diagnoses disappear after applying meta-actions. In other words, surgeries applied are very successful in curing patients disease. On the other hand, the neutral action sets $ActionConf$ is small, which confirms the assumption that patients react in a consistently different way to meta-actions with regards to attributes that remain unchanged. In addition, the likelihood of neutral action sets extracted is small, which means that very few diagnoses remain unchanged after the surgeries. Table 3 represents the meta-actions (procedures) and action sets elements (diagnoses) with their CCS codification [1].

Table 3. Meta-actions' Action Sets Confidence and Likelihood

Meta-action	**Action set**	**Type**	**ActionConf**	**Likelihood**
34	$\{127, 106\}$	Positive	88.88%	32
	$\{108\}$	Neutral	16.57%	29
43	$\{59, 55, 106]\}$	Positive	85.71%	18
	$\{106\}$	Neutral	11.76%	18
44	$\{62, 106, 55\}$	Positive	94%	16
	$\{257, 101\}$	Neutral	15.62%	10
45	$\{59, 55\}$	Positive	89%	33
	$\{58\}$	Neutral	14.97%	28

In addition, we report in Figure 2 the meta-action confidence for 15 different meta-actions. We show in Figure 2 that the meta-actions are consistently successful for all their action sets regardless of the patients preconditions for these meta-actions. Figure 2 shows meta-actions with their CCS codes [1].

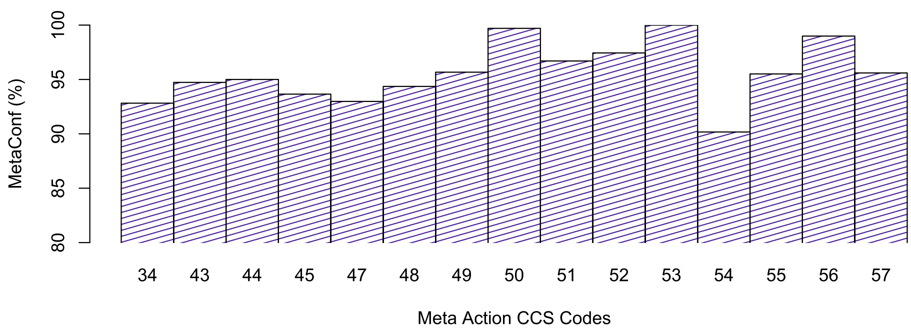

Fig. 2. Meta-action Confidence for Surgical Treatments

6 Conclusion

Mining surgical meta-actions is a hard task because patients may react differently to meta-actions applied, and surgery outcomes are different from one patient to another. In this paper, we presented a meta-action effects mining technique for surgical datasets with variable number of diagnoses (multivalued attributes). Furthermore, we presented the ontology representation of meta-action effects, and used the SID dataset that is part of HCUP to demonstrate the usefulness of our methodology in comparison with the action terms based techniques.

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