Risk Mediation in Association Rules: Application Examples

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RISK MEDIATION IN ASSOCIATION RULES: APPLICATION EXAMPLES

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Abstract. *This technical report presents example cases for the algorithm introduced in our paper Risk Mediation in Association Rules: The Case of Decision Support in Medication Review.*

Keywords: Association Rules, Decision Support, Risk Management

1 INTRODUCTION

This technical report is meant to be read in conjunction with our paper *Risk Mediation in Association Rule Mining: The Case of Medication Reviews* (Meulendijk, Spruit, & Brinkkemper, 2017). This report provides examples of the algorithm introduced in that paper.

2 APPLICATION

With the risk model validated in the domain of medication review in primary care, its application can be discussed. Rules with high impact and high confidence, and those with low impact and low confidence, can be considered for risk assessment. These two scenarios are illustrated with implemented examples from STRIPA. In Figure 1 it is clearly illustrated how generic decisions, taken with domain-dependent values, can be followed to determine whether or not an association rule can be safely inferred.

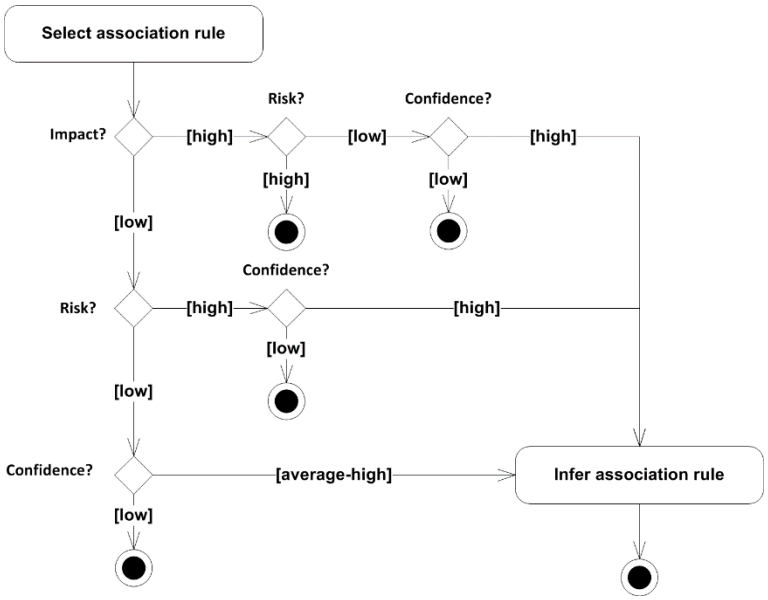

Figure 1. Activity diagram illustrating the generic conditions with domain-dependent values that determine whether or not an association rule can be safely inferred.

2.1 High Impact and High Confidence Rules

Among the most prominent reasons the authors considered risk a promising concept to use in conjunction with association rules, are their limitations in precarious domains. Implementing association rules by automatically following up on their consequences may lead to dangerous situations. In the case of STRIPA, association rules were discovered with potentially far-reaching implications, where risk assessment was needed in determining their implementation and presentation. Association rules in this domain can be formulated as follows:

$$cause_1 \cup \ldots cause_n \xrightarrow{confidence} prescribe(drug) \quad (1)$$

An advice suggesting ace inhibitors for patients suffering from heart failure was followed up on in 61% of the cases:

$$heart\ failure \xrightarrow{0.61} prescribe(ace\ inhibitor) \quad (2)$$

Similarly, a recommendation for a vitamin D-supplement for elderly patients with osteoporosis was heeded in 59% of the cases:

$$age > 65 \cup osteoporosis \xrightarrow{0.59} prescribe(vitamin\ D) \quad (3)$$

These association rules could be presented to the user in a variety of ways for patients matching the criteria. In the recommender system's user interface they could take the form of open suggestions, modal dialogs prompting a response, or even undoable prescriptions. Combining the rules' confidence with risk assessment aids in determining an appropriate implementation option.

Vitamin D-supplements do not have any known side effects associated with them, whereas for ace inhibitors a number of rare and very rare side effects have been reported, leading to a risk outcome for

the latter drug of $(5 * 0.1) + (10 * 0.01) = 0.6$. When prescribing the default dose, the toxicity factor can be discarded.

When incorporating these values, vitamin D-supplements are safer to prescribe in a more automated fashion than ace inhibitors. The complete risk model can be used to assess specific patients' risk and the safety of either association rule. For a patient having two risk factors in his or her health record, the risk assessment for the vitamin-D rule would yield: $(1 - 0.59) * (2 + 0) = 0.82$, while the ace inhibitor rule would result in: $(1 - 0.61) * (2 + 0.6) = 1.01$. Using a threshold of 1.0 in STRIPA, for this patient the ace inhibitor-advice was presented as an open suggestion, whereas the vitamin D-rule was shown as a modal dialog, forcing the user to respond.

2.2 Low Impact and Low Confidence Rules

While the previous scenario showed how risk can be used to determine the implementation of rules with high confidence and potentially high impact, it can also be used for rules with opposite characteristics. Rules with little impact and a low confidence level can be employed after passing a risk assessment. In the case of STRIPA, this approach was used in the assignment of drugs to diseases. One of the tasks users have to perform is assigning drugs to diseases for which they have been indicated; paracetamol, for example, will often be prescribed for the treatment of pain. This assignment task could be made more efficient by automatically suggesting frequent drug-disease combinations. Association rules were discovered which revealed which drugs and diseases were often combined:

$$disease \xrightarrow{confidence} assign(drug) \quad (4)$$

The confidence with which this assignment could be inferred varied. The sleeping drug temazepam, for example, was prescribed for anxiety in 66% of the cases:

$$anxiety \xrightarrow{0.66} assign(temazepam) \quad (5)$$

For the same disorder, the antidepressant fluoxetin was prescribed in 66% of cases as well:

$$anxiety \xrightarrow{0.66} assign(fluoxetin) \quad (6)$$

Using only this data to automatically assign these drugs to anxiety is error-prone; in a third of the cases, these drugs were prescribed for other diseases instead. Disregarding the data completely, however, hinders a potentially useful functionality.

This problem, too, could be solved using risk as a mediating factor. Only cases in which the possible implications were low were automatically performed. Temazepam and fluoxetin have risk factors of respectively $(7 * 0.1) + (5 * 0.01) = 0.75$ and $(3 * 0.3) + (12 * 0.01) = 1.02$; incorporating the association rules' probabilities yields risks of 0.25 for the sleeping pill and 0.34 for the antidepressant. Using 0.3 as a tradeoff point in the application, the safer drug of the two (temazepam) was automatically assigned to anxiety, while the riskier one (fluoxetin) was not. Note that in this scenario, patients' risk factors were disregarded, as all drugs being assigned had already been prescribed to them.

3 REFERENCES

Meulendijk, M., Spruit, M., & Brinkkemper, S. (2017). Risk Mediation in Association Rules: The Case of Decision Support in Medication Review. *AIME 2017 16th Conference on Artificial Intelligence in Medicine.* Vienna, Austria.