

# Chapter 6.7

## Cost–Sensitive Learning in Medicine

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### **ABSTRACT**

This chapter introduces cost-sensitive learning and its importance in medicine. Health managers and clinicians often need models that try to minimize several types of costs associated with healthcare, including attribute costs (e.g. the cost of a specific diagnostic test) and misclassification costs (e.g. the cost of a false negative test). In fact, as in other professional areas, both diagnostic tests and its associated misclassification errors can have significant financial or human costs, including the use of unnecessary resource and patient safety issues. This chapter presents some concepts related to cost-sensitive learning and cost-sensitive classification and its application to medicine.

Different types of costs are also present, with an emphasis on diagnostic tests and misclassification costs. In addition, an overview of research in the area of cost-sensitive learning is given, including current methodological approaches. Finally, current methods for the cost-sensitive evaluation of classifiers are discussed.

### **INTRODUCTION**

Data mining and machine learning methods are important tools in the process of knowledge discovery and, in medicine, knowledge is crucial for biomedical research, decision making support and health management.

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Classification methods, an important subject in data mining, can be used to generate models that describe classes or predict future data trends. Their generic aim is to build models that allow predicting the value of one categorical variable from the known values of other categorical or continuous variables. In its generic concept, classification is a common and pragmatic tool in clinical medicine. In fact, it is the basis for deciding for a diagnosis and, therefore, for the choice of a therapeutic strategy. In addition, classification can play an important role in evidence-based medicine as it can be used as an instrument for assessing and comparing results (Bellazzi and Zupan, 2008).

The majority of existing classification methods was designed to minimize the number of errors, but there are many reasons for considering costs in medicine. Diagnostic tests, such as other health interventions, are not free and budgets are limited. In fact, real-world applications often require classifiers that minimize the total cost, including misclassifications costs (each error has an associated cost) and diagnostic test (attribute) costs.

In medicine a *false negative* prediction, for instance failing to detect a disease, can have fatal consequences, while a *false positive* prediction although mostly being less serious (e.g. giving a drug to a patient that does not have a certain disease) can also induce serious safety consequences (e.g. being operated for a non-existing cancer). Each diagnostic test has also a financial cost and this may help us to decide whether to use it or not. It is thus necessary to know both misclassification and tests costs.

Misclassification and test costs are the most important costs, but there are also other types of costs. Cost-sensitive learning is the area of machine learning that deals with costs in inductive learning.

In this chapter we give an overview of different types of costs associated with data used in medical decision making, present some strategies that can be used to obtain cost-sensitive classifiers and discuss current cost-sensitive approaches in more

detail. We also present some techniques to visualize and compare the performance of classifiers over the full range of possible class distributions and misclassification costs. Finally, we conclude and point out some future trends.

## COST-SENSITIVE CLASSIFICATION

Classification is one of the main tasks in knowledge discovery and data mining (Mitchell, 1997). It has been object of study in areas as machine learning, statistics and neural networks. There are many approaches for classification, including decision trees, Bayesian classifiers, neural classifiers, discriminant analysis, support vector machines, and rule induction, among many others.

The goal of classification is to correctly assign examples to one of a finite number of classes. In classification problems the performance of classifiers is usually measured using an *error rate*. The error rate is the proportion of errors detected in all instances and is an indicator of the global classifier performance. A large number of classification algorithms assume that the errors have the same cost and, because of that, are normally designed to minimize the number of errors (the zero-one loss). In these cases, the error rate is equivalent to assigning the same cost to all classification errors. For instance, in the case of a binary classification, false positives and false negatives would have equal cost. Nevertheless, in many situations, each type error may have a different associated cost.

In fact, in the majority of daily situations, decisions have distinct costs, and a bad decision may have serious consequences. It is therefore important to take into account the different costs associated to decisions, i.e., classification costs.

In this context, we may designate *cost-sensitive classification* when costs are ignored during the learning phase of a classifier and are only used when predicting new cases. In the other hand, we may call *cost-sensitive learning* when costs are considered during the learning phase and

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