

# Chapter 20

## Adding Context into Classification Reasoning Based on Good Classification Tests

**Xenia Naidenova**  
*Military Medical Academy, Russia*

### ABSTRACT

*In this chapter, classification reasoning is considered. The concept of good classification test lies in the foundation of this reasoning. Inferring good classification tests from data sets is the inductive phase of reasoning resulted in generating implicative and functional dependencies supporting the deductive phase of reasoning. An algorithm of inferring good classification tests is given with the decomposition of it into subtasks allowing to choose sub-contexts for each obtained dependency and to control sub-contexts during both deductive and inductive phases of classification reasoning.*

### INTRODUCTION

The symbolic methods of machine learning work on objects with symbolic, Boolean, integer, and categorical attributes. With this point of view, these methods can be considered as ones of mining conceptual knowledge. We concentrate on the supervised conceptual learning. Now, the theory of conceptual learning does not include classification reasoning as its inalienable component, although precisely this reasoning constitutes an integral part of any mode of reasoning (Mill, 1872; Michalski & Kaufman, 1998; Spencer, 1898; Piaget & Inhelder, 1954; Sechenov, 2001). Furthermore, current models of commonsense reasoning do not include classification too (Russel & Norvig, 2010). However, classification, as a process of thinking, performs the following operations (Polia, 1954; Bynum, 1972, Mill, 1872; Quinlan, 1989):

- Generalizing or specifying object descriptions;
- Interpreting logical expressions on a set of all thinkable objects;
- Learning concepts from examples;
- Decision tree construction;

DOI: 10.4018/978-1-4666-8767-7.ch020

### ***Adding Context into Classification Reasoning Based on Good Classification Tests***

- Extracting hierarchical object classifications from examples;
- Forming knowledge and data contexts adequate to a current situation of reasoning;
- Reducing the domain of searching for a solution of some problem;
- Revealing essential elements of reasoning (objects, attributes, values of attributes etc);
- Revealing the links of object sets and their descriptions with external contexts interrelated with them.

This list can be continued.

We believe that conceptual learning is a special class of methods based on mining and using conceptual knowledge the elements of which are objects, attributes (values of attributes), classifications (partitions of objects into disjoint blocks), and links between them. These links are expressed by the use of implications: “object  $\leftrightarrow$  class”, “object  $\leftrightarrow$  property”, “values of attributes  $\leftrightarrow$  class”, and “subclass  $\leftrightarrow$  class”.

We understand classification reasoning as a process of thinking based on which the causal connections between objects, their properties and classes of objects are revealed. In fact, this reasoning is critical for the formation of conceptual knowledge or ontology in the contemporary terminology.

Studying the processes of classification within the framework of machine learning and knowledge discovery led to the necessity of reformulating the entire class of symbolic machine learning problems as the problems of finding approximations of a given classification of objects (Naidenova, 1996). This reformulation is based on the concept of a good diagnostic (or classification) test (GDT) for the given classification of objects (Naidenova & Polegaeva, 1986; Naidenova, 2006). A GDT has a dual nature. On the one hand, it is a logical expression in the form of implication or functional dependency; on the other hand, it generates the partition of a set of objects equivalent to a given classification of this set or partition that is nearest to the given classification with respect to the inclusion relation between partitions.

If we take into account that implications express relations between concepts (the object  $\leftrightarrow$  the class, the object  $\leftrightarrow$  the property, the property  $\leftrightarrow$  the class), we can assume that schemes of extracting and applying implications (rules of the “if-then” type) form the core of classification processes. Deductive steps of reasoning imply using known facts and statements of the “if-then” type to infer consequences from them. Inductive steps imply applying data and existing knowledge to infer new implicative assertions and correct those that turned out to be in contradiction with the existing knowledge. Inductive rules of reasoning are the inductive canons stated by British logician John Stuart Mill: the Methods of Agreement, the Method of Difference, the Joint Method of Agreement and Difference, the Method of Concomitant Variations and the Method of Residues (Mill, 1872).

The analysis of algorithms of searching for all GDTs in terms of constructing Galois lattice (Naidenova, 2011) allowed us to decompose this problem into sub-problems and operations that represent known deductive and inductive modes (modus operandi) of classification reasoning. Each step of constructing a classification lattice can be interpreted as a mental act (Naidenova, 2006). These acts can be found in any reasoning: stating new propositions, choosing the relevant part of knowledge and/or data for further steps of reasoning, involving a new rule of reasoning. Lattice construction engages both inductive and deductive reasoning rules. The implicative dependencies (implications, interdictions, rules of compatibility) generated in a process of GDTs are used immediately in this process for pruning the search space with the aid of deduction.

Classification reasoning requires a lot of techniques related to increasing its efficiency. One of the important techniques is decomposition of the main problem into sub-problems. As a whole, reasoning can be considered as gradually extending and narrowing the context of reasoning.

19 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

[www.igi-global.com/chapter/adding-context-into-classification-reasoning-based-on-good-classification-tests/138714](http://www.igi-global.com/chapter/adding-context-into-classification-reasoning-based-on-good-classification-tests/138714)

## Related Content

---

### Comparing Different Sparse Matrix Storage Structures as Index Structure for Arabic Text Collection

Basel Bani-Ismail and Ghassan Kanaan (2012). *International Journal of Information Retrieval Research* (pp. 52-67).

[www.irma-international.org/article/comparing-different-sparse-matrix-storage/74784](http://www.irma-international.org/article/comparing-different-sparse-matrix-storage/74784)

### Clustering Web Information Sources

Athena Vakali, Geroge Pallis and Lefteris Angelis (2008). *Personalized Information Retrieval and Access: Concepts, Methods and Practices* (pp. 98-117).

[www.irma-international.org/chapter/clustering-web-information-sources/28070](http://www.irma-international.org/chapter/clustering-web-information-sources/28070)

### Data Storages in Wireless Sensor Networks to Deal With Disaster Management

Mehdi Gheisari and Mehdi Esnaashari (2018). *Information Retrieval and Management: Concepts, Methodologies, Tools, and Applications* (pp. 2035-2062).

[www.irma-international.org/chapter/data-storages-in-wireless-sensor-networks-to-deal-with-disaster-management/198636](http://www.irma-international.org/chapter/data-storages-in-wireless-sensor-networks-to-deal-with-disaster-management/198636)

### Analysis and Outcome Prediction of Crowdfunding Campaigns

Parmmeet Kaur, Sanya Deshmukh, Pranjal Apoorva and Simar Batra (2022). *International Journal of Information Retrieval Research* (pp. 1-14).

[www.irma-international.org/article/analysis-and-outcome-prediction-of-crowdfunding-campaigns/289575](http://www.irma-international.org/article/analysis-and-outcome-prediction-of-crowdfunding-campaigns/289575)

### Generating and Adjusting Web Sub-Graph Displays for Web Navigation

Wei Lai, Maolin Huang and Kang Zhang (2004). *Intelligent Agents for Data Mining and Information Retrieval* (pp. 241-253).

[www.irma-international.org/chapter/generating-adjusting-web-sub-graph/24167](http://www.irma-international.org/chapter/generating-adjusting-web-sub-graph/24167)