Chapter 4.8 A European Virtual Enterprise on Collaborative Data Mining and Decision Support

Dunja Mladenić Jožef Stefan Institute, Slovenia

Nada Lavrač Jožef Stefan Institute, Slovenia

INTRODUCTION

One of the challenging research problems is to develop data mining and decision support integration techniques and to propose new methods for collaborative data mining. Advances in this area were achieved within the European project *Data Mining and Decision Support for Business Competitiveness: A European Virtual Enterprise* (*SolEuNet, 2000-2003*), in which a virtual enterprise model was proposed as a dynamic problem-solving link between a network of experienced data mining and decision support experts on the one hand, and customers in need of specific solutions on the other.

Successful applications of data mining and decision support technologies in a real-world setting the need for their further development. Directions for extending the existing technologies include collaborative problem solving and integration of the technologies at different levels, which were addressed in the European 5FP IST project *SolEuNet: Data Mining and Decision Support for Business Competitiveness: A European Virtual Enterprise* (Mladenić & Lavrač, 2003a; Mladenić, Lavrač, Bohanec, & Moyle, 2003b), whose aim was to develop a framework, methods, and tools for the integration of data mining and decision support, as well as their application to business problems in a collaborative setting.

show great potential of these technologies and open

Data mining and decision support are, each on their own, well-developed research areas, but until recently there has been no systematic attempt to integrate them. The main innovation achieved in So-

DOI: 10.4018/978-1-59904-885-7.ch069

IEuNet was the bridging of these two technologies, that had a significant impact on the developments of both fields, by improving approaches for problem solving in real-world settings, enabling the fusion of knowledge from experts and knowledge extracted from data, and consequently enabling the successful solution of new types of problems.

To enhance competitiveness and find new collaborative business opportunities in the global market, the objective of the project was also to provide access to cutting-edge ICT technologies through a proposed model of a European virtual enterprise composed of companies and research laboratories with highly specialized expertise in data mining and decision support. The SolEuNet virtual enterprise was envisioned as a business structure made of small, cross-organizational, time-focused, task-driven work teams, providing problem solutions to end users in industry, businesses, and public services. The work included the development and evaluation of the virtual enterprise model, enhancement of tools and method for cooperative work, combining problem solutions and consensus building, advances in decision support and data mining techniques enhancing the CRISP data mining methodology, advances in text mining and Web mining methods and tools, as well as new education and training methods, and Web information source maintenance.

The rest of this contribution describes the background by describing the methodology for collaborative data mining projects, the main SolEuNet achievements, the e-collaboration aspects of the project, and the conclusions describing the lessons learned.

BACKGROUND: METHODOLOGY FOR COLLABORATIVE PROBLEM SOLVING

The core of data mining is the extraction of useful patterns or models from data (Hand, Mannila, & Smyth, 2001). However, to reach actionable results

from data usually requires a long and non-trivial process (Berry & Linoff, 1997) involving aspects of business and technology (Pyle, 1999), as well as human skill; the human factor is one of the most important success factors, including project management and control. A well-defined process is important for achieving successful data mining results, particularly if the number of participants involved in carrying out the data mining tasks is large, involving teams of individuals with different expertise, skills, habits, and cultural backgrounds.

Many authors have suggested broadly defined process models to perform data mining (Adriaans & Zantinge, 1996; Fayyad, Piatetsky-Shapiro, & Smyth, 1996). The emerging standard data mining process model is the CRoss Industry Standard Process for Data Mining (CRISP-DM) (Chapman et al., 2000). CRISP-DM subdivides a data mining project into six interrelated phases: (1) business understanding, (2) data understanding, (3) data preparation, (4) modeling, (5) evaluation, and (6) deployment. Like in alternative data mining processes, there are numerous feedback loops connecting the phases in CRISP-DM. As data mining is multi-disciplinary it often requires the expertise of numerous individuals. The business understanding phase requires communication skills to work closely with the data mining client (the organization interested in the data mining results). The modeling phase-which requires the use of statistics or machine learning-can be undertaken largely independently of others, making it possible to perform parts of a data mining process in a remote e-collaboration setting. To ensure that collaborative data mining is successful, we propose well-defined collaboration principles and support tools (Jorge et al., 2003a; Mladenić et al., 2003a, 2003b).

A data mining project that is collaborative involves more complexity than the one that is small and local, but there are benefits to combining expertise. To realize such benefits it is vital that all collaborating parties share their results, either complete or intermediate. For example, in the data 5 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/european-virtual-enterprise-collaborativedata/44124

Related Content

Skillset to Assimilate Information Technologies in Accounting SMEs

Ku Maisurah Ku Bahadorand Abrar Haider (2015). *Business Technologies in Contemporary Organizations: Adoption, Assimilation, and Institutionalization (pp. 122-154).* www.irma-international.org/chapter/skillset-to-assimilate-information-technologies-in-accounting-smes/120755

Elements that Can Explain the Degree of Success of ERP Systems Implementation

Carmen de Pablos Herederoand Mónica de Pablos Heredero (2010). *Business Information Systems: Concepts, Methodologies, Tools and Applications (pp. 1916-1945).* www.irma-international.org/chapter/elements-can-explain-degree-success/44176

Expanding the Strategic Role of Information Interactions in the Enterprise Environment: Developing an Integrated Model

Judit Olahand Ole Axvig (2010). *Business Information Systems: Concepts, Methodologies, Tools and Applications (pp. 325-342).* www.irma-international.org/chapter/expanding-strategic-role-information-interactions/44081

Information Technology Projects System Development Life Cycles: Comparative Study

Evon M. O. Abu-Taieh, Asim A. El Sheikh, Jeihan M. Abu-Tayehand Maha T. El-Mahied (2010). *Business Information Systems: Concepts, Methodologies, Tools and Applications (pp. 1812-1834).* www.irma-international.org/chapter/information-technology-projects-system-development/44170

Technology-Push or Market-Pull?: A Model for Managing the Innovation Process in Malawian Firms

Edwin Saidi (2013). Business Innovation, Development, and Advancement in the Digital Economy (pp. 176-187).

www.irma-international.org/chapter/technology-push-market-pull/74144