What you see is what you can change: Human-centered machine learning by interactive visualization

Dominik Sacha, Michael Sedlmair, Leishi Zhang, John A. Lee, Jaakko Peltonen, Daniel Weiskopf, Stephen C. North, Daniel A. Keim

University of Konstanz, Konstanz, 78457, Germany
Middlesex University, London, NW4 4BT, United Kingdom
University of Vienna, Vienna, 1090, Austria
Université catholique de Louvain, Louvain-la-Neuve, 1348, Belgium
Aalto University, Aalto, FI-00076, Finland and University of Tampere, Tampere, 33014, Finland
University of Stuttgart, Stuttgart, 70174, Germany
Infovisble, Oldwick, 08858, New Jersey, United States

A R T I C L E   I N F O
Article history:
Received 11 July 2016
Revised 7 December 2016
Accepted 23 January 2017
Available online 29 April 2017
Keywords:
Machine learning
Interactive visualization
Interaction
Visual analytics

A B S T R A C T
Visual analytics (VA) systems help data analysts solve complex problems interactively, by integrating automated data analysis and mining, such as machine learning (ML) based methods, with interactive visualizations. We propose a conceptual framework that models human interactions with ML components in the VA process, and that puts the central relationship between automated algorithms and interactive visualizations into sharp focus. The framework is illustrated with several examples and we further elaborate on the interactive ML process by identifying key scenarios where ML methods are combined with human feedback through interactive visualization. We derive five open research challenges at the intersection of ML and visualization research, whose solution should lead to more effective data analysis.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Real-world data analysis usually relies heavily on both automatic processing and human expertise. Data size and complexity often preclude simply looking at all the data, and make machine learning (ML) and other algorithmic approaches attractive, and even inevitable. However, the power of ML cannot be fully exploited without human guidance. It remains a challenge to translate real-world phenomena and analysis tasks, which are often under-specified, into ML problems. It is difficult to choose and apply appropriate methods in diverse application domains and tasks. Moreover, it is crucial to be able to incorporate the knowledge, insight, and feedback of human experts into the analytic process, so that models can be tuned and hypotheses refined.

In a typical setting, domain experts use ML and visualization methods provided by common software tools (e.g., SPSS, R, Tableau) “out of the box”. Realistically, the domain experts’ proficiency in ML may be limited, and the underlying computations may not be transparent and comprehensive enough to provide the feedback needed to guide model refinement. Visualizations are often used to display the ML model results without offering interactions that trigger recalculations. This results in a very standardized configuration of the ML and visualization pipelines based on default parameters that domain experts may not know how to adapt. The situation may be improved by having domain experts collaborate with data scientists, improving the effectiveness of analysis, but also leading to a much more costly iterative design process. ML researchers usually know how to tune models directly in ML platforms (e.g., Matlab, R, Python) and provide results to domain experts. However, domain experts generally find it necessary to learn how models behave and how to evaluate results to provide useful feedback.

By integrating ML algorithms with interactive visualization, visual analytics (VA) aims at providing visual platforms for analysts to interact directly with data and models [1]. Tam et al. [2] illustrated in case studies that human-centric ML can produce better results than purely machine-centric methods. In such cases, an analyst is enabled to steer the computation and interact with the model and data through an interactive visual interface. Despite much effort to date, though, solutions from ML and VA are still not interwoven closely enough to satisfy the needs of many real-world applications [3,4]. For example, in existing toolkits (such as WEKA, Elki, or JavaML), tight integration between interactive
visualization and ML process is missing. Most of these tools present modeling results as static visualizations; interactions are often limited to command line interfaces or user interface controls that are not intuitive and accessible to end-users. Toward better integration of ML and VA, in recent years conceptual frameworks that characterize the interplay between them have been proposed [1,3–5]. It appears most frameworks were designed from the perspective of interactive visualization, focusing on the role of the “human in the loop”. A closer connection between visualization and common ML paradigms (such as unsupervised and (semi-) supervised learning; classification, regression, clustering, etc.) including specifics of these methods (e.g., SVM vs. random forests in classification) and their implementations is needed. In this paper, we put a sharper focus on scenarios in which complementary ML and VA methods are combined, and propose a framework for a tighter relationship between ML and VA. To do so, we identify aspects of automated ML techniques that are amenable to interactive control, and illustrate these with examples. We further describe human factors within this process that should be considered carefully in the design of interactive visual ML systems, and enumerate analysis scenarios. The proposed conceptual framework opens perspectives on new ways of combining automated and interactive methods, which will lead to better integrated, and, ultimately, more effective data analysis systems.

Researchers in both ML and visualization have realized for some time that closer collaboration could help to solve this problem. An interdisciplinary team with experts from the ML and visualization communities was formed at a Dagstuhl Seminar on “Bridging Information Visualization with Machine Learning” [6]. The framework proposed in this study is the outcome of several iterations of discussions, feedback, and framework refinements made by this team. The initial version of this framework [6] was based on a survey of several earlier frameworks and systems combining ML and interactive visualization. Subsequently, the framework was refined by applying it to a larger set of example applications (identified in the visualization, ML, and HCI literature) and by incorporating external feedback from experts, such as conference submission reviews. This led to a process of framework refinement, carried out over 1.5 years, including extensions and simplifications, validation, and evaluation by analyzing existing VA systems and ML techniques. This paper presents an initial report in ESANN 2016 [7] to include an extended review of prior work, a more detailed framework, examples of providing automated support for each stage, identification and description of scenarios where analysis and feedback take place, and additional discussion throughout.

The rest of this paper is structured as follows. Section 2 discusses related work on the interplay of machine learning and human feedback. Section 3 introduces our conceptual framework and the key stages in its interactive pipeline, and they are illustrated with examples in Section 4. Section 5 examines the human interaction loop in more detail, describing the stages of action and analysis scenarios where interaction occurs. Section 6 identifies five challenges and associated opportunities in creating systems that fully use the framework. Section 7 gathers conclusions and final discussions.

2. Related work

The literature describes related models that capture the interplay between ML system components and human feedback loops. We will discuss several different perspectives on this topic, divided into VA models, interaction taxonomies, interactive ML, and human-centered design. This section concludes with a high-level summary for interested readers without ML expertise.

2.1. Visual analytics models

Pipeline-based models such as the Reference Model for Information Visualization [8] or the Knowledge Discovery Process in Databases (KDD) [9] usually contain feedback loops that cover all the subcomponents with the potential for user interaction. In the standard VA model [1], the analysis process is characterized by interactions between data, visualizations, models of data, and users, for knowledge discovery (see Fig. 1). ML interaction in this framework is aimed at model building and parameter refinement. Sacha et al. extended this model [4] to encompass the process of human knowledge generation. This extended model clarifies the role of humans in knowledge generation, and highlights the importance of supporting tighter integration of human and machine. Several other models focus on a clear depiction of the human data analysis process, including Piroli and Card’s sensemaking process [10], and Pike et al.’s science of interaction [11]. Endert et al. characterized the interaction process between a human analyst and automated analysis techniques as the “human is the loop” [12] and proposed a model for coupling cognition and computation [3]. More recently, Chen and Golan [13] provided an abstract model to describe six classes of human–machine workflows in combination with an information-theoretic measure of cost-benefit. Their model allows one to analyze workflows composed of machine computations and human interactions supported by different “levels” of visualizations. All these models reflect a high-level understanding of system and human concepts.

2.2. Interaction and task taxonomies

Another set of models related to our endeavor seek to characterize and organize the tasks and interactions in a visual data analysis process. For example, Brehmer and Munzner [14] propose a comprehensive visualization task taxonomy. However, model interactions only arise in tasks they refer to as “aggregate” or “derive” tasks. Landesberger et al. [15] define a taxonomy that includes interaction and data processing. Their taxonomy provides two types of data processing interactions: data changes, such as editing or selecting data, and processing changes, such as scheme or parameter changes. They incorporate Bertini and Lalanne’s [16] distinction of human intervention levels, that distinguishes, for example, between scheme tuning (e.g., parameter refinement) and scheme changing (e.g., changing the model) interactions. Mühlbacher et al. [17] investigate and categorize several types of user involvement for black box algorithms with different characteristics. The characterization of interactions in our framework is orthogonal to these taxonomies and extends them with a dedicated view on interaction with ML components.