Human-centered Machine Learning Through Interactive Visualization

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Abstract. The goal of visual analytics (VA) systems is to solve complex problems by integrating automated data analysis methods, such as machine learning (ML) algorithms, with interactive visualizations. We propose a conceptual framework that models human interactions with ML components in the VA process, and makes the crucial interplay between automated algorithms and interactive visualizations more concrete. The framework is illustrated through several examples. We derive three open research challenges at the intersection of ML and visualization research that will lead to more effective data analysis.

1 Introduction

Many real-world data analysis problems are intrinsically hard. On the one hand, data complexity and scale preclude simply looking at all the raw data, and make algorithmic approaches such as ML seem very attractive and even inevitable. On the other hand, the resulting analysis or learning problems are often ill-specified, and it becomes apparent that the analytical power of ML cannot be fully exploited without effective human involvement to guarantee that real-world phenomena are translated into ML problems effectively and appropriate ML methods are applied. More importantly, it is crucial to incorporate the knowledge, insight and feedback of the human into the analytical process, such that hypotheses can be refined and the models can be tuned. By integrating ML algorithms with interactive visualizations, VA aims at providing a visual platform for the analyst to interact with their data and models [1]. Despite much effort to date, though, solutions from each field (ML and VA) are still not interwoven closely enough to satisfy many real-world applications [2, 3]. Toward effective integration, previous studies have proposed a series of conceptual frameworks that characterize the interplay between these approaches [1, 2, 3, 4]. However, these frameworks were mostly designed from an interactive visualization perspective, focusing on characterizing the role of the "human in the loop". A tighter connection with algorithmic implementations of the different ML paradigms is still largely missing.

We aim to bridge this gap by proposing a new framework that conceptualizes how the integration between ML and interactive visualization can be implemented. While illustrating inspiring examples, we identify aspects of ML methods, which are amendable to be controlled interactively by the analyst. The framework opens the perspective for new ways of combining automated and interactive methods, which will lead to more tightly integrated and ultimately more effective data analysis systems.

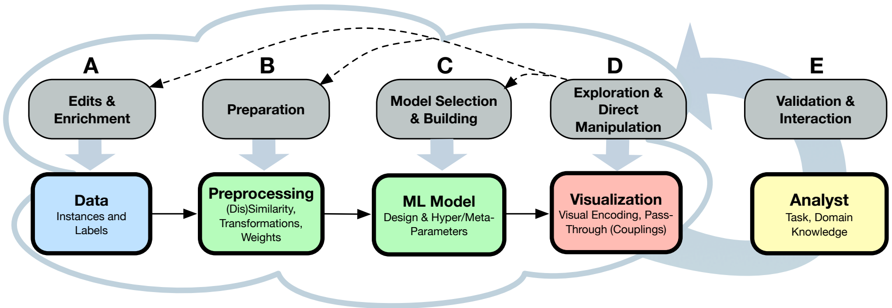

Fig. 1: Proposed conceptual framework: A typical interactive VA/ML pipeline is shown on the left (*A*-*D*), complemented by several interaction options (*top*). Interactions generate changes to be observed, interpreted, validated, and refined by the analyst (*E*). Visual interfaces (*D*) are the "lens" between ML models and the analyst.

2 Human-centered Machine Learning Framework

Our framework combines, embeds and complements existing theories on interactive ML and VA by integrating and generalizing observations from outstanding examples that have emerged. The framework (Figure 1) consists of a typical VA/ML pipeline (*A*-*D*) and the analysts' validation/refinement process (*E*). An analyst might interact with each single step in this pipeline through a visual interface (*D*), which acts as a mediator or "lens" between the human and the ML components (*dashed arrows*). The changes are then traversed back to the visual interface and shown to the analyst (*solid arrows*).

Edits & Enrichment (A): While in ML data is usually seen as "un-touchable", many visualization systems allow and support analysts in cleaning, wrangling, editing, and enriching data [5], also during the analysis process. For example, a domain expert may iteratively add more labels in the training of a classification. Several strategies have been developed to make this process more efficient (e.g., inter-active learning [6]). Alternatively, an analyst might also simply want to run through some "what-if scenarios" to understand hypothetical assumptions about the data. Data operations are then followed by a "warm restart" of the ML pipeline, iteratively traversing through to the analyst. Consider iPCA [7] (Figure 2-a), an interesting example that allows analysts to move/adjust a point in several views/spaces (e.g., projection or eigenvector view/space) and at the same time enables the analyst to observe the changes of that items' values in data space. Removing data items allows observing how the projection changes. In ForceSPIRE [8] (Figure 2-c), analysts may add textual annotations to documents, which are then included into the analysis process (i.e., similarity calculation).

Preparation (B): Many ML models incorporate model independent preprocessing steps. Whereas edit and enrich interactions focus on single observations, preprocessing affects a uniform transformation of features for a larger set of observations. Typical examples are transformations, such as standardization, scaling, or more complex methods (e.g., Fourier or wavelet transform), and weightings. Weightings may be filtering (0-weights) of data items, as well as feature selection. Feature weighting can be supported in the form of relevance, metric, or kernel learning. With this respect, we often observe a gap

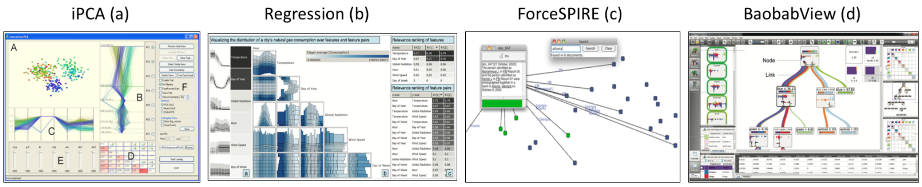

Fig. 2: A selection of examples that effectively involve analysts into the ML processs.

in the "judgment of (dis)similarity" between human and "default" ML methods. Analysts often focus on specialized characteristics of their data. This requires us to include feature weightings or more complex (dis)similarity functions. The Dis-Function [9] system, for instance, allows analysts to drag and drop data points, causing the system to calculate a new distance function. By immediately revealing the resulting changes in the underlying model, such approaches give the analysts a convenient way to explore possible parameterizations of preprocessing steps.

Model Selection & Building (C): At the very core of VA, analysts might need to directly interact with ML models. We distinguish two general forms of model interactions. In *Model Selection* an analyst needs to choose among different ML algorithm families/designs, or a set of pre-built model results, a process that can also be supported (semi-) automatically (e.g., cross validation, bootstrap) but also visually. For example, the analyst may select and refine regression models [10] (Figure 2-b) or build classifier ensembles by discovering several combination strategies [11]. *Model Building* interactions focus on directly changing a given ML model through adjusting parameters. While internal parameters are optimized automatically, others such as design/form, and meta/hyper parameters, need to be adapted by the analysts according to their assumptions. We found several model building interactions that can roughly be grouped into ML model changes that affect its *form*, *constraints*, or *quality/accuracy*. *Form* parameters define the basic structure (such as the number of neurons in a neural network), whereas *constraints* may reflect more detailed assumptions (e.g., pinning a node in a force-directed layout [8]). Other examples allow for adjusting the *quality/accuracy* of the ML result, e.g., by interacting with the confusion matrix of a classifier [12].

Exploration & Direct Manipulation (D): Interactive visualizations serve as an aid or "lens" that facilitates the process of interpretation and validation, but also make ML interactions accessible to analysts. Usually, simple exploration interactions, such as changing the visual encoding or navigation, do not feed back to ML components. However, the previous paragraphs contain various examples that allow interactions in visual interfaces, which are "passed through" to ML changes, indicated by the dashed arrows in Figure 1. This concept has become known as "semantic interaction" that maps intuitive interactions to complex ML changes [8]. Therefore, different aspects of the ML parts may be visualized, such as data and model spaces (Figure 2-a), pre-built model variants including their characteristics (Figure 2-b) and quality (Figure 2-a/b/d), but also the ML structures (e.g., [13], Figure 2-d).

Validation & Interaction (E): In VA systems following our framework, analysts would be actively involved in an iterative process of observing, interpreting, and validating the system's outputs followed by subsequent refinement through interaction. Such an approach would foster direct usage of ML tools by domain experts. Visual interfaces that are easy-to-use and -understand enable such analysts to bring in their domain knowledge more effectively (as illustrated in the previous paragraphs) and consequently adapt the underlying ML components in order to further advance in data-intensive, yet ill-defined analysis tasks [14].

3 Challenges & Opportunities

Designing Interaction for ML Adaption: A variety of different ML algorithms including a large set of design options and parameters do exist. Yet, there is no general way to interface these with visualizations. Consequently, existing systems are often limited to a small set of ML techniques and parameters. Furthermore, when switching between the different ML models with current interfaces, such changes, however, would likely result in discontinuous interruptions of the human's analysis process. Hence, novel approaches will become necessary that smoothly support analysts to make sense of such changes. In addition, existing examples such as ForceSpire and iPCA have nicely illustrated how understandable, direct interactions can be combined with model changes in a simple setup. Direct manipulation has been proven to be an effective and easy-to-use access to computational tools [16]. It has, however, been rarely explored in the context of ML so far. Often, ML models are designed for unique configurations, whereas in VA iterative refinement is needed. Mapping user inputs to more complex algorithmic actions (along the entire ML pipeline) remains an open challenge, which is then to translate these inputs to either, data-, preprocessing- or ML model-adaptions or even combinations. — *Opportunities:* At the core of our conceptual framework lies the idea that the underlying ML design options and meta-parameters (which cannot be optimized automatically) can be steered via iterative, and accessible user interactions. Accessible interactions and smooth transitions between different ML models will support analysts to form an intuition, or mental model [15] about the underlying data as well as the function or behaviour of complex ML methods. Consider the case of switching between different ML models: At which point does the system realize—from user feedback—that the chosen ML model might not be proper anymore? It then could select an alternative and smoothly transfer between the two. Instead of linear projection with PCA, it might for instance suggest some more complex nonlinear dimensionality reduction method like multidimensional scaling or t-SNE. Continuous model spaces [17] give first ideas towards such solutions, which are dependent on the ML models' meta/hyper-parameters and their interpretability. Further, more general ways to use and adapt ML through very simple expert feedback (e.g., labeling or rating) would allow to leverage a larger and more powerful set of ML methods. The previous examples illustrate that there is huge space for future research, given the large variety of ML techniques and their associated parameter spaces. A joint effort from both communities (ML and VA) is needed.

Guidance: Another major challenge is how to sufficiently support domain experts in steering this ML pipeline. Analysts are often overwhelmed, due to the variety of ML variants and parameters in addition to the large amount of data and tasks. Furthermore, their analysis problems are often ill-defined resulting in a rather exploratory, or complex analysis process. Consequently, analysts may change, adapt, or switch between tasks very often. While the analyst may be able to provide crucial missing information towards solving ill-defined problems, they might lack programming and statistical expertise and therefore require very individual guidance. — *Opportunities:* It will be important to better understand the tasks, practices, and stumbling blocks of domain experts (which likely will differ from those of ML experts). Design study methodology is a viable approach towards gaining better understanding of such user characteristics [14] and providing appropriate guidance. Furthermore, enhanced measures and tools could be used in order to point analysts to interesting data, parameterizations, and ML models through automatic recommendations. While many measures exist, both depicting data and perceptual characteristics, currently it is not well understood how they can be effectively leveraged in interactive analytical processes. Consider a relevance feedback learning approach, where an analyst provides iterative feedback about the interestingness of different ML models/visualizations. How could the system detect if a pattern was spotted and the analysis task changes from overview to detail? Therefore, we envision the usage of data and analytic provenance information (e.g., interaction logs) in order to guide the analysis process according to the analysts needs, which may be derived based in their behavior. In the VA community research has been carried out on recording, visualizing, and reusing analysis provenance. However, no work has been carried out on modeling such information to help shape/refine analysis problems or even ML methods. This could be an interesting topic for involving the ML community.

Measuring Quality & Consistency: In the envisioned rich human-in-the-loop analysis process, it will be crucial to assure both *ML model quality* and *visualization quality*. Yet, the two types of quality assurance do not always align. For example in a visual embedding, there might be a trade-off between the preservation of the original data structure and the readability of patterns due to intrinsically high dimensionality. While quality measures exist for both aspects, the challenge will be to help analysts to find the right balance between the two, so meaningful analysis can be carried out. Beyond measuring ML and visualization quality, our framework suggests a third type of quality assessment, the *level of consistency* between the ML model and the analyst's expectations. While an ML model will surely seek to "truthfully" reflect the data, essential pieces of information known by analysts may be unavailable to the machine. In this case, the set of ML assumptions may be incomplete, a common challenge in exploratory data analysis. —*Opportunities:* To externalize this missing human information, it is necessary to check the consistency between what the model presents, and what the analyst expects. If inconsistent, the analyst will either suspect a problem with the ML model and provide feedback about missing information, or accept that the expected patterns do not exist in the data. If consistent, analysts will usually conclude with a confirmation of their exception. Note, though consistency between human and machine is desirable, it does not guarantee correct reflection of the underlying ground truth in the data per se. Currently the consistency check is often done manually. Automatic methods that systematically check consistency, highlight inconsistencies, and recommend appropriate actions could help. Joint effort from both communities (ML and VA) is needed to enhance these measures, especially in combing and bridging them.

4 Conclusions

We propose a framework that characterizes potential forms of human interaction with ML components in a VA process. In general, VA tools have the potential for improved support of ML interpretation, understandability, validation, and refinement through interaction. However, current VA tools and ML components are posing many interesting challenges for future work. Towards addressing these challenges, closer collaboration between ML and visualization researchers is vital.

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