Adaptive Business Data Visualizations and Exploration: A Human-centred Perspective

Christos Amyrotos[a,b], Panayiotis Andreou[a,b] and Panagiotis Germanakos[c,b]

[a] UCLan Cyprus, University Ave 12-14, Pyla 7080, Cyprus
[b] InSPIRE Center, Agamemnonos 20, Pallouriotissa, Nicosia 1041, Cyprus
[c] UX S/4HANA, Product Engineering, IEG, SAP SE, Dietmar-Hopp-Allee 16, 69190 Walldorf, Germany

Abstract

Today's business environments are characterized by an indisputable growth in the volume, complexity and multivariate nature of business processes, data structures and sources. For the business end-users, this is many times an overwhelming and demotivating experience when interacting with rich business data visualizations and scenarios. As they need to explore demanding use cases, create fast an understanding and make informed decisions so to meet their business goals. This position paper addresses this challenge by introducing a human-centred model that consists of four main dimensions: User, Visualizations, Data, and Tasks, and which is maintained at the core of an adaptive data analytics platform in the business domain. The aim is two-fold: To provide (a) best-fit representation of data for the unique end-users, and (b) personalized and transparent path of exploration towards accomplishing purposeful end-to-end business activities. Thus, enabling explainable and intuitive interactions for accurate decision making and problem solving – saving time and costs.

Keywords

Adaptation, Personalization, Human Factors, User Modelling, Artificial Intelligence, Business Analytics, Data Visualizations

1. Introduction

Modern business intelligence and data analytics platforms use real time visual analytics to continuously monitor and analyze business transactions and historical data so to facilitate real-time decision support. The result of this process is then exported into various standard format artifacts (e.g., tabular forms, graphs, etc.) offering customization options to end-users as means for (visual) data exploration for obtaining insights and unveiling complex patterns. However, according to IBM, every day we create 2.5 quintillion bytes of data – so much data that 90% of all the data in the world today has been created in the last two years alone [1]. These data come from a variety of sources and in diverse formats, both structured and unstructured, creating a business ecosystem that brings new insights but also generates a number of complications and problems (e.g., delays in real-time processing, ineffective delivery of multi-purpose information). As a consequence, this may disorient end-users that need to navigate and take decisions faster than ever when performing their daily business activities using data analytic solutions. Although such platforms may provide data visualizations that are considered more usable than others [2], often their recipients (i.e., the decision makers) are overloaded from the vast amount of

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camyrotos@uclan.ac.uk (C. Amyrotos); pgandreou@uclan.ac.uk (P. Andreou); panagiotis.germanakos@sap.com (P. Germanakos)
http://scrat.cs.ucy.ac.cy/pgerman (P. Germanakos)

visual information, which in turn severely decreases their ability to efficiently assess situations and plan accordingly [3, 4]. It is evident that current business data exploration and most of data visualizations are: (i) created based on task and/or data-driven models and methods; (ii) extracted based on data mining algorithms that do not consider any role-based specifications and/or user needs and requirements; and (iii) following an one-size-fits-all approach, presenting the same visualization type and content to all users irrespective of their needs, requirements, and unique characteristics.

This position paper argues that the complex nature of business processes, tasks, objectives and many data visualizations makes it indispensable to include human intelligence in the data analysis and visualization process at an early stage. It is vital to enrich the current business analytic platforms with adaptation techniques and new possibilities for interactions that will bring the human-in-the-loop by considering the end-users' individual differences and their business context (e.g., role, purpose, requirements, tasks) in combination. It proposes a human-centred model (as the main component of an intuitive data analytics platform), that is composed of four main dimensions: User, Visualizations, Data and Tasks, and considers human factors like perceptual preferences, cognitive capabilities in information processing, affective states, domain expertise, experience, etc., amongst others. Ultimately, the goal is to enable human-centred adaptive data visualizations that will facilitate explainable exploration and transparent analysis of complex and multivariate business processes and datasets, and will support and enable more effective decision making on critical business tasks.

2. Background Work and Motivation

Today, with the growing expectations of business end-users and the proliferation of heterogeneous business processes and datasets, traditional approaches for data interpretation and visualization often cannot keep pace with the continuous escalating demand, so there is the risk of delivering unsatisfactory and misleading results. Business data models and processes characterized by significant complexity, making the analysis and understanding of data by managers, data analysts, business experts, etc., challenging, time consuming, if not many times impossible. In many cases, a single activity combines even custom-made developments (e.g. using Excel) for the subsequent execution of steps creating a dispersed, inconsistent and error-prone reality. Hence, it is widely accepted that the increasingly large amount of data requires novel, seamless, transparent and user-friendly solutions [5]. As such, handling, analyzing and gaining insights into these large multivariate processes and datasets through interactive visualizations is one of the major challenges of our days [6, 7].

In recent years, many powerful computational and statistical tools have been developed by various organizations in the business sector, such as SAS Visual Analytics[1], IBM Analytics[2], Microsoft Power BI[3], SAP Busines Business Intelligence Platform [4], Tableau Business Intelligence and Analytics[5], Qlik Business Intelligence[6], etc., offering a number of solutions like interactive maps, charts, and infographics, visual business intelligence anal-

[1]https://www.sas.com
[2]www.ibm.com/analytics/us/en/technology/products/cognos-analytics/
[3]https://powerbi.microsoft.com/en-us/
[4]https://www.sap.com/products/bi-platform.html
[5]http://www.tableau.com
[6]http://www.qlik.com

ysis, recommend actions, etc. Interestingly enough, these applications are currently designed to execute the same operations following a pure machine learning approach (based on data models and rigid tasks and objectives) and with power users (e.g. data analysts) in mind. They embrace the power of the statistical methods to identify relevant patterns, typically without human intervention. Inevitably, the danger of modeling artifacts grows when end-user comprehension and control are not incorporated. To this end, although modern business intelligence and data analytics platforms offer vast repositories of data analysis tools and myriads of customizable visualizations; they have not kept up to the challenge when it comes to their dynamic adaptation and personalization depending on the role, experiences, intrinsic characteristics or abilities of end-users and still follow a one-size-fits-all paradigm. This poses an issue as the effectiveness of a visualization in terms of usability and understanding differs amongst users [2]. The vast amount of visual uncertain information overwhelms the user's perception, which in turn, severely decreases their ability to understand the data and make decisions [3, 4].

On the other hand, the joint benefits of adaptation and personalization, and data visualizations and exploration that consider specific human factors in the core of their user models have been highlighted repeatedly in a variety of fields and applications, mostly in academia. Indicatively, research works have identified noteworthy associations of users' cognitive abilities like perceptual speed, in relation to performance, accuracy, and satisfaction when interacting with alternative data visualization [8, 9]; others focus on optimizing data visualizations based on the users' goal, behaviour, cognitive load and skills [10, 11]; investigate how human factors like personality and working memory affect user performance when interacting with visualizations [12, 13]; how individuals' cognitive styles, like Field Dependent-Independent, impact interactions with various information visualizations and in relation to individual aid choices and preferences [14]; or how effective are emotion-triggered (e.g., boredom and frustration) adaptation methods for visualization systems [15]. Hence, although significant effects have been shown in domains like public facing applications, educational and navigation contents, or health datasets, these ideas have rarely been applied, to our knowledge, to the business sector despite the encouraging results of prior studies [16]. The current position paper addresses this research gap by highlighting the effect of a multi-dimensional human-centred model in data visualizations and analytic applications that facilitate the execution of specific end-to-end business scenarios and tasks. The overarching innovation lies upon (a) the generation of knowledge and theory, rules, adaptive interventions, personlization conditions and explanations triggered by the joint influence of cognitive and affective characteristics on business data visualizations and exploration, and (b) the development of computational techniques, tools and methods that will put the theoretical model into practice considering the requirements, constraints and policies of real-life business settings.

3. A Proposed Human-centred Model

This complex nature of information visualizations necessitates the development of a comprehensive theoretical model that captures important factors, such as users' cognitive characteristics, affect, domain expertise and experience, as well as understanding of the end-user roles, objectives, context and the characteristics of the data [16, 17]. These factors can be utilized within the data analysis and vis-

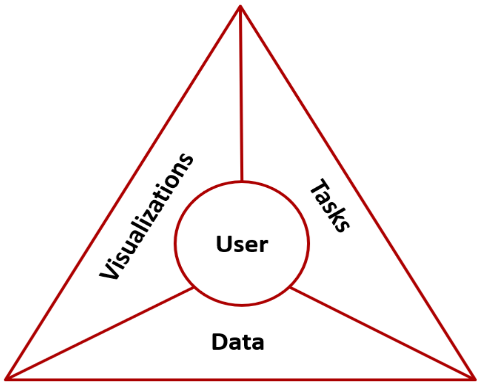

Figure 1: Proposed Human-centred Model

ualization process to enable powerful adaptation techniques generating more effective interactions. In this respect, the following theoretical model is proposed (see Figure 1), comprised from four main dimensions: User, Visualizations, Data and Tasks, which will be used as the main driver for further development and realization.

3.1. User

This dimension is the central point of our endeavour, referring on one hand to the understanding of the business users' roles, nature and their contexts of functioning and interaction, and on the other hand to the definition of the human cognitive and affective states and their transitions during the interaction process with data exploration and visualizations. As such, various interventions and adaptive conditions may be proposed restructuring the respective contents and functionality to the needs and abilities of users, e.g., presenting more explanations, additional navigation support and clarity, reducing the number of simultaneously presented stimuli and the volume of content. More specifically, building upon previous research (see section 2), a number of human factors will be investigated with regard to their applicability in specific business settings and actions optimizing current multi-dimensional human-centred user models [18] that may consider factors like *perceptual and cognitive processing characteristics* – have an effect on the complexity of the content regarding users' task performance, overall efficiency and cognitive control of information [19], for problem solving and comprehension during the interaction process; *affect* (or affective states) – referring at some extent to Emotional Arousal and Emotion Regulation, influencing people's performance, judgement and decision making process [20] while interacting with data visualizations; *domain expertise and experience* – directly related to graph comprehension, accuracy and performance of users when interacting with graph tasks as well as to user preference [11], satisfaction and the capability of being familiarized or switching between graphs to obtain information; and *business role* – a person or an entity that is defined by specific objectives, responsibilities and tasks and is the one that makes decisions and triggers a process, or specific activities, using one or more business scenarios of an organization. Data visualizations should be adjusted to the requirements of each role aligned to the variability of tasks, level of knowledge, constraints, etc., conveying the adequate information, when and how it is needed, and on the expected breadth and depth that could support and facilitate a fast and accurate decision making; along with the more static ones (e.g. name, age, education, etc.)

3.2. Visualizations

Data visualizations are most often used to convey some meaning out of data and to communicate information. Currently, there are different types of visualizations (e.g. graphs, plots, tables, etc.) which are used interchangeably depending on the scope and the needs of a task. For example, the typical bar and column charts are some of the most used visualization techniques for comparing data across categories (single or multiple), since in a coordinate system the occurrence of a value is compared directly to its neighbours; or the line charts show a connection of data points in a coordinate system generating a sequence of values which is used to view trends and cycles over a period of time. Visualizations that have some common and comparable features, a recognizable impact of individual differences on them, and apply at a large extend in the business domain will be qualified. Once data visualizations are defined, they and their sub-optimal counterparts will constitute a number of subsequent objects which will be enriched with metadata (semantic augmentation) enabling the filtering process according to the human-centred model and the data attributes and structure. Thereupon, adaptation and personalization techniques will be crafted to offer: (a) Dynamic alteration of the content presentation and hierarchical structure of data visualization attributes (e.g., reordering, salience, size, saturation, texture, color, orientation, shape, etc.); (b) provision of various navigation tools and support (e.g., visual prompts, explanations) for data/ visual exploration during end-to-end business tasks execution; (c) variable amount of user control (e.g., allowing further (deeper) data exploration); and (d) additional assistive tools (e.g., data properties and details), etc.

3.3. Data

A big challenge currently for the research community, is to develop intelligent data mining mechanisms that can support the efficient extraction and fusion of multivariate data from different locations, their integration into a unified information model so that it can seamlessly support exploratory data analysis for understanding, interpreting and modelling the outcomes/ messages. At the same time, main concern is to co-op with the risk of uncertainty and data quality derived from situations where not only the types of data or features can be different, but there is also a variety of uncontrolled effects (e.g. dependency to data acquisition organizations typically reside), that could hinder the more competent discovery of patterns and useful information that in turn could enable a more effective decision making. The mechanisms that will be considered at this stage will provide high quality business knowledge that will also determine (based on their properties) the significance of the data objects and the yielded adaptive data visualizations. This dimension will make sure that data integration is possible, by means of intelligent pre-processing and fusion of data; to render data from different locations or in different types so to be comparable, and to create mappings among features so that integrated data analysis will be possible. Several unaddressed issues will be tackled in supporting data analysis of business datasets especially through the use of visualization, such as (a) very large, i.e., scalability, (b) dynamic, i.e., addressing the velocity aspect within the V's of Big Data, and (c) heterogeneous, i.e., consisting of different data types both in terms of acquisition method and representation [21].

3.4. Tasks

Business tasks refer to role-based units of work, as a sequence of actions, undertaken by the end-users. They are usually part of a wider constellation of business activities and processes that are executed with the purpose of accomplishing a specific business goal (e.g., define/ maintain material and external services demand, or oversee stock, material demand and supply). Transparency, explainability and support of end-to-end tasks execution is a big challenge currently in the business domain, as users many times strive to understand the flow, dependencies and contents of multi-variate information (usually generated by different business processes and data models) while at the same time are not included in the subsequent decisions that lead to a result or to actionable knowledge. Hence, recognizing the essential role of the end-user in the data visualization and exploration process, it is important to enable effective human control during the tasks execution by extending the usability and usefulness of computational process models and visual analytic methods to gain insights and value out of the data towards informed business decision making. In this respect, machine learning techniques may be employed for analyzing big datasets arising from complex business processes and scenarios, for e.g., discovering patterns in data simulations or for modelling uncertainties increasing transparency of tasks execution (e.g. change of a product's demand). Additionally, many problems in the business area can be formulated as probabilistic inference problems. Thus, a focus on probabilistic-based data mining methods, including graph-based data mining, topological data mining and other information-theoretical-based approaches (e.g., entropy-based), as well as on the human-in-the-loop concept for increasing explainability while users interact with respective business use cases will be considered.

It is apparent that the successful realization of the above human-centred model adheres to a number fundamental research questions that need to be addressed, such as: Which parameters and human factors are considered significant so to define an inclusive human-centred user model in the context of business data visualizations? What, how and when data visualizations content can be enriched/ altered and delivered to the end-users? What adaptation techniques and interventions are feasible for generating best-fit data visualizations and explanations? How to design and develop transparent and personalized conditions that can ensure seamless end-to-end data/ visual exploration support? What kind of computational intelligence algorithms need to be developed to ensure data integration and fusion of various dispersed datasets/ sources? How to verify the validity of the theoretical human-centred user model? Subsequently, a rigorous methodological approach need to be embraced, following an incremental design and development iterative process. The proposed theoretical model will guide the implementation of an intuitive data analytics platform that will dynamically adjust (i.e., offering alternative representations) to the unique end-users characteristics, data structure and semantics of data visualizations, and exploration tactics derived from the various business data sources/ processes of an organization.

4. Expected Benefits and Impact

Given the users' diversified individual differences in cognitive processing, affect, perceptual preferences, role, requirements, needs, and expertise, as well as the size, diversity and processing overhead of big business data sets, it is expected that this research will yield flexible best-fit data visualizations and exploration methods that will support the unique end-users with the expected transparency and explainability during an end-to-end interaction. The suggested adaptive interventions build on the premise that graphics and text have a complementary role in information presentation – while graphics can convey large amounts of data compactly and support discovery of trends and relationships, text is much more effective at pointing out and explaining key points about the data, in particular by focusing on specific temporal, causal and evaluative aspects. Crafting different modalities not only makes the presentation more engaging, but could also better suit users with different cognitive abilities and affective states. In a broader perspective, the results of this research work will have a wider business and economic impact by helping users to comprehend and familiarize themselves with usable data visualizations adjusted to their knowledge and abilities, enhancing their satisfaction and acceptability of related end-to-end business workflows and services. Main vision is that such practices, which provide human-centered data visualizations and visual analytic services, will be incorporated in future tools and systems, increasing the support and effectiveness of decision making in critical tasks, enabling fast and inclusive action plans, and cutting down unnecessary iterations and costs.

5. Conclusion

A vital requirement for any business that wants to stay competitive in today's data driven economy is to use business intelligence platforms and data analytics that offer advanced data visualizations and exploration capabilities, beyond the traditional data-driven filtering (drill-down) and customization. The objective is to facilitate end-users (e.g., data analysts, business experts) during tasks executions to obtain insights and unveil complex patterns that lie within data and processes for making informed decisions. Accordingly, this position paper proposes a multi-dimensional human-centred model – composed of factors, such as users' roles, cognitive individual differences in information processing, affective states, perceptual preferences, domain expertise and experience – as the theoretical cornerstone of an intuitive data analytics platform, that may offer seamless adaptive data visualizations and exploration of data sets and processes. The aftermath is to increase the users' understanding through explainable visual information as well as their ability to quickly act upon it while engaging into purposeful transparent explorations of end-to-end business tasks.

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