ADVisE

Adaptive Data Visualizations FramEwork

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University of Cyprus
Department of Computer Science

PROJECT DELIVERABLE

Analysis of Existing Information Visualizations and Adaptation Processes and Techniques

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TABLE OF CONTENTS

TABLE OF FIGURES

1. INTRODUCTION

This deliverable presents an overview of existing data visualizations methods, frameworks, state-of-the-art, tools and research outcomes from the business and academic sectors. Moreover, it discusses the main adaptation processes and mechanisms and refers to a selection of success stories and adaptive interactive systems. The topic of data visualizations could be regarded by nature as rather broad and fuzzy, driven most of the times of domain specific challenges, particularities and user requirements. In this respect, researchers and practitioners have demonstrated during the years numerous solutions and techniques, approaching the topic from different viewpoints, to align at a sufficient extent with users' expectations, needs and backgrounds. A convergent point to all is to increase the user experience and decision making in the respective application fields while engaging in complex and high demanding tasks. Even though an attempt to generalize the solutions or research results in the area of data analytics and visualizations could be considered as an ambitious endeavor, on the other hand the polymorphism and distinctiveness of each situation facilitates the study of adaptive methods and paradigms that could compensate on disorientation and exploration difficulties while users interacting with data visualizations for executing their daily business activities.

Therefore, it focuses on the investigation and understanding of three main research questions: (a) What are the various types of data visualizations and prominent application areas (with emphasis on the business sector), how they can be decomposed and what purpose they serve (e.g. comparison, relationship, trend) given the task and intent, (b) what information is important to the end-user for accomplishing his objectives, and subsequently how to extract and represent (visualize) it, and (c) which adaptation techniques and interventions can be employed for generating best-fit data visualizations and how these can be communicated given the unique users' characteristics and contextual conditions.

To answer these questions and ensure ADVisE's framework usability and acceptability, this deliverable also further refers to research outcomes and practices utilized in more generic adaptive interactive systems, to learn by experience and be able to adopt best practices and successful interaction processes with respect to the content and navigation of adaptive data visualizations. The main aim is to gain knowledge of current state-of-the-art data visualizations and adaptation mechanisms in adaptive interactive systems so to provide input to the development of the various components of the ADVisE framework. It will trigger the specification of the content structure, mapping rules, adaptation engine and the design of ADVisE framework as well as the architecture in WP4 – ADVisE Framework Definition and WP5 – Platform Architecture and Design, respectively. Finally, it will provide input to WP6 – Platform Development and Integration and on various deliverables as all identified issues may affect some of the decisions taken during the integration of theory and practice.

This deliverable is structured as follows: Section 2 is focused on data visualizations considerations, elements and challenges in the academic and business sector, discussing the proposed methods, tools and platforms. We then proceed in Section 3 focusing on the adaptation processes and techniques presenting the state-of-the-art on adaptation mechanisms and effects, while in section 4 we outline a selection of success stories sharing their experiences and lessons learned. Finally, Section 5 concludes this deliverable.

2. DATA VISUALIZATIONS CONSIDERATIONS, ELEMENTS AND CHALLENGES

The volume of data collected, stored and analyzed by organizations around the world is rapidly growing at an exponential rate: In the last 4 years, an indicative 2.5 exabytes of data is estimated to be created every day[i]. Moreover, multiple research findings confirm that our reliance on data has grown to the level that 90% of all the data since humanity began has been generated in the last two years (SINTEF, 2013). These data come from a variety of sources and in diverse formats, both structured and unstructured, creating a business ecosystem that unveils new business insights but also generates a number of challenges, complications and problems (e.g., delays in real-time processing of historical data, ineffective delivery of multi-purpose information). In this respect, the process from data capture, transformation, data analysis, modelling and knowledge discovery has become the study of lots of researchers in the past 20-30 years. Decision making systems have further grown to incorporate additional tools to aid in understanding data such as import tools from various sources e.g. SQL Databases and flat CSV files, or incorporating enriched customization possibilities for data representation, facilitating the users to look at or interact with different perspectives of the same data sets.

End-users may use multiple devices and portals, to navigate through historical and real time databases and retrieve data, analyze, visualize, compose and decompose them into dashboards, KPIs, reports and other visualizations. These data compositions and data abstractions enable them to understand the data, committing into critical business decisions and commercial strategies in a very competitive and globalized economy. Nowadays, technology can even offer decision makers strong Business Intelligence (BI) related tools, methods and algorithms, such as predictive statistical algorithms and machine learning that facilitate on one hand the discovery of optimized paths and smart actions during data exploration and on the other hand meaningful data representation. In light of this, many powerful computational and statistical tools have been developed by various organizations, such as SAS Visual Analytics[ii], SAP Lumira (and SAP BusinesObjects)[iii], Tableau[iv], QlikSense and Analytics[v], etc., offering a number of solutions like interactive maps, charts, and infographics, visual business intelligence analysis, recommend actions, etc. Many models such as the CRISP-DM[vi] reference model or the Knowledge Discovery in Databases (KDD) process (1997)[vii] have offered a structured approach for managing data from source to decision, figuring as the cornerstone of today's new academic and practitioners' field called Data Science. The field of Data Science blends different individual disciplines such as mathematics/ statistics, computer science, UX Design, Computer programming and business management at its core of investigation. The majority of data visualization tools have the capacity to generate different types of visualizations (Schneiderman, 1996) to allow users to make sense of data coming from a variety of sources and in diverse formats (e.g., structured and unstructured). However, even though there are data visualizations models and platforms that are considered better than others in terms of usability and understanding often their recipients, information skill workers who have different background and levels of expertise (i.e., data analysts, business experts, decision makers), are overloaded from the vast amount of high quality visual information, which in turn severely decreases their ability to efficiently assess situations and plan accordingly. This mostly happens because the current tools offer a multitude of options for the "customization" of data visualizations; they have not kept up to the challenge when it comes to their dynamic "personalization" depending on the role, experiences, intrinsic characteristics or abilities of

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[i] Big Data: The Management Revolution by Andrew McAfee and Erik Brynjolfsson – HBR Oct 2012 [Online] available at: https://hbr.org/2012/10/big-data-the-management-revolution (accessed at 15 March 2017)

[ii] Online: http://www.sas.com

[iii] Online: http://getlumira.sapstore.com/data-visualizations

[iv] Online: http://www.tableau.com

[v] Online: http://www.qlik.com

[vi] CRISP-DM 1.0 - Step-by-step data mining guide by Pete Chapman (NCR), Julian Clinton (SPSS), Randy Kerber (NCR),Thomas Khabaza (SPSS), Thomas Reinartz (DaimlerChrysler), Colin Shearer (SPSS) and Rüdiger Wirth (DaimlerChrysler)

[vii] The Knowledge Discovery in Databases (KDD) process (1997) -AI MAGAZINE Fayyad Vol 17, No 3 [Online] available at : http://www.aaai.org/ojs/index.php/aimagazine/article/view/1230 (accessed at 15 March 2017)

end-users and still follow a one-size-fits-all paradigm, providing only rudimentary support for customisation based on the assumptions of providers that are expressed through predefined data visualization alternatives and options.

Indicatively, in a real-life business scenario a Local Demand Planner needs to take decisions based on a variety of dynamic statistical data such as: stock availability, shelf-time (expiration date), vacation period, available employees, demand per customer group, historical data, weather data, seasonal best-selling product types, etc., in order to prepare a realistic short- to mid-term demand plan. The criticality of her tasks lies also in the fact that she needs to make accurate and timely (as early as possible) estimations since her decision will determine the production levels that should always be adjusted to the need; saving unnecessary costs (from e.g. excessive production) and utilization of resources. Usually, in this kind of real-life scenarios, the daily responsibilities of such a role presuppose the engagement with more than one tools in combination to assign some meaning to data and extract useful knowledge for decision making. In many cases, a single activity is supported from custom-made developments (e.g. using Excel) for the subsequent execution of steps necessary towards the primary objective. Therefore, It is widely accepted that the increasingly large amount of data requires novel, efficient, and user-friendly solutions.

As such, handling, analyzing and gaining insights into these large multivariate datasets through interactive data visualizations is one of the major challenges of our days. For the end-users to be able to understand the data and leap to information and knowledge, throughout the decision-making process, data needs to be transformed and presented in an easily comprehensible manner (adhering to various related theories such as the Cognitive Fit Theory (Vessey, 1991); suggesting that there is a strong correlation between the task at hand (or related tasks) and the information presentation, influencing individuals' performance during tasks execution and decision making). The level of understanding and usefulness of the data presented to different business roles can vary based on many individual user and role characteristics, both static and dynamic, cognitive skills and abilities in relation to information processing, mental states, user traits, educational and other background information, and pre-existing knowledge of the data/ information and the suggested visualizations (Loboda & Brusilovsky, 2010; Nazemi et al., 2011). Considering these aspects into solutions would allow users to take effective decisions, benchmarking historical and real-time data and analytics.

In this respect, modern BI platforms have managed to provide comprehensive and high-quality data visualization/ representations, but it seems they are failing to recognize the uniqueness of the users in the whole process, who need to take quick actions on the provided data and suggested options. Interestingly enough, the respective 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. A possible optimization of users' data visualization (and exploration) experience would aim to provide them with the most appropriate guidance and best-fit representation of data that looks visually attractive and still provide the required knowledge for their tasks. Visualization optimization is applied on either explanatory or exploratory data[i]. *Explanatory* data aim to answer a specific question with the data. These kinds of visualizations are usually clean from noise, broken down into the simplest form (i.e. a piece of information) and their main purpose is to tell a story. In contrast, with *exploratory* data the story is not in place. Here, main aim is to familiarise the user with large data sets and evoke questions that provides better understanding about the data. They could be characterized imprecise, with no clear dimensions or meaning, patterns or relationships. The challenge here is to find a story and uncover useful messages and meanings (i.e. that serve a purpose or intent) and are hidden within the data.

Adaptation and personalization figures as a promising research direction in this area that can facilitate the development of components and interaction conditions that are tailored to each individual based on his role, user model and activities he executes. At a more technical level, main research trend is to blend and integrate more rigid rule-based techniques used currently in data analytics with dynamic

[i] FusionCharts. (2016). Principles of Data Visualization - What We See in a Visual. [Online] available at: http://www.fusioncharts.com/whitepapers/downloads/Principles-of-Data-Visualization.pdf (accessed 15 March 2017)

adaptation methods that utilize a form of intelligence, like machine learning, case based reasoning, fuzzy logic, etc. The impact, especially in situations that entail complex and demanding business scenarios, will be significant since in this case it is hard to define a priori a set of appropriate interaction behaviors that relate to given tasks with visualization, as well as to their suboptimal counterparts, that support open ended or exploratory tasks. In more general terms, the benefits of user adaptive interactions have been demonstrated since the early years of the Web in a variety of fields and applications (Brusilovsky et al., 2007). These ideas though have again rarely been applied to visual analytics, mainly due to the limited understanding of which user characteristics are relevant for adaptivity in this domain. Some related works refer to methods for actively detecting user's changing goals based on multi-purpose visualizations and accordingly adapting a specific visualization (Brusilovsky et al., 2006a; Gotz, 2009), while other researchers started only recently to examine how users' cognitive abilities might be employed to adapt visualizations to individuals (Toker et al., 2012; Ziemkiewicz et al., 2011). Still, most of the current works are referring to standalone paradigms, with relatively limited scope in highly controlled environments (e.g. Educational). Nevertheless, the need for a more holistic approach through a systemic research towards further formalizing user-depended intrinsic factors and in what situations users would benefit from adaptive interventions during a dynamic interaction with data visualizations is an open key challenge.

2.1 Research on (Adaptive) Data Visualizations

During the years, research on data visualizations has taken multiple directions. The first direction discusses *abstract improvements to visualizations regardless of the specific types or actions*. One example is Healey's earlier work on selecting the right colours and contrast for visualizations (Healey, 1996). The paper claims that users can easily scan through five-colour graphs and struggle to quickly understand the visualization when it uses more than seven colours. The paper also demonstrates that using colour categories with consistent linear separation on the colour wheel better influences users' comprehension of visualization. This is valid when combined with other techniques as each attribute alone shown negligible effect on the user performance. But using different colours the result is not the same; rainbow colour map which the prevalent colouring map separates the colours by wavelength order (from shortest to longest), does not imply perceptual order. Borland and Taylor li have run experiments where people were asked to order greyscale chips, then to order chips using the rainbow colour map; results were consistent on grey scale, but varied per user on the rainbow-coloured chips (Borland & Taylor Ii, 2007). Another example of visualization research targeted towards abstract findings is the comparison of MacEachren on using multiple attributes to visualize uncertainty; their work shows that changing the attributes generically had no significant impact on the user comprehension of the graphs, although they claim that modifying abstract shapes (e.g., fuzziness of the icons) provides faster and more intuitive graphs comprehension (Borkin, 2013).

The second direction for visualization improvement focuses on more *specialised approaches that aim to optimise one specific type of visualization* such as Collins and Veras' attempt to optimise hierarchical uneven tree maps and sunburst visualization and remove the clutter by applying Minimum Description Length (MDL) (Collins & Veras, 2017). MDL is a principle for data compression in statistics. Their research has resulted in faster rendering of visualization since less items are loaded. It also led to better accuracy when loading data on mobile devices where users' chances of clicking elements by mistake was lowered. Another example is Tanahashi and Ma's work focusing on improving storyline graphs by coining an algorithm that reduces graph clutter and its improvement is seen through reduced line wiggles, crossovers and white space gaps (Tanhashi & Ma, 2012).

It is important to note that the technology is still evolving and is not yet making use of the full potential for big data visualization. One example is visual scalability where the difference between the amount of data to be visualised (often terabytes) exceeds the pixels available on screen to represent correlating data, and thus more reduction techniques are required (Keim, et al., 2006). Another issue is the lack of mature integration between customisable visualization tools with data platforms; tackling this challenge would open the door to more capabilities with data such as automation. MacEachren confirms the issue of integration for geo-visualization. He further points another issue of the lack of personalisation in specific visual space where the representation could be made easier for users to navigate such complex representation in a personal manner (MacEachren & Kraak, 2001).

A third research direction emphasizes on *employing adaptation techniques* for facilitating users' ease of use and understanding when interacting with data visualizations. The analyzed data through different visualizations would dynamically adjust their representation parameters (colours, axis, etc.) in real time leveraging the data being analyzed, the user's comprehension level and the particular purpose for which the data/visualization is used. Some of the very first research studies investigating the user perception of graphics and other visualizations were based on the Web and adaptive hypermedia technologies. Studies like the one in Brusilovsky (2002), provided the foundation to build the understanding that the same webpage or visualization cannot satisfy the different and diversified needs of many users. Through the use of three adaptation techniques, adaptive content selection, adaptive navigation, and adaptive presentation, he was able to prove that the unique differences in the users and their comprehension level can define what content should rendered on a Web-page and how users should interact with it.

Adaptive visualization is an approach that emphasizes on improving visualization of data by incorporating adaptation paradigms and methods on various levels of realization. For example, visualization that adapts depending on the visualization limitation (e.g., space available for visualization). Research on 2D visualization tackled tree maps and sunburst charts by applying Minimum Description Length (MDL) principle to prune the charts to maximize the use of space and user focus (Veras & Collins, 2017). In 3D visualization, one example is Tong et al.'s work on designing a visual adaptation for glyph-based visualization. The system uses the context of user view to declutter the visualization by removing elements out of the focus area (Tong et al., 2017). Furthermore, the ability to change visualization depending on various user features that can be explicitly provided or inferred from the trace of user actions. Through adaptation, users can modify the way in which the system visualizes a collection of elements (or documents) (Roussinov & Ramsey, 1998). Despite its relatively recent introduction, quite diverse adaptive visualization ideas have been proposed. They can be categorized into four groups: (1) visualization method adaptation, (2) visual structure adaptation, (3) adaptive annotations, and (4) user model visualization.

The first visualization method adaptation group prepares multiple visualization methods and provides them selectively according to different user characteristics. ERST (External Representation Selection Tutor) provided a selection of information display formats (plot chart, table, pie chart, sector graph, bar chart, Euler diagram) mapped to users background knowledge of external representations (KER) and task types (Grawemeyer & Cox, 2005). The visual structure adaptation methods adapt the structures either by varying the visualization layouts or by providing easy exploration methods. CVI and RF-Cones (Teraoka & Maruyama, 1997) tried to help users to navigate the problem space with dynamically changing view points and similarity-based layouts. WIVI (Lehmann et al., 2010) provided an adaptive navigation system for Wikipedia articles. Opinion Space (Bitton, 2009) let users easily see where their opinions were located among high-dimensional survey attributes. Roussinov & Ramsey's (1998) multi-level SOM (Self Organizing Map) helped users to explore multi-level maps that were adaptively regenerated following users' exploration commands.

Using the visual elements such as colors or icons, some adaptive annotation approaches focused more on a specific part of visualizations. ADaptive VIsualization for Education 2D (Brusilovsky et al., 2006b) implemented this approach based on the well-known Force Directed Placement (FDP) visualization. QuizVIBE (Ahn et al., 2006) is based on a similar approach but used a relevance-based visualization as a platform. It made use of the VIBE visualization, where the C language quizzes were displayed according to their similarities to the C language concepts. Gansner et al. (2009) used the FDP visualization to adaptively visualize TV programs with color-based adaptation instead of icons. Knowledge Sea (Brusilovsky & Rizzo, 2002) utilized the SOM visualization for the personalization and social annotation of educational content by adapting foreground/background colors of icons and cells.

The Light-house (Leuski & Allan, 2004) introduced an interesting adaptive search visualization mechanism. The estimated relevancy calculated through user feedback was marked on the document icons and textual titles using different colors and lengths of the colored-shades. The last group attempts to show the contents of the user models to the users and even let them edit the user models, so that the users could control the user model contents. YourNews (Ahn et al., 2007) explored an on-line news filtering system that was equipped with a user model viewer/editor. TaskSieve (Ahn et al., 2008) continued to examine the potential of open user models but it focused more on the query and the user model fusion interface, rather than the keyword level user model exploration. IntrospectiveView (Bakalov et al., 2010) visualized concepts in ontologies in a circle and used different levels of colors and font sizes according to user interests. MyExperiences (Kump et al., 2010) visualized the open learner model (OLM) in order to permit the adaptive learning system users to see and construct their user models. The learner model was represented as a tree structure using the Treemap algorithm. In comparison, Adaptive VIBE implemented by Ahn & Brusilovsky (2013) support high-level interactivity for personalized search through adaptive exploratory visualization. Ahn & Brusilovsky (2013) conducted a full-scale user study and the results revealed that the adaptive VIBE improves the precision and productivity of, for example, a personalized search system, while helping users to discover more diverse sets of information.

Still, in line with the adaptation and personalization of data visualizations, there are research works that bring more *inclusively the user in the whole process of data visualization generation* by investigating methods for understanding more accurately his requirements, needs, and intrinsic perceptual and cognitive characteristics and accordingly adapting the visualization content. This research direction could be considered closer to the generic aims of the ADVisE. In this realm, Yelizarov and Gamayunov argue that users may get overwhelmed even with reduced amount of information, and that can lead to taking the wrong decision (Yelizarov & Gamayunov, 2014). They proposed a low-level context aware visualisation system that adapts the complexity of the data visualisation based on the user cognitive load. They explain that the cognitive load can be measured physiologically e.g. heart rate, PET, fMRI or using Dual-task paradigm; this includes asking the user to perform two tasks and comparing their performance to each task separately and this allows them to measure if the tasks are using common resources. Their findings showed an efficiency by up to 40%, but the test duration was shorter than the realistic work duration of the user. A series of research papers have been produced by the Department of Computer Science, University of British Columbia, Canada, that form a slowly progressing motive to allow for user cognitive adaptation of visualizations based on a static user profile. More specifically, the papers published during the years from 2008 until 2017 shed light to the correlations of data visualizations with various cognitive factors[i] (however not applied in the business domain). Conati and Maclaren in their paper (Conati & Maclaren, 2008) have shifted the focus from adaptation of specific channels (such as Adaptive Hypermedia and Adaptive Web – see Brusilovsky's work above) and data adaptation, to exploring the differences between the perception of users to differentiate between two different data visualization techniques (radar graph and coloured boxes). The research included a number of cognitive abilities that were tested. All user cognitive profiling and the actual experiment testings were done through a series of questions with a small sample of participants. The paper concluded that for very specific type of questions, comparing the values of two (2) sets of variables comparatively changes, the results were correlated to the user's Perceptual Speed (i.e. the speed of recognizing and comparing different symbols, diagrams or figures, involving visual perception). The main drawback of the study is the limited usage of real time cognitive reading devices (such as eye tracker) or methods to measure the cognitive concentration of the users as the experiment was progressing. In 2011, in continuation of the first 2008 publication, Conati et al. (2011) publish a second paper that documents their results of measuring user's cognitive understanding of the provided chart using an interface. More specifically an eye tracker device was employed to record and measure the user's gaze data while evaluating data visualizations. The intention of the study was to use the eye tracker collected data along with user's cognitive measures from a survey, as feedback to create adaptive visualizations. This study take a step ahead of the previous publication in providing a more realistic evaluation of the user's state, but at the same time the participants and visualization variations used were not sufficient to provide a concreate correlation between the two (2) visualization methods and the cognitive traits of the user. In their paper Toker et al. (2012) a more broaden set of user characteristics that could influence the effectiveness of utilizing a visualization for specific goal were evaluated. The paper was based on the previous work of Velez et al. (2005), that attempted to correlate between spatial abilities and proficiency in visualization tasks in identifying objects. The gap between user traits and the adaptive information was addressed in their paper Carenini et al. (2014) where visual highlighters to important information in charts (such as colours and lines) were utilized to evaluate if they can improve user information visualization processing and how the differences between users (specific traits again) can impact the information delivery. The study only used one chart type, the bar graph, with two interventions: colour and reference lines/arrows. Users were presented different charts with

[i] Online: http://www.cs.ubc.ca/cs-research/lci/research-groups/intelligent-user-interfaces/userchar.html

information to comprehend and answer questions. The study concluded that the interventions had a positive correlation with improve visualization processing. But the study raises questions if different charts can offer different results and if different visualization/ interventions could work different for different types of users. In Toker & Conati (2017), authors have taken a step further to use an automated way of measuring user visual processing with different cognitive loads. An eye tracker interface was employed to measure the pupil dilation and compare the survey results against the collected data. The result of the study showed that measure of pupil dilation could be used to measure the effectiveness of interventions as well as cognitive load. In a more recent publications by Lallé et. al. (2017), a practical application of measuring user satisfaction of the user interface and the visualizations provided from a public facing application. The study tried to find a correlation between the individual needs and abilities, including cognitive abilities (perceptual speed, working memory) on how the affect the users' performance in getting meaningful data out of the application and their respective satisfaction level. The study concluded that the individual user differences do affect the way the user interact with the application as well as their satisfaction level.

The areas that we see the existing work lacking in terms of exploring the relationship between adaptive visualizations and the user differences are the limited set of traits and variations used. For example, working memory can have up to seven stages (7), but the studies only evaluate the first level. Additionally, in some studies the results are solely based on the participants responses to the survey questions, and in some studies an eye tracker is used in combination with the user profile. Our aim is to measure and compare multiple real-time indicators and through a model try to correlate and evaluate which variables affect different types of users accordingly, in order to create unique cognitive profiles.

Figure 1. Snapshot from the Data Viz Project

Finally, research has also delved into *algorithms that aids us in picking the right chart type in general*. In order to evaluate how different users, with distinct usage patterns, cognitive traits and specific goals of analysing and using the data through visualizations, we need first to understand what types and interventions are available and how they can correlate the fore mentioned dimensions. A graph schema is a learned cognitive structure that describes the components of charts of different types (Kosslyn, 1989; Lohse, 1993; Pinker, 1990). A large number of different types of visualizations are utilized by data analysts depending on different parameters such as the nature of the data (e.g. geographical and partial data vs statistical data), the number of parameters, the medium through which it will be presented, if the data will be correlated, the end user, if the data is real time or historical or both etc. The main uses of a chart can be divided into general directions (goal-directed actions) like comparison, trend and distribution. Organizations have attempted to catalogue all the different types of visualizations and provide guidelines. Multiple available resources provide trees that help users pick the right chart for the goal they are trying to achieve. One of the largest online catalogues of visualizations can be found on the Data Viz Project[i] (see Fig. 1) or the Data Visualization Catalogue[ii] (see Fig. 2).

Figure 2. Snapshot from the Data Visualization Catalogue

However, the main issue with these graphs is the unsupported claim and lack of justification behind their choices. Upon closer inspection, some research aims to back these assertions; Doumont & Vandenbroeck (2002) present a breakdown of each chart creation and comprising elements. While the creation purpose is offered, it does not necessarily mean that a certain chart is the most effective when used in its original creation context.

In summary, the table below (see Table 1) demonstrates the main uses for each chart type according to the goal-directed actions which might be related to a specific request for data analysis. A more detailed break-down can be found in Fig. 3, Fig. 4 and Fig. 5

Table 1: Chart types according to goal-directed actions for data analysis (exploration)

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[i] Data Viz Project – A project in beta by Ferdio. http://datavizproject.com/

[ii] The Data Visualization Catalogue. https://datavizcatalogue.com/search.html

Chart Type	Comparison	Distribution	Composition	Trend	Relationship	Table
Alternating Rows Table	X		X		X	X
Bar Chart	X	X	X			
Bubble Chart	X				X	
Bullet Bar Chart	X					
Circular Area Chart	X					
Column Chart	X	X		X		
Column Histogram		X				
Column Line Chart				X	X	
Groupings Table	X		X		X	X
Line Chart	X			X		
Line Histogram		X				
Pie Chart			X			
Pie Chart with Highlight			X			
Quartiles Table	X		X		X	X
Scatterplot Chart		X			X	
Stacked Area Chart			X			
Stacked Bar Chart	X		X			
Stacked Column Chart			X	X		
Table	X					
Waterfall Chart			X			

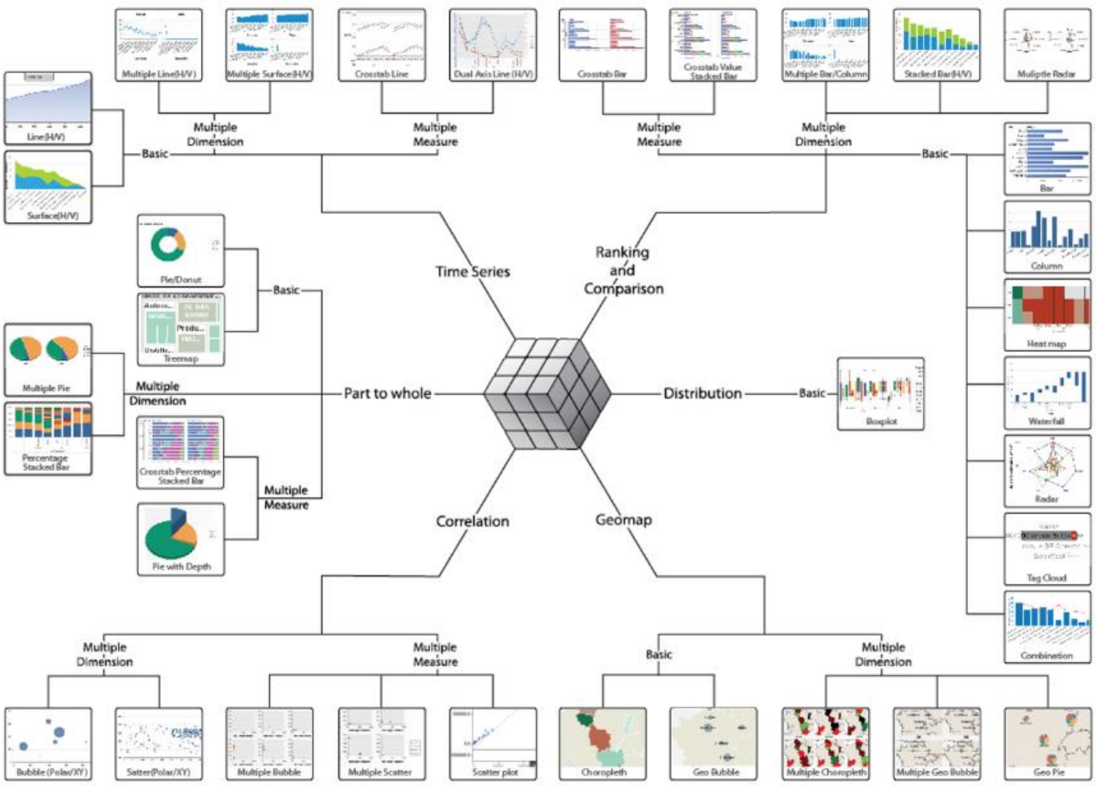

Figure 3. CVOM Charting Map

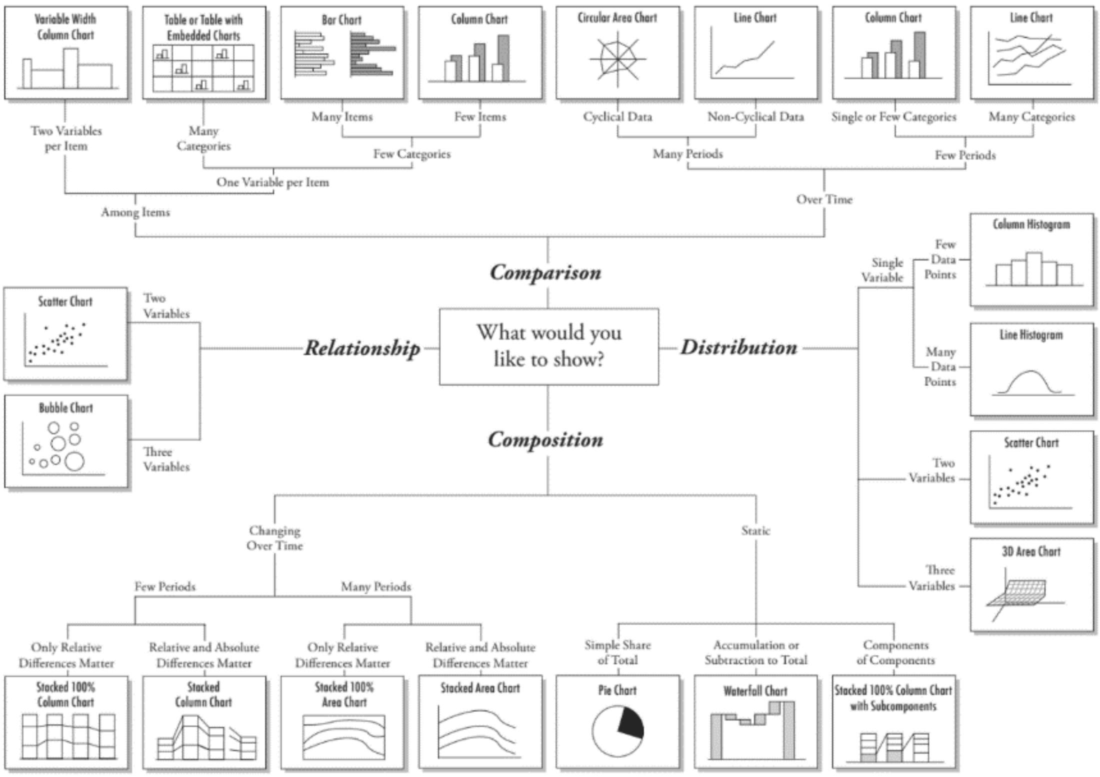

Figure 4. Chart Suggestions – A Thought Starter

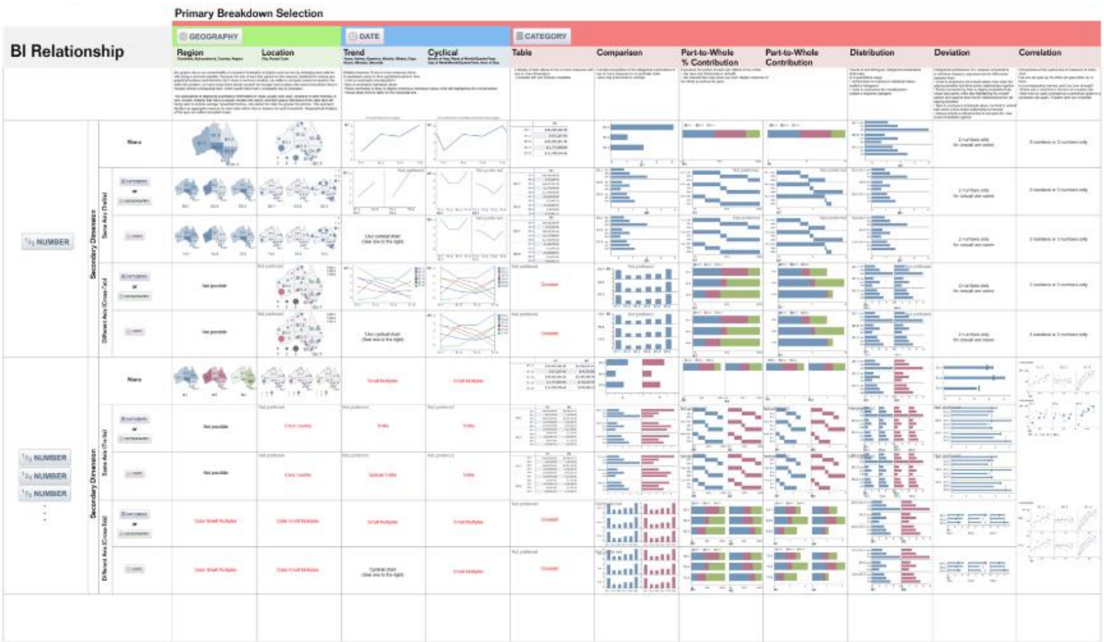

Figure 5. Visualization Suggestion Matrix Based on User Selection of Table Columns

2.2 Market Analysis and Enterprise Solutions

The demand for data analysis and business intelligence skills and solutions, has rapidly increased in the last 5 years, with an average rate of 25% to 50% per year. Today the market for intelligent data analysis and business decision support solutions is at its peak. The demand is driven by the business segment for solutions that would allow business experts, managers and other information workers, to take quicker and effective decisions, increasing both customer satisfaction and corporate revenue. Statistics show that nearly 50% of the enterprises are already either deployed a Big Data/BI solution or are in the process[i]. Therefore, it is recognized that efficient data exploration and recommendations on data visualizations provide great insights and value to businesses (Gentile, 2014), and multiple business solutions have developed to support the growth in interest. At a higher level, business visualization tools follow two main approaches. The first refers to expert users, mainly developers and data analysts, providing an interaction environment in the form of programming language libraries such as D3 and HighCharts; D3 is highly customisable and allows for the creation of new types of visualizations[ii], whereas HighCharts is aimed more towards bootstrapping a common chart type that would be used by any developer[iii]. On the other hand more user friendly solutions aim at users with no programming knowledge like Tableau that gives business experts the ability to explore data visually without the need for programming proficiency through providing an interactive user interface that allows for moving data through basic interfacing actions such as browsing selection and drag-and-drop[iv].

More specifically, with the increasing commercial interest in data visualization for large datasets due to increasing data amounts and computational capabilities, automation of data visualization development became an important topic. Self-organized dashboards based on recommendation systems were developed as an answer to the proportions of handling data to doing science of 9:1 (Howe & Cole, 2010). From early frameworks like the APT, which introduced expressiveness and effectiveness as criteria to select visualizations (Mackinlay, 1986), to complex setups like Polaris (Stolte & Hanrahan, 2000) which developed to the current Tableau application with the Show Me app (Mackinlay, Hanrahan, & Stolte, 2007) and approaches like IBM Multi-Eyes (Viegas et al., 2007) or SeeDB (Vartak et al., 2015), recommendations came a long way. To structure these recommendation systems, the dimensions visual encoding (= how to visualize) and data query (= what to visualize) seem fruitful, as shown in Table 2 (Wongsuphasawat, et al., 2016). Hybrid recommendations engines such as Voyager 2 (Wongsuphasawat, et al., 2017) are gaining increasing attention, as they combine the best of both system classes. Behavior and interaction pattern driven recommendations were researched to a limited extent (Gotz & Wen, 2009).

Table 2: Classification of recommendation systems taken from (Wongsuphasawat, et al., 2016, p. 2)

		Visual Encoding	
		Completely Specified	*Completely or partially suggested*
Data Query	*Completely specified*	Manual specification tools (Polaris, ggplot2 for R, Vega-Lite)	Encoding Recommenders (APT, Spotfire Recommendations, Tableau's show me)
	Completely or partially	Data Query Recommenders	Hybrid Recommenders (Small

[i] IDG Enterprise 2016 Data & Analytics Research, July 5, 2016 - https://www.forbes.com/sites/louiscolumbus/2016/08/20/roundup-of-analytics-big-data-bi-forecasts-and-market-estimates-2016/#21efeb026f21

[ii] D3, 2011. D3. [Online] available at: https://d3js.org/

[iii] HighchartsJS, 2011. HighchartsJS. [Online] available at: https://www.highcharts.com/

[iv] Tableau, 2003. Tableau. [Online] available at: https://www.tableau.com/

	suggested	(SeeDB, Scagnostics)	multiples, large singles, Voyager 2, VizDeck)

How data visualization recommendation systems should work is generally outlined best along the axes are data characteristics, intended task or insight, semantics and domain knowledge, visual ease of understanding as well as user preferences and competencies (Vartak et al., 2017). Building on the highly researched area of product recommendation, the taxonomy of recommendation methods of content-based filtering, collaborative filtering and knowledge-based filtering, "the heavy lifting must be performed by knowledge-based filtering" (Vartak et al., 2017, p. 37).

In order to appreciate the breadth and depth of the business solutions, frameworks and platforms, and understand if the global market offers products/services which are direct or indirect substitutes or are transforming to our targeted solution in ADVisE, we did a market research of the most prominent enterprise data analysis and visualization application software platforms. The challenge in this endeavour is that technology and marketed product offerings change at a very rapid rate, making it difficult to select the top tier companies and map and compare each of their platforms in a conscience way. Our first step in identifying which platforms we needed to compare was to select a global market authority that ranks the different suites based on both market penetration as well as features and innovation. For this study, we have used the Gartner 2017 Magic Quadrant for Business Intelligence and Analytics Platforms Report, published in Feb 2017[i].

Figure 6. Gartner (Feb 2017) Magic Quadrant for BI and Analytics Platforms

[i] Gartner Magic Quadrant for Business Intelligence and Analytics Platforms. (2017). [Online] available at https://www.gartner.com/doc/reprints?id=1-3RTAT4N&ct=170124&st=sb. Analyst(s): Rita L. Sallam, Cindi Howson, Carlie J. Idoine, Thomas W. Oestreich, James Laurence Richardson, Joao Tapadinhas

The report assesses companies and their products in five use cases (Agile Centralized BI Provisioning, Decentralized Analytics, Governed Data Discovery, OEM or Embedded BI, Extranet Deployment) and a combination of fifteen critical capabilities (such as Interactive Visual Exploration, Smart Data Discovery, workflows, ease of use and Visual Appeal etc). Companies are then scored and ranked against their ability to execute using the above metrics and their completeness of vision (which includes a combination of innovation, market strategy and penetration and sales strategy). Companies which excel in both areas are mapped in the Leaders quadrant, whereas companies which have currently less capabilities but are targeting through innovation a higher market segment are mapped in the visionaries' quadrant. Supplementary, another primary information source that was used to select the market predominant software and use them to compare and gauge the innovative nature of ADVisE was the blog article: "Is Big Data Still a Thing?"[i]. Fig. 7 provides a map of the application as extracted from the blog.

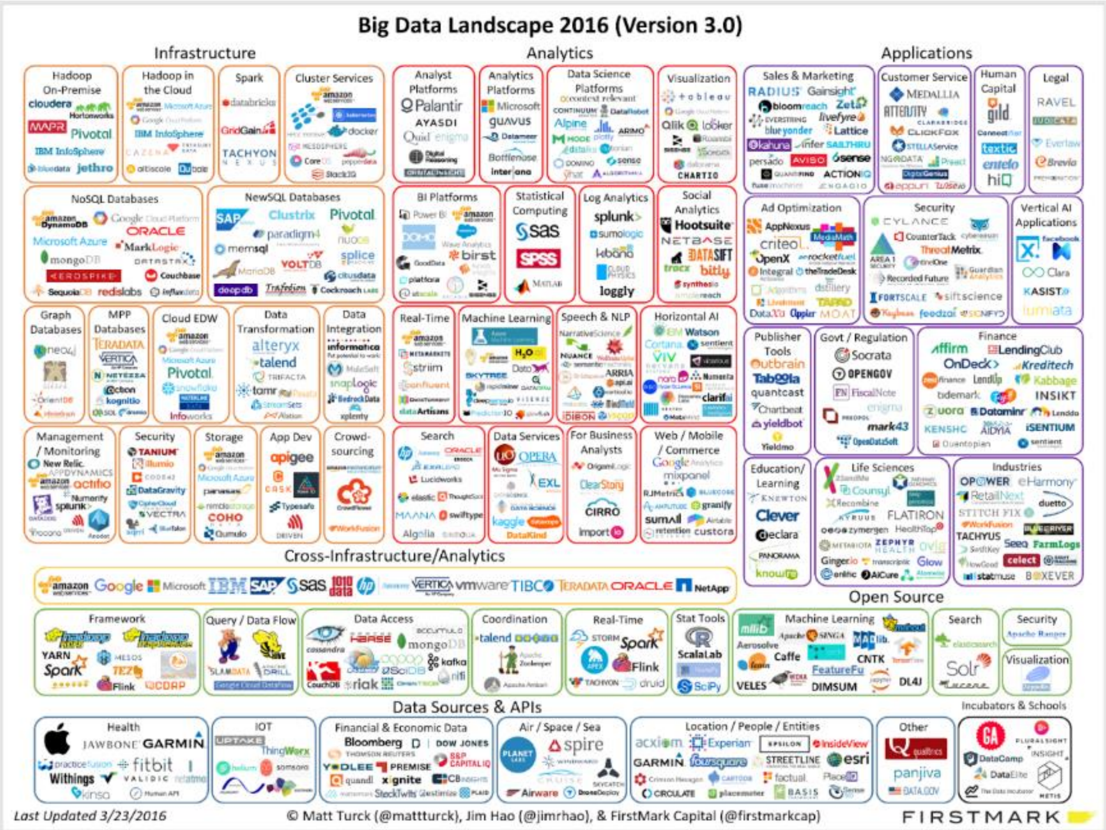

Figure 7. Big Data Landscape 2016 (Version 3.0)

Our market research focused on all the companies in the Leader Quadrant, and a selected number of companies in the Visionaries Quadrant based on how related their offerings are to our research and targeted solution. A representation of the ranked companies in a graph is displayed in Fig. 6 - extracted from the relevant report. The companies and their respective product selected for the analysis are:

- Microsoft Power BI[ii]
- Qlik: Qlik Sense and QlikView[iii]
- Tableau: Tableau Suite[i]

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[i] Matt Turck: Is Big Data Still a Thing? (The 2016 Big Data Landscape) – [Online] available at http://mattturck.com/big-data-landscape/#more-917

[ii] Online: https://powerbi.microsoft.com

[iii] Online: https://www.qlik.com

- SAS: SAS Visual Analytics (SAS BI)[ii]
- SAP: SAP BusinessObjects Lumira[iii] and BusinessObjects Cloud[iv]

For the current study, we evaluated a number of parameters that would allow us to determine if their offering provided or will provide in the near future features in the area of cognitive data adaptive visualizations. These parameters also provide expansive understanding of what are the capabilities of the platform that can be used in future enhanced editions for visualization adaptation (both user and data based) and understand what type of R&D was executed in developing the products.

The list of comparative parameters are:

- Offering Model:
    - On Premise
    - Cloud based
- Types of charts offered and adaptation to the data loaded of each chart
    - Bar Chart
    - Stack or Area chart
    - Line Chart
    - Combo Chart
    - Gantt Chart
    - Milestone trend analysis (MTA)
    - Radar Chart
    - Scatter Chart
    - Grid Chart
    - Pie Chart
    - Polar Chart
    - Doughnut Chart
    - Block Chart or Heat map
    - Funnel Chart
    - Gauge Chart
    - Mekko Chart
    - Pivot Table
    - KPI Charts
    - Table/Matrix
    - Map
    - Bullet Graph
    - Histogram
    - KPI
    - TreeMap
    - Bubble chart
    - Packed Bubbles
    - Waterfall charts
    - Box-and-whisker Plot
    - Sankey Diagram
    - Network Diagram

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[i] Online: https://www.tableau.com

[ii] Online: https://www.sas.com

[iii] Online: https://saplumira.com

[iv] Online: https://www.sap.com/products/cloud-analytics.html

    - Correlation Map
    - Decision Tree
    - Word/Text Map
    - Custom Visualization
- Visual Drill Down
- Number of Data Sources that can be used
- Expressions / Formulas
- Ability for Real Time Data and Dashboards and adaptation
- Complex Data Modelling
- Custom Queries
- Surrounding technologies
- Update Schedule ability
- Quick Insights (ability to provide automatic data insights)
- Drag and Drop
- Dashboard Concept
- Predictive Analytics
- Automated visualization suggestion
- Natural Language Commands (Query)
- Natural Language Audio Support
- Visualization Description and Insights Feedback in natural language (natural language generation)
- Other language based query or feedback Capabilities
- Mobility
- API capability for extending

A detailed comparison map of each solution is included in Appendix A (Enterprise Platform Comparison). Comparing the solutions in respect to visualization adaptation, most of the solutions are focused on either user manual customization of the visualization parameters (e.g. type of chart, colours, axis scales, etc) or basic data driven automatic customizations that application infers the most appropriate parameters based on the number of values and dimensions of the loaded data. Some applications have adopted AI and Machine learning features to recognize business value of the data and provide generalized descriptions, which are not most of the times particularly correlated to the user's task data analysis and decision-making process. Drill down and partitioning of the data seem to be the predominant data scavenging techniques, and in some the software natural language entry (i.e. describing in plain language the intended query) has substituted the mouse and keyboard commands for manipulating the charts and data. It is rather evident that industry leaders (Microsoft, Tableu, Qlik, SAP, SAS, IBM, Oracle) are investing in new technologies and tools to facilitate the engagement of non-specialised or enthusiast users, who are not trained in advanced statistics or data science (Sallam et al., 2017), to perform complex data analysis tasks; a job historically assigned to highly trained database experts. Consequently, these "new user types" are now faced with an unprecedented number of tools and options, and are required to orchestrate them in a proper way, so as to make sense of the data and articulate their meaning using the most appropriate visualization; a cumbersome task even for experts. This is especially complex in the business sector, where the data exploration process necessitates: (i) the integration of multiple diverse types of datasets (e.g., data coming from ERP, CRM and Social systems); (ii) the knowledge of the full spectrum of analytics algorithms to infer for example, what has happened or could happen, and what relevant ations the company must take (i.e., descriptive, predictive and prescriptive analytics); and (iii) the understanding of complex business data models, processes and constraints that the business adopts. However, as a general observation, what existing commercial solutions seem to almost ignore are the specific traits of the user, both in the context of his functional role in previewing and analysing to get a business or other decision, as well as the flexible and changing cognitive traits of the end user. Hence, without an effective adaptation mechanism to support holistically the data exploration process, the aforementioned challenges make the analysis and understanding of data by decision makers (e.g., managers, data analysts, business experts) particularly demanding, time consuming, costly, if not many times impossible (Kerren et al., 2008; Chaomei, 2005; Liu et al., 2014).

3. Adaptation Processes and Techniques

This section is focused on the adaptation side of adaptive interactive systems. Specifically, the analysis specifies which visible aspects of the user interface should be adapted and how, what adaptation mechanisms should be implemented, how should the system's content and functionality should be structured and prepared for input to the adaptation mechanism, and how the adaptation effects on the user interface should be communicated. Accordingly, this section discusses the state of the art in adaptive user interfaces (i.e., various adaptation ways and effects), and adaptation mechanisms in various domains; discussed intentionally beyond the scope of the data visualizations area in an attempt to inclusively consider the outcome and lessons learned for a more optimized solution.

3.1 Adaptation Mechanisms

Adaptation mechanisms apply specific algorithms that decide what adaptation will be performed on the content and functionality of the system. Various approaches have been proposed in the literature, including among others user customization, rule-based, content-based and collaborative mechanisms.

3.1.1 User Customization

User customization provides a mechanism that allows users to construct a custom interface representation based on their own preferences. Once the user has entered this information, a matching process is used to find items that meet the specified criteria and display them to the user. The system in this case is not considered adaptive, but rather adaptable because it is explicitly configured by the user how to adapt its content and functionality. Yen & Acay (2009), for example, proposed a novel idea for adaptation of the user interface for complex supervisory tasks. An adaptive interface can be controlled by its user in the following ways (Horvitz, 1999; Kühme, 1993; Keeble & Macredie, 2000; Oppermann, 1994)

1. Providing means to activate and deactivate adaptation partially or completely.
2. Providing means to set parameters in the adaptation algorithm.
3. Giving control over the use of behavior records and their evaluation (control over privacy).
4. Offering the adaptation in the form of a proposal (the user can accept or reject the adaptation).
5. Providing means to review and manage completed adaptations (the user can save/load previous adaptations).
6. Providing information on the effects of the adaptation.
7. Providing information on the rationale of the adaptation (transparency or predictability).

Wang et al. (2010), for example, described a framework for collaborative tagging social media systems, which allows users to annotate the resulting user-generated content, and enables effective retrieval of otherwise unstructured data. The personalized environment developed would be especially appropriate for the following tasks: collaborative tagging, collaborative browsing and collaborative search.

3.1.2 Rule-based Mechanisms

Rule-based mechanisms refer to the process of producing high-level information from a set of low-level metrics, related to both static and dynamic user context information. Bearing in mind that the dynamic part of the context data model can be updated in real time it becomes obvious that reasoning capabilities supported provide an added value supporting users in different tasks. Such rules can initiated automated system actions or compare predictive user interaction models with actual user interaction data gathered in real time, providing thus valuable insights related to the current user goals and efficiency of interactions. For example, an online banking system may contain a rule "If ([USER].logged=False and [USER].loginattempts.count>2) then [UIOBJECT.LiveSupport.show=True]", which indicates that the system should automatically offer a live customer support option to users who could not succeed to login in the system after trying to login for more than two times. Based on another usage scenario such a rule-based adaptation mechanism could extremely increase usable security by offering a live customer support option to users whose e-

Banking web accounts were locked due to numerous unsuccessfully login attempts. A detailed analysis and comparison of rule-based mechanisms can be found in (Smyth, 2007).

3.1.3 Content-based Mechanisms

Content-based mechanisms suggest labelling of links by analyzing the content of pages. A typical content-based mechanism includes the following steps: i) pre-fetch the content behind the links of the current page, ii) parse the pre-fetched pages to create a weighted keyword vector of each page, iii) compare the weighted keyword vector of each page with the user's preferences, that are also usually represented using a weighted keyword vector, iv) suggest pages whose keyword vectors are the same with the user's preferences. FishWrap (Chesnais et al., 1995), for example, was one of the first prototypes of personalized newspapers using profiles of individual members of the MIT community. The system provided general news about the world and the university community. The user profile was developed by asking the user three questions: origin, affiliation in MIT and major interests and by recording user navigation. Additionally, the user could update their profile.

In web sites such as Yahoo[i], and MSN[ii], the user typically selects categories of interest and the page is built on-the-fly to match the available content to his or her preferences. The content categories are usually quite broad and the personalization lacks dynamic updating of user interests over time, and all changes are made manually. Consequently users receive information on out-of-date categories until they update their fields of interest. This strategy consists in suggesting items similar to others that gained the target user's interest in the past (Bridge et al., 2006), which is quite simple to implement. However, the recommendations tend to be repetitive for considering that a user will always appreciate the same kind of content. This overspecialization may not pose a problem with users who want to remain informed on specific topics (e.g. people with chronic diseases), but it does so in general.

3.1.4 Collaborative Mechanisms

In response to the problem of overspecialization, researchers came up with collaborative filtering to consider the success of the recommendations previously made to users with similar interests (the neighbors of the target user) (Pazzani, 1999). This approach solves the lack of diversity, but works poorly with users (the gray sheep) whose preferences or needs are dissimilar to those of the majority. Collaborative mechanisms exploit the social process of people of recommending something they have experienced with (e.g., read a book, watched a movie, etc.) to other people. Collaborative mechanisms are based on the assumption that if users X and Y rate n items similarly, or have similar behaviors (e.g., buying, watching), hence will have similar interests. Adaptive interactive systems utilize collaborative mechanisms to provide navigation support by recommending links of interest to the user based on earlier expressed ratings or navigation behaviour of similar users. Amazon[iii] is largely based on this method, where a user's past shopping history is used to make recommendations for new products.

Das et al. (2007) describe an approach to collaborative filtering for generating personalized recommendations for users of Google News[iv]. The site is not an online version of a traditional printed newspaper; but rather a collection of the most visited news article on the web. The user can change or delete the layout of topics and can state a number of keywords he or she would like to have in an article. Aggarwal & Yu (2002) describe a system for personalizing web portals containing news feeds services. The system employs collaborative filtering techniques, and the personalization is achieved by both the user entering explicit information and by implicit input. ANATAGONOMY (Kamba et al., 1997) personalizes web pages by monitoring user operations on articles and creating user profiles based on both explicit and implicit feedback from the user. The system uses both content based and collaborative filtering techniques.

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[i] Online: https://www.yahoo.com/news/

[ii] Online: www.msn.com

[iii] Online: www.amazon.com

[iv] Online: http://news.google.com

The most recent strategy is item-based collaborative filtering, which consists in recommending items related to others that the target user liked in the past, considering two items related when users who like the one tend to like the other as well (Sarwar et al., 2001). This approach still faces several problems that were also apparent with collaborative filtering. One of those problems is sparsity, implying that when the number of items available to recommend is high (as it happens in many domains of recommender systems application nowadays), it is difficult to find users with similar valuations for common subsets. Another important drawback is that of latency, related to the inability to recommend recently added items, as long as there are no user ratings available for them. Nores et al. (2012) presented a new strategy, called property-based collaborative filtering in the context of health-aware recommender systems, as a means to tackle the aforementioned problems in general settings. This approach depends on having a semantic characterization of the items that may be recommended, which is not necessarily true for other mechanisms of adaptation (see also Blanco-Fernandez et al., 2011).

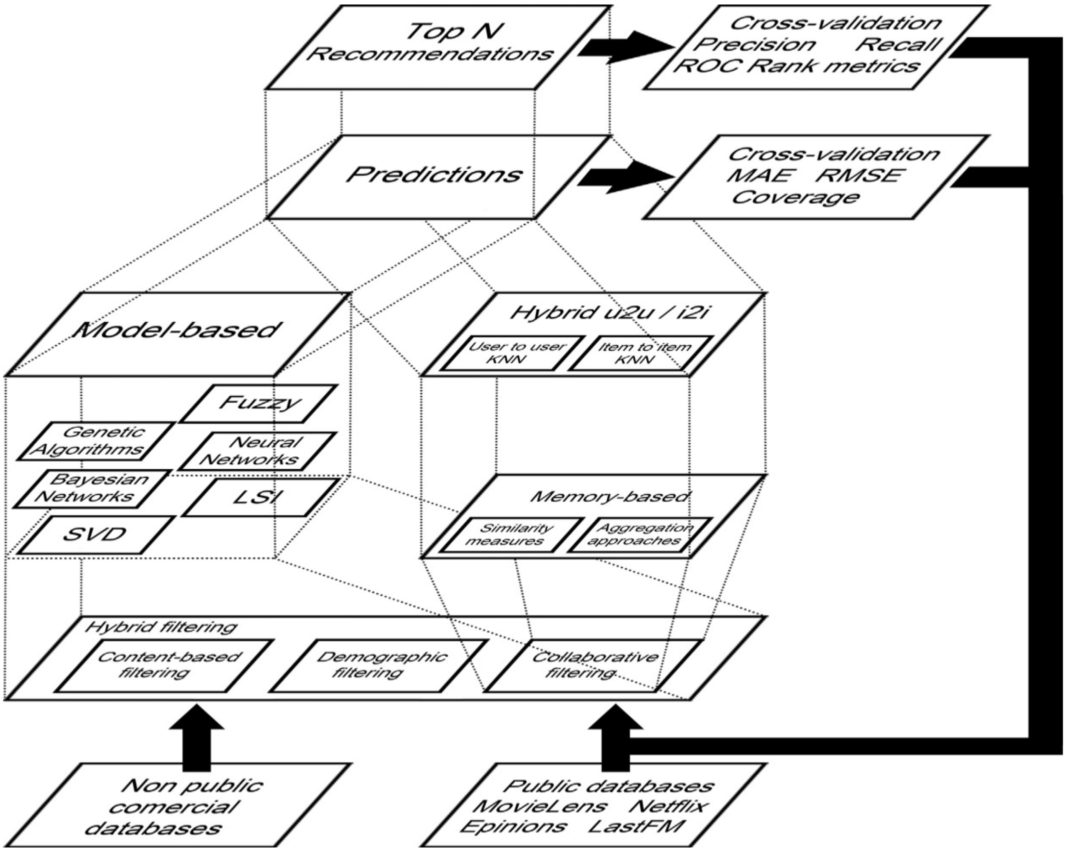

Figure 8. Traditional models of recommendations and their relationships (Bobadilla et al., 2013)

Bobadilla et al. (2013) provides a detailed overview of the area of recommender systems (see Fig. 8) arguing that currently these systems may incorporate user social information (friends, followers, trusted users). Bobadila et al. (2013) argue that in the future, systems will use implicit, local and personal information from the Internet of things/integrated devices on the Internet (e.g. location information, data from devices and sensors, real-time signals, weather parameters).

3.2 Adaptation Effects

Adaptation effects can include special navigational tools such as table of contents, index, maps and recommendations that could be used to navigate users to all accessible pages that can be adapted here are the page (content-level adaptation) and the appearance and behavior of the links (link-level adaptation). In adaptive hypermedia literature they are referred respectively as adaptive presentation and adaptive navigation support. *Adaptive Presentation* is to adapt the content of a hypermedia page to the user's goals, knowledge and other information stored in the user model. There could be multiple reasons to use adaptive presentation. Two typical cases in the area of education are comparative explanations and explanation variants. The idea of comparative explanations is to connect new content to the existing knowledge of the learner. *Adaptive Navigation* support is to help users to find their paths in hyperspace by adapting link presentation to the goals, knowledge, and other characteristics of an individual user.

A good design practice aims to establish a common ground among designers and users related to the aspects of user-system interaction by formalizing the information architecture of the interactive system and specifying the interaction flow for accomplishing specific tasks. A well-used and simple approach to modeling interactive systems is to analyze the user actions in several levels of abstractions and identify on each level the most appropriate terminology, content presentation and interaction flow. The high level architecture of modelling interactive systems is illustrated in Fig. 9.

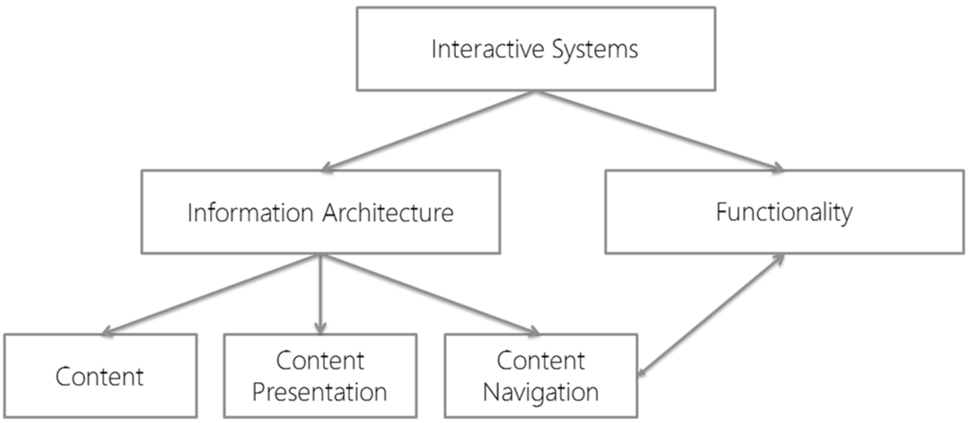

Figure 9. High-level Architecture of Interactive Systems

An important adaptation issue in adaptive interactive systems is which visible features of the system can be adapted by a particular technique. According to Brusilovsky (2001), there exists a number of ways to adapt hypermedia. These are classified under two main classes of adaptation technologies; content-level adaptation, called adaptive presentation and link-level adaptation, called adaptive navigation support.

Adaptive presentation relates to the adaptation of hypermedia elements inside nodes, and adaptive navigation support relates to the adaptation of links inside nodes, indexes and maps. These are discussed next.

3.2.1 Adaptive (Content) Presentation

Adaptive presentation relates to the adaptation of hypermedia elements inside nodes. The idea behind adaptive presentation is to adapt the information elements (or content) inside a node accessed by a particular user to the needs and preferences of that user. Adapting the presentation of content within a node is most often performed as a manipulation of fragments. Such manipulations aim to provide prerequisite, additional or comparative explanations. For example, additional information can be shown for users with a specific state of knowledge to provide missing prerequisite knowledge, additional details, or a comparison with a previously known concept.

Techniques that are used to provide adaptive presentation include: i) inserting/removing relevant to the user fragments, ii) expanding/collapsing content fragments (e.g., expand additional explanations to novice users), iii) altering content fragments (e.g., present a diagrammatical representation of a concept to an Imager cognitive style user (Germanakos et al. 2008)), and iv) sorting content fragments (e.g., some users may prefer to see an example before a definition, while others prefer it the other way around).

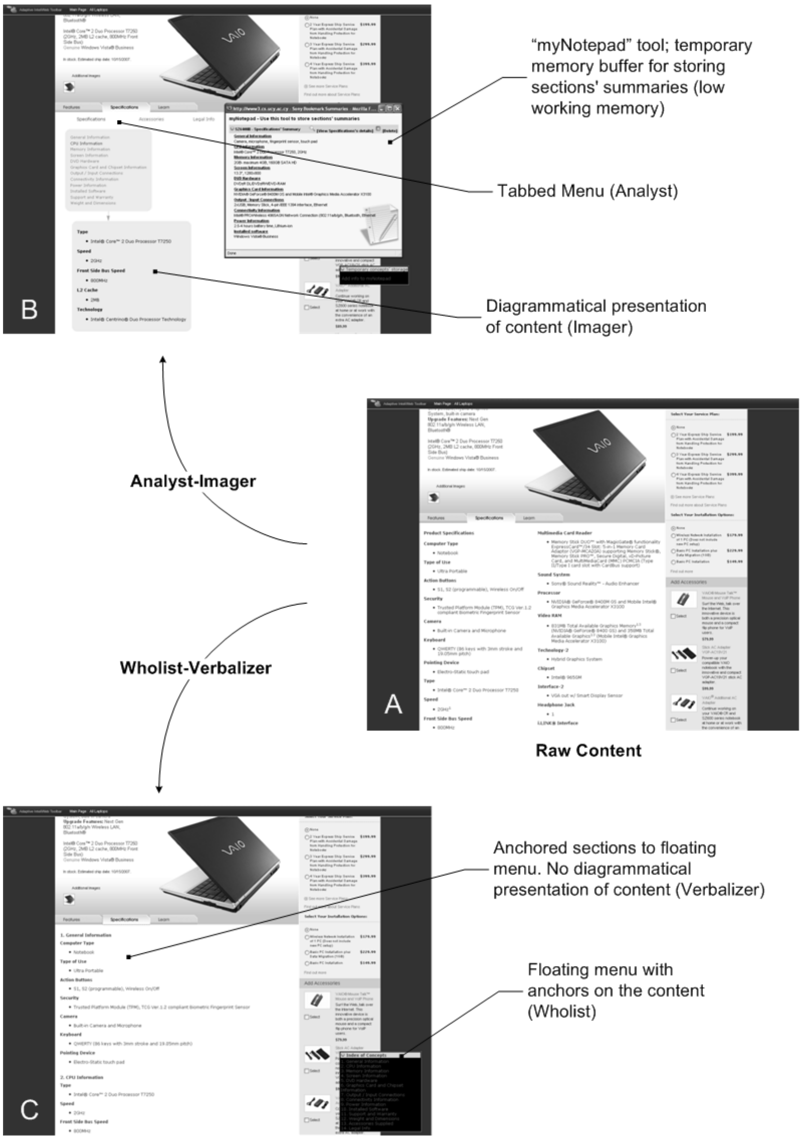

Figure 10. Content Adaptation based on Cognitive Styles of Users

Fig. 10 illustrates an example of content adaptation utilized in a previous study of the authors (Germanakos et al. 2008) where users with different cognitive typologies (i.e., Verbalizer, Imager, Intermediate) were provided with different content fragment variations, i.e., users belonging to the Verbalizer class (that process textual content efficiently) where presented with more textual content, whereas users belonging to the Imager class (that process graphical content efficiently) where presented with more graphical content. Furthermore, this study provided adaptive navigation support based on other cognitive factors (i.e., Wholist-Analyst) (Germanakos et al. 2008) that affect navigation behaviour of users in interactive systems.

We also provide an example of Pandora music recommender system (see Fig. 11), where the user interacts with the system with the goal of finding a music item, and the system recommends items based on what it has learned about the user's interests.

Figure 11. Pandora music recommender example screenshot

Park & Han (2011), for example, proposed a method of coupling adaptable and adaptive approaches to the design of menus. The proposed complementary menu types incorporate both adaptability and adaptivity by dividing and allocating menu adaptation roles to the user and the system. The results showed that adaptable and adaptive menus were superior to the traditional one in terms of both performance and user satisfaction. Specifically, providing system support to the adaptable menu not only increased the users' perception of the efficiency of selection, but also reduced the menu adaptation time. Park & Han (2011) suggested the possibility of designing adaptive web interfaces with user control (partly adaptable), which may provide additional advantages, such as psychologically increasing user control of the interaction, and requiring less effort for adaptation to his/her needs. Recently, Kardaras et al. (2013) applied Fuzzy logic techniques (Delphi method and Cognitive Maps) to content presentation and media adaptation on a tourism web site prototype. This research highlighted service features that are most preferred by users and ways to adapt presentation media and layout based on user preferences.

3.2.2 Adaptive Navigation Support

Adaptive navigation support relates to the adaptation of links inside nodes. This kind of adaptation supports user navigation in an interactive system by adapting to the goals, preferences and knowledge of the individual user. The core idea behind this kind of adaptation is to adapt the presentation of hyperlinks/functionality within a node. Adaptive navigation support can be achieved by: i) guiding the user in the system by suggesting the "next best" node to visit according to the user's goals, preferences and knowledge, ii) prioritizing links that are relevant to the user closest to the top, iii) by hiding, removing or disabling links to restrict navigation space to irrelevant nodes, iv) by augmenting links with additional information about the node behind the link, with some form of annotation, v) by dynamically generating new, non-authored links based on the user's interests and/or current context (i.e., location) in the system. Since a considerable amount of works have been published based on these adaptation techniques, they are further discussed in the next sub-sections.

For example, an adapting toolbar a) predicts the user's most likely task and b) changes the presentation and organization of UI functionality to support user with this task (see Fig. 12).

Figure 12. Adapting toolbar example taken from Microsoft Word

Within this research stream, social navigation provides excellent opportunities for tailoring navigation advice to individual users' tasks, knowledge or abilities. When looking at social navigation in the real world we observe interesting phenomena. When conducting direct social navigation (e.g. communication with another person to solve a navigational task) it is often the case that "advice-givers" tailors their navigational instructions to the "advice- seeker" subconsciously. Of course, this tailoring may not always be a benefit, but if we can match the right giver and seeker the likelihood of success increases.

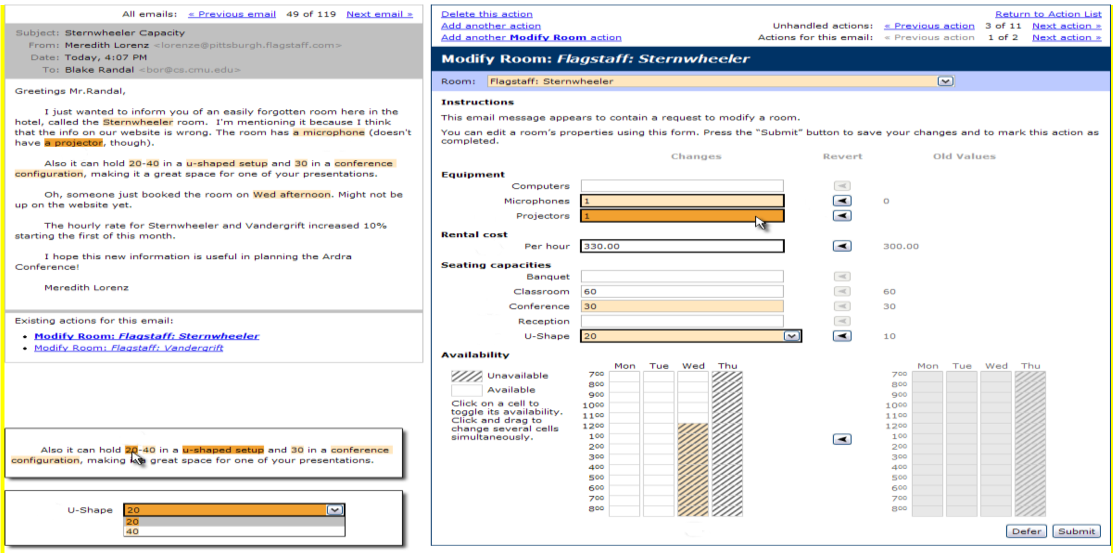

Figure 13. Assisted form-filling in RADAR

For instance, the chat system PowWow7 uses something called on-line guides. These are expert PowWow users that have been granted "guide" status. Newcomers to the system can at anytime during the day go to a special "chat room" and ask guides questions concerning the system. This is an easy way to tailor (or personalise) the PowWow help system. RADAR[i] also support users to cope with email overload by a) identifying tasks requested in email messages b) classifying and prioritizing the tasks, and c) providing task-aware tools that partly automate task execution (see Fig. 13).

3.2.2.1 Direct Guidance

This technique "guides" the user by suggesting the "next best" node to visit according to the user's goals, preferences and knowledge. The suggested nodes are presented on the user's interface by emphasizing existing hyperlinks or by generating a new "next" hyperlink which is connected to the suggested node. Direct guidance is popular in adaptive educational hypermedia systems where students get suggested nodes based on their level of knowledge on the specific subject. Brusilovsky (2003) reviewed several studies on direct guidance and demonstrated that users with poor knowledge on the domain can be best supported by direct guidance techniques. An interesting

[i] Online: http://www.radar.cs.cmu.edu

adaptive education hypermedia system that provides direct guidance is ELM-ART (Weber & Specht, 1997).

3.2.2.2 Link Ordering

Adaptive link ordering prioritizes all hyperlinks of a node that are relevant to the user closest to the top. Despite its effectiveness in navigation times and steps reduction, an important drawback of adaptive link sorting is its limited applicability. Adaptive link sorting can only be used in hyperspaces where hyperlinks do not have a stable and predefined order. Thus, it can never be used with contextual links and rather difficult to be used for index pages or table of contents which usually have a predefined list of order.

In this respect, an appropriate context includes systems that contain non-contextual hyperlinks such as, adaptive news systems and commercial Web shops. Adaptive news systems typically recommend a prioritized list of news articles based on the modeled user's interests and preferences. In the same way, commercial Web shops recommend a prioritized list of products based on the modeled user's interests and product ratings. Link ordering is typically performed by content-based mechanisms.

3.2.2.3 Link Hiding

Link hiding aims to restrict navigation space by removing, hiding or disabling hyperlinks to irrelevant nodes. Link hiding has been very popular in the area of adaptive educational hypermedia systems that aim to protect the users from the complexity of the whole hyperspace and reduce their cognitive overload by hiding irrelevant to them nodes. For example, if the user has novice level of knowledge on a particular concept, the system restricts the user from navigating to it.

Variants of link hiding are: i) link hiding preserves the hyperlink's functionality (i.e., navigate to the corresponding node), but removes all visual indications that it is a hyperlink (e.g., orange color and underlined), ii) link removal completely removes the hyperlink, and iii) link disabling removes the functionality of the hyperlink.

3.2.2.4 Link Annotation

Link annotation augments the hyperlink with additional information about the node behind the annotated hyperlink, with some form of annotation. Link annotations are provided with different visual signs, for example different icons, different color and intensity of anchors, or different font sizes. Furthermore, Web technologies enabled adaptive Web systems annotate hyperlinks with verbal annotations on hyperlink mouse-overs, for example display information on the browser's status bar or as a "balloon" over the hyperlink when the user moves the mouse pointer over the hyperlink.

3.2.2.5 Link Generation

Link generation has been very popular in adaptive Web systems, due to the rapid increase of open corpus document collections. Link generation dynamically creates new, non-authored hyperlinks on a Web-page.

Link generation is popular in the field of adaptive navigation support systems and Web recommender systems for the dynamic generation of links that are useful within the current context to the current user. Web recommender systems attempt to recommend a prioritized list of relevant to the user items, typically based on the user's interests. In this respect, Web recommender systems focus in the underlying technology. On the other hand, adaptive navigation support systems focus on helping users to find their way through hyperspace by adapting links on a page. Link adaptation in adaptive navigation support systems take into account various features of the user, including user's interests, goals, knowledge, and current context (i.e., location in hyperspace). In all cases, navigation support techniques provide guidance that takes into account the user's current location in hyperspace (Brusilovsky and Millán, 2007). Thus, adaptive navigation support systems focus on the interface. Accordingly, although the difference between adaptive navigation support systems and Web recommender systems is not clear, an important difference between these two groups is that adaptive navigation support systems primarily focus on the user's current location in hyperspace and aims to guide the user by introducing additional hyperlinks that may be useful in the current context, while Web recommender systems primarily focus to recommend hyperlinks that are related with the user's short- and long-term interests.

There also exists a small class of systems that generate hyperlinks based on user's interests and current location, for example Amazon that recommend hyperlinks to products that were similarly rated or purchased by other users who viewed the current product.

4. Adaptation and Personalization Systems & Best Practices

Given the multidimensional character of adaptation and personalization research and paradigms, building a complete adaptive system is a challenging endeavor. Thus, the literature reveals a high number of research works that focus and investigate targeted issues than complete personalization systems. For example, incorporating human factors in the design of personalized user authentication mechanisms requires first investigating whether specific human factors affect user interactions in authentication-related tasks. In this context, this section presents a selection of adaptation and personalization systems and architectures starting from recent systems to early and pioneering works. Main aim is to acquire the knowledge on challenges, difficulties, techniques and best practices of other domains so to build upon and adopt these lessons learned more comprehensively to the requirements and constraints of the ADVisE.

4.1.1 PAC

PAC (Personalized Authentication and CAPTCHA) (Belk et al., 2015) is an extensible personalization framework that adapts and personalizes specific design factors of user authentication and CAPTCHA mechanisms based on a set of human cognitive factors. In particular, the personalization framework follows a two-phase method for adapting and personalizing the user authentication and CAPTCHA task as follows: i) adapt the type of the security mechanism (textual or graphical) based on users' cogni-tive styles (i.e., Verbal/Imager and Wholist/Analyst); and ii) adapt the complexity level of the security mechanism (number of characters/images) based on users' cognitive processing abilities (i.e., limited/enhanced).

4.1.2 PersonaWeb

PersonaWeb (Germanakos et al. 2015) focuses on adapting and personalizing content and functionality of E-Commerce environments based on human cognitive factors. In the frame of the PersonaWeb system, new adaptation effects have been proposed for adapting the visual and interaction design of E-Commerce product views. An additional sub-system, called PersonaCheck (Constantinides et al. 2015) has been included that is responsible to recommend the “best-fit” checkout process design based on the way individuals process and mentally organize information (holistically or analytically). PersonaWeb experimental studies have shown that users’ task completion efficiency and effectiveness improves when E-Commerce product views and checkout designs are adapted to the users’ cognitive characteristics, in contrast to the original, baseline design.

4.1.3 Adaptive Notifications in Virtual Communities

In the work of Kleanthous-Loizou and Dimitrova (2013) a framework has been proposed for supporting knowledge sharing in virtual communities through adaptive notifications. It employs a novel computational approach for community-tailored support underpinned by the area of organizational psychology, aiming to facilitate the functioning of the community as a whole entity. The framework makes use of a community model that represents the community based on key processes (i.e., transactive memory, shared mental models and cognitive centrality) aiming to derive knowledge sharing patterns from community log data that are used to generate adaptive notifications.

4.1.4 EKPAIDEION

EKPAIDEION (Tsianos et al., 2008) is an adaptive educational hypermedia system that adapts and personalizes the content presentation and navigation support within computer-based educational environments. The system utilizes a human factor based user model that incorporates a combination of human cognitive factors based on a novel, unified theoretical model. The theoretical model entails a set of elementary cognitive processes (visual attention, speed and control of processing, working memory), cognitive styles and emotional factors (anxiety, emotional regulation) and accordingly adapts and personalizes the content presentation, learners’ support, navigation menus as well as provides adaptive navigational support during user interactions in E-Learning environments.

4.1.5 AdaptiveWeb

The AdaptiveWeb system (Germanakos et al., 2008) was one of the early systems of the authors that aimed to personalize content and functionality of interactive systems based on intrinsic human factors. In particular, AdaptiveWeb is a Web-based adaptation and personalization system that is based on a comprehensive user model, incorporating "traditional" user characteristics (i.e., name, age, education, experience, profession, etc.) and intrinsic human factors such as the users' perceptual preference characteristics (visual, cognitive and emotional processing parameters). According to the user model, the system provides adaptive content presentation and adaptive navigation support in the context of an E-Learning environment aiming to assist users during information processing, comprehension and assimilation.

4.1.6 Knowledge Sea II

Knowledge Sea II (Brusilovsky et al., 2006a) is a personalized information access system aiming to assist users to effectively organize and maintain Web-based educational resources. It is an extension of Knowledge Sea project that was designed as a mixed corpus C programming resource aiming to bridge the gap between closed corpus materials in the form of lecture notes and open-corpus materials in the form of the set of the links to online resources for C programming. Knowledge Sea II helps users navigate from lectures to relevant online tutorials in a map-based horizontal navigation format. Knowledge Sea II contains a map with hyperlinks pointing to online material and facilitates the navigation by providing traffic and annotation based social navigation support.

4.1.7 mPERSONA

mPERSONA (Panayiotou & Samaras, 2004) is a flexible personalization system for the wireless user that takes into consideration user mobility, the local environment and the user and device profile. The system utilizes the various characteristics of mobile agents to support flexibility, scalability, modularity and user mobility. It avoids tying up to specific wireless protocols (e.g., WAP) by using, as much as possible, autonomous and independent components. To achieve a high degree of independence and autonomy mPERSONA is based on mobile agents and mobile computing models such as the "client intercept model".

4.1.8 INSPIRE

INSPIRE (Papanikolaou et al., 2003) is an Adaptive Educational Hypermedia system, which emphasizes the fact that learners perceive and process information in very different ways, and integrates ideas from theories of instructional design and learning styles. Its aim is to make a shift towards a more "learning-focused" paradigm of instruction by providing a sequence of authentic and meaningful tasks that matches learners' preferred way of studying. INSPIRE, throughout its interaction with the learner, dynamically generates learner-tailored lessons that gradually lead to the accomplishment of learner's learning goals. It supports several levels of adaptation: from full system-control to full learner-control, and offers learners the option to decide on the level of adaptation of the system by intervening in different stages of the lesson generation process and formulating the lesson contents and presentation. Both the adaptive and adaptable behavior of INSPIRE are guided by the learner model which provides information about the learner, such as knowledge level on the domain concepts and learning style. The learner model is exploited in multiple ways: curriculum sequencing, adaptive navigation support, adaptive presentation, and supports system's adaptable behavior.

4.1.9 SQL-Tutor

SQL-Tutor (Mitrovic & Martin, 2002) is a knowledge-based teaching system which supports students learning SQL. The intention was to provide an easy-to-use system that will adapt to the needs and learning abilities of individual students. The tailoring of instruction is done in two ways: by adapting the level of complexity of problems and by generating informative feedback messages.

4.1.10 Proteus

Proteus (Anderson et al., 2001) is a system that constructs user models using artificial intelligence techniques and adapts the content of a Web-site taking into consideration also characteristics of the wireless connection. The Proteus Web-site personalizer performs a search through the space of possible Web-sites. The initial state is the original Web-site of non-adapted pages. The state is transformed by any of a number of adaptation functions, which can create pages, remove pages, add links between pages, etc. The value of the current state (i.e., the value of the Web-site) is measured as the expected utility of the Web-site for the current visitor. The search continues either until no better state can be found, or until computational resources (e.g., time) expire.

4.1.11 WBI - Web Browser Intelligence

Web Browser Intelligence (WBI, pronounced "WEB-ee") (Maglio & Barret, 2000) is an implemented system that provides a loosely confederated group of agents on a user's workstation capable of observing user actions, proactively offering assistance, modifying resulting web documents, and performing new functions. For example, WBI will annotate hyperlinks with network speed information, record pages viewed for later access, and provide shortcut links for common paths. WBI is an architecture in which small programs, or agents, connect to the information stream by registering their trigger conditions and then performing operations on the stream. This structure provides rich opportunities for personalizing the web experience by joining together personal and global information, as well as enabling collaboration among web users.

4.1.12 ARCHIMIDES

ARCHIMIDES (Bogonicolos et al., 1999) which personalized the search results of users according to their interests. The system was based on agent technologies aiming to provide adaptive and personalized navigation to users within Web-based environments. Given a set of keywords that characterize the content on a Web server, ARCHIMIDES retrieves information intelligently and then constructs a personalized version in the form of an index pointing to pages that present some interest to the user.

4.1.13 TANGOW

TANGOW (Carro et al., 1999) is a tool for developing Internet-based courses, accessible through any standard WWW browser. Courses are structured by means of Teaching Tasks and Rules which are stored in a database and are the basis of TANGOW guidance ability. In TANGOW a Student Process is launched for each student connected to the system. Each Student Process consists of two main modules: a Task Manager that guides the students in their learning process, and a Page Generator that generates the HTML pages presented to the student. The Student Process also maintains information about the actions performed by the student when interacting with the course in the Dynamic Workspace. This information is used by TANGOW to adapt the course contents to the student's learning progress. TANGOW has also information about student profiles, which is used to select, at run-time, the contents of each HTML page presented.

4.1.14 InterBook

InterBook (Brusilovsky et al., 1998) is a tool for authoring and delivering adaptive electronic textbooks on the World Wide Web. InterBook provides a technology for developing electronic textbooks from a plain text to a specially annotated HTML. InterBook also provides an HTTP server for adaptive delivery of these electronic textbooks over WWW. For each registered user, an InterBook server maintains an individual model of user's knowledge and applies this model to provide adaptive guidance, adaptive navigation support, and adaptive help.

4.1.15 AHA!

AHA (De Bra & Calvi, 1998) is an open Adaptive Hypermedia Architecture that is suitable for many different applications. This system maintains the user model and filters content pages and link structures accordingly. The engine offers adaptive con-tent through conditional inclusion of fragments. Its adaptive linking can be configured to be either link annotation or link hiding. Even link disabling can be achieved through a combination of content and link adaptation.

4.1.16 SKILL

SKILL (Neumann & Zirvas, 1998) is a scalable Internet-based teaching and learning system. The primary objective of SKILL is to cope with the different knowledge levels and learning preferences of the students, providing them with a collaborative and adaptive learning environment utilizing new World Wide Web technologies. Basic components of SKILL are course material based on concepts organized in an ordinal rating derived from pre-requirements, an annotation facility suited for collaboration work, and a configuration environment for tailoring the system. Topics discussed include: (1) SKILL functionality, including adaptivity/progress control and collaboration through annotations and course extensions; (2) components, including security, document management, and tutoring components; (3) implementation issues; and (4) related work.

4.1.17 ELM-ART II

ELM-ART II (Weber & Specht, 1997) is an intelligent interactive textbook to sup-port learning programming in LISP. ELM-ART II demonstrates how interactivity and adaptivity can be implemented in WWW-based tutoring systems. The knowledge-based component of the system uses a combination of an overlay model and an episodic user model. It also supports adaptive navigation as individualized diagnosis and help on problem solving tasks. Adaptive navigation support is achieved by annotating links. Additionally, the system selects the next best step in the curriculum on demand. Results of an empirical study show different effects of these techniques on different types of users during the first lessons of the programming course.

4.1.18 BASAR

BASAR (Building Agents Supporting Adaptive Retrieval) (Thomas & Fischer, 1997) provides users with assistance when managing their personal information spaces. This assistance is user-specific and done by software agents called Web assistants and active views. Users delegate tasks to Web assistants that perform actions on their views of the World Wide Web and on the history of all user actions.

5. CONCLUSIONS

Given the explosive growth of multivariate data and complex business processes and tasks, data visualizations figure nowadays as a promising research direction of expressing huge amounts of data, exposing new underlying patterns of behaviours or showing relationships of data on specific contexts of use. No matter the messages or observations that data reveal the overarching aim of any successful tool or system is to assist the end-user (irrespective the role, background and experience) to achieve more effective and efficiently his goal-directed actions and decisions. In parallel, Adaptive and personalized environments represent a fascinating and evolving field of software systems that find particular success in Web environments (e.g. Brusilovski, 2001). In this respect, adapting the functionality and content, of any interactive system, to satisfy the users' needs and increase their level of understandability and acceptability in an intuitive manner and empower them to complete specific tasks more efficiently and effectively is a challenging endeavor. It entails understanding and modeling human behaviour for diverse user groups, with regard to structural and functional user requirements, which needs to be translated into usable computer-human interaction designs and workflows, whilst minimizing the overall users' cognitive, perceptual and learning load.

This document described key considerations, methods and research works regarding data exploration and visualization trying to extract a more holistic view of the available solutions and approaches in the academic and business sector. Main emphasis has been placed on the utilization of human factors in the whole process of adaptation of data visualizations. Furthermore, the main processes, mechanisms, and adaptation effects used in adaptive interactive systems have been analysed as well as an extensive reference to success cases and systems. The outcome of this deliverable will provide valuable input primarily to WP4 – ADVisE Framework Definition, and secondarily to WP5 – Platform Architecture and Design. This analysis enables the research consortium to compile an optimal deployment strategy for the development of standalone components and their integration in the final ADVisE framework. Moreover, this deliverable provides preliminary input in the identification of the human-centered model in T3.3 (see D13 – Human-centered User Modelling Analysis and Specification).

The top three lessons learned from the current review regarding data visualizations and adaptive interactive systems design, are:

1. The data visualizations area is highly diversified, with a variety of paradigms and algorithms trying to capture specific needs and requirements in a number of application fields. Human factors, mostly in relation to cognitive capabilities, perceptual characteristics and visuo-spatial abilities, have only recently started to be researched but not in the business domain. Main outcome of the background work conducted is that it is rather improbable to generalized any findings especially across different domains.
2. Currently, most of the strategies used in adaptive visualization solutions are rather static. They lack the inherent dynamicity and interactivity to explore the objects that help users' learning and understanding of complicated information needs. The lack of interactivity can be problematic in data exploration because it can make harder to understand the hidden links of data that can lead fast to informed decisions regarding specific business tasks.
3. Adaptation mechanisms support users in their cognitive process of categorizing and customizing content when interacting with Web-based systems (e.g. Lavie et al., 2010). Personalization may positively affect users' attitude towards the device, raising their tendency to use it repeatedly (Blom & Monk, 2003). According to Oulasvirta & Blom (2008), personalization can promote autonomy (unpressured willingness to engage in an activity), support competence (by increasing the effectiveness of the users' actions), and maintain the need for relatedness (the need to establish close emotional bonds with and attachments to other people). The authors also discussed a number of positive effects of personalization, including engagement, performance, persistence, identity, social acceptance, and social status (Oulasvirta & Blom, 2008). However, it is important to determine appropriate depth of content personalization, and assess the extent to which users' explicit expressions of interest to specific content can be used as a basis for personalization. Lastly, the main adaptation effects and their benefits for users; combining different approaches may better support users in their informational/navigational needs.

We believe that the aforementioned approaches may contribute to the adaptation quality and diversity of end-users needs and requirements, especially with regard to the cognitive goal-directed user behavior. The successful design of adaptive interactive data visualizations may improve monitoring and comprehension of information as well as ultimately lead to improved users' navigation and situation awareness. Recent advances in adaptive systems research call for attention to multi-contextual and expansive learning aspects that could positively affect user experience and integration with user business workflow.

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APPENDIX A - ENTERPRISE PLATFORM COMPARISON

Table 1: Microsoft Comparisons

Company	Microsoft
Software	Power BI
Version	April 2017 Update (2.45.4704.442)
Price	9.99
On Premise	Data can reside on-premises, but for sharing and collaboration the dashboards are stored in the Microsoft Azure cloud.
Cloud	Yes
Mobility	**Yes**
API	DAX/M,R
Number of Data Sources	~80
Real Time Data and Dashboards	Yes, Power BI is part of the Microsoft Data Platform and can stream data. Azure Stream Analytics, IoT, predicted results from Machine Learning.
Complex Data Modeling	Yes
Custom Queries	Yes, visual query editor +ribbon like in Excel allows to perform tasks such as: - Connect to Data - Shape and Combine Data - Group Rows - Pivot Columns - Create Custom Columns - Query Formulas
Surrounding technologies	Tight integration with Microsoft ecosystem, supports Excel Based Add-ons (Power Query, Power Pivot, Power View and Power Map. Good level of supporting features including alerts, print to pdf, etc.
Expressions / Formulas	DAX. Consensus seems to be that DAX is the most powerful and versatile, with the added benefit that it is similar to Excel expressions.
Software Update Schedule	Weekly (Online) Monthly (Desktop)
Quick Insights	Power BI lets you generate quick insights from any dataset and points out (in Natural Language form) insights such as correlations and outliers. Qlik Narratives and Tableau Storytelling are NOT USPs and have nothing to do with Quick Insights. Also, Power BI has the same third party Narratives visual as Qlik
Community	Power BI has a flourishing community, excellent documentation, and gives users the ability to suggest and vote for new features.
Custom Visuals & Download Gallery	Yes
Misc.	Power BI is younger than competition and so has many lacking features and some are not implemented as well as they could be. For example, poor forecasting and no what-if scenarios, missing pivot tables, cannot show subtotals in the table visual, etc.
Visual Drill Down	Average
Drag and Drop	Partial
Bar Chart	Yes

Stack or Area chart	Yes
Line Chart	Yes
Combo Chart	Yes
Gantt Chart	Custom VIZ
Milestone trend analysis (MTA)	No
Radar Chart	Yes
Scatter Chart	Yes
Grid Chart	Yes
Pie Chart	Yes
Polar Chart	No
Doughnut Chart	Yes
Block Chart or Heat map	Yes
Funnel Chart	Yes
Gauge Chart	Yes
Mekko Chart	Custom VIZ
Pivot Table	Yes
KPI Charts	No
Table/Matrix	Yes
Map	Advance
Bullet Graph	No
Histogram	No (but workaround provided)
KPI	Yes
TreeMap	Yes
Bubble chart	Yes
Packed Bubbles	Custom VIZ
Waterfall charts	Yes
Box-and-whisker Plot	Custom VIZ
Sankey Diagram	Custom VIZ
Network Diagram	Custom VIZ
Correlation Map	No
Decision Tree	Custom VIZ
Word/Text Map	Custom VIZ
Custom Visualization	Yes
Dashboard Concept	Yes
Predictive Analytics	Yes, but through Azure ML. Difficult to combine and link the data
Automated visualization suggestion	Yes, based on the structure of the loaded from the data. But does not identify industry or business patterns
Natural Language Commands (Query)	Yes, but limited dictionary of commands. No industry or context related features
Natural Language Audio Support	Yes, through windows 10 clients with limited dictionary of commands. Cortana Analytics
Visualization Description and Insights Feedback in natural language (natural language generation)	No
Other language based query or feedback Capabilities	Get answers based on questions including a fixed set of aggregate and calculation commands, feature names and visualization types

Table 2: Qlik Comparisons

Company	Qlik
Software	Qlik Sense QlikView

Version	Qsense 3.1 (sep-2016)
Price	20
On Premise	Yes
Cloud	Yes
Mobility	Qlik Sense
API	Qlik Analytics Platform (QAP)
Number of Data Sources	71
Real Time Data and Dashboards	Automatic refreshes but not in real time.
Complex Data Modeling	Yes
Custom Queries	Yes, but uses SQL
Surrounding technologies	Good integration with Office Suite to generate reports with NPrinting. Also offers scheduling of report distribution through email, and even publishing online.
Expressions / Formulas	Expression Editor
Update Schedule	Every few months
Quick Insights	No
Community	Average forums, poor tech support according to Gartner.
Custom Visuals & Download Gallery	Yes, but no gallery
Misc.	Qlik Sense, is the result of the competition pressure from companies such as MS and Tablaue in the cloud area. it provides a more user friendly self-service interface for data exploration and visualization than QlikView. QlikView did not get decommission, but sold in the enterprise users space
Visual Drill Down	Excellent
Drag and Drop	Yes
Bar Chart	Yes
Stack or Area chart	Yes
Line Chart	Yes
Combo Chart	Yes
Gantt Chart	No (but workaround provided)
Milestone trend analysis (MTA)	No
Radar Chart	Yes
Scatter Chart	Yes
Grid Chart	Yes
Pie Chart	Yes
Polar Chart	Yes
Doughnut Chart	Yes
Block Chart or Heat map	Yes
Funnel Chart	Yes
Gauge Chart	Yes
Mekko Chart	Yes
Pivot Table	Yes
KPI Charts	No
Table/Matrix	Yes
Map	Yes
Bullet Graph	No
Histogram	No
KPI	Yes
TreeMap	Yes
Bubble chart	Yes
Packed Bubbles	No
Waterfall charts	No

Box-and-whisker Plot	Yes
Sankey Diagram	No
Network Diagram	No
Correlation Map	No
Decision Tree	No
Word/Text Map	No
Custom Visualization	Limited
Dashboard Concept	Yes
Predictive Analytics	No, but it can be done through extensive scripting with R
Automated visualization suggestion	Limited and not industry or context related
Natural Language Commands (Query)	No
Natural Language Audio Support	No
Visualization Description and Insights Feedback in natural language (natural language generation)	Additional capabilities to describe the generated visualization - 'Narrative Science' a free extension
Other language based query or feedback Capabilities	N/A

Table 3: Tableau Comparisons

Company	Tableau
Software	Tableau
Version	10
Price	42
On Premise	Yes
Cloud	Yes
Mobility	Yes
API	REST APIs and JavaScript
Number of Data Sources	~90
Real Time Data and Dashboards	No
Complex Data Modeling	Poor capabilities in combining data from different sources. Poor performance handling large and complex data has forced Tableau to plan to release a stand-alone data preparation tool (code-named Project Maestro) to address this issue.
Custom Queries	Yes, but uses SQL
Surrounding technologies	Many features are a work in progress, for example: event-based scheduling, conditional alerting, printing to PDF and PowerPoint, and collaboration and social platform integration are only available through partners, which adds to the TCO.
Expressions / Formulas	LOD Expressions (Level of Detail).
Update Schedule	~Semester + major update ever 1-2 years
Quick Insights	No
Community	Average forums.
Custom Visuals & Download Gallery	Yes
Misc.	Good forecasting, what-if scenarios, good data interaction like highlighting data on a visual, removing certain elements temporarily, easy drilldown.
Visual Drill Down	Good
Drag and Drop	Partial
Bar Chart	Yes
Stack or Area chart	Yes
Line Chart	Yes

Combo Chart	Yes
Gantt Chart	Yes
Milestone trend analysis (MTA)	No
Radar Chart	Yes
Scatter Chart	Yes
Grid Chart	Text Table (Crosstab) Highlight Table
Pie Chart	Yes
Polar Chart	Through a workaround with Radar Chart
Doughnut Chart	Yes
Block Chart or Heat map	Heat Map
Funnel Chart	Yes
Gauge Chart	No
Mekko Chart	No (but workaround provided)
Pivot Table	No
KPI Charts	Yes
Table/Matrix	Text Table (Crosstab) Highlight Table
Map	Yes and also symbol map
Bullet Graph	Yes
Histogram	Yes
KPI	Yes
TreeMap	Yes
Bubble chart	Circle view
Packed Bubbles	Yes
Waterfall charts	No
Box-and-whisker Plot	Yes
Sankey Diagram	No
Network Diagram	No
Correlation Map	No
Decision Tree	No
Word/Text Map	No
Custom Visualization	Limited
Dashboard Concept	Yes
Predictive Analytics	No, but it can be done through extensive scripting with R or integration with 3rd party platform such as SAS
Automated visualization suggestion	Limited and not industry or context related
Natural Language Commands (Query)	Yes, NLP is supported
Natural Language Audio Support	No, but part of their roadmap
Visualization Description and Insights Feedback in natural language (natural language generation)	Wordsmith extension to describe the data and the visualizations
Other language based query or feedback Capabilities	--

Table 4: SAP Comparisons

Company	SAP
Software	SAP BusinessObjects Lumira and BusinessObjects Cloud
Version	4.2
Price	185
On Premise	Yes
Cloud	Yes

Mobility	Yes - but needs improvement
API	REST API,Java
Number of Data Sources	Limited
Real Time Data and Dashboards	Yes
Complex Data Modeling	Yes
Custom Queries	Both visual query builder and customer queries
Surrounding technologies	Tight integration with SAP technologies and products such as Crystal Reports Enterprise, Crystal Reports 2016, Web intelligence
Expressions / Formulas	simple formulas, SQL Based expression, visual query builders
Update Schedule	Varies, but usually long release cycles between major releases. A number of incremental SP are made available from 3-12 months accordingly
Quick Insights	No
Community	Average forums.
Custom Visuals & Download Gallery	No download gallery or market place, but capability of script based visuals
Misc.	Gartner " Digital Boardroom is a differentiator: SAP's Digital Boardroom solution, which is built to be used with large touchscreen displays, has gained a lot of attention. It speaks well to the vision of a data-driven company and is particularly attractive to executives because it includes "what if" analysis and simulations. SAP can leverage its strategic position in a customer base of large enterprises and also protect its installed base against smaller vendors with less access to (and visibility with) senior executives."
Visual Drill Down	Good
Drag and Drop	Extensive
Bar Chart	Yes
Stack or Area chart	Yes
Line Chart	Yes
Combo Chart	Yes
Gantt Chart	Yes
Milestone trend analysis (MTA)	Yes
Radar Chart	Yes
Scatter Chart	Yes
Grid Chart	Basic
Pie Chart	Yes
Polar Chart	Yes
Doughnut Chart	Yes
Block Chart or Heat map	Yes
Funnel Chart	Yes
Gauge Chart	Speedometer
Mekko Chart	MarimekkoChar
Pivot Table	Yes, but limited interactivity
KPI Charts	Yes
Table/Matrix	Spreadsheet
Map	Yes, with a lot of options
Bullet Graph	Yes
Histogram	Yes
KPI	Yes
TreeMap	Yes
Bubble chart	Yes
Packed Bubbles	No
Waterfall charts	Delta Chart
Box-and-whisker Plot	Limited support through Candlestick chart
Sankey Diagram	Extension
Network Diagram	No
Correlation Map	No

Decision Tree	No
Word/Text Map	No
Custom Visualization	Yes
Dashboard Concept	Yes
Predictive Analytics	SAP BusinessObjects Predictive Analytics
Automated visualization suggestion	Limited and not industry or context related
Natural Language Commands (Query)	N/A
Natural Language Audio Support	N/A
Visualization Description and Insights Feedback in natural language (natural language generation)	N/A
Other language based query or feedback Capabilities	N/A