Shaping Problems, Not Decisions:

When Decision Makers Leverage Visual Analytics

Full Paper

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Abstract

Just as modern software development strategies have introduced agile methods and rapid prototyping to organizations. Visual analytic tools now bring the same spirit of prototyping and iteration directly into the decision-making process. Yet decision makers and analysts may not yet be as "agile" as the tools they are using and instead tend to remain in their traditional roles during analytic tasks.

The emerging analytic leaders are managers who do not merely act on the findings of others but rather find and shape problems by constantly interacting with data and scrutinizing and adjusting to changes in real-time data. Our research found that: 1) managers need to develop new competencies to cognitively adapt to visual decision making; 2) managers need to become more humble and share data widely across their organizations in order to facilitate a comprehensive analytic culture; and 3) roles and responsibilities of analysts and managers need to be reconsidered.

Keywords

Data visualization, visual analytics, interaction, agile decision making, iterative decision making

Introduction

Visual analytics have become a key performance differentiator between organizations (LaValle et al. 2013). Yet, in the midst of a rapidly changing information environment, visual analytic strategies are still not widely adopted and managers tend to stick to their current work habits (Aigner 2013). In order to complex information environments, managers also continue to rely more and more an analysts and data scientists to support their decision making (Dobbs et al. 2011). So much so, that a recent McKinsey report predicts that shortage of analytic talent will be between 140,000 to 190,000 by 2018 ("Big data" 2011).

Literature has explored how our analytic systems are changing (Wang et al. 2011), the evolution of data visualization (Few 2007; Shedroff 1999; Ware 2008), and the role of effective dashboard design to facilitate deeper analytic reasoning (Meyer et al. 2010; North et al. 2011; Pike et al. 2009). Scant attention has been focused on how managers and decision makers interact directly with data in a more self-service fashion.

Our qualitative study explores this widening competency gap because the existing literature is not focused on the changing experiences and skills needed when working with visual analytics (Buchanan and O Connell 2006). Management science has long asserted that "the most important managerial decision to be made about information is interpretation" (Churchman 1968). If this is true, then why do decision makers typically leave analysis up to analysts?

Research Question

In organizations that facilitate real-time interaction with data, decision making is changing from a one-time event to a new iterative way of working: an agile culture of analytics in which decision making and analysis are becoming one iterative process. Therefore, our research set out to address the following question: *How does the managerial ability to interact with real-time data visualization affect the decision-making process within organizations?* Like most qualitative studies, this original question served as the starting point for our research and evolved through each interview and our subsequent analysis.

The remainder of this paper first will discuss the relevant literature, laying the foundation for how interaction with data affects the decision-making process. We then outline the research design used to complete this qualitative study. Finally we share our findings and discuss the implications and possible directions for further research building on this first phase of our work.

Literature Review

Though we may use phrases such as data visualization, visual business intelligence, and visual analytics interchangeably, we will maintain Visual Analytics ("VA") as the primary term used in this paper with following definition: visual analytics is *the science of analytical reasoning facilitated by interactive visual interfaces* (Thomas and Cook 2005, p. 4). VA is as a multi-disciplinary phenomenon with relevant literature spanning a range of areas including computer science, human cognition, design, statistics, data mining, psychology, as well as the graphic and visual arts (Ziemkiewicz and Kosara 2009).

The Context for Visual Analytics

Management information systems. The potential of systems to improve decision quality and make efficient use of the time of decision makers is not yet realized, in part due to the assumptions sometimes made by designers of systems (Ackoff 1967). Agile methodology prioritizes a focus on individuals and interactions over processes and tools, collaboration over negotiation, and responsiveness to change over following a plan (Cockburn and Williams 2003). This type of responsive behavior and design creates a state of constant iterations that arise from the inclusion of end users earlier in the design process (Hartwick and Barki 1994).

Built on data. Organizations need to prioritize system speed and performance in relation to other goals, including access to data, quality, cost, and risk (Lyytinen and Rose 2006) to establish such environments. Agile systems are better equipped to handle and actually facilitate disruption of current business practices (Rouse 2007) and enable a more dynamic decision-making environment (Brehmer 1992). With the volume and velocity of big data, users need interfaces and graphical representations that can quickly call attention to outliers and anomalies. Static views of data need to be replaced with *semi-confusing* systems that can help identify problems, stimulate curiosity, and purposefully disrupt the status quo (Hedberg and Jönsson 1978). Further visual displays of changing data enable such detection of anomalies more easily than simple numeric and text displays can ever accomplish (Eick and Fyock 1996).

Visual Display of Data. The graphic display of data to communicate meaning and elicit emotional response has a centuries-old legacy (Friendly 2008; Tufte and Graves-Morris 1983). Standards for effective graphical representations have been established for the design of information visualization (Card et al. 1999). VA tools allow analysts and managers to engage in a data-driven analysis process in order to understand the knowledge that the data represent (Lycett 2013). VA tools do not need to be derived from a fixed data set or one pre-defined visual display (Wang et al. 2011).

Anyone navigating such a decision space must oscillate between structured and unstructured ways of thinking (Perer and Shneiderman 2008a) and follow their hunches and intuition in order to anticipate the next opportunity. Over time, various software tools have not done a good job of supporting this creativity and user curiosity during problem solving (Shneiderman 1998). Analytic tools should support exploratory data analysis by decision makers without compromising the underlying statistical power that information systems provide (Perer and Shneiderman 2008b).

Analysts as Interactive Designers

The literature reveals an emerging choice for analysts: present findings or shift to creating interfaces that allow decision makers to become partners in analysis. Interface designs that facilitate end user interaction can change the analyst and decision-maker paradigm (Isenberg et al. 2008). Analysts find themselves at a crossroads of being data *scientists* and data *artists* (Dou et al. 2009; Kosara et al. 2003; Pohl et al. 2012; Ziemkiewicz et al. 2012). Interactive design encourages analysts to invite the decision makers *directly* into the analysis process while making efficient and effective use of their time (Pirolli and Card 1995).

Theories of Interaction

While effective data visualizations (Card et al. 1999) should follow best practices in information design (Cleveland and McGill 1984; Shneiderman 1996; Shedroff 1999; Tukey 1977), they need to only provide a design that is sufficient to serve as a starting point for interaction. In fact, users tend to prefer inferior visualizations that allow interaction over superior visualizations without any interaction features (Saraiya et al. 2006). Compelling and beautiful design does not need to be a primary concern of analysts in business settings.

To the extent that manipulation of the interface is easy and seamless, it will maintain user focus (Yi and ah Kang 2007) in order to let users concentrate more on the data itself (Pike et al. 2009; Sedig et al. 2012) and find their "aha" insights into their data (Kreuseler and Schumann 2002).

Exploratory Analysis and Reasoning

Frequently, managers using an interactive visualization system may not have a specific goal or question in mind and simply are curious and just want to play with their data (Fekete et al. 2008). When exploring, the manipulations of the interface and the insight gained along the way are often just as important as the finished product itself (North et al. 2011; Pike et al. 2009). For managers to become active participants in this analytic process (Keim et al. 2008), they need to have a strong understanding of the underlying information in order to gain insights that lead toward actionable results (Eick 2001). By controlling their own pathway, the interaction helps them go from a hunch to a hypothesis in creating a new insight and observations (Chang et al. 2009; Perer and Shneiderman 2008a).

In a similar manner, visual analytics brings together the trends of the past and the forecasts of the future (Boland 2008). Interacting with data presents a constant updating of data and the ability to dynamically and rapidly explore alternatives. Management scientists are goal-seeking in nature and focused on inquiry as an activity that produces knowledge; not just on solving problems and acting on findings (Churchman 1968). Visualization moves from being a proposed solution to a problem to becoming an information-problem space (Robertson et al. 1993) where problems are discovered. Therefore managers shift from being *problem solvers* to *problem finders* in their analytic processes (Pike et al. 2009).

Gaps in Existing Literature

Theories regarding interactive analytics, while well documented (Fekete et al. 2012), are still nonetheless hard to quantify and measure. Currently the majority of VA studies are intended for analysts and designers (Pohl et al. 2012) in order to create better systems (Amar et al. 2005). With newer VA tools and environments, even fewer empirical studies have been conducted on the benefits of such systems (Kang et al. 2009). Such studies are not written with the experience of "end users" and managers in mind. More research is needed that can focus on understanding individual differences in decision making during analytic tasks (Fisher et al. 2011). We need to understand better how the decision makers perform using VA when they more engaged and involved the analysis process.

Research Design

Methodology

We interviewed users in organizations that are deeply committed to visual analytics so that we could identify the key factors and traits that may accelerate user adoption. Grounded theory was selected as a preferred inductive methodology because our objective was to listen for new theories and allow them to emerge from our data and evolve from our original research question in an iterative fashion (Charmaz 2006; Glaser and Strauss 1967). While the literature and existing theories served as a guide to our research, it was not used as a constraint to our analysis. Qualitative research founded on semi-structured field interviews allowed all study participants to focus on their recollection of lived experiences and expertise as practitioners in the field (see *Interview Protocol* – Appendix A).

Sample

Participants were recruited from a diverse sample within our professional network and were sought out due to their familiarity with Tableau Software (http://www.tableausoftware.com). While this was not a tool-specific study (users talked about many different software systems), we selected a constrained sample[1] for several reasons. Beyond the researcher's own extensive experience with this software, Tableau has been recognized by Gartner as a 2014 Magic Quadrant leader ("Magic Quadrant for Business Intelligence and Analytics Platforms" 2014). Also, Tableau's innovative blend of statistical soundness and intuitive interaction elements (Stolte et al. 2002) further epitomize the type of visual analytic culture this study seeks to understand.

We completed semi-structured field interviews with twenty-three domain experts in various analyst and decision-making roles across seven industries. All interviews occurred between April 2014 and December 2014. Seventeen interviews were face-to-face, and web conferencing was utilized for the remaining six interviews.

Category	Detail
Gender	• Male (17) • Female (6)
Industry	• Technology (5) • Higher Education (5) • Social Media/Networking (3) • Professional Sports (3) • Insurance (3) • Consulting (3) • Healthcare/Medical (1)
Role	• 56.5% Analysts • 39.1% Decision makers/managers • 4.4% Database Administrator (1 subject)

Table 1. Interview Subject Demographics (N=23 subjects)

Data Collection, Coding, and Analysis

We began our initial code pass *in-vivo* without any reference to preconceived ideas (Saldaña 2012). We created excerpts from any words, phrases, or full sentences of potential interest and relevance to our study. An iterative coding process guided our analysis, coding all our excerpts until the point where theoretical saturation was reached and no new categories emerged from our review (Strauss and Corbin 1998). During this first phase of coding, we generated 143 distinct codes and 840 excerpts from our transcripts, yielding a matrix of 2,079 coded instances for our subsequent analysis.

We were then able to focus on establishing conceptual categories across our coding. By the end of this phase of analysis, common themes began to emerge across various transcripts. These themes informed further reflection on our research topics and helped us refine our probing questions in future interviews. Our findings coalesced into a theoretical framework that spanned interaction with data, decision making and organization roles that we now share.

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1 This was not a commissioned study and the researchers received no compensation for this work.

Findings

Finding 1: Visual analytic tools allow decision makers to have unmediated access to their data.

A consistent priority across many organizations we researched was to get data into the hands of decision makers as soon as possible and to let them interact with minimal interference. Figure 1 shows the paradigm shift we experienced and a clear movement toward self-service analytics. Typically it is an analyst that goes into an information space to explore and find answers to questions. This mediating role consistently changed with visual analytics with the decision maker having more direct access to data.

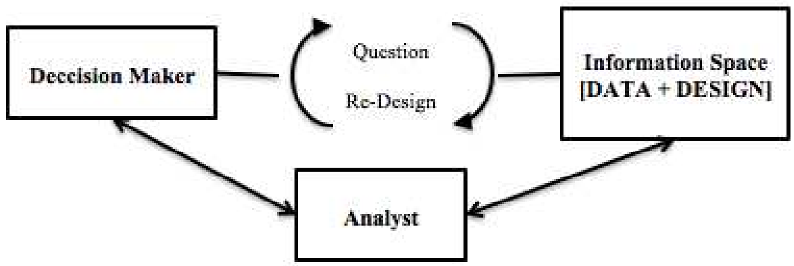

Figure 1. Mediated vs. Unmediated Data Access for Decision Makers

1.a. When provided direct access to data, decision makers feel less overload and gain a higher tolerance for ambiguity. When decision makers (DMs) control the scope and direction of analysis, it increases their desire to have more and more data. Contrary to the literature that big data can be overwhelming (Sparrow 1999; Bawden and Robinson 2009; Edmunds and Morris 2000), DMs using VA tools embrace data and take on a problem-finding posture and a desire to understand the data underpinning their decision making.

Coding	Examples
Closeness to Data • 100% of DMs • 89 total comments	*It leaves you with a feeling that you want more because there is probably a couple of endpoints that I couldn't get to because I didn't have access to the data before. When I've done any sort of visual analysis, it always leaves me with the feeling that I want more data.*
	If you can remove that technical barrier and just allow people to explore on their own and be able to answer the questions on their own without these constant syntax issues and "blah, blah, blah" that they're struggling with now; that's really what's going to get people to the next level. Everybody will be like Tom Cruise in Minority Report and they can just kind of swipe and answer questions.
	To be honest, I didn't even know I could get this kind of information out. But when I realized I could do it myself, I was able to ask a lot more questions than I normally would have.

Table 2. Excerpts related to direct access to data

However, desire for more data has consequences that organizations must address. One example is the constant changing nature of analysis. As one interviewer stated: "*One of the items that always come up is just being confused about which data set -- where to get the data, which data to use, trusting it because it comes from a hundred different places, we refresh it, -- even if it's correct, if it refreshes again and that changes, people are like, "what's the real number?"* The other pressure is from being constantly monitored: "*We've never had this sort of view of performance before; a real-time, day-in day-out view of performance. How can somebody measure me based on this live information? Look at me at the end of the quarter or the year or whatever it may be!*"

1.b. When decision makers work directly with data, they become explorers in data, gaining insight by being more curious. Decision makers recounted various ways they interacted with data and how proud they were to create something visual. 10.6% of all our codes were specific to decision makers and their ability to explore and how their curiosity was enabled.

Curiosity	*I think we still need to come at our data and everything it holds with a sense of wonder and astonishment, and sense of being open to surprise as to what might come about or what might be there. But clearly we're trying to figure out 5 or 10 or 15 or 20 things from our data.*
	As an organizational leader, your job is to make sure that you are getting your staff trained and developed to understand that you are pushing them to say, "Great you've told me we are up 20% why are we up 20%? Tell me why. Should we have been up 30%? Are we out passing where we were?"
	[Decision makers] should not be afraid to try things, they should not be afraid to click around.
	It would be nice if everybody made information-based decisions and even if it was somebody who is not as technically savvy or not as data savvy as long as they are curious and they are presented with some kind of an interface.
	It is somebody who is curious and in it and accept change. They need to be somebody who is typically a little bit more innovative and creative and thinking outside the box.
Ability to Create Visuals	*I think most people who work with data very heavily, the ones I've talked to in the conversation I've observed, they're usually excited about creating charts from their data or things like that. It's something that I think most humans identify with pretty closely.*
	People need to do a little more drilling, a little more investigation, and be able to perform at a level that would be acceptable. Users want to build their own things.
	We worked very closely with them to make them feel confident that the data they are looking at is correct and they have started to create a lot of great stuff on their own.

Table 3. Excerpts related to creativity and user curiosity

Finding 2: The interactive nature of visual analytics facilitates rapid iterations during decision making.

Practitioner literature focuses on rapid insight and making quicker decisions. However, our interviewees often talked about prolonging analysis so they could fully explore a decision from various angles (Appendix B). This ability to iterate during decision making was discussed by 19 of 23 interviewees. Iteration was talked about both as a way to use a tool to interact with data, but also as steps in the analytic process. DMs talked about iterating until a discovery or insight was found.

Iteration also presented strong connects with feedback for many of those interviewed. It seemed that the desire to iterate came from a place of curiosity during analysis and the ability to interact with data was an enabler of curiosity. It allows more immediate answers to questions and the ability to pursue a path of interest without required a prolonged back-and-forth reliance on analysts.

Finding 3: When managers share data with others, it increases trust and confidence not only in decision quality but also in their leadership.

They talked about how sharing data with others was easy with VA systems and that doing so increased trust and confidence across the organization (Appendix C). Decision makers wanted to provide the same opportunity to interact with data with the rest of their organizations.

Finding 4: Traditional tendencies of both analysts and decision makers create barriers to realizing the full potential of visual analytics.

When analysts and managers do not both embrace a similar agile mindset, it creates a lack of role clarity in the analytic process. When analysts were focused on presenting findings or limiting interaction with data, frustration was voiced often from both analysts and managers. In those cases, revisions were seen as "not getting it right."

Discussion

Our findings emerged from our original research question and evolved as our interviews progressed, leading us to revise our thinking and inform our analysis throughout the research process. Across all our findings, we suggest that leaders of visual organizations need to present a blend of curiosity and creativity. Controlling the scope of information brings DMs direct into the analysis process. When presented with real-time decision making environments where they can interact with data, such leaders must be inquisitive and possess a cognitive capacity to operate flexibly with a blend of openness and focused attention (Good 2014).

When feelings of doubt or uncertainty arise, managers need to manage the scope of data and seek feedback from the data and from others across the organization. This allows them to move from insight to action not only for themselves but also for shared understanding across the organization. In this regard, decisions do not imply finality; decisions are not just choices at the end of deliberation and a commitment of a specific course of action. A visualization strategy must be about identifying problems and allowing decision makers to hone in rather than just be presented with findings (Morris et al. 2005).

The problem-shaping manager

Our experience in the field supports the idea that visual analytics brings managers closer to their data and that agile systems best support inviting them into exploratory analysis. Because decision making and analysis become one iterative process, decision makers need to shift away from a *problem-solving* posture and embrace an inquisitive and constantly vigilant *problem-finding* leadership style. Iterative decision makers must be inquisitive problem finders that can absorb and “sweep in” as much data as possible into their decision making process.

Decision makers face these decision points where they must take on a satisficing role (Simon 1979; Brown 2004) and determine when enough exploring has been done, and when enough information allows them to take immediate action. The changing nature of data can lead to doubt and seconding-guessing a decision among managers. Further, a desire to feel “decisive” in the face of constantly changing information may impact performance and confidence of decision-making quality.

Our research surfaced various traits of decision makers that may help them overcome information overload and gain a tolerance to the ambiguity that can come with it. While curiosity and creativity may be help tolerate ambiguity (Tegano 1990), further research specific to working with data can help us better understand how various traits of managers may improve VA adoption and effectiveness.

Empowering the Organization

Managers in a VA culture need to share data in order to facilitate a more comprehensive analytic culture (Popovič et al. 2014). Data-informed decisions and enabling interaction with data can help move an organization from a self-enhancing culture to an other-enhancing culture (Morris et al. 2005).

VA systems allow immediate feedback and real-time responses that can increase confidence so that all members of the organization can see together, learn together, and act together. Visualization of data leads to an appetite for more and more data. By providing open access to the data, we are creating organizations that eliminate knowledge differentials and can increase decision quality at both the tactical and strategic levels.

Reconsidering Roles

Rigid system designs are yielding to more nimble VA tools. Rigid organizational roles will need to give way to more agile roles as well. Decision-maker reliance on analysts and analyst tendencies to hide complexity of data emerged as two key points of new tension in the analyst/decision maker relationship. At the heart of the role tension was the analyst tendency to create dashboards and minimize the scope of analysis; on the other side, decision makers adept with data want to widen the scope of analysis.

Analysts and data scientists must play essential roles in continuing to create more sophisticated information environments. We do not contend that managers simply need to learn technical skills, but we did find that due to data complexity, various analysts and designers choose to hide such complexity from decision makers to make efficient use of their time. Interactive VA environments require quick changes in thinking. It is not about rushing to be decisive. Interactive analysis is an iterative process and managers need to have more intimate knowledge of the data and the tools available to them.

Limitations

Various factors limit the generalizability of our study. First, in a limited sample of twenty-three subjects in analyst and decision making roles, we may not have seen wider patterns and variances that a larger sample would afford. Second, we only interviewed a dyad of analyst and decision maker within the same organization in two instances. Understanding role conflict between analysts and decision makers would have been more robust if we had been able to interview dyads explicitly in more organizations to study roles more than traits of the decision makers specifically. Third, by focusing our interviews on users of the same analytic software, it is possible that further interviews with participants who use other tools might have yielded different results and points of view. Lastly, as with any qualitative study, researcher bias also could be a possible limiting factor to our findings.

Implications for Future Research

The intent of this study was to begin to understand the impact that visual analytics have on decision making and decision makers. We have raised various issues related to the decision maker characteristics and organizational roles that enable or prevent VA adoption across various industries. For practitioners, it is our hope that adoption of visual analytics is not just seen as something to relegate to technical staffs to implement.

Various themes across this study warrant further research into the traits of decision makers that thrive as analytic leaders. We found strong links to creativity, curiosity, and tolerance of ambiguity that should be pursued more systemically. It is our hope that subsequent studies will continue to inform organizational roles and lead to the development of analytic talent across an organization not just within technology-specific roles. As visual analytics become more prevalent such studies may help establish new curriculum for management coursework in order to instill the quantitative reasoning and visual analytic competencies that are needed to lead data-rich organizations\ and compete in the knowledge economy.

Conclusion

Visual analytics and the era of big data are still taking hold in our organizations and there is no one tool, process, role configuration, or strategy that will fit all data and all organizations. Agility in our systems is necessary but not sufficient to facilitate a visual analytic culture. More importantly, managers themselves also must embody an agility in their decision making in order to take full advantage of all the potential that visual analytics provides and become the analytic leaders of their organizations.

Appendix A: Qualitative Interview Protocol

Step 1: Introductions and Explanation of Study. Confidentiality & Permission to Record

Step 2: Opening Ice-breaker & Background Question

Question 1: Can you please tell me about yourself?

Sample probing questions:

- What was your first job?
- How did you get started with data visualization?
- What formal and informal training regarding data visualization have you received?
- How long have you utilized data visualization in your work?

Step 3: User Experiences with Data Visualization

Question 2: Please tell me about a time when visualizing data brought you a great insight into your work?

Sample probing questions:

- Where were you?
- Who helped you with your data gathering or the design?
- What is the status of that report now?

Question 3: Beyond your own interaction with data, I am curious about your overall team or organizational culture with interactive data. So, can you give me an example of how visualization has changed your work relationships with others in group settings?

Sample probing questions:

- Who within your organization comes in contact with data the most?
- Are there any pockets of success in your organization? Tell me more about them.
- Are there any pockets of resistance in your organization? Tell me more about them.

Question 4: Can you tell me about what you think a thriving visual organization would look like?

Question 5: When you consider your work and responsibilities, can you tell me if you experience any differences in your decision-making process when you are able to interact with data visualizations versus when you are not?

Step 4: Closing

That concludes our interview. Thank you very much for all the time and sharing your insight. Are there any other questions you were expecting me to ask that I did not ask you about? I really appreciate your time. If I need to clarify anything we've discussed, would it be okay for me to follow up with a brief phone call or email?

Appendix B: Excerpts regarding iteration during analysis

Analyst	*I think that those questions are around how quickly can you show something with this data to allow people to then iterate on it as fast as possible. You can throw something out there as fast as possible, then allow the person you are working with to react to it.*
Analyst	*I think that our senior executives always wanted information fast to be able to make decisions based on not just numbers, but just more about being able to change the numbers on the fly, so they can start to see the data much more quickly and answer different questions.*
Analyst	*I mentioned iteration where we'll build a dashboard and then we just go right in and we start building it with some very basic guidelines as far as what they want to see. And then we immediately get feedback and we have this loop and we do lots of iteration on it. And then we thrash it around a lot.*
Decision Maker	*I've come out of the agile software development background. So I'm very anti-long meetings and documentation wherever possible. I believe in creating a visual even if you need to do it standing in a hallway and ask how do you like it? Take those notes go back and create it again. That's pretty much the way things like these work.*

Appendix C: Excerpts regarding information/data sharing culture

I think just having a level playing field and having community access to the data and to the views, organizationally, is a good thing. Everybody sees that you are being measured, everybody sees that there's one version of the truth, everybody is pulling from the same source. I think that's been key here.
If we don't have the data, let's find it. Let's make sure it's clean. Let's duplicate it, let's put it in the right place so that it's available for the end-users to then consume and do what they want. So they can always trust the data, they can always find the data and it's always fast to get that data and their role is just to visualize it.
I think about how narrowly focused people can be but also about how making data available and democratizing it has a huge effect on the attitude and the trust and the extent to which people are just going to believe you when you say something, because the data you put out is the same data for everyone. You can't spin the information for one group of people because everyone has access to the same stuff!
The trust is that data is available to anybody, anybody can use … the magic I guess, is giving people the tools to say you can manipulate this any way you want, feel free to have at it, download the workbook if you want, do it yourself if you don't believe it, compare it to any report we've ever published and see if it doesn't make sense to you.

Appendix D: Excerpts regarding role conflicts

My belief is always 80 percent of what an analyst gives you, you don't need or want; and 80 percent of what you want an analyst isn't going to give you.
Me as the analyst, and you as the audience; I am going to assume you know more and I should really just give you the data and let you form your own conclusions. Whereas the audience, I think, more often is looking to the analyst who's been knee-deep or shoulder-deep in data to say, "No, you know it best, tell me what I should do."
If I am the senior manager and I'm looking to make a business decision, maybe I don't have the skills or it's the not the best use of my time to go digging after, right? That's what you analysts are paid to do.
An analyst's role hopefully starts to kind of go away as just sort of this idea of what an analyst is right now; sort of a glorified data manager in my head. And I mean 'analyst' is probably the most general term – it's like half the people I know are analysts. And you know, hopefully that roles starts to go away or it starts to become more.

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