

# Content, Context, and Critique: Commenting on a Data Visualization Blog

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## ABSTRACT

Online data journalism, including visualizations and other manifestations of data stories, has seen a recent surge of interest. User comments add a dynamic, social layer to interpretation, enabling users to learn from others' observations and social interact around news issues. We present the results of a qualitative study of commenting around visualizations published on a mainstream news outlet, The Economist's Graphic Detail blog. We find that surprisingly, only 42% of the comments discuss the visualization and/or article content. Over 60% of comments discuss matters of context, including how the issue is framed and the relation to outside data. Further, over one third of total comments provide direct critical feedback on the content of presented visualizations and text articles as well as on contextual aspects of the presentation. Our findings suggest using critical social feedback from comments in the design process, and motivate the development of more sophisticated commenting interfaces that distinguish comments by reference.

## Author Keywords

Information visualization; commenting; data journalism.

## ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation].

## General Terms

Human Factors; Design; Measurement.

## INTRODUCTION

With the launch of sites like Nate Silver's FiveThirtyEight [17] and the New York Times' The Upshot [15], data journalism has become a mainstream means of presenting news to the public. These sites, along with data blogs published by the Guardian [6] and The Economist [3], present the news using a data-driven approach to storytelling. Information visualization techniques are frequently used to make the data accessible to large public audiences. We seek to understand how audiences of online data-driven news outlets comment on data visualization-based posts.

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We analyze the commenting discourse that emerges on The Economist's Graphic Detail (GD) blog. GD posts integrate visualizations and commenting within an online news ecosystem with an active community of users who are intrinsically motivated to reason about the content [13] (Figure 1). Related research has looked more generally at commenting in online news ecosystems [2, 12, 21] or on blogs [5, 14] but is limited to users commenting on text-only articles. Visualization commenting, on the other hand, has been investigated primarily through laboratory studies or smaller-scale deployments of research systems [1, 8, 19, 23]. These studies characterize commenting as a means for individuals to better understand a data presentation by sharing observations, hypotheses, and other insights derived from presented data, as well as to socially interact through jokes and affirmations of one another's findings [8, 20, 22].

We contribute findings from a qualitative analysis of over 1,100 manually-coded comments on GD posts. Our results provide evidence of several forms of visualization-based commenting behavior that emerge when sensemaking occurs "in the wild" of a mainstream data journalism outlet. While our findings reinforce prior observations that comments support collaborative sensemaking around *content* such as the visualized data and article, surveying GD comments overall indicates an even stronger preoccupation among commenters with matters of *context*, such as how the presentation can be reconciled with non-present yet related data or how the issue was framed by the author.

Additionally, we find that over half of content-oriented comments and over one third of context-oriented comments offer explicit *criticism* of the presentation. Commenters use such comments to reference or "point" to perceived obstructions to interpretation presumed to stem from issues with the design of representations or framing of the issue. Our work contributes a coding scheme that can be used to distinguish content-oriented versus context-oriented and critical versus non-critical foci in subsequent studies of visualization-based commenting. We also provide detailed examples of subclasses of content, context, and critical comments, and describe how properties of the commenters themselves relate to the content-context distinction.

By deepening understanding around commenting behavior in such sites, we aim to identify new uses for numerous comments that arise in data journalism environments, and

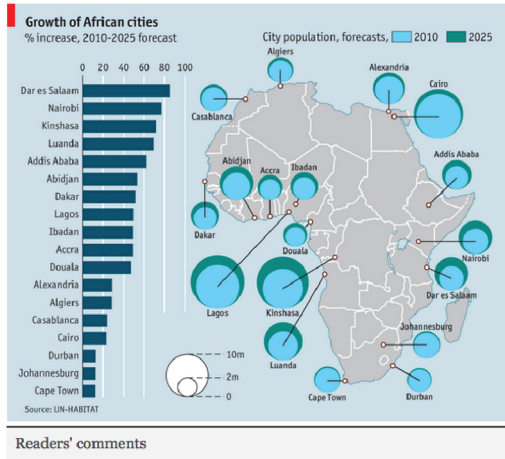
# Growth areas

Dec 13th 2010, 13:12 BY THE ECONOMIST ONLINE

Timeskeeper | Like 429 | Tweet 124

## Africa's cities are set to swell in size

OVER a third of Africa's 1 billion inhabitants currently live in urban areas, but by 2030 that proportion will have risen to a half. According to a recent report from UN-HABITAT, the United Nations agency for human settlements, the population of some cities is set to swell by up to 85% in the next 15 years. The most populous city in 2010, Cairo, will grow by 23% to 13.5m people. By 2025, however, it will have been overtaken by both Lagos (15.8m) and Kinshasa (15m). Food and water shortages, poor infrastructure and a lack of housing are among the problems faced by governments during such rapid urbanisation. Progress in meeting these challenges would be shown by a fall in the proportion of slum-dwellers, who currently account for 70% of urban inhabitants.



### Readers' comments

Sort: Newest first | Oldest first | Readers' most recommended

Tooto Dec 13th 2010, 17:24

Turns out that it's not only people on the move. By 2025 Durban will have migrated 1000kms down the south coast. Looks like Cape Town is moving north (probably trying to get away from Durban...)

Recommend | 73 | Report | Flag

**Figure 1: A post from the Economist's Graphic Detail about urbanization in Africa.**

new design features to enhance the user's experience. We conclude with a discussion of directions for future research aimed at incorporating comments in the content design process and for enhancing the user's experience via new design features in commenting platforms.

### STUDY DESIGN: COMMENTING ON THE GD

We provide a general characterization of the GD context and describe the dataset and methods.

#### General Characterization of GD

GD is a publicly accessible blog that is part of The Economist online. GD (originally the "Daily Chart") has been published since August 2010. Each workday the blog publishes "charts, maps and infographics", which are mostly static but sometimes include interactive visualizations. Posts also include a one or two paragraph text article contextualizing the graphic. In line with "a belief that what is written is more important than who writes it," post authorship on GD is left anonymous. User comments are pseudo-anonymous, and appear below the visualization in paged blocks of twenty. Comments are sorted in reverse chronological order by default, but can be sorted chronologically or by recommendation score. Threading (added in late 2011) allows users to respond directly to another comment.

### Data Collection and Coding Methodology

In April 2011 we collected all comments from 168 posts on GD resulting in a dataset of 4,468 comments across 118 posts containing one or more comments. We randomly sampled the posts to arrive at a more manageable set of 38 posts with one or more comments each and a total of 1,103 comments across the sample. Statistics reported in our findings below refer to this manually coded sample unless the full sample of 4,468 comments is noted. For each post we noted the format of its visualization. We observed a variety of chart types (10+ distinct types); eight of the posts (21%) contained interactivity. The mean GD article was 167 words and 29 comments (median=20). We observed 764 unique users (mean=1.4 comments/user). Across the full sample, most users (72.5%) only commented once.

We analyzed comments through iterative qualitative coding, affinity diagramming, typologizing, and memoing [11]. Comments were analyzed in the context of the original webpage (including the article, visualization, and comments). Two of the authors analyzed one half of the comments to build the codebook and obtain ground truth. We resolved differences to arrive at elemental categories.

During the coding process, we observed various *anchors*, aspects of the presentation that a comment could use as a basis for interpretation. Anchors included the visualization and/or data, the article, related information external to the GD presentation, and the issue itself (e.g., obesity), including how it was framed (e.g., as an epidemic). We explain these categories in detail in the next section. Anchors were not mutually exclusive, as a single comment could address multiple aspects.

We also observed in coding that some comments (spanning all anchor types) directly criticized the presentation. We coded a mutually exclusive "critical" class for all comments. A subsequent coding of the 1,103 comment sample sought to distinguish frequencies and patterns of anchor usage. Fifty of the 1,103 comment sample were sampled and coded independently by each coder, with Cohen's kappa computed for each category of reference to which comments were directed: the Visualization/Data 0.80, Article: 0.91; Critical Visualization, Data, or Article: 0.78, Related Data: .92; or Issue Framing: .92, Critical Related Data or Issue Framing: 0.72. The coders split the remainder of the 1,103 sample and recoded anchor usage.

### FINDINGS

#### Summary: Comments Debate Content & Context

A general lens for understanding the sensemaking activity we observed on GD is that of *critical interpretation of content and context*. At the highest level, our analysis revealed two dimensions along which comments could be meaningfully distinguished that have not surfaced in prior visualization commenting work.

Firstly, we observed a distinction between comments that focused on the *content* that was explicitly available (the

**Table 1: Prevalence of types (percentage of manually coded comments, N=1,103).**

| Description                      | Prevalence | Examples   |
|----------------------------------|------------|--|
| <b>Content-oriented comments</b> | 42.2%      |  |
| <b>Non-critical</b>              | 20.9%      | Question asking/answering, data-based observations.  |
| <b>Critical</b>                  | 21.4%      | Discuss data exclusion or obfuscation, critique aggregation, question definitions.   |
| <b>Context-oriented comments</b> | 62.1%      | <b>Related Data (39.7%)</b> <b>Issue Framing (28.3%)</b>   |
| <b>Non-critical</b>              | 38.9%      | Relate issue to personal knowledge; link to potentially related sources.      Suggest solutions, expose hopes or fears around issue. |
| <b>Critical</b>                  | 23.2%      | Add related data for comparison, expose overlooked conditions.      Question metric of success or significance of problem.           |

visualization, data, or article that was presented) or comments that reflected on matters of *context*: broadly speaking, how the issue is located with a broader set of knowledge and conditions. References to the *content* of the visualization, data, and/or article appeared in 42.2% of comments. An example is this reference to an edge in a visualized telephone network: “*That big connection between Glasgow and London is probably about 50% my mum.*” References to matters of *context* appeared in 62.1% of comments. We observed two main forms of context-oriented comments. Related Data context-oriented comments (39.7% of sample) discussed how the presentation would be impacted by considering other variables and conditions external to the presented data. For example, a comment on a post about youth unemployment suggested that “*another factor is that young people, prior to having children, are the most likely to ‘rock the boat’, and least likely to lay back and take bad treatment by management, etc.*” On the other hand, issue-framing context-oriented comments (28.3% of sample) debated how the information was framed, including the ultimate significance, possible solutions to, or moral implications of the issue being discussed. This comment on a post about obesity reflect on the ostensible awareness of the issue: “*Obesity is a puzzling condition. Even without any study, nearly everybody seems to know exactly what causes it and what the solutions are.*”

As stated above these categories are not mutually exclusive: 35.5% of comments were associated with two or more foci including Visualization, Data, or Article; Related Data; or Issue Framing. However, a relatively small proportion (15.4%) of comments referenced both content *and* context matters, suggesting that these orientations tend to be distinct. An analysis of commenter-based statistics (see “Who Comments on What”) shows that the distinction between content- and context-oriented comments may result from a difference in commenters’ levels of engagement with GD.

A second meaningful dimension of commenting behavior, we observed that a significant proportion of comments (38.3%) directly *criticized* aspects of the news presentation.

A critical orientation characterized 50.6% of all content-oriented comments (21.4% of total coded sample), including this one questioning the accuracy of a statement in an article about China’s economy: “*How could any economy have 6 - 9 % GDP growth in a phase of deflation, as shown for Q3 and Q4 08 and Q1 09?*” Context-oriented comments were also frequently critical in nature (37.4%), albeit in more subtle ways that often implied a goal to understand the rhetorical intentions behind the overall presentation, such as this comment on a post about political prisoners, which implies that certain information has been wrongly overlooked: “*Is it the Human Rights Watch or the Economist that can't see the reality? Where is the "selection of political prisoners" held in Russia?*”

Below, we detail the main distinctions between these types of comment feedback, including statistics and examples.

#### **Content Orientation (Visualization, Data, Article)**

We describe sensemaking activities in GD comments that reinforce the results of prior commenting studies. We then provide examples of the many comments that focus instead on criticizing the design of content like the visualization.

##### *Non-Critical Sensemaking in Content-Oriented Comments*

Among the 49.3% of content-oriented comments that did not explicitly critique the representations (20.9% of total coded sample), we observed categories of sensemaking activity that have been described in prior studies on visualization commenting [8, 18, 22]. These included sharing of hypotheses and observations based on the visual (e.g., “*The data clearly show that it takes three quarters of declining growth rate to cap inflation (Q1-Q3 of 2007)*”), and posing of questions (“*Is there any relation between the number of delegates and 'value' they can offer to solve the global warming problem?*”). The article text served as another form of reference. Direct quoting of the article occurred in 1.3% of the 4,468 comment sample (e.g., as “*The Economist asks: ‘So why did China's central bank raise reserve requirements for six banks ...?’ It sure caught the world, particularly the West and the Economist by surprise.*”)

### *Critical Content-Oriented Comments*

Among the half of content-oriented comments that criticized the visualization or article, topics discussed included barriers to comparative operations, such as using inconsistent baselines, depicting normalized (e.g. percentage) values instead of absolute, or comparing apples to oranges. Other noted barriers include dynamic axis labeling, the validity of a data transformation such as a rank ordering, and the appropriateness of mappings to visual attributes. For instance, this comment was made in response to a chart depicting relative city population forecasts using circles, “*I have trouble discerning that, for example, the projected circle for Dar es Salaam is almost twice the area for 2010. To me, it looks about 1/4 bigger... If I note that the diameter is about 40% larger and the area is squared, then I get to about two times. But that is not intuitive which is what a good graphical presentation should be.*”

Some content-oriented comments (3.7%) were directed at the data aggregation, indicating an awareness of how aggregation can skew distributions. Most often this was expressed as a desire to disaggregate the visualized data. For instance, commenters indicated a desire to disaggregate continents into countries, and countries into states or regions. Comments also suggested that an aggregate might be disproportionately inflated by certain observations.

Other comments that explicitly critiqued the visualization focused more on the limitations of the selected data. For instance, 8.9% of coded comments referenced the exclusion, inclusion, or obfuscation of specific values of a variable shown in the visualization (e.g. “*I notice that the inclusion of the United States excluded the land mass of Alaska, which is material*”).

Critiques oriented at the visualization were sometimes directed at its anonymous *creator*, as is the prior comment. 3.6% of coded comments explicitly addressed both the visualization and the creator. Other comments directed at the creator indicate that commenters perceived traces of the designer’s intentions in the visualization. For example, one commenter suggested “*This graphic is imaginative but I think too much effort went into making it clever rather than accurate.*” Others reflect on the point that is intended by the creators (e.g., “*what G.D. is trying to say*”).

Critiques of the definition or choice of words or labels (3.0% of coded comments) could be anchored both on the visual as well as the article text, including critiques of graph annotations, labels, or the article title. Assessments of how a measure or label is defined sometimes also indicated a desire to understand the designer’s intentions: “*Your headline refers to waist lines, so the Waist to Hip Ratio would be a better measure than BMI. BMI does not adjust for muscularity.*” Comments relating to definitions (3.0%) often pointed out nuances in terminology (such as measure labels like “entitlements” or “economic wealth”) that could influence interpretations of the content.

Among those critiques oriented toward the content of the accompanying article, we observed comments criticizing specific claims in the articles, questioning or disagreeing with them, adding clarifications, suggesting corrections, or adding a caveat to a claim.

### **Context Orientation (Related Data and Issue Framing)**

We describe two forms of context-oriented discussion—concerning Related Data and Issue Framing—that we observed in the 62.1% of comments that focused on matters of context, then detail how critical feedback manifested in context-oriented comments.

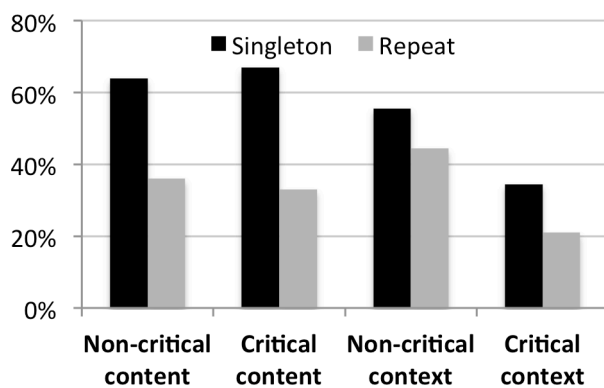
#### *Two Varieties of Context-Oriented Comments*

Related Data comments contribute information from external sources, data, and personal experiences that may be useful for interpreting the presentation. One obvious form is direct linking using URLs to external sources (e.g. blog posts, news articles, visualizations, or other data), which occurred in 5.9% of comments (full sample), and are often used to support one’s arguments or explanations.

Another 4.9% of Related Data comments drew on personal knowledge, opinions, experiences, or narratives to add context or argue. The following comment on a post about youth employment illustrates how these comments add context by bringing in personal storytelling, “*I’m 25 in China and thank goodness I have found a nice job. And as well as many of my classmates. We’ll graduate next July. However, a good job is still hard to get for those who don’t has [sic] a relatively high and famous degree.*”

Other distinguishable subsets of Related Data comments including adding related data in order to point out comparisons that impact interpretation (20.9%); or to explicate conditions surrounding the sources of data used in the graph (20.4%). An example of the former case includes citing statistics so that others could compare them with the presented data. For instance, one comment introduced population statistics correlated with the visualized data. Examples of commenters’ interests in conditions surrounding the data sources includes a comment characterizing the agenda of the sources responsible for the data (e.g. “*The Bertelsmann Foundation is surely no leftist organization. It’s a liberal/neocon [sic] think tank...*”).

Issue Framing comments are a second form of context-oriented comments (28.3% of total comments) focused on the *framing of the issue*. Subsets of these comments interpreted causality, reflected on the moral considerations associated with an issue, and suggested solutions for the issue, touching on many established facets of media frames [3]. Other issue framing comments put the presented issue in perspective against another (ostensibly relevant) issues that it might impact, such as a comment on a post about food prices that introduced the issue of obesity. Such comments can be distinguished from Related Data comments in that the former direct the focus from the current issue (food



**Figure 2: Percentage of comments of varying types contributed by singleton versus repeat commenters. Singletons are more likely than repeat commenters to provide comments on content.**

prices) to a related issue (obesity), rather than surfacing factors to improve understanding of the current issue.

#### Critical Context-Oriented Comments

We observed directly critical feedback occurring in 37.4% of all context-oriented comments. Critical Related Data comments implied that incorporating the information the commenter was adding would improve the accuracy of the presentation. Others asked pointed questions implying overlooked factors in the analysis: *“The approach to compare the current ratio of house prices to rents seems overly simplistic... How is rent control taken into account for apartments?”* Suggestions of other variables to include in analysis were the most common form of Related Data critique. These comments differ from critical content-oriented comments around data exclusion in that Related Data comments focused on the overlooking of entire factors or variables rather than a single datum.

Critical issue framing comments often questioned the significance of a “problem,” as in this comment on a post about the upcoming World Economic Forum *“Hey, a way more game changing event is taking place in Egypt. Forget Davos.”* Such comments indicated sensitivity among commenters to how media frames select and emphasize different perspectives or ways of thinking about an issue.

Other critical issue framing comments provided “meta-insights:” realizations that seek to understand not just the single presentation, but the nature of the domain from which the data comes. For example, one commenter concluded that a conventional approach to describing economic relationships was not appropriately complex or dynamic: *“social justice has always been-and always will be a fuzzy term with no meaning... instead of making and publishing indexes of social justice, separate indexes on poverty, education, and so on should be made.”*

#### Who Comments on What

Previous research finds that high “facticity” (i.e. reporting on concrete actions or events) attracts fewer average comments per user on political news articles [21]. Here, we

pose a similar question: do aspects of the presentation that are most obviously factual and concrete (the content such as the data and visualization) attract more singleton or repeat commenters? Our of 764 unique commenters across the 4,468 comment set, 602 of these commenters commented once (singletons), implying that 87% of comments were written by the other 21% of users (repeat). This aligns with observed content generation dynamics where a few core users contribute the majority of content [15].

Figure 2 compares the percentage of the four subclasses based on the content- vs. context and non-critical versus critical distinctions that are contributed by singletons versus repeat commenters. The biggest disparity is for content anchors. Singletons provide the majority of non-critical comments about content (64%) and the majority of critical comments about content (67%). Repeat commenters more frequently focus on matters of context (67.2% of all comments from repeat commenters discuss context critical or not critically). These results suggest that the lower average comments per user on high facticity posts found in [21] is due to an attraction of singletons to high facticity content.

#### DISCUSSION AND FUTURE WORK

Our results show several interesting differences compared to prior work in visualization commenting. Prior studies emphasize the focused, analytical nature of comments posted when interacting with research-based systems [8,19,22], such as how comments represent hypotheses and observations around a dataset. Subsets of the content and context categories we observe fit these characterizations. However, matters of context were more frequently discussed in our sample. Discussions ranged from listing “overlooked” variables to questioning the moral significance of an issue.

Additionally, a considerable proportion of the comments we observed showed a preoccupation with *removing perceived obstructions* to allow for accurate interpretations. Commenters on the GD seem to naturally engage in what has been termed “visualization criticism” [9]: a practice in which the shortcomings of visualization designs are discussed with reference to aesthetic criteria. In this case, however, the most common criteria appeared to be an expected journalistic ethic. Commenting behavior diverged from prior study results in that commenters frequently alluded to decisions made in framing the data, visual, and other content [9] including facets of media frames like problem definition, causality, moral significance, etc. [3].

The content-context dichotomy and prevalence of criticism may result from novel aspects of GD compared to laboratory studies or research prototypes. The potential for a text article to paint an issue in broad strokes may compel commenters to similarly consider the broader context surrounding the issue as opposed to the content alone. Awareness of the media source of the presentation may cue a critical mindset among commenters wary of the power of media frames to persuade. Future research should continue to explore how these aspects impact commenting activity.

### Design Implications

The frequent direct criticism in comments motivates using comments in the design process, as a mean of incorporating a mutually beneficial “social feedback loop.” As an audience considers a designer’s decisions in light of their expectations, their comments uncover specific design choices that may have led to misunderstandings, misinterpretations, or strong criticism. Content critiques provide designers with direct advice for adjusting the design of a visualization or article to improve its accuracy or interpretability. Future work should explore developing interfaces that automatically categorize content critiques for easier integration into the designer’s process.

Critiques discussing related data could similarly be consulted to make a presentation more comprehensive or “complete” in its representation of an issue, such as through adding textual qualifications to explain the reasoning behind omissions. The prevalence of Related Data comments suggests that platforms incorporate features that allow commenters’ to more directly link related yet external evidence with aspects of a presentation. Finally, interfaces that make the anchor schema visible, such as by enabling commenters to link their comments to the appropriate part of the presentation, could simplify the sensemaking process of subsequent commenters.

### CONCLUSION

We presented a study of collaborative visual analysis via comments in a naturalistic data journalism setting. We report rich observations and quantitative measures describing how commenters direct their attention to matters of content but more frequently, context. We describe how this content versus context distinction is related to whether commenters are singletons or repeat commenters. Our results also indicate that over one third of comments provide explicit critical advice for how to improve the presentation. We observe a sensitivity to framing choices in particular that has not been surfaced in prior work. We contribute a novel coding scheme for differentiating content versus context-oriented and critical versus non-critical comments in studying comments around data presentations. Our results motivate new users for comments as social feedback that is potentially useful in the design process, and also suggest new features for commenting platforms.

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