

Conservatism in Digital Trends: Findings from a differentialist analysis of influence graphs

(accepted manuscript)

Frederick M.C. van Amstel

trends, visualization, graphs, social changes, patterns, digital humanities

Digital trends are signs of imminent social changes that appear linked to the use of digital technologies. It is believed that digital media, due to its decentralized structure, induces more radical differences than centralized analog media. The aim of this research is to assess the potential for social differentiation implied in the dissemination of trends by digital media. To achieve this end, the research analyzed a corpus of 1,700 digital trends mapped on graph visualizations. Interpreting the results through Henri Lefebvre's materialist-dialectical differentialism, this research came to the conclusion that digital trends produce minimal differences, that is, they tend to maintain the status quo instead of questioning it, contradicting their association with phenomena such as revolution, disruption and innovation. In addition to investigating this specific issue, this research points towards possible collaborations between Information Design and Digital Humanities fields.

1. Introduction

Trends are often defined as signs of imminent social change (Caldas, 2004; Erner, 2015). These signs represent new values, new economic orders, new gender relations, or any other type of novelty that introduces social differentiation. Design practice intentionally reproduces trends, but it is common for such reproduction to take place without awareness of the fact, especially when other design projects are used as a reference. The search for references is a common habit among designers to assimilate and reproduce trends without further reflection.

In addition to the unsystematic search, there are systematic methods for the inclusion of relevant trends, such as benchmark analysis. The differentiation captured by benchmark analysis is usually restricted to formal or functional variations; however, there are other methods that identify, analyze, and accommodate social differences in design projects (Dragt, 2017; Caldas, 2004). Companies specializing in trend research offer standardized or customized information services based on these methods (Rasquilha, 2015), but even so, most design projects do not have enough resources to pay for such services. What is available to most design projects is searching for references in digital media such as Instagram, Behance and Dribbble. Due to its reach and customization, digital media has become such an important vehicle for the reproduction of trends that there is already a niche for specific trends born in this media, the so-called digital trends.

Digital trends can be defined as signs of social changes that appear linked to the use of digital technologies, as if such technologies were capable of determining society through the introduction of new functions — beliefs associated with technological determinism and design functionalism. This capability is emphasized by adjectives that often accompany such trends, such as revolutionary, disruptive, radical, or innovative, and number sequences typical of software versioning, such as Web 2.0, Industry 4.0, or Society 5.0, just to name a few. From a critical perspective that rejects technological determinism and functionalism (Vieira Pinto, 2005), digital trends can, however, be seen as a self-fulfilling prophecies that mobilize actors interested in producing their own existence through exploiting the trend. By prophesying the trend, they make the trend stronger. The more actors are mobilized, the stronger the trend becomes. This mobilization around digital trends is popularly known as hype (Linden & Fenn, 2003).

Digital trends circulate quickly across all types of media, but in digital media they circulate even faster, taking advantage of its tradition of metalanguage, self-reference, and recursion. Not all trends circulating digital media are digital by nature. Haircuts, cooking recipes, and songs quickly flow through digital media, even if they are not digitally born. In fact, there are many of these trends that would never be distributed by analog media. Due to the centralized power structure, analogue media tend to circulate trends with lesser degree of differentiation, similar to what already exists.

Digital media have decentralized power structures that do not depend on massification for financial sustainability (Erner, 2015; Rasquilha, 2015). To the opposite, digital media profits from Long Tail, the possibility of fulfilling niche demands through customized fabrication and distribution (Anderson, 2006). Following this logic, digital trends would have the greatest potential for social change, as they would take advantage of the intrinsic differentiation of the digital medium.

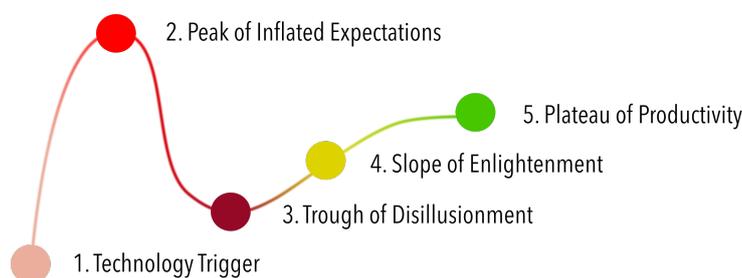
Does digital media make that much of a difference? And, from the point of view of social change, are the differences induced or produced, minimal or maximal? Such questions become relevant to Information Design research as several researchers publicly manifest a progressive political agenda, committed to social changes that strengthen equality, sustainability and democracy in times of sheering complexity and contradiction (Bonsiepe, 2006; Manzini, 2019; Souza et al., 2016). If digital trends provide greater differentiation, then they should be prioritized by Information Design as a strategic resource to promote social change.

The aim of this research is to assess the degree of social differentiation involved in the process of disseminating digital trends. To achieve this end, this research performed an analysis of digital trend graphs cataloged by students of a Digital Trends Laboratory course. The analysis is supported by graph visualization and guided by the combination of social network analysis concepts (Zago, 2015). The next section presents such theoretical concepts, followed by the study methodology. The result analysis will be presented with the support of evidence collected in the graph visualizations.

2. Trend dissemination model

With the objective of helping managers to decide on investing in new technologies, Gartner Group, a consultancy specializes in digital trends, developed the Hype Cycle model in 1995 to classify and predict the maturity degree of a given technology in a given period (Linden & Fenn, 2003). Currently, this model is widely used in industry, including design practice; however, there are only a few empirical studies that confirm its heuristic validity or usefulness (Dedehayir & Steinert, 2016). The model expects to see a trend developing through five consecutive phases. When a trend is in Technology Trigger phase (1 – pink color), it still does not have a viable commercial product and few people know about it. At the Peak of Inflated Expectations (2 – red color), the trend becomes recognized as such, yet many still doubt that it is really useful, as the proposed applications seem naive. If there are too many frustrated expectations, the trend falls into the Trough of Disillusionment (3 – burgundy color) and may even disappear. If it recovers, it finds specific niches where it makes sense and starts climbing the Slope of Enlightenment (4 – yellow color). Finally, a stable and lasting trend is found in the Plateau of Productivity (5 – green color). Figure 1 offers an adapted version of the original HypeCycle model that uses color to convey phases.

Figure 1: HypeCycle model of digital trends (based on Linden & Fenn, 2003).



The HypeCycle model considers the evolution of trends as a linear progression, as if every trend followed a process of homogenization and stabilization. In this way, it ignores the interaction between trends, that is, the influence that one exerts over the other. As a matter of fact, trends often appear as counter-trends or as alternatives to alternatives, expressing differences linked to imminent social changes (Caldas, 2004; Erner, 2015). Although the HypeCycle model allows for measuring the current level of dissemination at a given time, it is not able to capture the genesis of trends within the broader process of social change.

As a complement to the HypeCycle model, we developed an expanded interpretation of this model based on the materialist-dialectical differentialism of Henri Lefebvre (1972). This theory proposes that social changes arise from differentiation processes in two moments: quantitative accumulation and qualitative leap. The first moment is characterized by pattern repetition through similar forms, structures, or functions. Pattern repetition accumulates qualities such as values, meanings, emotions, and information at a certain point in social space, which corresponds to a current trend. At each repetition, there is a small variation of the same pattern up to the moment when the pattern becomes saturated. The addition of small differences no longer produces new qualities, and there is a trend crisis or a decay. In contrast to the HypeCycle model, differentialism predicts the possibility of one trend giving rise to another by transforming quantitative accumulation into a qualitative leap, which corresponds to a breaking of patterns or production of a crucial difference. This possibility is based on the second law of dialectical logic (van Amstel, 2009).

In differentialism, broad social change occurs through the conflict between homogenizing forces — which benefit from maintaining the status quo — and differentiating capacities — which grow with the decay of the status quo and the inability of normality to satisfy everyday desires (Lefebvre, 1972). When homogenizing forces predominate over differentiating capacities, the production of differences is reduced to a minimum, that is, it is reduced to the accumulation of small variations in pattern repetition. The products and services generated by these trends tend to be marketed quickly due to the commodity equalization process. The trends produced by the homogenizing force are usually conservative, as they aim at rapid circulation and decay. When differentiating capacities predominate, the production of differences is maximum. There are qualitative leaps, radical innovations, unexpected changes, and the creation of works that mark epochs. For this very reason, trends escapes the process of equalizing commodity value and end up generating unique use values. The trends produced in this phase are deliberately progressive, that is, they produce more radical and lasting social changes.

The HypeCycle model revised from the differentialist perspective no longer represents a linear quantitative progression, but rather a non-linear progression of qualitative changes. The passage from one phase to another takes place through the gain or loss of qualities. Thus, it is possible that the qualitative leap leads the trend to any other phase. The quality of the trend will depend on the pattern of social differentiation implied by it.

By allowing an interdisciplinary approach to the study of reality, this revised model of HypeCycle can be used to study digital trends from the perspective of Digital Humanities, a new field that combines “the traditional tools of humanistic thinking (interpretation and criticism, historical perspective, cultural comparative analysis and social, contextualization, archival research) with the tools of computational thinking (information design, statistical analysis, geographic information system, database creation, and computer graphics) to formulate, interpret and analyze the humanities-based research problem” (Burdick et al., 2020, pp.95). The next section explains how the revised Hypecycle model was used to analyze the problem of social differentiation in the spread of digital trends.

3. Methodology

The objective of this research is to verify if digital trends are associated with minimum or maximum social differences, in other words, to check if they are conservative or progressive. For this end, it was necessary to revise the HypeCycle dissemination model and build a materialistic-differentialist trend analysis approach which we call *differential analysis*. Differential analysis consists of identifying patterns of social differentiation expressed through the maturity degree and patterns of influence in a series of cataloged digital trends. The catalog used for this research was produced by 228 undergraduate students enrolled in the Digital Trends Laboratory course from the Undergraduate Studies in Digital Design at Pontifical Catholic University of Paraná (PUCPR). The study, which took place from 2015 to 2018, followed the 8 steps of the Eis Dragt Trend Research Cycle (2017):

- 1) **Detection:** the trend is identified in different sources such as websites, social networks, informal conversations, street observations, and so on. In this mapping, only digital sources were used;
- 2) **Documentation:** The trend is captured in images and described in draft text and annotation;
- 3) **Grouping:** trends that have something in common are grouped according to an explicit or

implicit criterion. In the case of this research, a collaborative Google spreadsheet was used to record links between trends through numerical indicators. This data was used to build visual graphs that show the links between all cataloged trends;

- 4) **Validation:** the comparison between the trends already recognized allows to verify if there are enough differences to consider that is a new trend;
- 5) **Labeling:** after identifying the main characteristics of the trend and positioning it in relation to other trends, a distinctive name for this trend was created or selected;
- 6) **Scope:** trends can apply to certain domains, contexts, or media. In the case of this research, each trend was classified according to a type (Style, Behavior, Interfaces, Games, Social Networks, Technology, and Video). This metadata was ignored by this study for being inconsistently applied by students;
- 7) **Communication:** after defining the trend, the text is published in an appropriate vehicle. In the case of this research, a website was used for that <<https://medium.com/tendências-digitais>>;
- 8) **Translation:** the trend is not always understandable outside of its original context, whether it is a matter of spoken, written or visual language, thus lacking adequate translation. Therefore, in this research, explanatory texts and diagrams were elaborated.

The mapping took place in cycles that corresponded to the academic semesters of the Digital Trends Laboratory course. Students were encouraged to check on the spreadsheet whether a trend they had just identified had already been identified by students from previous classes. Backward checking was crucial to avoid duplication and to allow for the survey to expand its sampling cumulatively. Also, by checking the spreadsheet, students were exposed to past trends that could influence new trends. In the document, students registered this influence with a unique numerical identification for each trend, referred to in the linkage columns of the worksheet. This feature was crucial for generating graph visualizations with the Open Source Gephi 0.9.2 application, which can read data from spreadsheet files. The visualizations were generated by the end of each semester, published together with an explanation text by the teacher/author on the lab website.

4. Results

From 2015 to 2018, students identified 1,700 digital trends, at an average of 7.4 trends per student. During this same period, the teacher published 6 texts with graph visualizations that synthesized the partial findings in a website section <<https://medium.com/tendências-digitais/mapas/home>>. The visualizations were particularly useful for the purpose of this research, as signs of social differentiation that could be identified in the node connection patterns. Several Information Design patterns (Lima, 2011) were experimented to represent and interpret the production of differences between trends: 1) trends represented by nodes; 2) influence between trends represented by arrows (directional edges) going from the influencing trend to the influenced trend; 3) node size proportional to the number of connections received (in-degree); 4) spatial distribution of nodes based on algorithms that generate visual networks (explained below).

The first visualization generated (Figure 2) allowed for the immediate highlight of the most influential trend in that year: “Easy to use web interfaces”, “YouTube as a learning tool”, “GIFs as a mode of expression in social media”, and “Voice commands”. Furthermore, it allowed for cluster identification within mutual connections. From that point on in the research project, the graph visualizations were called digital trend maps. The clusters that appeared across several maps were called megatrends, trends that are capable of generating new trends.

The maps were compared in a variety of ways, mostly from a historical perspective, with the aim of capturing imminent social changes. Map changes, from one semester to the next, could reflect social changes during that same period. Clusters offered a more or less stable unit of analysis amidst the variation of Information Design patterns (Figure 3), as they are capable of capturing minimal differences between interlinked trends, while also expressing maximum differences between unlinked trends.

Figure 2: Excerpt from a graph visualization for the expected digital trends in 2016.

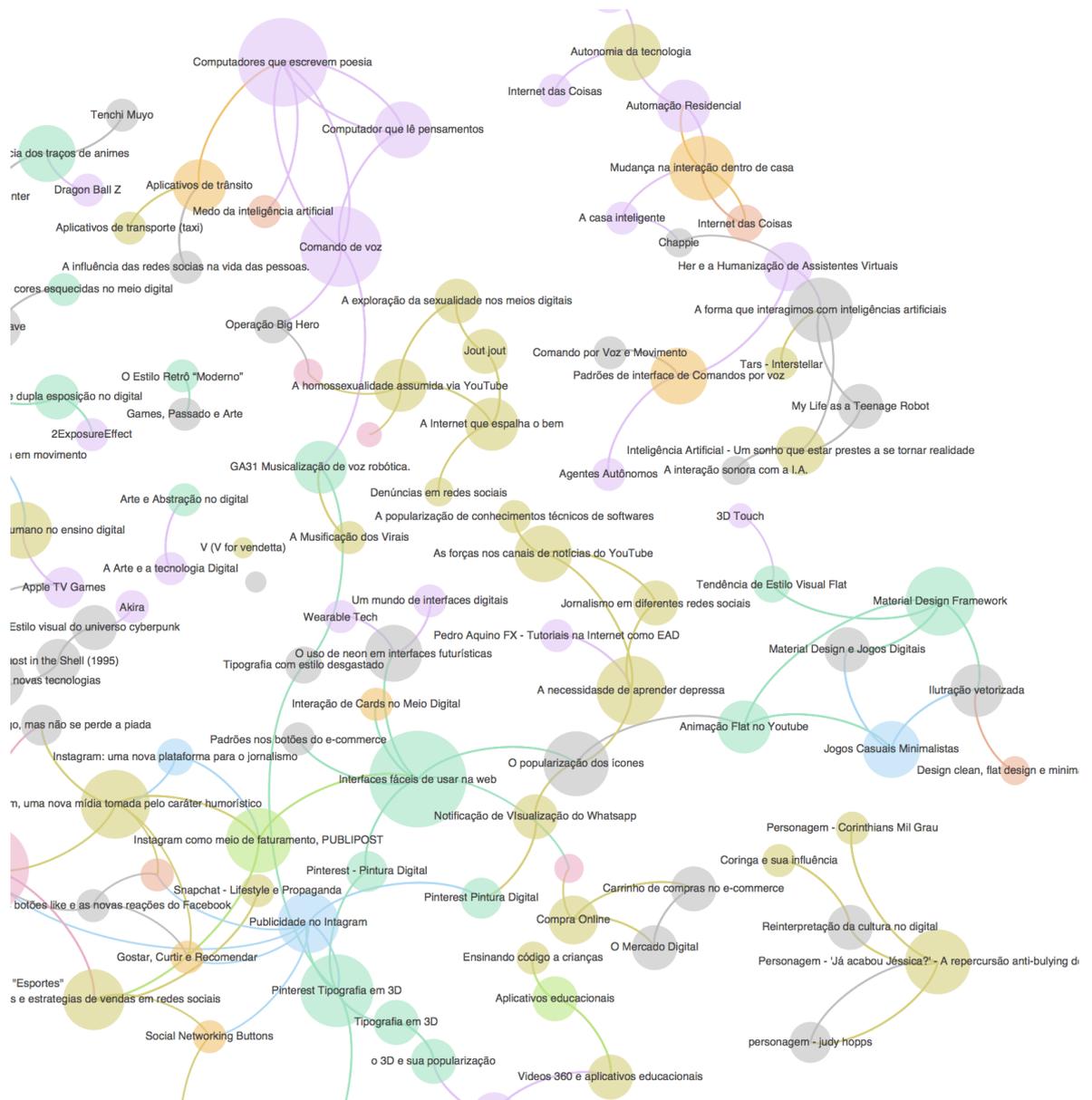
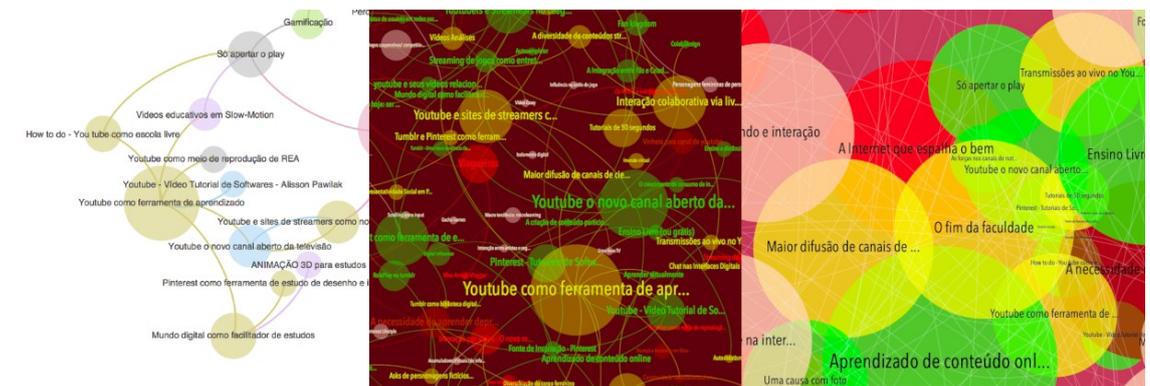


Figure 3: Densification of the Youtube cluster along trend maps for 2016 (ForceAtlas algorithm), for 2017 (Fruchterman Reingold algorithm), and for 2018 (Louvain algorithm).



New clusters were formed as the data set grew, mainly due to the accumulation of links between trends (Table 1). Clusters that appeared consistently from the various algorithms used received most attention in the comparisons. After including the modularity index in 2018, which greatly advanced cluster identification, big clusters came to be considered megatrends, since they could not only represent the mathematical reality of the graph, but they could also represent broad influence patterns. Students were encouraged to write about these megatrends, making sense of the clusters while theorizing about their origins.

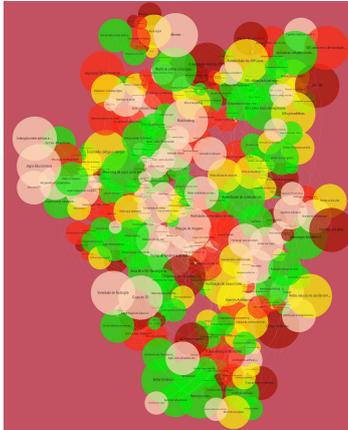
Table 1: Algorithms used in each map and the resulting groupings.

Map	Spatial distribution algorithm	Clusters found
2016	ForceAtlas: it generate attraction forces between nodes that connect to each other, while generating repulsion between nodes that are not connected to each other. Clusters spread through the graph (Jacomy et al., 2014). This algorithm was chosen due to its ease of interpretation, even if it is not very efficient to identify clusters in small networks. The most important visual pattern used was proportional node size based on in-degree connectivity.	Virtual Reality, Augmented Reality, Youtube
2017(a)	ForceAtlas: same as above, however, with the growth of the network, greater emphasis was placed on the connections between nodes than on individual node relevance, as new clusters appeared.	GIFs, Instagram, Virtual and Augmented Reality, Robotics and Artificial Intelligence, Youtube
2017(b)	Fruchterman Reingold: it considers the mutual link between nodes as vectors pointing to a resulting direction. The nodes move in this direction until the resulting forces cancel each other and come into balance, generating a circle with several overlapping clusters (Fruchterman and Reingold, 1991). This algorithm was chosen for its ability to visualize patterns that are broader than clusters, allowing for better understanding of the whole network. The HypeCycle phase received the greatest visual emphasis on this map.	Clean Design, Drones, GIFs, Artificial Intelligence, Robotics, Youtube, Virtual Reality
2018(a)	Louvain: this algorithm recognizes communities among interlinked nodes, a type of cluster formed from common modularity indices. These indices are calculated from the mutual links between nodes in relation to the expectation of mutual links in the hypothetical case of a randomly-connected network (Blondel et al., 2008). This algorithm was used to improve cluster precision, as previous algorithms did not always represent trends that made sense to human analysts. This algorithm was used in combination with Circle Path, which takes advantage of modularity indices to spatially distribute nodes in mutually connected circles.	Digital Learning, Digital Culture, Clean Design, GIFs, Artificial Intelligence
2018(b)	OpenOrd: a variation of the Fruchterman Reingold algorithm with well-defined phases of node reordering: liquid, expansion, cool-down, crunch, and simmer. In the expansion phase, the least connected nodes distance from each other, while in cool-down, the interconnected nodes come closer (Martin et al., 2011). This algorithm offers the possibility of configuring each phase, enabling more complex usages to effectively highlighting megatrend clusters.	Learning at home, Clean Design, Playful experiences, GIFs, Artificial intelligence, Minimalist retro, Digital consumers
2019	Yifan Hu: Algorithm similar to ForceAtlas, but with an additional technique of thickening the graph to reduce its complexity and reduce the number of clusters. The resulting graph usually has a super-node at its center, with progressively smaller clusters at the edges (Hu, 2005). This algorithm was chosen to highlight megatrends' influence: the closer to the center of the graph, the more influence the megatrend has.	Online Shopping, GIFs, Artificial Intelligence, Games, Minimalism, Nostalgia, Virtual Reality, Social Media, Youtube

The trend maps were presented to students and discussed in the classroom. The discussion about the first map for 2018 (Figure 4) focused on trying to explain why the map center features more trends in the Technology Trigger phase (pink). The conclusion of the teacher-student collaborative interpretation is that these trends could be part of several groups and have, therefore, diluted influence. The trends positioned in the later phases of the HypeCycle appeared in stronger clusters, as they would have needed to stand over the others in the past to climb the Slope of

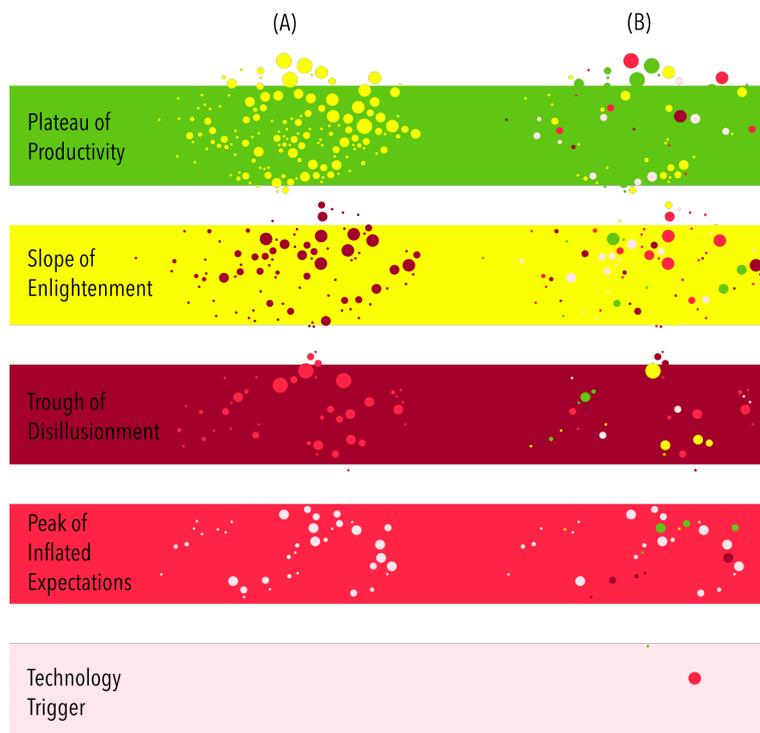
Enlightenment (yellow). Although not as influential, trends in the Plateau of Productivity (green) appeared at the center of most clusters. This means that they have several neighbors inside the cluster, but not outside of the cluster, leaving Technology Trigger trends at the margins (pink).

Figure 4: Digital Trend Map for 2018(a).



In the 2018(b) map, trends were reclassified again according to the HypeCycle model, to reflect progress in social differentiation. The model predicts that influential trends may move to a later phase, eventually skipping the Trough of Disillusionment. The differences found between 2017(b) and 2018(b) maps do not confirm this prediction. Figure 5 highlights differences between the expected HypeCycle phases as expressed by the background color (2017b) and the actual trend phase in the node foreground color (2018a). If the trend remained within the same phase, the node simply does not appear in the right side of the analytical map (B). This analytical view allows us to perceive the discrepancy between the linear evolution expected by the model and the real evolution mapped by the study.

Figure 5: Analytical visualization contrasting the expected HypeCycle phase change from 2017 to 2018 in the most connected trends (A) and the actual classification performed by students (B).

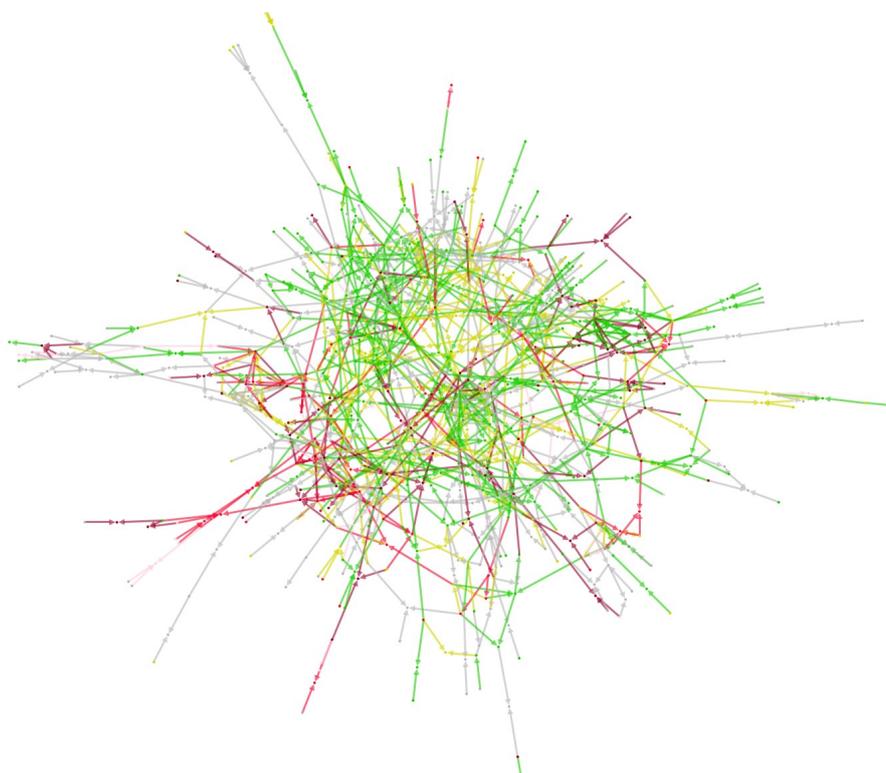


Several trends positioned at the Peak of Inflated Expectations in 2017(b) felt onto the Trough of Disillusionment in 2018(b), meaning their hypes were debunked, as predicted by the HypeCycle model. The main finding from this analysis is that several trends in the Trough of Disillusionment also came from the Slope of Enlightenment and from the Plateau of Productivity, suggesting that digital trends never reach a level of stability. Regression to Technology Trigger was identified in 3 cases, implying that, once the trend has a relatively stable technology base, trends vary only in their applications.

We also noticed that several trends went from the Peak of Inflated Expectations straight to the Slope of Enlightenment, without necessarily going through the Trough of Disillusionment. The Plateau of Productivity has several trends coming from the Technology Trigger, Peak of Inflated Expectations and Slope of Enlightenment, but only a few that came straight from Trough of Disillusionment. This means that once a trend falls into disrepute, it really needs time in another phase to recover from this fall.

The trend linkage pattern seems fundamental for stabilization, as shown in Figure 6. The arrow color represents the influenced trend maturity degree. This analytical view shows that trends in the Plateau of Productivity (green) intertwine intensely with each other, forming robust but isolated clusters. Trends in the Peak of Inflated Expectations (red) tend to cross clusters, creating a sort of circular movement on the map. Speculation at this phase is so great that the trend acquires the potential to connect with virtually any other trend. As for trends in the Trough of Disillusionment (burgundy), they do not form clusters, that is, they do not drag the others into oblivion. This map also features nodes that were not yet classified according to the HypeCycle model (gray), which appeared randomly distributed across the graph.

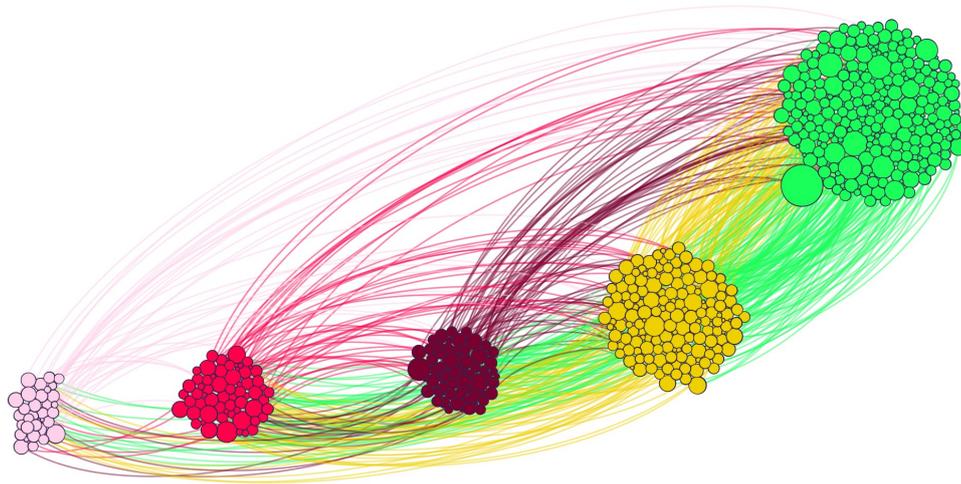
Figure 6: Analytical view of links between digital trends mapped in 2018(a).



By looking at Figure 6, we asked ourselves: do trends established in the Plateau of Productivity try to conserve their influence over the others? This question is answered by Figure 7, where nodes are grouped according to HypeCycle phases on a multi-linear scale. Most of the connections that starts from the Technology Trigger phase (pink) reaches the nodes in the Plateau of Productivity phase (green). The same is true for trends in the Trough of Disillusionment (burgundy). Trends in these two phases seems to need connecting to established trends in order to gain influence. On the other hand, trends in the Plateau of Productivity phase (green) are mostly looking for links to the same degree or with trends at the Slope of Enlightenment (yellow). It is more likely that a trend in this closed cycle of stable trends will give rise to a slight variation of the trend rather than seeking

to update itself with a new Technology Trigger (pink). This evidence, combined with the smaller amount of new trends, suggests that there is a greater movement to maintain the current digital design culture than to transform it. This evidence contradicts the expectation that digital trends represent more radical social changes, as the literature suggests.

Figure 7: Analytical view of digital trends mapped in 2018(b). The node color represents the HypeCycle phase of that trend, whereas the link color represents the HypeCycle phase of the link origin, that is, the trend that seeks to influence another.



In the analytical graphs (Figures 5-7), we found the following connection patterns:

- 1) Stable trends are linked to other stable or stabilizing trends;
- 2) Unstable trends are linked to stable trends;
- 3) Unstable trends rarely link with other unstable trends;
- 4) Unstable trends that can connect to many stable trends become stable on subsequent evaluations.

5. Conclusions

The interpretation of the generated graph visualizations suggest that the stable digital trends — located in the so-called Plateau of Productivity, instead of acting in isolation, act in concert, creating a sort of filter for new trends. Thus, if the unstable trend is not consistent with the stable trends, it ends up isolating itself and falling into disrepute. The social difference implied by the trend, therefore, needs to be small to achieve stability. This conservative filter contradicts the belief that digital trends would be signs of maximum social change. The result of this analysis suggests that the spread of digital trends induces minimal differences in society and maintains the status quo, rather than questioning it. It is also possible to infer from the data that the role of design in the digital trend cycle is to modify formal patterns while maintaining structural and functional patterns, thus inducing only minimal changes. This evidence contradicts the discourse of change associated with digital trends (Kostin, 2018) and also of Digital Design itself (Royo, 2008).

The conclusion of this study is that digital trends tend to be conservative when disseminated by their own digital medium. This was demonstrated through the qualitative analysis of graph visualizations. The study also showed that this type of visualization, despite having its origin in quantitative study approaches, can also be used in research with qualitative approaches, such as Digital Humanities (Burdick et al., 2020; Alves, 2017). For this purpose, it is essential that Information Design patterns are not only applied to optimize the representation interpreted information, but that they become an essential tool in the data interpretation process. In the case of this research, the consecutive exploration of different patterns and graph visualization algorithms made it possible to increasingly recognize patterns of social differentiation implied by digital trends.

Researches that relate Information Design and Digital Humanities usually emphasize the

contribution of the first field to the second (Burdick et al., 2020), whereas this research demonstrates the contribution of the second field to the first field. Here, Henri Lefebvre's (1972) materialist-dialectical differentialism allied with social network analysis (Zago, 2015) helped to identify patterns of differentiation in graph visualizations. In Design Studies, graph visualizations are traditionally used to map design spaces in a given situation (Goldschmidt, 1997). These graphs are also used to map the social production of design spaces, that is, to map possibilities considered in various projects (Van Amstel, Cayley, & Botter, 2021; Van Amstel et al., 2016). If we consider the social production perspective of differentialism, then we can consider that the graph visualizations depicts moments in the broader social change process in which the various design projects are inserted in.

With this broader perspective, it is possible to state that the design practice relying on digital trends tend to reproduce minimal changes in society. This explains why benchmark analysis, so trivialized by the ease of access to diverse content in digital media, presents mediocre results in terms of generating differentials and breaking fads. According to materialist-dialectical differentialism, the quantitative accumulation of references is not enough to produce maximum differences. To break with established patterns, it is necessary to make qualitative leaps.

In a political moment marked by conservatism (Bonsiepe, 2006; Manzini, 2019; Souza et al., 2016), the search for qualitative leaps is fundamental for teaching and research Information Design. Digital trends by themselves proved to have the opposite effect to that expected in the literature: they produced minimal rather than maximal differences. However, awareness of this phenomenon and the biases embedded in digital media allowed students to develop critical perspectives over the reproduction of digital trends in design practice. In their future practices, these students will perhaps be able to choose between reproducing conservative or progressive patterns, according to their political views and the wishes expressed by the people around them participating in the production of design space (Van Amstel et al., 2016). This research contributes to highlight the relevance of materialist-dialectical thinking (Van Amstel, 2015; Van Amstel, 2009) — and of the Humanities in general — for developing further critical and progressive approaches in Information Design.

Acknowledgment

I thank the students of the Digital Trends Laboratory course from the Undergraduate Course in Digital Design, Pontifical Catholic University of Paraná (PUCPR), who collaborated with the data collection for this research, as well as Mateus Filipe Pelanda and Hugo Cristo, who offered constructive comments in previous versions of this article.

References

- Alves, M. G. de C. (2017). Grafos na leitura de AD. *Entremeios, Revista de Estudos do Discurso*, 15, 109–126.
- Amstel, F. M. C. Van, Cayley, G., & Botter, F. (2021). Prospecting a systemic design space for pandemic response. *Strategic Design Research Journal*, 14, 66–80.
- Anderson, C. (2006). *A cauda longa*. Elsevier Brasil.
- Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10), P10008.
- Bonsiepe, G. (2006). Design and Democracy. *Design Issues*, 22, 27–34.
- Burdick, A., Drucker, J., Lunenfeld, P., Presner, T., & Schnapp, J. (2020). Um breve guia para as Humanidades Digitais. *TECCOGS: Revista Digital de Tecnologias Cognitivas*, 21 (jan/jun 2020), 69-98. Tradução de Isabel Jungk.
- Caldas, D. (2004). *Observatório de sinais: teoria e prática da pesquisa de tendências*. Senac.
- Dedehayir, O., & Steinert, M. (2016). The hype cycle model: A review and future directions. *Technological Forecasting & Social Change The*, 108, 28–41.
- Dragt, E. (2017). *How to Research Trends: Move Beyond Trend Watching to Kickstart Innovation*. BIS Publishers.

- Erner, G. (2015). *Sociologia das Tendências*. São Paulo: Gustavo Gili.
- Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and experience*, 21(11), 1129-1164.
- Goldschmidt, G. (1997). Capturing indeterminism: representation in the design problem space. *Design Studies*, 18, 441-455.
- Hu, Y. (2005). Efficient, high-quality force-directed graph drawing. *Mathematica journal*, 10(1), 37-71.
- Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PloS one*, 9(6), 1-12.
- Kostin, K. (2018). Foresight of the global digital trends. *Strategic Management*, 23, 11-19.
- Lefebvre, H. (1972). *El manifiesto diferencialista*. Ciudad del Mexico: Siglo XXI.
- Lima, M. (2011). *Visual Complexity: Mapping Patterns of Information*. Princeton Architectural Press.
- Linden, A., & Fenn, J. (2003). Understanding Gartner's hype cycles. *Strategic Analysis Report N° R-20-1971*. Gartner, Inc, 88, 1423.
- Manzini, E. (2019). *Politics of the Everyday*. London: Bloomsbury Visual Arts.
- Martin, S., Brown, W. M., Klavans, R., & Boyack, K. W. (2011). OpenOrd: an open-source toolbox for large graph layout. In Proceedings of the *Visualization and Data Analysis 2011*. Vol. 7868, p. 786806). International Society for Optics and Photonics.
- Rasquilha, L. (2015). *Coolhunting e Pesquisa de Tendências-observar, identificar e mapear as tendências e mentalidades emergentes do consumidor*. Almedina.
- Royo, J. (2008). *Design digital*. Rosari.
- Souza, E. A., Oliveira, G. A., Miranda, E. R., Coutinho, S. G., Waechter, H. da N., & Filho, G. P. (2016). Alternativas epistemológicas para o design da informação: a forma enquanto conteúdo. *InfoDesign*, 13, 107-118.
- Van Amstel, F. M. C. (2009). Em busca de uma metodologia de design de interação materialista-dialética. In C. Spinillo, P. Bendito, & S. Padovani (Orgs.), *Selected Readings on Information Design: Communication, Technology, History and Education*, 124-134.
- Van Amstel, F. M., Hartmann, T., van der Voort, M. C., & Dewulf, G. P. (2016). The social production of design space. *Design studies*, 46, 199-225.
- Van Amstel, F. M. C. (2015). *Expansive design: Designing with contradictions*. Doctoral thesis. University of Twente.
- Vieira Pinto, Á. (2005). *O Conceito de Tecnologia - Volume 1*. Rio de Janeiro: Contraponto.
- Zago, G. da S. (2015). Design da Informação e Análise de Redes Sociais: explorando formas de visualização de redes. *Anais [Pôster] do 7º Congresso Internacional de Design da Informação*. São Paulo: Blucher, 1217-1225.

About the author

Frederick M. C. van Amstel, Dr., UTFPR, Brasil <vanamstel@utfpr.edu.br>

[paper submitted in XX/XX/XXXX, approved in XX/XX/XXXX]