Big Data Through Cross-Platform Interest-Based Interactivity

Asta Zelenkauskaite
Drexel University
Philadelphia, Pennsylvania, USA
Email: az358@drexel.edu

Bruno Simões
Fondazione Graphitech
Trento, Trentino, Italy
Email: bruno.simoes@graphitech.it

***Abstract*—Given the ubiquity of social media, we capitalized on interest-based relevance as a key component to enhance user experience. Interest-based relevance modeling was extracted from user interaction in a cross-platform social media Big Data repository. The goal of this study was twofold: first we addressed theoretical dilemmas of a cross-platform user experience; second, we implemented an android-based mobile application and designed a cloud architecture to account for theoretical parameters of Big Data User-centric approach and interactivity. To address cross-platform Big Data challenges, we relied on cloud computing to perform computationally intensive operations such as searching, data mining, and data processing at large scale.**

Our use case was based on a cross-platform interest-based navigation and content filtering across multiple radio content streams. The streams consisted of tags from radio stations' programming and social media content through a discovery process. User interaction was geared to enable preferred topic filtering, flexibly shifting participation roles, notifications, and navigation through external data sources. We tested our application on a list of popular radio stations and their social media content streams (including Facebook, Twitter, Google+) to generate a Big Data scenario. Even if diverse and nature, data stream traffic generated through a mobile application *KASU* has proven to be a robust Big Data source with a list of ad hoc user-centric applications.

Keywords*—*big data, interest-based content discovery, user-centric approach, cross-platform media, cloud computing.

I. Introduction

A myriad of social media platforms emerged in recent years with services geared towards users through adds-on such as mobile texting, Facebook [1] with increasing popularity of Twitter, Google+ and WhatsApp, especially in entertainment contexts. These social media platforms, predominantly consisting of social networking sites (SNSs), heavily rely on individual users for content creation, in contrast to professionally-produced content. SNSs' success hinged on constant user involvement and participation [2]. With forty-one percent of the US population finding photos and videos online, interest-based content discovery became the driving force for new content generation and redistribution [3].

As social media permeates all spheres of our lives and these applications generate considerable percentage of Internet traffic, content streams remain fragmented thus limiting to discover interest-based relevant content to their users. We considered interest as an individual experience, continuously stimulated by relevant content discovery. Single-platform access inevitably leaves a proportion of interest-based content underexposed. Single-platform SNSs, even historical ones, varied technologically and scope-wise, ranging from user demographics, geographical attributes, or mere maintenance of pre-existing relationships. Since 2003 specialized social networking sites became mainstream, focusing on specific interests such as traveling, activism, religion, photosharing, music listening, and video sharing to mention a few [2]. SNSs evolved and broadened their scope over time. For example, access to Facebook is open to everyone, even if initially it was restricted to college student networks.

Some of these limitations were addressed to overcome limited content access, platform interoperability issues, and lack of relevant content segmentation across multiple platforms. Attempts to facilitate interest-based content access thus started to be modeled within a single platform. Some of the techniques included "like" feature on Facebook; Twitter content following and filtering were implemented by using "hashtags." Regardless of these attempts, interest-based content still can be searched solely within a single platform rather than across multiple platforms, not even considering user interaction with other users or content across through various platforms.

Several social media cross-platform applications pioneered to account for single-platform content access limitations. Interest-based content redistribution was facilitated by "share" function (e.g [4] and [5]); easier content access to multiple platforms was provided through a open identity [6]; to account for increased content variety content aggregation tools we developed to combine functionalities from multiple external sources (e.g. [7] and [8]). In addition, for users, it takes time, effort, and cognitive capacity to follow multiple platforms with equal dedication [9].

However, all these cross-platform applications continue to bear limitations. Although the "share" function allowed content to be broadcast or duplicated across various platforms, the downside of such approach was that the user could engage in one-to-many content distribution, but remained limited to receive contents from each separated platform individually. Open identity [10] facilitated access to content by allowing users to sign in to multiple websites with a single identity (ID). Such an open ID remained limited to a targeted platform rather than to multiple parallel platforms. Content aggregation platforms in turn provided users with larger amounts of content access, yet did not support interaction and content discovery through other user experiences.

To account for the above mentioned limitations, we developed a unified access model to interest-based content modeling. We capitalized on existing SNSs to create a Big Data repository – term used to describe a large and complex collection of growing datasets that is difficult to manage and process using traditional database management tools – to model an interest-based content segmentation and content discovery through user interaction. The need to maximize social media stream potential was driven by the prosumer culture – the current trend in media contexts in which users not only passively consume content but also actively engage with content [11]. Users thus became key actors in content consumption and production yet posing new challenges to Big Data repositories to create meaningful streams that could be constantly modeled through content discovery and interaction. This research was built on theoretical parameters of Interactivity, to model and discover interest-based content through user interaction, which in multimodal contexts was found somewhat limited [12], [13], [14], [15]. We proposed a mobile-oriented framework to leverage on mobile devices' ubiquity. The third generation mobile devices serve not only as communication devices but also provide access to information social media data. As a use case of interest-based content access and content discovery through interaction, we implemented an android mobile application *KASU* that converges multiplatform social media content streams of user interaction on a dozen of popular radio stations.

This paper is structured as follows. First, through a concept of Interactivity we explicated theoretical premises of Big Data User-centric model, which served as a basis for our application. Second, we identified user requirements for content access to account for the user-centric model. Third, we outlined the architecture of the application and evaluated its implementation. Finally we engaged in a discussion regarding conceptual data access issues among media companies, user relevance to Big Data context, and limited user benefits associated with it.

II. Theoretical Premises

To account for an enhanced user experience, we employed the Big Data User-centric model presented in [16] foregrounded in a Big Data paradigm. Big Data paradigm explicates benefits and challenges of increasing quantities of data sources and serves as an analytical and conceptual framework through five parameters. The parameters include volume, variety, velocity, veracity, and value [17], [18]. Volume involves large amounts of data that has to be manipulated. Variety refers to filtering of the uncorrelated and unstructured data sources as well as high scalability of the data [19]. Velocity refers to a gained advantage to process large and dynamic amounts of data in a timely manner. Veracity quantifies the trust associated with inhomogeneous data, which is often gathered from unverified sources.

The Big Data User-centric model is particularly concerned with value creation for users [16]. We defined value as a meaningful information extraction through data analysis going beyond the plurality of its definitions such as "the monetary value of something," "the market price," or "something intrinsically valuable or desirable" [20]. Therefore the value extraction in a Big Data User-centric model for the purposes of this research dealt with interest-based relevance extracted from multiple

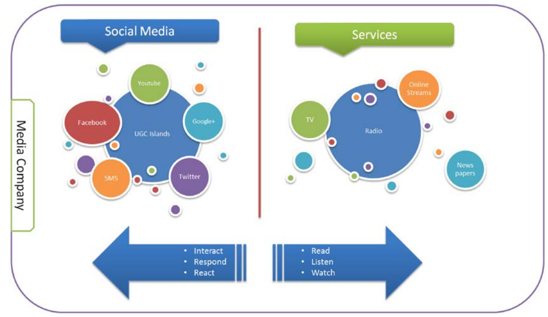

Fig. 1. User roles and experiences in interactive services

streams and content navigation and interaction, focusing on dimensions of Interactivity defined in the following section.

A. *Interactive interest-based environments*

Departing from the Big Data User-centric model for social media platforms, we conceptualized value as a meaningful interest-based content discovery through interaction with other users, content, and the system. Interactivity refers to the "quality or condition of interaction" [9]. Interactivity conditions consists of non-interactive state, when new messages are not related to previous messages; reactive, when new messages are related only to a specific, often times prompted message; and interactive, when new messages can be related to a number of previous messages having a specific relationship between them [14]. Interactive interest-based environment thus aimed to increase degrees of adaptability, user agency, choices, and flexibility leading to some of the positive outcomes of Interactivity such as user satisfaction [21].

In a specific mass media context, so far, Interactivity was included through social media outlets. Figure 1 exemplifies how traditional media – such as TV, radio, and newspapers – integrated interactive applications through social media to enhance user experience.

Regardless of the promise of interactivity in traditional media settings, it was found to be limited. Limits were attributed to structural constraints inherent to a rigid hierarchical architecture, limited interaction [12], and control over the content. Organizations still maintain control over 80% of the content, even if half of it is produced by users [13]. Even if users attempted to maximize content push by repeatedly posting content, user role still remains marginal [15].

The goal of this study is to provide a conceptual framework to overcome some of the limitations of interactivity described above. To enhance interest-based content discovery, we drew on seminal research of interactivity [22], [23], [24]. To implement our mobile-oriented framework geared towards user-centric experience, we utilized the following six dimensions of perceived interactivity proposed by [22]. Direction of communication – the ability to receive return messages, in addition to one-way communication, prevalent in traditional mass media such as TV or radio; time flexibility – the ways to engage in communication in real time as well as being able to retrieve archival conversations; sense of place – creation of a common virtual communicative context; level of control – user agency to select responses in the most appropriate context, ability to track messages and identify if they were delivered; responsiveness – relates to the concept of sequential interrelation between messages where three-message-sequence model was proposed as an ideal one [24], [14]; and perceived purpose of communication – which identifies goals of communication and makes interaction meaningful.

To implement these dimensions, we focused on all three proposed interactivity traditions. Human-to-human interaction – the interaction between users in a mediated environment. Human-to-document interaction – user interactions with a specific content, created by other users and with the creators of the content themselves. Human-to-system – adaptive system that enables users to get higher levels of control and encompasses the previous two dimensions by combining interface components and human components [23].

B. Challenges of interactive interest-based content discovery

Interest-based content discovery in a cross-platform context not only enhanced user interaction, but it also raised challenges to the Big Data repositories. One of challenge's was ascribed to a potential cognitive overload [9]. The issue of cognitive overload in mediated settings was discussed since mid-nineties [25], [26]. However the increasing amounts of users and their produced content made the issue of cognitive overload even more pronounced. It was found that when information supply exceeded individual processing capacity, the overload led to stress and to segmented engagement [27].

Wilson [25] identified seven techniques to ease the information overload associated with interactive Big Data models: *information retrieval*, aiming at finding information pertinent to a given subject through the use of keywords [28]; *information filtering*, relying on filtering techniques to highlight relevance from a continuous flow of information [29]; *rank filtering*, providing omission techniques to identify relevant items, using predefined factors such as the number of recommendations, user acceptance and popularity within the community; *brute-force interaction*, defining techniques that enable immediate and effortless initiation of interaction; *content approximation*, to help users selecting the most important and relevant items by providing users with a brief preview of a given item extracted from each of the properties; *contextualization*, introducing techniques to organize the information, i.e. to highlight its significance; and *information stack*, combining the aforementioned techniques with actions to postpone and redefine the priority of an item.

Another Big Data challenge refers to inhomogeneity of cross-platform social media content that comprises not only text, but also large quantities of data encapsulated in other formats, such as images, video, and other online user traffic data [13]. To manage Big Data streams, we relied on cloud computing as a processing infrastructure and storage framework. Cloud computing for our model served as an essential component to handle data-intensive needs required to maintain and promote user interaction over the Internet. It defines a new *delivery model* that embraces a set of existent technologies, where all computing and networking resources (e.g. infrastructures, software, applications, and business processes) are delivered as flexible and scalable services that are sold as on-demand with self-service, pay-as-you-go variable cost subscriptions [30].

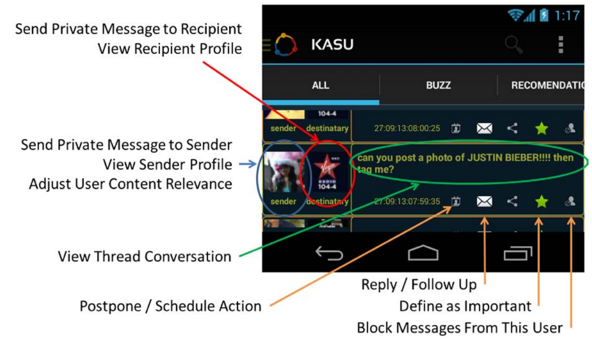

Fig. 2. User generated content feed and messenger in a seamless interface

III. Mobile-oriented framework

Considering challenges of Big Data and cross-platform user interaction, we developed a mobile-oriented framework entitled *KASU*. Its name was inspired by the word's dual meaning, translated as "of the strings or braids" and "I dig" [31], which entails the thread multiplicity and a persistent search, associated with new and relevant interest-based content and users. This framework not only facilitates the use and understanding of different sources of information, but also locates, navigates, customizes, and interacts with flexible and fluid user roles in an interest-based context. Moreover, it capitalizes on cloud computing as a processing infrastructure, which aids users to discover and manage social media content through services that perform analytics at large scale.

This mobile application accounts for six dimensions of perceived interactivity introduced previously in Section II, as well as the following interactivity traditions: human-to-human interactivity and human-to-system interactivity.

A. Human-to-system interaction

Building on techniques to tackle information overload, *KASU* delivers three essential mechanisms for accessing and managing social media content.

1) Subscription management: defines a set of features necessary to subscribe (or unsubscribe) to specific topics and user-related activities. Subscription topics are subdivided into two categories: topics expressed through well-defined user search rules (e.g. expression matching), which can also employ the use of tags – tag subscription; and topics emerging from content analysis performed by cloud computing services, to discover new interest-aware topics that have good coverage and acceptance. We named this type of results as a "group" of content.

We created a unique set of functionalities that were geared towards a seamless access to non-interoperable data and an environment to reduce information overload for users to make their reading-data discovery more effective.

2) Content management: delivers a set of features to manage subscriptions' content, e.g. features to automatically bring to the top the latest and the most relevant items by clearly marking those that have been read. Three main components are: activity buzz, content filtering, and analytics-oriented content management.

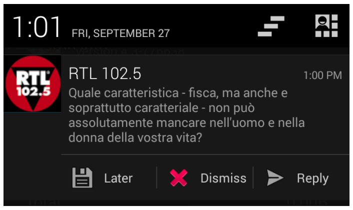

Fig. 3. Enhancing interaction using interaction-oriented notifications

Activity buzz. Primes all items classified as important. The algorithm used to select relevant items is based on several factors such as: the most read items, created by "opinion makers" and user acceptance. It also provides a short glance of recent social media content. This feature aims to create a sense of community, encourage discussing commonly read content, and to support serendipity.

Content filtering. Through this feature users can define priority schemes for processing a subset of information while ignoring its complementary set, that is, to prioritize or exclude content using a set conditional rules. Additionally, information concerning the usage of this feature is gathered and processed by the analytics-oriented content management module, to obtain further insights.

Analytics-oriented content management. For analytical purposes, we also implemented a tag cloud per user to create an automatic profile that maps user's interests. The user profile included additional statistics that were calculated and presented, such as activity frequency, number of recommendations of items related to a specific topic, and information extracted from the platform profile, etc. Exploring tags' statistics page could result in different outcomes: users could decide removing a tag that was apparently not followed by a significant number of users, or adopt a tag that was highly used by others; alternatively users could decide to change their reading habits after discovering that an important tag had diverged interpretations by the community.

3) Content interactivity: Several mechanisms were implemented to provide higher levels of user-content interactivity. From the main screen, users can access all the content – i.e. user profiles and thread messages with a one-click mechanism. They can reply and/or identify the source, medium, destination, and message, see Figure 2.

B. Human-to-human interaction

Apart from the spatial navigation, which is intrinsically associated with the features described in the previous section, the application also introduced novel mechanisms to foster temporal dimension i.e. real-time interaction across various platforms. On one hand, it focused on a notification system's ability to provide invitation opportunities to novice users to engage in a sustained interaction with and through the interface. It also served to inform experienced users – in real-time – about ongoing activities that might be of interest (see Figure 3). Notification interaction alerted users about the latest updates, yet did not require them to take an immediate action; freeing users from the constant urge to pay attention to content streams.

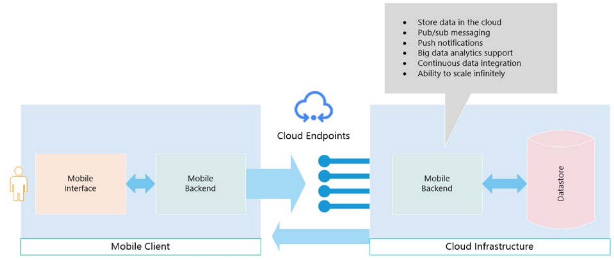

Fig. 4. Mobile-oriented Service Architecture

We designed content notifications to be personalized with specific sounds to identify the source and type of interaction; without even unlocking the mobile device. Additionally, the notification system capitalized on a one-click interface to give users the possibility to: promptly engage with other users and groups; postpone the interaction – to give users the possibility to place information on hold as suggested by [32]; and to foster relevance as a cornerstone aspect of a given community. Through rating mechanisms users indirectly inform other users about the relevance of a certain item to ensure coverage of important issues.

C. Cloud computing as a Big Data analytics solution

Although *KASU* provided multiple opportunities to prioritize and filter information through content analysis, such techniques remain insufficient to overcome information overload. On one hand, the quality and quantity of results depends on how users configure their systems. For example, the use of erroneous content filters greatly contributes to the unsatisfactory user experience and low content quality [33]. On the other hand, extracting and analyzing all the social media content is unfeasible, not only because of mobile devices' low processing capabilities – that would lead to incomplete outputs or irresponsiveness – but also because of the unrealistic amount of network connections required to access necessary data. Moreover, restricted number of requests permitted within a certain time window by data providers – mainly social networking sites – introduces even greater complexity. Hence, *KASU* required a backbone architecture to continuously extract social media content from Big Data repositories and to handle all the management and processing tasks, to overcome mobile devices' bandwidth and processing limitations.

Our mobile-oriented framework – based on a concept of cloud computing and built on top of a Hadoop framework presented in detail in [16] – was strategically designed to provide support to mobile devices in data-intensive operations, see Figure 4. First, it handled the access and extraction of data from inhomogeneous data sources - SNSs. Second, it was responsible for processing the acquired data into a unified data model that was ready to be consumed by mobile devices. Lastly, it was in charge of loading the social media content into the analytics pipeline and served mobile devices with features for data analytics.

The Big Data analytics process was responsible for computing the relevance of all social media content according to a small list of parameters, to ensure that users did not miss relevant items. Some of the parameters used were: the number of user recommendations, tags, coverage, user engagement, and relevance to user interests, etc. The relevance and coverage of a tag was calculated by measuring the number of items read out of the total items posted. Hence, our goal is that results would be automatically shaped by community's interaction. Finally, this process is also responsible for regulation of the maximum amount of notifications received by users.

IV. Use-case: a seamless radio context

Entertainment radios represent a large set of real-time changing data streams that include professionally-produced content such as music, news, and talk shows; that are further shaped by user-generated social media streams through Facebook, Twitter, and Google+ to name a few. Prevalence of multiple data streams made radio stations a good candidate for Big Data. Variety of Big Data streams – that is diverse social media platforms provided new opportunities for interest-based community formation. Finally, this cross-platform reconfiguration impacted value as well in terms of the emergence of new interactive contexts.

In traditional mass media, users are constrained to access radio content through the hierarchical architecture that is based on one-to-many model, which focuses on an individual radio's content. In contrast to the hierarchical one-radio access architecture, we propose a user-centric architecture that departs from the interest-based content rather than a specific radio. This model is geared to enable a fluid content access of various radio stations and contents associated with it, to foster content discovery and content management. Access to specific radio programs can be exemplified by the following scheme: radio-programs/DJ-songs/artists/albums. In addition to music content, the primary radio stations' content, users could access radio stations' social media content streams as well. Finally, all radio stations' contents would generate a unified Big Data repository form which individually tailored interests could be extracted.

To run initial tests on a cross-radio Big Data repository, with the developed application *KASU* we analyzed the top ten radios from the "Top Facebook Radio Pages" list [34]. The sample of radios analyzed included RTL 102.5, Mosaique FM, Radio Sawa, Alwakeelnews, Jawhara FM, HIT Radio, Mazaj FM, Play 99.6, Virgin Dubai, and Hala FM Radio. Social media platforms consisted of Facebook, Twitter, and Google+. Table I breaks down the distribution of 12,312 messages produced during a period of one week by social media platforms (i.e. users) and radios.

TABLE I. User activity on top radios' social media platforms

	Facebook		Google+		Twitter	
	msgs	users	msgs	users	msgs	users
RTL 102.5	2363	1887	1	1	239	58
Mosaique FM	2255	1658	10	1	188	7
Radio Sawa	360	250	0	1	76	2
Alwakeelnews	570	252	0	1	23	1
Jawhara FM	689	479	20	1	133	1
HIT Radio	2392	1976	3	2	182	3
Mazaj FM	666	440	20	1	117	3
Play 99.6	296	239	0	1	109	2
Virgin Radio Dubai	466	395	62	30	127	5
Hala FM Radio	4369	137	0	1	126	1

Table I shows that majority of content traffic on these radios were generated by Facebook users (given that we have selected the top radios based on Facebook).

To account for user engagement through interactivity with radios, we studied how radios used interactive question prompts to stimulate user responses in the process of content creation. RTL 102.5, HIT Radio and Virgin Radio Dubai stimulated their users the most: respectively 13, 11, and 7 question prompts on Facebook, followed by RTL 102.5 with 3 prompts on Twitter. The frequency of prompts differed across the radios and the platforms, as did the number of user messages. RTL 102.5 users generated more content on Facebook than on Twitter. Nevertheless, it remains an empirical question to what degree these prompts would influence content generation. Given the initially diverse technological structure and social practices of social media platforms that we analyzed, it may lead to unattended consequences of social shaping regarding content modeling and discovery.

It is also worth mentioning that our test sample purposefully connected a very limited set of radios. Our sample could be easily scaled to larger numbers. Also this application could be adapted to any context that goes beyond radio or entertainment media presented via this use-case. Additionally, the quantity and quality of data being exchanged through this framework depends on the actors involved. Nevertheless, the quantity of messages being exchanged was sufficient to understand the interactivity in a Big Data context and to test the techniques to address it.

V. Conclusion

In this paper we proposed a model that encompassed the interconnectedness between services and social media platforms. We considered Big Data as ways to highlight user value and bridge user needs through social media and professional content by enabling users to model interest-based relevant streams and create their own individualized social radio experience. In practical terms, we developed a mobile-oriented framework built on top of social media streams and professional radio content. This android application aimed to facilitate user immersion and an interactive experience through non-hierarchical customization and enhanced individual choice in a continuously dynamic unstructured content environment. Due to bandwidth and mobile processing limitations we also developed a service architecture based on the concept of cloud computing. Cloud computing served as an essential element to ensure the access and processing of inhomogeneous data (SNSs).

Our approach extended previous implementations of user-centric services of Big Data that were predominantly geared to strengthen internal services through multiplatform content access and fluid content sharing. This study is based on the interest-based architecture that leads to access professional and social media content streams posted to the radios. Our adaptive Big Data User-centric model capitalized on a flexible environment, sensitive to changing data fluxes between services provided by radio stations and social networking sites. The value proposed here focused on user enhanced experience with radio content.

The goal of this research was to offer a conceptual Big Data User-centric framework that focuses on user relevance and facilitates user engagement, content discovery, and its modeling. The next steps in this research are to provide an assessment of this application in terms of user experience. Furthermore, even if we proposed potential solutions to account for content overload and interactivity, future studies should test social shaping of this application by the users. Future studies should also address potential shifts in business models for media companies that would go in accordance with an expanded interest-based goals of Big Data User-centric model.

ACKNOWLEDGMENT

This research was supported by the European Commission (EC) under the project c-Space (Grant Agreement N. 611040). The authors are solely responsible this work which does not represent the opinion of the EC. The EC is not responsible for any use that might be made of information contained in this paper.

REFERENCES

[1] Y. Beyer, G. S. Enli, A. J. Maasø, and E. Ytreberg, "Small talk makes a big difference: recent developments in interactive, sms-based television," *Television & New Media*, vol. 8, no. 3, pp. 213–234, 2007.

[2] N. B. Ellison *et al.*, "Social network sites: Definition, history, and scholarship," *Journal of Computer-Mediated Communication*, vol. 13, no. 1, pp. 210–230, 2007.

[3] K. P. R. Lee, J. Brenner. (2012, Sep 13) Photoes and videos as social currency online. [Online]. Available: http://pewinternet.org/Reports/2012/Online-Pictures/Main-Findings.aspx?view=all

[4] H. M. Inc. (2013) Social media management. [Online]. Available: https://hootsuite.com/

[5] I. Inc. (2013) If this then that. [Online]. Available: https://ifttt.com/

[6] D. Recordon and D. Reed, "Openid 2.0: a platform for user-centric identity management," in *Proceedings of the second ACM workshop on Digital identity management*, ser. DIM '06. New York, NY, USA: ACM, 2006, pp. 11–16. [Online]. Available: http://doi.acm.org/10.1145/1179529.1179532

[7] Twitter. (2013) An app that brings more flexibility and insight to power users. [Online]. Available: http://tweetdeck.com/

[8] Yoono. (2013) Your social networks united. [Online]. Available: http://www.yoono.com/

[9] E. P. Bucy, "Interactivity in society: Locating an elusive concept," *The information society*, vol. 20, no. 5, pp. 373–383, 2004.

[10] O. Foundation. (2013, Sep 13) Openid foundation website. [Online]. Available: http://openid.net/

[11] A. Bruns and J.-H. Schmidt, "Produsage: a closer look at continuing developments," *New Review of Hypermedia and Multimedia*, vol. 17, no. 1, pp. 3–7, 2011.

[12] J. Van Dijck, "Users like you? theorizing agency in user-generated content," *Media, Culture, and Society*, vol. 31, no. 1, p. 41, 2009.

[13] J. Gantz and D. Reinsel, "The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east," Technical report, IDC, Tech. Rep., 2012.

[14] S. Rafaeli, "Interactivity: From new media to communication," *Sage annual review of communication research: Advancing communication science*, vol. 16, pp. 110–134, 1988.

[15] A. Zelenkauskaite and S. Herring, "Television-mediated conversation: Coherence in italian itv sms chat," in *Hawaii International Conference on System Sciences*, 2008.

[16] A. Zelenkauskaite and B. Simões, "The big data user-centric model," in *The 2013 World Congress in Computer Science, Computer Engineering, and Applied Computing*, ACM. CSREA Press, 2013.

[17] D. Laney, "3-d data management: Controlling data volume, velocity and variety," META Group, Research Note, February 2001, http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf.

[18] TDWI. (2012, July 24) Big data – why the 3vs just don't make sense. [Online]. Available: http://tdwi.org/Articles/2012/07/24/Big-Data-4th-V.aspx?Page=1

[19] A. Cuzzocrea, I.-Y. Song, and K. C. Davis, "Analytics over large-scale multidimensional data: the big data revolution!" in *Proceedings of the ACM 14th international workshop on Data Warehousing and OLAP*, ser. DOLAP '11. New York, NY, USA: ACM, 2011, pp. 101–104. [Online]. Available: http://doi.acm.org/10.1145/2064676.2064695

[20] value. (2013, May) Merriam-webster.com. [Online]. Available: http://www.merriam-webster.com/dictionary/value

[21] S. S. Sundar and S. S. Marathe, "Personalization versus customization: The importance of agency, privacy, and power usage," *Human Communication Research*, vol. 36, no. 3, pp. 298–322, 2010.

[22] S. J. McMillan, "A four-part model of cyber-interactivity some cyber-places are more interactive than others," *New Media & Society*, vol. 4, no. 2, pp. 271–291, 2002.

[23] E. J. Downes and S. J. McMillan, "Defining interactivity a qualitative identification of key dimensions," *New Media & Society*, vol. 2, no. 2, pp. 157–179, 2000.

[24] S. Rafaeli and F. Sudweeks, "Networked interactivity," *Journal of Computer-Mediated Communication*, vol. 2, no. 4, pp. 0–0, 1997.

[25] P. Wilson, "Interdisciplinary research and information overload." *Library Trends*, vol. 45, no. 2, pp. 192–203, 1996.

[26] A. Edmunds and A. Morris, "The problem of information overload in business organisations: a review of the literature," *International journal of information management*, vol. 20, no. 1, pp. 17–28, 2000.

[27] M. J. Eppler and J. Mengis, "The concept of information overload: A review of literature from organization science, accounting, marketing, mis, and related disciplines," *The information society*, vol. 20, no. 5, pp. 325–344, 2004.

[28] R. Baeza-Yates, B. Ribeiro-Neto *et al.*, *Modern information retrieval*. ACM press New York, 1999, vol. 463.

[29] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *Knowledge and Data Engineering, IEEE Transactions on*, vol. 17, no. 6, pp. 734–749, 2005.

[30] R. Buyya, C. S. Yeo, and S. Venugopal, "Market-oriented cloud computing: Vision, hype, and reality for delivering it services as computing utilities," in *High Performance Computing and Communications, 2008. HPCC'08. 10th IEEE International Conference on*. Ieee, 2008, pp. 5–13.

[31] Lietuvių kalbos žodynas. (2005, May) Lietuvių kalbos žodynas. [Online]. Available: http://lkzd.lki.lt/Zodynas/Visas.asp

[32] J. G. Miller, "Information input overload," *Self-Organizing Systems*, pp. 61–78, 1962.

[33] C. J. Jacoby, "Understanding the limitations of keyword search," Equivio, white paper, 2012.

[34] SocialWatchlist.com. (2012, Sep 13) Social watchlist - middle east and north africa. [Online]. Available: http://www.socialwatchlist.com/