Types of contextual information in the social networks era

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***Abstract*—Data analysis always played a crucial role in computer science towards a more efficient understanding of its various trends. Focusing on digital content - generated, shared and consumed within the framework of social networks - this task is getting both more interesting and difficult to tackle. Nowadays social media platforms and networks have provided researchers with tools and opportunities to analytically study social phenomena, but at the same time significant and rather complex computational challenges are yet to be tackled, due to the huge rate of new content and information production imposed by social interactions. The ultimate goal of this position paper is to provide interested stakeholders a state-of-the-art overview of major contextual information types to be identified within the social networks' environment.**

Keywords—context; social networks; knowledge representation; context representation and analysis; context-driven social network analysis

I. INTRODUCTION

After almost half a century of informatics and a decade after the social media hype was introduced, it is rather common knowledge by now that information does not occur in isolation. In particular, when dealing with human communication, text words are typically surrounded by their linguistic environment, called co-text, and this text takes place in an even broader environment, called *context* [1]. In the case of computer interaction, the importance of context in modern computing applications is widely acknowledged and has become a major topic of interest especially in multimedia content analysis systems. The notion of context is of utmost importance in the identification of semantic meaning. Consequently, contextual information may be ultimately considered as any information about the situation, circumstances and user state when a user is either producing or consuming a digital content item [2]. Still, effective use of available contextual information within computer science structures remains an open and challenging problem, although a categorization of context-aware applications according to subjective criteria has been tried out in the past [3].

One of the ongoing tasks within the multimedia search and retrieval field of computer science is the identification of different types of context. The goal of this paper is to provide an overview on the definition and utilization of a context variation exploited within social network content analysis approaches and applications. In this framework the most complex and difficult thing to model is the relationship between context and the actual user decision making. In addition, such contextual information is extremely difficult to acquire in the first place, since the acquisition process usually interferes with the decision making process; thus it may alter the acquired context and consequently corrupt the acquired data.

The structure of the rest of this paper is as follows: in Section II we explain in more detail the motivation behind investigating context in social networks. In Section III we provide a brief overview of current social networks interpretation, whereas Section IV is devoted to the first aspect of socio-linguistic context. In Section V we focus on rather traditional context-aware recommendations still widely applicable in the framework of social networks and Section VI provides the main details on the research opportunities that exist in the mobile/travel context research field. Section VII concludes this work by briefly introducing our final comments on the topic.

II. MOTIVATION

The proliferation of multimedia content production, sharing and consumption over the Internet-based social networks led to the creation of huge, increasing communities. The information search and retrieval domain attempts to provide solutions to the problems of organization, storage, search and retrieval of all this chaotic information. A first basic categorization may be introduced, according to the different contextual information categories one may identify in the process; the latter directly affecting respective social interactions. As one may expect, several research approaches have been proposed over the last years with respect to each context category.

In addition to this, multimedia search and retrieval significantly benefitted from the recent advances with respect to social networking sites. The fact that the latter made it rather easy for their users to generate, produce, share and publish their own digital content online, led to an unprecedented focus on this computer science field. Still, this opportunity quickly revealed other aspects, whereas related efficiency problems have been risen. In other words, the form of multimedia usage and applications changed radically on the social media era, thus revolutionary and out-of-the-box multimedia indexing, search and retrieval approaches are now desperately needed. More specifically, the easiness of the

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aforementioned user content capturing and sharing process, combined together with hardware advances that resulted to market changes towards better and cheaper hardware, concluded to the need for efficient search and retrieval management of huge amounts of shared multimedia content within generated social media collections.

One way to deal with this observation is to consider metadata information that accompany multimedia content per se. Still, the amount and diversity of metadata collected and shared through these enormous social media content collections introduce higher computational complexity issues to consider towards efficient indexing and retrieval [4]. Although, in principal, this additional kind of knowledge, namely *contextual information*, increases the complexity of the retrieval tasks, the differentiation of metadata sources (e.g., user tags, sensors' information, social graph relations, etc.) builds a rich environment that helps to narrow down these sets to manageable clusters of information.

In the following Sections of this paper we attempt to present related works roughly classified based on the exploitation of the notion of context they perform and the utilization of social metadata and targeted applications in the process.

III. SOCIAL NETWORKS

According to Wikipedia[1], "social media are computer-mediated tools that allow people or companies to create, share, or exchange information, career interests, ideas, and pictures/videos in virtual communities and networks". Still, one may not seek a single robust definition, since the variety of current social media services introduces significant challenges in the process. For the sake of the herein introduced way of thinking, we may undertake them as Internet-based applications that carry user-generated content, which encompasses "media impressions created by consumers, typically informed by relevant experience, and archived or shared online for easy access by other impressionable consumers" [42]. Several functionalities are considered in the process, including "posting", "tagging", "digging" or "blogging" of online information.

Content generated within these social media is typically of multimedia nature and may be created, initiated, circulated, and used by users. Compared against multimedia content provided by marketers and content providers, we may here stress out a clear differentiation, namely social media are generated by people in order to be consumed in a peer to peer manner by other people or even shared among themselves. the latter forms the so called *collective intelligence* of current social networking and forms one of its great benefits. As we may see in the following Sections, this observation is of great importance in all discussed contextual fields, ranging from the socio-linguistic to the travel aspect. In principle, we may adopt the definition imposed by Blackshaw et al. back in 2006, which states that user-generated content supported through social media is "a mixture of fact and opinion, impression and sentiment, founded and unfounded tidbits, experiences, and even rumor" [43].

Nowadays, information exchange plays the main role in online media. New applications emerged that aid significantly to this end. In addition, Web 2.0, offers a variety of new technological applications such as mash-ups, media and content syndication, tagging, wikis, web forums, user ratings and evaluation systems and blogs [44]. The emergence of social networks took the form of a large-scale avalanche under the Facebook[2], Twitter[3], Flickr[4] and Instagram[5] skins. Online travel-related user reviews sites also represent a significant amount of social media for travel purposes, as depicted by the popular TripAdvisor[6] and Booking.com[7] web portals ([45], [46]). The studies on this type of social media focus on its use, as well as its impact on travel decision making. Multimedia sharing (i.e., videos, photos, tags, etc.) in YouTube and/or Flickr attracted tourism researchers by generating interests in understanding the role of this type of social media content in transforming travel experiences as early as 2009 [30].

IV. SOCIO-LINGUISTIC CONTEXT

So, without any further doubt, the remarkable increase in user-generated multimedia content was caused by the rapid development of Web 2.0 communities in the social networks framework. To this end, contextual information is both crucial and critical in understanding user preferences and user intentions. One of the basic subjects of human communication in the digital era is the field of socio-linguistics, where we may clearly identify one valid context variation, the so-called *socio-linguistic context*, which may be further split into two smaller sub-categories, namely *verbal context* and *social context*.

A. Verbal context

Approaches dealing with the former context type focus on contextual elements such as click-through data or past queries of users. In a recent study Xie et al. [5] present a detailed overview of a verbal context model. More specifically, they introduce a verbal context graph to model contents and interrelationships into a folksonomy, as well as a ranking method for measuring the relevance of a resource to several factors, such as an issued query, a discovered context and an extracted user profile. They also deal with the identification of so called core contextual elements and the de-emphasizing of trivial elements in verbal contexts.

Another approach is the one introduced by White et al. [6] where context has been represented by the Open Directory Project (DMOZ)[8] categories of web pages and the effectiveness of different sources of contextual evidence, as

[1] https://en.wikipedia.org/wiki/Social_media

[2] https://www.facebook.com/
[3] https://twitter.com/
[4] https://www.flickr.com/
[5] https://www.instagram.com/
[6] https://www.tripadvisor.com/
[7] http://www.booking.com
[8] https://en.wikipedia.org/wiki/DMOZ

well as their overlap, has been studied. In particular, authors presented a systematic study of the effectiveness of five variant sources of contextual information for the purpose of user interest modeling, namely: (a) interaction, i.e., recent interaction behavior preceding the current page, (b) collection, i.e., pages with hyperlinks to the current page, (c) task, i.e., pages related to the current page by sharing the same search engine queries, (d) historic, i.e., the long-term interests for the current user, and (e) social, i.e., combined interests of other users that also visit the current page. In a consecutive work White et al. [8] assigned the topics from the taxonomy created by DMOZ to three types of contexts; the first type considered preceding queries only, while the second and third types added user clicked and browsed documents. In the same manner, Liao et al. [7] presented a context-aware query suggestion model by mining latent concept patterns in a search log. They proposed a novel approach to query suggestion using click-through and session data and unlike other related previous methods (e.g., [9]), their approach groups similar queries into concepts and models context information as sequences of concepts.

In the same application domain, Mei et al. [10] proposed using query sequences in sessions for four types of tasks, including sequence classification, sequence labeling, sequence prediction, and sequence similarity. Their findings verified that contextual information may be beneficial to tasks like segmenting queries in sessions according to user interests. Moreover in another study, Cantador et al. [11] depicted context using ontological terms and their semantic relationships for historic data. They proposed the notion of semantic runtime context defined as the background topics under which activities of users occur within a given timeframe. Finally, in another approach, Gouws et al. [18] conducted a more in-depth contextual analysis at the word level and investigated the writing conventions that different groups of users use to express themselves in microtexts. More specifically, they analyzed term characteristics that are commonly found in English Twitter messages, but at the same time are not to be seen within a large collection of news articles. The results showed that a very small number of terms account for a large proportion of the out-of-vocabulary terms. Following TABLE I. provides a detailed overview of the discussed verbal context research efforts by categorizing them according to their context type incorporated, illustrates their advantages and disadvantages and reasons on their suitability within the broader research field.

TABLE I. VERBAL CONTEXT APPROACHES

Work	Task(s)	Method	Pros	Cons	Dataset
[5]	verbal context model overview	verbal context graph	folksonomy, mathematical notation		Movielens
[6]	DMOZ categories	study of 5 context sources	analytical study		
[8]	DMOZ categories expansion	activity-based context study	combination of 3 context types	model simplicity	
[7]	query suggestion	context-aware query suggestion model	mining latent concept patterns		4B queries, 5,9B clicks, 1,9B query sessions
[9]	user search query refinement	query refinement clustering	document-clicks & user sessions	importance of context info	
[10]	query sequences	user behavior capture framework	evaluation, local & global features		1,2M queries & 17355 queries
[11]	context in recommender system	semantic interpretation ontological terms	evaluation, runtime context	semantic ambiguities problems	17 ontologies, 137254 Wikipedia entries
[18]	microtexts context-aware analysis	Twitter posts & news articles analysis	contextual analysis	lexical transformations	1M Twitter posts

B. *Social context*

In general, social context is context explored within social network analysis threads. This context may facilitate user interactions in the context of social computing. Compared to verbal context, social context typically requires domain knowledge to build predefined contextual attributes, as well as additional user data input. Still, most of prior researches do not consider users' contextual information in the social graph. For instance, information about how quickly a user changes her/his status (e.g., the rate of social activity) is considered to be of great importance [47]. This is mainly because such contextual information is important in studying social phenomena, like dispersal and distributions of activities. In principal, approaches taking into account social context, model contextual information as predefined attributes, with each contextual attribute having certain values. In an interesting and rather novel pioneer approach, Adomavicius et al. [12] proposed this kind of context to be represented by multiple dimensions; each dimension (e.g., user, time, item, etc.) is supposed to be a subset of a Cartesian product of some predefined attributes that define a specific domain of values. In addition they offer a comparison between multidimensional and two-dimensional rating estimations.

Social context has also been widely adopted in domain-specific applications like contextual personalization. The latter has received much attention in the last few years due to the fact that, among other factors, context affects the way users are consuming provided multimedia content and affects the decisions the user makes about the latter. In this spirit, Kosir et al. [13] presented a dataset for contextual personalization and defined the context as a set of contextual variables (such as time, location, mood) related to respective movies and their audiences. Another related aspect is the one of pervasive social context introduced in [49] and further studied in [48], which attempts to mix social network context provided from the social network sphere with device sensing capabilities in order to adapt to the physical and social situation of users. The latter [48] aims at the production of meaningful social interactions between users by introducing a new taxonomy in the process, whereas the former [49] uses social context in a restricted sense of partial temporal and spatial chunks.

There also other attempts to define social context in the computer science framework that are worth mentioning, namely Adams et al. [50] expand the term typically referring to people, groups, and organizations with which an individual is interacting by adding important locations and activities in the mix. Endler et al. [51] introduce a four dimensions (Spatial-Temporal-Inference-People) taxonomy to define social context in the area of social computing. Their ultimate goal was to classify pervasive social systems according to the defined notion of the so-called situated social context. In [52] an interconnected graph of socially relevant information from different sources is presented, whereas Demirbas et al. [53] focus their social context research on crowd-sourced sensing and sharing of the physical environment's status. Finally, following TABLE II. presents the herein discussed social context approaches according to their type and illustrates each one's main features.

TABLE II. SOCIAL CONTEXT APPROACHES

Work	Task(s)	Method	Pros	Cons	Dataset
[47]	social graph context	social information diffusion analysis	mathematical notation, comparable	dataset scope	crawl-based 465K users form Twitter
[12]	recommender systems	multidimensional context approach	mathematical notation, comparison	limited evaluation	1235 ratings
[13]	personalization and user adaptation	database for contextual personalization	novelty	limited dataset	90 users, 950 DB items, 1600 ratings
[49]	temporal and spatial context	four-tuple individual social situations model	novel representation model	limited application domain	
[48]	pervasive social context survey	STiPI taxonomy	taxonomy definition		
[50]	social context definition expansion	addition of important locations/activities	social context extraction algorithm	poor evaluation	8 users / devices
[51]	situated social context study	space-constrained social context STIP taxonomy	taxonomy definition	susceptible to SNS challenges	
[52]	middleware for mobile social ecosystems	Yarta middleware and interactions model	solid middleware architecture	limited evaluation	
[53]	Twitter data mining	Twitter crowd-sourcing system architecture	novel crowd-source approach	Focus solely on Twitter	

V. CONTEXT-AWARE RECOMMENDATIONS REVISITED

The research field of context-aware recommender systems has been analyzed for quite some time now. Still, the term "context-aware" appeared initially in [21], where authors described context as "location, identities of nearby people, objects, and changes to those objects". Applying the widely accepted definition of context as "any information that can be used to characterize the situation of entities" to a recommendation scenario, context may be considered as any feature that affects a user's or an item's situation, such as the time of day, day of the week, location, weather, mood, presence of other users, and many others. The great significance of context and contextualized user data for accurate recommendations has only been widely recognized over the last decade (e.g., [12], [17]). It comes as quite a surprise to acknowledge that the majority of existing techniques still focus on recommending the most relevant items and take contextual information into consideration only up to a limited factor. This concludes into a somewhat static form of recommendations that can change only after a substantial amount of user interaction. Hence, in today's social networks' environment dominated by rapid changes or shifts of interest, the recommendations a user is presented with are often not reflective of the actual real-time contextual conditions. Although these recommendations can be reasonably accurate, there is room for improvement by incorporating updated contextual factors. For instance, in [16] authors consider the problem of quantitatively assessing context relevance and actually decide on whether contextual information actually matters in the framework of a recommender system. In a more domain-specific approach Wang et al. [14] present context by five different daily activities to facilitate a context-aware mobile music recommendation. Applying a similar idea onto a restaurant recommender system, Vargas et al. defined several contextual variables and adopted a feature selection method to obtain the relevant ones [15].

In a relevant survey, Anagnostopoulos et al. [20] report on software architectures for context awareness, sensor centric systems and context modeling issues. Defining architecture for supporting context-aware applications explicitly implies a scalable description of how to represent contextual information and which are the abstraction models capable of handling it. Taking this a step further and in order to generate relevant recommendations, a context-aware recommender system should not only make use of user preferences, but also exploit information about the specific contextual situation in which the recommended item will be consumed, as depicted in [19]. A summary of the aforementioned studies is provided in TABLE III. , which classifies them accordingly.

TABLE III. CONTEXT-AWARE RECOMMENDATIONS

Work	Task(s)	Method	Pros	Cons	Dataset
[21]	context-awareness definition	context-aware computing definition	pioneer context definition	mobile network oriented approach	
[12]	multidimensional approach	MD model	significance of context	custom dataset	1457 ratings, 62 users, 202 movies
[17]	cross-context reasoning	semantically-enriched descriptions	cross-context model, reasoning	abstract interpretation	
[16]	context relevance assessment	contextual features	context factors analysis, math notation	limited and domain specific evaluation	
[14]	context-aware music recommendation	5 context daily activities	probabilistic model	application/domain specific	24224 songs (Grooveshark/ YouTube)
[15]	recommender system optimization	contextual variables	simple feature selection	application/domain specific	111 users, 237 restaurants, 1251 ratings
[20]	context awareness architecture survey	context modeling	model-oriented approach		

[19]	context relevance assessment	rating influence by contextual factors	analytical context factors survey	subjective user evaluation	1664 ratings, 30 POIs, 20 users

VI. MOBILE/TRAVEL CONTEXT

Lastly, user-generated content produced and consumed in blogs, virtual communities, wikis, social networks, and related media files shared on social network sites like Facebook and/or Flickr have gained extensive popularity among users that seek online (travel) information [28]. The current trend is to assist social media users in posting and sharing their travel-related comments, opinions, and personal experiences, which then serve as a collective source of information for others. At the same time, the Internet also increasingly mediates tourism experiences as tourists use these social media sites to describe or even recreate their travels ([29], [30]). In addition, searching within social media has become an increasingly dominant mode in travelers' Internet utilization, mainly because of the huge amount of information available therein [27]. In other words social media are playing an increasingly important role as reliable information sources for world travelers.

In this framework contextual information has an important impact and a direct involvement since it forms the main source of implicit cues about the main items of interest, such as the "who", the "where", the "when", and the "with what". The latter is depicted in both the existing literature on travelers' tourism design needs (e.g., [24], [31]) and the recent research on context-awareness in travel (e.g., [25], [26]). Still, nowadays people are literally traveling in computer-aided networks, both in an physical and a virtual manner [32]. Thus, new relationships are built and innovativ technological solutions are offered to travelers affecting their interactions with time, space, as well as the physical and virtual world ([33]). Augmented reality features, provide travelers with additional rich contextual information and immerse them in semi-virtual worlds ([38], [39]) and such new emerging technologies are endorsed by social networks. Current mobile technology allows also for ubiquitous connection in an "anytime, anywhere" manner, offering new opportunities for trip planning and coordination, as well as increasing respective social interactions (e.g., [40], [41]).

Last but not least, current mobile technology achievements (i.e., 4G+ data plans, smartphones, GPS devices, etc.) assist travelers in all stages of their trip, i.e., on a pre-trip, on-site, and post-trip basis ([34]). This observation is attributed not only to the related advances of the technology, such as ubiquity and portability of mobile devices and communications, but also to the advanced features, the functionalities and overall exploitation of related contextual information being supported by developed context-aware systems ([35], [36]) that make it highly relevant to the spatiotemporal context of travel [37].

On the other hand, context may also be broadly categorized as network context and/or mobile terminal context (e.g., [22]), thus focusing on contextual information either about the actual hardware device capabilities or the mobility context providing information about the current location of the user. Due to the increasing utilization of mobile technologies, travel behavior is becoming inherently dynamic and socially connected. As such, the concept of context is becoming increasingly important in travel and tourism and particularly within today's technology-supported mobile environment. In an indicative example, authors in [23] build upon existing literature describing recent developments in context-aware system design with the aim of defining the notion of context as it relates to the mobile technological environment for tourism. TABLE IV. summarizes all above observations, respectfully.

TABLE IV. MOBILE/TRAVEL CONTEXT APPROACHES

Work	Task(s)	Method	Pros	Cons	Dataset
[28]	user web search	eye tracking	combination of ocular and behavioural data	limited dataset	behavioral and ocular data, 22 subjects
[29]	travel blogging	survey	connection of tourism to the		
[30]	travel videos as tourism mediators	video content analysis	video summarization and text analysis	user interaction dependable	120 Youtube videos, 576 viewers' comments
[27]	travel-related social media search	study	illustrates link between the Web and social media	limited dataset (keywords and destinations)	10 keywords, 9 destinations, 90 queries
[24]	purpose-destination recommender systems	study on personal characteristics influence on travel information search & decision-making	a tourism-specific theoretical framework	theoretical study with short practical impact	
[31]	tourism experience design	theoretical study emphasizing on design concepts	robust theoretical framework, meta-concept of tourism experience	theoretical study with short practical impact	
[25]	context awareness in tourism	innovative model for context information management	new model presentation, focuses on dynamic context		

Work	Task(s)	Method	Pros	Cons	Dataset
[26]	context-aware research	rule-based semantic contextual information system for tourism	user evaluation, mathematical notation	controlled laboratory environment user testing	30 participants, lab simulation
[32]	context-based recommendations	smartphone push recommendations study	real-life user evaluation	short timeframe	275 participants
[33]	interactive travel	mobile devices, social media, and networking technologies	analytical study		
[38]	virtual reality	explores social implications	practical approach	outdated	
[39]	tourism virtual reality	study on VR applications for tourism	analytical survey	outdated	
[40]	unplanned tourist attraction	conceptual model proposition	real-life user evaluation		551 travelers
[41]	smartphones impact on travel	adaptive structuration theory	real-life user evaluation	limited dataset (interviews)	24 interviews ("informants")
[34]	smartphones mediation mechanisms	analytical study	narrative interpretation of touristic experience influenced by smartphones		
[35]	mobile tourist guide	mobile tourism recommendation system	laboratory tests, real-life field trials		
[36]	mobile tourist guide	user-centered approach	real-life user evaluation		705 tourists
[37]	pattern identification of tourists' interactions with social networks	scheme for designing Mobile 2.0 applications	real-life users	limited dataset (users)	49 participants
[22]	mobile battery life prediction	application-centric definition of context			
[23]	travel behavior monitor	context definition for mobile tourism environments	robust conceptual framework		

VII. Conclusions

In this work we briefly presented and discussed several types of contextual information suitable for utilization, exploitation and usage within the social networks' framework. We identified three major types of such context, namely socio-linguistic context comprising of verbal and social context subcategories, the domain of context-aware recommendations and the extremely popular aspect of mobile/travel context. We observed and analyzed why contextual information may be extremely helpful in computational tasks relating to social media analysis, especially with respect to handling typical information search and retrieval problems. We believe and hope that based on the challenging discussion and interpretation of each context group we provided, future useful research directions may be identified by interested fellow researchers and that they may be able to use this survey work as a point of reference. According to the herein presented works across all discussed context variations, we may identify a clear trend in the research community towards incorporating contextual information as a means of information search and retrieval tasks optimization within the popular Internet-based social networks framework. As a future plan, we intend to extend this work and combine it with traditional computer science context aspects, like, e.g., typical multimedia content analysis problems.

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