An overview of context types within multimedia and social computing

Phivos Mylonas
Ionian University
Platia Tsirigoti 7
P.C. 49100, Corfu, Greece
+30 26610 87741
fmylonas@ionio.gr

ABSTRACT
The importance of contextual information is widely acknowledged and has become a major topic of interest, investigation, and experimentation for quite some time, generating numerous papers and many scientific works. In this position paper we attempt to present the role of context, tackling it from the humanistic scope of its utilization within the modern social networking applications framework. Three major types of relevant contextual information may be identified in the literature, namely multimedia content retrieval and analysis systems that utilize the notion of context towards improved results, context-aware systems, and contextual semantics, i.e., works that utilize semantic technologies for mining and intelligent information access to social media. For each type we shall present a brief review of its context definition and modeling methods, as well as identify and discriminate its useful types focusing on multimedia computing applications.

Keywords
context, context-aware, multimedia analysis, knowledge representation, context representation and analysis

1. INTRODUCTION
As expected the term *context* in general has numerous different interpretations and meanings. If we attempt to focus on the field of computer science, there are still many different disciplines, such as information search and retrieval, artificial intelligence, multimedia analysis, ubiquitous computing, and more recently mobile and social computing, that undertake their own way of understanding and thus defining what the term context really represents. Still, given the burst of social media and networks we may not accept a unique solid definition that would cover its usage within most modern computer science fields.

Among the main reasons that justify the existence and utilization of contextual information in computer science tasks are two well-known fundamental research problems, namely the bridging of two fundamental gaps; the *semantic* and *sensory gap* [9]. Being an issue inherent in most multimedia applications, the semantic gap is described as the gap between high-level semantic descriptions humans ascribe to everyday objects they interact with, and low-level features machines can automatically parse. On the other hand the sensory gap is described as the gap between an object and the computer's ability to sense and describe this object. Consequently it is contextual knowledge the single source of information that may enable computational systems to bridge both gaps.

With the advent of all kind of new multimedia-enabled devices and multimedia-based systems, coupled by the fact that user-generated content exploded through the utilization of social media and networks, new opportunities arise to infer media semantics and contextual metadata, capable of playing the role of a semantic interpreter. Information from low-level sources, such as sensors, that has been acquired without any further interpretation, may be meaningless, trivial, vulnerable to small changes, or uncertain, after all [40]. As a side-effect, limitation of low-level contextual cues when modeling human interactions and behavior risks reducing the usefulness of context-aware applications. On top of that and as observed early enough by Schilit et al. [30], context encompasses more information than, e.g., the user's location, because other things of interest, including the user's social situation, are also changing at the same time or pace.

As an additional motivation to this work, it is rather common knowledge that context itself appears in various forms and modifications; thus, researchers commonly emphasize distinctions between different types of context. This paper provides in the following an overview on the definition of three basic aspects of context exploited within current computer systems and applications, introducing some envisioned usage scenarios in the area. The rest of this paper is organized as follows: in Section 2 we present the importance of context identification within multimedia analysis tasks in the form of two useful types of context, namely the *context of content analysis* and the *context of use*. Section 3 deals with context-aware systems, whereas Section 4 addresses some interesting works in the field of semantic context. Final comments on the topic and relevant conclusions are drawn in Section 5.

2. CONTEXTUAL INFORMATION IN MULTIMEDIA ANALYSIS & RETRIEVAL TASKS
It is well-acknowledged that the type of knowledge required for multimedia content analysis is by definition thought to be context-sensitive. Consequently, to define and identify the appropriate type of context to be utilized in the process is a very important and complicated task. If we attempt to follow a breakdown approach, the first task would be the definition of the suitable aspect of context at hand, providing conceptual and audiovisual

16th EANN workshops, September 25 - 28, 2015, Rhodes Island, Greece

ACM 978-1-4503-3580-5/15/09…$15.00
DOI: http://dx.doi.org/10.1145/2797143.2797184

information. As already introduced in [22], there are mainly two relevant types of context in broad multimedia analysis:

i. the *context of content analysis,* and
ii. the *context of use*.

The first one refers to the context exploited during preparatory content analysis tasks and aids the extraction of semantic metadata. These may take the form of plain low-level semantic concepts, like for example the *name* of a person, or composite ones, like events and/or high-level concepts, like the *person* itself. The latter forms clearly a *composite* concept since its instances are related to instances of *name, age*, or *gender*. In the framework of multimedia analysis, in general, and, for example, within the task of scene classification, in particular, such interpretation maybe used to detect whether a picture or video sequence represents *urban* or *countryside* scenery; a crucial decision with respect to many applications.

More specifically, when low-level visual features are employed to globally analyze the scene content and classify it in one of a number of pre-defined categories, e.g., urban/countryside, we have the top-down case of s*cene classification*. Quite on the contrary, the bottom-up approach that focuses on local analysis to detect and recognize specific objects in limited regions of an image, without explicit knowledge of the surrounding context, e.g., recognize a building or a tree, characterizes the task of *object detection/recognition*. As the interested reader may observe, above multimedia content analysis fields actually discuss the same problem, since, in principle, detection of a human-made urban construction in an image might very well imply an urban environment, whereas pre-classification of the still image as *urban* would favor the recognition of the particular structure compared to vegetation.

Classical attempts worth mentioning in the area include Saber et al. [29], where low-level *color classification* is utilized in order to detect sky. Further in the context of content-based image retrieval, Smith and Li [31] assumed that a blue extended patch at the top of an image is likely to represent clear sky. An exemplar-based approach is presented in [33] that uses a combination of color and texture features to classify sub-blocks in an outdoor scene as sky, assuming correct image orientation. The latter brings up the issue of utilizing context orientation information in object class detection algorithms, a task that is generally avoided due to the fact that such contextual information is not always present.

On the other hand the *context of use* is focused on collecting and analyzing detailed information about its intended users, their tasks, as well as the technical and environmental constraints present. Such data may be gathered using personalized interviews, site surveys, observational studies, etc.. Its main goals are to ensure that all factors relating to the use of a multimedia application are identified before its design work starts and to provide a basis for future usability tests [41]. As a result all information about context of use is an essential input to the problem definition, goals, requirements, conceptual and detailed design, as well as the planning of other usability methods to follow and is heavily exploited by search/retrieval and personalization applications [24].

As far as *multimedia content retrieval* is concerned, contextual information may transform into several forms regarding the way content searches are performed, the type of searches users expect to issue and the constraints they impose in the process. Context is of special interest when tackling traditional retrieval tasks, such as query analysis, search by visual or metadata similarity, browsing and rendering of retrieved content, personalization and relevance feedback issues. In any case, research efforts focusing on the semantic part of the analysis [34] and search by visual similarity [18] may definitely benefit from the use of such contextual information.

Another important variation of context used in multimedia analysis tasks is the so-called *location context*. This context type is typically associated to spatial relationships between objects or regions identified within the contents of a still digital image. We identify two types of such contextual relationships, namely relationships that exist between co-occurrence of objects in natural images and relationships that exist between spatial locations of certain objects in an image. In the case such information is considered as location, or identities of nearby people or objects, a methodology to sense and deliver the current context to the application is of great importance. Thus, a significant distinction is identified: some approaches try to infer the location where the still image has been captured [19], in comparison to approaches that try to infer the location of the actual content of the still image ([9],[18]). An idea to resolve this ambiguity would be to consider additional characteristics or still image metadata, such as the fact that when two still images are captured in the same nearby geo-tagged location within a few minutes time, they are probably in or around the same actual location [27].

The so far discussed context, defined by typical relationships among locations of different materials in a scene, without taking into account exactly what the actual scene type is, is the one that it is used mostly within the framework of a multimedia content application. In another approach the overall description of the entire scene may also help towards the extraction of a certain type of contextual information. The latter is known as *scene context* and is possible to help also the identification of individual objects in the scene. One of its main goals is the effective combination of local and global information, towards implementing robust methods to use in traditional multimedia content analysis problems [25].

3. CONTEXT-AWARENESS

Now, apart from the traditional computing environments, mobile devices such as smartphones, phablets, tablets, laptops, etc. are becoming increasingly popular these days. In addition tremendous amounts of user-generated content are captured every day by social network users. In conjunction to both these observations, devices and usage contexts of media capture are undergoing rapid transformation from the traditional *capture device to personal computer to (social) network* paradigm to an integrated networked media service provider experience, which combines actual media capture (i.e., digital still images and video sequences) with programmable processing using powerful operating systems and programming languages, as well as wireless networking coupled together with enriched user interaction (such as user and location metadata). As a result, *context-awareness* is broadly defined as "the ability to provide services with full awareness of the current execution environment" and is widely recognized as one of the foundations of modern mobile and ubiquitous systems ([5], [17]).

As the first step, a context-aware applications' classification has been introduced in the early years of this emerging field by Schilit et al. [30], defining important aspects of contextual information as a basic set of fundamental questions, such as "who you are with", "when", "where you are", "what resources are nearby", etc.. Other approaches provided some plain synonyms for context, whereas Ryan et al. [28] include context as information about each user's location, environment, identity and time. Quite similarly, Ward et al. [37] view context as the state of an application's surroundings. A broader interpretation of context was introduced by Abowd et al. [1], where context may be formalized as a combination of 4 contextual types, namely: location (e.g., geo-localization), identity (e.g., gender, age, children), time and activity (e.g., what is occurring). In the framework of real-world, context-aware, human-computer interaction computing applications, context is defined as any information that can be used to characterize the situation that is relevant to the interaction between users and the system [30]. Finally, in an effort to summarize the key aspects of context with respect to human interaction behavior is proposed in [10].

One of the main drawbacks of above presented context-aware systems is that they attempt to model all relevant context parameters of the environment. The latter depends heavily onto the application domain and as a result they all do not provide a clear context modeling nor a viable comparative evaluation. In the semantically close area of pervasive computing, the work of Henricksen et al. [14] refers to context in environments, taking into account users' activity and their inter-relationships, the devices being used, available resources and communication channels. Another idea that allowed developers to consider richer information as activities and abstract knowledge about the current global context and to model specific knowledge of the current sub-domain was formed by the ontology-based approach introduced by Gu et al. in [12]. Two levels of contextual information were introduced that allowed modeling of both low- and high-level information.

In the era of Big-Data, technological advances in the field of hardware and devices' processing power empowered utilized devices with capabilities that allowed them to collect instantly large amounts of contextual information, such as their geographic position, their proximity to other people, their multimedia environment, etc. for extended periods of time. Consequently, the research field of Big-Data analytics emerged rapidly and provided information about context [8] and its effect on users' behavior ([21],[20]). A final important research question that forms a great challenge within the discussed framework is how to represent this contextual information in a way that can aid bridging the gap between applications using contextual information and the deployment of context-aware services [7]. Development of such applications requires tools that are based on clearly defined models of context. The simplest approach would be to use a plain model with context being maintained by a set of environment variables.

4. CONTEXTUAL SEMANTICS

In real-world everyday life humans are considered to be able to perceive, combine, process, respond and evaluate information in real-time. The latter includes semantics meaning of the content of an interaction, non-verbal information, such as facial and body gestures and context, i.e., events happening in their surroundings or broad environment that in principle are full of ambiguities. One may identify these ambiguities ranging from the multimodal nature of emotional expressions in different situational interactional patterns [4] to intra- and interpersonal relational context [13].

One of the main objectives in the field is the combination of contextual parameters extracted from low-level visual features with high-level concepts and interpretation (e.g., fuzzy sets) to facilitate additional semantic knowledge processing tasks [35]. The second objective is high-level context analysis, i.e., to take into account the extracted/recognized concepts during content analysis in order to find the specific context, express it in a structural description form, and use it for improving or continuing the content analysis, indexing and searching procedures, as well as for personalization purposes.

In terms of knowledge-assisted content analysis and processing, a set of core context functionalities of the multimedia application requires to be defined, regarding the way such a system is expected to execute knowledge-assisted image analysis functions automatically or in a supervised mode, so as to either detect or to recognize parts of content [35]. Additionally, semantic context is thought to generate or assist end-users classify their contents and metadata, through suggestions or sorting being performed in a sophisticated way, making quite naturally implicit use of its analysis functionalities. For example, in a face recognition scenario, visual clues may help the system detect the right person. Issues relating more to the automatic creation of metadata even after analysis, e.g., through inference, make use of context, as different sources of information (different analysis modules, textual inputs) may also be integrated.

In this framework the current backbone of the Semantic Web, as well as of a growing number of knowledge-based systems are, of course, ontologies. The fact that manual construction of ontologies is considered to be a tedious and not efficient task resulted into numerous research efforts ([39],[23]) on automated development of contextual information in the form of domain ontologies. Typically domain ontologies consist of concepts, semantic relations among these concepts, and a set of inference rules. Thus, the process of a contextual ontology creation comprises of three main aspects, namely: i) learning of the concepts that will constitute the ontology, ii) learning of the semantic relations among these concepts, and iii) learning of a set of inference rules.

Recently, a young, still very important field has emerged, the so-called social computing, which typically includes social networking services (SNSs, such as Skype) and social networking platforms (SNPs, such as Facebook or LinkedIn). It sets the boundaries of an area of computer science that is concerned with the intersection of social behavior and computational systems. Its main building block is the creation of social conventions and social contexts through the use of software and technology, specifically designed for user-driven applications that facilitate communication, collaboration and sharing of knowledge through multimedia [36]. Still, common human intelligence and behavior is not captured by aforementioned components. The main challenge lies on the different possibilities of incorporating existing SNSs into context-aware techniques that would include Semantic Web, social search and social recommendations in the process. In other words the task is to integrate contextual information within SNSs in an efficient and productive manner, so as to sufficiently incorporate human preferences, mood, behaviors, and emotions [26]. The amazing enlargement of social computing during the recent years clearly raised the need for novel methodologies to address all above social relations [16].

It should have been evident by now that contextual semantics play a significant role in computer science even with respect to tasks that do not fall directly under the researcher's eye, such as programming. As depicted in [11] contextual semantics influence the composition, location and flows of operative code in a program. A variety of context information types and their relationships is presented in [3], where emphasis has been given on high-level contextual abstractions that describe real life situations together with the role of uncertainty of context information. Contextual information interpreted from the perspective of data distribution is followed by Bellavista et al. [2], where a unified architectural model and a taxonomy for context data distribution is presented. In a more recent work focusing on social computing, Irfan et al. [15] provide an overview of ideas in the fields of social search and recommendation that may be utilized to provide better social communication capabilities within the social networks environment. In addition the work performed in [6] focuses on the tasks of mining semantics and intelligent information accessing from/to social media, providing, whereas et al. [38] issued a large-scale user survey on the roles that social media, recommendations, reviews, and other forms of user-contributed contextual information play in archival research. Last, but not least, Sohn et al. [32] utilized semantic context so as to be able to provide context-based personalized services within a smart home environment; a trending topic in the field.

5. CONCLUSIONS & FUTURE WORK

In this paper we briefly attempted to summarize the state-of-the-art with respect to contextual information that supports gathering, evaluation and dissemination of context information in three distinct fields of computer science that focus and are applied on current social media. It is rather obvious that existing approaches to context information handling differ in the expressive power of the context information models, in the support they can provide for semantic interpretation, and in their computational performance. Since we believe this is a promising research direction, we discussed some relevant research issues to be investigated.

More specifically, within the multimedia analysis domain we identified two types of context, namely the *context of content analysis* and the *context of use*. We observed why context information may be extremely helpful in knowledge extraction, especially when handling typical multimedia analysis problems like scene classification and object detection. As far as retrieval is concerned, closest match search capabilities together with image search by visual similarity depict clearly possible future benefits from exploiting contextual information parameters. In the field of a multimedia system's content adaptation, the task of correction of image orientation or even general enhancements is tackled by methods dealing to a great degree with context, whereas effective use of available contextual information within multimedia structures remains an open and challenging problem, although interesting steps have been performed towards the categorization of context-aware applications. Semantic interpretation of context plays also a significant role for the social media context and forms a broad area of research interest that we believe will be of great interest in the near future.

6. REFERENCES

[1] Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., and Steggles, P. 1999. Towards a better understanding of context and context-awareness. In Proceedings of the 1st international symposium on Handheld and Ubiquitous Computing (HUC '99), Hans-Werner Gellersen (Ed.). Springer-Verlag, London, UK, UK, 304-307.

[2] Bellavista, P., Corradi, A., Fanelli, M., and Foschini, L. 2012. A survey of context data distribution for mobile ubiquitous systems. ACM Comput. Surv. 44, 4, Article 24 (September 2012), 45 pages.

[3] Bettini, C., Brdiczka, O., Henricksen, K., Indulska, J., Nicklas, D., Ranganathanf, A., Riboni, D. 2010. A survey of context modelling and reasoning techniques. Pervasive and Mobile Computing, Volume 6, 161-180, 2010

[4] Bock, R., Wendemuth, A., Gluge, S., and Siegert, I. 2013. Annotation and classification of changes of involvement in group conversation, In Proceedings of the Humaine Association Conference on Affective Computing and Intelligent Interaction, 803-808, IEEE

[5] Bolchini, C., Curino, C. A., Orsi, G., Quintarelli, E., Rossato, R., Schreiber, F. A., Tanca, L. 2009. And What Can Context do for Data?. Communications of the ACM, Vol. 52 No. 11, 136-140

[6] Bontcheva, K., Rout, D. 2012. Making Sense of Social Media Streams through Semantics: a Survey. Semantic Web – Interoperability, Usability, Applicability, IOS Press, http://www.semantic-web-journal.net/sites/default/files/swj303.pdf

[7] Chen, H., Chiang, R. H. L., Storey, V. C. 2012. Business Intelligence And Analytics: From Big Data To Big Impact. MIS Q. 36, 4, 1165-1188

[8] Cuzzocrea, A., Song, I.-Y., and Davis, K. C. 2011. Analytics over large-scale multidimensional data: the big data revolution!. In Proceedings of the ACM 14th International workshop on Data Warehousing and OLAP (DOLAP '11), ACM, New York, NY, USA

[9] Davis, M., King, S., Good, N., and Sarvas, R. 2004. From context to content: leveraging context to infer media metadata. In Proceedings of the 12th annual ACM international conference on Multimedia (MULTIMEDIA '04), New York, NY, USA, 188-195

[10] Duric, Z., Gray, W. D., Heishman, R., Li, F., Rosenfeld, A., Schoelles, M. J., Schunn, C., and Wechsler, H. 2002. Integrating perceptual and cognitive modeling for adaptive and intelligent human-computer interaction. In Proceedings of the IEEE, 90(7), 1272-1289

[11] Goldberg, D. E., O'Reilly, U.-M. 2006. Where does the good stuff go, and why? How contextual semantics influences program structure in simple genetic programming. Genetic Programming, Lecture Notes in Computer Science Volume 1391, 16-36

[12] Gu, T., Wang, X. H., Pung, H. K., and Zhang, D. Q. 2004. An ontology-based context model in intelligent environments. In Proceedings of Communication Networks and distributed Systems Modeling and simulation Conference, 270-275

[13] Hammal, Z., and Cohn, J. F. 2014. Intra-and interpersonal functions of head motion in emotion communication. In Proceedings of the 2014 Workshop on Road-mapping the Future of Multimodal Interaction Research including Business Opportunities and Challenges, 19-22

[14] Henricksen, K., Indulska, J., and Rakotonirainy, A. 2002. Modeling context information in pervasive computing systems. In Pervasive Computing, 167-180, Springer

[15] Irfan, R., Bickler, G., Khan, S. U., Kolodziej, J., Li, H., Chen, D., Wang, L., Hayat, K., Madani, S. A., Nazir, B., Khan, I. A., Ranjan, R. 2013. Survey on social networking services. IET Networks

[16] Irwin, K. 2010. Introduction to social computing. In Proceedings of Int. Conf. Database System for Advanced Applications, 482-484

[17] Jones, Q., and Grandhi, S. A. 2005. P3 systems: Putting the place back into social networks. IEEE Internet Computing, 9(5), 38-46

[18] Kalantidis, Y., Tolias, G., Avrithis, Y., Phinikettos, M., Spyrou, E., Mylonas, Ph., Kollias, S. 2011. VIRaL: Visual Image Retrieval and Localization. Multimedia Tools and Applications, Springer, vol. 51, no. 2, 555-592

[19] Kumar, J. P., and Devi, B. R. 2014. Inferring Location from Geotagged Photos. International Journal of Advanced Research in Computer Science and Software Engineering, Volume 4, Issue 9

[20] Lemen, C. 2010. The new knowledge processing: integrating semantic web with web 2.0. In Computer Application and System Modeling (ICCASM), 2010 International Conference on, vol. 2, 314-317

[21] Lin, J., and Ryaboy, D. 2013. Scaling big data mining infrastructure: the twitter experience. SIGKDD Explor. Newsl. 14, 2, 6-19

[22] Mylonas, Ph. 2012. Understanding How Visual Context Influences Multimedia Content Analysis Problems. In Artificial Intelligence: Theories and Applications, Lecture Notes in Computer Science, Volume 7297, 361-368

[23] Nefzi, H., Farah, M., Farah, I. R., Solaiman, B. 2014. A critical analysis of lifecycles and methods for ontology construction and evaluation. Advanced Technologies for Signal and Image Processing (ATSIP), 2014 1st International Conference on , 48-53

[24] Patel, D. 2014. Usability Testing of Context-Aware Mobile Applications. Bachelor Thesis, Lancaster University, IT for Creative Industries, http://www.lancaster.ac.uk/postgrad/pateld1/Dissertation%20(Dharmendra%20Patel).pdf

[25] Pereira, E., Castelhano, M. 2012. On-Line Contributions of Peripheral Information to Visual Search in Scenes: Further Explorations of Object Content and Scene Context, Journal of Vision, Vol. 12, 740

[26] Roblyer, M. D., Michelle, M., Webb, M., Herman, J., Witty, J. V. 2010. Findings on Facebook in higher education: a comparison of college faculty and students uses and perception of social networking sites. Internet and Higher Education, Vol. 13, (3), 134-140

[27] Rost, M., Cramer, H., Holmquist, L. E. 2012. Mobile Exploration of Geo-tagged Photos. Personal and Ubiquitous Computing, Volume 16, Issue 6, 665-676

[28] Ryan, N., Pascoe, J., Morse, D. 1997. Enhanced Reality Fieldwork: the Context-Aware Archaeological Assistant. Gaffney,V., van Leusen, M., Exxon, S. (eds.), Computer Applications in Archaeology

[29] Saber, E., Tekalp, A. M., Eschbach, R., Knox, K. 1996. Automatic image annotation using adaptive colour classification. CVGIP: Graphical Models and Image Processing, vol. 58, 115-126

[30] Schilit, B., Adams, N., Want, R. 1994. Context-Aware Computing Applications. IEEE Workshop on Mobile Computing Systems and Applications, Santa Cruz, CA, USA

[31] Smith, J. R., Li, C.-S. 1998, Decoding image semantics using composite region templates. IEEE Int. Workshop on Content-based Access of Image & Video Database

[32] Sohn, M., Jeong, S., Lee, H. J. 2014. Case-based context ontology construction using fuzzy set theory for personalized service in a smart home environment. Soft Computing, Vol. 18, 1715-1728

[33] Vailaya, A., Jain, A. 2000. Detecting sky and vegetation in outdoor images. SPIE, vol. 3972

[34] Wallace, M., Akrivas, G., Mylonas, Ph., Avrithis, Y., Kollias, S. 2003. Using context and fuzzy relations to interpret multimedia content. 3rd International Workshop on Content-Based Multimedia Indexing (CBMI), IRISA, Rennes, France

[35] Wallace, M., Athanasiadis, T., Avrithis, Y. 2004. Knowledge Assisted Analysis and Categorization for Semantic Video Retrieval. Image and Video Retrieval, Lecture Notes in Computer Science Volume 3115, 555-563

[36] Wang, F.-Y., Carley, K. M., Zeng, D., Mao, W. 2007. Social Computing: From Social Informatics to Social Intelligence. Intelligent Systems, IEEE , vol.22, no.2, 79-83

[37] Ward, A., Jones, A., and Hopper, A. 1997. A new location technique for the active office. Personal Communications, 4(5), 42-47

[38] Washburn, B., Eckert, E., and Proffitt, M. 2013. Social Media and Archives: A Survey of Archive Users. Dublin, Ohio: OCLC Research

[39] Xu, Y., Li, G., Mou, L., Lu, Y. 2014. Learning Non-Taxonomic Relations on Demand for Ontology Extension. International Journal of Software Engineering and Knowledge Engineering, Volume 24, Issue 08

[40] Ye, J., Coyle, L., Dobson, S., Nixon, P. 2007. Using situation lattices to model and reason about context. In 4th International Workshop on Modeling and Reasoning in Context, MRC 2007

[41] Context of Use Analysis, http://www.usabilitybok.org/context-of-use-analysis, last retrieved: May 12, 2015