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Analytical mapping of opinion mining and sentiment analysis research during 2000–2015

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ABSTRACT

The new transformed read-write Web has resulted in a rapid growth of user generated content on the Web resulting into a huge volume of unstructured data. A substantial part of this data is unstructured text such as reviews and blogs. Opinion mining and sentiment analysis (OMSA) as a research discipline has emerged during last 15 years and provides a methodology to computationally process the unstructured data mainly to extract opinions and identify their sentiments. The relatively new but fast growing research discipline has changed a lot during these years. This paper presents a scientometric analysis of research work done on OMSA during 2000–2016. For the scientometric mapping, research publications indexed in Web of Science (WoS) database are used as input data. The publication data is analyzed computationally to identify year-wise publication pattern, rate of growth of publications, types of authorship of papers on OMSA, collaboration patterns in publications on OMSA, most productive countries, institutions, journals and authors, citation patterns and an year-wise citation reference network, and theme density plots and keyword bursts in OMSA publications during the period. A somewhat detailed manual analysis of the data is also performed to identify popular approaches (machine learning and lexicon-based) used in these publications, levels (document, sentence or aspect-level) of sentiment analysis work done and major application areas of OMSA. The paper presents a detailed analytical mapping of OMSA research work and charts the progress of discipline on various useful parameters.

1. Introduction

OMSA is a natural language processing task that uses an algorithmic formulation to identify opinionated content and categorize it as having ‘positive’, ‘negative’ or ‘neutral’ polarity. “What other people think” has always been an important piece of information for most of us during the decision-making process (Pang & Lee, 2008). Opinions of users not only help individuals in taking informed decisions but also help organizations in identifying customer attitudes/ opinions about products/ services. The new user-centric, participative Web allows extremely large number of users to express themselves about virtually endless topics ranging from reviews about movies, products, services to different socio-political events. However, the immense volume of data available on the Web (including various social media platforms) becomes information overload

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Table 1
Details of dataset.

Source/index	Category	Time period	Query to extract data	No. of papers retrieved	Total no. of fields in each publication record	Date of download
Web of Science	Articles, reviews, proceeding papers, editorial material and book chapters	2000–2015	(TS = ((“Sentiment Analysis”) OR (“Sentiment Classification”) OR (“Opinion Mining”) OR (“Opinion Classification”) OR (“Affect Analysis”) OR (“Affective Computing”) OR (“Sentiwordnet”) OR (“Sentic”) OR (“mining sentiment”) OR (“mining sentiments”))) *AND* LANGUAGE: (English)	697	60	27.02.16

in absence of automated methods to extract relevant and comprehensive information. OMSA fills this gap by identifying opinionated content and producing opinion summaries. It has been this major reason that research work on OMSA has grown tremendously during the recent past.

In this paper, we present a scientometric mapping exercise to analyze and chart the progress of research work in OMSA. The primary motivation of our work has been to understand the trajectory of research work done on OMSA from the period of inception till now. We have used both computational and manual analysis for this purpose. The research publication data obtained from Web of Science (WoS) database is analyzed computationally to identify year-wise number and rate of growth of publications, types of authorship of papers on OMSA, collaboration patterns in publications on OMSA, most productive countries, institutions, journals and authors, citation patterns and an year-wise citation reference network, and theme density plots and keyword bursts in OMSA publications during the period. Thereafter a somewhat detailed manual analysis of the research publication data is performed to identify popular approaches (machine learning and lexicon-based) used in these publications, levels (document, sentence or aspect-level) of sentiment analysis work done and major application areas of OMSA. This analysis is aimed to provide an analytical account of progress of the discipline from its inception to state of the art today, major milestones in the journey, the disciplines that OMSA research has drawn inspiration from and the areas it has been applied, major approaches and methods used in the OMSA research, and a meme map of major concepts and keywords in the area. More precisely, our analytical mapping can answer research questions of the following types:

- What is the period of origin of OMSA research publications and how research work on OMSA has grown over time?
- In which countries and institutions most of the initial and subsequent research work on OMSA has been done?
- What are the top publication sources (journals) publishing research on OMSA?
- Who are most productive and most cited authors in OMSA research during the period under study?
- What is the amount of international collaboration in OMSA research?
- What kind of authorship patterns are observed in OMSA research output?
- What are the major concepts occurring in OMSA research publications and what kind of theme density plot is observed in OMSA research output?
- What are the main approaches and methods of OMSA and which of them is used in what proportion of the reported research output?
- What are the main data sources on which OMSA work is done?
- What are main application areas of OMSA research?

The paper tries to answer the questions of the type mentioned above. Knowing answer to these questions may be very useful for an understanding the origin and growth of research work in OMSA. It will help in charting the course of development of the discipline and analyze different aspects of OMSA research. The readers can trace the broader landscape of OMSA research filed and obtain a highly useful overview and understanding of the research discipline, from its origin to the current state of the art. To the best of our knowledge this work is first of its kind and is different from regular survey papers on OMSA in many respects. The rest of the paper is organized as follows: Section 2 describes the data collection and analytical methodology used. Section 3 presents analytical outcomes of the scientometric mapping of OMSA research. Section 4 presents a detailed/ manual analysis of OMSA approaches and levels, major data sources and application areas. The paper concludes in Section 5, with a short summary of the work and its usefulness.

2. Data and methodology

We have obtained research publications indexed in WoS on OMSA for a considerably large period of 16 years (2000–2015), which almost covers the entire period of origin and growth of computational OMSA research. The WoS database collection indexes documents of different types namely articles, reviews, proceeding paper, editorial material, book review etc., in various languages. We have downloaded data for articles of all types on OMSA written in English. Table 1 illustrates the query used and statistics of the data downloaded.

We obtained a total of 697 papers as a result of query. We did a manual cleaning of the data to find out those papers that directly (and significantly) describe OMSA research work. Out of the 697 papers, 488 papers are found to be directly on OMSA research. This check required downloading the full text of the papers and understanding the work reported to identify if the paper reports a research work directly on OMSA theme or not. Thus analytical mapping is done on the refined set of 488 research papers. The references of the relevant records are listed in the references section (Abadi et al., 2015; Abbasi, Chen, & Salem, 2008; Abbasi, Chen, Thoms, & Fu, 2008; Abbasi, France, Zhang, & Chen, 2011; Abdul-Mageed, Diab, & Kübler, 2014; Abrahams, Jiao, Wang, & Fan, 2012; Agarwal & Mittal, 2014; Agarwal, Mittal, Bansal, & Garg, 2015; Agarwal, Poria, Mittal, Gelbukh, & Hussain, 2015; Agrafioti et al., 2012; Aguwa, Monplaisir, & Turgut, 2012; Alemi & Jasper, 2014; Ali et al., 2015; Alonso-Martín, Malfaz, Sequeira, Gorostiza, & Salichs, 2013; Al-Rowaily, Abulaish, Haldar, & Al-Rubaian, 2015; Al-Subaihin and Al-Khalifa, 2014; Archak et al., 2011; Arias et al., 2013; Arndt et al., 2014; Bae and Lee, 2012; Bagheri, Saraee, & de Jong, 2014; Bagheri, Saraee, & de Jong, 2013; Bai, 2011; Bailenson et al., 2008; Bakhtiyari & Husain, 2014; Bakhtiyari et al., 2015; Balahur & Jacquet, 2015; Balahur & Perea-Ortega, 2015; Balahur and Turchi, 2014; Balahur et al., 2012; Balahur, Kabadjov, Steinberger, Steinberger, & Montoyo, 2012; Baldominos Gómez, Luis Mingueza, & García del Pozo, 2015; Barbosa et al., 2015; Basiri et al., 2014; Baveye, Dellandrea, Chamaret, & Chen, 2015; Becker-Asano & Wachsmuth, 2010a, 2010b; Biyani, Bhatia, Caragea, & Mitra, 2014; Boehner et al., 2007; Bohlouli et al., 2015; Boiy & Moens, 2009; Boldrini, Balahur, Martínez-Barco, & Montoyo, 2012; Bollegala, Weir, & Carroll, 2013; Bosco, Patti, & Bolioli, 2013; Bravo-Marquez et al., 2014; Breazeal & Aryananda, 2002; Broekens, Jonker, & Meyer, 2010; Callejas & López-Cózar, 2008; Calvo & Mac Kim, 2013; Cambria & Hussain, 2015; Cambria & Hussain, 2012; Cambria et al., 2014; Cambria et al., 2012; Cambria, Grassi, Hussain, & Havasi, 2012; Cambria, Mazzocco, & Hussain, 2013; Cambria, Schuller, Xia, & Havasi, 2013; Cañamero, 2005; Canhoto & Padmanabhan, 2015; Cao et al., 2014; Cao et al., 2015; Cao et al., 2014; Cardie, 2014; Carrillo-de-Albornoz & Plaza, 2013; Casaburi et al., 2015; Casoto, Dattolo, & Tasso, 2008; Ceron et al., 2015; Ceron, Curini, Iacus, & Porro, 2014; Chamlertwat et al., 2012; Che et al., 2015; Chelaru et al., 2013; Chen et al., 2014; Chen et al., 2008; Chen et al., 2015; Chen et al., 2015; Chen, Chen, & Wu, 2012; Chen, Liu, & Chiu, 2011; Chen, Liu, Chang, & Tsai, 2013; Cheng Lin et al., 2013; Cheng, Leung, Liu, & Milani, 2014; Chenlo and Losada, 2014; Cheong & Lee, 2011; Chew et al., 2012; Chiu et al., 2015; Chmiel et al., 2011; Chmiel et al., 2011; Cho et al., 2014; Choi, Hwang, Kim, Ko, & Kim, 2014; Chung and Tseng, 2012; Clavel, 2015; Clavel et al., 2013; Cruz, 2012; Cruz et al., 2012; Cruz, Troyano, Pontes, & Ortega, 2014; Da Silva et al., 2014; Dai et al., 2015; Dang et al., 2010; del Pilar Salas-Zárate et al., 2014; Denecke and Deng, 2015; Z.-H. Deng et al., 2014; Deng et al., 2015; Deng et al., 2014; Devitt & Ahmad, 2013; Dey & Haque, 2009; Di Caro & Grella, 2013; Dong et al., 2015; Dragoni, Tettamanzi, & Costa Pereira, 2015; Driscoll, 2015; Du and Tan, 2010; Dueñas-Fernández, Velásquez, & L' Huillier, 2014; Duric and Song, 2012; Duwairi and El-Orfali, 2014; Duwairi et al., 2015; Earnshaw et al., 2012; Efron, 2006; Eirinaki, Pisal, & Singh, 2012; el Kaliouby, Picard, & Baron-Cohen, 2006; Fan & Chang, 2010; Fang et al., 2014; Fang et al., 2015; Fang, Xu, Sang, Hossain, & Muhammad, 2015; Fattah, 2015; Feidakis, Daradoumis, Caballe, Conesa, & Gañán, 2013; Feng et al., 2011; Feng et al., 2011; Fersini, Messina, & Pozzi, 2014; Fink et al., 2011; Frank et al., 2013; Fu, Abbasi, Zeng, & Chen, 2012; Gangemi et al., 2014; García-Cumbreras, Montejo-Ráez, & Díaz-Galiano, 2013; García-Moya, Kudama, Aramburu, & Berlanga, 2013; Ghazi et al., 2014; Ghiassi et al., 2013; Ghose and Ipeirotis, 2011; Gîfu and Cioca, 2014; Godnov & Redek, 2014; Gong et al., 2015; González-Bailón & Paltoglou, 2015; Grassi, Cambria, Hussain, & Piazza, 2011; Greaves, Ramirez-Cano, Millett, Darzi, & Donaldson, 2013; Groshek and Al-Rawi, 2013; Grosse et al., 2015; Guangwei & Araki, 2008; Gunter et al., 2014; Guo, Peng, & Wang, 2013; Guoliang et al., 2006; Habernal, Ptáček, & Steinberger, 2014a, 2014b; Hajek et al., 2014; Hajmohammadi et al., 2014; Hajmohammadi et al., 2014; Hajmohammadi, Ibrahim, Selamat, & Fujita, 2015; Hao et al., 2013; Hassan Khan et al., 2016; He & Zhou, 2011; He, Lin, Gao, & Wong, 2013; Hidalgo-Muñoz, López, Pereira, Santos, & Tomé, 2013; Hogenboom, Frasincar, de Jong, & Kaymak, 2015; Hogenboom, Heerschop, Frasincar, Kaymak, & de Jong, 2014; Homburg, Ehm, & Artz, 2015; Hopper & Uriyo, 2015; Hosseini, Khalilzadeh, & Changiz, 2010; Htay & Lynn, 2013; Hu & Li, 2011; Hu, Duan, Chen, Pei, & Lu, 2005; Huang et al., 2014; Huang et al., 2015; Huang, Zhao, Yang, & Lu, 2008; Hudlicka, 2003; Hudlicka & Mcneese, 2002; Hung & Lin, 2013; Iftene & Ginsca, 2014; Ishizuka & Prendinger, 2006; Jang, Sim, Lee, & Kwon, 2013; Jeong et al., 2011; Ji, Chun, Wei, & Geller, 2015; Jiang et al., 2015; Jiang, Wang, & Ren, 2012; Jing et al., 2015; Johansson & Moschitti, 2013; Jurado & Rodriguez, 2015; Justo et al., 2014; Kaiser et al., 2011; Kalaivani & Shunmuganathan, 2015; Kalampokis et al., 2013; Kanayama and Nasukawa, 2012; Kang & Park, 2014; Kang, Yoo, & Han, 2012; Kapur, Kapur, Virji-Babul, Tzanetakis, & Driessen, 2005; Katsimerou et al., 2015; Katz et al., 2015; Kennedy and Inkpen, 2006; Kergosien, Laval, Roche, & Teisseire, 2013; Khairnar & Kinikar, 2015; Khan et al., 2014; Kim & Kim, 2015; Kim & Lee, 2014; Kim et al., 2015; Kim et al., 2015; Kiritchenko, Zhu, & Mohammad, 2014; Kobayashi, Iida, Inui, & Matsumoto, 2006; Koelstra et al., 2012; Kolodyazhniy, Kreibig, Gross, Roth, & Wilhelm, 2011; Kontopoulos et al., 2013; Koppel & Schler, 2006; Korenek & Šimko, 2014; Kranjc et al., 2015; Krcadinac, Pasquier, Jovanovic, & Devedzic, 2013; Ku & Chen, 2007; Landowska, 2014; Lau, Li, & Liao, 2014; Lau, Liao, Wong, & Chiu, 2012; Lee, 2013; Lee et al., 2014; Lee, Yang, Tsai, & Lai, 2014; Lek & Poo, 2014; Leong, Lee, & Mak, 2012; Leony et al., 2013; Leung, Chan, Chung, & Ngai, 2011; Li & Liu, 2014; Li & Liu, 2012; Li & Tsai, 2013; Li and Wu, 2010; Li and Xu, 2014; Li et al., 2014; Li et al., 2014; Li et al., 2014; Li et al., 2012; Li et al., 2014; Li et al., 2011; Li et al., 2015; Li, Laurent, Poncelet, & Roche, 2010; Li, Liang, Li, Wang, & Wu, 2009; Li, Ye, Zhang, & Wang, 2011; Liao, Zhang, Zhu, Ji, & Gray, 2006; Lin et al., 2012; Lin et al., 2014; Lin, Wang, Li, & Zhou, 2015; Lindgren, 2012; Lisetti, Nasoz, LeRouge, Ozyer, & Alvarez, 2003; Liu & Chen, 2015; Liu et al., 2013; Liu et al., 2013; Liu et al., 2015; Liu, Yao, & Wu, 2005; Livingstone, Mühlberger, Brown, & Loch, 2007; Lizhen et al., 2014; Loia and Senatore, 2014; Lu et al., 2006; Maks & Vossen, 2012; Malandrakis, Potamianos, Iosif, & Narayanan, 2013; Malouf and Mullen, 2008; Man, Yuanxin, & Hao, 2014; Mantovani et al., 2006; MAO et al., 2012; Marrese-Taylor, Velásquez, & Bravo-Marquez, 2014; Martínez-Cámara et al., 2014;

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The downloaded data for these research publications consists of 60 fields per publication record. These 60 fields[1] describe basic metadata of each publication record such as Title (TI), Author (AU), Year Published (PY), Author identifiers (AI), Accession Number (UT), Address (AD) etc. We have mainly used Title (TI), Author (AU), Abstract (AB), Publication Name (SO), Year Published (PY) and Total Times Cited Count (WoS, BCI and CSCD)[2] (Z9) fields for our computational analysis.

The analytical methodology used by us involves both computational and manual tasks. First we performed computational analysis of data and computed different indicators as defined in standard Scientometrics literature. The main scientometric indicators measured and/ or computed include TP (Total Papers), TC (Total citations), Average Citations Per Paper (ACPP), Relative Growth rate (RGR), Doubling Time (DT), and International Collaborative Papers (ICP). The computational analysis

[1] http://images.webofknowledge.com/WOK46/help/WOS/h_fieldtags.html.

[2] WoS: Web of Science BCI: Book Citation Index CSCD: Chinese Science Citation Database.

Fig. 1. Year-wise publication.

using Scientometric methodology aimed at identifying year-wise research output on OMSA, rate of growth, country and institution-wise distribution of publications, international collaborative paper instances, top publication sources, most productive and most cited authors, citation network etc. We have then performed text analysis of all research papers to identify major keywords occurring in them and their occurrence bursts. The major thematic keywords are selected and a thematic density plot is also generated for the research output data obtained. This helps in identifying main keywords, their origin and occurrence bursts indicating the key areas where OMSA research revolves at a particular point of time. Analytical outcomes of the Scientometric analysis are described in Section 3.

The second kind of analysis involved manual effort. It required that certain annotators (Doctoral and Masters students having worked in OMSA area) read each paper and identify the major approaches/ methods of OMSA used in these publications, the levels of OMSA work done in different papers, main data sources used in OMSA research and identify different application areas. The results of manual analysis are presented in Section 4. These results help in understanding which major approaches and methods have been used for OMSA task over different years and their general trend. OMSA work done at different levels (document, sentence and aspect levels) is also categorized and reported in results with year wise statistics. Similarly, major data sources used by various researchers are identified along with their usage frequency. The various application areas in which OMSA is being applied have also been identified through the manual analysis.

3. Scientometric mapping and analysis

We are now going to describe the important scientometric indicators computed through computational analysis of the data. The subsections below present details of various indicators computed and tables and figures illustrating the resultant values.

3.1. Year-wise publication and growth pattern

First of all we have measured the number of published papers on OMSA for each of the years 2000 to 2015. Fig. 1 shows the number of published papers in OMSA on a year-wise plot. We can observe that this curve has been more or less flat till 2009, after which there is a steep rise. From 2010 to 2014, the number of published papers has increased by about six times. The lesser number for 2015 is understandable since many of the publications from 2015 are yet to be indexed in WoS database. OMSA has now emerged as is a widely researched area, with applications into different domains.

We have also computed the relative growth rate (RGR) and doubling time (D_T) (Mahapatra, 1985) for OMSA publication data obtained. While, RGR is a measure denoting the rate of growth with respect to time, the parameter D_T measures the time required for the number of publications in a particular year to become double. The parameters RGR and D_T are defined as follows:

$$RGR = (\ln N_2 - \ln N_1)/(T_2 - T_1) \quad (1)$$

Table 2
Year-wise research output and growth pattern.

S. No.	Year	NOP	Cumulative	RGR	Mean RGR	DT	Mean DT
1	2001	1	1	0.00	0.44	0.00	2.14
2	2002	3	4	1.39		0.50	
3	2003	3	7	0.56		1.24	
4	2004	1	8	0.13		5.19	
5	2005	7	15	0.63		1.10	
6	2006	11	26	0.55		1.26	
7	2007	6	32	0.21		3.34	
8	2008	15	47	0.38		1.80	
9	2009	12	59	0.23		3.05	
10	2010	21	80	0.30		2.28	
11	2011	48	128	0.47		1.47	
12	2012	58	186	0.37		1.85	
13	2013	82	268	0.37		1.90	
14	2014	122	390	0.38		1.85	
15	2015	98	488	0.22		3.09	

Table 3
Country-wise OMSA contribution (top 15 countries year-wise).

S. No	Country/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
1	China	0	0	0	0	3	2	0	4	6	7	21	10	21	38	33	145
2	USA	1	3	2	0	1	4	4	7	3	6	11	11	19	20	17	109
3	UK	0	0	0	1	1	1	0	2	2	0	5	10	10	4	9	45
4	Spain	0	0	0	0	0	0	0	1	0	0	2	10	10	12	8	43
5	Italy	0	0	0	0	0	2	0	1	0	0	2	5	6	7	8	31
6	Germany	0	0	0	0	0	0	0	0	0	1	5	1	7	3	6	23
7	Japan	0	0	0	0	1	2	0	2	1	0	3	3	3	4	3	22
8	Singapore	0	0	0	0	1	0	0	0	2	1	1	5	3	7	2	22
9	Taiwan	0	0	0	0	0	0	1	0	0	2	2	1	7	5	3	21
10	France	0	0	0	0	0	0	0	0	0	1	2	1	3	6	7	20
11	Canada	0	0	0	0	1	1	0	0	1	1	1	4	3	6	1	19
12	South Korea	0	0	0	0	0	0	0	0	0	1	2	3	2	5	4	17
13	India	0	0	0	0	0	0	0	0	1	0	1	0	1	2	8	13
14	Netherlands	0	0	1	0	0	0	0	0	0	1	0	4	3	2	2	13
15	Australia	0	0	0	0	0	0	1	1	0	0	1	2	1	3	2	11

$$D_T = (T_2 - T_1)\ln 2/(\ln N_2 - \ln N_1) \tag{2}$$

where, T_1 and T_2 are two chronological time periods and N_1 and N_2 are number of publications at time periods T_1 and T_2. In our case, the values are computed on a yearly basis, therefore $(T_2 - T_1)$ can be taken as 1. Eqs. (1) and (2) can be accordingly re-written as:

$$RGR = (\ln N_2 - \ln N_1) = \ln\left(\frac{N_2}{N_1}\right) \tag{3}$$

$$D_T = \frac{\ln 2}{RGR} \tag{4}$$

We have computed both these parameters for the OMSA research publication data. Table 2 below presents the computed values for *RGR*, Mean *RGR*, D_T and Mean D_T of OMSA research publications during the period 2001–2015 in. We can observe that the *RGR* in 2015(0.22) is almost double to that of the value in 2004(0.13). We can also observe that as *RGR* increases, D_T will decrease and vice-versa. The mean *RGR* and mean D_T are also calculated for the whole period and we can see from the table that these values are 0.44 and 2.14, respectively. A D_T value of 2.14 indicate that number of research publications in OMSA are doubling in 2 years' time, which is an indicator of very rapid growth in amount of research work being done on OMSA.

3.2. Country-wise distribution of OMSA research publications

We have analyzed the country-wise distribution of OMSA research publications during the full 16 year period to understand the places where OMSA research work originated and progressed during the 2000–2015 period. Table 3 presents the year-wise number of research publications from 15 different countries contributing highest number of research publications on OMSA during the whole period. We can observe that most of the initial papers are from USA, after which other countries have seen major growth on OMSA research work. In fact now China contributes highest number of research papers

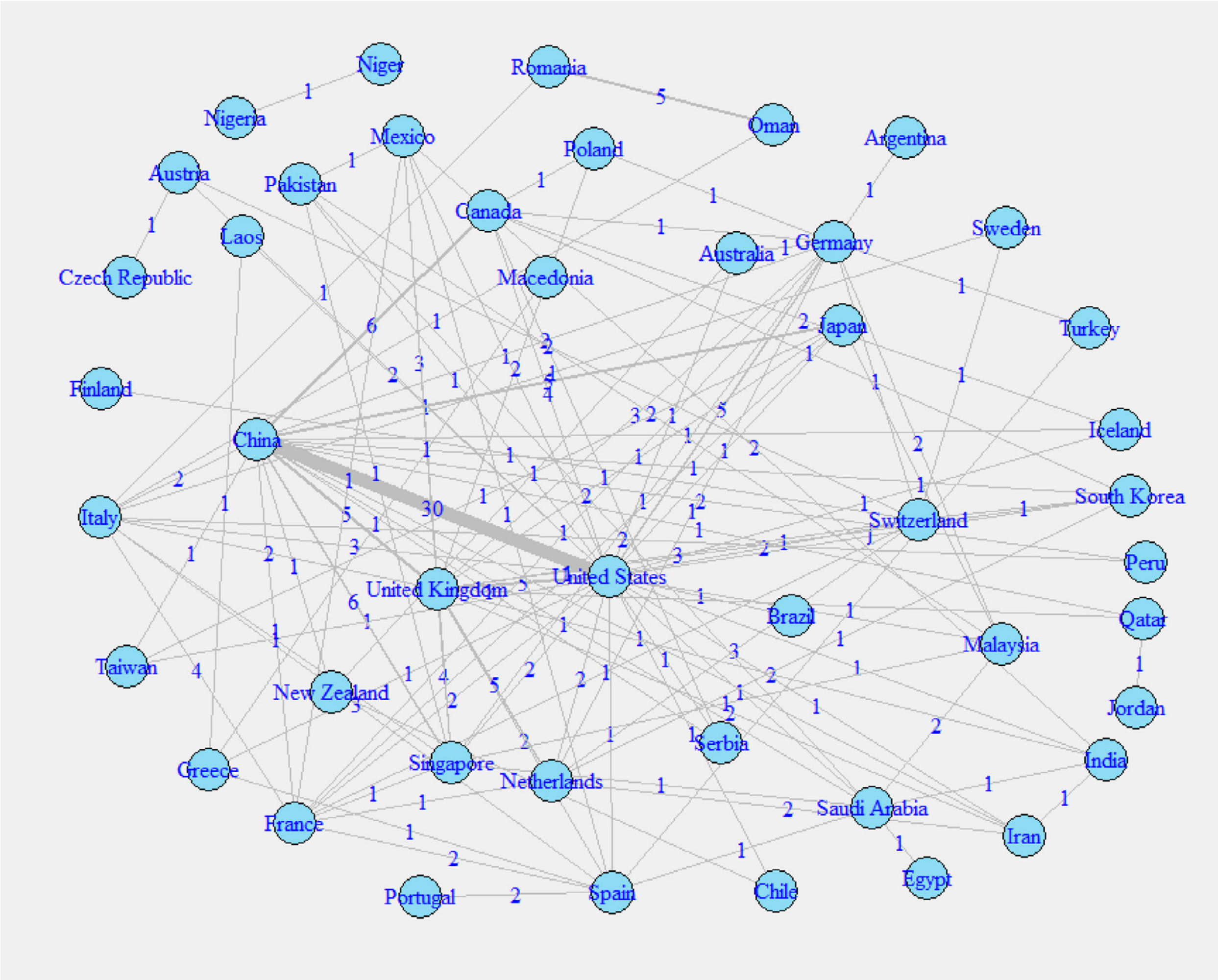

Fig. 2. International collaboration in OMSA research publications.

on OMSA research, contributing about 30% of the total research publications during the 2000–2015 period. USA is now second major contributor with about 22% research publications followed by Spain with approximately 9% contribution to total research output in the period. The other major countries from where OMSA work is reported include UK, Italy, Germany, Japan, Singapore, Taiwan, France, Canada, South Korea, India etc.

3.3. International collaboration in OMSA research output

We have analyzed the research publication data obtained to understand the international collaboration patterns in OMSA research. For this purpose, the metadata of publication records is analyzed to extract those instances which contain authors from at least two different countries. We have found that out of the total 488 papers selected, a total of 148 papers are instances of international collaboration. We have extracted all papers which are instances of international collaboration and identified the different countries from which the collaborating authors are. All these instances of international collaboration output are then plotted as an International Collaboration Pattern graph in Fig. 2. Here, the vertices represent countries and edges represent collaborative associations between two pair of countries. The thickness of an edge between two vertices (countries) is proportional to the number of international collaboration instances between them. The edge thickness can thus be understood as collaboration weight. We can observe from the figure that China and United States collaborate a lot on OMSA research. This pair has produced highest number of international collaboration instances. In general a good number of OMSA research publications involve international collaboration.

Table 4
Most productive 15 institutions on OMSA research.

S. No.	Institution name	TP	TC	ACPP	*h*-index
1	Chinese Academy of Sciences, China	17	122	7.18	17
2	Tsinghua University, China	13	74	5.69	13
3	Massachusetts Institute of Technology (MIT), USA	12	888	74.00	12
4	Harbin Institute of Technology, China	11	108	9.82	11
5	University of Wolverhampton, UK	11	179	16.27	4
6	Nanyang Technological University, Singapore	10	51	5.10	4
7	University of Jaén, Spain	10	21	2.10	2
8	City University of Hong Kong, China	9	3	0.33	1
9	National University of Singapore, Singapore	9	142	15.78	5
10	University of Arizona, USA	9	160	17.78	6
11	University of Stirling, Scotland	9	100	11.11	5
12	Beihang University, China	8	3	0.38	1
13	Hefei University of Technology, China	8	15	1.88	2
14	Hong Kong Polytechnic University, China	8	144	18.00	5
15	University of Illinois, USA	8	136	17.00	4

3.4. Institution-wise distribution of OMSA research publications

After analyzing research OMSA research publications to extract country-level results, we tried to understand the institution-level research output share and dynamics. First, we have tried to identify the major institutions contributing significantly to OMSA research work during 2000–2015 period. In Table 4, we list the top 15 institutions in descending order of the total number of OMSA research publications originating from them. We can observe that the Chinese Academy of Sciences has the highest number of research papers with its affiliation. This is followed by Tsinghua University, again from China. The table shows four different indicators, namely TP (Total Papers), TC (Total Citations), ACPP (Average Citations Per Paper) and h-index for the OMSA research output originating from various institutions. Here, it would be worth mentioning that ACPP value is defined as:

$$ACPP = \frac{TC}{TP} \tag{5}$$

The *h*-index metric measures both the productivity and impact of the published work of a scientist or a scholar. It is defined as: a scientist has index h, if h of his/her N_p papers have at least h citations each, and the other (N_p-h) papers have at most h citations each (Hirsch, 2005). The *h*-index can be calculated for individuals, institutions, journals etc. We can observe that most producing institutions are not necessarily most cited. For example the Chinese Academy of Sciences and Tsinghua University contribute highest number of research papers with their affiliation address but Massachusetts Institute of Technology (MIT), USA and University of Wolverhampton, UK achieve highest number of citations. Similarly on ACPP indicator, MIT performs the best. We can see that out of top 15 productive institutions, 7 are from China. Other major institutions are from USA, Singapore, UK and Spain.

3.5. Top publications sources – journals

We have analyzed the OMSA research publication data to identify the major publication sources (mainly journals) where OMSA research work has been reported during 2000–2015 period. We computed the total number of research articles published in each of the distinct journal names found in the downloaded data. Table 5 presents the list of top 15 journals in terms of number of research publications. Among these top 15 journal publication sources, Expert System with Applications accounts for highest number (total 37) of OMSA research publications. This is followed by the journal Knowledge-Based Systems (23 research publications) and IEEE Transactions on Affective Computing (22 research publications). We have also calculated TC, ACPP and h-index values for all the journals for the OMSA research publication data. The journal Computational Linguistics obtain highest ACPP value for OMSA research publication data, while IEEE Transactions on Affective Computing received highest total citations for OMSA research publications data. The two most productive journals Expert System with Applications and IEEE Transactions on Affective Computing have the highest h-index value.

3.6. Most productive and most cited authors

We have also analyzed the OMSA research publication data to identify the most productive and most cited authors. Highly productive authors are those who produce high amount of research publications during the given period. Similarly, highly cited authors are those whose research work published during a given period is cited the most. We present a list of 20 most productive authors in Table 6. We can observe that Cambria Erik is the most productive author on OMSA research published in SCIE journals during 2000–2015. This is followed by authors Hussain Amir, Thelwall Mike and Balahur Alexandra. In terms of total citations, Thelwall Mike is the most cited author followed by Cambria Erik and Chen Hsinchun. We

Table 5
Top publication sources.

S. No.	Journal name	TP	TC	ACPP	*h*-index
1	Expert Systems with Applications	37	326	8.81	10
2	Knowledge-Based Systems	23	39	1.70	4
3	IEEE Transactions on Affective Computing	22	329	14.95	10
4	Decision Support Systems	19	99	5.21	6
5	Journal of Information Science	13	41	3.15	2
6	IEEE Transactions on Knowledge And Data Engineering	12	158	13.17	5
7	Information Processing & Management	10	16	1.60	2
8	IEEE Intelligent Systems	10	135	13.50	6
9	Journal of The American Society For Information Science And Technology	9	98	10.89	5
10	Information Sciences	8	79	9.88	2
11	Computational Intelligence	8	150	18.75	4
12	PLoS One	7	31	4.43	1
13	Computer Speech And Language	7	17	2.43	3
14	Computational Linguistics	7	160	22.86	4
15	IEICE Transactions on Information and Systems	7	5	0.71	2

Table 6
Most productive 25 authors.

S. No.	Author name	TP	TC	ACPP
1	Cambria Erik	12	150	12.50
2	Hussain Amir	9	100	11.11
3	Thelwall Mike	8	179	22.38
4	Balahur Alexandra	7	17	2.43
5	Paltoglou Georgios	7	98	14.00
6	Chen Hsinchun	6	127	21.17
7	Li Qing	6	2	0.33
8	Teresa Martin-Valdivia M.	6	10	1.67
9	Wang Hongwei	6	8	1.33
10	Alfonso Urena-Lopez L.	5	10	2.00
11	Martinez-Camara Eugenio	5	4	0.80
12	Tan Songbo	5	46	9.20
13	Abbasi Ahmed	4	94	23.50
14	Buckley Kevan	4	92	23.00
15	Chen Li	4	0	0.00
16	De Jong Franciska	4	1	0.25
17	Mohammad Saif M.	4	4	1.00
18	Montejo-Raez Arturo	4	3	0.75
19	Montoyo Andres	4	9	2.25
20	Na Jin-Cheon	4	39	9.75

have also shown, in Fig. 3, a TP-TC plot with most productive and most cited authors plotted on it for a better visualization of the results. Further, by using CiteSpace[3] software, we have also plotted top 20 references with strongest citation burst in OMSA research publication data obtained, as shown in Fig. 4. This gives us an idea about the initial research papers on OMSA which are being cited often by researchers during recent times as well. As we can observe from the figure, many of these papers with strong citation bursts are published during 2002–2005 period. This is easy to understand that since many of these works were the initial pioneering research works in the area, they have been cited a lot by later papers.

3.7. Authorship patterns

We have analyzed the OMSA research publication data to find out the authorship pattern in published works. More precisely, we have identified the number of research publications that are authored singly, authored by two or more authors. The author details of each publication record are processed for this. We found that approximately 3.7% of the OMSA publications are single authored, whereas 96.3% of papers have two or more than two authors. Fig. 5 shows the distribution of papers with one, two, three or more authors, plotted year-wise since 2005 onwards. We have also identified the co-authorship network for some highly productive authors. One such co-authorship network is shown in Fig. 6, which presents the co-authorship network of highly productive author Cambria Erik. In this co-authorship network, one author (Hussain Amir and Poria Soujanya) are also among the list of 25 most productive authors.

[3] http://cluster.cis.drexel.edu/~cchen/citespace/.

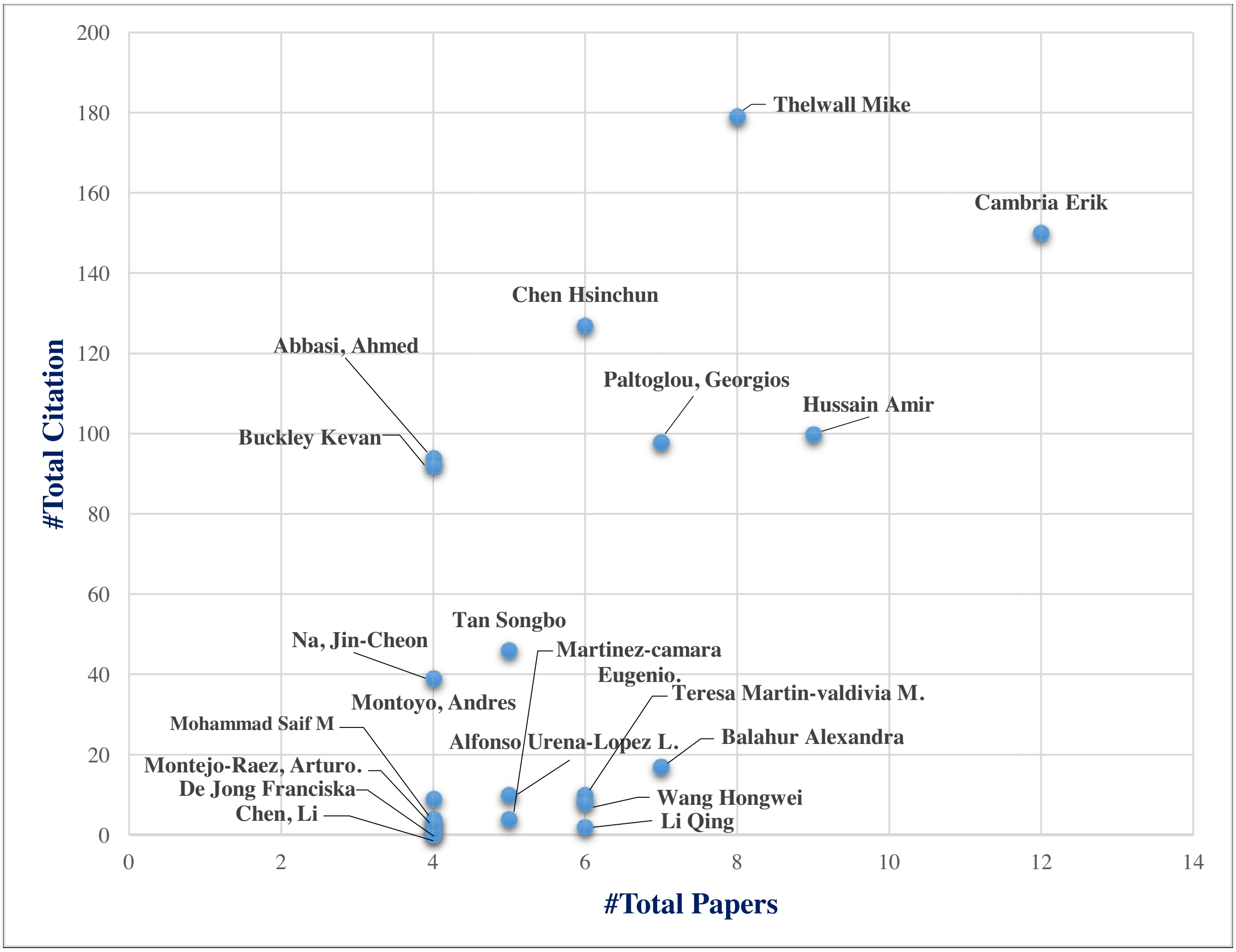

Fig. 3. Total citation verses total papers plot for some authors on OMSA.

References	Year	Strength	Begin	End	2000 - 2015
PICARD RW, 1997, AFFECTIVE COMPUTING, V, P	1997	4.8749	**2000**	2005	
COWIE R, 2001, IEEE SIGNAL PROC MAG, V18, P32, DOI	2001	4.3854	**2003**	2008	
PICARD RW, 2001, IEEE T PATTERN ANAL, V23, P1175, DOI	2001	3.5134	**2003**	2009	
PANG B, 2004, P 42 ANN M ASS COMP, V,, P	2004	9.064	**2005**	2012	
DAVE K, 2003, P 12 INT C WORLD WID, V,, P	2003	8.5635	**2005**	2011	
PANG B, 2002, PROCEEDINGS OF THE 2002 CONFERENCE ON EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING, V, P79	2002	12.0147	**2005**	2010	
TURNEY P D, 2002, P 40 ANN M ASS COMP, V,, P	2002	4.766	**2005**	2010	
WIEBE J, 2004, COMPUT LINGUIST, V30, P277, DOI	2004	4.0931	**2006**	2012	
YU H, 2003, PROCEEDINGS OF THE 2003 CONFERENCE ON EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING, V, P129	2003	4.3308	**2006**	2011	
RILOFF E, 2003, PROCEEDINGS OF THE 2003 CONFERENCE ON EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING, V, P105	2003	3.5396	**2006**	2011	
TURNEY PD, 2002, P 40 ANN M ASS COMP, V,, P	2002	6.5161	**2006**	2010	
KIM SOO-MIN, 2004, P 20 INT C COMP LING, V,, P	2004	4.5275	**2007**	2012	
RILOFF E, 2003, P 7 C NAT LANG LEARN, V, P25	2003	4.6486	**2007**	2011	
LIU B, 2005, P 14 INT C WORLD WID, V,, P	2005	4.0715	**2007**	2012	
MULLEN T, 2004, P C EMP METH NAT LAN, V, P412	2004	5.3071	**2008**	2011	
TURNEY PD, 2003, ACM T INFORM SYST, V21, P315, DOI	2003	14.1933	**2008**	2011	
POPESCU A M, 2005, P HUM LANG TECHN C C, V, P339, DOI	2005	3.8263	**2009**	2012	
HU MQ, 2004, PROCEEDING OF THE NINETEENTH NATIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE AND THE SIXTEENTH CONFERENCE ON INNOVATIVE APPLICATIONS OF ARTIFICIAL INTELLIGENCE, V, P755	2004	2.9294	**2009**	2012	
HU M, 2004, P 10 ACM SIGKDD INT, V,, P	2004	10.2591	**2010**	2012	
WILSON TS, 2005, PHIL EDUC, V, P347, DOI	2005	4.2716	**2010**	2013	

Fig. 4. Top 20 references with strongest citation bursts.

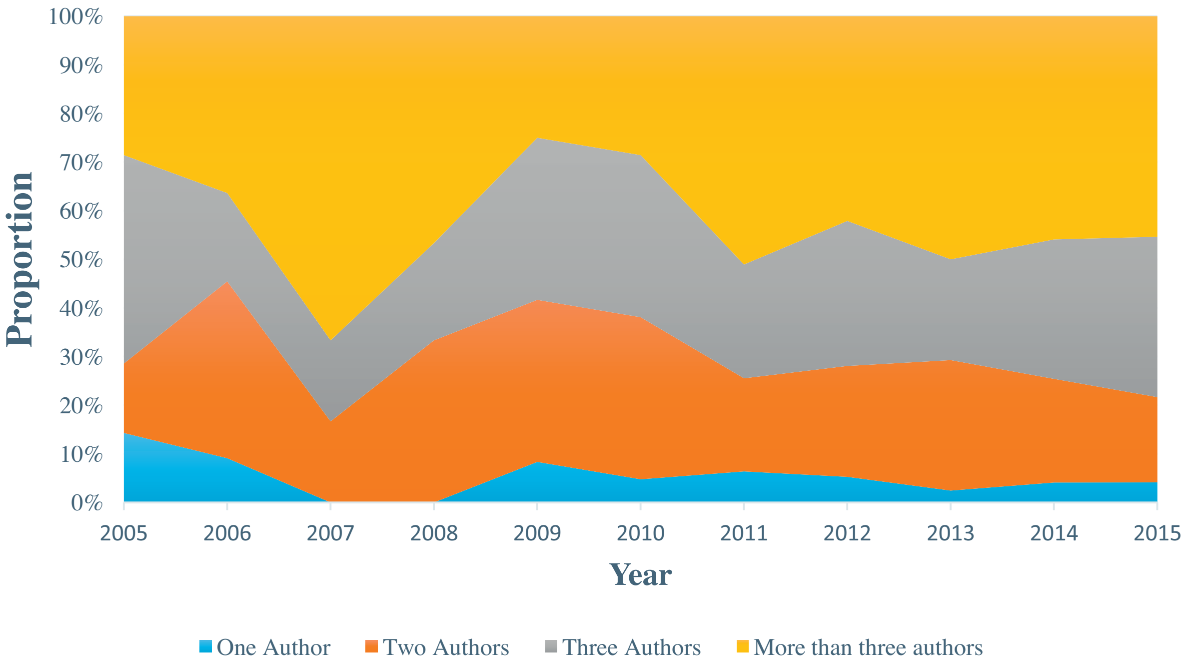

Fig. 5. Author-ship pattern plotted year-wise.

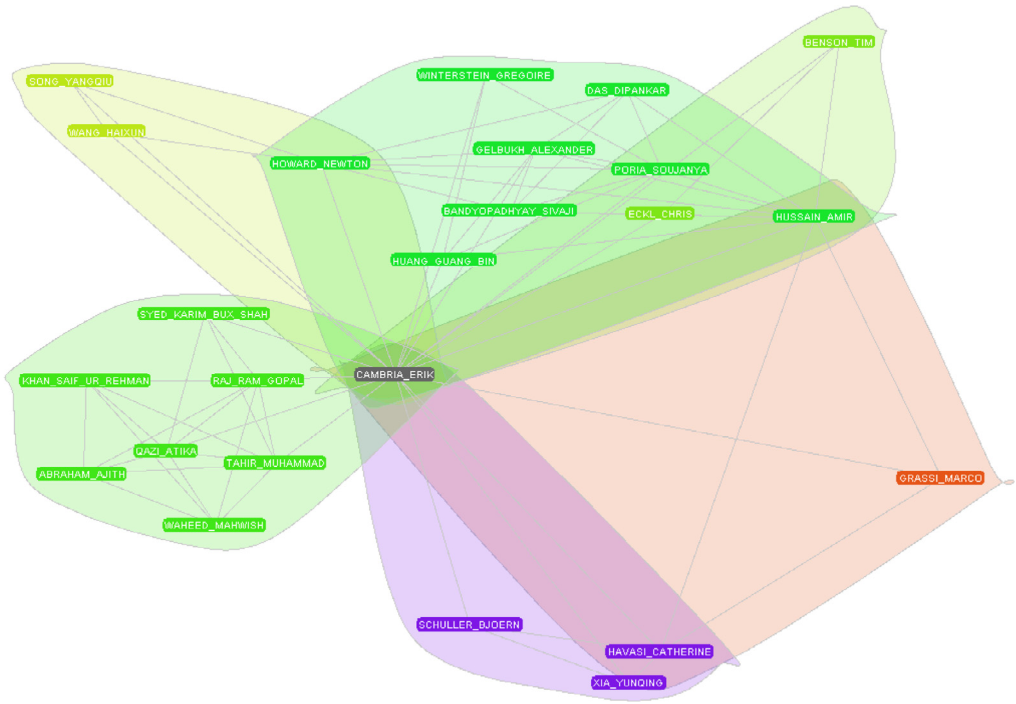

Fig. 6. Co-authorship network of highly productive author Cambria Erik.

3.8. Citation network

We have analyzed the OMSA research publication data to obtain citation pattern among the 488 articles in the data. We computationally analyzed the whole data, reading each reference in each of the 488 papers. We found a total of 19,643 references. Out of these, 813 references (approx. 4.2%) are references to papers within the dataset (i.e. 488 paper dataset). Remaining 18,830 references are to other papers (including conference papers on OMSA). Fig. 7 shows the citation pattern

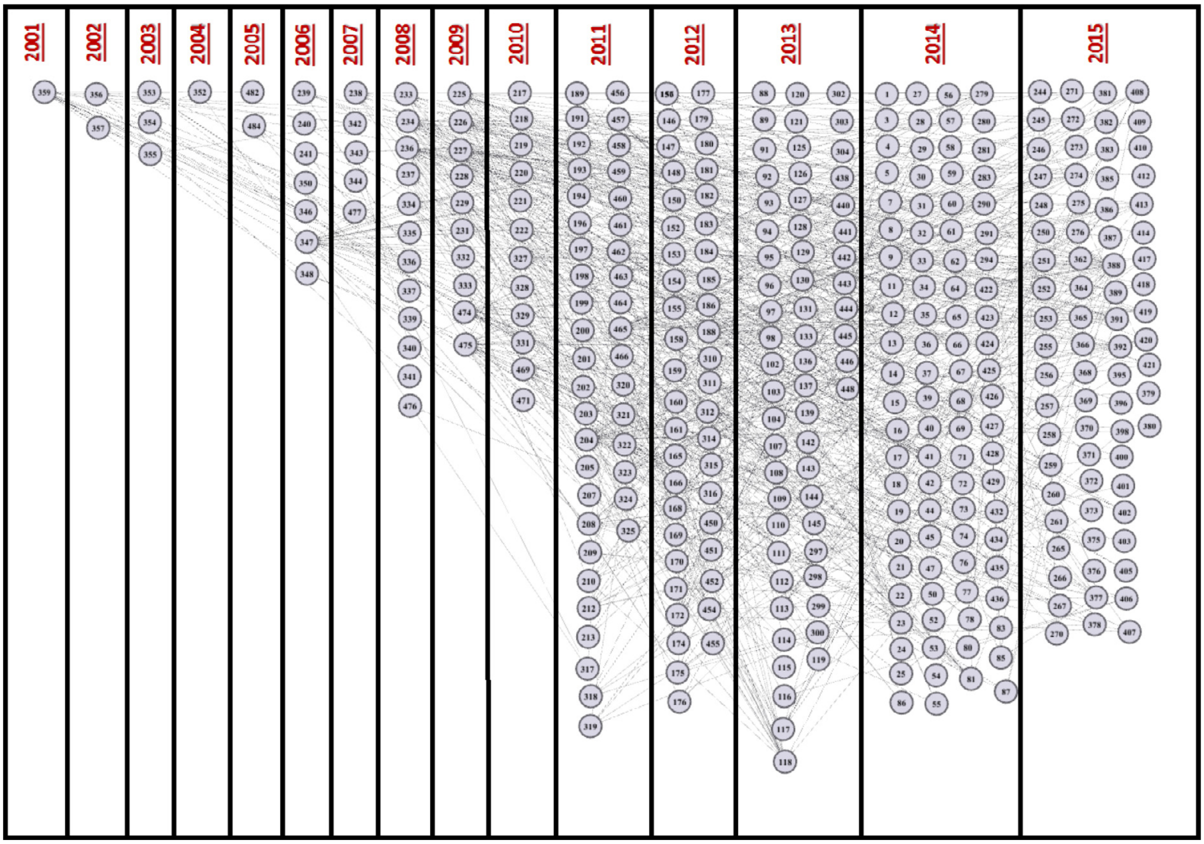

Fig. 7. Citation pattern in research papers in dataset.

Table 7
Subject category wise output.

S. No.	Subject category name	TP	P	CP
1	Computer Science	390	80.41	80.41
2	Engineering	101	20.82	101.24
3	Operations Research & Management Science	59	12.16	113.40
4	Information Science & Library Science	52	10.72	124.12
5	Telecommunications	23	4.74	128.87
6	Business & Economics	17	3.51	132.37
7	Science & Technology – Other Topics	16	3.30	135.67
8	Neurosciences & Neurology	14	2.89	138.56
9	Linguistics	12	2.47	141.03
10	Psychology	12	2.47	143.51
11	Acoustics	9	1.86	145.36
12	Automation & Control Systems	8	1.65	147.01
13	Social Sciences – Other Topics	7	1.44	148.45
14	Mathematics	6	1.24	149.69
15	Communication	5	1.03	150.72

within the dataset (i.e. 4.2% of citation references). The figure is a directed graph, where nodes represent articles and occurrence of a link from node A_i to node A_j indicates that paper A_i cites paper A_j. The figure presents the reference connections between 488 articles, where the numbers in nodes represent numbers of papers as appearing in the references of this paper. Though no specific information is added by the citation reference network, it still helps in observing the citation flows among the papers in the dataset.

3.9. Subject category wise division of OMSA publications

We have also computationally analyzed the OMSA research data to identify the different subject categories in which OMSA research has been done. The research publications are grouped on the basis of subject categories of WoS. Table 7

Table 8
Year wise occurrence of selected control terms.

S. No.	Control terms/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
1	Sentiment Analysis	0	0	0	0	0	2	0	4	3	4	16	32	31	57	47	**196**
2	Opinion Mining	0	0	0	0	0	1	0	2	3	4	11	19	16	24	17	**97**
3	Sentiment Classification	0	0	0	0	0	1	0	0	3	1	9	1	7	11	11	**44**
4	Text Mining	0	0	0	0	0	0	0	1	0	2	3	7	4	8	6	**31**
5	Machine Learning	0	0	0	0	0	2	0	3	2	2	4	1	2	7	8	**31**
6	Social Media	0	0	0	0	0	0	0	0	0	0	2	3	1	10	13	**29**
7	Twitter	0	0	0	0	0	0	0	0	0	0	2	0	6	10	4	**22**
8	Data Mining	0	0	0	0	0	0	0	1	0	0	4	3	1	2	2	**13**
9	Feature Selection	1	0	0	0	0	0	0	1	0	0	2	2	2	1	1	**10**
10	Polarity Classification	0	0	0	0	0	0	0	0	0	0	0	0	2	5	2	**9**
11	Feature Extraction	0	0	0	0	0	0	0	0	0	0	1	1	2	2	3	**9**
12	Emotion	0	0	0	0	0	1	0	1	0	0	1	0	3	2	0	**8**
13	Classification	0	0	0	0	0	0	0	0	0	0	0	1	0	3	3	**7**
14	Topic Modeling	0	0	0	0	0	0	0	0	0	0	0	1	1	4	0	**6**
15	Business Intelligence	0	0	0	0	0	0	0	0	0	0	0	5	0	1	0	**6**
16	Stock Market	0	0	0	0	0	0	0	0	1	0	0	0	1	3	0	**5**
17	Semantic Orientation	0	0	0	0	0	1	0	0	0	0	1	2	1	0	0	**5**
18	Microblogging	0	0	0	0	0	0	0	0	0	0	2	0	1	1	0	**4**
19	Affect Analysis	0	0	0	0	0	0	0	0	0	1	0	0	2	1	0	**4**
20	Clustering	0	0	0	0	0	0	0	0	0	0	0	1	0	2	1	**4**
21	Sentiment Dictionary	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	**3**
22	Subjectivity Analysis	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	**3**
23	Reviews	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**1**

lists the 15 most frequent categories based on total papers (TP). The largest numbers of publications are found in four categories, namely Computer Science, Engineering, Operation Research and Management Science and Information Science & Library Science. Majority of the publications are however in Computer Science. We have also calculated the Percentage (P) and Cumulative Percentage (CP) for each subject category. Here, CP is more than 100% because some papers fall in more than one subject category.

To further understand the main research topics and their trends in OMSA research, we have identified certain control terms. These control terms are one of the most frequently occurring author keywords in the OMSA research publication data. Table 8 shows the year-wise occurrence frequencies of the selected control terms. The terms ‘sentiment analysis’ and ‘opinion mining’, being the subject matter of study are found to be most frequent. We can also observe that other frequently occurring control terms include ‘text mining’, ‘data mining’, ‘machine learning’, and ‘topic modeling’ etc. Some other frequently occurring terms are ‘social media’, ‘microblogging’, ‘emotion’, ‘business intelligence’, and ‘affect analysis’ etc. Fig. 8 plots the occurrence frequency based density plot of selected control terms. These results present a meme map of the major concepts/ keywords in OMSA research area.

For a more systematic and detailed analysis of introduction and life span of important terms in OMSA research, we used the Science of Science[4] (Sci2) for a temporal analysis using Burst detection. The burst detection algorithm was developed by Kleinberg (Kleinberg, 2003) on the basis of bursty and hierarchical structure in stream. It is valuable for text stream analysis when we want to know the activity of the stream during the period of time. The Table 9 shows the top 20 keywords with their starting and ending time of the burst. A higher weight could be resulted by the longer length, the higher level or both. The length shows the period of burst. Table 9 shows the top 20 keywords with their starting and ending time of the burst. A higher weight could be resulted by the longer length, the higher level or both. The length shows the period of burst. We can observe that words like “feature selection”, “affective” and “emotion recognition” initiated in 2001 and continued till 2013. Some of the words that are still continuing in the burst are “machine learning”, “sentiment classification” etc. The burst helps in identifying the important keywords occurring in OMSA research publications and their periods of usage.

4. Detailed manual analysis

In addition to the computational analysis using scientometric methodology, we have also performed a detailed manual analysis of the 488 research publications on OMSA. The main purpose of the manual analysis was to identify the finer details about publication characteristics and trends in OMSA research. For the detailed analysis all the 488 papers are read

[4] https://sci2.cns.iu.edu/user/index.php.

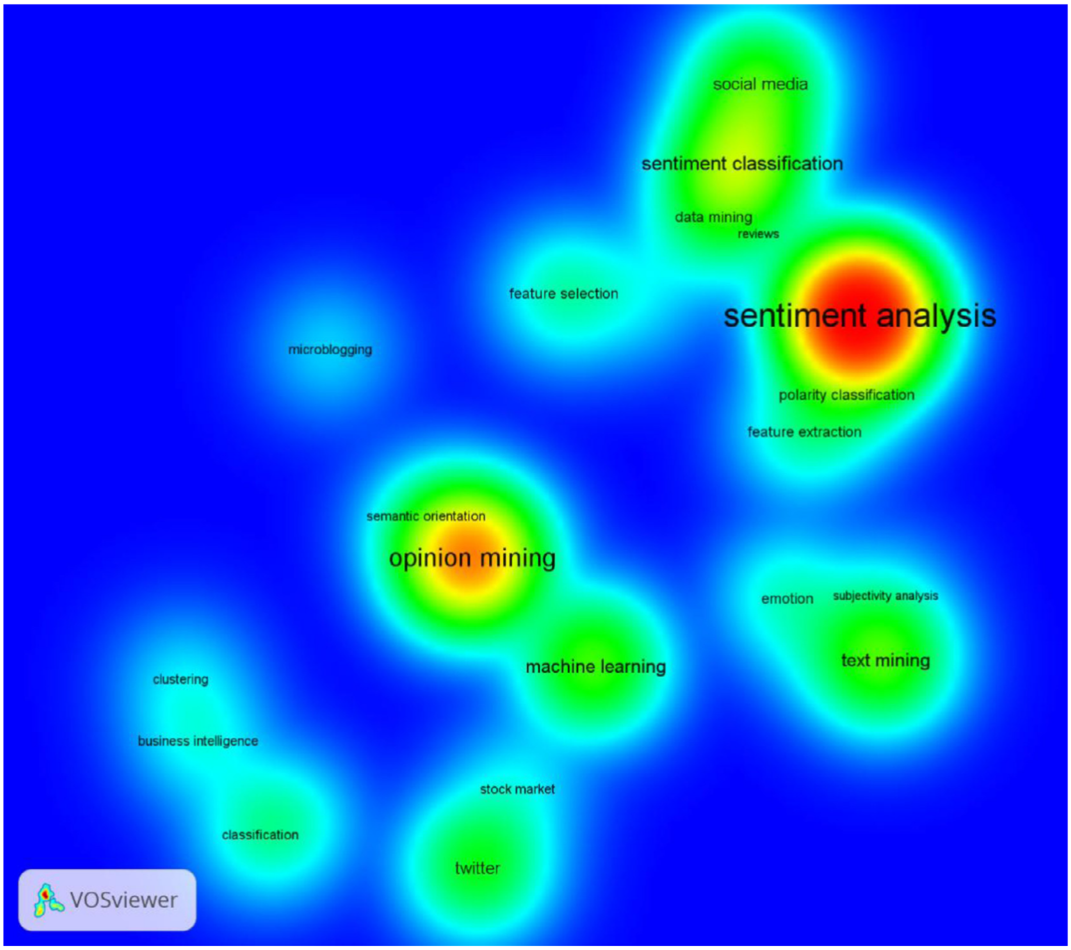

Fig. 8. Density plot for control terms.

Table 9
Top 20 results with burst detection.

S.No.	Word	Level	Weight	Length	Start	End
1	Feature Selection	1	2.10	13	2001	2013
2	Affective Computing	1	9.59	13	2001	2013
3	User Interface	1	1.06	12	2002	2013
4	Emotion Recognition	1	2.01	10	2001	2010
5	Facial Expressions	1	1.22	10	2004	2013
6	Machine Learning	1	3.62	10	2006	–
7	Affect Recognition	1	1.36	8	2003	2010
8	Human-Computer Interaction	1	1.82	7	2002	2008
9	Online Reviews	1	3.05	7	2009	–
10	Sentiment Classification	1	3.91	7	2009	–
11	Text Classification	1	0.73	6	2008	2013
12	Multimodal Human-Computer Interaction	1	0.78	5	2003	2007
13	Ontology	1	0.74	5	2011	–
14	Performance	1	0.64	4	2012	–
15	Topic Modeling	1	0.64	4	2012	–
16	Wearable Sensors	1	0.52	4	2009	2012
17	Sentiment Analysis	1	6.18	4	2012	2015
18	Aspect Detection	1	0.58	3	2013	–
19	Social Networks	1	0.38	3	2013	–
20	SVM	1	0.42	3	2011	2013

Table 10
Summary of use of different OMSA approaches (year-wise).

S.No.	Method/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	%
1	ML	1	3	3	1	4	8	2	9	7	10	26	20	36	60	60	250	67.20
2	LBM	0	0	0	0	0	0	1	3	1	2	11	17	21	22	23	101	27.15
3	ML_LBM	0	0	0	0	1	0	0	0	3	1	0	3	2	7	4	21	5.65

Table 11
Year-wise distribution of levels of analysis in ML-based publications.

S.No.	Level/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	%
1	DL	1	3	3	0	4	7	1	8	6	6	23	18	33	50	57	220	92.44
2	AL	0	0	0	0	0	0	0	0	0	1	2	1	3	8	3	18	7.56
3	DL_AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 12
Year-wise distribution of levels of analysis in LBM-based publications.

S.No.	Level/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	%
1	DL	0	0	0	0	0	0	0	3	0	1	7	10	13	10	16	60	65.22
2	AL	0	0	0	0	0	0	0	0	0	1	1	5	8	10	6	31	33.70
3	DL_AL	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1.09

manually by all the three authors, first independently and then jointly. The aim for manual reading was identifying: (a) what major approaches/ methods have been used for OMSA in these publications; (b) which of the three levels (document, sentence, aspect) are prevalent in these publications; (c) what major data sources have been used in these publications; and (d) what are the main application areas of OMSA work? We have been able to extract necessary details from most of the publications. In the sub-sections below we describe our findings on these four aspects.

4.1. OMSA – approaches and methods

OMSA research during these years primarily used two kinds of approaches/ methods: machine learning approach and lexicon-based method. Some of the works also try to combine both and some others compare both approaches. We have, therefore, tried to identify which of the publications in the dataset use machine learning approach and which ones use lexicon-based method. We also identified the papers that either combine both or try to compare both approaches. We present year-wise summary of the approaches used in publications in Table 10. We can observe that a greater number of publications (total 250) use machine learning approach for OMSA work as compared to only about 27% research papers reporting use of lexicon-based approach (total 101 research papers). There are also some publications (precisely 21 in the data set) which either try to combine both the approaches or to compare them. Further, the trend to use machine learning approach increased in the recent past with more publications in recent years (60 each in 2014 and 2015).

4.2. OMSA – levels

Our second manual task was to identify what level of OMSA work: document or aspect; has been carried out and reported in the journal publications in the dataset. We pursued all the publications on both machine learning and lexicon-based approach groups and identified the level of OMSA performed. Tables 11 and 12 show the distribution of publications among document and aspect level work from the machine learning and lexicon-based papers, respectively. The observed results confirm findings of some previous survey papers on OMSA, which showed that document-level work in OMSA has been more prevalent. We can observe that about 92.44% of the publications that use machine learning approach are document-level work. Further, the work on application of machine learning approach for aspect-level sentiment analysis started lately, with the first publication found in 2010, contributing only 7.56% of publications. In the papers on application of lexicon-based approach for OMSA, about 65.22% of the publications are on document-level OMSA and 33.70% of the publications are on aspect level OMSA. Lexicon-based method seems to be more popular for aspect-level OMSA. It is clear that in the publications using either of the approaches, document-level work is more prevalent. However, an increasing trend towards aspect-level OMSA work is also observed in the recent publications. There are comparatively lesser number of research papers that talk about both document and aspect level OMSA.

4.3. OMSA – major data sources

We have manually analyzed the research publication data obtained to find out which kinds of datasets are used by the published works on OMSA. We pursued the dataset description section of all the papers that reported some experimental

Table 13
Year-wise usage distribution of dataset types.

S.No.	Data sources/year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	%
1	Reviews	0	0	0	0	2	2	0	1	5	5	24	13	29	44	43	168	39.53
2	Twitter	0	0	0	0	0	0	0	0	0	0	1	3	8	16	19	47	11.06
3	News Articles	0	0	0	0	0	0	1	1	3	0	2	8	5	11	0	31	7.29
4	Forums	0	0	0	0	0	0	0	4	0	2	3	4	2	9	4	28	6.59
5	Videos	1	1	2	1	1	1	1	4	0	2	2	3	2	1	4	26	6.12
6	Blogs	0	0	0	0	0	0	1	1	0	0	4	3	4	6	6	25	5.88
7	Web Pages	0	0	0	0	2	0	0	0	0	0	3	0	4	6	6	21	4.94
8	Messaging Service	0	0	0	0	1	0	0	0	1	0	1	5	0	6	3	17	4.00
9	Speeches	0	1	0	0	0	1	1	2	0	1	1	0	3	1	4	15	3.53
10	Medical Data	0	0	1	0	0	1	0	0	1	1	0	1	2	2	4	13	3.06
11	News	0	0	0	0	1	0	0	0	0	0	1	1	1	1	4	9	2.12
12	Miscellaneous	0	0	0	0	1	0	0	0	0	0	1	1	2	0	0	5	1.18
13	Keystroke Patterns/Mouse Touches	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	5	1.18
14	Images	0	0	0	0	0	1	0	0	0	0	0	1	0	1	1	4	0.94
15	Music	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	3	0.71
16	Lexicon	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2	0.47
17	EEG Signals	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	2	0.47
18	Tales	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0.24
19	Airforce Data	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.24
20	Questionnaires	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0.24
21	Physiological Data	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0.24

Table 14
Year-wise distribution of application areas of OMSA.

Application name /year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
Emotion	0	1	0	0	1	2	1	2	0	3	7	7	9	4	8	45
Business Intelligence	0	0	0	0	0	0	0	0	0	2	3	7	6	8	0	26
Social Network and Media	0	0	0	0	0	1	0	1	0	1	5	5	3	3	0	19
Opinion Summarization	0	0	0	0	0	1	1	0	1	3	0	0	2	1	0	9
Psychology	0	0	0	0	1	0	1	0	0	0	0	0	2	2	1	7
Recommender System	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	6
Health	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	6
Finance	0	0	0	0	0	0	0	0	1	0	0	2	1	0	0	4
Computational Advertising	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	2
Crawling	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	2
Traffic	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	2
Election	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2
Airlines	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
Disaster Management	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Land Use	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1

work. Table 13 presents summarized picture of dataset types used in various publications. We observe that reviews are the most used datasets for OMSA work. This is quite understandable since OMSA work revolves around identifying opinionated content and its sentiment polarity. A total of 168 publications are found that use review type dataset for OMSA work. News articles and Twitter are the other popular dataset types used in OMSA work, as evident from their usage in the publications analyzed. OMSA work has also been carried out on other dataset types such as blogs, messaging services, speeches etc.

4.4. OMSA – applications areas

OMSA work has application in various domains and hence it is imperative that OMSA research work would have been done in different application areas. We have analyzed the research publication data to identify major application areas of OMSA work. First of all, we identified the papers that are on application of OMSA techniques in some domain and then identified the area of application. Table 14 presents the distribution of publications along different application areas. We observe that Emotion is the major field of application of OMSA work. Business Intelligence and Social Networks and Media also have good number of publications. Other application areas of OMSA work encompass varied disciplines ranging from Finance and Health to Election and Traffic. OMSA work is thus an important area of research with applications to wide domains.

5. Conclusion

In this paper, we have performed a comprehensive scientometric as well as detailed manual analysis of research output in OMSA published in SCIE journals during 2000–2015. The research publication dataset has been computationally and manually analyzed to map the OMSA research landscape during last 16 years. The scientometric analysis helped in identify year-wise number and rate of growth of publications, types of authorship of papers on OMSA, collaboration patterns in publications on OMSA, most productive countries, institutions, journals and authors, citation patterns and an year-wise citation reference network, and theme density plots and keyword bursts in OMSA publications during the period. The manual analysis helped in identifying popular approaches (machine learning and lexicon-based) used in these publications, levels (document, sentence or aspect-level) of sentiment analysis work done and major application areas of OMSA. The analysis has successfully provided an analytical account of progress of the discipline from its inception to state of the art today, major milestones in the journey, the disciplines that OMSA research has drawn inspiration from and the areas it has been applied, major approaches and methods used in the OMSA research, and a meme map of major concepts and keywords in the area.

This computational and manual analysis provided us the answers to various research questions stated in Section 1. First of all, year-wise growth pattern indicates that there is a constant and significant growth in research output on OMSA (with number of publications doubling every two years). The country-wise distribution of OMSA research shows that OMSA research is now geographically widespread, though China and United States of America still produce most of the research papers. In terms of International Collaborative Paper (ICP) instances, China and United States of America again stand at the top with most ICP instances as well as the strongest collaboration link during the period. This study also identifies that the most productive institutions in OMSA research are Chinese Academy of Sciences (according to TP), MIT (according to ACCP) and Chinese Academy of Sciences (according to *h*-index). We also observe that the top publication sources are Expert System with Applications (according to TP), Computational Linguistics (according to ACCP) and Expert System with Applications and IEEE Transactions on Affective Computing (according to H-index). The analysis identifies Cambria Erik as the most productive and Thelwall Mike as the most cited author on OMSA research. On authorship pattern, we identify that there are more multi-authored publications in OMSA than single authored publications. The analysis further identifies that OMSA publications are in wide variety of disciplines. A control term-based analysis identifies social media, microblogging, emotion, topic modeling, machine learning etc. as important terms seen in the research output, which is further elaborated by Burst detection algorithm. The computational results present a first of its kind analytical overview of the OMSA research area. Researchers in the area can benefit a lot from these results.

The manual analysis helped in answering other research important questions. We observe that more OMSA research output is based on machine learning approach (67.20% of the output) as compared to lexicon-based approach (27.15% of the output). Further, more OMSA work is seen on document-level sentiment analysis (92.44% for machine learning approach and 65.22% for lexicon-based approach). It is also observed that reviews constitute the most frequently worked on dataset for OMSA research followed by twitter and news articles. The analysis helps in identifying the primary application areas/ domain in which OMSA work is being done. We can observe that OMSA as a research area is both growing rapidly and has applications in a wide variety of areas. Overall, this paper presents a detailed analytical account of OMSA research during 2000–2015 by computationally and manually analyzing the research publication data in OMSA. The paper helps in understanding the broader landscape of OMSA research and presented results useful for researchers (and those planning to start research) in the area. The analytical results are, to the best of our knowledge, are first of their kind. The results would be useful from various perspectives to researchers/ professionals working in the area.

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