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METHODOLOGIES AND APPLICATION

A personal knowledge management metamodel based on semantic analysis and social information

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Abstract This article describes the development of a functional architecture for personal knowledge management (PKM), defined from the lessons-learnt concept registered in a mass-use social network analyzed with an algorithm of machine learning. This functional architecture applies, in practical manner, the implementation of a registry system of the personal lessons learnt in the cloud through a Facebook social network. The process starts by acquiring data from the connection to a non-relational database (NoSql) in Amazon's SimpleDB and to which a complementary analysis algorithm of machine learning has been configured for the semantic analysis of the information registered from lessons learnt and, thus, to study the generation of organizational knowledge management from PKM. The result is the design of a functional architecture that permits integrating the Web 2.0 application and a semantic analysis algorithm from unstructured information by applying machine learning techniques.

Keywords Knowledge management · Tacit knowledge · Knowledge model · Organizational learning

1 Introduction

One of the trends in the study of knowledge management (KM) that has gained notoriety in recent years is personal knowledge management (PKM), which is held as a process prior to organizational knowledge Management (OKM). This work focuses on the design and implementation of machine learning for support the functional architecture for knowledge management as a basic tool to integrate systems supported on cloud computing through social networks. The work seeks to show the possibility of a KM metamodel evidenced in a prototype of an application implemented in the Facebook social network, which demonstrates the possibility of doing OKM from PKM; the latter is developed from the base concept of the lessons learnt by individuals.

The work was carried out in phases, with the first phase being the development of the conceptual aspects that define its structure. It starts with the conceptualization of the aspects that define and comprise a metamodel (Montenegro Marín et al. 2011) and the stages that must be considered for its construction. Thereafter, the definitions of KM and PKM are presented. Regarding PKM, the work delves into and shares the new research trend that stipulates that flexible scenarios are required to support the knowledge generated by each human being (Nasiri et al. 2013). At the end of this conceptualization phase, social network aspects will be worked on along with their support for the generation and socialization of knowledge, closing with the detailed concept of the lessons learnt as the type of knowledge that will be worked on in the metamodel developed as the proposal in this work.

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The second part focuses on describing in detail the design, implementation, and verification of the prototype for Facebook. This will be implemented in the cloud through a non-relational database that will support the real registry of an undefined and random number of lessons learnt, which—in turn—apply and evidence the concept of flexibility of scenarios for PKM.

The final phase presents the second component of the applied model, which is the ontological analysis system, as tool and big data technique that verifies the real possibility of conducting OKM from PKM. Examples implemented in the prototype show the use of the socialization strengths generated in social networks in recent years and in the possibility of combining structured and unstructured knowledge for OKM.

2 State of the art

2.1 Knowledge management

Tacit knowledge as the first state of knowledge (Nonaka and Peltokorpi 2006) has peculiarities characterized to define the strategies of its management. This knowledge can be divided into knowledge yet to be formalized and knowledge that cannot be formalized (Kakabadse et al. 2001). Knowledge that can be formalized and described explicitly is particularly characterized as "know how," also called "tacit cognitive" knowledge, and when it is specified through some tangible means, it becomes "explicit knowledge". Stemming from this concept, KM theories focus on the mechanisms that permit keeping knowledge within organizations (Haas and Hansen 2007; Moon and Lee 2014) and in said evolution different models have been proposed, which now lead us to prefer working on the PKM concept, as one of the last work trends in this area.

2.2 Personal knowledge management

According to Razmerita et al. (2009), Miller (2005) and Pauleen (2009), PKM is a trend that manages to complement and rethink the dynamics of research and formalization of KM at organizational levels. These authors have delved into its conceptualization, highlighting the importance of PKM, as base nucleus of any greater magnitude process of KM, concluding on the need to for more experimental research on it. The first versions of KM systems have been mainly concerned with establishing integrated organizational systems that have often overlooked the basic parameters for "the person," who is the center of the generation of knowledge, to register, organize, and collaborate with the generation of new knowledge (Miller 2005).

Also, PKM is supported on Web 2.0 through a set of tools that permit individuals to create, encode, organize, and share knowledge, as well as socialize, broaden personal networks, collaborate in its organization, and create new knowledge (Razmerita et al. 2009; Pauleen 2009). These authors base the characteristics of a system for PKM from the use of Web 2.0 resources to avail of online communication and socialization mechanisms. For example, Chatti (2012) proposes evolving in models that visualize performance indicators and PKM as objects and processes toward models based on an ecological view, which starts from the principles of socialization networks. Other works like Alonsoet al. (2013) propose other type of applications for web 2.0 communities, based on linguistic consensus models.

The interaction between the tacit and explicit dimensions of knowledge defines its nature by studying the source from where it is generated. A creation perspective exists related to the knowing entity (Nonaka and Peltokorpi 2006), which defines collective knowledge as an aggregation of individual knowledge. This aggregation cannot be generalized linearly as a sum of elements, given that its evolution generates a synergy that establishes that collective knowledge be a more complex process that integrates structures, dynamics, and relationships (Spender 2006).

2.3 Lessons learnt

Social capital has emerged as an adequate framework to explain knowledge exchange and transference mechanisms in organizations (Widén 2011). One of those mechanisms is denominated lessons learnt, which are defined as a type of explicit knowledge that results specifically from two main opportunities:

- Errors and/or strengths obtained during any process of knowledge application or generation.
- And from the possibility of innovation of an objective sought to be reached (Brent Robertson 2008).

These can also be defined as a type of knowledge that results from experience through complex, systemic, asynchronous, and individual reflection processes (Greer 2008). For knowledge transference to satisfy the needs of organizations, lessons learnt must be presented now and within the adequate context, thus defining the principle of opportunity. Thereby, knowledge generated can be reused (Richter and Weber 2013).

Additionally, the conclusions of related works recommend that any process of generation of lessons learnt be supported on information systems with databases that permit diversity of models and objects of knowledge (Greer 2008). This seeks to facilitate precise location and rapid consultation of information required for knowledge to be subsequently distributed and accessed in timely manner by all those involved or interested in the context or situation being worked on Cardenas and Spinola (2013).

In complementary manner, the opportunity to use lessons learnt also depends on systemic aspects that integrate, manage, and support an actual and closer concept of KM. Among these aspects, the following may be described: i. interested personnel; ii. a theme requiring their generation and consultation; iii. related experts; and iv. a system that supports the interaction and flow of said management (Fahey and Burbridge 2008).

2.4 Machine learning in the analysis of social behavior for knowledge management

Analysis of social behavior by applying semantic techniques (machine learning) is considered a new paradigm in OKM (Delen et al. 2013). Recently, the use of data and information extraction stemming from structured sources like Web 2.0 applications is gaining terrain in the study of the social web (Lancieri and Lepretre 2015; Schatten 2013). Cases of interest and publications have been reported in the field of social networks integration and their analysis (Mochón 2016). This new semantic approach permits the dynamic change of the semantic social network and establishment of knowledge management models (Herrero et al. 2016) from and toward people in organizations.

Modern organizations had never had new needs and opportunities to use their knowledge more rapidly and efficiently from the implementations of applications supported on semantic analysis. Construction of sophisticated knowledge bases, decision support systems (De Maio et al. 2014; Cabrerizo et al. 2015; Molinera et al. 2016; De Maio et al. 2016; Morente-Molinera et al. 2016), as well as other intelligent systems often takes time and considerable economic resources (Breslin and Decker 2007). Studies like those by Cantador and Castells (2006) have implemented diverse web mining techniques to extract the semantics of the social structure underlying people's behavior, preferences, and tendencies. Although it is important to analyze existing online social networks, the data and information extraction process related to profiles of users in applications supported on social web from structured sources, inevitably provokes a loss of the real semantics of the social system.

The semantic analysis is identified as the tool that allows the combination of complex algorithms applied to the generation of knowledge in large strings of data and texts mainly. This has developed and evolved from the basic concepts of analysis of qualitative data and today already shows significant progress for machine learning (Wiedemann 2016), to new techniques such as search engine vertical that already operate on unstructured data (Laura and Gianluigi 2015).

3 Methodology

3.1 Architecture

The KM metamodel applied herein was derived from the metamodel developed by Ammann (2008). Its structure is described through six entities: people, processes, documents, themes, tacit knowledge, and explicit knowledge. It abstracts essential entities from a domain of interest and its interrelations with the concepts of metamodels applied to KM and to software development.

For its dynamic part, advanced processing techniques are included for application through the "big data" technique, denominated "latent semantic indexing (LSI)". Figure 1 shows the flow or relationship among elements or entities that make up the metamodel proposed: data-information-knowledge. The metamodel proposal integrates entities in the following manner:

The previous architecture is structured so that each of the components is interrelated for transmission within the chain of organizational data, information, and knowledge given through the following elements:

- *Processes*: The definition of necessary processes for the interaction of people and resources or platforms that comprise the system.
- *People*: The metamodel should be based on the interaction of tacit knowledge from the lessons learnt of each participant.
- *Repositories*: The opportunity to develop in the model and prototype the necessary documents and evidence of said lessons and of the model itself.
- *Topics (themes)*: Represented in the possibility of defining categories and themes to generate knowledge from the different profiles of people who interact with the system.
- *Tacit knowledge*: Described and evidenced through the lessons learnt that exists in each human being.
- *Explicit knowledge*: Reflected through the treatment of the lessons learnt in new forms of knowledge, using advanced processing techniques.
- *Machine learning (semantic analysis)*: The semantic analysis process is applied on an unstructured base, that is, sets of terms in a domain determined in text format. Each of data analyzed behaves as taxonomy; the process oversees identifying key terms and classifies the terms the vocabulary contains within the database; this is to enable a simpler search for the system.

The taxonomy gathers various terms around a set of concepts to then map and fraction these through the text mining flow implemented in Konstanz Information Miner (KNIME) (Berthold et al. 2008). The semantic analysis process, hence,

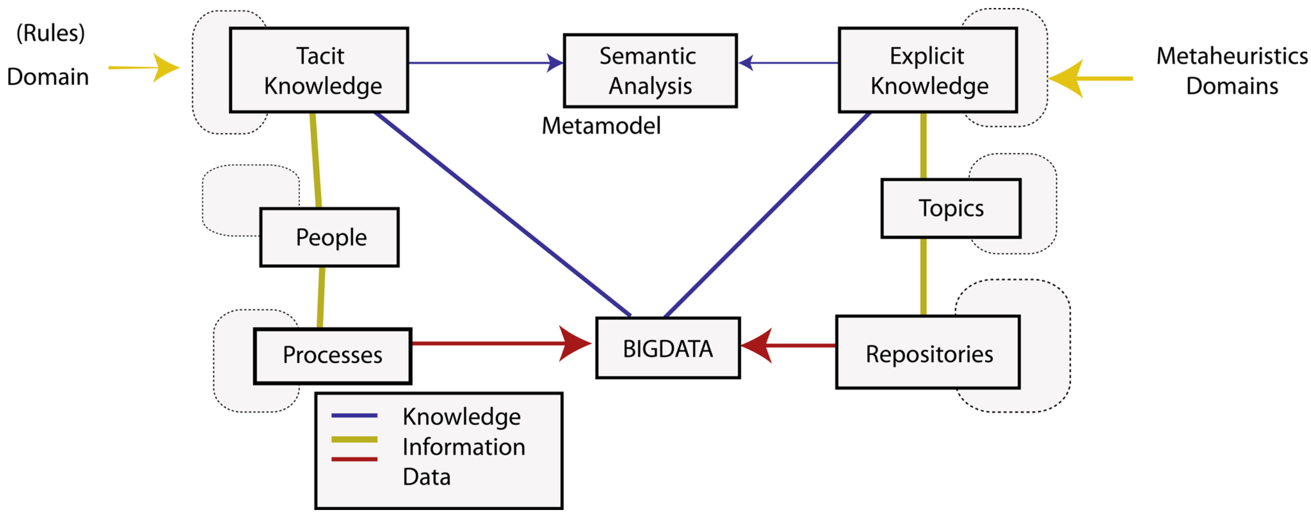


Fig. 1 Global architecture of the KM metamodel

facilitates the inference of the concepts in which users are interested, even if those concepts are not explicitly among the terms users have shared.

The metamodel uses the logical sequence of data, information, and knowledge. These three elements circulate through each of the entities of the model. The upper layer evidences the execution of a semantic analysis fed by sources of tacit and explicit knowledge. Tacit knowledge and explicit knowledge gather information from people and themes of interest, primarily. These, in turn, receive information from processes and repositories and, simultaneously, provide data to be processed by the Big Data LSI technique.

Besides, the characteristics sought from the lessons learnt for this metamodel are: flexibility, diversity during generation moments and the ways these can be generated. These characteristics correspond to those previously linked to those exposed from PKM; hence, lessons learnt can be reasserted as a type of knowledge that represents the characteristics of PKM systems.

3.2 General model: QIRISYA

The QIRISYA prototype, as the application will be identified ahead, was generated from the same conception of the model of lessons learnt within a social network environment. For its design, software has been developed to permit registering the lessons learnt by each user with a structure defined in three levels: profile, categories, and subcategories. These can be established in personalized and flexible manner by each user. Given the vast amount of contributions expected, a non-relational database will be used to avoid the possibility of application saturation. The prototype can be seen in Fig. 2 with its explicit components: 1. User or knowing entity. 2. The application in the social network (Facebook). 3. The platform that supports the application: non-relational database. 4. The semantic analysis system.

The user records the lessons learnt initially in the form of explicit knowledge, describing in text format the knowledge or experience acquired and recording it on the profile, category and subcategory in which he/she seeks to relate it. These lessons do not have text limit, can be described as reflections, both simple on very punctual events and complex on the analysis on the participation in a project or on the reflection about another professional, personal, or educational activity.

To complement the prototype, a semantic analysis application was developed to permit precisely identifying and quantifying trends in the generation of knowledge, using key words and making the configuration for group analysis in the social network (Facebook). This facilitates the characterization of knowledge generation in work teams, i.e., this last module permits bringing PKM in practical manner to an application of OKM. Convergence of knowledge is an interesting topic as discussed in Pandey and Nandi (2016).

To develop the functional application of lessons learnt, it was necessary to use different libraries that permit making structured connections and designs, these are:

– *Facebook SDK PHP* (Facebook 2013): Used to make the communication of the external application with Facebook, defining the necessary permits and obtaining this platform's necessary data, like name, profile image, and identifying number of the user's account.
– *The FancyApps & Skarnelis* (2013): Used to manage the iframes on transparent backgrounds in the deployment of some of the notifications.
– *GoogChart* (Pettersson 2008): Used to generate pie graphs and bar diagrams.

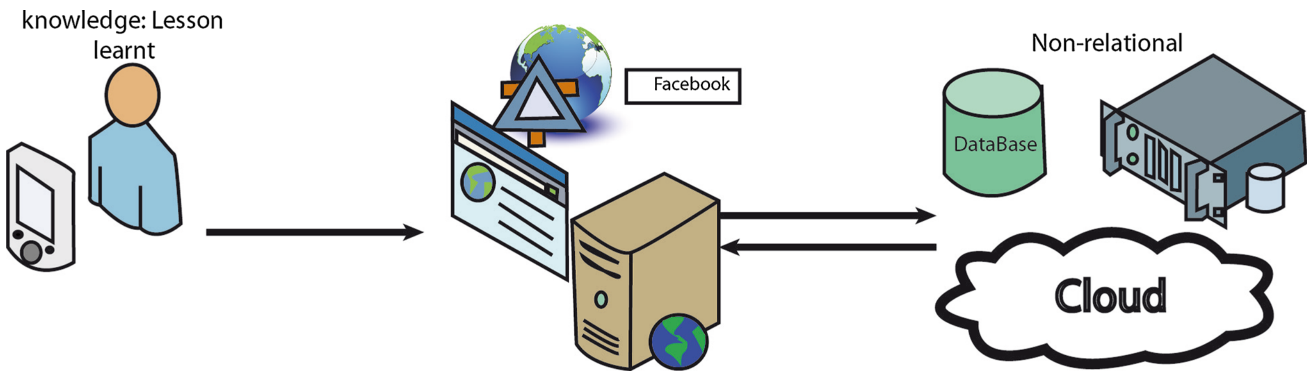


Fig. 2 General prototype diagram

- *JQuery API* (jQuery Foundation 2013): It is a javascript framework used to give dynamism to html pages and it is used as base by different APIs.
- *jsDatePick* (Arjuan and Walsh 2013): It is a javascript calendar that permits selection of dates upon defining the limits to generate graphics.
- *AWS SDK for PHP* (Amazon Web Services 2013): Used to establish communication between SimpleDB and the application, permitting manipulation of the necessary data through a development interface.

3.3 Design of the functional architecture and semantic analysis algorithm

For this part, we are reminded that semantic-supported social analysis is a type of explicit specification of a shared formalization of behaviors. It represents the concepts, objects, and other entities that supposedly exist within an area of interest together with its relationships (Schatten 2013). Semantic analysis studies the conceptual aspects of social graphs. It is established in knowledge engineering and, particularly, in the semantic web, along with the principles of text mining and web mining. Currently, some important applications of these two research fields have been published and applied to solve the evident needs of innovative applications, for example, in consumption tendencies in e-commerce or in the publicity segmentation in social networks.

This section presents the development of the functional architecture that permits semantically analyzing lessons learnt from a data source defined and incorporated by each user onto the prototype (*QIRISYA)*; crossing the structure of profile, categories, and subcategories defined by it. Semantic analysis on lessons learnt permits determining in an organization the current trends and behaviors that are a support for a foresight study of possible strategic planning goals, specifically in the management of human capital. In conclusion, the functional architecture will be applied in practical manner to analyze the profile behavior of users of an organization supported on social web applications.

Given the large quantity of contributions expected, an unstructured data source is used that permits reducing the possibility of application saturation. Graphically, the architecture is shown in Fig. 3, where the flow is shown: data, information, knowledge through a logical sequence given among the application, the data source, and the segmentation of groups of people. The flow is guided from the social behavior of specific groups given by the social analysis process from the textual sources incorporated.

The model is supported on the use of social graphs, specifically in social networks (Web 2.0), in which leaders can be identified and due to the rate of information circulation in the web, new analysis possibilities may emerge, given the existence of a continuous flow of information. The architecture proposes mechanisms for simple consultations seeking to facilitate support of decisions by connecting existing databases and corporate information systems through web services. The result proposes the development of a comprehensive solution aimed at KM and whose objective is to establish the current state of the organization and its environment regarding the determination of work profiles and competencies. Implementation and use of this framework was conducted from several characterizations of users with different profiles and needs. Users selected followed the application's linking procedure and started to define their profiles and categories, permitting—in turn—to register lessons learnt in the application.

Figure 4 shows a chronological behavior of a user with his/her respective categories and profiles within the framework established by the application. Here, the system permits registering several lessons and, upon using the distinct options (like private and public records), information is managed from lesson-suppression operations, modification and visualization of statistics, and record of evidence of typifying the lessons learnt in the distinct profiles and categories.

Within the architecture proposed, the application of concepts requested by various authors is evident, when they state that further development is needed to facilitate PKM and which in this project has been visualized from the concept

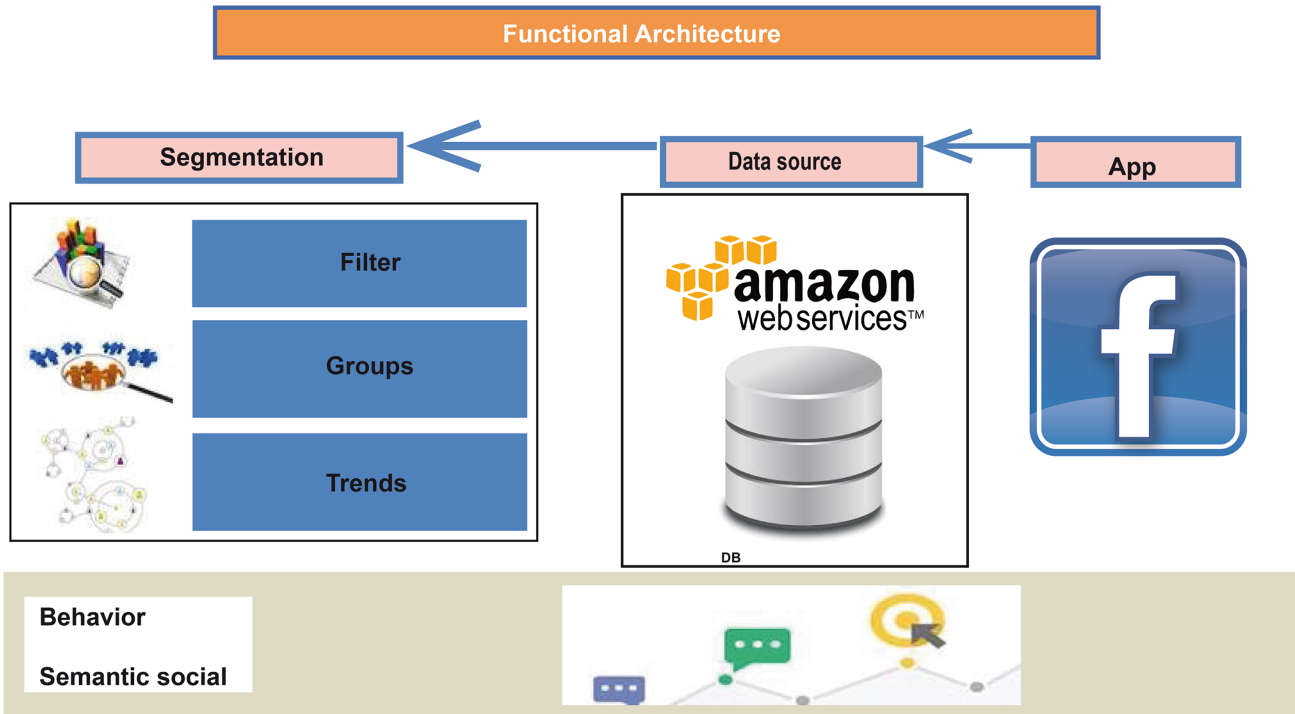


Fig. 3 General structure of the semantic analysis algorithm

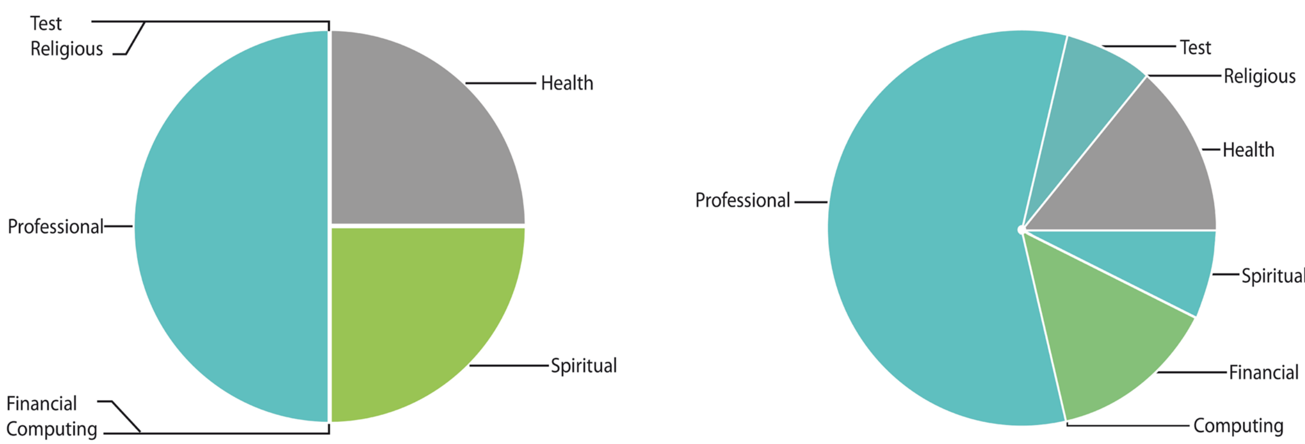
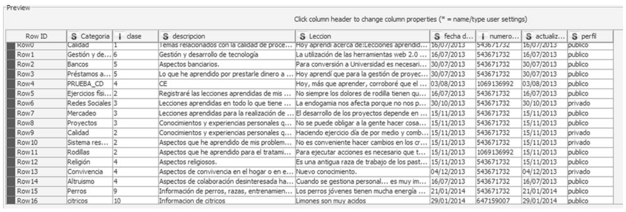


Fig. 4 Lessons-learnt typifying diagram

of the "lessons-learnt typifying diagram" through a social network (tacit knowledge → explicit knowledge), as shown in Fig. 1. Hence, it is permitted to profile each individual or groups of people, their generation of knowledge, showing the emphasis or progress of their lessons learnt in ranks or time periods defined by each user of the prototype. Finally, by applying an algorithm supported on textual analysis techniques at semantic level like LSI (Suárez Barón and Kathleen 2009), we can inquire on trends and on the reality of the generation of knowledge being carried out in work teams, thus using the dissemination of lessons learnt from each of its members.

3.4 Semantic and social analysis algorithm on lessons learnt in Web 2.0 applications

Suppose the organization involves in its profiles three trends: a) project management, b) knowledge management, and c) management of innovation and technological development. An analysis process of social behavior is of special interest for KM, especially in dynamic environments where roles and profiles must be analyzed by the members of an organizational unit (López-Cruz and Nelson Obregón 2015). This is done to establish if a member has or does not have certain skills and/or knowledge; and, also, to analyze that other



Preview

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Row ID	S Categoria	I clase	S descripcion	S Leccion	S fecha d...	I numero...	S actualiz...	S perfil
Row0	Calidad	1	Temas relacionados con la calidad de proce...	Hoy aprendí acerca de:Lecciones aprendid...	16/07/2013	543671732	16/07/2013	publico
Row1	Gestión y de...	6	Gestión y desarrollo de tecnología	La utilización de las herramientas web 2.0 ...	16/07/2013	543671732	16/07/2013	publico
Row2	Bancos	5	Aspectos banciarios.	Para conversión a Universidad es necesari...	30/07/2013	543671732	30/07/2013	publico
Row3	Préstamos a...	5	Lo que he aprendido por prestarle dinero a ...	Hoy aprendí que para la gestión de proyec...	30/07/2013	543671732	30/07/2013	publico
Row4	PRUEBA_CD	4	CE	Hoy, más que aprender, corroboré que el ...	03/08/2013	1069136992	03/08/2013	publico
Row5	Ejercicios fisi...	2	Registraré las lecciones aprendidas de mis ...	No siempre los dolores de rodilla tienen qu...	16/07/2013	543671732	16/07/2013	publico
Row6	Redes Sociales	3	Lecciones aprendidas en todo lo que tiene ...	La endogamia nos afecta porque no nos p...	30/10/2013	543671732	30/10/2013	privado
Row7	Mercadeo	3	Lecciones aprendidas para la realización de ...	El desarrollo de los proyectos depende en ...	15/11/2013	543671732	15/11/2013	publico
Row8	Proyectos	3	Conocimientos y experiencias personales q...	No se puede obligar a la gente hacer cosa...	15/11/2013	543671732	15/11/2013	publico
Row9	Calidad	2	Conocimientos y experiencias personales q...	Haciendo ejercicio día de por medio y comb...	15/11/2013	543671732	15/11/2013	privado
Row10	Sistema res...	2	Aspectos que he aprendido de mis problem...	No es conveniente hacer cambios en los cr...	15/11/2013	543671732	15/11/2013	privado
Row11	Rodillas	2	Aspectos que he aprendido para el tratami...	Para ejecutar acciones es necesario que t...	15/11/2013	1069136992	15/11/2013	publico
Row12	Religión	4	Aspectos religiosos.	Es una antigua raza de trabajo de los past...	15/11/2013	543671732	15/11/2013	publico
Row13	Convivencia	4	Aspectos de convivencia en el hogar o en e...	Nuevo conocimiento.	04/12/2013	543671732	04/12/2013	privado
Row14	Altruismo	4	Aspectos de colaboración desinteresada ha...	Cuando se gestiona personal... es muy im...	16/07/2013	543671732	16/07/2013	publico
Row15	Perros	9	Información de perros, razas, entrenamien...	Los perros jóvenes tienen mucha energía ...	21/01/2014	543671732	21/01/2014	publico
Row16	citricos	10	Informacion de citricos	Limones son muy acidos	29/01/2014	647159007	29/01/2014	publico

Fig. 5 Data set obtained

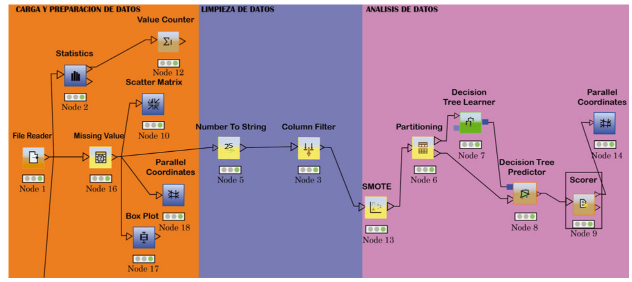

Fig. 6 Algorithm and analysis flow developed

members should and can support other members of the organization in very particular or special roles. Thus, the question arises: How do you find the most suitable person for a given function, considering the social network? (Thovex and Trichet 2011). To answer said inquiry on the practical use of the prototype, a textual analysis algorithm is presented applied to the data source from the Web 2.0 application. The algorithm is elaborated via a KNIME data environment that permits performing a predictive non-probabilistic social analysis from machine learning techniques to determine possible behaviors and social tendencies in lessons learnt in the QIRISYA Web 2.0 application. Machine learning is applied to solve a great range of different problems such as Anacleto et al. (2015) to facilitate step characterization avoiding the use of the Global Navigation Satellite System, and is the topic of a great number of different research topics (e.g., García-Díaz et al. 2015).

The algorithm elaborated through the KNIME flow permits determining, from machine learning techniques, a set of classifications, groups, and predictions on the current state of acquisition and KM on certain lessons learnt managed through the web service. Now, the data source corresponds to nominal attributes and unstructured text sources that contain information about the classes, profiles, categories, descriptions, codes, dates of registry, and control, along with all the terminology appertaining to a set of lessons learnt in KM.

The characteristics of the data source include that in their totality they can be considered sequential multivariate data on time line. In the data cleansing and filtering process, information is converted from text chain type to nominal attributes that facilitate follow-up and interpretation of results. However, filtering of columns considered not having relevant information during the analysis process and, finally, a data balancing process was applied from the nearest-neighbor technique to give an oversampling to the minority class to mitigate deviations due to data still lacking. Figure 5 shows the result obtained of preliminary data cleansing which will lead to the following data analysis phase.

The data source provided by the model comes specifically from a relational database embedded in a web service (Amazon web Services); this web service inter-operates with a web application (QIRISYA) aimed at management of Web 2.0 lessons learnt.

During the information analysis process through machine learning, supervised analysis techniques were applied given that work was undertaken from a classification; for this the attribute "profile class" was determined as class; application of decision trees became a fundamental tool in the process. A type of gain ratio without pruning was implemented to the decision tree with 70% training data and 30% prediction data.

Development of the graphic environment for the social analysis in Fig. 6 shows part of the model comprising of a series of nodes, which encapsulate the machine learning algorithms and time-line sequences, representing the data flows deployed and combined in interactive manner.

4 Results

As mentioned in previous sections, the repository analyzed corresponds to the information from the (QIRISYA) application database; the need to apply a cleaning and transformation process was also determined to proceed to the analysis. The attributes analyzed correspond to information of lessons learnt within an organizational context in determined times, as observed in Table 1; the data stored in the database are finally categorized and synthesized, thus:

The social analysis of the data source using machine learning algorithms applies two experimental scenarios. The first scenario shows the correlation among the lessons learnt on a given theme and the profiles assigned to each category. In an exploratory scenario, it can be noted how some skills are identified within the data set of lessons learnt; Fig. 7 permits graphically comparing the class behavior (profile) in distinct groups of lessons learnt; for example, for classes 2 to 5 we find the highest continuous concentration of lessons in each time space. Meanwhile, Fig. 8 identifies and evidences the correlation among the class, category, and lessons learnt attributes. Here, classes 2, 3, 4, and 5 make up a direct social and semantic correlation with any of its categories. Likewise, the conformation of special relationships is evidenced in certain classes with some lessons learnt; for this reason, natural groupings can be preliminarily identified among pro-

Table 1 Description of data set attributes

Category	Class	Description	Lesson
Defines the category of lessons learnt	Identifies the profile classifier	Describes the type of profile	Determines the lesson learnt in a category
Date of record	Record number	Profile update	Profile
Indicates the date of incorporation of the lesson	Record consecutive	Date of consolidation of lessons learnt	Public or private

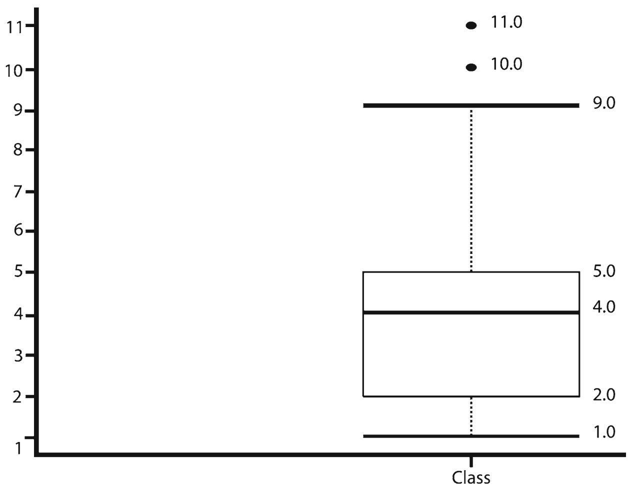

Fig. 7 Continuous distribution of the class attribute

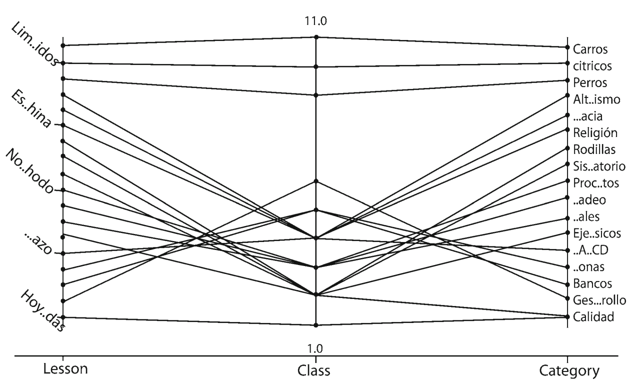

Fig. 8 Correlation among attributes

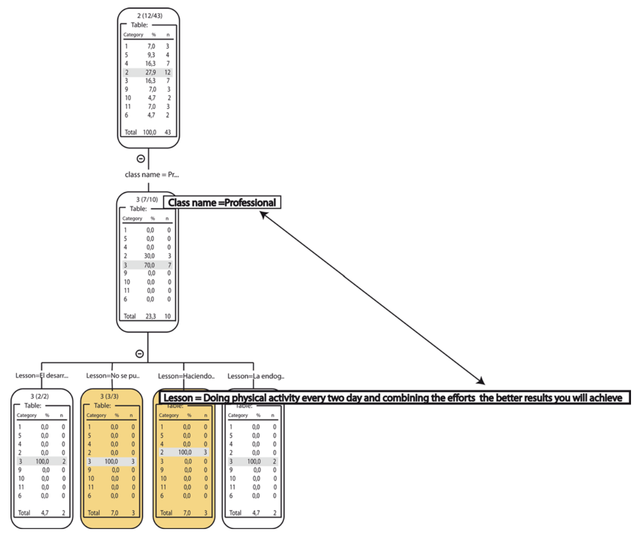

Fig. 9 Partial decision tree generated in the social analysis model

file class, categories of lessons learnt, and the same lessons learnt. Within this context, an organization needs to use KM to guarantee successful implementation of change, as well as to maintain long-term competitive advantages from its intellectual capital.

The second scenario evidences the supervised classification criteria from decision trees that permit determining the tendencies and projections of the lessons learnt. The experimentation approached for the study of social behavior on lessons learnt in KM allows determining from a classifier (class) what the tendencies within a group in acquisition of knowledge from experience, which is a key factor (Alberto Carrasco et al. 2015).

Observation of the results obtained for the sample of skills acquired from lessons learnt studied demonstrates that the model produces part of the lessons learnt and results in themes like "health in the profession" and "experiences in the profession," originating a projection and tendency that can help to improve "quality," "professional skills" and "health conditions at work". Although, both "health" and "profession or labor" are different categories; semantically, the model determines that a direct relationship exists between the "labor activity" and "health" activities. Observing the decision tree in Fig. 9, which is generated in the machine learning process in the model developed, it can be identified that the initial node on the tree congregates nine of the 11 labor profiles controlled by the class attribute.

The decision tree provides an adequate structure to determine skills from the lessons learnt; it may be extrapolated as a multidisciplinary, dynamic, and non-probabilistic model to optimize performance, organizational learning, and organizational behavior, which are vital premises in the construction of KM systems. Herein, experiments are being conducted with a first multidisciplinary model of classical

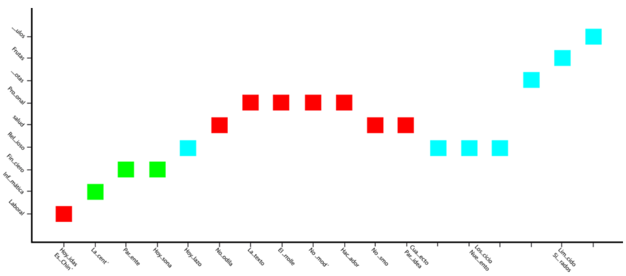

Fig. 10 Conformation of group profile (clusters)

measures to unify competencies, skills, and lessons learnt. This is to bring them to the application of the analysis and engineering of knowledge, supported on machine learning techniques to provide and extract semantic relationships between concepts and propose as the following phase a meta predictive non-probabilistic model of broadened semantic social network analysis.

Also, three natural groupings emerge in the experimental study of the people who have relative knowledge and who provide different learning perspectives. A group is inclined to diminishing in uniform and weak manner its activity related to a knowledge domain, in the sense of applying lessons learnt in the "pets" and "vehicles" domain, while another natural group invites other profiles to consume significantly less knowledge to focalize on priority themes. It may be interpreted as a need of academic formation, or of a tutorial imparted by the individuals who already had the competency.

The third group, as shown by Fig. 10, represents a close social and semantic relationship among category, profiles, and lessons without regard to the time series, under three natural groups of profiles; in this scenario, the financial, religious, and labor profiles mark a mutual relationship with the health profile.

5 Conclusions and future work

This work permits inferring that the development of empirical systems to apply PKM from algorithmic techniques supported by semantic social analysis is a latent, but real organizational alternative to manage knowledge and define improvement alternatives.

It is important to recognize that we successfully proposed an architecture (based on previous experiences such as García-Díaz et al. (2009)) that is applied and adapted to the world's most used social network and it is, likewise, supported on tools that facilitate their exponential growth, such as Amazon's SimpleDB database.

This work has several extensions in its practical and research application, arising from each of its functional and structural modules, for example, from the functional point of view it would be important to continue delving into the systemic use of the application on knowledge generation routines for each person involved in the lessons-learnt generation process. It may also be possible to delve into the dynamic generation of more lessons when including modules like early warnings in the use of the application. From the structural point of view, it would be necessary to verify the characterization in using the database to measure efficiency in its use, to reach a commercialization and massive-use process of the prototype at organizational levels.

In large volumes of data, a semantic analysis applied on a big data tool will permit asking a team or work group how their dynamic capacities are being generated for KM and what is the profile developed in it, from a systematic analysis of the individual or personal profiles of each of its members in a time line.

As indicated by some authors referenced in this work, the knowledge needs to continue its development of comprehensive and adequate spaces where each person or individual is comfortable and to facilitate the flow of it. In this way, you can build the ability to carry tacit knowledge to explicit knowledge, and thus allow the joint with learning objectives within the contexts that are developed. Finally, this model would be the first version to achieve a powerful version of a predictive non-probabilistic model of broadened semantic social networks analysis as basic component of the metamodel proposed in the functional architecture.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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