A Semantic Approach to Model Multimedia Information and Social Networks for Cultural Heritage

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Abstract.
The social aspect of information has a crucial role in our everyday life. In this context, the representation and management of Online Social Networks (OSNs) represent a new challenge in the research community. In particular, the use of heterogeneous data needs an extension of OSNs to Multimedia Social Networks (MSNs). In this paper we propose a general high-level model to represent and manage MSNs. Our approach is based on a property graph represented by a hypergraph structure due to the intrinsic multidimensional nature of social networks and semantic relations to better represent the networks contents using semantic web vision. In addition, the use of the proposed graph structure allows to discriminate different levels of knowledge analyzing the relationships defined between nodes of the same or different type. Moreover, the introduction of low-level multimedia features and a formalization of their semantic meanings give a more comprehensive view of the social network structure and content. Using this approach we call the represented network Multimedia Semantic Social Networks (MS^2N). The proposed data model, based on a top ontological model for knowledge representation, could be useful for several applications. We also propose a case study on cultural heritage domain.

Keywords: Multimedia social networks, Ontologies, Semantics, Data integration, Graph DB

1. Introduction

The social aspects of internet technologies, along with the arise of many online communities and social networks are leading to a massive production of information content that need novel formal data structures to represent this kind of information and the retaliations among contents. Moreover, the pervasive use of mobile devices feeds this phenomenon, generating an enormous amount of data in terms of volume, velocity and variety [1] and such ubiquity change the Internet into a global channel for the delivery of a huge quantity of multimedia contents. To give an idea, according to [2] data generation in 2017 has been estimated at 2.5 Exabytes (1Exabyte=1.000.000 Terabytes) of data per day.

In fact, the development of mobile technologies and the improvement of Internet bandwidth capabilities led the transition from text-only communications to a richer multimedia experience allowing users to share multimedia data, such as video, images and text. On the other hand, the fast growing up of people using Online Social Networks(OSNs) create new scenarios where data have to be collected and represented in a more efficient way and transformed into information. The new challenges are mainly focused on problems such as data processing, data storage, data representation, and how data can be used for pattern mining, analysing user behaviors, and visualizing and tracking data, among others.

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The combination of multimedia data and social networks has resulted in Multimedia Social Networks (MSNs) that support new ways of user-to-user and user-to-content interaction.

In this context, user-shared multimedia objects are playing an increasingly central role, becoming an interesting trend in the literature. The term Multimedia Social Network (MSN) has been increasingly used over the last years together with Social Multimedia Network or Social Media Network to indicate information networks that leverage multimedia data in a social environment for different purposes [3–6].

This kind of structure provides new perspective from which the multimedia context can be understood, but all these approaches focus only on single problems addressing specific aspects like the popularity and the status of given users [7], moral ethics [8], users' privacy protection [9].

The methodologies introduced so far are basically application-oriented and can deal only with data from a limited number of MSNs.

The information networks we are used to, such as the Web, contains several relationship between contents, OSNs instead, have a quite different structure, containing few relationships between content objects and a substantial number of links between users and content or between users, if we limit to these kind of nodes. In this context, we have at least, but possibly more, two levels of interaction among the entities involved which allow to extract knowledge from the network.

In this perspective, one of the most important aspect to consider is the contents heterogeneity coming from MSNs.

As a matter of fact, the tons of data produced everyday are mostly unstructured and don't follow any schemes or standards which could be helpful for building general and abstract models. In the last years many efforts were made following this direction and the result was a return of interest for semantic-web related technologies and languages.

These questions are stressed in the context of Semantic Web [10], because multimedia contents need to be semantically annotated in order to be discovered and exploited by services, agents and applications. However, bridging the gap between the concepts behind MSNs entities and the available low-level multimedia descriptors is an open problem and some approaches have been proposed to smooth it [11].

Even though the significant progresses made on automatic segmentation or structuring of multimedia content and the recognition of low-level features, the generation of multimedia content descriptions is still problematic both for the complexity of data and the subjectivity of descriptions generated by human agents. Ontology-oriented solutions have been widely used in order to reduce or possibly delete conceptual or terminological messes. Some approaches use linguistic matching to integrate in a unified and global common view the concepts related to entities coming from two or more different ontologies [12–14]. On the other hand, graph-based models have been exploited in order to define comprehensive models able to integrate networks that combine the information on users belonging to one or more social communities, with all the multimedia contents that can be generated and used within the related environments.

Starting from all these considerations, we can argue that MSNs applications stress all the dimensions that typically characterize the 5Vs Big Data model:

- the *volume* of generated data is huge
- the speed(*velocity*) at which data is produced is impressive
- many types of structured and unstructured data come from MSNs (*variety*)
- we cannot trust all data from MSNs (*veracity*)
- data can generate huge competitive advantages (*value*)

If we combine the issues related to MSN and Bigdata we have to define a data model with generic features to be used with a different types of social networks and heterogeneous data and, at the same time, a scalable framework based on it that is able to manage large volume of information.

The model we propose introduces novel functionalities based on hypergraph structure. From a conceptual point of view it is a semantically-labelled graph, whose properties are properly weighted in order to express the strength of relations among the model entities. In particular, we are interested in representing in a formal way the knowledge in a MSN using multimedia "*signs*" defined as "something that stands for something, to someone in some capacity" [15]. Generally speaking, all of the ways in which information can be communicated as a message by any sentient, reasoning mind to another.

In our vision, we want to represent a Multimedia Semantic Social Network (MS^2N). As a matter of fact, the main contribution of our approach is to allow the integration of heterogeneous information coming from OSNs, or related to multimedia sharing systems, like multimedia contents and relationships typical of such environments, with the information related to high-level semantic concepts. The whole, efficiently managed with a unique semantic and social model.

The definition of weights for arcs brings capabilities, like flexibility and extensibility of our model to new levels. Moreover it allows for the definition of new similarity metrics, which could be leveraged by applications relying on recommendation systems and so on. The combination of semantic and multimedia information also gives birth to new unseen relations between the entities involved, establishing as-well a high-level abstraction of contents, that is understandable by both humans and machines.

This paper is structured as follows. Section 2 provides a detailed overview of related works presented in literature; in Section 3 we describe the proposed model and its properties, with some using examples. Section 4 shows a real applicative case study in the cultural heritage domain. In Section 4 some experimental results are also presented and discussed. Eventually, Section 5 presents a discussion of our approach, the effectiveness of our novel model in different domains and illustrates the future work and possible improvements.

2. Related Work

Nowadays, multimedia social networks, along with their analysis, modeling and content retrieval are one of the most investigated research topics. In the last recent years several models, approaches and techniques have been proposed using ontologies or graph-based models. There is not a clear distinction between these two kind of approaches because they could be see as two sides of the same coin but we prefer discuss them in separate a fashion in order to better present the literature and the difference with our framework. The approaches based on ontologies provide well-structured information to improve the accuracy in knowledge representation, mining and retrieval processes. Moreover, Semantic web technologies also facilitate the integration of heterogeneous information sources and formats therefore, well-structured formalism are crucial to provide advanced methodology for several aspects in the context of data and application management.

One of the first proposed system [16] uses ontologies for images semantic annotation. The system has some tools to annotate photos and search for specific images. An approach to build a multimedia ontology using MPEG-7 descriptors has been proposed in [17]. In [18], the authors present a knowledge infrastructure for multimedia analysis, which is composed by a visual description ontology and a multimedia structure ontology, while [19] shows how the definition of a top-level and extensible ontology is an essential step for knowledge engineering tasks proposing the independence of ontology from any domain-specific metadata vocabulary. In [20], the author developed a core multimedia ontology based on a re-engineering of MPEG-7, and using DOLCE as foundational ontology. An approach for multimedia ontology modeling is presented in [21], in which the authors combine semantic hierarchy of multimedia content and MPEG-7 standard to create a multimedia ontology proposing a support to spatial-temporal relation of multimedia data. An ontology mediated multimedia information retrieval system is described in [22], where a combination of logic-based strategies and multimedia feature-based similarity are used. An end-to-end adaptive framework based on an ontological model has been presented in [23]. The framework aims at enhancing the management, retrieval and visualization of multimedia information resources based on semantic techniques. The relevant data are retrieved using metadata formats such as MPEG-7, RDF and OWL taking advantage of the semiautomatic annotations created by the system. The framework implement also a P2P method to share data and metadata with other systems.

A framework for the semantic retrieval of multimedia contents based on domain ontologies, user preferences and context analysis is presented in [24]. Wang et al. [25] investigate on the selection of semantic concepts for lifelogging which includes reasoning on semantic networks using a density-based approach. In [26, 27], the state-of-the-art techniques in semantic multimedia retrieval are highlighted and discussed addressing the performances of multimedia retrieval systems based on combination of techniques, such as low-level multimedia feature extraction and common semantic representation schemes. A study about several multimedia retrieval techniques based on ontologies in the semantic web is discussed in [28] where the authors perform a comparison of the used techniques to put in evidence the advantages of text, image, video and audio based retrieval systems.

These works don't address as a whole the problem of using multimedia from a complete ontological point of view and the knowledge represented by this kind of systems is usually only organized around metadata or low-level features without a comprehensive knowledge model. In addition, very few studies have been made in using multimedia ontologies along with social components.

The use of ontologies taking into account multimedia components is still limited and often they are too much oriented to information related with low-level descriptors, losing in generality. Furthermore, they don't consider at all the social component.

One of the first attempt to include this aspect in semantic networks is presented in [29] by means of the widely known "folksonomies" to derive better semantic schemes in particular types of social contexts.

Several complex models for social information networks, embedding multimedia data, have been introduced and it is possible to classify them on the base of four main categories. The first category includes all models that consider social networks as a graph composed by heterogeneous vertices, such as users, tags, multimedia objects and so on. In [30], the authors propose an algorithm that combines both context and content network information for multimedia annotation purposes. Jin et al. [31] use network and content-based information to propose a new image similarity concept. The second type of approaches is based on bipartite graphs. Zhu et al. [32] propose a user-content bipartite graph model to compute the influence diffusion in a social network, while Gao et al. [33] exploit a bipartite graph - composed by users' group and objects - in order to address a consensus maximization problem. The third category uses tripartite graphs. In [34], a strategy that exploits users, tags and resources for clustering goals is proposed. A similar approach is then proposed by Qi et al [35], they leverage a tripartite graph in order to cluster multimedia objects. In [36], the authors propose a different approach that allows to model the interaction existing between user, query and videos in order to define a personalized video recommendation. Eventually, the last group contains the approaches based on hypergraph theory. In [37] the authors propose an approach based on hypergraph network in order to develop a music recommendation exploiting both social and acoustic based information. In [38], authors propose a tensor decomposition approach for communities learning in 3-uniform hypergraph. Finally, a news recommender system via hypergraph learning is described in [39]. In [40], authors describe the use of a semantically labelled and property-based graph model in order to represent the information coming from OMSNs by exploiting linguistic-semantic properties between terms and the available low-level multimedia descriptors.

Regarding to the classifications of these works, only few of them have models for social networks, and a small number of them consider multimedia objects as a structured data type. They rather focus on specific aspects and applications related to MSNs, like for example user behavior analysis in online social networks in [6], overlapping community detection in [41], information propagation over the network, development of a trust model for multimedia social networks [4] or measuring influence in online social network [32].

In our model we propose a clear distinction between the basic components of a MSN and how these components are related among them. Moreover, the use of a semantic ontology based model allows the representation of all possible relations to express the meanings of "signs" used to represent MSN knowledge. Other innovations of the proposed approach are the following:

- it is independent from specific application fields;
- it provides linguistic, syntactic and semantic relationships, to give a well defined meaning to generic relationships typical of the most common social networks;
- it adds weights to the relations to better represent and quantify the relationship strength among entities and allow the design of applications that use measures on them, such as recommendation systems, ranking metrics, social networking analysis, collaboration systems.

Moreover, we implement our model using a graph based NoSQL technology and we also provide a real use case.

3. The Proposed Model

In this section we will describe our model for multimedia social networks defining involved entities, relations and semantics. Our model is an extension of a top-level multimedia ontological model, presented in [11] and used to integrate multimedia representations of knowledge with abstract concepts. It is composed of a triple $\langle \boldsymbol{S,P,C} \rangle$ where:

S is a set of signs;
P is a set of properties used to link the signs in S;
C is a set of constraints on P.

The base model is hierarchical and two top classes are present. The first, *Concept*, is used to denote concepts from a textual-linguistic point of view. The second class, *MM* is intended to contain all audio-visual data and pertinent feature extracted.

In our view, an MSN can be seen as a set of three main types of nodes and a number of directed arcs between them. We make a distinction between nodes introducing the following categories:

- *Users (U)*: this kind of node represents persons, institutions, companies, organizations , bots, and other entities that are part of a social network. Information about user profile, preferences and other features of these entities are also considered in our model as attributes.
- *Concepts (C)*: as the name suggests, anything having a specific meaning in real life. It is represented using signs.
- *Multimedia (M)*: all kind of resources collected from an MSN, like images, videos, files, posts, etc. fall into this category. From a general point of view, it is any kind of sign used to represent a concept

On the other hand, starting from the graphs theory, relationships can be classified dividing them into categories based on their domain and co-domain, i.e. the types of nodes involved in the relation.

We define the following general categories for relationships:

- *User to User*: these relationships represent all the interactions between users, like friendship, following, co-working, similar to, etc..
- *User to Multimedia*: it represents the interaction that a user has with multimedia objects, as posting, like, comment, etc..
- *Multimedia to User*: the inverse of the previous category. This relationship is fundamental for finding new links between unrelated users based on multimedia content.
- *Multimedia to Multimedia*: with this type we this category we define all the relationships between multimedia objects. For example, a possible kind of relationship is to link an audio track to an image, a caption to a video, etc..
- *Multimedia to Concept*: a multimedia object could represent one or more concepts. We call this relationship *hasConcept*.
- *Concept to Multimedia*: the inverse of the previous category. The name of this relationship is *hasMM*.
- *Concept to concept*: all the possible relationships between concepts from a linguistic a semantic point of view as hyperonymy, hyponymy, meronymy, holonymy, etc..

The introduced relations can be associated to three main categories, namely *semantic-linguistic*, *social* and *similarity*.

Table 1 shows a schematic description of relationship and macro-categories previously defined and in Figure 1 the proposed model has been drawn.

Combining the ontological model with the multimodal approach presented in [42] it is possible to retrieve the information stored in the network both from a multimedia point of view and a geographic point of view.

3.1. Model formalization

In the rest of this Section we provide a theoretical foundation of our model. We first give definitions of Multimedia Social Network and relationships according to our vision previously described; then we present some metrics useful to recognize network topology and structure. The last subsection is devoted to present some practical examples showing details on the use of our model.

Definition 1. *(Multimedia Social Network): A Multimedia Social Network Γ, or MSN, is a graph represented by a triple $(V; E; w)$ where $V = (U \cup M \cup C)$ represents a finite set of nodes that are in the network; E is a finite set of arcs linking two or more nodes in the network; w is a weighting function defined on each arc E in the network. This function can assume values in the range $[0, 1]$ and represents the strength of the considered link.*

Both nodes and arcs have their own sets of properties which characterize them. These properties are represented by attributes. For each kind of node or arc, there is a number of mandatory attributes, while others can be optionally defined for a specific application. All nodes and arcs have attributes with regards to of their type. A subset of attributes is listed in the following:

- *id*: this attribute gives an unique identification to a node or an arc in the network, i.e. two nodes or two arcs cannot have the same id.
- *name*: it is an representative term for a node
- *date_of_creation*: this attribute stores the time in which an entity in the network was created. It provides useful information about, for example, novelty of contents. It could also be exploited for time-based queries on the network, for editing weigths according to time of creation and so on.

Table 1

Taxonomy of relationships

	Semantic-Linguistic	Social	Similarity
User to User		✓	✓
User to Multimedia		✓	
Multimedia to Multimedia			✓
Multimedia to Concept	✓		
Multimedia to User		✓	
Concept to Multimedia	✓		
Concept to Concept	✓	✓	
Concept to Multimedia	✓		

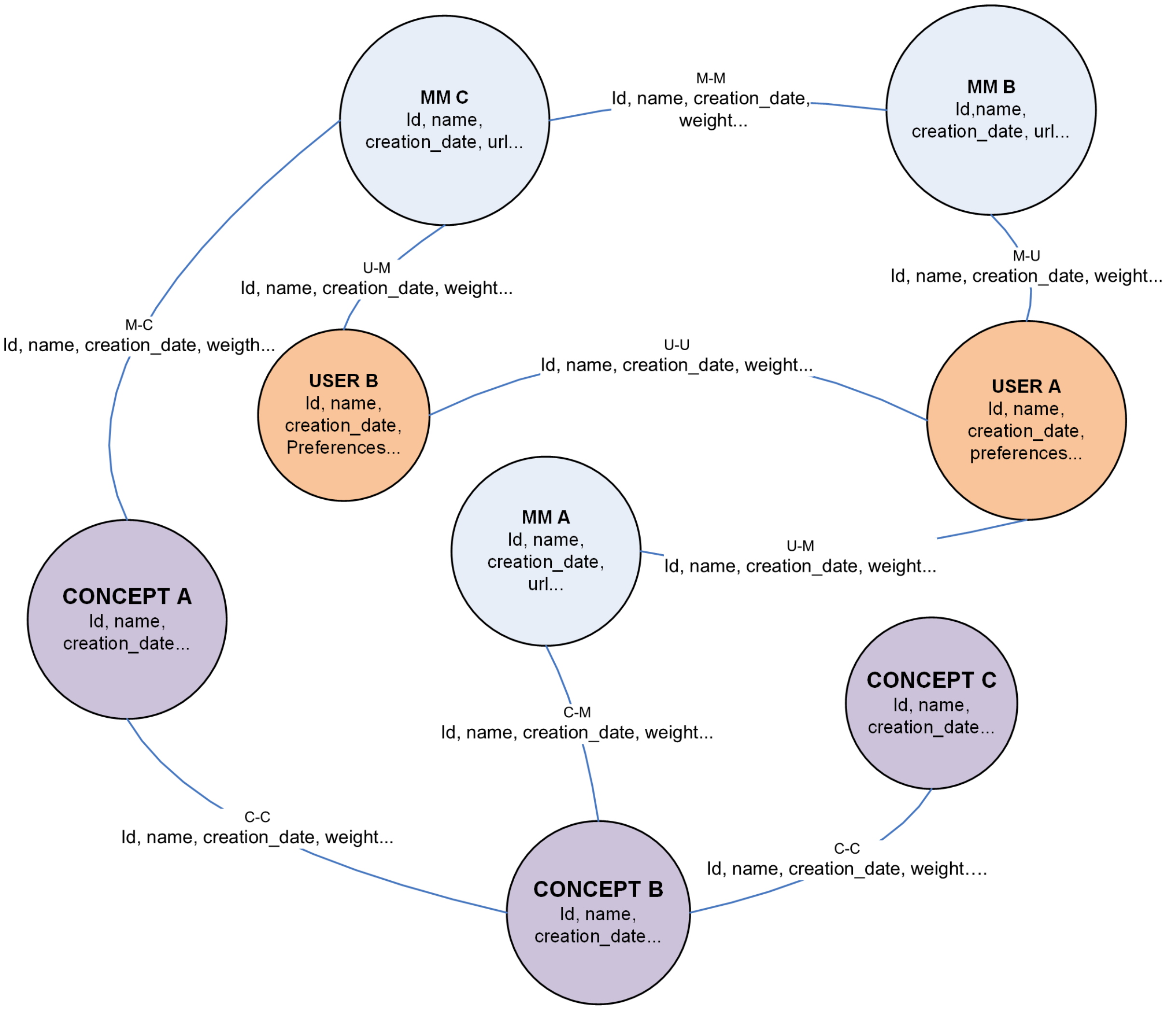


Fig. 1. MS^2N Model

Other details about attributes will be shown in the end of this Section, when we will present some examples.

Definition 2. *(Relationship):*
A relationship r is a weighted directed hyperarc $e \subset E$ having a weight $w \longrightarrow [0,1]$ in Γ, connecting a finite set $\hat{V}$ of nodes $\{v_i, v_j, ..., v_t\} \subset V$. The set of nodes $\mathring{V} \subset$

$\hat{V} \subset V$ from which the hyperarc starts is called source set, the set $\mathring{V} - \hat{V}$ in which the hyperarc ends is called destination set.

Starting from the definition of relationship, we can specialize it in different categories, according to the type of nodes involved in the relationship.

Definition 3. *(User to User relationship U-U): Let $\hat{U} \subset U \subset V$ and $\mathring{U} \subset U \subset V$, with $\hat{U} \cap \mathring{U} = \varnothing$, two disjoint subsets of of U in Γ, a user to user relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in $\hat{U}$ with nodes in $\mathring{U}$.*

User to User relationships are useful to highlight the interactions between users in a social network and can be used as a starting point for deeper analysis of the network in order to find hidden affinities between users ore strong relations among them.

Definition 4. *(User to Multimedia relationship U-M): Let $\hat{U} \subset U \subset V$ and $\hat{M} \subset M \subset V$ two subsets of U and M respectively, in Γ, a user to multimedia relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in subset $\hat{U}$ with nodes in subset $\hat{M}$.*

User to Multimedia relationships allow to model user' activities and preferences about multimedia contents they share in the network.

Definition 5. *(Multimedia to User relationship M-U): Let $\hat{M} \subset M \subset V$ and $\hat{U} \subset U \subset V$ two subset of nodes of M and U respectively in Γ, a multimedia to user relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in $\hat{M}$ with nodes in $\hat{U}$.*

This kind of relationship is the inverse of the previous one.

Definition 6. *(Multimedia to Multimedia relationship M-M): Let $\hat{M} \subset M \subset V$ and $\mathring{M} \subset M \subset V$, with $\hat{M} \cap \mathring{M} = \varnothing$, two disjoint subsets of nodes of M in Γ, a multimedia to multimedia relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in subset $\hat{M}$ with nodes in subset $\mathring{M}$.*

Multimedia to Multimedia relationships are used for example to relate multimedia contents by exploiting metadata, features extracted from the contents, low-level multimedia descriptors, etc..

Definition 7. *(Concept to Multimedia relationship C-M): Let $\hat{C} \subset C \subset V$ and $\hat{M} \subset M \subset V$ two subsets of of U and M respectively, in Γ, a concept to multimedia relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in $\hat{C}$ with nodes in $\hat{M}$.*

This relationship called *hasMM* is used to define a link between the Concept and Multimedia nodes.

Definition 8. *(Multimedia to Concept relationship M-C): Let $\hat{M} \subset M \subset V$ and $\hat{C} \subset C \subset V$ two subsets of nodes of M and C respectively, in Γ, a multimedia to concept relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in $\hat{M}$ with nodes in $\mathring{C}$.*

With this relationship we are able to associate a multimedia "sign" to a set of concepts. As previously described, we use the *hasConcept* property defined in the top level ontological model.

In this formalization, each multimedia is related to the concept it represents by the *hasConcept*, whereas a concept is related to multimedia that represent it using *hasMM*.

Definition 9. *(Concept to Concept relationship C-C): Let $\hat{C} \subset C \subset V$ and $\mathring{C} \subset C \subset V$, with $\hat{C} \cap \mathring{C} = \varnothing$, two disjoint subsets of C in Γ, a concept to concept relationship is a weighted hyperarc $e_i \subset E$ with a weight $w \longrightarrow [0, 1]$ connecting the nodes in $\hat{C}$ with nodes in $\mathring{C}$.*

This kind of link is used to exploit the semantic and linguistic properties between Concept nodes.

The use of general top level ontological model for Multimedia and Concepts [11] allows us to exploit all the potentials of ontologies, highlighting the importance of a strong formalization and organization of data.

In this way we can extend the model and improve the representation of our MSN. In fact, an ontology containing details of Audio-Visual Features, Words and their related properties, like for example 'entailment', 'cause' or 'verbGroup', could be linked to the top-level ontological model made of Concepts and Multimedia Objects.

3.2. Metrics

Several studies in the field of social network analysis have highlighted the importance of understanding the network topology and the relative importance of nodes in a network [43, 44]. In fact, the use of a quantitative analysis could be useful to rank nodes and find social network structures. The proposed model can be exploited to retrieve information about the network structure, the degree of interaction between two or more users, their distances or to extract a ranking score about topics by means of metrics defined for a MSN.

Definition 10. *Density*
The density of a specific social network is the result of the division between the number of all the connections between the nodes and the number of potential connections within the same set of nodes [45].

Dense networks are typical of small, stable communities, not connected to external contacts and with a high level of social compactness. On the other hand, loose social networks are organized into larger and more unstable communities that have many external contacts and show a lack of social cohesion[46].

Definition 11. *Member closeness centrality*
Member closeness centrality is the measure of the proximity of a single user to all the other users in the network.

Such metric could be useful, for example, to identify popular members or members under pressure in a community. A user with high closeness centrality is a central member, and therefore has frequent interactions with other members of the network. A central member of a community tends to be under pressure to maintain the rules of that network, while a peripheral member of the network (i.e. with a low closeness centrality score) is not exposed to this pressure [47].

Definition 12. *Multiplexity*
Multiplexity is the number of separate social connections between any two users. It has been defined as the "interaction of exchanges within and across relationships" [48].

We explicit point out that using our formalization a number of additional metrics could be defined in different applicative contexts.

A single interaction between individuals, such as a shared workplace, is an uniplex relationship. An interaction between individuals is multiplex when those individuals interact in multiple social contexts [45]. For instance, *John* is the boss of *Bob*, and they have no relationship outside work, so their relationship is uniplex. However, while *Albert* is both *Bob*'s coworker and friend, so the relationship between *Bob* and *Albert* is multiplex, since they interact with each other in more than a single social context.

3.3. Examples

We are now in a position to describe a subset of possible social community relations that could be defined with our model. We introduce some real examples to investigate some domains of interest and their range of validity.

3.3.1. User to user relationships

In order to characterize the interaction between users in a MSN, several types of relationships can be defined among them.

Example 1. *(Co-worker relationship):*
A co-worker relationship is a user to user relationship, useful for modelling the professional level of interaction between two users of a social community. Typical real examples of this relationship can be found in LinkedIn.

Figure 2(a), shows an example of co-worker relationship. One possible exploit could be the discovering of common professional interests between two or more individuals which do not know each other but have common colleagues as in the case of *User A* and *User C*.

Example 2. *(Following relationship):*
A following relationship is a user to user relationship, useful for modelling the interest of a user w.r.t other user's activities in a social community. Typical real examples of this relationship can be found in Twitter.

The following relationship can also be considered as a strong and reliable indicator of users having great popularity and influence among the community.

Example 3. *(Friendship relationship):*
A friendship relationship is a user to user relationship, useful for modelling a strong interaction between two users in a social community. Typical real examples of this relationship can be found in Facebook and Google+.

Figure 2(b), shows an example of friendship relationship. One possible exploit could be the discovering of new friends starting from common friends as in the case of *User B* and *User C*, having *User A* as a common friend. It is worthy to note that the verse of the link is used to define who sent the friendship request and who received it.

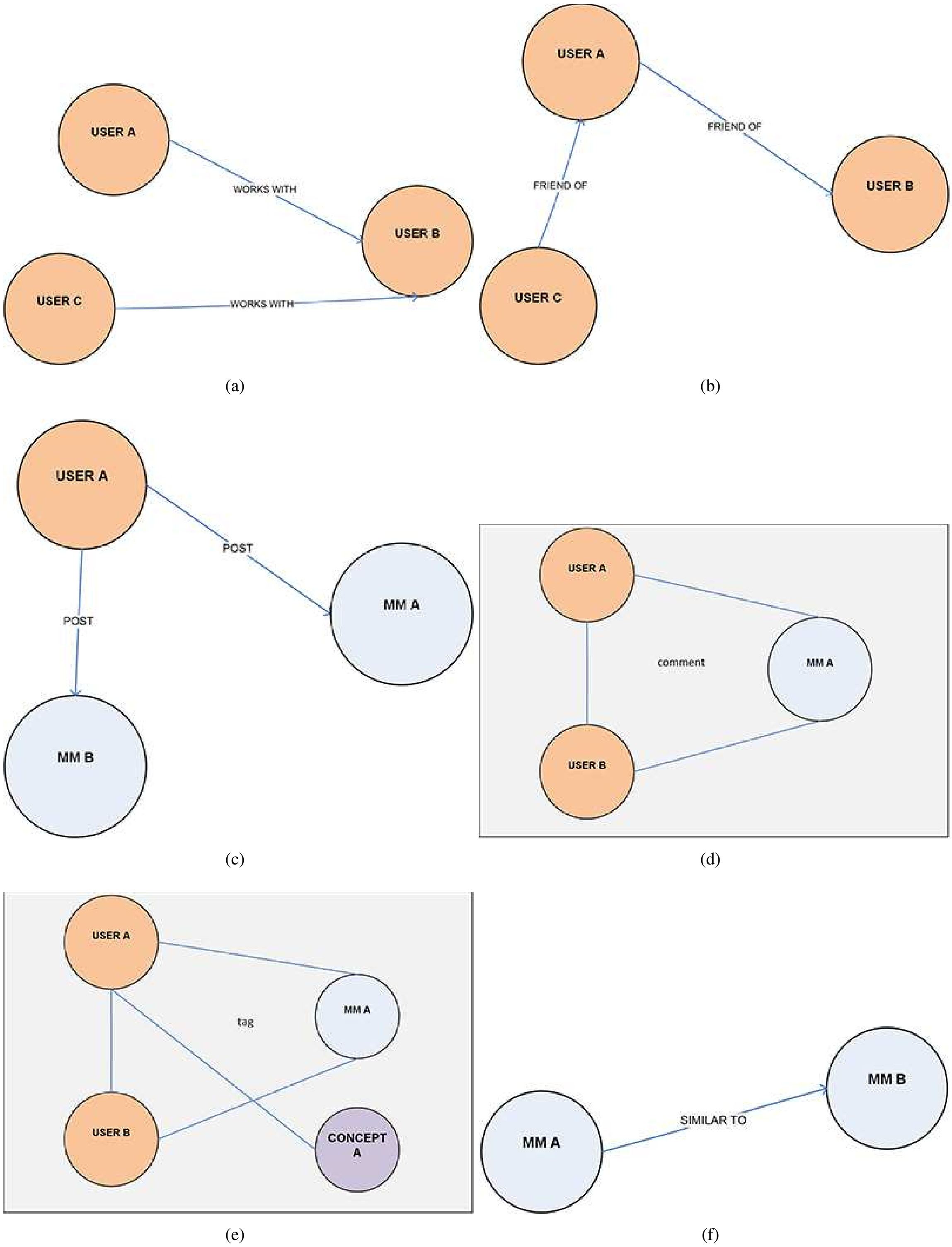


Fig. 2. MS^2N relationships. Comment and tag relationships (grey background) make use of hyperarcs.

Example 4. *(Acquaintance relationship):*
An acquaintance relationship is a user to user relationship, useful for modeling a weak interaction between two users in a social community.

For instance, two or more users in a multimedia social network exchanging occasional messages or cooperating for solving tasks can be considered as acquaintances. It is important to note that this relation is totally independent from the friendship relation, since two user can be acquaintances, being or not friends at the same time. More interesting, also the contrary can be true, i.e. two user can be friends without knowing each other.

3.3.2. User to Multimedia relationships

Example 5. *(Post relationship):*
A post relationship is a user to multimedia relationship, useful for modeling the action of a user publishing some multimedia contents on his/her wall.

Figure 2(c), shows an example of post relationship. One possible exploit could be that the discovering of new friends that posted similar multimedia contents or finding similar contents shared in the MSN that could be interesting for a user.

Example 6. *(Comment relationship):*
A comment relationship is a user to multimedia relationship, useful for modelling the action of a user in commenting on multimedia contents posted in the network.

Figure 2(d), shows an example of comment relationship. We can see all the expressive power of the hypergraph structure. The gray background stands for the new space in which nodes are immersed and the hyperarc allows to connect *User A* with the multimedia content *Multimedia A* and *User B*, who can be for example the owner of such content or a user who has posted it in the MSN.

Example 7. *(Like relationship):*
A like relationship is a user to multimedia relationship, useful for modelling the action of a user who likes some multimedia contents published on the social network. It is one of the most famous used relationships.

This relationship can also be exploited to investigate how much a user is actually interested in the posted content in a network or if it is more interested in the user that posted that content.

Example 8. *(Tag relationship):*
A tag relationship is a user to multimedia relationship, useful for modeling the tagging action of a user over some multimedia contents.

Figure 2(e) shows an example of tag relationship. In this case *User A* tags both *User B* and *Concept A* over the multimedia content *Multimedia A*.

3.3.3. Multimedia to Multimedia relationships

Example 9. *(Content Similarity relationship):*
A Content similarity relationship is a multimedia to multimedia relationship, useful for modeling the similarity between multimedia contents in the MSN.

Figure 2(f), shows an example of content similarity relationship. The similarity could be expressed for example by means of low-level multimedia features, tags present on the content or whatever is considered valid measure for a similarity assessment.

Example 10. *(Synonymy relationship)*
A synonymy relationship is a multimedia to multimedia relationship, linking two multimedia objects representing the same concept.

It is useful to note that the synonymy relationship is not a relationship between concepts, but it is a relationship between different "sign" representing the same concept. Hence, we have defined here this kind of link as an extension of the commonly known synonymy relationship to multimedia objects.

3.3.4. Multimedia to Concept and Concept to Multimedia relationships

Example 11. *(HasConcept relationship):*
A hasConcept relationship is a multimedia to concept relationship. It links the multimedia object with one or more Concept, adding semantic and linguistic capabilities to the analysis that can be performed on the meaning of the multimedia represent.

Example 12. *(HasMM relationship):*
A hasMM relationship is a concept to multimedia relationship. It links the Concept with one or more Multimedia Objects, adding multimedia information to specific concepts.

3.3.5. Concept to Concept relationships

In our framework we use a semantic approach to represent relations between concepts in the MSN. Some examples of the possible semantic relations are:

Example 13. *(Hyponymy relationship):*
A hyponymy relationship is a concept to concept re-

lationship, useful for describing a Concept more specific with respect to another Concept. For example the Concept snake is a hyponym of the Concept animal

Example 14. *(Hypernymy relationship):*
A hyPeronymy relationship is a concept to concept relationship, inverse of hyponymy relationship.

Example 15. *(Meronymy relationship):*
A meronnymy relationship is a concept to concept relationship, useful for describing a concept that is part of another concept, like for example a page is meronym of a book.

Example 16. *(Holonymy relationship):*
A holonymy relationship is a concept to concept relationship, inverse of meronym relationship.

Considering the high level of abstraction of the starting ontological model, the extension we defined for the inclusion of a group of users belonging to a social community or a multimedia social network follows that line. This allows our model to hold a high degree of independence from specific domains, making it adaptable to various application contexts. In other words, whatever the final user set, the model is still able to meet the requirements for it.

4. Case study and experiments

In this Section we will show how our model can be used in a real scenario introducing a possible application related to cultural heritage. The choice of this domain is justified by the strong correlation between social information technologies and tourism. The case study was set up with a tourist in mind as the final user, who visits cultural places using an application built on top of our model. In our scenario the network is composed of tourists which are interested in visiting cultural heritage sites around the world, like museums or, more generally, cities. Each user has some preferences about places, and can interact with other users sharing his/her opinions. Users may post multimedia contents(e.g. text, photos, videos) of places they are visiting or they would like to visit.

In addition the presence of geospatial and temporal information extends the number of functionalities for the application also allowing spatial queries.

With respect to our general model, the entities involved in our scenario for tourists visiting cultural heritage locations are defined on the basic nodes previously defined, as:

- *Tourists* ⇒ Users: every person interested in cultural heritage, being either a tourist or a visitor looking for Places.
- *Places* ⇒ Concepts: a place is a generic term, used in this context to identify each entity containing cultural heritage, i.e.cities and attractions to explore like museums, collections, events, etc..
- *Text, photos, videos* ⇒ Multimedia Objects: every content shared by social network users related to places, photos and videos of paintings, landscapes, etc..

We create a dataset for our application using the graph database *Neo4J* by means of *Cypher* queries. Figure 3 shows an excerpt of the used dataset. Graph visualization is challenging task in data representation and analysis [49, 50] and in our case we use *ScreenCast*, the native Neo4J browser to show and highlight some capabilities of the proposed model.

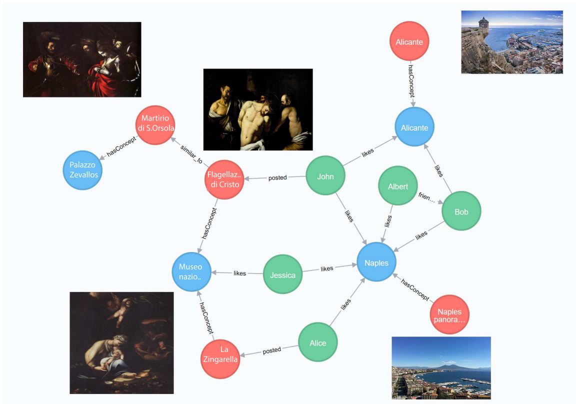


Fig. 3. Excerpt database for tourists recommendation

Low-level multimedia features represent the information extracted from an image in terms of numerical values, also often referred as descriptor.

For our purpose, we decided to store global descriptor *Pyramid of Histograms of Orientation Gradients(PHOG)*, and the *Joint Composite Descriptor(JCD)* due to their performances [51]:

- PHOG: The basic idea [52] is to represent an image by its local shape and the spatial layout. This descriptor consists in a histogram of orientation gradients over each image subregion at each resolution level. The distance between two PHOG image descriptors reflects the property of images to contain similar shapes in the correspondent spatial layout.

- JCD: It is a combination of two *MPEG-7* [53, 54] descriptors, CEDD and FCTH. Based on the fact that the color information given by the two descriptors comes from the same fuzzy system, it is assumed that joining the descriptors would result in the combining of texture areas carried by each descriptor. JCD is composed of seven texture areas, with each of those made up of 24 subregions that correspond to color areas (the 24-bins histogram of FCTH and CEDD).
- Auto color correlogram: This color feature has been presented in [55]. The main characteristics of the Auto Color Correlogram feature are: spatial correlation of colors; possibility to be used to describe global distribution of local color spatial correlation; low computational effort; small size of the feature.
- Edge histogram descriptor: This feature [56] represents the spatial distribution of five types of edges, that is four directional edges and one non-directional edge. According to the MPEG-7 standard, the image retrieval performance is significantly improved combining the edge descriptor with other descriptors such as the color histogram feature. This descriptor is scale invariant and supports rotation invariant and rotation sensitive matching operations.

These multimedia descriptors are used as a weighted similarity metric for evaluating the content similarity score between images.

4.1. Functionalities

In the following we will show some functionalities that can be implemented in our scenario using the proposed model. The application might be seen as a recommendation system for interconnecting users who share the same interests, for suggesting new places to be visited, trending places and so on.

4.1.1. Trending places

The first and more intuitive operation is to find trending places i.e. the most visited and liked by users. In order to achieve this task, we need to query our database searching for places, for example, with a higher number of likes relationships.

Figure 4(a) shows the results obtained for a simple *Cypher* query.

```
MATCH p=()-[r:likes]->(c:Concept)
RETURN c
```

Adding some complexity to the query it could be also possible to rank places or select only those above a certain threshold and so on.

4.1.2. Friend suggestion

A tourist can discover new friends by means of classical ways used in social networks like for example common friends, neighbours, or common interests with other users for similar places or multimedia contents.

Figure 4(b) is the result of the following query:

```
MATCH (m:Multimedia),(m2:Multimedia)
WHERE m.feature=m2.feature
WITH m,m2
MATCH p=(u:User)-[r:posted]->(m),(m2)
RETURN u
```

It highlights the possible relationship of friendship that can be established between users *Alice* and *John* since they posted two similar images of paintings *Flagellazione di Cristo* and *La Zingarella*, which are both exposed at *Museo Nazionale di Capodimonte*.

4.1.3. Place suggestion

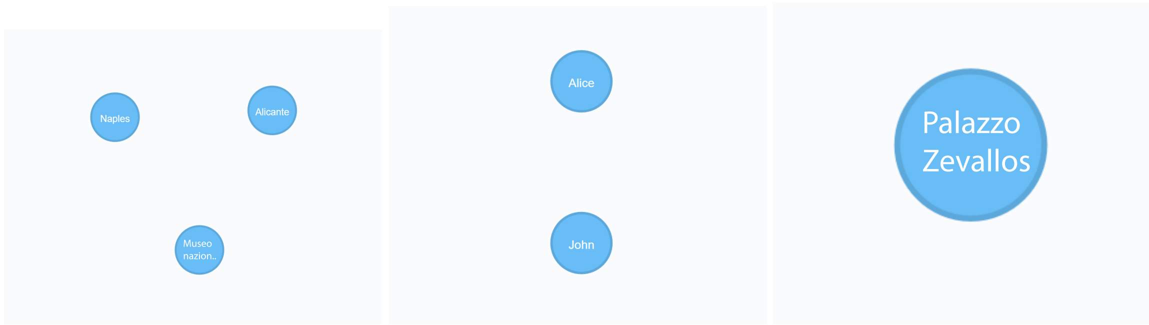
A tourist can find new places in which him/her that could be interested. A place can be considered interesting for a user if it is close or similar to places he/she visited, if it is related to multimedia objects similar to multimedia objects he/she liked, posted, etc. or if it is a place related with friends' activities.

In this case we use the relation of similarity defined between multimedia objects posted by the user, that is the painting *Flagellazione di Cristo* exposed at *Museo Nazionale di Capodimonte* and the painting Martirio di Sant'Orsola exposed at Palazzo Zevallos, hence possibly being an interesting place to visit for user *John*. Figure 4(c) shows the query result.

```
MATCH p=(u:User)-[r:posted]->
(m:Multimedia)
WITH p
MATCH (m)-[r2:similar_to]->
(m2:Multimedia)
WITH m2
MATCH (m2)-[r3:hasConcept]->(c:Concept)
RETURN c
```

The previous examples have been used to better explain our model and its efficiency in representing real applicative scenario.

Moreover we implemented a mobile application focused on digital cultural heritage. In particular, our



(a) (b) (c)

Fig. 4. Query results

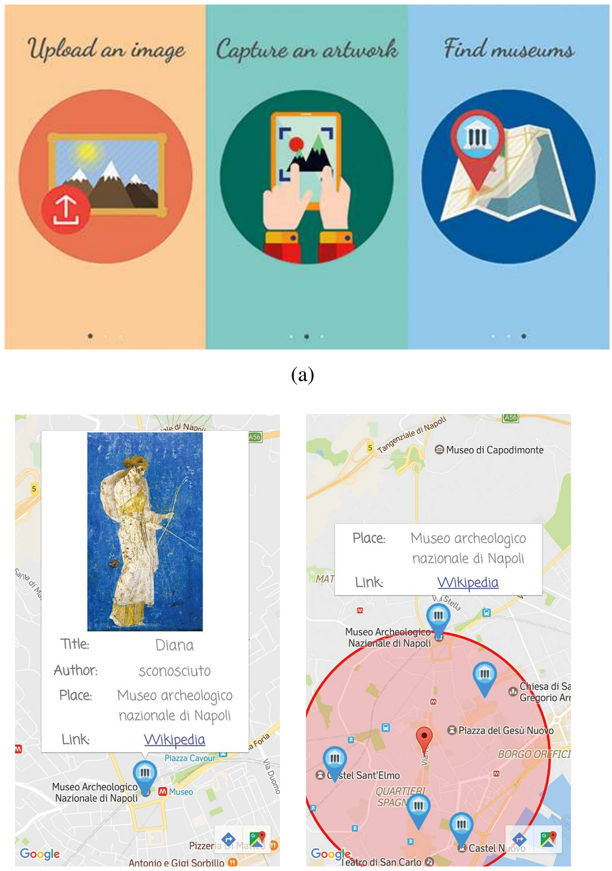
efforts have been aimed at collecting digital images, multimedia descriptors, and geographic coordinates for paintings and sculptures currently located in some museums in Naples and relationships among them by means of our model. The test was conducted by a real person acting as a tourist who takes photos of artworks using the aforementioned mobile application. Explicit consent was granted by the managers of the cultural sites being tested.

The whole Neo4j instance has been indexed into *Apache Solr* search engine using Neo4j *JDBC Driver* and Solr *Data Import Handler* (DIH).

The Solr queries are computed by servlets deployed on an *Apache Tomcat* server. These servlets use *Lucene Image Retrieval* (LIRe), a library for Content-Based Image Retrieval functions and *LIRe Request Handler*, a Solr plug-in to execute multimedia queries.

An Android application has been implemented to allow users to manage the proposed system. The communication between the application and the server is based on *HTTP* protocol and, in particular, through HTTP *POST* requests.

The client-side application provides a multimodal user interface for three main system functionalities: Multimedia Query, Multimedia&Geographic Query and Geographic Query. The server-side servlets are implemented for receiving and management of data sent by the Android application, establishing connections with the Solr server, performing Solr queries and handling their results to send back to the client. Figure 5 shows some images of the multimodal user interface.



(a)

(b) (c)

Fig. 5. Android application example

4.1.4. Experiments

We are now in a position to present experimental results. We are mainly interested in the third scenario presented in section 4 due to the involvement of social and multimedia features. In the quantitative tests we choose to carry out the evaluation task using a test set of previously catalogued documents to perform a comparison with the results by our system using the proposed approach. The evaluation process has been conducted in a real scenario. For our experiments, a dataset composed of 1000 paintings and sculptures images from three museums of Naples has been used in the evaluation process:

1. Museo Nazionale di Capodimonte;
2. Gallerie di Palazzo Zevallos;
3. Museo Nazionale di San Martino.

The complete dataset (i.e. museums and artworks) has been added to our GraphDB using the related nodes and relations. In the evaluation process the visual features stored in the GraphDB have been extracted from each dataset image and indexed into a Solr core using the *ParallelSolrIndexer* class provided by LIRe plug-in.

Then, the *Multimedia Query* is used following the steps listed below:

– a single feature is selected and set as parameter of the features extraction;
– the extraction is performed on one image at a time, representing one of the image in the dataset, with possible variations in scale, brightness or viewpoint to simulate images posted by different users. The image is loaded in the system and the response value is passed as parameter in *search by feature* query. In this phase results are still taken as a ranked list and the position of the correct answer in this ranking is stored to later evaluate the effectiveness of the considered feature;
– once all the images are scanned, the process comes back to the first step, selecting a different feature and so on for all of them.

The ratings of features have been calculated considering the position of the correct answer in the ranked result list. In the evaluation the percentage of the exactly matched artworks is considered, that is the artworks correctly retrieved and resulted in first position in the ranking, and in this way the accuracy of each feature is estimated. This test had the aim to choose the feature to use in the system *Multimedia Query* functionality.

The results of the tests in Figure 6 highlight that the PHOG feature shows the best performances on our dataset. Hence, we decided to use this descriptor for the implementation of the image features extraction task.

In our scenario, the use of the proximity relation of our model allows the implementation of geographic query and therefore its combination with social and multimedia information. In this way, we can submit a multimodal query taking into account these features.

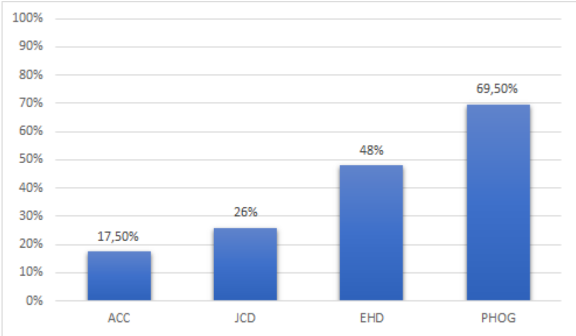


Fig. 6. Features evaluation – Exact matching test

In particular, the accuracy of the multimedia analysis could be improved by geographic proximity given by social interaction. We test this approach "on the field" in museums that granted the access in their rooms for the testing. These museums have been: Museo nazionale di Capodimonte, Museo Nazionale di San Martino and Gallerie di Palazzo Zevallos. For each artwork in the dataset and located in these places, both a *Multimedia Query* and a *Multimedia&Geographic Query* has been tested.

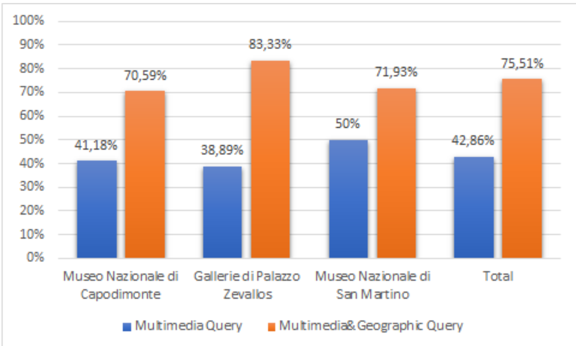


Fig. 7. Global system evaluation

The improvement given by the integration between geographic and multimedia data is clearly visible in Figure 7 and quantifiable with an improvement of 32.65% considering the correctly retrieved artworks of *Multimedia Query* and *Multimedia&Geographic Query*.

5. Conclusion and future work

The constant production of digital data coming from different ICT sources gives us tons of data, from which we could extract precious and useful information. This issue becomes more highlighted introducing multimedia data deriving from social networks. In this context the use of formal model to represent and manage data is a silver bullet task to implement intelligent information systems. The aim of our work has been to provide a novel model to represent in a formal a complete way the structure and knowledge of a generalized multimedia social networks. In this article we have described the problem of data heterogeneity and the impact of the multimedia social networks have had in last few years. In this scenario, we propose a formal model combining top-level ontology models and property graph represented by a hypergraph structure to take into account both semantic, multimedia and social aspects. We show a real application to demonstrate that our model properly handles the heterogeneous information that can be retrieved from existing social networks in a complex scenario as digital cultural heritage. Extensive experiments will be carried out, testing the application in a more robust and distributed environment including a significant number of users to further evaluate the system. Having set up such a test environment, it will also be possible to evaluate the system using the metrics proposed in this article. There are other research lines to be investigated as the implementation of a system based on our model in different applications domains with a particular interest on spatio-temporal data, the definition of strategies for heterogeneous knowledge sources using our model and, the implementation of a very large knowledge base to support intelligent information systems. In addition, we are also interested in finding more efficient techniques to visualize and analyze data stored in very large knowledge bases and to define strategies and perform experiments for the evaluation of our model and approaches.

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