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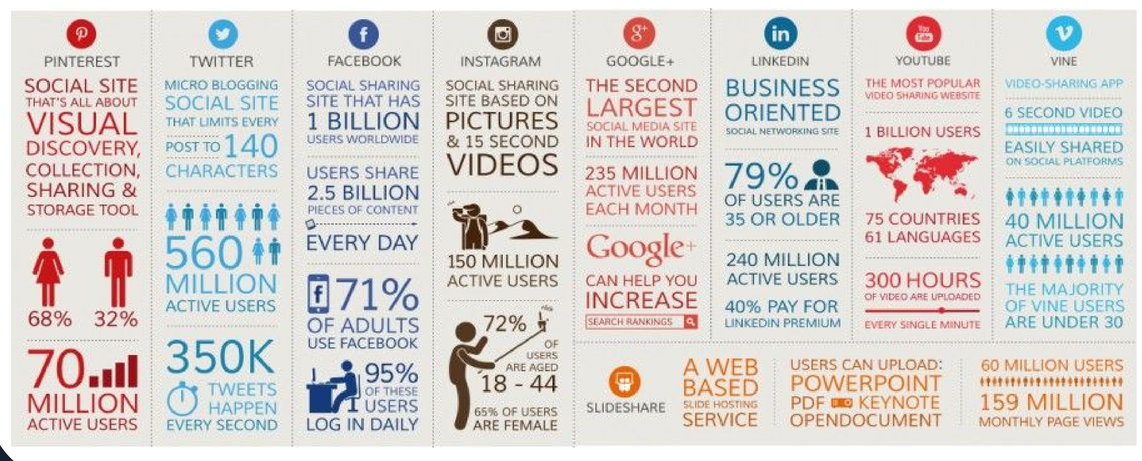
XXX Cycle - II year presentation

Multimedia Social Network

Nowadays, social media networks provide users an interactive platform to create and share multimedia content such as text, image, video, audio, and so on. Within these “interest-based” networks, each user interacts with the others through a multimedia content and such interactions create “social links” that well characterize the behaviors of involved users in the networks.



Representing and understanding user-multimedia interaction mechanisms can be useful to predict user behavior, to model the evolution of multimedia content and social graphs and so on.

Several research questions have to be addressed:

- It possible to exploit multimedia features and the notion of similarity to discover more useful links?
- Can all the different types of user annotations (e.g. tag, comment, review, etc.) and interactions with multimedia objects provide a further support for an advanced network analysis?
- Is it possible to integrate and efficiently manage in a unique network the information coming from different social media networks (for example, a Twitter user has usually an account also on Instagram or Flickr)?
- How can we deal with a very large volume of data?
- In this context, how is possible to model all the various relationships among users and multimedia objects? Are the “graph-based” strategies still the most suitable solutions?

We adopt the term **Multimedia Social Networks (MSNs)** to indicate “*integrated social media networks that combine the information on users, belonging to one or more social communities, together with all the multimedia contents that can be generated and used within the related environments*”.

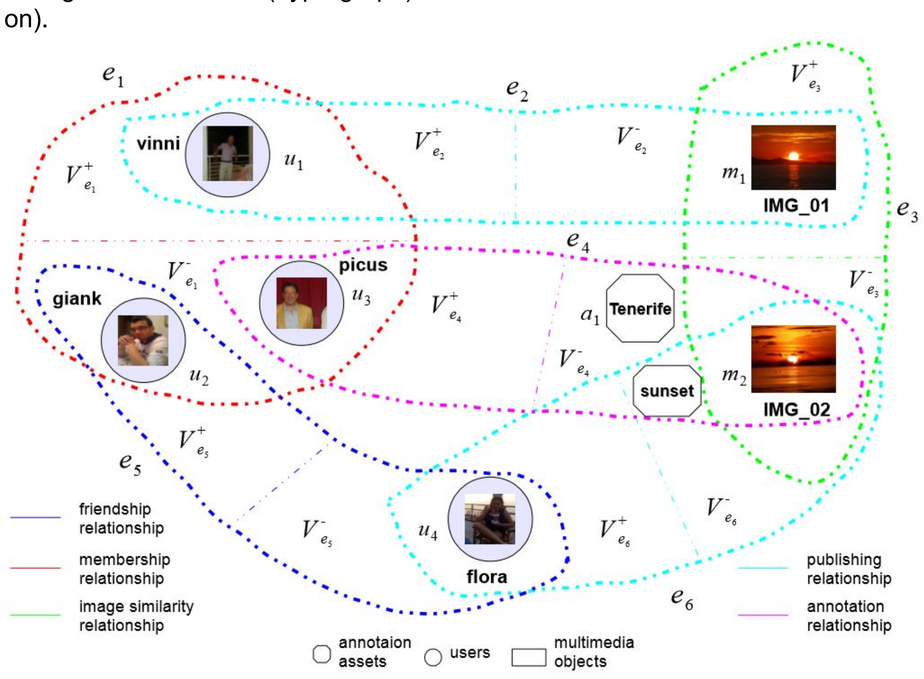
We propose a novel data model to merge in a single data structure (hypergraph) the information derived from different kinds of social networks (Facebook, Twitter, etc.) and social media networks (Youtube, Flickr, Last.FM and o so on).

Entities:

- **Users** - the set of persons and organizations constituting the particular social community.
- **Multimedia Objects** - the set of multimedia resources (i.e. images, video, audio, etc.) that can be shared within a MSN community.
- **Annotation Assests** - the most significant terms or named entities - whose definition can be retrieved from dictionaries, ontologies and so on - of a given domain, or topics, exploited by users to annotate multimedia data and derived from the analysis of textual information such as keywords, labels, tags, comments etc.

Relationship:

- **User to User** relationships: describing user actions towards other users;
- **Similarity** relationships: describing a relatedness between two multimedia objects, users or annotation assets;
- **User to Multimedia** relationships: describing user actions on multimedia objects, eventually involving some annotation assets or other users.



Ranking Function

User Ranking Function

$$\rho_{u_i}\left(\widehat{U}\right) = \frac{\left|NNU^{\lambda}_{u_i} \cap \widehat{U}\right|}{\left|\widehat{U}\right|}$$

Multimedia Ranking Function

$$\rho_{m_i}\left(\widehat{U}\right) = \frac{\left|NNU^{\lambda}_{m_i} \cap \widehat{U}\right|}{\left|\widehat{U}\right|}$$

Topic User Ranking Function

$$\rho^{a_j}_{u_i}\left(\widehat{U}\right) = \frac{\left|NN^{\lambda}_{ij} \cap \widehat{U}\right|}{\left|\widehat{U}\right|}$$

Topic Multimedia Ranking Function

$$\rho^{a_j}_{m_i}\left(\widehat{U}\right) = \frac{\left|NN^{\lambda}_{kj} \cap \widehat{U}\right|}{\left|\widehat{U}\right|}$$

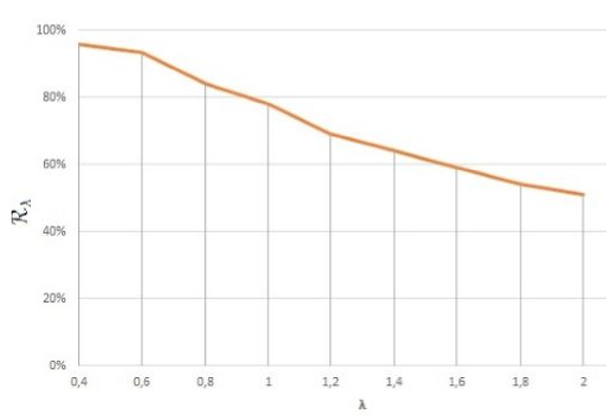
	τ	ρ
MSNMR - PR	0,92	0,95
MSNMR - KS	0,76	0,89
MSNTMR - PR	0,48	0,58
MSNTMR - KS	0,65	0,78
MSNTMR - TSIM	0,94	0,96
MSNMR - HR	0,71	0,74
MSNTMR - HR	0,80	0,91
PR - HR	0,70	0,74
KS - HR	0,67	0,82
TSIM - HR	0,78	0,89

Ranking Comparison: (PageRank(PR), K-Step Markov(KS), MSN Multimedia Ranking(MSNMR), MSN Topic Multimedia Ranking(MSNTMR), Human Ranking(HR), Topic-Sensitive Influencer Mining (TSIM).

We performed 50 queries by example (target images were randomly chosen from our dataset subset of the *Yahoo Flickr Creative Commons 100 Million Data* (YFCC100M)) and computed the related results using LIRE (customized with CEDD features and Tanimoto distance and assumed as a sort of gold standard) and our system facilities.

For measuring the performance of our system with respect to LIRE we use the following metric:

$$\mathcal{R}_\lambda = \frac{|R_{MSN_\lambda} \cap R_{LIRE}|}{|R_{MSN_\lambda} \cup R_{LIRE}|}$$



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Future Works

The future works will be focused on:

- Identification of better way to represent hypergraph model based on specific application
- Distribution of hypergraph model based on Big Data architecture

In order to perform an experimental evaluation of the proposed model, we are planning to exploit the introduced ranking functions to support different types of applications:

- Multimedia recommendation
- Influence analysis