Towards Storytelling by Extracting Social Information from OSN Photo's Metadata

Mukesh Saini, Fatimah Al-Zamzami, Abdulmotaleb El Saddik
[1]Multimedia Communications Research Laboratory, University of Ottawa, Ottawa
[2]Division of Engineering, New York University Abu Dhabi, UAE
{msain2, falza094, elsaddik}@uottawa.ca

ABSTRACT

The popularity of online social networks (OSNs) is growing rapidly over time. People share their experiences with their friends and relatives with the help of multimedia such as image, video, text, etc. The amount of such shared multimedia is also growing likewise. The large amount of multimedia data on OSNs contains in it a snapshot of user's life. This social network data can be crawled to build stories about individuals. However, the information needed for a story, such as events and pictures, is not fully available on user's own profile. While part of this information can be retrieved from user's own timeline, a large amount of event and multimedia information is only available on friend's profiles. As the number of friends can be very large, in this work we focus on identifying subset of friends for enriching the story data. In this paper we explore social relationships from multimedia perspective and propose a framework to build stories using information from multiple-profiles. To the best of our knowledge, this is the first work on building stories using multiple OSN profiles. The experimental results show that with the proposed method we get more information (events, locations, and photos) about the individuals in comparison to the traditional methods that rely on user's own profile alone.

Categories and Subject Descriptors

H.3.3 [**Information Systems Applications**]: Information Search and Retrieval

Keywords

Storytelling; Photo; Metadata; Online Social Networks; Relationship Strength

1. INTRODUCTION

The first step towards creating a story using OSNs is to detect life events and collect corresponding multimedia information with spatio-temporal attributes [13]. A story is composed of events that users have experienced. In another words, the story tells what places user has visited, when, and with whom. Multimedia content, which is uploaded by users or tagged by friends, can be found on user's personal profile. Although personal profile is a great source of information about a user, it may not have sufficient multimedia to build a complete, interesting, and informative story. Some users may be not-active or lazy to engage in activities on OSNs and rely on their friends to share the event related multimedia. Hence, we can say that user's friend's profiles can be treated as a complementary source of information about their social life. However, the number of friends on OSNs is usually large and it is challenging to find a subset of friends as complementary resources.

To meet this challenge, we propose a multimedia-based relationship strength model that allows us to obtain more information to enrich the targeted story with a small number of additional profiles. The overview of the proposed framework is shown in the Figure 1. We leverage photos metadata to obtain geo-location and capture time data as well as copresence of people in photos. From these simple abstract data, and user's basic profile information, we derive degree of interaction and similarity between users to find the relationship strength; and eventually extract more story data. Being able to collect more events that are not available directly from user's profile will fill the missing blanks of the user's initial timeline.

We conducted experiments on Facebook dataset by collecting data from five main users and 1252 sub-users. We compared the information retrieved using proposed framework with the information retrieved only from the user's own profile. Results show that with the proposed method we are able to retrieve 2 to 3 times more information on average with only 10 additional profiles.

This paper presents two specific contributions:

- First, we propose a novel framework to build social personal stories from multiple profiles on OSNs.
- Second, we propose a multimedia-based relationship strength model that allows us to retrieve additional information to enrich the stories.

The rest of the paper is organized as follows. Current trends on online social networks and motivations are described in Section 2. In Section 3 we discuss related works. A brief overview of social storytelling is provided in Section 4, followed by a social strength model in Section 5. Section 6 shows experiments and results. Finally, Section 7 concludes the paper.

WISMM'14, November 7, 2014, Orlando, FL, USA.
Copyright 2014 ACM 978-1-4503-3157-9/14/11 ...$15.00.
http://dx.doi.org/10.1145/2661714.2661721.

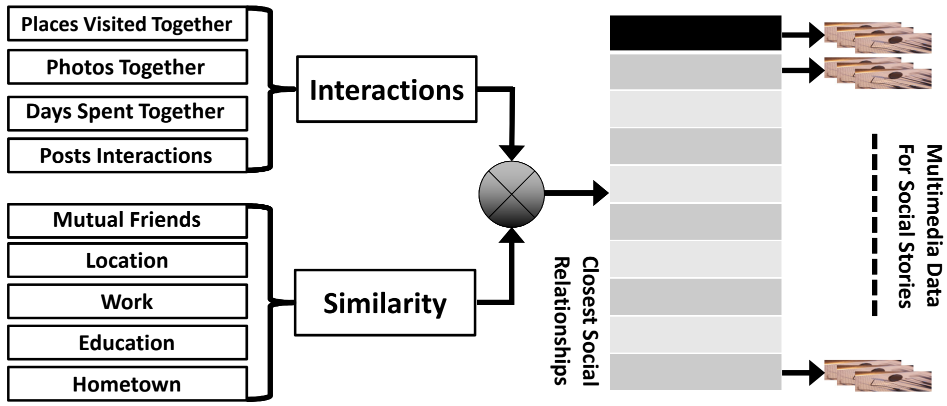


Figure 1: Proposed storytelling framework. We first calculate the strongest relationships of the user and then fetch multimedia data from their profiles (in addition to user's own profile).

2. MOTIVATION

With the rapid evolution of web technologies, the communication platforms between Internet users have been significantly increased. The communities have been enhanced to what we call online social networks (OSNs). The OSNs, such as Facebook and Google+, facilitate the information sharing and dissemination among users in different parts of the world. Instagram community has grown from 1 million to 200 million active users monthly since it was first launched on October 2010. Its library has 20 billion shared photos with an average of 60 million photo uploads per day. The size of Facebook photo library alone is 250 billion, and currently average of over 350 million photos are being uploaded every day. With the ability to tag people in the photo, location where the photo is taken, and time when the photo is taken, the photos have become a rich source of information about their owner's social life [7].

Digital cameras and smartphones cameras have also become pervasive, which allows more and more people to take photos and create their own digital photo collections. Fortunately, with the digital photography, it is easy to add contextual data to the images. This contextual data is referred to as photo metadata. Photo metadata usually includes timestamp, GPS location, and other camera settings. By using face detection/recognition technologies, it is possible to obtain identities of people depicted in photos automatically [3]. Bluetooth technology has also been used to detect people presence at the time of photo capture [5].

In our work, we exploit this huge amount of data associated with digital photos in order to extract meaningful information about people's social life. For this, we focus on three pieces of photo metadata: people co-appearance in photos, capturing time, and location. A photo with two or more people appearing together indicates that they know each other and hence they have a social connection. The frequency of co-appearing in different pictures taken during different events at different locations implies that they meet each other more often; and more likely they share a strong social connection. These social connections can be exploited to access additional multimedia content related to the users. This huge amount of information can be used to build multimedia rich stories about the social individuals [10].

We observe that in cinematography the same scene is shot multiple times with multiple cameras, resulting in a large number of video clips; only few of which are chosen for the final video. Hence, although we may not be able encompass all collected data in the final stories, having more information about the user would enable us to build more interesting and informative stories. In this work our main focus is to collect information relevant to the users. In our future work we will develop methods to combine this information and create stories.

3. RELATED WORKS

There have been many works that utilize photo metadata to support the process of browsing, search, and retrieval of photos [18]. The increased load of digital photos being generated everyday makes the manual annotation of photos a difficult and time consuming task. This has instigated a number of research works on automatic photo annotation based on metadata [5] [22]. Photo metadata has also been used to extract additional contextual information [17]. For instance, from photo's timestamps, it is possible to derive status of the day (i.e. day or night) and weather conditions at the time of the capture. Accordingly, several context-aware content delivery systems have been proposed, e.g., tourism guidance based on shared photos [15]. Discovering social connections from a user's own photo collections has been an interesting topic in multimedia research domain. People occurrence data and co-occurrence information are mainly used to understand social relationships between people depicted in photos and to determine the type of relationships (e.g. family, friends, etc.) [8] [2] [19].

There have been only few related works on building stories of individuals, which are also limited to photo collection retrieval and summarization [4] [21]. Obrador et al. [21] introduced a photo storytelling approach for social photo albums. However, the generated stories lack context and are only limited to one specific album. Early this year, Facebook celebrated its 10th birthday with personalized "Look Back" videos for all Facebook users. The video summarized user's timeline information on Facebook since the time they joined. Nokia Lumia has launched a storyteller application that automatically clusters photos into interactive groups. In both efforts, stories lack concrete context because: (1) they rely on information from single user and (2) they ignore user's social context such as events, locations, and close friends.

Another important aspect of the proposed work is relationship strength. Most of the traditional studies in social network analysis have focused on binary relations (i.e., friends or not friends) [12]. Such a coarse indicator cannot provide an accurate insight into the strength of relationship between people. Some recent studies have addressed this issue by introducing social relationship strength modeling. Recent relationship strength models have been using interaction activity [20], profile similarity [23], amount of shared time [6], geographical location [14], and mutual friends [11]. However, we believe that to build multimedia-based stories we need a new definition of relationship strength that includes photos metadata. Previous works on finding strength of connections mainly focused on interactions such as commenting, tagging and chatting but did not leverage photos metadata to estimate the relationship strength. In this work we not only exploit posts and their related actions (i.e. comment, likes), we also focus on the metadata of shared photos to calculate the strength of connections from multimedia perspective.

4. SOCIAL STORY

A story consists of different pieces of information presented in chronological order. In this work we have modelled story as a set of events and related information, including location of event, day of event, and people involved. In other words, a story $\mathcal{S}$ is represented as:

$$\mathcal{S} = \{(e_i, l_i, d_i, p_i) | e_i \in \mathcal{E}, l_i \in \mathcal{L}, 1 \leq i \leq n\} \tag{1}$$

where $\mathcal{E}$ is the set of events, $\mathcal{L}$ is the set of locations, d_i is corresponding day, and p_i is the set of people involved, i.e., closest friends. Note that all these elements of the story have associated photos. Our goal in this paper is to maximize $n_e = |\mathcal{E}|$, $n_l = |\mathcal{L}|$, and total number of photos n_p so that we can create a multimedia enriched story. To do that, we examine user's social relationship strength with friends and retrieve additional event and multimedia information, which is missing from user's own profile, from profiles of a certain number of closest friends (Figure 1).

We need the social bonds between individuals on OSNs because we believe that close friends are more reliable sources of additional information about the user [16]. We need to fetch additional information in order to generate a story that covers as many life experiences as possible. Hence, we propose a model that exploits the amount of shared time between people, frequency of interactions, personal relationships and shared activities to measure the interpersonal relationship strength.

5. SOCIAL STRENGTH MODEL

To determine the strength of relationship, we consider amount of social interactions and degree of similarity between the users, as shown in Figure 1. Granovetter [9] defined interpersonal ties as combination of amount of shared time, intensity, intimacy and reciprocal services. We exploit the amount of time a pair of users have spent together (amount of time), number of places they have visited together (intimacy and intensity), number of mutual photos taken together (intimacy and intensity), frequency of interactions (intimacy), clique of mutual friends (intimacy), and the scope of shared activities (reciprocal Services). Hence, we first calculate degree of social interactions, then degree of similarity, and finally combine these two to get the final rank. The degree of interactions and profile similarity are combined as follows [6]:

$$r = \frac{r_i + r_s}{2} \tag{2}$$

where r is final strength used for ranking, r_i is degree of interactions, and r_s is the degree of similarity. From this equation we have a full spectrum of relationship strengths between social users. We rank the inferred strengths and choose the top γ candidates to find more information, where γ depends on the amount of additional information required for story.

5.1 Degree of Social Interactions

The interactions are further divided into two types: interactions through photos and interactions through posts.

5.1.1 Interaction Through Photos

People use photos to document their memories and share it with family and friends. People can also add context to their photos such as geo-location (where photo was taken), capture time, and friends co-present in the photos. Every digital photo has descriptive information that describes its contents. This information is called photo metadata. From the available photos and their metadata, we are able to extract the following information:

Number of Photos Together: People with close ties tend to capture more than one picture together in the same activity/event and usually they appear close to each other in the pictures [1]. This observation has inspired us to consider the amount of mutual photos of user and friend as an indicator of their bond. If the main user has N_p photos in total, out of which N'_p photos are mutual, the mutual photo degree is defined as $\sigma_p = N'_p/N_p$.

Number of Days Spent Together: From the available photos on a user's profile, we are able to learn where (geotags data) and when (capture time data) and with whom (social data) the user was. With this information, we estimate the number of days two users spent together. If N_d is the total number of days the main user has spent on OSN and N'_d the number of days spend together, the time togetherness degree is defined as $\sigma_d = N_d/N'_d$.

Number of Places Visited Together: In the similar way, we use image metadata to calculate the number of places visited together. Auto geo-tagging features come with almost all devices these days. Accordingly, we assume that all photos on OSNs are geo-tagged. If N_p is the total number of places the main user has visited and N'_p the number of places visited together, the degree of location togetherness is defined as $\sigma_l = N_l/N'_l$.

5.1.2 Interaction Through Posts

People interact in social media by posting or sharing different media such as text posts (status updates), link posts, photo posts, video posts, etc. Interactions with the posts come in two forms: likes and comments. Responding to friends posts in a frequent rhythm gives an insight on the social ties between social users. If N_{pt} is the total number of posts of the main user and N'_{pt} number of posts which the friend liked or commented, degree of post interactions between the main user and the friend is calculated as

$\sigma_{pt} = N'_{pt}/N_{pt}$. One post can have multiple comments by the same user, which is another indicator of close relationship. Hence, we also measure total number of comments by a friend on user's posts and divide by total number of posts to measure degree of comment interactions, i.e. σ_c.

5.1.3 Final Degree of Social Interactions

We use linear combination to obtain the final degree of social interactions:

$$r_i = w_p * \sigma_p + w_l * \sigma_l + w_d * \sigma_d + w_{pt} * \sigma_{pt} + w_c * \sigma_c \quad (3)$$

where w_*'s are corresponding weights. Because people with large interactions are generally similar, we assume that if $r_i > T_i$, then $r_s = 1$ and do not analyse similarity to save processing. Here, T_i is an empirically derived threshold value. T_i can be set to 1 if processing time is not a major concern.

5.2 Degree of Similarity

In the previous step, we calculated the interaction degree between the user and her friends based on photos and posts. So far we are able to know which friends are in contact and active with the user. If a friend is active with the user, we consider her as a strong connection. The challenge occurs when a friend is not that much active with the user, but still there is a strong bond between them. To separate this friend from other friends with weak bonds, we propose to study another factor –profile similarity– to support the process of finding the strength of connection between the user and her friends. We study five profile features to detect the similarity between users: mutual friends, current geo-location, hometown, education and work.

5.2.1 Mutual Friends

In the absence of significant interactions between the users, mutual friends play a major role in detecting social bonds between them. Friends associated with acquaintances are different than those who have social connections with close friends [6]. In our work, we consider the clique (i.e. social ties) of mutual friends to support finding close friends. Previous studies have claimed that more common friends between users indicate stronger relationship [24]. Hence, we define degree of mutual friendship, ρ_m, which refers to the ratio of mutual friends and total friends of the main users. We define a threshold T_f for mutual friend's strength. Again, if $\rho_m > T_f$, we assume $r_s = 1$ and we do not need to examine the other similarities. Otherwise, we consider similarities of current location, hometown, education, and work. A higher value of T_f will result in more accurate results, while a lower value can be used to save processing.

5.2.2 Current Location, Hometown, Education, and Work

When interaction and mutual friends information does not provide an insight into the strength of social connections, we need to explore more information to discover strong social ties between users.

Current Location: People tend to have more connections to the ones living in the same city or country than others in different cities or countries. Current location similarity is measured with two parameters, one for city (δ^l_{ct}) and one for country (δ^l_{cn}). If the friend is from same city/country, then $\delta^l_{ct}, \delta^l_{cn} = 1$, otherwise $\delta^l_{ct}, \delta^l_{cn} = 0$. The effective similarity measure of current location is defined as:

$$\delta^l = \frac{\delta^l_{ct} + \delta^l_{cn}}{2}. \quad (4)$$

Although same city will always result in same country, we are giving more weightage to living in the same city because it implies more closeness than the country.

Hometown: People who live outside their hometown usually tend to make group of friends from their own hometown. In every country, people from the same hometown create their own communities to enjoy home culture. For hometown also we define similarity measures corresponding to city and country and measure hometown similarity index δ^h as average of the two.

Education and Work: School and work are among the best mediums to meet people and make friends. We believe that school and work have the same importance for making friends. The similarity measures for education δ^e and work δ^w are 1 if the venue of the friend is same as the main user, otherwise they are zero, respectively.

5.2.3 Final Degree of Similarity

Finally, we calculate the similarity r_s between the main user and the friend by combining all similarity measures, i.e.,

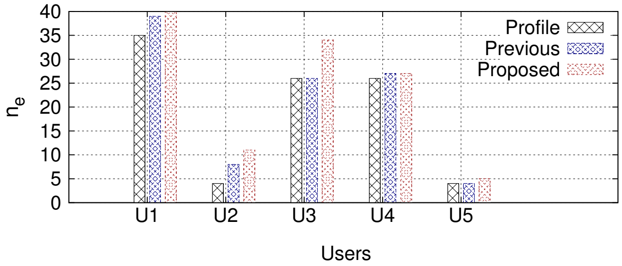
$$r_s = w_m * \rho_m + w_{lhew} * (\delta^l + \delta^h + \delta^e + \delta^w) \quad (5)$$

where w_m and w_{lhew} are corresponding weighting coefficients. The degree of interactions (Equation 3) and similarity (Equation 5) are combined according to Equation 2 to obtain final strength r. We rank the friends in decreasing order of r and extract information from top γ friends to build stories. The ranking is also used to identify closest friends to be included in the story.

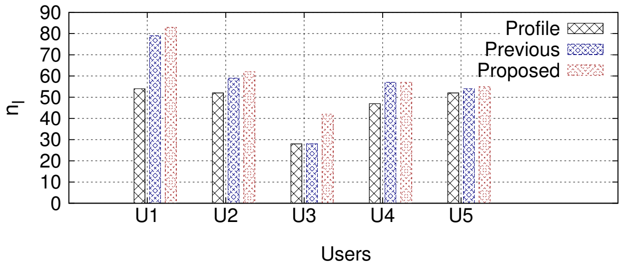
6. EXPERIMENTS

The main purpose of the experiments is to prove that with the proposed framework we can extract more information about individuals. The experiments were conducted on a real-world data collected from Facebook. We collected data of 5 main users and their friends. Each main user has an average of 250 friends which brings the total number of sub-users in our dataset to 1252. From each profile, we retrieved personal information and interaction information. The personal information includes name, current city, hometown, school and education, and mutual friends. We collected two types of interactions for each user: photos and posts. We extracted tags data (i.e. photo metadata) of photos which includes geotags, capture time, and people tags. From posts, we retrieved likes and comments information. The same information was collected for friends of the main users. Facebook API's are employed to collect data.

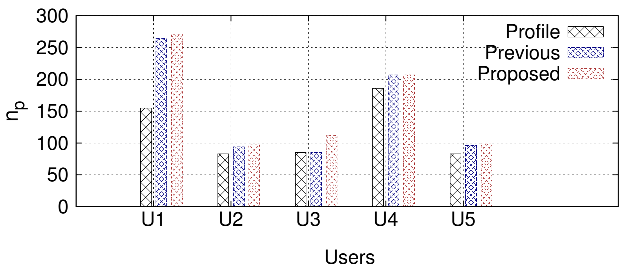
To evaluate the performance of our proposed method, we analyzed the data of two years for the main users. We calculated the total number of photos, places and events from the photos available on user's profiles. Then we applied our proposed multimedia-based relationship strength model to find the top ten strongest connections in order to find more photos and, in turn, more places and events. In the experiments we used $\gamma = 10$. Then we did comparison of the number of photos, places and events. The results are shown in Figure 2 for 2013 and Figure 3 for 2014. In the figures,



(a) Events

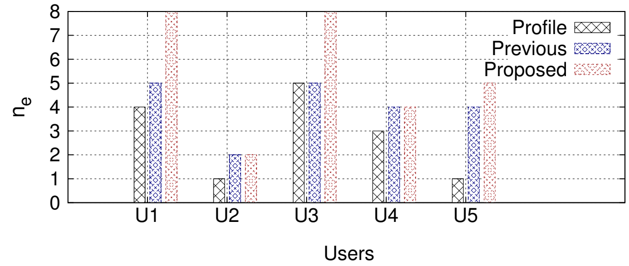


(b) Locations

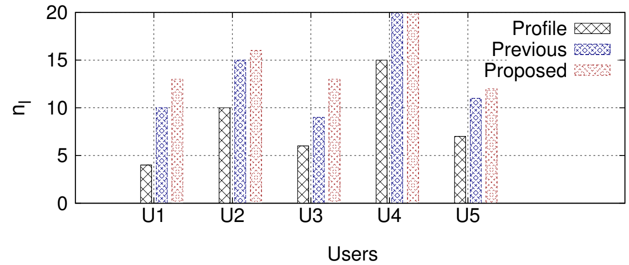


(c) Photos

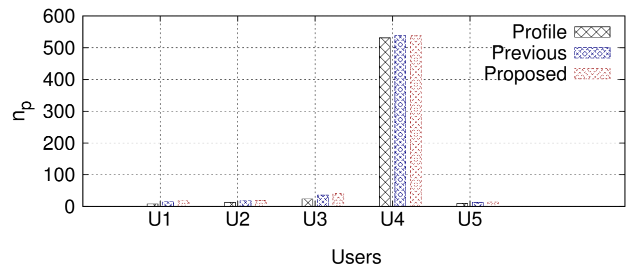
Figure 2: Results for 2013 for five users. With proposed method we are able to retrieve more events, locations, and photos about individuals to build story.



(a) Events



(b) Locations



(c) Photos

Figure 3: Results for 2014 for five users. Although it is a short span of 4 months, we were able to extract at least 10 events for each user.

"Profile" represents information from profile alone and "Proposed" gives the results obtained using proposed method. To compare the proposed work with previous works, we also collected user's data from profiles of 10 closest friends chosen based on the traditional definition of relationship, which is mainly based on the number of mutual friends. The results of the previous approach are shown as "Previous" bars in Figure 2 and 3. We can see that the proposed method could find more photos, events, and locations from the ten top closest friend. The number of photos, places and events collected from year 2013 increased by an average of 55.45 for photo, places and events. For 2014, the performance is increased by an average of one element more than the average in personal profiles alone. With these positive results we can conclude that our algorithm could recognize the top ten strongest connections of the given main user from a set of 250 friends on average for each user.

6.1 Discussion

In the proposed method, we first search for strongest connections of a user and then go to their (strong connection's) profiles and search for user's photos. Once we have the photos, we use their metadata to determine events and locations. One of the obvious ways of finding relevant photos is face recognition. Current face recognition methods have very high accuracy; the probability of false detections is very less and essentially depends on the accuracy of the face recognizer. Because this is not main focus of the paper, we used tag information to determine relevant images in the experiments. Note that with the face recognition technique we will also be able to collect photos that are not tagged by the user. One limitation of the current evaluation is limited number of users. Note, however, that each user in our experiments has on average of 250 friends. Because the results of 5 users are consistent, we feel they can be considered representative in this case.

7. CONCLUSIONS

In this work, we proposed a social personal storytelling framework that is intended for individual social users and their friends. Due to the possibility that user's personal profile may miss important information (e.g. events), we propose a multimedia-based relationship strength model to find the close friends of users in hope to find more information to complement the information on user's own profile. With a complete sequence of events, we can build a reliable social story that depicts real-life experiences of the users. To validate the proposed framework we conducted experiments with 5 main users and 1252 sub-users of Facebook. The experimental results have proved that with proposed data collection method and new model of relationship, we are able to extract 2 to 3 times more information. In this paper we have kept our main focus on data collection for building stories. In the future we want to build multimedia presentations and evaluate interestingness, completeness, and accuracy of the collected information and stories.

8. REFERENCES

[1] P. Aarabi. Relational social image search. In *IEEE International Symposium on Multimedia (ISM)*, pages 520–521. IEEE, 2013.

[2] M. Bloess, H.-N. Kim, M. Rawashdeh, and A. El Saddik. Knowing who you are and who you know: Harnessing social networks to identify people via mobile devices. In *Advances in Multimedia Modeling*, pages 130–140. Springer, 2013.

[3] J. Choi, W. De Neve, Y. M. Ro, and K. N. Plataniotis. Face annotation for personal photos using collaborative face recognition in online social networks. In *16th International Conference on Digital Signal Processing*, pages 1–8. IEEE, 2009.

[4] N. Datia, J. Moura-Pires, and N. Correia. Summarised presentation of personal photo sets. In *MultiMedia Modeling*, pages 195–206. Springer, 2014.

[5] M. Davis, N. Van House, J. Towle, S. King, S. Ahern, C. Burgener, D. Perkel, M. Finn, V. Viswanathan, and M. Rothenberg. Mmm2: mobile media metadata for media sharing. In *CHI'05 extended abstracts on Human factors in computing systems*, pages 1335–1338. ACM, 2005.

[6] E. Gilbert and K. Karahalios. Predicting tie strength with social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 211–220. ACM, 2009.

[7] S. Golder. Measuring social networks with digital photograph collections. In *Proceedings of the nineteenth ACM conference on Hypertext and hypermedia*, pages 43–48. ACM, 2008.

[8] J. A. G. Gómez and B. Shneiderman. Understanding social relationships from photo collection tags. *Human Computer Interaction Lab, University of Maryland*, 2011.

[9] M. Granovetter. The strength of weak ties. *American journal of sociology*, 78(6):l, 1973.

[10] L. Jin, Y. Chen, T. Wang, P. Hui, and A. V. Vasilakos. Understanding user behavior in online social networks: A survey. *IEEE Communications Magazine*, page 145, 2013.

[11] T. H.-J. Kim, A. Yamada, V. Gligor, J. Hong, and A. Perrig. Relationgram: Tie-strength visualization for user-controlled online identity authentication. In *Financial Cryptography and Data Security*, pages 69–77. Springer, 2013.

[12] D. Liben-Nowell and J. Kleinberg. The link-prediction problem for social networks. *Journal of the American society for information science and technology*, 58(7):1019–1031, 2007.

[13] X. Liu, R. Troncy, and B. Huet. Using social media to identify events. In *Proceedings of the 3rd ACM SIGMM international workshop on Social media*, pages 3–8. ACM, 2011.

[14] J. McGee, J. Caverlee, and Z. Cheng. Location prediction in social media based on tie strength. In *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*, pages 459–468. ACM, 2013.

[15] K. Meehan, T. Lunney, K. Curran, and A. McCaughey. Context-aware intelligent recommendation system for tourism. In *IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, pages 328–331. IEEE, 2013.

[16] A. Mislove, B. Viswanath, K. P. Gummadi, and P. Druschel. You are who you know: inferring user profiles in online social networks. In *Proceedings of the third ACM international conference on Web search and data mining*, pages 251–260. ACM, 2010.

[17] M. Naaman, S. Harada, Q. Wang, H. Garcia-Molina, and A. Paepcke. Context data in geo-referenced digital photo collections. In *Proceedings of the 12th annual ACM international conference on Multimedia*, pages 196–203. ACM, 2004.

[18] N. OâĂŹhare, H. Lee, S. Cooray, C. Gurrin, G. J. Jones, J. Malobabic, N. E. OâĂŹconnor, A. F. Smeaton, and B. Uscilowski. Mediassist: using content-based analysis and context to manage personal photo collections. In *Image and video retrieval*, pages 529–532. Springer, 2006.

[19] E. Raad, R. Chbeir, and A. Dipanda. Discovering relationship types between users using profiles and shared photos in a social network. *Multimedia Tools and Applications*, 64(1):141–170, 2013.

[20] M. Roth, A. Ben-David, D. Deutscher, G. Flysher, I. Horn, A. Leichtberg, N. Leiser, Y. Matias, and R. Merom. Suggesting friends using the implicit social graph. In *Proceedings of the 16th ACM SIGKDD*, pages 233–242. ACM, 2010.

[21] P. Sinha, H. Pirsiavash, and R. Jain. Personal photo album summarization. In *Proceedings of the 17th ACM international conference on Multimedia*, pages 1131–1132. ACM, 2009.

[22] W. Viana, J. Bringel Filho, J. Gensel, M. Villanova-Oliver, and H. Martin. Photomap: from location and time to context-aware photo annotations. *Journal of Location Based Services*, 2(3):211–235, 2008.

[23] R. Xiang, J. Neville, and M. Rogati. Modeling relationship strength in online social networks. In *Proceedings of the 19th international conference on World wide web*, pages 981–990. ACM, 2010.

[24] J. Zhuang, T. Mei, S. C. Hoi, X.-S. Hua, and S. Li. Modeling social strength in social media community via kernel-based learning. In *Proceedings of the 19th ACM international conference on Multimedia*, pages 113–122. ACM, 2011.