

Towards Multimedia-Based Storytelling in Online Social Networks

by

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Thesis submitted to the
Faculty of Graduate and Postdoctoral Studies
In partial fulfillment of the requirements
For the Degree of Master in Computer Science

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Abstract

Human activities can now be captured in real-time using sensor technology. The growth in sensor applications and smart mobile phones that come equipped with built-in sensors has led to the integration of sensors with social networks. These days, people are heavily dependent on online social networks (OSNs); they migrate their real-life activities online through various types of multimedia such as photos, videos, text, etc., which turns OSNs into a soft-sensory resource about users' events. The users use these forms of multimedia to tell their friends about their daily lives. This social network data can be crawled to build personal context-aware stories about individuals. However, the number of social users and the quantity of multimedia that is produced on social media are both growing exponentially, which leads to the challenge of information overload on OSNs. The information needed for stories, such as events and their locations, is not fully available on user's own profile. It is true that part of the information can be retrieved from the user's timeline, but a large number of events and related multimedia information is only available on friends' profiles. In this thesis, we focus on identifying a subset of close friends in order to enrich the content of the story. The amount of time people spend together has been proven to play a key role in determining close ties between people. We propose a DST (Days Spent Together) algorithm to find a user's closest friends based on the days they spent together interacting face-to-face. With the closest friends information, we are able to find additional information to complement what was found on the user's own profile, as well as to personalize the stories to ensure that they are only about the users and their closest friends. Due to the possibility of multimedia (photos in this thesis) overload for events, we propose to use the duration of events measured by DST, to determine the number of representative photos for each event. Our experiments show that the proposed approach could recognize the close friends of users and rank them from the strongest to the weakest. The results also show that with the proposed method we get days-spent-together values that are close to the corresponding true values provided by users.

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Professor Abdulmotaleb Elsaddik, who guided me towards the completion of my thesis research. He has been caring, motivating, and understanding throughout my masters studies. This work would not have been successfully done without his genuine support and immense knowledge. It has been an honor to be supervised by such a tremendous mentor.

Also, I would like to extend my sincere thanks to Dr. Mukesh Saini, for his excellent assistance during the work for this thesis. I do appreciate his patience with me and the fact that he believes in me. His comments and feedback have been always valuable during the progress of this thesis work.

A special and warm thanks goes to my beloved mother for her unconditional love and faith in me throughout my graduate studies. I would not have achieved my goals without her endless inspiration. Words are never enough to describe how grateful I am to you for everything you have done for me in my entire life. You have given me more than I ever could have asked for. Also, I would like to thank my father for giving me the opportunity to come to Canada and pursue my graduate studies there. I would also like to thank my sisters, my brothers, my nieces and nephews for being a nice part of my life.

I am also grateful to all my friends for being there for me to help me during the hard times and to cheer me up for keeping the great work up. They were a major part of my journey here in Canada and have become a second family to me as well. Their support has helped me to stay strong and focused all the time.

Finally, I would like to thank my colleagues in the Multimedia Computing Research Lab (MCRLab) who have made every day at MCRLab a good day. We truly have shared good moments together.

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Chapter 1

Introduction

The popularity of online social networking is growing over time. Online social networks (OSNs) have changed the way people communicate, express themselves, and share information with each other. People can share their real-life experiences with their friends and relatives through various types of multimedia such as photos, videos, text, etc. The quantity of such shared multimedia is also increasing constantly. Fortunately, online social communities consist of thousands of registered users and contain their friendships and personal information, as well as information about their multimedia-based interactions; this vast pool of data makes online social networks very rich sources of information that can help us understand peoples social lives.

The large amount of multimedia data on OSNs provides a snapshot of users' lives. This social network data can be crawled to build personal stories about individuals. The first step towards creating a story using OSNs is to detect life events and collect corresponding multimedia information with spatio-temporal attributes [1, 2]. In general, a story is made up of a chain of events that users have experienced at some point in their lives. In the context of this thesis, the story explains which places users have visited, when, for how long, and with whom. Multimedia content, which is uploaded by users, or uploaded/tagged by friends, can be found on users' personal profiles as well as on their friends' profiles.

Every story contains a chain of events that starts at one point and ends at another. A story can be generated for different purposes including personal, historical, cultural, educational, etc. Therefore, every story contains a selective batch of information that serves its purpose. In this work, we are targeting personal stories about people’s social lives using their information from online social networks, more specifically Facebook. In this thesis, our story is multimedia-based and is composed of video, photos, text, and audio. The story is triggered by events and their related context: times of events, location of events, and people involved in events. Each of these contextual components represents one aspect of the story. The temporal and spatial components can be leveraged to derive an additional component, which can then be added to the story. We define the additional component as the duration of the event. As mentioned earlier, each event starts at one place at a specific time, and ends at another. Duration information is an important aspect, which is directly related to the event. Our ultimate goal is to generate stories in an automatic way from events on OSNs.

1.1 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 information sharing and dissemination among users in different parts of the world. The Instagram community has grown from 1 million to 300 million monthly active users since it was first launched in October 2010 [3]. Its library has 20 billion shared photos, with an average of 60 million photo uploads per day. The size of the Facebook photo library alone is 250 billion, and currently an average of over 350 million photos are being uploaded every day [4].

Digital cameras and smartphone cameras have also become pervasive, which allows an increasing number of people to take photos and create their own digital photo collections.

Fortunately, with 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 a timestamp, GPS location, and other camera settings. By using face detection/recognition technologies, it is possible to automatically obtain the identities of the people depicted in the photos [6]. Bluetooth technology has also been used to detect people's presence at the time of the photo capture [7].

The availability of advanced social interactions in online social networks (OSNs) provides important data for various social analyses of their users. Nowadays, people can transfer their real-life moments/activities to OSNs such as Facebook using different forms of multimedia such as text, photos, videos, etc. Interestingly, they can describe the content of the shared multimedia by adding descriptive tags such as geo-tags (where the multimedia was generated), time-stamps, and people who were present when the multimedia was generated. This has turned OSNs into a rich source of information about users' personal lives [8]. Advanced technologies have promoted the e-social lifestyle. Almost everybody carries smart mobile devices equipped with cameras and built-in GPS sensors. These devices are used for data acquisition during people's face-to-face experiences. People's face-to-face interactions can be captured using sensing, sharing, and tagging tools. For example, taking a photo with a camera on a mobile device equipped with a GPS sensor will automatically record the location coordinates of the capture. Fortunately, there are many applications that transform these abstract coordinates into readable user-friendly representations such as city name, restaurant name, etc. These applications are now integrated into OSNs and have become essential in order to describe the geo-context of various multimedia interactions. Moreover, OSNs provide people tagging features on shared photos; this feature describes people's context at the time of capture. Users can manually tag people in photos with the associated names, or automatically using face recognition techniques. Multimedia sharing, with the use of features that give its content a descriptive context, makes online social networks a digital mirror of users' real-life experiences. In other words, the sensed data that represents a users

real-life activities are widely exposed on social media. The fact that this data is available on OSNs provides grained data to understand a users social life. More specifically, by having sensed geo-tags, time stamps, and people presence data of photo collections shared on OSNs, it is possible to discover a users social relationships and predict the closeness of these relationships.

In our work, we exploit this huge amount of data associated with face-to-face interactions (i.e. photos, in this work) in order to extract meaningful information about people’s social lives. For this, we focus on three pieces of photo metadata: people co-appearance, 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-appearance, in different pictures taken during different events at different locations, implies that they meet each other more often; they are therefore more likely to share a strong social connection. These social connections can be exploited to access additional multimedia content related to the users [9]. In addition, they can be used to personalize the stories of social individuals.

We observe that in cinematography, the same scene is shot multiple times with multiple cameras, resulting in a large number of video clips, few of which are chosen for the final movie [5]. Hence, although we may not be able to encompass all collected data in the final stories, having more information about the user would enable us to build more interesting and informative stories.

1.2 Research Challenges

The more the social communities expand, the more difficult it is to manage the information streams. Besides information management, there are lots of user-generated data embedded in online social networks that have not been exploited sufficiently, especially for multimedia-based storytelling purposes. In 2014, Facebook celebrated its 10th birthday with personalized ”LookBack” videos for all Facebook users. The video summarized the

user’s timeline information on Facebook, starting from the time they joined the network. Also, 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 a single user and (2) they ignore user’s social context such as events, locations, and close friends. The close relationships of users are an important part of personal stories. People are interested in telling stories about their personal lives with those with whom they have close ties [10]. Most of the OSNs relationship strength studies have not focused on interpersonal ties [11, 12]. Their works did not focus on multimedia content around real-world objects and activities. Instead, they considered traditional interactions such a tagging, liking, and commenting on posts [12, 13, 14].

In order to build a context-aware multimedia-based storytelling model, we face the following challenges:

- **Information Overload:** The information needed for a story, such as events and photos, is initially available on users’ own profiles. Although personal profiles are a great source of information about users, it may not have sufficient events and multimedia to build a complete, interesting, and informative story. Some users may be not-active or simply too lazy to engage in activities on OSNs and may rely on their friends to share event related multimedia. Hence, we can say that a user’s friends’ profiles can be treated as a complementary source of information about their social lives. However, the number of friends on OSNs is usually large [15] and it is challenging to find a circle of friends to act as complementary resources. In this work, we focus on identifying a subset of friends that can help enrich the story.
- **Event Enrichment:** From OSN users’ profiles we can obtain a list of activities that users experienced over a given period of time. However, when retrieving additional interaction information related to users from their strongest connections, some interactions might represent an event already found on users’ own profiles. However, the event information might be incomplete. Hence, intelligent techniques

are needed to group all related interactions (i.e. from users' profiles and additional profiles) into one event, in order to provide a complete picture of the event as well as its related photo collection. As a result, more informative stories could be generated. Additionally, the fact that some interactions (i.e. photos) of events are shared by the users themselves, while the rest are shared and tagged by their friends, can cause the interactions (i.e. photos) to be scattered and unorganized. As a result, it is more likely that we might miss some interactions (i.e. photos) containing extra information about events, which in turn will result in incomplete stories about these individuals.

- **Story Context:** People with whom we spend more time should be given higher priority in our personal stories. In our work, we combine the duration of all mutual events to determine the time spent together by two users. Moreover, the duration of events is an important addition to our stories, along with the social, temporal and spatial context. The duration of events is not explicitly available with events shared on OSNs. In this work, we developed an intelligent algorithm to estimate the duration of each event.
- **Photo Overload:** As we consider events of one full year, the number of photos for all of the events is expected to be quite large. We therefore need to use certain techniques to estimate how many photos per event will be used and which photos will represent each event. In this work, the number of representative photos used for each event should reflect the event duration. The context of the photo interactions (i.e. likes and comments per photo) will be used to decide which photos will be chosen as representatives for each event.

1.3 Thesis Contributions

From all the previously mentioned problems, we have been strongly motivated to propose a Days Spent Together (DST) model to meet these challenges in order to satisfy the objective of this thesis. Our proposed solution is represented in the following contributions:

1. We propose a novel framework to build personal social stories from multiple profiles on OSNs.
2. We propose a multimedia-based relationship strength model that allows us to personalize stories and to retrieve additional information to enrich these stories.
3. We design and implement an intelligent algorithm that detects events and recognizes if similar interactions belong to one event or to separate events.
4. We developed an intelligent model to estimate the duration of events and hence the amount of time people spent together, interacting face-to-face, by only using information from OSNs.
5. We propose a context-aware technique for building multimedia-based personal stories on OSNs.

1.4 Publications Resulting from this Research

- Saini, Mukesh Kumar; **Al-Zamzami, Fatimah**; and El Saddik, Abdulmotaleb. "Towards Storytelling by Extracting Social Information from OSN Photo's Metadata." Proceedings of the First International Workshop on Internet-Scale Multimedia Management. ACM, OCT. 2014.

1.5 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2: will cover the background and related work to the research covered in this thesis. Also, It will explain how the proposed work is different from the previous works

Chapter 3: will detail the methodology and the evaluation of our proposal on generating personal stories from multiple profiles. A preliminary version of DST is introduced in this chapter as well.

Chapter 4: will present the framework of the enhanced version of DST. It will explain in details our proposed DST algorithm after initial testing.

Chapter 5: will cover the details of the DST model evaluation and the results. This includes the data collection and the experiments in details.

Chapter 6: will cover the conclusion of our thesis research and propose future directions to which this thesis may lead.

Chapter 2

Literature Review

This chapter provides a background of the literature related to multimedia and its contributions to social networks. It describes different types of media and multimedia that are used to extract different types of knowledge, and its applications. In Section 2.2, we provide an overview of current trends on multimedia and online social networks. Section 2.3 discusses the analysis of social relationships between users on online social networks. In Section 2.3, we provide an overview on the applications of integrating sensors into social networks, followed by a description and related studies on human face-to-face interactions on sensed social networks. Finally, we review existing works on storytelling from a social networks perspective.

2.1 Multimedia and Social Media

With the evolution of Web 2.0/3.0 technologies, the communication platforms available to Internet users have significantly increased. The communities have been enhanced to what we now call online social networks. The online social networks facilitate the generation, sharing, and dissemination of information among users in different time zones and locations.

2.1.1 Overview

With the increased dependence of users on online social networks to share and distribute information, these networks can be considered as rich resources of information, especially in terms of multimedia data; a quick check on a friend's timeline is enough to catch up with them. From online social networks, we can easily know the places users have recently visited, the people with whom they generally socialize, their educational status, their personal thoughts and opinions, etc. A general scan of a user's albums can give us an idea of what they like to do, where they like to go, when, and with whom. It can also show the circle of friends who are the closest to the user.

Thus, the e-social style of life has changed the way people communicate. People migrate their real life experiences to online social networks to share them with friends and family. Online social networks provide a variety of multimedia resources that serve peoples need to document their real life events. These services vary between online interactions and real-world multimedia objects. The increasing dependence on OSNs played a role in the explosion of the amount of multimedia content, social activities, and contextual information that are generated. This has opened new avenues of understanding users and communities and hence accumulating different types of knowledge about them. Table.2.1 shows some examples of the knowledge that can be extracted using only contents shared on social media.

As shown in Table.2.1, different types of media and multimedia are available on different OSNs such as Facebook, Twitter, Google+, Instagram, etc. It may be text, URLs, photos, and/or videos. Photos are by far the most commonly shared multimedia on OSNs. The Instagram community has grown from 1 million to 300 million active monthly users since it was first launched in October 2010. Its library has 20 billion shared photos, with an average of 60 million photo uploads per day. The size of the Facebook photo library alone is 250 billion, and currently an average of over 350 million photos are being uploaded every day. With the ability to tag people in photos, the

Knowledge	Application(s)	Media	Social Network
Products rates, reviews, trust relationship between users, effect of marketing on customer ([16], 2002)	Viral marketing	Text	Epinions
The relationships between users, topical trends ([17], 2007)	Discovering temporal communities from documents	Text	CiteSeer, synthetic datasets
The interaction between the bloggers ([18], 2007)	Terrorism and Crime Detection	Text, URLs	Weblog Social Networks
Persons skills and knowledge area ([19], 2007)	Finding experts	Text	W3C Website
Rates, reviews, comments, chattings of users ([20], 2007)	Customer relationship management	Text	E-Commerce websites
Relation among research topics, authors, and research groups ([21], 2008)	Building topical co-author networks	Text	Citeseer
Context of emails between users ([22], 2008)	Extracting Topic of Textual Conversations	Text	Email Archive
Users' interests and favourites ([23], 2008)	Advertisement	Text	E-mails
Key topics in user interactions ([24], 2009)	Advertising, viral marketing	Text	E-mails Archive
Friendship closeness, users activities, level of importance/involvement of user's albums ([25], 2009)	Predicting the future social activities of the users	Text, Photos	Facebook
Criminal relationships and suspicious people identification ([26], 2009)	Criminal Investigations, Criminal Group	Text, Photos	SBNS Datasets
Tags, groups on interests ([27], 2009)	Personalizing image searching	Photos	Flickr
Tagging activities of users, topical interests of users ([28], 2010)	Predicting Social Link from Shared Metadata	Photos	Flickr , Last.fm
Malicious content and activities ([29], 2011)	Finding malicious people	Text	Facebook
Group information, group users' behaviours ([30], 2012)	Friend recommendation	Text	Whrrl , Meetup
US President Barack Obama's activities ([31], 2012)	Interpreting political strategy	Text	Twitter
Photo properties, photo based interactions, and user information ([32], 2012)	Image classification and group recommendation	Photos	Flicker
Locations, landmarks ([33], 2012)	Tourist plans	Photos	Flicker
Social ties, places of interest check-in habits ([34], 2013)	"Predicting whether user meetings	Photos	Gowalla

Table 2.1: Review of earlier works that extract knowledge using contents shared on social media.

location where the photo was taken, and the time when the photo was taken, photos have become a rich source of information about people’s social lives and relationships. Digital cameras and smartphone cameras have also become pervasive, which allows an increasing number of people to take photos and create their own digital photo collections, as shown in Fig. 2.1. Moreover, photos are the most important type of content generated on mobile devices; they are easy to produce and quick to consume.

Photos Alone = 1.8B+ Uploaded & Shared Per Day... Growth Remains Robust as New Real-Time Platforms Emerge

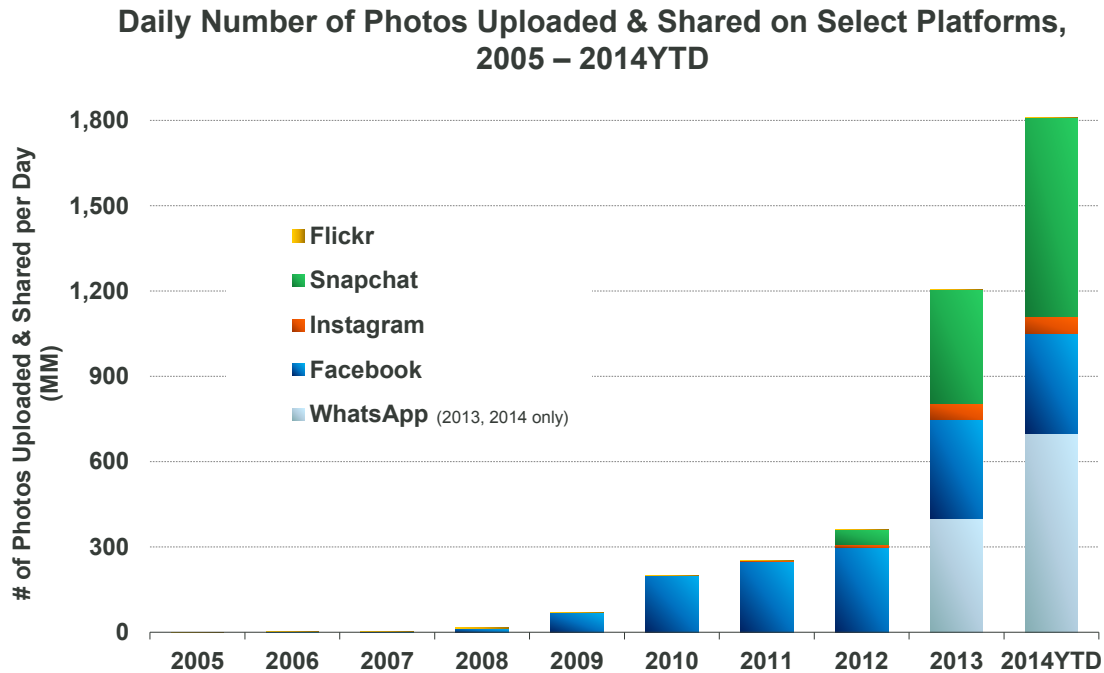


Figure 2.1: Daily number of photos uploaded and shared on selected platforms (2005-2014YTD). Source: KPCB estimates based on publicly disclosed company data, 2014 YTD data per latest as of 5/14. [95]

The huge amount of data and context associated with digital photos has led to numerous research issues including indexing, searching and retrieval, annotation, etc. Interestingly, this data greatly contributes to the extraction of meaningful information about

people and their social lives and relationships.

2.1.2 Photos and Metadata

In general, metadata is the data that describes other data; it provides descriptive information about a certain resource. For example, a text documents metadata includes information about the size, the author, and the creation date of the document.

Overview

Photo metadata represents descriptive information about photos and their contents. In this age of digital photography, photo metadata has become increasingly important and storing information with images is now very common. Almost all digital cameras generate metadata (i.e. camera-specific metadata) that includes the date and time of the capture, the resolution, the camera settings used for the shot, whether or not the flash was fired, the shutter speed, the camera model, the camera owner, etc. The camera-specific metadata is called EXIF data (Exchangeable Image File Format). The type of information stored in EXIF varies depending on the camera model, however there are different metadata formats that allow users to add their own information within their photos. This data might include photo copyright, credits, special instructions, created locations, keywords, and other data. IPTC and XMP are two of the most commonly used metadata formats for this purpose. In photo-sharing websites like Facebook, Google+, and Flickr, there are tagging services where users can add extra information to their photos such as the data/time and geo-location of the capture, the people present at the time of the capture, and user-generated descriptive keywords or captions. This type of photo tags data is also considered as photo metadata since it describes the photos the same way as EXIF does. Therefore, any information describing images or image files, and their contents, is referred to as photo metadata.

The main purpose of metadata is to improve the delivery and retrieval of contextual information. Furthermore, metadata is important to understand the content of resources,

and has become increasingly essential in various multimedia applications. There have been many studies that utilize photo metadata to support the processes of browsing, search, and retrieval of photos [35]. Photo metadata has also been used to extract additional contextual information [36]. For instance, from photo timestamps it is possible to derive the status of the day (i.e. day or night), as well as the weather conditions at the time of the capture. Accordingly, several context-aware content delivery systems have been proposed, for example tourism guidance based on shared photos [37].

Yanai et al. [38, 39] have discovered cultural semantics across different geographical regions by mining location data from geo-tagged images. Bageshri et.al [40] detected events to annotate images using personal information and social contexts. Lyndon et.al [41] extracted semantic patterns from photo tags to retrieve images of geography-related landmarks from the Flickr dataset. Authors in [6, 42] leveraged social co-occurrence data of people depicted in images for automatic face recognition and friends recommendation. Experiments in [42] show the efficacy of co-occurrence data for the recommendation of friends in social networks. In [43] the social context has been taken into consideration for tourism guidance in a way that recommendations differ based on the tourist group (family, friends, etc.). In our work we introduce a multimedia storytelling application. The stories contents are based on three types of metadata: spatial, temporal, and social.

Photo Annotation

In recent years, digital cameras have seen an enormous rise in popularity, leading to a huge increase in the quantity of digital photos being taken, which in turn brings the challenge of organizing, retrieving, and visualizing these large collections. Hence, the need for indexing the images is growing rapidly. The volume of photos available on the web has created an unimaginable depth and breadth of new research opportunities. The demand for effective image indexing and searching is growing at an incredible pace. Image annotation is an effective method for content based image retrieval. The increased load of digital photos being generated every day 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, as explained next.

Search and Retrieval O'Hare et.al.[44] proposed a method to organize digital photo collections based on the date/time and geo-location data of the captures. Additional contextual metadata was derived from the date/time, location, and EXIF data such as the weather conditions, the indoor/outdoor classification, and the light status, in order to help organize the photo collections. The availability of this metadata has improved the utilization of the search criteria because it allows us to narrow the scope of the search results and therefore gives only the most desired results. Marc et al. [7] developed a camera-phone application MMM2 prototype that exploits social information (i.e. people co-presence) along with the spatial and temporal metadata of photos at the time of capture for photo management and auto-sharing with suggested recipients. Kennedy et.al. [41] proposed a location-tag-vision-based approach to retrieve photos of geo-related landmarks on Flickr. They extracted patterns from photos generated tags and spatial/temporal metadata to create a practical knowledge base of important events and locations. They showed that integrating a visual analysis with the extracted knowledge showed greater results for the visual recognition of landmarks than when using the extracted knowledge only. Authors in [44] also showed that contextual information is not always sufficient in image retrieval from large photo collections. They combined image content analysis with contextual information to return images of known objects from large photo collections. The experiments showed that combining content analysis with contextual information results in better image retrieval than when using only contextual information.

Automation of Photo Annotation The ability to understand and analyze photos is now of great importance, especially when we wish to search for and retrieve specific photos [44, 45]. Keyword tags (i.e. text tags) are currently the primary way of searching and retrieving photos, which is why annotation methods are so desired. The huge

volume of photos shared on social media made traditional annotation very difficult [46], hence the need to automate the annotation process. Fortunately, many applications and photo-sharing websites encourage users to tag their images; Google Plus, Google Picasa, Facebook, and Flickr now enable users to label the images with people (face, non-face), places, date/times, and user-specific tags.

There has been a wide range of studies on semi-automatic/automatic image annotation. Shuangrong et.al [47] proposed a mobile-application prototype that implements semi-automatic image annotation to mobile devices. They annotate photos with the time and place of capture, as well as the events at which the photos were taken, in order to facilitate the search and retrieval of photos from various photo collections. To do the annotation, they leveraged EXIF metadata including spatial, temporal, and photographer information. By exploiting personal calendars and email, they were able to extract personal contexts such as scheduled events. If a photo was taken at the time of a scheduled event, there is a high chance that the photo is related to that event. Experiments showed that the proposed method reduced the overhead of manual annotation and improved image retrieval. The MediAssist system is a photo management system that was developed in [48] to facilitate semi-automatic people annotation in personal photos. Photos in MediAssist are indexed based on the temporal information of captures. Temporal and spatial information is used to detect events for photo summarization and event filtering. Other contextual analyses determine weather conditions and light status at the time of capture. Additional EXIF data is exploited to determine whether photos were taken indoors or outdoors. MediAssist recognizes people's identities based on the analysis of both image content and context. It uses time, location, and co-occurrence data to annotate people in given photos. Time proximity information is used to calculate the probability of a person appearing in a photo given all of the annotations within a specific time period of the queried photo. The same procedure is used with the spatial proximity information. Co-occurrence information is used to calculate the frequency of people co-occurring together in the same photos or at the same events, to calculate the

probability of a person occurring in a given photo. Experiments showed that a combined context and content analysis outperformed a content-only or context-only analysis. In [49], authors proposed an automatic annotation approach to annotate photos based on OWL-DL ontologies and the use of mobile devices. They designed ContextPhoto, which is an ontology to represent spatial and temporal contexts of photos and SWRL rules to infer the social contexts (i.e. who was nearby at the time of capture) of the photos. Photo metadata produced from mobile devices is used to derive high-level annotations using ContextPhoto ontology. Location coordinates are converted into a meaningful representation, for instance a city name. Cardinal spatial relationships (i.e. North of Ottawa) and 3D spatial relations (i.e. in front of Rideau Canal) are inferred using a combination of location, orientation, and spatial reasoning data. Date/time metadata is translated into a readable representation such as the day of the week, the month of the year, the time of the day, and the year information, which can be easily remembered. Time and location data can be combined to infer spatiotemporal data such as weather condition and light status, which can enrich the description of the photos. The social context of photos is described by associating the Bluetooth addressees of personal devices to personal profiles in order to detect people's presence at the time of capture. The system searches for the profiles of the people that belong to a user's social network. To evaluate their approach they developed a mobile and web location-based application "PhotoMap" for photo annotation. It provides spatial, temporal, and social annotations for personal photos. At the time of the photo, it captures the geographical location of the device, the date/time data, the data of the Bluetooth addresses of nearby devices, and the camera settings, which will be used by ContextPhoto to generate representative annotations of the photos. It also provides a web interface for spatial and temporal navigation of photos. Moreover, it helps users organize their photos into events based on time and location data, and improve photo retrieval using temporal, spatial, and social information. Additionally, researchers have been interested in context-aware annotation approaches in photos. Many works have been done on face annotation (i.e. face recognition) in photos

[50, 51]. Event detection and annotation in social photos has also been an interesting area among multimedia researchers and has shown notable progress [52].

Other Applications of Photos and Metadata

As the number of photos being uploaded to social media increases, related research challenges multiply. Since the majority of uploaded photos need to be organized, the album summarization direction was explored [53, 54]. Emotion recognition was studied in [55] by analyzing the facial expressions of the people depicted in the photos. This helped add emotional information to the list of photo metadata. Photos are also involved in the process of criminal group discovery in social networks [26]. Discovering social relationships from photos has been useful to a wide range of studies and applications such as friend recommendations [42], types of relationships [57], people identification [58], and close friendship recognition [59]. The studies have been expanded to explore the strength of social relationships on social media, as seen in [11, 59, 60, 61]. The content and context associated with the photos are the primary elements used to discover and solve the above photo-related multimedia research issues.

2.1.3 Summary

Photo annotation plays a major role when it comes to adding meaning to photos. It restores memories of past times and of places we visited with various people we met. It helps deliver multimedia content according to users contexts. Moreover, photo annotations allow for the development of more efficient multimedia applications. As an example, geo-tagged photos on OSNs have contributed to landmark recommendations for tourism guidance and to mine peoples trips. Spatial metadata can improve the search for photos in multimedia search engines, instead of using filenames and text keywords. Location-based search engines help people find the photos that correspond to a particular context. With GPS service on mobile devices and geotagged photos, one can search for photos taken within a specific distance from their current geographical location by

providing longitude and altitude coordinates or locations names.

2.2 Social Relationships on OSNs

Online social networks (OSNs) consist mainly of users who communicate with one another. Understanding the relationships between the social users has proven to be very useful for social network analysis and services such as friends recommendation.

2.2.1 Overview

The understanding of social relationships on OSNs has been a popular topic in the field of multimedia research for a number of years. Recent studies have focused on using profile similarities and interaction information to understand the social behaviors of users. Surprisingly, photos shared on OSNs have been beneficial for the understanding of social relationships [62]. Users' personal photo collections have been used to discover social relationships. People occurrence and co-occurrence in photos are mainly used to discover such relationships and to determine the types of relationships in question (e.g. family, friends, etc.) [57].

For instance, in [20], authors developed a mobile application 'PhasePhinder' to find meaningful social connections between two users. They proposed a Fusion Probabilistic Latent Semantic Analysis (FPLSA) model that uses the connections of social friends with peoples co-occurrence in images, based on the Probabilistic Latent Semantic Analysis (PLSA). The Hidden-Markov Model was used to recognize faces in this work, and it was proven to be more accurate when gender context was used along with the pictures. FPLSA outperformed other algorithms when the number of pictures increased. FPLSA provided more accurate social paths than the PLSA, according to the user study conducted in the work. Another example can be found in [21], where face recognition methods were combined with users' social contexts based on Community-Based Group Associations (CBGA) in order to know who would most likely appear in a given photo.

Their fusion algorithm automatically recommends tags for the faces that appear in images where there is already a tagged face. The results show that combining social relationships with face recognition improves the process of recommending face tags in images. Moreover, the authors in [22] proposed an image retrieval approach that returns a collection of images of a specific user using Relevance feedback of people's co-occurrence relations. It leverages the visual features of the queried person and those who appear with her in the same images. Relevance feedback identifies people who appear with the queried user, the strength of the users' co-occurrence relations, and their faces. Results show that retrieving images of a specific user considering co-occurrence relations feedback outperforms the retrieval considering only the queried user.

2.2.2 Relationship Strength on OSNs

In order to better understand social relationships between users on OSNs, we need techniques to measure these relationships. Measuring social relationships is a well-known problem and is used to study possible social processes, for example friend recommendations. Finding reliable social relationships in a social network is a challenging issue.

Granovetter *et al.* [60] introduced the concept of social tie strength. The authors defined the strength of tie as a combination of four factors: amount of shared time, emotional intensity, intimacy, and reciprocal services. The theory of Homophily [63] suggests that people tend to bond with other similar individuals. Hence, people who are more similar tend to have stronger ties, and the stronger the ties, the more there are interactions between these people. Several studies (e.g. [12, 63]) harnessed the principle of Homophily to measure the social ties between users in social networks.

Two types of social ties, strong and weak, characterize people's relationships in social networks [60]. Strong relationships connect people who exchange trust and share interests. Often, people with strong ties also have overlapping social circles. People with weak ties are merely acquaintances [11]. Although weak-tied relationships are an interesting topic in the field of social network analysis, it is out of the scope of this study.

Recently, the problem of modeling social relationship strengths has been widely investigated. Most of the social strength modeling studies have focused on a binary classification of relationships, strong and weak [63, 64]. Such a coarse indicator cannot provide an accurate insight into the strength of relationships between people. In addition, these works adapted supervised learning methods, which require human intervention to annotate the strength of the relationships with their friends [13]. The problem is that the performance of learning models is largely affected by the quality of the annotations provided by the people [12]. In addition, the definition of strong and weak ties varies from person to person [11]. For example, a user might describe an old ex, with whom she has not communicated in ten years, as a close friend. In [13], a learning model was proposed to determine social strengths between users in OSNs. The model represents continued-valued tie strengths rather than binary values (i.e. strong and weak). To compute the profile similarity they considered gender, difference in age, close friends, mutual friends, number of events, number of interested pages, number of shared tagged photos. For the interaction activity, posts and photos were considered. For posts, number of posts, number of comments, number of likes (i.e. from user i to user j and from user j to user i), and number of shares were considered. In [14] the authors measured the social strength based on fields of activities instead of on interaction activity in general. For example, co-worker friends usually comment on posts related to work, while close friends do not. They estimate the relationship strength by considering not only profile similarity and interaction activity, but also by studying the fields of interactions. They used a variety of profile attributes to compute the profile similarity (i.e. current city, hometown, gender, language, high school, university, employer, religion, political views, music, books, movies, television, activities, interests, sports) between users. For user interactions, they considered news feeds, messages, and events. The activities are transformed into text documents and the interactions are analyzed based on the similarities between documents. It is to be noted that they used a supervised learning method to infer the strength of the relationships. In [12], the authors proposed a latent variable

model that leverages users similarity and their interactions on Weibo. The interactions were re-tweets, replies, mentions, comments, etc., while the similarities were treated as common interests (i.e. sports, technology, and entertainment). They identified the strength of the connection as a cause of past interactions and as an effect of similarities and future interactions. Jinfeng et.al [65] introduced a kernel-based learning approach to infer social strength between users in Flickr. They combined profile similarity and interaction activity to infer the strength of the relationship. For the profile data they used user country, labels, and tags, and for the interactions they used mutual friends, mutual tags, mutual comments, and mutual groups. The model computes the similarities between two users using profile and interaction information. A linear combination method was proposed to calculate the strength. The work in [59] considered relationship strength as a hidden effect of user similarity and as a hidden cause of interaction activity. Sheng *et al.* [12] claimed that frequent interactions between users directly impacts the strength of their relationship. Therefore, they considered user similarity and past interaction activity hidden effects of tie strength, and treating tie strength as a hidden cause of future interactions. The studies above are mainly dependent on the frequency of interactions. It is obvious that the more interactions there are between users on OSNs, the more likely they are to have a certain social relationship. However, frequency of interactions is not novel. One example can be found in [8], where different aspects of co-occurrence have been proposed under the assumption that it might reveal more detail about the social relationships between people. The number of people appearing together in photos provides valuable clues about how close the people are socially. If there are two photos of user A and user B , where one contains only the two of them and the other involves 30 other people as well, the first photo (only user A and user B) might indicate that a stronger social relationship exists between the two of them than would the second photo. Another example is in [66], where they extended the work in [8] by analyzing the distance between faces depicted together in the same photos.

Applications of Social Relationship Strength

The study of social relationship strength on social media has led to many applications of different purposes. We list examples of some of these applications as follow:

Prediction:

The contents on OSNs vary between news, friends, items, etc. Here we present some examples of applications related to prediction:

- **Reviews Ratings**

Bingkun et.al [67] incorporate the social relations of reviewers into content-based analysis methods to review the rating predictions of movies. The results show a better performance of review rating predictions when the social relations are incorporated into the content-based methods compared to when using only the content-based methods.

- **Relationship Strength on Different Social Media**

Knowing the strength of the ties in a specific social network can be used to predict the strength of social ties in other social networks. Facebook was used as the main medium to study the tie strengths and predict the relationship strength in Twitter. 'We Meddle' is a Twitter application that was employed for tie strength estimation. The results showed that the tie strength in Facebook generalizes to Twitter. The findings suggest that important online relational properties may manifest similarly between social networks [68].

- **Location Proximity**

It has been discovered that there is a relationship between the tie strength of social users and their location proximity. They propose a network-based approach that leverages the tie strength between social users to accurately estimate the locations where they live. Twitter was used for the experiments and evaluations, which show

that users with weak relationships are likely to be distant while users with stronger relationships are likely to be local [69].

Recommendations

The same applies to the applications related to recommendation:

- **Friend Recommendations**

OSNs such as Facebook automatically recommend friends to users. Having relationship strength information between users could improve this process by suggesting the most relevant friends-to-be [42, 58].

- **Item Recommendations**

The automatic recommendation services provided by OSNs could be improved with the relationship strength information, since users' preferences are very likely similar to those their close connections. Recommending groups to join or articles to read is one example [59].

Newsfeeds

Personalized Newsfeeds is an important feature to be offered in OSNs such as Facebook. It can be done by prioritizing the updates based on the users strongest connections, which will enhance the users online experience [59].

People Search

Due to information overload on OSNs, the search for a desired item might be a difficult task. Searching for wanted people is one example. By ranking search results based on the connection strength between users, the results are more likely to be reliable. [59].

Visualization

Visualizing peoples social network could benefit from relationship strengths, by scaling the links according to their social strength values [59].

2.2.3 Discussion

All of the studies above exploited profile information and interaction activity to measure the strength of social relationships. However, different works studied different multimedia resources and different data in online social networks. Although a large number of features of many heterogeneous resources have been studied in these works, most of them have not effectively leveraged the rich information contained in the data they collected from OSNs. In some works, the metadata of photos as well as the geographical data have been neglected, while in other works they have been insufficiently exploited. Moreover, the amount of shared time between users was never considered. A few studies have considered the length of friendships as the number of days since the first communication but have never considered the intensity of the communications afterwards. Furthermore, recent work on finding relationship strengths has focused on traditional interactions such as commenting, tagging, and chatting, but did not leverage face-to-face interactions. Face-to-face interactions on social media represent real-life interactions that describe where, when, and who were involved in various activities. These types of interactions can be seen in photos and their associated metadata. Finally, we can conclude that the previous works available do not adequately measure the strength of interpersonal relationships on OSNs. Our conclusion is supported by other studies [10, 11], which state that social media sites like Facebook do not consider interpersonal relationships between users.

2.3 Integrating Sensors with Social Networks

There has been a huge increase in the number of sensory applications that can collect real-time data related to humans and their interactions [70, 71, 72]. One of the most popular sensors currently used in applications is GPS. The sensory data can be used to model underlying interactions and relationships. The reason for integrating sensors with

social networks is to increase the real-time awareness between the users, either directly or indirectly, and to better understand the behaviors of users and communities [70]. What has helped the sensor's social network integration is the advance of hardware and software technologies. For example, GPS-enabled devices can now be used to determine the location of people and therefore of their activities at any time.

Applications of Sensor-Social Networks Integration

The integration of sensors into social networks has a wide range of applications, some of which are listed as follow:

- **The City Sense Application**

The City Sense application collects data from mobiles and taxi cars that are equipped with GPS sensors to determine where people are. This information is then delivered to the subscribers of this application. This kind of electronic social networking can help people make the right decisions when planning their activities [73].

- **WikiCity**

WikiCity provides local contents on events and places, which could be of interest to various people. It is used as a wiki for cities guide. It uses real-time data generated from GPS-enabled mobile phones in order to discover spatial trends in different locations within a city [74].

- **MacroSense**

MacroSense uses location data generated from GPS-enabled mobile phones in order to study human behaviors based on the places they visit. The analysis includes learning the patterns related to where people go and how much they move. This analysis, therefore, is useful for real-time recommendations based on similar places of interest [75].

- **Biketastic**

Biketastic uses location data using GPS-enabled mobile phones to track the paths taken by different users. Also, GPS sensors are used to determine the speed of bikers. Other embedded sensors such as microphones and accelerometers are used to infer the noise levels of routes. All the sensed data are then combined in order to find the safest and most enjoyable paths for bikers. This kind of social networking application can enhance bikers overall experience [76].

- **Human’s Social Lives Applications**

There are a variety of applications targeting face-to-face human interactions in sensed social networks. Sociometer [77] is an application that records if and when people are conversing in order to analyze whom people talk to and how they talk. A similar work has been done in [78], where face-to-face interactions collected using sensory phones were used to determine patterns in peoples daily lives. Another application has been discovered in [79, 80], where face-to-face interactions collected using Bluetooth sensors embedded in mobile phones were used to identify the close friendships of participants.

2.4 Face-to-face Interactions on Sensed Social Networks

The availability of advanced data acquisition techniques that record the daily activities and interactions of individuals have led to new opportunities for learning about human social lives. The use of these techniques has turned the process of collecting analysis data into a much easier task, as personal interviews and surveys are no longer needed. Instead, the use of digital devices that come equipped with embedded sensors provides access to more precise data than using interview techniques. Human face-to-face interactions in real-world settings can now be recorded by using such technology. The popularity of

smart phones embedded with sensors like GPS, IR, and Cellular-Tower Identifiers have hit a milestone of 1 million shipments in 2013. This means that around one-seventh of the world population has one [81]. As a result, mobile phones can be used as sensors for human movements, locations, interactions, and friendships [82, 83]. The work of [77] was among the first that explored face-to-face interactions in offline social networks using sensor technologies. The team has developed a Sociometer device that records when people are having conversations. Chudhary et.al [78] expanded the previous work by analyzing the recorded conversations. By using sensors, they constructed a dataset that describes people’s daily patterns of activities. The study in [84] showed that CDR (i.e. Call Detail Record) contains information that can define spatial and temporal patterns in human movements.

Oluritm et.al [79] investigated the impact of the homophily theory and of the duration of interactions between humans on the definition of close friendship ties. They conducted their experiments on 42 participants from an American university undergraduate dormitory, where each participant was given a socially aware phone with Bluetooth sensor technology. They calculated the duration of peoples interactions using Bluetooth proximity. When a phone detects another phone it recognizes its identifier and records the time duration of both phones being connected in proximity. In this study, close friends are defined as those friends with whom you feel comfortable talking about personal topics, or the ones that you seek for emotional support. The close friends information was obtained by interviewing the participants in order to construct a close friend graph. The interactions graph was constructed by using the logged information obtained from the sensors. They used social network analysis techniques on the constructed graphs at different periods of time. The results showed that participants spent more time interacting with close friends than with non-close friends, while they interacted with more non-close friends but for shorter durations. Moreover, gender similarities and period of interactions can also define close friendship. Oloritun et.al [80] have extended the scope of previous analysis by further investigating domestic partnerships and places of recreation, as well

as the closeness of ties and the length of interactions. The same approach was used for both data collection and network analysis. The participants were members of a young family residential living community in North America. All of the participants were couples and at least one member was a graduate student. The information on friendship closeness and domestic partnerships was collected from users using online surveys. They were also asked to give information on the locations where they exercise, as well as their home address. Five networks were constructed from the collected data and analyzed with social network analysis techniques. The results show that people tend to give high ratings to people whom they spend more time with. The authors found a correlation between friendship closeness and places but not with length of interactions [80].

2.5 Multimedia Story Telling

A story consists of different pieces of information presented in chronological order. The concept of multimedia storytelling is new and not widely explored yet. Some research has been completed on building stories of individuals, but are limited to photo collection retrieval and album summarization [54]. Social storytelling plays an important role in peoples lives. It helps people present themselves and express their personal and interpersonal experiences [54]. Also, going through stories of our own with our beloved ones takes us back to relive past moments. Therefore, it helps generate feelings of connectedness and strengthen our ties [10].

The first step toward creating a personal photo story using OSNs is to collect and organize photo collections in a meaningful way. There has been related works that explored the areas of photo collection retrieval [35, 44] and summarization [53, 85, 86] as well as event detection [40]. Obrador *et al.* [54] introduced a photo storytelling approach for social photo albums. However, the generated stories lack context and are only limited to one specific album. In 2014, Facebook celebrated its 10th birthday with personalized "*Look Back*" videos for all Facebook users. The video summarized users

timeline information on Facebook, from 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 a single user and (2) they ignore user’s social context such as events, locations, and close friends.

2.6 Comparison and Summary

From the discussions above, it becomes clear that there exist limitations of previous proposed methods on social relationships strength modeling for the purpose of storytelling systems. These limitations can be summarized in the following points:

- Spatial and temporal metadata of interactions (i.e. photos) was insufficiently utilized in relationship strength modeling and storytelling systems.
- Soft-sensory information (i.e. F2F interactions) was not exploited in relationship strength modeling and storytelling systems.
- Interpersonal relationship was not considered in previous related work on the field of relationship strength modeling.
- Psychological perspective of close friendship, amount of shared time together in particular, was not well studied in modeling relationship strength between social users.
- Finding the complete information of events from different OSNs profiles was not explored in previous work.
- Concrete Context of stories was ignored in previous efforts in storytelling systems and applications.

Hence, we find the need to design and develop a system to solve most of the previous systems disadvantages. Our proposed DST system is designed to estimate the time spent by two people in order to use it as an index to infer strongest friendships. The information of face-to-face (F2F) interactions and geographical home references of users is fed into the DST system. DST computes this information in order to detect events and estimate their duration. The information of events duration is then used to infer how much time people spent together based on their co-occurrences in the events. The complete set of event information (i.e. social, temporal, and spatial) along with strongest friendships are then used to build our personal stories. It is important to note that event duration should reflect the number of representative photos in our storytelling system. Chapter 3 and 4 will present detailed explanations on our proposed system.

Table.2.2 presents a summary of the previous proposed methods on social relationship strength modeling and the comparison to our system DST.

	Time Spent Together	Interactions		Photos Metadata			Profile Similarities	Mutual Friends	Relationship Strength	Dataset
		F2F	Non-F2F	Time	Location	People				
DST	✓	Photos		✓	✓	✓	✓		Ranked list	Facebook
Saini et al. ([87], 2014)	✓	Photos	Posts Comments Likes	✓	✓	✓	✓	✓	Ranked list	Facebook
Golder ([8], 2008)		Photos				✓			Ranked list	Personal Photo Collections
Gilbert and Karahalios ([11], 2009)		Photos	Posts Messages			✓	✓	✓	Binary	Facebooks
Zhao et al. ([14], 2012)			Posts Messages				✓		Ranked list	Facebooks
Sheng et al. ([12], 2013)			Comments Re-tweet Reply					✓	Ranked list	Sina Weibo
Khadangi et al. ([13], 2013)		Photos	Posts			✓	✓	✓	Ranked list	Facebook
Xiang et al. ([59], 2010)		Photos	Posts				✓	✓	Ranked list	Facebook
Zhuang et al. ([65], 2011)		Photos	Comments		✓		✓	✓	Ranked list	Flicker

Table 2.2: Table of Comparisons between DST and Related Work on Social Relationship Strength

Tables 2.3, 2.4, and 2.5 summarize related work on finding time-spent together by people using information from social networks. In our comparison, we consider the type of social network, type of used sensors, resources, definition of close friendship, measuring unit, and experiments period.

	Social Network	Sensors			
		Physical		Virtual	
		GPS	Bluetooth	Geo-tag	People-tag
DST	Online	✓		✓	✓
Saini et al. ([87], 2014)	Online	✓		✓	✓
Oloritun et al. ([80], 2013)	Offline		✓		
Oloritun et al. ([79], 2013)	Offline		✓		

Table 2.3: Table of comparisons between DST and related work on finding time-spent-together between people as relationship strength index, considering the type of social networks and sensors

	Resources						
	Photos	Photos Metadata			Sensors Readings		
		Location	Time	People	Location	Time	People
DST	✓	✓	✓	✓	✓	✓	
Saini et al. ([87], 2014)	✓	✓	✓	✓	✓	✓	
Oloritun et al. ([80], 2013)						✓	✓
Oloritun et al. ([79], 2013)					✓	✓	✓

Table 2.4: Table of Comparisons between DST and Related Work on Finding Time Spent Together between People as Relationship Strength index, considering the used resources

	Close Friendship Definition	Measuring Unit	Experiment Period
DST	Friends with whom you spend a lot of time with where the time does not have work or commitment as its purpose	Day	1 year
Saini et al. ([87], 2014)	Friends with whom you spend a lot of time with where the time does not have work or commitment as its purpose	Day	1 year
Oloritun et al. ([80], 2013)	Friends with whom you feel comfortable talking about personal topics, or the ones that you seek for emotional support	Hour	1 year
Oloritun et al. ([79], 2013)	Friends with whom you feel comfortable talking about personal topics, or the ones that you seek for emotional support	Hour	3 months

Table 2.5: Table of Comparisons between DST and Related Work on Finding Time Spent Together between People as Relationship Strength index, considering the definition of close friendship, the measuring unit, and period of experiments

Tables 2.6, 2.7, and 2.8 show a summary of comparison between our proposed work and the previous works on storytelling systems. In the comparison, we consider the resources of the story if they are multiple albums/events that are from multiple profiles/users, the elements of the story, and the method of choosing the representative photos of the story.

	Multiple Events/Albums	Multiple Profiles/Users
Our method	✓	✓
Obrador et al. ([54], 2010)		
Facebook 'LookBack' (2014)	✓	
Nokia Lumia storytelling (2014)	✓	

Table 2.6: Table of Comparisons between the proposed story of our work and previous works. considering information of multiple events from multiple profiles

	Multimedia				Contextual Content						Likes & Comments
	Photo	Video	Text	Audio	Event	Spatial	Temporal		Social		
							Time	Duration	People involved in Event(s)	Closest Friends	
Our method	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Obrador et al. ([54], 2010)	✓	✓	✓	✓	✓		✓		✓		
Facebook 'LookBack' (2014)	✓	✓	✓	✓							✓
Nokia Lumia storytelling (2014)	✓	✓	✓	✓	✓	✓	✓				

Table 2.7: Table of Comparisons of between the proposed story of our work and previous works, considering the elements of the story

	Image Processing		Context Analysis		
	Face Detection/Recognition	Image Aesthetics	Event Duration	Likes	Comments
Our method			✓	✓	✓
Obrador et al. ([54], 2010)	✓	✓			
Facebook 'LookBack' (2014)				✓	✓
Nokia Lumia storytelling (2014)					

Table 2.8: Table of Comparisons between the proposed story of our work and previous works. considering the method of choosing representative photos

Chapter 3

Story from Multiple Profiles

In this chapter, we present the framework of our proposed storytelling system and introduce the preliminary version of DST model, to generate personal stories from multiple OSNs profiles, and discuss the methodology for performing the system functions.

3.1 Social Story

Storytelling is one of the oldest art forms used by humans to communicate. The methods used by humans to share information and emotions with each other consist of either verbal or non-verbal communications, and both of these are a form of storytelling. Storytelling is a method used to describe event experiences in words, images, videos, audio, or multimedia, for different purposes such as education, history, entertainment, etc.

Everybody enjoys a good story, whether it is a movie or a simple explanation of an experience, and they enjoy stories even more if a narrative of the event is provided. A good story has a good set of events and related information that can be arranged in a way that conveys the desired message. Therefore, the first step towards creating a story using OSNs is to detect life events and collect corresponding multimedia information with spatio-temporal attributes [2]. In this thesis, a story is made up of different pieces of information presented in chronological order. The story tells what places users have

visited, when, and with whom. We have modeled the story as a set of events and related information, including location of event, time of event, and people involved. In other words, a story \mathcal{S} is represented as:

$$\mathcal{S} = \{(e_i, l_i, d_i, p_i) | e_i \in \mathcal{E}, l_i \in \mathcal{L}, 1 \leq i \leq n\} \quad (3.1)$$

where \mathcal{E} is the set of events, \mathcal{L} is the set of locations, d_i is the corresponding temporal information, and p_i is the set of people involved (i.e. closest friends). Note that all these elements of the story have associated F2F interactions (i.e. photos in this thesis). Our goal in this thesis is to generate a database of all possible events and related contextual information about each event. We want to maximize $n_e = |\mathcal{E}|$, $n_l = |\mathcal{L}|$, and the total number of photos n_p , and to extract additional contextual information so that we can create a multimedia enriched story. To do that, we propose to examine the strength of the user’s social relationships with her friends. In this chapter, we explain how to retrieve additional events and multimedia information, which is missing from user’s own profile, from the profiles of a certain number of closest friends (Figure 3.1). Next chapter will include an explanation about the additional story context that can be added to enrich our stories.

We need the social bonds between individuals on OSNs because we believe that close friends are reliable sources of additional information about the user [89]. 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, the frequency of interactions, personal relationships, and profile similarity, to measure the strength of the interpersonal relationship.

We observe that in cinematography the same scene is shot multiple times with multiple cameras, resulting in a large number of video clips, of which only a few are chosen for the final movie [5]. Hence, although we may not be able to encompass all the data collected into the final stories, having more information about the user would enable us to build more interesting and informative stories. In this chapter, our main focus is to

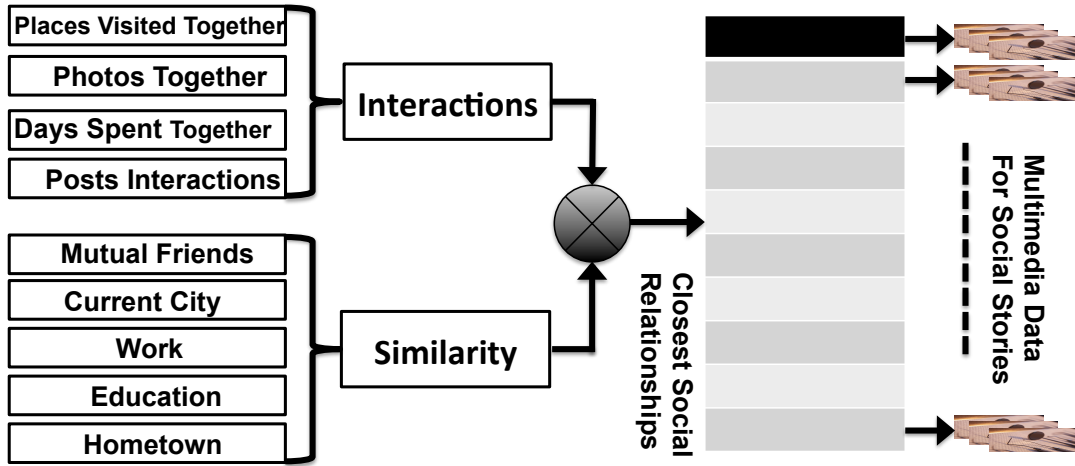


Figure 3.1: Proposed framework of the storytelling system from multiple profiles using preliminary DST. We use F2f and non-F2F interactions and profile similarity to first calculate the user’s strongest relationships and then fetch multimedia data from their profiles (in addition to the user’s own profile).

collect more information that is relevant to the users. Next chapter will show how to utilize this information in order to infer more context to add to the stories.

3.2 Social Strength Model with Preliminary DST

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 friends’ 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.

To determine the strength of relationship, we consider the amount of social interactions and the degree of similarity between the users, as shown in Figure 3.1. Granovetter [60] defined interpersonal ties as a combination of the amount of shared time, intensity, intimacy and reciprocal services. We utilize the amount of time a pair of users have spent together (amount of time), the number of places they have visited together (intimacy and intensity), the number of mutual photos taken together (intimacy and intensity), the frequency of interactions (intimacy), the clique of mutual friends (intimacy), and the scope of shared activities (reciprocal services). Hence, we first calculate the degree of social interactions, then the degree of similarity, and finally we combine these two to get the final rank. The degree of interactions and the profile similarity are combined as follows [11]:

$$r = \frac{r_i + r_s}{2} \quad (3.2)$$

where r is the final strength used for ranking, r_i is the 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 the story.

3.2.1 Degree of Social Interactions

The interactions are further divided into two types: F2F interactions (interactions through photos) and non-F2F interactions (interactions through posts).

F2F Interactions (Interactions through Photos)

F2F interactions are the interactions that represent real-life events. Real-life events can be captured using digital photography. People usually use digital photos to document

their experiences and share them with family and friends. People can also add context to their photos such as geo-location (where the photo was taken), capture time, and friends presence. Every digital photo has a 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 take more than one picture together during a specific activity/event, and they usually appear close to each other in the pictures [88]. This observation has inspired us to consider the amount of mutual photos that the user has with each 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 (geo-tags data) and when (capture time data) and with whom (social data) the user was. With this information, we calculate 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 is the number of days spend together, the time togetherness degree is defined as $\sigma_d = N_d/N'_d$. Note that this component represents the preliminary version of our DST model.

Number of Places Visited Together: In a 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 is the number of places visited together, the degree of location togetherness is defined as $\sigma_l = N_l/N'_l$.

Non-F2F Interactions (Interactions 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. With posts, interactions come in two forms: likes and comments. Responding to friends posts at 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} the number of posts that the friend liked or commented on, the 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 a close relationship. Hence, we also measure the total number of comments made by a friend on a user's posts and divide it by the total number of posts, in order to measure the degree of comment interactions, i.e. σ_c .

Final Degree of Social Interactions

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

$$r_i = w_p * \sigma_p + w_l * \sigma_l + w_d * \sigma_d + w_{pt} * \sigma_{pt} + w_c * \sigma_c \quad (3.3)$$

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

3.2.2 Degree of Similarity

In the previous step, we calculated the degree of interaction between the user and her friends based on photos and posts. So far, we are able to know which friends are actively in contact with the user. If a friend is active with the user, we consider her as a strong connection. It becomes challenging when a friend is not that active with the user, but there is still 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 the 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.

Mutual Friends

In the absence of significant interactions between the users, mutual friends play a major role in detecting social bonds between two people. Friends associated with acquaintances are different than those who have social connections with close friends [11]. In our work, we consider the clique (i.e. social ties) of mutual friends to help find close friends. Previous studies have claimed that the greater the number of common friends between users, the stronger the relationship [65]. Hence, we define the degree of mutual friendship, ρ_m , which refers to the ratio of mutual friends to total friends, for the main user. We define a threshold T_f for the 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 the similarities in 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 time.

Current City, Hometown, Education, and Work

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

Current City: People tend to have a better connection with friends living in the same city or country compared to friends in different cities or countries. Current location similarity is measured with two parameters, one for the city (δ_{ct}^l), and one for the country (δ_{cn}^l). If the friend is from the same city/country, then $\delta_{ct}^l, \delta_{cn}^l = 1$, otherwise $\delta_{ct}^l, \delta_{cn}^l = 0$. The effective similarity measure of current location is defined as:

$$\delta^l = \frac{\delta_{ct}^l + \delta_{cn}^l}{2}. \quad (3.4)$$

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

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

Final Degree of Similarity

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

$$r_s = w_m * \rho_m + w_{lhw} * (\delta^l + \delta^h + \delta^e + \delta^w) \tag{3.5}$$

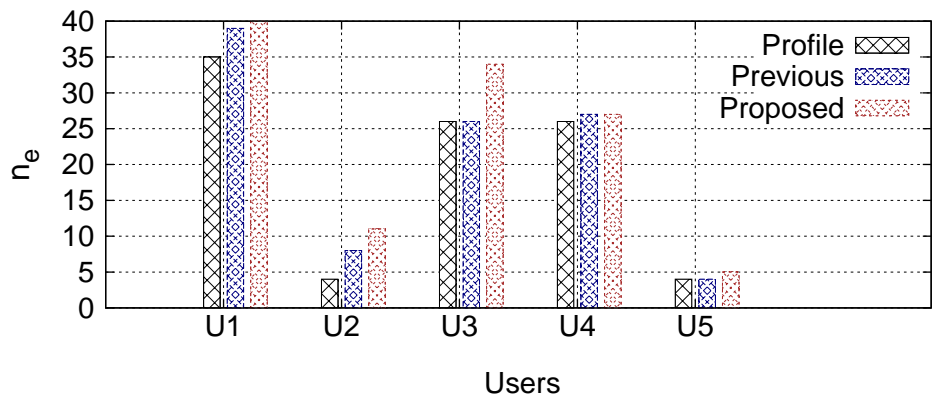
where w_m and w_{lhw} are corresponding weighting coefficients. The degree of interactions (Equation 3.3) and similarity (Equation 3.5) are combined according to Equation 3.2 to obtain a final strength of r . We rank the friends in decreasing order of r and extract information from the top γ friends in order to build our stories. The ranking is also used to identify the closest friends, who need to be included in the story.

3.3 Experiments

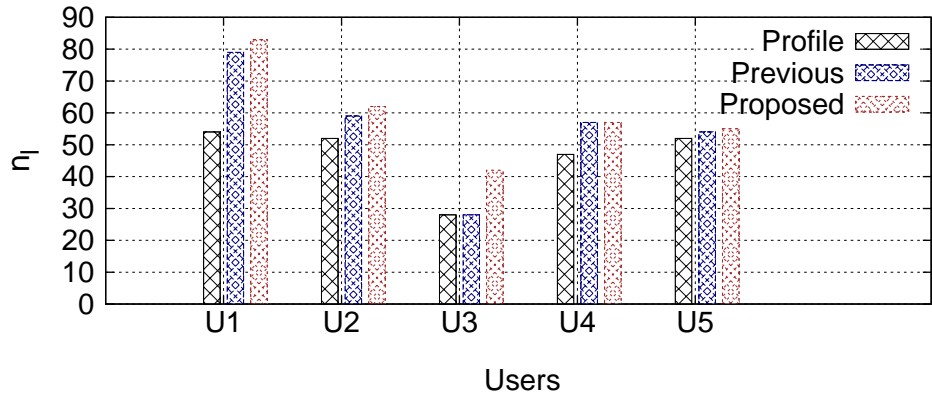
The main purpose of the experiments is to prove that with the proposed framework we can extract more information about individuals. The experiments were conducted on real-world data collected from Facebook. We collected data from 5 main users and their friends. The main users had an average of 250 friends, which brings the total number of sub-users in our dataset to 1252. From each profile, we retrieved personal information and

interaction information. 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 the tags data (i.e. photo metadata) of photos, which includes geotags, capture time, and people tags. We assume that all photos uploaded by users or uploaded and tagged by friends are correctly tagged since Facebook users will be notified of tags and most likely they will remove it if it is incorrect. From posts, we retrieved likes and comments information. The same information was collected for the friends of the main users. Facebook API's are employed to collect data.

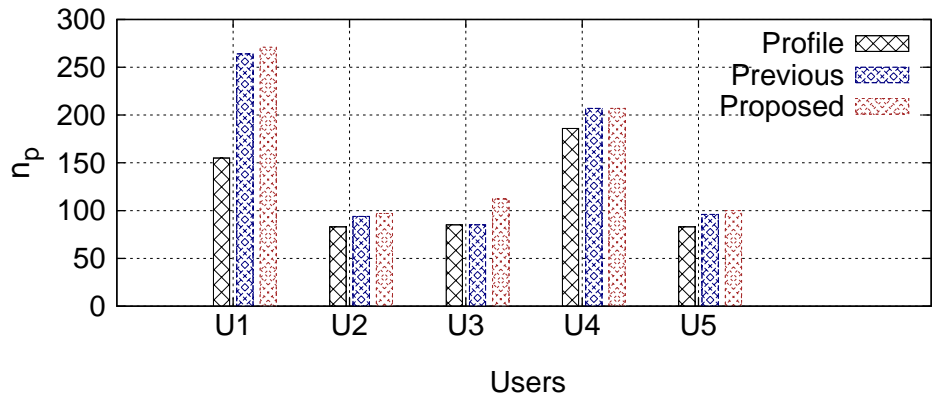
To evaluate the performance of our proposed method, we analyzed users data for two years (for the main users). We calculated the total number of photos, places and events from the photos available on the users profiles (i.e. uploaded by the users). We then applied our proposed multimedia-based relationship strength model to find the ten strongest connections in order to find more photos and, in turn, more places and events. In the experiments we used $\gamma = 10$. We then did a comparison of the number of photos, places and events. The results are shown in Figure 3.2 for 2013 and Figure 3.3 for 2014.



(a) Events

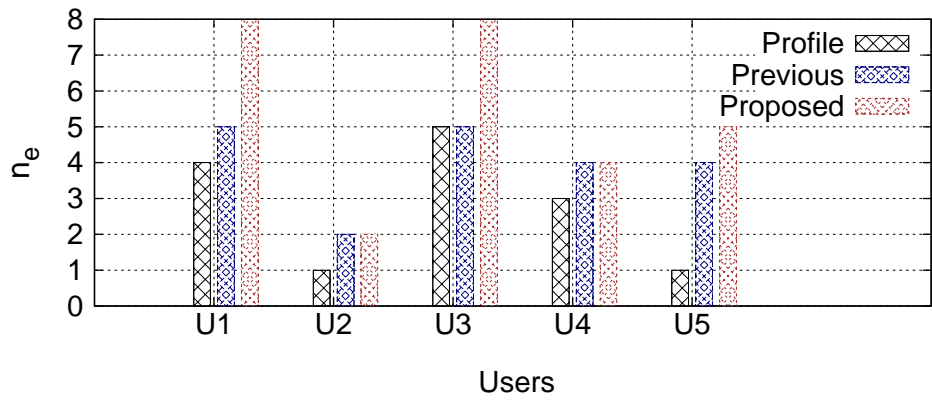


(b) Locations

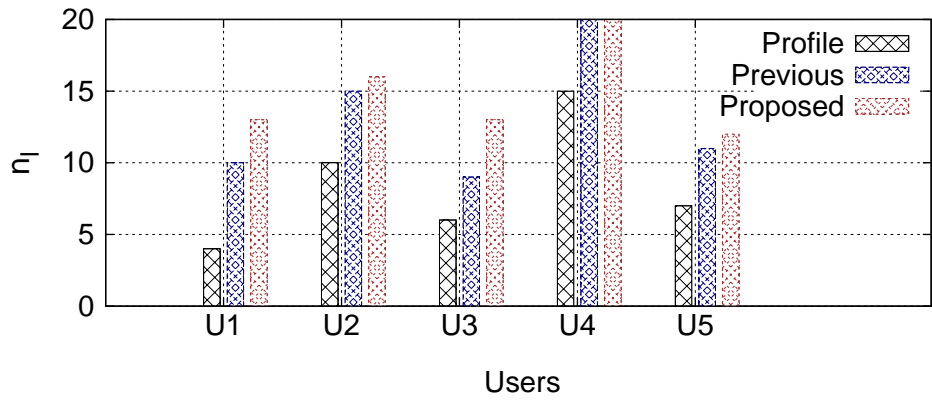


(c) Photos

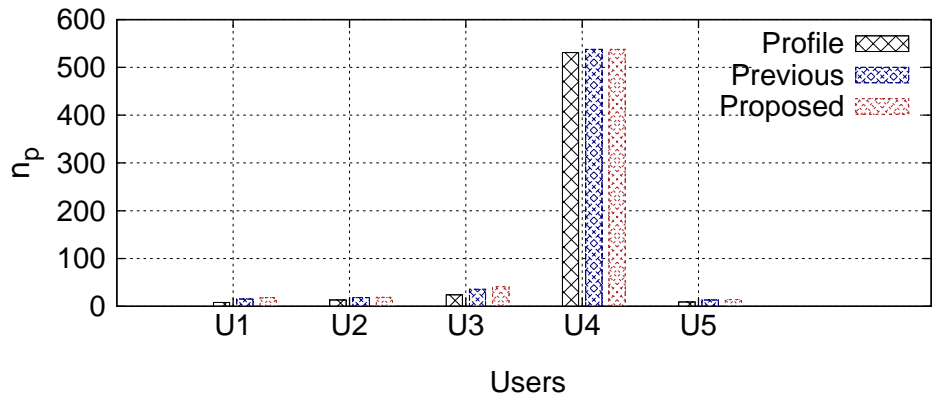
Figure 3.2: Results for 2013 for five users. With the proposed method, we are able to retrieve more events, locations, and photos about individuals, which will allow us to build a better story.



(a) Events



(b) Locations



(c) Photos

Figure 3.3: 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.

In the figures, “Profile” represents information from the profile alone and “Proposed” gives the results obtained using the proposed method. To compare the proposed work with previous works, we also collected user’s data from the profiles of 10 of her closest friends, chosen based on the traditional definition of a relationship, which is mainly based on the number of mutual friends and non-F2F interactions (i.e. comments and likes). The results of the previous approach are shown as “Previous” bars in Figures 3.2 and 3.3. We can see that the proposed method could find more photos, events, and locations from the ten closest friends. The number of photos, places and events collected for 2013 increased by an average of 55.45%. For 2014, the number was increased by an average of one element more than the amount from the personal profiles alone. With these positive results we can conclude that our algorithm could recognize the top ten connections of the given main user from an average of 250 friends.

3.4 Discussion

In the proposed method, we first search for the strongest connections of a user and then go to those people’s profiles and search for photos of the main user. 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 are very accurate; the probability of false detections is very low and essentially depends on the accuracy of the face recognizer. Because this is not the main focus of the paper, in our experiments we used tag information to determine relevant images. Note that with the face recognition technique we will also be able to collect photos that are not tagged by the user. One constraint of the current evaluation is the limited number of users. Note, however, that each user in our experiments has an average of 250 friends. Since the results of the 5 users are consistent, we feel they can be considered representative.

Chapter 4

DST Model

In the previous chapter, we introduced the preliminary version of DST as a part of the multimedia-based strength model. Our empirical experiments showed that days-spent-together (DST) is the most important factor that accurately determines the closest interpersonal ties between social users. Even though the preliminary DST has shown good results, it did not provide accurate days-spent-together values. Therefore, we want to do more analysis on the DST factor and accordingly we propose a new method to improve its accuracy and therefore the quality of the interpersonal relationship strength. In addition, DST is an important factor for building our story. It provides very useful context that can be exploited to select the story elements accordingly.

4.1 DST Framework

The overview of the proposed framework is shown in Fig. 4.1. It consists of two main steps. In the first step, we analyse the soft-sensory information available on the OSNs to obtain a list of events. Only those interactions are considered to provide information about co-presence of the users. These interactions are called F2F interactions, and corresponding events are called F2F events. Fig. 4.2 and Fig. 4.3 show the difference between F2F and non F2F interactions. The time information of events is generally

incomplete on OSNs since it is heavily dependent on users inputs (i.e. when and what they upload/share). While the event (e.g. a trip) can span over multiple days, user might not share photos everyday. Therefore, the exact duration of events is difficult to determine in the absence of true start and end dates.

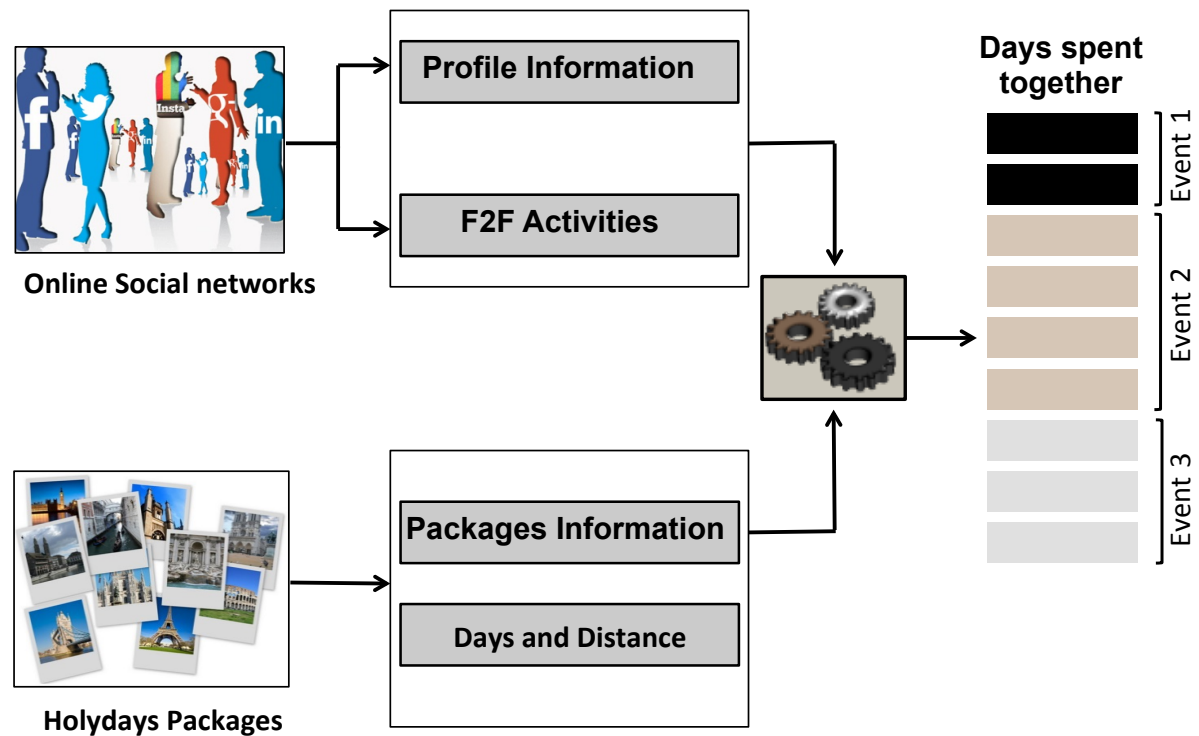


Figure 4.1: Architecture of the proposed Days-Spent-Together (DST) Framework.

To overcome this limitation, we propose to exploit the geographical information of events in the second step. We consider the distance of event location from users' hometown and current city (Geographical Profile) to estimate the duration of each event. In addition, we also consider the time difference between co-located events to merge duplicate events. These distances are mapped to number of days based on learning from popular tour packages. The details of the method are listed as a pseudo code in the Algorithm 1. We will explain the details of the algorithm along the description of the framework below.

Algorithm 1 DST Algorithm

```
1: procedure DAYS( $u1, u2$ )
2:    $I \leftarrow$  mutual f2f interactions of  $(u1, u2)$ 
3:    $c1 \leftarrow$  current city of  $u1$ 
4:    $c2 \leftarrow$  current city of  $u2$ 
5:    $h1 \leftarrow$  hometown of  $u1$ 
6:    $h2 \leftarrow$  hometown of  $u2$ 
7:   initialize  $totalDays \leftarrow 0$ 
8:   initialize  $i \leftarrow 1$ 
9:   while  $i \leq size(I)$  do
10:     $l \leftarrow Location(I_i)$ 
11:     $t \leftarrow Date(I_i)$ 
12:    initialize  $r' \leftarrow 0$ 
13:    if  $l \neq c1 \ \&\& \ c1 \neq c2$  then
14:       $dc_1 \leftarrow Distance(l, cc)_{u1}$ 
15:       $dc_2 \leftarrow Distance(l, cc)_{u2}$ 
16:       $dh_1 \leftarrow Distance(l, ht)_{u1}$ 
17:       $dh_2 \leftarrow Distance(l, ht)_{u2}$ 
18:       $\alpha \leftarrow (\min(dc_1, dh_1) + \min(dc_2, dh_2))/2$ 
19:       $r \leftarrow Duration(\alpha)$ 
20:      if  $1 \leq r \leq 4$  then ▷ Short event
21:         $\beta = 4$  ▷ Threshold for short event
22:      else ▷ Long event
23:         $\beta = r$  ▷ Threshold for long event
24:      end if
25:       $previousLocation = l$ 
26:       $previousDate = t$ 
27:       $i ++$  ▷ Increment photo counter
```


Algorithm 1 DST Algorithm

```
28:     nextLocation = location( $I_i$ )
29:     nextDate = date( $I_i$ )
30:     if previousLocation = nextLocation then
31:         repeat
32:              $\Delta$  = (nextDate - previousDate)
33:             if  $\Delta \leq \beta$  then
34:                  $r' = r' + \Delta$ 
35:                 previousLocation = location( $I_i$ )
36:                 previousDate = date( $I_i$ )
37:                  $i++$  ▷ Increment photo counter
38:                 nextLocation = location( $I_i$ )
39:                 nextsDate = date( $I_i$ )
40:             else
41:                 break
42:             end if
43:         until previousLocation  $\neq$  nextLocation
44:     end if
45:      $r_e = \max(r, r')$ 
46: else
47:      $r_e = 1$ 
48:      $i++$ 
49: end if
50:     totalDays = totalDays +  $r_e$ 
51: end while
52: return totalDays
53: end procedure
```

4.2 Soft-Sensory Information

The soft-sensory interactions are directly associated with face-to-face human interactions. They represent the real-life experiences of users as they transfer their face-to-face interactions from the real world to the digital world (i.e. online social networks) with the help of multimedia, particularly images. More importantly, they provide descriptions of where and when interactions happened, as well as who was involved. Online social networks applications are now able to produce sensory data. Many among these applications are mobile-based and include sensors like GPS, Bluetooth, and Infrared. When a media is produced by one of these applications, it automatically captures its geo-location, time, and people identities (i.e. face recognition) or presence (i.e. Bluetooth detects near-by people) which will be added as metadata to the media element. Even in the absence of sensors, users can still annotate captured media manually by using tagging services (i.e. places, time, and people) provided on OSNs. Interestingly, geo-location tagging tools work in a similar way that a GPS sensor does. It means that the geo-tagging tools provide grained geo-coordinates data, as does the GPS. They also provide a high level readable representation of the geo-coordinates such as place name, address, postal code, city, province, and country. In other words, geo-tagging tools play the role of location sensors for content shared on OSNs. Similarly, facial-recognition and people-identifying tagging tools play the role of people presence sensors. The same applies to time-tagging tools. The combination of these sensors turns online social networks into soft sensors that can track human face-to-face interactions, which is where the name soft sensor came from. We refer to soft-sensory interactions as face-to-face (F2F) interactions. Note that the DST algorithm is not dependent on how spatio-temporal attributes of the events are obtained. Depending on the availability and computing resources, these attributes can also be obtained from metadata of the media element, or through content processing, e.g., face detection and landmark detection.



 **Yogita Saini** with Mukesh Kumar Saini at Grand Canyon National Park.
Like · Comment · Share · December 25, 2013

From: Photos of Mukesh
Kumar Saini in Grand Kenyon

Figure 4.2: A Face-to-face Interaction. The user shared a photo of a real-life event with her friend. She was F2F interacting with her friend in Grand National Park, AZ on December 25th, 2013.



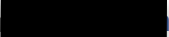
Abdulmotaleb El Saddik

December 28, 2014 ·

“If you can't explain it to a six year old, you don't understand it yourself.”

— Albert Einstein

Like · Comment · Share

Mohammed Huda,  and 18 others like this.

1 share



 That's true!

December 28, 2014 at 8:53pm · Like

Figure 4.3: A non face-to-face interaction. The user shared a thought with his friends and they interacted back with him by likes and comments.

4.3 Face-to-Face Events (F2F Events)

The first step of the proposed framework is to extract the F2F-events list by analysing the soft-sensory information available on OSNs (Algorithm 1, Line 2). Face-to-face interactions on online social networks can be seen in different forms of multimedia including photos. In this work, we focus on using photos as a tool to extract F2F-interactions from OSNs. Initially, interactions that occur on a single day are considered as one F2F-event. It is assumed here that people spend at least one day at one place.

Each F2F-event consists of three pieces of information: spatial (location), temporal (time), and social (people). In other words, a F2F-event e_i is represented as:

$$e_i = (l_i, d_i, p_i), 1 \leq i \leq n \quad (4.1)$$

where l_i is the corresponding location, d_i is the corresponding day, and p_i is the set of people involved in e_i . In the later sections we merge duplicate events into one event and estimate more accurate duration of each event.

4.4 Distance-Duration Relationship and Effective Distance

There are many facets that need to be taken into consideration when planning a trip to a specific destination. While distance might affect the cost of the trip, the attractiveness of the destination might influence the duration of the stay. Even though the attractiveness of the destination might reflect the length of stay, distance from home might influence the duration of the visit. Since the cost of the trip is related to its distance, we can infer that the duration of stay in a destination is correlated with that destination's distance from home. There are many facets that need to be taken into consideration when deciding on a trip to a specific destination. While distance might affect the cost of the trip, attractiveness of the destinations might influence the duration of stay. Even though the attractiveness of destinations might reflect the length of stay, distance from home might influence the duration of visits. Since the cost of trips is related to their distances, we can infer that the duration of stay in a destination is correlated with its distance from home.

The literature considers duration of stay as one of the most important issues to take into account when deciding to make a trip. In the 1950s, the trip by ship from the US West Coast to Hawaii took approximately 5 days, and visitors stayed for more than three weeks. The same trip now, via airplane, takes five hours and visitors stay less than ten days on the island [91]. Reuben Gronau [91] observed that people stay shorter durations for trips of less than 800 miles, whereas they tend to stay longer when trips exceed 800 miles.

Fig. 4.4 shows that the distance varies based on the geographical locations of places. As we know, closer distances require less travel time. Individuals prefer to stay for shorter durations when taking shorter distance trips (i.e. one-day or long-weekend trips) [90]. On the other hand, long-distance trips tend to have longer durations of stay [91].

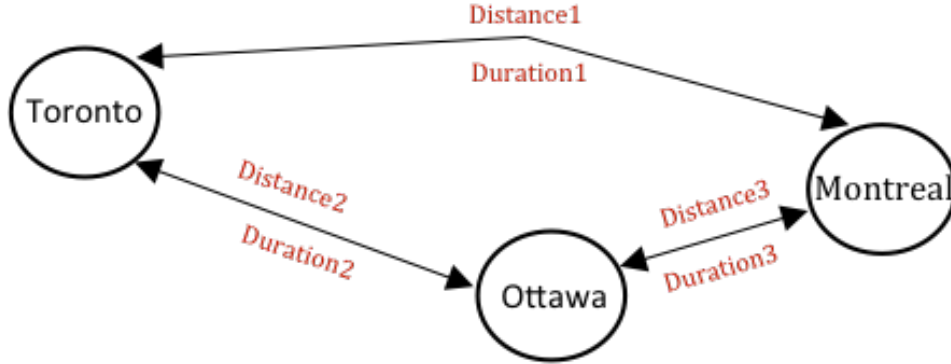


Figure 4.4: The figure shows that events durations vary according to traveled distance.

People usually engage in activities where they live or at least begin activities where they live before heading to their desired destinations. Hence, we believe that people's home information is an important decision-making factor when planning activities. The best example is that when people decide to travel they look for flights from their current city to the desired destination. Having this information helps us define the variable attributes of the desired destinations from the users' home, such as the trips distance and cost. These attributes directly impact the decisions that need to be made during the trip (i.e. activities), and the length of the trip (i.e. duration of activities). In this work, we use distance information to decide the duration of events and hence the amount of time that people spent together interacting face-to-face. The distance is defined based on the locations of the events and on the geographical location of users' current cities and hometowns. We measure the amount of time spent together by days. In lines 3-6 of Algorithm 1, we extract the current city (c_1, c_2) and home city (h_1, h_2) of both users from the profile information. Similarly, lines 14-17 measure the distance of event under consideration from current (dc_1, dc_2) and home city (dh_1, dh_2) of the users. Effective Distance α (line 18) is calculated as follows:

$$\alpha = \frac{\min(dc_1, dh_1) + \min(dc_2, dh_2)}{2}. \quad (4.2)$$

Here we assume that the closeness with both current and home city would affect the

duration of the trip. Hence, we take the minimum of the current and home city distances as representative distance for each user. Because the ‘togetherness time’ depends on the presence of both users, we take the average of the minimum distances of both users from the event location.

4.5 Duration of Events

To understand the relation between origin-destination distance and trip (event) duration, we collected details of 192 tour packages with different origins and destinations. We first use geographical coordinates (i.e. latitudes, longitudes) to calculate distance between origin and destination; and then note the duration of the trip. We repeat this process for each tour package. We observed that there is a strong positive correlation between them as shown in Fig. 4.5. Our finding is supported by the work in [90].

In Fig. 4.5, we divided the distance into equal sized segments of 1000 KM each and calculated the average package length for each range. However, we noticed that with this uniform segmentation, the package durations within a segment vary largely. Hence, we identified a non-uniform segmentation of the distance to minimize the variation within a given segment. The revised segment details and corresponding average package durations are given in Table 4.1. We use this table in Line 19 of Algorithm 1 to measure the duration of an event r for a given distance α . For events that take place in the current city of both users, we take the duration as 1 day (Line 47).

4.6 Merging Duplicate Events

The event durations obtained in the previous step are measured in isolation assuming the existence of only single event at a time, which means each day of a trip results in an event. If a user uploads photos on multiple days, this may result in multiple events for a single trip leading to inaccurate estimation of the time spent together. Also, there

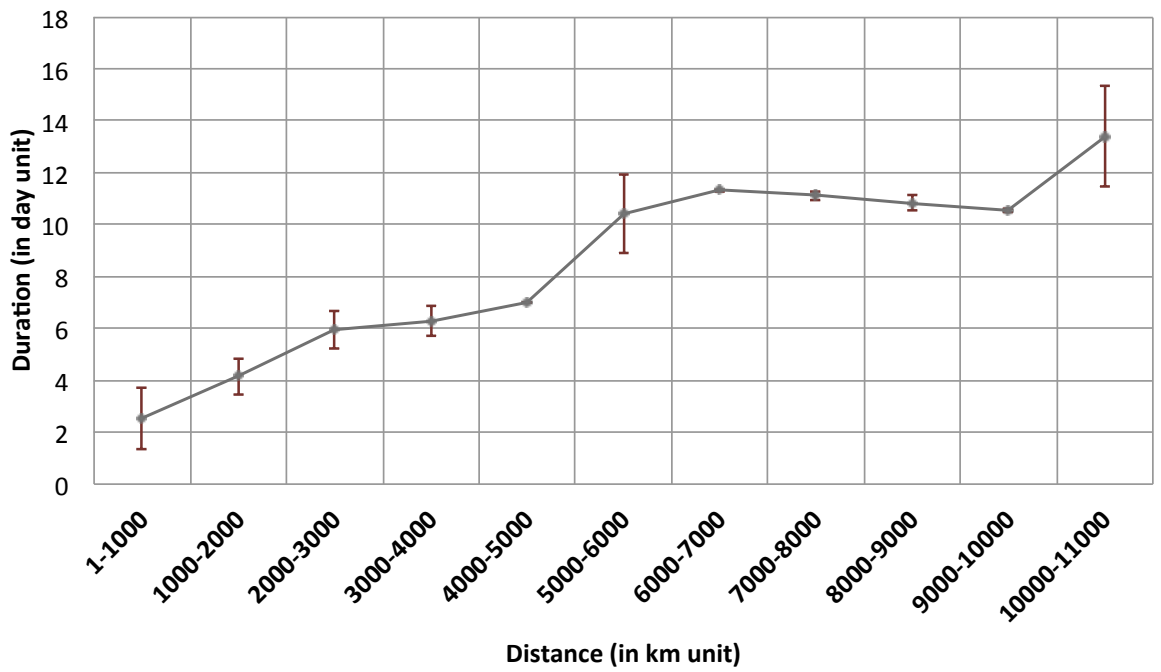


Figure 4.5: Relation between distance and event durations. The x-axis shows the distance range and y-axis shows average tour package length for the given distance.

Segment (in KM)	Average Package Duration	Standard Deviation
1-104	1	0.213
105-253	1.25	0.447
254-300	2.095	1.414
301-534	2.94	0.249
535-592	3.185	0.534
593-1198	3.43	0.499
1199-1659	4.765	0.707
1690-3800	6.1	1.099
3801-5218	8.765	2.828
5219-13542	11.43	1.558

Table 4.1: The distance segment and average tour package duration for that segment. We use this table to map the event distance to the event duration.

are cases when people extend their stay on trips and visits beyond standard duration. Duplicate events from this extended period should also be merged with other events of the trip.

To merge the events belonging to a single trip, we consider the available time-sequence information of the events that is available on OSNs. There are two important characteristics of the duplicate events: (1) they have the same location and (2) they appear next to each other on the timeline. To identify whether two co-located events belong to the same trip or not, we use the following heuristics (Line 20-24, Algorithm 1):

- For short events (with duration less than or equal 4 days), any event that occurs within 4 days of the previous event is a duplicate event and belongs to the same trip.
- For long events (with duration more than 4 days), any event that occurs within the duration r of the previous event is a duplicate event and belongs to the same

trip.

We arrange the events in an increasing order of time and apply these heuristics iteratively from Line 32 to 45 of Algorithm 1, until we encounter an event that cannot be merged. An event would not be merged if it has a different location or it is too far on the timeline (more than 4 days for short events and more than r days for long events). We measure the number of days between the earliest and latest merged event (i.e., r'), and compare it with the duration estimated using Table 4.1, i.e., r . The effective duration of the merged events is taken as maximum of r and r' (Line 47, Algorithm 1). The threshold of 4 for short event is chosen based on the observation that the short visits to nearby cities are generally done over long weekends, which are 4 days long (including the departure day and arrival day) [90].

4.7 Number of Days Spent Together

The total number of days two people spend together $D_{i,j}$ is measured by adding together the effective durations of merged events in Line 52, Algorithm 1. Here we again assume that the people are together during the whole event or trip. Note that this measure only represents the time spent together for leisure during social activities such as dinner outings, trips, and group activities. This does not include the routine time spent together at home or workplace, which makes it a better measure of social closeness.

4.8 Degree of Togetherness

To determine whether two people spent time together over a span of time throughout a specific period of time, we consider the frequency of their mutual F2F interactions throughout a defined period of time. In this work, we define the period of time λ as one year and the frequency γ is measured in months.

$$G_{i,j} = (D_{i,j} * \gamma) \quad (4.3)$$

where G is the function of the degree of togetherness of two users u_1, u_2 .

4.9 Context-Aware Social Story

In chapter 3, the main focus is to collect additional information and events that is relevant to the users in order to build a database of all possible events of the users. Because we rely on multimedia tags information to find the additional F2F interactions (i.e. photos), the advancement of OSNs APIs has allowed us to access the tagged photos of users which were uploaded by their friends. Hence, we assume that we have all the available events of the users.

In this chapter, our main focus of the storytelling is on the context of both multimedia elements and content elements of stories. With our DST model, we are able to personalize our stories based on the inferred context. Note that DST was able to solve the issue of duplicate events by intelligently combining them into one event. Having the complete information of events will result in more explanatory and interesting stories.

4.9.1 Context-Aware Content Element of a Story

Our story contains a set of events that are defined by DST. The set of events and their related information can be large and include some information that is not of interest to users. Therefore, we aim towards creating personalized stories from events information shared on OSNs. We want to personalize memories of people with their close ties because going through stories of our own with our beloved ones takes us back to relive past moments [10]. Therefore, we give more importance ,in our story, to the people whom we spend more time with (i.e. close friends). The context of 'close friends' is inferred from DST algorithm and will be used to personalize the stories so they include the circle of our close ties only.

4.9.2 Context-Aware Multimedia Elements of a Story

Every multimedia-based story is composed of more than one media component such as a photo, video, audio, or text. In this thesis, photos are the main components that represent users' events. The number of photos that users upload on OSNs or are tagged by friends can be very large. Therefore, we want to reduce the information overload and focus on choosing a subset of representative photos for each event, in order to add them to the story. In the current work, we do not focus on image processing or on aesthetic measure aspects. Instead, we exploit the context that comes with photos, as follows:

- The photos of an event are ranked according to the number of received engagements (i.e. likes and comments), and top n photos are chosen for the story
- The number of the event's photos, n , is chosen based on the duration of the events which was inferred by DST

The overview of the proposed storytelling system using DST is shown in Fig.4.6 The DST component is responsible for finding the closest friends of users based on the number of days they spent together interacting face-to-face, and to infer the duration of individual F2F events. Since our goal is to generate personalized stories, we use the closest friends information to retrieve the mutual events of the users and their closest friends (i.e. the list of the closest friends generated by DST). For each event, we retrieve the associated photo(s) as well as the temporal, spatial, and social information. The number of photos for an event can be large, therefore we only choose a subset of representative photos based on the context of the event's duration and the number of received engagements on photos, as discussed earlier (Fig.4.7). The temporal information of each event includes two pieces of information: the time, which is taken from the time photo-metadata, and the duration, which is inferred from DST. We repeat this process for each event. We then combine the representative photos for all of the events along with the contextual information of their time, duration, location, and people involved, in order to generate

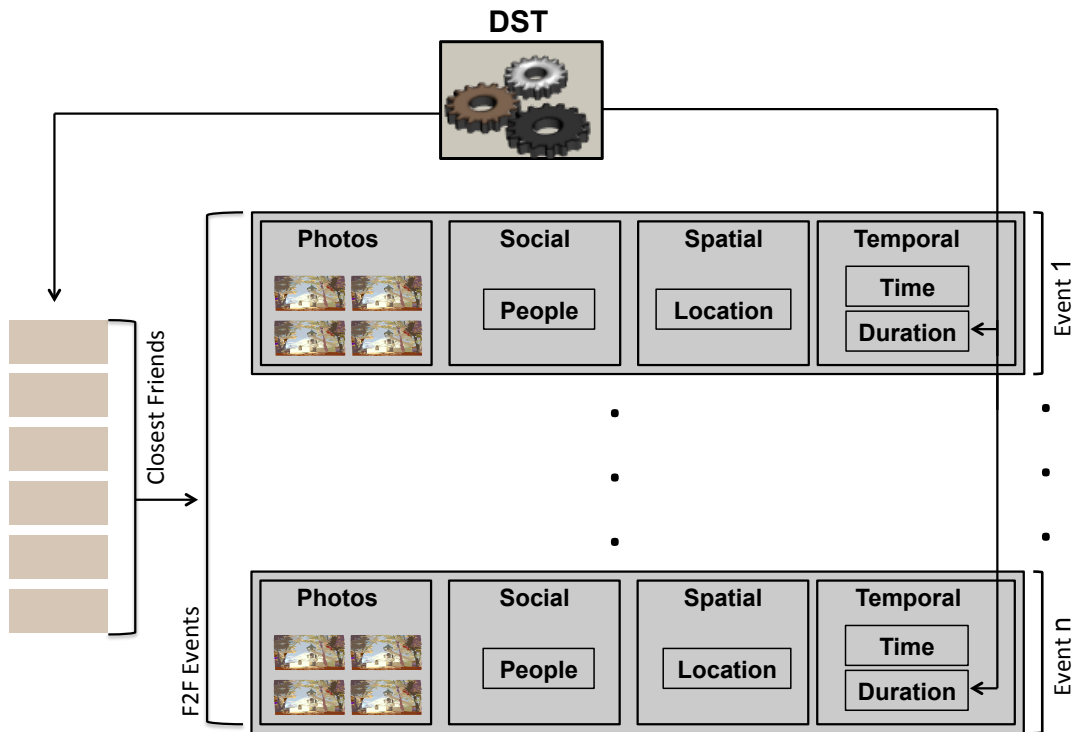


Figure 4.6: Proposed framework of the storytelling system using DST. First, DST finds a list of the user’s closest friends based on the days they spent together. It then retrieves the mutual F2F events of the users and their closest friends. Each event contains a set of related photos and contextual information about the event’s time, duration, location, as well as about the people involved.

the story. To choose the multimedia elements of our stories, we follow the concept of the Facebook video story ‘A LookBack’. We use photos, text, and audio to generate a video of the personal stories. We use the representative photos to present each event, and text to explain their temporal, spatial, and social context. We combine the photos and text with audio to generate a storytelling video about the user’s life for a period of time (one year in this thesis). Note that the events in the story are presented in a chronological order.

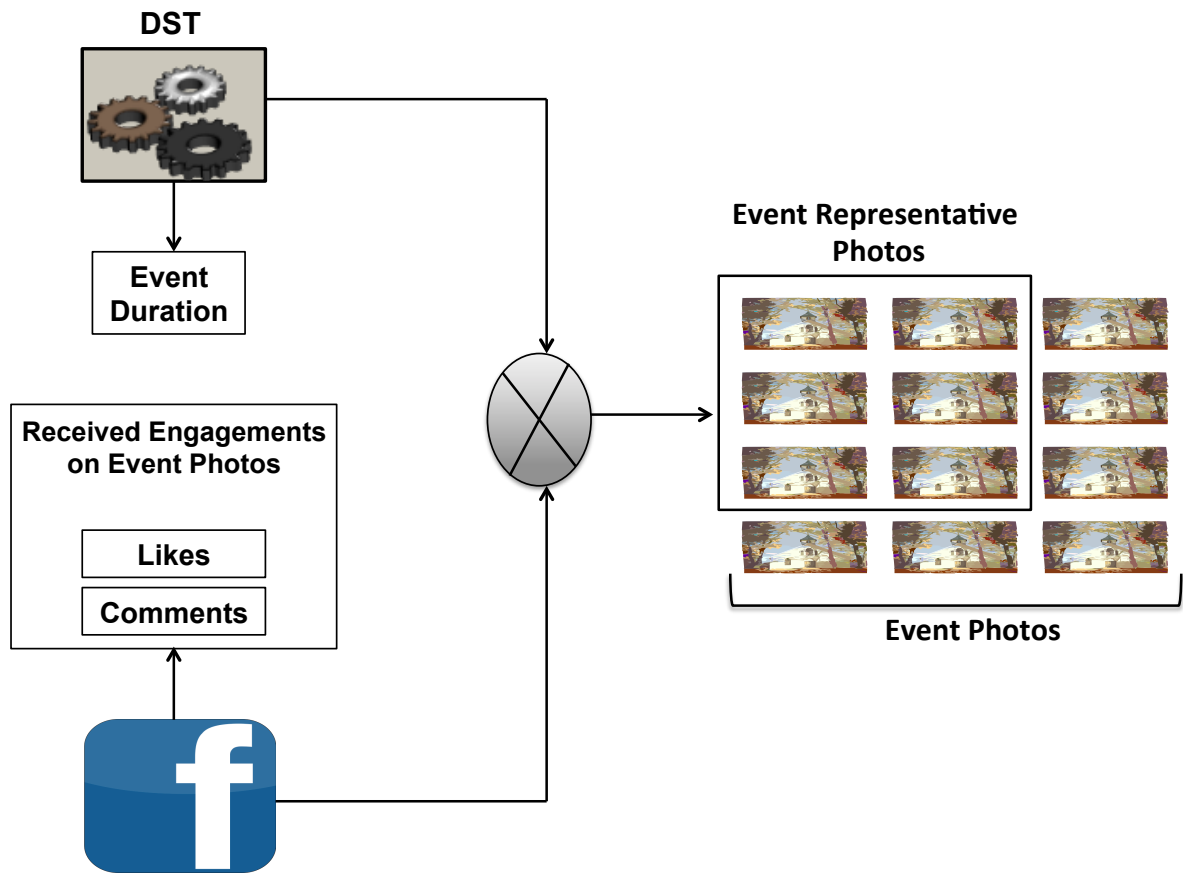


Figure 4.7: The number of representative photos for an event is chosen based on the event duration inferred from the DST model, while the representative photos themselves are chosen based on the number of likes and comments they have received. The likes and comment of photos are obtained from Facebook using Facebook APIs.

Finally, Fig.4.8 shows the overall storytelling system layout. It illustrates the high level architecture of the system.

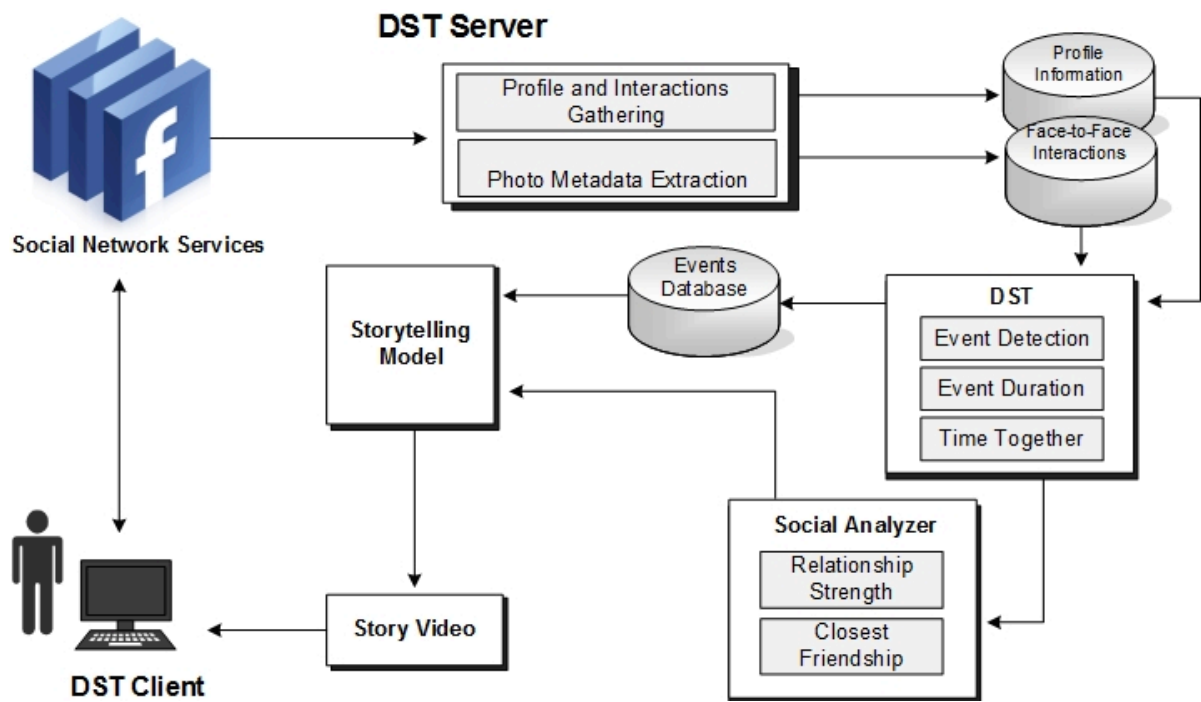


Figure 4.8: The storytelling system layout.

Chapter 5

DST Evaluation

The main purpose of the experiments is to assess the accuracy of the proposed DST algorithm. In this chapter, we present the evaluation methodology we followed to validate our proposed DST model. The dataset and ground truth collection is discussed in detail in Sections 5.1 and 5.2. We also detail the performance measures we used for our system evaluation in Section 5.3. The rest of the chapter presents the experiments and discusses the results, which show how DST performs in comparison to different approaches.

5.1 Data Collection

We have collected two types of data that we used in our evaluation process. One is the dataset that we used to conduct our experiments on and the other is the ground truth to evaluate the performance of DST algorithm.

5.1.1 Dataset

We conducted our experiments on a real-world data collected from Facebook. We collected data from 9 users and their friends. Each primary user has on average of 339 friends, which adds up to 3061 sub-users in our database. From each profile, we retrieved personal information and interactions activities. The personal information in-

Number of Primary Users	9
Sub-Users Size	3061
Users with Current City	2237
Users with Hometown	2028
Album Gathered Size	28827
Photos Gathered Size	1027559
Photos Tagged with People	408297
Photos Tagged with Locations	136128
Locations Gathered from Photos	12093

Table 5.1: Statistics of the data collected from Facebook for our 9 primary users

cludes name, geographical information (current city and hometown), education and work, and mutual friends. We collected two types of interactions from each user: F2F interactions and non-F2F interactions. In these experiments, Photos represent F2F interactions (i.e. uploaded by the users or uploaded and tagged by their friends). Statuses and shared posts represent non-F2F interactions. We extracted the tags data (i.e. metadata) of photos, which includes geo-tags, capture time, and people tags. We also retrieved likes and comment information from posts and photos. In order to access users information on Facebook, we asked our users to grant us permission to retrieve the said data. We requested a permission to access their friends' data as well. Facebook API's are mainly used to develop an application to collect the data. Users can log-in with their FB accounts and the said data is retrieved in the background and saved in our database. Table 5.1 and 5.2 show the details of our database after 9 primary users have granted permission to our application.

It is important to note that this method only considers photos that are tagged with date, location, or people. People presence tags cover face-photos and non-face photos. We assume uploading time as the capture time of the photo. Our method mainly relies on the manual tags (i.e. people, location, date) done by users. There is no guarantee

Number of Primary Users	9
Number of Sub-Users	3061
Album Gathered Size	8559
Photos Gathered Size	170286
Photos Tagged with People	65000
Photos Tagged with Locations	36875
Locations Gathered from Photos	4557

Table 5.2: Statistics of data for 2013 from the 9 primary users

that the tags are actually correct. For example, if a location is tagged incorrectly, there is no way of detecting the mistaken tag. Hence, we assume that all tags are correct.

5.1.2 Ground Truth Collection

In order to evaluate the performance of our DST estimating model, we need an ideal model response as a reference. We therefore need to obtain the actual days people (i.e. users) have spent together F2F interacting according to what they report. Obtaining the ground truth from the users was done in two rounds.

Pre-Round 1

Before we start the first round, we wished to provide the users with a few explanations in order to help them give the right answers. We define:

- **Time spent together as the time spent for leisure only.** We explain to users that by 'time spent together' we mean the time that does not have work or commuting as its purpose, for example traveling, get togethers, birthdays, celebrations, parties, going out, special occasions.
- **Events (i.e. activities) as local (i.e. happened in the current city) and outside current city.** We defined events to users as activities that happened

within their current city or the activities (i.e. trips) that happened outside their current city.

- **Duration of local events as 1 day unit.**

Round 1

Once we were sure they understood the definitions, we started round 1. For each volunteer, we:

1. Asked them to list all the activities (i.e. events) they have done in the year 2013, mentioning when each activity happened, if possible.
2. Asked them to report the duration of each event (i.e. measured in days).
3. Asked them to report the people involved in each event.
4. Asked them to list the 10 friends with whom they were most socially connected in the year 2013. For each friend, we asked them to report how much time they spent together throughout in 2013, from January to December. In other words, we asked for the time spent together each month. We also asked for the duration of each outside event.
5. Asked them to rank their top 10 friends, according to the time they spent together throughout 2013. We asked them to exclude any personal emotions when selecting. The top 10 friends lists were created based on a three point Likert scale, where the ranks are: 1- very poor, 2- good, 3- very good.

Pre-Round 2

We compared the events given by users in round 1 with the events found by our system. When we found extra events not mentioned by users, we added them to the given list from that round. We organized all the combined events in chronological order, according to their dates.

After obtaining the combined list, we start round 2 only if extra outside events were found.

Round 2

For each user we:

- Asked them to validate the extra events. For outside events, we provided users with one event before and one after, and then we asked them for the duration of these events, in case of a positive response. We also asked them to change the duration of the previous or post events according to the extra events if necessary. In the case of a negative response, we marked the event as a false event. There were cases where previous or post events were similar, and in such a situation we asked them if they had been there twice within that period of time (i.e. a month in our case).

Discussion

While collecting the ground truth information, the users recalled most of the outside events (i.e. events outside their current city), as well as their duration. What they did forget are the short trips within the long trips. For example, one user mentioned that she travelled to Philadelphia to visit her sister for 10 days, but forgot to mention that they went to Atlantic City, which is 200 KM away from Philadelphia. The users response on not mentioning that in round 1 was 'Oh! I forgot. Anyways it is part of the Philadelphia trip and it is just a 1-hour drive'. This was the case when we found extra outside events that users did not recall. It is important to mention that our model doesnt detect the routes of the trips. This was the reason for conducting round 2 of the ground truth procedure. Interestingly, all users reported that it is hard to remember local events but they succeeded in recalling special events such as birthdays, graduations, baby showers, farewell parties, and special occasions including religious and cultural, etc. On the other hand, they failed to remember casual local events such as outings and get-togethers.

They occasionally had a flashback and gave random answers. In general, they preferred to give an approximation of the time they spent with their friends/family throughout 2013. The responses in this case were generalized, and the answers looked like: 2/months, 3/weeks, 3/weeks including our trip to place x, etc.

5.2 Performance Measures

5.2.1 Accuracy

To measure the accuracy of the model, the error between the estimated value and the true value is used. In this case, a lower error means a better performance.

$$Accuracy = 1 - Error \quad (5.1)$$

In order to evaluate the performance of our DST estimator, we need to use a measure that shows how far or close our results were from the actual values. This can be shown in the amount of error between an estimated value of a quantity and its actual value. There are two common ways to measure errors: absolute error and relative error.

5.2.2 Absolute Error

Absolute error is defined as the difference between the actual and estimated values. It shows how large or small the error actually is. However, It doesnt necessarily show how important the error is. For instance, the absolute error of both $x=10, y=9$ and $x=2, y=1$ is 1. While both examples show an absolute error of 1, the relevance of the error is very different. The error is only 1% for the former example and 50% for the latter one. Therefore, it is more desirable to compare the error against the actual value. We can achieve this by expressing the error as a relative error.

$$AbsoluteError = |EstimatedValue - ExactValue| \quad (5.2)$$

5.2.3 Relative Error

The relative error shows how large or small the error is in relation to the actual value. In other words, it is the ratio of an error in an estimated value, to its true value. We use it to estimate the accuracy of our model. In other words, it shows how close our models estimation is to the true value.

$$RelativeError = \frac{|EstimatedValue - ExactValue|}{ExactValue} \quad (5.3)$$

5.2.4 DCG

Discounted Cumulative Gain is a measure of ranking the quality of lists in information retrieval. DCG measures the gain of entities based on their positions in the retrieved list. We use it to measure the effectiveness of the top 10 friends list

$$DCG_p = rel_1 + \sum_{i=2}^p \frac{rel_i}{\log_2(i)} \quad (5.4)$$

where rel_i is an entity i and i is the position of the entity in the list.

5.2.5 nDCG

DCG alone does not show the actual performance of algorithms on ranking lists. Normalized DCG is used to compare the quality of ranking in the resulted lists of different algorithms. It is computed by dividing the DCG by the ideal DCG ($IDCG$). The higher the nDCG is, the better the ranked list is.

$$nDCG_p = \frac{DCG_p}{IDCG_p} \quad (5.5)$$

5.3 Duration of Event Estimating

To assess the duration of events estimation, we chose all the true events that were provided or validated by the users and found on their Facebook profiles. We excluded the events that users did not provide nor validate; we refer to these events as false events. Note that all the experiments were conducted on 90 pairs of (users, friends). We have 9 users and each user has a 10 top friends list.

In order to estimate the duration of events, we first need to detect individual events. This is done by our proposed intelligent model, which recognizes if similar F2F interactions belong to one event or to separate events, as discussed in Chapter 4. We compare our estimated results with the ground truth provided directly from the users. Table 5.3 shows DST performance on the 9 users in estimating individual events duration. The results show that our algorithm estimated days-spent-together values, of individual events, close to the true values with average of 11.71 % of relative error and standard deviation of 0.100589.

These results show the duration estimation performance for both local events and outside events. Note that we assume that the duration of the local event has a 1 day measure; the model recognizes all the local events as 1 day. This is obvious since the distance to-from the same location is 0.

User 5 has shown the highest estimation error. The reason for the increase in the estimation error is a result of a lack of enough F2F activities information that the user has provided on her OSNs profile. In one (user4, friend) scenario, the user has shared only one interaction (i.e. photo) on a visit-trip (i.e. outside event) to her friend. The user has reported 1-week of stay with her friend in that visit while the corresponding online F2F interaction contains the information of only 1-day of stay. Based on the traveled distance, the event is short-term with standard duration of 2 days. The insufficiency in interaction information on that event has affected the algorithm performance with 0.66 of relative error.

Subject	Average Relative Error	Percentage Relative Error	Standard Deviation
u1	0.083	8.36%	0.065
u2	0.0593	5.93%	0.091
u3	0.231	23.10%	0.160
u4	0.055	5.55%	0.175
u5	0.328	32.86%	0.220
u6	0.110	11.07%	0.137
u7	0.097	9.73%	0.079
u8	0	0%	0
u9	0.088	8.83%	0.122

Table 5.3: Performance of individual events estimation on 9 users

Our results show that DST is able to successfully detect the types of events. It is able to recognize short-term events (i.e. outside short-trip), where people usually do not stay for long times, and long-events where people stay longer. For example, a (user, friend) shared two F2F interactions of the same location. DST recognized the type of the interactions as short-trip based on the traveled distance from users' home. The time gap between the two interactions is 10 days apart which violate the short-trip duration. DST could successfully recognize that the two F2F interactions represent two different short events and performed two separate estimations. DST, also, has shown its ability to recognize long-term events (i.e. long trips). With little interactions information on a long-term event, DST could estimate the duration of the stay. One user had traveled to Mexico, for 6 days, from Ottawa with a friend who lives in Montreal. She shared an album of the trip where all the photos in the album have the same date/time. Photos date alone does not tell much about the length of stay of the trip even though human know that the trip is defiantly more than 1 day. By using our algorithm, we were able

to estimate 7 out of 6 days with relative error of 0.166667.

Moreover, DST algorithm has shown its intelligent capability of recognizing users' events that happened on their visits to their hometown. It treats it the same way it does with the current city (i.e. users home) except that it still considers the events as outside events which is very obvious as they are visiting not actually living there. This is shown in a user-friendly scenario where the user visited her hometown. The user's hometown is 11332.27 KMs away from her current city. She made a short-distance trip to a nearby city to her hometown with her friend who lives in the same current city and is from the same hometown as well. The user reported that they stayed together there for 5 days. The results show that our algorithm could successfully estimate 4 out of 5 days, with relative error of 0.2, from only 2 different interactions (i.e. photos) shared on Facebook. Note that the two interactions themselves contain the information of only 2 days. Another example is when a user visited her hometown and stayed with her sister for 1 month. She shared only 8 different interactions (photos) with her sister while in their hometown. Our model estimated 17 out of the 30 days. The relative error in this case is 0.43, which is relatively high compared to the rest and that explains the error increase in her case. Finally, we want to mention that user 4 has an error of 0 since all of her events are local. In other words, she did not travel anywhere outside her current city at any time during the year.

The algorithm is also able to estimate the duration of events that are longer than the standard durations. It was apparent in the case where a user from Ottawa reported that she visited her friend who lives in Montreal for 13 days. According to the standard duration of 200 km of traveled distance for leisure-purpose visits, it is average of 1 day of visit. Our system could recognize that it is a short trip but not a 1-day standard visit. It could estimate 9 out of 13 days by merging 7 different F2F-interactions (i.e. photos) with a relative error of 0.307692. This shows the efficiency of our algorithm for being able to recognize that all the seven interactions belong to one event.

Finally, we want to mention that user 4 has an error of 0 since all of her events are

Accuracy	88%
Relative Error	0.117
Percentage Relative Error	11.71%
Standard Deviation	0.100

Table 5.4: Overall average DST performance on estimation of event duration for 90 pairs of (user, friend)

local. In other words, she did not travel anywhere outside her current city at any time during the year.

Overall, the DST model performed very well, with an accuracy of 88% (Table 5.4). It could correctly detect most of the events, recognize their type (i.e. short, long events), and accurately estimate their duration.

Discussion

It is important to mention that our model does not detect the route of outside events. For instance, a user from Montreal has traveled to Philadelphia for 10 days. During her stay there, she visited Atlantic City, which is 200 Km away from Philadelphia, and came back to Philadelphia. Our model failed to recognize Philadelphia - Atlantic City - Philadelphia as one event (i.e. trip). Instead, it divided it into 3 events and did 3 estimation processes. In other words, it recognized Montreal- Philadelphia as one event and estimated 5 out of 5 days, Montreal- Atlantic City as another event, and Montreal- Philadelphia as a third event, estimating 3 out of 1 and 3 out of 4 days for the last two events, respectively. The model overestimated the duration of Philadelphia -Atlantic City by 200%, as it recognized it as Montreal- Atlantic. This limitation could affect the detection accuracy for the duration of events, since it might cause an overestimation problem, and as a result affect the accuracy of our system. The overestimation occurred in this case as well as when users spent less than the suggested average time in their destination, based on the travelled distance. The system cannot detect if people stay

less than the average duration suggested by a travelled distance. The minimum it can estimate is the duration suggested by a traveled distance. The reason is that it is very difficult to tell when exactly events happened, as it really depends on user inputs (i.e. when and what they share). While some users might share an activity at the same time as it is happening, others might share it hours or days later. It is also important to mention that some social media such as Facebook and Instagram wipe out the original metadata of photos when uploading them. We, hence, must heavily rely on the uploading time for our estimation. As there is no guarantee that an event happened at the time of the photo upload, it is difficult to recognize cases where the duration of events is less than the expected length of stay since we cannot tell when the event actually started. These cases are rare for leisure visits but are more common for business trips. We can see this in our data, where we have only one case where a user stayed less time than the expected duration for the corresponding traveled distance.

5.4 Days Spent Together

In order to be able to estimate how much time people spent together interacting (i.e. measured in days), we first need to find the mutual activities (i.e. events) they have done together. Since each activity lasts a certain amount of time, we are interested in inferring the time of each activity in order to make our estimation on the days people spent F2F interacting. This has been done as shown in the results of the previous section. We have seen that the algorithm performed very well when estimating the duration of both local and outside activities (i.e. events). In this experiment we chose all the events provided by users and found on their profiles, including false ones (i.e. not provided or validated by users but found on FB). We found the sum of the duration of all events and compared it to the sum of the duration of all events obtained from the ground truth. The algorithm performed on average with a 31.39% of relative error and a standard deviation of 0.130283.

We observed an increase in the performance error when estimating the overall duration in comparison to the error of estimating the duration of individual events. There are three reasons for the increased error:

- Lack of data on when users do not share activities on OSNs. When users do not provide data or share activities, there is no way of knowing.
- Inclusion of falsely detected events. While collecting the ground truth from users, the users did not recall all the local events like normal outings and get-togethers. They preferred to give an approximation of how much time they spent F2F interacting, for example with a response of twice a week. Due to inaccurate human memory, the users recall of such events affects the performance of our system. One user reported that she met a friend three times a month throughout 2013, but for certain months we did not find any activity information on her profile. Without any event information shared on her profile, there is no way of knowing that they were together doing an activity.
- Inherent error in the ground truth. Since users did not precisely recall local events and just gave an approximation of the time spent together, it is possible that what they reported for local events might be inaccurate. For instance, the user reported seeing her friend 3 times per month, but in reality she might have seen her for some months and not for others. The user herself could not accurately recall how much time she spent with her friend. Another user reported that she saw her friend 3 times per month in 2013 but we only found 3 different mutual interactions. She reported that she does not like to share activities on social media when she is with this friend.

This clearly explains why we have an increase in the estimation error for the overall duration (31.39%) compared to the error of individual events duration (11.7%).

According to the results, we observed that there is a relation between the number of interactions (i.e. of unique dates) shared on social media and the performance of

our system. The more interactions users share on social media the better the results. We conducted an analysis on our data to find the relation between the number of interactions shared on OSNs and the performance of our algorithm. Since the number of interactions varies from one user to another, using the number of interactions alone will not illustrate the correlation. Therefore, we decided to normalize the number of interactions with respect to the total days provided from users, to show the percentage of shared interactions with respect to overall days. For example, one user reported 42 days spent with a friend and we found 31 mutual interactions on her profile. We can see that the user provided around 74% of information with respect to the number of total days spent together. Another example is when a user provided 4 interactions and reported a total of 7 days spent with a friend; we can see that around 60% of the information was provided with respect to the total number of days spent together. Note that the number of interactions is relative to the users and each individual friend. We applied Pearson's Correlation function on our data. Fig. 5.1 shows that there is a negative correlation between the number of interactions and DST error. This means, the more interactions we have the lower the performance error will be. Note that there is a point of 150% of shared interactions and relative error of 0.5. This happened due to the overestimation of days spent together by our system since user 8 reported less days spent together with a friend, than what she shared on her profile.

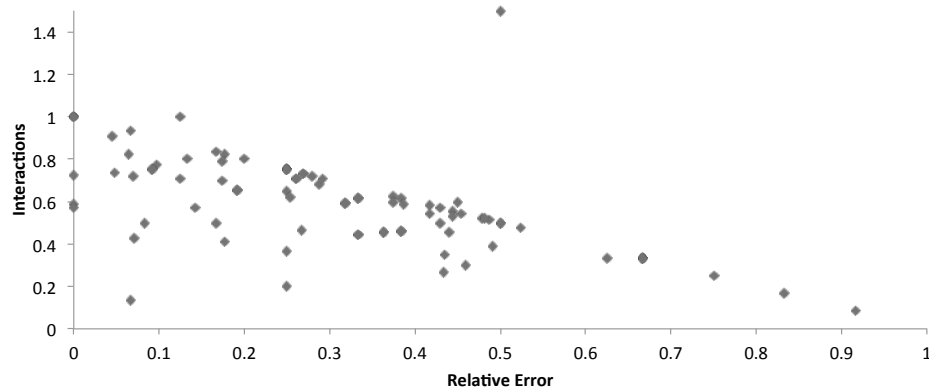


Figure 5.1: Negative correlation between No. of interactions and Performance of DST

Overall, DST algorithm performed well with $\approx 70\%$ of estimation accuracy and standard deviation of 0.130283 on overall days-spent-together throughout the year 2013 (Table 5.5 and 5.6).

Subject	Average Relative Error	Percentage Relative Error	Standard Deviation
u1	0.217	21.74%	0.146
u2	0.328	32.86%	0.267
u3	0.310	31%	0.101
u4	0.545	54.56%	0.202
u5	0.153	15.34%	0.101
u6	0.254	25.48%	0.146
u7	0.205	20.50%	0.161
u8	0.491	49.13%	0.270
u9	0.318	31.867%	0.166

Table 5.5: Performance of estimation of overall days-spent-together throughout the year 2013 on 9 users

Accuracy	$\approx 70\%$
Relative Error	0.313
Percentage Relative Error	31.38 %
Standard Deviation	0.130

Table 5.6: Overall Average DST performance on estimation of overall days-spent together throughout the year 2013 for 90 pairs of (user, friend)

Discussion

It is important to mention that to estimate the overall days we included both true and false events. False events do not necessarily mean wrong interactions between users; they are usually related to users since tagging is done on purpose. For instance, one user tagged some friends in a photo of a special occasion, where they were not physically there with her, according to what she reported. Her response was 'I tagged them because I wished that they were with me on that day'. Moreover, when users receive an irrelevant tag of them, they most likely will remove it.

5.5 Days Spent Together Outside Current City

Due to the uncertainty of the information reported by the users for local events, the performance of the DST has been affected. We therefore decided to show its performance on the events where users were confident about their durations when collecting the ground truth.

Figure 5.2 and table 5.7 show that the error decreases when excluding local events during the estimation. This shows that the inaccuracy of human's recalling the exact event information can affect the performance of our algorithm. On the other hand, we have observed that users are interested in sharing outside events (i.e. events outside their current cities aka trips) and special events like birthdays, graduations, national days, etc. Even though most special events are local, they still could successfully recall them. From this, we can infer that users might not be as interested in sharing casual local events (e.g. a normal get-together or an outing) as they are when it comes to trips and special events. This can also explain the lack of information on local events that were reported by users but not found on social media.

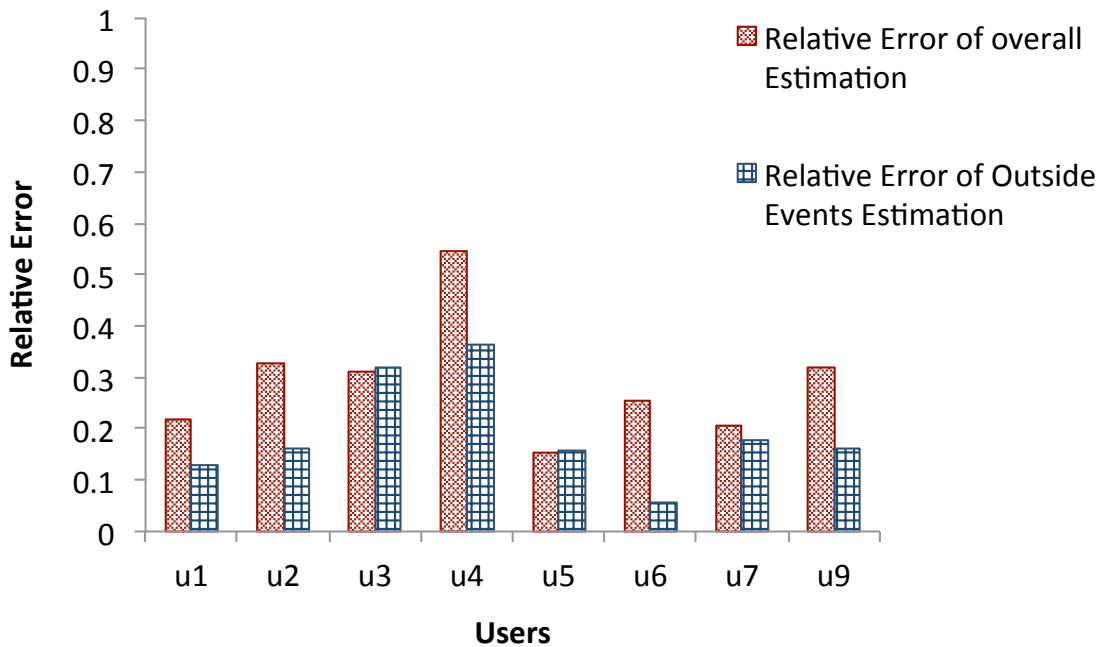


Figure 5.2: Comparison between DST Performance on Overall Days and Days from Outside Events only for 80 pairs of (user, friend). User 8 did not have any outside events.

	Accuracy	Relative Error	Percentage Relative Error	Standard Deviation
DST for overall days	$\approx 70\%$	0.314	31.4%	0.130
DST for outside events	$\approx 81\%$	0.191	19.1%	0.101

Table 5.7: Comparison between DST Performance on overall days and days from outside events only

5.6 Comparison to Previous Work

In order to validate the performance of our DST model, we must compare it to another work in the same field, using the same data. The results from different algorithms are compared to the actual days provided by users. We could not find any related algorithms that measure the number of days spend together by two OSN users. Hence, we compare the DST results with its preliminary version [87] that uses only interaction activities shared on OSNs.

Using Only Interactions Shared on OSNs

In this algorithm [87], each mutual interaction (i.e. photo) of the same date is consider as one event. We then add all the events together to find the total number of events. Since each event represents a different date, the total number of events represents the total number of days spent together by two users.

$$Days(u_1, u_2) = \sum_{i=1}^m n_i \quad (5.6)$$

Fig.5.3 compares the total number of days calculated from this algorithm, number of days estimated by DST, and the ground truth for all 9 main users (90 user-friend pairs). We can see that DST algorithm estimates number of days closer to the ground truth values than the previous method's thanks to the geographical information and the learning from tour packages.

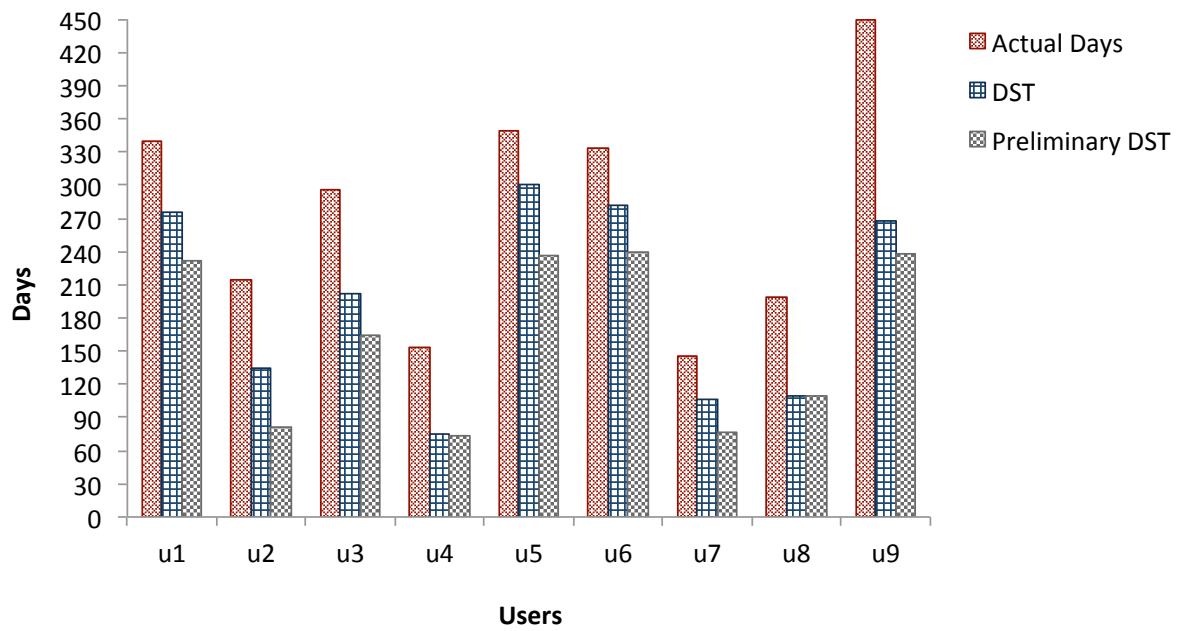


Figure 5.3: Comparison between the performance of DST and previous work against the actual values

Fig.5.4 shows the same comparisons but in more details about each pair of (user, friend).

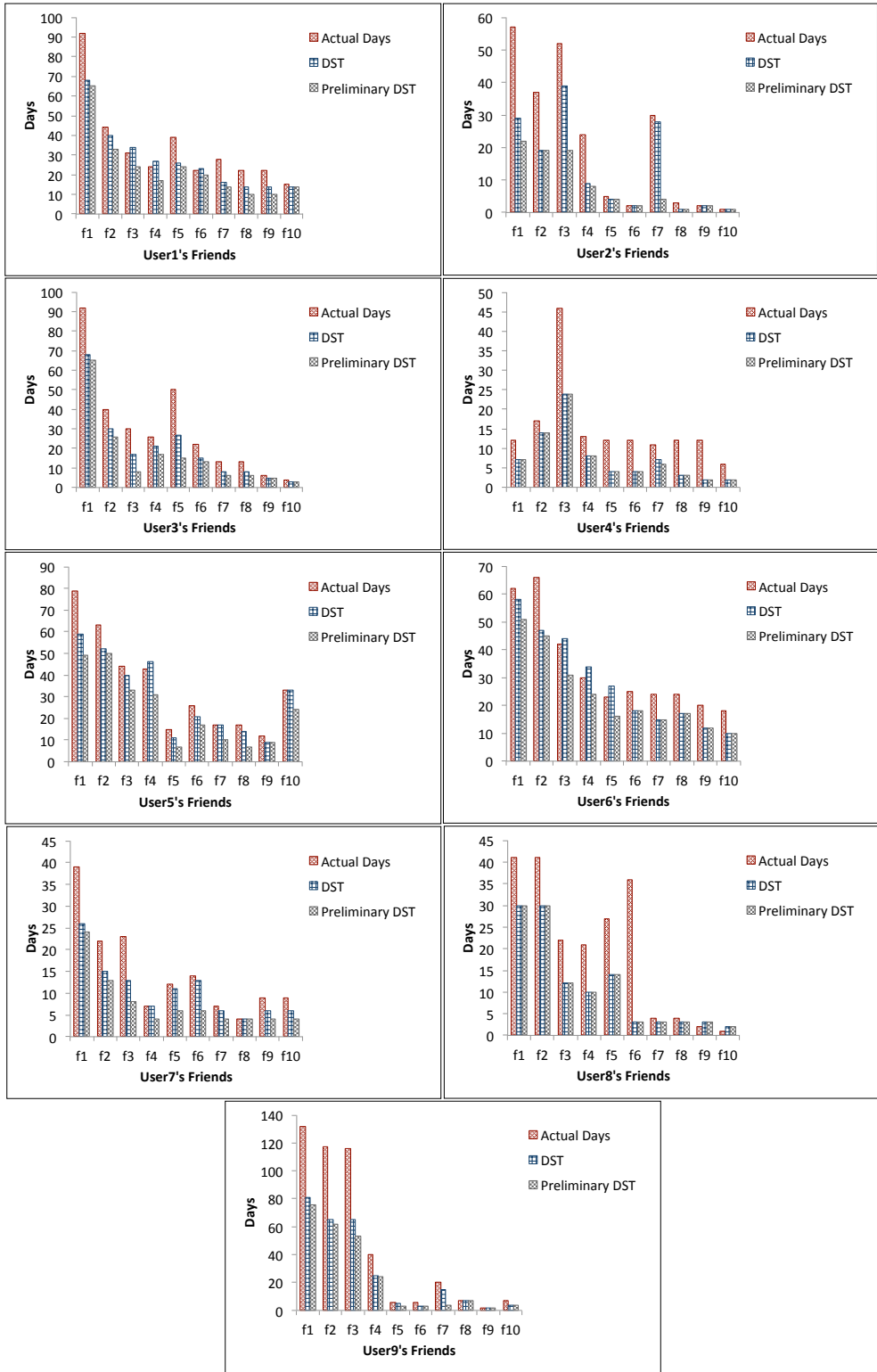


Figure 5.4: Comparison between the performance of the DST and previous work for each pair of (user, friend) on 9 users.

For these comparisons we applied the same data on all the algorithms and compared the estimated results from each algorithm against the actual number of days provided from our users.

When looking at all 9 users, we saw that the DST model greatly outperformed all the testing algorithms; its estimation is the closest to the true value of days. We can conclude that every single piece of interactions on social media is important when it comes to the analysis of social users and their behavior.

When looking at user 8, we can see that the performances of DST and previous work are the same. This is because all the events of user 8 and her friends are local (i.e. she did not go out of her current city and she did not have a friend visit her from another city). Therefore, both the algorithms measured 1 day for each event resulting in the same error. User 4 also had majority of her events as local which resulted in similar performance for both algorithms, with DST performing slightly better.

Summary

The DST model has proven efficient at estimating the number of days people spend together. Its estimation values are close to the actual days reported by the users. It could infer hidden information using photos and their metadata along with the personal geographical information of social users. It uses the inferred information in order to make its estimation on the number of days people spent together F2F interacting.

Strongest Friendships Comparisons

In this experiment, we want to use the results obtained by DST to create a list of the user's top ten closest friends. While collecting the ground truth from the users, we asked them to list their 10 closest friends for the year 2013 and to give them a score on a three point Likert scale, where the ratings are: 1- poor, 2- good, 3- very good. We use this as a reference to validate the top ten closest-friends list created by our system. Note that we give a rating of 0 to a user that is not included in the top ten list, and we do not

provide our list to the users. Also, we compare our top ten list with the user’s top ten list, based on the following:

- **The Length of Friendship**

The concept of length of friendship was used in [11] to represent the amount of time shared between social users. In their work, they calculated the number of days since the first communication between users in order to find this duration variable. In this experiment, we apply the same data that we apply on DST algorithm.

- **Number of Faces in Photos**

The algorithm proposed in [8] used the information from people co-occurring in photos to measure the strength of their relationship. Their method is based on two principles: 1) the number of mutual photos between users and 2) the number of people depicted in the photos. The greater the number of photos in which two people appear together, the stronger the relationship. Also, more photos in which fewer people are depicted indicates an even stronger relationship:

$$STR(P_a, P_b) = \sum_{i=1}^m \frac{1}{\sqrt{n_i - 1}} \quad (5.7)$$

where $STR()$ is the strength of the social relationship between two people, m is the number of mutual photos, and n_i is the number of people depicted in the i^{th} photo. In this experiment, we apply the same data that we apply on DST algorithm.

- **Profile Similarity**

We used mutual friends, geographical profile (current city and hometown), and education and work information to find the similarity between two people. We then used the similarity to find the ten closest friends of users.

- **Non-F2F Interactions**

We used posts (statuses and shared videos/photos/links) and their received engagements (likes and comments) to calculate the non-F2F interactions between two people. Note that the engagements received on F2F photos were included as well. We then used the degree of non-F2F interactions to find the ten closest friends of users.

- **Combination of Profile Similarity and non-F2F Interactions**

We combined the profile similarity and non-F2F interactions in a linear combination, in order to determine the users' ten closest friends.

Table 5.8 shows the average rating for each algorithm based on the top ten list provided by the users while collecting the ground truth. Table 5.9 shows the normalized Discounted Cumulative Gain (nDCG), in order to illustrate the quality of the ranking for each algorithm. A Larger value of nDCG means a better ranking quality.

Subject	Average Closes-Friends						
	DST	Friendship Length since First Interaction	No. of Faces in Photos	Mutual Friends	Profile Similarity	non-F2F Interactions	Profile Similarity & non-F2F Interactions
U1	2.2	1.9	2	0.3	0.6	0.4	0.3
U2	2	1.6	1.9	1.2	1.2	1.3	1.4
U3	1.9	1.5	1.8	0.5	1.1	1	0.7
U4	1.8	0	1.6	0	0.2	0.2	0
U5	2.2	2.1	2.2	0.6	0.6	0.2	0.8
U6	2.3	1.9	2.3	0.3	0.4	0.5	0.3
U7	1.8	1.6	1.7	0	0	0	0
U8	2	1.9	2.1	1	1.1	1.5	1.6
U9	1.8	1.6	1.6	1.2	0.7	0.9	1.2

Table 5.8: Average Top 10 Closest Friends from Different Algorithms

nDCG								
Subject	DST	Friendship Length since First Interaction	No. of Faces in Photos	Mutual Friends	Profile Similarity	non-F2F Interactions	Profile Similarity & non-F2F Interactions	
U1	0.981	0.732	0.882	0.070	0.248	0.153	0.116	
U2	0.975	0.794	0.948	0.532	0.501	0.581	0.647	
U3	1	0.866	0.939	0.317	0.469	0.670	0.388	
U4	0.834	0	0.810	0	0.045	0.076	0	
U5	0.997	0.890	0.991	0.460	0.345	0.066	0.235	
U6	1	0.870	0.946	0.228	0.109	0.210	0.228	
U7	1	0.922	0.924	0	0	0	0	
U8	0.945	0.915	0.957	0.451	0.495	0.729	0.759	
U9	0.947	0.868	0.828	0.726	0.421	0.639	0.726	

Table 5.9: Normalized Discounted Cumulative Gain Feedback on Top 10 Closest Friends from Different Algorithms

Although this is a very limited experiment (since the users were not involved to rate the top ten lists of each algorithm directly), our system does outperform the others in recognizing the closest interpersonal relationships of users from the strongest to the poorest.

5.7 Discussion

While analyzing the data and the results we have observed some interesting findings from DST model:

- Based on the results, we can determine when the first and last F2F interactions of the year occurred between two people. We can also estimate the time of the year during which they interacted the most. Interestingly, for all the 9 users in our study, we have observed that the number of activities (i.e. interactions) have increased between spring and fall. This is actually true for most people living in Canada (since all our users live in Canada). The mild-hot weather between spring and fall allows for many more indoor/outdoor activity options than does the cold weather. According to [92], warmer weather positively affects recreation and tourism in Canada. The study shows that summer activities vary between dry-terrain and water based activities, while in winter there are only ice/snow based activities. Accordingly, we can infer that people could be happier in seasons with nice weather than in cold seasons [93]. To summarize, when people engage in more activities they tend to share more interactions on social media. When people are happy they also tend to share more of their moments with friends on social media. Moreover, summer is vacation season for most people, which means that they have more time to enjoy and socialize with friends and family.
- Another interesting finding of this study is what we observed about the types of events people like to share. They are more interested in sharing special events such

as birthdays, graduations, national days, baby special religious/cultural occasions, etc. They are also interested in sharing their journey outside their current cities (i.e. trips). On the other hand, they are not as interested in sharing casual events such as normal dinners or get-togethers.

- An additional finding of the study reveals that most users tend to use their mobile devices to share interactions on Facebook [94]. This was shown from the information of the albums where the photos are located. From this we can infer that users tend to share their moments on the fly, or most likely within a few hours to at most a few days, after the activities happened. Not to mention that users are connected to the Internet most of the time if not all of the time [94]. Hence, it is valid to treat the uploading time of photos as an approximate time of events in the absence of the original capture time of the photos (i.e. time metadata). According to this argument, we are able to infer an approximation of the time of the events shared on social media, for example the seasons when they happened.

According to our findings and results, we have proven that online social networks can act as virtual sensors or soft sensors for social users and their social lives.

Chapter 6

Conclusion and Future Work

In this thesis, we presented a novel multimedia-based storytelling framework to generate context-aware personal stories using sensory information from online social networks. A good story contains a good set of events and related information, which can be arranged in a way that tells a narrative about the events. The amount of social users and multimedia that is produced on social media has been exponentially increasing, which leads to information overload on OSNs. Due to the possibility that users' personal profiles may lack important information (e.g. events) and that their number of friends can be very large, we propose a multimedia-based relationship strength model to find the closest friends of the users and therefore obtain additional information to complement the information already available on the users' own profiles. With a complete sequence of events, we can build a reliable personal story that depicts the real-life experiences of the users. The amount of time people spend together (the time that does not have home or work commute as its purpose) has proven to be important in order to determine the quality of the ties between people. Hence, we proposed a DST (Days Spent Together) algorithm to estimate the number of days people spent together over a given period of time. The DST algorithm uses soft-sensory information along with geographical profile information from OSNs in order to detect users' real-life events. It performs its estimation of individual event duration based on the distance from the users' home and current city. With com-

plete information of individual event duration, we estimate the overall amount of time that people spent together interacting face-to-face (F2F). We then use that information as an indicator of their closest friends (top 10). We personalize the stories of the users to include only the events they experienced with their closest friends. Due to the possibility that the number of multimedia (photos in this thesis) of events can be very large, we use the duration information (i.e. inferred by DST) of the events to decide on the number of representative photos for each event. The number of received engagements (likes and comments) on photos is used to choose the representative photos for each event. The chosen photos, along with their spatial, temporal, and social context, are used to build multimedia presentations that present users' personal stories. A major limitation of the algorithm is false events. Users may tag friends in a picture just because the picture is interesting. Such pictures are detected as F2F interactions and events, resulting in an overestimation problem.

There are also other limitations in our proposed DST algorithm. It does not detect the route of outside events. If a user visits multiple countries on the same trip, DST will count them as separate events and therefore overestimate the days spent together by users. This limitation is hard to overcome using the timeline information. Users might share an activity at the same time as it is happening, or they might share it hours or even a few days later. It is also important to mention that Facebook wipes out the original metadata of photos while uploading, and that consequently we must rely heavily on the uploading time for our estimations. Similarly, the algorithm overestimates when users spend less than the average duration time, as suggested by tour packages, on their trips.

For future work, we plan to address the limitations of the work that cause the overestimation issues. Also, we plan to evaluate the degree of interestingness, completeness, and accuracy of our stories. Moreover, we plan to visualize the stories in a three-dimensional (3D) presentation. We also plan to investigate the optimal timeline quantization for the stories, in order to decide the duration of the story presentation based on the number of events. Furthermore, we plan to deploy a mobile application based on the proposed

algorithm to enable story generation on the fly.

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