A Technique for Human-readable Representation and Evaluation of Media-based Social Interactions in Social Networks

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ABSTRACT

Social networks are increasingly present on the Web, especially those supported by multimedia platforms, allowing social interaction, communication, sharing and collaboration among users. In social network analysis, some models for the representation of user's interactions have been proposed in the literature. However, those models do not explain what actions were taken by users during social interactions. In particular, this also occurs when social interactions involve media. We present a technique for a human-readable representation of social interactions in the form of *if-then* rules, and for evaluation of the rules using data mining procedures. Our technique allows the representation and the evaluation of media-based social interactions by making explicit both the actions performed by users, and the media used in the interaction. We present the results of applying our technique to describe interaction among a group of Facebook users.

Categories and Subjects Descriptors: H.5.1 [Multimedia Information Systems]: Evaluation/ Methodology.

General Terms: Human Factors, Measurement.

Keywords: Media Usage, User Behavior, Facebook.

1. INTRODUCTION

Increasingly present in daily life, social networks allow social interactions, communication, information and media sharing and collaborative activities among users. Social network analysis [28] is a recent research field that studies social entities (people, actors or users) and their interactions and relationships. Some models for the analysis of social networks and the evaluation of the interactions among users are proposed in the literature, for example, based on graph theories [25] [31], based on individual network's usage patterns [4] [17], and based on semantics [7] [19].

WebMedia'11: Proceedings of the 17th Brazilian Symposium on Multimedia and the Web. Full Papers.
October 3 -6, 2011, Florianópolis, SC, Brazil.
ISSN 2175-9642.
SBC - Brazilian Computer Society

Following the small-world principle [21] [29], existing models have been investigated to allow the representation of relationships based on interactions among users — this is usually achieved by applying data mining techniques [18]. In other words, the models target at identifying clusters representing relationships among users. In this scenario, there is an opportunity of providing a human-readable model to allow the representation and the evaluation of situations which involve users in social interactions, making explicit both the actions performed by social network users, and the media types used in the interactions.

Results from Experimental Social Psychology argue that social interactions may be specified as *behavioral contingencies* in the form of *if-then* rules, which correspond to observations of what people do, or not do, in a variety of situations [23]. As an example, upon observing a particular social interaction involving users a and b that perform actions A_1 and A_2 leading to consequence C_1, this observation may be registered as the rule $aA_1 \cap bA_2 \rightarrow abC_1$. A set of such rules, extracted from observing a particular social interaction, is used in qualitative evaluations relative to the social interaction itself. For instance, in a game setting, behavioral contingencies (*if-then* rules) may be analyzed to determine how the game is played [24].

In the Rule Learning [9] research field, *if-then* rules are general implications, in the form of $B \rightarrow H$, which can be evaluated by a variety of measures [2]. In this paper we propose the application of an established data mining procedure to evaluate *if-then* rules [22] by computing measures such as *confidence*, *support* and *cosine correlation* [18] from observations of social interactions.

The main contribution we present in this paper is a technique for human-readable representation and evaluation of media-based social interactions, proposing both the representation of media-based social interactions as behavioral contingencies (*if-then* rules), and the evaluation of the rules using data mining procedures. Our technique suggested to be useful in our previous research [11] [13] involving collaborative annotation of video and involving the identification of social situations in which Facebook users are involved the most [14].

When applying our technique in the analysis of media-based social interactions, we are able to make explicit the use of media objects within *if-then* rules. For example, in the analysis of media-based social interactions among Facebook[1] users, we were able to identify that social interactions involving only the Facebook action *Like* is the most frequent in explicit use of media objects of the type *video*, the Facebook action *Comment* is the most frequent in explicit use of media objects of the type user *status*. Also, social interactions involving Facebook actions *Comment* and *Like* are most frequent in explicit use of media type *photo*.

This paper is organized as follows. Section 2 discusses related works; Section 3 summarizes main concepts involving *behavioral contingencies*. Section 4 details our proposed technique for representing and evaluating social interactions; Section 5 reports the results of a study involving a group of Facebook users; and Section 6 presents our final remarks.

2. RELATED WORKS

Based on graph theory, Mislove et al. [25] presented a large-scale measurement and analysis of the structure of multiple online social networks. Wilson et al. [31] studied interactions among Facebook users, and propose the use of interaction graphs to impart meaning to online social links.

Analyzing the user behavior, Barkhuus and Tashiro [3] presented a study from perspective of both mobile and stationary platforms related to online and offline social practices in Facebook. The role of users as evangelists and detractors on Twitter has also been investigated [5].

Examining impressions based on Facebook profiles, Gosling et al. [16] compared those users profiles with how the targets users see themselves and they are seen by close acquaintances. Modeling the usage patterns in YouTube, Benevenuto et al. [4] studied users sessions to understand the characteristics of requests that arrive on online video servers, aiming to identify the corresponding user access patterns.

The research results outlined above have in common the use of data mining techniques in Twitter such as clustering [1], prediction [10] and classification [20], in the analysis of interactions among users. In this context, we have identified the need of a human-readable model that allows the representation and the evaluation of social interactions based on media objects involving social network users.

In previous works we studied contingencies as social interactions associated with the asynchronous sharing of video links and annotations sessions [11] and, the synchronous and asynchronous sharing of collaborative annotations [13] on YouTube videos, exploring a social approach for authoring media [8] in an application of *Watch-and-Comment* paradigm [6].

Our current research involving the analysis of social interactions on Facebook, for instance, in order to identify social situations in which users are involved the most [14]. We present our proposed technique for representation and evaluation of media-based social interactions, as detailed next.

[1]www.facebook.com

3. BEHAVIORAL CONTINGENCIES AND SOCIAL INTERACTIONS

Experimental social psychology results propose that *behavioral contingencies* model ubiquitous situations in the form of rules that specify what people do or do not do. In a social environment, ubiquitous situations correspond to actions started by one person, which may be perceived or not by other persons — as a reaction to the first person *social stimulus*. For example, if one person smiles, the other person may or not smile back [27].

In social science, everyday interactions between people, i.e., any kind of social interactions, may be specified as behavioral contingencies [27]. For example:

- Laws consist, in general, in rules such as "If a person does or does not perform certain acts, certain consequences for that person will follow". In essence, laws are behavioral contingencies intended to regulate, modify or influence behavior in a society.
- In education systems, behavioral contingencies govern the interactions among students, teachers, parents, administrators and members of the community.
- Rules of games, e.g. tic-tac-toe, are behavioral contingencies that determine how the game are played.

Mechner [23] has presented one of the first notation systems for codifying any behavioral contingency by using boolean algebra. Weingarten and Mechner [30] have extended the original work of Mechner [23] for representing social interactions as independent variables in the form of *if-then* rules. The *if* part specifies some aspects of behavior, and the *then* part specifies a resulting state of party(ies). A rule *if-then* is generally represented by R.

More recently, Mechner [24] has presented a formal symbolic language, with its own specialized vocabulary and grammar, for codifying any behavioral contingencies involving several participants. In the *Mechner Language*, behavioral contingencies are logic implications which can be evaluated as independent variables. Some important elements of this language are:

1. *Action (or actions)*: matching the antecedent of the contingency, i.e., $A \rightarrow$. If there are more than one action, they are represented as $A_1 \cap A_2 \cdots \rightarrow$.
2. *Agent(s) of action(s)*: represented by lowercase letters and placed in front of one A. For example, agent a performed action A, i.e., aA. One letter can represent a single agent or a group of agents that perform a action.
3. *Consequence*: corresponds to the consequent of the contingency, i.e., $\rightarrow C$. If there are more than one consequence, they are represented as $\cdots \rightarrow C_1 \cap C_2$.

For example, some behavioral contingencies codified in Mechner Language in the form of an *if-then* statement are:

- $aA_1 \cap bA_2 \rightarrow abC_1$. *If* a execute action A_1 and b execute action A_2 *then* the consequence C_1 is perceived by a and is perceived by b.
- $\overline{a}A_1 \cap bA_2 \rightarrow \overline{a}bC_2$. *If* a not execute action A_1 and b execute action A_2 *then* the consequence C is not perceived by a and perceived by b.
- $aA_1 \cap bA_2 \rightarrow aC_1 \cap bC_2$. *If* a execute action A_1 and b execute action A_2 *then* the consequence C_1 is perceived by a and the consequence C_2 is perceived by b.

Although other notation systems have been proposed to codify behavior in experimental analysis processes (e.g., [26]), in our work we use the Mechner Language [24] because it allows that behavioral contingencies as implications can be written in disjunctive normal form, mathematical property demanded by the data mining procedures we adopt.

4. REPRESENTING AND EVALUATING SOCIAL INTERACTIONS IN SOCIAL NETWORKS

We present our technique for representation and evaluation of social interactions in a human-readable model. The social interactions are represented as user's behavioral contingencies using the Mechner Language, and they are evaluated using data mining procedures.

4.1 Representing Behavioral Contingencies

We use Mechner Language to represent situations involving users in social interactions, and identify the elements of the Mechner Language in the social network. In other words, we have to identify *actions A*, *agents of actions* (e.g., user a, or group (of users) k and l), and *consequences C*.

Examples of actions in some social networks are: A_1 = *to make a post on one´s wall* in Facebook; A_2 = *to publish a video* in YouTube[2]; A_3 = *to publish a music file* in SoundCloud[3].

Users in a social network are *agents of actions*, and they can perform one or more actions, individually (e.g., user a or b) or in groups (e.g., group k or l), according to permissions provided by the social network. As a result, users may be notified of one or more *consequences C* of other users' actions. Moreover, based on the permission they have, users may also act as a result of another users' action. For example, user b can act Like *a post* (C_1), or can Comment *a post*(C_2) after being notified that user a act *post on his wall.* When modeling behavioral contingencies, the granularity of actions is defined by the experimenter.

After identifying *actions*, *agents of actions* (users), and *consequences*, we have to represent the situations that involve users in social interactions. For example,

- *if* a Facebook user a performs the action A_1 = *post a text message* on his wall,
  - *then* user a and users in groups k and l C_1 = *are notified of this posting*,
  - *if* users in groups k perform the action A_2 = Comment *that post* (after notified of the post of user a),
    - *then* user a and users in groups k and l C_2 = *are notified of this* Comment,
  - *if* users in group l perform the action A_3 = Like *that post* (after notified of the post of user a),
    - *then* user a and users in groups k and l C_3 = *are notified of this* Like,
- then, using the Mechner Language, we represent this social interactions as $aA_1 \rightarrow aklC_1$, $aA_1 \cap kA_2 \rightarrow aklC_1 \cap aklC_2$, and $aA_1 \cap lA_2 \rightarrow aklC_1 \cap aklC_2$.

The action that starts the social interaction, as it is the case of A_1 in the example above, is called the *social stimulus* [27].

4.2 Evaluating Behavioral Contingencies

Behavioral contingencies are generically represented as implications $Body \rightarrow Head$ (rules R), in short, $B \rightarrow H$. For example, considering $R = aA_1 \cap kA_2 \rightarrow aklC_1 \cap aklC_2$ as a behavioral contingency, $B = aA_1 \cap kA_2$ and $H = aklC_1 \cap aklC_2$.

Using data mining techniques, an implication $B \rightarrow H$ can be evaluated by comparing it with a set of observations [22]. For example, the number n of behavioral contingencies observed during a particular social experience can be computed using using classic data mining contingency values $bh, b\overline{h}, \overline{b}h, \overline{bh}$ as follows

$$n = bh + b\overline{h} + \overline{b}h + \overline{bh}$$

where

- bh number of observed situations for which body b and head h are true.
- $b\overline{h}$ number of observed situations for which the body b is true and the head h is false.
- $\overline{b}h$ number of observed situations for which the body b is false and the head h is true.
- $\overline{bh}$ number of observed situations for which body b and head h are false.

As an application of the mapping of Mechner contingencies into data mining rules, contingency values can be used to calculate measures for the *confidence*, *support* and *cosine correlation* levels of a given rule in a set of observations as follows:

- the *confidence* measure for a rule R is given by
$$ConR = \frac{bh}{bh + b\overline{h}} = \frac{bh}{b}$$
this measures the reliability of the inference made by the rule R, determining how frequently H appears in observations that contain B. This measure reflects the certainty of discovered rules.

[2]www.youtube.com
[3]www.soundcloud.com

- the *support* measure for a rule R is given by

$$SupR = \frac{bh}{n}$$

  this measure determines how the rule R is applicable to a given set of observations, determining how frequently H *and* B appears in the set of observations. This measure reflects the usefulness of discovered rules.

- the *cosine correlation* measure for a rule R is given by

$$CosR = \frac{bh}{n * \sqrt{\frac{b*h}{n^2}}}$$

  this measure determines the strength (or lack of strength) of association between B and H.

Such thresholds can be set by users or domain experts. By convention, values of these measures occur between 0% and 100% rather than 0 to 1 [18]. One rule with maximum confidence, i.e., *confidence* = 100%, it means that this one rule satisfy (identify) all observed situations in the set of observations. The support value of one rule with maximum confidence is the maximum support for this one rule. The cosine correlation value of one rule with maximum confidence is the maximum cosine correlation for this one rule. Rules that satisfy a minimum confidence threshold, minimum support threshold and minimum cosine correlation threshold are called *strong*.

5. MEASURING SOCIAL INTERACTIONS ON FACEBOOK

The objective of the experiment presented in this section is to verify the application of our proposed human-readable technique. We apply our technique for representing and measuring behavioral contingencies that involve users in media-based social interactions on Facebook. Details are as follows.

5.1 Data Collection and Preparation

We have implemented a Facebook crawler using a Python[4] script and run it three times with fifteen days difference among them. We have authorized access to more than 1,000 profiles from various countries. We have collected informations as the type of a post (photo, status, music, link, etc), about user's activities as *Comment* and/or *Like* of a post, the number of users that perform *Comment* or *Like* of a post, the number of users that perform *Comment* and even *Like* of a post, and the number of users that was mentioned (marked) in *Comments* of a post. Posts at same time with no *Comment*, no *Like* and no shared, i.e., posts that not start social interactions, were not counted.

In first round, 117,438 actions were collected and 13,050 behavioral contingencies observed (set of observed behavioral contingencies: OBC 1). In the second round, 107,988 actions were collected and 12,469 behavioral contingencies observed (OBC 2). In the third round, 113,822 actions were collected and 12,998 behavioral contingencies observed (OBC 3). These three rounds collected 339,248 actions and 38,517 behavioral contingencies (total sum of sets of observed behavioral contingencies: SOBC).

[4]www.python.org

5.2 Social Interactions and its Evaluation

A social interaction starts in Facebook when a user make a post on his wall or on a friend wall, a user provides the social stimulus to start a social interaction. So, the social stimulus can be a web link, photo, swf multimedia file, video, music, text message or other type of user status. We represent the user which provides the social stimulus as user a.

When user a and the group of his friends f are notified of this posting. The group of users k perform the action *make a* Comment *of that post* and/or users in group l perform the action *make a* Like *of that post*. When $k = l$, this group of users are represented as m. In addition, $\overline{k}$ represents the group of users that do not *make a* Comment *of that post*, $\overline{l}$ represents the group of users that do not *make a* Like *of that post*, and when $\overline{k} = \overline{l}$, this group of users are represented as $\overline{m}$. In a *Comment* of a post, users can mark name(s) of friend(s). The group of users that mark name of friend(s) is represented as $k1$.

Considering users activities, the following actions and consequences have been identified for representation of social interactions on Facebook:

- A_1 = to make a post on the wall
- A_2 = to make *Comment* about that post
- A_3 = to make a *Like* on that post
- A_4 = to mark user(s) name(s) in that *Comment*
- C_1 = to be notified of a post (social stimulus)
- C_2 = to be notified of *Comment*(s) of a post
- C_3 = to be notified of *Like*(s) of a post
- C_4 = to be notified of user(s) name(s) marked in a *Comment*

When user a performs the actions A_1, i.e., user a provides the social stimulus, user a and its friends in $\overline{a}$ can perform or not action A_2 and A_3. Only users that perform A_2 can perform the action A_4. Users a and $\overline{a}$ can perceive the consequences C_1, C_2, C_3 and C_4. The not perception of the consequences C_1, C_2, C_3 and C_4 is not represented.

Given a set of observed actions and consequences, we have represented social interactions as behavioral contingencies on Facebook as detailed in Listing 1.

R1. $aA_1 \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R2. $aA_1 \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R3. $aA_1 \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R4. $aA_1 \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R5. $aA_1 \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$

Listing 1: Behavioral Contingencies on Facebook

The rules in Listing 1 are described as:

R1 *if* user a performs action A_1 and users ak perform action A_2 and users al perform action A_3 (user a provides the social stimulus that receive *Comment*s and *Like*s) *then* user a and group of users k and l (user a and its friends) are notified of C_1 and C_2 and C_3.

R2 *if* user a performs action A_1 and users ak perform action A_2 and users al not perform action A_3 (user a provides the social stimulus that only receive *Comment*s) *then* user a and group of users k and l (user a and its friends) are notified of C_1 and C_2.

R3 *if* user a performs action A_1 and users ak not perform action A_2 and users al perform action A_3 (user a provides the social stimulus that only receive *Like*s) *then* user a and group of users k and l (user a and its friends) are notified of C_1 and C_3.

R4 *if* user a performs action A_1 and users m perform action A_2 and action A_3 (user a provides the social stimulus that receive *Comment*s and *Like* from the same users) *then* user a and group of users k and l (user a and its friends) are notified of C_1 and C_2 and C_3.

R5 *if* user a performs action A_1 and users k perform action A_2 and users $k1$ perform action A_4 (user a provides the social stimulus that receive *Comment*s and user's name(s) are marked in the *Comment*s) *then* user a and group of users k and l (user a and its friends) are notified of C_1 and C_2 and C_4.

The rules in Listing 1 were evaluated with sets of observed behavioral contingencies OBC 1, OBC 2, OBC 3 and SOBC.

Table 1: Contingencies and Measures - OBC 1

	bh	$b\bar{h}$	$\bar{b}h$	$\overline{hb}$	ConfR	SupR	CosR
R1	8450	4600	0	0	100%	64.75%	80.47%
R2	9922	3128	0	0	100%	76.03%	87.20%
R3	11578	1472	0	0	100%	88.72%	94.19%
R4	5667	7383	0	0	100%	43.43%	65.90%
R5	6950	6100	0	0	100%	53.26%	72.98%

Table 2: Contingencies and Measures - OBC 2

	bh	$b\bar{h}$	$\bar{b}h$	$\overline{hb}$	ConfR	SupR	CosR
R1	7929	4540	0	0	100%	63.59%	79.74%
R2	9335	3134	0	0	100%	74.87%	86.52%
R3	11063	1406	0	0	100%	88.72%	94.19%
R4	5284	7185	0	0	100%	42.38%	65.10%
R5	6491	5978	0	0	100%	52.06%	72.15%

Table 3: Contingencies and Measures - OBC 3

	bh	$b\bar{h}$	$\bar{b}h$	$\overline{bh}$	ConfR	SupR	CosR
R1	8378	4620	0	0	100%	64.46%	80.28%
R2	9780	3218	0	0	100%	75.24%	86.74%
R3	11596	1402	0	0	100%	89.21%	94.45%
R4	5625	7373	0	0	100%	43.28%	65.78%
R5	6192	6806	0	0	100%	47.64%	69.02%

Table 1 summarizes the contingency table and measures values, as results of the evaluation of the rules presented in Listing 1 with the set of observed behavioral contingencies OBC 1. Table 2 summarizes the results of the evaluation of the rules presented in Listing 1 with the set of observed behavioral contingencies OBC 2. Table 3 summarizes the results of the evaluation of the rules presented in Listing 1 with the set observed behavioral contingencies OBC 3.

It must be observed that confidence value is maximum for each rules in Tables 1 to 3. It means that the support value for each rules is maximum, as mencioned in Section 4.2. Rules in Tables 1, 2 and 3 can be ranked from maximum to minimum support and maximum to minimum confidence levels as $R3, R2, R1, R5$ and $R4$.

It indicates that Facebook users are more involved in social interaction where the social stimulus only receive *Like*s than in social interaction where the social stimulus only receive *Comment*s. So, users are more involved in social interaction where the social stimulus receive *Comment*s and *Like*s than in social interaction where the social stimulus receive *Comment*s and user's name(s) are marked in *Comment*s. Finally, users are involved in social interaction where social stimulus receive *Comment*s and *Like* from the same users.

Table 4: Contingencies and Measures - SOBC

	bh	$b\bar{h}$	$\bar{b}h$	$\overline{bh}$	ConfR	SupR	CosR
R1	24757	13760	0	0	100%	64.28%	80.17%
R2	29037	9480	0	0	100%	75.39%	86.83%
R3	34237	4280	0	0	100%	88.89%	94.28%
R4	16576	21941	0	0	100%	43.04%	65.60%
R5	19633	18884	0	0	100%	50.97%	71.39%

Table 4 summarizes results of the evaluation of the rules presented in Listing 1 with the set of observed behavioral contingencies SOBC. Rules in Listing 1 can be ranked from maximum to minimum support and cosine correlation levels. The ranking result is $R3, R2, R1, R5$ and $R4$.

As mentioned in Section 4, confidence, support and cosine correlation thresholds can be used to identify *strong* rules. In this work, we set the most frequent media usage within strongest rules as those ones that have confidence = 100% and, for each rule $R1$ to $R5$, cosine correlation higher than the values presented in Table 4.

Next, we present the representation and evaluation of media usage within behavioral contingencies in order to identify which types of media are used in social interactions, i.e., we analyse media-based social interactions.

5.3 Media Usage in Social Interactions

On Facebook mural, a user can make posts by using text messages, web links or other media objects. Posts type *status* must be text messages or other type of post provided by Facebook application, for example, to identify the localization of user in a city or, climatic conditions of the location where the user is. If a user post a web link directly on your mural, Facebook identify this post as type *link*. However, if the web link is shared by the user accessing the web site (for instance, accessing YouTube site, soundclond site, etc), the post can be identified as type *video* or type *music* depending on the content shared. If a user post a YouTube link directly on your mural, we have compute this post as type *youtube*.

The Figure 1 presents the count of media usage as social

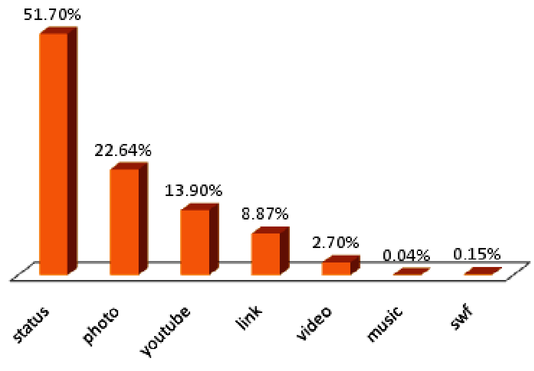

Figure 1: Media Usage as Social Stimulus - SOBC

stimulus considering junction of observed situations of sets OBC 1 + OBC 2 + OBC 3 (SOBC). It must be noticed that social interactions started by social stimulus *status* represent 51,%70 of the total of observed behavioral contingecies. *Photo* and *Youtube* video represent respectivelly 22,64% a 13,90%. Youtube video link starts more social interactions than other type of *links*. The type *link* is represent 8,87%. The types *video* represent 2,70% and types *music* and *swf* represent respectivelly 0,04% and 0,15%.

Representing the media usage within A_1 to identify the social stimulus that starts a social interaction, it was obtained a set of A_1 with media usage:

- $A_1.status$ = to make a post of the type status
- $A_1.photo$ = to make a post of the type photo
- $A_1.YouT$ = to make a post of the type YouTube link
- $A_1.link$ = to make a post of the type link
- $A_1.video$ = to make a post of the type video
- $A_1.music$ = to make a post of the type music
- $A_1.swf$ = to make a post of the type swf

Each rule in Listing 1 can be rewritten making explicit the type of media usage. Then, social interactions are represented as behavioral contingencies. In Table 5 to 9 are presented the contingency table and measures values as result of the evaluation of the rules presented in Listing 2 to 6. These values are computed considering 38,517 of observed behavioral contingencies SOBC.

R1.1. $aA_1.status \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.2. $aA_1.photo \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.3. $aA_1.YouT \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.4. $aA_1.link \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.5. $aA_1.video \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.6. $aA_1.music \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R1.7. $aA_1.swf \cap akA_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$

Listing 2: Media-based Contingencies R1

The media usage within $R1$ is made explicit in Listing 2. For instance, $R1.1$ is described as *if* user a provides a post type *status* as social stimulus that receive *Comments* from users ak and *Likes* from users al *then* user a and its friends perceive C_1 and C_2 and C_3.

Table 5: Contingencies and Measures for R1

	bh	$b\bar{h}$	$\bar{b}h$	$\bar{b}\bar{h}$	ConR	SupR	CosR
R1.1	13433	6484	0	18600	100%	34.86%	82.11%
R1.2	6318	2406	0	29793	100%	16.40%	85.12%
R1.3	2923	2426	0	33168	100%	7.59%	73.92%
R1.4	1442	1971	0	35104	100%	3.75%	64.97%
R1.5	625	416	0	37476	100%	1.62%	77.53%
R1.6	10	5	0	38502	100%	0.03%	76.98%
R1.7	6	52	0	38459	100%	0.02%	32.16%

Table 5 presents the results of evaluation of rules presented in Listing 2. In comparison with Table 4, it must be observed that $CosR(R1.1)$ and $CosR(R1.2)$ are higher then $CosR(R1) = 80.17\%$, it means that usage of posts type *status* and post type *photo* are most frequent in social interaction $R1$.

R2.1. $aA_1.status \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.2. $aA_1.photo \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.3. $aA_1.YouT \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.4. $aA_1.link \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.5. $aA_1.video \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.6. $aA_1.music \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$
R2.7. $aA_1.swf \cap akA_2 \cap \overline{al}A_3 \rightarrow aklC_1 \cap aklC_2$

Listing 3: Media-based Contingencies R2

The media usage within $R2$ is made explicit in Listing 3. For instance, $R2.1$ is described as *if* user a provides a post type *status* that only receive *Comments* from users ak *then* user a and its friends perceive C_1 and C_2.

Table 6: Contingencies and Measures for R2

	bh	$b\bar{h}$	$\bar{b}h$	$\bar{b}\bar{h}$	ConR	SupR	CosR
R2.1	16163	3754	0	18600	100%	41.95%	90.08%
R2.2	6822	1902	0	29793	100%	17.71%	88.45%
R2.3	3375	1974	0	33168	100%	8.77%	79.42%
R2.4	1957	1456	0	35104	100%	5.09%	75.70%
R2.5	703	338	0	37476	100%	1.82%	82.21%
R2.6	11	4	0	38502	100%	0.03%	84.95%
R2.7	6	52	0	38459	100%	0.02%	61.29%

Table 6 presents the results of the evaluation of the rules presented in Listing 3. In comparison with Table 4, it must be observed that $CosR(R2.1)$ and $CosR(R2.2)$ are higher then $CosR(R2) = 86.83\%$, it means that usage of posts type *status* and post type *photo* are most frequent in social interaction $R2$.

R3.1. $aA_1.status \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R3.2. $aA_1.photo \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R3.3. $aA_1.YouT \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R3.4. $aA_1.link \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R3.5. $aA_1.video \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$
R3.6. $aA_1.music \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$

R3.7. $aA_1.swf \cap \overline{ak}A_2 \cap alA_3 \rightarrow aklC_1 \cap aklC_3$

Listing 4: Media-based Contingencies R3

The media usage within $R3$ is made explicit in Listing 4. For instance, $R3.1$ is described as *if* user a provides a post type status as social stimulus that only receive *Like*s from users *al then* user a and its friends perceive C_1 and C_3.

Table 7: Contingencies and Measures for R3

	bh	$b\bar{h}$	$\bar{b}h$	$\bar{b}\bar{h}$	ConR	SupR	CosR
R3.1	17187	2730	0	18600	100%	44.61%	92.89%
R3.2	8220	504	0	29793	100%	21.33%	97.06%
R3.3	4897	452	0	33168	100%	12.72%	95.69%
R3.4	2898	515	0	35104	100%	7.53%	92.14%
R3.5	963	78	0	37476	100%	2.50%	96.19%
R3.6	14	1	0	38502	100%	0.04%	93.88%
R3.7	58	0	0	38459	100%	0.15%	100%

Table 7 presents the results of the evaluation of the rules presented in Listing 4. In comparison with Table 4, it must be observed that $CosR(R3.2)$ and $CosR(R3.3)$ and $CosR(R3.5)$ and $CosR$ $(R3.7)$ are higher then $CosR(R3) = 94.28\%$, it means that usage of posts type *photo*, *youtube*, *video* and *swf* are most frequent than *status*, *link* and *music* usage in social interaction $R3$.

R4.1. $aA_1.status \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.2. $aA_1.photo \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.3. $aA_1.YouT \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.4. $aA_1.link \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.5. $aA_1.video \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.6. $aA_1.music \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.7. $aA_1.swf \cap amA_2 \cap amA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$

Listing 5: Media-based Contingencies R4

The media usage within $R5$ is made explicit in Listing 5. For instance, $R5.1$ is described as *if* user a provides a post type *status* as social stimulus that receive *Comment*s and *Like* from the same users *am then* user a and its friends perceive C_1 and C_2 and C_3.

Table 8: Contingencies and Measures for R4

	bh	$b\bar{h}$	$\bar{b}h$	$\bar{b}\bar{h}$	ConR	SupR	CosR
R4.1	6162	13755	0	18600	100%	16.10%	52.20%
R4.2	3376	5348	0	29793	100%	8.82%	58.57%
R4.3	1265	4084	0	33168	100%	3.31%	45.93%
R4.4	571	2842	0	35104	100%	1.49%	38.39%
R4.5	312	729	0	37476	100%	0.81%	52.04%
R4.6	4	11	0	38502	100%	0.01%	54.60%
R4.7	2	56	0	38459	100%	0.01%	18.57%

Table 8 presents the results of the evaluation of the rules presented in Listing 5. In comparison with Table 4, it must be observed that none $CosR$ in Table 8 is higher then $CosR(R4) = 65.60\%$, it means that none usage of posts are most frequent in social interaction $R4$.

R5.1. $aA_1.status \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.2. $aA_1.photo \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.3. $aA_1.YouT \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.4. $aA_1.link \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.5. $aA_1.video \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.6. $aA_1.music \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$
R5.7. $aA_1.swf \cap akA_2 \cap ak1A_4 \rightarrow aklC_1 \cap aklC_2 \cap aklC_4$

Listing 6: Media-based Contingencies R5

The media usage within $R6$ is made explicit in Listing 6. For instance, $R6.1$ is described as *if* user a provides a post type *status* as social stimulus that receive *Comment*s and user's name(s) are marked in a *Comment then* user a and its friends perceive C_1 and C_2 and C_4.

Table 9: Contingencies and Measures for R5

	bh	$b\bar{h}$	$\bar{b}h$	$\bar{b}\bar{h}$	ConR	SupR	CosR
R5.1	10986	8931	0	18600	100%	28.52%	74.26%
R5.2	4940	3784	0	29793	100%	12.83%	75.29%
R5.3	2111	3238	0	33168	100%	5.49%	62.73%
R5.4	1129	2284	0	35104	100%	2.94%	57.41%
R5.5	458	583	0	37476	100%	1.19%	66.38%
R5.6	5	10	0	38502	100%	0.01%	56.33%
R5.7	4	54	0	38459	100%	0.01%	35.47%

Table 9 presents the results of the evaluation of the rules presented in Listing 6. In comparison with Table 4, it must be observed that $CosR(R5.1)$ and $CosR(R5.2)$ are higher then $CosR(R5) = 71.39\%$, it means that usage of posts type *status* and post type *photo* are most frequent than the others media usage in social interaction $R5$.

5.4 Summary of Results

We are able to represent media usage within social interactions as rules. Using rule evaluation measures we are able to rank these rules. The frequency of occurrence of social interactions started by explicit use of media objects type *status* and type *photo*, which involve Facebook users actions *Comment*s and *Like*s or only action *Comment*, are most frequent social interaction. The frequency of occurrence of social interactions started by explicit use of media objects type *photo*, *youtube*, *video* and *swf*, which only involve users action *Like*, are most frequent than social interactions started by explicit use of media object type *status*, *link* and *music*.

Also, the frequency of occurrence of social interactions started by explicit use of media objects type *status* and *photo*, which involve action *Comment* and action *user's name(s) are marked in a* Comment, are most frequent than social interactions started by other types of medias. Social interactions started by explicit use of media objects *photo* which involve actions *Comment* and *Like* are most frequent than other media-based social interactions.

6. FINAL REMARKS

In previous work, our goal was to identify and document, through a human-readable notation, recurring situations in social interactions between users involved in collaborative activities for video annotation [11]. After preliminary studies to document the interaction between Facebook users resulting from the use of *Like* and *Comment* [14], this study investigated how to identify and document the social interaction between users when this is based on shared media.

We present a technique for codifying media-based social interactions as behavioral contingencies by using Mechner language, and for its evaluation by using data mining procedures for computation of *confidence*, *support* and *cosine correlation* measures. Our technique allows the representation and the evaluation of social interactions, making explicit not only the actions performed by users, but also the use of media objects.

We studied the social interactions involving a group of over 1,000 users. With respect to this group of users, we were able to identify that interactions involving the Facebook action *Like* is the most frequently associated with media objects of the type *video*. Moreover, the Facebook action *Comment* is the most frequently associated with objects of the type user *status*. Finally, we observed that social interactions involving Facebook actions *Comment* and *Like* are most frequently associated with media objects of the type *photo*.

We currently investigating social interactions carried out by means of smartphones[12], as well as those interactions involving several media servers (including YouTube and Soundclound) [15]. In future works, we plan to define a procedure to be used in the analysis of social interactions using the technique we have been developing.

Acknowledgments: We thank CAPES, CNPq, FAPESP (TIDIA-AE and Webmedia support), MCT and FINEP. We also thank Diogo C. Pedrosa.

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