Evaluation of Media-Based Social Interactions: Linking Collective Actions to Media Types, Applications, and Devices in Social Networks

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Abstract There is a growing number of opportunities for users to perform collective actions in social networks: Such collective actions engage users in correspondents social interactions. Although some models for representing users and their relationships in social networks have been proposed, to the best of our knowledge, these models do not explain what the underlying social interactions are. In previous work, we have proposed a human-readable technique for modeling and measuring social interactions, which resulted from users' actions that involved, for instance, media types, interaction devices, and viral content. In our technique, social interactions are represented as behavioral contingencies in the form of *if-then* rules, which are then measured using an established data mining procedure. After being able to represent and measure a variety of social interactions, we identified the opportunity of transforming our technique into a method for capturing, representing, and measuring collective actions in social networks. In this chapter, we present our method and detail how it was applied to represent and measure social interactions among a group of 1,600 Facebook users over the period of 7 months. Our results report the link among actions (e.g., *like*), media objects (e.g., photo), application type (Web or mobile), and device type (e.g., Android).

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1 Introduction

Social networks allow the engagement, communication, sharing, realization of collaborative activities, and social interactions among users. Many alternatives for accessing social networks through Web, tablet, and smartphone applications allow users to experience new types of social interaction (Bentley and Metcalf 2009) (Cowan et al. 2011).

Social interactions have been defined as the acts, actions, or practices of two or more people mutually oriented toward each other (Rummel 1976). Results from behavioral sciences 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 do not do, in a variety of situations (Mechner 1959). Results from sociology suggest that the *relationships* among individuals may be modeled as graphs (Granovetter 1973; Holland and Leinhardt 1970), and in social networks, the user *interaction* has been represented as a directed graph called *interaction graph* (Wilson et al. 2009).

A social network may be defined as a set of social entities (actor, points, nodes, or agents) that may have relationships (edges or ties) with one another. In the social network analysis research field, social networks are modeled as graphs (or sociograms) (Freeman 2004; Scott 2000; Wasserman and Faust 1994). As in social environments, users are social entities, and their relationships may be bidirected (i.e., friend) or directed (i.e., following).

In social network analysis, models for the evaluation of user interaction are usually based on graph theory (Mislove et al. 2007; Tan et al. 2011) and, according to the small-world principle (Kleinberg 2000; Watts 1999), are investigated using data mining techniques such as clustering (Abrol and Khan 2010; Negoescu et al. 2009), classification (Bonchi et al. 2011; Ekenel and Semela 2011), and prediction (Jin et al. 2010; Shi et al. 2011).

Considering the importance of understanding the underlying social interactions in social media environments, in previous work we have proposed a human-readable *if-then* rule–based technique for the representation and evaluation of social interactions in social networks (Gomes and Pimentel 2011d). Our technique combines the representation of social interactions as *if-then* rules in a behavioral contingency language with the evaluation of behavioral contingencies by means of data mining procedures.

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 interaction 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 game-setting behavioral contingencies, *if-then* rules may be analyzed to determine how the game is played (Mechner 2008).

We have applied our technique to study many social interactions among Facebook users (Gomes and Pimentel 2011a, c, 2012a, b) as well as to study collaborative scenarios (Gomes et al. 2011; Gomes and Pimentel 2011b) supported by a social approach for the *Watch-and-comment* paradigm (Fagá et al. 2010). This chapter contributes to the proposed research topic by presenting a method for capturing, representing, and measuring collective actions in social networks. In regard to validating the method, we detail how it was applied to represent and measure the social interaction among a group of 1,600 Facebook users over a period of 7 months. Our results report the use of actions (e.g., *like*), media objects (e.g., *photo* or *link*), application type (e.g., Web or mobile), and device type (e.g., Android).

The chapter is organized as follows: Sect. 2 discusses related work; Sect. 3 revisits our human-readable technique for representing and measuring social interactions; Sect. 4 details the new proposed method; Sect. 5 reports the results of a study involving a group of Facebook users; and Sect. 6 presents our final remarks.

2 Related Work

Related work investigates the computation of behavioral sciences, the evaluation of sociability in social media systems, and the modeling of interaction among users in Twitter and Facebook.

The computation of behavioral sciences is an emergent research field, which permits processing several nonverbal behavioral cues including facial expressions, body postures and gestures, and vocal outbursts such as laughter. Boulard et al. (2009) propose a set of recommendations for enabling the development of the next generation of socially aware computation. A range of simple techniques to access personal information relevant to social research matters on the Web are presented by Wilkinson and Thelwall (2011). However, the researchers do not build a model for representation and evaluation of social interactions among users.

Sociability-related issues play an important role in the design of social media applications in the scenario of mobile digital TV, as demonstrated by Geerts (2010) and Chorianopoulos (2010). In the context of evaluation of social TV applications, Geerts and Grooff (2009) heuristics and guidelines—established to support the assessment of social skills in computer systems—aimed at social TV and social video. Such evaluations do not consider the underlying social interactions when computing quantitative measures.

Based on a combination of a user's position, polarity of opinion, and textual quality of *tweets*, Bigonha et al. (2010) propose a technique for ranking users as evangelists and detractors. They made a topological analysis of the network by using typical measures and by analyzing *retweets* and *replies*. By using Twitter as a test bed, Choudhury et al. (2011) propose an iterative clustering technique for selecting a set of items on a given topic that matches a specified level of diversity. They also observed that content was perceived to be more relevant when it was either highly homogeneous or highly heterogeneous.

Both the above-mentioned research papers make use of textual analysis of the messages shared among Twitter users. In contrast with the work presented in this paper, research carried out here does not represent users' activities (*tweet*s, *retweet*s, and *replies*) as actions, and it does not consider any type of media that can be shared in the messages apart from text. Furthermore, the models employed in the presentation and in the analysis of results do not focus on a human-readable interpretation.

The interaction among Facebook users has been studied by Wilson et al. (2009), and results have shown that a social network user interaction graph is a subset of a social graph. Using data from Facebook, Backstrom et al. (2011) found that the balance of attention is a relatively stable property of an individual over time and that there is an interesting variation across both different groups of people and different modes of interaction.

These research papers have used Facebook data and analyzed users' activities, but they do not analyze user behavior, action, and media. Just as the research that uses Twitter data, the models employed in the presentation and in the analysis of results do not explicit how user engagement in social interactions takes place.

In the next section, we revisit our proposed human-readable technique for representing and evaluating media-based social interactions.

3 A Human-Readable Technique for Representing and Evaluating Social Interactions

Our technique for representing and evaluating social interactions uses the Mechner language for representing social interactions as *if-then* rules and data mining procedures to evaluate the rules.

3.1 Social Interactions in the Mechner Language

In behavioral science, any kind of social interactions can be specified as a conditional relationship in the form of *if-then* statements, e.g., *behavioral contingencies* (Skinner 1953). For example,

- A given law may be written as a rule such as "If a person does or does not perform a certain act, certain consequences for that person will follow." In essence, laws are behavioral contingencies intended to regulate, modify, or influence behavior.
- Game rules, e.g., tic-tac-toe, are behavioral contingencies that determine how the game is played.

Mechner (1959) presented one of the first notation systems for codifying any behavioral contingency which combined Boolean algebra with a set of diagrams. Weingarten and Mechner (1966) detailed Mechner's original work by representing social interactions as independent variables in the form of *if-then* rules. More recently, Mechner (2008) presented a formal symbolic language for codifying any behavioral contingencies which involved several participants. In the *Mechner language*, behavioral contingencies are logic implications that 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 is 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 placed in front of an 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 an action.
3. *Consequence*: corresponds to the consequence of the contingency, i.e., $\rightarrow C$. If there is more than one consequence, they are represented as $\cdots \rightarrow C_1 \cap C_2$.

For example, behavioral contingencies codified in the form of an *if-then* statement using the Mechner language is:

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

The action that starts the social interaction, which is the case of A_1 in the above example, is called *social stimulus* (Skinner 1953). Although other notation systems have been proposed to codify behaviors in experimental analysis processes (e.g., Mattaini 1995), in our work we use the Mechner language (Mechner 2008) for representing behavioral contingencies as Boolean expressions in disjunctive normal form, i.e., implications within $-$, $\cap$(*not*, *and*) connectives. This mathematical property is necessary for the data mining procedure we have adopted, which we describe next.

3.2 Behavioral Contingencies Representation

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

Each social network has a specific set of *actions* A, *agents of actions*, and *consequences* C. Figure 1 presents some actions that can be performed in social networks. As examples of *social stimuli*, we have on Facebook: A_1 = post on one's Wall; on Twitter: A_1 = Tweet (post a text message with maximum 140 characters); on Google+: A_1 = post news.

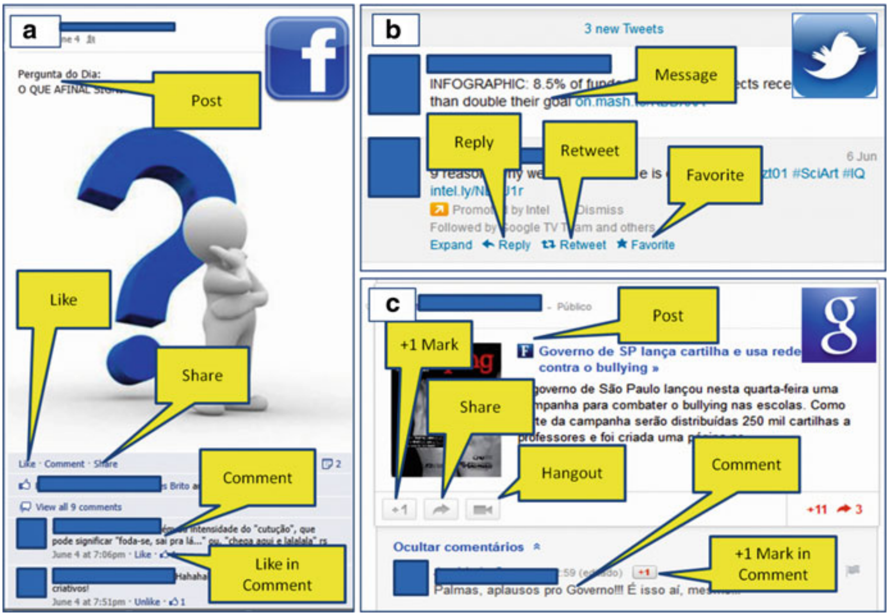


Fig. 1 Actions in social networks: (**a**) Facebook; (**b**) Twitter; and (**c**) Google+

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, depending on the permission they have, users may also act as results of other users' actions. For example, user *b* can *like a post* (C_1) or can *comment a post* (C_2) after being notified that user *a posted on his wall*.

After identifying *actions*, *agents of actions* (users), and *consequences*, we represent social interactions. For example,

- *if* a Facebook user *a* performs the action $A_1 =$ *post a message* on his Wall,
  - *then* user *a* and user *b* $C_1 =$ *are notified of this post*,
  - *then if* user *b* the action $A_2 =$ *like that post* (after being notified of the posting),
  - *then* user *a* and user *b* $C_2 =$ *are notified of this like*,

Using the Mechner language, we represent this social interaction as $aA_1 \rightarrow abC_1 \rightarrow bA_2 \rightarrow abC_2$, e.g., $aA_1 \cap bA_2 \rightarrow abC_1 \cap abC_2$.

When modeling behavioral contingencies, the identification of a user or a group of users and the granularity of actions and consequences are defined by the analyst with support from specialists to identify social interactions.

3.3 Behavioral Contingency Measurement

In our work, behavioral contingencies codified in the Mechner language as *if-then* statements are represented in the form $Body \rightarrow Head$ (in short, $B \rightarrow H$). For example, considering $B = aA_1 \cap bA_2$ and $H = abC_1 \cap abC_2$, an *if-then* behavioral contingency is represented as $R = aA_1 \cap bA_2 \rightarrow abC_1 \cap abC_2$.

In the Rule Learning (Fürnkranz et al. 2011) research field, *if-then* rules are general implications in the form of $B \rightarrow H$, which can be evaluated by a variety of measures (Azevedo and Jorge 2007; Lavrac et al. 1999) such as *confidence*, *support*, and *cosine correlation* (Han and Kamber 2005; Martínez-Ballesteros and Riquelme 2011). These measures can be used in quantitative evaluations.

Using a data mining procedure, the value of a rule $B \rightarrow H$ can be measured by comparing it with a set of observations (Lavrac et al. 1999). For example, the number n of behavioral contingencies observed during a particular social experience can be computed 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 is the number of observed situations for which head b and body h are true

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

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

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

As an application of the mapping of Mechner contingencies into data mining rules, contingency values can be used to calculate measures of a given rule in a set of observations. Table 1 details how the contingency values bh, $b\overline{h}$, $\overline{b}h$, and $\overline{bh}$ are used in the computation of four classic rule evaluation measures (Martínez-Ballesteros and Riquelme 2011):

- The *Support* measure for a rule R determines the applicability of such a rule to a given set of observations, which in turn determines how frequently *H and B* will appear in the set of observations. This measure reflects the usefulness of the discovered rules.
- The *Confidence* measure for a rule R computes the reliability of the inference made by rule R, thus determining how frequently H appears in observations that contain B. This measure reflects the certainty of the discovered rules.
- The *Cosine correlation* measure for a rule R determines the strength (or weakness) of the association between *B and H*.
- The *Leverage* measure for a rule R computes the proportion of additional cases covered by both B and H and those cases in which expected B and H were independent of one another.

Table 1 Rule evaluation measures

Support	Confidence	Cosine correlation	Leverage
$\frac{bh}{n}$	$\frac{bh}{b}$	$\frac{bh}{n * \sqrt{\frac{b*h}{n^2}}}$	$\frac{bh}{n} - \left(\frac{h}{n} * \frac{b}{n}\right)$

Measures for rule evaluation can be *symmetric* or *asymmetric* (Tan et al. 2005). The measures Support (SupR), Cosine Correlation (CosR), and Leverage (LevR) are *symmetric* measures because their values are identical for rules $B \rightarrow H$ and $H \rightarrow B$. In contrast, Confidence (ConR) is asymmetric because its values may not be the same for rules $B \rightarrow H$ and $H \rightarrow B$. Symmetric measures are generally used for evaluating B and H as independent values, while asymmetric measures are more suitable for analyzing rules, i.e., rules involving B and H. Conventionally, these measures are represented as 0–100 % values rather than 0–1 (Han and Kamber 2005).

3.4 Experiences from Applying our Technique

We first studied contingencies as social interactions associated with the asynchronous sharing of video links and annotation sessions (Gomes et al. 2011) and the synchronous and asynchronous sharing of collaborative annotations (Gomes and Pimentel 2011b) on YouTube videos.

We then applied the approach to analyze social interactions on Facebook in order to identify the social situations in which users are most involved (Gomes and Pimentel 2011c). In the context of our research, we identified the need for a tool which allowed both the description and the evaluation of behavioral contingencies, which then led us to propose a human-readable *if-then* rule–based technique for the representation and evaluation of social interactions in social networks (Gomes and Pimentel 2011d). As result, the technique guides a researcher on how to combine the Mechner language and rule-based data mining procedures in order to carry out the description and the evaluation of social interactions.

The technique was applied to study social interactions where users provide media objects via smartphones (Gomes and Pimentel 2011a) as well as interactions in which users make use of media servers to provide media objects (including YouTube and Soundcloud) (Gomes and Pimentel 2011e).

Building upon a recurring sequence of the steps employed in the application of the technique, we detailed an interactive and iterative procedure to apply such a technique and used it to identify viral content shared on Facebook (Gomes and Pimentel 2012b). Through such the procedure, it was also possible to identify, among the everyday social interactions in a particular country, those where Facebook users were engaged in social manifestations against corruption (Gomes and Pimentel 2012a).

After applying the procedure, we observed the need to further specify the executed steps, which will be discussed next.

4 A Method for Representing and Measuring Social Interactions

As summarized in the previous section, the technique we have been developing has been successful in allowing the identification of a variety of details involved in interactions among users of social networks. In order to provide a more detailed guidance on how the procedure can be replicated, in this section we propose a method which structures both the steps involved in the analysis and the inputs and outputs in each step.

This method aims at detailing actions, media objects, and application and device types within rules. The method comprises six phases: Capturing, Representation, Measurement, Interpretation, and Specialization. From one phase to the other, output generated is used as input for the following phase: a list of attributes of interest, raw data set, projected data sets, sets of rules, rule measures, and new specified attributes. Given the exploratory character of the investigation, the method is iterative. Next, we will detail each of the phases. Figure 2 presents an overview of the method.

4.1 Capturing

Data capturing happens automatically, for example, when using APIs (Gomes and Pimentel 2011a, c, 2012b) or when analyzing logs generated from the use of social media systems (Gomes et al. 2011; Gomes and Pimentel 2011b). The identification, selection, and preparation of the data to be captured are typical activities of this stage and take into account observations on the social interaction. Users' personal information must be collected (name, address, sex, preferences, etc.). Other necessary information includes the content of a post, the server which provides the media object within a post, the international standard language, the URL, the source, the caption, the description, the timestamps, the location available for each post, etc.

- *Input*: social media environment; a list of attributes of interest: actions, consequences, media types, user identification, language, URL, caption, description, timestamps, location, etc., captured via API or log analysis
- *Output*: raw data, description of social interactions

4.2 Preparation

All collected data can be cleaned, selected, and/or transformed in order to be used in the subsequent phases of representation and measurement of social interactions. In this phase, the identification of the elements of the Mechner language (actions,

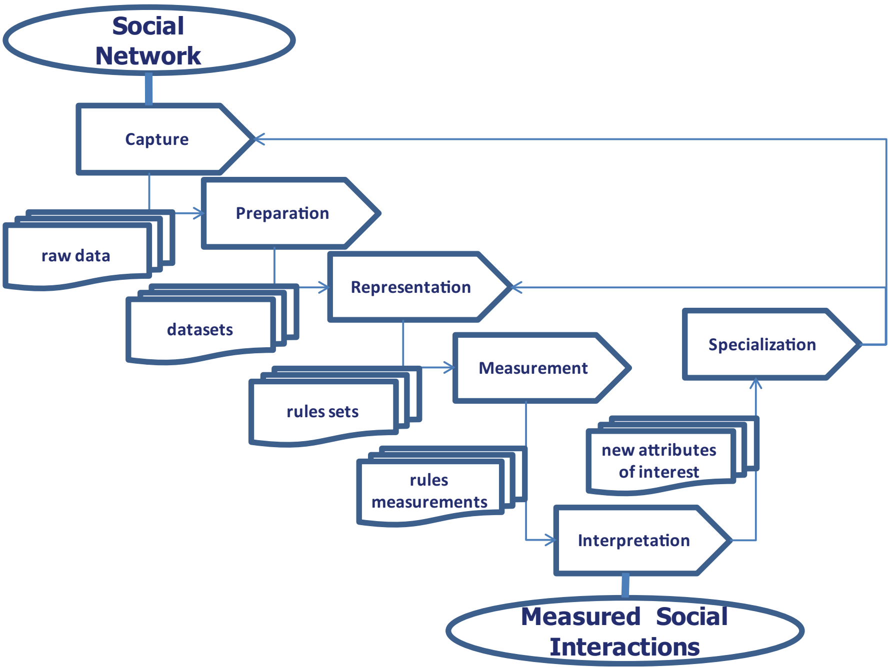


Fig. 2 An overview of our six-phase method: from social networks to measured social interactions

users, and consequences) is needed (Gomes and Pimentel 2011b, 2012b). For example, specified attributes can be the media type posted in a message, users' actions performed around the media object posted, or the notification of each posting or action performed.

- *Input*: raw data, description of social interactions
- *Output*: projected data set with actions, action agent, and consequences

4.3 Representation

Social interactions are represented as behavioral contingencies, in the form of *if-then* rules, in scenarios which involve Facebook users in social interactions (Gomes and Pimentel 2011c, d) provided via smartphone applications (Gomes and Pimentel 2011a), and in social interactions which spread viral content (Gomes and Pimentel 2012b) and social manifestations against corruption in Brazil (Gomes and Pimentel 2012a). The manual acquisition of behavioral contingencies can be made from observing social situations in the social media system, and their representation is made with support from specialists in social interactions after identifying the elements of the Mechner language.

- *Input*: projected data set with actions, action agents, and consequences
- *Output*: sets of rules

4.4 Measurement

Each social interaction described as an *if-then* rule is represented in the general form $B \to H$ for computing bh, $b\overline{h}$, $\overline{b}h$, and $\overline{bh}$ values. After that, each rule is measured by using computing rule evaluation measures. The measures *Support*, *Confidence*, and *Cosine Correlation* are used to measure media-based social interactions (Gomes and Pimentel 2011a, c, d, 2012a) and *Sensitivity* and *Laplace* to measure social interactions which spread viral content (Gomes and Pimentel 2012b) on Facebook.

- *Input*: sets of rules
- *Output*: rule measurements

4.5 Interpretation

The measurements must be interpreted by analyst or specialist users who are interested in analyzing social interactions. If the results are sufficient, the process is completed at this stage. Otherwise, the rule specialization can be carried out, and the process can be repeated from the phases Representation or Preparation. For example, underlying social interactions can be specialized in media-based social interactions by (1) detailing media types within social interactions (Gomes and Pimentel 2011c, d), (2) detailing smartphone user applications (Gomes and Pimentel 2011a), (3) server content providers (Gomes and Pimentel 2012b) and specific bags of words to feature social movements (Gomes and Pimentel 2012a) within media-based social interactions.

- *Input*: rule measures
- *Output*: social interaction measurements (completed process) or a new list of attributes of interest

4.6 Specialization

Rule specialization is achieved by detailing other elements of interest for the analyst (for example, web and mobile applications) within rules. If such elements were collected attributes, new rules are generated in the Representation phase. The preparation phase for capturing new data is repeated.

- *Input*: new list of attributes of interest
- *Output*: setup for representing rules with new attributes in the Representation phase or setup for capturing new data in the Capturing phase

Next, we detail how the method has been used to study interactions that involve a group of Facebook users.

5 Representing and Measuring Social Interactions on Facebook

The objective of the experiment presented in this section is to verify the applicability of our method. We represent and measure behavioral contingencies that involve Facebook users in social interactions. Such rules are specialized with media types, and next media-based social interactions are specialized with web applications and devices.

In this paper, we use a data set collected between May 2011 and August 2011 and compare the results with new results obtained from a data set collected between September 2011 and November 2011. Some information about each collected data set is summarized in Table 2. The comparison of the results shows that our method remains consistent over time and generalizes the application of our technique for capturing, representing, and measuring collective actions around media types in social media environments.

5.1 Data Capturing and Preparation

We implemented a Facebook crawler using a Python[1] script, and we ran it between May 2011 and November 2011. We extracted data from more than 1,400 profiles[2] whose owners gave us authorized[3] access.

We collected data about post type (checkin, photo, status, video, link, swf, music, etc.), about user activity (e.g., the addition of *comments* **or** *likes* to a post, the number of users that add both *comments* **and** *likes* to a post, the web application and the mobile device which provides the media object used in social interactions).

[1] www.python.org

[2] Most users (954) are from Brazil. Other users come from a variety of countries, such as USA, Canada, Mexico, Argentina, Uruguay, Colombia, England, Portugal, Spain, France, Italy, Belgium, Holland, Russia, Czech Republic, Kosovo, Israel, Turkey, Australia, New Zealand, among others.

[3] We have built a separate Facebook network in which each of the users have both accepted friendship and explicitly authorized the use of information associated with their social interactions.

Table 2 Summarization of information about datasets collected

Dataset	Time of collection	# of users	# of contingencies
OBC 1	May/2011 and August/2011	1,398	102,688
OBC 2	September/2011 and November/2011	1,423	212,138

5.2 Representing and Measuring Social Interactions

In Facebook, a social interaction starts when a user posts on his or on a friend's wall, i.e., a user provides a social stimulus for the social interaction to start. We represent the user who provides the social stimulus as user a.

When user a and the group of his friends f are notified of this post, the group of users k performs the action comment *on that post* and/or users m perform the action like *in a* comment *on that post* and/or users in group l perform the action like *that post*.

In addition, $\bar{k}$ represents the group of users that does not comment *on that post*, $\bar{l}$ represents the group of users that does not like *that post*.

Through observing users' activities on Facebook, the following actions and consequences have been identified for representing social interactions:

- A_1 = post on the wall
- A_2 = *comment* on that post
- A_3 = *like* that post
- A_4 = *like* in a *comment* on that post
- C_1 = be notified of a post (social stimulus)
- C_2 = be notified of *comment*(s) on a post
- C_3 = be notified of *like*(s) for a post
- C_4 = be notified of *like*(s) in a *comment* on a post

Given the set of actions = $\{A_1, A_2, A_3, A_4\}$, users = $\{a, k, l, m\}$ and consequences = $\{C_1, C_2, C_3, C_4\}$ extracted from observing social interactions on Facebook, we have represented these social interactions as behavioral contingencies in Listing 1:

Listing 1

Behavioral Contingencies on Facebook

R1. $aA_1 \cap \bar{k}A_2 \cap \bar{l}A_3 \rightarrow aklC_1$
R2. $aA_1 \cap kA_2 \cap \bar{l}A_3 \rightarrow aklC_1 \cap aklC_2$
R3. $aA_1 \cap \bar{k}A_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_3$
R4. $aA_1 \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R5. $aA_1 \cap kA_2 \cap \bar{l}A_3 \cap mA_4 \rightarrow aklmC_1 \cap aklmC_2 \cap aklmC_4$
R6. $aA_1 \cap kA_2 \cap lA_3 \cap mA_4 \rightarrow aklmC_1 \cap aklmC_2 \cap aklmC_3 \cap aklmC_4$

The implications of Listing 1 are described in the form of *if-then* rules:

R1 *if* user a performs action A_1, users in group k do not perform action A_2, and users in group l do not perform action A_3, *then* user a and users in groups k and l (only) receive consequence C_1 (i.e., user a provides a social stimulus which does not receive any *comment*s or *like*s).

R2 *if* user a performs action A_1, users in group k perform action A_2, and users in group l do not perform action A_3, *then* user a and users in groups k and l receive consequences C_1 and C_2 (i.e., user a provides a social stimulus that only receives *comment*s).

R3 *if* user a performs action A_1, users in group k do not perform action A_2, and users in group l perform action A_3, *then* user a and users in groups k and l receive consequences C_1 and C_3 (i.e., user a provides a social stimulus that only receives *like*s).

R4 *if* user a performs action A_1, users in group k perform action A_2, and users in group l perform action A_3, *then* user a and users in groups k and l receive consequences C_1 and C_2 and C_3 (i.e., user a provides a social stimulus that receives both *comment*s and *like*s).

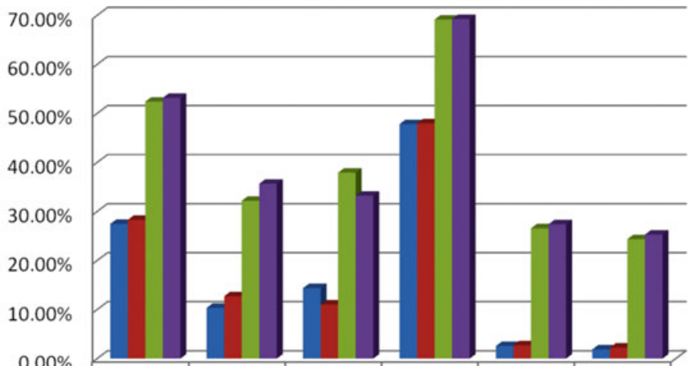
R5 *if* user a performs action A_1, users in group k perform action A_2, users in group l do not perform action A_3 and users m perform action A_4, *then* user a and his friends (users l, k and m) receive consequences C_1, C_2 and C_4.

R6 *if* user a performs action A_1, users in group k perform action A_2, users in group l do not perform action A_3 and users m perform action A_4, *then* user a and his friends (users l, k and m) receive consequences C_1, C_2, C_3 and C_4.

Figure 3 presents a comparison between the measures of support and cosine correlation for the evaluation using the data sets OBC 1 and OBC 2. The value of *ConR* is 100 % and the *LevR* are 0 %. It must be observed that for each social interaction, if the support (frequency of occurrence) increases, the cosine correlation increases, and if the support decreases, the cosine correlation decreases too. In other words, the increases (or decreases) of frequency of occurrence and the strength (or lack of strength) of association between *B and H* are directly related.

After ranking the rules from maximum to minimum support and cosine correlation levels, we have the rank $R4$, $R1$, $R3$, $R2$, $R5$, and $R6$. This indicates that Facebook users are more engaged in social interactions where the social stimuli receive *comment*s *and like*s. So users are engaged in social interactions where social stimuli do not receive *comment*s and do not receive *like*s. Next, users are engaged in social interactions where the social stimuli only receive *like*s. Finally, users are engaged in social interactions where the social stimuli only receive *comment*s.

Next, we specialize the social interactions $R4$ (the social interaction which engage Facebook users the most) linking actions performed by users to media types (content of post).



	R1	R2	R3	R4	R5	R6
SupR - OBC 1	27.46%	10.35%	14.38%	47.81%	2.56%	1.88%
SupR - OBC 2	28.29%	12.72%	11.03%	47.97%	2.73%	2.25%
CosR - OBC 1	52.40%	32.18%	37.92%	69.14%	26.56%	24.36%
CosR - OBC 2	53.18%	35.66%	33.21%	69.26%	27.39%	25.29%

Fig. 3 Support and cosine correlation of social interactions

5.3 Media Types Within Social Interactions

On the Facebook mural, users can post media by using text messages, web links, and other media objects. The type of post is automatically identified. The *link* type is used to identify Web links posted on the Facebook Wall via copy/paste—even if it is a Web link for a video, music, photo, etc., from a nonidentified server. The *status* type is used to identify text messages done by the user. The *video* type is used to identify videos shared by users either directly posted on their Facebook Wall, or shared from a Web content provider using an explicit link to Facebook.

The *photo* type is used to identify photos posted by users. The *swf* type identifies applications (generally, animations) in Flash format. The *music* type is used to identify music files posted from a Web content provider. The *checkin* type is the newest type of media (from 1 September 2011) which allows users to confirm their presence in physical locations.

Listing 2

Social Interaction R4 specialized in $aA_1.media$

R4.1. $aA_1.link \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.2. $aA_1.status \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.3. $aA_1.video \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.4. $aA_1.photo \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.5. $aA_1.swf \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.6. $aA_1.music \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.7. $aA_1.checkin \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$

Through the representation of media types categorized for Facebook, a set of A_1 specialized with the media types was obtained to identify the social stimulus that starts a social interaction.

The media usage within $R4$ is detailed in Listing 2. For example, rule $R4.1$ is described as *if* user *a* provides a post type *link* as a social stimulus that receives *comment*s from users *k* and *like*s from users *l*, *then* user *a* and its friends perceive C_1, C_2, and C_3.

It must be noted that social interactions started by social stimuli *status* and *photo* are frequently shared types of media, whereas *swf* and *music* are less frequently shared types of media.

Table 3 presents the results of the evaluation of the rules presented in Listing 2 with data sets OBC 1 and OBC 2. It must be observed that rule $R4.7$ is not evaluated because the media *checkin* is not present in set OBC 1. We can rank the rules from maximum to minimum levels of *SupR*, *CosR*, and *LevR* like $R4.2$, $R4.4$, $R4.3$, $R4.1$, $R4.5$, and $R4.6$. We can also rank the rules for OBS 2 from maximum to minimum levels of *SupR*, *CosR*, and *LevR* as $R4.2$, $R4.4$, $R4.3$, $R4.1$, $R4.7$, $R4.5$, and $R4.6$.

It must be observed that the *status*, *photo*, *video*, and *link* media types engage Facebook users the most with actions *comments and likes* then other media types.

Next, we present the specialization of media-based social interactions, linking actions performed by users and media types for web applications and mobile devices.

5.4 *Web Applications and Mobile Devices Within Media-Based Social Interactions*

Facebook offers a variety of web applications and mobile devices for users' access and interaction in the social network. By downloading specific applications for mobile devices (e.g., Facebook for iPad, iPhone, Blackberry, and Android), Facebook users can share media types and perform actions *comment and like*. The action *Share* is not available for all mobile devices.

We detail web applications and mobile devices within A_1 to specialize social interactions. For example, aA_1*.video.Links* means that user *a* makes a post type *video* provided via web application *Links*. A_1*.status.iPhone* means that user *a* makes a post type *status* provided via *iPhone* device.

Table 3 Contingencies $R4.1$ to $R4.7$ and measures for OBC 1 and OBC 2

Rule Number	Media	SupR OBC 1 (%)	SupR OBC 2 (%)	CosR OBC 1 (%)	CosR OBC 2 (%)	LevR OBC 1 (%)	LevR OBC 2 (%)
R4.1	Link	2.30	2.07	44.19	41.15	2.03	1.82
R4.2	Status	22.62	22.44	77.59	80.37	14.12	14.64
R4.3	Video	5.70	4.77	55.10	56.89	4.95	4.24
R4.4	Photo	11.29	11.92	65.51	65.40	7.09	7.53
R4.5	SWF	0.02	0.03	37.80	60.01	0.02	0.03
R4.6	Music	0.02	0.02	55.71	52.34	0.02	0.02
R4.7	Checkin		1.77		65.47		1.68

Listing 3

Web Applications and Mobile Devices Within Media-Based Social Interactions

R4.10 $aA_1.video.Links \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.11 $aA_1.photo.Photos \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.12 $aA_1.link.Links \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.13 $aA_1.status.Twitter \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.14 $aA_1.status.iPhone \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.15 $aA_1.photo.iPhone \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.16 $aA_1.status.Mobile \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.17 $aA_1.status.Blackberry \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$
R4.18 $aA_1.status.Android \cap kA_2 \cap lA_3 \rightarrow aklC_1 \cap aklC_2 \cap aklC_3$

Table 4 presents the results of the evaluation of the rules presented in Listing 3 with the data sets OBC 1 and OBC 2. It must be observed that the media object types *video* and *photo* provided, respectively, via web applications *Links* and *Photos* ($R4.10$ and $R4.11$) engage Facebook users the most with the actions *comment and like*. Also, the *checkin*, *status*, and *photo* media types provided via mobile device *iPhone* ($R4.14$ and $R4.15$) engage Facebook users the most with actions *comment and like*.

5.5 Summarization of Results

By applying our method, we are able to identify that Facebook users engage in social interactions by performing actions *comment and like*. Considering media-based social interactions, the *status* and *photo* types engage Facebook users more by performing actions *comment and like* than other media types.

Table 4 Measures for contingencies *R*4.10 to *R*4.22

Rule number	Media and applications	SupR OBC 1 (%)	SupR OBC 2 (%)	CosR OBC 1 (%)	CosR OBC 2 (%)	LevR OBC 1 (%)	LevR OBC 2 (%)
R4.10	Video, Links	3.77	1.07	63.16	64.81	3.42	1.05
R4.11	Photo, Photos	2.50	0.97	58.01	62.13	2.31	0.95
R4.12	Link, Links	0.86	0.27	50	50.44	0.84	0.27
R4.13	Status, Twitter	1.12	0.35	60.37	60.14	1.08	0.35
R4.14	Status, iPhone	9.17	2.38	80.60	83.98	7.88	2.30
R4.15	Photo, iPhone	7.48	2.16	79.35	80.31	6.60	2.09
R4.16	Status, Mobile	4.51	1.36	76.98	80.10	4.16	1.33
R4.17	Status, BlackBerry	1.76	0.62	75.94	82.91	1.70	0.62
R4.18	Status, Android	1.49	0.52	74.08	75.95	1.45	0.51

Next, we were able to identify that media types *video* and *photo* provided, respectively, via web applications *Links* and *Photos* engage Facebook users the most with actions *comment and like*. Media types *status* and *photo* provided via mobile device *iPhone* also engage Facebook users the most with the actions *comment and like*.

Application designers may use the results of this analysis to evaluate the sociability of the applications they designed, both as a complementary way to the use of inspection methods of sociability and/or as a model to facilitate the high level of human interpretation of the dynamics of the interaction. This type of analysis is as facilitated by a human-readable model as the one we propose. The method we present in this paper can also be useful to social scientists who want to analyze social interactions, e.g., to investigate the evolution of user behavior in social multimedia environments.

6 Final Remarks

In this chapter, we present a method for capturing, representing, and measuring collective actions around media types as a generalization of applying our human-readable technique used in previous studies. In regard to validating the method, we detail how it has been applied to represent and measure social interactions among a group of 1,600 Facebook users during 7 months.

We verify the application of our method in the representation and measurement of behavioral contingencies that involve Facebook users in social interactions. Such rules are specialized with media types, and next, media-based social interactions are specialized with web applications and devices. Our results report the use of actions *comment and like* after the sharing of *video* and *photo*, respectively, via *Links* and *Photos* web applications and after the sharing of *status* and *photo* provided via the mobile device *iPhone*.

In future works, we plan to apply our method for representing and measuring media-based social interactions in Twitter and Google+ as a follow-up. We also plan to specify a process for software development. By extending the method, we are developing mining algorithms to extract social interactions automatically, including media-based web applications and device-specialized social interactions. Also, we are developing a rule-based model to predict users' behaviors in social media environments.

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References

Abrol S, Khan L (2010) Tweethood: agglomerative clustering on fuzzy k-closest friends with variable depth for location mining. In: IEEE international conference on social computing (SocialCom). Minneapolis, MN, pp 153–160

Azevedo PJ, Jorge AM (2007) Comparing rule measures for predictive association rules. In: ACM European conference on machine learning (ECML '07). Berlin, pp 510–517

Backstrom L, Bakshy E, Kleinberg J, Lento T, Rosenn I (2011) Center of attention: how Facebook users allocate attention across friends. In: Proceedings of the international AAAI conference on Weblogs and social media

Bentley F, Metcalf C (2009) The use of mobile social presence. Pervasive Comp IEEE 8(4):35–41

Bigonha CAS, Cardoso TNC, Moro MM, Almeida VAF, Gonçalves MA (2010) Detecting evangelists and detractors on twitter. In: Proceedings of 16th Brazilian symposium on multimedia and Web (WebMedia'10), pp 107–114

Bonchi F, Castillo C, Gionis A, Jaimes A (2011) Social network analysis and mining for business applications. ACM Trans Intell Syst Technol 2:22:1–22:37

Chorianopoulos K (2010) Scenarios of use for sociable mobile TV. In: Marcus A, Sala R, Roibs AC (eds) Mobile TV: customizing content and experience. Springer, London, pp 243–254

Cowan LG, Weibel N, Pina LR, Hollan JD, Griswold WG (2011) Ubiquitous sketching for social media. In: Proceedings of the 13th international conference on human computer interaction with mobile devices and services. ACM, New York, NY, pp 395–404

De Choudhury M, Counts S, Czerwinski M (2011) Identifying relevant social media content: leveraging information diversity and user cognition. In: Proceedings of the 22nd ACM conference on hypertext and hypermedia. ACM, New York, NY, pp 161–170

Ekenel H, Semela T (2011) Multimodal genre classification of TV programs and Youtube videos. Multimedia Tools Appl 63:547–567. doi:10.1007/s11042-011-0923-x

Fagá R Jr, Motti VG, Cattelan RG, Teixeira CAC, Pimentel MGC (2010) A social approach to authoring media annotations. In: ACM symposium on document engineering (DocEng '10). ACM, New York, pp 17–26

Freeman LC (2004) The development of social network analysis: a study in the sociology of science. Empirical Press, Vancouver, CA

Fürnkranz J, Gamberger D, Lavrac N (2011) Rule learning: essentials of machine learning and relational data mining, 1st edn. Springer, Dordrecht

Geerts D (2010) The sociability of mobile TV. In: Marcus A, Sala R, Roibs AC (eds) Mobile TV: customizing content and experience. Springer, London, pp 25–28

Geerts D, Grooff DD (2009). Supporting the social uses of television: sociability heuristics for social TV. In: Proceedings of the 27th international conference on human factors in computing systems, CHI 2009. ACM, New York, pp 595–604

Gomes AK, Pimentel MdGC (2011a) Measuring media-based social interactions provided by smartphone applications in social networks. In: Proceedings of the 2011 ACM workshop on social and behavioral networked media access (SBNMA '11). ACM, New York, NY, pp 59–64
Gomes AK, Pimentel MdGC (2011b) Measuring synchronous and asynchronous sharing of collaborative annotations sessions on ubi-videos as social interactions. In: Proceedings of the 2011 international conference on Ubi-media computing (U-MEDIA '11). Sao Paulo, pp 122–129
Gomes AK, Pimentel MdGC (2011c) Social interactions representation as users behavioral contingencies and evaluation in social networks. In: Proceedings of the 2011 I.E. international conference on semantic computing (ICSC '11). Palo Alto, CA, pp 275–278
Gomes AK, Pimentel MdGC (2011d) A technique for human-readable representation and evaluation of media-based social interactions in social networks. In: Proceedings of the 17th Brazilian symposium on multimedia and the Web (WebMedia '11), pp 119–126
Gomes AK, Pimentel MdGC (2011e) Um método para análise de interações sociais na web social como regras se-então (in portuguese). In: Workshop sobre Aspectos da Interação Humano-Computador para a Web Social (WAIHCWS '11) no X Simpósio Brasileiro de Fatores Humanos em Sistemas de Computação (IHC '11)
Gomes AK, Pimentel MGC (2012a) Measuring media-based social interactions in online civic mobilization against corruption in Brazil. In: Proceedings of the 18th Brazilian symposium on multimedia and the Web (WebMedia '12). ACM, New York
Gomes AK, Pimentel MGC (2012b) A media-based social interactions analysis procedure. In: Proceedings of the 27th annual ACM symposium on applied computing (SAC '12). ACM, New York, NY, pp 1018–1024
Gomes AK, Pedrosa DdC, Pimentel MdGC (2011) Evaluating asynchronous sharing of links and annotation sessions as social interactions on internet videos. In: Proceedings of the 2011 IEEE/IPSJ international symposium on applications and the internet (SAINT '11). Munich, pp 184–189
Granovetter MS (1973) The strength of weak ties. Am J Sociol 78(6):13–60
Han J, Kamber M (2005) Data mining: concepts and techniques, 2nd edn. Morgan Kaufmann, Amsterdam
Holland PW, Leinhardt S (1970) A method for detecting structure in sociometric data. Am J Sociol 76(3):492–513
Jin X, Gallagher A, Cao L, Luo J, Han J (2010) The wisdom of social multimedia: using flickr for prediction and forecast. In: ACM international conference on multimedia (MM '10). ACM, New York, pp 1235–1244
Kleinberg J (2000) The small-world phenomenon: an algorithm perspective. In: ACM symposium on theory of computing (STOC). ACM, New York, pp 163–170
Lavrac N, Flach PA, Zupan B (1999) Rule evaluation measures: a unifying view. In: International workshop on inductive logic programming (ILP). Springer, London, pp 174–185
Martínez-Ballesteros M, Riquelme JC (2011) Analysis of measures of quantitative association rules. In: Proceedings of the 6th international conference on hybrid artificial intelligent systems - part II. Springer, Berlin, pp 319–326
Mattaini M (1995) Contingency diagrams as teaching tools. J Behav Anal 18:93–98
Mechner F (1959) A notation system for the description of behavioral procedures. J Exp Anal Behav 2:133–150
Mechner F (2008) Behavioral contingency analysis. J Behav Process 78(2):124–144
Mislove A, Marcon M, Gummadi KP, Druschel P, Bhattacharjee B (2007) Measurement and analysis of online social networks. In: ACM conference on internet measurement (ICM). ACM, New York, pp 29–42
Negoescu R-A, Adams B, Phung D, Venkatesh S, Gatica-Perez D (2009) Flickr hypergroups. In: ACM international conference on multimedia (MM '09). ACM, New York, pp 813–816
Rummel R (1976) Social behavior and interaction – chapter 9. In: Sage Publications (ed) Understanding conflict and war – the conflict. Wiley, New York

Scott JP (2000) Social network analysis: a handbook, 2nd edn. Sage, Thousands Oaks, CA
Shi X, Li Y, Yu P (2011) Collective prediction with latent graphs, In: Proceedings of the 20th ACM international conference on information and knowledge management. New York, NY, pp 1127–1136
Skinner BF (1953) Science and human behavior. New York Press, New York
Tan P-N, Steinbach M, Kumar V (2005) Introduction to data mining. Addison Wesley, Boston
Tan S, Bu J, Chen C, Xu B, Wang C, He X (2011) Using rich social media information for music recommendation via hypergraph model. In: ACM transactions on multimedia computing, communications, and applications (TOMCCAP), 7S, pp 22:1–22:22
Bourlard H, Vinciarelli A, Pantic M (2009) Social signal processing: survey of an emerging domain. Image Vis Comput 27:1743–1759
Wasserman S, Faust K (1994) Social network analysis: methods and applications. Cambridge University Press, Cambridge
Watts DJ (1999) Small worlds: the dynamics of networks between order and randomness. Princeton University Press, Princeton, NJ
Weingarten K, Mechner F (1966) The contingency as an independent variable of social interaction. In: Verhave T (ed) Readings of experimental analysis of behavior. Appleton Century Crofts, New York, pp 447–459
Wilkinson D, Thelwall M (2011) Researching personal information on the public Web. Soc Sci Comput Rev 29(4):387–401
Wilson C, Boe B, Sala A, Puttaswamy KP, Zhao BY (2009) User interactions in social networks and their implications. In: ACM European conference on computer systems. ACM, New York, pp 205–218