Face-to-Face Contacts during a Conference: Communities, Roles, and Key Players

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Abstract. This paper analyzes profile data and contact patterns of conference participants in a social and ubiquitous conferencing scenario: We investigate user-interaction and community structure of face-to-face contacts during a conference, and examine different roles and their characteristic elements. The analysis is grounded using real-world conference data capturing descriptive profile information about participants and their face-to-face contacts.

1   Introduction

During the last decade, Web 2.0 and social semantic web applications have already woven themselves into the very fabric of everyday life. Many applications, e.g., social networks (Facebook, LinkedIn, Xing) or Web 2.0 messaging tools (Twitter) are extensively used in various application domains. However, conferences usually do not make use of more dynamic and community-based features, e.g., schedules are commonly arranged in a static way. Knowledge discovery techniques could often be applied ahead of the conference, e.g., for recommending reviewers to submissions or later talks to participants. Furthermore, dynamic adaptions are enabled during the conference by ubiquitous computing approaches, e.g., based on RFID-tokens.

In this paper, we focus on the analysis of social data and contact patterns of conference participants: We consider communities of participants and their visited talks. Additionally, we analyze face-to-face contacts of conference participants during the duration of the conference. We examine different explicit and implicit roles of the participants, validate the community structures, and analyze various structural properties of the contact graph.

Our contribution is three-fold: We present an in-depth analysis of the social relations and behavioral patterns at the conference, identify characteristics of special roles and groups, and sketch approaches on how the mined information can be implemented in social conferencing applications. We focus on profiles of the participants and their face-to-face contacts. Considering these, we analyze community structures during the conference. Additionally, we consider the special interest groups as given by

a participant during registration in comparison to the emerging communities at the conference. Finally, we perform a description and characterization of different roles and groups, e.g., organizers and different subcommunities at a conference, in order to identify characteristic factors.

The rest of the paper is structured as follows: In Section 2 we discuss some social applications for conferences, and issues of privacy and trust. After that, Section 3 considers related work. Next, Section 4 provides the grounding of our approach presenting an in-depth analysis and evaluation of real-world conference data. Finally, Section 5 concludes the paper with a summary and interesting directions for future research.

2 Social Conferencing

During a conference, participants encounter different steps and phases: Preparation (before the conference), during the actual conference, and activities after the conference. Appropriate talks and sessions of interest need to be selected. Talks and discussions, for example, need to be memorized. Additionally, social contacts during a conference are often essential, e.g., for networking, and are often revisited after a conference, as are the visited talks. All of these steps are supported by the CONFERATOR system: It is under joint development by the School of Information Sciences, University of Pittsburgh (conference management component, as a refinement of the Conference Navigator [1]) and the Knowledge and Data Engineering group at the university of Kassel (social and ubiquitous PEERRADAR[3] component).

A first prototype of CONFERATOR [2], developed by the Knowledge and Data Engineering group was successfully applied at the LWA 2010 conference at the University of Kassel in October 2010. The applied system is based on the UBICON framework featuring the PEERRADAR application for managing social and ubiquitous/real contacts. This is implemented by embedding social networks such as Facebook, XING, and LinkedIn. Furthermore, advanced RFID-Proximity technology for detecting the location of participants and contacts between conference participants is implemented utilizing active RFID proximity-tags, cf., [3]. The system also provides the conference information using a visual browser for managing the conference content and phases, i.e., by providing information about talks and the conference schedule, in preparation for integrating the Conference Navigator application.

In CONFERATOR, privacy is a crucial issue: A variety of user data is collected and therefore appropriate steps for their secure storage and access were implemented.

CONFERATOR implements privacy measures using a refined trust system: It features several privacy levels (private, trusted, public) for organizing access to different items, e.g., location, profile, and contact information. In addition, in the analysis we aim at providing implicit k-anonymity in the presentation and discussion, since we provide results at the level of special interest groups, or provide detailed results only targeting groups containing at least five participants.

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[3] http://www.ubicon.eu

3 Related work

Regarding the tracking and analysis of conference participants, there have been several approaches, using RFID-tokens or Bluetooth-enabled devices. Hui et al. [4] describe an application using Bluetooth-based modules for collecting mobility patterns of conference participants. Furthermore, Eagle and Pentland [5] present an approach for collecting proximity and location information using Bluetooth-enabled mobile phones, and analyze the obtained networks.

One of the first experiments using RFID tags to track the position of persons on room basis was conducted by Meriac et al. (cf., [6]) in the Jewish Museum Berlin in 2007. Cattuto et al. [7] added proximity sensing in the Sociopatterns project[4]. Barrat et al. [8] did further experiments. Alani and colleagues, e.g., [3], also added contact information from social online networks. Our work uses the same technical basis (RFID-tokens with proximity sensing), on top of the Sociopatterns project, which allows us to verify their very interesting results independently. Furthermore, in this paper we significantly extend the analysis, since we are able to use further techniques in order to characterize different roles, communities and participant relations.

The conference navigator by Brusilovsky [1] allows researchers attending a conference to organize the conference schedule and provides a lot of interaction capabilities. However, it is not connected to the real live activity of the user during the conference. In the application, we measured face-to-face conctacts, increased the precision of the localization component compared to previous RFID-based approaches, and linked together tag information and the schedule of a workshop week. Furthermore, we implemented a light-weight integration with BibSonomy and other social systems used by participants. This is the basis for new insights into the behavior of all participants.

Thus, in comparison to the approaches mentioned above, we are able to perform a much more comprehensive evaluation of the patterns acquired in a conference setting, since our data provides a stable ground truth for communities (the special interest groups). This provides a grounding not only considering the verification of the structural properties of the mobility patterns, but also given by the roles, and communities.

Considering different "roles" of nodes and finding so called "key actors" has attracted a lot of attention. Ranging from different measures of centrality (cf., [9]) to the exploration of topological graph properties [10] or structural neighborhood similarities [11]. We focus on a metric of how much a node connects different communities, cf., [12], since it allows to consider initially given community structures.

4 Grounding

In this section, we present an analysis of the collected conferencing data. After introducing some preliminaries, we first discuss a grounding of the communities given through the assignment of participants to special interest groups. After that, we consider explicit roles (Prof., PostDoc, PhD-Student, Student) and organizing roles (organizers vs. regular participants).

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[4] http://www.sociopatterns.org

4.1 Preliminaries

In the following section, we briefly introduce basic notions, terms and measures used throughout this paper. We presume familiarity with the concepts of *directed* and *undirected* Graphs

$$G = (V, E)$$

for a finite set V of nodes with edges $(u, v) \in V \times V$ and $\{u, v\} \subseteq V$ respectively.

In a *weighted* graph, each edge is associated with a corresponding edge weight, typically given by a mapping from E to $\mathbb{R}$. We freely also use the term *network* as a synonym for a graph. For more details, we refer to standard literature, e.g., [13,14].

In the context of social network analysis, a *community* within a graph is defined as a group of nodes such that group members are densely connected among each other but sparsely connected to nodes outside the community [15] (based on the underlying observation that individuals tend to interact more tightly within a group of somehow related persons). Community structure was observed in several online social networks [16,17] and is sometimes also called "virtual community" [18].

For formalizing and assessing community structure in networks, this work focuses on the modularity measure [15] which is based on comparing the number of edges within a community to the expected such number given a null-model (i.e., a randomized model). Thus, the modularity of a community clustering is defined to be the fraction of the edges that fall within the given clusters minus the expected such fraction if edges were distributed at random.

This can be formalized as follows: The modularity Mod of a graph clustering is given by

$$Mod = \frac{1}{2m} \sum_{i,j} \left(A_{i,j} - \frac{k_i k_j}{2m} \right) \delta(C_i, C_j) \,,$$

where A is the adjacency matrix, C_i and C_j are the clusters containing the nodes i and j respectively, k_i and k_j denote the degree of i and j, $\delta(C_i, C_j)$ is the *Kronecker delta* symbol that equals 1 if $C_i = C_j$, and 0 otherwise; $m = \frac{1}{2} \sum_{ij} A_{ij}$ is the total number of edges in the graph.

A straightforward generalization of the above formula to a modularity measure $wMod$ in weighted networks [19] considers A_{ij} to be the weight of the edge between nodes i and nodes j, and replaces the degree k_i of a node i by its strength $str(i) = \sum_j A_{ij}$, i. e., the sum of the weights of the attached edges.

4.2 Available Data

For capturing social interactions, RFID proximity tags of the Sociopatterns project were applied. 70 out of 100 participants volunteered to wear an RFID tag which (approximately) detected mutual face-to-face sightings among participants with a minimum proximity of about one meter. Each such sighting with a minimum length of 20 seconds was considered as a contact which ended when the corresponding tags did not detect an according sighting for more than 60 seconds.

Using the contact data we generated undirected networks $\mathsf{LWA}[\geq i]_*$, $\mathsf{LWA}[\geq i]_\Sigma$, and $\mathsf{LWA}[\geq i]_\#$. An edge $\{u, v\}$ is created, iff a contact with a duration of at least i *minutes* among participants u and v was detected ($i = 1, \ldots, 15$). For $i \geq 5$[minutes], for example, we can filter out "small talk" conversations. In $\mathsf{LWA}[\geq i]_\#$ the edge $\{u, v\}$ is weighted with the *number* of according contacts, in $\mathsf{LWA}[\geq i]_\Sigma$ it is weighted with the *sum* of all according contact durations whereas $\mathsf{LWA}[\geq i]_*$ is unweighted.

Table 1 contains some statistics for $\mathsf{LWA}[\geq i]_*$, $i = 0, 5, 10$. The diameters and average path lengths coincide with those given in [8] for the Hypertext Conference 2009 (HT09). Figure 1 shows the degree and contact length distribution for $\mathsf{LWA}[\geq 0]_*$. The latter exhibits characteristics comparable with those given for HT09, whereas the degree distributions differ by exhibiting two peaks – one around 10 and one around 20 – in contrast to only one peak around 15 for HT09. We hypothesize that this deviation is due to a more pronounced influence of the conference organizers at LWA 2010 in relation to the total number of participants (approx. 15% of the participants in $\mathsf{LWA}[\geq 0]_*$ were organizers). This hypothesis is supported by removing all organizers from $\mathsf{LWA}[\geq 0]_*$ and recalculating the degree distribution, yielding a single peak in the interval $[15, 20)$.

Other statistics (e. g., strength distribution, among others) also suggest evidence for structural similarities among HT09 and LWA 2010. Therefore, we conclude, that LWA 2010 was a typical technical conference setup, and results obtained at the LWA 2010 are expected to hold in other conference scenarios with similar size, too.

Table 1. High level statistics for different networks: Number of nodes and edges, Average degree, Average path length APL, diameter d, clustering coefficient C, number and size of the largest weakly connected component #CC and $|CC|_{max}$ respectively. Additionally the size of the contained special interest groups is given.

Network	$\|V\|$	$\|E\|$	Avg.Deg.	APL	d	Density	C	#CC	$\|CC\|_{max}$	$\|KDML\|$	$\|WM\|$	$\|IR\|$	$\|ABIS\|$
$\mathsf{LWA}[\geq 0]_*$	70	812	23.20	1.72	4	0.34	0.55	1	70	37	16	10	7
$\mathsf{LWA}[\geq 5]_*$	65	227	6.99	2.53	5	0.11	0.33	1	65	34	15	9	7
$\mathsf{LWA}[\geq 10]_*$	56	109	3.89	3.09	7	0.07	0.31	3	50	31	12	7	6

Furthermore, we extracted the "*visited talks*", i.e., the talks visited by each participant using the RFID information, resulting in 773 talk allocations for the conference participants.

4.3 Community Structure

LWA 2010 was a joint workshop week of four special interest groups of the German Computer Science Association (GI).

– **ABIS** focuses on *personalization and user modeling*.
– **IR** is concerned with *information retrieval*.
– **KDML** focuses on all aspects of *knowledge discovery and machine learning*.
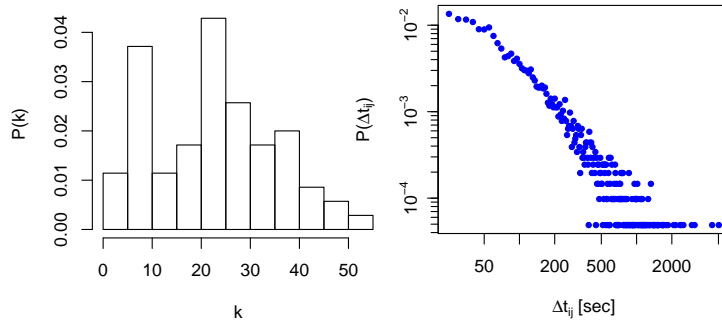– **WM**, for 'Wissensmanagement', considers all aspects of *knowledge management*.

Fig. 1. Degree distribution $P(k)$ (left) and distribution of the different contact durations (right) in LWA$[\geq 0]_*$.

During the registration for LWA 2010, each participant declared his affiliation to exactly one special interest group: KDML (37), WM (16), ABIS (7), IR (10), for a total of 70 participants. Since these interest groups capture common research interests as well as personal acquaintance, the set of participants is naturally clustered accordingly.

As a first characteristic for the interest groups, we aggregated the visited talks groupwise per track. Although several sessions were joint sessions of two interest groups, Figure 2 clearly shows for each group a strong bias towards talks of the associated conference track.
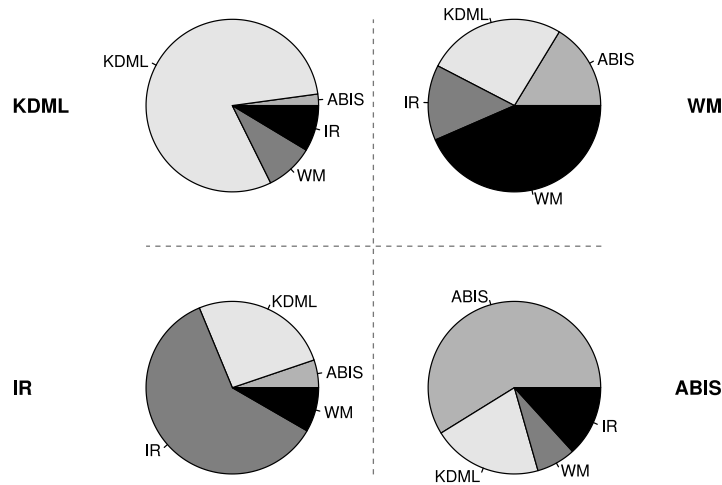

Fig. 2. Distribution of the conference tracks of the talks visited by members of the different interest groups. The top-left figure, for example, shows the distribution of tracks visited by the KDML special interest group.

The question arises, whether or not an according community structure may be observed in the contact graphs obtained during the conference. Figure 3 shows the obtained weighted and unweighted modularity scores for the contact graphs $\mathsf{LWA}[\geq i]_\Sigma$ and $\mathsf{LWA}[\geq i]_\#$ with $i = 1, \ldots, 15$, considering the interest groups as communities. We first observe that the modularity monotonically ascends with increasing minimal conversation length. This conforms to the intuition that more relevant (i. e., longer) conversations are biased towards dialog partners with common interests, as captured by the interest group membership.

For analyzing the impact of repeated or longer conversations, we calculated the weighted modularity score on the same networks, given the number of conversations or the aggregated conversation time between two participants as edge weights. Figure 3 shows that the obtained modularity scores are nearly constant across the different networks. This suggests that peers tend to talk more frequently and longer within their associated interest groups. To rule out statistical effects induced by structural properties
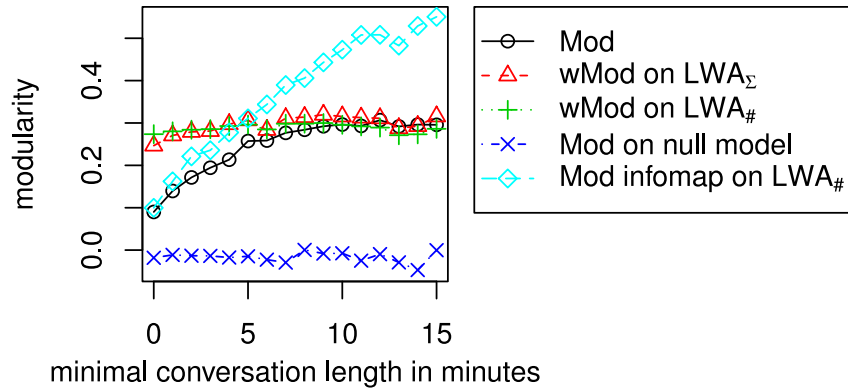

Fig. 3. Modularity score for varying minimum conversation length.

of the contact graphs, we created a null model by repeatedly shuffling the group membership of all participants and averaging the resulting unweighted modularity scores. As Figure 3 shows, the shuffled group allocation shows no community structure in terms of modularity as expected.

Additionally, the standard community detection algorithm Infomap [20] which is shown to perform well [21] was chosen for reference and applied to the same contact graphs. Figure 3 also shows the unweighted modularity scores for the obtained communities. The resulting line strictly ascends with increasing minimal conversation length. It coincides with the modularity scores of the interest group induced community structure, with parity around five minutes and nearly doubles both weighted and unweighted modularity scores in $\mathsf{LWA}[\geq 15]_\Sigma$ and $\mathsf{LWA}[\geq 15]_\#$.

Inspection of the obtained communities suggests that the applied algorithm yields communities in $\mathsf{LWA}[\geq 0]_*$ which are similar to the given interest groups and mines more specialized (i. e., sub communities) in $\mathsf{LWA}[\geq i]_*$, $i \geq 5$. Figure 4 shows for

reference in $\mathsf{LWA}[{\geq}0]_*$, that ABIS and IR are nearly perfectly captured by Infomap but KDML is split mainly across two communities, one of which shared with WM. We do not aim at evaluating any community detection algorithm: We rather exemplify the application of such algorithms and approximate an upper bound of the modularity score in the contact graphs.
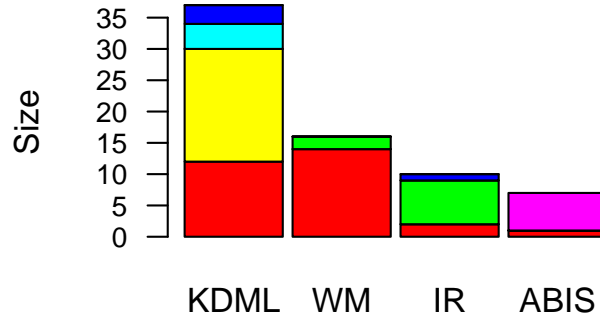

Fig. 4. Distribution of the interest groups across the six communities mined by the Infomap algorithm on $\mathsf{LWA}[{\geq}0]_*$. Each color corresponds to a single (non-overlapping) community.

For analyzing social interactions across different interest groups, Table 2 shows the density in correspondingly induced sub graphs – that is, for each pair of interest groups $V_i, V_j \subseteq V$ in the complete contact graph $G = (V, E)$, the fraction of all actually realized edges in the set of possible edges between V_i and V_j.

Within the interest groups, the density values are strictly above the global density (cf., Table 1), but strictly below across different groups. This suggests that participants actually tend to interact more frequently with members of their own interest group.

Table 2. Density in the the contact graph $\mathsf{LWA}[{\geq}0]_*$.

	ABIS	IR	KDML	WM
ABIS	**0.62**	0.23	0.19	0.28
IR	0.23	**0.44**	0.21	0.20
KDML	0.19	0.21	**0.38**	0.31
WM	0.28	0.20	0.31	**0.58**

4.4 Roles and Key Players

The assignment of roles to nodes in a network is a classification process that categorizes the players by common patterns. In this section, we discuss the connection between the academic status of the conference participants and the classic centrality measures and a community based role assignment. The latter was introduced in [12] together with the

Table 3. Group size and average graph centralities per academic position and for organizers and non-organizers in LWA[$\geq$5]$_*$: degree deg, strengths $str_\#$ and str_Σ, eigenvalue centralities eig_*, $eig_\#$ and eig_Σ, betweenness bet, closeness clo and the average community metric $rawComm$.

position/ function	size	deg	$str_\#$	str_Σ	eig_*	$eig_\#$	eig_Σ	bet	clo	$rawComm$
Prof.	10	7.500	16.700	11893.200	0.310	0.285	0.337	49.565	0.407	0.525
PostDoc	11	7.727	15.545	9793.364	0.303	0.213	0.198	75.973	0.419	0.675
PhD-student	33	7.152	15.091	9357.182	0.309	0.201	0.165	46.221	0.409	0.567
Student	5	3.600	12.400	6514.400	0.099	0.068	0.027	17.989	0.347	0.417
Other	6	6.667	14.333	8920.000	0.288	0.211	0.209	38.234	0.413	0.581
Organizer	11	10.000	23.727	15227.545	0.459	0.424	0.417	94.497	0.447	0.699
Non-Organizer	54	6.370	13.389	8408.056	0.256	0.162	0.144	39.565	0.397	0.542

$rawComm$ metric that it is based on. The metric is defined as the sum:

$$rawComm(u) = \sum_{v \in N(u)} \tau_u(v) \,,$$

where the function $\tau_u(v)$ assigns the contribution of a node v to connect communities of u given by

$$\tau_u(v) = \frac{1}{1 + \sum_{v' \in N(u)} \left(I(v, v') * p + \bar{I}(v, v')(1 - q) \right)} \,.$$

In the formulas $N(u)$ is the neighborhood of a node u, $I(v, v') = 1$ if there is an edge between v and v' and 0 else; $\bar{I} = 1 - I$, p is the probability that an edge in the graph connects two communities and q is the probability that two non-linked nodes are in different communities.

The $rawComm$ score can be interpreted as a measure of how much a node connects different communities (for details, cf., [12]). To estimate the probabilities p and q we used the community clustering given by the four special interest groups.

Global Characterization Table 3 displays the average values of several graph structure metrics of LWA[$\geq$5]$_*$ aggregated by academic position and for the conference organizers and non-organizers (regular conference participants), respectively. Note, that while the categories referring to academic status are disjoint (the category *other* includes all participants that do not fit one of the other four) organizers and non-organizers both include participants from all the 'status' categories.

A first observation is that the organizers have significantly higher scores in all nine measures under observation. In the considered conference scenario this is highly plausible due to the nature of an organizer's job during a conference – which in the case of LWA 2010 also included the supervision and maintenance of the RFID-experiment and the CONFERATOR. Among the four academic positions, striking differences can be noticed. First of all, the student scores in all centralities are lower than those of the other

categories. We attribute this phenomenon to the fact, that students are less established in their scientific communities than scientists in higher academic positions and usually have little conference experience. This example motivates the need of social tools that assist participants in initiating contact to their communities and persons of interest.

Within the categories "Prof.", "PostDoc" and "PhD-student" the eigenvalue centralities show a particular behavior. While the unweighted eigenvalue centrality eig_* does not fluctuate much, the weighted versions eig_Σ and $eig_\#$ increase strongly from one position to the next higher one. Eigenvalue centralities are considered a measure of importance. It seems plausible, that in a contact graph among scientists, the players with longer scientific experience – including a higher and broader degree of knowledge within scientific areas and more previous contacts and collaborations with their colleagues – are considered more important and that this attitude is reflected in their contacts. The node strength measures show similar results. While the degree deg is only slightly different among the three positions, the weighted versions $str_\#$ and especially str_Σ show large differences and increase together with the position. The considerable difference between the weighted and unweighted measures can be indicates the relevance of the frequency and the length of the contacts: Professors, for example, have longer and more contacts to other participants than postdocs.

Another aspect is illustrated by the betweenness (bet) scores: Relatively to the other groups, a lot of shortest paths of $\mathsf{LWA}[\geq 5]_*$ run through nodes of PostDoc's. We attribute this to the structure of scientific institutes, where usually one professor supervises several PostDocs who again each supervise several PhD-students. PostDocs are the connection between professors and the postgraduates and thus assume the role of gatekeepers in their working environment.

Finally, for the $rawComm$ metric it is harder to come up with a plausible explanation for the difference and order of the academic positions. However, as described in [12], it can be combined with $ndeg$ – the degree divided by the maximum degree – to gain a role classification for the network's nodes in the following way: One out of four roles is assigned to a node v according to

$$
role(v) := \begin{cases}
\text{Ambassador} & ndeg(v) \geq s, rawComm(v) \geq t \\
\text{Big Fish} & ndeg(v) \geq s, rawComm(v) \lesssim t \\
\text{Bridge} & ndeg(v) \lesssim s, rawComm(v) \geq t \\
\text{Loner} & ndeg(v) \lesssim s, rawComm(v) \lesssim t
\end{cases}
$$

where s and t are thresholds that we chose as $s = t = 0.5$ – the same choice as in [12].

Ambassadors are characterized by high scores in both degree and $rawComm$ which means that they connect many communities in the graph. A *Big Fish* has contacts to a lot of other nodes, however, mostly within the same community. *Bridges* connect communities, however, not as many as ambassadors. Finally, *Loners* are those with low scores in both measures.

In the following, we investigate how nodes in their explicitly given roles like the academic position and the job (organizer) fill those implicitly given graph structure-based roles. Therefore, we applied the role classifier to the graphs $\mathsf{LWA}[\geq 0]_*$ through $\mathsf{LWA}[\geq 15]_*$ to determine – under the assumption, that longer contacts indicate more serious and scientific discussions – how this changes the community roles.

The first immediate finding is, that in none of the graphs any participant was ever classified as Big Fish, i. e., whenever a node has a high degree it also has a high *rawComm* score. We attribute this peculiarity to the fact, that the very nature of social interaction at conferences usually is exchanging ideas with participants outside the own peer group. Especially during the LWA 2010, participants were encouraged to engage in interdisciplinary dialogue for example by including several joint sessions in the schedule and a combined event of social dinner and poster session.

The first of the three diagrams in Figure 5 displays the percentage of participants with a common academic position or job that were classified as Ambassador. The line marked with triangles displays that fraction of all participants together. The second and third diagram display the same fractions for the roles Bridge and Loner. For example in $\mathsf{LWA}[\geq 0]_*$, 40% of the professors were classified as Ambassador, 60% as Bridge and 0% as Loner. In each diagram the size of the nodes indicates the size of the group of participants with the examined position/job in the respective graph. The PhD-students, for example, are the largest section, while the students form the smallest. For $\mathsf{LWA}[\geq 5]_*$ those sizes are given in Table 3.

While all curves in Figure 5 fluctuate, there are several clearly visible tendencies. In all three diagrams, the fractions of PhD-students is very close to the fraction of all participants. The simple reason for that is, that PhD-students are the majority within the conference population and therefore dominate the general behavior. Many of the organizers start out as Ambassador or Bridge. This is again consistent with their job description. However, filtering out short contacts and thus the typical quick organizational conversations, the relevance of the organizers decreases with a higher limit to the minimum contact length. More and more organizers become Loners; in the last graph $\mathsf{LWA}[\geq 15]_*$, they are almost equally distributed among the three roles. On should keep in mind, that organizers contain persons in all academic positions. Therefore, after filtering out most of the contacts that presumably contain their organizational work, the organizers act mainly in their different role as conference participants, which might explain the stronger fluctuations in the right part of the curve.

Very consistent with the findings described above is the role distribution among the students. While in the first graphs, where short contacts dominate the longer ones, some of them are classified as Bridge or Ambassador, they quickly disappear from those roles and are classified as Loner.

Compared to the PhD-students, the fractions of the PostDocs are with few exceptions higher for the roles Ambassador and Bridge and lower for Loner. This is again consistent with the previous observations concerning the graph structure measures. Due to their greater experience PostDocs seem to have more access to colleagues in other communities. However, with the increasing filter limit, like most of the participants they become classified as loners.

Finally, the curve of the professors in the role Ambassador shows the most radical deviation from the mainstream. While in that role all other group's fractions decrease, that of the professors increases significantly up to 70% which is far more than any of the other academic positions. In summary, we observe, that the chosen method of role assignment seems to be highly correlated to the roles like academic position and the organizer job.

Characterization of Explicit Roles In the following, we aim to characterize the roles in more detail; for the dataset, we focus on the majority classes, i.e., we consider the target concept *non-organizer* concerning roles, and the target concept *PhD-students* concerning academic position. For the analysis, we applied a method for mining characteristic patterns [22] based on subgroup discovery techniques, e.g., [23]. For the data preprocessing, we first discretized the numeric features described above into three intervals (low, medium, high) using equal-width discretization.

The most descriptive factors for the role *non-organizer* are shown in Table 4 (upper). They confirm the averaged results shown above, in that the most characteristic *single* factors are given by the closeness, eigenvalue centrality, and the degree of the non-organizers, for which lower values than those of the organizers are measured.

However, if we consider combinations of factors, we observe, that there are subgroups regarding the role non-organizer for which extreme values, e.g., of the closeness together with the eigenvalue centrality yield a significant increase in characterization power, as shown by the quality increase in Table 4.

Table 4. Role = Non-Organizer / Position = PhD-student for the aggregated count information with an aggregated contact length ≥ 5 min. The tables show the lift of the pattern comparing the fraction of non-organizers / PhD-students covered by the pattern p compared to the fraction of the whole dataset, the size of the pattern extension (number of described non-organizers / PhD-students), and the description itself.

target	#	lift	p	size	description
Non-Organizer	1	1.06	0.88	51	$clo=\{low; medium\}$
	2	1.05	0.87	61	$eig_*=\{low; medium\}$
	3	1.04	0.86	59	$deg=\{low; medium\}$
	4	1.10	0.92	12	$clo=\{low; medium\}$ AND $deg=\{high; medium\}$
	5	1.12	0.93	30	$clo=\{high; low\}$ AND $eig_*=\{low; medium\}$
PhD-student	1	1.07	0.54	59	$bet=\{high; low\}$
	2	1.07	0.54	48	$str=\{high; low\}$
	3	1.14	0.58	26	$deg=high$
	4	1.31	0.67	12	$bet=\{high; low\}$ AND $eig_*=high$
	5	1.38	0.70	20	$deg=high$ AND $bet=\{high; low\}$
	6	1.58	0.80	10	$deg=high$ AND $bet=\{high; low\}$ AND $eig_*=\{high; low\}$

If we consider the largest group *PhD-student* (concerning the academic positions), we observe the single factors shown in Table 4 (lower), also confirming the averaged results presented above. Similarly to the non-organizers, we see that extreme values, i.e., sets of high and low values, are also very significant for distinguishing PhD students. As expected the combination with other strong influence factors increases the precision of the patterns (indicated by the *lift* parameter).

5 Conclusions

In this paper, we have presented results of an in-depth analysis of user-interaction and community structure of face-to-face contacts during a conference.

We have performed various analyses on data collected during the LWA 2010 in Kassel in October 2010 by using a social conference guiding system. We analyzed and described high-level statistics of the collected network data, examined the different communities, the roles and key players concerning these and the conference in total, and discussed various issues of user interaction.

The results of the analysis show that there is consistent community structure in the face-to-face networks, and that structural properties of the contact graphs obtained at the LWA conference reflected different aspects of interactions among participants and their position and roles.

For future work, we aim to consider the community related methods further, since communities play a central role for a social conferencing system and should allow and support emergence and evolution of community structure. Furthermore, identifying key actors according to their roles is an interesting task, e.g., being used for creating virtual sessions or recommendations.

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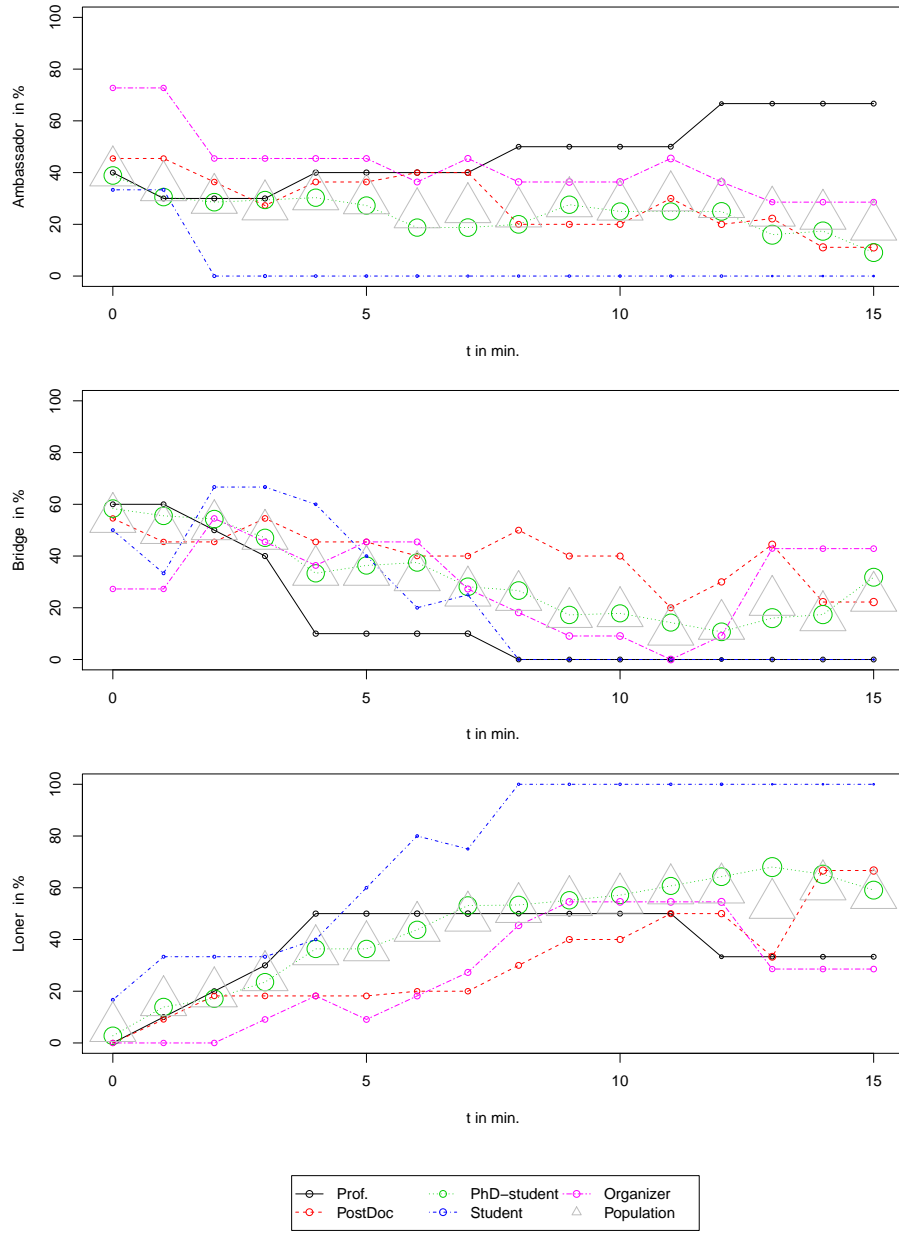
Fig. 5. Fraction of participants that assume the roles Ambassador, Bridge and Loner.