Working Well Together: introducing a measure of performance-based cohesiveness inside groups

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***Abstract*—Existing approaches in studying relationship between workers inside an organization focus more on the fact that relations exists, rather than on the assumption that relations should be "positive" for the organization, not damaging the performance of organizational processes and performance of workers. In this paper, we'll introduce a framework to define a Working Well Together metric between individuals. This metric shows to be useful in splitting the work group in sub-groups that effectively work well when they work together, detecting possible conflictual situations and the social loafing effect. From this framework, we'll also introduce a performance-based Cohesiveness measure on work groups, that show correlation with being able to cope with workload and also with stability of Transactive Memory. These ideas lead to important theoretical and practical implications.**

I. Introduction

Social networks are useful objects in organizational contexts (Tichy et al. [1979], Chow and Chan [2008]), in order to understand relationships between individuals, and which groups of people are there in the organization. Some Social networks can be extracted from event logs (Van Der Aalst et al. [2005]), that are ordered collections of events happening inside an organization, and are particularly interesting because they are based effectively on professional relations rather than on trying to measure social ties (i.e. how much e-mails are exchanged) between two individuals in the organization. These relations are measured from logs using a metric (Van Der Aalst et al. [2005]). One of these metrics is Working Together ($WT(p_1, p_2)$), which is a measure of collaboration based on the percentage of instances that are worked together by two workers p_1 and p_2. The Working Together metric is useful in finding work groups, i.e. groups of people working together inside an organization, using a clustering algorithm[1].

However, nothing is said by WT on the effectiveness of work groups[2], that in organizational contexts means performance. An organizational group with higher performances is considered to have a better fitness than one other with lower performances. Working with social networks extracted from event logs, we have several ways to measure performance of the worker from the log[3]. However, little study has been done to assigning a fitness value to groups. A relatively recent approach is estimation of Transactive Memory (Liang et al. [1995], Austin [2003], Lee et al. [2014]), that is related to specialization and coordination of individuals inside work groups (Austin [2003]).

Nothing can be done by the Working Together metric in understanding dynamics inside groups: there can be individuals (social loafers) that work better when they work individually rather than when they are together others, or it may happen than a big work group contains many sub-groups that work well together, in the sense that when a process instance is worked only by members of a such sub-group, the completion time is usually lower than the one of instances worked by a more heterogeneous group of people. This is important information in understanding work group effectiveness, and to find individuals that systematically ruin work group's performance.

For the previous reasons, we'll introduce a new metric, Working Well Together (WWT) that is able to find groups of people working well together (in the meaning of performance), and joining the information obtained by the Working Together metric we'll be able to understand how a work group is split in sub-groups. This approach is also useful in finding individuals that we'll call "weak social loafers". The term "weak social loafers" include social loafers, and refer to individuals working badly when they are outside their most-known sub-group. We'll also introduce a measure of (performance-based) Cohesiveness inside work groups, based on the same concepts of WWT metric, that is useful to understand which work groups effectively work better.

The proposed approaches were validated on the BPI Challenge 2014 event log and on a private event log. We'll show how our measure of Cohesiveness is related to team's being able to cope with workload, and to team's stability of Transactive Memory.

II. Background and theoretical development

Social networks

Always the same thing (hard copy??)

Social loafing

Social loafing (Latane et al. [1979], Karau and Williams [1993]) is related to an individual's reduced effort when working collectively rather than when working individually. Several motivations has been proposed for Social Loafing. The

[1] See (Xu et al. [2005]) for a survey on clustering algorithms.

[2] See, for better understanding, (Jehn et al. [1999])

[3] A simple way is measuring if the average activities completion time is lower or higher than the one of other workers.

most famous one (see as example Mulvey and Klein [1998]) is related to the perceived "sucker effect", i.e. one worker may feel he is doing also the fatigues of others. Other motivations include: low team cohesiveness (Williams and Karau [1991], so an individual isn't fully motivated to do things for others), identifiability (Williams et al. [1981], so when there isn't a clear way to know who do what, then performances tend to be lower), undifferentiated and simple tasks (Harkins and Petty [1982]). We must however remark that, working with event logs, we have embedded identifiability.

Existing literature does not speak largely about propagation of social loafing effect: however, Comer [1995] and Murphy et al. [2003] suggest that if a loafer behaviour is perceived as winner, other team members may feel possible to become loafers, so further reducing the group's ability to work together. So, it's important to avoid as possible social loafing by increasing team cohesiveness (Williams and Karau [1991]), for example through leadership (Wang et al. [2005], Stashevsky and Koslowsky [2006]), the improvement in coordination in the work group (Fussell et al. [1998]), and identifying social loafers, with the proposal of controlling them.

In this paper, we introduce the concept of "weak social loafer", that is related to workers performing better when working in small groups rather than when working in big groups. Social loafers are included in this category[4]. Causes, consequences and remedies to "weak" social loafing are the same of social loafing, so the previously cited results can be used also for this purpose.

Transactive Memory

Transactive Memory is a concept related to groups of people, introduced by Wegner in 1985 (Cardelli and Wegner [1985]), referring to the collective memory and the shared knowledge possessed by the group. This type of memory, according to Cardelli and Wegner [1985], can be more efficient than the one possessed by the single individual.

The quantity of Transactive Memory can be measured directly by *recall measures* (Hollingshead [1998a,b]): these take in account the increase in the ability of remembering things when people are put together, compared to the ability of remembering things when they are alone. Transactive memory could also be measured by its effects: Faraj and Sproull [2000] "measure of expertise location" is referring to the fact that, when there is a good quantity of T.M., members of the groups know who knows what. Moreover, Moreland and Myaskovsky [2000], relating to business contexts, propose that specialization, credibility and coordination behaviours reflect the "distributed, cooperative memory characteristic of Transactive Memory".

In business contexts, several studies (including Wegner [1987], Moreland et al. [1996] and Austin [2003]) have analysed the relationship between Transactive Memory and performance: higher quantities of T.M. relates with higher performance. Some studies (Moreland [2006], Peltokorpi [2008]) remark the importance of stability in the work group for keeping a stable quantity of T.M.: the loss of a team member, according to Peltokorpi [2008], can have heavy effects on the quantity of T.M. possessed by the work group. Moreover, having a good quantity of T.M. can lead the work group to being more adaptive and reactive (Roberts and Goldstone [2009]).

Having a good quantity of T.M. has been connected also to being able to cope better with workload (Michinov et al. [2008], Theiner [2010]) and to having problem solving abilities. Other interesting papers (Lewis [2004], Moreland and Argote [2003]) regard longitudinal studies, inside a group, about the quantity of Transactive Memory: in particular, Moreland and Argote [2003] analyses dynamic organizations and see how they are adaptive to changes.

In this context, our paper ... have introduced the concept of Relative Transactive Memory (RTM), that reflects the flows and the ebbs over time of the quantity of Transactive Memory inside a group. Although the values of RTM are not directly comparable between groups, ... have introduced the notion of Stability relatively to RTM, that is connected to group's performance, adaptability to changes and cope with workload.

Group Cohesiveness

Group cohesiveness (Mudrack [1989]) is related to group's members having positive relations with other members of the group, and several studies show the relation between cohesiveness and performance (Mullen and Copper [1994], Lott and Lott [1965], Darley et al. [1952]). However, as the same Mudrack [1989] points out, it is a difficult task to define when a relation inside a group is positive or not.

In the literature, there are two mainly approach in studying the relation between cohesiveness and performance: the "correlational" approach (see as example Darley et al. [1952]) measures at the same time the cohesiveness and the performance, and then evaluate the correlation. The "experimental" approach (Schacter et al. [1951]) is instead focused on implementing good cohesion groups and bad cohesion groups, and only after that measures the performance. While the correlational approach says that cohesiveness strongly imply performance, the experimental approach measures a less strong relation. This lead Mullen and Copper [1994] to say that is performance that imply cohesiveness, while the vice versa is less strong.

Given Mullen and Copper [1994], in this paper we'll introduce a measure of Cohesiveness that is based on the performance expressed by the group in the "most" difficult process instances.

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Having an event log, indeed, means having more informations than the ones contained in Social Networks extracted from metrics: you have a full insight on business processes, and you can do a BPI analysis (van Dongen et al. [2005]). An interesting analysis might regard instances completion times. Indeed, instances with an high duration may be dangerous (for example, breaking Service Level Agreements); while ones with low duration may signal some positive things inside the organization. This concept, in Lean Manufacturing terminology, is called Lead Time. Indeed, focusing on a process, we may calculate the average (avg) completion time of instances, the standard deviation (std) of completion times, and fixing a constant k (as example, $k = 1$) we can consider

[4] As they work better individually, and their small group is the individual.

- “Positive” instances: the ones whose duration is below $avg - k \cdot std$.
- “Normal” instances: the ones whose duration is between $avg - k \cdot std$ and $avg + k \cdot std$.
- “Negative” instances, or instances whose duration exceeds Lead Time: the ones whose duration is above $avg + k \cdot std$.

So, “negative” instances are the ones that were more difficult to complete for the group, and focusing on these instances you can have a clear insight on possible group problems.

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So, replying to Mudrack [1989], our approach will be based on measuring “negative” relations, based on “negative” instances, to find “positive” relations (Working Well Together metric) and having a measure of the group cohesiveness. In doing so, we are also measuring “negative” conflicts inside the work group. Existing literature (see, as example, Jehn and Mannix [2001], Pelled et al. [1999]) is not severe with conflict, and generally do not see a relation between conflicts and performance. But, basing on measuring “negative” relations inside the work group, you can have an idea on which are the conflicts that effectively ruin group’s performance.

We’ll test the previous approach on two event logs. Particularly, we will focus on testing the following hyphotesis:

1) Using Work Well Together metric, we are able to find, inside a work group, sub-groups that effectively work well together, and identify social koafing effect.
2) Using Cohesiveness measure, we are able to see which groups are more cohesive (they have better cope with workload and better stability of Relative Transactive Memory).

III. Method

Sample, Partecipants, Procedure

For the assessment of our framework, we’ll use two event logs:

- BPI Challenge 2014 event log, freely available on http://www.win.tue.nl/bpi/2014/challenge.
- A private event log, that contains data relative to an organizational process. This process involves 221 workers, and there are several different work groups (e.g. the stabilized Label Propagation algorithm on the Working Together metric generates 38 discrete clusters).

It was necessary to split the assessment, as in BPI Challenge 2014 event log there is one work group that is way bigger than others, and our Cohesiveness measure is more useful when comparing not small and similar size groups. We are sorry in having to use a private event log for part of the assessment, so damaging the repeatability of our analysis, but we didn’t find a freely available event logs that serves our purposes[5].

[5]BPI Challenge 2012 event log, for example, relatively to the Working Together contains two clusters of 4 workers and many clusters of 3 workers.

BPI Challenge 2014 event log contains data provided by the Rabobank Group ICT, and applying the stabilized Label Propagation algorithm on the Working Together metric, we can find clusters described in Table 2.

Analytical approach

Our following measures are based on finding two weighted graphs, applying always the Working Together metric:

1) The first graph (we’ll call it *Working Together* graph) is found applying the Working Together metric to all instances contained in the log. This let you to understand which work groups are there in the organization.
2) The second graph (we’ll call it *critical* graph) is found applying the Working Together metric to the instances which duration exceeds Lead Time. Lead Time was set by us to be $avg + k \cdot std$ with $k = 1.5$. This let you to find the relationship network when working difficult instances, and to underline possible “negative” relations among workers.

The choose of k is arbitrary, and depend mainly on the organizational process and on which instances you want to consider as critical. With $k = 1.5$, for both BPI Challenge 2014 event log and our private event log, the number of instances exceeding Lead Time was below 10%.

After that, Working Well Together metric can be built by subtracting weights on the second graph to the first graph,

Measures

Workload

We consider, as work group’s workload, the overall (in the log) number of process instances worked by the group.

Working Well Together metric

Working Well Together metric is a metric between individuals that expresses “positive” relations among individual.

Our way to define it is subtracting the previously defined critical graph to the Working Together graph. In this way, we remove the weight of “negative” relations to relations measured over all the instances. We can call the obtained graph the Working Well Together graph. The approach is visualized in Figure 1.

We must note that the value of relations (edges weight) in the Working Well Together metric is less or equal than the value of relations in the Working Together metric, as there is a difference between two non-negative metrics.

Sub-groups that work well together

Applying a proper clustering algorithm (for example, stabilized Label Propagation algorithm described in Xie and Szymanski [2013]), you can find two clusterings:

- A clustering found applying the clustering algorithm to the Working Together graph.
- A clustering found applying the clustering algorithm to the Working Well Together graph.[6]

[6]You can freely remove negative weight edges, if it is a problem for your clustering algorithm.

Cluster	Contained workers (originators)
1	TEAM0007, TEAM0008, TEAM0087, TEAM0075, TEAM0044, TEAM0039, TEAM0191, TEAM9999, TEAM0050, TEAM0046, TEAM0057, TEAM0091, TEAM0023, TEAM0127, TEAM0049, TEAM0092, TEAM0052, TEAM0113, TEAM0020, TEAM0097, TEAM0135, TEAM0031, TEAM0069, TEAM0086, TEAM0013, TEAM0059, TEAM0001, TEAM0093, TEAM0033, TEAM0076, TEAM0041, TEAM0132, TEAM0100, TEAM0051, TEAM0094, TEAM0139, TEAM0063, TEAM0088, TEAM0040, TEAM0108, TEAM0042, TEAM0101, TEAM0045, TEAM0085, TEAM0077, TEAM0043, TEAM0121, TEAM0064, TEAM0151, TEAM0047, TEAM0125, TEAM0074, TEAM0128, TEAM0032, TEAM0133, TEAM0131, TEAM0152, TEAM0119, TEAM0137, TEAM0155, TEAM0186, TEAM0192, TEAM0190, TEAM0205, TEAM0207, TEAM0176, TEAM0210, TEAM0187, TEAM0181, TEAM0166, TEAM0143, TEAM0173, TEAM0188, TEAM0185, TEAM0175, TEAM0198, TEAM0202, TEAM0208, TEAM0170, TEAM0222, TEAM0213, TEAM0197, TEAM0221, TEAM0212, TEAM0180, TEAM0219, TEAM0193, TEAM0184, TEAM0214, TEAM0237, TEAM0165
2	TEAM0066, TEAM0004, TEAM0048, TEAM0078, TEAM0134, TEAM0129, TEAM0141
3	TEAM0104, TEAM0058, TEAM0199, TEAM0216, TEAM0241
4	TEAM0014, TEAM0038, TEAM0016, TEAM0102
5	TEAM0018, TEAM0019, TEAM0017, TEAM0123
6	TEAM0025, TEAM0037, TEAM0179
7	TEAM0002, TEAM0003, TEAM0171
8	TEAM0111, TEAM0112, TEAM0028
9	TEAM0010, TEAM0138
10	TEAM0021, TEAM0203
11	TEAM0065, TEAM0182

TABLE I. All clusters found by stabilized Label Propagation algorithm in BPI Challenge 2014 event log, when Working Together metric is applied. Originators (workers) that were not reported are isolated workers (so, they have few connections with other workers, and don't belong clearly to a group). We can see that Cluster 1 is much bigger than others.

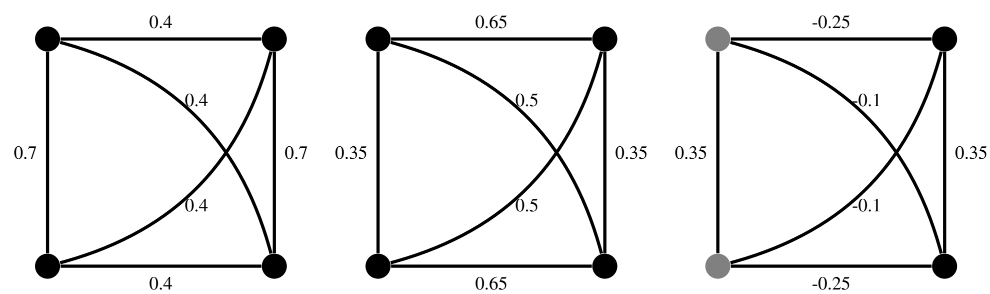

Fig. 1. How Working Well Together metric is calculated on an example log. Graph on the left represent relations among workers measured using Working Together metric on all process instances. Graph in the middle represent relations among workers measured using Working Together metric on proces instances which duration was above Lead Time (which we set to be $avg + k \cdot std$ with $k = 1.5$), so "negative" relations among workers. Relations in the right graph are calculated as the difference between the left graph and the middle graph, so value on edges represent how much "positive" are the relations. Applying stabilized Label Propagation on the left and the middle graph, only a cluster is found (e.g. there is only one work group), while on the right graph two clusters (black and gray coloured), are found. Given we have only one work group in the log, these are the sub-groups of the group that are working well together.

Now, assuming the fact that a cluster found in the Working Together graph is a work group, you can split a work group into sub-groups in the following way, described visually always in Figure 1. Focusing on a work group, sub-groups contains individuals that are clustered together both in the Working Together metric and the Working Well Together metric (roughly speaking, it's an "intersection").

Weak Social Loafing

Weak social loafing (see the Background) is referring to the fact that some individuals inside a work group are working better in small, known, sub-groups than in bigger ones. The workers which have caused (weak) social loafing are called (weak) social loafer.

For seeing whether an individual is a (weak) social loafer, we will define a *loafing index*, and consider as (weak) social loafer an individual with loafing index ≥ 0.

For defining loafing index for a worker i , we need to define two following ancillary sets:

- $N_{WT}(i)$, that is the set of workers in the same cluster, relating to the Working Together metric, of i.

$$N_{WT}(i) = \{i' \mid C_{WT}(i) = C_{WT}(i')\}$$

- $N_{WWT}(i)$, that is the set of workers in the same cluster, relating both to the Working Well and the Working Well Together metric, of i (i.e., workers in the same sub-group).

$$N_{WWT}(i) = \{i' \mid C_{WT}(i) = C_{WT}(i'), C_{WWT}(i) = C_{WWT}(i')\}$$

And then the following ancillary functions:

- $I_{WT}(i)$, i.e. the sum of the weights connecting i to other workers in his sub-group, related to weights measured in the Working Together metric.

$$I_{WT}(i) = \sum_{i' \in N_{WWT}(i)} w_{WT}((i, i'))$$

- $I_{WWT}(i)$, i.e. the sum of the weights connecting i to other workers in his sub-group, related to weights measured in the Working Well Together metric.

$$I_{WWT}(i) = \sum_{i' \in N_{WWT}(i)} w_{WWT}((i, i'))$$

- $O_{WT}(i)$, i.e. the sum of the weights connecting i to workers external to his sub-group, related to weights measured in the Working Together metric.

$$O_{WT}(i) = \sum_{i' \in N_{WT}(i) \setminus N_{WWT}(i)} w_{WT}((i,i'))$$

- $O_{WWT}(i)$, i.e. the sum of the weights connecting i to workers external to his sub-group, related to weights measured in the Working Well Together metric.

$$O_{WWT}(i) = \sum_{i' \in N_{WT}(i) \setminus N_{WWT}(i)} w_{WWT}((i,i'))$$

Then we can define the loafing index for worker i as:

$$LI(i) = \frac{O_{WT}(i) - O_{WWT}(i)}{O_{WT}(i)} - \frac{I_{WT}(i) - I_{WWT}(i)}{I_{WT}(i)}$$

if $O_{WT}(i) \neq 0$ and $I_{WT}(i) \neq 0$, and 0 otherwise.

We can see that the previous quantity is positive if relations outside sub-group are getting weaker in Work Well Together metric than inside relations. One example of Social Loafing is described in Figure 2.

Cohesiveness

We can define a measure of Cohesiveness of a work group taking always in consideration the Working Well graph and the critical graph, defining then a *cohesiveness graph* G_{CH} in which each edge's weight is the maximum between 0 and the difference between weight on the critical graph and on the Working Well graph.

$$w_{CH}((i,j)) = \max\{0, w_{CR}((i,j)) - w_{WT}((i,j))\}$$

This graph is meaningful as the non-zero edges are the ones where the number of "negative" relations is prevalent. We then define a measure of cohesiveness, for each work group W, taking in account the average of the squares of the weights of edges, contained in the work group, on the cohesiveness graph.

$$CH(W) = 1 - \frac{\sum_{(i,j) \in G_{CH}} w_{CH}((i,j))^2}{\sum_{(i,j) \in G_{CH}} 1}$$

We see that the previous measure is high when there are many positive edges. These edges express a situation in which the relationship result to be critical.

Hypothesis testing

Hypothesis 1

We have assessed the ability of Working Well Together measure to find sub-groups working well together on the BPI Challenge 2014 event log, focusing on the first cluster, which contains a very high number of workers. Our algorithm manages to find the following sub-groups:

Sub-group 1: TEAM0008, TEAM0091, TEAM0023, TEAM0049, TEAM0075, TEAM0092, TEAM0052, TEAM0113, TEAM0135, TEAM0031, TEAM0069, TEAM0013, TEAM0001, TEAM0076, TEAM0041, TEAM0132, TEAM0100, TEAM0051, TEAM0039, TEAM0094, TEAM0139, TEAM0040, TEAM0077, TEAM0043, TEAM0064, TEAM0125, TEAM0032, TEAM0131, TEAM0152, TEAM0119, TEAM0137, TEAM0155, TEAM0192, TEAM0190, TEAM0205, TEAM0207, TEAM0176, TEAM0187, TEAM0181, TEAM0166, TEAM0173, TEAM0175, TEAM0198, TEAM0170, TEAM0222, TEAM0213, TEAM0197, TEAM0221, TEAM0180, TEAM0219, TEAM0193, TEAM0184, TEAM0237, TEAM0165
Sub-group 2: TEAM0085, **TEAM0121**, **TEAM0151**
Sub-group 3: TEAM0007, **TEAM0063**
Sub-group 4: TEAM9999, TEAM0074
Sub-group 5: TEAM0050, TEAM0087
Sub-group 6: TEAM0044, TEAM0020

Cluster	No of workers	Instances worked	RTM Stab.	Cohesiveness
A	6	1036	75.26	0.988
B	6	195	63.07	0.639
C	6	1543	22.62	0.603
D	6	148	29.52	0.312
E	6	256	30.22	0.492
F	6	280	22.89	0.581

TABLE II. ASSESSMENT OF OUR COHESIVENESS MEASURE ON A PRIVATE EVENT LOG, FOCUSING ON SIMILAR-SIZE GROUPS (EACH ONE WITH 6 WORKERS). WE CAN SEE THAT THE COHESIVENESS MEASURE IS STRONGLY CORRELATED WITH THE NUMBER OF INSTANCES WORKED AND THE STABILITY OF RELATIVE TRANSACTIVE MEMORY.

Highlighted workers are some of the ones found by our Loafing Index as (weak) social loafers (our algorithm finds the following workers as loafers: TEAM0151, TEAM0063, TEAM0121, TEAM0002), and we can indeed see that they don't belong to the bigger sub-group, but to smaller sub-groups.

We can think that these loafers the main reason the considered cluster does not work as a unit: they are workers that outside their (small) sub-group tend to perform badly.

Hypothesis 2

In Table II we have assessed our Cohesiveness measure on a private event log. We have focused on groups whose common size is of 6 workers. We can see a strong correlation of our Cohesiveness measure with the number of worked instances (by the cluster / group; Pearson correlation is 0.750) and with the stability of Relative Transactive Memory (Pearson correlation is 0.515).

IV. DISCUSSION

Theoretical Implications

In this paper we have defined a framework to calculate a Working Well Together metric, that is different from exhisting metrics (i.e. the Working Together metric defined in Van Der Aalst et al. [2005]) because it takes in accounts also the performance of collaborations between individuals. This framework is important for two main reasons:

- It lets to understand that a big work group is often split in sub-groups of people that effectively work well together; while there some collaborations that work negatively for the organization.
- It lets to find "weak" social loafers.

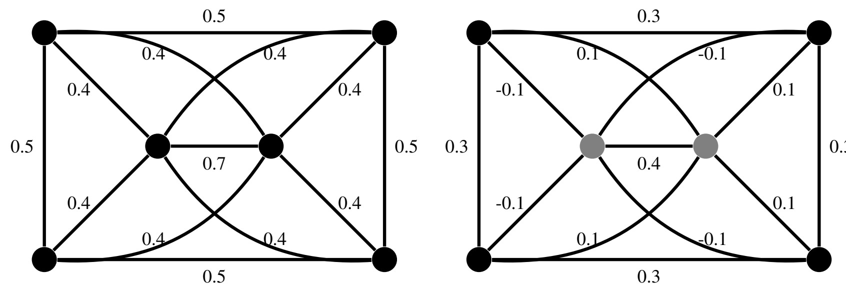

Fig. 2. Social loafing phenomena in a work group. Left graph represent the relations found by applying the Working Together metric. Right graph represent the relations inside the group found in the Working Well Together metric. We can see that the applied clustering algorithm manages to find two different sub-groups inside the work group (the black and the gray one). Worker in the middle-left is a social loafer: it works systematically worse when working outside its sub-group, i.e. without worker in the middle-right.

In particular, we think that the latter point is a positive development, as it extends the concept of loafing from working better individually to working better when working in a small group.

In assessment we have been able to see relation between the introduced Cohesiveness measure and the Stability of RTM. So, having a good Cohesiveness is related to have a clear specialization and coordination in the work group; and good Cohesiveness is related also to performance.

Practical Implications

We find that our framework is useful because:

- It can give a measure of Cohesiveness of all work groups in an organization. This lets to understand which groups are less cohesive than others, and so give an insight on which work groups should be considered in more specific analysis.
- Once you have focused on a work group, it lets you to find sub-groups of people working well together inside the group, and possibly social loafers inside the group, and so you can examine possible conflictual situations inside the work group.

The described methods can be applied to event logs, which themselves help to improve identifiability of workers, so already reducing social loafing effect, in a computable feasible way (all proposed metrics are linear on the number of instances; while there are some very fast clustering algorithms). It is an easy, automatic, type of analysis, that don't require anything other from the event log.

While the methods don't give an insight on how to solve organizational problems, it surely gives information on where (in which groups, for which workers) the problems are.

Study Limitations

The comfort of applying our methods to discover problems inside organizational work groups, starting from event logs, is limited only by the fact that the methods are applicable only to event logs. Unfortunately, only a small part of organizations store automatically informations inside event logs.

Moreover, there are only few public event log, and in our assessment for some reasons we had to split the analysis in two different event logs. The first one (BPI Challenge 2014) is public, so explained results are easily repeatable from you. The second come from a private organizational event log, and results based on it are not repeatable.

It can also be tricky to choose a good threshold for Lead Time. In this paper, we have set Lead Time to be $avg + k \cdot std$ with $k = 1.5$, for compromise reasons, but you can choose a stricter or slender threshold depending on the event log.

Even when you have calculated the relations, you have to use a clustering algorithm to find groups and sub-groups. Although there are several good clustering algorithms (for example, Blondel et al. [2008] and Xie and Szymanski [2013]), clustering is always an ill-defined task and you have to be careful about it.

Conclusions

In this paper, we have introduced a framework to define a novel metric (Working Well Together, WWT), that shows to be useful in identifying, inside work groups, sub-groups that work well together. This has let us to detect the possible social loafing effect inside groups, and also to define a measure of Cohesiveness inside groups. This measure shows to be related both with the ability of cope with workload of the work group, and to the Stability of Relative Transactive Memory.

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