Learning Folksonomies for Trend Detection in Task-Oriented Dialogues

Gregory Moro Puppi Wanderley
Postgraduate Program in Informatics - PPGIa
Pontifícia Universidade Católica do Paraná - PUCPR
Curitiba, Brazil
gregory@ppgia.pucpr.br

Emerson Cabrera Paraiso
Postgraduate Program in Informatics - PPGIa
Pontifícia Universidade Católica do Paraná - PUCPR
Curitiba, Brazil
paraiso@ppgia.pucpr.br

Abstract— **Dialogues are created by the interaction between people, who speak different kinds of topics using natural language. Task-oriented dialogue aims the solution of a given task in a given domain. Folksonomies are knowledge structures composed of users, tags and resources. Folksonomies emerge from the tagging process in collaborative tagging systems. Dialogues and folksonomies have in common their social dimension. One of the main characteristics of the folksonomies is its social dimension (users), which is also presented in dialogues, through the interaction between human beings. In this research, we describe a method that performs the learning of folksonomies, represented by a quadripartite model, from task-oriented dialogues. Using the learned folksonomies, we propose an approach for trend detection (those topics being discussed more than others). The main difference from others approaches is that we use the content of each resource in this process. This can be useful for instance, to retrieve the topics addressed by the interlocutors of the dialogues, in different time intervals. Experiments with a real-world task-oriented dialogue corpus were done.**

Keywords - Folksonomies, Dialogue, Trend Detection.

I. INTRODUCTION

Dialogue is essentially the interaction between speakers and listeners, called interlocutors, composed of utterances. Among the types of dialogues that exist, task-oriented dialogue aims the solution of a given task in a given domain. Such dialogue brings the concise sequence of the solution of a task, based on the request of someone in order to accomplish something, until the solution given by another interlocutor, which may be used to determine the solution path of that task. Task-oriented dialogues have two kinds of interlocutors (see Table I for an example), one asking for help (named *user* in this research) and another with the knowledge of the domain (the *attendant*), aiming to support the former in solving the task. For Traum and Hinkelman [1], one of the main characteristics of task-oriented dialogues is the dissemination of knowledge, i.e., the interlocutor with more knowledge transfers it to the one asking for help [2].

[1] (DOI reference number: 10.18293/SEKE2015-098)

Folksonomies are structures of knowledge representation that emerge from the tagging process in collaborative tagging systems [3]. The tagging process corresponds to the assignment of tags to resources by users. Thus, folksonomies are composed by users, tags and resources. Resources can be any object that users are interested in tag, such as photos and videos. One of the main characteristics of the folksonomies is its social dimension (users), which is also presented in dialogues, through the interaction between human beings.

TABLE I. EXCERPT OF A TASK-ORIENTED DIALOGUE.

Interlocutor	***Utterance***
u_1	Hello, I'd like to ask a question.
a_1	Of course, go ahead!
u_1	How many years of work I need to have in order to ask for retirement?
a_1	According to the constitution, 35 years for a men or 30 years for women.

This research introduces a method to perform the learning of folksonomies from dialogues. We intent to retrieve information from the dialogues, for instance, the topics addressed by people in different time intervals. Trending topics are those topics being discussed more than others.

This article is organized as follows: Section 2 presents the concept of folksonomy. Section 3 describes the method to obtaing a folksonomy from dialogues. Section 4 presents our proposed approach. Experiments and results obtained are shown in Section 5. Finally, conclusions and future work are presented in Section 6.

II. FOLKSONOMIES

Collaborative tagging systems are characterized by the idea of tagging resources or objects through terms or keywords (tags). Such terms are freely created by different users in their own words and serve as reference for a particular resource or object of their interest. Examples of tagging systems and their resources include Delicious (URLs), Flickr (pictures), and last.fm (music). In such systems, users tag resources (URLs, pictures, or music) in order to describe or categorize them [4]. According to [5], tagging systems offer benefits including future information retrieval, contribution and sharing, task organization, expression of opinion, among others.

The structure of knowledge representation that emerges from the tagging process is called a folksonomy [3]. According to Thomas Van der Wal [6], who coined the term "folksonomy," the word is a portmanteau of "folk" and "taxonomy," i.e., taxonomy created by the people.

Folksonomies can be defined using a formal and well-accepted model called the "tripartite model" [7], compounded by three entities – users, tags, and resources – beyond a relationship that connects them. Based on the approach suggested by Schmitz and his colleagues [8], a folksonomy can be defined as a tuple $\mathbb{F} \coloneqq (U, T, R, Y)$, where: U, T, R are the finite sets of users, tags and resources, respectively, and Y is the ternary relation between them, i.e., $Y \subseteq U \times T \times R$. This relation is also called "Tag Assignment."

The "personomy" P_u of some user $u \in U$ is the restriction in $\mathbb{F}$ for u, i.e., $P_u := (T_u, R_u, I_u)$ with $I_u := \{(t, r) \subseteq T \times R : (u, t, r) \in Y\}$. The personomy of a user corresponds to the set of all tag assignments that he/she has generated while tagging a given domain. Based on this, we can infer that a folksonomy is the union of all personomies of all users who participated in tagging the domain in question.

Computationally, folksonomies can be represented by a tripartite graph $G := (V, E)$ composed of users, tags and resources [9]. This graph has the following characteristics:

- The set V of vertices is formed by the three entities users, tags and resources, that is, $V := U \cup T \cup R$;
- An edge $e \in E$ (set of edges) connects two nodes, only if exists a Tag Assignment (a user has assigned a tag to a resource) that correlates them:
  - $\forall u, r\ E_T\ (u, r) \rightarrow \exists t\ Y\ (u, t, r)$ (a tag linking a user to a resource)
  - $\forall u, t\ E_R\ (u, t) \rightarrow \exists r\ Y\ (u, t, r)$ (a resource linking a user to a tag)
  - $\forall t, r\ E_U\ (t, r) \rightarrow \exists u\ Y\ (u, t, r)$ (a user linking a tag to a resource)

So, $E := E_T \cup E_R \cup E_U$.

Figure 1 shows an example of folksonomy. The ternary relationship Y between the entities is represented by the lines connecting them.

The fact that two any tags often appear together tagging the same resources is a sign of the existence of a relationship between them. Thus, in a folksonomy it is possible to associate its tags, such as using the number of resources they have tagged together [10]. In this case, two any tags t_A and t_B have a relationship b between them if and only if they have appeared together (tagging the same resources) at least x times. Moreover, x can be considered to be the weight w in this relationship. Formally, the sentence that defines the existence of the co-occurrence relationship between two tags is given by: $\forall u, r, t_A, t_B \mid (u, t_A, r) \in Y \wedge (u, t_B, r) \in Y \rightarrow b(t_A, t_B) \wedge t_A \neq t_B$.

III. The Learning Method

In this section we present a method for learning folksonomies from task-oriented dialogues. In order to explain better our approach, firstly we present an extension of the formal definition of the tripartite model of Folksonomies.

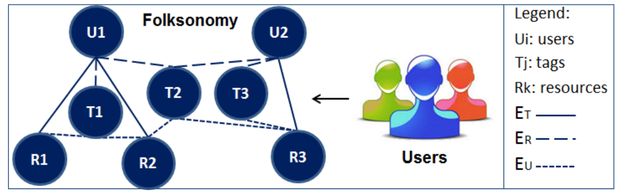

Figure 1. An example of folksonomy.

A. Formal Definition of Folksonomy Obtained from Task-oriented Dialogues

We represent users, tags, and resources of folksonomies as follow: users are "attendants" of task-oriented dialogues, resources are the utterances of attendants, and tags are the nouns of these utterances. Tagging is implicitly carried out according to our conception, i.e., tags assigned to resources are obtained from utterances generated in dialogues. Nevertheless, these utterances (resources) and, consequently, tags (nouns) are created, in this case, by the interlocutors of dialogues. We have chosen to use attendants as the users of folksonomies and their utterances as the resources because we assume that attendants have complete knowledge of a given domain. By contrast, interlocutors of type "user" need help to solve a problem or carry out a task.

According to [11], in order to refer and distinguish between objects, humans use "nouns." This is one reason for using only nouns (instead of verbs, etc.) of the attendants' utterances as tags of the folksonomies. Furthermore, in collaborative tagging systems, users typically use nouns to represent objects, such as "house," "airplane," and "violin." According to [12], in the Delicious system, objects represent the vast majority of tag assignments performed by users and account for 76% of all tags. In terms of nouns as the grammatical class of tags used, this percentage is still higher at 88%.

Now, we present the necessary definitions related to a folksonomy learned from task-oriented dialogues:

Definition 1. A subset of users l belongs to a given attendant a and is composed of all users with whom he/she has dialogued in a given domain. Each attendant has one, and only one, subset of users. Formally, let

- A be the finite set of attendants (a be an attendant belonging to A);
- U be the finite set of users (u be a user belonging to U);
- D be a dialogue corpus (d be a dialogue belonging to D);
- Du be a function Du: $A \times D \rightarrow U$ that returns the user attended by an attendant in some dialogue;
- Ut be the set of utterances of all dialogues.

The subset of users for the attendant a (a is a constant) can then be defined by the predicate l: $\forall d\ ((a, d) \in A \times D) \rightarrow l(Du(a, d))$.

Definition 2. Formally, a folksonomy obtained from task-oriented dialogues can be defined as a tuple $\mathbb{F} \coloneqq (A, T, R, U, Y')$, where

- A is the finite set of the users of the folksonomy. That is, the attendants of the task-oriented dialogues (who have full knowledge of a given domain);
- T is the finite set of tags, which are the nouns of the utterances that attendants have generated in the dialogues;
- R is the finite set of resources of the folksonomy, and consists of the attendants' utterances;
- U is the finite set of users;
- Y' is the quaternary relation among the above, i.e., $Y' \subseteq A \times T \times R \times U$. This relation is also called "tag assignment."

Thus, a folksonomy obtained from task-oriented dialogues is represented by a "quadripartite model" in that it has four dimensions – attendants, tags, resources, and subsets of users – in contrast to the three dimensions of the tripartite model (users, tags, and resources).

The personomy P_a of a given attendant $a \in A$ is the restriction in $\mathbb{F}$ on a, i.e., $P_a := (T_a, R_a, l_a, I_a)$ with $I_a := \forall t, r, u\ I_a(t, r, u) \rightarrow (a, t, r, u) \in Y'$. Intuitively, the personomy of a given attendant corresponds to the set of all tag assignments obtained from utterances produced by the attendant. Based on this, we can infer that a folksonomy is the union of all personomies of all attendants who have participated in the dialogues of a given domain.

We also adopted the notion of "relationship between its tags" as described in Section 2. Any two tags t_A, t_B of a folksonomy will have a relationship $b \in B$ (set of relationships between tags) between them if and only if such tags appear together (tagging the same resources) at least x times. Formally, this is given by the sentence: $\forall a, u, r, t_A, t_B\ b(t_A, t_B) \rightarrow ((a, t_A, r, u) \in Y' \wedge (a, t_B, r, u) \in Y' \wedge t_A \neq t_B \wedge w(t_A, t_B) \geq x)$.

The weight w adopted in this research for the relationship between two tags is the number of dialogues in which the relevant tags have appeared together. It is important to note that for two tags to be considered as appearing together does not require that they be in the same utterance in a given dialogue. These tags may belong to different utterances, but must belong to the same dialogue. The weight w of the relationship between two tags t_A and t_B belonging to T can be defined as a function $w: T \times T \rightarrow \mathbb{N}$, where $\mathbb{N}$ is the set of natural numbers.

B. Learning Folksonomies

The method of learning consists of two steps: preprocessing and learning. It is important to note that this method is based on the principle that utterances in dialogues are identified in the dialogue corpus according to type of the interlocutor (attendants or users) that have generated them. It does not require or use information regarding people (attendants/users) that have generated the dialogues of the corpus.

Firstly, the preprocessing activity receives the dialogue corpus as input and makes it fit for use in the remainder of the process. As shown in Figure 2, the steps that compose preprocessing are "Extract Attendants' Utterances," "Extract Nouns," and "Remove Duplicate Nouns."

"Extract Attendants' Utterances" receives the dialogue corpus and extracts only the attendants' utterances from it. The main purpose of this "filtering" is to forward to the subsequent steps of the method only utterances that represent the relevant domain.

Formally, we can represent obtaining the set of the attendants' utterances as an unary predicate $Ut = \forall a, d, ut\ Ut(ut) \rightarrow (a, d, ut) \in A \times D \times Ut$, where ut is an utterance of the attendant a in a dialogue d belonging to the dialogue corpus D.

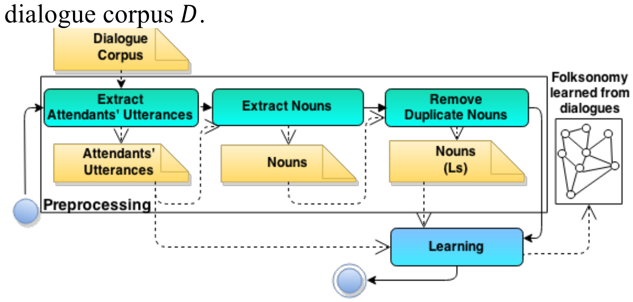

Figure 2. The Preprocessing step.

The next step is "Extract Nouns," which extracts the nouns from the attendants' utterances obtained in the previous step. The purpose of this extraction is to initiate the process of obtaining the nouns that are later converted into tags of the learned folksonomy. The nouns in the attendants' utterances of Ut are identified by a morphological analysis using a parser. Formally, the nouns extracted from Enu can be represented by a multiset (which admits repetitions in its elements) $S := \{\infty . sub : (sub \in ut) \wedge (ut \in Ut)\}$, where sub represents the nouns in the utterances of the attendants.

"Remove Duplicate Nouns" eliminates repetitive nouns from S. The final output of this step, and of the preprocessing stage, is a set Ls of unique nouns. Formally, Ls can be represented by the set $Ls := \{sub : (sub \in S)\}$, where sub is a noun of the multiset S.

The "Learning" activity builds a folksonomy automatically from the dialogue corpus. It consists of the following steps: "Obtain Folksonomy Tags," "Obtain Folksonomy Resources," "Obtain Relationships between Tags," "Obtain Attendants of the Folksonomy," "Obtain Users of the Folksonomy," and "Generate Folksonomy," as shown in Figure 3.

"Obtain Folksonomy Tags" selects nouns from Ls as candidates for tags of the folksonomy. For this, the method performs a "ranking of nouns." The aim of this ranking is to obtain the inverse document frequency (IDF) [13] of each noun of Ls in the dialogues of the dialogue corpus. The nouns ("sub") with IDF values (called "IDFsub") below a threshold frequency fc_1 (see (1)) are discarded. In the context of this research, the IDF represents the importance of each noun of Ls in the dialogue corpus. Moreover, we assume that nouns that have a lower value (are less important) than the threshold represented by fc_1 should not be part of the given domain. Thus, if those nouns are incorporated into the folksonomy as tags, the representation of the domain will be divergent. The nouns that are retained after applying fc_1 are considered part of the domain and are tags of the set T of tags of the folksonomy. Formally the set T can be represented as: $T = \{ sub : (sub \in Ls) \wedge (\text{IDFsub} \geq fc_1)\}$.

$$fc_1 = \frac{\sum_{i=1}^{|Ls|} IDFsub_i}{|Ls|} \qquad (1)$$

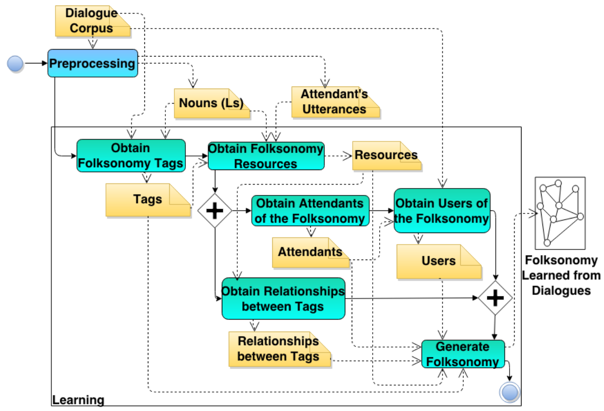

Figure 3. The Learning activity.

"Obtain Folksonomy Resources," obtains the resources (attendants' utterances) of the folksonomy that is being learned. To select the attendants' utterances "ut", which will subsequently become resources, we use tags of the set T (output of the previous step). Given that these tags are nouns belonging to the given domain, we count the number of nouns ("sub") of a given utterance that belong to T, i.e., are tags. The purpose of this is to verify the attendants' utterances that belong to the domain so that these can be adopted as resources. For each utterance, it calculates a Ratio of Inclusion p_{ut} (see (2)). This ratio measures the percentage of nouns of an utterance that are tags of the folksonomy, i.e., those belonging to the domain. Utterances with a Ratio of Inclusion p_{ut}, greater than or equal to p_1 (see (3)) are adopted as folksonomy resources. It is important to note that, we calculate the Ratio of Inclusion only for utterances containing more than one noun. This is because utterances containing only a noun may be generic and therefore may not add any knowledge to the given domain.

$$p_{ut} = \left(\frac{|\{sub : (sub \in ut) \wedge (sub \in T) \wedge (ut \in Ut)\}|}{|\{sub : (sub \in ut) \wedge (ut \in Ut)\}|}\right) \times 100 \quad (2)$$

$$p_1 = \frac{\sum_{i=1}^{|Ut|} p_{ut_i}}{|Ut|} \quad (3)$$

The step "Obtain Relationships between Tags" locates possible relationships between tags that comprise the folksonomy being learned. For this, all possible pairs of tags from the set T are first generated, i.e., a combination C_2^k, where k is the number of tags of T. For each generated pair of tags, we calculate the frequency (*fpar)*, which indicates that the two relevant tags appear to tag the same resources. That is, the pairs of tags with frequencies (*fpar)* lower than fc_2 (see (4)), are discarded. By contrast, pairs of tags with frequencies greater than or equal to fc_2 represent a relationship between members of the pair, and thus will be part of the set B of relationships between tags. Formally, $B := \{b\}$, where b is a relationship between two given tags, and b can be given by: $\forall a, u, r, t_A, t_B$ $b(t_A, t_B) \rightarrow ((a, t_A, r, u) \in Y' \wedge (a, t_B, r, u) \in Y' \wedge t_A \neq t_B \wedge fpar \geq fc_2)$.

$$fc_2 = \frac{\sum_{i=1}^{|C_2^k|} fpar_i}{|C_2^k|} \quad (4)$$

The "Obtain Attendants of the folksonomy" step obtains the set A of attendants of the folksonomy. For each resource of the set R, the method extracts all attendants a, and this forms the set A of the folksonomy. Formally, $A := \{a : (a \in r) \wedge (r \in R)\}$, where $r \in R$.

The step "Obtain Users of the Folksonomy" acquires the set U of users. The set U of interlocutors of type "user" (asking for the assistance of the attendants) is obtained by extracting all interlocutors of type u from the dialogue corpus used as input in the method. Formally, U is obtained as follows: $U := \{u : (u \in d) \wedge (d \in D)\}$, where d is a dialogue of the dialogue corpus D.

The last step is "Generate folksonomy," which generates the final structure of the folksonomy. Given sets A, T, R, U, and B obtained in the preceding steps of the learning activity, the method connects the elements of these sets through the quaternary relation Y' (from Definition 2 in this section). For each element from the set A of attendants, who are the "users" of the proposed folksonomy, we extract their personomies P_a based on Y'. The set of personomies of all attendants represents the folksonomy $\mathbb{F}$, i.e., $\mathbb{F} := (\forall a \in A) \cup \{P_a\}$, where $P_a := (T_a, R_a, l_a, I_a)$ with $I_a := \forall t, r, u\ I_a(t, r, u) \rightarrow (a, t, r, u) \in Y'$. The tags of the personomies are then connected through relationships in set B (relationships between tags).

IV. TREND DETECTION THROUGH FOLKSONOMIES

In our context, trend detection refers to retrieving topics addressed at different time intervals by interlocutors in a dialogue. Trending topics are issues that are being discussed more often than others. The topics detected in a given time interval are retrieved from a folksonomy learned from dialogues in the dialogue corpus belonging only to that particular time interval. Thus, for a sufficiently long period of time, we might have several folksonomies (each learned from dialogues within a given time interval).

Once found, each topic may be compared with topics from other learned folksonomies in order to find common elements. If a given topic appears at different time intervals, i.e., in distinct folksonomies, it can be considered a trend. In other words, this means that interlocutors of the type "user" have been addressing some topic at different time intervals. Furthermore, by ranking each retrieved topic according to the number of dialogues in which it has appeared within a particular time interval, one may retrieve the most discussed topics in a given period of time. It is also possible to verify whether a given topic has gained or lost popularity in different time intervals. This can be accomplished by checking to see whether a given topic has appeared in different folksonomies, and whether it has changed its position in the rankings of those folksonomies.

The main difference from others approaches is that we use the content of each resource in the process. The first step is to divide the dialogue corpus according to time intervals. For this partitioning, the dialogues must either contain information that identifies the period in which they were produced, or they should only be organized in chronological order inside the corpus. The number of partitions can vary, and depends on the time period from which topics are retrieved.

Having partitioned the dialogue corpus, we use each partition as an input to build a distinct folksonomy. We then retrieve from each learned folksonomy topics that were addressed in the dialogues used to learn them. This step is shown in detail in Figure 4, which also shows the content generated by artifacts. The "Retrieve the Topics Addressed" is done using the sets T, U, and R, of tags, users, and resources, respectively. It is important to note that the set U is the result of using a characteristic of task-oriented dialogues, i.e., the interlocutor of type "user," who looks for help to solve a given task (Section 1). For the "Retrieve the Topics Addressed," we need three more definitions:

Definition 3. A "Tag in Focus" is a tag t of folksonomy $\mathbb{F}_d$, which has a number of users ($u \in U$) connected to it.

Definition 4. A "Tag of Context" is a tag t of folksonomy $\mathbb{F}_d$, which is connected to a given Tag in Focus through a relationship $b \in B$.

Definition 5. A "Topic Addressed" is composed of a Tag in Focus, a Tag of Context, and resources ($r \in R$), with the following nomenclature: Tag in Focus + Tag in Context + Resource(s). These resources (i.e., utterances) are resources that both the Tag in Focus and the Tag of Context have marked together. The primary goal of the Tag of Context and the resource(s) is to contextualize the Tag in Focus, thus forming a Topic Addressed. For example, in the airline domain, suppose that the Tag in Focus is "seat," its Tag of Context is "reservation," and resources are available to help contextualize them. According to the definitions, the Topic Addressed would be "seat + reservation + resources." This indicates that users have addressed "seat reservation" in the relevant dialogues.

The Topics Addressed are extracted from a given learned folksonomy in a list h_1 with all the tags ($t \in T$) that it contains. The tags of h_1 are in descending order according to the number of users ($u \in U$) connected to each. In this study, we define interlocutors of type "user" as unique, i.e., each dialogue features a distinct user. It is possible to infer that the number of users connected to some tag is the number of dialogues in which the tag has appeared, with the tag at the top of h_1 being the most used in distinct dialogues. This is to prepare the Topics Addressed for ranking, so that the topics at the top are the most addressed. These tags are named Tags in Focus (Definition 3).

The next step in extracting a Topic Addressed is to obtain the Tags of Context of tags in h_1. This is because if the topics were formed only by the Tags in Focus, they would not accurately describe the Topics Addressed. For example, in the context of human resources, a subject formed only by the Tag in Focus "month" may be related to various topics, such as month of vacation, month of retirement, etc. However, it would not be possible to know which of these topics it would be referring to. Thus, given a Tag in Focus of h_1, the learned folksonomy can help verify the tags ($t \in T$) that have a relationship ($b \in B$) with this Tag in Focus. The tag that has the relationship with the highest weight with this Tag in Focus will be its Tag of Context. The Tags in Focus and their Tags of Context are stored in list h_2.

Following this, for each element in h_2, we retrieve all resources that a given Tag in Focus and its Tag of Context have tagged together. The output is a temporary list of Topics Addressed. The last step in obtaining a Topic Addressed is to remove its duplicates.

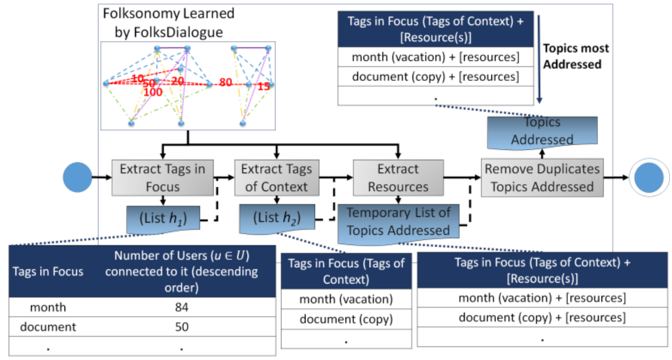

Figure 4. Retrieving Topics Addressed in the trend detection approach.

Once we have obtained the Topics Addressed from each learned folksonomy, the last part of the trend detection method involves verifying the Topics Addressed that have trended over a given time period. Each of the Topics Addressed of a given folksonomy is compared with the Topics Addressed of other folksonomies to see if it appears in them. If a Topic Addressed appears more than once over the given time, it is considered a trend.

V. RESULTS

In order to test our approach we used a dialogue corpus obtained from a City Hall in Paraná, Brazil. It is composed by 901 real task-oriented dialogues written in Brazilian Portuguese from 2006 to 2009. The 901 dialogues consisted of 7,064 utterances involving five interlocutors of type "attendant" and 901 interlocutors of type "user." Since the users are not identified, we suppose that each dialogue involves a different user. The domain is related to human resources. The interlocutors dialogued on issues including retirement, rights of general order, probation, and vacations.
Trend Detection Experiment

In order to test the trend detection method, the corpus was first split into "time intervals." The corpus was arbitrarily chosen to be divided into eight equal parts or eight "time intervals," each representing six months of the corpus. Each of the eight parts was used as an input to the method and generated a distinct folksonomy. The Topics Addressed in each folksonomy were then retrieved, as shown in Table II. A domain expert validated all the Topics Addressed by analyzing whether they were actual topics from the dialogues. For each Topic Addressed the domain expert validated if its resources are related to its Tag in Focus and Tag of Context.

The number of Topics Addressed for each folksonomy varied because each folksonomy was learned from different dialogues taking place at different time intervals. In each period, the attendants that produced the dialogues were different and, consequently, their manner of uttering sentences was distinct.

"Folksonomy II" had only one Topic Addressed, likely because of the manner in which attendants uttered their sentences in that particular time interval. For instance, comparing "Folksonomy I" with "Folksonomy II," the former is composed of 192 tags and 106 resources and the latter of 168 tags and a mere 64 resources. This is because the terms used by the attendants in the utterances used for the learning of "Folksonomy II" were not considered important by the IDF (by the Obtain folksonomies Tags step). The likelihood of some utterance becoming a resource in a folksonomy is small when it has few tags and, consequently, the probability of a relationship ($b \in B$) between two tags is small as well.

Following the retrieval of the Topics Addressed for all time intervals, we looked for possible trends in these intervals, i.e., whether a Topic Addressed appeared in different time intervals.

TABLE II. TOPICS ADDRESSED RETRIEVED FROM FOLKSONOMIES.

Folksonomy	*# of Topics Addressed*	*Folksonomy*	*# of Topics Addressed*
I	11	*V*	39
II	1	*VI*	67
III	14	*VII*	49
IV	34	*VIII*	63

We found that 39 Topics Addressed were repeated over time. Table III shows a few of the Topics Addressed that became trends. The Topic Addressed "Registration" + "Problem" + "resource(s)" appeared in three time intervals (represented by Folksonomies I, III, and VII). This means that in dialogues, users reported registration problems in the first six months of 2006 (dialogues of Folksonomy I), 2007 (Folksonomy III), and 2009 (Folksonomy VII). This Topic Addressed could be useful to advise someone of the recurring problem. Another example is the Topic Addressed "Classification" + "Career" + "resource(s)", which is about classification in the process of admission in the enterprise of the given human resource. This topic appears in the first semesters of 2007 and 2009, which are probably the periods of the selection for new employees.

TABLE III. AN EXCERPT OF TOPICS ADDRESSED RETRIEVED FROM FOLKSONOMIES.

Trend (Topic Addressed)	*Folksonomies Containing Trends*
"Registration" + "Problem" + "resource(s)"	I, III, VII
"Son" + "birth" + "resource(s)"	IV, VIII
"Classification" + "Career" + "resource(s)"	III, VII
"Test" + "Application" + "resource(s)"	VI, VII

VI. CONCLUSION AND FUTURE WORK

In this research we propose a method to perform the learning of folksonomies, from task-oriented dialogues, represented by a quadripartite model. Computationally, the folksonomies generated by the proposed method are represented by graphs. We also proposed an approach for trend detection, which can be useful, for instance, to retrieve the topics addressed by the interlocutors of the dialogues, in different time intervals.

Through an experiment with a real-world task-oriented dialogue corpus, we could see that it is possible to retrieve information and detect trends over time in a dialogue corpus.

In the near future, we intend to deal with some natural language enhancement, such as abbreviations and correcting spelling errors. Even if we do not found a different dialogue corpus to test our approach, we intend to do so. Moreover, in relation to the trend detection approach, a future work that can be done is a *concept drift* [14] study. Given the fact that there is no guarantee about the behavior of users in the dialogues and consequently stability in the extracted trends (as they can change at any moment of time), this may result in inconsistencies in folksonomies learned with data from different periods of time. Thus, it may be important to study the problem and techniques to identify concept drift in order to avoid such inconsistencies.

REFERENCES

[1] D. R. Traum, E. Hinkelman, "Conversation acts in task-oriented spoken dialogue." *Computational Intelligence. Special Issue on Non-literal Language*, 8(3), 1992.

[2] J. Carletta, A. Isard, S. Isard, J. C. Kowtko, G. Doherty-Sneddon, and A. H. Anderson, "The reliability of a dialogue structure coding scheme." *Computational Lingustics*, 23(1), 1997, pp. 13–31.

[3] I. Peters, "Folksonomies: Indexing and retrieval in Web 2.0," De Gruyter Saur, ISBN-10: 3598251793, 2009.

[4] C. Körner, D. Benz, A. Hotho, M. Strohmaier, and G. Stumme, "Stop Thinking, Start Tagging: Tag Semantics Emerge from Collaborative Verbosity." In *Proc. of the 19th International Conference on World Wide Web*, 2010, pp. 521–530.

[5] M. Gupta, R. Li, Z. Yin, and J. Han. "Survey on social tagging techniques." *SIGKDD Explor*, vol.12, 2010, pp. 58-72.

[6] T. Van der Wal, "Folksonomy Coinage and Definition". *Website: <http://vanderwal.net/folksonomy.html>* Accessed: 10 mar. 2015.

[7] P. Mika, "Ontologies are us: A unified model of social networks and semantics." *Web Semantics: Science, Services and Agents on the World Wide Web*, 5(1), 2007, pp. 5–15.

[8] C. Schmitz, A. Hotho, R. Jäschke, and G. Stumme, "Mining Association Rules in Folksonomies." In *Lecture Notes in Computer Science - The Semantic Web: Research and Applications*.Vol. 4011, 2006, pp.411–426.

[9] S. Chojnacki, and M. Klopotek, "Random graph generative model for folksonomy network structure approximation". *Procedia Computer Science*, 1(1), 2010, pp. 1683-1688.

[10] G. Belgeman, P. Keller, and F. Smadja, "Automated Tag Clustering: Improving search and exploration in the tag space." In *Collaborative Web Tagging Workshop at WWW'06*, 2006, pp. 15-33.

[11] D. W. Embley and B. Thalheim, "Handbook of concept modeling: Theory, practice, and research challenges." *Springer*, ISBN: 978-3-642-15865-0, 2011, p. 226.

[12] L. Spiteri, "The Structure and form of folksonomy tags: The road to the public library catalogue." *Information Technology and Libraries*, 27(3), 2007, pp. 13-25.

[13] G. Salton, and C. Buckley. Term-weighting approaches in automatic text retrieval. *Information Processing and Management* 24, 5, 1988, pp. 513–523.

[14] A. Tsymbal, "The problem of concept drift: definitions and related work." *Technical Report TCD CS-2004-15*, Computer Science Department, Trinity College, Dublin. 2004.