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Fine-Grained Context-aware Ad Targeting on Social Media Platforms

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***Abstract*—One of the most important sources of revenue for social media platforms, like, Twitter, Facebook, Reddit, etc., is advertising. An effective social media advertising plan moves people from awareness and interest in desire and action. Despite the potentiality, campaigns and marketing strategies should be improved. One of the challenges is to identify the right target audience at the right time, considering both communities of interests and locations and the development of these conditions along the timeline. This is crucial to create the right communication strategy and the right advertising message. This paper proposes a context-aware ad-targeting methodology using time, locations, and inferring users' interests by analyzing published content. The method relies on a fuzzy extension of Triadic Formal Concept Analysis for identifying Location-based and Content-based communities of users. Then, a task of community fusion takes place, named Join, for matching a target audience. The matching may be tuned for identifying a wide or narrow community and implementing a fine-grained ad targeting. Experimental results are given.**

***Index Terms*—Triadic Formal Concept Analysis, Ad Targeting, Location-based Systems, Information Granularity**

I. Introduction

Social media spread is considered as an opportunity in terms of targeted advertising. Users' tendencies, habits, and routines can guide sophisticated methods aiming to minimize waste advertising and reach as many interested customers as possible. Social networks enable customers' analysis in terms of check-in time, location, and post contents. These features are crucial in most of the recommendation scenarios, from mobile marketing to disaster relief.

Existing approaches either recommend contents that match users' interests [1], [2], [3], or recommend contents based on high social popularity [4], [5]. Context-aware solutions that consider users' needs, temporal, and spatial dimensions are considered the most promising ones. On this line, in Ref. [6], authors adopt a context-aware advertisement recommendation framework on social networks aiming to discover the most relevant advertisements for users. Besides, as explained in [7], efficient communication must be achieved based on a proper understanding of the audience's needs.

Triadic Formal Concept Analysis (TFCA) [8] is suitable for extracting the internal relationships among objects, attributes, and conditions at different information granularity levels. In this research, the proposed method adopts a fuzzy extension of TFCA for ad-targeting on Twitter. The need to adopt a fuzzy methodology [9] for representing Triadic Formal Context is for managing the uncertainty of the real world about users' position and the ambiguity of text of the tweet content. More in detail, TFCA is performed two times. The first time, objects, attributes, and conditions are respectively users, locations, and check-in time. The resulting triadic lattice reveals location-based community of users [10]. The second time, objects, attributes, and conditions are respectively users, tweets topics, and check-in time. In this case, the extracted triadic lattice uncovers a hierarchy of concepts of semantics-based community of users in dependence of tweets content and the corresponding time dimension. Finally, location- and semantics-based triadic lattice are joined to identify a fine-grained Ad targeting.

Regarding tweets' content analysis, leveraging the DBpedia Spotlight service enables text disambiguation by annotating natural language mentions with DBpedia resources (i.e., URI) [11], [12]. In particular, DBpedia associates a sense to main concepts and named entity contained in the tweet with a corresponding disambiguation weight based on specific similarity metrics. Then, adopting the fuzzy Triadic Formal Concept Analysis to convert tweets into time-dependent triadic concepts in a hierarchical way. Finally, fuzzy Triadic Formal Concept Analysis concepts are merged by means of specific metrics.

The paper is structured as follows: Section II describes the motivation of this research work; the theoretical background (i.e., the fuzzy Triadic Formal Concept Analysis) is described in Section III; Section IV describes the main phases of the proposed methodology: *Semantic Annotation*, *Concept Data Analysis*, and *Ad Targeting Model*, which will be described in Sections V, VI, and VII, respectively; experiments aiming to evaluate the proposed approach on a real-world Twitter data are detailed in Section VIII, and finally, Section IX concludes the work.

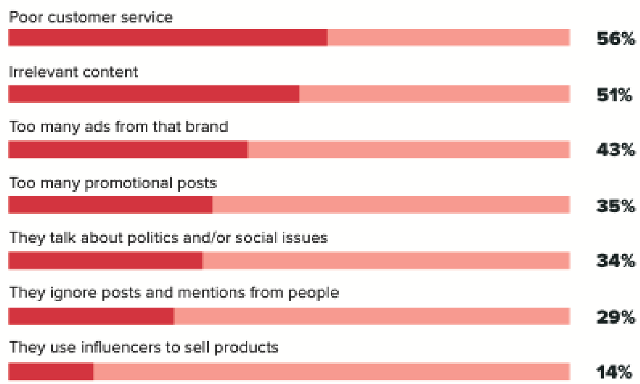

Fig. 1. Why consumers unfollow brands on social media - https://sproutsocial.com/

II. Motivations

Why is it crucial to select the right Ad Targeting?

The latest Sprout Social Index [1], published in 2019, highlights the data on users' perceptions against brands and their presence on social networks. Furthermore, they are to be considered a useful guide for the setting of a social network ad strategy.

As a result, despite the immense potential promotional offered by the Internet, campaigns and marketing strategies do not always seem to be right. In essence, the consequence of these operations often leads to indifference or discomfort of the user. It is helpful to understand what brands do or say on social media that turn consumers away. Analyzing the Sprout Social Index Report, as we can see in Figure 1, for 51% of users, one of the primary reasons they stop following a brand is lack of relevant information, following, by posting the excessive amount of advertising content, 43%. From the research data, it transpires that it is essential to know the target audience, it cannot just define the brand type target, but it needs to deepen as much as possible the audience to capture as much detail as possible. So, it follows one of the major challenges that is to identify and understand the target audience. Details such as interest and geographical area of origin can be acquired; conversations that have created or participated in a brand or products/services can be intercepted. By collecting all these data, a series of extensive and useful details are obtained in order to define the public in a precise manner. We aim to address the Ad-Targeting problem by modeling Twitter users' interests and locations to a different granularity level through the Fuzzy Triadic Formal Concept Analysis. In this way, we can identify a wide or narrow community and implement a fine-grained ad targeting according to Advertiser requirements.

[1]Sprout Social offers deep social media listening and analytics, social management, customer care, and advocacy solutions to more than 25,000 leading brands and agencies -https://sproutsocial.com/

III. Fuzzy Triadic FCA: Theoretical Background

The formal model behind the proposed Ad Targeting methodology is the fuzzy extension of Triadic Formal Concept Analysis (briefly, Fuzzy TFCA). In particular, Fuzzy TFCA incorporates fuzzy logic into TFCA, representing the uncertainty through membership values in the range [0, 1]. The proposed context-aware Ad Targeting considers users' posts, check-in locations, and the time dimension. To tackle uncertainty and ambiguity of such kind of features, we propose a method that relies on the fuzzy extension of Triadic FCA. Fuzzy TFCA deals with fuzzy relations between objects (i.e., users), their features (e.g., topics, locations, and so on) and timing, considering membership varying in [0,1], instead of binary relation of traditional TFCA. So it allows us to specify more or less relevant features enabling the granular representation of them.

Following, some definitions of Fuzzy TFCA are given [13].

Definition 1. A Fuzzy L-Triadic Formal Context is a quadruple $\langle G, M, Z, I\rangle$ where G, M, and Z non-empty sets, are a set of objects, attributes, and conditions, respectively; and $I : G \times M \times Z \rightarrow L$, is a fuzzy relation, such that each triple $(g, m, z) \in G \times M \times Z$ has a membership value $\mu_I(g, m, z)$ in $[0, 1]$. In particular, $\langle g, m, z\rangle \in I$ is interpreted as the degree to witch object g has attributes m under condition z.

For convenience, a triadic fuzzy context K is denoted by $\langle X_1, X_2, X_3, I\rangle$.

Definition 2. For every $\{i, j, k\} = \{1, 2, 3\}$ and a fuzzy set $C_k \in L^{X_k}$, a triadic L-context $K = \langle X_1, X_2, X_3, I\rangle$ induces a dyadic L-context (formal context) $K^{ij}_{C_k} = \langle X_i, X_j, I^{ij}_{C_k}\rangle$ by

$$I^{ij}_{C_k}(x_i, x_j) = \wedge_{x_k \in X_k}(C_k(x_k) \rightarrow I\{x_i, x_j, x_k\} \quad (1)$$

for every $x_i \in X_i$ and $x_j \in X_j$. The concept-forming operators induced by $K^{ij}_{C_k}$ are denoted by ${}^{(i,j,C_k)}$. That is, for a fuzzy set C_i in X_i, we define a fuzzy set $C_i^{(i,j,C_k)}$ in X_j by

$$C_i^{(i,j,C_k)}(x_j) = \wedge_{x_i \in X_i} C_i(x_i) \rightarrow I^{ij}_{C_k}\{x_i, x_j\} \quad (2)$$

Similarly, for a fuzzy set C_j in X_j, we define a fuzzy set $C_j^{(i,j,C_k)}$ in X_i by

$$C_j^{(i,j,C_k)}(x_i) = \wedge_{x_j \in X_j} C_j(x_j) \rightarrow I^{ij}_{C_k}\{x_i, x_j\} \quad (3)$$

A triadic fuzzy concept of $\langle X_1, X_2, X_3, I\rangle$ is a triplet $\langle C_1, C_2, C_3\rangle$ consisting of fuzzy sets $C_1 \in L^{X_1}$, $C_2 \in L^{X_2}$, and $C_3 \in L^{X_3}$, such that for every $i, j, k = 1, 2, 3$ we have $C_i = C_j^{(i,j,C_k)}$, $C_j = C_k^{(i,k,C_i)}$, and $C_k = C_i^{(k,i,C_j)}$. In this case, C_1, C_2, and C_3 are called the extent, intent, and modus of $\langle C_1, C_2, C_3\rangle$.

The set of all triadic concepts of $K = \langle X_1, X_2, X_3, I\rangle$ is denoted by $\tau(X_1, X_2, X_3, I)$ and is called the *concept trilattice* of K.

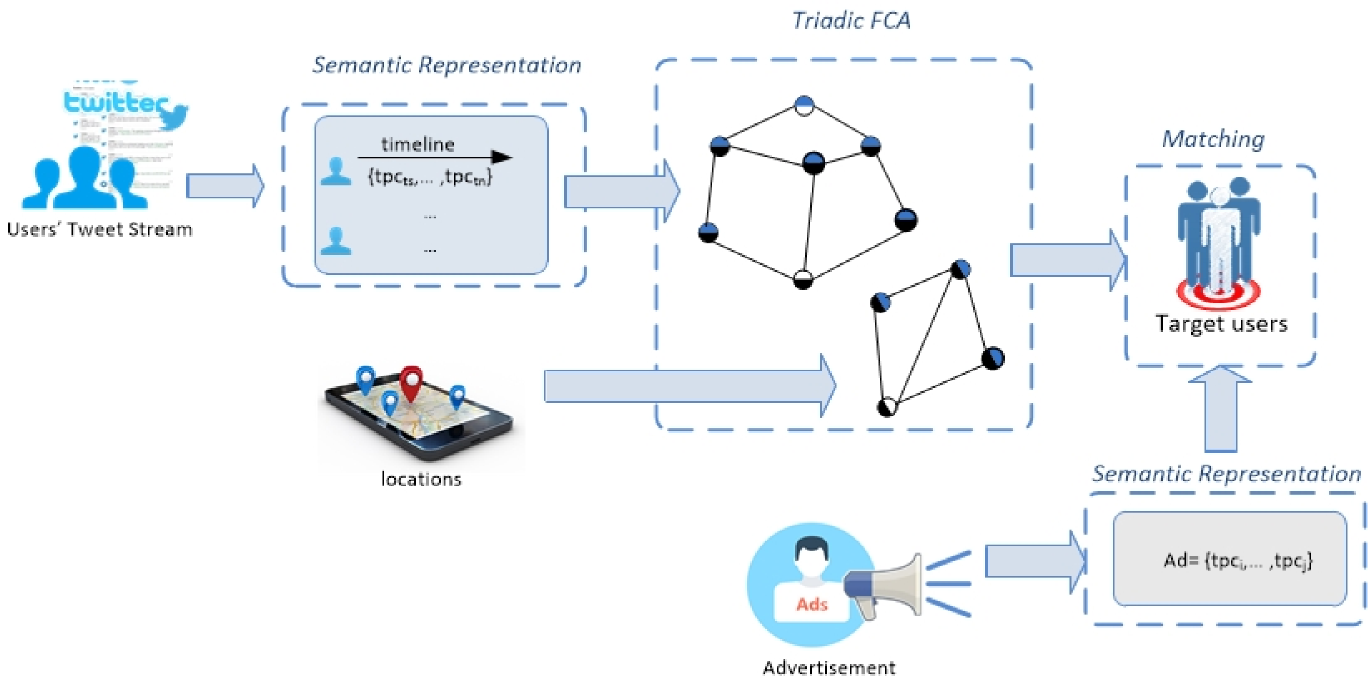

Fig. 2. Overall Approach

IV. Overall Approach

The paper proposes a fine-grained Ad-Targeting model based on users' context (i.e., tweets, locations, and time). Specifically, the model defines a fuzzy Triadic Formal Concept Analysis methodology designed to perform a context-aware (content, spatial, and temporal) tweets analysis. The model, shown in Figure 2, consists of three macro-phases:

- *Semantic Annotation*. This phase automatically annotates mentions of DBpedia resources in the text (i.e., tweet stream or advertisement).
- *Concept Data Analysis*. The fuzzy triadic formal concept analysis application is used to discover the location and content-based community of users on Twitter during the timeline.
- *Ad Targeting Model*. Given the explored community and a specific advertisement, the methodology examines the data and selects the highest number of target users interested in at a given location and time.

V. Semantic Annotation

The Semantic Annotation phase means the knowledge extraction from the unstructured text, by exploring a commonsense knowledge available in DBpedia[2]. In particular, we use the DBpedia Spotlight API for automatically annotating tweets' contents in natural language with DBpedia URIs (Linked Open Data in DBpedia). Thus, from each tweet, it extracts a pair $< URI,\ score >$ corresponding to a DBpedia resource (i.e., URI) and its semantic relation (i.e., $score$), in the range $[0, 1]$, with the referring entity's in the tweet.

[2]https://www.dbpedia-spotlight.org/

For instance, consider the next post:
"The Greatest Day Ever! Music Festival and Carnival 2019 lineup is here! Tickets on sale this friday".

The Semantic Annotation step elicits a set of URI characterizing the text's meaning, from the above tweet text:

- "URI": "http://dbpedia.org/resource/Greatest_Day_(Take_That_song)", "score":"0.96";
- "URI": "http://dbpedia.org/resource/Carnival", "score":"0.966";
- "URI": "http://dbpedia.org/resource/Music_festival", "score":"0.998";
- "URI": "http://dbpedia.org/resource/Ticket_(admission)", "score":"0.732";
- "URI": "http://dbpedia.org/resource/Sales", "score":"0.753".

So, for each $tweet_i$, the text will be annotated via DBpedia Spotlight as:

$$tweet_i = \{ \langle URI_1, score_1 \rangle, \langle URI_2, score_2 \rangle, \ldots, \langle URI_n, score_n \rangle \}.$$

The goal is adopting a vector representation of each tweet and exploiting it to construct the matrix describing the fuzzy triadic formal context. This matrix will show the relationships (in terms of score values) between extracted topics (i.e., URIs), time, and tweets in the application domain.

VI. Concept Data Analysis

The Concept Data Analysis phase is applied to elaborating on the implementation details of location and content-aware Ad Targeting on Twitter. Using the fuzzy Triadic FCA theory, location-based and content-based community are identified by analyzing the user's tweet stream.

TABLE I
CONSTRUCTED TRIADIC FORMAL CONTEXT OF USER' CHECK-IN DATA BETWEEN t_1 AND t_4: $H_1 = (U, M, T, I)$, WITH $\alpha > 0.6$

	t_1					t_2				
	m_1	m_2	m_3	m_4	m_5	m_1	m_2	m_3	m_4	m_5
U_1	1.0	0	0	0	0	1.0	0	0	0	0
U_2	0	0.8	0	0	0	0	0.8	0	0	0
U_3	0	0	0	0	1	0	0	0	0	1
U_4	0	0	0	0.8	0	0	0	0	0.8	0
U_5	0	1	0	0	0	0	1	0	0	0
U_6	0	0	0	0	1	0	0	0	0	1

	t_3					t_4				
	m_1	m_2	m_3	m_4	m_5	m_1	m_2	m_3	m_4	m_5
U_1	1	0	0	0	0	0	0	0	0	0.7
U_2	0	0	1	0	0	0	0	1	0	0
U_3	0	0	0	0	0.75	0	0	1	0	0
U_4	1	0	0	0	0	1	0	0	0	0
U_5	0	1	0	0	0	0	1	0	0	0
U_6	0	0	0	0	1	0	0	0	0	1

A. *Construction of fuzzy TFCA for users' check-in data*

Given the users' check-in data, let users, locations, and time, the objects, attributes, and conditions of the fuzzy triadic FCA. Formally, it is defined as:

$$H_1 = (U, M, T, I) \tag{4}$$

where I refers to the distance d among user's check-in, locations M as well as check-in times T. Furthermore, each location is defined as $\langle longitude, latitude \rangle$, which can be utilized to evaluate the distance among locations. Let two locations $l_1 = (lon_1, lat_1)$ and $l_2 = (lon_2, lat_2)$ their distance, denoted as d_{l_1,l_2}, is calculated as follows:

$$\begin{aligned} d_{l_1,l_2} = R * \arccos [\sin Lat_1 * \sin Lat_2 + \\ + \cos Lat_1 * \cos Lat_2 * \cos (Lon_2 - Lon_1)] \end{aligned} \tag{5}$$

where R is the radius of the earth ($R = 6371km$) and lat and lon are latitude and longitude, respectively.

Example 1. Given a user's tweet stream along the timeline between t_1 and t_4, that includes 6 users $U = \{u_1, u_2, \cdots, u_6\}$, and 5 locations $M = \{m_1, m_2, \cdots, m_5\}$, its corresponding triadic formal context (as a $[0, 1]$ matrix) is shown in Table I, where all relationships with membership values lesser than the threshold $\alpha = 0.6$ are not shown.

Clearly, a value close to "1" means that a user visited a location near its position; on the contrary, a value close to "0" means that it is far from its position. So, given a location $m \in M$, the triadic concepts where the attribute is m, termed *m-triadic* concepts, are represented as

$$TC(m) = (U, m, T) \tag{6}$$

So, given a set of users' check-ins H and a location m, the problem on dynamic detection of location-based communities (termed $Comm(H, m)$) is converted into obtaining m-triadic concepts from the triadic lattice extracted from the user's tweet stream in t_1 and t_4 (termed $P_m(H)$) data.

$$Comm(H, m) \equiv P_m(H) \equiv TC(U, \{m\}, T) \tag{7}$$

The working process to identify the $Comm(H, m)$ is shown in Algorithm 1.

Input: A set of check-ins data H and a given location m
Output: A set of location-based communities Comm(H,m)

1 $Comm(H, m) = \Phi$;
2 **Begin**
3 Construct a triadic formal context $H_1 = (U, M, T, I)$;
4 Build a concept lattice, given a threshold α;
5 **end**
6 **for** each triadic concept (U, M, T)
7   **Begin**
8   **if** $M = \{m\}$
9     $Comm(H, m) \leftarrow Comm(H, m) \cup M$
10   **end**

Algorithm 1: Algorithm for location-based communities detection

The algorithm is working as follows. It takes a set of check-ins data H and a given location m as input; then, a set of location-based online communities $Comm(H, m)$ is initialized (Line 1). After the algorithm's initialization, it enters into the triadic formal context construction of check-ins data (Lines 2, 3). Line 4 builds the corresponding concept lattice, taking in input all relations, in the triadic formal context, whose membership values are higher than a threshold α. The m-triadic concepts extraction and their insertion into the $Comm(H, m)$ are done through Lines 6–10.

B. *Construction of fuzzy TFCA for users' tweets*

The fuzzy triadic FCA for users' tweets content termed TFC, is composed of three dimensions, users, topics, and time (i.e., objects, attributes, and conditions, respectively). Formally,

$$TFC = (U, URIs, T, I) \tag{8}$$

where I corresponds to the $score$ extracted by Semantic Annotation phase, indicating the triple fuzzy relationships between users U, topics $URIs$ and time T [14].

Example 2. Let us assume to have a user's tweet stream between t_1 and t_2, including 6 users $U = u_1, u_2, \ldots, u_6$, and 5 topics $URIs = URI_1, URI_2, \ldots, URI_5$. Table II represents the corresponding triadic formal context, where all relationships with membership values lesser than a threshold $\alpha = 0.6$ are not shown.

Analogously to the detection of location-based communities, Algorithm 2 is defined to perform the content-based users' communities detection (i.e., $Comm(TFC, uri)$) . Therefore, given the user's tweet stream, a set of triadic concepts are extracted. It is formalized as follows.

$$Comm(TFC, uri) \equiv TC(U, \{uri\}, T) \tag{9}$$

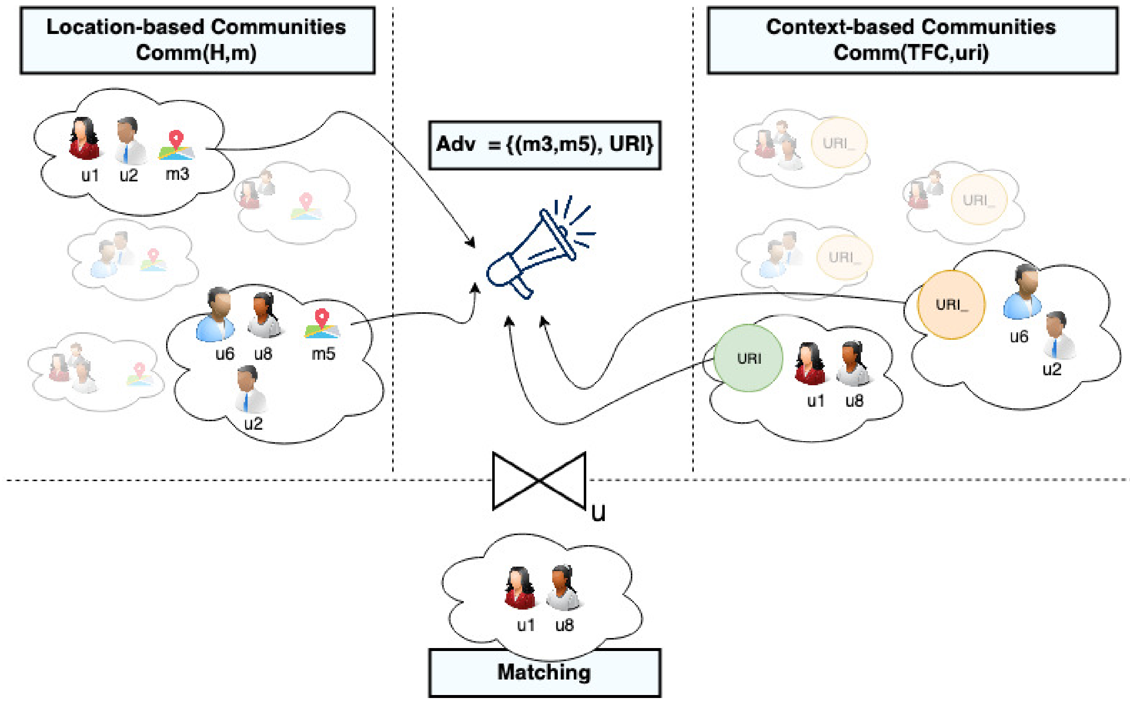

Fig. 3. Ad Targeting Model

TABLE II
CONSTRUCTED TRIADIC FORMAL CONTEXT OF USER' TWEET STREAM BETWEEN $t1$ AND $t2$: $(U, URIs, T, I)$, WITH $\alpha > 0.6$

	t_1				
	URI_1	URI_2	URI_3	URI_4	URI_5
U_1	1.0	0	0	0	0
U_2	1.0	0	0	0	0
U_3	0	0	0.9	0	0
U_4	0	1.0	0	0	0
U_5	0	0	0	0	1.0
U_6	0	0	0.7	0	0

	t_2				
	URI_1	URI_2	URI_3	URI_4	URI_5
U_1	1.0	0	0	0	0
U_2	0	0	0	0.8	0
U_3	0	0	0.8	0	0
U_4	0	0	0	0	0.75
U_5	0	0	0	0	0.8
U_6	0	0	1.0	0	0

Input: A set of users U and a topic $\{uri\}$.
Output: A set of content-based communities Comm(TFC,uri)

```
1   Comm(TFC, uri) = Φ;
2   Begin
3   Construct a triadic formal context
    TFC_1 = (U, URI_s, T, I) ;
4   Build a concept lattice, given a threshold α ;
5   end
6   for each triadic concept (U, URI_s, T)
7     Begin
8       if URI_s = {uri}
9       Comm(TFC,uri) ← Comm(TFC,uri) ∪ URI_s
10    end
```

Algorithm 2: Algorithm for content-based community detection $Comm(TFC, uri)$.

Given a topic $\{uri\}$ as input U, the set $Comm(TFC, uri)$ (Line 1) is initialized; then, the algorithm proceeds with the construction of the triadic formal context URI_s (Lines 2 - 3). The corresponding concept lattice (Line 4) is then built, considering only the relations whose membership values are higher than a threshold α. Finally, triadic concepts are joined to the set $Comm(TFC, uri)$ (Lines 6 - 10).

VII. AD TARGETING MODEL

Given an Advertisement, the Ad Targeting model aim is to reach the Target audience. Formally, let the Advertisement context defined by the set of location m^*, timing t^*, and concepts (i.e., DBpedia URIs) P. The model assures matching the Advertisement context and Twitter users.

The main activities of the model, illustrated in Figure 3, are:

- *Location-based Communities (U-L) matching*: evaluates the intersection between each location m^* in the Advertisements context, and the location-based Communities $Comm(H, m)$ at a given time. Formally, the intersection is defined as:

$$TC_{m*} = \bigcup_{\forall m^*} Comm(H, m^*) \tag{10}$$

- *Context-based Communities (U-C) matching*: evaluates the intersection between each URI in the Advertisement, and the Content-based User Communities $Comm(TFC, URI)$ at a given time. Formally, the intersection is:

$$TC_{URI} = \bigcup_{\forall URI \in P} Comm(TFC, URI) \quad (11)$$

- *Cross Join*: returns an ordered list of users, according to the filtering and ranking criteria. More formally, for each pair of the Cartesian product:

$$TC_{URI} \times TC_{m^*} = \{(a, b) | a \in TC_{URI}, b \in TC_{m^*}\} \quad (12)$$

where $a = (C_{1a}, C_{2a}, C_{3a})$ and $b = (C_{1b}, C_{2b}, C_{3b})$, that are two triadic formal concepts (see Definition 2), we measure the matching degree:

$$w(a, b) = \frac{|C_{1a} \bigcap C_{1b}|}{|C_{1a} \bigcup C_{1b}|} \quad (13)$$

This matching measures the overlap degree, in terms of users, between the two communities.

The final result of this computation is the list of the w values for each couple. By ordering w, we select communities that maximize the probability of taking the highest number of people interested in the specific "Adv". We assume that people who share interests and locations are more tendentially oriented to make the same consumer choices.

VIII. Experimental Results

To evaluate the performance of the proposed methodology, we conduct experiments by adopting real-world Twitter data.

We acquired the tweets by using the Twitter API[3]. In particular, for three months [September – November 2019], we collect about 450.000 tweets posted from 15.000 users, and we selected 15 tweets as advertising.

Given an Adv "A", time slot t, and location m, let us introduce two sets:

- Ground truth of users, $U^* = u_1^*, u_2^*, \ldots, u_m^*$, interested to "$A$" at time t in location m, manually selected from the tweet stream;
- Inferred users, $\tilde{U} = \tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n$, retrieved by joining the triadic concepts belonging to set TC_{URI} and TC_{m^*}, via $\bowtie_u$.

The performance were evaluated in terms of Precision and Recall measures as follows:

$$Precision_t = \frac{\left|U^* \bigcap \tilde{U}\right|}{\left|\tilde{U}\right|} \quad (14)$$

$$Recall_t = \frac{\left|U^* \bigcap \tilde{U}\right|}{|U^*|} \quad (15)$$

Figure 4 shows the results of Precision and Recall for two time slots, morning (i.e., [01:00am – 08:00am]), and afternoon (i.e., [01:00pm – 08:00pm]). with different values of the threshold $\alpha \in [0.0, 1.0]$. Let us note that by varying the threshold α, the users set results differ for both location and content based communities (see subsection VI-B).

As shown in Figure 4, the best performance of Precision and Recall are obtained with a threshold $\alpha \in [0.6, 0.8]$ in the afternoon, $[01 : 00pm - 08 : 00pm]$. This is due to the availability of more tweets posted by users in the afternoon that enables the system to better understand users interests.

[3]Twitter Streaming APIs: https://dev.twitter.com/streaming/overview

IX. Conclusion

This paper proposes a fine-grained ad-targeting methodology on Twitter using time, locations, and inferring users' interests by analyzing published tweets. The methodology relies on the theoretical model of Triadic Formal Concept Analysis. Fuzzy extension of TFCA allows to manage the uncertainty of the real world about users' position and the ambiguity of text of the tweet content. Two executions of TFCA are orchestrated for extracting location-based and content-based communities of users. Finally, a cross join operation is defined to carry out targeting audiences that fits better the advertisement topics and location.

The experimental results reveal good performance on a collected tweets dataset. The best performance is achieved in the afternoon due to the availability of richer tweets set for classifying users' interests. Future works will be aimed at generalizing the proposed approach by applying it to a different social media and by collecting more contextual features for improving the matchmaking between ad and users.

Acknowledgment

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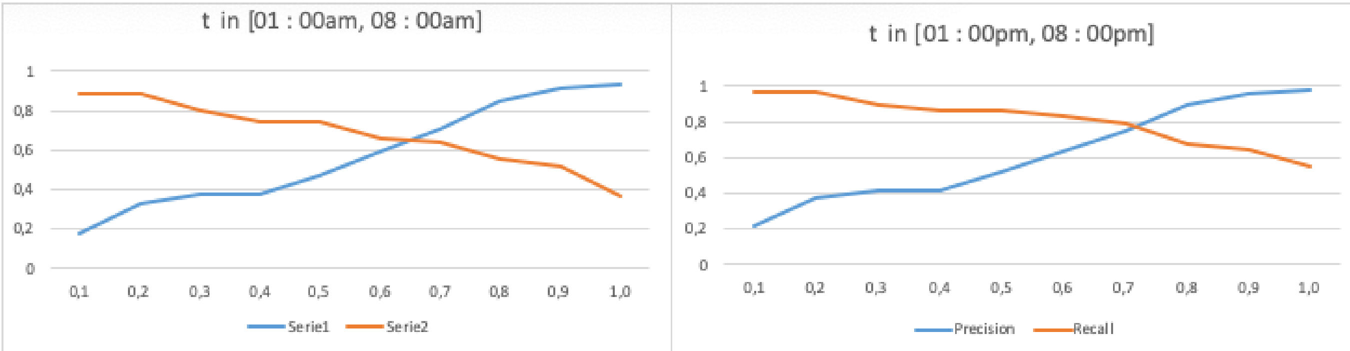

Fig. 4. Precision and Recall evaluated by varying the level of threshold $\alpha \in [0, 1]$ in two time slots [01:00am – 08:00am] and [01:00pm – 08:00pm]

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