Who and where: context-aware advertisement recommendation on Twitter

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Abstract
Advertising is becoming a business on social networks. Billions of people around the world use social media, and fastly, it has become one of the defining technologies of our time. Social platforms like Twitter are one of the primary means of communication and information dissemination and can capture the interest of potential customers. Therefore, it is crucial to select suitable advertisements to users in specific times and locations for capturing their attention, profitably. In this paper, we propose a context-aware advertising recommendation system that, by analyzing the users' tweets and movements along a timeline, infers the personal interests of users and provides attractive ads to users through the triadic formal concept analysis theory.

Keywords Triadic concept analysis · Time-aware analysis · Ads recommendation · Location-based analysis

1 Introduction

Context Users' check-in at a specific location and social posts are two crucial features in most of the recommendation scenarios, which facilitate the emergence of a variety of location-based services, from mobile marketing to disaster relief. These utilities aim to provide custom location-based and context-aware services, by interpreting the user's interest in a better way, at the right location and time.

Problem This work tries to face the following problem. Given a topic-focused timestamped tweet stream, exploring the geographic, temporal, and semantic dimensions of tweets to provide context-aware personalized services (e.g., an advertisement).

Proposed solution This work defines the triadic timed formal concept analysis as a new methodology to solve the problem of location and context-aware advertisement recommendation on Twitter. Triadic concept analysis (TCA) is an extension of formal concept analysis (dyadic case); introduced by Wille (1995), it is based on a formalization of the triadic relation connecting objects, attributes, and conditions, under which objects may have certain attributes. In particular, two types of triadic timed formal concept analysis are defined, the first one focuses on location dimension data of users for uncovering the social location-focused online communities, and the second one focuses on topics to arrange resources (i.e., tweets) into a hierarchy of time-dependent concepts. The final process is achieved, taking into account both locations and semantics of the tweets to personalized advertising recommendation.

Some existing researches reported that the social ties contained in a location-focused online community are denser than that in offline networks. In other words, the location is becoming additional information for enhancing social

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interactions and further providing ads recommendations for target users. So, location-focused groups of users, as proposed in our previous work (Hao et al. 2018), are identified. Specifically, users' check-in data are constructed as a triadic formal context where users, check-in locations, and check-in time are viewed as objects, attributes, and the condition, respectively. With this constructed triadic formal context, an m-triadic concept defined in Hao et al. (2018) can be used for characterizing the formation procedure of location-focused online communities. Consequently, it is easier to capture the evolution of location-focused online communities by observing the evolution of the m-triadic concept. Second, the tweets' contents are annotated by using DBpedia Spotlight that is the practice to find and disambiguate natural language mentions of DBpedia resources (i.e., URI) (Daiber et al. 2013; Mendes et al. 2011). In particular, DBpedia enables us to recognize the sense of main concepts and the named entities are contained in the tweet and the corresponding weight representing the score similarity of the disambiguation result. Then, taking into account the meaning of the tweet content and the time, the triadic timed fuzzy formal concept analysis is performed in order to convert tweets into the time-dependent triadic concepts in a hierarchical way.

Finally, a metric for integrating the results of two triadic timed FCA concepts is defined.

Outlines. The paper is structured as follows: Sect. 2 describes some related works; Sect. 3 describes the macro-phases of the proposed system, *Semantic Representation*, *Time-Aware Concept Analysis*, and *Ads Recommendation Model*, which will be detailed in Sects. 4, 5, and 6, respectively; Sect. 7 presents a case study about the ads recommendation in social networks, and finally, Sect. 8 closes with conclusions.

2 Related works

This section deals with the main relevant areas of related works: (1) topic-aware ads recommendation in social network and (2) location-based recommendation.

2.1 Topic-aware Ads recommendation in social network

Social media or social networks are very popular communities on the Internet. Millions of users all over the world find themselves interacting with each other. These new forms of aggregation are also an extraordinary marketing tool, ideal to advertise your business, expand your network of contacts, and interact with your customers. Social recommendation is a popular area in recommender systems research. Existing approaches either recommend contents that match users' interests (Ronen et al. 2014; Sedhai and Sun 2014), or recommend contents based on high social popularity (Li et al. 2015, 2017). Furthermore, another approach takes into account the user's relationships and individual attributes to predict users' interests (Qu et al. 2018; Guo et al. 2015).

Recently, the challenges are the increasing investment in advertising on social media and how to obtain numerous benefits for businesses. According to the literature, these challenges could be addressed by introducing context-aware solutions considering users' needs, temporal, and spatial dimensions. Some researches take advantage of using user context to deliver the advertisements directly to the target audiences. On this line, recent works (Li et al. 2016; Boffa et al. 2018) propose a new context-aware advertisement recommendation framework on social networks taking into account spatial, temporal, and social dimensions to discover most relevant ads for users. Also, the literature (Dennett et al. 2016) discussed the importance of understanding the audience's needs for efficient communication. Others identify some influencers in the social networks as the seeds to propagate the advertisements through them into users' social circles (Mei et al. 2017; Bokunewicz and Shulman 2017).

2.2 Location-based recommendations

The wide use of mobile devices equipped with GPS modules and the continuous development of positioning technologies brought the emerging popularity of location-based services.

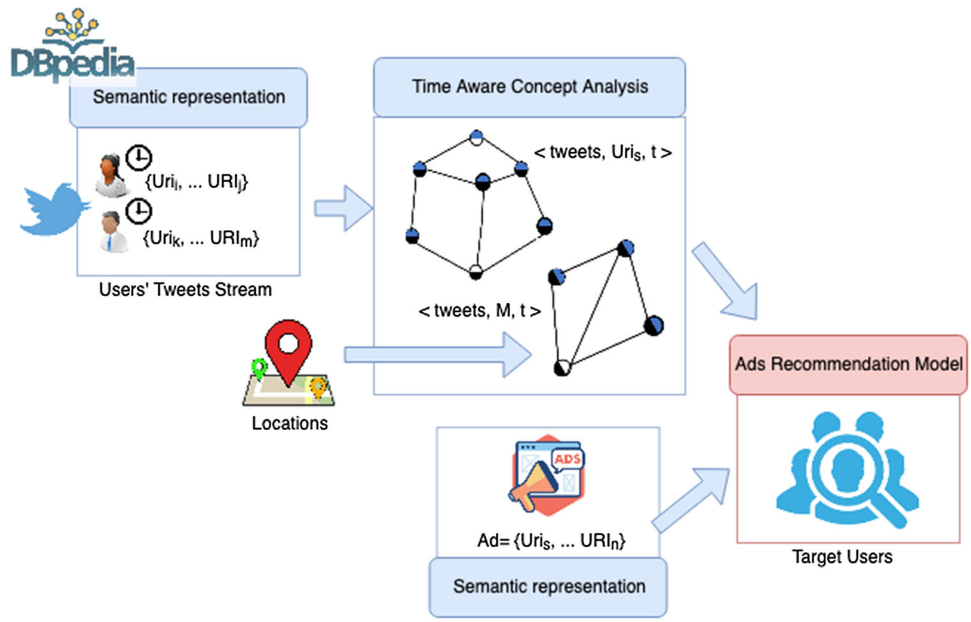
In the literature, there exist many research studies that use the location and the time shared by users on a social network for quantitative analysis of users, mobility characteristics, social graphic and attribute correlations, and so on Silva et al. (2019) and Guo et al. (2019).

Several social platforms such as Foursquare, Yelp, and Facebook, where users can share their positions and social activities with their friends, are a popular social space (Zheng 2011) in which born new social communities according to users interactions (Brown et al. 2012; Bao et al. 2015). The increasing popularity of the usage of these networks provided an increase in studies on collective behavior and interaction of peoples (Hao et al. 2014, 2015; Bao et al. 2015). However, one of the major issues in this context is to detect location-focused online communities (Hao et al. 2018; Wang et al. 2013).

3 Framework overview

The proposed framework aims to provide custom context-aware (i.e., location and time-based) services, to identify targeted advertisements. Specifically, the framework defines the triadic timed formal concept analysis methodology aiming to perform geographic, temporal, and conceptual data analysis of social media.

Fig. 1 Overall approach



Let $U = \{u_1, u_2, \ldots, u_n\}$ be the set of users, $T = \{t_1, \ldots, t_k\}$ be the set of range of time (e.g., morning, afternoon, weekend, etc.), $\mathrm{URI}_i = \{\mathrm{URI}_{i_1}, \ldots, \mathrm{URI}_{i_m}\}$ be the set of topics URIs extracted from the ith user's tweet, and $M = \{m_1, m_2, \ldots, m_L\}$ be the set of locations where users have checked in, and we are looking for a methodology that taken in input the features T, M, U, and URIs is able to retrieve groups of potential users located in a specific area that may be interested in a particular event, topic, etc., and recommend a personalized advertisement.

Figure 1 shows the overall process of the proposed system that is composed of the following macro-phases:

- *Semantic representation* Given the input data (i.e., tweet stream or advertisements), this step performs text annotation by means of DBpedia Spotlight to detect the meaning of the text and performing ad hoc term weighting.
- *Time-aware concept analysis* The applications of the triadic concept-based approach on two fronts: on the one hand, to discover the evolution of the frequent user locations; on the other hand, to classify during the timeline, users based on their social content.
- *Ads recommendation model* Given as input users, times, semantic representation of tweet stream, locations, and advertisings, the methodology analyzes the data and selects the target users interested in a specific advertisement at a given time.

4 Semantic representation

The primary step in the process concerns the extraction of concepts from the unstructured text (e.g., the content of the users' tweets or Ads). In particular, we exploit common sense knowledge DBpedia,[1] through the use of the available DBpedia Spotlight API, which allows us to analyze the tweet's content to characterize its text content semantically. In particular, it provides links between a text in natural language and Linked Open Data in DBpedia by means of three main steps:

- *Text preprocessing*, allows the preprocessing of a fragment of raw text before being passed to the DBpedia Spotlight web service;
- *Named entity recognition*, allows the recognition and annotation of named entities in the text with DBpedia RDF resources;
- *Searching for relations*, allows the search for relations between every pair of RDF resources returned in the previous step.

So from every tweet, we extract pairs <URI, score> corresponding to DBpedia resources (i.e., URIs) and their semantic similarity, belonging to [0, 1], with an entity in the tweet (i.e., the similarity score, score).

For example, considering the following tweet:
"The nation's best volleyball returns tomorrow night. Here's how our coaches think the CW women's teams stack up.".

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

Table 1 Constructed triadic formal context of user' check-in data between t_1 and t_4: $H_1 = (U, M, T, I)$

	t_1					t_2					t_3					t_4				
	m_1	m_2	m_3	m_4	m_5	m_1	m_2	m_3	m_4	m_5	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	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
U_2	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
U_3	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0
U_4	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
U_5	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0
U_6	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1

The semantic representation step extracts a set of topics (i.e., URI) characterizing the meaning of the text:

– "URI": "http://dbpedia.org/resource/Nation", "score": "0.66";
– "URI": "http://dbpedia.org/resource/Volleyball", "score": "1.0";
– "URI": "http://dbpedia.org/resource/The_CW", "score": "1.0";
– "URI": "http://dbpedia.org/resource/Team", "score": "0.432";

So, for each $tweet_i$ the content will be annotated via DBpedia Spotlight Web Service as:
$\text{tweet}_i = \{<\text{URI}_1, \text{score}_1>, <\text{URI}_2, \text{score}_2>, \ldots, <\text{URI}_n, \text{score}_n>\}$.

5 Time-aware concept analysis

This section is devoted to elaborating on the implementation details of the context-aware ads recommendations in social networks. By using *Time-Aware Concept Analysis*—TFCA, first, location-based ads recommendations are investigated to identify location-based communities from the user's tweet stream. Then, a same theory is applied to the content-based topic identification on users' social posts. Finally, given a specific advertisement, we detect the target users as a fusion result of the above two steps.

5.1 Identification of location-based communities from user's tweet stream

Based on our previous work (Hao et al. 2018), we mainly detect the location-based communities from users by the following steps.

5.1.1 Construction of triadic timed FCA for users' check-in data

In order to construct the triadic timed FCA for users' check-in data, users, locations, and time are viewed as objects, attributes, and the condition, respectively. Formally, it is represented as $H_1 = (U, M, T, I)$; here, I refers to the relationships among user, location as well as check-in time.

Example 1 For a given user's tweet stream between t_1 and t_4, it includes six users $U = \{u_1, u_2, \ldots, u_6\}$ and five locations $M = \{m_1, m_2, \ldots, m_5\}$ (see Table 1).

Clearly, the element "1" indicates that a certain mobile user had visited a certain location at a certain time. Hence, this constructed triadic formal context is a 0–1 matrix.

5.1.2 Dynamic detection of location-based communities

Since the triadic concepts where the attribute is m (termed m-triadic concepts) are regarded as the skeleton of location-based communities, this section will focus on the elaboration of dynamic m-triadic concepts in LBS (Location-based Services) (Hao et al. 2018). Formally, once a set of users' check-ins H and a location m are given, the problem of dynamic detection of location-based communities (i.e., $\text{Comm}(H, m)$) is transformed into extracting m-triadic concepts from the concept lattice generated from constructed triadic formal context of user's tweet stream between t_1 and t_4 (termed $P_m(H)$). It is formalized as follows.

$$\text{Comm}(H, m) \equiv P_m(H) \equiv \text{TC}(U, \{m\}, T) \quad (1)$$

5.1.3 Detection algorithm

This section presents a detailed algorithm according to the proposed detection approach. In particular, Algorithm 1 shows the working process of identification of location-based communities from the user's tweet stream. The algorithm works as follows. First, a set of check-in data H and a

Input: A set of check-ins data H and a given location m
Output: A set of location-based communities Comm(H,m)
$Comm(H, m) = \Phi$;
Begin
Construct a triadic formal context $H_1 = (U, M, T, I)$ according to Section 5.1.1.;
Build a concept lattice;
end
for each triadic concept (U, M, T)
  Begin
    if $M = \{m\}$
    Comm(H,m)$\leftarrow$ Comm(H,m) $\cup$ M
  end

Algorithm 1: Algorithm for Detection of Location-based Communities from User's Tweet Stream

given location m are the input of the algorithm; then, a set of location-focused online communities Comm(H, m) are initialized (Line 1); after the initialization, the algorithm makes the triadic formal context construction of check-in data (Lines 2, 3). Line 4 attempts to build the corresponding concept lattice. Lines 6–10 are in charge of extracting the m-triadic concepts and then inserting them into the Comm(H, m).

5.2 Knowledge extraction from user's tweet stream

Taking into account the meaning of the tweet content and timing, Triadic timed FCA will be performed in order to arrange tweets into a hierarchy of time-dependent concepts.

5.2.1 Construction of Triadic timed FCA for users' tweets

The triadic timed FCA for users' post contents is composed of three dimensions, i.e., users, topics (linguistic terms extracted from tweets' content in the semantic representation phase), and time (i.e., objects, attributes, and condition) TFC $= (U,$ URIs, $T, I)$ in which I indicates the triple fuzzy relationships (De Maio et al. 2016) belonging to [0, 1] among user U, topics URIs, and time T.

Example 2 For a given user's tweet stream between t_1 and t_2, it includes six users $U = u_1, u_2, \ldots, u_6$, and five topics URIs $=$ URI$_1$, URI$_2$, ..., URI$_5$. Let us note that each element of the table contains a membership value in [0, 1] that indicates the fuzzy relation between the user and topics at a certain time. So, the corresponding triadic formal context is a [0, 1] matrix (see Table 2 where all relations whose membership values are higher than a threshold $\alpha = 0.6$ are shown) (De Maio et al. 2014).

5.2.2 Context-based identification of users communities from Twitter posts

Similarly, to the detection of location-based communities, an algorithm for identifying the context-based users communities is defined. Formally, given the user's tweet stream, a set of triadic concepts are extracted. It is formalized as follows.

$$\text{Comm(TFC, uri)} \equiv \text{TC}(U, \{\text{uri}\}, T) \tag{2}$$

The algorithm to identify the context-based user's communities is detailed in Algorithm 2.

Input: A set of users U and a topic $\{uri\}$.
Output: A set of context-based communities Comm(TFC, uri)
$Comm(TFC, uri) = \Phi$;
Begin
Construct a triadic formal context $TFC_1 = (U, URI_s, T, I)$ according to Section 5.2;
Build a concept lattice, given a threshold α ;
end
for each triadic concept (U, URI_s, T)
  Begin
    if $URI_s = \{uri\}$
    $Comm(TFC, uri) \leftarrow Comm(TFC, uri) \cup URI_s$
  end

Algorithm 2: Algorithm to identify the context-based users communities from User's Tweet Stream

Given as input a set of users U and a topic {uri}, the algorithm first initializes the set Comm(TFC, uri) (line 1); then, it constructs the triadic formal context URI$_s$ (Lines 2–3) and the corresponding concept lattice (Line 4). Finally, the set of triadic concepts are added to the set Comm(TFC, uri) (Lines 6–10).

6 Ads recommendation model

The ads recommendation model takes as input the advertisement context containing information about location m^*, timing t^*, and ads concepts P (i.e., DBpedia Spotlight URIs). Then, the model guarantees the matching between the advertisement context and the two triadic timed FCA about user's check-in data and user's tweets, respectively, in order to evaluate the matching size between them. The main activities of the model (as you can see in Fig. 2) can be enclosed in three sub-phases:

– *Location-based communities (U-L) matching* this step computes the intersection for each location m^* in the ads context, with the location-based communities in a specific time. Specifically, let us consider Comm(H, m) as the location-based communities from user's tweet

Table 2 Constructed triadic formal context of user's tweet stream between $t1$ and $t2$: (U, URIs, T, I), with $\alpha > 0.6$

	t_1					t_2				
	URI_1	URI_2	URI_3	URI_4	URI_5	URI_1	URI_2	URI_3	URI_4	URI_5
U_1	1.0	0	0	0	0	1.0	0	0	0	0
U_2	1.0	0	0	0	0	0	0	0	0.8	0
U_3	0	0	0.9	0	0	0	0	0.8	0	0
U_4	0	1.0	0	0	0	0	0	0	0	0.75
U_5	0	0	0	0	1.0	0	0	0	0	0.8
U_6	0	0	0.7	0	0	0	0	1.0	0	0

stream; the intersection between $Comm(H, m)$ and m^* is:

$$\text{TC}_{m*} = \bigcup_{\forall m^*} \text{Comm}(H, m^*) \tag{3}$$

- *Context-based communities (U-C) matching* this step computes the intersection for each URI $\in P$ in the ads, with the context-based user communities in a specific time. Specifically, let us define Comm(TFC, URI) as the context-based communities from user's tweet stream; the intersection between Comm(TFC, URI) and P is:

$$\text{TC}_{\text{URI}} = \bigcup_{\forall \text{URI} \in P} \text{Comm}(\text{TFC}, \text{URI}) \tag{4}$$

- *Matching* this step generates an ordered list of users, according to the filtering and ranking criteria. The final result is the set of users resulting from the join $\bowtie_u$ of users in the triadic concepts belonging to set TC_{URI} and TC_{m^*}

$$\text{TC}_{\text{URI}} \bowtie_u \text{TC}_{m^*} \Rightarrow \{U, \text{URIs}, m, T\} \tag{5}$$

To demonstrate the potential of the proposed model, a simple scenario of advertisement recommendation on Twitter has been implemented as described following. Let us suppose that five users, Tom, Luke, Anna, Sam and Lia, post several tweets during the time slots t_1 = morning, $t2$ = afternoon, and $t3$ = evening, in three different locations m_1, m_2, m_3. We select for the scenario only six topics (i.e., URI) to characterize the meaning of the users' tweets. In particular,

- "URI": "http://dbpedia.org/resource/Nation",
- "URI": "http://dbpedia.org/resource/Volleyball",
- "URI": "http://dbpedia.org/resource/The_CW",
- "URI": "http://dbpedia.org/resource/Team",
- "URI": "http://dbpedia.org/page/Adidas.

Considering the triadic formal context represented in Tables 3 and 4, the following triadic concepts are easily obtained for the two contexts.

- triadic concepts extracted from (U, M, T, I)

$$\begin{aligned}
\text{TC}_1 &= (\{\text{Tom, Luke, Anna, Sam, Lia}\}, \{m_1, m_2, m_3\}, \{\emptyset\})\\
\text{TC}_2 &= (\{\text{Luke, Lia}\}, \{m_2\}, \{t_1, t_2\})\\
\text{TC}_3 &= (\{\text{Tom}\}, \{m_1\}, \{t_1, t_2, t_3\})\\
\text{TC}_4 &= (\{\text{Luke}\}, \{m_3\}, \{t_3\})\\
\text{TC}_5 &= (\{\text{Sam}\}, \{m_1\}, \{t_3\})\\
\text{TC}_6 &= (\{\text{Lia}\}, \{m_2\}, \{t_1, t_2, t_3\})
\end{aligned}$$

- triadic concepts extracted from (U, URIs, T, I)

$$\begin{aligned}
\text{TC}_1 &= (\{\text{Tom, Luke, Anna, Sam, Lia}\}, \{\text{URI}_1, \text{URI}_2,\\
&\quad \text{URI}_3, \text{URI}_4, \text{URI}_5\}, \{\emptyset\})\\
\text{TC}_2 &= (\{\text{Sam, Lia}\}, \{\text{URI}_5\}, \{t_2\})\\
\text{TC}_3 &= (\{\text{Tom, Luke}\}, \{\text{URI}_1\}, \{t_1\})\\
\text{TC}_4 &= (\{\text{Tom, Anna}\}, \{\text{URI}_3\}, \{t_3\})\\
\text{TC}_5 &= (\{\text{Tom}\}, \{\text{URI}_1\}, \{t_1, t_2\})\\
\text{TC}_6 &= (\{\text{Sam}\}, \{\text{URI}_2\}, \{t_1, t_3\})\\
\text{TC}_7 &= (\{\text{Luke}\}, \{\text{URI}_4\}, \{t_2\})\\
\text{TC}_8 &= (\{\text{Luke}\}, \{\text{URI}_1\}, \{t_1, t_3\})\\
\text{TC}_9 &= (\{\text{Lia}\}, \{\text{URI}_5\}, \{t_1, t_2, t_3\})\\
\text{TC}_{10} &= (\{\text{Anna}\}, \{\text{URI}_3\}, \{t_1, t_2, t_3\})
\end{aligned}$$

So, given the advertisement context containing information about location, time, and URIs, then we can easily find the location-focused communities and the context-based communities. According to the phases described in Sect. 6, given a location $m2$, and an adv about the "Adidas" brand characterized by URIs: URI_1 and URI_2, we have that:

- TC_{m_2} are TC_2 and TC_6.
- TC_{URI_1} are TC_3, TC_5 and TC_8.
- TC_{URI_2} is TC_6.

At the end, in the matching phase, the set of users resulting from the join $\bowtie_u$ of users in the triadic concepts is:

$$\text{TC}_{URI} \bowtie_u \text{TC}_{m^*} \Rightarrow \{\text{Luke}\} \tag{6}$$

Fig. 2 Ads recommendation model

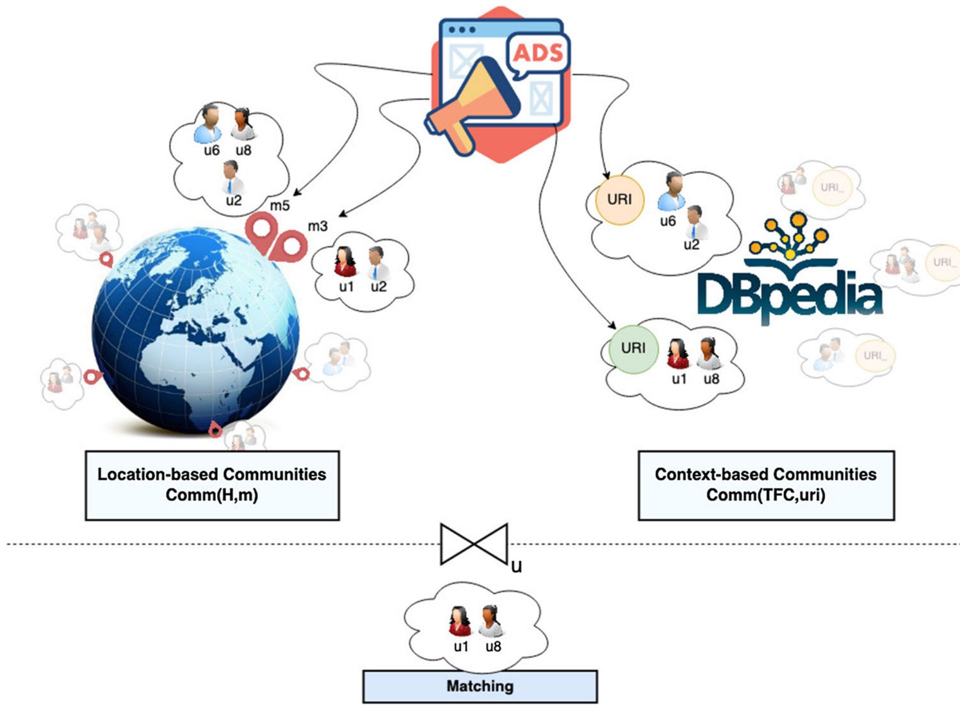


Table 3 Constructed triadic formal context of user's check-in data between t_1 and t_3: $H_1 = (U, M, T, I)$

	t_1			t_2			t_3		
	m_1	m_2	m_3	m_1	m_2	m_3	m_1	m_2	m_3
Tom	1	0	0	1	0	0	1	0	0
Luke	0	1	0	0	1	0	0	0	1
Anna	0	0	0	0	0	0	0	0	0
Sam	0	0	0	0	0	0	1	0	0
Lia	0	1	0	0	1	0	0	1	0

Hence, the ads recommendation model, in order to capture attention, addresses the advertisement to user Luke in the time slots t_1 and t_3 that are morning and evening.

7 Experimental results

In this section, we conduct experiments to assess the proposed approach adopting real-world Twitter data. By using the Twitter API, we acquired the tweets during the month of April 2019 posted by 31 users in 29 different locations, and we selected five tweets as branding ads. The performances were evaluated in terms of F-score, a measure of accuracy. The F-score is defined as the weighted harmonic mean of the Precision and Recall measures. As we can see in Figs. 3 and 4, the performances were tested for two time slots [05:00am–01:00pm] and [01:01pm–08:00pm] with different thresholds $\alpha \in [0.0, 1.0]$.

So, given an Ad "A," a specific time slot t and a location m, let:

- $U^* = u_1^*, u_2^*, \ldots, u_m^*$ all users interested to "A" in the specific time t and location m, manually selected by domain experts by analyzing the tweet stream;
- $\tilde{U} = \tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_n$ all users resulting from the join $\bowtie_u$ of users in the triadic concepts belonging to set $\mathrm{TC}_{\mathrm{URI}}$ and TC_{m^*}.

F-Score is defined as follows:

$$F\text{-Score}_t = 2 \cdot \frac{|\mathrm{Precision}_t \cdot \mathrm{Recall}_t|}{|\mathrm{Precision}_t + \mathrm{Recall}_t|} \tag{7}$$

where

$$\mathrm{Precision}_t = \frac{\left|U^* \bigcap \tilde{U}\right|}{\left|\tilde{U}\right|} \tag{8}$$

$$\mathrm{Recall}_t = \frac{\left|U^* \bigcap \tilde{U}\right|}{|U^*|} \tag{9}$$

The F-score can provide a more realistic measure of a test's performance by using both precision and recall. These metrics evaluate how much the set of discovering users covers U^* into a specific time slot. Furthermore, by varying the threshold α, the user's set results differ only for context-based communities (see Sect. 5.2) and remain constant for location-based communities (i.e., the triadic formal context varying on

Table 4 Constructed triadic formal context of user's tweet stream between $t1$ and $t3$: (U, URIs, T, I), with $\alpha > 0.6$

	t_1					t_2				
	URI_1	URI_2	URI_3	URI_4	URI_5	URI_1	URI_2	URI_3	URI_4	URI_5
Tom	1.0	0	0	0	0	1.0	0	0	0	0
Luke	1.0	0	0	0	0	0	0	0	0.8	0
Anna	0	0	0.9	0	0	0	0	0.8	0	0
Sam	0	1.0	0	0	0	0	0	0	0	0.75
Lia	0	0	0	0	1.0	0	0	0	0	0.8

	t_3				
	URI_1	URI_2	URI_3	URI_4	URI_5
Tom	0	0	0.8	0	0
Luke	1.0	0	0	0	0
Anna	0	0	1.0	0	0
Sam	0	1.0	0	0	0
Lia	0	0	0	0	1.0

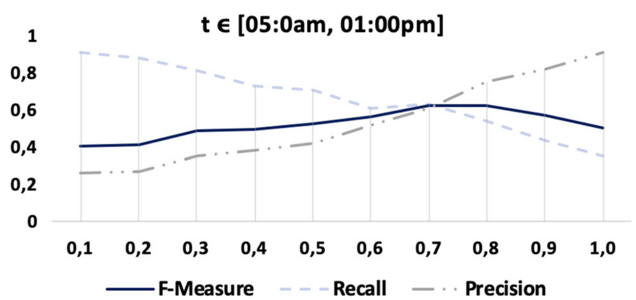


Fig. 3 F-Measure evaluated by varying the level of threshold $\alpha \in [0, 1]$ in two time slots [05:00am–01:00pm]

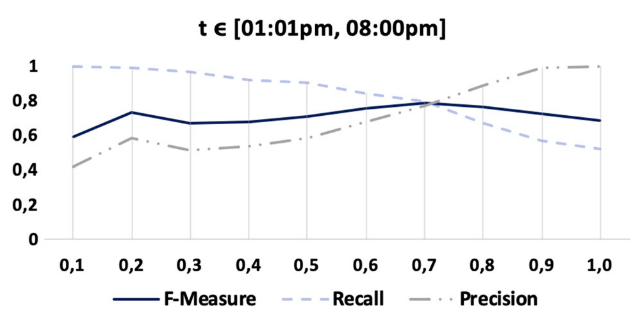


Fig. 4 F-Measure evaluated by varying the level of threshold $\alpha \in [0, 1]$ in the time slot [01:01pm–08:00pm]

threshold α and remains constant for location-based communities). The performances are acceptable as the result reveals high values of precision (i.e., more relevant results than irrelevant ones) and recall (i.e., most of the relevant results). The two metrics explain how much the result set of Twitter users ($\tilde{U}$) are really interested (i.e., included in U^*).

As is shown in Figs. 3 and 4, the framework reveals the best performance with a threshold $\alpha \in [0.65, 0.75]$. Furthermore, as we can see, better results are obtained in the second time slot [01:01pm–08:00pm] because it has a higher intensity of the posted tweets compared to other time slots. This more flow allows an enriched classification of users that provides more successful matching.

8 Conclusion

In this paper, we have proposed an advertisement recommendation model on Twitter for determining whether a user u at the time t and in a specific location m might be interested or not in a given advertisement. The scenario is constituted by the social network platform and an advertiser willing to expose its products to potentially interested users. The system uses text analysis services (like DBpedia Spotlight!) to extract knowledge from the social network posts and advertisements, and location-based system for location-focused online communities detection by using the triadic formal concept analysis theory. The experimental results indicated better performances in the time slot [01:01pm–08:00pm] due to the more intensive tweet stream that ensures a better classification of users. As future work, we aim to analyze in details the experimental results on real social stream data and compare our model with existing approaches like latent Dirichlet allocation (LDA), Gaussian Decay Topic Model (GDTM), and Decay Topic Model (DTM).

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Human and animal rights This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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