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Original

Twitter data laid almost bare: An insightful exploratory analyser / Xiao, Xin; Attanasio, Antonio; Chiusano, SILVIA ANNA; Cerquitelli, Tania. - In: EXPERT SYSTEMS WITH APPLICATIONS. - ISSN 0957-4174. - STAMPA. - 90:(2017), pp. 501-517. [10.1016/j.eswa.2017.08.017]

Availability:

This version is available at: 11583/2679661 since: 2021-04-07T18:41:05Z

Publisher:

Elsevier

Published

DOI:10.1016/j.eswa.2017.08.017

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Twitter data laid almost bare: an insightful exploratory analyser

Xin Xiao^a, Antonio Attanasio^a, Silvia Chiusano^{a,*}, Tania Cerquitelli^a

^a*Control and Computer Engineering Department, Politecnico di Torino, Corso Duca degli Abruzzi, 24 - 10129 Torino, Italy*

Abstract

In today's world, social networks and online communities continuously generate tons of data that reflect users' habits, personal interests, opinions and emotions. However, little profit can be gained from such huge raw data collections unless we are able to translate them into useful knowledge. Twitter, currently the leading microblogging social network, has attracted a great body of research works. Indeed, the rather heterogeneous dimensions characterizing Twitter data, such as space, time and text content, impose innovative methods in the data mining discovery process.

This paper presents TCHARM, a data analytics methodology based on clustering and pattern discovery, to gain interesting knowledge from large complex collections of tweets. Cluster analysis is driven by a novel combined distance measure, named TASTE, to group tweets according to their spatio-temporal features and text content. In TASTE, the contributions of temporal and spatial distances are parametric and grounded on exponential proportionality. Each computed cluster is then locally characterized through association rules to ease the inspection of its Twitter messages. A categorization of rules into a few reference classes and topics is also proposed. TCHARM exploits the computational advantages of distributed computing frameworks, as the current implementation runs on Apache Spark. The experimental evaluation performed on real datasets demonstrates the effectiveness of the proposed approach in discovering cohesive clusters and actionable

*Corresponding author. Tel.: +39 011 0907176.

Email addresses: `xin.xiao@polito.it` (Xin Xiao), `antonio.attanasio@polito.it` (Antonio Attanasio), `silvia.chiusano@polito.it` (Silvia Chiusano), `tania.cerquitelli@polito.it` (Tania Cerquitelli)

knowledge from Twitter data.

Keywords: Cluster analysis, Association rules, Text-spatio-temporal distance, Tweets, Social networks, Apache Spark

219 1. Introduction

220 Microblogs like Twitter have recently become a popular platform with
221 millions of users and an impressive flow of messages (tweets) are published
222 daily and spread by exchanges among users. The conciseness of their text
223 messages (up to 140 characters) allows a very large number of tweets to be
224 published at extremely low cost, thus making Twitter a timely and fresh
225 source of data. Tweets can also be enriched with additional information
226 describing their spatio-temporal publication context, such as when it was
227 posted and the geographical location of the user.

228 The collection of tweets provides useful information to help understand
229 peoples opinions and preferences on different *topics*, how peoples interests
230 are spread *across geographical areas* and how they evolve *over time*. This
231 better understanding of the collective dynamics of user interests can play
232 a significant role in devising the most appropriate strategies and effective
233 actions in various domains. From a business perspective, analyzing the trends
234 of topics like sports, movies, and/or fashion, in different areas and time
235 periods can help companies improve their services/products, the distribution
236 of products as well as the planning of targeted promotional campaigns for
237 specific services/products. In the Internet for instance, the analysis of social
238 dynamics in different geographical areas helps characterize and predict the
239 demand and supply of specific goods (Ikeda et al., 2013). On the other hand,
240 policy makers can exploit microblogs in order to better understand peoples
241 opinions regarding highly debated topics such as transport networks, taxes,
242 healthcare systems, and public safety in different urban, regional or country
243 areas and over time. The hidden knowledge in user messages allows policy
244 makers to identify significant problems and devise targeted actions as well as
245 evaluate how citizens perceive their effectiveness.

246 Although a large body of research focused on Twitter data analysis has
247 already been proposed (e.g., (Phelan et al., 2009; Steiger et al., 2016)),
248 the potential impact of mining social data is still largely unexplored because
249 various critical issues are yet to be addressed when analyzing tons of tweets to
250 identify insightful nuggets. (i) Since a large number of tweets are continuously
251 being posted worldwide, the size of tweet collections to be explored grows
252 at an ever increasing rate. (ii) The collection of tweets generally tends to
253 be scattered in spatio-temporal dimensions, and the conciseness of the tweet
254 messages increases the brevity of their textual content (iii) Furthermore, the
255 distribution of tweets can be characterized by different spatial and temporal

256 granularities. (iv) Mined knowledge should be represented using concise and
 257 understandable patterns to enable its exploitation by domain experts. Thus,
 258 innovative data analytics solutions are needed to effectively and efficiently
 259 mine large Twitter data collections.

260 In this work we propose a novel exploratory analyser which enables end-
 261 users to gather insightful information, including a spatio-temporal-text view-
 262 point from tweet messages. Our data analytics methodology, named Tweets
 263 CHARACTERization Methodology (TCHARM), explores large collections of
 264 Twitter data along the three dimensions characterizing tweets (i.e., text con-
 265 tent, posting time and place) to support context-aware topic trend analysis.

266 TCHARM is based on two exploratory data mining techniques: (a) *Clus-*
 267 *ter analysis*, to identify cohesive groups of tweets with similar text con-
 268 tent posted from nearby geographical areas and at close time instances, and
 269 (b) *Association rule analysis*, to find significant patterns that concisely de-
 270 scribe each computed cluster. To make the proposed methodology scale up
 271 to larger datasets, TCHARM exploits the computational advantages of dis-
 272 tributed computing frameworks since the current implementation runs on
 273 Apache Spark (Zaharia et al., 2010).

274 Unlike previous works (e.g.,(Kim et al., 2011; Lee, 2012; Cunha et al.,
 275 2014; Arcaini et al., 2016)), TCharM drives the clustering process by making
 276 joint use of the tweet spatio-temporal features and text content. A novel Text
 277 And Spatio-TEmporal distance measure, denoted by TASTE, is proposed in
 278 this study in order to combine the contributions of all three tweet features in
 279 one step. Through TASTE, spatial and temporal distances between tweets
 280 are used to modulate the text content distance. By taking into account
 281 both spatio-temporal features and text content in the clustering of tweets,
 282 TCHARM findings can provide useful insights to identify the users topics
 283 of interest in different areas and time periods. For instance, events such as
 284 sports, culture and politics, which have widespread visibility, can be useful
 285 to understand topics that are popular in different geographical areas. The
 286 information provided by the spatio-temporal distribution of such clusters may
 287 help characterize peoples involvement in different time frames. TCHARM has
 288 been currently integrated into the *K-means* clustering algorithm (Pang-Ning
 289 T. and Steinbach M. and Kumar V., 2006), to generate clusters of tweets
 290 that can be concisely represented by their centroids.

291 TCHARM then locally investigates each computed cluster to mine signif-
 292 icant patterns which reveal underlying correlations among frequent topics,
 293 tweeting times and places that simultaneously emerge from cluster analysis.

294 This task has been carried out using association rule analysis (Pang-Ning
295 T. and Steinbach M. and Kumar V., 2006), an exploratory data mining
296 technique to extract correlations among data items. Quality indices (e.g.,
297 confidence, support, and lift) are used to distinguish the most significant
298 correlations. Association rule analysis allows the extraction of the most re-
299 current spatio-temporal-text patterns in a systematic and structured way.
300 These patterns describe the cluster content using a concise and clear knowl-
301 edge representation. To further support the exploration of discovered pat-
302 terns, four different classes of association rules have been defined. By “class”
303 we mean a subset of patterns which determines significant relationships be-
304 tween tweet dimensions which can be used to perform a similar in-depth
305 analysis. The identified patterns can provide domain experts with valuable
306 support to identify which topics are most appealing to users in different areas
307 and time periods.

308 It is worth mentioning that our methodology can be exploited to support
309 knowledge discovery in different contexts, and in this study TCHARM has
310 been thoroughly evaluated using the large number of tweets collected during
311 the 2014 FIFA World Cup championship. This football competition was
312 selected as a representative case because it included a variety of events (e.g.,
313 football matches with different teams, ceremonies, celebrities statements)
314 spread over a set time period. Moreover, as it is of worldwide interest, peoples
315 interest in, and perceptions of, this kind of event may vary depending on
316 their geographical location. The experimental evaluation demonstrates the
317 effectiveness of TCHARM in identifying interesting knowledge regarding the
318 spatio-temporal distribution of peoples reactions to the events. The identified
319 clusters provide useful findings regarding hot topics for users, in the different
320 areas and time periods. Mined clusters are timely centered around an event
321 related to the 2014 FIFA World Cup Championship and they mainly include
322 messages about specific topics. Moreover, they show good spatio-temporal
323 cohesion around their centroid.

324 The rest of the paper is organized as follows: Section 2 summarizes the
325 related work regarding cluster analysis of Twitter data. Section 3 provides
326 an in-depth description of the TCHARM characteristics, while Section 4 dis-
327 cusses the experimental study conducted on the 2014 FIFA World Cup Cham-
328 pionship dataset. Section 5 provides a theoretical and analytical comparison
329 between TCHARM and some previous works on tweet clustering. Section
330 6 discusses the significance of TCharM findings and their possible exploita-
331 tion. Section 7 draws conclusions and future developments of the proposed

332 approach.

333 2. Related Work

334 In the last few years the application of data mining techniques to discover
335 relevant social knowledge from tweets collections has become an appealing
336 research topic. Proposed approaches, mainly based on text processing and
337 its extensions to heterogeneous data, can be classified into the following two
338 main categories.

339 The first category refers to methods addressing the analysis of tweet tex-
340 tual content with the aim of (i) characterizing online communities (Rabiger
341 & Spiliopoulou, 2015), (ii) performing spam detection (Thomas et al., 2011),
342 (iii) detecting topics to analyse trends (Baralis et al., 2013; Vicient & Moreno,
343 2015; Yang & Rim, 2014), and (iv) addressing recommendation tasks (Phelan
344 et al., 2009).

345 The second category includes methods considering spatio-temporal infor-
346 mation in addition to tweet textual content. Different types of analysis have
347 been addressed as (i) discovering regional social activities or nearby events
348 using geo-tagged tweets (Kim et al., 2011), (ii) detecting events based on
349 cluster analysis (Lee, 2012; Steiger et al., 2016), (iii) extracting insightful
350 summaries of citizen perceptions from tweets (Bernabe-Moreno et al., 2015;
351 Lee et al., 2015), (iv) discovering contrasting situations by means of gener-
352 alized itemsets (Cagliero et al., 2014), (v) identifying the period in which a
353 burst of information diffusion took place (Saito et al., 2015), and (vi) mining
354 user opinions (Lloret et al., 2012).

355 Various approaches have been proposed to cluster tweets collections tak-
356 ing into account textual content and spatio-temporal information (Kim et al.,
357 2011; Steiger et al., 2016), though such works do not jointly exploit all these
358 features in the clustering process. Instead, they typically use a subset of
359 features for clustering, while remaining features are considered either in the
360 post-processing phase, for instance to refine or characterize discovered clus-
361 ters, or in the preprocessing phase, for example to specify spatial or temporal
362 segments in which tweets are locally clustered based on textual content. Kim
363 et al. (2011) cluster tweets based on their GPS coordinates using the K-means
364 algorithm, while Steiger et al. (2016) use a spatio-temporal clustering based
365 on Self Organizing Maps (SOM). In both approaches, discovered clusters are
366 then analysed to identify the main targeted topic. Density based clustering,
367 mainly based on the DBSCAN algorithm, has been also adopted to detect

high spatial concentrations or temporal bursts of tweets about specific topics (Arcaini et al., 2016; Lee, 2012; Lee et al., 2015; Sakai et al., 2015). For instance, Lee et al. (2015) group user trajectories derived from geo-tagged tweets and explore massive crowd movements, while Sakai et al. (2015) extract local bursty keywords and identify their dense areas to enhance local situation awareness.

Differently from all the works above, the TCHARM framework *jointly* exploits the spatio-temporal features and tweet textual content to drive the clustering process. Our main purpose is to discover cohesive clusters focused on single topics and, at the same time, with precise spatio-temporal references. Through the TASTE distance measure, TCHARM explores the three dimensions characterizing tweets, to discover, in one step, groups of messages with similar content but posted in nearby time and space.

As an additional contribution with respect to all the works mentioned above, TCHARM performs a further step of clusters characterization through association rules extraction. The use of association rules to characterize clusters of tweets was proposed by Baralis et al. (2013). However, in TCHARM rules are additionally categorized into few reference classes, according to their semantics, to ease the comprehension and exploitation of the extracted knowledge. Moreover, association rule analysis explores correlations not only in the textual content, but also between textual content and the time and location of tweet posting.

In this study, the TCHARM framework has been deployed on Apache Spark. Several open source data mining platforms, like Scikit-learn, Rapid-Miner, Apache Mahout and Apache Spark have proposed their own scalability strategies to analyse the huge and rapidly growing amount of data. Such platforms include libraries implementing common machine learning algorithms which can be extended or modified by researchers. The adoption of Apache Spark in many research works (including but not limited to tweets) is mainly motivated by both the support for stream analysis (Dasgupta et al., 2015) and the scalable computing framework that makes it possible to speed up existing algorithms for different applications (Capdevila et al., 2016).

Tweets about the 2014 FIFA World Cup has been considered as a reference case study for the validation of the proposed framework. Various studies have addressed the analysis of tweets related to this event, with different targeted analyses devoted to (i) performing sentiment analysis to characterize U.S. soccer fans’ emotional responses (Yu & Wang, 2015); (ii) addressing

topic detection through a combined approach based on the DBSCAN algorithm and Non-Negative matrix (Godfrey et al., 2014); (iii) tracking user behavior through Latent Dirichlet Allocation (LDA) (Kim et al., 2015). All these approaches analyse the textual content only, while TCHARM clusters the tweet collection besides characterizing the cluster content based on textual and spatio-temporal dimensions.

3. TCHARM architecture

The main components of the Tweets CHARACTERization Methodology (TCHARM) architecture are shown in Figure 1. The components are briefly introduced below while a more thorough description of each of them is given in the following subsections.

The first activity is *data collection and preprocessing*. All information about tweets, including text content, publication time and user geographical location, are retrieved through the Twitter Stream Application Programming Interfaces (APIs) specifying a set of filter parameters (e.g., keywords, hashtags). The collected data then undergo a preprocessing phase to be represented in a format suitable for the subsequent clustering analysis. The adopted data model is described in Section 3.1. The output of the preprocessing is a dataset where each record corresponds to a single tweet and contains basically three features: *text content*, *time* of tweet posting and *location* of the user when posting the tweet.

Once the dataset is ready, the *cluster analysis* elaborates its records in order to partition the tweets collection into cohesive groups (clusters). For this activity, a novel combined distance measure, called Text And Spatio-TEmporal (TASTE), is used to cluster Twitter messages considering their spatio-temporal information and the text content as well.

Finally, TCHARM analyses each discovered cluster to mine a set of patterns describing the cluster content. Specifically, through *association rule analysis*, patterns of relevant correlations among tweets text contents, posting times and geographical areas are extracted for each cluster. Extracted rules are then categorized into four classes defined according to the types of correlation among the tweets attributes while, to ease their semantic interpretation, the same rules are associated with one of the few reference topic families according to the word set they contain.

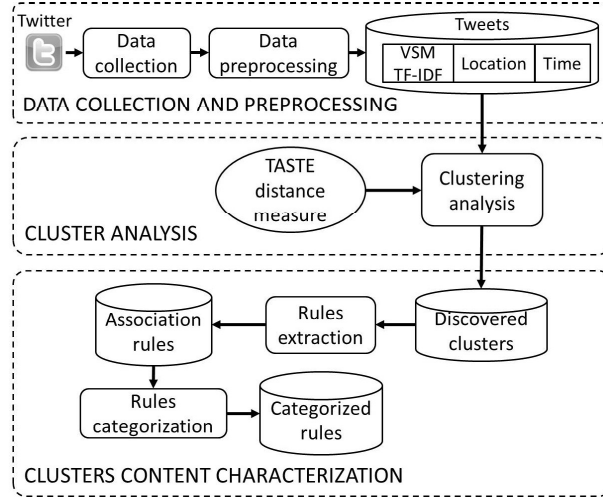


Figure 1: The TCHARM architecture

3.1. Twitter data representation

This study aims at the characterization of groups of tweets with similar text and posted in close geographical areas and time instants. To support this analysis, the following three features have been considered for the representation of Twitter data: (i) *tweet text content* (ii) *tweet temporal feature*, i.e. tweet posting time, and (iii) *tweet spatial feature*, i.e., user geographical position at posting time.

Tweet text content. Tweets are posts published by Twitter users that include also *text messages* 140 characters long at most. Such messages represent the text content used in our analysis. Due to the limited size of the single message and to the high dimensionality of many text content representations, the represented samples are inherently sparse. This property leads to higher levels of noise in the tweet collection, thus adding complexity to the clustering process, which requires an adequate treatment (Jing et al., 2007). Moreover, Twitter messages are usually extremely impure because they include a wide variety of Unicode data, symbols, numbers and links. They therefore need to be properly cleaned and prepared before the analysis.

Tweet temporal feature corresponds to the *timestamp* including date and time instant when the tweet was posted. In this study, we omit the temporal information possibly appearing in the tweet message, since it is considered less relevant for discovering tweets posted in nearby time.

Text	England 2-0 I still believe
Time	Friday June 20 09:26:53 +0000 2014
Location (latitude, longitude)	52.076, -1.363

Table 1: Example tweet including text content and spatio-temporal features

Tweet spatial feature can be acquired as *geographical coordinates* of the user when she/he posted the tweet, with the location specified in the user profile, and location mentioned in the tweet text content. Geo-coordinates (i.e., latitude and longitude) are available when GPS enabled devices are used and localization is enabled. They specify the spatial position of people right when posting the tweet. Instead, the location reported in the user profile is free-text information provided by the same user. It usually corresponds to the place (such as city, state or country) where people come from. Similarly, locations mentioned in the tweet message do not necessarily correspond to the user position when the tweet was sent. Since our aim is to discover tweets with similar text content but posted in nearby geographical areas (and time periods), we focused mainly on the spatial information provided through geo-coordinates.

Table 1 reports an example tweet including the three features. The tweet refers to the 2014 FIFA World Cup, considered as a reference case study in this paper. The tweet was posted on Friday morning, June 20th 2014, at 9:26 a.m. from Banbury City (UK), according to geo-coordinate values.

In TCHARM the tweets collection is represented as a dataset where each record corresponds to a single tweet and contains basically three attributes, corresponding to the three features above, i.e., tweet text content, and tweet temporal and spatial features. For the purposes of this study, the text content has been represented using the *Bag-of-Words* (BOW) model usually adopted in text mining (Steinbach et al., 2000). The message is represented as the multiset of its words, disregarding grammar and even word order, but keeping word multiplicity. A more formal definition of the adopted representation for tweet data is the following one.

Definition 3.1 (Tweet data representation). Let $\mathcal{D}$ be a set of tweets and $\Sigma = \{w_1, \dots, w_k\}$ the set of words appearing in at least one tweet in $\mathcal{D}$. An arbitrary tweet $\tau_i \in \mathcal{D}$ is represented as a triplet $\tau_i = (t_i, s_i, W_i)$ where t_i and s_i are respectively the temporal and spatial features of τ_i , while $W_i \subseteq \Sigma$

491 *is the tweet text content.*

492 The *temporal feature* t_i is the *timestamp* indicating *when* tweet τ_i was
 493 posted, while the *spatial feature* s_i is the pair of *geo-coordinates* reporting
 494 from *where* tweet τ_i was posted. The *text content* W_i is given by the subset
 495 of words w_j ($w_j \in \Sigma$) appearing in tweet τ_i , with their respective frequencies.

496 Unweighted word frequencies do not properly characterize tweet text con-
 497 tent, since words related to more specific events may appear with lower fre-
 498 quency than common words. In this study, the Term Frequency (TF) -
 499 Inverse Document Frequency (IDF) scheme (Manning et al., 2008), usually
 500 used in text mining, has been adopted to highlight the relevance of specific
 501 words for each tweet, while reducing the importance of common terms in
 502 the collection. The adoption of the TF-IDF scheme in the message repre-
 503 sentation makes it possible to focus the tweet matching in the subsequent
 504 clustering phase on words specific for each subset of tweets rather than on
 505 words common to most tweets. To weight word relevance based on the TF-
 506 IDF scheme, the tweet text content is transformed using the Vector Space
 507 Model (VSM) representation (Salton et al., 1975). Each tweet text content
 508 is a vector in the word space. Each vector element corresponds to a different
 509 word and is associated with the TF-IDF weight describing the word relevance
 510 for the tweet, as in the following Definition 3.2.

511 **Definition 3.2 (Tweet text content representation).** Let $\tau_i =$
 512 (t_i, s_i, W_i) be an arbitrary tweet in collection $\mathcal{D}$. The tweet text con-
 513 tent W_i is a vector of k elements corresponding to words in Σ (i.e., $k = |\Sigma|$).
 514 Each vector element $W_i[j]$ contains the TF-IDF weight of word w_j for
 515 tweet τ_i . $W_i[j]$ is computed as $W_i[j] = TF(\tau_i, w_j) \cdot IDF(w_j)$, where terms
 516 $TF(\tau_i, w_j)$ and $IDF(w_j)$ are defined as follows:

- 517 1. $TF(\tau_i, w_j)$ is the relative frequency of word w_j for tweet τ_i .
 518 $TF(\tau_i, w_j) = f(\tau_i, w_j) / \sum_{l=1}^k f(\tau_i, w_l)$, where $f(\tau_i, w_j)$ is the number
 519 of times word w_j appeared in tweet τ_i and $\sum_{l=1}^k f(\tau_i, w_l)$ is the total
 520 number of words contained in τ_i .
- 521 2. $IDF(w_j)$ is the relative frequency of word w_j in $\mathcal{D}$. $IDF(w_j) =$
 522 $\log(|\mathcal{D}|/|\mathcal{D}_j|)$ where $|\mathcal{D}|$ is the number of tweets in $\mathcal{D}$ and $|\mathcal{D}_j|$, $\mathcal{D}_j =$
 523 $\{\tau_i \in \mathcal{D} : f(\tau_i, w_j) > 0\} \subseteq \mathcal{D}$, is the number of tweets in $\mathcal{D}$ which
 524 contain (at least once) word w_j .

Mathematically, the base of the *log* function for IDF computation in Definition 3.2 does not influence the overall results as it constitutes a constant multiplicative factor (Robertson, 2004). The TF-IDF weight $W_i[j]$ for word w_j in tweet τ_i is high when w_j appears with high frequency in tweet τ_i but low frequency in tweets in the collection $\mathcal{D}$. When word w_j appears in more tweets, the ratio inside the IDF *log* function approaches 1, and both the IDF(w_j) value and the TF-IDF weight $W_i[j]$ become close to 0. Hence, the approach tends to filter out common words. In short messages like tweets, the TF-IDF weighting score could actually be reduced to a pure IDF scheme due to the limited word frequency within each tweet. Nevertheless, we preserved the TF-IDF approach to consider also possible word repetitions.

3.2. Twitter data collection and preprocessing

Twitter data for the TCHARM framework are retrieved through the Twitter Stream Application Programming Interfaces (APIs) by specifying a set of filter parameters (e.g., keywords, hashtags). Collected data include all information characterizing tweets useful for the subsequent data analysis phase, i.e., tweet message, publication time and geographical location of the user. Of the tweets collected, only those in English are considered.

To enable the subsequent data analysis process on crawled tweets, the following data preparation steps are applied. Tweet messages are cleaned by removing numbers, usernames and URLs. After converting the letters into lowercase, messages are further cleaned by eliminating stop words (such as “is”, “at”, “the”, etc.). Finally, the text content is represented using the data model described in Section 3.1, i.e., the BOW data model is applied and the TF-IDF score schema is used to weight word relevance.

3.3. Cluster analysis of tweets

Cluster analysis partitions objects into groups so that objects within the same group are more similar to each other than to the ones assigned to different groups. Different kinds of clustering algorithms are available, like partitional (e.g., K-means, K-medoids), density-based (e.g., DBSCAN), and hierarchical (e.g., agglomerative) (Pang-Ning T. and Steinbach M. and Kumar V., 2006).

In TCHARM, the K-means algorithm is used for clustering tweet data collections. K-means has been widely used in different applications domains, including tweets analysis, providing good quality solutions. The K-means

algorithm discovers K clusters modeled by their representatives, named *centroids*, given by the mean value of the objects in the clusters. Initially, K tweets of the tweet collection $\mathcal{D}$ are randomly chosen as centroids. Then each tweet $\tau_i \in \mathcal{D}$ is assigned to the cluster of the nearest centroid. Finally, the centroids are relocated by computing the mean of the tweets features within each cluster. The process iterates until a convergence criterion is met, i.e., the centroids do not change or some objective functions are achieved.

The K-means algorithm used in TCHARM exploits the novel distance measure TASTE to discover clusters with similar content but also posted in nearby geographical areas and close time periods. The TASTE measure takes into account the three tweet features at once to determine an overall distance between tweets.

3.3.1. The TASTE distance measure

The proposed Text And Spatio-TEmporal (TASTE) distance measure is formally defined as follows.

Definition 3.3 (TASTE distance measure). Let $\tau_i = (t_i, s_i, W_i)$ and $\tau_j = (t_j, s_j, W_j)$ be two arbitrary tweets in collection $\mathcal{D}$. The TASTE distance measure between tweets τ_i and τ_j is defined as

$$d_{TASTE}(\tau_i, \tau_j) = d_W(W_i, W_j) \cdot (k_s \cdot e^{p_s \cdot d_s(s_i, s_j)} + k_t \cdot e^{p_t \cdot d_t(t_i, t_j)}) \quad (1)$$

where parameters $k_s, k_t, p_s, p_t \in \mathbb{R}$; $k_s, k_t \in [0, 1]$ and $k_s + k_t = 1$. Terms $d_W(W_i, W_j)$, $d_s(s_i, s_j)$, and $d_t(t_i, t_j)$ measure the distance on tweet text content, spatial feature, and temporal feature, respectively. These distances have been normalized in the range $[0, 1]$ using the *min-max* normalization method (Pang-Ning T. and Steinbach M. and Kumar V., 2006).

TASTE is defined as a measure of dissimilarity. Given tweets τ_i and τ_j , lower values of $d_{TASTE}(\tau_i, \tau_j)$ denote a higher similarity between τ_i and τ_j , while higher values of $d_{TASTE}(\tau_i, \tau_j)$ denote a lower similarity.

In the TASTE measure, spatial and temporal distances ($d_s(s_i, s_j)$ and $d_t(t_i, t_j)$) modulate the text content distance ($d_W(W_i, W_j)$) to determine the overall value of $d_{TASTE}(\tau_i, \tau_j)$. The exponential form is used for $d_s(s_i, s_j)$ and $d_t(t_i, t_j)$ to significantly penalize tweets with a large space and/or time distance.

The parameters of the TASTE measure can be conveniently tuned to fit scenarios with different spatial and temporal scales. Parameters k_s and k_t

weight the relevance of spatial and temporal distances in modulating the text content distance. Parameters p_s and p_t are included as exponents to adjust the (possibly differentiated) growth rates of exponential terms of spatial and temporal distances. For instance, to discover clusters of tweets with a high temporal cohesion, but possibly spread over a large geographical area, suitably higher values should be assigned to parameter p_t to penalize distances in time.

In TASTE, three different measures are used to compute $d_W(W_i, W_j)$, $d_s(s_i, s_j)$, and $d_t(t_i, t_j)$ based on the data type describing tweet text content, spatial feature and temporal feature.

Text content distance measure ($d_W(W_i, W_j)$). The distance between the weighted word frequency vectors W_i and W_j of tweets τ_i and τ_j is evaluated using the *cosine distance measure* (Pang-Ning T. and Steinbach M. and Kumar V., 2006), which has often been used to compare documents in text mining (Steinbach et al., 2000). We define the text content distance measure $d_W(W_i, W_j)$ as

$$d_W(W_i, W_j) = \arccos(\cos(W_i, W_j)). \quad (2)$$

Term $\cos(W_i, W_j)$ in Equation 2 represents the *cosine similarity* between W_i and W_j , and it is computed as

$$\cos(W_i, W_j) = \frac{\sum_{l=1}^k W_i[l]W_j[l]}{\sqrt{\sum_{l=1}^k W_i[l]^2} \cdot \sqrt{\sum_{l=1}^k W_j[l]^2}} \quad (3)$$

where k is the cardinality of the word set Σ in collection $\mathcal{D}$ ($k = |\Sigma|$).

The value range is $[0, 1]$ for the cosine similarity $\cos(W_i, W_j)$, while the value range for the content distance measure $d_W(W_i, W_j)$ is $[0, \pi/2]$. When $\cos(W_i, W_j) = 1$, then $d_W(W_i, W_j) = 0$ which describes the exact similarity of text content for tweets τ_i and τ_j . When $\cos(W_i, W_j) = 0$, then $d_W(W_i, W_j) = \pi/2$ which points out that tweets τ_i and τ_j have completely different texts.

Temporal distance measure ($d_t(t_i, t_j)$). The tweet temporal feature is an integer number representing the time instant when the tweet was posted. The *Euclidean distance* (Pang-Ning T. and Steinbach M. and Kumar V., 2006) is adopted here as the distance on temporal features t_i and t_j of tweets

τ_i and τ_j . As t_i and t_j are expressed as time instants, the Euclidean distance is computed as the absolute value of their difference, i.e.,

$$d_t(t_i, t_j) = |t_i - t_j|. \quad (4)$$

Spatial distance measure ($d_s(s_i, s_j)$). Both Haversine and Euclidean distance measures have been used in other works to calculate the spatial distance between two geographical points (Lee, 2012). However, the Haversine distance is usually considered as more appropriate and precise especially when the distance between two points gets larger and it cannot be approximated as a straight line. For this reason, in this study the *Haversine distance* is used for computing the spatial distance between tweets. The Haversine distance corresponds to the great-circle distance between two points, i.e., their shortest distance over the earth’s surface. Hence, the spatial distance between s_i and s_j for tweets τ_i and τ_j is computed as

$$d_s(s_i, s_j) = 2 \cdot R \cdot \arcsin(\sqrt{h}) \quad (5)$$

$$h = \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2) \quad (6)$$

where $\Delta\varphi$ and $\Delta\lambda$ are latitudinal and longitudinal differences between the tweets and R is a constant value equal to the Earth’s mean radius (6,371 km).

The content, spatial and temporal distance measures defined above satisfy the positivity, symmetry, and triangle inequality properties that characterize a metric (Pang-Ning T. and Steinbach M. and Kumar V., 2006). It easily follows that the TASTE measure also verifies these properties. Specifically, the following properties hold. (i) *Positivity*: $d_{TASTE}(\tau_i, \tau_j) \geq 0$ for all $\tau_j, \tau_i \in \mathcal{D}$, while $d_{TASTE}(\tau_i, \tau_j) = 0$ only if $\tau_i = \tau_j$. (ii) *Symmetry*: $d_{TASTE}(\tau_i, \tau_j) = d_{TASTE}(\tau_j, \tau_i)$ for all $\tau_j, \tau_i \in \mathcal{D}$. (iii) *Triangle inequality*: $d_{TASTE}(\tau_i, \tau_j) \leq d_{TASTE}(\tau_i, \tau_k) + d_{TASTE}(\tau_k, \tau_j)$ for all $\tau_i, \tau_k, \tau_j \in \mathcal{D}$.

As an example, Figure 2 reports four sample tweets (τ_1 to τ_4) with their text content, temporal and spatial features. The values of d_{TASTE} between tweet τ_1 and the other tweets are also specified. Tweets are about the 2014 FIFA World Cup. Aimed at easing the comprehension of the results, the figure shows the original text messages, in place of the corresponding data model based on both BOW representation and TF-IDF score. It is worth noting that tweets τ_2 and τ_3 have a higher similarity with τ_1 than with τ_4 . Tweets τ_1 , τ_2 and τ_3 have a similar text content as they all talk about the

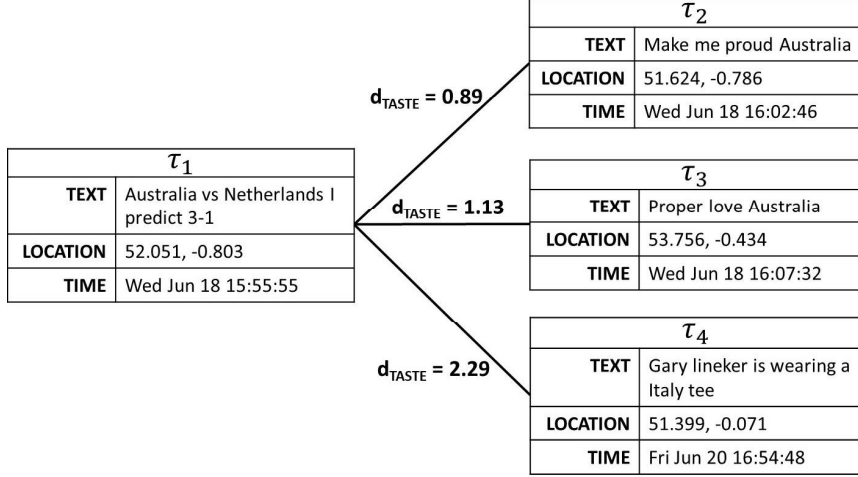


Figure 2: Sample tweets about 2014 FIFA World Cup with TASTE distance values

651 Australia football team. Tweets τ_2 and τ_3 were posted almost at the same
 652 time as τ_1 , but τ_3 exhibits a farther geographical location from τ_1 than τ_2 .
 653 This larger spatial distance penalizes the similarity on the text content and
 654 finally provides a higher value of d_{TASTE} for tweet τ_3 . Conversely, tweet τ_4
 655 exhibits a significantly higher TASTE distance from τ_1 even though it was
 656 posted in the neighbourhood, as τ_4 has a completely different content from
 657 τ_1 and it was posted two days later.

658 3.3.2. Clustering Evaluation

659 For the (internal) validation of clustering results, TCHARM adopts the
 660 *Sum of Squared Errors (SSE)* quality index, usually adopted for evaluating
 661 the quality of a cluster set computed with the K-means algorithm (García-
 662 Gavilanes et al., 2014). The *SSE* index measures the cluster cohesion in
 663 prototype-based clusters, i.e., how objects in a cluster are closely related
 664 to the corresponding centroid. SSE is defined as the sum of the squared
 665 distances between each member of the cluster and its centroid. In TCHARM,
 666 the SSE index is computed as

$$SSE = \sum_{i=1}^K \sum_{\tau_j \in C_i} d_{TASTE}(\tau_j, c_i)^2 \quad (7)$$

667 where c_i is the centroid of cluster C_i , and C_i is included in a cluster set with

668 K clusters. $d_{TASTE}(\tau_j, c_i)$ is the TASTE distance between a tweet $\tau_j \in C_i$
669 and the centroid c_i of C_i .

670 3.4. Clusters content characterization

671 After the cluster set is generated, in TCHARM each cluster is then locally
672 explored to characterize its content. Specifically, each cluster is analysed to
673 discover underlying correlations in the text content, and between text content
674 and the spatial and temporal features characterizing tweets. Cluster charac-
675 terization makes use of *association rules* as reference pattern type (Agrawal
676 et al., 1993).

677 3.4.1. Association rules extraction

678 Association rules analysis is an exploratory data mining technique to
679 mine correlations among data items (Agrawal et al., 1993). To enable the
680 association analysis process, tweets contained in the cluster under analysis
681 are tailored to a transactional data format.

682 Consider an arbitrary cluster C included in the cluster set computed on
683 tweet collection $\mathcal{D}$. The *transactional tweet dataset* $\mathcal{D}_{\mathcal{T}}(C)$ for cluster C is a
684 set of transactions. Each *transaction* $\mathcal{T}_i$ corresponds to a tweet $\tau_i \in C$ and
685 it consists of a set of tweet features called *items*, represented in the form
686 $\{\text{attribute} : \text{value}\}$. The items of the generic transaction $\mathcal{T}_i$ are (i) each
687 single *word* $w \in W_i$ appearing in the text content of tweet τ_i , (ii) the value
688 of the *spatial feature* s_i of τ_i , and (iii) the value of the *temporal feature* t_i of
689 τ_i .

690 An *association rule* is an implication in the form $r : X \Rightarrow Y$, where
691 X and Y are disjoint *itemsets* (i.e., sets of items). X and Y are denoted
692 as *rule antecedent* and *consequent*, respectively. Association rules extrac-
693 tion is commonly driven by rule support and confidence quality indexes.
694 Whereas the *support* index represents the observed frequency of occurrence
695 of rule r in the transactional dataset, the *confidence* index represents the
696 rule strength. Consider the transactional tweet dataset $\mathcal{D}_{\mathcal{T}}(C)$ for cluster
697 C ; let $r : X \Rightarrow Y$ be a rule mined from $\mathcal{D}_{\mathcal{T}}(C)$. Rule support (*supp*)
698 is the percentage of tweets in cluster C that contain both X and Y . Rule
699 confidence (*conf*) is the percentage of tweets in cluster C containing X that
700 also contain Y .

701 Consider, for example, association rule $r : \{\text{start}, \text{world}, \text{cup}\} \Rightarrow \{\text{love}\}$
702 (*supp* = 1.1%, *conf* = 60%) mined from cluster C . Rule r talks about people's
703 feelings on the World Cup game. The rule represents relationships that

emerge from tweets messages contained in C , i.e., the correlation between subset of words included in these messages. According to the rule support and confidence values, 1.1% of tweets in cluster C contain all the words appearing in the rule (i.e., *start*, *world*, *cup* and *love*), but the word *love* appears in 60% of tweets including the words *start*, *world* and *cup*.

In some cases, measuring the strength of a rule in terms of support and confidence values may be misleading. When the rule consequent has a high support value, the rule may be characterized by a high confidence value even if its actual strength is relatively low. To overcome this issue, the *lift* (or correlation) index (Pang-Ning T. and Steinbach M. and Kumar V., 2006) may be used, beyond the confidence index, to measure the (symmetric) correlation between sets X and Y . Lift values below 1 show a negative correlation between sets X and Y , while values above 1 indicate a positive correlation. In this study, to mine patterns representing strong correlations among features characterizing tweets, the selection of association rules is based on confidence and lift values.

3.4.2. Association rule categorization

Although association rules are a powerful method to discover data correlations, analyzing the (usually) large number of extracted rules is not a trivial task. To support the exploration of the mined rule set, TCHARM exploits a categorization of rules into few *classes*, built upon the attributes characterizing Twitter data, i.e., tweet spatial feature (denoted *Location* (L)), tweet temporal feature (*Time* (T)), and text content of the tweet message (*TextContent* (TC)). Each class refers to correlations among a subset of the above attributes. Specifically, four classes of rules have been defined which are aimed at progressively providing more detailed information about the cluster content. Classes are described below while an example rule is reported for each of them in Table 2.

1. *TextContent class* (TC). This class focuses on tweet text content. Patterns model correlations between words in tweet messages and these are aimed at capturing the peculiar characteristics of messages in the cluster (i.e., which topics attract/involve users). This class omits both spatial and temporal details on *when* and *where* each tweet was posted. Instead, this information is concisely represented by the location and time values of the cluster centroid, considered as representative points of the cluster.

- 740 2. *Location-TextContent class (L-TC)*. This class analyses the correlations
741 between the words in tweet messages and the locations where tweets
742 have been posted. It makes it possible to identify the topics attract-
743 ing/involving users in a given location.
- 744 3. *Time-TextContent class (T-TC)*. This class analyses the correlation
745 between words in tweet messages and the time when tweets have been
746 posted so as to discover the topics attracting/involving users in a given
747 time frame.
- 748 4. *Location-Time-TextContent class (L-T-TC)*. This class considers all the
749 properties characterizing tweets in order to analyse the correlation be-
750 tween the words in tweet messages together with the time when, and
751 the location where, the tweets were posted. It makes it possible to dis-
752 cover the topics attracting/involving users in a given time frame and
753 location.

		Example pattern	
Class	Example question	Association Rule	Meaning
TC	What are the topics attracting/involving users?	$\{\text{world, final}\} \Rightarrow \{\text{cup}\}$ $\text{centroid}(T = y, L = x)$	Users talked about world final cup event (reference time frame y and geographical area x)
L-TC	Given a spatial location, what are the topics attracting/involving users?	$\{L = x\} \Rightarrow$ $\{TC = (\text{german, win, argentina})\}$	Users talked about the match Germany-Argentina in the geographical area x
T-TC	Given a time frame, what are the topics attracting/involving users?	$\{T = y\} \Rightarrow$ $\{TC = (\text{best, player, playerName})\}$	Users talked about playerName as the best player in time frame y
L-T-TC	Given a time frame and a geographical area, what are the topics attracting/involving users?	$\{T = y, L = x\} \Rightarrow$ $\{TC = (\text{good, performance, playerName})\}$	Users talked about the good performance of playerName in time frame y and geographical area x

Table 2: Reference rule classes with example rules about 2014 FIFA World Cup tweets

Topic family ID	Family description
T1	emotional states
T2	events
T3	points of interest
T4	celebrities

Table 3: List of topic families for the 2014 FIFA World Cup use case

To facilitate the semantic interpretation of the rules discovered, TCHARM employs a list of reference *topic families*. A dictionary of the words characterizing each topic family is used to associate each rule with the proper family, based on the word set appearing in the rule. For instance, Table 3 reports an example list of reference *topic families* when targeting the analysis of tweets about the 2014 FIFA World Cup. The *events* family includes events such as the football matches and the opening and the closing ceremony. The *points of interest* family concerns where the events take place. Instead, the *celebrities* family regards players, coaches or other famous people somehow involved with the 2014 FIFA World Cup events.

Before applying the rule extraction process, the spatial and temporal features of tweets are processed to map their initial values into new ones with a coarse granularity in order to discover a limited but frequent set of rules. Indeed, too fine a granularity in the representation of spatio-temporal features can produce a fragmented rule set which may negatively affect the rule quality evaluation. For example, the geographical location of the user can be specified in terms of city, region, or country instead of using geo-coordinates. Similarly, the information about tweet posting time can be described with hourly or daily time slots instead of using the entire timestamp value.

3.5. TCHARM implementation

The entire data analysis process (preprocessing, clustering, and association rules extraction) in TCHARM has been implemented as a Scala application in the open source computing framework *Apache Spark* (version 1.5) (Zaharia et al., 2010). This framework was selected because it is currently one of the leading platforms for data analytics and provides a Machine Learning library (MLlib) which has been exploited and extended in this study to support all the functionalities of TCHARM.

782 Available packages in MLlib are used for the TF-IDF weighting score cal-
783 culation in the data preprocessing phase. For the subsequent cluster analysis,
784 the K-means algorithm available in MLlib has been extended by integrating
785 the TASTE measure. Moreover, to evaluate the quality of the generated
786 cluster set, the computation of the *Sum of Squared Error* (SSE) index was
787 implemented, based on TASTE and integrated in K-means too. For associ-
788 ation rule analysis, the FP-growth algorithm (Han et al., 2000) available in
789 MLlib was adopted to generate association rules from the computed clusters.
790 To point out relevant association rules in clusters, we used the formulas of
791 *support* and *confidence* values available in Apache Spark, but we also inte-
792 grated the calculation of the *lift* value.

793 The preliminary data collection step relies on Twitter’s Streaming Appli-
794 cation Programming Interfaces (APIs) to retrieve tweets data. The Stream-
795 ing APIs provide low latency access to Twitter’s global stream of tweets data
796 by establishing and maintaining a continuous connection with the stream
797 endpoint. A Java crawler is used to collect and parse tweets in real time
798 based on a predefined set of keywords (e.g., “worldcup2014”, “fifaworldcup”
799 in our case study), with a case-insensitive search.

800 4. Experimental Results

801 This section presents the results of the experiments with
802 TCHARMimplementation, regarding (i) *geographical and temporal dis-*
803 *tribution* of the computed cluster sets, (ii) *clusters content characterization*
804 through association rules analysis, and (iii) *performance evaluation* in terms
805 of overall execution time and scalability.

806 The experimental evaluation was conducted on a real collection of Twitter
807 data related to the FIFA World Cup held in Brazil in 2014. Experiments were
808 executed on a cluster of 3 master nodes (DELL PowerEdge R620 with 128GB
809 of RAM) and 30 worker nodes (18 DELL PowerEdge R720XD with 96GB
810 of RAM, 2 SuperMicro with 64GB of RAM, and 10 SuperMicro with 32GB
811 of RAM). Each node runs Cloudera distribution based on Apache Hadoop
812 including HDFS and Apache Spark (version 1.5) for Big Data distributed
813 applications on Linux Ubuntu 14.04.02 LTS.

814 4.1. Datasets

815 The public stream endpoint offered by the Twitter APIs was monitored
816 over a time period of 27 days from June 18th to July 14th 2014, by tracking

a selection of keywords related to the 2014 FIFA World Cup (e.g., “worldcup2014”, “fifaworldcup”). Tweets in English and with the exact GPS coordinates of the user location were extracted. The resulting collection includes 302,052 tweets. To ease the computation of temporal distances between tweets in the clustering phase, all timestamps have been converted according to the reference time zone of *America/Sao Paulo*, in Brazil, where the 2014 FIFA World Cup was held.

Since the collected tweets were widely spread over both time and space, the tweets collection was partitioned into subsets referred to disjoint spatio-temporal segments before applying the cluster analysis, as follows.

To analyse how the tweet text content developed over time, the tweet collection was partitioned according to three *time windows* following the official time schedule of the football matches. *Time window #1* and *time window #2* cover respectively the first and the second stage time period (i.e., from June 18th to June 27th and from June 28th to July 3rd), while *time window #3* covers the remaining time period from the quarter-finals to the end (i.e., from July 4th to July 14th). The number of tweets is comparable in the three windows.

The tweet spatial distribution was then locally analysed within each of the three time windows based on tweet geo-coordinates. In each time window tweets appeared to be widely dispersed and geographically partitioned into different areas. English speaking countries like the United Kingdom (UK), USA, and Central America show higher tweets concentrations than other areas. Following this evaluation of tweet spatial distribution, we selected two *spatial partitions*, corresponding to *UK* and *USA*, for each time window. Table 4 summarizes the main characteristics of the six resulting datasets which are used as reference case studies for the experimental evaluation. Each dataset was named using the corresponding spatio-temporal segment. For example, dataset $\mathcal{D}_{(TW1,UK)}$ contains tweets posted during time window #1 in UK.

4.2. Parameters configuration for cluster analysis

We set the parameters for the clustering analysis to best fit the use case considered, the 2014 FIFA World Cup, which involves people worldwide. Aimed at discovering clusters including tweets about the same topics but posted in nearby locations and time periods, we assigned the same relevance to spatial and temporal terms in modulating the text distance, i.e., we set $k_s = k_t = 0.5$. On the other hand, as usually happens on Twitter, we expect

Dataset	Time window	Geographical partition	Number of tweets	Average tweets length
$\mathcal{D}_{(TW1,UK)}$	1	UK	29,864	8.10
$\mathcal{D}_{(TW1,USA)}$	1	USA	26,447	8.02
$\mathcal{D}_{(TW2,UK)}$	2	UK	15,175	8.43
$\mathcal{D}_{(TW2,USA)}$	2	USA	19,828	8.27
$\mathcal{D}_{(TW3,UK)}$	3	UK	34,392	8.46
$\mathcal{D}_{(TW3,USA)}$	3	USA	50,028	8.06

Table 4: Main characteristics of selected reference datasets from 2014 FIFA World Cup tweets collection

854 most reactions to a given event (e.g., a football match) to be published as soon
 855 as the same event occurs (or within a short delay), even from quite distant
 856 locations. Indeed, while users interested in the same event can be also located
 857 in different areas, it is unlikely that they tweet at completely different times.
 858 Therefore, to group tweets with very close temporal distances, we set the
 859 weight of the temporal exponent p_t to a higher value than the spatial one p_s .
 860 We empirically found that $p_s = 3$ and $p_t = 6$ provide the lowest variability of
 861 SSE among clusters for different values of K (number of clusters) on datasets
 862 in Table 4. For each dataset, we evaluated the average SSE among the
 863 resulting clusters for a range of values of K . K was then set to 200 as a
 864 good trade-off to minimize SSE and to limit the number of clusters as well.
 865 As an example, Figure 3 plots the decrease of the average SSE for dataset
 866 $\mathcal{D}_{(TW1,UK)}$ when increasing the value of K . SSE abruptly decreases until
 867 $K = 150$, after which it goes down at a lower rate. Since we needed to
 868 limit both the desired number of clusters and the expected value of SSE, we
 869 assumed that $K = 200$ was a good trade off between these two objectives.

870 To address the problem of centroid initialization in K-means, a common
 871 approach was adopted. We performed multiple runs, each with a set of ran-
 872 domly chosen initial centroids, then we selected the cluster set with minimum
 873 SSE.

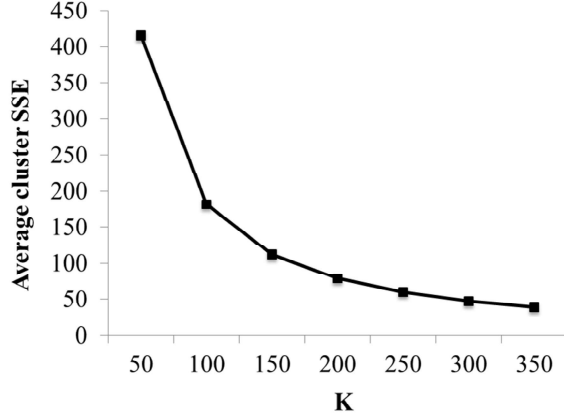


Figure 3: Variation of average cluster SSE with respect to the number of clusters (K) for dataset $\mathcal{D}_{(TW1,UK)}$ ($p_s = 3$, $p_t = 6$, $k_s = k_t = 0.5$)

874 4.3. Analysis of the clustering results

875 In this section the clustering results are characterized in terms of (i) *clus-*
876 *ter cardinality*, given by the number of tweets per cluster, and (ii) *spatio-*
877 *temporal cluster distribution*, given by the geographical area and the time
878 span covered by the clusters. As a reference case for the analysis, we selected
879 the collection of tweets posted in the UK partition during time window #1
880 (i.e., dataset $\mathcal{D}_{(TW1,UK)}$ in Table 4). This time window corresponds to the
881 first stage in the 2014 FIFA World Cup, when there was a larger number of
882 football matches involving many different teams. The tweets are thus poten-
883 tially characterized by a higher variability of text messages as well as spatial
884 and temporal feature values.

885 Figure 4 shows the distribution of clusters cardinality in the cluster set
886 computed on dataset $\mathcal{D}_{(TW1,UK)}$. Clusters are sorted along the x axis by
887 increasing value of cardinality. The cluster set includes one cluster with
888 about 800 tweets, while 16.5% of clusters contain from 200 to 400 tweets,
889 41.5% of clusters from 100 to 200 tweets, and the remaining 41.5% less than
890 100 tweets. The mean value of cluster size is 132 tweets, while the median
891 value is 111 tweets.

892 The spatial and temporal distributions of the cluster set are plotted in
893 Figures 5 and 6, respectively. To facilitate understanding of the results,
894 each cluster is concisely represented with the spatial and temporal features
895 of its *centroid*. Moreover, for both features a coarse-grained representation

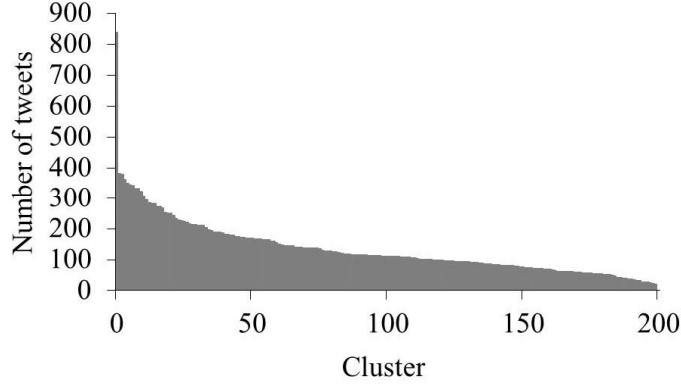


Figure 4: Distribution of number of tweets in the cluster set for dataset $\mathcal{D}_{(TW1,UK)}$

is adopted in place of the original one. Specifically, the *spatial feature* is represented as the *geographical area* where a centroid is located, instead of its GPS coordinates. Since the considered dataset contains tweets posted in UK, the *county* is used here as reference geographical area. County membership of a centroid is calculated based on the boundary GPS coordinates of each county¹ and on the GPS coordinates of the centroid. The *temporal feature* of a centroid is represented in terms of the corresponding *hourly time slot*, instead of the centroid timestamp.

The evaluation of the *spatial distribution* of centroids in the cluster set points out the *locations* in UK where people were more committed to tweeting about the 2014 FIFA World Cup 2014. Figure 5a shows the number of centroids located in each county, while Figure 5b reports the cardinality of the corresponding clusters. For each county, clusters are sorted along the x axis by decreasing value of cardinality. For readability, both figures focus on counties including at least seven centroids.

The results show that a limited subset of counties contain at least seven centroids (11 counties over 89), and about half of the centroids (98 over 200) are located in six counties (i.e., Buckinghamshire, Warwickshire, Greater London, Staffordshire, Lancashire, and Strathclyde). Clusters centered in these six counties overall include about 56% of tweets in dataset $\mathcal{D}_{(TW1,UK)}$. Moreover, thirteen of these clusters are among the fifteen largest clusters

¹<http://www.nearby.org.uk/downloads.html>

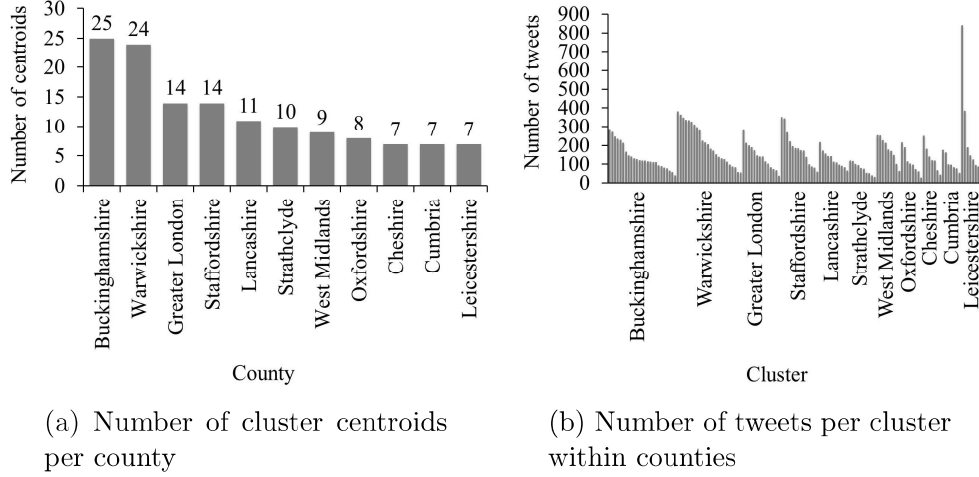


Figure 5: Spatial characterization of the cluster set for dataset $\mathcal{D}_{(TW1,UK)}$

in the cluster set (the two largest clusters in the cluster set are centered in Leicestershire county instead). Hence, we can consider the above six counties as the locations where most tweet activity was focused in UK during time window #1.

The evaluation of the *temporal distribution* of centroids in the cluster set reveals the *time periods* when people in UK were more involved in the 2014 FIFA World Cup. As an example, we report the results for a two-day time frame (from June 19th to June 20th) within time window #1. Figure 6a shows the number of centroids located in each hourly time slot, while Figure 6b reports the cardinality of the corresponding clusters. For each hourly time slot, clusters are sorted along the x axis by decreasing value of cardinality.

Results point out that the number of clusters, as well as the number of tweets per cluster, increases in correspondence of two events, i.e., the football matches *Colombia - Cote D'Ivoire* and *Italy - Costa Rica* (the starting hour for both matches is highlighted with a dashed line in Figures 6a and 6b). More specifically, in Figure 6a a peak occurs in the hourly time slot when goals were scored in each of the two matches. For match *Colombia - Cote D'Ivoire*, the peak of 28 centroids occurs in time slot 2014/06/19 [14:00-15:00) which corresponds to the second half of the match when three goals were scored. Instead, for the match *Italy - Costa Rica*, the peak of 21 centroids occurs in time slot 2014/06/20 [13:00-14:00) which corresponds to the first

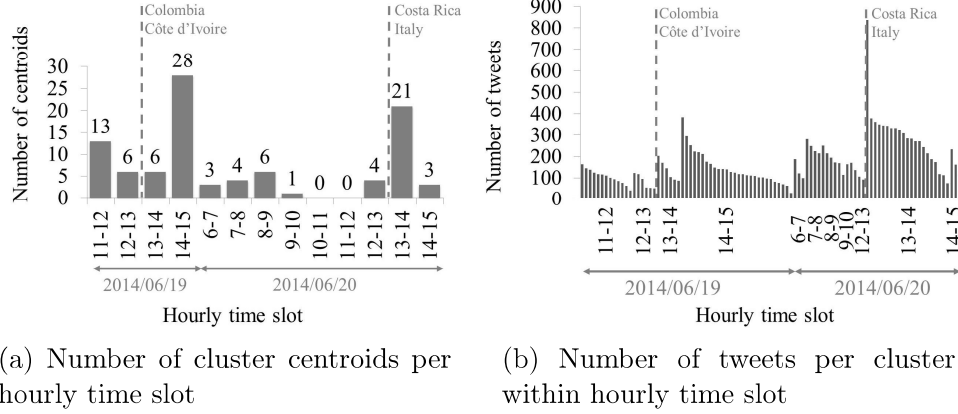


Figure 6: Temporal characterization of the cluster set for dataset $\mathcal{D}_{(TW1,UK)}$ during a two-days time frame

half of the match when the only goal of the match was scored.

To deepen the analysis of the spatio-temporal span for the discovered clusters, we focus on four example clusters selected among those with the centroid located in the Greater London county. The characteristics of these clusters are summarized in Table 5 in terms of (i) spatial and temporal features of the cluster centroid, (ii) cluster cardinality, (iii) cluster spatial cohesion as average geographical distance between tweets in the cluster and the cluster centroid, and (iv) cluster temporal cohesion as average time distance between tweets in the cluster and the cluster centroid. Since all the centroids are located in the Greater London county, to describe their spatial features Table 5 also reports the town where each centroid is placed.

Clusters manifest a good temporal cohesion since the average time distance is always about 20 minutes. This temporal span is suitable to associate clusters to some specific events. For example, clusters A and C span on time intervals including the *Colombia - Cote D'Ivoire* and *Italy - Costa Rica* football matches, respectively. Tweets in clusters B and D mainly discuss the elimination of the England football team that occurred the day before. These tweets may have been posted in response to news reporting this event on sports channels (also mentioned in tweet messages and taking place near the centroid time).

Clusters also demonstrate a reasonable spatial cohesion around their centroid, since tweets within each cluster are mainly (or even exclusively) posted

	Cluster centroid		Cluster content		
Cluster ID	Spatial location of centroid (County:City)	Temporal slot of centroid (Date:hourly time slot)	# of tweets	Avg GPS distance (km)	Avg time distance (min)
A	Greater London: Harrow	2014/06/19 [14-15)	113	59.25	26
B	Greater London: Stratford	2014/06/25 [08-09)	188	42.35	20
C	Greater London: Uxbridge	2014/06/20 [13-14)	283	68.73	23
D	Greater London: London	2014/06/25 [07-08)	197	42.24	19

Table 5: Characterization of four example clusters centered in Greater London county

in the same county where the centroid is located. The larger geographical area covered by each cluster is due to the fact that events related to the FIFA World Cup are of widespread interest.

As an example, Figure 7 reports the distribution of the number of tweets in the top ten counties and over time for the cluster with the highest cardinality in Table 5, i.e., cluster *C*. Most tweets were posted in the Greater London county where the cluster centroid is located, while the other tweets are mainly spread out in four of the neighboring counties. Furthermore, the tweets were mainly posted during the hourly time slots adjacent to the slot of the centroid.

4.4. Clusters characterization using association rules

The cluster content is concisely described here using association rules to model correlations among tweet features (text content, location, and time). The rules are extracted according to the rule templates defined in Section 3.4.2 and the topic families reported in the same section. To discuss the type of information that can be mined using these patterns, some example rules are reported in the next subsections. These rules have been extracted from (i) one sample cluster, (ii) clusters mined in time window #1

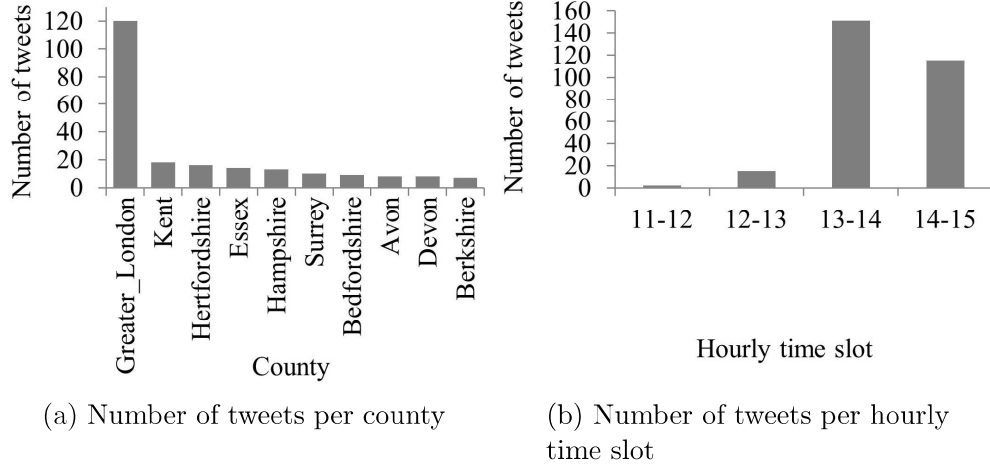


Figure 7: Spatial and temporal characterization of cluster C (from Table 5)

and from different geographical partitions, and (iii) clusters computed for different time windows from the UK partition. For the rule extraction, we enforced $support \geq 1\%$, and $lift > 1$ to prune both negatively correlated and uncorrelated item combinations.

4.4.1. Analysis of rules on a sample cluster

Cluster C (see Table 5) from dataset $\mathcal{D}_{(TW1,UK)}$ was selected as the reference case for the analysis. To reduce data fragmentation in the extracted patterns, caused by the spatio-temporal sparsity of the data collection, the tweet geo-coordinates have been mapped to the corresponding counties and the tweet posting timestamp to the corresponding 2-hours time slot.

Experimental results showed that the association rules generated from cluster C concern a variety of topics such as events, emotional states and celebrities, mainly related to the *Italy - Costa Rica* football match scheduled on June 20th, 2014. A selection of significant rules is reported in Table 6 and they are briefly described below.

Analysis of correlations in tweet text content (class TC). The rules in the class TC model correlations in the tweet text content. The information about when and where tweets were posted is concisely described as spatial and temporal details of the cluster centroid. Rules like R_1 and R_2 represent strong pairwise correlations (according to the lift value) among words in tweet messages. Rule R_1 captures a positive emotional state in people for the Costa

1000 Rica football team. Instead, in rule R_2 people talked about the celebrity
 1001 Gary Lineker, a retired English footballer and current sports broadcaster,
 1002 who wore an Italy shirt. The reason is that the victory of Italy over Costa
 1003 Rica would have allowed the England football team to keep their World Cup
 1004 hopes alive.

1005 *Analysis of correlations between the location where tweets were posted and*
 1006 *tweets text content (class L-TC).* Rules in the L-TC class, like rules R_3 and
 1007 R_4 , point out the geographical areas where certain topics are discussed. Rule
 1008 R_3 reveals that a negative emotional state about the England football team
 1009 arises from people located in the Greater London county. This opinion may
 1010 be due to the fact that the England football team did not win any match
 1011 in the first stage of the World Cup. Instead, rule R_4 reports that people in
 1012 the Greater London county are watching how the Costa Rica football team
 1013 performs in matches.

1014 *Analysis of correlations between the time when tweets were posted and tweets*
 1015 *text content (class T-TC).* Rules in the T-TC class, such as R_5 and R_6 ,
 1016 point out the time slot when certain topics are discussed. Rule R_5 describes
 1017 the association between people’s disappointment about the behavior of the
 1018 Italian football team and the time slot including the football match *Italy -*
 1019 *Costa Rica*. In fact, after the goal scored by Costa Rica in the first half of
 1020 the match, the Italian team did not respond with any winning actions in
 1021 the second half of the match. Rule R_6 highlights the people’s interest in
 1022 the comments on the *Italy - Costa Rica* match by a former English player
 1023 (Robbie Savage) hired as pundit by the British Broadcasting Corporation
 1024 (BBC) for the 2014 FIFA World Cup.

1025 *Analysis of correlations between location where, and time when, tweets were*
 1026 *posted and tweet text content (class L-T-TC).* R_7 and R_8 are example rules
 1027 belonging to this class and they both show that the goal scored by Costa
 1028 Rica and the consequent defeat of the Italian team in the time slot including
 1029 the first half of the match was a hot topic in the Greater London county.

1030 It is worth noting that the rules of classes *L-TC*, *T-TC* and *L-T-TC*,
 1031 characterized by positive correlation and high confidence values, always in-
 1032 clude the same county and hourly time slot of the centroid. This provides
 1033 further evidence in support of the high spatio-temporal cohesion of cluster C
 1034 around its centroid.

Rule class	Rule ID	Topic family	Rule	supp [%]	conf [%]	lift
TC	R_1	Emotional state	$\{\text{fancy, costa, rica}\} \Rightarrow \{\text{chances}\}$	1.1	75	53.25
	R_2	Celebrity	$\{\text{shirt, italy}\} \Rightarrow \{\text{lineker}\}$	1.1	100	56.80
L-TC	R_3	Emotional state	$\{\text{TC} = (\text{bad, england})\} \Rightarrow \{\text{L} = \text{Greater London}\}$	1.1	100	2.37
	R_4	Event	$\{\text{TC} = (\text{watching, costa, rica})\} \Rightarrow \{\text{L} = \text{Greater London}\}$	1.4	66	1.58
T-TC	R_5	Emotional state	$\{\text{TC} = (\text{bad, italy})\} \Rightarrow \{\text{T} = 2014-06-20 [12:00-14:00]\}$	1.1	50	1.23
	R_6	Celebrity	$\{\text{TC} = (\text{robbiesavage, playing, italy, costa})\} \Rightarrow \{\text{T} = 2014-06-20 [12:00-14:00]\}$	1.1	100	1.71
L-T-TC	R_7	Event	$\{\text{T} = 2014-06-20 [12:00-14:00], \text{TC} = (\text{lose, italy})\} \Rightarrow \{\text{L} = \text{Greater London}\}$	1.1	60	1.42
	R_8	Event	$\{\text{T} = 2014-06-20 [12:00-14:00], \text{L} = \text{Greater London}, \text{TC} = (\text{costa, rica})\} \Rightarrow \{\text{TC} = (\text{goal})\}$	1.1	15	10.65

Table 6: Example rules from cluster C ($\text{centroid}(\text{T} = 2014-06-20 [12:00-14:00], \text{L} = \text{Greater London})$) from dataset $\mathcal{D}_{(TW1, UK)}$ (see Table 5)

1035 4.4.2. Analysis of rules across geographical partitions

1036 In this section we analyse how people’s interest in events occurring within
1037 a given time window vary across different geographical areas. We compared
1038 the association rules mined from clusters computed in UK and USA areas
1039 when considering time window #1 (datasets $\mathcal{D}_{(TW1,UK)}$ and $\mathcal{D}_{(TW1,USA)}$). To
1040 reduce data fragmentation in the mined patterns, we adopted a coarse spatio-
1041 temporal data representation suitable for both cases considered. Specifically,
1042 tweet geo-coordinates have been mapped to the nearest city and the tweet
1043 posting timestamp to the corresponding day. Some sample rules modeling
1044 correlations in the tweet text content (class TC) are shown in Table 7, but
1045 the following discussion is based on the overall results.

1046 People in the UK area commented mostly on matches involving the Eng-
1047 land football team (e.g., rule R_1), or other teams included in the same group
1048 as England. Moreover, an odd episode involving a single player was the main
1049 topic of various clusters (R_2). Instead, clusters from many locations of the
1050 USA reveal that people were interested in matches involving various football
1051 teams, also those not included in the same group as their national team. For
1052 instance, rule R_3 refers to the match between Italy and Costa Rica and rule
1053 R_4 to the match involving Nigeria and Argentina.

1054 The behaviour observed may be related to the people’s different interests
1055 in the two geographical areas. Overall, football is more popular in England
1056 than in USA, where people are mostly interested in other sports. While in
1057 England people particularly focus on events related to their national team,
1058 in USA they show a more general interest in the FIFA World Cup, also for
1059 events involving teams other than their national team.

1060 4.4.3. Analysis of rules across time windows

1061 In this section we analyse how the interests of people tweeting from the
1062 same geographical area vary for events that occurred in different time win-
1063 dows. We compared rules mined from clusters computed in the UK area
1064 in the three time windows (datasets $\mathcal{D}_{(TW1,UK)}$, $\mathcal{D}_{(TW2,UK)}$, and $\mathcal{D}_{(TW3,UK)}$).
1065 We adopted the same spatio-temporal data representation used for the anal-
1066 ysis discussed in Section 4.4.2. Table 8 shows some example rules from the
1067 TC class, but the discussion is based on the overall results.

1068 It is worth noting how interests varied after the elimination of Eng-
1069 land team which happened at the end of time window #1. The extracted
1070 rules show that people in UK shifted their attention to matches involv-
1071 ing other teams. Various clusters in time window #2 are focused on the

Rule id	Partition	Topic family	Rule	supp [%]	conf [%]	lift
R_1	UK	Event	$\{\text{uruguay}\} \Rightarrow \{\text{england}\}$ $\text{centroid}(T = 2014-06-19,$ $L = \text{Perth})$	5.0	100	2.38
R_2	UK	Celebrity	$\{\text{suarez,someone}\} \Rightarrow \{\text{bite}\}$ $\text{centroid}(T = 2014-06-25,$ $L = \text{Rugeley})$	3.0	80	26.90
R_3	USA	Event	$\{\text{costa,rica}\} \Rightarrow \{\text{italy}\}$ $\text{centroid}(T = 2014-06-20,$ $L = \text{Whittier,CA})$	8.3	64	1.67
R_4	USA	Event	$\{\text{nigeria}\} \Rightarrow \{\text{argentina}\}$ $\text{centroid}(T = 2014-06-25,$ $L = \text{Banning,CA})$	2.1	53	7.16

Table 7: Example rules (class TC) characterizing clusters in UK and USA areas in time window #1 (datasets $\mathcal{D}_{(TW1,UK)}$ and $\mathcal{D}_{(TW1,USA)}$)

Germany – Algeria football match (played on June 30th, 2014), and are mostly about the tactics (R_5) and performance (R_6) of the German team.

During time window #3, the final match became one of the most popular topics (R_7). Nevertheless, the attention of people in UK also moved towards other topics loosely related to the competition. For instance, the latest transfer of player Luis Suarez away from an English club was mainly discussed on July 11th 2014, on the same day as the official announcement (R_8), while the next match of the England team, scheduled for November against Scotland (R_9), became popular just after the final World Cup match, on July 14th 2014.

4.5. Execution time and scalability

The execution time for the cluster set computation on the six datasets in Table 4 spans from 12m 13s for the smallest dataset ($\mathcal{D}_{(TW2,UK)}$, 15,175 tweets) up to 33m 34s for the largest one ($\mathcal{D}_{(TW3,USA)}$, 50,028 tweets). The execution time for association rules extraction is less variable and has an overall mean value of 53s. Increasing the number of executors does not yield better performance in terms of clustering execution time due to the limited size of these datasets. Thus, experiments for these datasets were performed using one execution node.

Rule id	Time window	Topic description	Rule	supp [%]	conf [%]	lift
R_1	1	Event	$\{\text{uruguay}\} \Rightarrow \{\text{england}\}$ $\text{centroid}(T = 2014-06-19,$ $L = \text{Perth})$	5.0	100	2.38
R_2	1	Celebrity	$\{\text{suarez, someone}\} \Rightarrow \{\text{bite}\}$ $\text{centroid}(T = 2014-06-25,$ $L = \text{Rugeley})$	3.0	80	26.90
R_5	2	Event	$\{\text{line, high}\} \Rightarrow \{\text{germany}\}$ $\text{centroid}(T = 2014-06-30,$ $L = \text{London})$	2.0	100	1.02
R_6	2	Emotional state	$\{\text{good}\} \Rightarrow \{\text{germany}\}$ $\text{centroid}(T = 2014-06-30,$ $L = \text{Stirling})$	2.0	58	1.22
R_7	3	Event	$\{\text{world, cup}\} \Rightarrow \{\text{final}\}$ $\text{centroid}(T = 2014-07-13,$ $L = \text{Newcastle})$	10.2	99	2.91
R_8	3	Celebrity	$\{\text{suarez}\} \Rightarrow \{\text{good, luck}\}$ $\text{centroid}(T = 2014-07-11,$ $L = \text{London})$	2.3	77	24.40
R_9	3	Event	$\{\text{november}\} \Rightarrow$ $\{\text{england, scotland}\}$ $\text{centroid}(T = 2014-07-14,$ $L = \text{Broxbourne})$	1.8	100	36.71

Table 8: Example rules (class TC) characterizing clusters across the three time windows in UK area (datasets $\mathcal{D}_{(TW1,UK)}$, $\mathcal{D}_{(TW2,UK)}$, $\mathcal{D}_{(TW3,UK)}$)

The capacity of the clustering algorithm integrating the TASTE measure to scale up to bigger data collections was assessed by measuring the execution time when varying (i) the number of tweets under analysis and (ii) the number of parallel executors. For scalability analysis, to get a larger number of tweets including all (text, temporal, and spatial) features, we have considered the location specified in the user profile as reference location information. Indeed the amount of tweets with geo-coordinates is much less than the number of tweets with location information in the user profile due to the limitation of GPS enabled devices. Geo-coordinates for the location extracted from the user profile have been calculated using Bing Maps Locations API. The

1101 resulting dataset, named $\mathcal{D}''$, includes about 23.5 million tweets.

1102 To study scalability by varying the number of tweets, we considered dif-
1103 ferent sample rates of dataset $\mathcal{D}''$ and one executor for process running. In-
1104 creasing the number of tweets from 50,000 to about 2.35 million (10% of
1105 whole $\mathcal{D}''$), we notice an increment of the execution time (from 33m 34s to
1106 14h 31m). However, the growth rate of the execution time (about 25) is
1107 almost half the growth rate of the dataset size (about 47).

1108 To study scalability by varying the number of executors, we considered
1109 the whole dataset $\mathcal{D}''$. The results show that, when increasing the number
1110 of executors from 4 to 8, the K-means algorithm integrating the TASTE
1111 measure scales almost linearly. The execution time is about 35h 43m with 4
1112 nodes; it decreases to about 19h 24m with 6 nodes, and to 10h 45m with 8
1113 nodes. Thus, with a suitable number of parallel executors, the clustering task
1114 is capable of handling also bigger data, evenly distributing the load across
1115 the nodes. When fewer than 4 executors are used, the process exceeded 48
1116 hours of execution and it was interrupted due to the very large dataset size.

1117 5. Comparison with previous studies

1118 This section discusses both a theoretical and analytical comparison be-
1119 tween our work and four previous studies on clustering Twitter data: (Kim
1120 et al., 2011), (Arcaini et al., 2016), (Lee, 2012), and (Cunha et al., 2014).
1121 These studies have proposed distance measures which combine the same
1122 tweet features considered in TASTE, or a subset of them. Specifically, the
1123 work in (Kim et al., 2011) takes into account the tweet spatial feature, while
1124 the spatio-temporal features are considered in (Arcaini et al., 2016), and both
1125 the text content and the spatial feature are evaluated in (Lee, 2012). A first
1126 attempt in considering all the three tweet features was proposed in (Cunha
1127 et al., 2014). Like in TCHARM, in these studies the geographic and tem-
1128 poral distances between tweets are computed using the Haversine and the
1129 Euclidean distance, respectively. The text content is represented with the
1130 BOW model, and the word relevance is weighted with the TF-IDF (Cunha
1131 et al., 2014) or the BursT (Lee, 2012) score; the cosine similarity is used to
1132 compare messages.

1133 For each study we present the objective of the work and the methodology
1134 for clustering tweets, including the clustering algorithm, the distance func-
1135 tions used and the strategy adopted for combining tweet features. Then, we
1136 discuss the analytical comparison between these works and our approach.

1137 In the following, we adopt the same notations as in Sections 3.1 and 3.3.
 1138 An arbitrary tweet τ_i is a triplet $\tau_i = (t_i, s_i, W_i)$ where t_i and s_i are respec-
 1139 tively the temporal and spatial features of τ_i , while $W_i \subseteq \Sigma$ is the tweet
 1140 text content. Given two tweets $\tau_i = (t_i, s_i, W_i)$ and $\tau_j = (t_j, s_j, W_j)$ their
 1141 temporal, spatial and content distances are denoted by $d_t(t_i, t_j)$, $d_s(s_i, s_j)$,
 1142 and $d_W(W_i, W_j)$, respectively.

1143 The work in Kim et al. (2011) aims at providing (near-)real time infor-
 1144 mation to users about events happening close to their location. Tweets are
 1145 clustered through the K-means algorithm by considering their geographic dis-
 1146 tance. The discovered cluster set is then analysed to detect clusters that can
 1147 reveal the occurrence of an event. The values of the tweet temporal feature
 1148 are used to filter computed clusters by comparing their temporal aspects. If
 1149 the number of tweets from a given cluster exceed far from those from clusters
 1150 found in vicinity in the past, the cluster is considered unusual and an event
 1151 may happen there. For tweets included in unusual clusters, the text content
 1152 is explored to extract representative keywords, which are sent to nearby users
 1153 to inform them about the possible events.

1154 The study in Arcaini et al. (2016) focuses on discovering spatio-temporal
 1155 periodic and aperiodic characteristics of events to support situation aware-
 1156 ness. Tweets collections are analysed off-line with a DBSCAN based algo-
 1157 rithm (GT-DBSCAN) to extract dense clusters of arbitrary shapes. The
 1158 tweet text content is explored in a preprocessing phase to filter the subset
 1159 of tweets relevant for the subsequent cluster analysis. Messages about spe-
 1160 cific events are selected by properly setting keywords for tweets search. To
 1161 drive the clustering process, three distance measures, considering the tweet
 1162 temporal and spatial features, are evaluated: (i) a temporal distance, (ii) a
 1163 geographic distance, and (iii) a geographic-temporal distance, basically a
 1164 combination of the two above. In this study we focus on the latter distance
 1165 measure for performance comparison. The geographic-temporal distance is
 1166 defined as the maximum value between the (normalized) geographic and
 1167 temporal distances.

1168 The work in Lee (2012) proposes a (near-)real time temporal-text cluster-
 1169 ing approach to detect bursts of tweets representing unexpectedly frequent
 1170 occurrences of a certain topic in a short period of time. A sliding window
 1171 of fixed time length is used to filter only the most recent tweets, which are
 1172 then considered in the analysis. Selected tweets are clustered using the Incre-
 1173 mentalDBSCAN algorithm (Ester et al., 1998), to detect dense clusters with
 1174 shapes changing over time and to remove uninformative tweets (outliers).

Study	Distance measure
Kim et al. (2011)	$d_{Kim}(\tau_i, \tau_j) = d_s$
Arcaïni et al. (2016)	$d_{Arc}(\tau_i, \tau_j) = [\text{Max}(d_s, d_t)]^\beta, \beta \in (0,1]$ d_s and d_t values expressed as the number of elementary units ϵ_s and ϵ_t , respectively
Lee (2012)	$d_{Lee}(\tau_i, \tau_j) = d_W \cdot e^{\zeta d_t/M}$ M : time unit; ζ : exponential decay rate factor.
Cunha et al. (2014)	$d_{Cun}(\tau_i, \tau_j) = w_W \cdot d_W + w_t \cdot d_t + w_s \cdot d_s + w_{So} \cdot d_{So}$ $w_W, w_t, w_s, w_{So} \in [0, 1]$ and $w_W + w_t + w_s + w_{So} = 1$
TCHARM	$d_{TASTE}(\tau_i, \tau_j) = d_W \cdot (k_s \cdot e^{p_s \cdot d_s} + k_t \cdot e^{p_t \cdot d_t})$ $k_s, k_t, p_s, p_t \in \mathbb{R}; k_s, k_t \in [0, 1]$ and $k_s + k_t = 1$.

Table 9: Distance measures for tweet comparison proposed in four reference previous studies and in TCHARM. For a pair of tweets (τ_i, τ_j) , their spatial distance $d_s(s_i, s_j)$ is shortly denoted by d_s , the temporal distance $d_t(t_i, t_j)$ by d_t , the content distance $d_W(W_i, W_j)$ by d_W , and the social distance $d_{So}(user_i, user_j)$ by d_{So} .

1175 Clusters are calculated by evaluating the temporal-text distance between
1176 tweets. In d_{Lee} , the temporal distance is used to module the text content
1177 distance. The exponential form has been adopted for the time distance to
1178 significantly penalize tweets far distant in time. Finally, geo-spatial keywords
1179 are extracted from message in each computed cluster to estimate location of
1180 detected events.

1181 The authors of Cunha et al. (2014) address the problem of identifying
1182 and displaying tweets profiles considering four different facets characterizing
1183 tweets: temporal, spatial, and context features and user social connections.
1184 Tweets are clustered with the DBSCAN algorithm Ester et al. (1996) to
1185 detect arbitrarily shaped clusters and to remove outliers from the results. The
1186 adopted distance measure is a linear combination of the four considered tweet
1187 features, i.e., the distance on time, space, text content, and social relations
1188 (d_{So}). The social distance term d_{So} evaluates the connections between users
1189 represented as nodes of a graph connected through edges. It is computed as
1190 the geodesic distance (i.e., the number of edges of the shortest path) between
1191 two nodes in the graph Bouttier et al. (2003).

1192 Based on the purposes of this paper, we want to evaluate the ability of
1193 each distance measure above in discovering cohesive clusters of tweets to be
1194 represented through their centroids. Hence, keeping the K-means algorithm

used in TCHARM as a reference clustering method, we applied in turn each distance measure. Since the TCHARM methodology aims at discovering cohesive clusters considering temporal and spatial tweet features and text content, we omitted the social distance for the measure proposed in (Cunha et al., 2014). For the sake of brevity, the resulting clustering methods are denoted by Cunha-14 (Cunha et al., 2014), Lee-12 (Lee, 2012), Arcaini-16 (Arcaini et al., 2016), and Kim-11 (Kim et al., 2011). The approach proposed in this study adopting the TASTE measure is denoted by TCHARM.

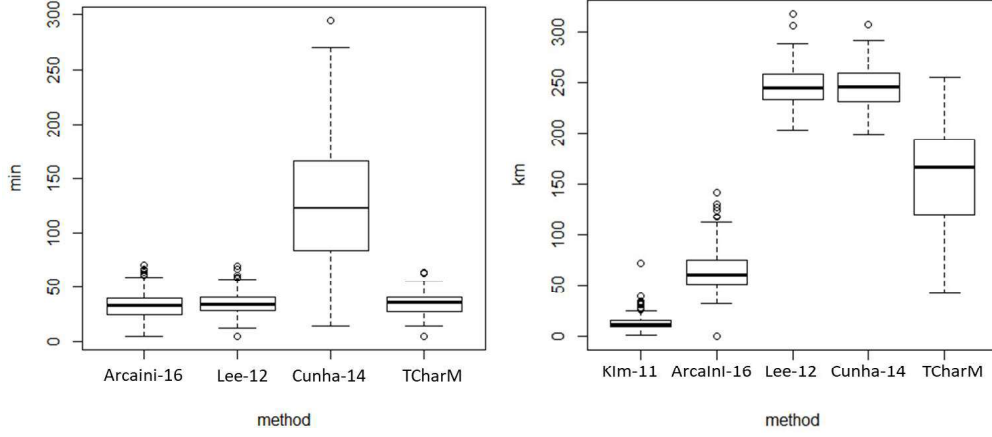
We evaluated the cluster cohesion as the average geographic/temporal/text content distance between tweets in the cluster and the cluster centroid. Lower values of these average distances point out a higher degree of cohesion on the corresponding tweet dimension.

The comparison was performed with the $\mathcal{D}_{(TW1,UK)}$ dataset. To produce comparable cluster sets, we forced $K=200$ as expected number of clusters for all the distance measures (i.e., the same value selected for TCHARM in Section 4.2). We suitably tuned the parameters to use each distance measure at its best with the $\mathcal{D}_{(TW1,UK)}$ datasets and with the K-means algorithm. Starting from the configuration proposed in each study (considered as default configuration), we performed several runs to tune the parameters of each distance measure, with the aim of reducing the average cluster SSE as well as the distance values for all the tweet dimensions they consider. Selected parameter values are reported in Figure 8.

For each method, box plots in Figure 8 illustrate the distributions of the average geographic/temporal/text content distance between tweets in each cluster and cluster centroid, while Table 10 reports the average values. Note that the temporal box plot for the Kim-11’s measure is not represented in Figure 8 as its values are too high compared to the other methods.

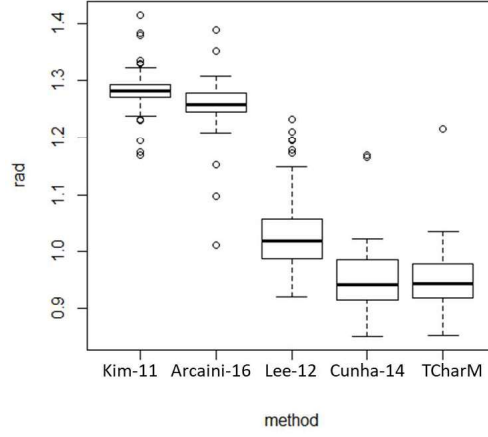
Clusters manifest the highest text content cohesion with TCHARM, Cunha-14 and Lee-12 distance measures, which provide comparable results. The highest temporal cohesion is provided by Arcaini-16, TCHARM and Lee-12, which achieve similar performance. The highest spatial cohesion is given by Kim-11, followed by Arcaini-16, and then TCHARM.

These results point out that TCHARM provides clusters with an overall good cohesion on all the three facets characterizing tweets. Specifically, computed clusters show the highest cohesion on the text content and on the temporal feature, and the third best spatial cohesion. Yet it should be noted that, when setting parameters in TASTE, we gave more importance to the temporal cohesion than to the spatial one.



(a) Average temporal distance from centroid

(b) Average spatial distance from centroid



(c) Average text content distance from centroid

Figure 8: Distributions of the average temporal, spatial, text content distances from cluster centroids, for each method. The temporal box plot for Kim-11 is not represented as its values are too high. Parameter configurations are as follows. Arcaini-16: ($\epsilon_s = 2km$, $\epsilon_t = 1200s$, $\beta = 1$), Cunha-14: ($w_s = w_W = 0.25$, $w_t = 0.5$, $w_{So} = 0$), Lee-12: ($\zeta/M = 12h^{-1}$).

Method	Avg time distance (min)	Avg GPS distance (km)	Avg text content distance (rad)
Kim-11	3905	14	1.28
Arcaini-16	33	66	1.26
Lee-12	35	246	1.03
Cunha-14	126	245	0.95
TCHARM	35	158	0.95

Table 10: Average value of mean temporal, spatial, and text content distances between tweets and their centroids for each distance measure.

Clusters provided by Arcaini-16, Lee-12, and Kim-11 methods show a good cohesion on the tweet features considered in their proposed distance measures, but the cohesion on the remaining features is far lower than TCHARM. Clusters tend to be spread over a larger geographic area (Lee-12) or a longer time period (Kim-11) than TCHARM, or to discuss more different topics (Kim-11, Arcaini-16). These results demonstrate that, to obtain clusters suitable for a subsequent characterization of their spatial, temporal and text features, it is convenient to consider all the three dimensions directly in the clustering phase. Otherwise, further post-processing steps would be required to characterize the clusters with the features previously left out.

Results also highlight that, when all three features are considered to cluster tweets, their contributions should be properly weighted in the distance measure. A liner combination of the content, spatial, and temporal distances as the one proposed in Cunha-14 turns out to be less suitable than our approach since discovered clusters manifest a temporal and spatial cohesion lower than TCHARM.

To deepen into the comparison of the methods above, we used the Adjusted Rand Index (ARI) (Hubert & Arabie, 1985) to evaluate the agreement between the cluster sets generated using the TASTE measure and those obtained with the other distance measures. The ARI computes the rate of pairwise agreements between two partitions of a set. It allows a more accurate estimation of the agreement between two partitions than the standard

Rand Index (Rand, 1971). Basically, ARI rescales the Rand Index value **with respect to its expected value for two independent clustering algorithms**. ARI has a maximum value of 1 for two identical partitions, and an expected value of 0 for two independent random partitions. Higher ARI values imply higher levels of agreement between two partitions.

The computed values of ARI report a moderate agreement between the cluster set provided by TCHARM and the one computed by Cunha-14 (ARI = 0.45). The agreement decreases with Lee-11 (ARI = 0.13), Arcaini-16 (ARI = 0.03), and Kim-11 (ARI = 0.005) methods which consider a subset of tweet features.

The results from the analytical comparison suggest that clusters discovered using other distance measures have quite different properties than those provided by TCHARM.

From a temporal perspective, clusters can have a higher temporal span. Indeed, while our clusters are centered around events of interest (see Section 4.3), we noticed that clusters computed with other methods (Kim-11 and Cunha-14) can include more than one event (e.g., more football matches). Similarly, the distance measures that do not provide a good cluster spatial cohesion lead to clusters of tweets spread across more counties (Lee, 2012). The two aspects above prevent from performing qualitative analyses based on fine-grained temporal and spatial resolutions. Finally, the lower text similarity among tweets in the clusters (Arcaini-16) makes it difficult to associate a single prevailing topic with each cluster and to generate significant association rules (i.e., with high values of quality indices as support, confidence and lift).

Thus, with the adoption of other distance measures than TASTE, a further level of segmentation would be required to identify the main topics in each cluster, or to partition the cluster content into subsets which refer to shorter time windows or more limited geographic areas.

6. Discussion

In this section we discuss the results discovered through TCHARM. The discussion addresses the data analysis phases in TCHARM, the computational cost of TCHARM, and the possible exploitation of the TCHARM findings.

(i) *Discovering in one step cohesive spatio-temporal clusters focused on specific topics.* The TCHARM findings demonstrate the ability of the proposed methodology to properly analyse large tweet collections distributed over time and space as well as addressing various topics for automatically computing cohesive clusters. TCHARM allows data miners to discover clusters useful for identifying *when* and *where* people were more involved and about *which* topics. The 2014 FIFA World Cup use case considered in this study enables a thorough validation of computed clusters due to the availability of a time schedule for the main events (e.g., football matches) and web news about the other events or celebrities somehow involved. The experimental evaluation conducted on six different datasets showed that mined clusters are centered in time in correspondence with an event related to the 2014 FIFA World Cup and they mainly include messages about the event. Moreover, the clusters present a good spatio-temporal cohesion around their centroid.

Differently from previous work (see Section 2), TCHARM clusters Twitter data taking into account in one step both spatio-temporal features and text content. TCHARM relies on the TASTE measure which combines the contributions of all three features above. TASTE modulates the distance between tweet messages through their distance in time and space, and it is aimed at discovering groups of tweets about the same topic but posted in nearby time periods and locations. Parameters of the TASTE measure can be conveniently tuned to fit scenarios with different spatial and temporal granularities.

The analytical comparison in Section 5 shows that TCHARM is competitive in terms of cluster cohesion, in almost all dimensions. In particular, it overperforms all the other measures in the text average distance. Indeed, the multiplicative (exponential) factors for time and space distances are suitably applied to the text distance, based on the hypothesis that a tight temporal and spatial proximity can contribute in detecting clusters of tweets about the same topic. As already demonstrated in Section 4.3, such clusters are temporally centered within the time interval of the event they refer to (e.g., a football match).

None of the measures considered for comparison performs far better than TASTE in more than one dimension. Moreover, the lower spatial cohesion obtained with TASTE is mainly due to our choice to assign a lower weight to spatial distance ($p_s = 3$), preferring the temporal cohesion ($p_t = 6$).

1327 *(ii) Cluster characterization through rules analysis.* TCHARM deeply ex-
1328 plores the resulting clusters through association rule analysis to discover cor-
1329 relations among topics (such as events, celebrities, emotional states) and
1330 spatio-temporal features. While rule class TC makes possible the identifica-
1331 tion of the main topics discussed in each cluster, the other rule classes enable
1332 a deeper characterization by correlating topics with time periods (class T-
1333 TC), geographical areas (L-TC), or both of them (class L-T-TC). This cluster
1334 characterization allows data miners to better understand popular topics in
1335 different geographical areas and through different time windows. Moreover,
1336 association rules represent the mined knowledge in a concise and easily un-
1337 derstandable form.

1338 The 2014 FIFA World Cup use case allows us to qualitatively validate
1339 various mined rules. Rule analysis pointed out some of the interests and
1340 reactions of sports fans and supporters that were in some cases predictable
1341 (e.g., the disappointment of people from England over the English team’s
1342 defeats). However, it also highlighted some aspects not so evident a priori,
1343 like those about celebrities statements or the major interest in USA for the
1344 team of Argentina. We believe that TCHARM can be applied also in other
1345 scenarios, for understanding people’s reactions and interests.

1346 *(iii) TCHARM performance.* From a computational point of view, TCHARM
1347 has a major advantage with respect to related works, since it is implemented
1348 on Apache Spark and can distribute computational load across parallel ex-
1349 ecutors. Tests performed on big collections of tweets (Section 4.5) prove the
1350 good scalability of our implementation of TCHARM and, in particular, of
1351 the clustering algorithm integrating the TASTE measure. Thus, TCHARM
1352 can be applied also to use cases with a higher cardinality of data and it is
1353 still capable to provide results in a reasonable time.

1354 *(iv) Exploitation of the mined knowledge.* TCHARM findings provide a
1355 spatio-temporal overview of people involvement in occurred events. This
1356 knowledge, hidden in Twitter data collections, can have a variety of practi-
1357 cal applications in different domains.

1358 In case of events with a wide and spread out audience (as FIFA World
1359 Cup), TCHARM findings can provide useful insights to understand how peo-
1360 ple located in different geographical areas perceive an event and to char-
1361 acterize the different facets of people involvement in different time frames.
1362 From a business perspective, this knowledge can be very useful to improve

service/product provision and support targeted advertising of certain services/products. For instance, the information about favourite teams or players in specific areas and moments can be used to provide targeted advertising that leverages on such features. Also during 2014 FIFA World Cup, advertising companies demonstrated great interest in social trends to plan marketing strategies. This was particularly evident with some viral topics as some brands gained visibility by proposing advertisements based on viral marketing strategies, mostly on social networks (Jenkins, 2014; Bud, 2014). TCHARM can thus be an effective methodology to enable a deeper analysis of spatio-temporal trends on social networks, showing when and where certain topics spread among users.

We believe that TCHARM can be profitably applied also in different domains. In a smart urban environment, for example, social networks are currently recognized as powerful instruments to enable citizen interaction and participation. Citizens may use Twitter to report information related to a variety of aspects such as urban safety, traffic and services (e.g., bike sharing, public transport offer, etc.). City administration is interested in better understanding where and when citizens report issues about the above aspects, to eventually undertake appropriate and targeted responses to citizens' concerns. The application of TCHARM to such collections of tweets would help to find out in which areas of the city and in which periods of time citizens discuss and complain about some issues. Clustering analysis would extract spatio-temporally defined clusters of topics reported by citizens. Rule analysis would then better highlight the degrees of correlation among topics, times and places of discussion and describe how the same topics evolve across different periods and through nearby urban areas.

7. Conclusion

In this paper we introduce TCHARM, a novel exploratory data mining methodology to analyse Twitter datasets. Its aim is to discover significant and cohesive groups of tweets by considering three facets of Twitter data: spatial, temporal, and text content information. The TASTE measure is one of the main added values of TCHARM as it allows the K-means algorithm to discover clusters with suitable levels of spatial and temporal cohesion, centered on specific events and including tweets which can be concisely represented by their centroids with an acceptable approximation. Moreover, through association rules mining, TCHARM provides us with a set of pat-

1399 terms that concisely describe the most significant characteristics of tweets in
1400 clusters. The TCHARM system has been deployed on Apache Spark to dis-
1401 tribute computational load across parallel executors and reduce the overall
1402 execution time also with huge amounts of data.

1403 The experimental validation conducted on tweets collected for the 2014
1404 FIFA World Cup demonstrated the ability of TCHARM in efficiently charac-
1405 terizing collections of tweets in terms of distribution of people involvement,
1406 topic identification, and correlations among tweet features. As a matter of
1407 fact, we managed to isolate groups of tweets focused on a few topics, tem-
1408 porarily associated to actual events (e.g., football matches), and posted from
1409 a limited geographical area. Compared with other approaches for tweet clus-
1410 tering, clusters computed using the TASTE measure confirmed an overall
1411 better cohesion balanced between the three tweet features.

1412 TCHARM can be an effective methodology to enable a deeper analysis of
1413 spatio-temporal trends on social networks, showing the different patterns of
1414 user involvement in certain topics or events. TCHARM can be used to anal-
1415 yse global events like the FIFA World Cup at a local scale and, for instance,
1416 to assess the popularity of soccer matches and football players in different
1417 areas and time periods. This information could be very useful for compa-
1418 nies to improve their services and products and to optimize their marketing
1419 strategies. For example, information about favourite teams and players in
1420 specific areas and moments can be used to provide targeted advertising that
1421 leverages on the characteristics of the computed clusters.

1422 There is still room for improvement of the TCHARM methodology in
1423 order to mitigate some of its weaknesses. Five promising future research
1424 directions have been identified.

1425 In the current implementation of TCHARM, the number of expected clus-
1426 ters for the k-means algorithm and the parameters in the TASTE measure
1427 should be experimentally tuned by trading-off the cardinality of the cluster
1428 set and the expected quality of clusters. However, the selection of the proper
1429 TCHARM configuration can be a very time-consuming activity. The design
1430 of innovative *self-tuning configuration strategies* Di Corso et al. (2017) to
1431 automatically identify the suitable TCHARM set up for each targeted data
1432 collection can permit the use of TCHARM in various application domains.
1433 These strategies would simplify the analysts role by relieving the end-user of
1434 the burden of configuring the overall cluster analysis process.

1435 The ability of TCHARM to discover cohesive and significant clusters may
1436 decrease when data sparseness further increases. In this case, a larger number

of clusters should be generated to discover groups with good quality, but these groups may be limited in size. To deal with this issue, *data taxonomies* on the three facets characterizing tweets can be climbed during the clustering process. The use of data taxonomies can result into coarse-grained data representations with a lower degree of sparseness and allows the evaluation of data correlations at different abstraction levels.

The use of K-means clustering, rather than other clustering algorithms as density-based methods, was motivated in this study by the purpose of generating clusters of tweets that can be concisely represented by their centroids. However, TCHARM inherits one of the main weaknesses of K-means, which is more sensitive to outliers in the dataset. A future task is to conduct a detailed study on evaluating the *integration of other candidate clustering methods* in TCHARM and their ability to identify more cohesive and significant clusters of tweets.

Currently, the proposed TASTE measure weights various tweet facets, but omits other aspects such as the characteristics of users who posted tweets and their social relationships. Considering also *user information* in the cluster analysis would be very helpful to discover spatio-temporal patterns of communities of users and to better profile how the user interests evolve over time. As a future work, we will study an improvement of the TASTE measure with the aim of evaluating also data about users.

Finally, in this study we have applied the TCHARM engine for the off-line analysis of spatio-temporal-text information from tweets posted within a (relatively large) time window. As a future study, TCHARM can be applied for the (near-)real time analysis, for instance of tweets collected every hour, to investigate the spatial evolution of clusters and related topics with a low time granularity. This approach would provide a deeper overview of the spatio-temporal dynamics of people’s interests. Thanks to the deployment on a cloud-based platform as Apache Spark, TCHARM can analyse huge amounts of data thus providing results in a reasonable time consistent with a near-real time analysis.

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