Analysing Human Migrations Patterns Using Digital Social Network Analysis

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***Abstract*—The success of smartphones and digital social networks has permitted a constant increase in the mobile social networks of users in the last decades. It is now possible for anyone to share content with enriched metadata, providing user's context and, in particular, times and locations. Contextual information associated with messages' content allows for the large-scale analysis of users' spatio-temporal behaviour, affording various possible applications (e.g., geo-marketing, security, smart cities). A number of studies have focused on spatio-temporal social data analyses for event detection and the identification of region of interests. This paper proposes a methodology that relies on social network analyses to identify the migrations of users between regions of interest. The proposed methodology allows for the capture of similar events and their characterization by participants' behaviour (source location and destination, etc.). The methodology is tested on 3 millions tweets from the San Francisco Bay Area.**

***Keywords*–Social media, Social network analysis, Region of Interests, Migration,Spatio-temporal graphs, Twitter.**

I. Introduction

The emergence of smartphones, in conjunction with the success of social platforms, has led to an increase in mobile social applications. Smartphones capture spatio-temporal traces of interactions with an internal clock and a GPS. This allows for new services to be available to users and also becomes an opportunity for research activities to understand communication and relations between humans in space and time at a large scale.

The Twitter microblogging platform is an example of a mobile application that allows the public to share contextual information. It is currently one of the top public sources of spatio-temporal data with an estimated 20% of tweets geolocated [1]. Microblogging is a type of blogging that allows for brief text updates. Due to the short length of messages, approximately half of Twitter users access the platform through a mobile application installed on their smartphones, generating large amounts of spatio-temporal data to be analysed.

It is common to represent a social network as a social graph denoted $G(N, E)$, where N represents the set of nodes and E the set of edges. Profiles are represented by nodes while edges represent relationships between profiles. These relationships illustrate any type of interaction captured online between a given pair of profiles. Social platforms compute the social graph from connections between individuals based on their inclusion in a contact list. However, other types of interactions may be retrieved and analysed. For example, two individuals communicating about the same subject may be considered connected in examining communities of interests. A diffusion graph is an another example, wherein two individuals are connected when one retweets the other. Diffusion graphs are often used for analysing virality in social networks.

This article proposes the study of two different types of relationships related to spatio-temporal data. First, spatio-temporal graphs of meetings between people capture the quality of spatio-temporal data and the number of users concerned about such types of analyses. Second, using previous observations, the study proposes computing the migration graph of regions of interest (ROI). Dynamic analyses of such a graph highlight the relationships between ROI at multiple scales. It is likely that this contribution will allow for a better understanding of human mobility patterns and could allow for the identification and qualification of ROI from a novel perspective (variety of people concerned, temporality of event, distance of people coming to the event, etc.).

The remainder of the article is organized as follows. Section II introduces the related works. Section III describes an approach to building and analyzing the spatio-temporal patterns of users. Section IV reports the results on a dataset of 3 millions tweets collected from Twitter. The article ends with a brief discussion and a conclusion.

II. Related works

Many works have modelled and analysed human mobility patterns. While in the past, collecting such data required specific devices [2], [3], smartphones and social media have helped in overcoming this limitation.

A common method to model spatio-temporal interactions is to use temporal graphs. As defined in [4], a temporal graph is a graph observed at different times as a sequence of time windows. A temporal graph is denoted $G_t^w(t_{min}, t_{max})$, where w is the time between two snapshots, the starting time of the experiment t_{min} and the ending time t_{max}. The temporal graph is a sequence of the following graphs: $\{G_{t_{min}}, G_{t_{min+w}}, \ldots, G_{t_{max}}\}$. At each frame, one observes the relationships between actors are observed and represented as a graph.

Various, state-of-the-art approaches differ in the way that graphs are built using spatio-temporal data. The authors of [5]

 ISBN: 978-1-61208-534-0

propose a time aggregated graph to model temporal graphs. Each relationship (i.e., edges) is represented with a series of time labels indicating the type of relationship observed in each time frame. Such an approach reduces storage and computational costs. In their work to detect malicious circles of users, the authors of [6] employed a spatio-temporal co-occurrence graph. This graph is generated from posts published on Facebook whose spatio-temporal constraints are adapted to match an original friend graph. They found that particular constraints allow for finding strong correlations between the two graphs. In [7], authors analysed data generated by smartphones using Bluetooth. They proposed a proximity network, composed of people and connections between them. Connections are established when people spend more than a certain number of minutes together. The authors of [8] propose the concept of encounter networks. Such a network is deduced from the number and duration of meetings between two individuals. Each edge is weighted using a friendship probability measure that depends on the number and duration of meetings.

In [9], the authors analysed fluctuations in the activity of mobile phone users based on the number of calls per hour and per geographical location. The approach permits the detecting of abnormal spatio-temporal patterns, such as events. The authors of [10] also present a statistical approach to detect events from mobile devices. The approach discovers the busiest locations at a city-wide scale and detects unexpectedly busy locations. In [11], the authors estimate the centres of earthquakes and the trajectories of typhoons from Twitter activity. A method for detecting ROI from Twitter network is proposed by [12]. Such geo-social event detection relies on the geographical regularities observed in user behaviour with regard to the normal level of interest from a geographical region.

Spatio-temporal considerations have also been integrated into collaborative filtering [13]. The approach relies on the calculation of user similarity, such as spatio-temporal proximity. Spatio-temporal proximity is calculated as the ratio of items that each pair of users has consumed in the same time and at the same place. The authors of [14] studied the geography of the Twitter network, finding that geographical distance, language, and country have a role in determining the creation of a connection on Twitter. In [15], the authors show that it is possible to detect the location of users depending solely on the content of their tweets and are able to estimate a Twitter user's location in a city with the technique.

The authors of [16] proposed a method to evaluate the relationship between social ties and spatio-temporal patterns. The approach divides the world into discrete cells and counts co-occurrences based on the observation of individuals in the same cell at the same time. The approach proposes a probabilistic model to infer friendship on the Flickr networks. Co-occurrences are based on the fact that two users took pictures in the same spatio-temporal frame.

In [17], authors analysed spatio-temporal data generated by smartphone users. Their analysis focuses on the contact duration and frequency between two individuals. They propose applying a community detection based on a graph weighted by contact duration. The authors of [18] propose integrating spatio-temporal considerations in multi-layer friendship modelling. This friend recommendation system takes into account the social graph layer, interests graph layer, and co-occurrence graph layer. The location metric between two users is defined as the minimum value of the update distance divided by the sum of updates times in the two locations. They show a clear correlation between such indicators and the fact to be friend or not on the mobile social network.

The mobility patterns of Foursquare users were analysed in [19]. The authors expose geo-temporal rhythms, check-in dynamics, and activity transitions to highlight possibilities of integrating spatio-temporal patterns into recommendation systems. The authors of [20] analysed the event-based social network (EBSN). The paper highlights the specificities of such networks, such as the correlations between online and offline relationships. The authors apply this cyber-physical analysis to study community detection and information diffusion. A study of 100,000 anonymous mobile phone users over a period of 6 months was conducted by the authors of [21]. The authors highlight that human trajectories have a high degree of spatio-temporal regularity. Moreover, humans tended to only move within a set of limited locations during the experiment. This observation is important as it indicates that human mobility observations follow simple, reproducible patterns.

To the best of the current study's knowledge, this article is one of the first to focus on how social users migrate between events.

III. Methodology

This section presents the general methodology for building migration networks from contextual social data. Such networks allow for connections between locations of interest (medium to large-scale events) based on the migration of Twitter users. The first subsection presents the process to identify ROI based on Twitter users meetings. The second subsection presents an algorithm for creating the migration graph. Applications of this methodology are discussed later in the paper.

A. *Overview*

Figure 1 displays the main steps of the methodology proposed in this paper. First, Twitter data in the San Francisco Bay Area was crawled for a period of 3 months. The crawler relies on the Twitter streaming application programming interface (API) and provides tweets belonging to the defined area (step I). More than 3 million tweets were collected during this step. From the collected tweets, spatio-temporal proximity was computed between the most active users to identify meetings between people (step II). In step III, a spatio-temporal graph of meetings is analysed. Such analysis allows for a better understanding of the physical interactions between users and provides an overview of the most active users (step IV). In step V, a migration graph is built to identify dynamic changes in ROI. Social network analysis (SNA) metrics applied in step VI aid in further understanding of the size and the characteristics of the ROI.

B. *User selection and spatio-temporal meetings*

Some profiles, despite geolocated tweets, are not suitable for the current spatio-temporal analysis. Two different typologies of geolocated users were observed: (1) individuals whose profiles are located and whose tweets are associated

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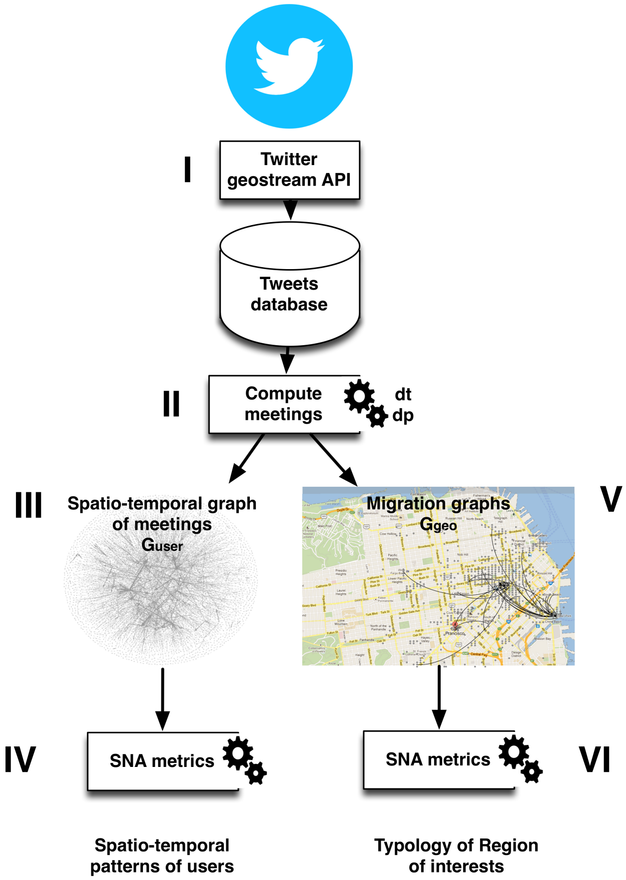

Figure 1. Methodology for analysis of migrations of Twitter users between regions of interest.

with the location of their profile; (2) profiles that share their location at the moment tweets are sent. The current study only included tweets belonging to the 2 types of profiles in this analysis. To ensure that only relevant profiles were included in the analyses, a set of locations related to users' tweets was computed and it was verified that multiple locations exist in the list. Profiles whose location remain constant were removed from the analysis. Profiles that shared less than two updates a day were also removed.

Meetings between profiles were computed as follows. If two profiles belong to the same geographic area (the raw ρ of a circle around the location of a user) at the same time (denoted δt), they are concidered *met*. The global time frame for the observation of profiles is identified by the interval $I = [0, T]$. For each observation time t_k, the function of sharing local spatio-temporal windows of dimension $\rho * \delta t$ is proposed. Given that $d(u, v)$ is a geographical distance between two profiles $(u, v) \epsilon P^2$, a spatio-temporal meeting at a given time step t_k can be identified as follows.

$$Meet_k(u,v) = \begin{cases} 1 & \begin{array}{c}\text{if } v \in \{n \in P| \\ \min_{[t_k-\delta t,\, t_k+\delta t]} d(u,v) \leq \rho\}\end{array} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Using the list of meetings, a spatio-temporal user proximity graph is computed-denoted $G_{user}(N, E)$- where N denotes profiles and E denotes meetings between them. For this purpose, a weight is attached to each edge that corresponds to the number of spatio-temporal meetings observed between these two individuals as in (2).

$$w(u,v) = \sum_{k=1}^{n} Meet_k(u,v) \quad (2)$$

When $w(u, v) = 0$, no meeting is recorded during the full time of the experiment and no connection is created between the two profiles. If $Meet_k(u, v) = 1$, at least one meeting was recorded during the time frame of the experiment. The choice of the parameters (spatio-temporal frame $\rho * \delta t$) depends on the desired level of precision. For example, analysing global spatio-temporal patterns over one year does not require strong spatio-temporal constraints. However, detecting an event at a city-scale requires strong spatio-temporal constraints. The next section presents the capture of user migration between ROI.

C. Migration graph construction

As shown in Figure 2, the given area is divided into a set of squared cells of length δz. The choice of the size depends on the level of precision required for the performance of the detection of spatial patterns and can be adapted as necessary. The aim of the current approach is to assign each cell to a geographical node and to evaluate the relationship between these nodes based on the recorded meetings of users. In the current study, two locations are connected whenever a user meeting has been detected in both distinct locations. The meetings need not to involves the same pair of individuals, but instead at least one of the two individuals is required in both locations. The edge is weighted by the number of moves made between locations to capture ROI and migrations in a unique algorithm. Note that ROI is this article are defined as relatively small geographical areas that receive a large number of users over a short period of time. This is made possible without any additional analysis due to the spatio-temporal constraints applied to meetings. Indeed, Twitter users who tweet in the same area at the same time are detected as met and this is more likely to occur during events attracting a particular density of individuals at a normal time. An individual sending a tweet without other active users in the area is not included in the analysis as they do not belong to a ROI. If a location is not associated with an edge, it is considered irrelevant and removed from the set of nodes (ROI).

Figure 3 presents the algorithm for computing the geo-spatio-temporal graph. For each time step and each couple of profiles (lines 1-2), the meet function (line 3) tests whether or not a meeting is recorded. Each meeting is tracked and associated with a timestamp and geolocation (line 4).

When all meetings are recorded, the relationships between cells of the geographical space, delimited by the A and B points, are extracted. Each cell is identified as a node with a unique identifier. The algorithm creates an edge between two cells (i.e., two locations) when an individual has *met* (as stated in equation 1) persons at least once in each location (line 10). A matching function is used to identify the cells concerning each meeting.

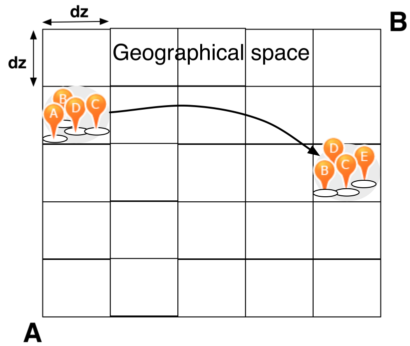

Figure 2. Construction of spatial cells and identification of meetings for building edges of $G_{geo}(N^{'}, E^{'})$.

Inputs:
Set of profiles P
Cell size δz
Spatio-temporal frame $\rho * \delta t$
Spacial borders $A(Lat_{min}, Lng_{min})$ and $B(Lat_{max}, Lng_{max})$
Time frame of observation $I = [0, T]$
Output:
$G_{geo}(N^{'}, E^{'})$ the spatio-temporal geo graph

foreach time step **k**
  foreach $(u, v) \epsilon P^2$
    if $Meet_k(u, v) = 1$ (see equation 1)
      $Meetings$ ←Record a meeting between u and v at period k at location l
    endif
  endforeach
endforeach
N' ←set of squared cells of size δz delimited by A and B (see Figure 2)
foreach couple of cells $(c_1, c_2)\epsilon N^{'2}$
  $e_k(c_1, c_2)$ ←Number of $Meetings$ that both belong to c_1 and c_2
  $E' \leftarrow e(c_1, c_2)$
endforeach
return $G_{geo}(N^{'}, E^{'})$

Figure 3. Pseudo-code for computing the spatio-temporal geo graph

The resulting graph $G_{geo}(N^{'}, E^{'})$ of spatial locations reveals the frequency at which users meet at a particular place. Since meeting is directly dependent on the online activity of users online (e.g., sending messages), the graph permits to illustrating the importance of each location for user activity. In performing the algorithm, locations where individuals tend to meet can be retreived, in addition to the migration of individuals between locations.

The methodology allows for a vision of migration ROI, but further analysis can be applied to the final $G_{geo}(N^{'}, E^{'})$ graph to characterize the events. Table I presents the potential interpretations of SNA metrics on the characteristics of an event (nodes of the $G_{geo}(N^{'}, E^{'})$ graph). The unweighted indegree captures the number of locations people come from, providing an idea of the variety of individuals than an event attracts (in particular when applied worldwide). The unweighted outdegree captures the variety of locations people goes after leaving an event. The PageRank captures the importance of an event based on its ability to attract people coming from important location [22]. For example, analysing information technology-related tweets at a large spatio-temporal scale may allow for the capture of the fact that a Consumer Electronics Show (CES) event attracts many people coming from WebSummit, contributing to the importance of both events. Finally, the Hyperlink-Induced Topic Search (HITs) algorithm can provide interesting interpretations when applied to $G_{geo}(N^{'}, E^{'})$. The algorithm assumes that nodes can be ranked in terms of their ability to be good hubs and authorities [23]. In the present case, a good hub could be concidered a ROI that points to many other ROI, and a good authority would be an ROI that is linked by many different hubs. A good hubs would typically be an airport or a train station, while a good authority is an event that succeeds in attracting people from many hubs. This would be a way to capture popular events within a country, region, or city.

TABLE I. SNA METRICS APPLIED TO NODES OF $G_{geo}(N^{'}, E^{'})$ AND THEIR POTENTIAL USE FOR BETTER UNDERSTANDING OF ROI.

SNA Metric	ROI Characteristics
Unweighted Indegree	Number of ROI people comes before arriving to the event.
Unweighted Outdegree	Number of ROI people go after leaving the event.
PageRank	Importance of the ROI in terms of ability to attract people from other important ROI.
HITS	Identify ROI that are hubs and authorities.

IV. EXPERIMENT AND RESULTS

The analysis was performed on a sample of 3 millions tweets sent by 50,000 active, geolocated Twitter users in and around San Francisco. Figure 4 represents the spatio-temporal graph extracted from the footprints of users in the area over a period of 3 months. This sample is composed of 3,781 users twith dynamic, geographical data associated with their messages. The spatio-temporal constraints in the analysis are $\rho = 0.6\,miles$ and $\delta t = 1\,min$. The graph is composed of 4,720 edges which indicates the number of recorded meetings. Table II indicates the graph metrics, revealing the general activity of San Francisco users. On average, people have between 2 and 3 meetings during the observation time. The maximum observed degree is 135, which is high. Nodes with many meetings appear larger in figure 4. The modularity of the graph is high, meaning that the network tends to organize into clusters (spatio-temporal constraints tend to organize people in communities).

The degree distribution highlights that a few nodes have a high degree (10 nodes have a degree up to 50), while most nodes have a low degree. This observation suggests that some profiles have a central role in spatio-temporal meetings, meaning that they are able to be very active and are regularly observed in ROI.

TABLE II. GRAPH METRICS OF THE SPATIO-TEMPORAL USER GRAPH

Graph Metric	Value
Nodes	3781
Edges	4720
Average Path Length	5.347
Modularity	0.769
Number of Communities	241
Density	0.001
Average Degree	2.497

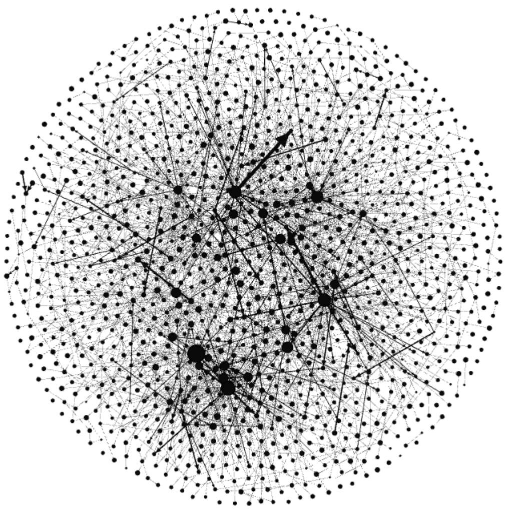

Figure 4. Aggregated spatio-temporal user graph from the full duration of the experiment.

Figure 5 illustrates the results of the algorithm for two distinct choices of δz and ρ spatial parameters. The background image illustrates the relationship between ROI regarding the meeting of users in the San Francisco Bay Area. A meeting is identified if two users have been observed in the same neighbourhood ($\rho = 0.8\,miles$) and at the same time ($\delta t = 30\,s$). Airports appear to be important ROI. Many events also occur in the city center. The foreground image illustrates the same algorithm when performed in the shortest space area and with shorter geographical cells (i.e., $\rho = 0.08\,miles$). This more precisely highlights more precise possible ROI, such as AT&T Park, Westfield San Francisco Centre, Yerba Buena Center for the Arts (YBCA), etc. The two figures illustrate the performance of the algorithm at different scales. Note that these graphs are based on all observations captured during the experiment.

Moreover, analysis of the evolution G^k_{geo} graphs allows for the discovery of particular temporal locations of interest for users. Figure 6 highlights two graphs for different intervals of time. One can observe the changes between the central locations in the graph. Centrality indicates that an event has occurred within the time interval. In other words, the location has attracted many individuals who were previously meeting in different locations.

Events can be detected by comparing the time frame degree of nodes regarding their average degree. A high variation indicates that an event likely occurs in the particular spatio-temporal context. Due to constraints, more details concerning

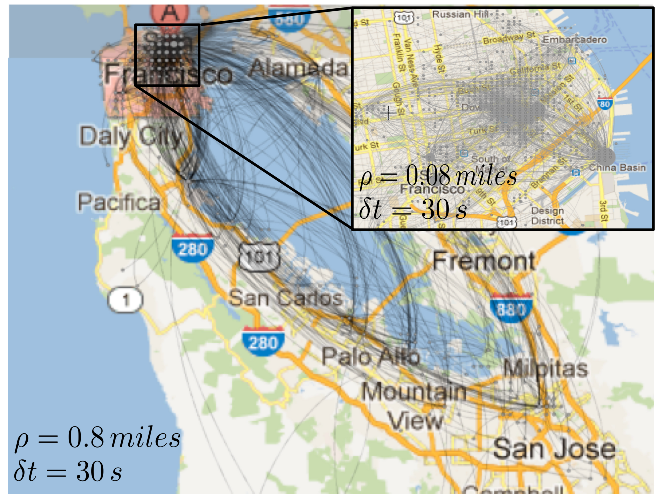

Figure 5. Example of ROIs relationships at two different spatial scales: $\rho = 0.8\,miles$ for the San Francisco Bay Area map and $\rho = 0.08\,miles$ for the San Francisco city map.

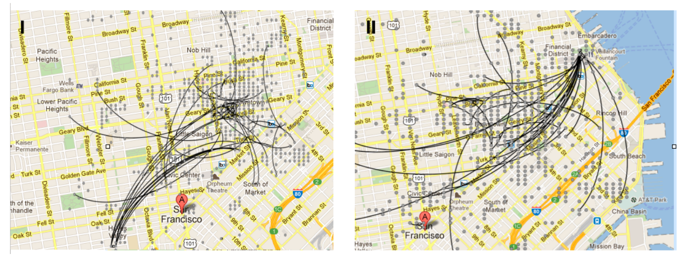

Figure 6. Samples of the spatio-temporal graphs at three different time steps, revealing multiple ROI and their relationships.

SNA metrics applied to the graph are not provided.

V. DISCUSSION

This current study has several applications and potential extensions to be discussed. For example, the study does not include content-based analysis of tweets. A potential improvement would be the automatic identification of the main discussion topic of events using content-based analysis. The current study can also be a first step in the prediction of the next location of users based on common patterns found. It is likely that the graph parameters (nodes, edges, density, degree distribution) can allow for the automatic identification of ROI. The best parameters may be found by optimizing some of the graph features, such as modularity, or by analysing the obtained degree distribution (e.g. parameters of the power law). That study relies on tweets for measuring spatio-temporal meetings provides some advantages and disadvantage. A disadvantage is the lack of a regular vision of the location of users, which complicates the detection of small-scale events. However, it is observe that people tend to tweet more when participating in events, which, by construction, allows for most of the captured meetings to be related to ROI.

VI. CONCLUSION

The success of digital, social media, combined with smartphones, contributes to an increasing amount of spatio-temporal

 ISBN: 978-1-61208-534-0

data. Its availability for analysis can contributes to improving of multiple fields. The current paper proposes a novel approach to detecting spatio-temporal changes in crowds of Twitter users. The study shows that the relationship between locations based on the meetings of users can contribute to the detection of large-scale events. This contribution allows not only for the identification of ROI for users, but also their evolution and characterization at multiple scales. The efficiency of the methodology is shown with a sample of 3 millions tweets in the San Francisco Bay Area, analysed at different scales.

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 ISBN: 978-1-61208-534-0