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Forecasting event attendance with anonymized mobile phone data

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Abstract

No reliable tool exists to forecast the attendance to large events. In this paper, we propose two methods using anonymized mobile phone data to forecast the time of the maximum attendance, for exceptional events known in advance. Our contributions are:

- a comparison between the time evolution of the number of text messages, voice calls, Foursquare check-ins, Twitter messages and headcounts, for three different events;
- a forecast method of the time at which people do not flow anymore to the event, based on the fluxes of people heading towards the event;
- a forecast method of the time at which people do not flow anymore to the event, based on text messages sent to the event;
- an insight into a forecast of the number of attendants.

We stressed the usefulness of anonymized mobile phone data with respect to social network data by showing that the social network data are noisier than mobile phone data, and not always consistent with them. The flux method is able to forecast 9 to 183 minutes in advance an upper bound on the time at which people do not flow anymore to the event, with an absolute accuracy of 10 to 53 minutes. The interactions method is able to forecast 35 to 43 minutes in advance a minimal footprint of the people calling to the event with an accuracy of -35 to -21 minutes. Finally, we were able to provide upper and lower bounds on the number of attendants 39 to 174 minutes in advance.

Keywords: mass gatherings, crowd, forecast, mobile phones, social networks, public preparedness

Introduction

From Olympics to local performances, mass gatherings bring along specific health and security challenges. A large crowd not only increases the probability of stampede, but also makes individual

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injuries and illnesses more likely. Respiratory diseases, dehydration, epileptic seizures and cardiovascular strokes are commonly reported during such events and their number increases with the crowd size. Moreover, flows of people need to be specifically managed. Failures in crowd management often result in crowd-related disasters, impairing the health and the life of numerous people, putting a high strain on the community resources, on both short and long term, and affecting the reputation of their leaders [37, 23, 50, 26, 53, 54, 45, 58].

For instance, the 2010 Love Parade in Duisburg (Germany) gathered more than one million of people on a site where only 250,000 were allowed. Nothing enabled the authorities to forecast and properly react to such a high attendance [26, 22]. Even for lower-profile events, the situation can rapidly become critical. In Lille (2004), a concert has been canceled because the police has been overwhelmed by the arrival of 60,000 people instead of the 25,000 expected [12]. According to news reports and emergency services, in Brussels a concert organized during the Music Festival in June 2011 attracted more than 50,000 people instead of 22,000. Because the planning had been done on a low risk basis, the medical and security services have been submerged: numerous syncopes and injuries had to be treated, which led to the call of back-up personnel and ambulances at the worst moment [42].

To guarantee to the attendants the same level of care and security as in their daily life, without overwhelming the local emergency and security services, medical workers and security officers are often deployed in advance. The exact staffing depends on the risk profile of the event, as determined by a pre-event risk assessment, accounting for variables such as the type of event and of public, the presence of alcohol or the expected influence of the weather [13, 21, 24, 35].

The crowd size is one of the main risks drivers [4]. It is also one of the most difficult to forecast, even a few hours in advance. Even the simple estimation of the crowd size, be it during or after the event, is challenging for large open events, and the results may differ because of the different stakes at play [43, 57, 61, 62, 15]. Today, only rough forecasts can be obtained using past experience or hotel bookings [39]. These methods are at least inaccurate, time consuming and worryingly unable to cope with last minute fluctuations.

There is therefore a need for tools to reassess the risk level of events on short term, and in particular to forecast the crowd size well before people arrive at the event. These tools would give time to the authorities to increase the medical and security staff, to call back-up ambulances and material, and to redirect the flows of people by closing subway stations or highways exits.

To be efficient and affordable even for a priori low risk events, and to be able to work on country-scale, the tool cannot depend on a dedicated infrastructure or require an active participation of the users. This rules out monitoring of radio interfaces such as Bluetooth [60, 59] and Wifi [1], and collaborative solutions under the form of smartphone applications [67], even if they are suited for crowd monitoring at event-scale. At the same time, event monitoring and prediction from online social media, like Twitter and Foursquare, is still in their infancy and far too inaccurate [30, 29, 2, 27, 18], even if social media might be suited for user recommendation systems [19].

If an existing country-wide infrastructure is to be used, the most promising way to collect data therefore rests on anonymized mobile phone data. Even tough mobile phone data have been used for retrospective urban sensing [41, 10, 44, 20, 14, 7], real-time monitoring solutions are appearing [51, 9, 38, 52], and could be used for instance to detect events [55].

Many studies have been devoted to the predictability of human mobility using mobile phone data. Up to now, the conclusions they have drawn mostly rely on the recurring behavior of people [6, 20, 49, 25, 46]. Moreover, predictive modeling has been mainly limited to traffic prediction and mobile network management. For instance, Aoudjit et al. [3] used association rules discovery to infer the next cell of a user and Lin et al. [31] designed a model to forecast the motion of people in the adjacent cells. Some other work focus on the prediction of the next place of people [56, 16, 70]. These predictive models rely on space-time evolution of the mobile users. Curiously, mobile point-to-point communications have been of little attention for forecast methods, despite the study of Calabrese et al. [11] about their potential to predict face-to-face meetings.

At the same time, the use of anonymized mobile phone data to study crisis and events is emerging [34, 47, 28, 33, 5, 17], even if no operational system is in view. Xavier et al. [69, 68] described the attendance to large events in Brazil, aiming at characterizing the mobility of users at such events. In view of a predictive system using anonymized mobile phone data, Ponieman et al. [40] showed that knowing the past attendance of fans to soccer matches increased the user location predictability. Such an historical information can however not be used to forecast the attendance to new, non recurrent events. Finally, Morlot et al. [36] developed a predictive model for people displacements between hotspots in a city-wide event, using a Markov chain process. They however assume that people moved inside the city from one hotspot to another, which is not the case at the beginning of a large event.

In this paper, we address the issue of short term crowd forecasting for exceptional events known in advance, using anonymized mobile phone data, and stress the usefulness of using interactions data (person A at position x calls person B at position y) in addition to presence data (A at x) only. We are interested in the participation of people to exceptional mass gatherings, i.e. in the moments of their life they do not present a regular or recurring pattern; we therefore do not rely on historical data about the subscribers' behavior. Finally, our aim is to forecast crowd dynamics, which appeals to different methods than individual mobility forecasts.

Our contributions are :

- a comparison between the time evolution of the number of text messages, voice calls, Foursquare check-ins, Twitter messages and headcounts, for three different events ;

- a forecast method of the time at which people do not flow anymore to the event, based on the fluxes of people heading towards the event (flux method);
- a forecast method of the time at which people do not flow anymore to the event, based on text messages sent to the event (interactions method);
- an insight into a forecast of the number of attendants.

Methods

Dataset

We illustrate our findings on three different events (Tab 4). For these events, we acquired anonymized mobile phone data (events A-C), Twitter data (events A-B), Foursquare data (events A-C) and manual headcount (event C).

Anonymized mobile phone data

We used anonymized call detail records (CDR) of a Belgian telecommunication operator. Each time a call is issued or a text message is sent, the mobile operator generates a CDR containing the identifiers of the sender (A-number) and of the receiver (B-number), a timestamp, the cell where the sender was at the beginning of the call, and the duration of the call. A similar CDR is generated when the call or the text message is received, with the position of the receiver at the beginning of the call. For one call or text message for which both the sender and the receiver are customers of the same mobile phone operator, the database therefore contains two half-CDRs. When we needed to know the relationship between the caller and the callee, the two half-CDRs have been unified in one full-CDR as follows. For voice calls, a unique number identified the call, so that the two legs have been unambiguously linked. It is not the case for text messages. As a text message is not received at the same moment it is sent, time differences might occur between the cells. We therefore unified the half-CDRs by taking, in the set of half-CDRs with corresponding A and B-numbers, the first text message that was received in the same minute the text message was sent. Tab 5 summarize the characteristics of the data sets used.

The time was rounded to the minute. The identifiers of the subscribers have been anonymized differently for each dataset, a measure that has been judged sufficient by the Belgian Privacy Commission to consider the data as anonymous. Within these data, we define a *check-in text message* (resp voice call) as the first text message (resp. voice call) issued by a person at a venue during the time of the study.

For privacy reasons, these data could only be processed within the mobile operator premises.

Social network data

We collected 6.229.573 geo-tagged tweets from 129.506 users between 29/10/2013 and 18/2/2014, for which the geographical coordinates fell into a rectangle surrounding Belgium using the Twitter API. Among these data, we selected tweets issued around the 3 venues (see Fig 6 D-F). We also collected public Foursquare check-ins through the Scraperwiki platform [66], by extracting tweets containing the keyword '4sq.com' and one of the following keywords : "I Love Techno 2013", "Stade Maurice Dufrasne", "Stade Roi Baudouin".

Manual headcount data

We received figures of the attendance to event B from the organizers and we estimated the attendance to event A and C from websites (see Tab 6).

Moreover, for event C, we counted manually the time evolution of the number of people exiting from the main subway station close to the stadium [1]. Between 6:15 pm and 8:45 pm, we counted 4400 people exiting from the station. We estimate the relative error on our measurements to 5 % on average and to 10-15 % during the peak of arrivals, which is accurate enough to identify the peak of arrivals.

Results

Comparison between mobile phone, Twitter, Foursquare and manual headcount data

We divided the time line into 15-minutes intervals and counted the number of calls and text messages in each time interval. Fig 1-3 show the rate of incoming and outgoing voice calls and text messages for both the day of the event and the previous day. The voice calls before the start of event A are probably issued or received by the customers of a large store nearby the event venue[2]. On Saturday, the shop closes at 8 pm, and on Friday at 9 pm, which is visible on the reference day on the right. Overall, the number of text messages is 12 to 28 times higher than the number of voice calls (see Tab 7 in section **Methods**). Moreover, from the difference between the check-in volumes curves and the total volumes curves, we observe that, on average, one person issues more text messages than voice calls during the event. The two dippings in voice calls volumes and in text messages volumes during the events B and C correspond to the game, as already observed in Xavier et al. [69].

Fig 4 shows the Foursquare, Twitter and check-in text messages for the three events. Our observations emphasize the lower noise in text messages data with respect to social network data. Moreover, depending on the event, the Foursquare/Twitter volume is in advance (events A and C), or in phase with the check-in text messages volume (event B).

[1] subway Heysel, (latitude, longitude) = (50.8966, 4.3366) in WGS-84 coordinates
[2] (latitude, longitude)=(51.023, 3.688) in WGS-84 coordinates.

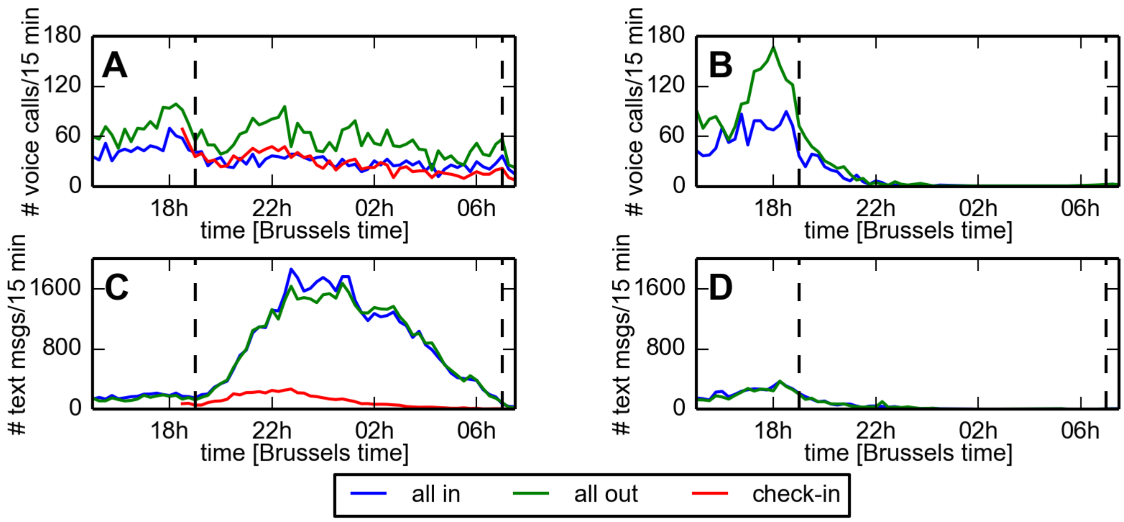

Figure 1: **Calls and sms volumes per 15 minutes for event A (left) and reference day for the same venue (right).** (a-b) Voice calls incoming to the venue (blue), voice calls issued from the venue (green) and check-in voice calls placed when at the venue (red). (c-d) Text messages sent to the event (blue), text messages issued from the event (green) and check-in text messages (red). All the values are numbers per 15 minutes. Points are drawn at the beginning of each time interval. The vertical dashed lines denote the beginning and the end of the event.

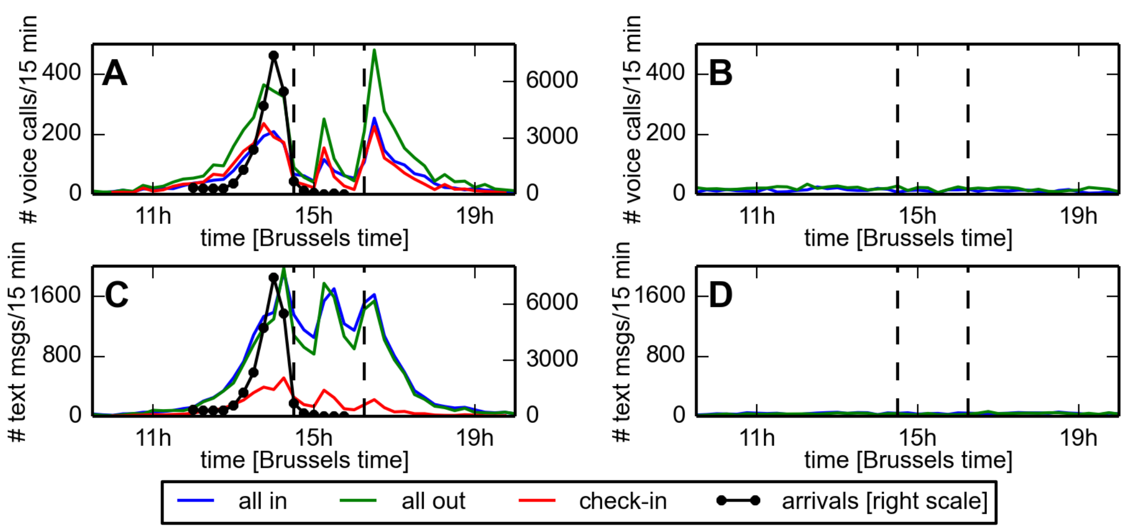

Figure 2: **Calls and sms volumes per 15 minutes for event B (left) and reference day for the same venue (right).** (a-b) Voice calls incoming to the venue (blue), voice calls issued from the venue (green) and check-in voice calls placed when at the venue (red). (c-d) Text messages sent to the event (blue), text messages issued from the event (green) and check-in text messages (red). Right scale: number of arrivals (black). All the values are numbers per 15 minutes. The time at which the points are drawn correspond to the beginning of the 15 minutes time interval. The vertical dashed lines denote the beginning and the end of the event.

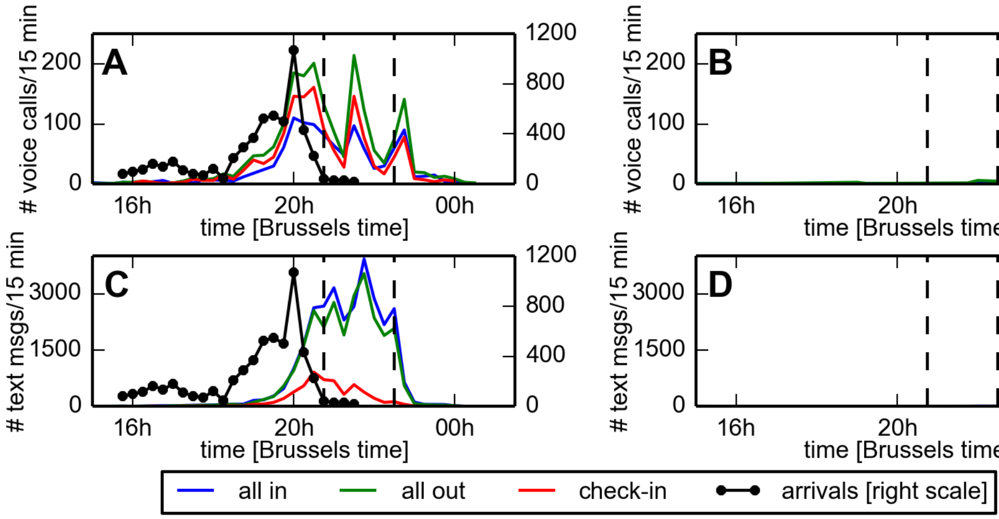

Figure 3: **Calls and sms volumes per 15 minutes for event C (left) and reference day for the same venue (right).** (a-b) Voice calls incoming to the venue (blue), voice calls issued from the venue (green) and check-in voice calls placed when at the venue (red). (c-d) Text messages sent to the event (blue), text messages issued from the event (green) and check-in text messages (red). Right scale: number of arrivals (black). All the values are numbers per 15 minutes. The time at which the points are drawn correspond to the beginning of the 15 minutes time interval. The vertical dashed lines denote the beginning and the end of the event.

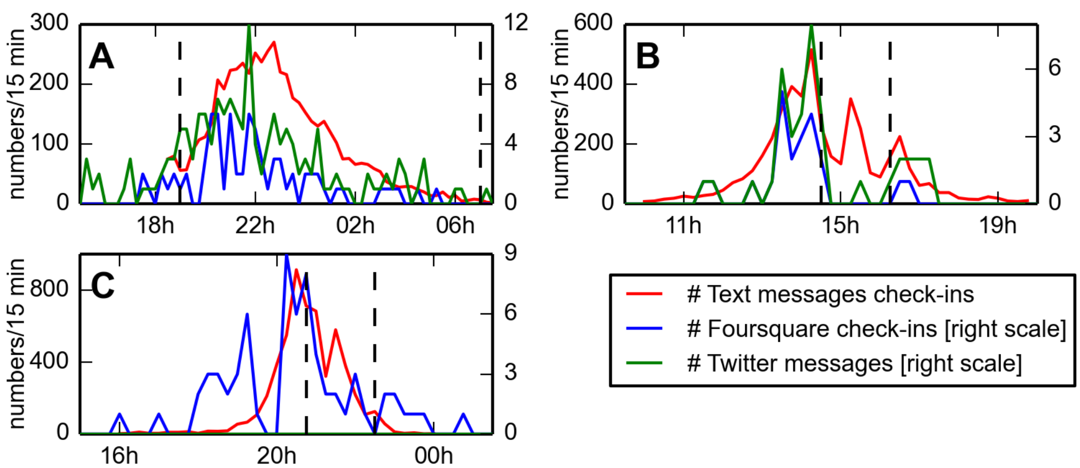

Figure 4: **Twitter messages, Foursquare check-ins and check-in text messages for the 3 events.** Volume of Twitter messages (green), Foursquare check-ins (green) and text-message check-ins (red) per 15 minutes, for events A-C. The text message volumes are less noisy than the social network volumes. No Twitter messages could be recorded during event C due to a failure of the server.

Detailed study: international soccer match

Fig 3 (A,C) shows the time evolution of the number of arrivals (black), the check-in voice calls (A, red) and the check-in text messages (C, red) for event C (an international soccer match).

There is a 30 minutes-delay of the check-in text messages peak with respect to both the headcounts and the check-in voice volume; this delay is more than one hour for the tail. Oppositely, the first peak of the check-in voice coincides with the peak of arrivals (Fig 3 C). The check-in voice peak is however broader than the arrival headcount peak; it falls immediately after the beginning of the game, to rise again at half-time. A similar behavior has been observed for event B (Fig 2).

If voice calls are used mainly before the game, at half-time and at the end of the game, text messages are used during the game; the text messages volume decreases less than the voice calls volume, meaning that people use the voice calls to coordinate a meeting when arriving on site, whereas text messages are preferentially used to share about the event during the event. This is further reflected by peak in outgoing text messages 7-8 minutes after each goal (see Fig 9 in **S1**). The phone and text message behavior are thus very different, even at the filling of the event.

Finally, mobile phone and social media behaviors are different. For instance, there is no Foursquare check-in during the peak of arrivals 4(C), and 44 pc of the check-ins occurred after the beginning of the match, even tough no supporters flux has been observed in the main subway station. Our observation therefore suggests that people wait to be seated before they check in.

Forecast

Predicting the moment when no more people will arrive to the event is critical for emergency services. We investigated the value of anonymized mobile phone data to forecast this moment, by concentrating on methods that focus on the crowd as a whole rather than on the mobility of individuals. To evaluate the approaches, we define the *forecast horizon* as the time interval between the *end* of the last time interval used to make the forecast and the *beginning* of the time interval of the prediction, and the *forecast accuracy* as the time between the forecast and the observed time. The forecast accuracy is positive if the forecast is larger than the observed time.

Flux method

We leveraged the collective tendency of people to place or receive multiple calls and text messages increasingly close to the event venue as they approach. For instance, Fig 5 depicts the time evolution of the distance between the venue of event A and the cells where one subscriber placed or received calls and text messages.

To assess the collective displacement of people towards the event, we divided the area surrounding the venue into three concentric rings with bounds [0, 2[km, [2, 5[km and [5, 15[km and with as center the main cell of the venue (events A-B), or the geometrical center of the venue (event C) (Fig 6).

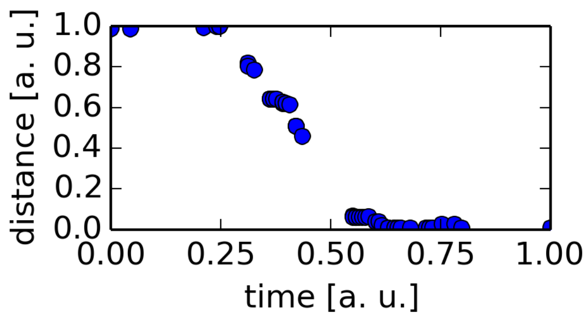

Figure 5: **Distance of a subscriber to the venue of event A in function of the time.** Time and distance are squeezed to arbitrary units to protect the user's privacy.

For each time interval t and each ring r, we computed the average distance $d_{i,t,r}$ of customer i to the event. For each subscriber, we built an array $[d_{i,t_1,r}, d_{i,t_2,r}, \ldots d_{i,t_N,r}]$, where $t_1, \ldots t_N$ depict the time intervals where subscriber i has been observed (either calling, sending an sms, receiving a call or an sms). Subscriber i has then been counted as approaching (resp leaving) the event at time t_k if $d_{i,t_k,r} - d_{i,t_{k-1},r}$ was $< 1m.$ (resp $> 1m.$). We then defined the *subscribers flux* at time t as the difference between the number of subscribers approaching and the number of subscribers leaving. To get rid of the noise, we arbitrarily considered that the subscribers flux was zero as soon as the subscribers flux curve reached 10 pc of its maximum.

Fig 7 (A-C) shows the net number of people moving towards the venues, for the events A-C, and the different rings. The subscribers flux in [0-2[km stands out of the noise for event A and C, whereas the [2-5[km flux is relevant for events B and C. Fig 6 allows to interpret these differences. Event A attracts a young population from very distant places, even from abroad. Therefore, most of the inbound flux should occur along the main roads. The cells in the second ring, which are mostly located in the city of Ghent probably only play a minor role. Therefore, the fluxes are only visible in the smallest ring. Event B attracted people from Bruges (about 1000 according to the organizer), but mainly from Liège (about 23,000 according to the organizer), situated in the second ring, so that the second ring displays most of the flux. Finally, for event C, people came from the whole Belgium, by car and by public transportation. The density of the cells of the two first rings along the main roads and public transportation lines is large enough for the fluxes to be visible in these two first rings.

In the case of event C, the maximum of the subscribers flux of the [2-5[km ring occurs 45 minutes before the maximum of the flux in the [0-2[km range, which leads to a "group velocity" of a approximately 4.5 km/h. Moreover, the flux of [0-2[km ring crosses the 10 pc line 16 minutes after the flux in the [2-5] km ring and 39 minutes *after* the beginning of the game. Our headcount showed that no more people flowed to the event after the beginning of the game, hence the vanishing of the flux curve

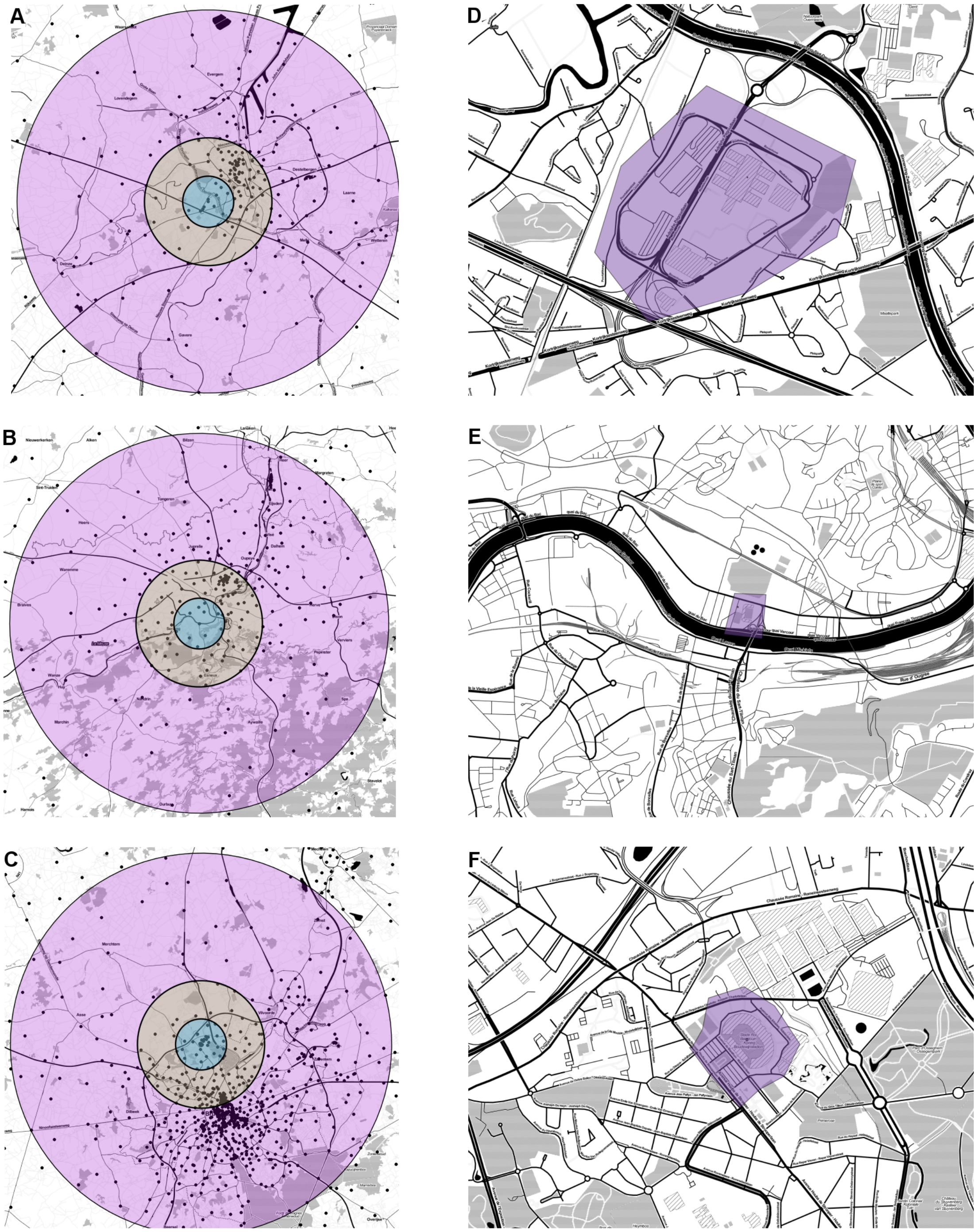

Figure 6: **Concentric circles with radii 2, 5 and 15 km around the venues (left) and area within which the tweets were collected (right).** From top to bottom: venues of events A-C. The black dots on the pictures of the left column depict the sites of the antennas. Cartographic background by Stamen Design under CC BY 3.0. Cartographic background data by OpenStreetMap, under CC BY SA.

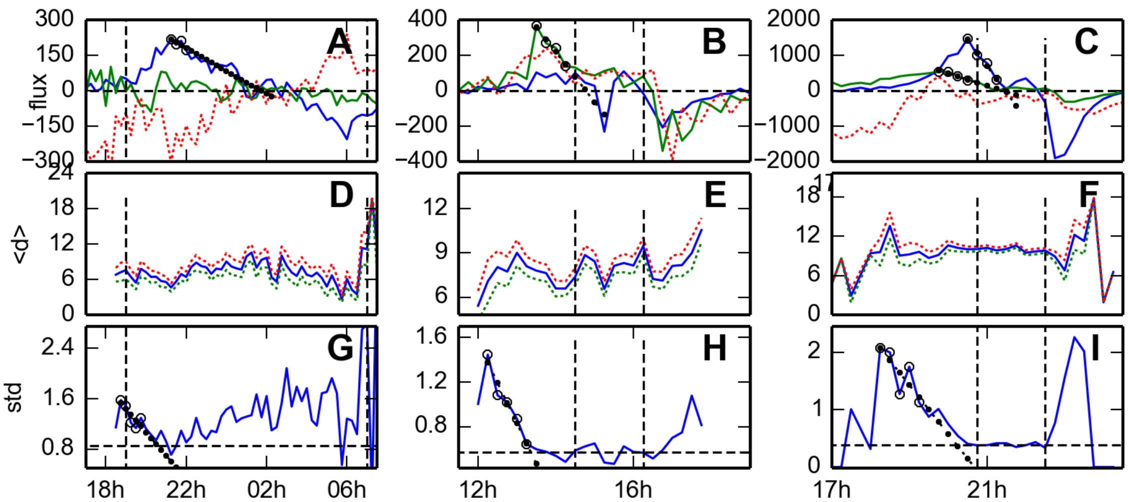

Figure 7: **Subscribers fluxes (A-C), mean distance to the event $\langle d(t)\rangle$ of the text messages sent to the event (D-F) and standard deviation $\sigma_d(t)$ (G-I)** A-C: subscribers fluxes for rings [0,2[km (blue), [2,5[km (green) and [5,15[km (dotted red) versus time, and predictive fits (black dotted). The horizontal dashed line indicates a null flux. A positive flux is directed towards the event. D-F : mean distance between the event and the cells of the text messages sent to the event (blue) +/- standard deviation (dotted), G-I : standard deviation of the mean distance between the event and the cells of the text messages sent to the event ($\sigma_d(t)$, blue), and predictive fits (black dotted). The horizontal dashed line indicates the plateau reached by $\sigma_d(t)$. The vertical dashed lines indicate the official beginning and end of the event. The first (resp: second, third) column correspond to event A (resp B, C).

should be interpreted as a late indicator that the whole crowd is concentrated at the venue.

Finally, in events A and C, there is an outgoing subscribers flux in the [5-15[km ring before the event, probably due to the departure of the people from the nearby store (event A) and from the workers and students out of Brussels at the end of the workday (event C).

Using a linear regression on 4 points including the maximum subscribers flux, we forecasted the time at which the flux would cross the 10 pc line. Compared to the moment when the actual flux reaches the 10 pc line, we obtained an absolute accuracy of 10 to 53 minutes, and a forecast horizon of 9 to 183 minutes (Tab 1, columns 2-5). In one case (event C, flux in the [0,2[km ring), the forecast horizon is negative. However, as the flux is less noisy than for event A, three points are enough to make the prediction, leading to an accuracy of 5 minutes and a forecast horizon of 11 minutes (Tab 1, columns 6). The forecast of event B is 53 minutes ahead of the moment the flux curve crosses the 10 pc line. However, the flux curve does not vanish as expected during the event. In this case, the 10 pc crossing of the flux curve is not a good indicator of the performance of our forecast. Using this subscribers flux forecast method, we are therefore able to provide an upper bound on the time at which the whole crowd is concentrated at the venue.

Interactions method

People use their mobile phones to coordinate their meeting-ups [32]. When on the way to an event, they call or text to friends that are either on the way to the event or already arrived. Therefore, the probability that someone calling or texting to the event will eventually come is fairly high with respect to the probability that someone calling somewhere else will come to the event.

In the filling phase of the event, the volume of calls or text messages received at the event event increases exponentially (Fig 1-3) and depend both on the number of people arriving and on the number of people already present. These volumes can thus hardly be leveraged to forecast their own maximum. Contrarily, the mean distance of the callers to the event, denoted by $\langle d \rangle$, only depends on the mean position of the callers, regardless of their number. Fig 7 (D-F) depicts the mean position of the senders of text messages to the event that were within 20 km of the venues. We only took into account the first text message sent by each subscriber.

Let $\langle d(t) \rangle = \frac{1}{N} \sum_{i=1}^{N} d_i$ be the average distance of the N people that send a text message to the event between time t and $t + \Delta t$, and $\sigma_d(t) = \frac{1}{N} \sqrt{\sum_{i=1}^{N} (d_i - \langle d \rangle)^2}$ the standard deviation on $\langle d \rangle$. We consider here $\Delta t = 15$ min. Fig 7 (G-I) shows that, as time approaches the beginning of the event, $\sigma_d(t)$ decreases to reach a plateau between 0.39 km (event B) and 0.57 km (event C). The plateau values have been computed as the average $\sigma_d(t)$ during the event. Event A is particular: it is extended in time and people can arrive when other already leave. The plateau value of 0.85 km has therefore been fixed arbitrarily around the minimum of $\sigma_d(t)$. The first time $\sigma_d(t)$ crosses the plateau is significant. For instance, for event C, it corresponds to the moment where no one arrives anymore, as assessed by our manual headcount.

To predict the crossing with the plateau, we adjusted a linear polynomial using 5 points including the maximum of the curve found in the 4 hours before the event. By finding the intersection between the fitted line and the plateau value characteristic of the event, we were able to predict the plateau with a forecast horizon of 35 to 43 minutes and a forecast accuracy of -35 to -21 minutes (see Fig 2). This means that the actual crossing of the plateau occurs later than predicted. In one case (event B), the forecast horizon is negative. Four points could have been used for the fit, leading to an horizon of 7 minutes and an accuracy of -36 minutes.

Towards an event attendance forecast

As a first step towards an event attendance forecast, we combined the standard deviation $\sigma_d(t)$ with the volume of text messages sent from the event $V(t)$ as follows. First, we fitted a linear and an exponential function on the first five monotonically increasing data points of $V(t)$ following the maximum of the standard deviation $\sigma_d(t)$ (see **Interactions method**). Then, we forecasted a lower (resp an upper) bound on the maximum of $V(t)$ by computing the value of the linear (resp exponential) fit when the forecasted $\sigma_d(t)$ vanished (Fig 8). We finally obtained a lower (resp an upper) bound of the number of attendants by dividing the bounds on $V(t)$ by the maximum number of outgoing text messages per 15 minutes and per attendant of Tab 7. Tab 8 report the upper and lower bounds, together with the observed attendance (See Tab 3 in **S2** for details). We observe that the ration between the upper and the lower bound ranges from 1.8 to 7.

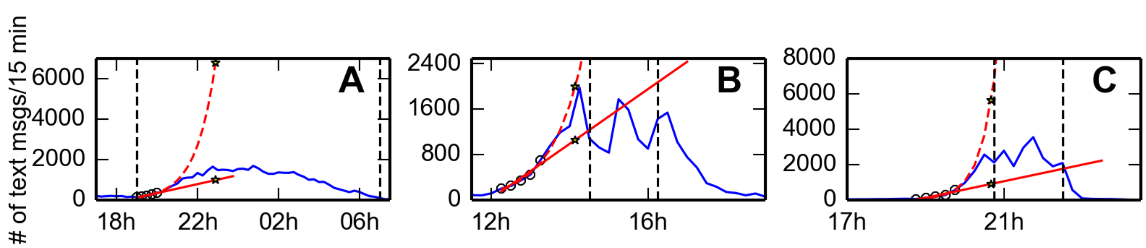

Figure 8: **Event attendance forecast for events A-C.** Number of outgoing text messages (blue) and projected attendance based on a linear fit (plain red) and an exponential fit (dashed red) on four data points (circles). The stars denote the projected attendance at the time where $\sigma_d(t) = 0$.

Discussion

Summary

In this work, we proposed two crowd forecast methods using anonymized mobile phone data, and illustrate them on three different events at three different venues. We stressed the usefulness of anonymized mobile phone data with respect to social network data by comparing the time evolution of text messages, voice calls, Foursquare, Twitter and manual headcount. We showed that the social network data are noisier than anonymized mobile phone data, and not always consistent with them. Moreover, we found that the time evolution of the text messages curve was shifted with respect to the participants arrival.

We then proposed two forecast method of the time at which people do not flow anymore to the event. This *flux method* is based on the flux of subscribers heading towards the event and is able to forecast a null flux 9 to 183 minutes beforehand with an absolute accuracy of 10 to 53 minutes. The *interaction method* is based on the text messages sent to the event and is able to forecast a minimal footprint of the callers to the event 35 to 43 minutes in advance with an accuracy of -35 to -21 minutes.

Anonymized mobile phone data and social network data

The volumes of voice calls and of text messages showed different time evolutions, indicating that they convey different pieces of information. Voice calls appear to be related to coordination of meeting, whereas text messages seem to be related to experience-sharing. Voice curves and text message curves should therefore not be merely added, but separately treated as two information on different processes.

In this study, we showed that social network data are noisier than anonymized mobile phone data. Moreover, at event C, no Foursquare check-ins were observed between 19:45 and 20:15, when a lot of people arrived. Combined to the ease to spoof geo-tagged social network data [71], our observations suggest that social network data are not reliable as only means to monitor the crowd at an event in public safety applications. However, whereas mobile phone data are not available instantaneously after the phone call or the text message has been issued, social network data are available in real time, and their content is public. It might be therefore interesting to combine both technologies in the same situational awareness tool. However, as the curves of the mobile phone data and of the social networks activities are not always aligned, careful analysis is needed to find the best way to match them.

Forecasts

Mobile phone volumes are increasing exponentially at the filling time of the event (Fig 1-3) and are therefore useless to forecast their own maximum without external information. In this work, we introduce two methods to forecast the moment at which no people flow to the event anymore, based on external information. The *flux method* is based on the flux of subscribers converging to the event, and the *interactions method* uses the standard deviation of the mean position of the people sending a text message to people at the event.

The flux method demonstrated that the data are rich enough to indicate the convergence of the people towards the event. Moreover, an ascending slope indicates that a crowd is forming ; this could be used in event detection, but is out of the scope of this paper. We hope that better forecasts will be achievable with a sharper definition of the fluxes and a careful account of the geography of the cell phone and public transportation network.

The interactions method depends on an external parameter, the plateau value. Further research should indicate if this value depends on the event or, more likely, on the characteristics of the venue, and its surrounding cells density. It is interesting to note that the forecast of the standard deviation method corresponds to the peak of the flux method, even tough these two forecasts are based on different information.

A deeper analysis of other events at the same venues and at other venues should enable us to refine these results. Finally, our work should be further validated by considering both events and non-events, and by performing a prospective study.

Limitations

The use of anonymized mobile phone data is limited by a call behavior that differ between people. Events however often attracts people of well-defined age or interests groups, wherein we can expect that the mobile phone behaviour is rather uniform. Therefore, classes of events, such as concerts, sport competition or classical festivals will probably need to be separately studied.

Importance of field validation of the hypothesis

This study enlightened the importance of headcounts to bridge the observed quantities (calls, text messages, Foursquare check-ins, Twitter messages) and the actual evolution of the crowd. This counting should be the most careful for safety applications.

In public safety applications, errors in the attendance forecasts might be deleterious if the crowd has been underestimated. We therefore suggest that, in the current state of our knowledge, the observations of the crowd with mobile phones should be used to indicate where high concentrations of people happen or might happen in the future, and should be less trusted when they indicate low figures. Moreover, depending on the accuracy required in the real time operational system, it might be wise to cross-validate the data with those obtained from some headcounts points inside the event.

Ethical issues

A forecast system such as the one we propose has definite benefits for the safety of the citizens, with minimal impact on the privacy. No personal data need to be disclosed to third parties, be it public agencies or event organizers. Most of the computation rely on aggregated data, even tough the observation of check-in voice calls and check-in text messages need to keep track of an anonymized identifier of the subscribers. However, to do so, we only need to build a list of the anonymized identifiers that have already been observed, without keeping the whole history of the user, making cross-events correlations impossible. In any case, no historical information of more than a few hours before the event should be stored, and no information, aside of the curves generated should be stored after the event.

Finally, our methods preserve the individual privacy but crowd forecast raise broader ethical issues. These issues should be addressed by involving all the stakeholders, among which the emergency and security services, the organizers, the civil society and the human right associations.

Other perspectives

The scaling between the number of calls or text messages and the number of attendants to the event might depend on several factors, which can be studied on an event type basis. However, how to precisely relate the fluxes and the standard deviation used to make the forecasts to the actual evolution of the number of attendants remains an open question.

The estimation and forecast of the fluxes should be improved by taking into account the road network and the coverage of the cells. The use of isochrone maps may help, even if they may be distorted when a large amount of people is converging towards the same event. In that case, we suggest that such maps should be computed from the anonymized mobile data themselves. The interaction method should be refined by accounting for the skewed nature of the distribution of the distance of the callers to the event, and should take into account the spatial distribution of the cells to determine the plateau value.

Our work demonstrated the ability of text messages and call meta-data to monitor and forecast the flows of people in large events. More accurate information could also be used, such as handovers or updates of the position of the cell phone even when no call is in progress. We hope that these would increase the forecast accuracy.

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Conflicts of interests

The researchers confirm to have no financial conflict of interests in this research. The research has been done inside the mobile phone operator premises. However, the operator did not contribute financially to the research, and the material used remained in their premises. One of us (CC) is a voluntary member of a medical emergency organization.

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Supplementary material S1

Text messages and phone calls during the international soccer match Belgium-Ivory Coast (March 5, 2014).

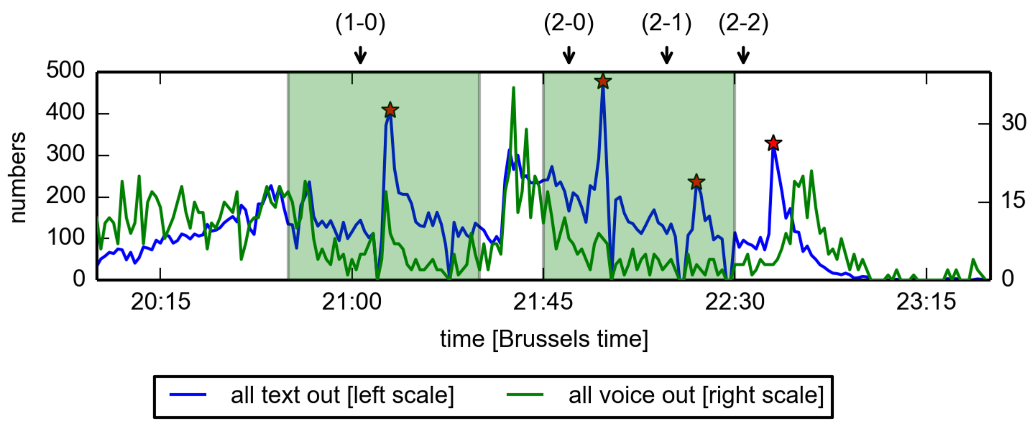

Figure 9: **Number of text messages (blue, left scale) and voice calls (green, right scale) per minute, issued from the event.** The arrows indicate the time of the four goals, along with the score [64, 65]. The stars indicate the corresponding peaks in the text messages volumes. The peaks are delayed by 7-8 minutes, presumably due to the combination of three factors: the misalignment between the mobile cell clock and the event clock, the delay in the beginning of the game, and the rising time of the peaks following the goals.

Supplementary material S2

Forecast horizons and accuracies

Table 1: **Flux method forecast: forecast horizon and accuracy**

	event A	**event B**	**event C**	**event C**	**event C**
Range [km]	[0, 2[	[2, 5[	[2, 5[	[0, 2[	[0, 2[
Number of points	4	4	4	4	3
End of last interval	13-11-09 22:15	13-11-10 14:30	14-03-05 20:45	14-03-05 21:30	14-03-05 21:15
Predicted	13-11-10 01:18	13-11-10 14:39	14-03-05 21:17	14-03-05 21:22	14-03-05 21:26
Observed	13-11-10 00:56	13-11-10 15:32	14-03-05 21:07	14-03-05 21:21	14-03-05 21:21
F. horizon (min)	183	9	32	-8	11
F. accuracy (min)	22	-53	10	1	5

Forecasts of the time when the subscribers fluxes in the indicated ranges cross thee 10 pc. line. The forecast uses the number of points specified in row 3, including the maximum of the fluxes. Row 4 indicates the end of the last time interval available to make the forecast, ie the moment at which the data are available. Row 5 and 6 report respectively the predicted and observed crossing with the 10 pc line, resulting in the forecast horizon and accuracy reported in the last two rows.

Table 2: **Interactions method: forecast prediction and accuracy**

	event A	**event B**	**event C**	**event B**
Number of points	5	5	5	4
End of the last interval	13-11-09 20:00	13-11-10 13:30	14-03-05 19:30	13-11-10 13:15
Predicted	13-11-09 20:35	13-11-10 13:21	14-03-05 20:13	13-11-10 13:22
Observed	13-11-09 21:09	13-11-10 13:58	14-03-05 20:34	13-11-10 13:58
Forecast horizon (min)	35	-9	43	7
Forecast accuracy (min)	-35	-37	-21	-36

Forecasts of the moment when the standard deviation $\sigma_d(t)$ crosses the plateau specific to the venue. The forecast uses the number of points specified in row 2. Row 3 indicates the end of the last time interval available to make the forecast, ie the moment at which the data are available. Row 4 and 5 report respectively the predicted and observed time when $\sigma_d(t)$ crosses the plateau, resulting in the forecast horizon and accuracy reported in the last two rows.

Table 3: **Event attendance forecast: forecast prediction and accuracy**

	event A	**event B**	**event C**
Number of points	5	5	5
End of the last interval	13-11-09 20:15	13-11-10 13:30	14-03-05 20:00
Forecasted max outgoing sms (lin)	973	1059	894
Forecasted max outgoing sms (exp)	6786	2003	5613
Time of the forecast	13-11-09 22:54	13-11-10 14:09	14-03-05 20:40
Forecasted max attendance (lin)	17,000	13,000	11,000
Forecasted max attendance (exp)	120,000	24,000	71,000
Observed max outgoing sms	1677	1982	3536
Time of the observation	13-11-10 00:45	13-11-10 14:15	14-03-05 21:45
Max attendance	30,000	23,848	45,000
Forecast horizon (min)	174	39	40
Forecast accuracy (min)	-111	-4	-65

Forecasts for the event attendance using the specified number of points (row 5) after the maximum of $\sigma_d(t)$, including the maximum. Row 4 and 5 indicate the forecasts of the outgoing sms volume. Row 6 and 7 indicate the corresponding forecasted attendance, using the figures of Tab 7.

Tables

Table 4: **Events studied in this work**

	type	**event & place**	**begin & end**	**reference day**
A	A techno music festival	I Love Techno Flanders Expo, Ghent (51.027, 3.692)	09-nov-2013 7 pm-6:30 am	08-nov-2013
B	A league 1 national soccer match	Standard - Bruges Dufrasne Stadium, Liège (50.610, 5.544)	10-nov-2013 2:30 pm-4:15 pm	09-nov-2013
C	An international soccer match	Belgium - Ivory Coast King Baudouin Stadium, Brussels (50.896, 4.334)	05-mar-2014 8:45 pm-10:30 pm	09-nov-2013

The figures between brackets are respectively the latitude and the longitude in the WGS-84 coordinate system.

Table 5: **Datasets**

	events A & B	event C
begin	7/11/13 6 pm	5/3/14 12 pm
end	11/11/13 2 am	6/3/14 1 am
voice calls outgoing	18,755,048	4,815,562
voice calls incoming	12,700,390	3,363,182
text messages incoming	88,818,139	19,893,495
text messages outgoing	83,896,027	18,732,016

Datasets used for events A, B and C (begin and end of the dataset, number of voice calls and text message sent and received).

Table 6: **Event attendance**

event	attendance	source
A	$\lesssim 30,000$	[48, 8]
B	23,848	organizer
C	$\sim 45,000$	[65, 63]

Table 7: **Number of voice calls and text messages per attendant during the events**

			event A	event B	event C
outgoing voice calls	max/15 min	$[\times 10^{-2}]$	0.33	2.0	0.48
	total	$[\times 10^{-2}]$	8.5	2.4	1.2
outgoing text messages	max/15 min	$[\times 10^{-2}]$	5.6	8.3	7.9
	total		1.5	0.30	0.34
check-in voice calls	total	$[\times 10^{-1}]$	0.5	1.1	0.3
check-in text messages	total	$[\times 10^{-1}]$	1.8	1.9	1.2

Number of outgoing voice calls, outgoing text messages, check-in voice calls and check-in text messages per attendant. Max/15 minutes refers to the maximum number observed in the 15 minutes time intervals. Total refer to the total volume during the whole event.

Table 8: **Upper and lower bound on the attendance forecast**

	Event A	Event B	Event C
Forecasted max attendance (lin)	17,000	13,000	11,000
Forecasted max attendance (exp)	120,000	24,000	71,000
Max attendance	30,000	23,848	45,000