A Digital Library for Crowds on the Real-Time Social Web

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ABSTRACT

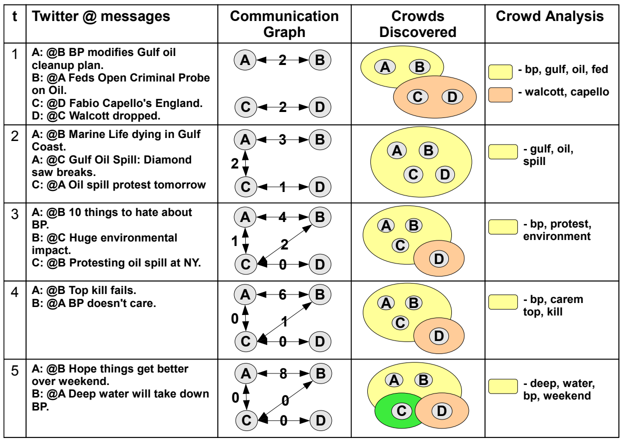
In this project, we want to build a digital library for transient crowds in highly-dynamic social messaging systems like Twitter and Facebook. A crowd is a short-lived ad-hoc collection of users, representing a "hot-spot" on the real-time web. For example, an event like super-bowl might result in formation of crowds that are discussing various happenings in the game. Successful detection of these hot-spots can positively impact related research directions in online event detection, content personalization, social information discovery, etc. We will build a framework that allows an analyst or curious user to find interesting crowds and see how they evolve. This framework will have three main parts: a database to store crowds, users, and their messages; a set of crowd detection algorithms and filters; and a tool for searching for crowds by topic, geography, or user-name.

1. INTRODUCTION

2. RELATED WORK

Twitter[1] is a microblogging platform which is fast gaining popularity[7] among broad sections of society and has a global outreach spreading from developed, urban nations like the United States where it has a high adoption rate [3], to developing countries in parts of Asia and South America.

Along with working on understanding microblogging usage and communities [3], the main author - Akshay Java was one of the first few who dealt with the measurement of the usage and nature of communities in microblogging. In his latter study [2], he presented his observations of the microblogging phenomena and user intentions by studying the content, topological and geographical properties of such communities. He found that microblogging provides users with a more immediate form of communication to talk about their daily activities and to seek or share information.



t	Twitter @ messages	Crowd Analysis
1	A: @B BP modifies Gulf oil cleanup plan. B: @A Feds Open Criminal Probe on Oil. C: @D Fabio Capello's England. D: @C Walcott dropped.	🟨 - bp, gulf, oil, fed 🟧 - walcott, capello
2	A: @B Marine Life dying in Gulf Coast. A: @C Gulf Oil Spill: Diamond saw breaks. C: @A Oil spill protest tomorrow	🟨 - gulf, oil, spill
3	A: @B 10 things to hate about BP. B: @C Huge environmental impact. C: @B Protesting oil spill at NY.	🟨 - bp, protest, environment
4	A: @B Top kill fails. B: @A BP doesn't care.	🟨 - bp, carem top, kill
5	A: @B Hope things get better over weekend. B: @A Deep water will take down BP.	🟨 - deep, water, bp, weekend

Figure 1: Example of crowd discovery and tracking in Twitter.

Identifying highly dynamic ad-hoc collections of users what we refer to as crowds in massive social messaging systems like Twitter and Facebook is important [4]. Kamath et al. in the study suggest an efficient locality-based clustering approach for identifying crowds of users in near real-time compared to more heavyweight static clustering algorithm. The study consisted of 711,612 users and 61.3 million messages, and tells what approaches to follow to efficiently and effectively identify Twitter-based crowds.

In the other study based on the previous one, Kamath et al [5], they add another salient feature - a novel crowd tracking and evolution approach for linking crowds across time periods. Unlike the more static and long-lived group-based membership offered on many social networks their goal was to support the discovery of organic and highly-temporal group affiliation, which they refer to as "transient crowds". A transient crowd according to them is a potentially short-lived ad-hoc collection of users bound together by some common thread - which can be communication-based, location-based or interest based. We are inspired by this idea of formation and detection of crowds. We try to implement detection of crowd in Crowdy in a similar fashion.

3. CROWD DISCOVERY ALGORITHM

To illustrate the problem of crowd discovery, consider the simple example in Figure 1. At time t=1, users A and B

[1] http://www.twitter.com

send messages to each other, as do users C and D.[2] The associated communication graph shows an edge between the two pairs, where for simplicity the edge is annotated with the number of messages between the users (2, in both cases). Further, suppose we identify crowds based purely on graph connectivity. So for time t=1, we see there are two crowds discovered {A,B} and {C,D}. For each crowd, we can characterize the semantics of their communication with simple keywords extracted from the content of the tweets: ("oil", "gulf") and ("walcott", "capello"). At time t=2, the communication graph is updated with a new edge (connecting User A and User C), and the existing edges are decayed by one (again, a simplifying assumption for the purposes of this example). A single crowd is discovered since all users are connected via edges with non-zero edge weights. At time t=3, User D leaves the main crowd since no messages to or from User D have been observed since time t=1. This process continues until time t=5 when User C also leaves the main crowd due to inactivity. Note that crowds are discovered from communication graph only and not from the content of the messages. As an example of crowd tracking, we can track the evolution of the yellow crowd across time periods, observing the changes it goes through as it grows in size from t=1 to t=2 and then reduces to two users by t=5.

The grouper deals with the transient crowd discovery and tracking in systems like Facebook and Twitter. For practical crowd discovery and tracking in a large time-evolving communication network, however, we face four key challenges:

- First, systems like Facebook and Twitter are extremely large (on the order of 100s of millions of unique users), placing huge demands on the computational cost of traditional community detection approaches (which can be $O(n^3)$ in the number of users [1]).
- Second, these services support a high-rate of edge addition (new messages) so the discovered crowds may become stale quickly, resulting in the need to re-identify all crowds at regular intervals (again, incurring the high cost of community detection). The bursty nature of user communication demands a crowd discovery approach that can capture these highly-temporal based clusters.
- Third, the strength of association between two users may depend on many factors (e.g., recency of communication), meaning that a crowd discovery approach based on graph clustering should carefully consider edge weights. With no decay at all (meaning that edges are only inserted into the network but never removed), all users will tend towards a single trivial large crowd. Conversely, overly aggressive edge decay may inhibit any crowd formation at all (since edges between users may be removed nearly as soon as they are added).
- Fourth, crowds may evolve at different rates, with some evolving over several minutes, while others taking several days. Since crowds are inherently ad-hoc (without unique community identifiers – e.g., Fans of LA Lakers), the formation, growth and dispersal of crowds must be carefully managed for meaningful crowd analysis.

With these challenges in mind, we propose to discover and track transient crowds through a communication based clustering approach over time-evolving graphs that captures the natural conversational nature of social messaging systems. Two of the salient features of the proposed approach are (i) an efficient locality-based clustering approach for identifying crowds of users in near real-time compared to more heavyweight static clustering algorithms; and (ii) a novel crowd tracking and evolution approach for linking crowds across time periods.

To support transient crowd discovery in Twitter-like services with 100s of millions of participants, we propose to leverage the inherent locality in social messaging systems. Concretely, we identify two types of locality that are evident in Twitter-like messaging systems: (i) temporal locality and (ii) spatial locality.

Temporal Locality: Transient crowds are intuitively short-lived, since they correspond to actively communicating groups of users. Hence, the composition of a crowd at a point-in-time should be impacted by recent messages as opposed to older messages. As more users interact with the crowd, the crowd should grow reflecting this *temporal locality* and then shrink as users in the crowd become inactive (that is, their last communication with the crowd becomes more distant in time).

Spatial Locality: Intuitively, transient crowds are made up of a very small percentage of users compared to the entire population of the social network. Hence, new messages (corresponding to the addition of edges to the communication network) should have only a local influence on the crowds that exist at any given time. That is, changes in a small region of a graph should not affect the entire graph. In a dataset of 61 million Twitter messages described in [6], we have confirmed the existence of this *spatial locality* by finding that only about 1% of users are within two hops, meaning that an edge insertion has only a local effect.

Hence, we can take advantage of both, local changes to the overall communication network (spatial locality) and recent changes to the network (temporal locality), for supporting efficient transient crowd discovery. The complete algorithm is decsribed in [6]

3.1 Sample Crowds Discovered

We illustrate some of the discovered crowds and their lifespans in Figure 2, with an annotation next to the crowd peak showing the topic of discussion. We see a crowd (shown in black) discussing Sarah Palin and the Vice-Presidential debate from the 40^{th} hour to 80^{th} hour that peaks around the time of the actual debate. We observe that crowds that talk about general everyday things have a greater lifespan than crowds discussing specific events. For example in Figure 2, a crowd (annotated with *thank, whats, wow*) discussing everyday things lives through the entire week, while, during the same period we observe several event-specific crowds, like crowds discussing the Red Sox, Sarah Palin, and Girl's Night Out (gno) forming and dispersing. These event-specific crowds start forming just before the event and die a few intervals after the completion of that event. This distinction between the crowds discovered clearly indicates two types of Twitter usage: first, it is used as a platform to discuss and debate specific events, and second, it as also used a means of everyday communication.

[2] For simplicity, the example discretizes time so that all messages between users occur in steps. In practice, the proposed algorithm relaxes this assumption and can handle arbitrary message sending times.

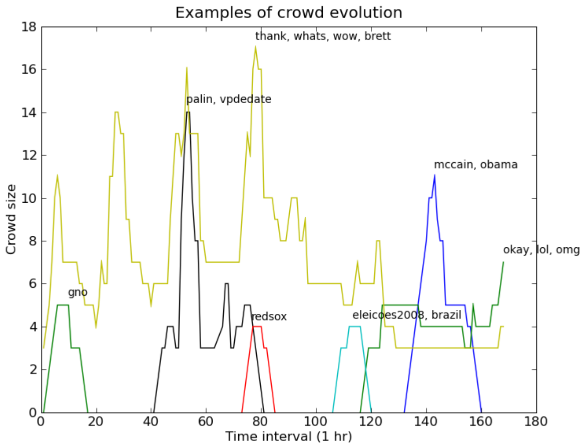


Figure 2: Examples of the crowds discovered in the dataset.

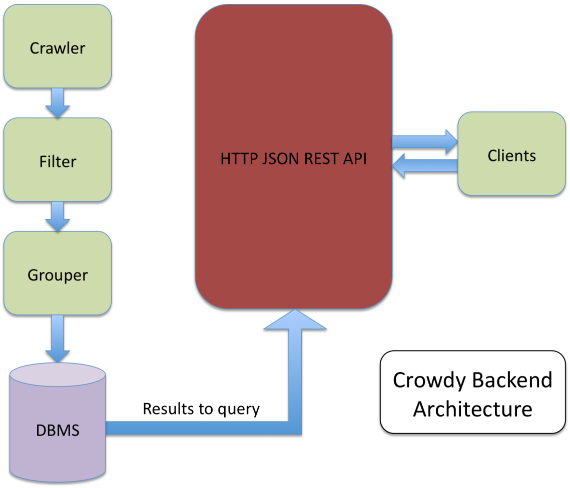


Figure 3: Examples for trending phrases discovery problem.

4. ARCHITECTURE

An architecture for the proposed solution is shown in Figure 1. The various modules of this architecture are as follows:

Crawler: This module deals with interacting with social media websites to collect information. For this project we will be collecting data from Twitter using Twitter Streaming APIs. We collected tweets from [xxxx] users. To collect this set of users we started with a set of 5 users and used snowball sampling to collect more users. We then used used the "follow" parameter of the filter method from Streaming API to generate a data stream for crowd detection.

Grouper: The grouper module analyses the data collected, to determine crowds and adds them to the DBMS. This is the central module that detects crowds of different types - communication, content, geo-graphical, etc. In this project we will be discovering crowds based on communication only. The algorithm to discover crowds is described in Section 3. Once crowds are discovered, this module formats crowds to a well defined crowds object and adds it to a DBMS.

Filter: This module is used to filter un-necessary data from the framework. It can appear both before and after the grouper module depending upon its funcationality. In the figure we have showed the module appear before grouper only. When the module appears before the grouper, it is used to weed out information unnecessary for the grouper. For example in case of crowd detection, it remove information like spam messages. When the module appears after the grouper, it cleans the data generated by the grouper. For, example in case of crowd detection, it analyzes crowds discovered by the grouper and removes un-necessary crowds, or crowds that don't meet specific quality guarentees. The module can also have additional functions that support features like search.

HTTP JSON RESTful APIs: This module provides client an interface to the digital library. The module exposes JSON APIs that the clients can use to browze and search the crowds archive.

4.1 Tools

The tool we used to develop this framework are as follows:

- **PyLucene**: To provide the search functionality we use Apache Lucene. It provides methods for text indexing and searching. To integrate Lucene with our framework we use Pylucene which is a Python wrapper for Lucene. This is used in the filter module of our architecture.
- **CherryPy**: This is an object-oriented web framework for Python. The JSON REST API that interface the digital library with clients is hosted using this web framework.
- **NetworkX**: This is a library for manipulating graphs in Python. We use this to determine quality of crowds generated by crowd detection framework and filter out crowds of poor quality. This sits in the filter module.
- **Beanstalk**: Beanstalk is a simple, fast work queue. We use it to connect the crawlers, filters, and groupers together.
- **MongoDB**: MongoDB is a scalable, high-performance, open source, document-oriented database. We store the crowds discovered by the framework in this DB. The API module interacts with this database to retrieve collections as required by the user query.

5. CONCLUSION

6. REFERENCES

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