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How social is OpenStreetMap?

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Abstract

This paper investigates the collaborative nature of spatial data collection and editing in OpenStreetMap (OSM) and seeks to answer the question of "how social is OpenStreetMap?". Is *the crowd* collaborating, in a similar manner to contributors to Wikipedia, to build the OSM spatial database? Or is the crowd a fragmented one comprising of individuals performing these tasks in isolation with little collaboration or interaction with each other. The entire OSM history of London (2005 - 2011) is used as a case-study. Our experimental analysis indicates that there is limited collaboration amongst contributors with a large percentage of objects (35%) having being edited only once or twice. We also find that contributors can be categorized as: object creators, tagging editors, and general editors (creation, tagging, and geometry). Some proposals for future work in this area are outlined at the end of the paper.
Keywords: OpenStreetMap, Social Networks, VGI, collaboration, crowdsourcing

1 Introduction

This paper appears at the confluence of two of the hottest topics in GIS and Internet technologies namely Volunteered Geographical Information (VGI) and Social Networking. Volunteered Geographic Information (VGI), the term coined by Goodchild [8], is the recent empowerment of citizens in the collaborative collection of geographic information. OpenStreetMap (OSM) is a collaborative project to create a free editable map database of the world as is probably the most well known example of VGI. Social networks are a ubiquitous part of everyday life. Although they have long been studied by social scientists, the mainstream awareness of their ubiquity has arisen only recently in part because of the rise of social networking sites on the World Wide Web [23]. Much related literature is found in work carried out by researchers on Wikipedia. Massa [17] argues that much academic effort in the analysis of Wikipedia has "focused on the product itself, analyzing the quality of the content with human language technologies" and has "somehow neglected the social side of these wikis". There have been many papers published on various aspects of OSM, and VGI in general: geometric quality of OSM ([9, 19]), the quality of tagging in OSM [18], trust and semantics in OSM and VGI ([11, 2]). None of these studies investigated the social aspects of OSM. Recently, Lin [14] derived empirical data from interviewing a small number of OSM contributors. She draws the conclusion from these interviews that OSM "itself acts as a boundary object that enables actors from different social worlds to co-produce the OSM Map through interacting with each other and negotiating the meanings of mapping, the mapping data and the Map itself". Crucially most studies focus on a current snapshot of the OSM [18] and we feel that this view of the crowdsourced element of OSM is too narrow. When a longer term historical view of OSM data is considered patterns of crowd contribution and OSM completeness become evident. The research questions that our paper will attempt to provide answers for are as follows. **Q1:** Are contributors to OSM ("the crowd") interacting and collaborating with each other "to create a free editable map of the world" or are many contributors working in isolation (such as mapping their own areas (like "pet articles" [1] or certain types of features only). There are differences in opinion amongst researchers regarding *why* citizens join "the crowd" to solve problems or join Wikipedia or OSM. Hung et al [10] find that increasing one's reputation served as a strong incentive while Yang et al [25] found "internal self-concept-based motivation" was by far the most important motivation. Crowdsourcing usually leads to a contribution to society at large but it does not necessarily indicate that there is social interaction between the actors involved. This brings us to research question two. **Q2:** In terms of crowdsourcing what types of contributions do key contributors to OSM make and what are the levels of interaction between key contributors in terms of collaborative editing.

Our paper is organized as follows. Section 2 provides an overview of related literature with discussions of social network topology (section 2.1) and the requirements for building social network data structures (section 2.2). In section 3 we provide the experimental results of our case-study and associated analysis. This includes an overview of the types of contributions to OSM, the social interaction amongst contributors, and types of contributors. The paper closes with Section 4 where some conclusions are drawn and some issues for immediate future work are outlined.

2 Overview of Related Literature

In this section we provide an overview of related literature. To organize the literature overview we have divided the discussion into two sections. We begin by discussing the topology of social networks in Section 2.1 and then proceed to discuss the building of social networking data structures in Section 2.2.

2.1 Social Network Topology

Actors in social networks tend to select partners that are socially or cognitively similar [22]. Wong et al [24] show that the degree of an actor is the number of social ties he/she has and conclude that in many social networks, a majority of actors have relatively small degrees, while a small number of actors may have very large degrees. Luthi et al [16] show that some social networks do not specifically choose neighbors using locality. By actually giving up a strictly local geographical structure, cooperation often still emerges, provided that the interaction patterns remain stable in time, which is a first step toward a social network structure. However, all these topologies can only be considered as approximations, as it has now become clear that many actual networks, social or otherwise, usually have a topological structure that is neither regular nor random but rather of the small-world type [16]. Luthi et al argue that intuitively, there must be a cut-off in the number of acquaintances or friends that a given node can have, and in many cases also a typical number of acquaintances, which gives a scale to the network. Ter Wal and Boschma [22] describe the process of "preferential attachment" which is the growth of a social network in which the probability that a new actor (node) will link to a given existing actor is proportional to the number of links that the existing actor already has. An outcome of this probabilistic process is that central actors tend to become more central, whereas peripherally positioned actor tend to stay peripheral. It is these actors or contributors that create and edit the content within these collaborative wiki-style projects.

In OSM there are thriving consultation and collaborative discussions on Wikis and mailing lists [3] and at "mapping parties" but these are not very easily quantifiable. Extracting social interaction, from datasets where social interaction is not explicitly stored, has been attempted in many other areas. In machine vision Cristani [5] attempts to detect social interaction from photographic images. In web forums Gómez et al [7] analyzed the structure and evolution of discussion cascades on discussion websites such as Slashdot as a means of extracting social interaction. In the next section we discuss building a social network data structure from the OSM spatial database.

2.2 Building social network data structures

Building a social network data structure involves the analysis of: the attribute information of the actors involved, logs of interaction between actors, explicit links between actors, or collaborations (such as articles). Massa [17] warns that the collection procedure for data about SNA on the Web, and the collection assumptions, highly influence the collected network and hence the findings that can be inferred from it. The most basic information in a social network is the number of nodes: in our case, each node represents a specific user or contributor [17]. Moreno, in the 1930's, was one of the first to introduce social network analysis by using a graph or network structure to represent the relationships between individuals and/or groups of people. Network structures are immediately appealing because of their ability to almost instantaneously reveal underlying patterns to the arrangements of nodes and edges [21]. Often it is straightforward to define the network's nodes whereas defining the edges can be more challenging [21]. In OSM there is no explicit "friendship" structure. The concept exists on the OSM wiki but there is no physical manifestation of this in the OSM database amongst contributors who are editing content or providing new spatial data and information. Inferring the presence of links is a challenge. Conventional methods for elucidating social structure in the editing process are possible but may not always be feasible. For example a survey or questionnaire could be used to ask OSM contributors to indicate who they are "friends" with or are "editing with". Problems associated with this are potential low response rates, the rate of growth of OSM contributors and contributions, and the fact that some authors seem to indicate that much OSM editing and contribution is performed in isolation [6] or amongst uncoordinated or only loosely groups of contributors. Rhodes and Keefe [21] use a Bayesian approach to infer social network structure but this is very dependent upon the availability of information on the individuals of interest ('attributes' such as age, gender, address, social background, etc). Very little of this data is available for contributors to OSM unless the contributors make it available on their wiki pages on the OSM wiki. The process of inferring links is dependent on the assessment of evidence for interaction against a known sample of positive and negative links in the network. Rhodes and Keefe [21] use a "gold-standard" dataset of known links and then see how other members of the social network "fit into this model". In the next section we show how a social network data structure is extracted from the OSM database using a proposal to infer edges between actors (contributors) from an analysis of the history of their contributions.

3 Experimental Results and Analysis

In this section we describe the construction of a social network from the history of OSM contributions for our study area. We outline the key characteristics of the contributions and data in the study area. Results of analysis of the types of contributors and types of contributions are also provided.

3.1 Constructing social networks from OSM history

There are two elements necessary to construct a social network from OSM: the contributors and the geographic objects which they create and edit. We have extracted the history of all OSM contributions to London, England using a bounding rectangle that extends to just outside the M25 motorway. There are a total of $3,811,876$ (verticles/points - called nodes in OSM terminology) and a total of $876,743$ ways (polygons or polylines). This history contains edits to London from April 2005 to October 2011 with $2,795$ unique contributors to London OSM over this period. In section 2.2 methods were discussed for problems where more explicit or easy to detect interaction information is available. Contributors in OSM do not "follow" or "be friends" with other contributors as is common in social media such as Twitter or Facebook [13, 4] or in online question answering communities [20]. To construct a social network from OSM we must carry out the following steps:

1. Download and process the OSM history for the region of interest. This history is stored in a PostGIS database. In addition to the OSM History Extraction software from [12] we developed some additional Python scripts to store this

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history data in this PostGIS database. For each way (polygon, polyline, and point) we stored: the geometry of the way, timestamp of edit, the user id of the contributor, all tags, edit version number, and the OSM changeset number.
2. Extract contribution history for each actor in OSM for the region of interest. This includes: their contribution history for each object, the type of contribution (create, edit, update), and the OSM actor whose contributions they have edited or updated. We call this information *edit interaction*.
3. Build the network graph data structure $G = (V,E)$ where V is the set of all contributors in OSM for the region and E is the set of edges or links between the contributors in V under some condition such as: co-edited an object in OSM, updated or edited each other's contribution, etc.

3.2 Study Area Characteristics

In our London OSM history dataset the quantity of contributions from the 2795 contributors is heavily skewed toward small numbers of contributions. 289 contributors provided 1 or 2 edits to *ways* over the period of the history. Almost 63% $(1,738)$ of contributors were responsible for 10 or less edits to *ways*. This rises to 72% $(2,002)$ contributors who were responsible for 20 or less edits. Given this distribution we decided to extract a subset of all contributors - those 250 contributors who have made 200 edits or more to ways in OSM London. Remarkably, these 250 contributors were the creators (first version contributions) for $404,135$ ways out of London's $876,743$ ways (just over 46%). In a similar fashion we needed to reduce the set of $876,743$ ways to a subset of ways which exhibited "social editing" or "collaborative editing". We extracted those ways with 5 or more edits or versions (this parameter can be changed in our analysis). In [REF TO OUR PAPER] we analyzed objects in OpenStreetMap with 15 or more versions. In Lipka and Stein [15] (and many similar studies) only featured articles (frequently edited with large numbers of contributors) in Wikipedia are considered. In our dataset there are $33,230$ ways with 5 or more versions. Surprisingly a large percentage of features have had little or no collaborative editing. For example $228,222$ (26%) ways have only one version while $324,594$ (37%) ways have one or two versions. In summary we use the edit histories of the 250 most frequent contributors to OSM in London and analyze $33,230$ objects in this region which have 5 versions of edits or more.

3.3 Contributions Summaries

In this section we analyze the contribution summaries of the top 250 contributors. Figure 1 shows the distribution of number of unique editors of objects in OSM London where these objects have 5 or more version. Twelve extreme outliers have been omitted for clarity. The mean μ number of contributors to these objects is 3.52 with $\sigma = 1.752$. As stated in section 3.2 above we decided to only analyze the top 250 contributors to OSM London because over 70% of contributors to this region had only created a very small number of contributions. Figure 2 provides a scatter plot of the number of changesets and total edit contributions of the top 250 contributors. In OSM a changeset is a logical means of grouping edits or modifications performed by a registered contributor and can subsequently be used for deletion or rollback to a previous state in the OSM database. Changesets remain *open* for 24 hours and can only contain a maximum of $50,000$ edits. Changesets can give an accurate picture of how long a contributor has been working on the OSM project as only one changeset can be opened at any time. The y axis shows a log scale of the total number of edits for each contributors while the x axis shows the number of changesets. Just over 90% of contributors have created less than 500 changesets. A changeset could be seen as equivalent to one day.

3.4 Edit Interactions

In Table 1 we summarize the edit interactions for 5 selected users from the top 250 contributors to London OSM. Their ranking in the top 250 is shown in the **Rank** column. The number of edit interactions is shown in **Actions**. An **Action** is the set of operations performed on a version of a feature (and it's metadata) which creates a new, updated, version of that feature in the OSM database. There can be several types of **Actions**, some of which can happen simultaneously : **Created** where the contributor only creates a given feature and performs no more edits; **CreatedEdit** where the contributor creates a given feature and proceeds to perform other actions; **Node Self** where the contributor performs an edit of the nodes of a feature they created; **Tag Self** where the contributor performs an edit of the tags of a feature they created; **Node** where the contributor performs an edit of the nodes of a feature a different contributor created/edit; and **Tags** where the contributor performs an edit of the tags of a feature a different contributor created/edited. The number of unique features or objects edited is given by **Objects**. The final column **People** indicates the number of contributors to OSM London whose work has been edited by the contributor identified by **ID**. Recall that these are objects with 5 or more versions of edits. There are some interesting observations. The first three contributors have edit interactions predominantly comprising of geometry operations (node editing of their own edits or those of others) whilst the final two contributors edit slightly more tags than geometries. Contributor 3937 is interesting in that their edit interactions are dominated by **Create** actions where he/she created the feature but did not edit it again. Not surprisingly contributor 88718 has had the most edit interactions with other OSM contributors where he/she has edited the content contributed by 232 other OSM contributors. In Figure 3 we show a distribution of the number of unique contributors to OSM who had their contributions edited by the top 250 contributors. The mean μ number of other OSM contributors whose work has been edited by the top 250 contributors is 49.15. In total 9 outliers of ≥ 232 have been omitted for clarity.

We performed $k-$means data clustering on the contribution history (similar to that in table 1) of each of the top 250 contributors in an attempt to ascertain if contributors can be classified based on the types of edit interactions they perform. Using a multivariate approach we selected $k = 4$ clusters and four variables for each contributor's history: percentage of objects they created but did not edit, percentage of geometry only updates or edits, percentage of tag only updates or edits, and percentage of geometry and tagging updates committed during the same contribution edit. Applying nearest neighbor cluster centroid selection and naive Bayes classifier we calculated that contributors formed clusters (which were then verified manually). 27 contrib-

Table 1: Edit interaction summaries for 5 selected users from the top 250 contributors to London OSM

ID	Rank	Actions	Objects	Created	CreatedEdit	Node Self	Nodes	Tags Self	Tags	People
88718	3	10594	3444	43	778	4219	1743	2687	1124	232
122934	30	792	318	8	38	336	238	118	54	77
97369	100	426	219	5	21	156	157	43	44	60
3937	166	192	176	108	0	2	22	4	56	26
54519	250	106	66	4	4	13	28	13	44	21

Figure 1: Number of unique contributors to ways with 5 or more versions of edits

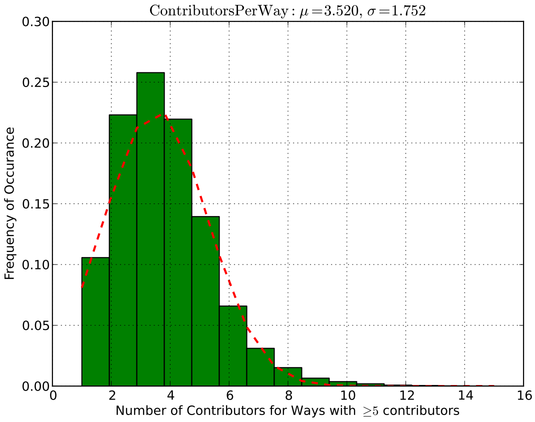
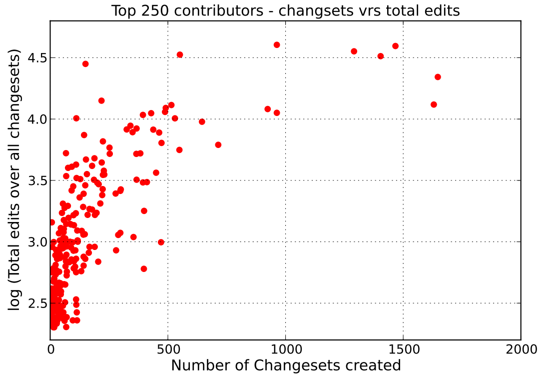


Figure 2: Changesets and Number of Edits of 250 most frequent contributors



utors were in the **only created** cluster, 98 contributors were in the **geometry** only cluster, 81 where in the **tagging** only cluster, whilst 35 were classified in the **geometry and tagging** cluster. 9 contributors remained unclassified as the results from both the nearest neighbor calculations and the naive Bayes classifier were inconclusive.

3.5 Visualization of social interaction in OSM

In Figure 4 we show a social network representation of the edit interactions of the top 250 contributors in London over the entire period of the history. In the graph $|N| = 1788$ and $|E| = 15765$. The reason for $|N| > 250$ is that we show the edit interactions between the top 250 contributors and other contributors they have edited (who may be outside the top 250). The average degree of nodes is 8.817, the average clustering coefficient is 0.396, and there are 1541 strongly connected components in the graph. The presence of strongly connected components in a social network graph can indicate that there is a "tight knit" group interacting together. A strongly-connected component is defined by a sub-graph in which there is at least one path (series of connections) from an arbitrary chosen node to the other arbitrary chosen node in the sub-graph. The largest strongly connected component has 17 nodes. Betweeness Centrality (BC) ranks nodes by how many shortest paths between other nodes they are on. High betweeness (close to 1) represents a single point of failure in a network but also an influence over what happens in a network. The mean BC for the network in Figure 4 is 0.12 with 12 contributors (nodes)

Figure 3: How many other contributors' work have the top 250 edited?

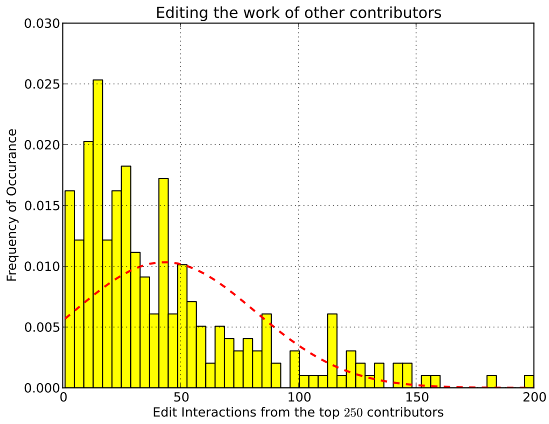


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Figure 4: A social network representation of the edit interactions of top 250 contributors in London

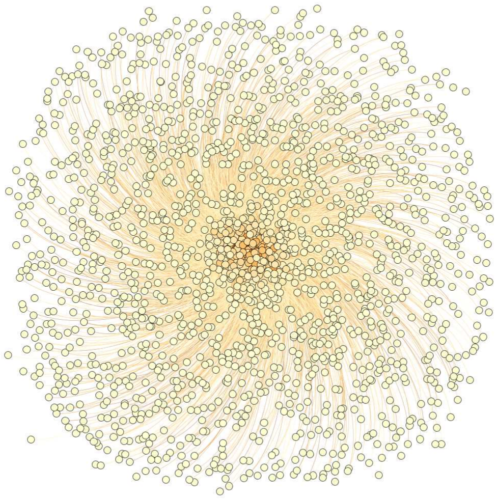
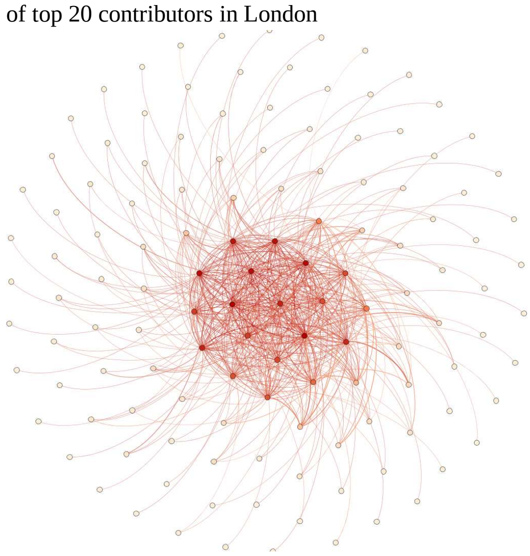


Figure 5: A social network representation of the edit interactions of top 20 contributors in London



having relatively high BC of over 0.45. Figure 5 shows a social network representation of the edit interactions of the top 20 contributors in London over the entire period of the history. The graph is directed so an edge existing between i and j indicates that i edited the previous contribution submitted by j. Darker red edges indicate higher frequency of edit interaction between the nodes. The darker red nodes represent nodes with higher edge degree. In the graph $|N| = 128$ and $|E| = 606$. The average degree of nodes is 4.734, the average clustering coefficient is 0.426, and there are 109 strongly connected components in the graph. The largest strongly connected component has 10 nodes. The mean BC for network shown in Figure 4 is 0.14 with 5 contributors (nodes) having high BC of over 0.25. This could indicate that their removal from the social network of the top 20 contributors would cause less network disturbance than their removal from the network in Figure 4

4 Conclusions

This paper discusses results of a social network analysis approach to the history of edits and contributions to OSM in London from April 2005 and October 2011. There is no explicit social network structure to the OSM spatial database. As discussed in Section 2.2 contributors in OSM do not "follow" or "link" to each other explicitly. In section 3.1 we described how we have constructed a social network representation of edit patterns in OSM using an analysis of the history of all edits and contributions to London. Section 3.3 showed that the mean number of contributors who collaboratively edit features is rather low (3.52) and that much of the work of editing is carried out over a long period of time by a small number of contributors as shown in Figure 2. Section 3.4 showed that contributors in London OSM could be clustered into four distinct groups of contributors with over 70% of these contributors predominantly editing the geometry of features or the tagging of features but not both. As shown in Figure 3 collaborative editing of contributed content is occurring. The mean number of other contributors work edited by our selected 250 contributors is 49.15. Finally, edit interactions between contributors are visualized as social network graphs in section 3.5. Very high frequency contributors exhibit relatively high values of betweeness centrality (from the social network graphs in Figure 4 and Figure 5). In the analysis of the top 250 contributors to OSM London strongly connected components ('tight knit groups') were detected. As an immediate part of our future work we shall perform a similar analysis for other cities in order to begin a comparison of the social network characteristics of OSM in these urban areas. Overall there appears to be a lack of significant collaboration amongst contributors. Could the lack of collaboration be a result of limitations of the available tools or interfaces? Are the majority of the crowd reticent about editing the work of contributors higher up the social hierarchy of OSM? Or is the collaborative editing process for spatial data objects fundamentally different to editing articles in Wikipedia? Finally, there is an obvious "long-tail" nature to the contribution patterns here. A small number of contributors do the majority of the work. This has been studied in other domains such as Open Source software development. Are there similiarities here in OSM? Combining these questions may form an interesting set of research questions for additional future work.

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