Who to query?
A two step querying technique for tracking variant/unknown event distributions

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ABSTRACT

In this paper, we propose a two-stage node selection technique for resource constrained systems based on the nodes location to track incidents in a $2D$ environment. In order to do that, the technique maximizes the dispersion of the locations with a portion of the available resources and based on the nodes' feedback, it selects the K nearest neighbors for the nodes that provide a positive feedback using the rest of the available resources. In addition, we test the two-stage technique on different distributions: uniform, clustered and long-tailed. We then apply the technique on a real harassment dataset provided by Hollaback. The proposed technique outperforms a random selection policy and a policy that relies on dispersion maximization without incorporating feedback from the nodes. We then discuss how to tailor the technique in the case of incorporating trust algorithms and in the case of knowledge about the prior distribution of the incidents.

1. INTRODUCTION

Sensors are a large part of our daily life. The common smartphone includes different sensors: camera, microphone, GPS, accelerometer, digital compass, light sensor, Bluetooth as proximity sensor among other sensors. In the near future, they are even envisioned to include more and more sensors. The ubiquity of sensors is not only prevalent in smartphones but also in the urban environment surrounding us. Examples include traffic sensors, agriculture sensors, wireless parking sensors, infrastructure sensors, weather, and pollution sensors among others. Another type of sensors lies in the power of analysis of datasets. In a sense, insights from data analysis can reveal important observations. For instance, [5] leverages the geographic and temporal data associated with taxis in NYC to gain insights into many different aspects of city life, from economic activity and human behavior to mobility patterns. With the recent plethora of crowdsourcing, humans' senses have been leveraged to generate, contribute and report about their surroundings. One example that comes to mind is the application "Waze", where users can report traffic jams, accidents and other road related incidents in real-time. The work introduced in [1] probes local workers to collect information in person at events and remote workers to curate the collected information and generate event reports.

Despite the ubiquity of sensors, whether these sensors are human or devices, the challenges of energy preservation or resource constraints always prevail. The truth is that all systems are bound by a fixed amount of resources. In this paper, we wish to investigate the problem of how can we probe a limited amount of sensors in a particular environment instead of probing the whole amount of sensors to either preserve energy or to simulate a resource constrained system. In particular, we envision a world where users/sensors can be probed to contribute to an unanswered question. An unanswered question can be related to a phenomenon that needs to be tracked under the constraints of N resources. Examples of resource constrained systems include disaster and safety applications or in general terms to track any spatial phenomenon.

Our contribution in this paper is three-fold. First, we propose a two-stage matching technique that probes/queries N nodes out of M available nodes to track a real-time phenomenon with no prior information about the event distribution. The technique outperforms the random user selection by up to 63% on average in terms of number of users chosen that are close to the events and outperforms the dispersion maximization technique by up to 68% on average. Secondly, we perform experiments to study the performance of our proposed technique under three different distributions: uniform, clustered and long-tailed. We also test the technique on a real dataset that is comprised of harassment cities in three different cities. Third, we discuss how the technique is altered based on trust variations and prior knowledge availability.

The rest of this paper is organized as follows. Section 2 surveys the related work while Section 3 describes the proposed two-stage technique. Section 4 experimentally evaluates the proposed technique, and Section 5 discusses tradeoffs and variations of the two-stage technique. Section 6 concludes the paper.

2. RELATED WORK

Since the introduction of the term crowdsourcing as a modern business term in 2006 [8], a huge body of work has been dedicated to the study and the implementation of crowdsourcing in real life applications. In particular, geo-crowd sensing where the crowd participation is bound by being in a particular geographic area has received significant attention lately. For instance, [11] introduces a location-based real-time social question answering service deployed where people can ask temporal and geo-sensitive questions and then receive answers that are crowdsourced from other users in a timely fashion. A crowdsensing platform was introduced in [4] to facilitate the collaboration of large groups of people participating in collective actions of urban crowdsourcing.

Using people as sensors, collective sensing, and citizen science has opened doors for interesting research problems. Some of these challenges are introduced in [3]. One important challenge in geo-crowd sensing is detecting unusual events. The work proposed in [10] leverages microblogging websites such as Twitter to detect unusual geo-social events by detecting unusually crowded regions. Another challenge is the refining of crowd sensed data and detecting fake data. Solutions based on a user's history and reputation were introduced in the literature. The work in [15] proposes a reputation-aware model that balances the workload between users. Another challenge is fusing untrustworthy estimates [14]. Taking into account spatial properties, [13] tackles the problem of fusing multiple spatial observations reported by possibly untrustworthy users using a heteroskedastic Gaussian process model.

Another related body of work is sensor networks [2] that include spatially and ubiquitously distributed autonomous sensors used to monitor physical and environmental conditions. Since the sensors are basically small, low-powered nodes, resource-constrained protocols emerged to preserve the energy of these devices. Examples of work targeting energy preservation include, but are not limited to, [12] where the authors achieve geographic localization using noise tolerant acoustic ranging mechanism to meet severe resource constraints. In [9], data aggregation methods were introduced and achieved significant performance gains in comparison to end to end routing. The work proposed by [6] implements a system that analyzes sensor behaviors and uncovers misbehavior corresponding to inefficient device usage that leads to energy waste.

3. RESEARCH QUESTION AND PROPOSED TECHNIQUE

In our system, we have a two-dimensional grid and a number of objects that can sense the environment around them. These objects can be humans, artificial sensors, mobile phones or even robotic sensors. If we are interested in answering the question "What is the answer to Question X in this grid?", we can basically ask or query all the objects in the two-dimensional space and aggregate their findings. In this paper, we assume that to answer this question, you can only query N objects. Hence, the question becomes: *Given N resources, who should you select to track a phenomenon?* Answering this question becomes essential in the case of limited resources. This is particularly important in emergency scenarios when a network's performance degrades and preserving energy and other resources become critical.

If we attempt to tackle this question from a probabilistic point of view, then the straightforward answer would be to try to select objects/users with the same probabilistic distribution as the phenomenon. For instance, if we know that a certain phenomenon occurs at different places in the two-dimensional grid uniformly, then we would have no bias in selecting the users to query, i.e. each user/object would have the same probability of selection to be queried. On the other hand, if we know the phenomenon we are interested in is more prevalent in certain areas of the grid as opposed to other areas, we would take that into consideration when we are selecting the users to select more users to query in this area and fewer users in areas where there is a smaller probability of occurrence.

The question becomes far more challenging if the distribution is not known or if it is time variant? The aforementioned question becomes more interesting in this case and we can then inquire if there is a systematic algorithm that can be used for querying/selecting users to track a phenomenon regardless of the probabilistic distribution or time variation.

3.1 Technique Description

We assume that there are M users in a two-dimensional grid and that the system that selects a user to query is bounded by N resources, where $N < M$. Each of the M users has a specific location in the grid, determined by a two-dimensional system, e.g. (x, y) or a (lat, long). We also assume that the users selected will participate in answering the question of interest to the system and fully co-operate. A pre-selection phase can be used to eliminate users that are not likely to co-operate such as requiring installation of an app to facilitate querying. Here, we focus on how to select N out of M users to where $N < M$ to keep track of events occurring in the two-dimensional grid.

Our technique combines K nearest neighbor (KNN) queries with querying users to maximize the dispersion of their location in the grid as depicted in Algorithm 1. We divide the selection of users into two stages. In the first stage, our goal is to select users with the goal of maximizing the dispersion of users' locations. We maximize the dispersion by selcting the set of points that maximizes the average distance between each point and its nearest neighbor as follows:

$$\text{argmax} \sum_{i=1}^{N} \|p(i) - NN(p(i))\|^2 \quad (1)$$

where p respresents a point in the $2D$ grid and NN represents the nearest neighbor and the distance is measured as the Euclidean distance. The algorithm attempts to maximize the dispersion up to the number of maximization trials. Based on the crowd feedback in the first stage, we then proceed to a more fine-grained selection. The users that provide a positive feedback (i.e. they witness an event/ emergency in their location) are called the *pivot users*. In the second stage, we want the K nearest neighbors for the pivot users.

This initial algorithm assumes that the first stage users will respond with unfalsified responses. To relax this assumption, we explore dividing the selection of the second phase users into two groups: a group that consists of the KNN of the trusted pivot users, and another group that aims to maximize the dispersion. In this section, we will focus on studying our two-stage querying technique with the assumption of having full trust in the crowd and discuss other variants of the technique in subsequent sections.

Algorithm 1 Two-stage querying algorithm

```
function selectUsersFromGrid (FSP, N)
    selectedUsers = {}
    firstStageCnt = ⌊(FSP * N)⌋
    secondStageCnt = M − firstStageCnt
    firstStageUsers = maximizeDisp(firstStageCnt)
    usersFeedback = feedback(firstStageUsers)
    if usersFeedback.size == 0 then
        selectedUsers = maximizeDisp(secondStageCnt)
    else
        selectedUsers.append(firstStageUsers)
    firstStageQuota = calculateQuota(firstStageUsers)
    for user_i in firstStageUsers do
        selectedUsers.append(KNN(user_i,
firstStageQuota_i))
    return selectedUsers
```

Environment settings: • matrix dimension: the length and the width of the $2D$ spatial matrix. We model the spatial area under investigation as a $2D$ square matrix. • incident count: number of incidents distributed across the cells of the spatial matrix • resources or crowd count: the M resources from which N, where $N < M$, will be chosen to query
Query settings: • N: the number of resources the system is limited by to query/sense • first stage percentage (FSP): the percentage of users/sensors of the N resources that will be selected to query in the first phase. In our analysis, we test the cases of selecting $20\%, 40\%, 60\%$ and 80% of the N resources in the first stage. • k setting: used to identify the KNN crowd individuals/sensors to an incident
Approximation settings: • maximization trials: number of attempts to maximize the dispersion of selected individuals/sensors from the crowd

Table 1: Different parameters of the two-stage querying technique.

4. EXPERIMENTS

To quantify the performance of our technique, we perform multiple experiments with three types of data spread: clustered, uniform and real datasets. In our experiments, we compare our algorithm in the selection of users to two policies as follows:

- Random user selection: For this policy, we select N users randomly based on a uniform distribution.
- Dispersion maximization selection: The selection of users in this policy depends on selecting N users from the crowd who maximize the dispersion of their locations.

4.1 Experiment Variables

There are multiple variables that can be controlled to test the behavior of the two-stage querying technique. Table 1 summarizes the most important.

The environment settings are related to the size of the $2D$ matrix, the number of incidents, the distribution of incidents across the matrix, and the number of resources from which to choose. In all of our experiments, except the case study, we set up the $2D$ matrix as a 10 by 10 matrix. We show results for incident count of 50 and number of resources (M) of 100. We varied the environment settings in our experiments and no noticeable differences were observed in performance. Instead, we focus on varying the query settings to better understand the two-stage technique. In this section, we focus on varying the first stage percentage and leave the variation of the k setting to the following section. We also show results for $t\_setting = 30$ which constitutes 30% of the available resources (M). We notice that the gap between the performance of our technique and the other techniques increases when $t\_setting$ decreases and all the techniques converge in performance when $t\_setting$ approaches M.

We compare the performance of our technique to two alternative selection approache: Random selection and Dispersion Maximization. To do so, we utilize two different metrics: count of nodes queried in the KNN of incidents, and the number of incidents covered by the nodes queried. The two metrics are formally defined as follows.

- Close node count: This is measured as the absolute number of people/resources in the KNN of each incident for all incidents. This is formally represented as follows:

$$Close\ node\ count = \sum \forall_{incident\ i}\ |(KNN_i \cap QU)| \tag{2}$$

  where QU (the "Queried Users" set) is the set of users selected for querying.

- Coverage: measured as the number of incidents covered out of the total number of incidents occurring in the $2D$ matrix. We define an incident as covered if at least one of the nodes in the incident's KNN was queried. This is formally measured as:

$$Coverage = \sum \forall_{incident\ i}\ Coverage_i\ where, \tag{3}$$

$$Coverage_i = \begin{cases} 1, & \text{if } (KNN_i \cap QU) \neq \phi \\ 0, & \text{otherwise} \end{cases}$$

4.2 Clustered data experiments

In this section, we aim to test our technique in a scenario where the events take a clustered form. Geographer Waldo R. Tobler's stated in the first law of geography: "Everything is related to everything else, but near things are more related than distant things." In this subsection, we assume that the incidents are related to each other in a clustered way i.e. they form clusters across the $2D$ spatial matrix as seen in Fig 1.

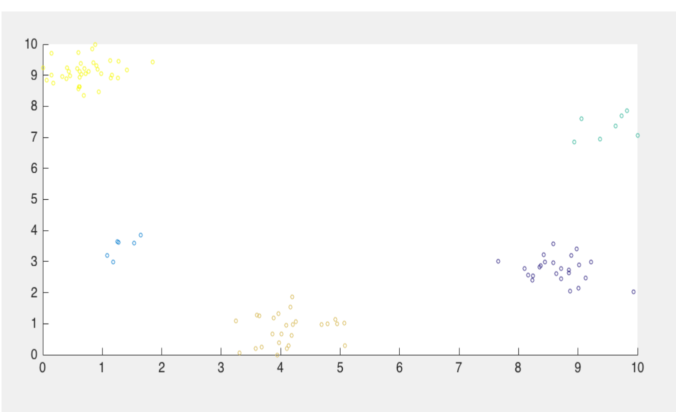


Figure 1: An example of a $2D$ spatial matrix with 5 clusters.

For this experiment type, we vary the number of clusters in our $2D$ matrix from one to ten clusters while fixing the resources or crowd count to be 100. To ensure data variability, we model the size of each cluster as a random variable while ensuring that the aggregated size of all the clusters is equal to the crowd count. For each case of number of clusters, we average over 100 different configurations. Our objective is to measure the effect of variation of the first stage percentage on our performance metrics.

Figure 2 depicts the results for Close node count when varying the first stage percentage from 20% to 80%. We notice that our two-stage querying technique always outperforms the Random node selection and the selection based on maximizing the dispersion only. Table 2 depicts the amount of surge in Close node count in comparison to the Random and Dispersion maximization techniques. As the amount of resources queried in the first stage decreases, the close node count increases. This is due to the fact that when the first stage percentage decreases, the second stage resources increase under limited resources constraints, which focuses on resources close to incidents detected in the first stage. On the other hand, incident coverage tends to increase as the first stage count increases. This is depicted in Figure 3. We also notice that both Close node count and Incident coverage tend to increase with the number of clusters until the number of clusters is around four or five. Then, it decreases.

First stage percentage	20%	40%	60%	80%
Surge over Random	62.5%	58.89%	35%	20%
Surge over Dispersion Maximization	67.8%	62.32%	39.8%	20.64%

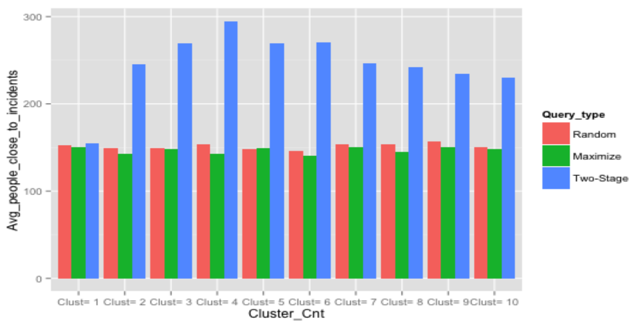
Table 2: Surge of Two Stage technique in comparison to Random and Dispersion Maximization techniques.

4.3 Uniformly distributed data experiments

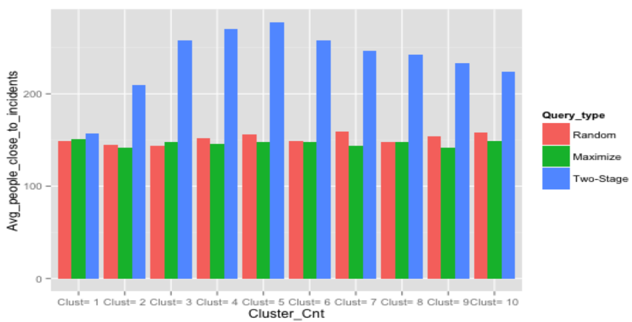
In this type of experiments, the probability of occurrence of incidents is uniform across the grid i.e. $P_I(j) = P_I(k)$ where $j \neq k$ and P_I denotes the probability of an incident occurring at a specific cell. We generate a 100 different matrices. We note that in the case that we know that the distribution of the incidents is uniform, the best we can do is to choose N nodes uniformly. Using the two-stage technique, we select N nodes without assuming any distribution about the incidents and check the performance in comparison to the uniform random selection which in this case is the best we can do. Figure 4 shows that the two-stage technique with $FSP = 20\%$ achieves the highest number of close nodes to the incidents while Figure 5 shows that the two-stage technique with $FSP = 80\%$ achieves higher coverage that the uniform random policy and it is close to the maximum coverage by an average of 1.32 incidents.

4.4 Long Tail Distribution

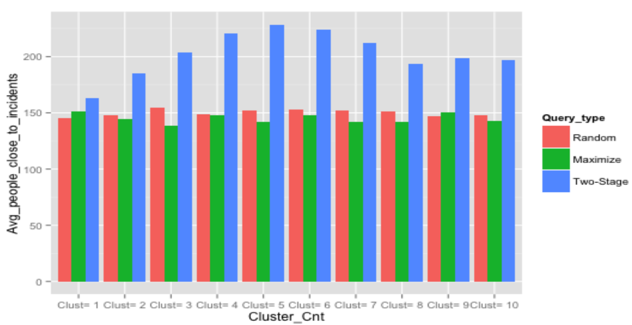
In this subsection, the incidents are generated according to a special case of the Long Tail distribution called the "Pareto principle". According to the Pareto principle, we assume that 20% of the matrix cells are home for 80% of the incidents and 80% of the matrix cells are home for 20% of the incidents. We generate a 100 different matrices applying the Pareto Principle randomly on the cells. We use a random uniform distribution to select 20% of the cells and generate 80% of the incidents uniformly for these cells and vice versa. Figure 6 shows that the two-stage outperforms both



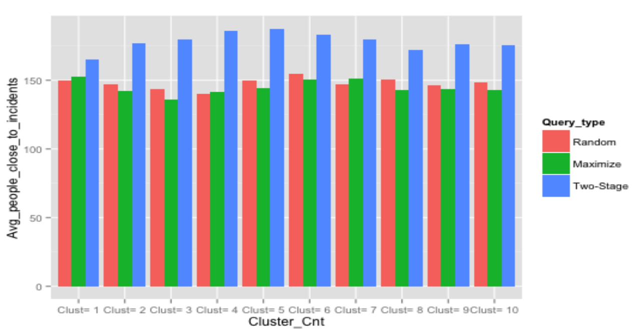
(a) Close node count with $FSP = 20\%$ of available resources.



(b) Close node count with $FSP = 40\%$ of available resources.



(c) Close node count with $FSP = 60\%$ of available resources.



(d) Close node count with $FSP = 80\%$ of available resources.

Figure 2: Average number of people close to the incidents (Close node count) as FSP varies.

the random policy and the dispersion maximization policy by up to 10.2% and 12.1% respectively in terms of close node

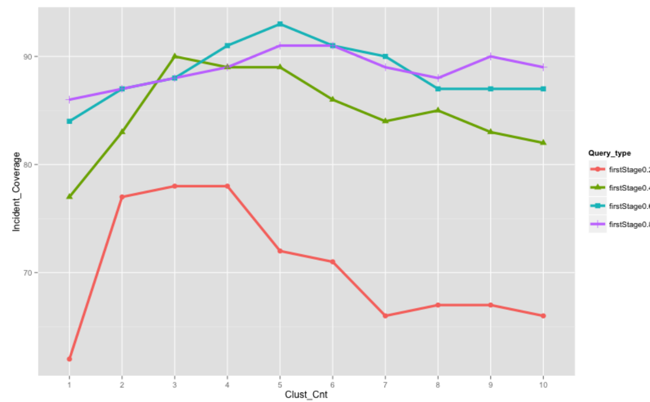


Figure 3: Incident coverage for different values of First stage percentage.

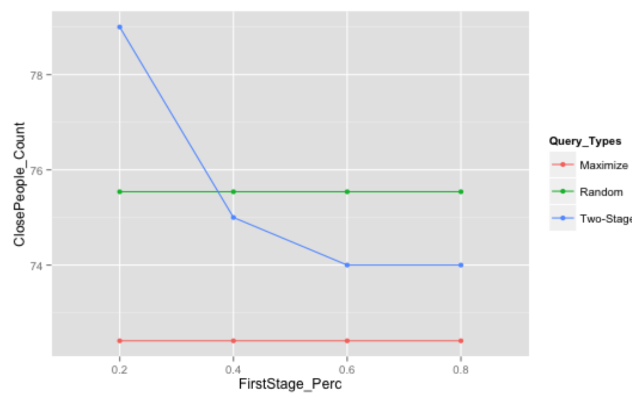


Figure 4: Close node count for different values of First stage percentage.

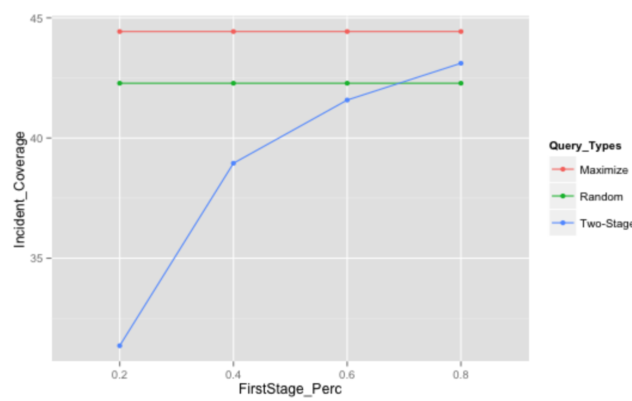


Figure 5: Incident coverage for different values of First stage percentage.

count. This is probably due to the clustering of events in only 20% of the grid which means that more than one incident is likely to occur in the same cell. So, if the two-stage technique reaches a node close to an incident in one cell, this same node will cover more than one incident in the same cell. Dispersion maximization achieves the best incident coverage as shown in Figure 7. The two- stage technique approaches the maximum incident coverage when $FSP = 80\%$ with a difference of 1.24 incidents on average.

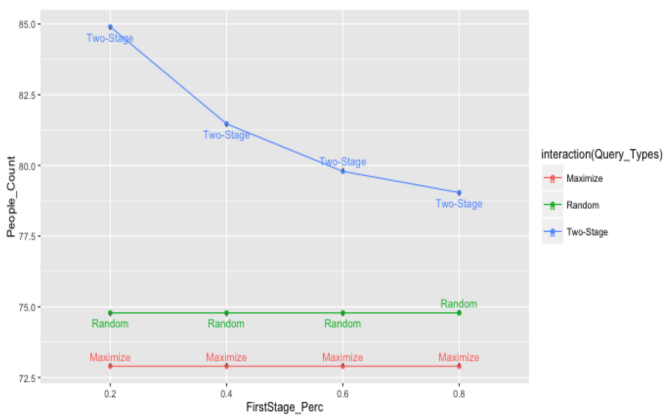


Figure 6: Close node count for different values of First stage percentage in the case of a long tail distribution.

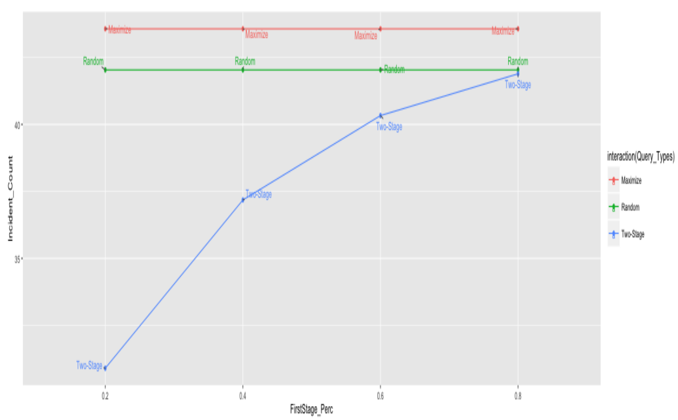


Figure 7: Incident coverage for different values of First stage percentage in the case of a long tail distribution.

4.5 Case Study: Hollaback harassment data set

After applying the two-stage querying technique to the previously mentioned three distributions (clustered, uniform and long-tail), we wish to examine the technique under real incident distributions. To do so, we test our querying technique on a global street harassment dataset provided by Hollaback [7].

4.5.1 *Data Overview*

Hollaback is a non-profit movement powered by local activists in 92 cities and 32 countries to end street harassment. The Hollaback project collects data on street harassment events worldwide. Through the Hollaback phone app and the online platform, users can report stories of street harassment to share with the Hollaback community. This empowers victims to speak out about everyday harassment and spread the word about the prevalence of these events. In some communities, local governments are informed in real-time about street harassment so that there is a system-wide level of accountability. In addition, the Hollaback app uses GPS to record a data set that represents the locations of street harassment events as a means of improving the collective understanding of street harassment and how it can be prevented. As of January 2016, over 8000 street harassment incidents have been recorded in their dataset since February 2011. It is on this data set that we wish to test the two-stage querying technique.

4.5.2 *Analysis*

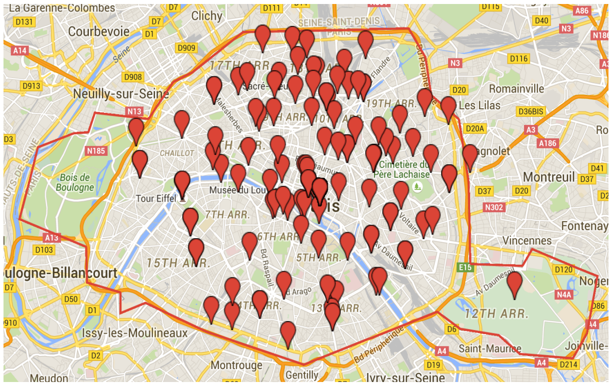
From the Hollaback dataset, we select multiple cities for which we have enough harassment samples for statistical significance (i.e. more than 30 samples). We test the performance of Random selection, Dispersion maximization selection, and the two-stage querying on six different cities: Paris, Brussels, Berlin, Baltimore, Buenos Aires and Istanbul. In this paper, we show results for Paris, Brussels, and Istanbul. These cities were in the top ten cities with respect to the number of harssment reports in this dataset.

As a first step, we must parse the Hollaback dataset such that incidents reports are grouped by city. To do so, we use bounding box coordinates. We then draw the border lines for the different cities and remove any outliers from our datasets. Figure 8 shows the resulting distribution of events for the different cities. The Paris dataset contains 197 harassment incidents and covers an area of 28.2 mi^2, while the Brussels dataset contains 154 incidents covering a geographic area of 28.4 mi^2. Istanbul had 87 reported incidents covering an area of 138 sq mi on the left of Bosporus Strait and 69 mi^2 on the right.

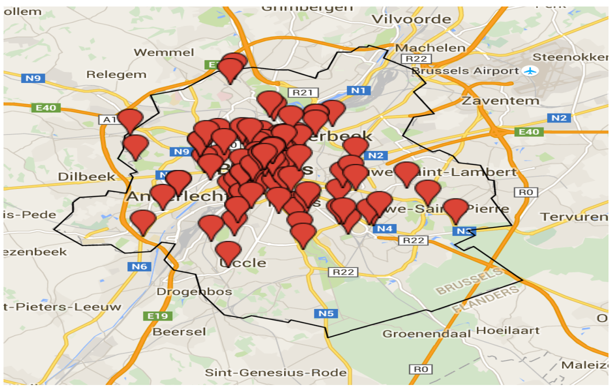
For each of the cities, we generate different variations of uniformly distributed crowd ($M = 100$) across the city. In this kind of analysis, the parameters, matrix dimension and incident count, are not generated by our analysis but rather taken from the dataset. We measure the Close node count and the Incident Coverage for all three querying techniques and plot the results in Figures 9 and 10, respectively. We notice that the Two-stage technique outperforms both the Random and Dispersion Maximization in terms of Close node count for all three cities. In terms of incident coverage, Figure 10 shows that dispersion maximization achieves maximum incident coverage. The figure also shows that the two-stage technique can achieve this maximum by setting the first stage percentage to be 80%. Figures 9 and 10 suggest that there is an inherent tradeoff between accuracy and coverage under constrained resources which we discuss in detail in later sections. The figures also suggest that the two-stage technique under setting the first stage percentage to be 80%, can achieve a balance between accuracy and coverage.

4.6 Stressing the two-stage querying technique (k=1)

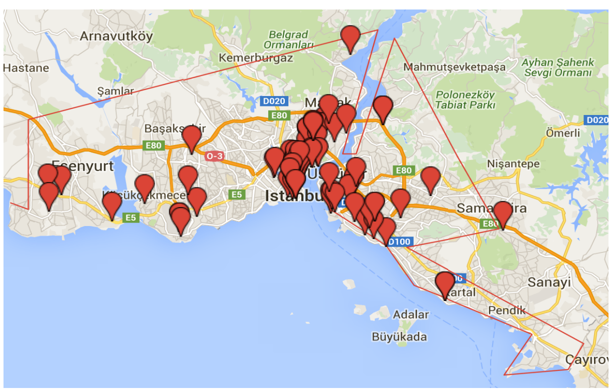
After applying the two-stage technique to different datasets, we wish to look at how the different selection policies, in terms of identifying the first nearest neighbor to the different incidents. This is beneficial in case of targeting first responders in case of an emergency scenario or just in case of spatial task distribution where you want to select the nearest neighbors to maximize spatial task assignment. This can be viewed as stressing the selection policies in order to de-



(a) Paris.



(b) Brussels.



(c) Istanbul.

Figure 8: Distribution of harassment incidents across Paris, Brussels and Istanbul.

termine which one achieves a higher number of first nearest neighbors.

In order to study first nearest neighbors, we examine the real Hollaback datasets for Paris, Brussels, and Istanbul. We examine the total close node count and for each incident, we look if we selected the first nearest neighbor in the queried users set or not. These results can be shown in Table 3, where NN denotes nearest neighbors, CNC denotes close node count, TS denotes the two-stage querying technique, Bruss denotes Brussels, and Istan denotes Istanbul. For Paris, the two-stage technique achieves a 9.5% surge on

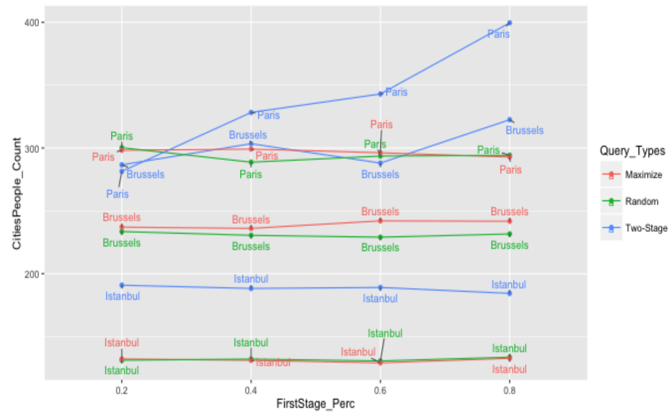


Figure 9: Close node count for different values of First stage percentage.

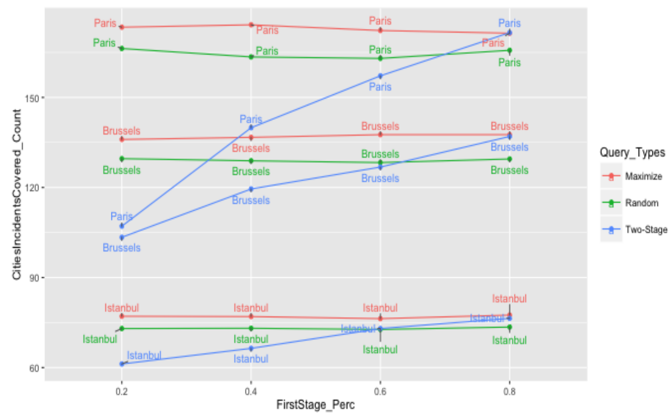


Figure 10: Incident coverage for different values of First stage percentage.

average in selecting nearest neighbors in comparison to dispersion maximization and 19% surge in comparison to random selection. For Brussels, the surge is 14.2% and 21.35% in comparison to dispersion maximization and random selection respectively. For Istanbul, the surge percentages were 26.7% and 36.5%.

5. DISCUSSION

5.1 Tradeoff

In the previous section, we examined the performance of the two-stage querying technique and we observed that as FSP decreases, the number of close node count tend to increases. We also observed that in this case the same node can be in the K nearest neighbors for multiple incidents. This means that the algorithm tends to select central nodes that are in proximity with other incidents. This is beneficial in cases where the centrality of nodes is important to the problem, e.g. minimizing trip costs to these incidents and maximizing task assignments. This observation ensures diversity of the feedback i.e. instead of relying on a small number of nodes close to the incidents, we have a greater sample that can contribute to the measurement. On the other hand, as FSP increases so does the probability of catching more incidents in the spatial environment which is crucial in applications

City	Random	Maximize	TS ($FSP=$ 0.2)	TS ($FSP=$ 0.4)	TS ($FSP=$ 0.6)	TS ($FSP=$ 0.8)
Paris-NN	58	63	54	69	69	84
Paris-CNC	300	298	281	328	343	399
Bruss-NN	48	51	55	58	55	65
Bruss-CNC	233	237	286	303	288	322
Istan-NN	26	28	36	37	35	36
Istan-CNC	131	132	190	188	188	184

Table 3: Nearest neighbors and close node count for Paris, Brussels, and Istanbul.

where coverage is important and where a false positive is less expensive than a false negative. This is due to the fact that more nodes are selected in the first stage and fewer nodes in the second phase. The conclusion is that under resource constrained conditions, there is a tradeoff between accuracy and coverage.

5.2 Technique variants

5.2.1 *Trust based responses*

In our second stage of our algorithm, we select users based on the pivot nodes that provided a positive feedback in the first stage. To incorporate trust into the algorithm, trust-based algorithms can provide feedback about certain nodes and their feedback. If some of the nodes queried in the first stage of the algorithm were deemed trust unworthy, the second stage can be divided among two querying parts. The first part is the KNN for the trustworthy-nodes and a second attempt of dispersion maximization.

5.2.2 *Prior knowledge availability*

The two-stage querying technique does not assume any knowledge about the distribution of events. Given some prior info about the distribution, the algorithm can be tailored to take the prior distribution into account. The idea is to divide the spatial area into bounding regions and for each region we give a specific weight that reflects the probability of occurrence in that bounding regions. For example, Figure 11 shows Baltimore divided into four bounding regions denoted as br1, br2, br3, and br4. Using the knowledge that br3 has more incidents than br2 which has more incidents than br1 and br4, a higher weight should be given to br3. In particular, $br3_w > br3_w > br4_w > br1_w$ where the subscript w denotes the weight assigned to the bounding region. The next step would be applying the algorithm on the different bounding regions taking into account the weights assigned when allocation resources as shown in 2.

Algorithm 2 Bounding regions two-stage variation.

function SELECTUSERSBRS $(BRs[], w[], N, FSP)$
    selectedUsers = {}
    BRQuota = calculateQuota(BRs[], w[], N)
    for br in BRs **do**
        brQuota = BRQuota(br)
        brUsers = selectUsersFromGrid(FSP, brQuota)
        brUsers.append(brUsers)
    return selectedUsers

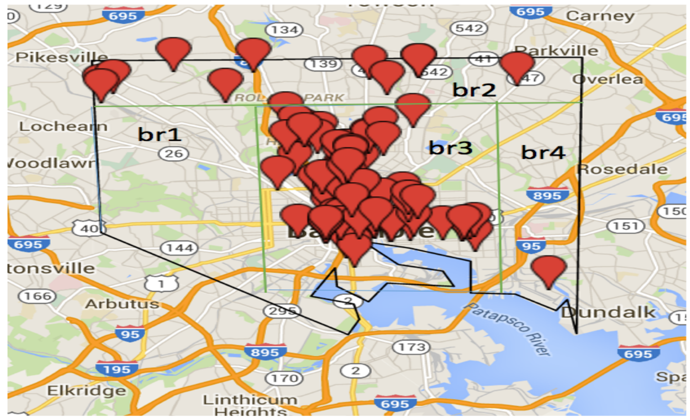


Figure 11: Baltimore divided into bounding regions depending on prior knowledge of harassment occurrence.

6. CONCLUSION

This paper proposed a two-stage spatial querying technique that attempts to probe nodes that are closer to the incidents in a $2D$ spatial environment. The algorithm maximizes the dispersion of location in the first stage and selects the K nearest neighbors in the second stage based on nodes' feedback. The experimental evaluation confirms the applicability of proposed approach. Important aspects that need to be taken into consideration include the sensing range and the sensing accuracy of the nodes. Nodes with accurate sensing and larger sensing ranges will provide a more robust effect on the two-stage technique. Another important parameter that can impact the performance of the technique is the distribution of the available nodes in the spatial environment. To ensure an optimal performance, nodes should be placed uniformly in the environment if the incident distribution is not known or following an approximate distribution of the incidents. Another important factor when choosing the number of nodes to query is the granularity of the incidents. For instance, when using human as sensors, incidents such as disasters can be sensed/detected by a lot of people in the range of the incident. On the other hand, incidents such as harassment require the presence of the human being at the same exact place of the incident otherwise, the incident would not be detected.

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