Modelling Under-reported Spatio-temporal Events

Álvaro J. Riascos[1,2], Jose Sebastian Ñungo[1,4], Lucas Gomez[1]
Mateo Dulce[3], Francisco Gomez[4]

[1]Quantil [2]University of the Andes [3]Carnegie Mellon University [4]National University of Colombia

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Contenido

Motivation

- The under-reporting of data is a common phenomenon in many data-related problems.
- For example: non-sampling errors in survey sampling, food inspection services, child services, pest controls, building's compliance safety regulations, animal poaching surveillance, crime incidents in a city, among many others.

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- Models that simultaneously estimate incidence and under-reporting rates of events can be used to improve the allocation of public resources.

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- Models that simultaneously estimate incidence and under-reporting rates of events can be used to improve the allocation of public resources.
- One can target and prioritize the allocation of resources to appropriately monitor and record incidents of interest.

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- However, true incidence rate may be elusive: (1) Partial observation (2) Change in behavior.
- In this paper we focus narrowly on the first problem.
- To solve this problem, we introduce a combinatorial multi-armed bandit model with under-reporting.
- For the first problem, the literature provides performance guarantees.
- For the second, we capitalize on the asymptotic performance of maximum likelihood estimation.

Introduction

- We provide a potential application of our methodology to the problem of crime victimization and reporting rates at the scale of a large city.

Contenido

Related Work

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- We draw heavily on this literature, by adapting their online algorithms to our problem and estimating our parametrized model of under-reporting in a online setup.

Contenido

The Model

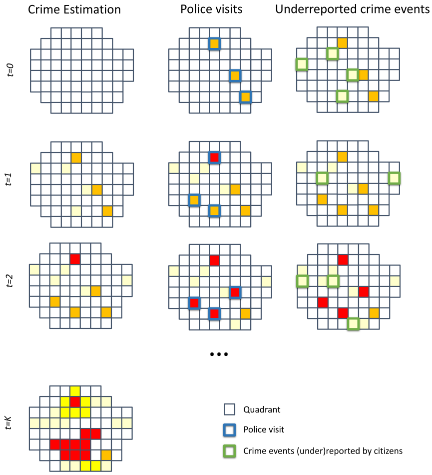


Figure: Schema

The Model

- **Spatial events**: $X_{i,t}$, where i indexes a spatial location and t indexes the round of the interaction.
- **Unobserved or filtered observations**: a random variable $\widetilde{X}_{i,t}$.
- **Parametrization**: $X_{i,t}$ binomial with parameter μ_i (i.e., $B(n, \mu_i)$) and $\widetilde{X}_{i,t} \mid X_{i,t}$ binomial parameter q_i (i.e., $B(X_{i,t}, q_i)$).
- **Objective**: in a repeated interaction with this environment learn the true mean of the distributions: $X_{i,t}$ and $\widetilde{X}_{i,t}$.

Algorithms:CUCB

Combinatorial Upper Confidence Bound Algorithm (CUCB) with under-reporting

1: For each arm i, set $\bar{\mu}_i = \min\left\{\hat{\mu}_i + \sqrt{\frac{3\ln t}{2T_i}}, 1\right\}$.

2: Play $S = \mathrm{Oracle}(\bar{\mu}_1, \bar{\mu}_2, \ldots, \bar{\mu}_m)$.

3: Update all T_i's and $\hat{\mu}_i$'s.

4: For $i \notin S$, observe $\widetilde{X}_{i,t}$ conditional to outcomes played by base arms i.

5: Update $\hat{q}_i = \frac{\text{Empirical mean of under-reporting so far observed}}{n\hat{\mu}_i}$

Algorithms: LLR, UCB1

- **Learning with Linear Rewards (LLR) algorithm** in the following way. Replace in CUCB:

$$\bar{\mu} = \hat{\mu}_i + \sqrt{\frac{(M+1)\ln t}{T_i}} \quad (1)$$

- **UCB1 algorithm** ignores the potential association between arms:

$$\hat{\mu}_i + \sqrt{2\frac{\ln t}{T_i}} \quad (2)$$

Validation: Basic parameters

- We did 4 experiments.

M	k	T_{max}	n
12	2	1000	1000

Table: Global parameters. M is the number of arms, K the size of the super arm, T_{max} the of maximum number of simulations and n is the number of trials of each binomial distribution.

Validation: Convergencia μ

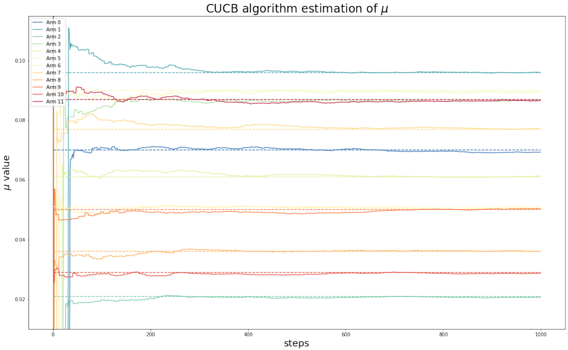


Figure: CUCB Convergence to true arms mean.

Validation: Convergencia q

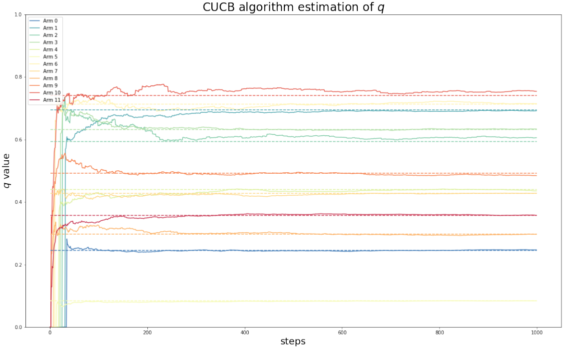


Figure: CUCB Convergence to true arms under-reporting parameters.

Validation: Error

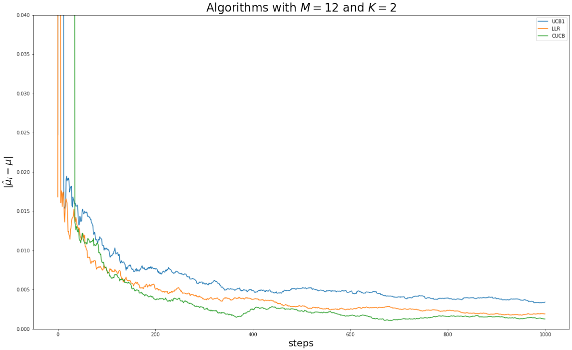


Figure: Convergence error of true arms mean for each algorithm. The error is measures as the euclidean distance between the true mean vector and estimated mean vector per round.

Validation: Visits

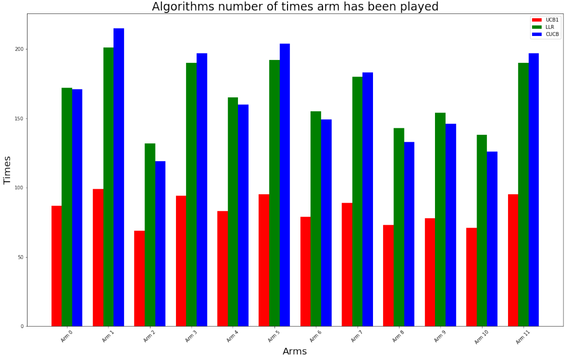
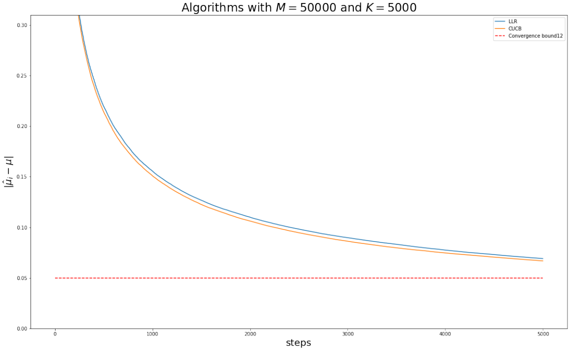


Figure: Number of visits (i.e., fired arms) of algorithms to each arm.

Validation: Error μ



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Validation: Time to Completion

	Case 1	Case 2	Case 3
UCB1	3 sec	38 sec	3 min 31 sec
LLR	4 sec	51 sec	4 min 15 sec
CUCB	4 sec	53 sec	4 min 12 sec

Table: Time to completion. Case 1: $M = 1,000$ and $K = 100$. Case 2: $M = 10,000$ and $K = 1,000$. Case 3: $M = 50,000$ and $K = 5,000$. Sec is seconds, min is minutes.

Contenido

Data Description

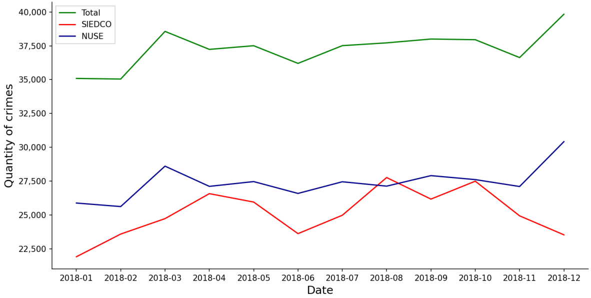

Figure: Crimes by source of information: SIEDCO is the official source of information of crimes in Bogotá. NUSE is the security emergency call center of the city. Total is the sum of both sources eliminating double counting as explained in the main body of the text.

Data Description

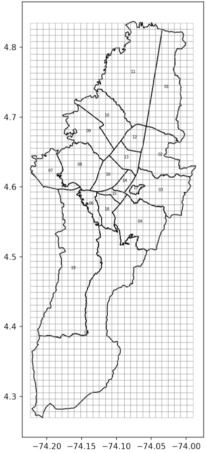

Figure: Bogotá, capital city of Colombia. Figure shows the 19 jurisdictions in which the city is divided and our grid of 1 km^2 cells.

Data Description

ID	District	Pop.	Vict. Rate	Rep. Rate
15	Antonio Nariño	109,176	15%	33%
12	Barrios Unidos	243,465	12%	22%
07	Bosa	673,077	13%	26%
17	Candelaria	24,088	12%	22%
02	Chapinero	139,701	9%	28%
19	Ciudad Bolívar	707,569	8%	17%
10	Engativá	88,708	11%	20%
09	Fontibón	394,648	10%	19%
08	Kennedy	1,088,443	13%	28%
14	Los Mártires	99,119	17%	25%
16	Puente Aranda	258,287	14%	32%
18	Rafael Uribe Uribe	374,246	12%	15%
04	San Cristóbal	404,697	13%	21%
03	Santa Fe	110,048	17%	17%
11	Suba	1,218,513	5%	19%
13	Teusaquillo	1,53,025	14%	19%
06	Tunjuelito	19,943	17%	23%
01	Usaquén	501,999	18%	13%
05	Usme	457,302	9%	33%

Table: Results of Bogotá's City chamber of commerce, Cámara de Comercio de Bogotá, victimization and reporting survey 2014. We use reported rates form each jurisdiction to estimate under-reporting simulated form our Poisson model. The table also reports the population of each jurisdiction and victimization rate.

Results

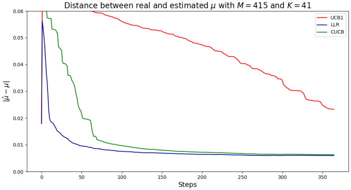

Figure: Convergence of the vector of incidence rates μ to the mean of all crimes per cell across time.

Results

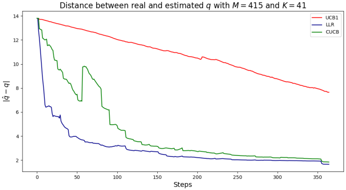

Figure: Convergence of estimated vector q per round to the empirical mean of the under-reporting rate for the whole sample. Euclidean distance reported.

Results

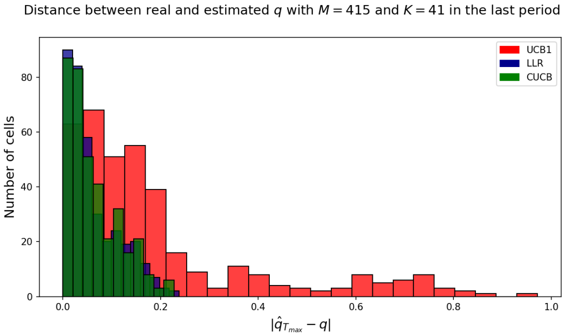

Figure: Histogram of convergence of estimated error of q in the last round to the empirical mean of the under-reporting rate for the whole sample. Absolute value reported.

Results

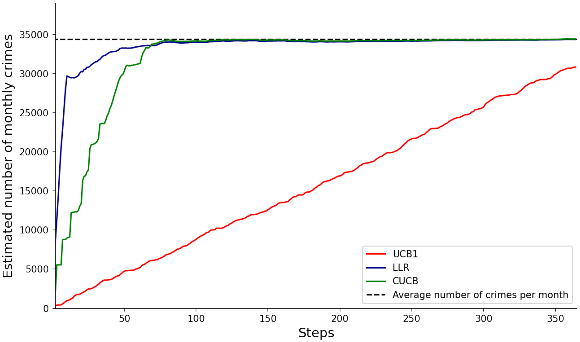

Figure: Convergence of the estimated total number of crimes to the observed number of crimes in the city.

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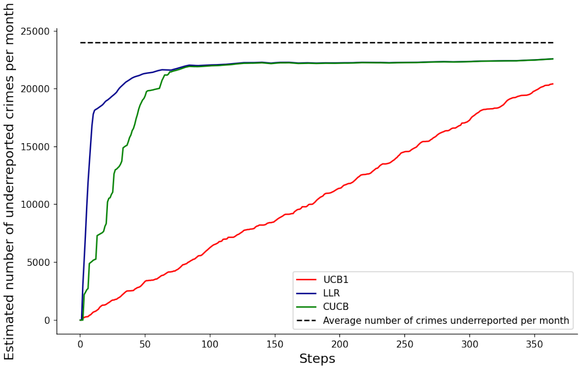

Figure: Convergence of the estimated total (aggregate across cells of) number of under-reported crimes implied by the model.

Results

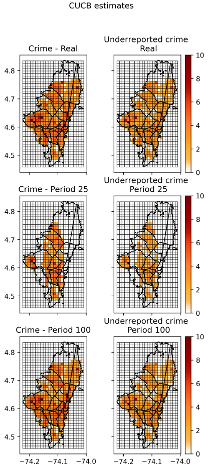

Figure: Heat map illustrating the convergence, using CUCB algorithm, of the estimated crime and under-reporting of events in the city, to the real values. The first column, second and third rows shows the heat map of the estimated crime incidence rates after 25 iterations and 100 iterations, respectively. The second column, first row shows real under-reporting as measured by NUSE dataset. The second column, second and third rows shows the heat map of the estimated under-reporting crime after 25 iterations and 100 iterations, respectively.

Contenido

In a nutshell

- We have introduced an under-reporting model of spatio-temporal events that fits well certain applications.
- We modified three well known multi-armed bandit algorithms and validated our methodology using simulations that showed the effectiveness of the CUCB algorithm.
- We then applied our methodology to crime victimization and reporting in Bogotá.
- In both cases, our method performs well and suggests that this methodology could be used to estimate, in an online setup, the under-reporting of events, an important problem in public policy.