Spatio-temporal models with street-level image features for robbery modeling

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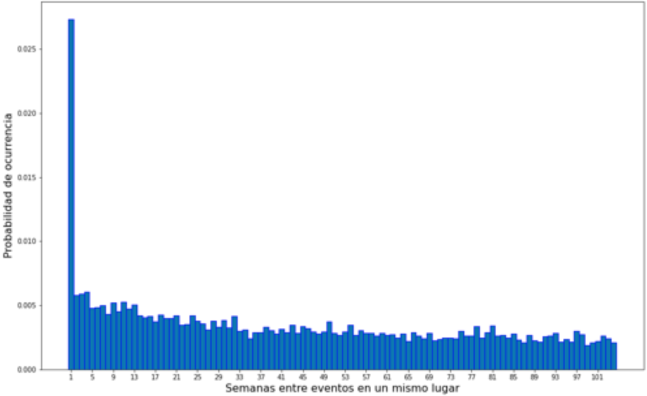
Introduction

- Omitting spatial covariates correlated with the occurrence of crimes potentially bias the estimated parameters.
- We include spatial variables in a crime prediction model to explicitly take into account the effect of the urban environment on the probability of crime occurrence.
- Avoid confoundedness and biased parameters by simultaneously considering patterns of nearby replicas and spatial risk factors.

Introduction: spatio-temporal patterns

Introduction: self-exciting processes



Self Exciting Point Processes

Following the self exciting point process model proposed by Mohler et al. (2011) we have that the crime intensity is given by:

$$\lambda(s,t) = \mu(s) + \sum_{i:\ t_i<t} g(s-s_i, t-t_i),$$

where $\mu(s)$ captures background crimes occurrence according to their spatial location and $g(s-s_i, t-t_i)$ captures how the crime (s_i, t_i) spreads in time and space.

Self Exciting Point Processes in Bogotá

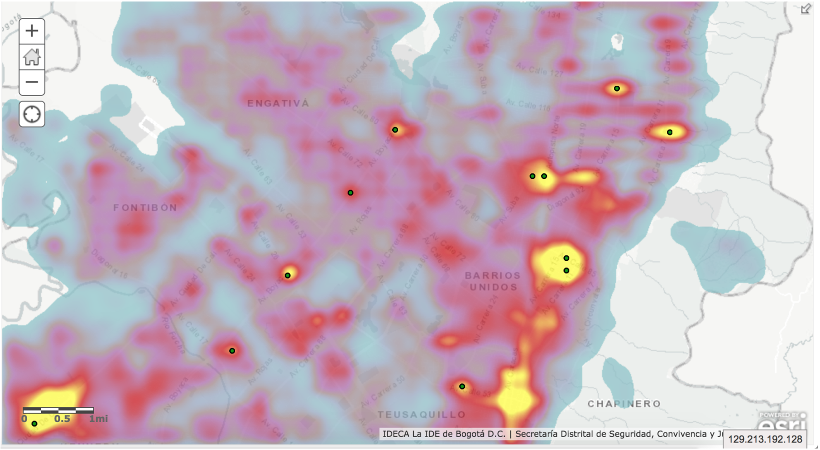


Figure: SEPP model deployed in Bogotá.

Confoundedness

- Reinhart and Greenhouse (2019) study the estimated coefficients of a crime prediction model over synthetic data generated without close repetitions ($\theta = 0$) and with many nearby replicas ($\theta \approx 1$).
- As self-excitation increases, the regression coefficients gradually become more biased.

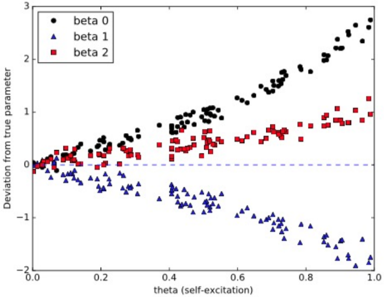


Fig. 2. As the near-repeat effect increases from 0 crimes triggered to 1 crime triggered for every observed crime, spatial Poisson regression coefficients gradually become more and more biased.

Self Exciting Point Processes **with spatial covariates**

- The background component $\mu(s)$ does not explicitly take into account the spatial characteristics or provide estimates of its effects.
- Reinhart and Greenhouse (2019) proposed a model that replaces $\mu(s)$ with a functional form that directly incorporates spatial information and avoids confoundedness.

Self Exciting Point Processes **with spatial covariates**

X is divided into cells c of arbitrary size, each with an associated vector of covariates X_c, resulting in the model:

$$\lambda(s,t) = \exp(\beta X_{c(s)}) + \sum_{i:\ t_i<t} g(s - s_i, t - t_i). \tag{1}$$

$$g(s,t) = \frac{\omega}{2\pi\sigma^2} \exp(\omega t) \exp(-\frac{||s||^2}{2\sigma^2}) \tag{2}$$

Model estimation

Given the log likelihood for specific spatio-temporal processes:

$$\ell(\theta) = \sum_i \log \lambda(s_i, t_i; \theta) - \int_0^T \int_S \lambda(s, t; \theta)\, ds\, dt,$$

and the natural interpretation of the model with covariants as a mixed model, Reinhart (2019) uses an Expectation Maximization approach for parameter (θ) estimation.

E-step: Estimate the latent variable that indicates whether an observation corresponds to a crime of background or replica.

M-step: Estimate the bandwidth (spatial contagion) and temporal decay parameters of the Kernel μ and g and the coefficients β.

Proposed model

- Use features from street images in Chapinero, Bogotá, as spatial covariates (Acosta y Camargo, 2019).

- Use a functional form of the background component that captures if an event corresponds to a background crime explained by the included spatial variables:

$$\lambda(s,t) = \exp(\beta X_{c(s)}) + \sum_{i:\ t_i<t} g(s-s_i, t-t_i). \tag{3}$$

Spatio-temporal Generalized Additive Models

- Model non-linear relationships between spatio-temporal attributes and crime intensity.
- GAMs can model continuous variables such as crime intensity or binary variables such as crime occurrence or incidence.
- Following Wang (2011), a dummy variable is used to record the information of when the last incident happened.

$$y \sim ExponentialFamily(\mu|midX)$$

$$h(\mu \mid X) = \beta_0 + \sum_{j=1}^{p} f_j(x_j)$$

$$\lambda(s,t) = \frac{1}{1 + \exp(-h(\mu \mid X))}$$

Spatio-temporal Generalized Additive Models

- The dummy variable to record when the last incident happened only accounts for discrete trigger effect of crime.
- We used the estimated g kernel funciton from SEPP+cov as a covariate for the ST-GAM.
- The kernel g allows to have smoother spatio-temporal trigger effects and allows to account for crime trigger between different spatial units.

$$h(\mu \mid X) = \beta_0 + \sum_{j=1}^{p} f_j(x_j) + \sum_{i:\ t_i<t} \frac{\omega}{2\pi\sigma^2} \exp(\omega(t-t_i)) \exp(-\frac{||s-s_i||^2}{2\sigma^2})$$

Street-level images

We used the images features obtained by Acosta and Camargo (2019):

- The image dataset was obtained by building a city street-level image crawler using the Google Street View API V3.0.
- The dataset is composed by 5,786 images with an average consecutive distance of 30 meters.
- Spatial covariates are obtained using a VGG19 for feature extraction, resulting in a 512-dimensional vector representation for each image.

Street-level images

Street-level images

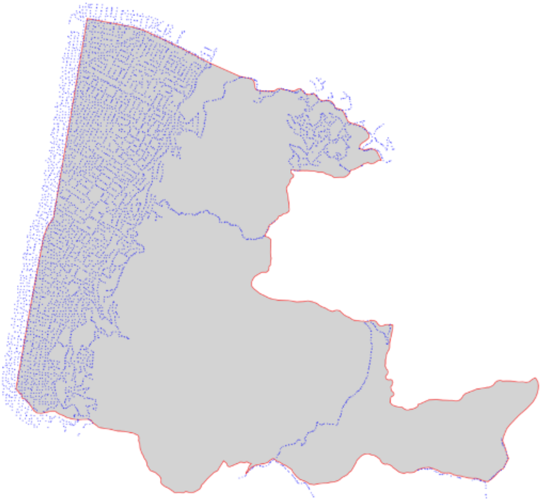


Figure: Grid over Chapinero determined by the location of street-level images

LDA for image feature reduction

- Features obtained by VGG19 do not, in general, allow a direct interpretation of the different visual attributes.
- We used a generative topic model that summarizes the information contained in each image into 14 visual topics: LDA model.

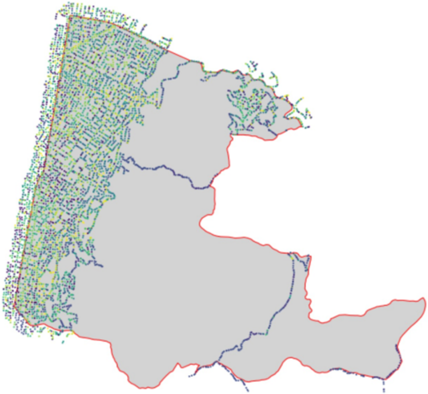
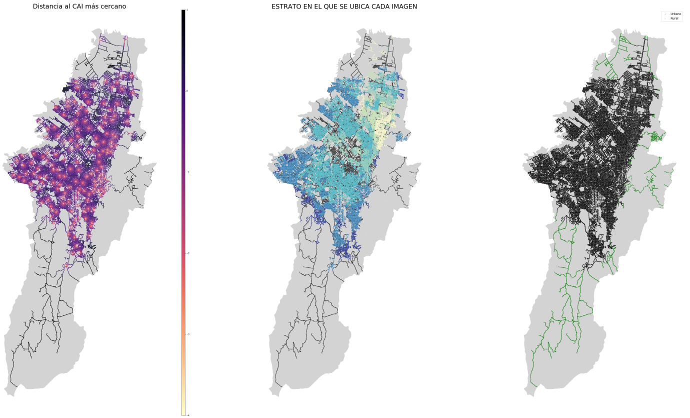


Figure: LDA dominant topic determined for each street-level image

Other spatial covariates

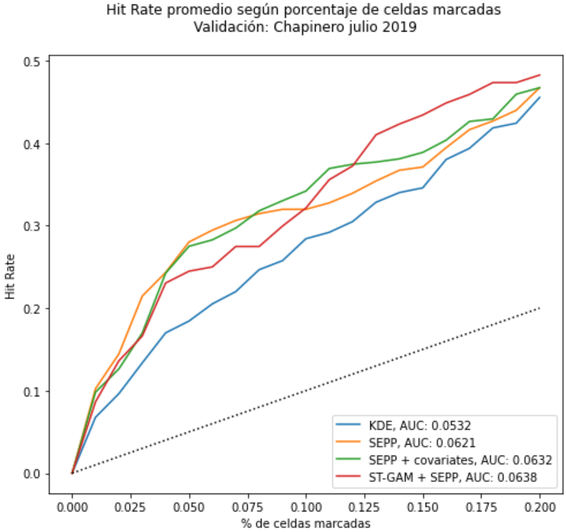
- Distance to closest police station (CAI)
- Socioeconomic level
- Urban area indicator



Implementation and preliminary results

- We use geo-referenced and time-stamped crimes occurring in Chapinero locality in Bogotá during January and June 2019 and evaluated for July 2019.
- We use an adapted Expectation-Maximization setting following Reinhart and Greenhouse (2019) for the estimation of SEPP and SEPP+cov models.

Implementation and preliminary results - **CAP curve**



Implementation and preliminary results - **KDE**

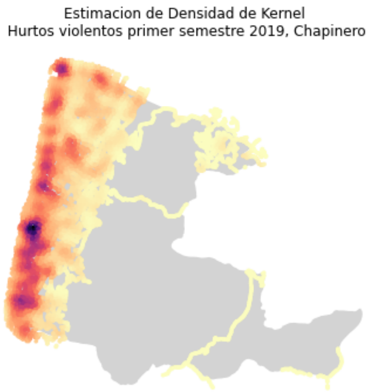


Figure: Crime intensity estimated by KDE

Implementation and preliminary results - **SEPP**

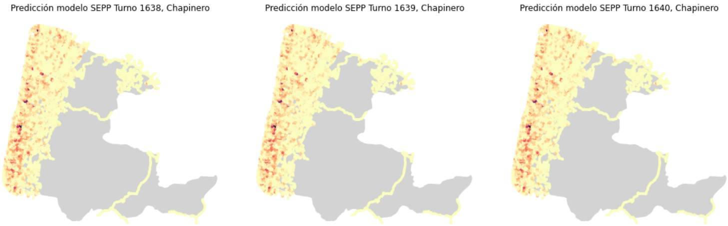
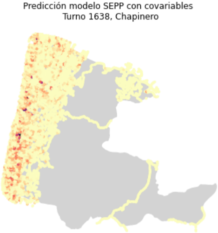


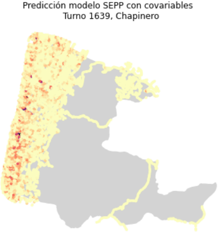
Figure: Crime intensity estimated by SEPP

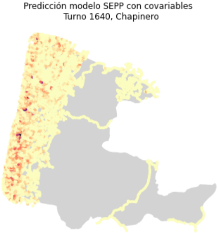
$$\sigma^2 = 4.55e - 8$$

$$\omega = 1.71e - 6$$

Implementation and preliminary results - **SEPP+cov**







$$\sigma^2 = 4.28e - 8$$

$$\omega = 0.0017$$

Implementation and preliminary results - **ST-GAM + SEPP**

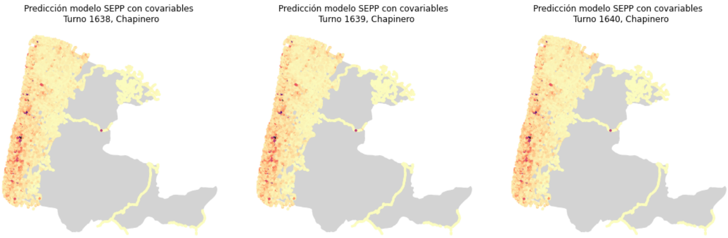


Figure: Crime intensity estimated by ST-GAM

Implementation and preliminary results - **ST-GAM + SEPP**

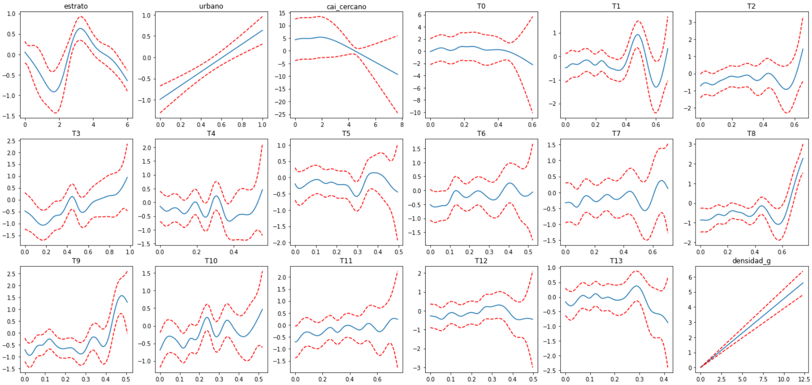


Figure: Partial dependent plots estimated by ST-GAM + SEPP

Further research

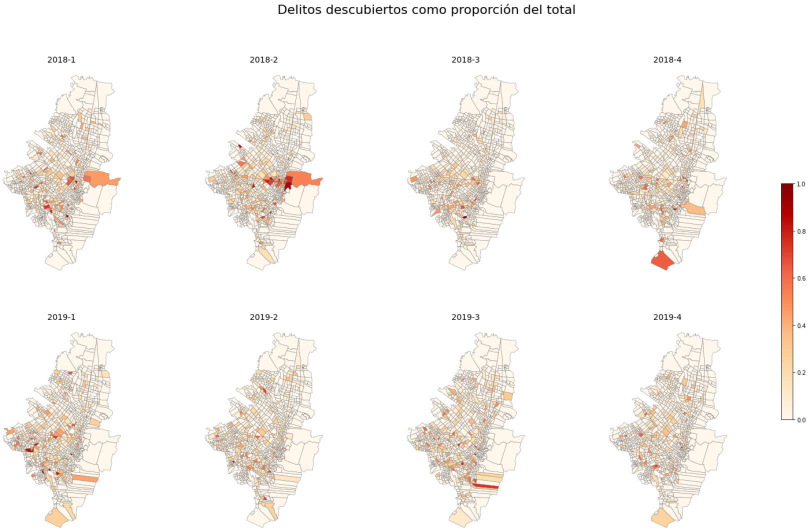
- Extend the implemented models to Bogotá.
- Add other spatial and temporal variables of interest.
- Study a functional form of the background component that captures whether the crime was background by the included spatial variables or by other external factors.

$$\mu(s)\exp(\beta X_{c(s)})$$

- Study other funcional forms that explain the relation between spatial covariates and crime ocurrences.

Further research

- Account for reporting bias and effect of police patrolling.



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