Log-Gaussian Cox processes and line transect sampling: optimal design critera

Abstract

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Keywords: log-Gaussian Cox process, optimal sampling, model-based design, spatial sampling design

1 Introduction

Spatial point processes models have long been considered generally infeasible because of their computational demands, but recent advances in Bayesian computing have made the Log-Gaussian Cox process an attainable model in practice (Rue et al. 2009, Lindgren et al. 2011, Illian et al. 2012, Simpson et al. 2016). Variable sampling effort leads to a degraded point pattern Chakraborty et al. (2011) and it is relatively simple to accomodate variable sampling effort in these models using modern computing tools (Yuan et al. 2017). However, the literature on optimal sampling for spatial point process models is in its infancy (Liu & Vanhatalo 2020).

Point pattern data are routinely collected in species distribution studies and ordnance response projects. These applications may use quadrat sampling or line-transect sampling, with transect sampling being more common. When the objective is mapping where events occur in space, various spatial mapping procedures have been used. Traditionally these have involved aggregating the data to grid cell counts or computing moving averages. These have the downside of introducing arbitrary structure into the data by the choice of gridding scheme or averaging window, and require uneccessary computation effort (Simpson et al. 2016). Software is now available to fit spatial point process models to data acquired via diastance sampling and simultaneously estimate the detection function (Johnson et al. 2014).

In ecological settings, sampling plans are often designed around the goal of estimating total abundance. Ordnance response surveys are typically designed with the objective of detecting (but not necessarily mapping) hotspots. However, to our knowledge, there has been very little work done in deciding *where* to collect data when the goal is to map the intensity using a spatial point process model.

1.1 Notation and Terminology

- process defined on $\mathcal{D} \subset \mathbb{R}^2$, domain of the intensity function, define $d = \dim(\mathcal{D})$
- observation window $\mathcal{S} \subset \mathcal{D}$
- define three regions:
  - the domain $\mathcal{D}$ over which the process mathematically operates

  - the study region $\mathcal{R}$ over which inferences are desired
  - the observed/sampled observation window $\mathcal{S}$

- general relationship is $\mathcal{S} \subset \mathcal{R} \subset \mathcal{D} \subset \mathbb{R}^d$ where all of the subset symbols taken to mean "subset or equal"
- $\mathcal{D}$ can be unbounded or bounded (often $\mathbb{R}^d$), $\mathcal{S}$ practically always bounded, $\mathcal{R}$ bounded or unbounded depending on application and inferential goals
- the "fully surveyed" situation is $\mathcal{S} = \mathcal{R}$
- $\mathbf{X}$ point process on $\mathcal{R}$, $\mathbf{x} = \{x_1, \ldots, x_n\}$ realized point pattern
- point $x \in \mathbf{x}$ called an event
- intensity function $\lambda(u)$
- types of "points" in space:
  - x event in the point pattern
  - s numerical integration node
  - u arbitrary location in $\mathcal{D}$ used to index intensity function and predictors
- $z(u)$ a column vector of covariates/predictors at u
- "point" refers to a u unless clearly stated otherwise
- bold for sets and spatial processes, normal italics for spatial vectors
- y and variations will be used for objects derived from the point pattern, e.g. marks, pseudodata

2 Model-Based Criteria

UXO: mapping a site for delineating high-intensity regions

- minimize time/distance
- minimize one of these:
  - maximum variance in intensity surface
  - maximum variance in intensity surface *at contours near action level*
  - integrated variance of intensity surface
  - error rates in thresholding at AL (sensitivity/specificity/AUC)
- minimize variance of coefficients for covariates

Ecology: mapping plants or animal nests using distance sampling

- minimize distance
- minimize variance in parameters of detection function and/or point process
- minimize one of these:
  - maximum variance in intensity surface
  - integrated variance of intensity surface
- minimize variance of coefficients for covariates

Also remember the weighted criterion from my proposal:

$$\int_{\mathcal{R}} \frac{\mathrm{Var}\left[\lambda(u)\right]}{p^{|\lambda(u)-A|}} \mathrm{d}u$$

Heuristics of a good transect sampling plan

- Space-filling, criteria might be maximizing the path integral of nearest neighbor distance along the transects
  - nearest neighbor distance $\text{nnd}_k(u) = \min |u - v|$ where v is any point in the set of path segments at least k steps away from the segment containing u
  - $k = 0$ would include v in the same segment as u so trivially $\text{nnd}_k(u) = 0$ for all u in the path
  - $\text{nnd}_1(u)$ includes all segments except the one containing u
  - $\text{nnd}_2(u)$ excludes the segment containing u and segments connected to it
  - segments not accessible by a connected path starting at u are always included
- Should start with a sparse design with regular spacing, then refine with infill
  - Provides good spatial coverage even if aborted early
  - Imagine downloading a high-resolution intensity jpeg over 56k
- Path should avoid sharp turns but is allowed to cross itself
- One option is to generate two segments at a time, first a short-to-medium length segment to get to the start of the next transect, then a medium-to-long segment for the transect
- Could have new segment length be negatively correlated with the previous segment length

add some citations: Lark (2016), classical space-filling designs, space-filling fractals

3 Sampling Situations

- SRS of parallel transects
- systematic sample of parallel transects
- inhibitory plus close pairs of parallel transects
- fractal curves with random starting points
- movement model
  - generate sequentially, two waypoints at a time
  - generate a jump distance and a direction
  - distance negatively correlated with previous distance (should approximately alternate between a short "transition" and a long "transect")
  - direction bimodal with modes near $\pm\pi/2$
  - if using location/scale beta for direction, allow any direction when the support

set up to think about adaptive sampling (adding a transect at a time or stopping early but don't actually do it here)

4 Results

look at examples of designs that minimize each criterion

look at examples of designs along the Pareto front

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