### Introduction to Point Processes

### Reminder: Point Process Research Questions

- Is the spatial pattern of points random?
- Is there clustering in the events?
- Do events repel each other?

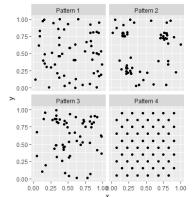


Figure: What pattern do you see?

## Steps to Analyzing a Point Pattern

- Descriptive statistics, such as the average intensity over a region
- Tests for Complete Spatial Randomness (similar to Moran's I for areal data)
- $\textbf{ Model for the intensity } \lambda \text{ (similar to spatial regression for areal data)}$

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  - How many points do we expect in a given region?  $(\lambda)$
  - How many points do we expect to be near a specific location?  $(\lambda(s))$
- The intensity is not known and must be estimated

### Intensity Estimate- Point Processes

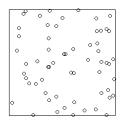
Basic estimator of the intensity,  $\lambda$ :

$$\hat{\lambda} = \frac{n}{a}$$

where n is the number of points  $(s_1, ... s_n)$  and a is the area of the window W.

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#### Point Pattern 1

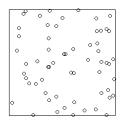


#### R output:

- Planar point pattern: 60 points
- Window: rectangle =  $[0, 1] \times [0, 1]$  units
- Window area = 1 square unit
- Average intensity  $(\hat{\lambda})$ :

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#### Point Pattern 1



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- Window: rectangle =  $[0, 1] \times [0, 1]$  units
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- Average intensity ( $\hat{\lambda}$ ): 60 points per square unit

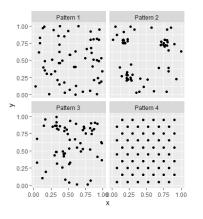


Figure: n = 60 and  $W = [0, 1] \times [0, 1]$  for all point patterns

What is the average intensity for each pattern?

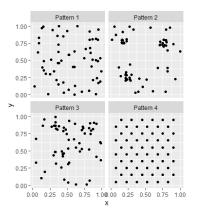


Figure: n = 60 and  $W = [0, 1] \times [0, 1]$  for all point patterns

What is the average intensity for each pattern?

$$\hat{\lambda} = \frac{t}{a}$$

## Descriptive Statistics- Crime Data



Figure: Crime Data Point Pattern

#### R output:

- Planar point pattern: 2511520 points
- Average intensity: 0.009470109 points per square unit
- Window: polygonal boundary
- Window area = 265205000 square units

## Complete Spatial Randomness

#### Randomness

Is the point process random?

- Deterministic: A process is deterministic if the process contains no elements of randomness, can be predicted with certainty
- **Stochastic**: A process is stochastic if the process contains elements of randomness (non-technical definition)

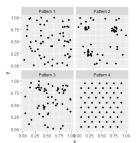


Figure: Which pattern is stochastic? Which is deterministic?

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- Clustering: there is attraction between points
- Inhibition: there is competition among points (leads to regular patterns)

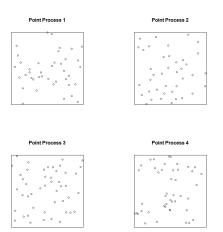


Figure: Which pattern exhibits CSR? Inhibition? Clustering?

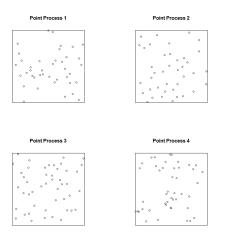


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1: CSR, 2 & 3: Inhibition, 4: Clustering It is really difficult to tell from images!!

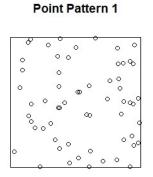
# Nearest Neighbors

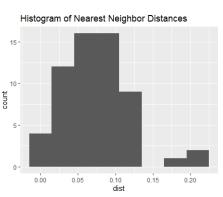
#### **Nearest Neighbors**

- Nearest neighbor of a location is the event that is closest (smallest distance) to this location
- Formally, nearest neighbor of event i is event j with shortest distance d from i

$$d_{ij} \leq d_{ik} \forall k$$

## Nearest Neighbor Example





# Nearest Neighbor Example

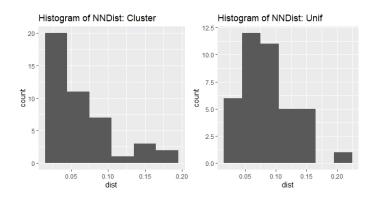
 What would you expect the distribution of nearest neighbor distances to look like for clustering vs CSR?





## Nearest Neighbor Example

• Smaller distances for clustering vs uniform data



#### G Function:

 Summary of the distribution of the distances from an arbitrary event to its nearest event

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- **Cumulative distribution function:** proportion of events that have a nearest neighbor at a distance less than *r*
- When distance r is very small, proportion of events with nearest neighbor at distance less than r is: small.
- When distance r is very large, proportion of events with nearest neighbor at distance less than r is: **large**.

### G function

$$\hat{G}(r) = \frac{\#\{d_i : d_i \le r, \forall i\}}{n}$$

- $d_i = min_i \{ d_{ij}, \forall j \neq i \}$  (distance to nearest event)
- numerator is the number of elements in the set of n.n. distances that are lower than or equal to *r*
- *n* is number of points

Compare the data to the **G function under CSR**:

$$G(r) = 1 - \exp(-\lambda \pi r^2)$$

where  $\lambda$  is the mean number of events per unit area.

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- Calculate G(r) under CSR
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- **3** Compare G(r) under CSR and  $\hat{G}(r)$  for our dataset
- **More formal test:** Can also repeatedly simulate datasets under CSR for your window and with the same intensity  $\hat{\lambda}$  and compare to the distribution of those simulations
  - Similar to permutation tests in areal data

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- Compare these simulated datasets to our dataset
- Does the G function for the data look different than for the simulated (spatially random) datasets?

# Application of G function

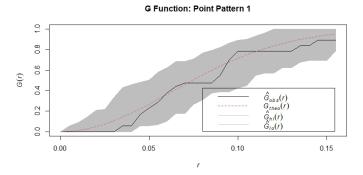


Figure: Is there evidence against CSR?

- Red line: G(r) under Complete Spatial Randomness
- Black line:  $\hat{G}(r)$  estimated from the data
- Grey shaded area: bounds from the "simulation envelope" from many many CSR simulations

## Application of G function

#### G Function: Point Pattern 2

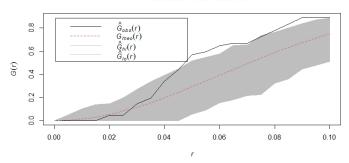


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# Application of G function

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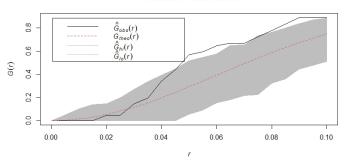


Figure: Is there evidence against CSR?

**Intuition:** The points are closer together than under CSR (indicates clustering)

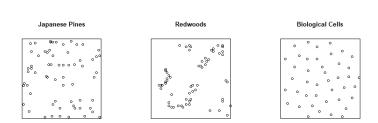


Figure: Which dataset looks like CSR? Inhibition? Clustering?

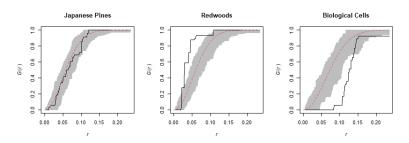


Figure: Which G function gives evidence for CSR? Inhibition? Clustering? (if any)

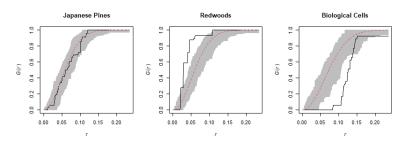


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What is the intuition behind this plot?

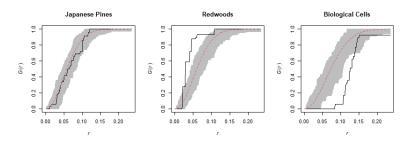


Figure: Which G function gives evidence for CSR? Inhibition? Clustering? (if any)

What is the intuition behind this plot?

With the redwood data (clustered), there are more points than expected under CSR at many radii. **Events are closer than expected.**With the cell data (inhibition), there are fewer points than expected under

Claire Kelling

CSR at most radii. **Events are further than expected.** 

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### F Function from the data

$$\hat{F}(r) = \frac{\#\{d_{ik}: d_{ik} \le r, \forall i\}}{n}$$

- $d_{ik}$  distance from point i to nearest neighbor event k
- Compare the data to the F function under CSR:

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## Application of the F function

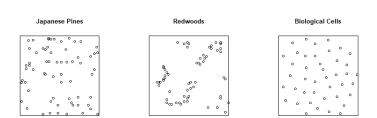


Figure: Reminder of the datasets

# **Empty Space Illustration**

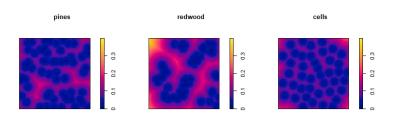


Figure: Comparison of empty space between datasets

- Blue: where points are located
- Pink/yellow: empty space

## Application of the F function

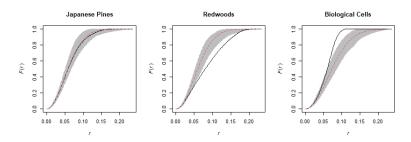


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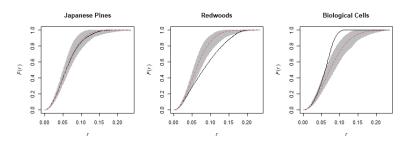


Figure: Which F function gives evidence for CSR? Inhibition? Clustering? (if any)

- Interpretation is opposite of the G function
- Inhibition: Empty spaces are closer to events than expected under CSR
- Clustering: Empty spaces are further than events than expected under CSR