# From neuroscience to national science Three problems across the union of geometry and policy

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## Outline

#### Voronoi estimator

Investigate and improve the Voronoi estimator Derivations of sampling distribution and bias Foundational result in stochastic geometry

## Optimal allocation of resources

Find the optimal placement of facilities

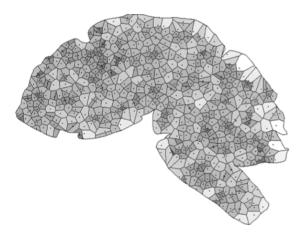
Versatile driver for solving a range of variants

Connect image analysis and operations research

## Climate change

Improve climate change legislation and air pollution mitigation Draw a connection and strengthen both cases Prime projects estimating gains from ancillary mitigation

# Section 1: The Voronoi estimator

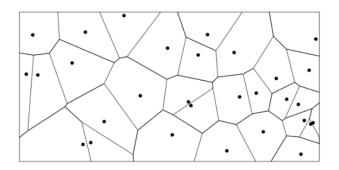


- Joint with Rick Schoenberg -

# Definition of a Voronoi diagram

Cell  $C_i$  contains all locations closer to point  $p_i$  than any other point

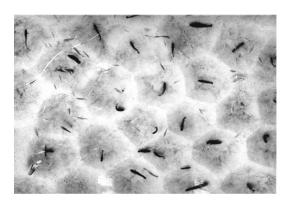
$$C_i = \{ y \in S : ||y - p_i|| \le ||y - p_j||, \ \forall p_j \in N \}$$



# Practical examples

## Voronoi diagrams have a natural interpretation as territories

Breeding regions of animals Cells growing in a dish at a constant rate



## Future Voronoi tessellation

Photo courtesy of Travis Gerke, 12-25-2009

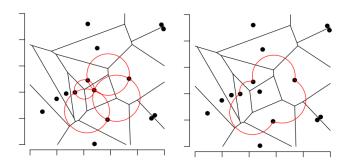
Text message: "Future Voronoi tessellation"



## Fundamental domain

Points outside the fundamental domain have no influence

$$FD(C_i) = \bigcup_{y \in C_i} B(y; ||y - p_i||)$$



# Motivation and goals

## Voronoi estimator proposed

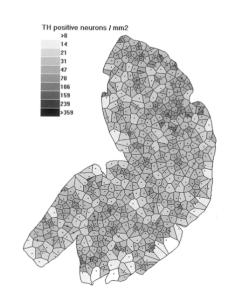
Neuroscience method Limited precedent

## Theoretical goals

Bias Sampling distribution

## Practical goals

Improvements Applicability



# A framework in stochastic geometry

#### The classic pursuit

Draw a realization from a point process Tessellate the point pattern Record a property associated with a random cell

#### Recent efforts

Moment type results in closed form Distributional results largely by simulation

## Two types of cells

Typical cell, randomly selected cell Voronoi estimator cell, cell covering a specific location

# Results for the typical homogeneous Poisson Voronoi cell

#### Closed form

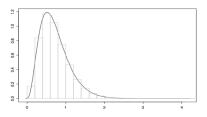
Expected cell area is  $\lambda^{-1}$ 

Expected cell perimeter is  $4\lambda^{-1/2}$ 

Expected number of sides is 6

#### Simulation

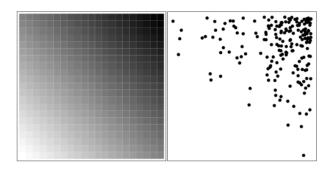
Distribution of cell area is gamma,  $\mathcal{A} \sim \mathcal{G}(x; \alpha, \beta)$ 



# Inhomogeneous Poisson point process

Regulate by an intensity function  $\lambda(y)$ 

$$Pr\{N(A) = i\} = \frac{[\int_A \lambda(y)d\mu]^i}{i!} exp\{-\int_A \lambda(y)d\mu\}$$



# Assumptions

## Area of the typical inhomogeneous Poisson Voronoi cell is gamma

Assumption 1: 
$$A_{t(y)} \sim G(x; \alpha_y, \beta_y)$$

## Intensity is bounded globally

Assumption 2: 
$$M_1^{(k)} < \lambda^{(k)}(r,\theta) < M_2^{(k)}, \forall (r,\theta) \in \mathcal{S}$$

## Intensity is locally homogeneous

Assumption 3: 
$$\lambda^{(k)}(r,\theta) = a_{(k)}$$
, if  $r < b_{(k)}$ 

#### Intensity is locally homogeneous

Assumption 4: 
$$\frac{\exp\{-\pi M_1^{(k)}b_{(k)}^2/4\}}{M_1^{(k)}}$$
 converges to 0 as  $k\to\infty$ 

## Theoretical results

Expected area of the typical cell is the reciprocal of the intensity

Theorem 1: 
$$E(A_{t(y)}) \rightarrow 1/\lambda_y$$

Sampling distribution of the Voronoi estimator is inverse gamma

Theorem 2: 
$$\hat{\lambda}_y \sim IG(x; \alpha_y + 1, 1/\beta_y)$$

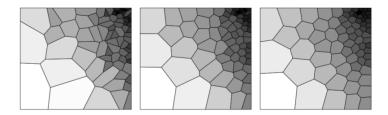
Voronoi estimator is approximately unbiased

Corollary 1: 
$$E(\hat{\lambda}_y) \rightarrow \lambda_y$$

## Centroidal Voronoi estimator

#### Points moved to centroid at each iteration

Will smooth to homogeneous if allowed



#### Kernel estimators

#### Kernel intensity estimation

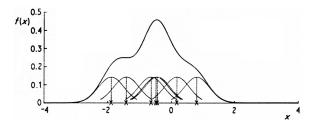
$$\lambda^{k}(y;\gamma,S) = \left\{\sum_{i=1}^{n} k(||y-y_{i}||;\gamma)\right\}/p(y;\gamma,S).$$

#### Gaussian kernel is common

Fixed and adaptive bandwidth techniques

#### Drawbacks

Bias, parameter selection



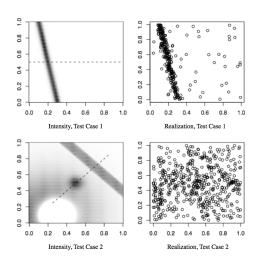
#### Two test cases

#### Test Case 1

Extreme variation Example to follow

#### Test Case 2

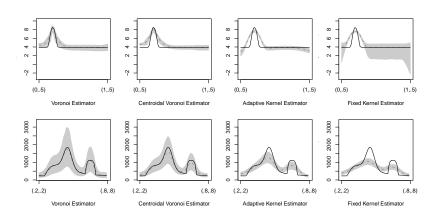
Heikkinen and Arjas Bayesian Voronoi



#### Performance

## Comparison along one hundred locations in each test case

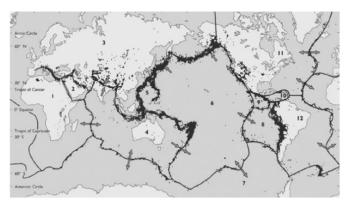
Centroidal Voronoi estimator trades bias for reduced variance



# Introducing earthquakes

## Global earthquakes with tectonic plates

High intensity along many plate boundaries



# Earthquake intensity

## Original data set

Magnitude > 3 Since January 1977

#### Voronoi estimator

Reasonable in the East Responsive in the West

#### Kernel estimator

Zero in the East Too smooth in West



Large magnitude earthquakes



Voronoi estimator



Fixed bandwidth kernel estimator

# Summary

## Challenge

Investigate and improve the Voronoi estimator

#### Contributions

Derivations of sampling distribution and bias Foundational result in stochastic geometry

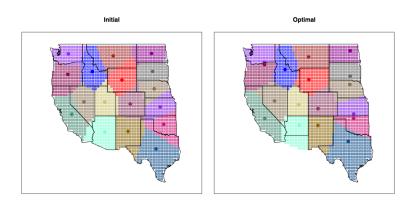
#### Future work

Iterations for centroidal estimator, neuroscience collaboration

#### Reference

Barr CD, Schoenberg FP. On the Voronoi estimator for intensity of an inhomogeneous planar Poisson process. *Biometrika*, tentatively accepted

# Section 2: Optimal allocation of resources



- Joint with Travis Gerke -

# Possible approaches

## Operations research

Placement of schools Gradient descent

## Bayesian image analysis

Model locations and colors Bayesian framework MCMC to search space





# Introducing the model

Locations and colors as the parameter space to be searched

$$\Theta = \{(u_i, v_i, c_i), i = 1, 2, ..., n\}$$

Starting with an uninformative prior

$$\Pi(\Theta) = \prod_{i=1}^{n} U(0,1)^{2} \times p_{c}^{I(c_{i}=\eta_{1})} (1-p_{c})^{I(c_{i}=\eta_{-1})}$$

Suppose Gaussian error

$$P(z|\Theta) \propto exp\left\{-\frac{1}{2\sigma^2}\sum_{j,k=1}^{N}(z_{jk}-\mu_{jk}(\Theta))^2\right\}$$

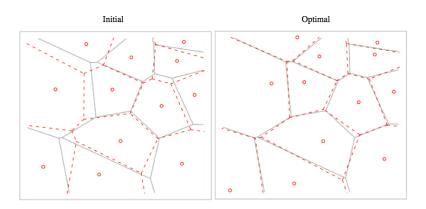
Posterior to be explored

$$P(\Theta|z) \propto \Pi(\Theta) \times P(z|\Theta)$$

# Recovering a tessellation

### Forming optimal Voronoi covers

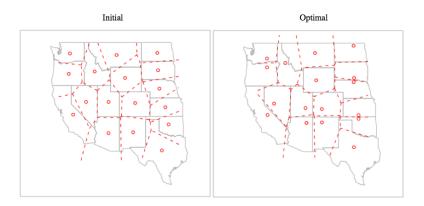
Regions that are Voronoi cells can be matched exactly



# Federal emergency response centers

#### Find the best location for one center per state

Notice Washington and Oregon, Kansas and Oklahoma

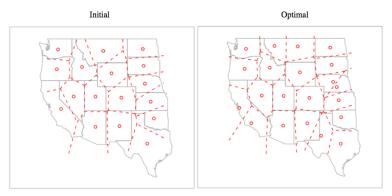


## Flexible framework

A solution more locally optimal Inhibitory prior on the location of points

# Variable number of facilities

Reversible jump MCMC



# Summary

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Find the optimal placement of facilities

#### Contributions

Versatile driver for solving a range of variants Connect image analysis and operations research

#### Future work

Theoretical underpinnings, broader applicability of driver

#### Reference

Barr CD, Gerke TA. Allocating point-type resources to form optimal Voronoi covers. *In progress*.

Section 3: Climate change



- Joint with Francesca Dominici -

#### The ACES Act

## American Clean Energy and Security Act (ACES) of 2009

Regulates carbon dioxide, methane, nitrous oxide and others Capped at 2005 annual levels and reduced by 2% per year Buy and sell pollution permits

Tariffs on countries that fail to pass similar legislation

#### Passed in the House

June 26, 2009 by a vote of 219-212

#### Debate

Economic costs and implied tax across the country Mitigation of global warming, associated public health issues

## Shared sources

## Co-pollutant: $NO_x$

NO <sub>x</sub>	21,450	21,070	19,004	15,612	14,701	14,250
Mobile Fossil Fuel Combustion	10,920	10,622	10,310	8,757	8,271	7,831
Stationary Fossil Fuel Combustion	9,689	9,619	7,802	5,857	5,445	5,445
Industrial Processes	591	607	626	534	527	520
Oil and Gas Activities	139	100	111	321	316	314
Incineration of Waste	82	88	114	98	98	97
Agricultural Burning	28	29	35	39	38	37
Solvent Use	1	3	3	5	5	5
Waste	0	1	2	2	2	2

## Greenhouse Gas: CO<sub>2</sub>

Gas/Source	1990	1995	2000	2005	2006	2007
CO <sub>2</sub>	5,076.7	5,407.9	5,955.2	6,090.8	6,014.9	6,103.4
Fossil Fuel Combustion	4,708.9	5,013.9	5,561.5	5,723.5	5,635.4	5,735.8
Electricity Generation	1,809.7	1,938.9	2,283.2	2,381.0	2,327.3	2,397.2
Transportation	1,484.5	1,598.7	1,800.3	1,881.5	1,880.9	1,887.4
Industrial	834.2	862.6	844.6	828.0	844.5	845.4
Residential	337.7	354.4	370.4	358.0	321.9	340.6
Commercial	214.5	224.4	226.9	221.8	206.0	214.4

# Quantifying the ancillary benefits of cap and trade

#### Reduction in air pollutants associate with cap and trade

Scenarios with different sectors National emissions inventory

## Connecting air pollution and human health

Top ten public health problems by World Health Organization 3000 hospital admissions for every 10  $\mu g/m^3$  Half a year of life lost for every 10  $\mu g/m^3$ 

# Summary

# Challenge

Improve climate change legislation and air pollution mitigation

#### Contributions

Draw a connection and strengthen both cases Prime projects estimating gains from ancillary mitigation

#### Future work

Quantify the benefits of ancillary air pollution mitigation

#### Reference

Barr CD, Dominici F. Cap and trade legislation for greenhouse gas emissions: additional public health benefits from air pollution mitigation. *JAMA* (2010).

#### Conclusion

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