

Closed-Form Likelihood Functions for SCR

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Estimate population density from ecological survey data

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- An *array* of detectors, such as traps, cameras and microphones.

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***Looks
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2

²<https://www.naturettl.com>

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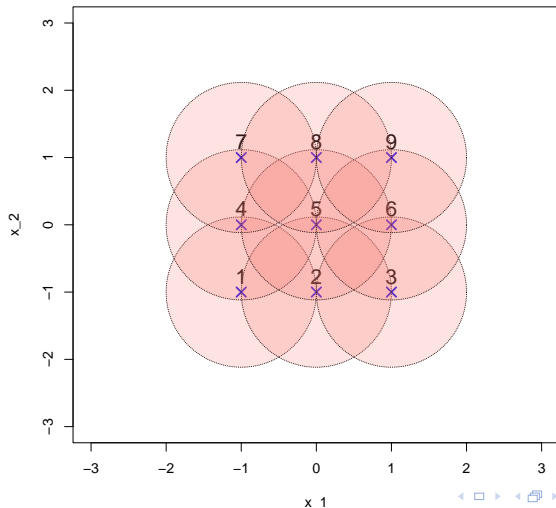


3

³<https://stock.adobe.com>

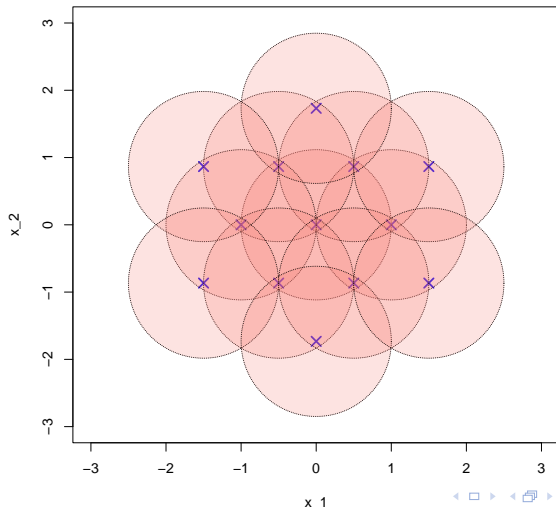
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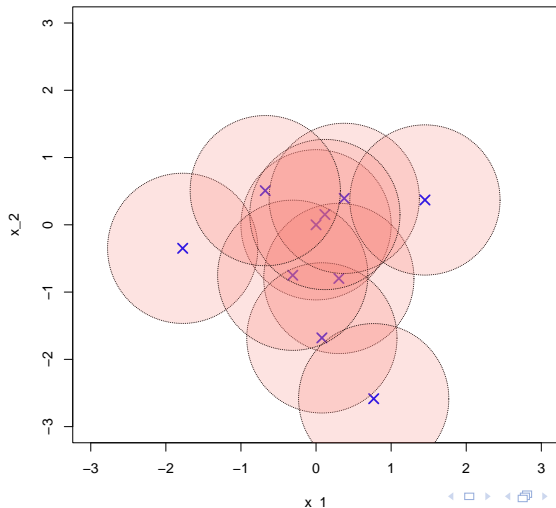
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Assumption I

⁴Image credits: Ilia Shalamaev

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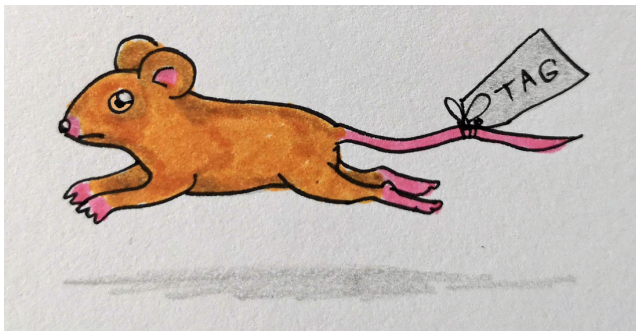


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5

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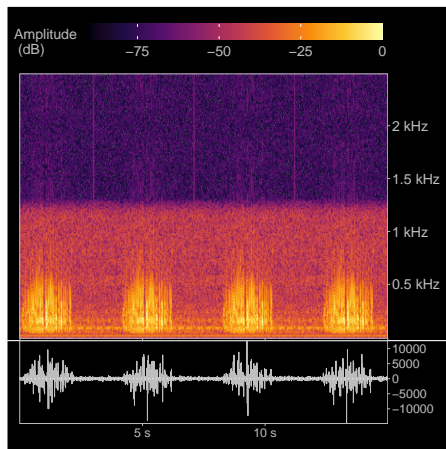
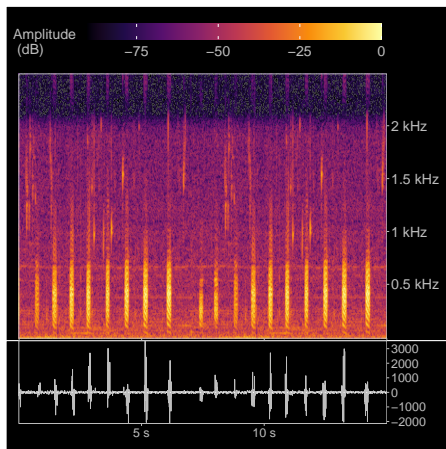


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Data

- In its simplest form, our survey data typically look like the following.

Animal ID	Animal Name	Binary Capture History at each Detector						
		d1 (-1,-1)	d2 (0,-1)	d3 (1,-1)	d4 (-1,0)	d5 (0,0)	d6 (1,0)	d7 (-1,1)
1	Homer	1	1	0	1	1	1	0
2	Marge	1	1	0	1	0	0	1
3	Lisa	1	1	1	0	0	1	1
4	Bart	0	0	0	1	1	1	0
⋮								
$N - 3$	Burns	0	0	0	0	1	0	0
$N - 2$	Apu	0	1	0	1	0	1	1
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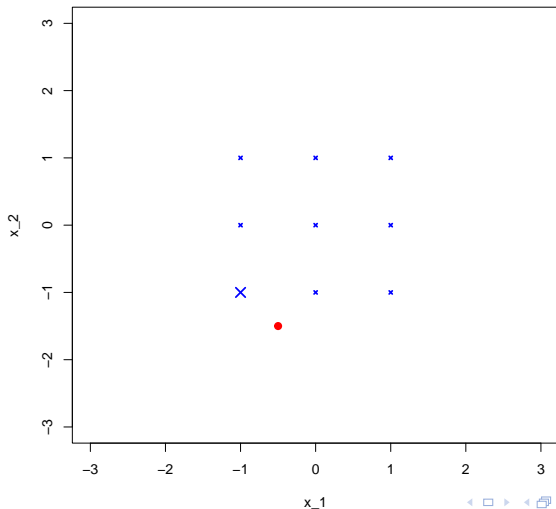
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- Let s denote the location of Homer and x the location of a detector.

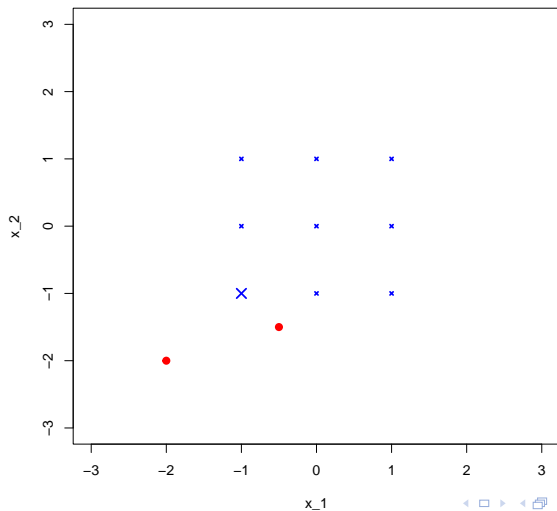
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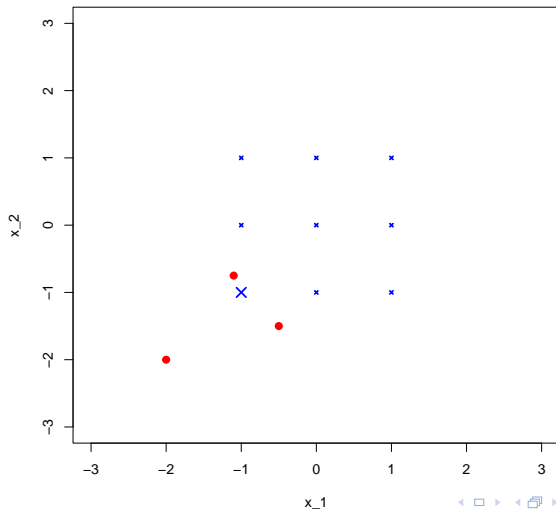
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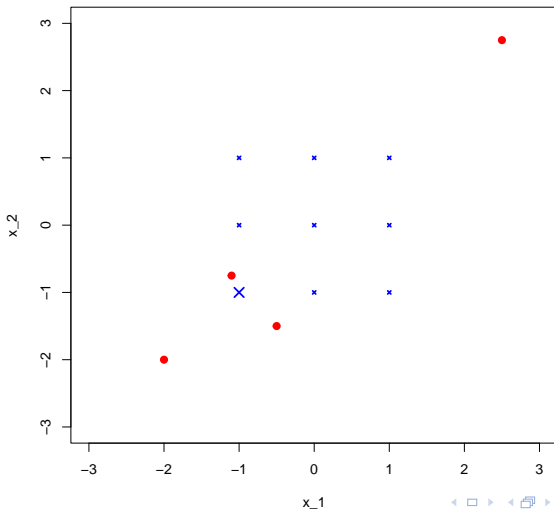
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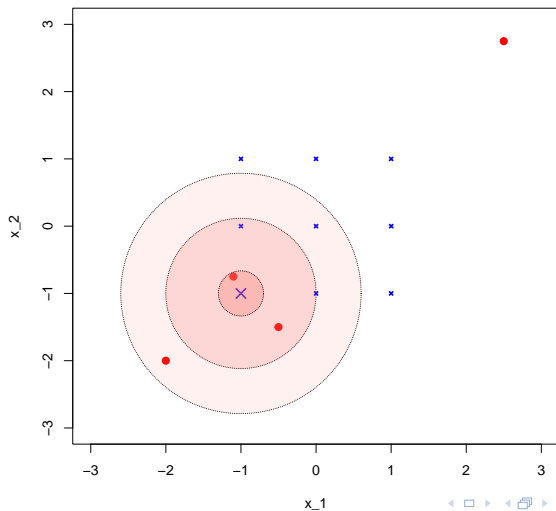
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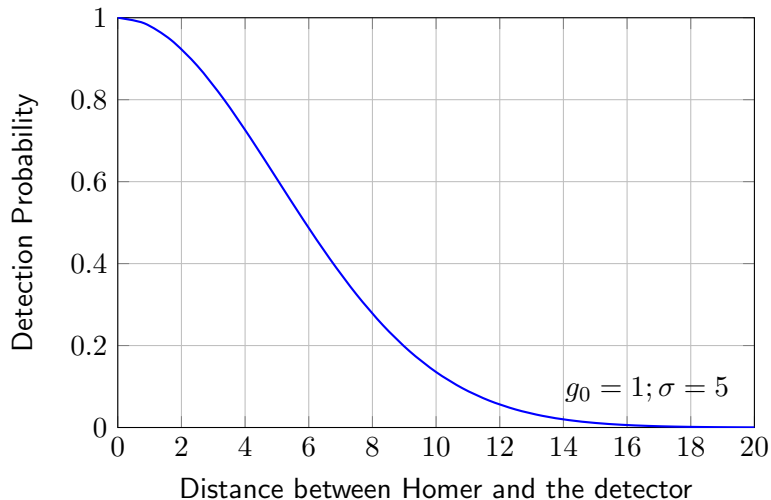
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Detection Function

Half-Normal Detection Function: $g(x) = g_0 e^{-\frac{\|s-x\|^2}{2\sigma^2}}$

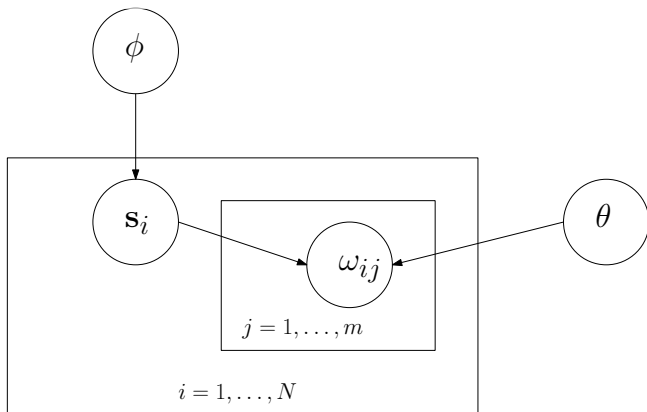


Spatial Capture-Recapture (SCR)

- Spatial capture–recapture models are hierarchical.

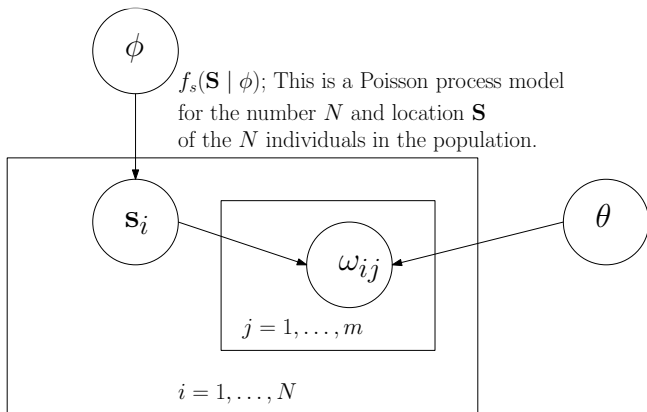
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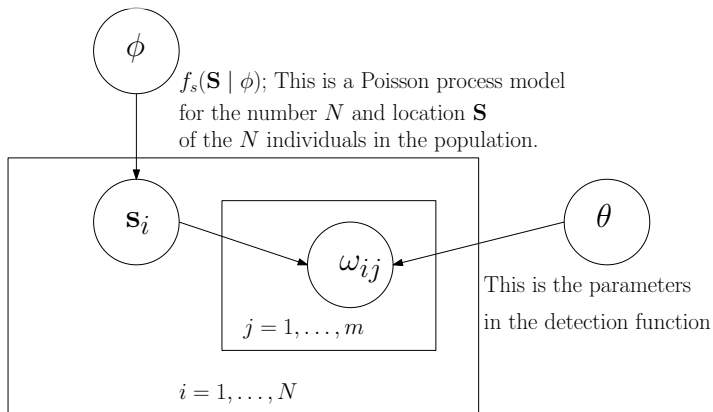
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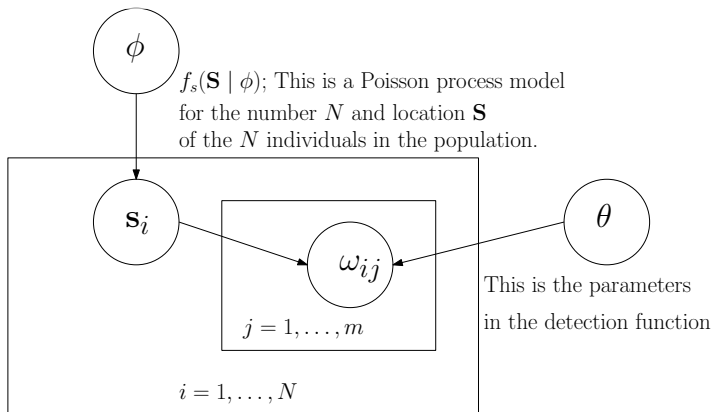
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$f_\Omega(\Omega | \mathbf{S}, \mathbf{X}, \theta)$; This is the probability model for the capture histories Ω , given individuals' locations, \mathbf{S} and detectors' locations, \mathbf{X} .

Unusual Scenario-Complete data

- If *all* N individuals were detected, given the locations \mathbf{S} and \mathbf{X} , then

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where $\boldsymbol{\theta} = (g_0, \sigma^2)$, and $g_j = g_0 \exp\left(-\frac{\|\mathbf{s}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right)$.

- Assume independence between individuals and detectors.
- Recall the capture history is binary, and the detection is halfnormal.

Assumption II

- If we force the Poisson point process to be homogeneous, then $\theta = D$,

$$f_s(\mathbf{S} \mid D) = \frac{(D \cdot A)^N \exp(-D \cdot A)}{N!} \prod_{i=1}^N \frac{1}{A}$$

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- Conditioning on location \mathbf{S} , we have the following likelihood

$$\begin{aligned} \mathcal{L}^c &= f_s(\mathbf{S} \mid D) \cdot f_\Omega(\Omega \mid \mathbf{S}, \boldsymbol{\theta}) \\ &= \frac{D^N \exp(-D \cdot A)}{N!} \prod_{i=1}^N \prod_{j=1}^m g_j^{\omega_{ij}} \cdot (1 - g_j)^{1 - \omega_{ij}} \end{aligned}$$

which is known as complete-data likelihood (King et al, 2016).

Latent variable

- Of course, the location \mathbf{s}_i in practice is a latent variable,

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- We have to marginalise over \mathbf{s} before we can estimate D , g_0 and σ .

$$\begin{aligned} & \int_{\mathbb{R}^2} \int_{\mathbb{R}^2} \cdots \int_{\mathbb{R}^2} \mathcal{L}^c(\boldsymbol{\theta}; \boldsymbol{\Omega}, \mathbf{S}, \mathbf{X}, N) d^2\mathbf{s}_1 d^2\mathbf{s}_2 \cdots d^2\mathbf{s}_N \\ &= \frac{D^N \exp(-D \cdot A)}{N!} \prod_{i=1}^N \int_{\mathbb{R}^2} \prod_{j=1}^m g_j^{\omega_{ij}} \cdot (1 - g_j)^{1 - \omega_{ij}} d^2\mathbf{s} \end{aligned}$$

Unobserved animals

- Of course, some animal would evade detection, then the following

$$\prod_{j=1}^m (1 - g_j) = \prod_{j=1}^m \left\{ 1 - g_0 \exp \left(-\frac{\|\mathbf{s} - \mathbf{x}_j\|^2}{2\sigma^2} \right) \right\} \quad (1)$$

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- Integrating p over \mathbf{s} gives the total probability of detecting an animal.

$$F_{\text{esa}}(g_0, \sigma^2, \mathbf{X}) = 1 - \int_{\mathbb{R}^2} \prod_{j=1}^m (1 - g_j(\mathbf{s})) d^2\mathbf{s} \quad (3)$$

Truncation and thinning

- In this case, we have the conditional probability of observing capture history Ω conditioning on **detecting n number of individuals**.

$$f_{\Omega}(\Omega | \mathbf{S}, \boldsymbol{\theta}) = \prod_{i=1}^n \prod_{j=1}^m \frac{g_j(\mathbf{s})^{\omega_{ij}} \cdot (1 - g_j(\mathbf{s}))^{1 - \omega_{ij}}}{F_{\text{esa}}} \quad (4)$$

- And instead of working with a Poisson point process for the number of animals, we have to work with the point process for the number of detected animals, which is also Poisson,

$$\mathcal{L} = \frac{D^n \exp(-D \cdot F_{\text{esa}})}{n!} \prod_{i=1}^n \int_{\mathbb{R}^2} \prod_{j=1}^m g_j^{\omega_{ij}} \cdot (1 - g_j)^{1 - \omega_{ij}} d^2 \mathbf{s} \quad (5)$$

Notation

- We need to solve two integrals before obtaining the closed-form likelihood,

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- Let $[m] = \{1, 2, \dots, m\}$ denote the set of the first m natural numbers, and

$$\mathcal{S}_k = \{\mathcal{B} \in \mathcal{P}([m]) \mid |\mathcal{B}| = k\}$$

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- That is, \mathcal{S}_k is the set of all k -combinations of $[m]$, e.g., if $m = 3$, then

$$\mathcal{S}_1 = \{\{1\}, \{2\}, \{3\}\}$$

$$\mathcal{S}_2 = \{\{1, 2\}, \{1, 3\}, \{2, 3\}\}$$

$$\mathcal{S}_3 = \{\{1, 2, 3\}\}$$

- The halfnormal detection function is separable,

$$g_j = g_0 \exp \left[-\frac{\|\mathbf{s} - \mathbf{x}_j\|^2}{2\sigma^2} \right], \quad \text{for } j = 1, \dots, n_d, \quad (7)$$

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$$F_{\text{esa}} = 1 - \int_{\mathcal{R}} \prod_{j=1}^m (1 - g_j) d^2\mathbf{s} \quad (9)$$

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How can we interpret this result?

- Let us use the case $m = 3$,

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$$\begin{aligned} F_{\text{esa}} &= P(\text{An animal is detected}) \\ &= \int_{\mathcal{R}} 1 - \prod_{j=1}^3 \left(1 - g_j(\mathbf{s})\right) d^2\mathbf{s} \\ &= - \sum_{k=1}^3 \sum_{\mathcal{B} \in \mathcal{S}_k} (-1)^k \int_{\mathcal{R}} \prod_{j \in \mathcal{B}} a_j \cdot b_j d^2\mathbf{s} \end{aligned}$$

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- Let us use the case $m = 3$,

$$\mathcal{S}_1 = \{\{1\}, \{2\}, \{3\}\}; \mathcal{S}_2 = \{\{1, 2\}, \{1, 3\}, \{2, 3\}\}; \mathcal{S}_3 = \{\{1, 2, 3\}\}$$

and E_i be the event that the animal is detected by detector i

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$$\text{P}\left(\bigcup_{j=1}^3 E_i\right) = \sum_{i=1}^3 \text{P}(E_i) - \sum_{i,j \in \mathcal{S}_3; i \neq j} \text{P}(E_i \cap E_j) + \text{P}(E_1 \cap E_2 \cap E_3)$$

- Reducing double to single by separating the integrals, we have

$$\int_{\mathcal{R}} \prod_{j \in \mathcal{B}} g_j d^2 \mathbf{s} = \underbrace{\int_{\mathcal{R}} \prod_{j \in \mathcal{B}} a_j ds_1}_{\alpha_{\mathcal{B}}} \cdot \underbrace{\int_{\mathcal{R}} \prod_{j \in \mathcal{B}} b_j ds_2}_{\beta_{\mathcal{B}}} \quad (12)$$

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where $\alpha_{\mathcal{B}}$ and $\beta_{\mathcal{B}}$ can be found, by using integration by parts, regrouping, and results in Gaussian integrals, which lead us to the following form

$$\gamma_{\mathcal{B}} = \int_{\mathbb{R}^2} \prod_{j \in \mathcal{B}} g_j d^2 \mathbf{s} = g_0^{|\mathcal{B}|} \exp \left[\frac{|\mathcal{B}|}{2\sigma^2} (\|\mathbf{c}_{\mathcal{B}}\|^2 - \mu_{\mathcal{B}}) \right] \frac{2\pi\sigma^2}{|\mathcal{B}|} \quad (13)$$

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- The term $\mathbf{c}_{\mathcal{B}}$ denotes the centroid of detectors defined by the set \mathcal{B} and $\mu_{\mathcal{B}}$ denotes the mean squared Euclidean norm of the detector coordinates

$$\mu_{\mathcal{B}} = \frac{1}{|\mathcal{B}|} \sum_{j \in \mathcal{B}} \|\mathbf{x}_j\|^2 \quad (14)$$

Detection integral

- The other type of integrals can be found in a similar way

$$\mathcal{L} = \frac{D^n \exp(-D \cdot F_{\text{esa}})}{n!} \prod_{i=1}^n \int_{\mathbb{R}^2} \prod_{j=1}^m g_j^{\omega_{ij}} \cdot (1 - g_j)^{1 - \omega_{ij}} d^2 \mathbf{s} \quad (15)$$

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which means we never need to deal with any integral in high dimension.

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$$\mathcal{S}_3^{\mathcal{N}_i} = \{\{3, 4, 5\}\}$$

- Using the above notation and a similar strategy, we can rewrite

$$F_{\text{det}} = \prod_{i=1}^n \int_{\mathbb{R}^2} \prod_{j=1}^m g_j^{\omega_{ij}} (1 - g_j)^{1 - \omega_{ij}} d^2 \mathbf{s} \quad (19)$$

(20)

(21)

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$$V_i = \sum_{k=1}^{|\mathcal{N}_i|} \sum_{\mathcal{B} \in \mathcal{S}_k^{\mathcal{N}_i}} (-1)^k \int_{\mathbb{R}^2} \prod_{j \in \mathcal{B} \cup \mathcal{N}'_i} g_j d^2 \mathbf{s} = \sum_{k=1}^{|\mathcal{N}_i|} \sum_{\mathcal{B} \in \mathcal{S}_k^{\mathcal{N}_i}} (-1)^k \gamma_{\mathcal{B} \cup \mathcal{N}'_i} \quad (23)$$

Closed-form marginal likelihood

The marginal semi-complete-data likelihood with half-normal detection function,

$$\mathcal{L}^{sc}(\boldsymbol{\theta}; \boldsymbol{\Omega}, \mathbf{X}, n) = \frac{D^n \exp(-D \cdot F_{\text{esa}})}{n!} \cdot F_{\text{det}_n} \quad (24)$$

$$= \frac{D^n}{n!} \exp \left(D \cdot \sum_{k=1}^m \sum_{\mathcal{B} \in \mathcal{S}_k} (-1)^k \gamma_{\mathcal{B}} \right) \cdot \prod_{i=1}^n \left(\gamma_{\mathcal{N}'_i} + \sum_{k=1}^{|\mathcal{N}'_i|} \sum_{\mathcal{B} \in \mathcal{S}_k^{\mathcal{N}'_i}} (-1)^k \gamma_{\mathcal{B} \cup \mathcal{N}'_i} \right) \quad (25)$$

where

$$\gamma_{\mathcal{B}} = g_0^{|\mathcal{B}|} \exp \left[\frac{|\mathcal{B}|}{2\sigma^2} (\|\mathbf{c}_{\mathcal{B}}\|^2 - \mu_{\mathcal{B}}) \right] \frac{2\pi\sigma^2}{|\mathcal{B}|} \quad (26)$$

and the term $\mathbf{c}_{\mathcal{B}}$ denotes the centroid of detectors defined by the set \mathcal{B} and $\mu_{\mathcal{B}}$ denotes the mean squared Euclidean norm of the detector coordinates

Thank you!