

Bayesian complementary clustering, MCMC and Anglo-Saxon Placenames

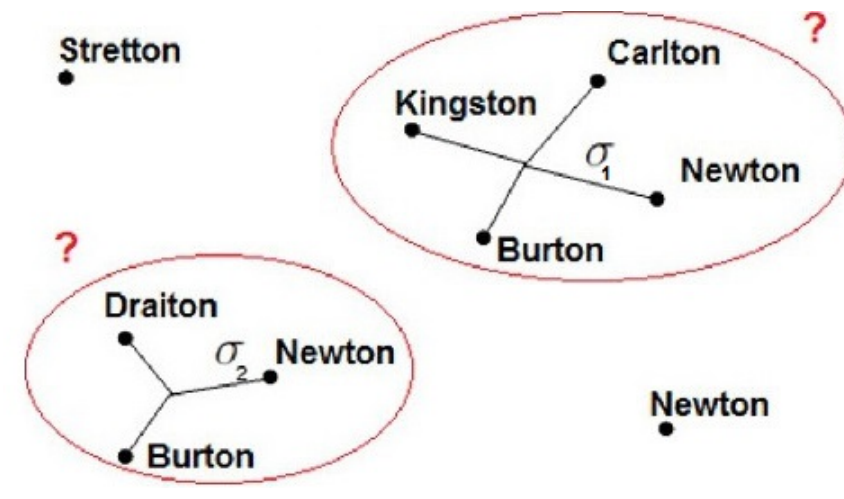
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MOTIVATION AND MODELING

HISTORICAL HYPOTHESIS

Anglo-Saxon settlements were grouped in clusters, each cluster collecting together settlements with distinctive administrative functions (hence names).



Questions:

- Does the geographical distribution of placenames support this?
- What is the typical intra-cluster dispersion σ ?
- Which subset of settlements is clustered?
- Which placenames tend to cluster together?

MODEL REQUIREMENTS

k-type point process:

Marks (colors) represent placenames.

Complementary clustering:

Each color occurs at most once in each cluster.

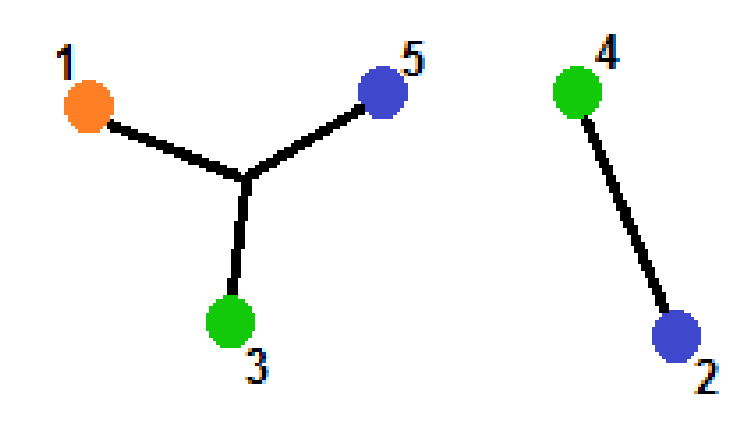
Inferences on cluster partition:

$\mathbf{x} = (x_1, \dots, x_{n(\mathbf{x})}) \leftrightarrow$ Given points

$\rho = \{C_1, \dots, C_{N(\rho)}\} \leftrightarrow$ Partition of \mathbf{x}

$$\pi(\rho|\mathbf{x}) \propto \pi(\rho)\pi(\mathbf{x}|\rho)$$

● = Burton
● = Charlton
● = Newton



A RANDOM PARTITION MODEL

Data generation:

Cluster centers \leftrightarrow Poisson Point Process driven by $\lambda g(\cdot)$

Cluster sizes $\leftrightarrow |C_j| \sim (p_1, \dots, p_k), j = 1, \dots, N(\rho)$

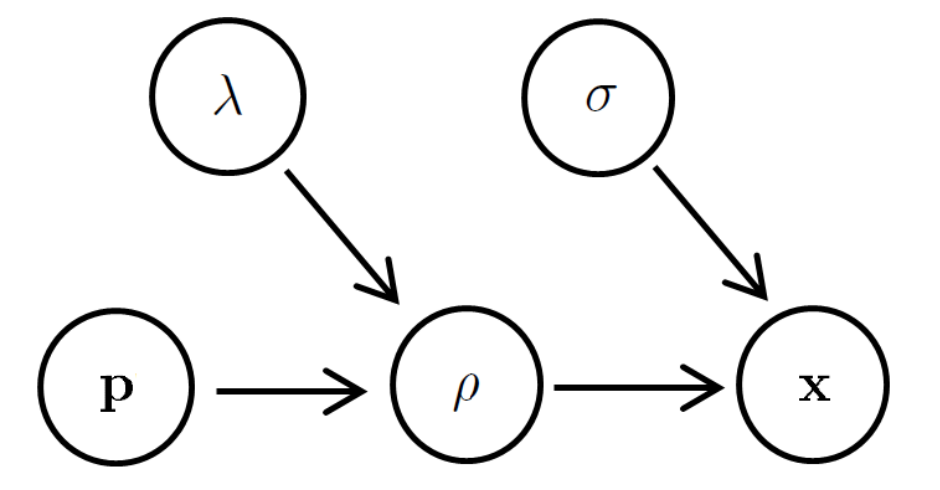
Locations \leftrightarrow Gaussian, mean at center, variance σ^2/π

Induced prior on ρ :

$$\pi(\rho|\mathbf{p}, \lambda) \propto \prod_{j=1}^{N(\rho)} \lambda^{p_j} p_j^{C_j}$$

with $\lambda \sim \text{Gamma}(k\lambda, \theta_\lambda)$ and

$\mathbf{p} = (p_1, \dots, p_k) \sim \text{Dir}(1, \dots, 1)$.



COMPUTATION: a Data Association problem

Intractability of the posterior

The full conditional posterior $\pi(\rho|rest)$ is intractable:

$$\frac{N(\rho)}{\prod_{j=1}^k |C_j|} \left(\frac{k}{|C_j|} \right)^{-1} \frac{p_{|C_j|} g(x_{C_j})}{(2\pi\sigma^2)^{|C_j|-1}} \exp\left(-\frac{\sum_{i \in C_j} |x_i - x_{C_j}|^2}{2\sigma^2}\right) \quad (1)$$

| | Finding MLE or MAP | Approximate Sampling |
|-----------------|---------------------------------------|--|
| 2 colors | $O(n^3)$ with the Hungarian Algorithm | polynomial-time MCMC* (Monomer-Dimer systems) |
| ≥ 3 colors | NP-hard Assignment Problem | Only heuristics (no guarantees of convergence) |

*Jerrum and Sinclair (1995), bound too large in practice.

MCMC for 2 colors

Sample space: matchings of a weighted bipartite graph.

Notation: ρ for matchings, (i, j) for edges and w_{ij} for weights.

Target distribution: $\pi(\rho) \propto \prod_{(i,j) \in \rho} w_{ij}$, with w_{ij} as in (1).

Algorithm: Metropolis-Hastings.

Proposal Distribution

1 - Given ρ_{old} , pick an edge (i, j) according to a distribution $q_{\rho_{old}}(i, j)$;

2 - Propose $\rho_{new} = \rho_{old} \circ (i, j)$.

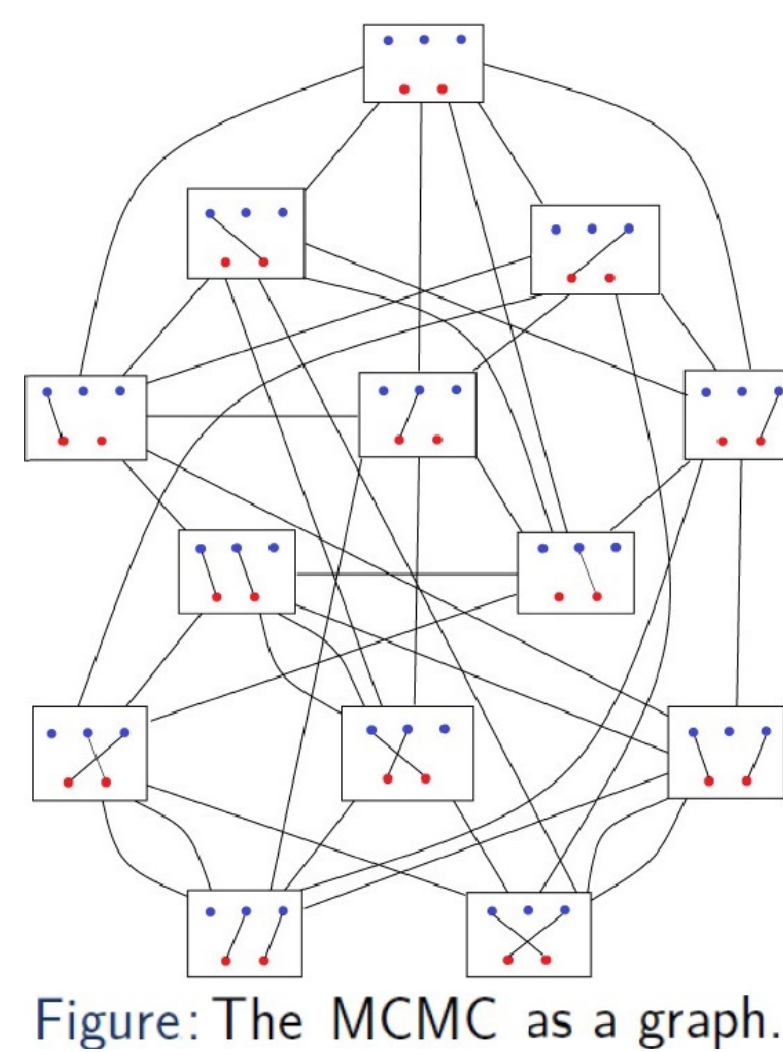


Figure: The MCMC as a graph.

What is the optimal choice for $q(i, j)$?

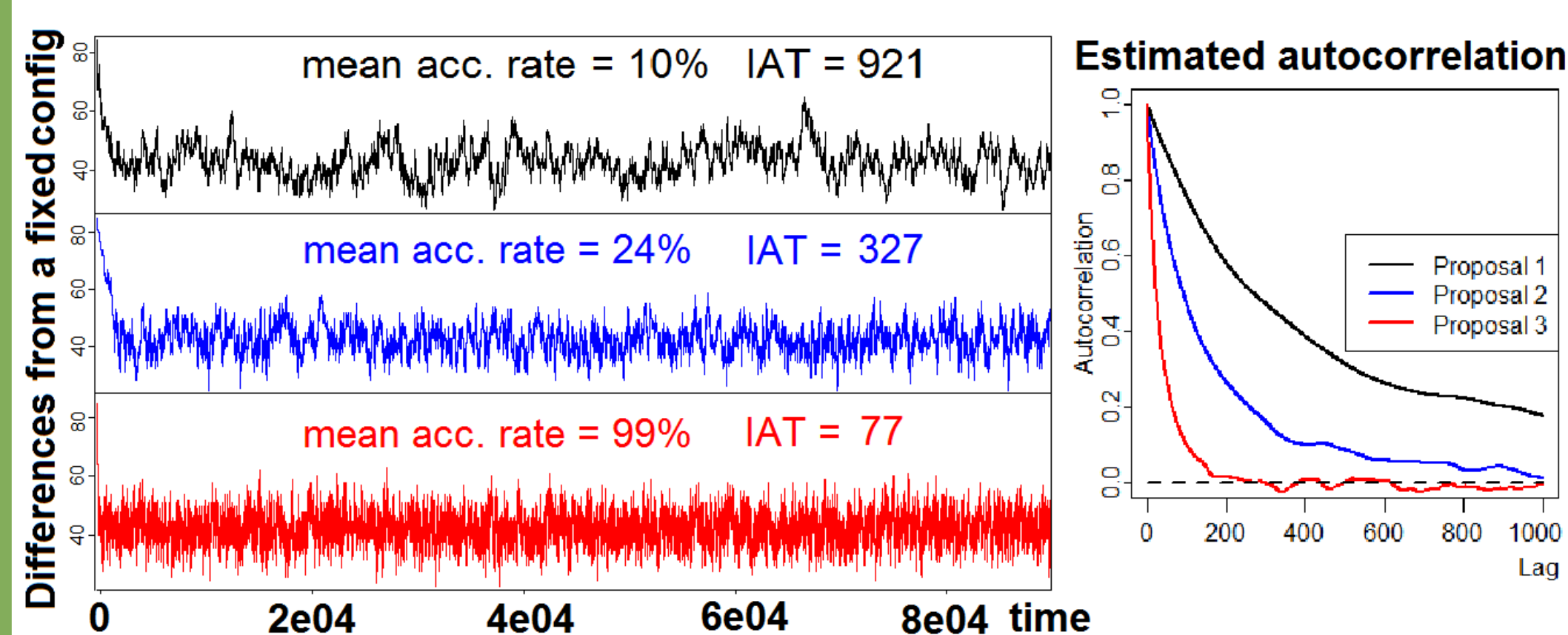
(A) **Intuition:** we seek $\frac{Q(\rho_{old}, \rho_{new})}{Q(\rho_{new}, \rho_{old})} \approx \frac{\pi(\rho_{new})}{\pi(\rho_{old})}$.

This is not obtained by $q(i, j) \propto \pi(\rho_{new})$. In fact

$$\frac{Q(\rho_{old}, \rho_{new})}{Q(\rho_{new}, \rho_{old})} = \frac{q_{\rho_{old}}(i, j)}{q_{\rho_{new}}(i, j)} \frac{\pi(\rho_{new}) / \sum_{i,j} \pi(\rho_{old} \circ (i, j))}{\pi(\rho_{old}) / \sum_{i,j} \pi(\rho_{new} \circ (i, j))} = \frac{\pi(\rho_{new}) \sum_{i,j} \pi(\rho_{new} \circ (i, j))}{\pi(\rho_{old}) \sum_{i,j} \pi(\rho_{old} \circ (i, j))} \approx \frac{\pi(\rho_{new}) \pi(\rho_{new})}{\pi(\rho_{old}) \pi(\rho_{old})} = \left(\frac{\pi(\rho_{new})}{\pi(\rho_{old})} \right)^2$$

(B) **Simulations:** compare three choices

$$q(i, j) \propto \mathbb{1}_{\{w_{ij} > \epsilon\}}, \quad q(i, j) \propto \pi(\rho_{new}), \quad q(i, j) \propto \frac{\pi(\rho_{new})}{\pi(\rho_{old}) + \pi(\rho_{new})}$$



(C) **Theoretical results?** (work in progress)

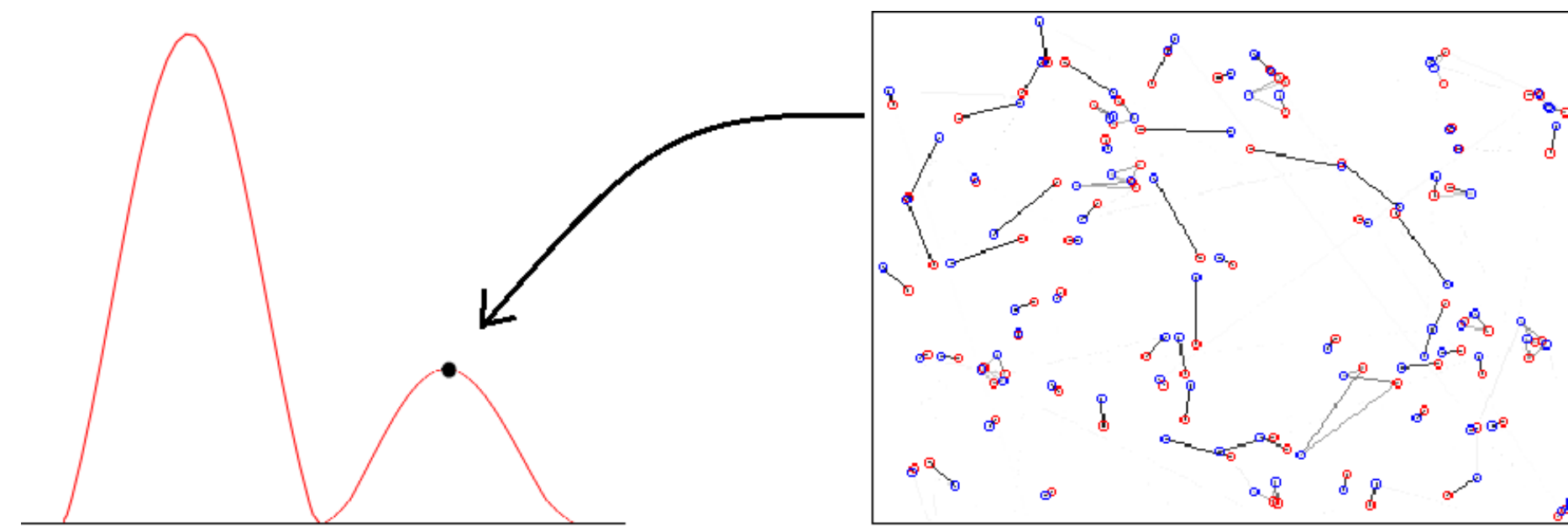
1) Any $\tilde{q}(i, j)$ is (asymptotically) Peskun-dominated by a $q(i, j)$ satisfying asymptotic detailed balance, i.e. $\frac{Q(\rho_{old}, \rho_{new})}{Q(\rho_{new}, \rho_{old})} \rightarrow \frac{\pi(\rho_{new})}{\pi(\rho_{old})}$.

2) Many choices satisfies asymptotic detailed balance, e.g. $q(i, j) \propto \frac{\pi(\rho_{new})}{\pi(\rho_{old}) + \pi(\rho_{new})}$, or $\sqrt{\pi(\rho_{new})}$, or $1 \wedge \frac{\pi(\rho_{new})}{\pi(\rho_{old})}$, or $1 \vee \frac{\pi(\rho_{new})}{\pi(\rho_{old})}$, ... None of those Peskun-dominates any other. How to choose?

3) In simple frameworks (e.g. hypercube with product target) it can be shown that $\frac{\pi(\rho_{new})}{\pi(\rho_{old}) + \pi(\rho_{new})}$ minimizes the mixing time.

Multimodality and Simulated Tempering

For certain parameters values, the target measure exhibits multimodality (with local modes being cycle-like matchings). Simulated Tempering techniques can be used in this case.

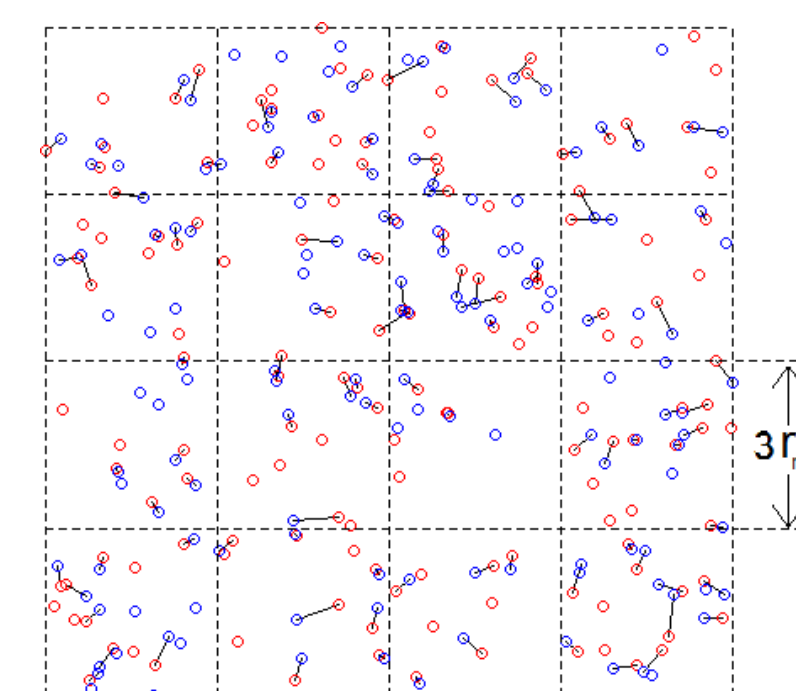


Multiple proposal scheme

Idea: propose a red-blue edge for each non-adjacent square of a grid.

Pros: simultaneous and independent proposal of many links (parallel computation).

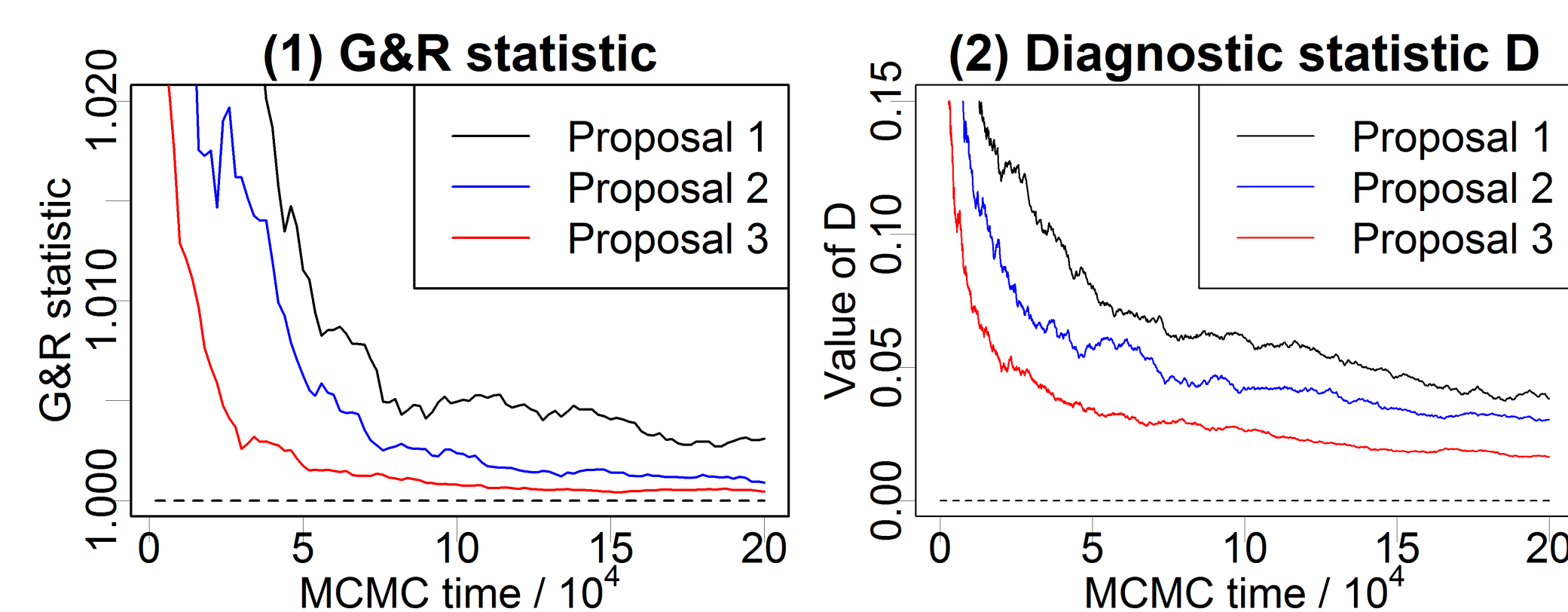
Cons: truncation requirement (link length $< r_{max}$).



Two Convergence Diagnostic tools

(1) Multi-dimensional Gelman and Rubin diagnostic.

(2) $D := \sup_{\{i,j\}} |\hat{p}_{ij}^{(1)} - \hat{p}_{ij}^{(2)}|$, where $p_{ij} = \mathbb{P}_\pi[(i, j) \in \rho]$ and $\hat{p}_{ij}^{(1)}, \hat{p}_{ij}^{(2)}$ are estimated with two independent MCMC runs.



MCMC for k colors

Sample space: matchings of a weighted k -partite hypergraph.

Notation: ρ for matchings, e for hyperedges, $w(e)$ for weights.

Target distribution: $\pi(\rho) \propto \prod_{e \in \rho} w(e)$, with $w(e)$ as in (1).

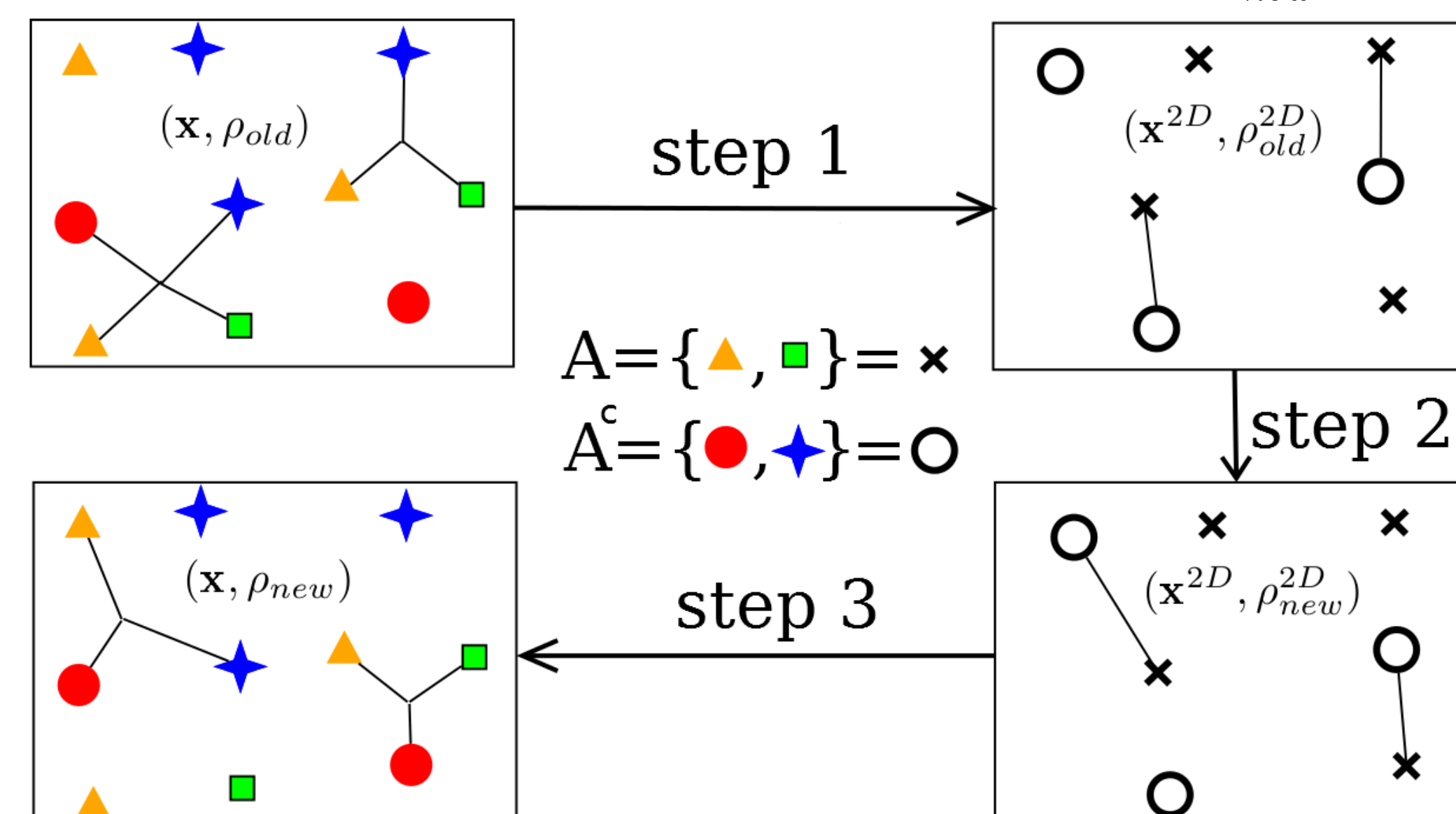
Algorithm: Mixture of Metropolis-Hastings.

Proposal Distribution: given a subset of colors A

Step 1: Project (x, ρ_{old}) to a 2-color configuration $(x^{2D}, \rho_{old}^{2D})$.

Step 2: Move in the 2-color space with the MCMC for 2-colors.

Step 3: Evaluate the new state ρ_{new} from x^{2D} and ρ_{old}^{2D} .



Remark: the projection of the target distribution π on the 2-color space (x^{2D}, ρ^{2D}) is the 2-color version of π itself!

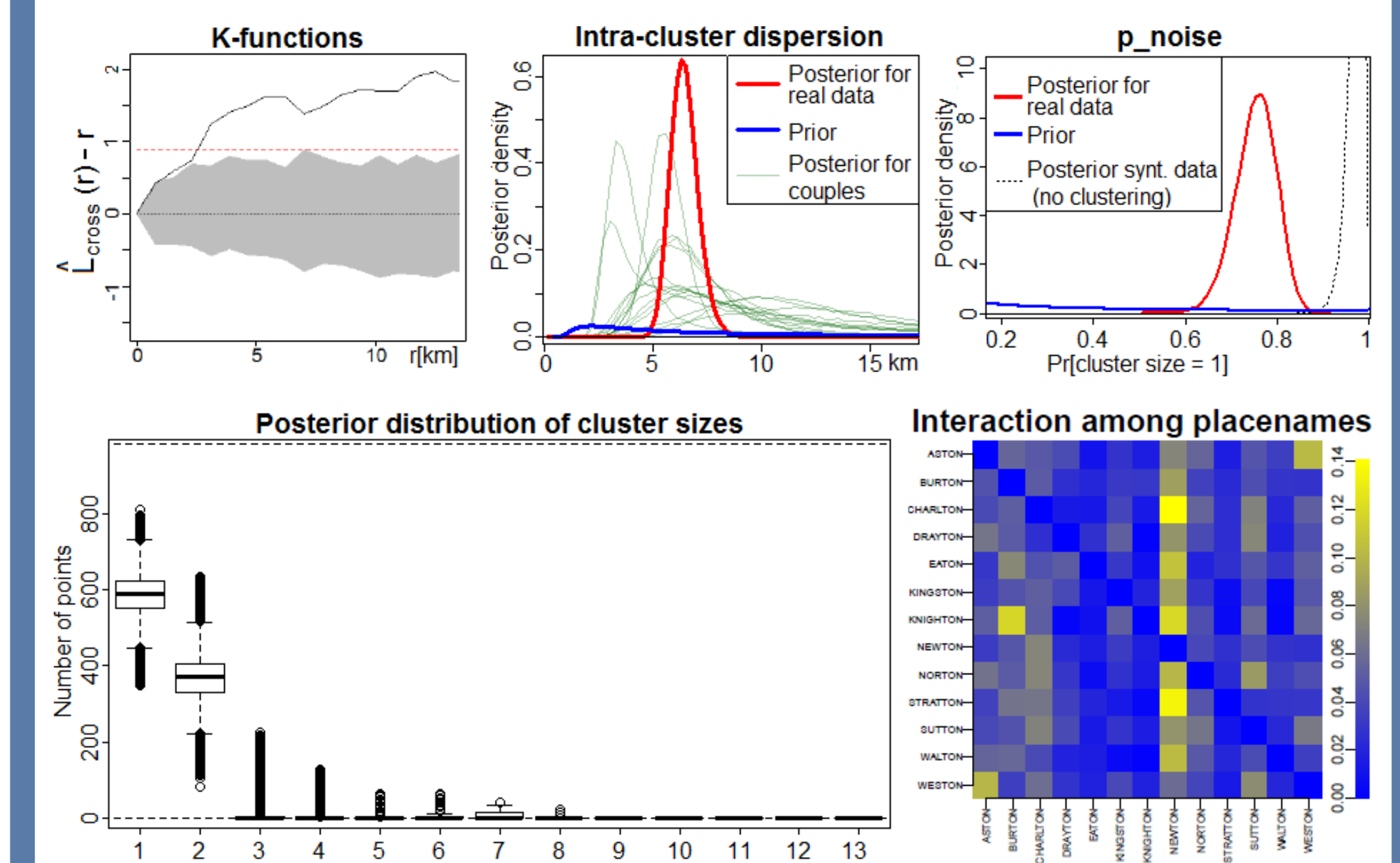
DATA ANALYSIS

Dataset: 1021 settlements with 13 placenames.

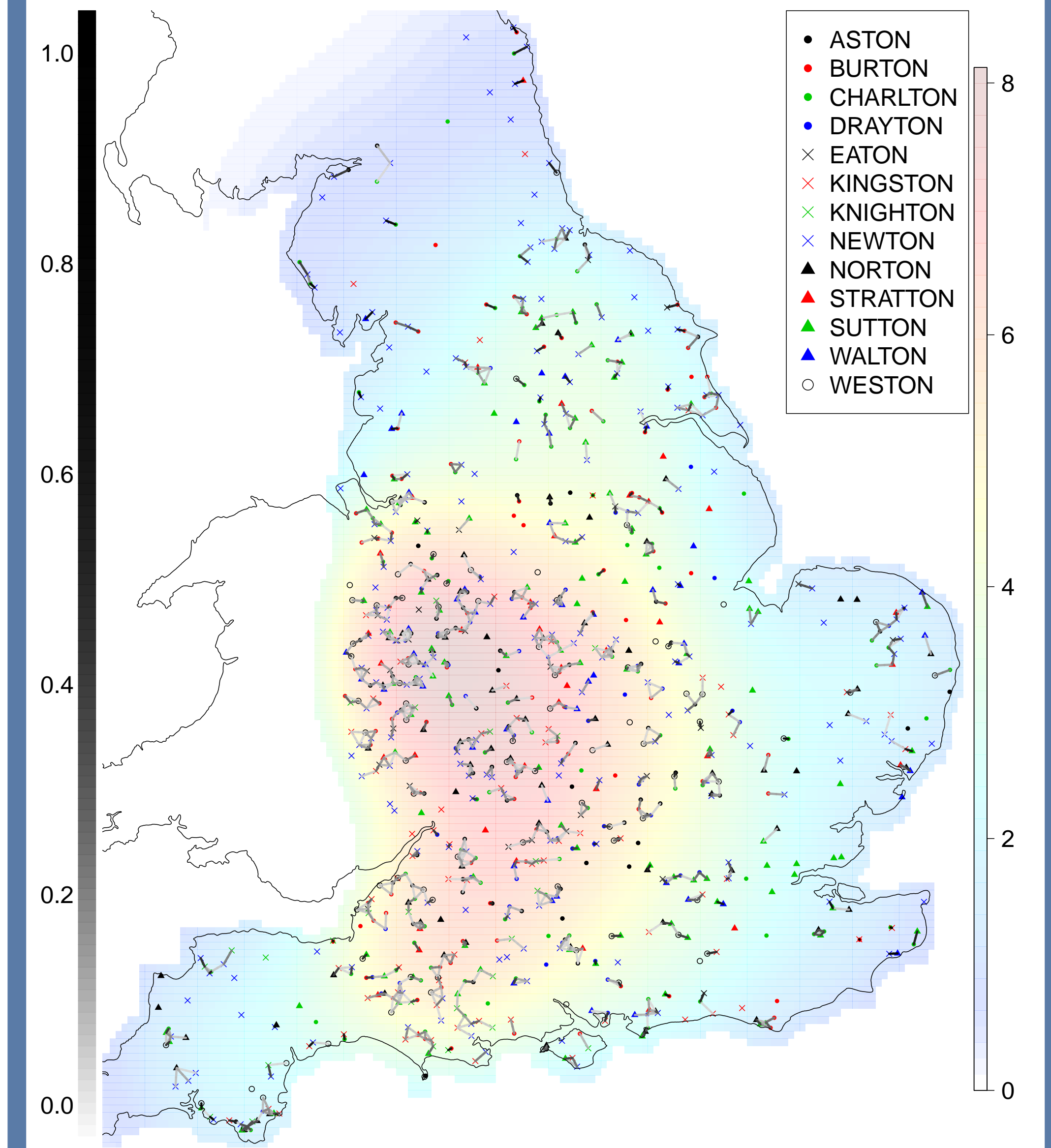
Preliminary analysis: K-functions suggest interaction.

Random Partition Model analysis:

- Mild evidences in favor of interaction: $p_{noise} \neq 1$.
- With a flat prior, we estimate σ to lie in the range 5-8 km (support historians hypothesis).
- Inferences on cluster partition and placenames interaction.



Posterior distribution of cluster partition for the selected dataset



Future Steps

- Include heterogeneity between high and low density region.
- Include other source of data (e.g. topology).
- Prove theoretical results related to the MH proposal.

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