## Appendix A. Position and mark data terms

## Appendix A.1. Position term

If we consider a simple energy model with no interactions such that:

$$
\begin{equation*}
U(Y \mid X)=\sum_{y \in Y} V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right) \tag{A.1}
\end{equation*}
$$

For any configuration of points $Y$ we have:

$$
\begin{align*}
p(y \mid Y, X) & =\frac{h(\{y\} \cup Y \mid X)}{h(Y \mid X)} \\
& =\frac{\exp \left(-\sum_{y^{\prime} \in\{y\} \cup Y} V_{\operatorname{pos}}\left(y_{i}^{\prime}, y_{j}^{\prime} \mid X\right)\right)}{\exp \left(-\sum_{y^{\prime} \in Y} V_{\operatorname{pos}}\left(y_{i}^{\prime}, y_{j}^{\prime} \mid X\right)\right)}  \tag{A.2}\\
& =\exp \left(-V_{\operatorname{pos}}\left(y_{i}, y_{j} \mid X\right)\right)
\end{align*}
$$

Here $p(y \mid Y, X)$ gives the probability of $y$ being a point given points in the configuration Y. Without interactions between points in the model, we have $p(y \mid Y, X)=p(y \mid X)$. From $p\left(y_{i}, y_{j} \mid X\right)=\sigma\left(A_{\text {pos }}(X)\left[y_{i}, y_{j}\right]\right)$, with $\sigma$ the sigmoid function, we deduce:

$$
\begin{equation*}
V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)=\ln \left(1+\exp \left(-A_{\mathrm{pos}}(X)\left[y_{i}, y_{j}\right]\right)\right) \tag{A.3}
\end{equation*}
$$

Appendix A.2. Mark terms
If we consider a simple energy model with no interactions such that:

$$
\begin{equation*}
U(Y \mid X)=\sum_{y \in Y} V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)+V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right) \tag{A.4}
\end{equation*}
$$

For any configuration of points $Y$ we have:

$$
\begin{align*}
p(y \mid Y, X) & =\frac{p(\{y\} \cup Y \mid X)}{p(Y \mid X)} \\
& =\frac{\exp \left(-\sum_{y^{\prime} \in\{y\} \cup Y} V_{\mathrm{pos}}\left(y_{i}^{\prime}, y_{j}^{\prime} \mid X\right)+V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right)}{\exp \left(-\sum_{y^{\prime} \in Y} V_{\operatorname{pos}}\left(y_{i}^{\prime}, y_{j}^{\prime} \mid X\right)+V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right)}  \tag{A.5}\\
& =\exp \left(-V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)-V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right)
\end{align*}
$$

Here $p(y \mid Y, X)$ gives the probability of $y$ being a point, given points in the configuration Y. Without interactions between points in the model, we have $p(y \mid Y, X)=p(y \mid X)$.

$$
\begin{align*}
p(y \mid X) & =\frac{1}{Z} \exp \left(-V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)-V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right) \\
p\left(y_{i}, y_{j} \mid X\right) p\left(y_{m} \mid y_{i}, y_{j}, X\right) & =\frac{1}{Z} \exp \left(-V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)\right) \exp \left(-V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right) \tag{A.6}
\end{align*}
$$

From the position energy definition, we have $p\left(y_{i}, y_{j} \mid X\right) \propto \exp \left(-V_{\mathrm{pos}}\left(y_{i}, y_{j} \mid X\right)\right)$, thus:

$$
\begin{align*}
p\left(y_{m} \mid y_{i}, y_{j}, X\right) & =\frac{1}{Z^{\prime}} \exp \left(-V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right) \\
\frac{\exp \left(A_{m}\left(X, y_{i}, y_{j}\right)\left[y_{m}\right]\right)}{\sum_{y_{m}^{\prime}} \exp \left(A_{m}\left(X, y^{\prime}{ }_{i}, y^{\prime}{ }_{j}\right)\left[y_{m}^{\prime}\right]\right)} & =\frac{1}{Z^{\prime}} \exp \left(-V_{m}\left(y_{m} \mid y_{i}, y_{j}, X\right)\right) \tag{A.7}
\end{align*}
$$

## Appendix B. Parallelization: Cell size and computation

Appendix B.1. Determining cell size
For two points $y, y^{\prime}$, we denote $y \underset{i}{\sim} y^{\prime}$ when the two points are interacting, i.e. $V(y \mid \ldots)$ depends on $y^{\prime}$. This is a generalization of the distance based interaction where $y \underset{i}{\sim} y^{\prime} \Longleftrightarrow d\left(y, y^{\prime}\right) \leq d_{\max }$. Then $\mathcal{N}_{y}^{Y}=\left\{y \in Y \mid y^{\prime} \neq y, y^{\prime}{\underset{i}{i}}^{\sim}\right.$ $y\}$.

Definition. [1] A point process of density $h$ is Markovian under the neighborhood relationship $\underset{m}{\sim}$ if and only if $\forall Y \in \mathcal{Y}$ such that $h(Y)>0$ :

1. $\forall \tilde{Y} \subset Y, h(\tilde{Y})>0$
2. $\forall u \in S \times M, h(Y \cup\{u\}) / h(Y)$ only depends on $u$ and its neighbors $\{y \in$ $Y, y \underset{m}{\sim} u\}$

Energy model. We consider a generic form for the energy of $Y$ :

$$
\begin{equation*}
U(Y)=\sum_{y \in Y} V\left(y \mid \mathcal{N}_{y}^{Y}\right) \tag{B.1}
\end{equation*}
$$

where $V$ is an arbitrary function that maps $y$ and its neighborhood into $\mathbb{R}$.

Markovian relationship. We can show that the PP derived from $U$, is Markovian for any relation $\underset{m}{\sim}$ such that

$$
\begin{equation*}
\forall u \in S \times M,\{y \in S \times M, y \underset{m}{\sim} u\} \supseteq\{y \in S \times M, \exists \tilde{y} \in S \times M, y \underset{i}{\sim} \tilde{y} \underset{i}{\sim} u\} \tag{B.2}
\end{equation*}
$$

Then the relation $\underset{i}{{\underset{i}{2}}^{2}}$ (second degree neighbors for $\underset{i}{\sim}$ defined above), satisfies the Markovianity condition for this PP.

Perturbations in a Markovian PP. We try to find the minimum distance between two perturbations $Y \rightarrow Y^{\prime}$ and $Y \rightarrow Y^{\prime \prime}$, so that acceptance rates (or Green ratio) for both moves are independent of each other.

We first will consider two births $Y^{\prime}=Y \cup\left\{y_{1}\right\}$ and $Y^{\prime \prime}=Y \cup\left\{y_{2}\right\}$. As acceptance ratio $r\left(Y \rightarrow Y^{\prime}\right)$ is function of $\exp \left(-\frac{U\left(Y^{\prime}\right)-U(Y)}{T}\right)=\frac{h\left(Y^{\prime}\right)}{h(Y)}$, it only depends on $y_{1}$ and its neighborhood according to relation $\underset{i}{\sim_{i}^{2}}$. Thus, for $d\left(y_{1}, y_{2}\right)>2 d_{\max }$ we have independence of $r\left(Y \rightarrow Y^{\prime}\right)$ and $r\left(Y \rightarrow Y^{\prime \prime}\right)$.

The demonstration is similar for a death move. A transform move $\left(Y^{\prime}=\right.$ $Y \backslash\left\{y_{1}\right\} \cup\left\{y_{1}^{\prime}\right\}$, with $y_{1} \in Y$, similarly for $Y^{\prime \prime}$ ) can be split into successive death and birth moves; then the acceptance ratio is function of the neighborhood of $y_{1}$ and $y_{1}^{\prime}$ for relation ${\underset{i}{i}}^{2}$. Under the condition $d\left(y_{1}, y_{1}^{\prime}\right) \leq \delta_{\max }$, we need $d\left(y_{1}, y_{2}\right)>2 d_{\max }+2 \delta_{\max }$ to maintain independence.

Proof of Equation B.2. We look for the minimal subset of $Y$ needed to compute $h(Y \cup\{u\}) / h(Y)=\exp (U(Y)-U(Y \cup\{u\})-)$. Unraveling, the energy difference $\Delta U=U(Y \cup\{u\})-U(Y)$, we get:

$$
\begin{equation*}
\Delta U=V\left(u \mid \mathcal{N}_{u}^{Y \cup\{u\}}\right)+\sum_{\substack{y \in Y \\ y \in \mathcal{N}_{u}^{Y}}}\left(V\left(y \mid \mathcal{N}_{y}^{Y \cup\{u\}}\right)-V\left(y \mid \mathcal{N}_{y}^{Y}\right)\right) \tag{B.3}
\end{equation*}
$$

Thus, $h(Y \cup\{u\}) / h(Y)$ is function of $u,\left\{y \in Y \mid y \in \mathcal{N}_{u}^{Y}\right\}$ and $\left\{y^{\prime} \in Y \mid \exists y \in\right.$ $\left.\mathcal{N}_{u}^{Y}, y^{\prime} \in \mathcal{N}_{y}^{Y}\right\}$. Those are all encompassed in the set $\{y \in S \times M \mid \exists \tilde{y} \in S \times$ $M, y \underset{i}{\sim} \tilde{y} \underset{i}{\sim} u\}$.

## Appendix B.2. Computational shortcuts

In sampling Algorithm 2 we need to compute $\Delta U\left(Y \rightarrow Y^{\prime}\right)$ for a proposed move from $Y$ to $Y^{\prime}$ in cell $c$. This computation is performed on multiple cells
at once. To reduce computational cost we show the equality bellow, where $\bar{c}$ is the subset of $S$ composed of $c$ and its 8 neighbors.

$$
\begin{equation*}
\Delta U\left(Y \rightarrow Y^{\prime}\right)=\Delta U\left(C_{\bar{c}}(Y) \rightarrow C_{\bar{c}}\left(Y^{\prime}\right)\right) \tag{B.4}
\end{equation*}
$$

Proof. The proof relies on the partition of $Y$ into subsets $P_{0}, \ldots, P_{3}$, and $Y^{\prime}$ into $P_{0}^{\prime}, \ldots, P_{3}^{\prime}$

|  |  | $P_{3}$ |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | $\begin{aligned} & y_{8} \\ & y_{y_{2}} \\ & y_{2} \end{aligned}$ | $\begin{gathered} P_{2} \\ -P_{1} \\ \hline \end{gathered}$ |  | $P_{0}=C_{c}(Y)$ |
| $y_{9}$ | ! | $P_{0_{0}}$ |  | $\begin{aligned} & P_{1}=\left\{y \in Y \mid \exists \tilde{y} \in c \times M, d(y, \tilde{y}) \leq d_{\max }\right\} \backslash P_{0} \\ & P_{2}=C_{\bar{c}}(Y) \backslash P_{1} \backslash P_{0} \end{aligned}$ |
|  | ${ }^{9} 6$ | $y_{4}$ |  | $P_{3}=Y \backslash C_{\bar{c}}\left(Y_{t}\right)$ |
|  |  |  |  |  |

Considering a birth or death kernel in $c\left(P_{0}\right)$, we have $P_{1}=P_{1}^{\prime}, P_{2}=P_{2}^{\prime}$, $P_{3}=P_{3}^{\prime}$.

By construction, with $|c|=2 d_{\max }+2 \delta_{\max }$, elements in $P_{0}$ can interact with points in $P_{0}$ and $P_{1}$. Similarly, points in $P_{1}$ only interact with points in $P_{0}, P_{1}, P_{2}$ and so on for $P_{2}$ and $P_{3}$.

We can split $\Delta U\left(Y \rightarrow Y^{\prime}\right)=\sum_{y \in Y} V\left(y \mid \mathcal{N}_{y}^{Y}\right)-\sum_{y \in Y^{\prime}} V\left(y \mid \mathcal{N}_{y}^{Y^{\prime}}\right)$ into energy differences in each partition $\sum_{y \in P_{k}} V\left(y \mid \mathcal{N}_{y}^{Y}\right)-\sum_{y \in P_{k}^{\prime}} V\left(y \mid \mathcal{N}_{y}^{Y^{\prime}}\right), k=0, \ldots, 3$. The differences cancel out on $P_{3}, P_{3}^{\prime}$ (since $P_{3}=P_{3}^{\prime}$ and $P_{2}=P_{2}^{\prime}$ ), and on $P_{2}, P_{2}^{\prime}$ (since $P_{3}=P_{3}^{\prime}, P_{2}=P_{2}^{\prime}$ and $P_{1}=P_{1}^{\prime}$ ). Energy difference $\Delta U$ is then a function of points in $P_{0}, P_{0}^{\prime}, P_{1}, P_{1}^{\prime}$ with their neighborhood in $P_{0}, P_{0}^{\prime}, \ldots, P_{2}, P_{2}^{\prime}$

The difference $\Delta U\left(C_{\bar{c}}(Y) \rightarrow C_{\bar{c}}\left(Y^{\prime}\right)\right)$, corresponds to the above $\Delta U(Y \rightarrow$ $\left.Y^{\prime}\right)$, setting $P_{3}=P_{3}^{\prime}=\emptyset$. As shown above such a change does not alter the result, as no dependency on $P_{3}, P_{3}^{\prime}$ remains.

For a translation kernel such that $Y^{\prime}=Y \backslash\{y\} \cup\left\{y^{\prime}\right\}$, with $y \in C_{c}(Y)$ and
$d\left(y, y^{\prime}\right)<\delta_{\text {max }}$, we redefine

$$
\begin{align*}
& P_{0}=\left\{y \in Y \mid \exists \tilde{y} \in c \times M, d(y, \tilde{y}) \leq \delta_{\max }\right\}  \tag{B.6}\\
& P_{1}=\left\{y \in Y \mid \exists \tilde{y} \in c \times M, d(y, \tilde{y}) \leq d_{\max }+\delta_{\max }\right\} \backslash P_{0} \tag{B.7}
\end{align*}
$$

and similarly for $P_{0}^{\prime}, P_{1}^{\prime}$. Then we have $y^{\prime} \in P_{0}^{\prime}$, this ensures $P_{1}=P_{1}^{\prime}, P_{2}=P_{2}^{\prime}$, $P_{3}=P_{3}^{\prime}$. The rest of the proof for birth and death kernels can then apply.

## References

[1] F. Lafarge, G. Gimel'farb, X. Descombes, Geometric feature extraction by a multimarked point process, IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (9) (2010) 1597-1609. doi:10.1109/TPAMI. 2009. 152.

