Rectangular Bounding Process: Supplementary Material

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1 Calculation of the expected side length in Proposition 1

The expected length of the interval in $u_k^{(d)}$ with value "1" is (some super/subscripts are omitted in this proof for conciseness):

$$
\mathbb{E}(l) \stackrel{\text{(1)}}{=} P(s=0)\mathbb{E}(l|s=0) + \int_0^L p(s)\mathbb{E}(l|s)ds \qquad (1)
$$
\n
$$
= \frac{1}{1+\lambda L} \left[\int_0^L l\lambda e^{-\lambda l} dl + Le^{-\lambda L} \right] + \frac{\lambda}{1+\lambda L} \cdot \int_0^L \left[\int_0^{L-s} l\lambda e^{-\lambda l} dl + (L-s)e^{-\lambda(L-s)} \right] ds
$$
\n
$$
= \frac{1}{1+\lambda L} \left[\lambda \cdot \left(-\frac{1}{\lambda^2} - \frac{l}{\lambda} \right) e^{-\lambda l} \Big|_0^L + Le^{-\lambda L} \right]
$$
\n
$$
+ \frac{\lambda}{1+\lambda L} \cdot \int_0^L \left[\lambda \cdot \left(-\frac{1}{\lambda^2} - \frac{l}{\lambda} \right) e^{-\lambda l} \Big|_0^{L-s} + (L-s)e^{-\lambda(L-s)} \right] ds
$$
\n
$$
= \frac{L}{1+\lambda L}
$$
\n(1)

where the first term after $\stackrel{(1)}{=}$ refers to the expected length of the interval when starting at 0 and the second term refers to the expected length when starting from a point larger than 0. We need to use the equality $\frac{d[(-\frac{1}{\lambda^2} - \frac{x}{\lambda})e^{-\lambda x}]}{dx} = xe^{-\lambda x}$ in the above derivation.

2 Proof for Proposition 2 (Coverage Probability)

For any data point $x \in X$ (including the boundaries of X), the probability of $x^{(d)}$ falling in the interval of $[s_k^{(d)}]$ $k^{(d)}, s_k^{(d)} + l_k^{(d)}$ $\binom{d}{k}$ on $u_k^{(d)}$ $\kappa_k^{(d)}$ is a constant $\frac{1}{1+\lambda L^{(d)}}$ (some super/subscripts are omitted in this proof for conciseness).

If $x^{(d)}$ locates on the initial boundary, $u^{(d)}(0) = 1$ *i.f.f.* $s^{(d)} = 0$, which is

$$
P(u^{(d)}(0) = 1) = \frac{1}{1 + \lambda L}
$$
 (2)

32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada.

If $x^{(d)} > 0$, we have the corresponding probability as

$$
P(u^{(d)}(x) = 1) = P(s = 0)P(l > x) + \int_0^x p(s)P(l > x - s)ds
$$
\n
$$
= \frac{1}{1 + \lambda L}e^{-\lambda x} + \frac{\lambda e^{-\lambda x}}{1 + \lambda L} \cdot \int_0^x e^{\lambda s}ds = \frac{e^{-\lambda x}}{1 + \lambda L} \left(1 + e^{\lambda s}|_0^x\right) = \frac{1}{1 + \lambda L}
$$
\n(3)

3 Proof for Proposition 3 (Self-Consistency)

Proposition 3.1: The number distribution of bounding boxes is self-consistent

Proof. According to the definition of Poisson process, the bounding boxes sampled from $RBP(Y, \tau, \lambda)$ (or RBP (X, τ, λ)) follow a homogeneous Poisson process with intensity $\prod_d(1 + \lambda L_Y^{(d)})$ (or $\prod_d(1 +$ (d) KBr (X, τ, λ) follow a nonlogeneous Following process with intensity $\prod_d (1 + \lambda L_Y^d)$ (or $\prod_d (1 + \lambda L_Y^d)$). Given the same budget τ , the result holds if we can prove the following equality of the two Poisson process intensities

$$
\prod_{d} (1 + \lambda L_Y^{(d)}) \cdot P\left(\pi_{Y,X}(\square^Y) \neq \emptyset\right) = \prod_{d} (1 + \lambda L_X^{(d)}) \tag{4}
$$

Due to the independence of dimensions, $P(\pi_{Y,X}(\Box^Y) \neq \emptyset)$ can be rewritten as

$$
P\left(\pi_{Y,X}(\square^Y)\neq\emptyset\right) = \prod_d P(|\pi_{Y,X}(u_Y^{(d)})| > 0)
$$
\n⁽⁵⁾

where we use $\vert \pi_{Y,X}(u^{(d)}_Y) \vert$ $|V(Y| \ge 0)$ to denote the case that the step function $u_Y^{(d)}$ would take value "1" in an interval of the d -th dimension of domain X .

W.l.o.g, we assume that the two domains, X and Y , have the same shape apart from the d' -th dimension where the length of dimension $L_Y^{(d')}$ $y^{(a)}$ in Y is larger than that of in X.

There are three cases to consider: (1) X and Y share the terminal boundary in the d' -th dimension; (2) X and Y share the initial boundary in the d' -th dimension; (3) X and Y do not share the boundaries in the d' -th dimension. Proving case (1) and case (2) together would obviously lead to case (3). In either case, by independence of dimensions, we need to prove the following equation.

$$
(1 + \lambda L_Y^{(d')}) \cdot P\left(|\pi_{Y,X}(u_Y^{(d')})| > 0\right) = (1 + \lambda L_X^{(d')})
$$
\n(6)

In case (1) where X and Y share the terminal boundary in the d' th dimension, we have

$$
P\left(|\pi_{Y,X}(u_Y^{(d')})| > 0\right)
$$
\n
$$
\stackrel{(2)}{=} P\left(s_Y^{(d')} \in (L_Y^{(d')} - L_X^{(d')}, L_Y^{(d')})\right) + P\left(s_Y^{(d')} = 0\right)P\left(l_Y^{(d')} > (L_Y^{(d')} - L_X^{(d')})|s_Y^{(d')} = 0\right)
$$
\n
$$
+ \int_{0^+}^{L_Y^{(d')} - L_X^{(d')}} P\left(s_Y^{(d')} \right)P\left(l_Y^{(d')} > L_Y^{(d')} - L_X^{(d')} - s_Y^{(d')}|s_Y^{(d')} \right)ds_Y^{(d')}
$$
\n
$$
= \frac{\lambda L_X^{(d')}}{1 + \lambda L_Y^{(d')}} + \frac{1}{1 + \lambda L_Y^{(d')}} \cdot e^{-\lambda(L_Y^{(d')} - L_X^{(d')} - s_Y^{(d')})}ds_Y^{(d')}
$$
\n
$$
+ \int_{0^+}^{L_Y^{(d')} - L_X^{(d')}} \frac{\lambda}{1 + \lambda L_Y^{(d')}} \cdot e^{-\lambda(L_Y^{(d')} - L_X^{(d')} - s_Y^{(d')})}ds_Y^{(d')}
$$
\n
$$
= \frac{1 + \lambda L_X^{(d')}}{1 + \lambda L_Y^{(d')}}
$$

where the first term after $\stackrel{(2)}{=}$ corresponds to the probability that $s_Y^{(d')}$ $y^{(u)}_Y$ locates directly in the interval of $(L_Y^{(d^\prime)} - L_X^{(d^\prime)}, L_Y^{(d^\prime)}$ $\mathbf{y}^{(d')}$], the second term corresponds to the probability that $\mathbf{s}^{(d')}$ $y^{(a)}_Y$ locates on the initial boundary and has the length larger than $L_Y^{(d')} - L_X^{(d')}$, and the third term corresponds to the probability that $s_Y^{(d')}$ $y_Y^{(d')}$ locates in the interval of $(0, L_Y^{(d')} - L_X^{(d')})$ (excluding the initial boundary) and has the length larger than $L_Y^{(d')} - L_X^{(d')} - s_Y^{(d')}$ $\mathop Y\limits^{\left({a} \right)}$.

In case (2) where X and Y share the initial boundary in the d' th dimension, we have

$$
P\left(|\pi_{Y,X}(u_Y^{(d')})| > 0\right) = \frac{1 + \lambda L_X^{(d')}}{1 + \lambda L_Y^{(d')}}\tag{8}
$$

since $|\pi_{Y,X}(u_Y^{(d')})|$ $|Y^{(d')}_Y| > 0$ requires the condition of $s_Y^{(d')} \in [0, L_X^{(d')}]$ because $s_Y^{(d')} \notin [0, L_X^{(d')}]$ would lead to the result that $\pi_{Y,X}(u_Y^{(d')})$ $\binom{a}{Y} = 0.$

The conclusion can be derived as above.

 \Box

Because of the same Poisson process intensity Eq. [\(4\)](#page-1-0), the following equality also holds

$$
P_{K_{\tau},\{m_{k}\}_{k=1}^{K_{\tau}}}^{Y}\left(\pi_{Y,X}^{-1}\left(K_{\tau}^{X},\{m_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right)\right)=P_{K_{\tau},\{m_{k}\}_{k=1}^{K_{\tau}}}^{X}\left(K_{\tau}^{X},\{m_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right)
$$
(9)

Proposition 3.2: The position distribution of a bounding box is self-consistent

Proof. W.l.o.g, we assume that the two domains, X and Y, have the same shape apart from the d'th dimension where Y has additional space of length L' ($L' > 0$) (the general case follows by induction). For dimensions $d \neq d'$, it is obvious that the law of bounding boxes are consistent under projection because the projection is the identity. Given the same budget τ , The result holds if we can prove the following equality

$$
P_u^Y\left(\pi_{Y,X}^{-1}(u_X^{(d')}) \mid |\pi_{Y,X}(u_Y^{(d')})| > 0\right) = P_u^X(u_X^{(d')})\tag{10}
$$

There are two cases to consider: (1) X and Y share the initial boundary in the d' th dimension; (2) X and Y share the terminal boundary in the d' th dimension. In each case, there are two cases (denoted as A & B in the following) regarding whether the terminal/initial (for Case 1/2, respectively) position locates on the boundary of X. In total we have four cases to discuss as follows.

In case (1) where X and Y share the initial boundary, according to Eq. [\(8\)](#page-2-0), we have $P\left(|\pi_{Y,X}(u_Y^{(d)})$ $\left| \begin{array}{c} (d) \\ Y \end{array} \right| > 0$ = $\frac{1 + \lambda L_X^{(d')}}{1 + \lambda L_Y^{(d')}}$.

For convenience of notation, we let $\theta_{\dagger} = P_s^Y(s_Y^{(d')})$ $\mathcal{L}_{Y}^{(d')} \mid s_Y^{(d')} \in X$), specifically $\theta_{\dagger} = \frac{1}{1 + \lambda L_X^{(d')}}$ if $s_Y^{(d')} = 0; \theta_\dagger = \frac{\lambda}{1 + \lambda L_X^{(d')}} \text{ if } s_Y^{(d')} > 0.$ [Case 1.A] For $0 < s_X^{(d')} + l_X^{(d')} < L_X^{(d')} < L_Y^{(d')}$ $Y^{(a)}$,

$$
P_u^Y\left(\pi_{Y,X}^{-1}(u_X^{(d')}) \mid |\pi_{Y,X}(u_Y^{(d')})| > 0\right) = \theta_\dagger \cdot \lambda e^{-\lambda l_X^{(d')}} = P_u^X(u_X^{(d')}).
$$
 (11)

[Case 1.B] For $0 < s_X^{(d')} + l_X^{(d')} = L_X^{(d')} < L_Y^{(d')}$ $Y^{\left(u\right)}$

$$
P_u^Y \left(\pi_{Y,X}^{-1}(u_X^{(d')}) \mid |\pi_{Y,X}(u_Y^{(d')})| > 0 \right)
$$

= $P(s_Y^{(d')}) (P(l_Y^{(d')} > (L_X^{(d')}-s_Y^{(d')}))) = \theta_\dagger e^{-\lambda (L_X^{(d')}-s_Y^{(d')})} = P_u^X(u_X^{(d')})$ (12)

In case (2) where X and Y share the terminal boundary, according to Eq. [\(7\)](#page-1-1), we have $P\left(|\pi_{Y,X}(u_Y^{(d)})$ $\left| \begin{array}{c} (d) \\ Y \end{array} \right| > 0$ = $\frac{1 + \lambda L_X^{(d')}}{1 + \lambda L_Y^{(d')}}$. Y

[Case 2.A] For $\pi_{Y,X}(s_Y^{(d')})$ $y(Y(Y|Y) = 0$, we have $s_X^{(d')} = 0$. What is more, we have

$$
P\left(\pi_{Y,X}(s_Y^{(d')})=0\right)
$$
\n
$$
=P(s_Y^{(d')}=0)P\left(l_Y^{(d')} > (L_Y^{(d')} - L_X^{(d')})|s_Y^{(d')}=0\right)
$$
\n
$$
+\int_{0^+}^{L_Y^{(d')} - L_X^{(d')}} P(s^{(d')})P(l > (L_Y^{(d')} - L_X^{(d')} - s^{(d')})|s^{(d')})ds^{(d')}
$$
\n
$$
=\frac{1}{1+\lambda L_Y^{(d')}}
$$

Thus we can get

$$
P_u^Y\left(\pi_{Y,X}^{-1}(u_X^{(d')}) \mid |\pi_{Y,X}(u_Y^{(d')})| > 0\right)
$$

= $P(\pi_{Y,X}(S_Y^{(d')}) = 0)P(l_X^{(d')})/P(|\pi_{Y,X}(u_Y^{(d')}| > 0)$
= $\frac{1}{1 + L_X^{(d')}} \cdot \theta_{\ddagger} = P_u^X(u_X^{(d')}),$ (14)

where $\theta_{\ddagger} = e^{-\lambda l_X^{(d')}}$ if $\pi_{Y,X}(s_Y^{(d')}$ $\left(\begin{matrix} (d') \\ Y \end{matrix} \right) + l_X^{(d')} = L_X^{(d')} ; \theta_{\ddagger} = \lambda e^{-\lambda l_X^{(d')}}$ if $\pi_{Y,X}(s_Y^{(d')})$ $y^{(d')}$ + $l_X^{(d')}$ < $L_X^{(d')}$. [Case 2.B] For $\pi_{Y,X}(s_Y^{(d')})$ $\binom{(d')}{Y} > 0$, we have $s_X^{(d')} > 0$,

$$
P_u^Y\left(\pi_{Y,X}^{-1}(u_X^{(d')}) \mid |\pi_{Y,X}(u_Y^{(d')})| > 0\right)
$$

= $P(\pi_{Y,X}(S_Y^{(d')}) = s)P(l_X^{(d')})/P(|\pi_{Y,X}(u_Y^{(d')}| > 0)$
= $\frac{\lambda}{1 + L_X^{(d')}} \cdot \theta_{\ddagger} = P_u^X(u_X^{(d')}),$ (15)

Consider all D dimensions, for each case, we have $P_{\Box}^Y \left(\pi_{Y,X}^{-1}(\Box^X) \mid \pi_{Y,X}(\Box^Y) \neq \emptyset \right) = P_{\Box}^X (\Box^X)$.

Proposition 3.3: RBP is self-consistent

$$
P_{\boxplus}^{Y}(\pi_{Y,X}^{-1}(\boxplus_X)) = P_{\boxplus}^{Y}\left(\pi_{Y,X}^{-1}\left(K_{\tau}^{X}, \{m_{k}^{X}, \Box_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right)\right)
$$
\n
$$
= P_{K_{\tau},\{m_{k}\}_{k}}^{Y}\left(\pi_{Y,X}^{-1}\left(K_{\tau}^{X}, \{m_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right)\right) \cdot P_{\Box}^{Y}\left(\pi_{Y,X}^{-1}\left(\{\Box_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}|K_{\tau}^{X}, \{m_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right)\right) (16)
$$
\n
$$
P_{\Lambda}^{Y}\left(\begin{array}{cc} -1 \left(\begin{array}{cc} rX & (r,X)K_{\tau}^{X} \\ rX & (r,X)^{K_{\tau}^{X}} \end{array}\right) & P_{\Lambda}^{Y}\left(\begin{array}{cc} -1 \left(\begin{array}{cc} rX & K_{\tau}^{X} \\ rX & (r,X)^{K_{\tau}^{X}} \end{array}\right) & P_{\Lambda}^{Y} \end{array}\right) \right) (17)
$$

$$
= P_{K_{\tau},\{m_k\}_k}^{Y} \left(\pi_{Y,X}^{-1} \left(K_{\tau}^{X}, \{m_k^{X}\}_{k=1}^{K_{\tau}^{X}} \right) \right) \cdot P_{\Box}^{Y} \left(\pi_{Y,X}^{-1} \left(\{ \Box_{k}^{X} \}_{k=1}^{K_{\tau}^{X}} | K_{\tau}^{X} \right) \right) \tag{17}
$$

$$
= P_{K_{\tau},\{m_k\}_k}^{Y} \left(\pi_{Y,X}^{-1} \left(K_{\tau}^{X}, \{m_k^{X}\}_{k=1}^{K_{\tau}^{X}} \right) \right) \cdot \prod_{k=1}^{K_{\tau}^{X}} P_{\Box}^{Y} \left(\pi_{Y,X}^{-1} \left(\Box_{k}^{X} \right) \right) \tag{18}
$$

$$
= P_{K_{\tau},\{m_k\}_k}^X \left(K_{\tau}^X, \{m_k^X\}_{k=1}^{K_{\tau}^X} \right) \cdot \prod_{k=1}^{K_{\tau}^X} P_{\square}^Y \left(\pi_{Y,X}^{-1} \left(\square_k^X \right) \right) \tag{19}
$$

$$
= P_{K_{\tau},\{m_k\}_k}^X \left(K_{\tau}^X, \{m_k^X\}_{k=1}^{K_{\tau}^X} \right) \cdot \prod_{k=1}^{K_{\tau}^X} P_{\square}^X \left(\square_k^X \right)
$$
\n
$$
= Y_{K_{\tau},\{m_k\}_k} \left(X_{\tau}^X, \{m_k^X\}_{k=1}^{K_{\tau}^X} \right) \quad -Y_{K_{\tau},\{m_k\}_k} \tag{20}
$$

$$
= P_{\boxplus}^{X}\left(K_{\tau}^{X}, \{m_{k}^{X}, \Box_{k}^{X}\}_{k=1}^{K_{\tau}^{X}}\right) = P_{\boxplus}^{X}(\boxplus_{X}).
$$

We can obtain Eq. [\(17\)](#page-3-0) from Eq. [\(16\)](#page-3-0) because

$$
P\left(\{m_k,\Box_k\}_{k=1}^{K_\tau}|K_\tau\right) = P\left(\{m_k\}_{k=1}^{K_\tau}|K_\tau\right) \cdot P\left(\{\Box_k\}_{k=1}^{K_\tau}|K_\tau\right)
$$

which indicates

$$
P\left(\{\square_k\}_{k=1}^{K_{\tau}}|K_{\tau},\{m_k\}_{k=1}^{K_{\tau}}\right) = P\left(\{\square_k\}_{k=1}^{K_{\tau}}|K_{\tau}\right)
$$

We can obtain Eq. [\(18\)](#page-3-0) from Eq. [\(17\)](#page-3-0) because of independence of bounding boxes. Eq. [\(19\)](#page-3-0) is derived from Eq. [\(18\)](#page-3-0) by applying Proposition 3.1 while Eq. [\(20\)](#page-3-0) is derived from Eq. [\(19\)](#page-3-0) by applying Proposition 3.2.