

We thank the reviewers for their feedback. We appreciate that further experimentation on human activity exploration is considered as part of future work and beyond the scope of this paper. In this letter, we discuss and address other concerns brought up by Reviewer #2 in more details below.

**Q1. The paper should expand the discussion about the limitations of the current experiments and sensitivity to the parameters.**

We thank the reviewer for the request. A clarification to the parameter sensitivity regarding the use of Equation 19 for normalisation has been included in the paper Section 8 - Exploring for Human Activities. Particularly the following explanations have been added to the fourth paragraph of ‘Exploration Evaluation’ subsection:

- “During the first few days of each 15 day phase the robot primarily explores since each model initially has a highly uncertain estimate of  $\lambda$ . Every three days, the sensor model for both the POPP and the POPP-Beta is updated to represent more accurate true positive and false positive rates. Note that the first 3 days of each exploration for the POPP and the POPP-Beta, the sensor model is set to follow a perfect sensor model (i.e. setting the true positive rate to 1.0 and false positive rate to 0.0) with the hyperparameters for the POPP-Beta set to follow uniform distribution.”
- “To create the baseline total for each model we take the true counts experienced for its first three days then multiply these by five to give an expected total over 15 days (the number of days of data available to every model). Three days are chosen to align with the 3-day periodical update of the sensor model for the POPP and the POPP-Beta and create a uniform baseline across different explorations since both the POPP and the POPP-Beta explorations should act similarly to the FOPP exploration in the first 3 days. This is the denominator in Eqn. 19, where  $s(n)$  is the (true) number of people observed on day  $n$ . This is used to divide the cumulative number of observations up to the current day”

We also add ‘Exploration Limitation’ subsection at the end of Section 8 - Exploring for Human Activities. The following paragraphs have been added to this subsection:

There are some limitations in our robot exploration experiment as a result of carrying them out on a real robot in an uncontrolled setting. A major limitation is how we stretched our assumption about (approximately) constant population dynamics throughout the 69-day exploration. It is clear that the population in a university building fluctuates within a single academic semester (e.g. students tend to be around in the middle of the semester—Figure 20b—than during the last week of the semester—Figure 20c). We mitigate this by normalising the raw counts following Equation 19. The normalisation is effective when the differences in population dynamics are within reasonable range.

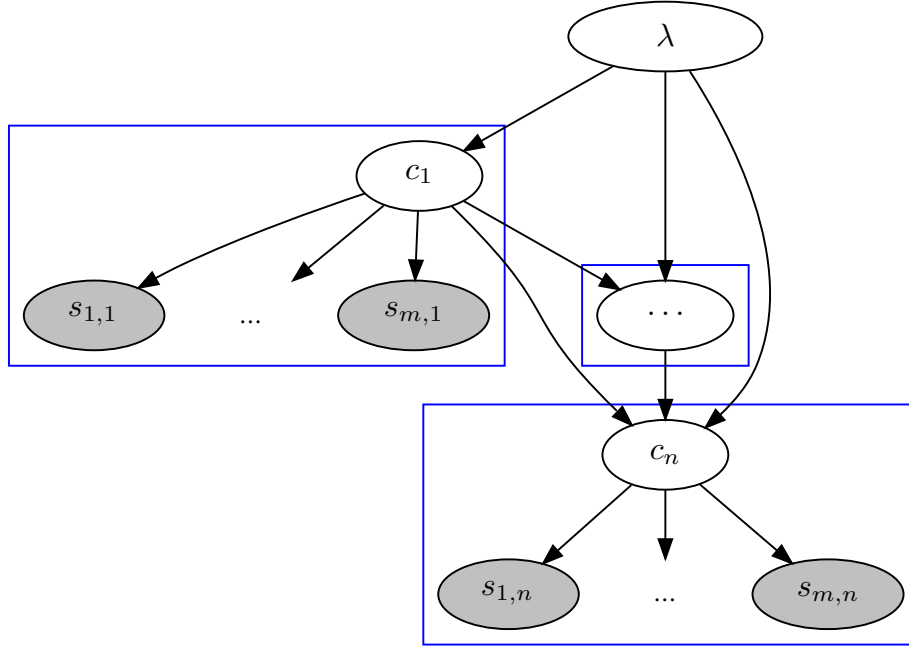


Figure 1: Graphically correct representation of the partially observable Poisson process. Observable random variables are represented in shaded grey.

Due to the impact of occasional hardware and sensor malfunctions, plus an external time limit for running the experiments (winter break was approaching), we further stretched our assumption by assuming the population dynamics during weekends were similar to weekdays. However, upon inspection, there were far fewer students on the weekends for the robot to observe than on the weekdays (see Figure 20c). The mismatch between our assumption and the experimental setting mostly affected exploration following the POPP-Beta policy, which was tested last. The inclusion of weekends creates a big deviation in the population dynamics that renders the normalisation ineffective. Although the POPP-Beta policy was affected by a large variation in population dynamics, the policy was still able to improve the number of people observed over time. This can be shown by removing the weekends from calculations in Equation 19, resulting 1.48 at day 15 for the POPP-Beta policy. An ideal experiment would be to run robot explorations with multiple identical robots employing different exploration policies at the same time.

**Q2. The paper should also confirm the validity of Eq. 4, as compared with the equation provided by Reviewer #2.**

We thank Reviewer #2 for their input regarding Eq. 4. We realised that Fig. 3 in our paper showed an incorrect graphical representation of POPP. The

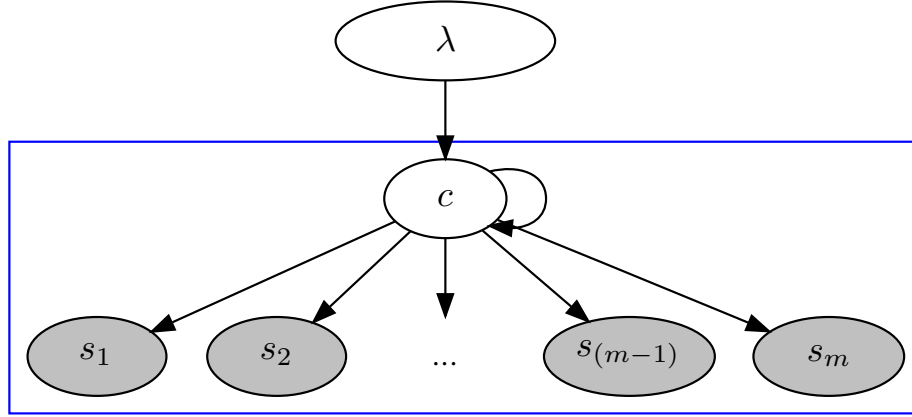


Figure 2: Graphical representation of the partially observable Poisson process. Observable random variables are represented in shaded grey.

initial Fig. 3 showed the graphical representation of the POPP during the  $i$ -th observation for any  $i \in \{1, \dots, n\}$ . The correct representation can be seen in Fig. 1 (this document) where the (latent) true count  $c_i$  has a dependency on all previous true counts  $\{c_1, \dots, c_{i-1}\}$ . This dependency relation can be seen in Eq. 7<sup>1</sup> in our paper with the use of  $P(c_i \mid \mathbf{c}_{-1})$  in that equation. Note that, in FOPP, the true count  $c_i$  is independently sampled from the true distribution (parameterised by  $\lambda'$ ). However, in POPP (and all its derivation),  $c_i$  is unobservable and an estimate of the distribution of  $c_i$  must be performed via the (observable) sensed count  $s_i$ . The sensed count  $s_i$  indirectly depends on its previous true count  $\mathbf{c}_{i-1}$ , as shown in Eq. 7. Based on Fig. 1, the inference

<sup>1</sup>the equation had notation errors which have now been fixed.

can be written as:

$$\begin{aligned}
P(\lambda | \mathbf{s}) &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n | \lambda) \dots P(c_1 | \lambda) P(\lambda) \prod_{j=1}^m P(s_{j,n} | c_n) P(c_n | c_{n-1}, \dots, c_1) \dots \\
&\quad \dots \prod_{j=1}^m P(s_{j,1} | c_1) P(c_1) \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n, \dots, c_1 | \lambda) P(\lambda) \prod_{j=1}^m P(s_{j,n} | c_n) P(c_n | c_{n-1}, \dots, c_1) \dots \\
&\quad \dots \prod_{j=1}^m P(s_{j,1} | c_1) P(c_1) \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) \prod_{j=1}^m P(s_{j,n} | c_n) P(c_n | c_{n-1}, \dots, c_1) \dots \\
&\quad \dots \prod_{j=1}^m P(s_{j,1} | c_1) P(c_1) \tag{Eq. 3 on the paper} \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) P(\mathbf{s}_n | c_n) P(c_n | c_{n-1}, \dots, c_1) \dots \\
&\quad \dots P(\mathbf{s}_1 | c_1) P(c_1) \tag{Eq. 6 on the paper} \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) \prod_{i=1}^n P(\mathbf{s}_i | c_i) P(c_i | c_{i-1}, \dots, c_1) \tag{Eq. 7 on the paper} \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) P(\mathbf{s}_1, \dots, \mathbf{s}_n | \mathbf{c}) P(\mathbf{c}) \tag{Eq. 7 on the paper} \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) P(\mathbf{c} | \mathbf{s}) \tag{1}
\end{aligned}$$

Equation proposed by Reviewer #2 is obtained by relaxing the dependency among chronological true counts (i.e. removing a direct line from  $c_i$  to  $c_j$  with  $i < j$ ). Assuming Fig. 1 with the relaxed assumption, the inference can be written as:

$$\begin{aligned}
P(\lambda | \mathbf{s}) &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n | \lambda) \dots P(c_1 | \lambda) P(\lambda) \prod_{j=1}^m P(s_{j,n} | c_n) \dots \prod_{j=1}^m P(s_{j,1} | c_1) \\
&= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n | \lambda) \dots P(c_1 | \lambda) P(\lambda) P(\mathbf{s}_n | c_n) \dots P(\mathbf{s}_1 | c_1) \tag{Eq.6 on the paper} \\
&= P(\lambda) \sum_{c_n=0}^{\infty} P(c_n | \lambda) P(\mathbf{s}_n | c_n) \dots \sum_{c_1=0}^{\infty} P(c_1 | \lambda) P(\mathbf{s}_1 | c_1) \tag{Rearrangement} \\
&= P(\lambda) \prod_{i=1}^n \sum_{c_i=0}^{\infty} P(c_i | \lambda) P(\mathbf{s}_i | c_i) \tag{2}
\end{aligned}$$

Upon further inspection, we agree with Reviewer #2 that the proposed equation

above is an alternative to our proposed equation with a more relaxed condition which may result a  $\lambda$  estimate that has wider distribution. In addition, our approach is based on the assumption of using conjugate prior of Poisson distribution to have a closed form of the posterior distribution for both  $\lambda$  and true count  $c_i$  (see Eq. 3 and Eq. 10 in our paper). With this restriction, we can't see a way to avoid the nested summation as shown in the equation below, adapted to Reviewer #2 equation:

$$\begin{aligned}
 P(\lambda | \mathbf{s}) &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n | \lambda) \dots P(c_1 | \lambda) P(\lambda) \prod_{j=1}^m P(s_{j,n} | c_n) \dots \prod_{j=1}^m P(s_{j,1} | c_1) \\
 &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n | \lambda) \dots P(c_1 | \lambda) P(\lambda) P(\mathbf{s}_n | c_n) \dots P(\mathbf{s}_1 | c_1) \quad (\text{Eq.6 on the paper}) \\
 &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(c_n \dots c_1 | \lambda) P(\lambda) P(\mathbf{s}_n | c_n) \dots P(\mathbf{s}_1 | c_1) \quad (\text{Rearrangement}) \\
 &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) P(\mathbf{s}_n | c_n) \dots P(\mathbf{s}_1 | c_1) \quad (\text{Eq. 3 on the paper}) \\
 &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} P(\lambda | \mathbf{c}) \prod_{i=1}^n P(\mathbf{s}_i | c_i) \quad (\text{Independent}) \\
 &= \sum_{c_n=0}^{\infty} \dots \sum_{c_1=0}^{\infty} \text{Gam}\left(\lambda \mid \alpha + \sum_{i=1}^n c_i, n + \beta\right) \prod_{i=1}^n P(\mathbf{s}_i | c_i) \quad (\text{Eq. 5 on the paper}) \\
 &\quad (3)
 \end{aligned}$$

Without the conjugate prior assumption, both a gamma filter and a switching filter (see  $\lambda$  Estimators subsection) can't be used, and we may end up with a slow histogram filter to approximate  $\lambda$ . The simpler graphical representation, Fig. 2 will be used in our paper instead of Fig. 1. A correction to all other graphical figures will be made accordingly.