IMPROVING TRANSIENT IDENTIFICATION WITH SWIFT-XRT

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1. Introduction

X-ray astronomy probes extreme processes—from black hole accretion to relativistic outflows. Swift-XRT's Living Swift-XRT Point Source Catalogue (LSXPS) offers near-immediate transient detections (Evans et al.), but low-count events are challenging. Measurement errors and the abundance of faint sources lead to Eddington bias, artificially boosting their apparent brightness and resulting in false transient identifications—especially for events with fewer than ~30 counts (Evans1 et al.).

Therefore, sources with ‹ 30 counts and which are ‹ 3σ above the historical upper limit are classified as "low significance" (Evans et al.). Such events are ~20 times more common than the "confirmed" transients. Our simulation-based approach refines transient classification by modeling this bias, thereby improving LSXPS's reliability for time-domain and multi-messenger astrophysics.

We focus on the key question: Given a measured peak rate, what is the probability that this source truly exceeds its historical flux limit?

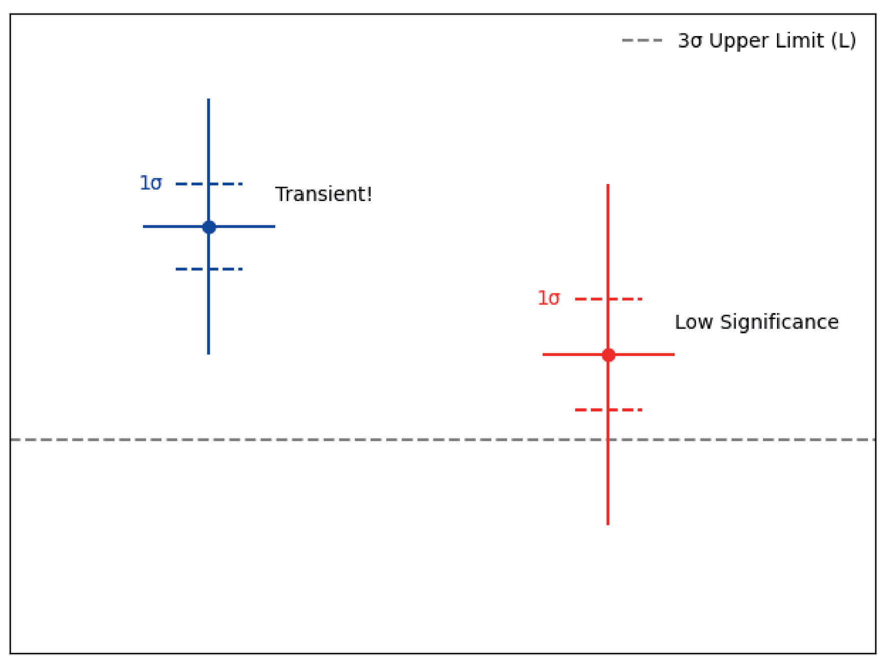

Fig. 1: Blue (left) is 3σ above the historical upper limit and is confirmed as a transient while Red (right) is classed "low significance"

2. Simulations

Our overall approach is shown in Fig 2.

- For each simulation, we generate synthetic source photons based on the true source intensity (T), add these to a real dataset and process the resultant files with the LSXPS code. This produces a measured intensity, M.
- We repeated this 30,000 times for each T value, the distribution of M values obtained gives us P(M|T), and did the simulations for 85 T values.

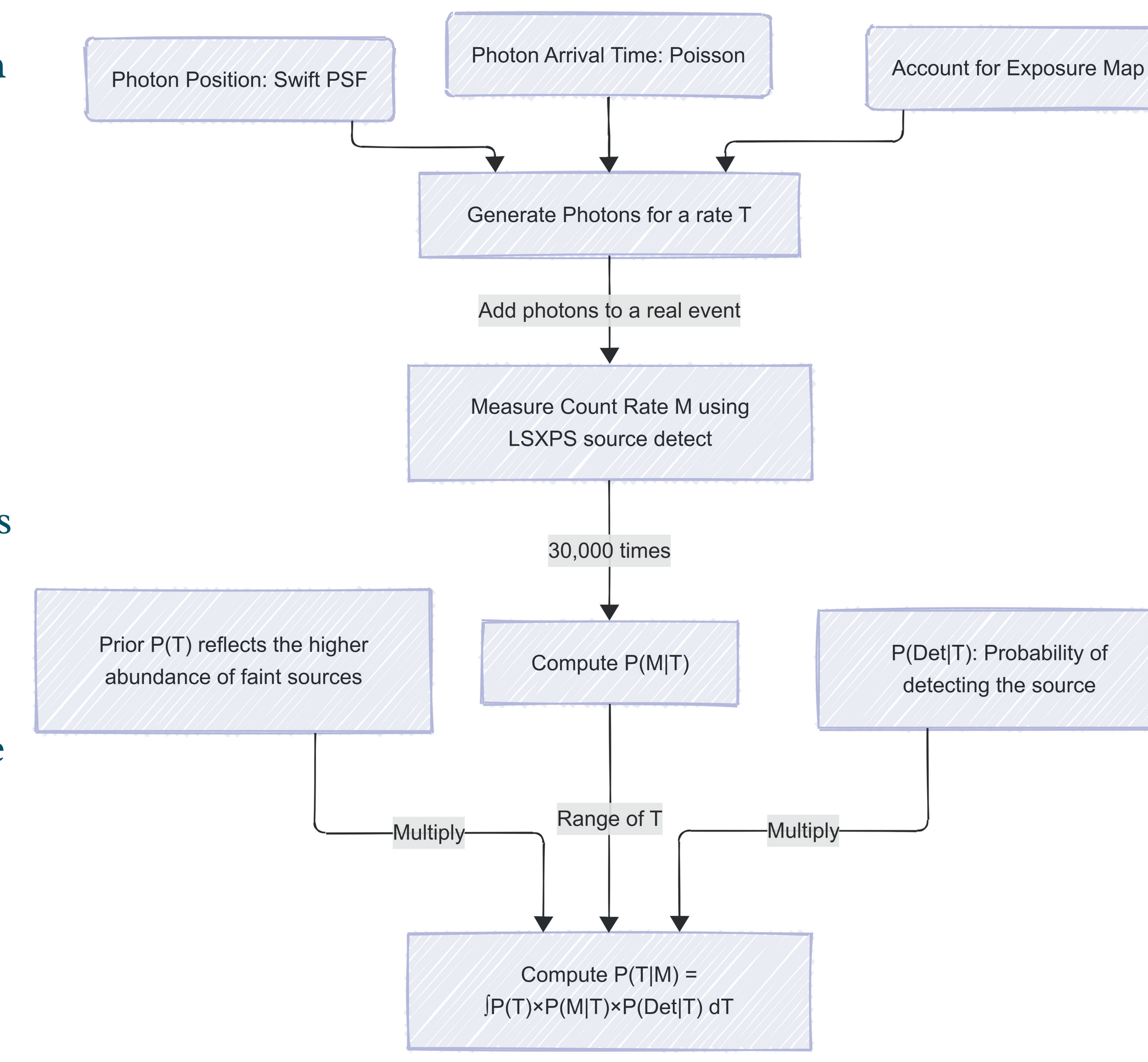

Fig. 2: Flowchart of the overall simulation and probability determination process

3. Determining the Probability

- Given a transient candidate with measured intensity M, we can use the simulation results, along with Bayes' theorem, to determine the probability distribution of the true source intensity, P (T|M).
- For each simulated T, we find the probability of measuring M counts from our simulations (Fig 3, left).
- We apply two priors: one for the detection probability by LSXPS and one reflecting the relative occurrence of sources based on the log N–log S relation (Mateos et al.; see Fig 3, center).
- We renormalize to obtain the final distribution (Fig 3, right) and integrate it above the historical upper limit L to yield the probability that the candidate is indeed transient.

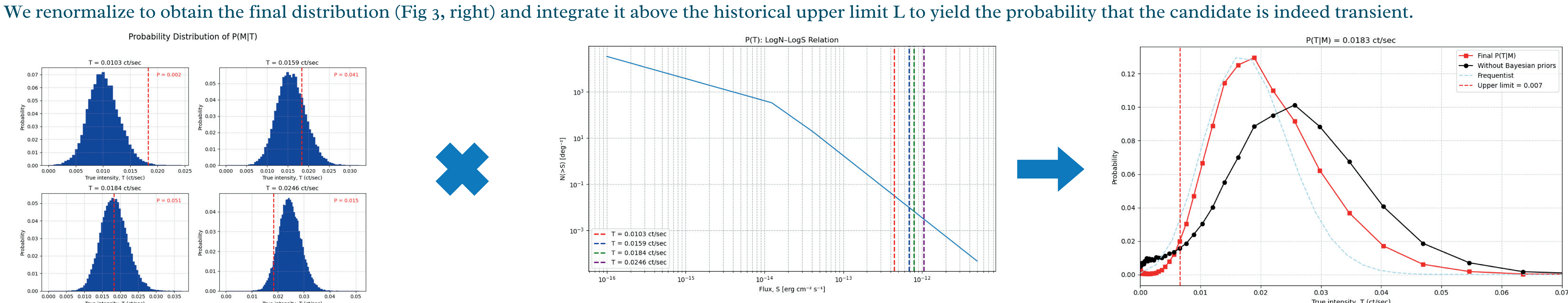

Fig. 3: Calculating the probability, for a source with intensity T (≈0.0183 ct/sec). Left: the simulation results; we read the probability of obtaining M in each case. Middle: The log N–log S distribution from Mateos et al. (2008), which indicates the relative frequency of sources as a function of T. Right: The final posterior P(T|M) (red), compared to (a) the distribution from the simulation step before applying the priors (black) and (b) a simple frequentist Poisson distribution with mean = M (blue). Our approach, in factoring in the Eddington bias, correctly shows a lower probable intensity than the other approaches.

4. Results

- Fig 4 displays the probability that the low significance source is above the historical upper limit, showing our new calculation against the one used in LSXPS.
- The LSXPS automatic ranking is intentionally conservative, as Eddington bias leads to an overestimate of significance.
- Our approach corrects for this bias, allowing us to use a lower threshold without increasing contamination.
- We define a threshold z as the probability that a transient candidate exceeds the historical 3σ upper limit.

Setting z at 3σ level (fig. 5) would yield 413 transients!!
(about 11 times of 36 already confirmed transients)

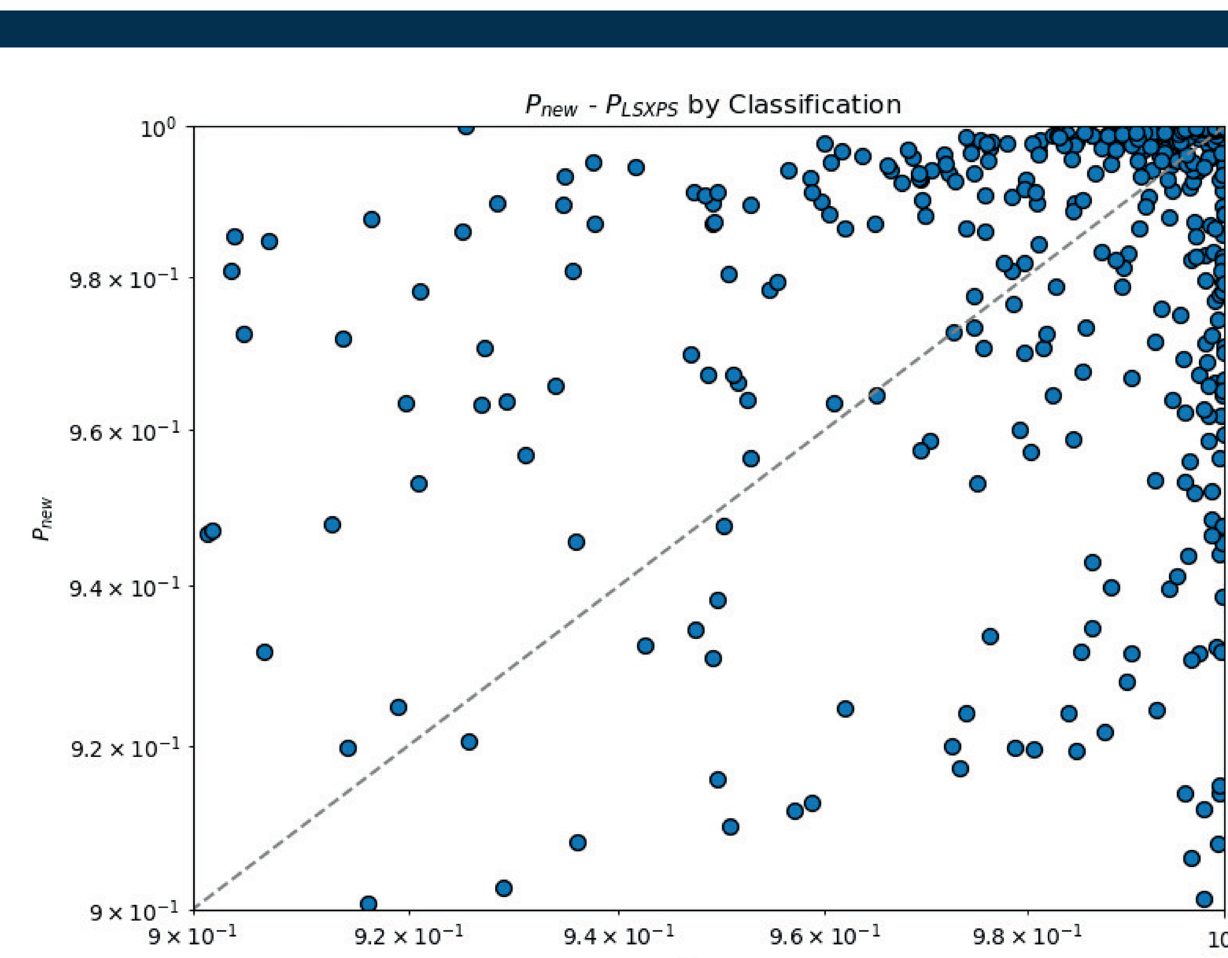

Fig. 4: Comparison of significance estimates for low-significance sources for our new calculation against the one used in LSXPS. Points above the diagonal indicate sources whose significance has increased under the new method, while those below show a decrease, highlighting how our revised approach can shift a source's significance.

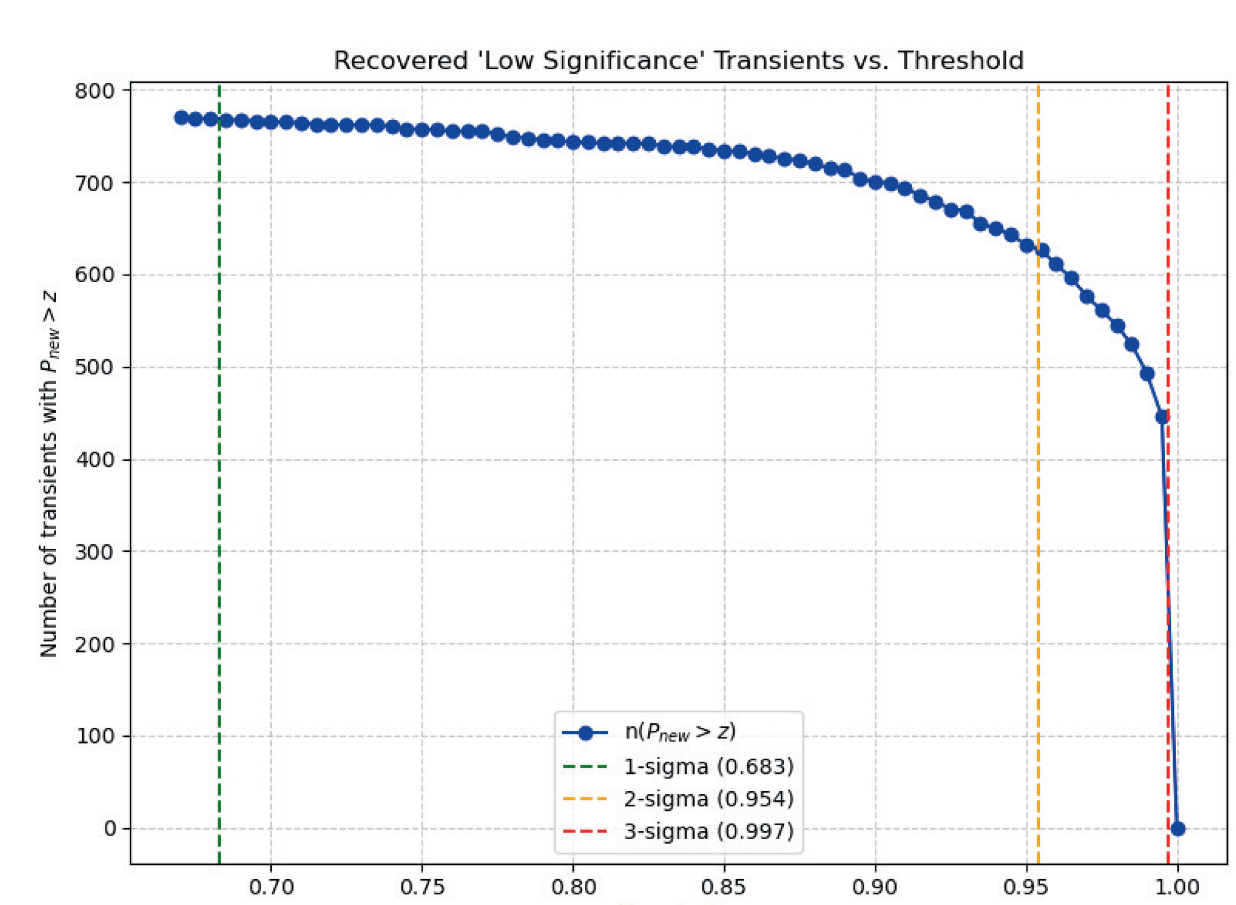

Fig. 5: Number of "low significance" events that are identified as transients using this approach, as a function of z.

5. Conclusion

Our rigorous approach corrects for Eddington bias and robustly estimates a source's transient probability, recovering significantly more confirmed transients. We will soon apply this method to both historical and new detections.

6. References

- Mateos et al. (2008): "High precision X-ray log N–log S distributions: implications for the obscured AGN population" MNRAS
- Evans et al.: "Areal-time transient detector and the Living Swift-XRT Point Source Catalogue"
- Evans1 et al. "1SXPS: A Deep Swift X-ray Telescope Point Source Catalog with Light Curves and Spectra" A&A