flashcurve Add-on: Bisection Method for Time-Bin Search Algorithm

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1 Introduction

Time-dependent analysis of high-energy gamma-ray sources often requires adaptive time binning techniques to effectively capture flux variations across different timescales. Traditional methods may use fixed time bins or adaptive binning based on arbitrary thresholds, but these approaches can either miss important short-term variations or create unnecessary computational overhead. Following up from the results of the original *flashcurve* paper [Glauch and Tchiorniy, 2025], this document presents an improved adaptive time-bin search algorithm based on a bisection method that efficiently converges to target significance intervals while optimising computational resources without the need for fine-tuning the search (energy and proximity filters are no longer needed with this method).

2 The Bisection Method

The bisection method is a root-finding algorithm that repeatedly divides an interval in half and selects the subinterval in which the root lies [Burden and Faires, 1985]. In our application, we adapt this concept to find optimal time bin sizes that achieve a Test Statistic (TS) value within some target interval, the TS being a measure of detection significance [Fermi-LAT Collaboration, 2009]. The algorithm dynamically adjusts time bin sizes until the TS value converges to a predefined target.

2.1 Algorithm Description

The algorithm proceeds through the following steps:

1. Begin with an initial time window spanning from t_{init} to $t_{end,0}$.
2. Calculate the TS value for this full time-window.
3. If the TS value exceeds the target threshold (Figure 1):
   - Store the current $t_{end,0}$ as $t_{old,0}$ for reference.
   - Divide the time window in half, creating a new endpoint t_0.
   - Recalculate the TS value for the reduced window from t_{init} to t_0.
   - Continue halving until the TS value approaches the target threshold.
4. If the TS value falls below the target threshold after halving (Figure 2):

- Bisect between the last known high-TS endpoint ($t_{old,0}$) and the current endpoint ($t_{end,0}$) to find a midpoint.
- Test the TS value at this midpoint.
- Continue bisecting between $t_{old,0}$ and successive endpoints until convergence.

5. Once the ideal time bin is found, continue the search for the next time-bins from that point with a new time window.

6. If the initial TS in a time window is too small, increase the window size by a factor (default: 0.3) and retry.

A depth counter is also implemented to prevent excessive recursion in case too many bisections occur without convergence, in which case the time window is again increased. The algorithm uses smaller initial time windows for greater accuracy, as larger windows may result in underprediction of TS values and produce overly significant time bins that could have been further subdivided. This can occur especially if time windows are set as more than 1-2 months, since *flashcurve*'s neural network model has only been trained on time-bins of at most 1 month.

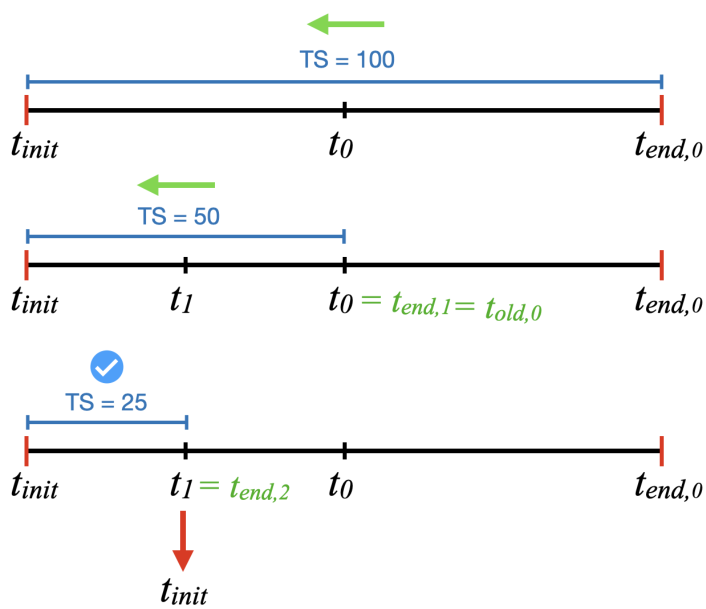


Figure 1: Bisection method; Scenario 1: Simple bisection with consistent TS reduction. The algorithm halves the time window until the TS value converges to the target of TS = 25. The search updates t_{old} at each successful step. The search then begins again from the optimal t_{end} as the new t_{init} for the next time-bins.

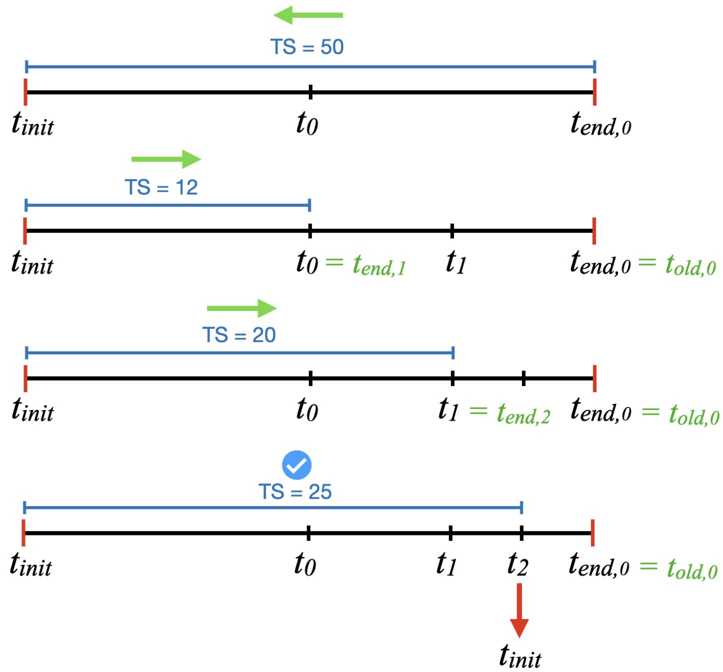


Figure 2: Bisection method; Scenario 2: Bisection with corrective adjustments. When the TS falls below threshold after initial halving, the algorithm bisects between the last high-TS endpoint (e.g. $t_{old,0}$) and the current endpoint (e.g. $t_{end,1}$ to continue finding the optimal time-bin end within this interval. The search begins again from the optimal t_{end} as the new t_{init} for the next time-bins.

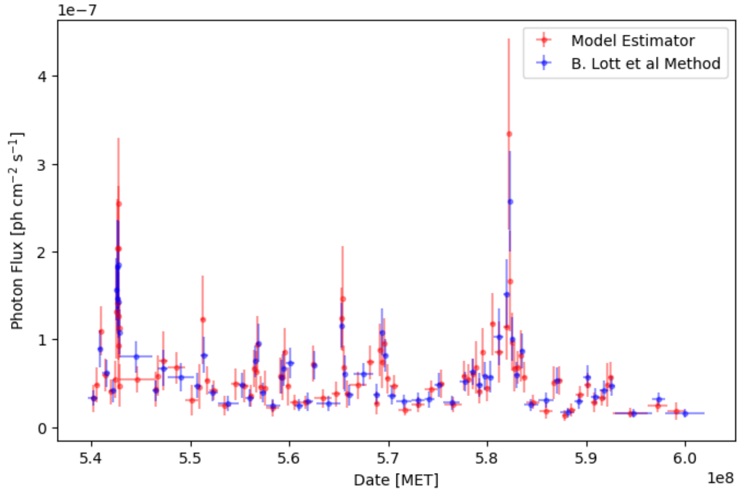
3 Application to Gamma-Ray Sources

We have applied this new adaptive time-bin search algorithm to two well-known gamma-ray sources: TXS 0506+056, a blazar associated with neutrino emission, and CTA 102, a highly variable flat-spectrum radio quasar, as done in the original *flashcurve* paper. Various relevant results are shown in Figure 3 and 4.

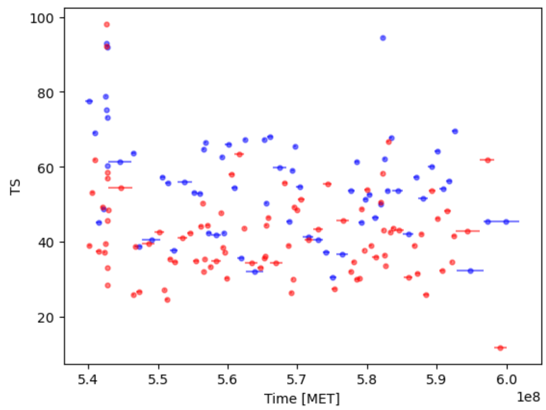
4 Discussion & Conclusion

The bisection method for the adaptive time-bin search offers a significant improvement over the previous method of *flashcurve* in terms of computational overhead, speed, and need for fine-tuning. The results for TXS 0506+056 and CTA 102 demonstrate the effectiveness of this approach in capturing complex flux variability patterns across diverse gamma-ray sources, still just as well and in some cases better than the previous method of *flashcurve* and the general method of Lott et al. [2012]. This method has therefore become the default method within the *flashcurve* software framework for the time-bin search algorithm, although the previous method (see Glauch and Tchiorniy [2025]) can still be used.

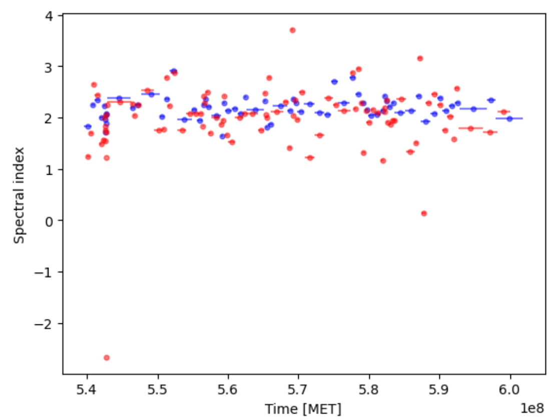
Future work could explore further training of *flashcurve*'s neural network model to allow for better prediction accuracy through the use of an infinite training loop. Also, one could explore training another model that can predict relative flux error instead of significance, in order to expand *flashcurve*'s capabilities to adaptive time-bins with constant relative flux error as done by Lott et al. [2012].



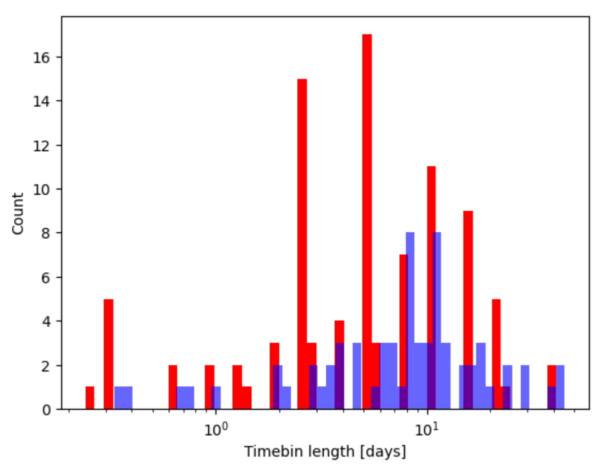
(a) TXS 056+0506 lightcurve.



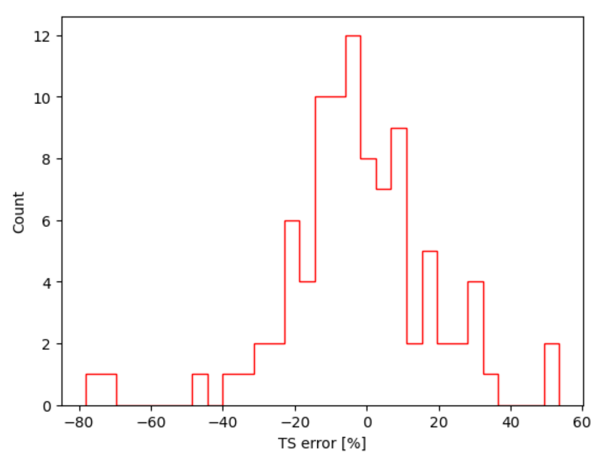
(b) TS values at corresponding time-bins.



(c) Spectral indices at corresponding time-bins.

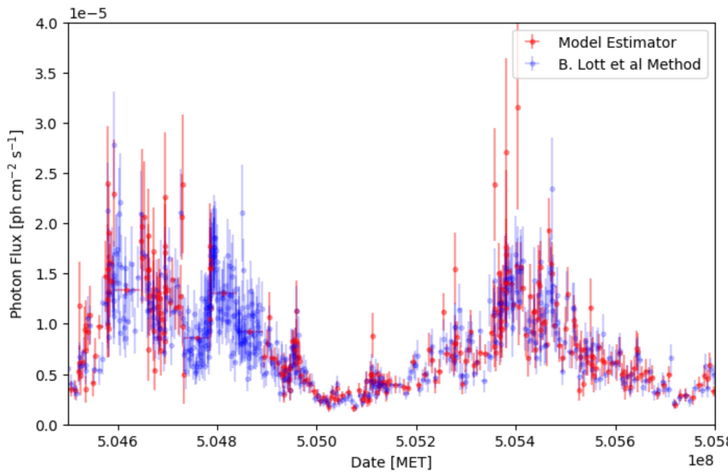


(d) Distribution of time-bin durations.

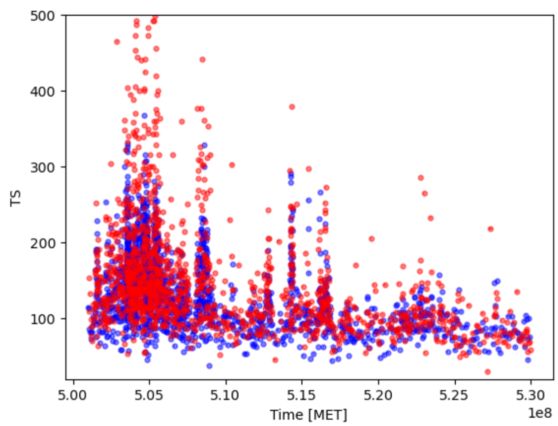


(e) Distribution of predicted TS error from truth.

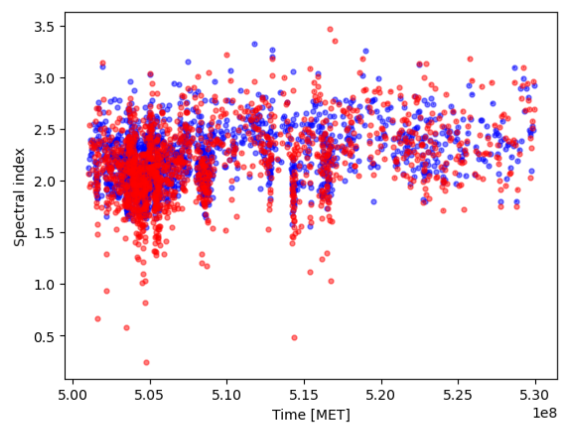
Figure 3: Various lightcurve analysis results for TXS 0506+056 using the bisection algorithm, with the results of the new method in red and the corresponding results from Lott et al. [2012] in blue.



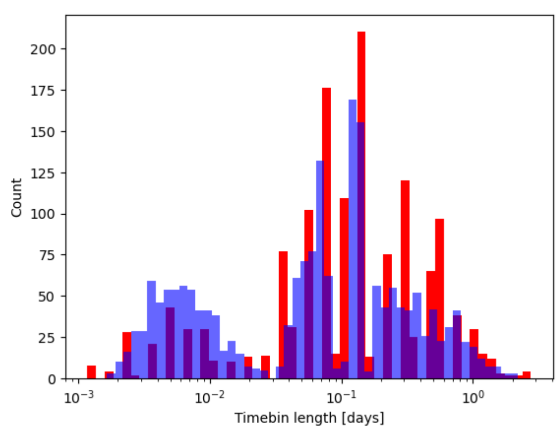
(a) First segment of the CTA 102 lightcurve.



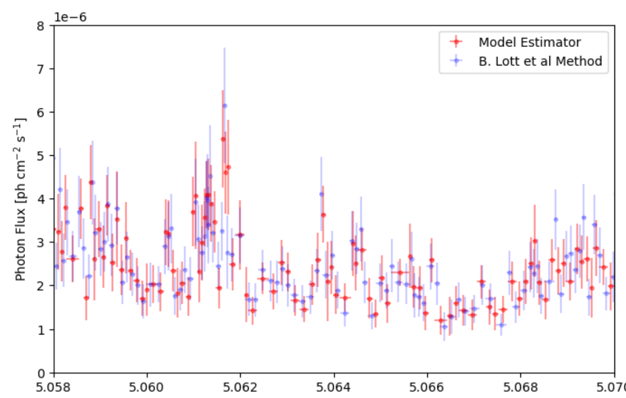
(b) TS values at corresponding time-bins.



(c) Spectral indices at corresponding time-bins.



(d) Distribution of time-bin durations.



(e) Second segment of the CTA 102 lightcurve.

Figure 4: Various lightcurve analysis results for CTA 102 using the bisection algorithm, with the results of the new method in red and the corresponding results from Lott et al. [2012] in blue.

References

R. L. Burden and D. J. Faires. *Numerical analysis*. PWS Publishing Company, Boston, 3rd edition, 1985. ISBN 0-87150-857-5.

Fermi-LAT Collaboration. Fermi/large area telescope bright gamma-ray source list. *The Astrophysical Journal Supplement Series*, 183(1):46–66, June 2009. ISSN 1538-4365. doi: 10.1088/0067-0049/183/1/46. URL `http://dx.doi.org/10.1088/0067-0049/183/1/46`.

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B. Lott, L. Escande, S. Larsson, and J. Ballet. An adaptive-binning method for generating constant-uncertainty/constant-significance light curves with fermi-lat data. *Astronomy Astrophysics*, 544: A6, July 2012. ISSN 1432-0746. doi: 10.1051/0004-6361/201218873. URL `http://dx.doi.org/10.1051/0004-6361/201218873`.