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Insight on GRB physics from a novel data driven method for systematic analysis of X-ray light-curves

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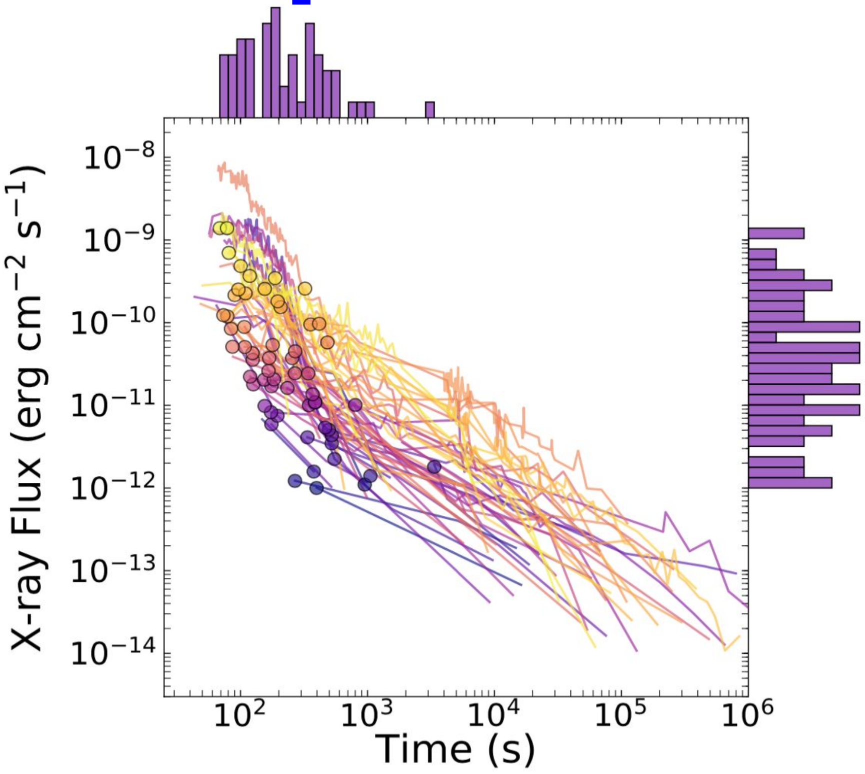
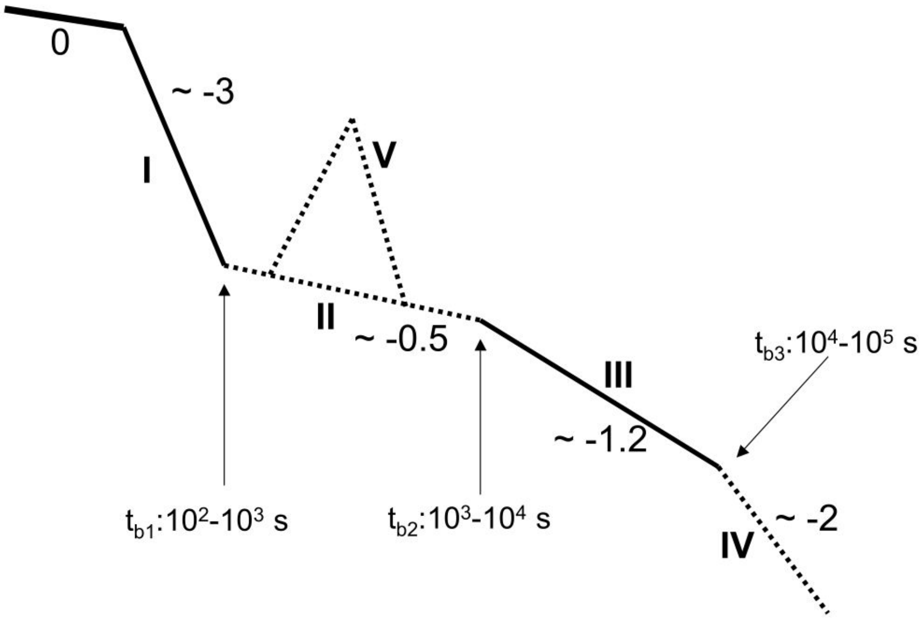
GRB x-ray afterglows: many shapes and behaviors





1. Beniamini et al., MNRAS 2024, DOI: 10.1093/mnras/stae1941
2. Zhang et al., ApJ 2006, DOI: 10.1086/500723

Limits of current analysis:

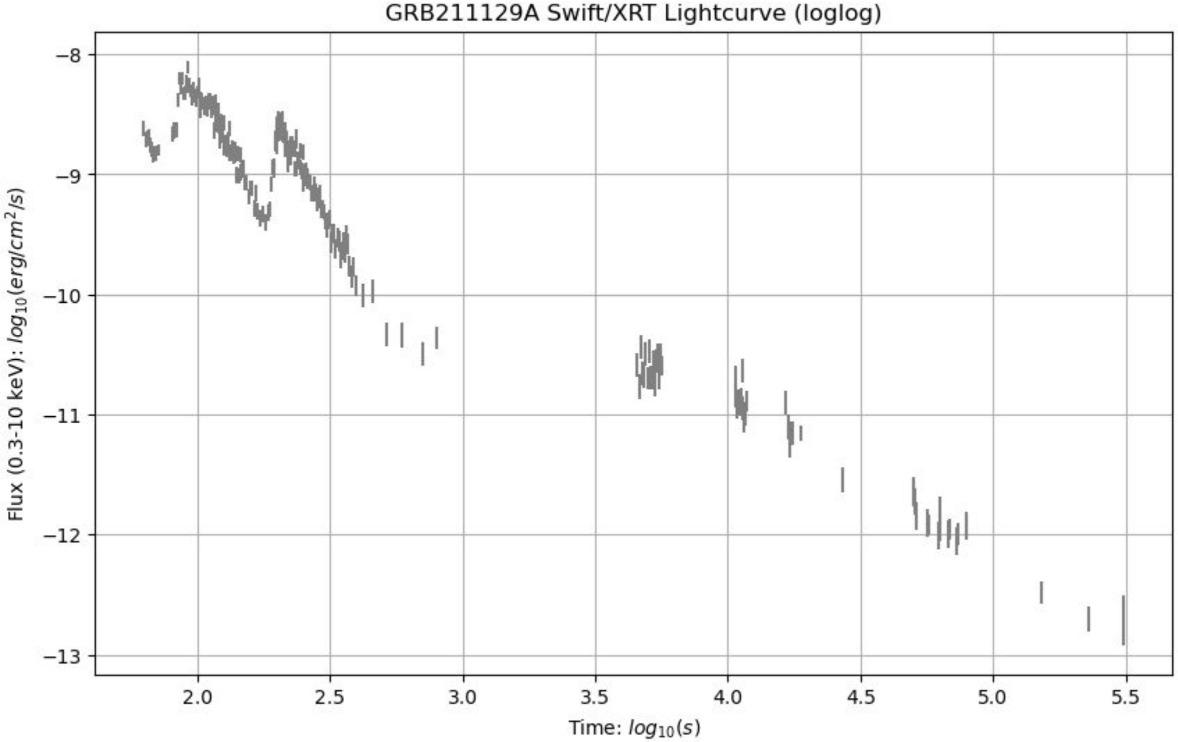
1. Limited samples of events (generally up to 60-80 events)
2. Strong (and varied) model dependance, both for flare identification and for the afterglow general behaviour

➡ Results are difficult to generalize and remain limited by statistics

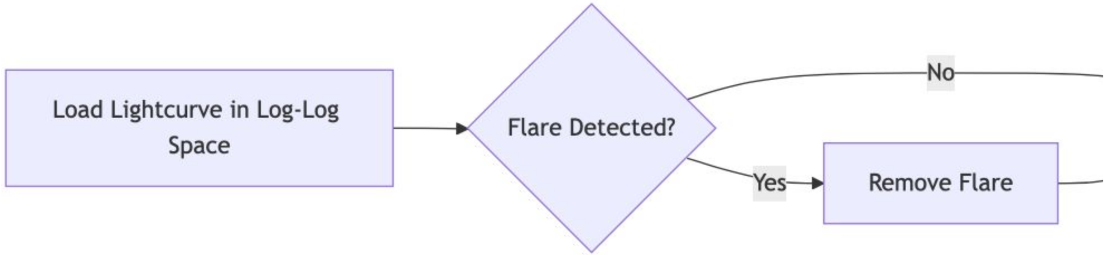
Aim of the new pipeline:

1. **Model-independent flare detection** and removal
2. Fits light curves with multiple **power-law segments**
3. **Flexible model selection**: supports BIC, AICc, BICc, and EvBIC for selecting the best model
4. Batch processing and **catalog analysis**: supports automated fitting of multiple light curves in parallel

Load Lightcurve in Log-Log Space

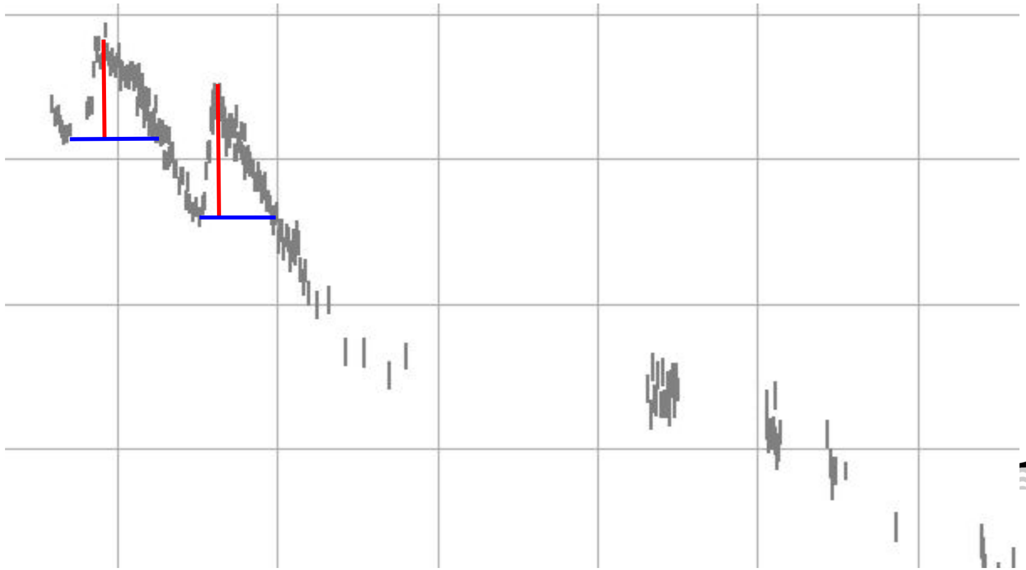


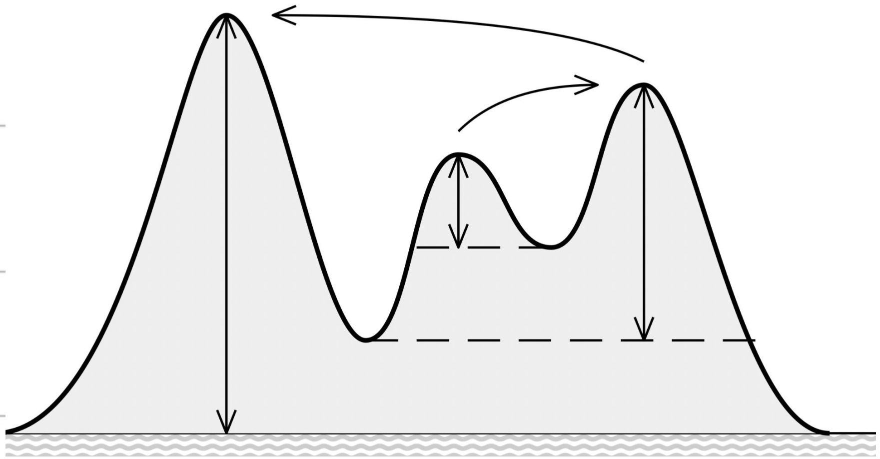
1. Load the lightcurve in Log-Log space
2. Quality checks: e.g. minimum number of data points

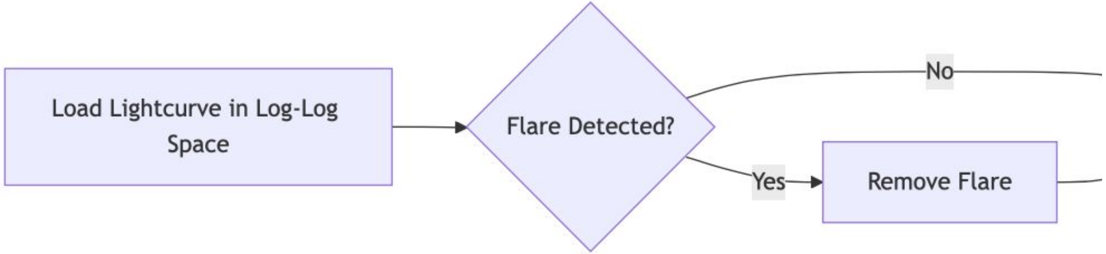


Only assumption: (except for flares) the lightcurve is generally decreasing

1. Identify peaks using their prominence and width



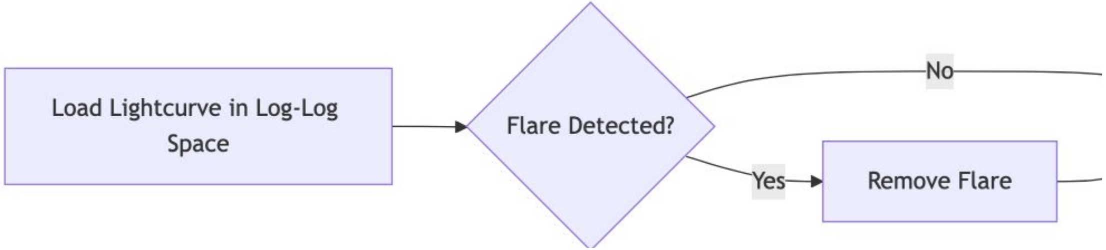


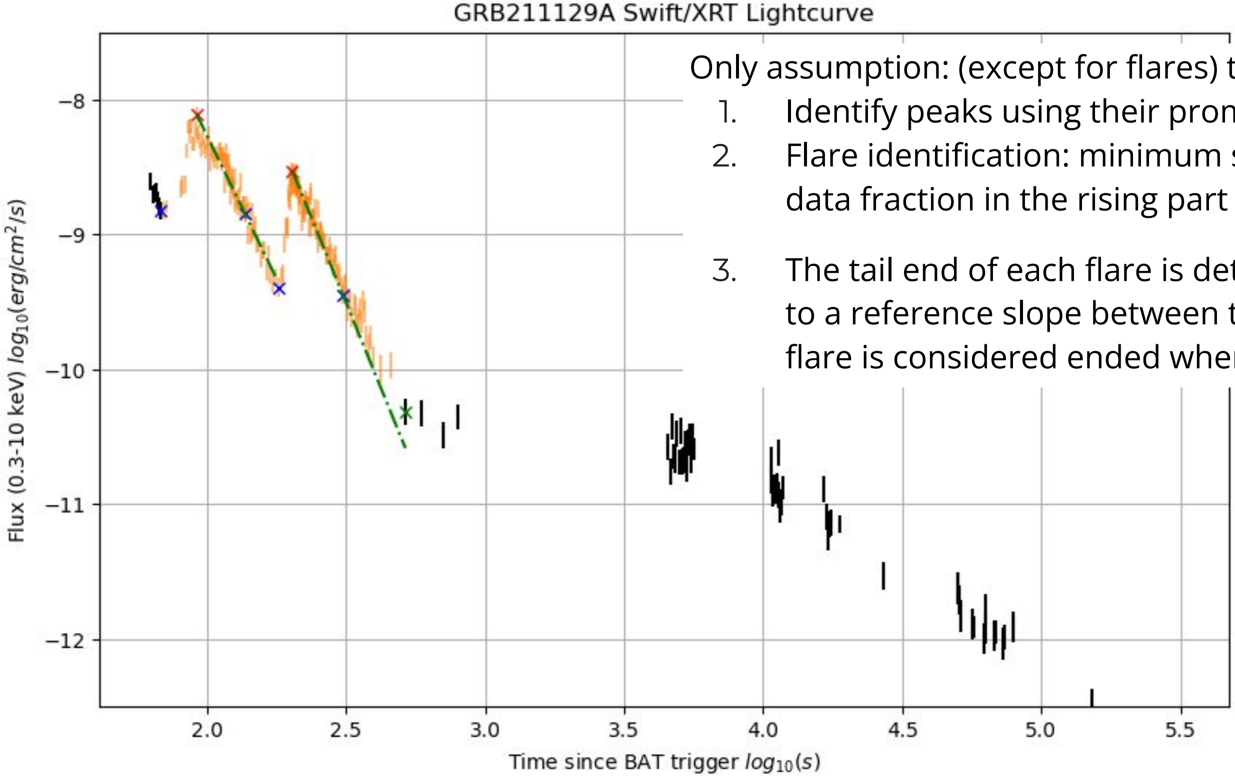


Only assumption: (except for flares) the lightcurve is generally decreasing

1. Identify peaks using their prominence and width
2. Flare identification: minimum significance of the peak and minimum data fraction in the rising part*

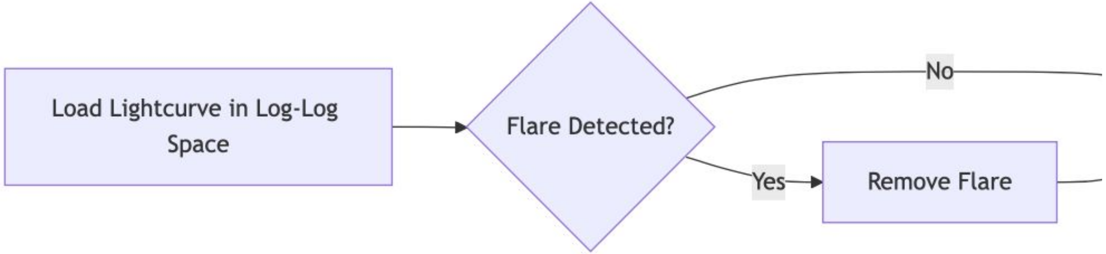
* inspired by the Swift automated analysis old pipeline
Evans et al., MNRAS 2009, DOI: 10.1111/j.1365-2966.2009.14913.x

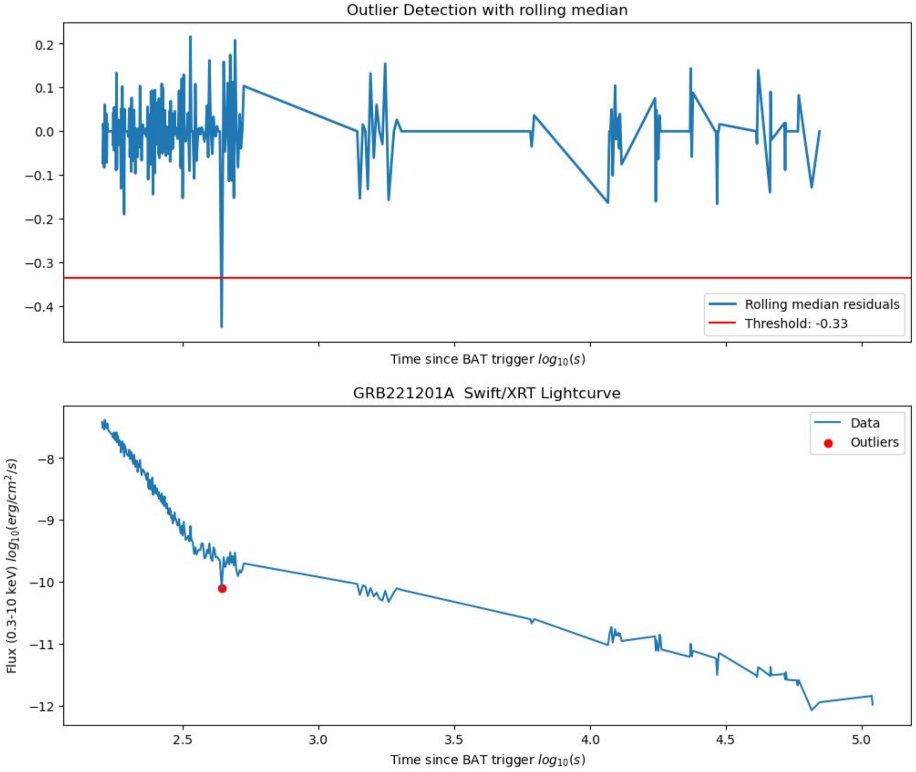




Only assumption: (except for flares) the lightcurve is generally decreasing

1. Identify peaks using their prominence and width
2. Flare identification: minimum significance of the peak and minimum data fraction in the rising part
3. The tail end of each flare is determined by comparing post-flare points to a reference slope between the peak and an initial parallel point. The flare is considered ended when deviations exceed a threshold





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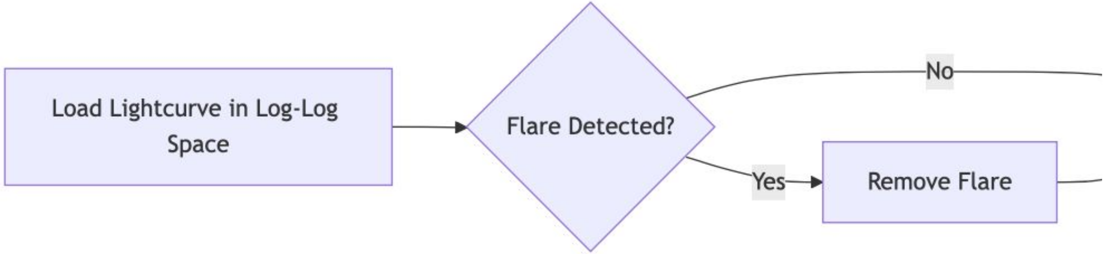
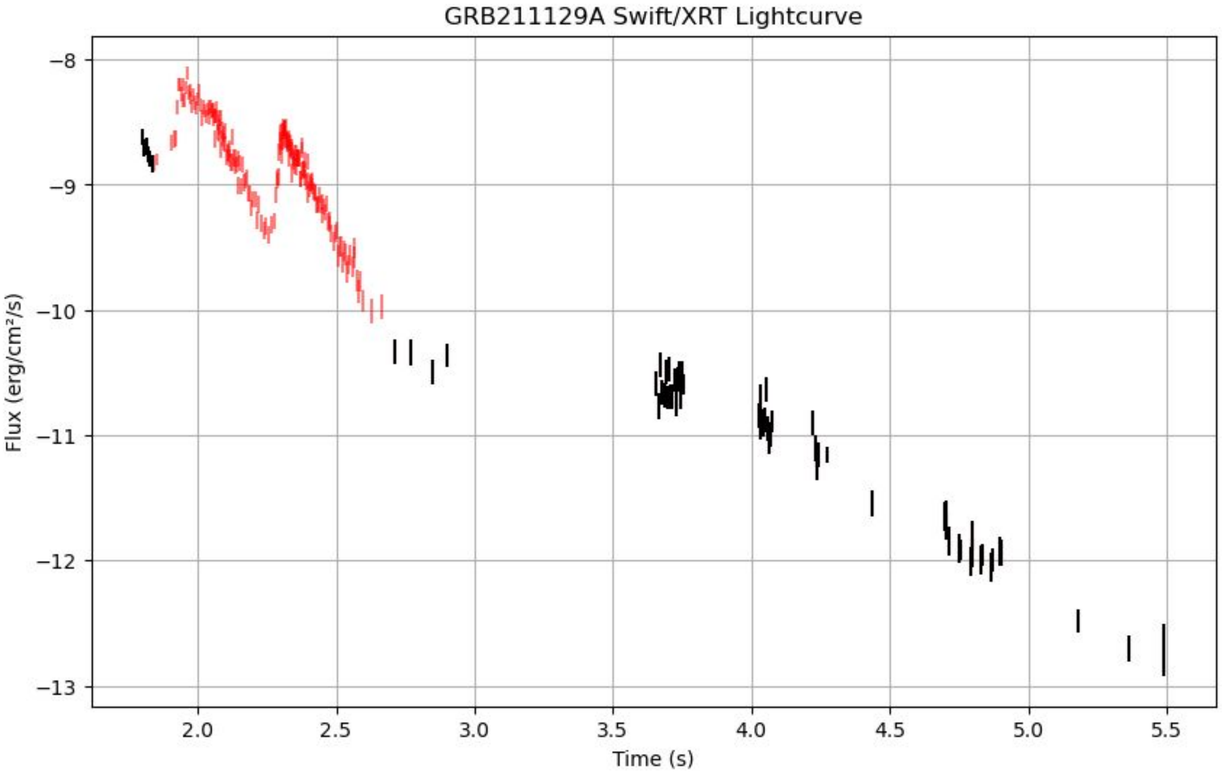
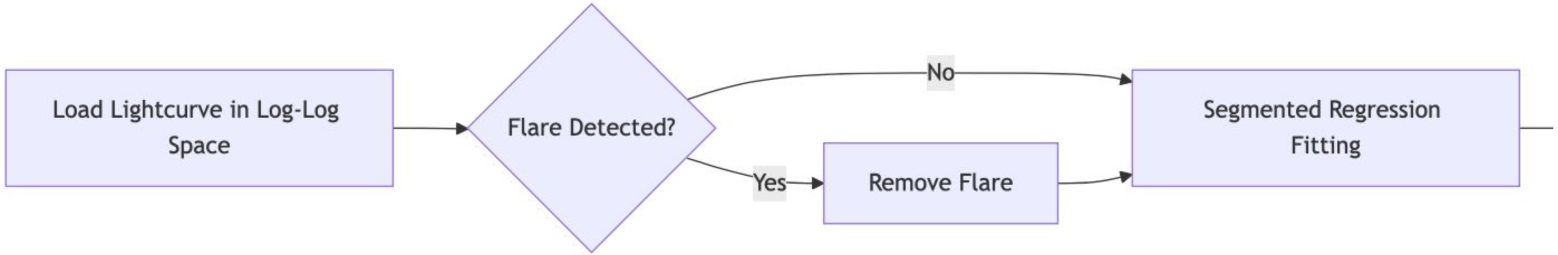
2. Flare identification: minimum significance of the peak and minimum data fraction in the rising part
3. The tail end of each flare is determined by comparing post-flare points to a reference slope between the peak and an initial parallel point. The flare is considered ended when deviations exceed a threshold
4. Quality checks: e.g. outlier detection



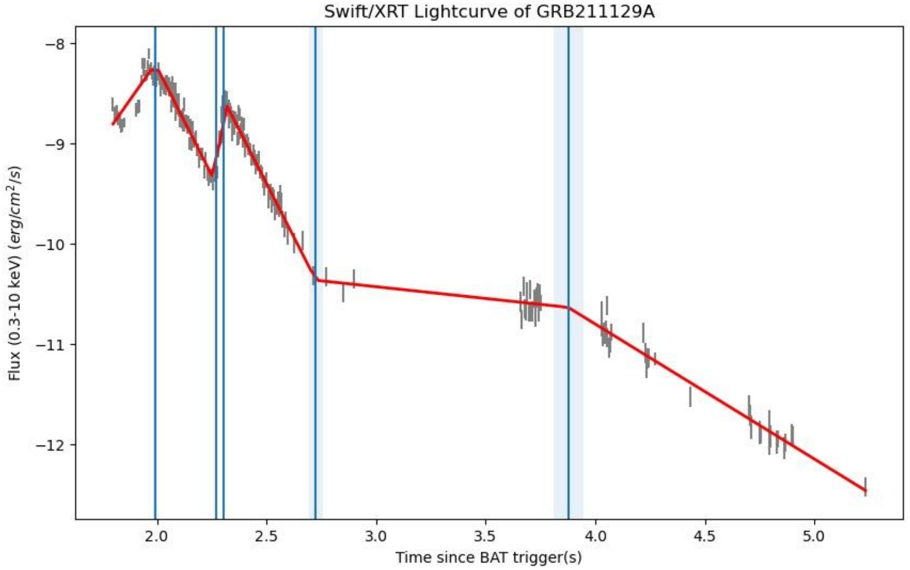


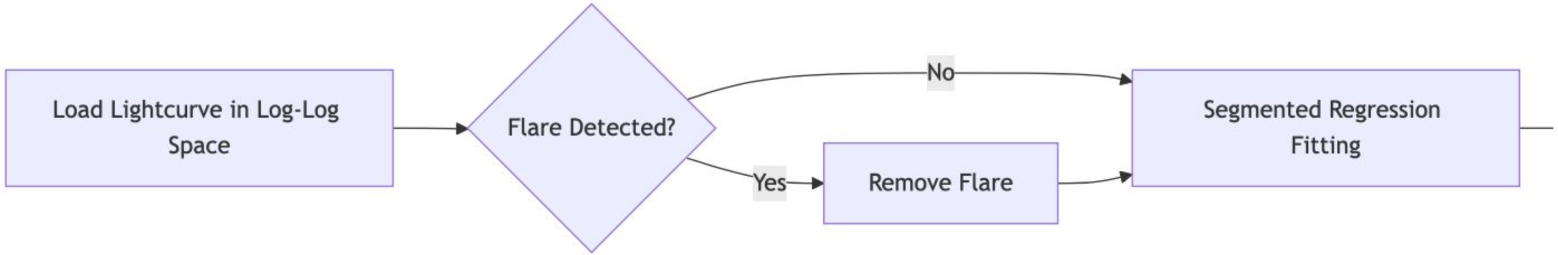
Approx. 29.5% of GRBs in the Swift-XRT catalog have at least one identifiable flare



Log-Log space -> segmented regression -> Muggeo's method (Muggeo, Wiley 2003, DOI: 10.1002/sim.1545)

$$y = c + \alpha_1 x + \sum_{k=1}^{N} \beta_k (x - \psi_k) H(x - \psi_k)$$



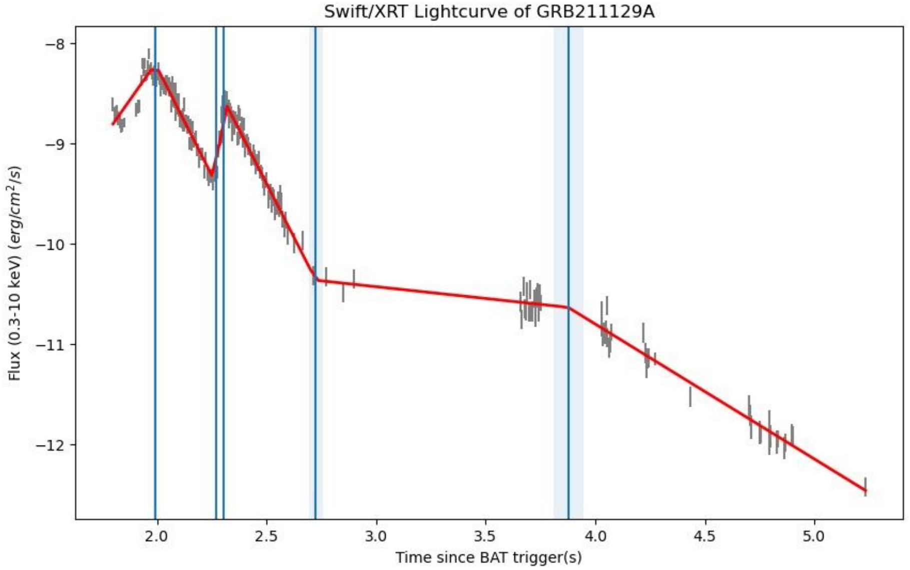


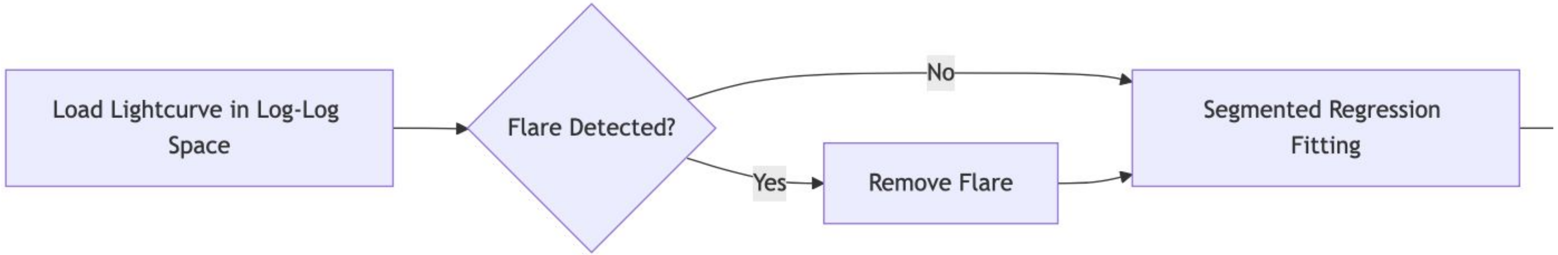
Log-Log space -> segmented regression -> Muggeo’s method (Muggeo, Wiley 2003, DOI: 10.1002/sim.1545)

$$y = c + \alpha_1 x + \sum_{k=1}^{N} \beta_k (x - \psi_k) H(x - \psi_k)$$

E.g.: for a single breakpoint:

$$y = \alpha x + c + \beta(x - \psi) H(x - \psi)$$





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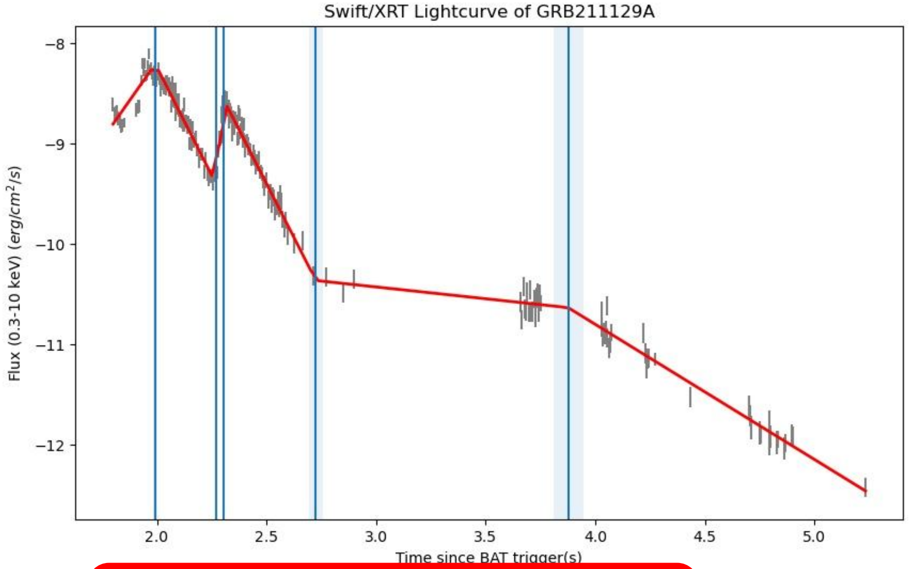
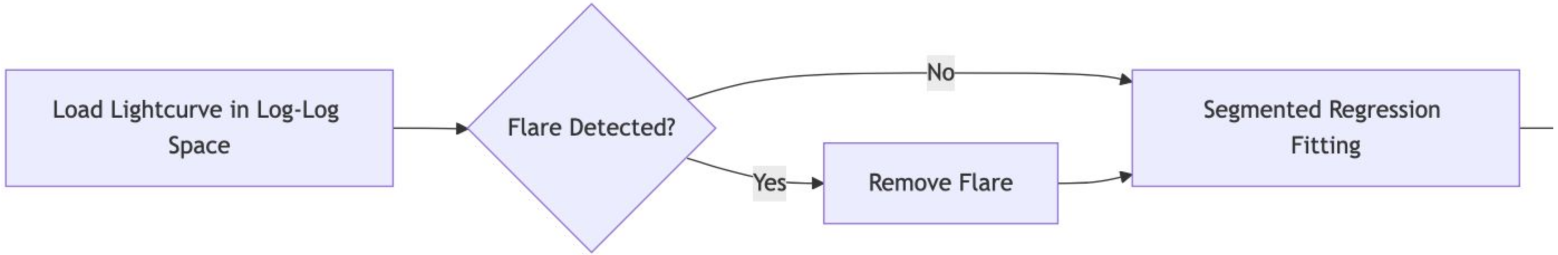


E.g.: for a single breakpoint:

$$y = \alpha x + c + \beta(x - \psi)H(x - \psi)$$

Taylor expansion around an estimate of the breakpoint:

$$y \approx \alpha x + c + \beta(x - \psi^{(0)})H(x - \psi^{(0)}) - \boxed{\beta(\psi - \psi^{(0)})H(x - \psi^{(0)})}$$



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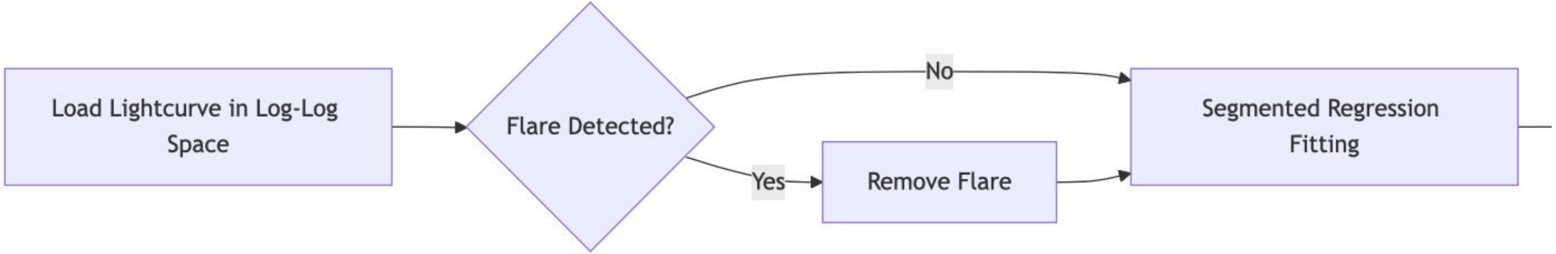
Taylor expansion around an estimate of the breakpoint:

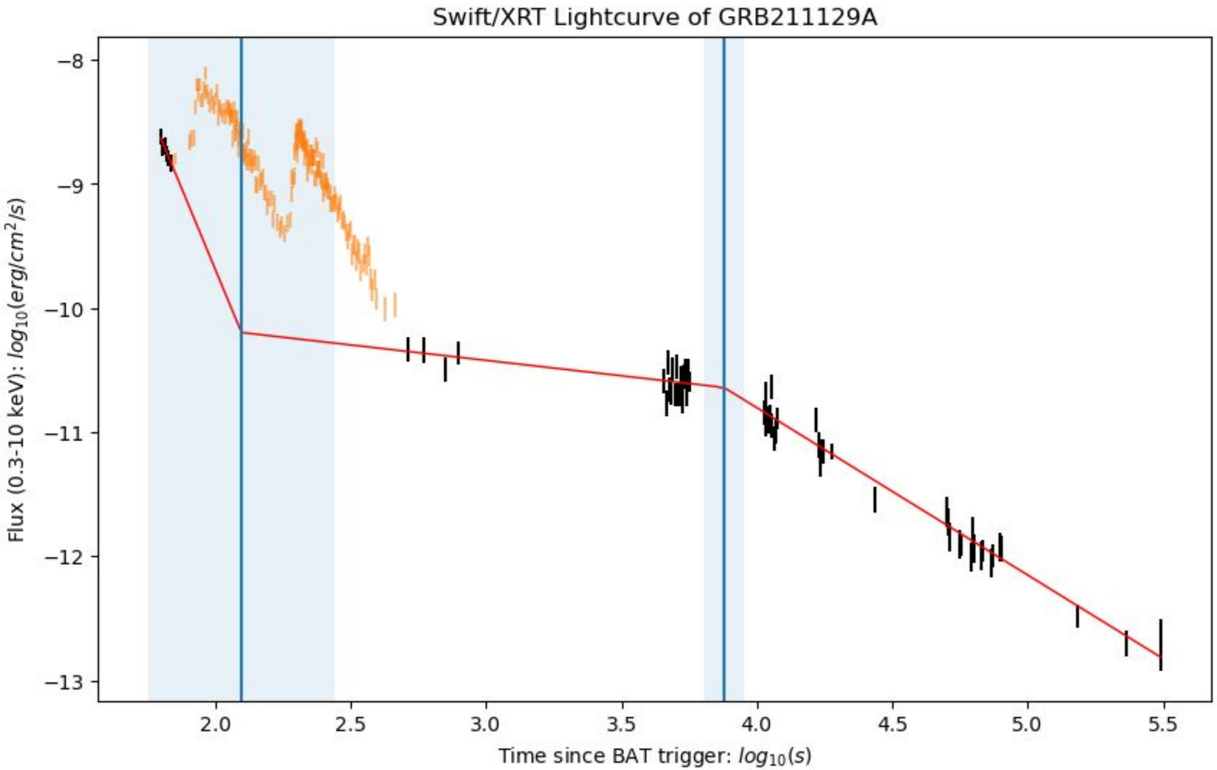
$$y \approx \alpha x + c + \beta(x - \psi^{(0)}) H(x - \psi^{(0)}) - \beta(\psi - \psi^{(0)}) H(x - \psi^{(0)})$$

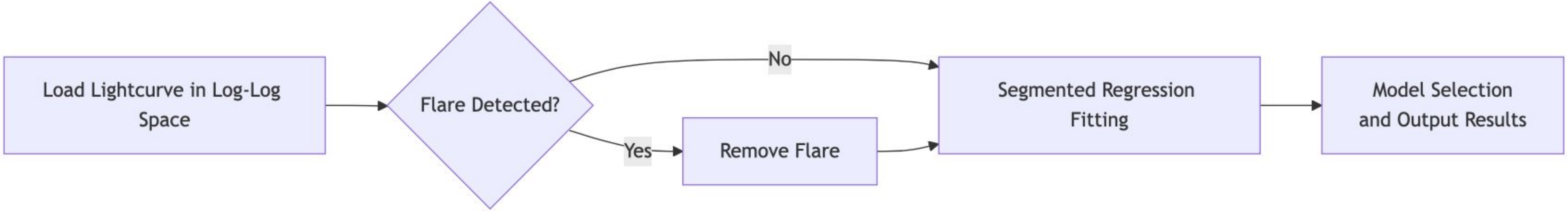
This is done with a custom version of the `Piecewise-regression` Python library

Pilgrim, JOSS 2021, DOI: 10.21105/joss.03859

https://github.com/chasmani/piecewise-regression


Load Lightcurve in Log-Log Space
Flare Detected?
No
Yes
Remove Flare
Segmented Regression Fitting


Swift/XRT Lightcurve of GRB211129A
Flux (0.3-10 keV): $log_{10}(erg/cm^2/s)$
Time since BAT trigger: $log_{10}(s)$
−8
−9
−10
−11
−12
−13
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5



- Need to compare all the models for selecting the best fit -> BIC
- Few datapoints? -> need flexibility to choose the best statistics:

$$\mathrm{BIC} := -2\log(L) + k\log(n),$$

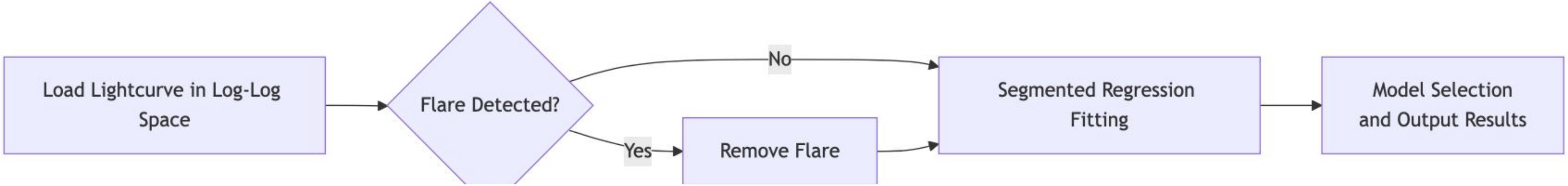
$$\mathrm{AICc} := -2\log(L) + \frac{2k(k+1)}{n-k-1},$$

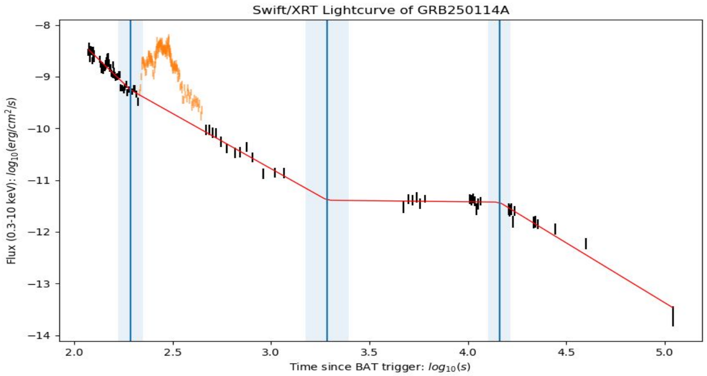
$$\mathrm{BICc} := -2\log(L) + \frac{n}{n-k-2}k\log(n),$$

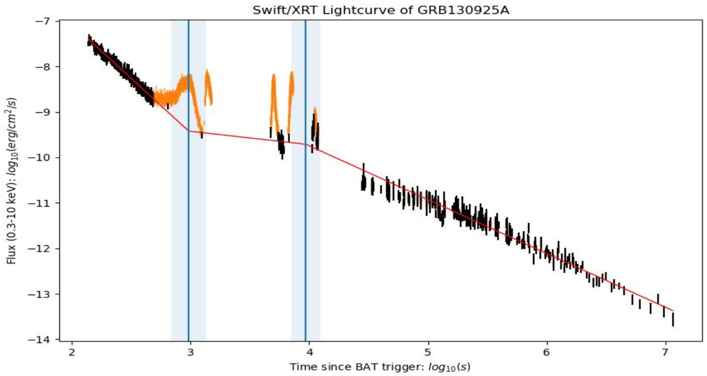
$$\mathrm{EvBIC} := -2\left(1-\frac{1}{n}\right)\log(L) + k\log(n),$$

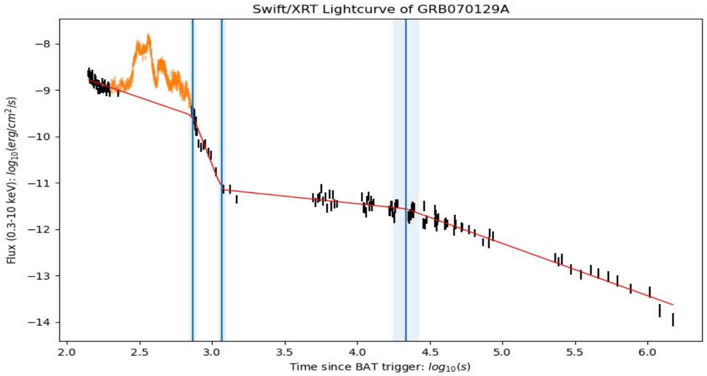
$$\begin{cases} n = \text{number of points} \\ k = \text{number of free parameters} = 2(1+N_{breaks}) \end{cases}$$

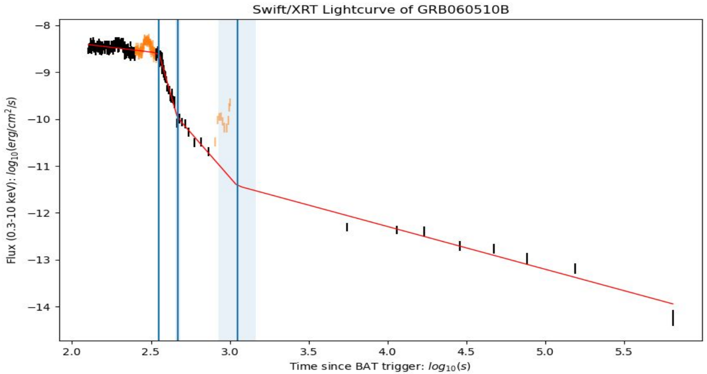
McQuarrie, S&PL (1999), https://doi.org/10.1016/S0167-7152(98)00294-6
Bickel, SP (2025), https://doi.org/10.1007/s00362-025-01682-1


Load Lightcurve in Log-Log Space
Flare Detected?
No
Yes
Remove Flare
Segmented Regression Fitting
Model Selection and Output Results


Swift/XRT Lightcurve of GRB250114A
Flux (0.3-10 keV): $log_{10}(erg/cm^2/s)$
Time since BAT trigger: $log_{10}(s)$

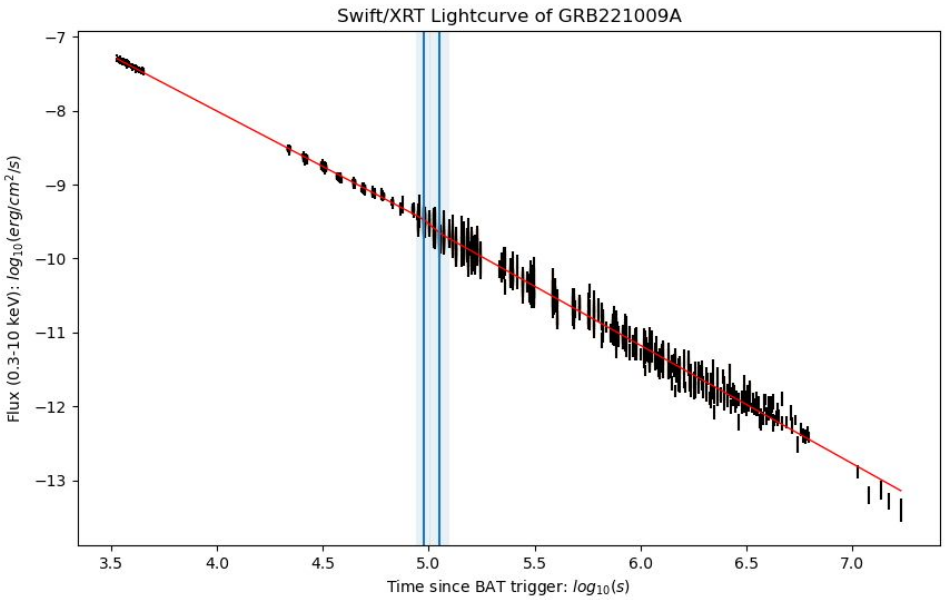

Swift/XRT Lightcurve of GRB130925A
Flux (0.3-10 keV): $log_{10}(erg/cm^2/s)$
Time since BAT trigger: $log_{10}(s)$


Swift/XRT Lightcurve of GRB070129A
Flux (0.3-10 keV): $log_{10}(erg/cm^2/s)$
Time since BAT trigger: $log_{10}(s)$

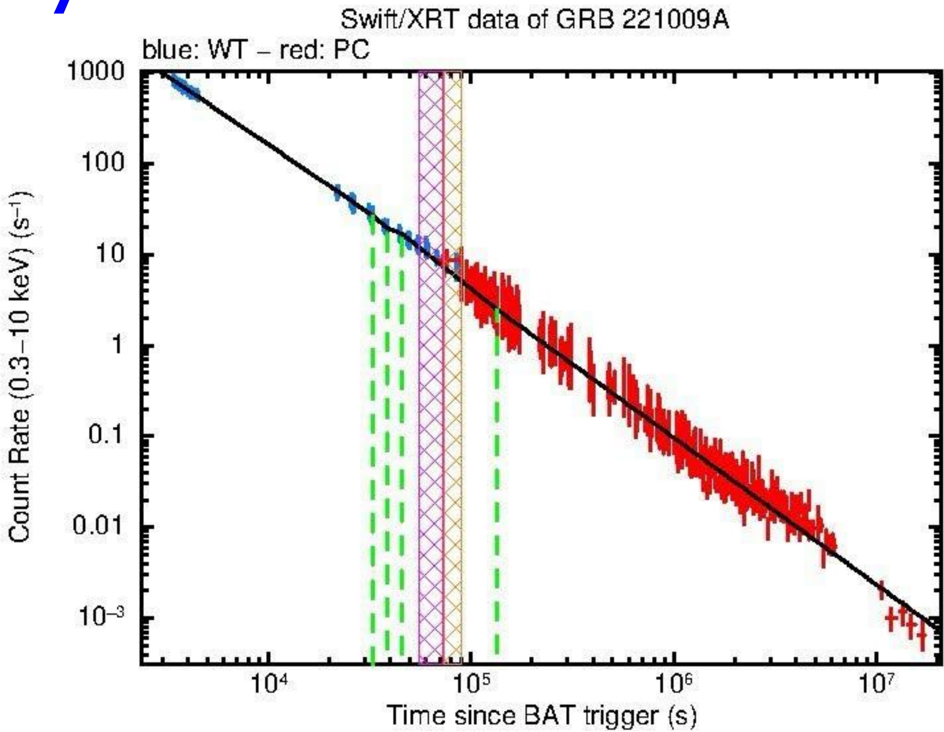

Swift/XRT Lightcurve of GRB060510B
Flux (0.3-10 keV): $log_{10}(erg/cm^2/s)$
Time since BAT trigger: $log_{10}(s)$

Some Results:

GRB221009A in GRBFit & Swift analysis



GRB221009A analysis with the new method: no flare and 2 breakpoints identified.

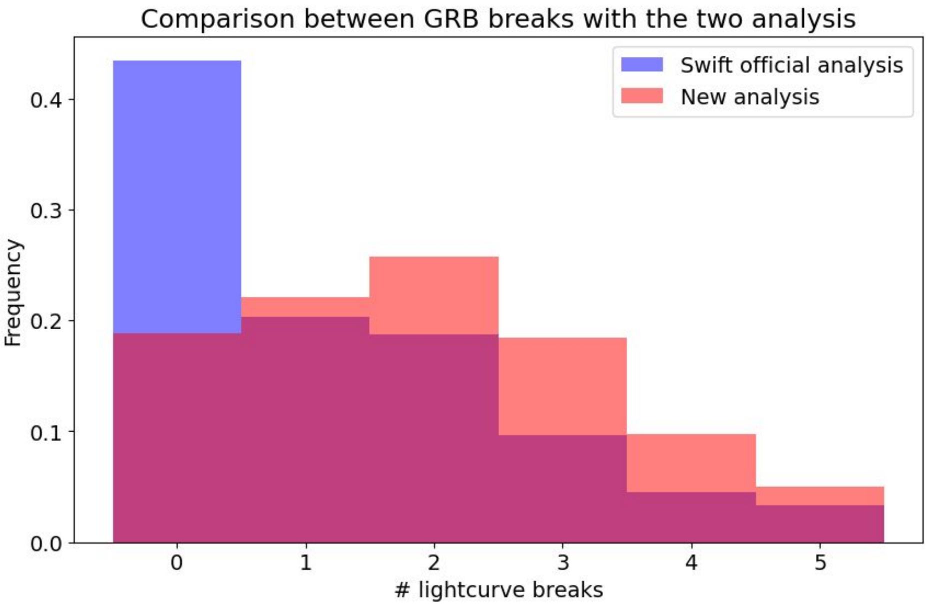


GRB221009A analysis with the Swift method: 2 flares and 4 breakpoints identified.

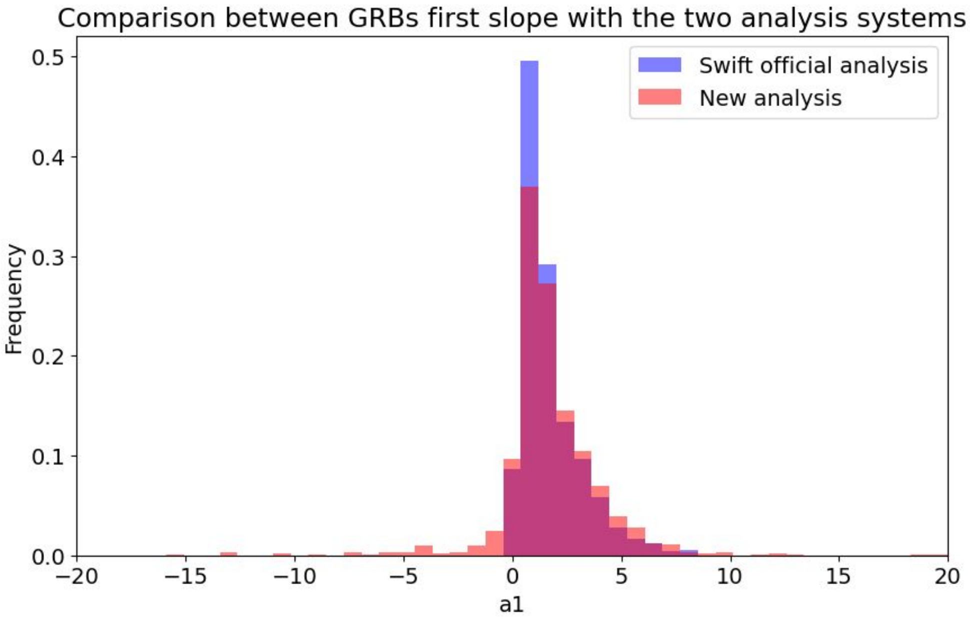
Evans et al., MNRAS 2009, DOI: 10.1111/j.1365-2966.2009.14913.x

Some Results:

parameter distributions in GRBFit & Swift analysis (~1400 GRBs)



Comparison of the number of breakpoints obtained with the two analysis methods.



Comparison of the slope of the first powerlaw segment.
Evans et al., MNRAS 2009, DOI: 10.1111/j.1365-2966.2009.14913.x

Future prospects:

1. Enables consistent feature extraction across a significantly large dataset
2. Allows robust trend identification in GRB afterglows
3. Model independent flare identification and characterization
4. Allows direct comparison of different GRB “families”
5. Applicable also to other sources and other energy bands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