Optimising a stochastic pulse-avalanche model of GRB light curves with a genetic algorithm

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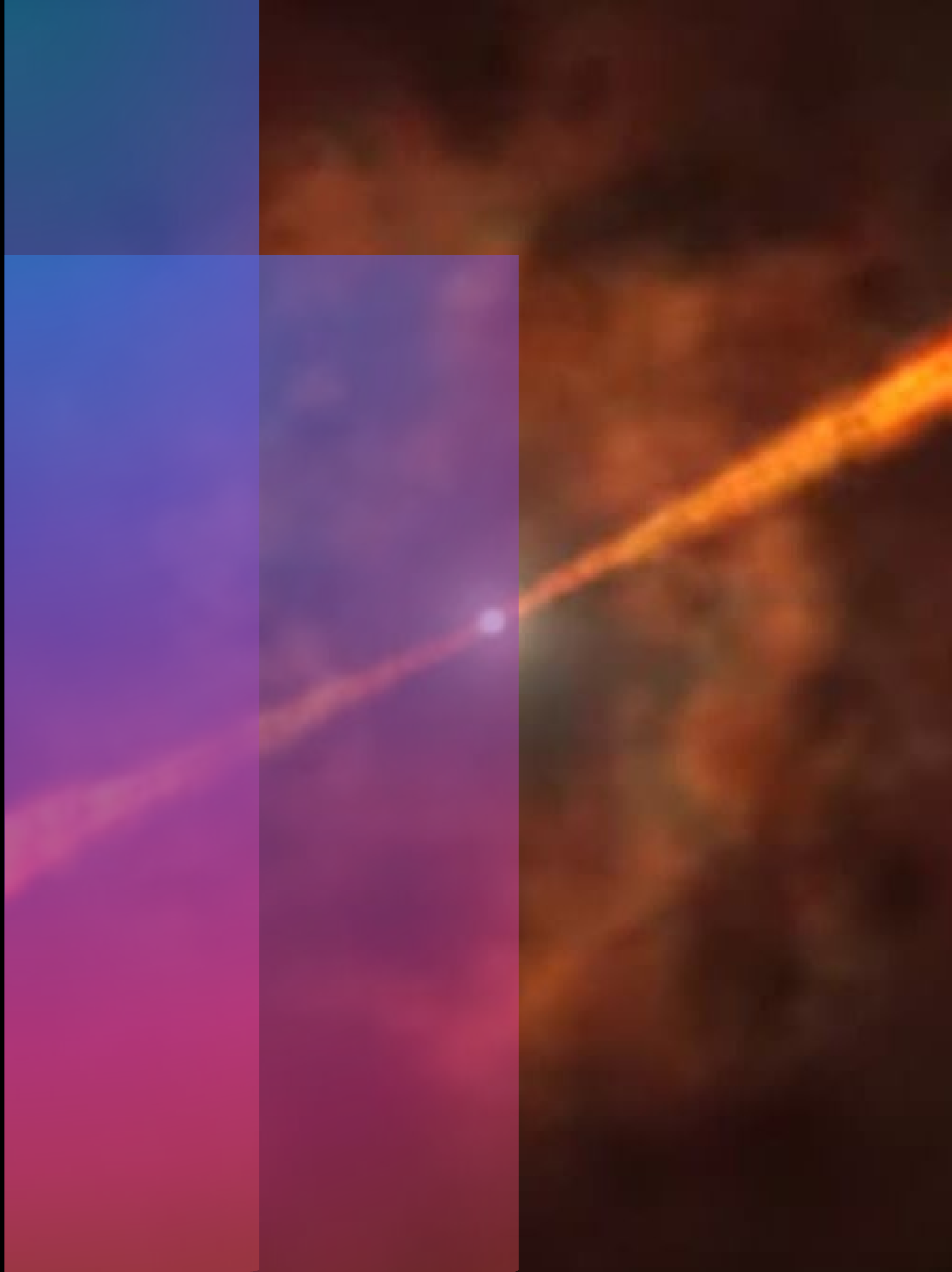

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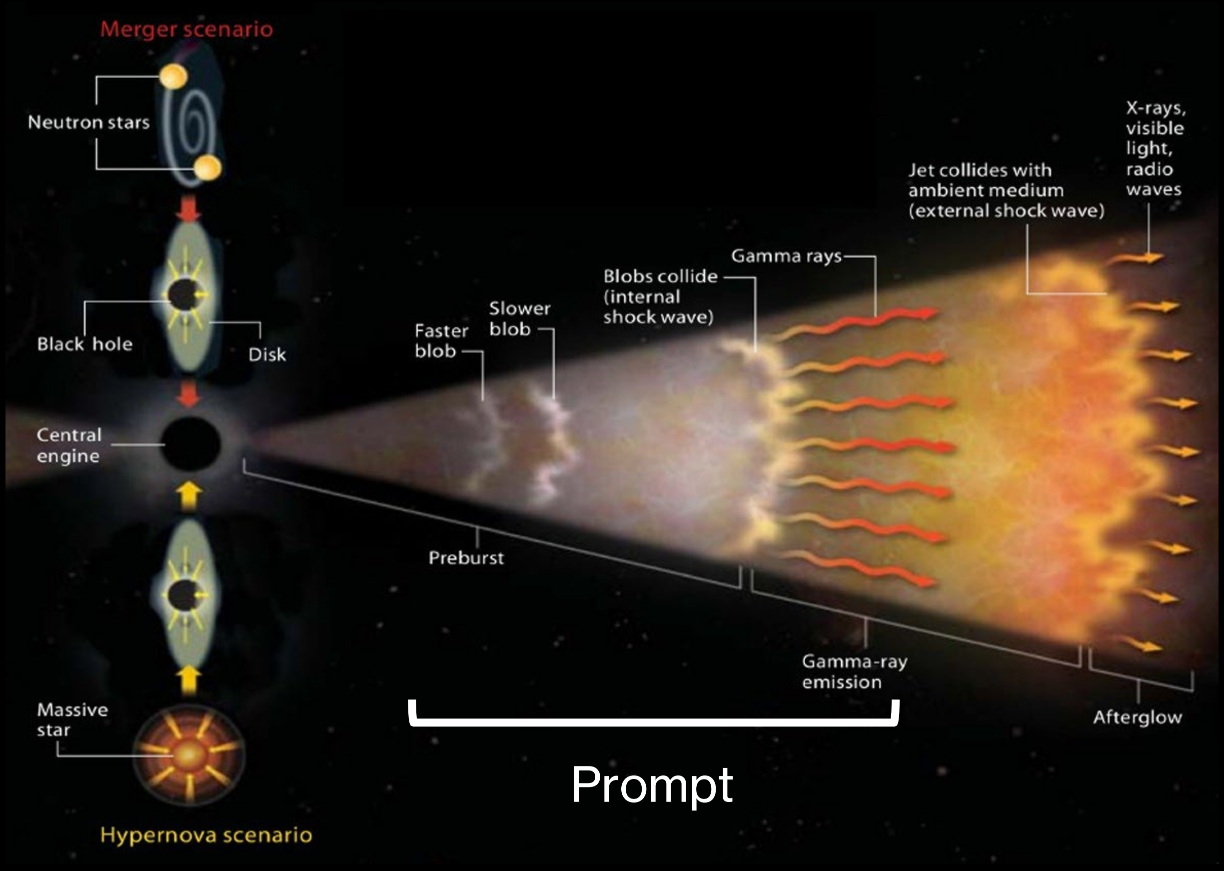
- GRB light-curves simulations
- Stochastic pulse avalanche models
- Genetic GRBs
- Results
- Conclusions and prospects

Gamma-ray Bursts: high energy explosions from the deep sky



Credits: NASA

Two classes:

1. **<u>Short GRBs</u>** (Duration $\lesssim$ 2 s). Progenitor: merger of a compact binary, with at least one NS.

2. **<u>Long GRBs</u>** (Duration $\gtrsim$ 2 s). Progenitor: ‘collapsar’, hydrogen stripped massive star, whose core collapses to a compact object.

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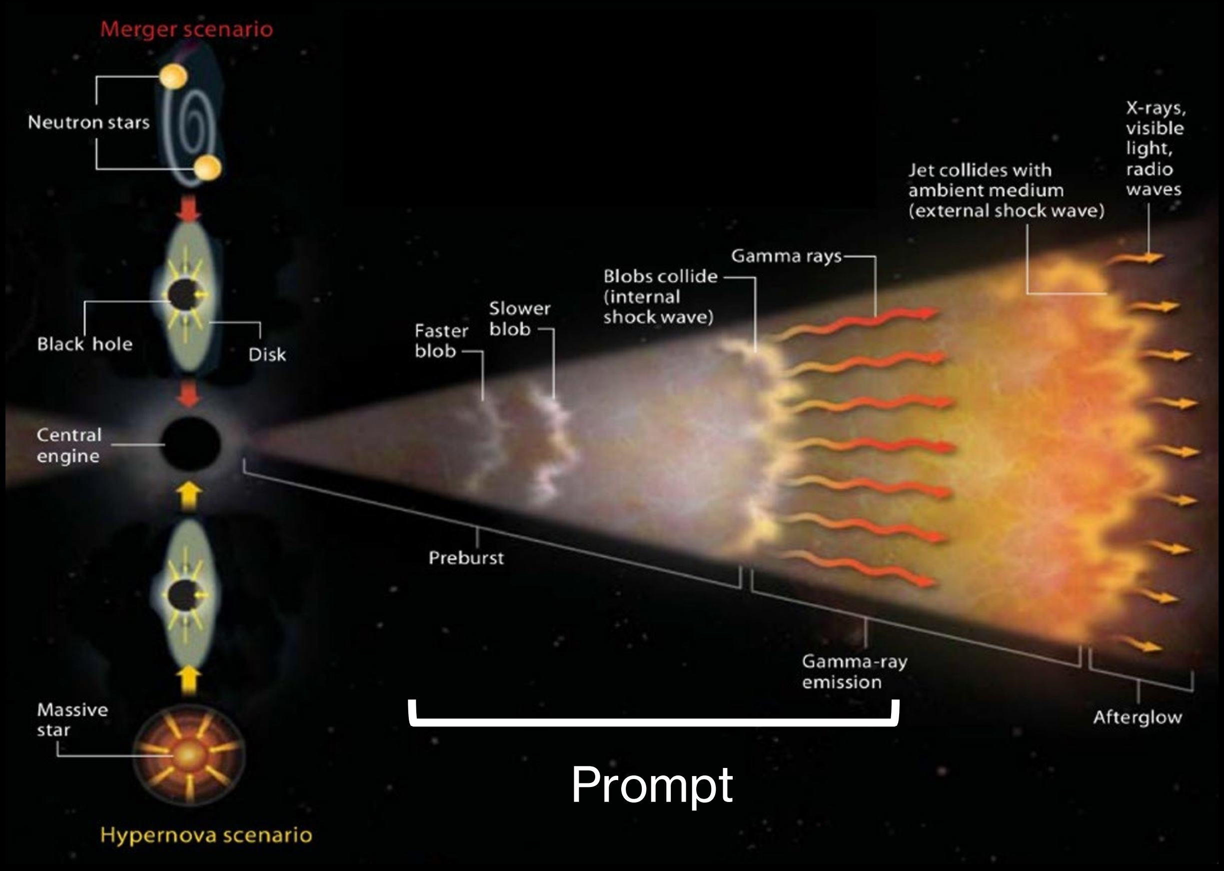

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OUR FOCUS

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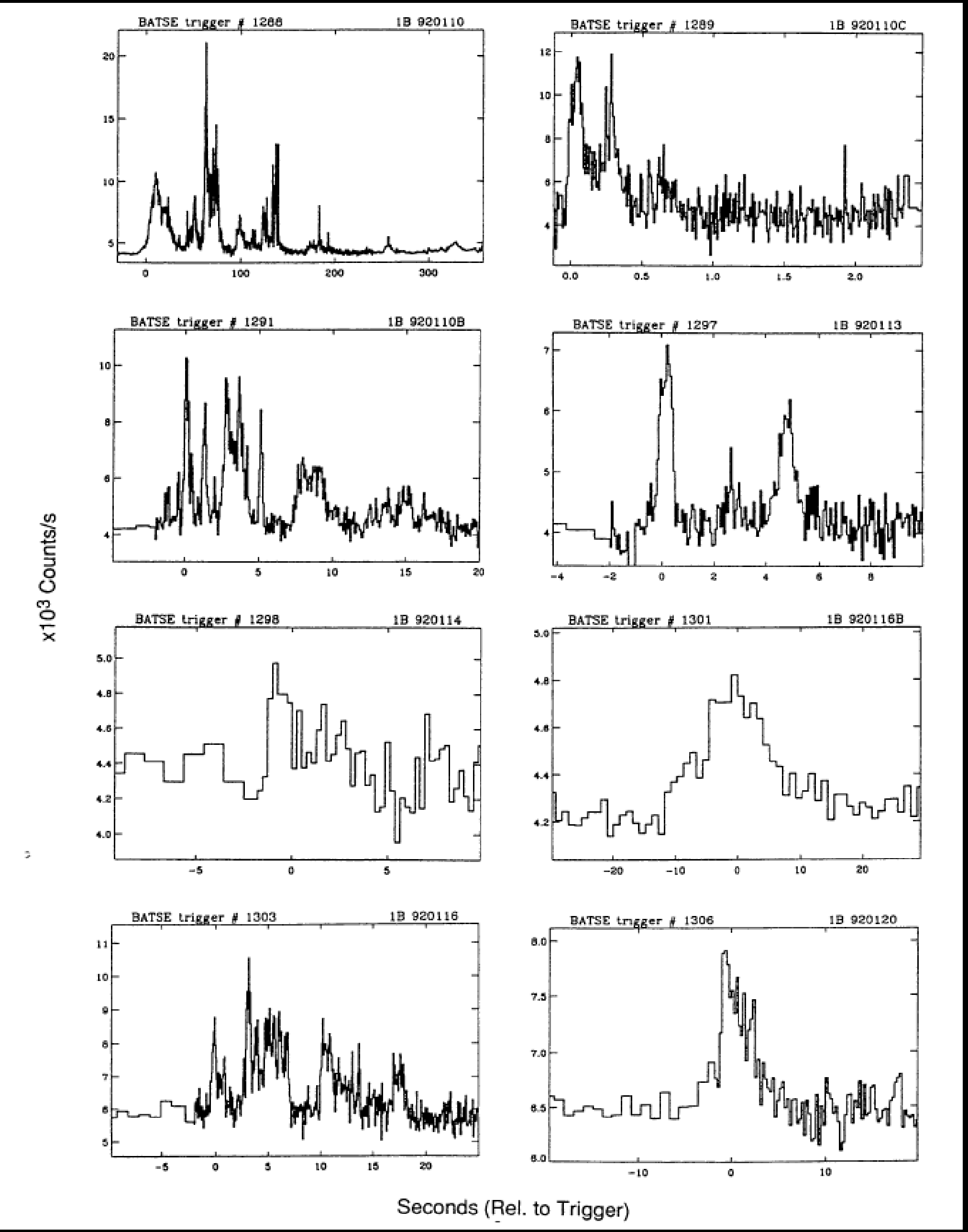
- GRB prompt emission LCs show a wide array of morphologies
- The mechanism responsible for GRB prompt emission is poorly understood

Fishman and Meegan, 1995



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- A description of the inner engine variability would help to constrain the mechanism that powers the GRB outflow
- Realistic GRB prompt emission simulations are needed to test trigger algorithms and characterise new instruments

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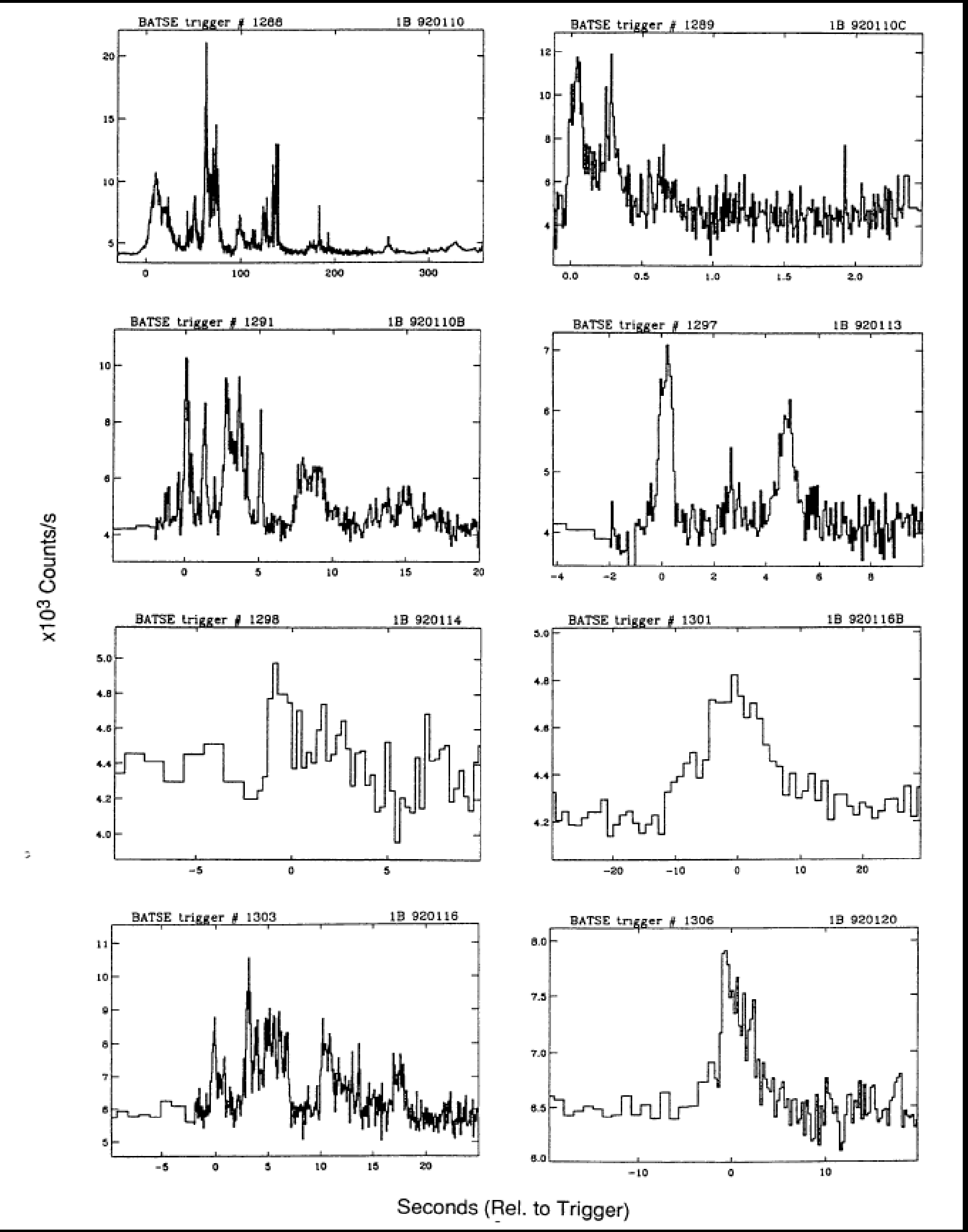

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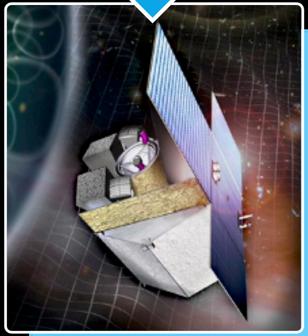

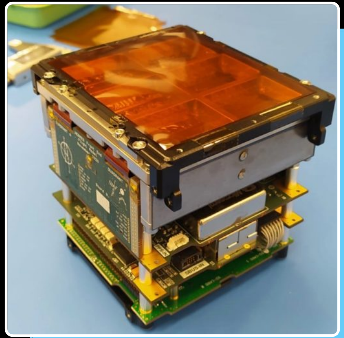

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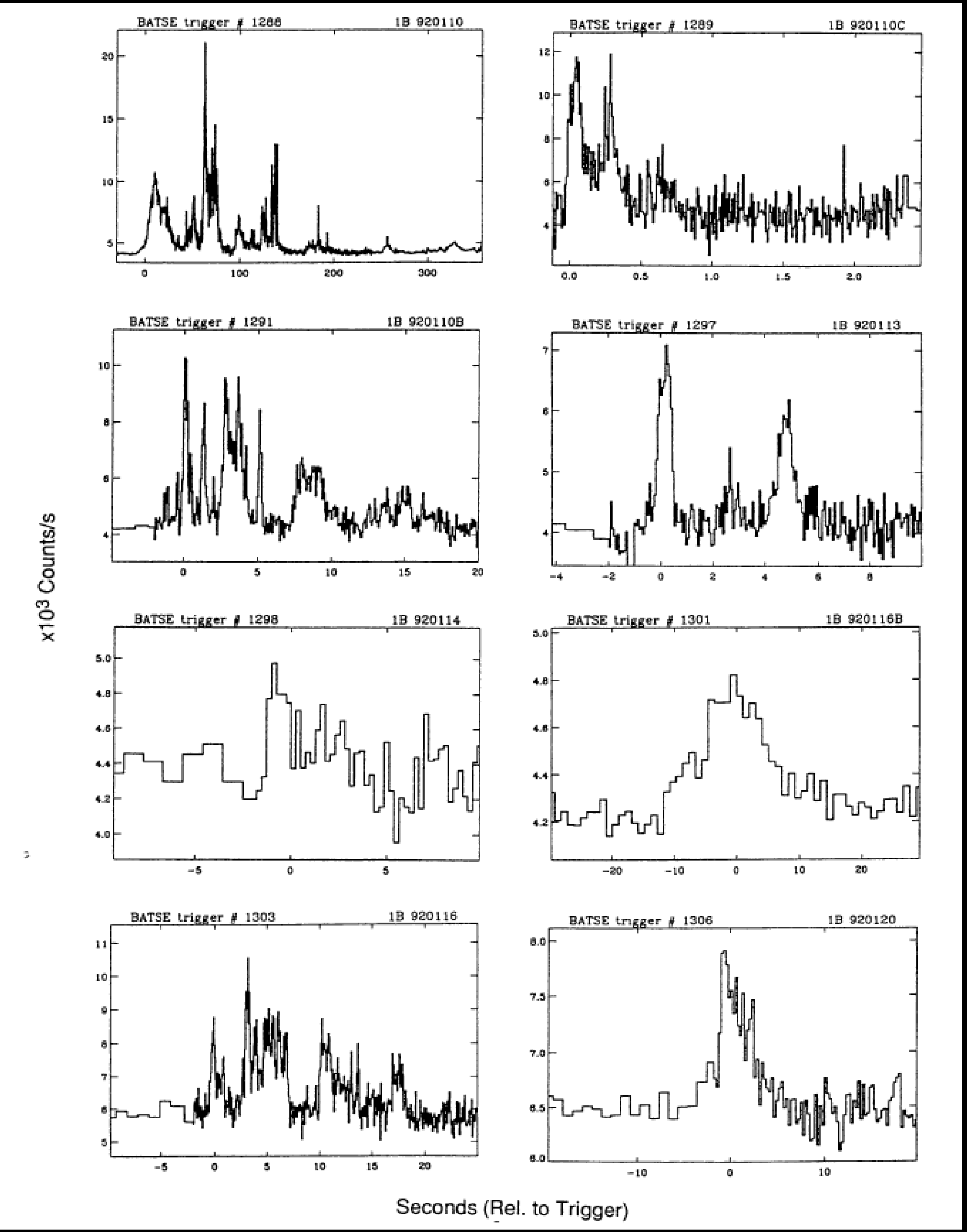
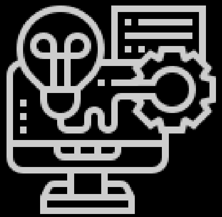


Motivations

- Two different simulation approaches:

Ex-novo simulations	Real data templates
Pro: statistical noise under total control	**Con**: Hard to decouple real signal from noise
Con: Cannot reproduce the full array of LC morphologies	**Pro**: Allows us to reproduce fully realistic LCs

- A promising approach to ex-novo LCs'simulations: LC as stochastic processes
- Machine learning (ML) comes to our aid



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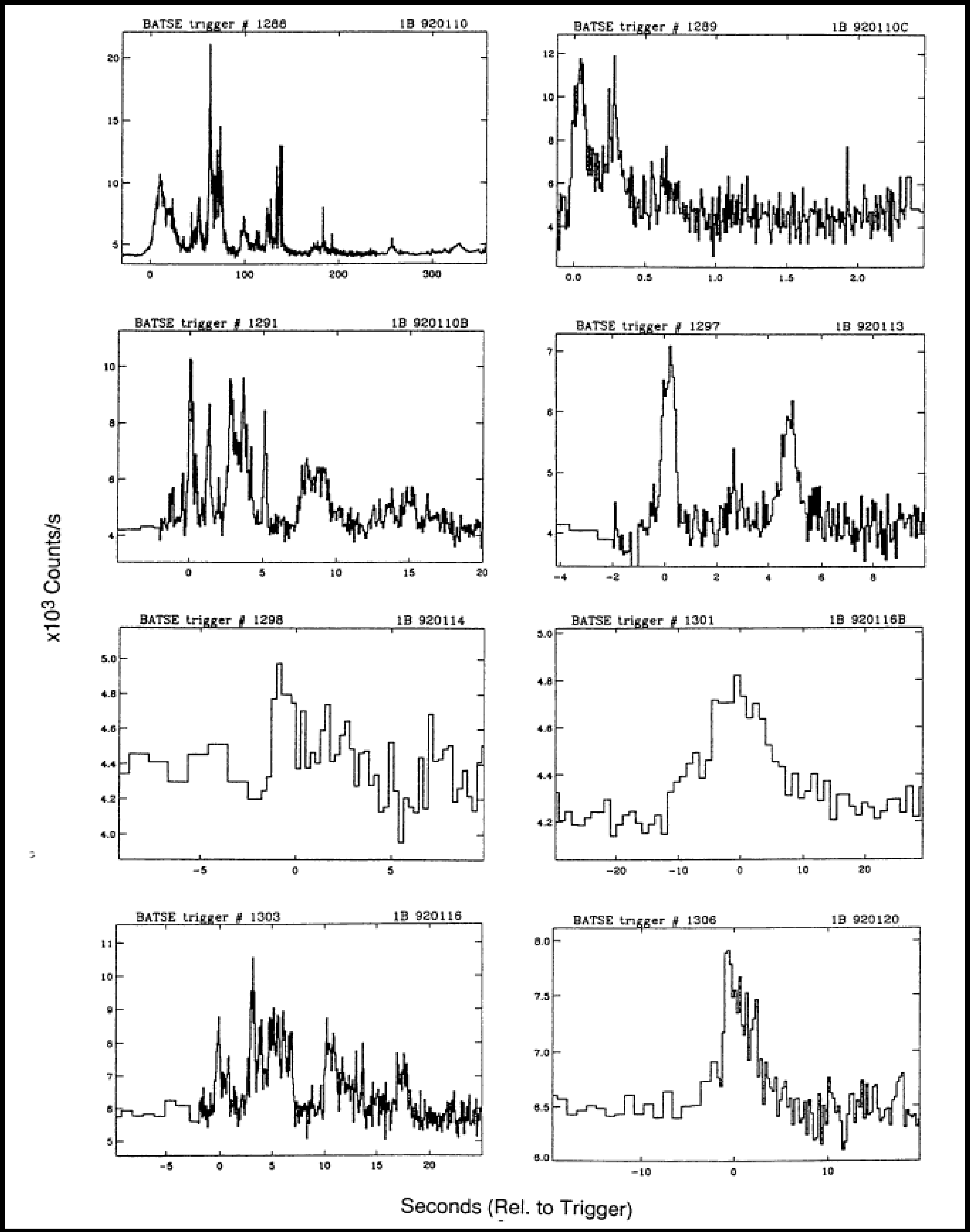

Summary

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Stochastic pulse avalanche model

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Stochastic pulse avalanche model

- Stochastic pulse avalanche model proposed by Stern and Svensson (1996, DOI:10.1086/310267): GRB LCs as stochastic processes in **nearly-critical regime**

EVIDENCE FOR "CHAIN REACTION" IN THE TIME PROFILES OF GAMMA-RAY BURSTS

BORIS E. STERN[1,2] AND ROLAND SVENSSON[2]

Received 1996 April 1; accepted 1996 July 24

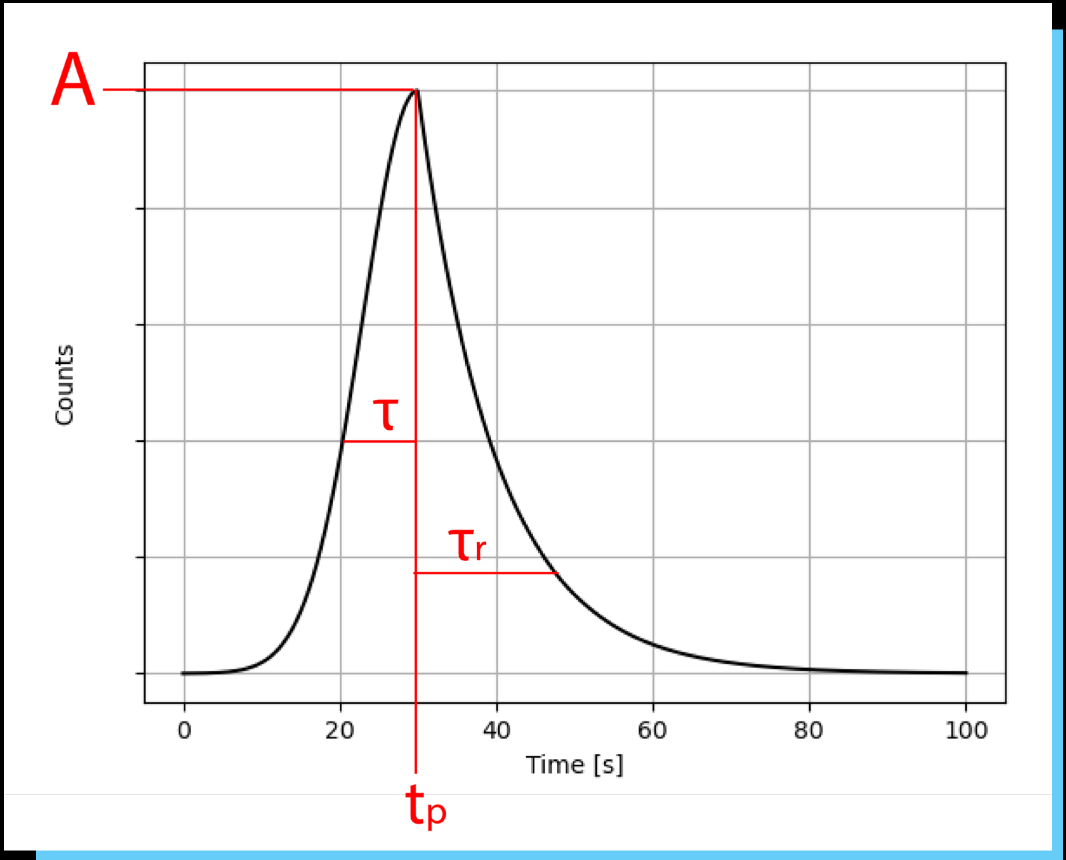
- SS96 tested the model on the CGRO/BATSE dataset
- Four metrics: (1) average peak aligned post-peak time profile, (2) average peak aligned third moment of post-peak time profile, (3) average auto correlation function, (4) distribution of the durations + visual evaluation of the GRBs'morphologies

Stochastic pulse avalanche model

- Series of primary pulses, which generates secondary pulses until the process reaches sub-critical condition and stops.
- Basic pulse shape: **FRED**, Norris pulse (Norris+1996)

$$f(t) = \begin{cases} A \exp\left\{-[(t - t_p)/\tau_r]^2\right\}, & \text{for } t < t_p \\ A \exp\left\{-(t - t_p)/\tau\right\}, & \text{for } t > t_p \end{cases}$$

- Seven model parameters: average number of primary pulses (μ_0), average number of child pulses per parent (μ), time delay between pulses parameter (α), limits of the distribution of the parents' time constants (τ_{min}, τ_{max}), limits of the distribution of child/parent time costants (δ_1, δ_2).



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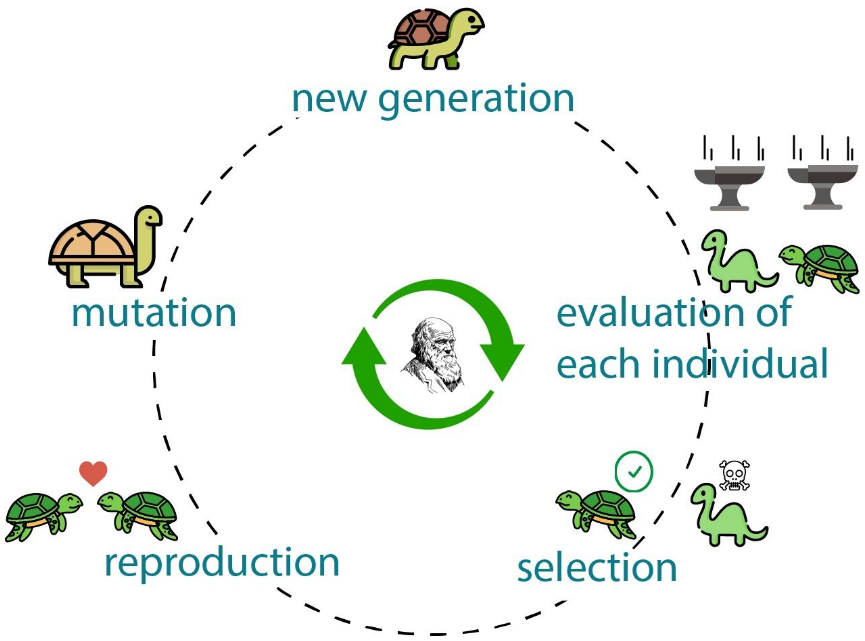
Genetich Algorithms

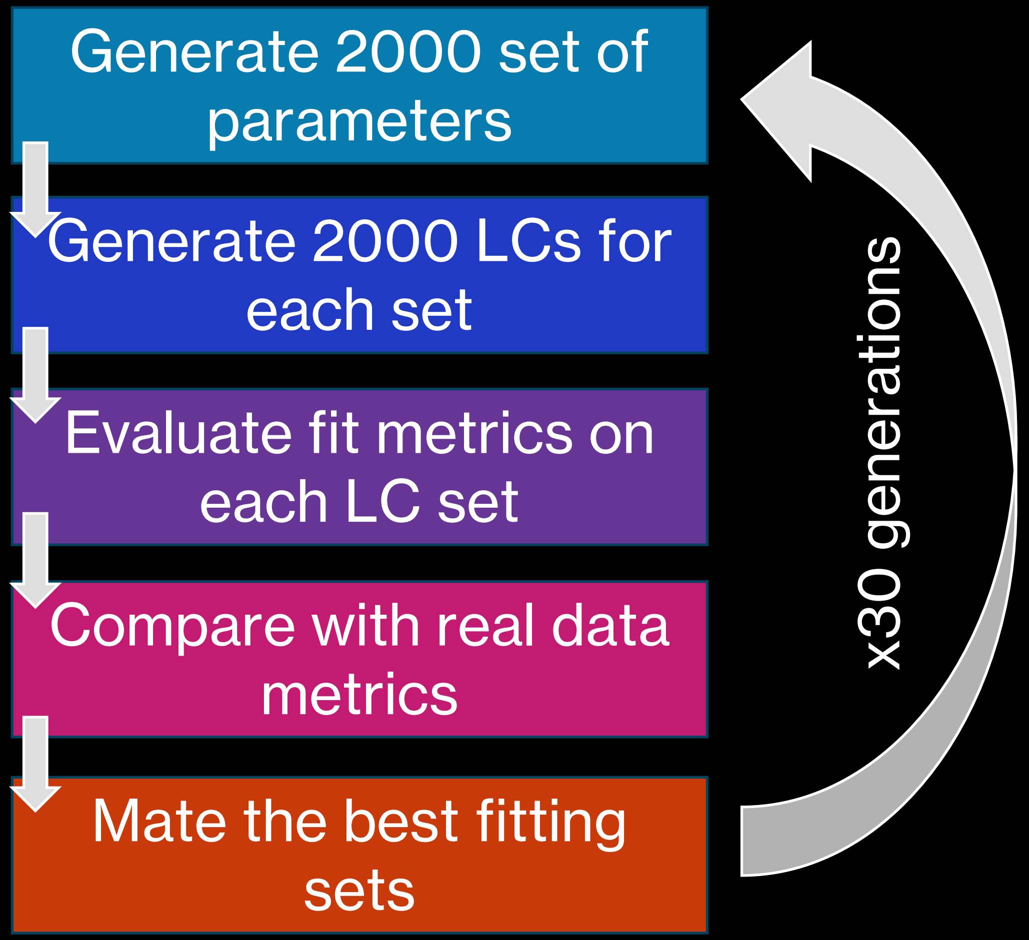
- **<u>Genetic algorithms</u>**: simulate a darwinian evolution process to find the parameters that minimize a function
- Optmisation process:

1. Generate a random population (genome = value of the 7 parameters)
2. Evaluate fitness of each individual
3. Mate (i.e. mix the genes) pairs of best fitting individuals
4. Some individuals undergo random mutation (i.e. the value of the genes is randomly selected from the parameter space instead of being inherited from the parents)
5. Repeat on new generation



Model optimisation with GA

- GA implemented with **PyGAD** (arXiv:2106.06158)
- **Fitness Metrics**: four metrics defined by SS96
- **Data Sets**: (1) CGRO/BATSE (long GRBs, S2N > 70), (2) Swift/BAT (long GRBs, S2N > 15)
- **Constraints**:
  - T90 > 2 s (i.e., long GRBs);
  - LCs last at least for 150 s after the peak;
  - $S/N_{BATSE} > 70$, $S/N_{Swift} > 15$.
- After constraints: 585 from BATSE and 531 from Swift LGRBs as the two training sets (same number as SS96).



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Optimised parameters

Parameter	$\mathrm{SS96}_{\mathrm{BATSE}}$	$\mathrm{GA}_{\mathrm{BATSE}}$	GA_{Swift}
μ	1.20	$1.10^{+0.03}_{-0.02}$	$1.34^{+0.03}_{-0.02}$
μ_0	1.00	$0.91^{+0.06}_{-0.07}$	$1.16^{+0.18}_{-0.10}$
α	4.00	$2.57^{+0.07}_{-0.52}$	$2.53^{+0.25}_{-0.00}$
δ_1	-0.50	$-1.28^{+0.16}_{-0.05}$	$-0.75^{+0.11}_{-0.29}$
δ_2	0	$0.28^{+0.01}_{-0.03}$	$0.27^{+0.01}_{-0.02}$
τ_{min}	0.02 s	$0.02^{+0.02}_{-0.01}$ s	$0.03^{+0.02}_{-0.02}$ s
τ_{max}	26.0 s	$40.2^{+0.9}_{-1.2}$ s	$56.8^{+0.4}_{-1.3}$ s
Loss (*Train* best)	–	0.72	0.38
Loss (*Train* avg.)	–	0.98	0.66
Loss (*Test*)	1.47	0.88	0.56

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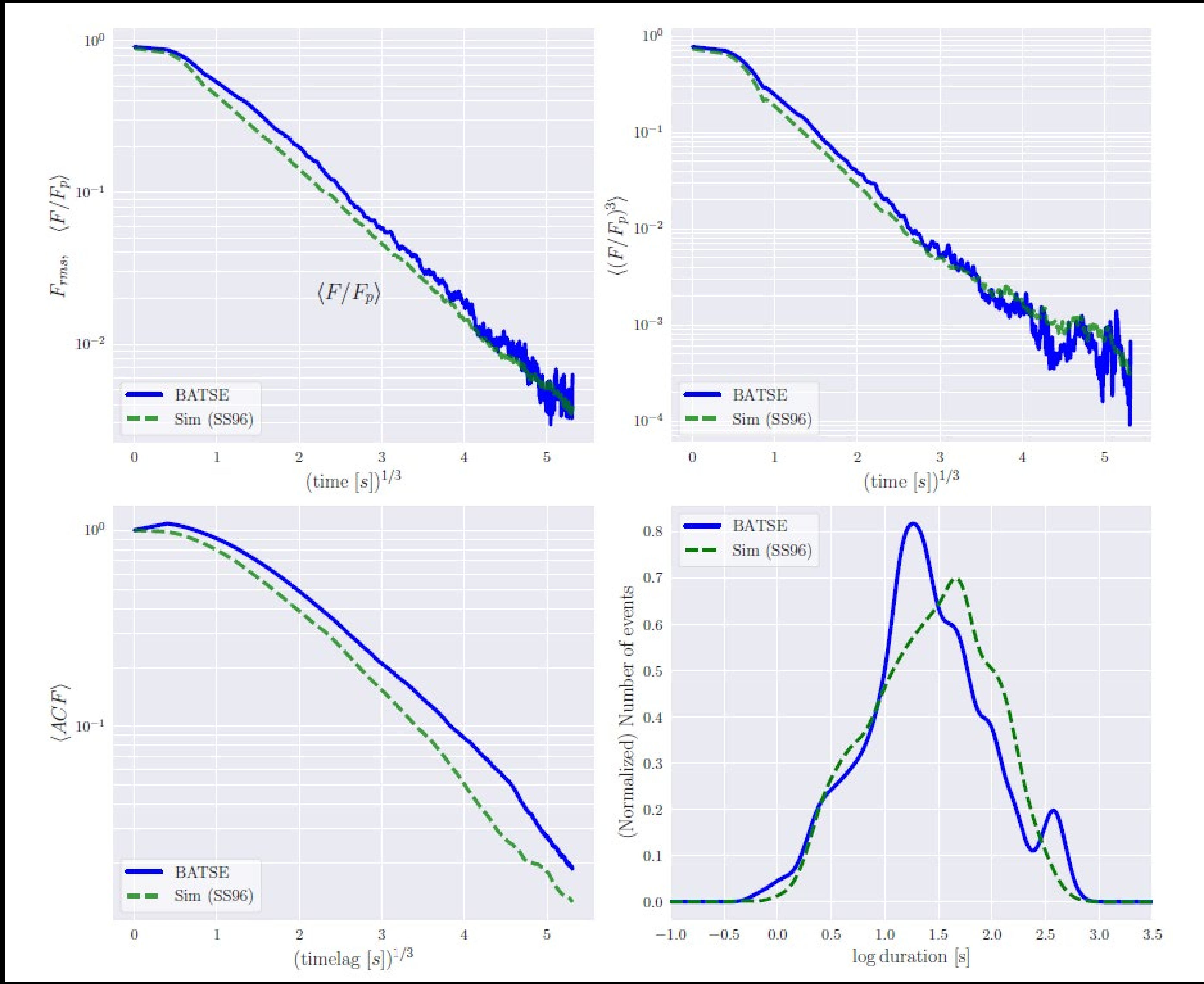
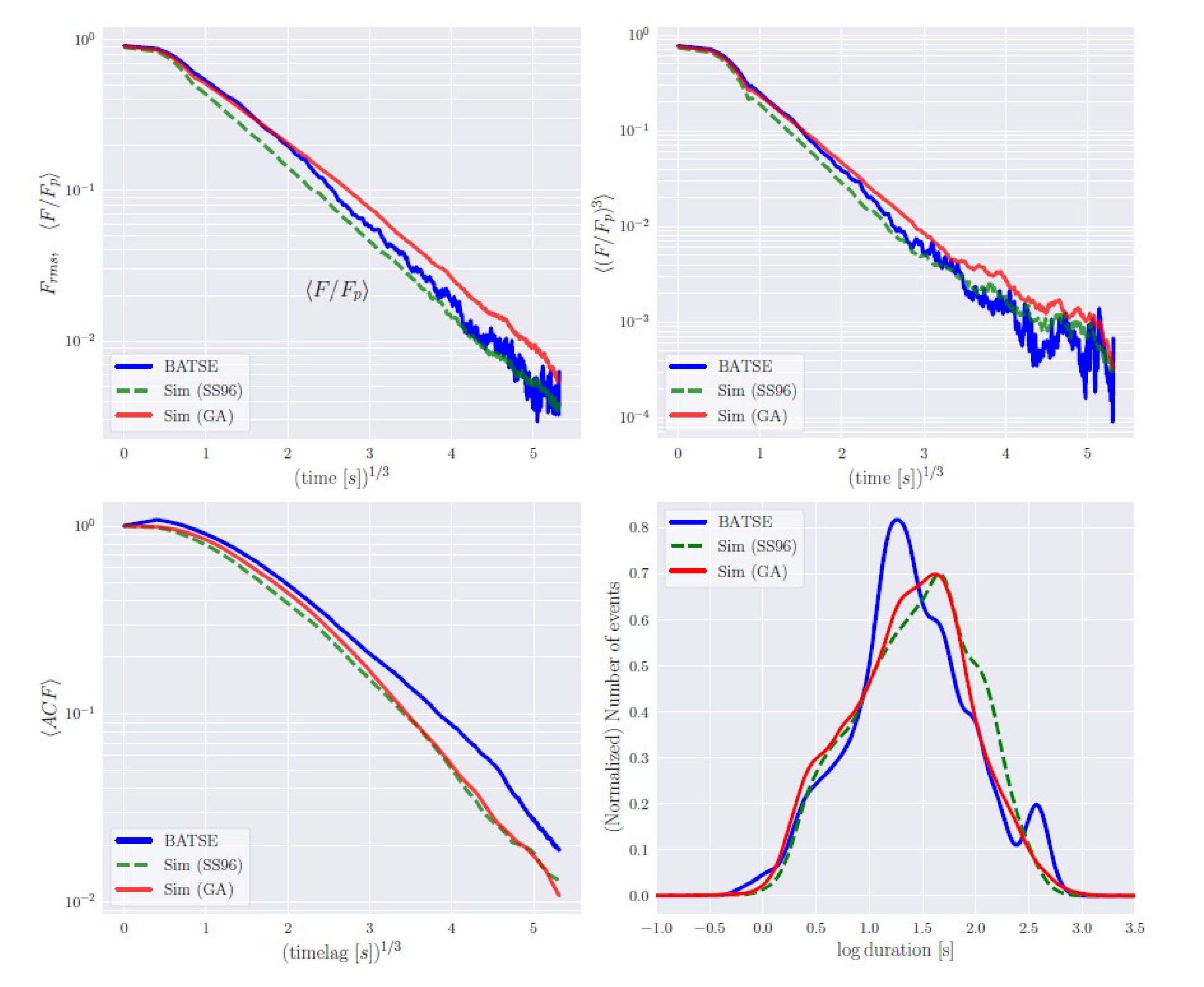
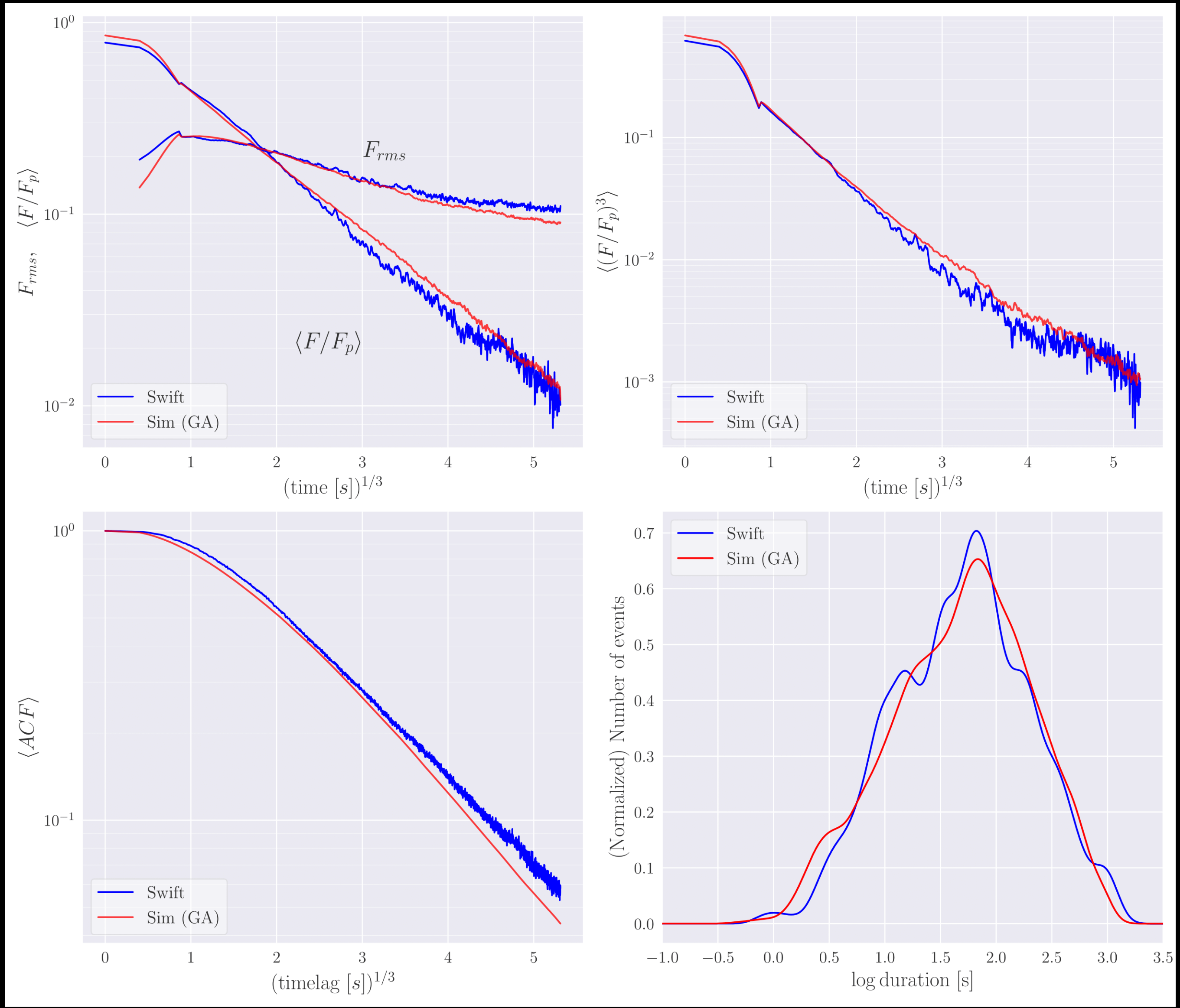


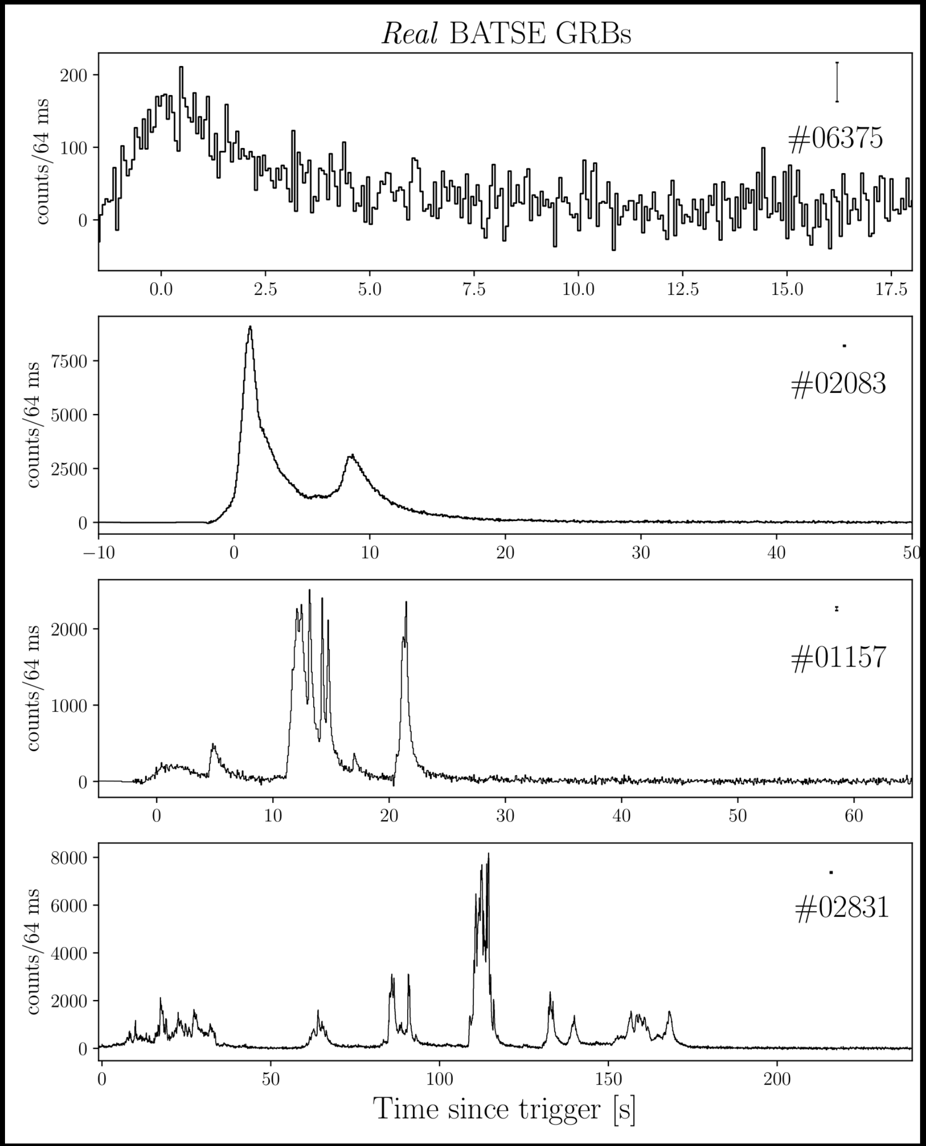
After BATSE optimization (GA)



Swift/BAT optimisation (GA)



Simulated light-curves: real vs fake



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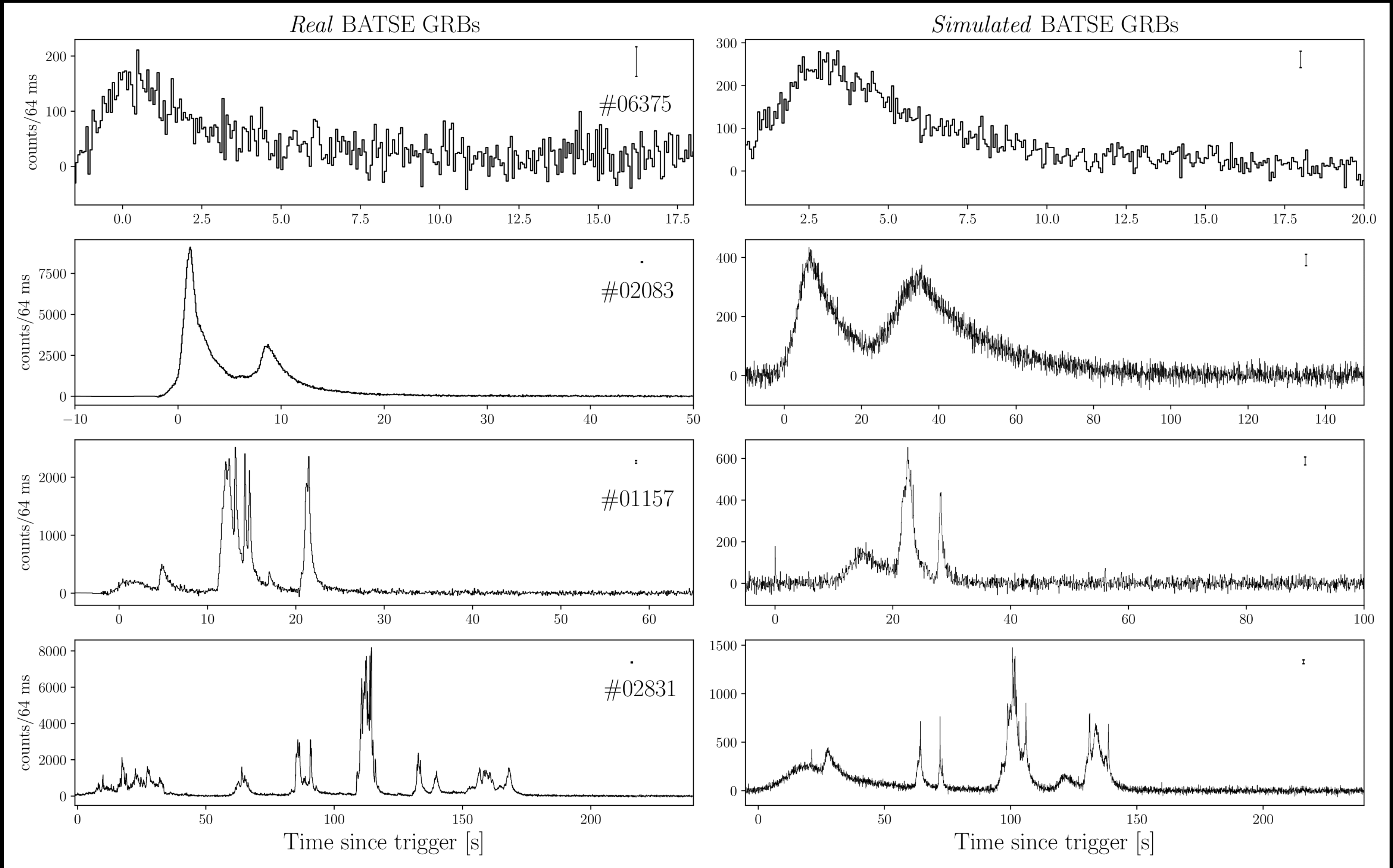

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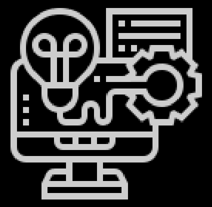

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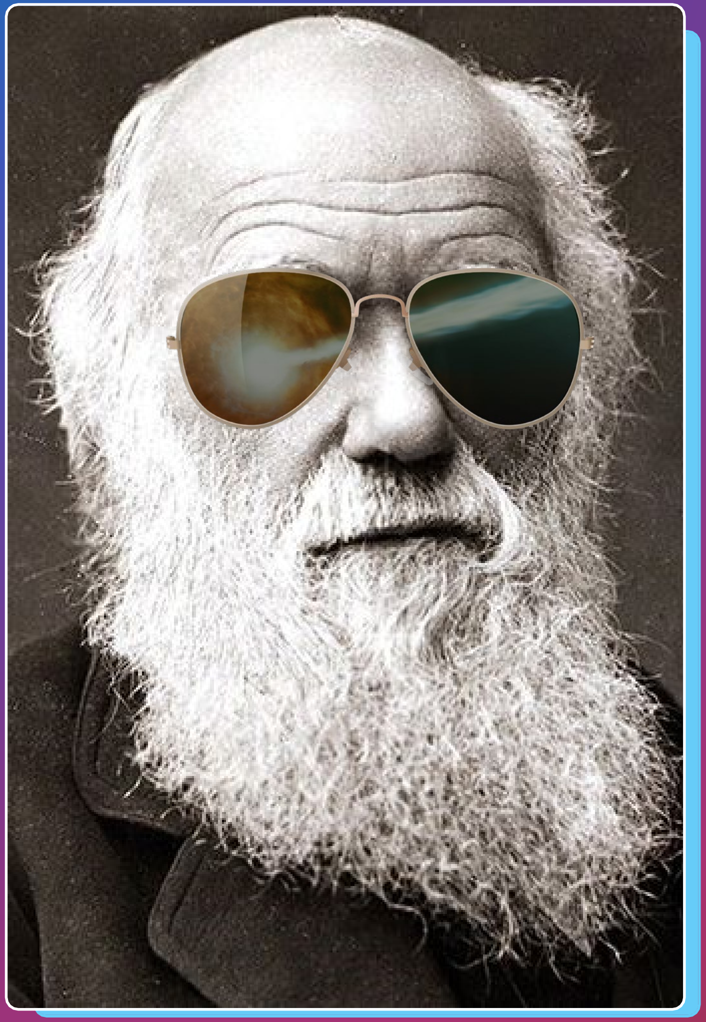
- Our results confirm the SS96 intuition, and propel the avalanche feature in a critical regime as a key trait of the energy release in GRB engines.
- The model allows us to simulate realistic LCs as seen by upcoming detectors (THESEUS, HERMES and more)
- Our technique can be extended to other datasets, and more physically-grounded GRB LCs models.



Thank you for your attention!

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- Or scan this QR-code: