Early Inference of Supernova Light Curve Parameters with Physics-Informed Neural Networks

Gabriel Teixeira

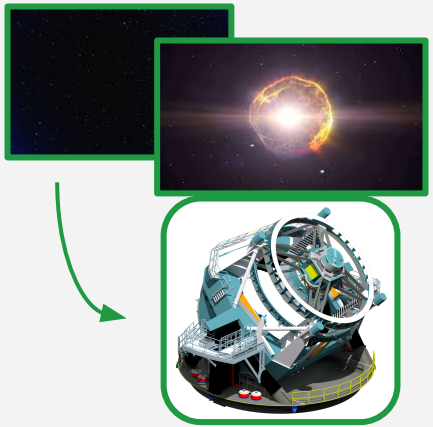
Lab-IA 4 Physics

CBPF Centro Brasileiro de Pesquisas Físicas

FINK BRAZIL

CNPq

The Fink Flow



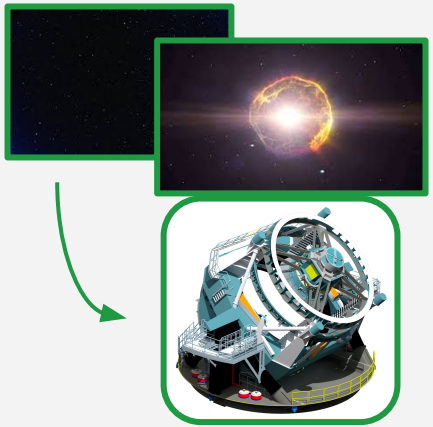
LSST/ZTF - Sky Imaging

Full Alert Stream

Fink Broker

Filtered Alerts

Scientific Community



LSST/ZTF - Sky Imaging

Full Alert Stream

FINK

Filtered Alerts

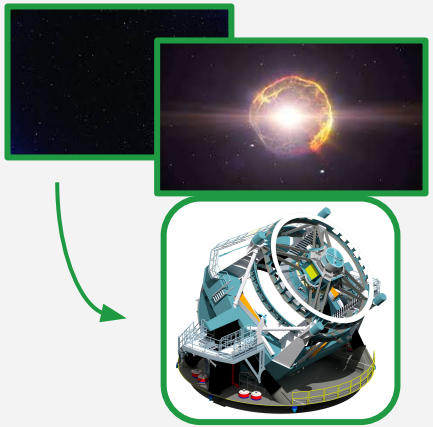
Scientific Community

Fink Broker

Processing

Classifier

Science Data



LSST/ZTF - Sky Imaging

Full Alert Stream

Fink Broker

Filtered Alerts

Scientific Community

Processing

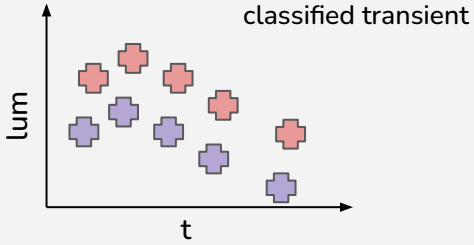
Classifier

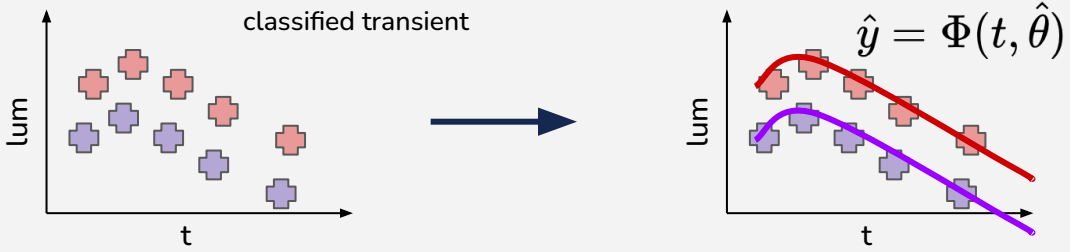
Science Data

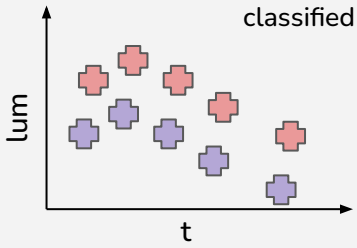
Physical Inference

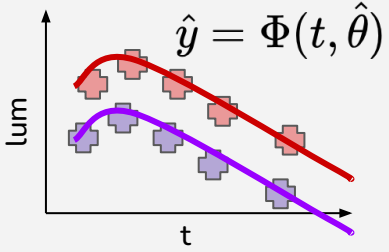
$\{\hat{\theta}\}$

Modeling a Light Curve


classified transient
lum
t


classified transient
lum
t
$\hat{y} = \Phi(t, \hat{\theta})$
lum
t

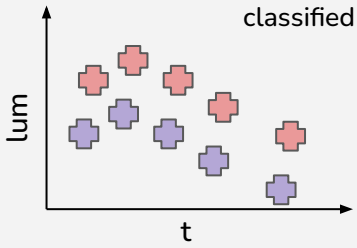


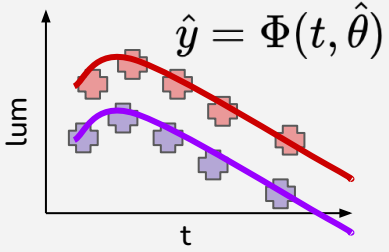


$$\hat{\theta}??$$

$$p(\hat{\theta}|\{y, x\})$$

observed data





$$\hat{\theta}??$$

$$p(\hat{\theta}|\{y, x\})$$

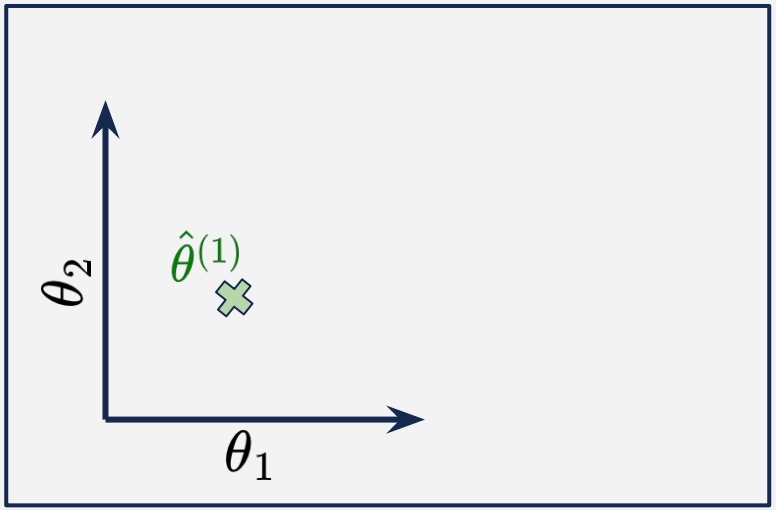
observed data

Posterior Likelihood

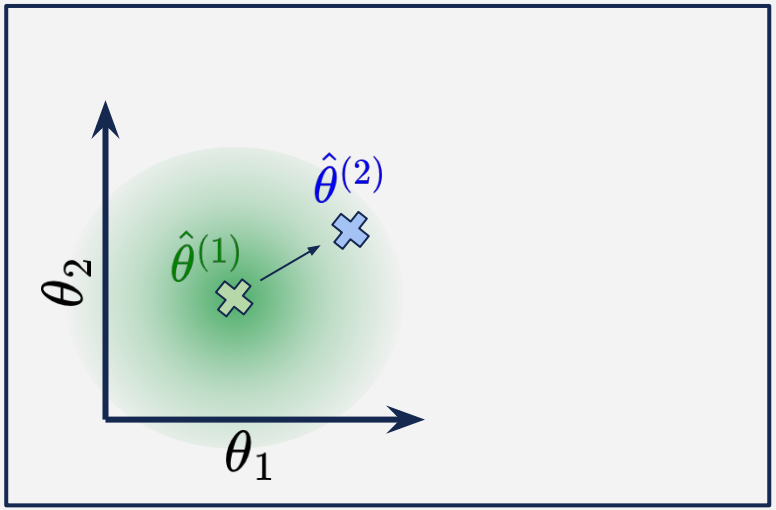
$$p(\hat{\theta}|\{y, x\}) \propto p(\{y, x\}|\hat{\theta})p(\hat{\theta})$$

Prior

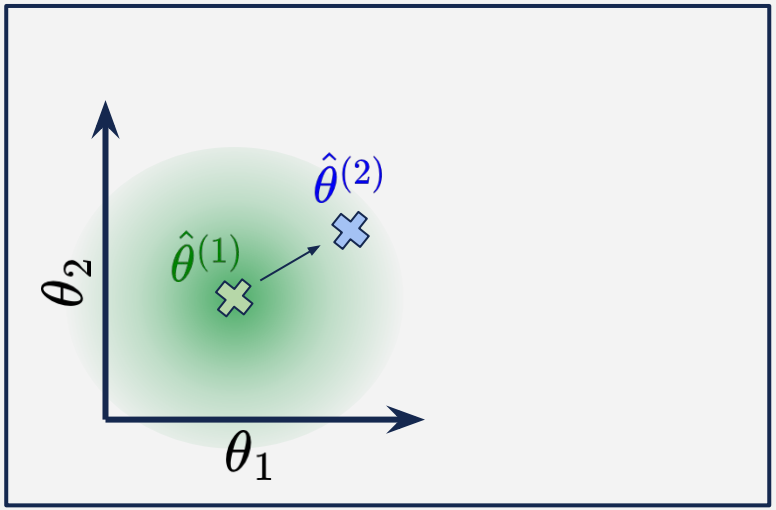
Markov Chain Monte Carlo



Markov Chain Monte Carlo



Markov Chain Monte Carlo



$$r = \frac{p(\{y,x\}|\hat{\theta}^{(2)})}{p(\{y,x\}|\hat{\theta}^{(1)})}$$

if r>1:
    keep $\hat{\theta}^{(2)}$
else:
    keep $\hat{\theta}^{(2)}$ with probability r

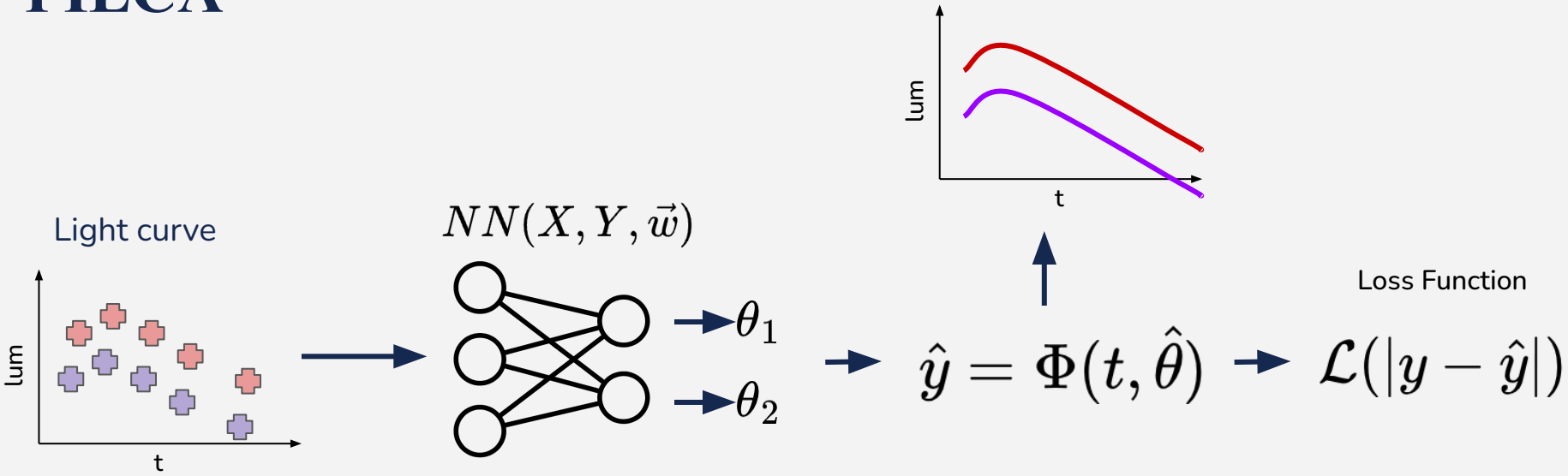
Markov Chain Monte Carlo

Pros	Cons
Explore the full posterior	Computationally Expensive
Converges	Does not work properly sparse light curve
Very well studied	Requires human in the loop

Physics Informed Machine Learning Light Curve Analyzer

PILCA

PILCA


Light curve
lum
t
$NN(X, Y, \vec{w})$
θ_1
θ_2
lum
t
$\hat{y} = \Phi(t, \hat{\theta})$
Loss Function
$\mathcal{L}(|y - \hat{y}|)$

PILCA

$$\hat{\theta} = NN(X, Y, \vec{w}) \longrightarrow \hat{\theta}^{(1)} = NN(X, Y, \vec{w}^{(1)})$$

$$\hat{\theta}^{(2)} = NN(X, Y, \vec{w}^{(2)})$$

$$\vec{w}^{(2)} = \vec{w}^{(1)} - \eta \nabla_w \mathcal{L}(y, \hat{y})$$

PILCA

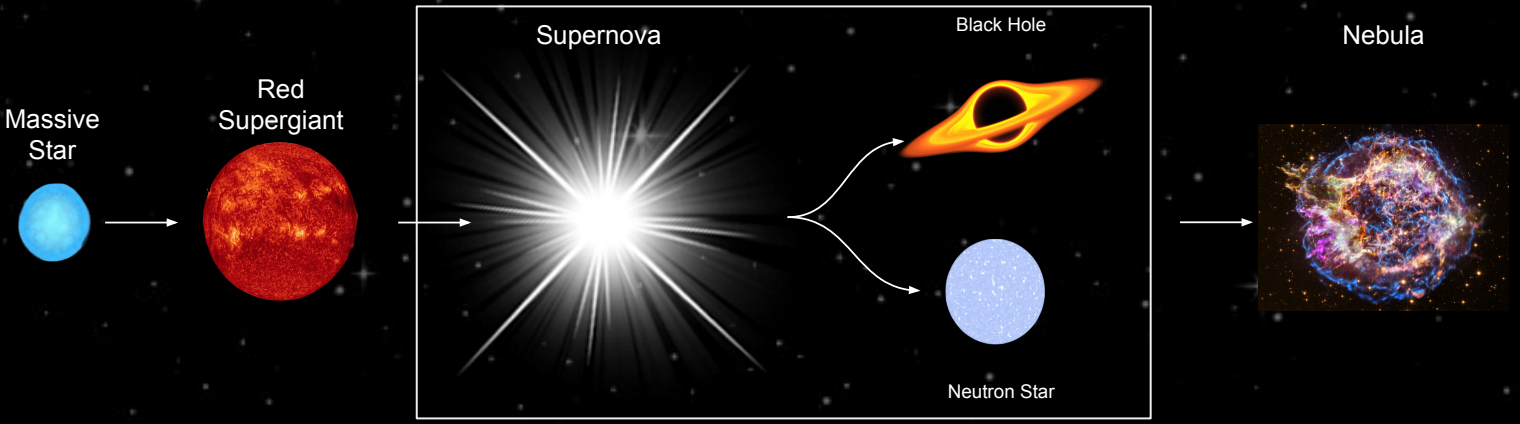
Physics Information from the model

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \hat{\theta}} \frac{\partial \hat{\theta}}{\partial w}$$

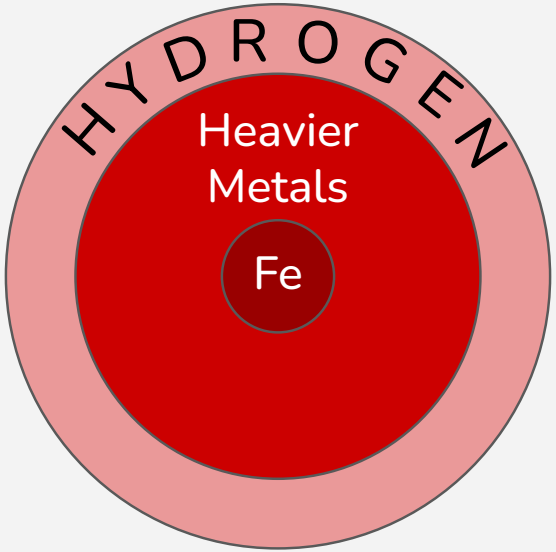
Neural Network

The case of Type II-P SNe

Type II-P SN


Massive Star
Red Supergiant
Supernova
Black Hole
Neutron Star
Nebula

Type II-P SN

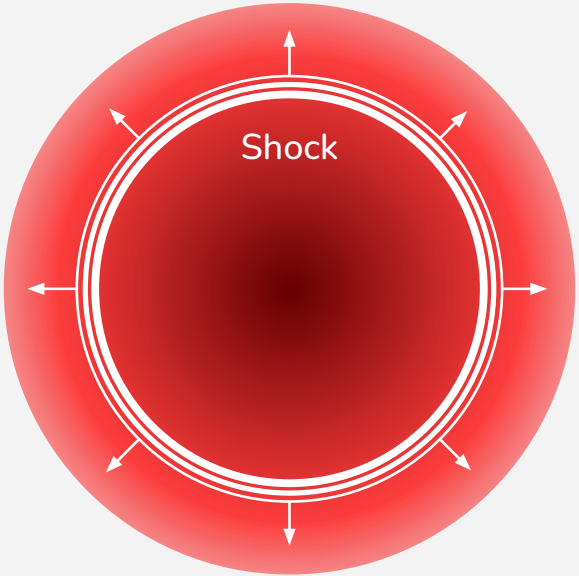


Red Supergiant

Type II-P SN

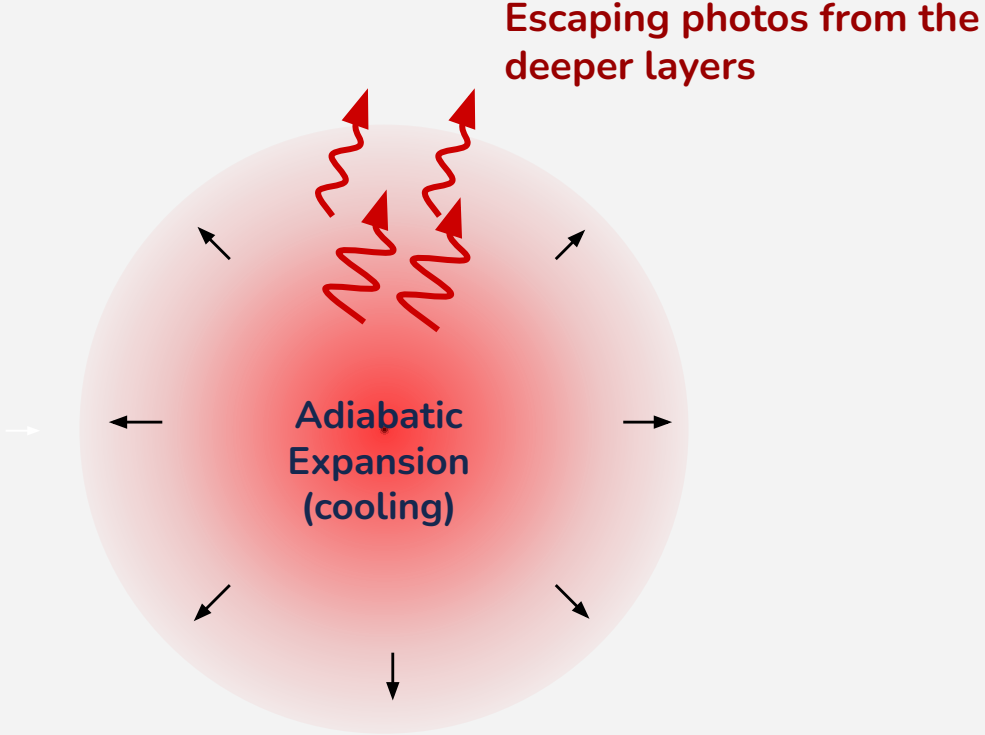
Core Collapse

Type II-P SN

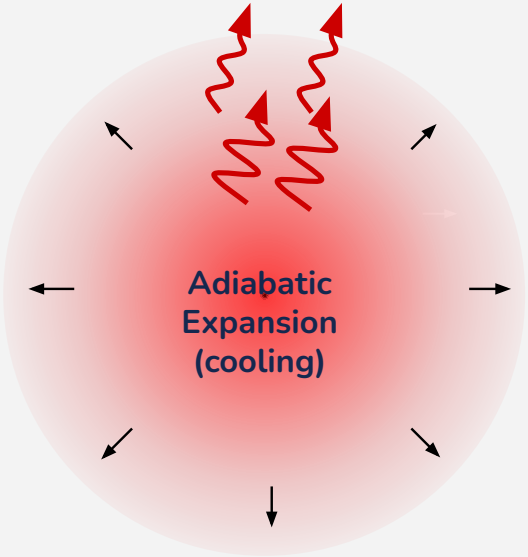


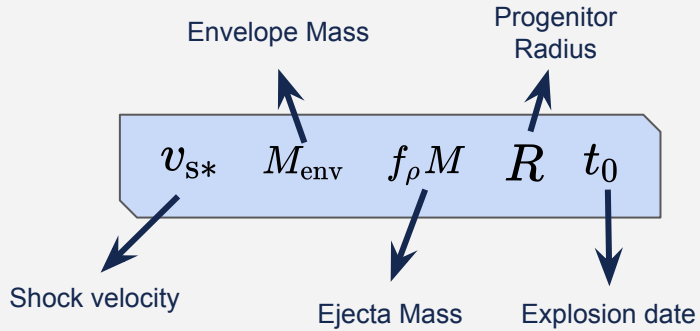
Ejecta heating at
shock breakout

Type II-P SN


Escaping photos from the deeper layers
Adiabatic Expansion (cooling)

Shock Cooling Models



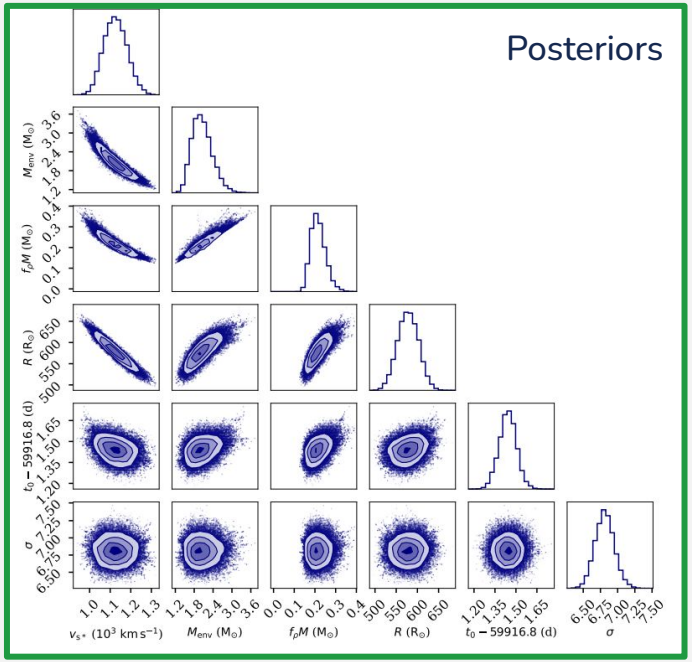


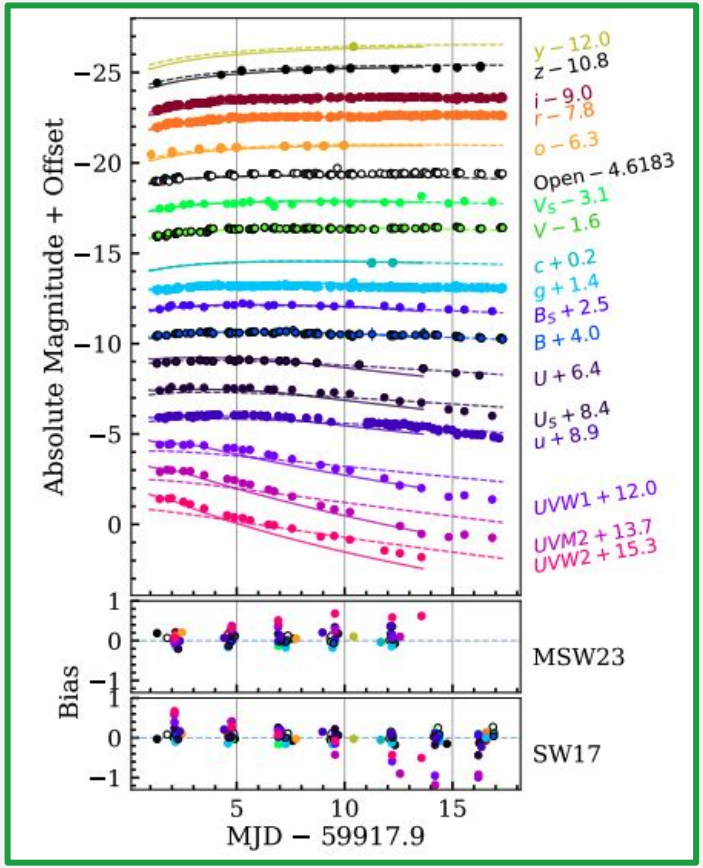
$$L(\tilde{t}) = L_{\rm br}\left\{\tilde{t}^{-4/3} + 0.9\exp\left[-\left(\frac{2.0t}{t_{\rm tr}}\right)^{0.5}\right]\tilde{t}^{-0.17}\right\}$$

$$L_{\rm br} = (3.69\times10^{42}\,{\rm erg\,s^{-1}})R^{0.78}v_{s*}^{2.11}(f_\rho M)^{0.11}\kappa^{-0.89}$$

The SN 2022acko

Teixeira et al.+25, submmited to ApJ
https://arxiv.org/abs/2509.04707





PILCA Preliminary Experiments

“Simulated Data”

1.4 points/filter/day

v_{S*} = 0.35

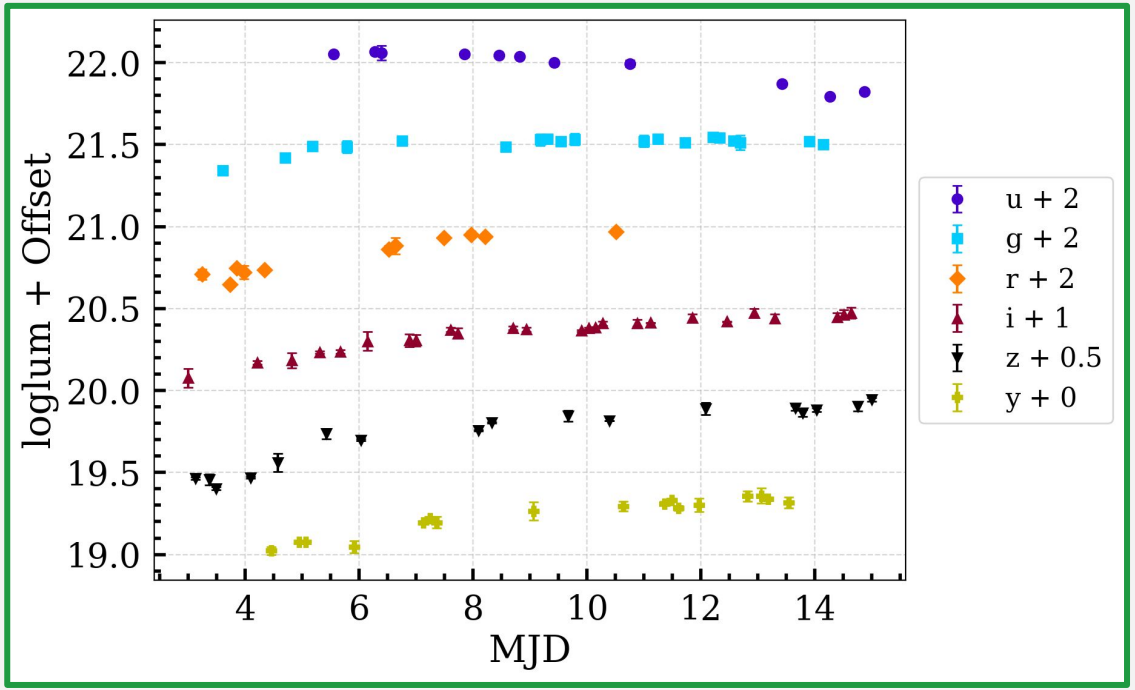
M_{env} = 2.0

$f_\rho M$ = 0.21

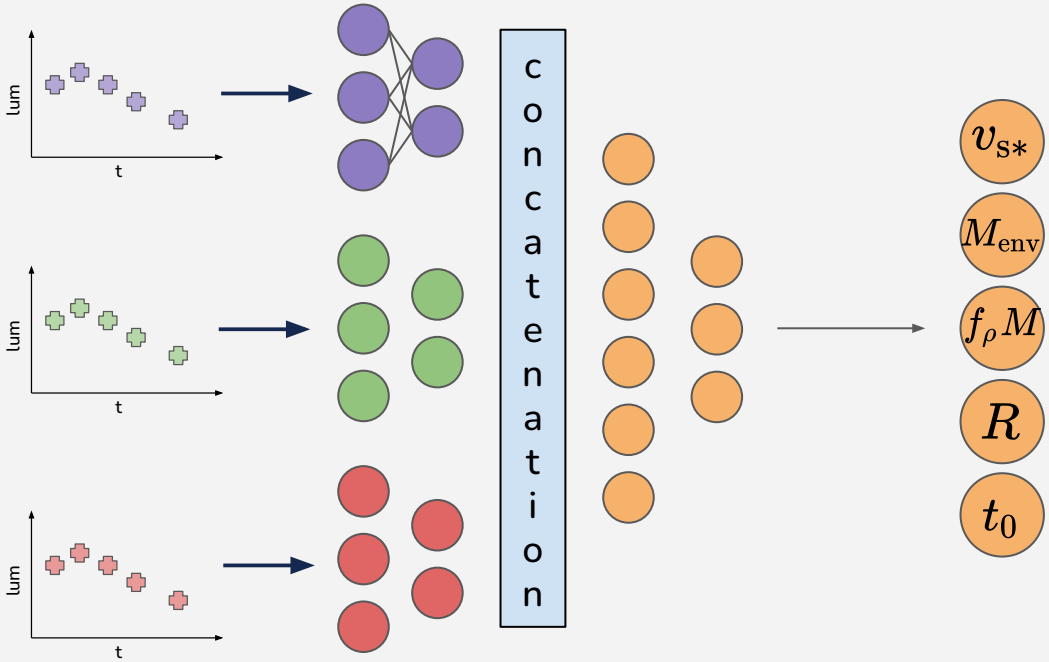
R = 4.0

t_0 = 2.5

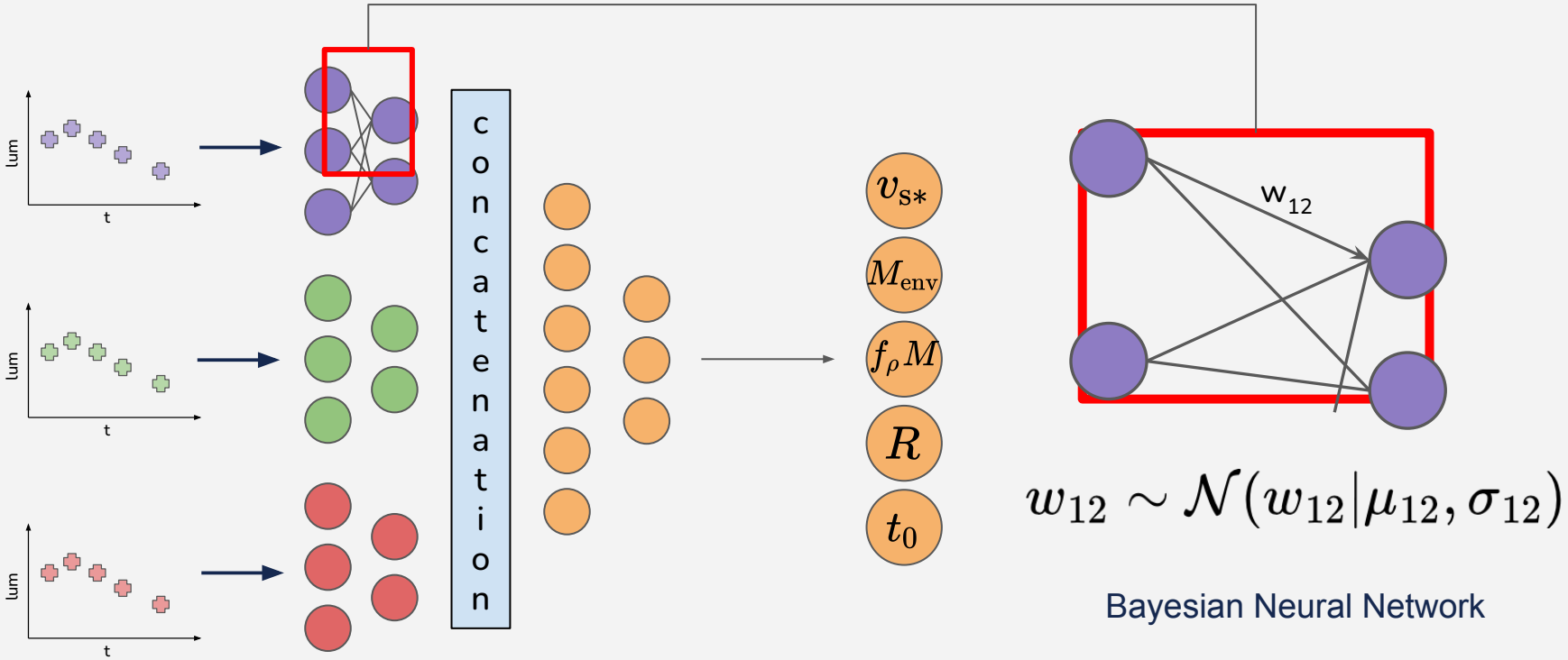
- parameters in model units



Network



Network


lum
t
lum
t
lum
t
concatenation
v_{s*}
M_{env}
$f_\rho M$
R
t_0
w_{12}
$w_{12} \sim \mathcal{N}(w_{12}|\mu_{12}, \sigma_{12})$
Bayesian Neural Network

Results

1.4 points/filter/day

v_{S*} = 0.4 (+14%)

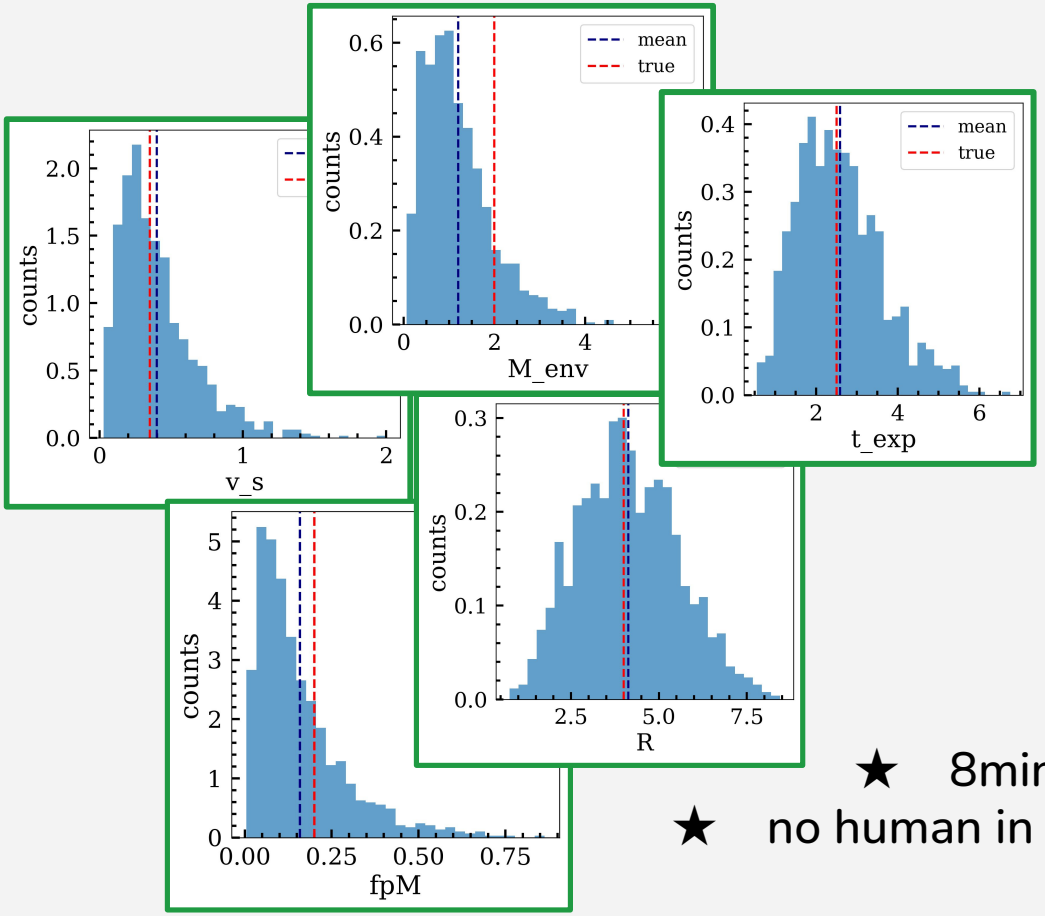
M_{env} = 1.2 (-40%)

$f_\rho M$ = 0.17 (-20%)

R = 4.1 (+3%)

t_0 = 2.6 (+3%)

- parameters in model units



★ 8min run

★ no human in loop

Results

1.4 points/filter/day

v_{S*} = 0.4 (+14%)

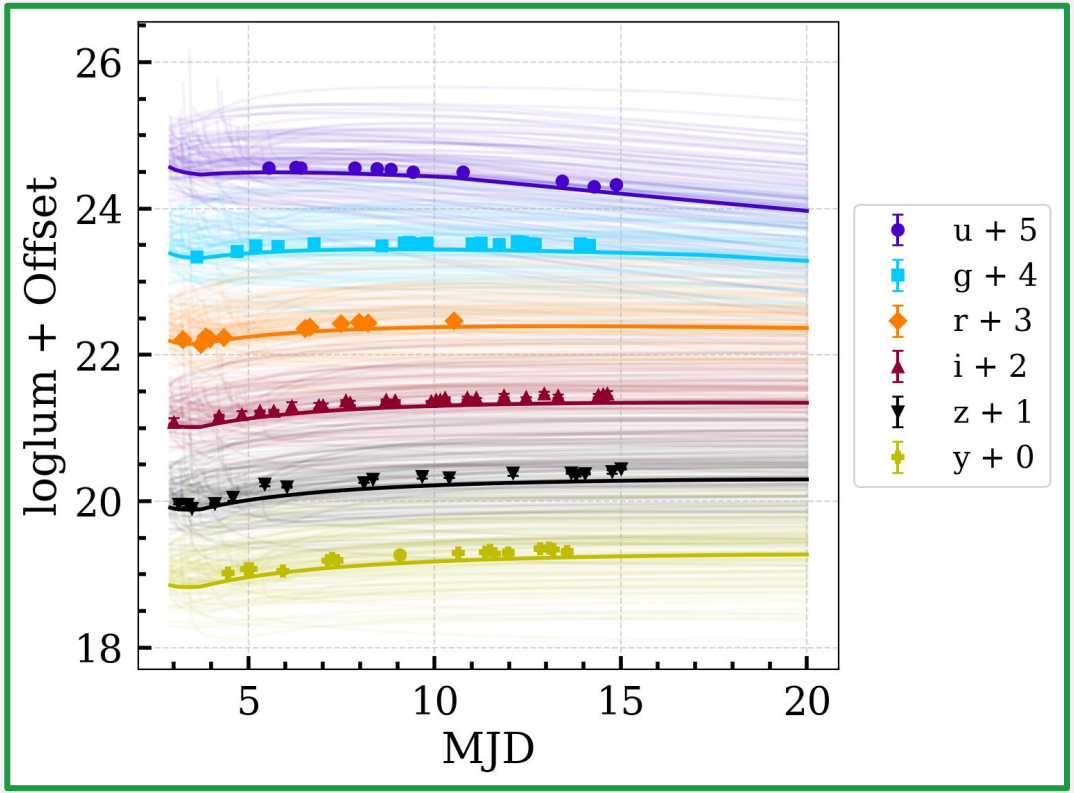
M_{env} = 1.2 (-40%)

$f_\rho M$ = 0.17 (-20%)

R = 4.1 (+3%)

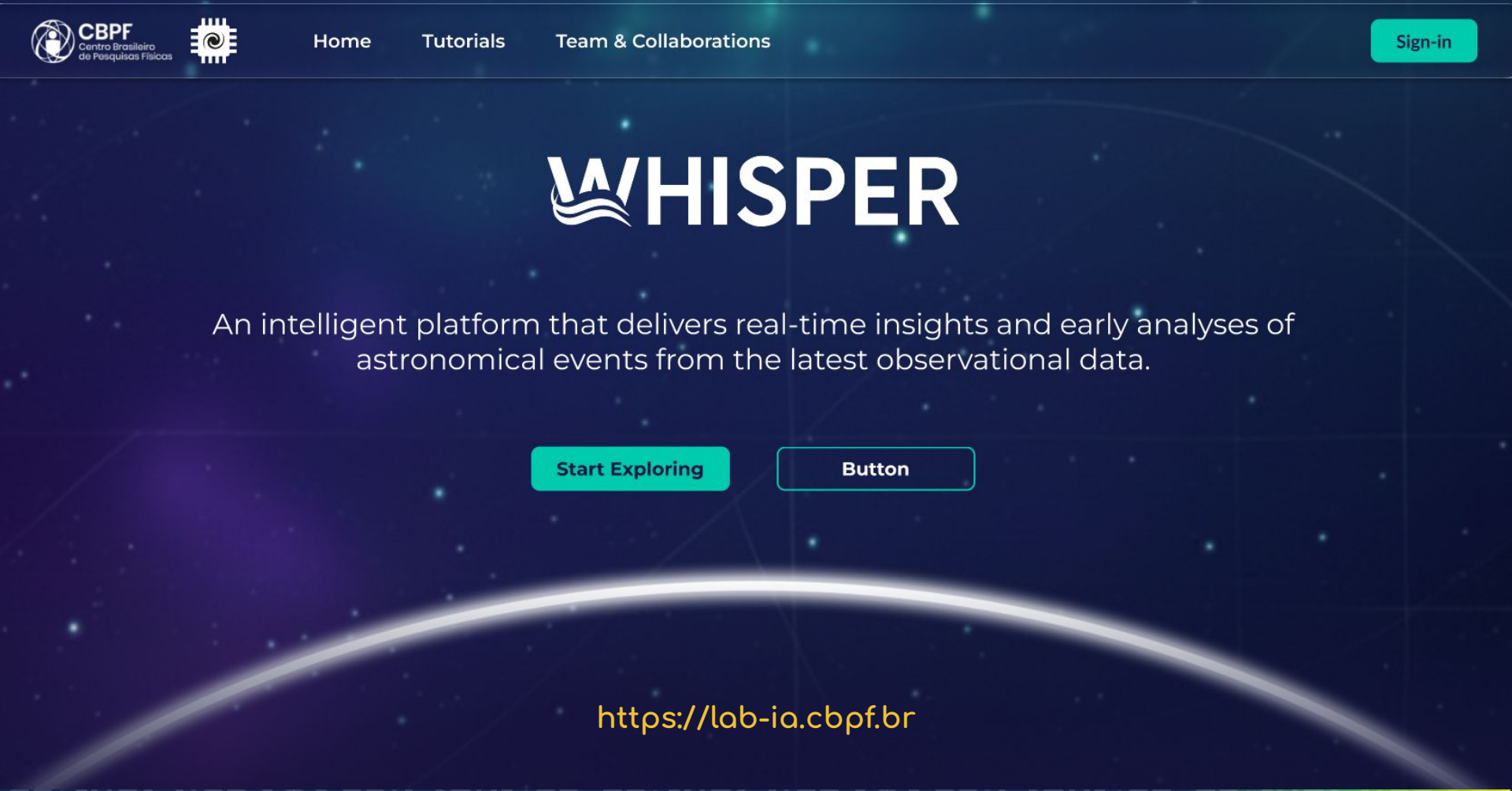
t_0 = 2.6 (+3%)

- parameters in model units



Plans


Search
Data Transfer
Xmatch
Gravitational Waves
Statistics
ZTF25abxcktl
SN CANDIDATE
UNKNOWN
TNS: SN 2025AAVM (SN II)
ZTF: 1.0"
PS1: 0.7"
GAIA: 15.8"
Discovery date: 2025-10-18 11:51:20
Last detection: 2025-11-09 12:46:10
Duration: 22.04 / 27.03 days
Detections: 22 good, 0 bad, 4 upper
RA/Dec: 11 28 25.40 +51 01 26.5
J2000
11 28 25.396 +51 01 26.49
SIN
Summary
Observability
Supernovae
Variable stars
Individual alert classification
SN candidate: 95%
Unknown: 5%
g band
r band
Difference magnitude
Observation date
Difference magnitude
DC magnitude
Difference flux
DC flux
Alert cutouts
Alert content
Coordinates
Download data
Neighbourhood
Other brokers
Share


CBPF
Centro Brasileiro de Pesquisas Físicas
Home
Tutorials
Team & Collaborations
Sign-in
WHISPER
An intelligent platform that delivers real-time insights and early analyses of astronomical events from the latest observational data.
Start Exploring
Button
https://lab-ia.cbpf.br

Take away

Take away

- ★ Natural next steps:
  - Incorporate variance corrections
  - Compare with MCMC
  - Test more simulations
- ★ PILCA has the potential to serve as a powerful general modeling framework in the Rubin Era
- ★ Preliminary results are encouraging, however several hypotheses need to be tested
- ★ In the worst case scenario (e.g. irreparable calibration issues), PILCA can be used for optimizing initial conditions for subsequent Bayesian analysis

Thank you !!

Obrigado !!

Gabriel Teixeira
teixeira.gsm@gmail.com

CBPF Centro Brasileiro de Pesquisas Físicas

Lab-IA 4 Physics

FINK

CNPq Conselho Nacional de Desenvolvimento Científico e Tecnológico

Results

0.7 points/filter/day

v_{S*} = 0.33 (-3%)

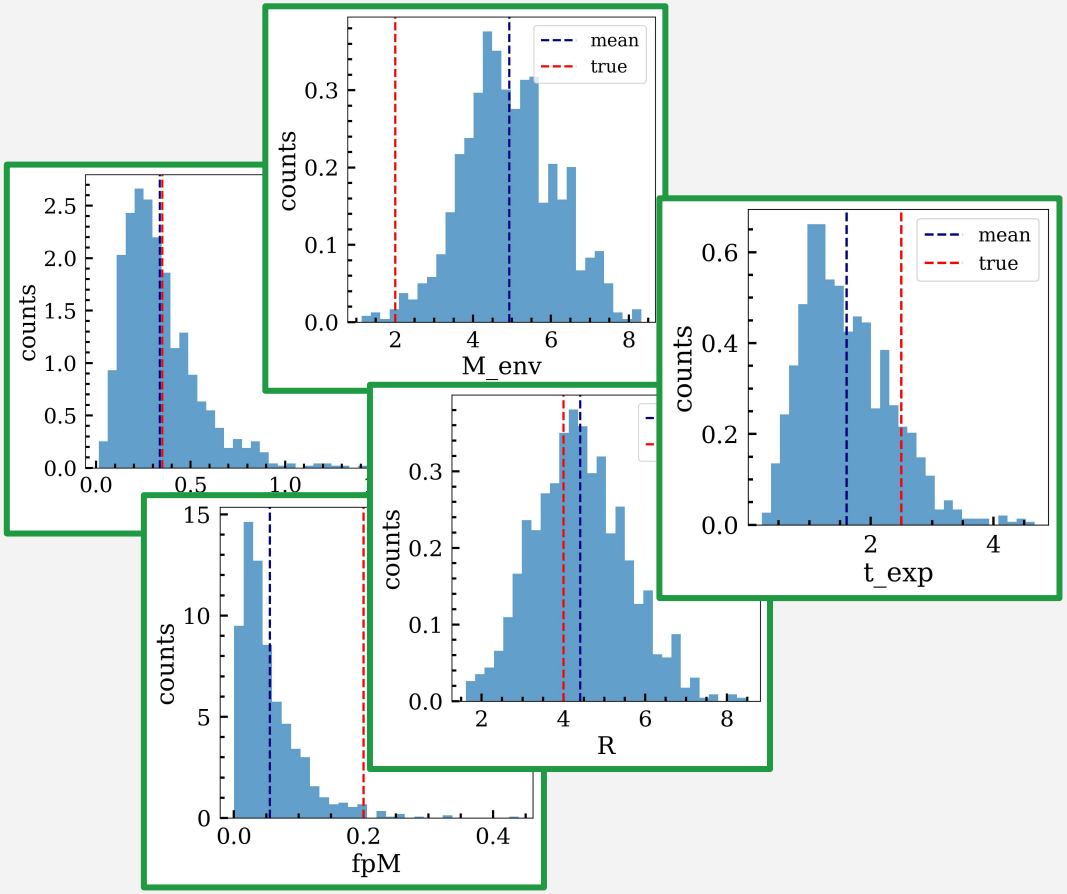
M_{env} = 4.9 (+146%)

$f_\rho M$ = 0.05 (-70%)

R = 4.4 (+10%)

t_0 = 1.6 (-35%)

- parameters in model units



Results

0.7 points/filter/day

v_{S*} = 0.33 (-3%)

M_{env} = 4.9 (+146%)

$f_\rho M$ = 0.05 (-70%)

R = 4.4 (+10%)

t_0 = 1.6 (-35%)

- parameters in model units