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Searching for Primordial Black Holes with LSST

& The Impact of False Positives on Microlensing Detection

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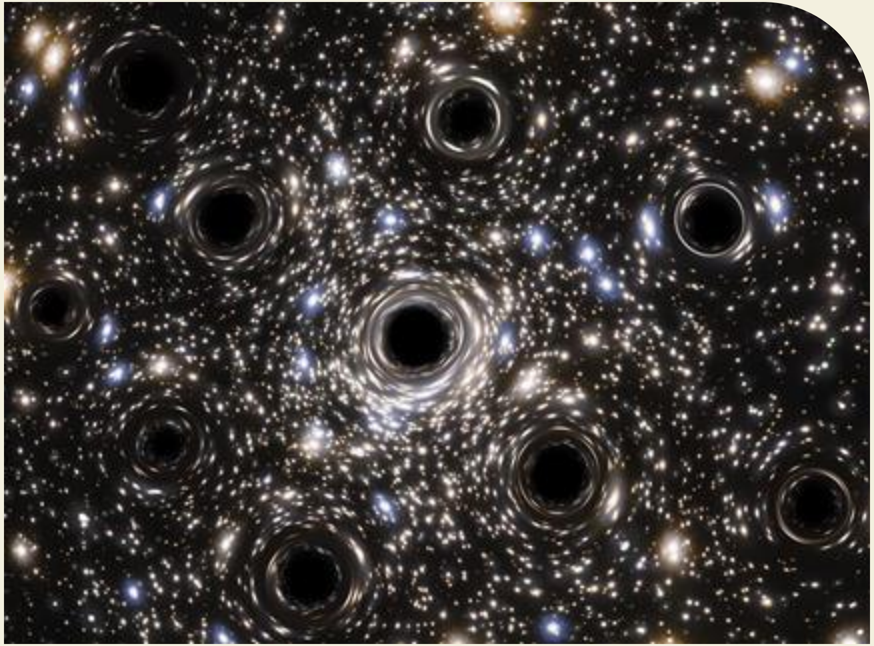
Credit: RubinObs/NOIRLab/SLAC/NSF/DOE/AURA

Introduction

- The Legacy Survey of Space and Time (LSST) is a full-sky survey which launched this summer at the Vera C. Rubin Observatory in Chile
- It will run for 10 years and observe ~10^9 stars in our galaxy
- Can be used to search for gravitational microlensing events
- Microlensing events can be used to identify – or put bounds on – primordial black holes (PBHs)



Credit: ESA/Hubble, N. Bartmann

Identifying Microlensing in LSST Data

- Simulated ~10^6 Constant and point-like Microlensing (ML) light curves using the Operations Simulator (OpSim) codebase from Rubin
- Due to LSST cadence, can only expect to see ~800 observations in the bulge over the full 10 years

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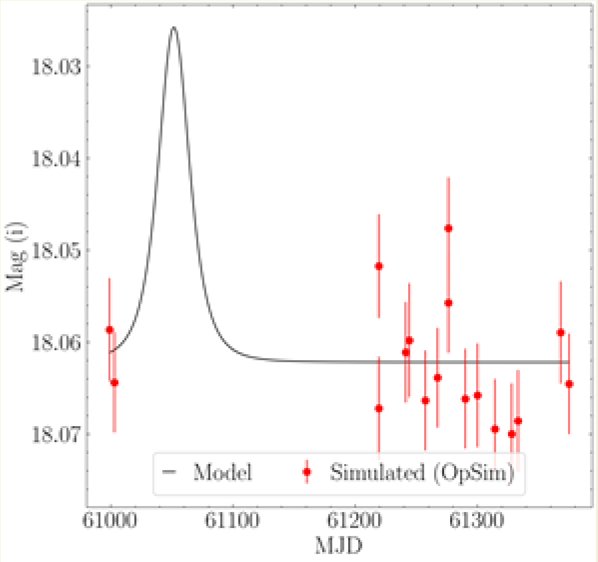

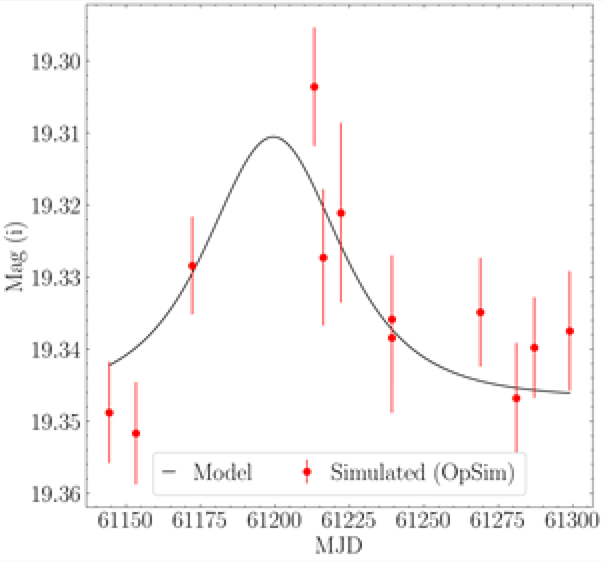

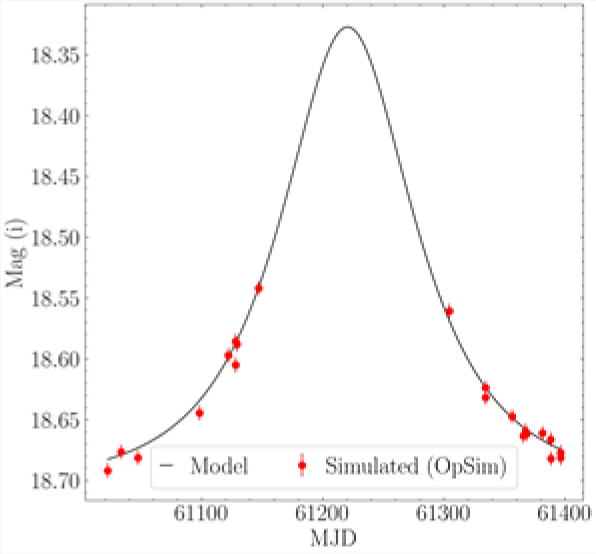

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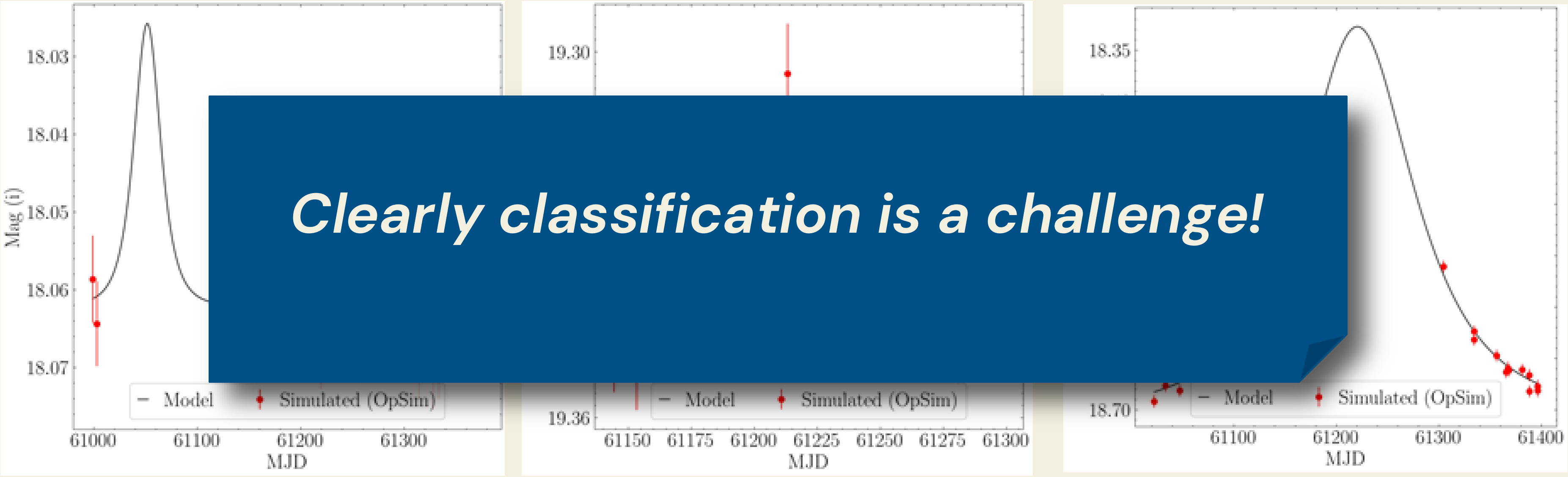

BDT and BIC Ratio as Classifiers

In order to distinguish between the two light curve classes (Constant and ML), we trained a boosted decision tree (BDT) on a subset of the data:

- 0 = Constant Class
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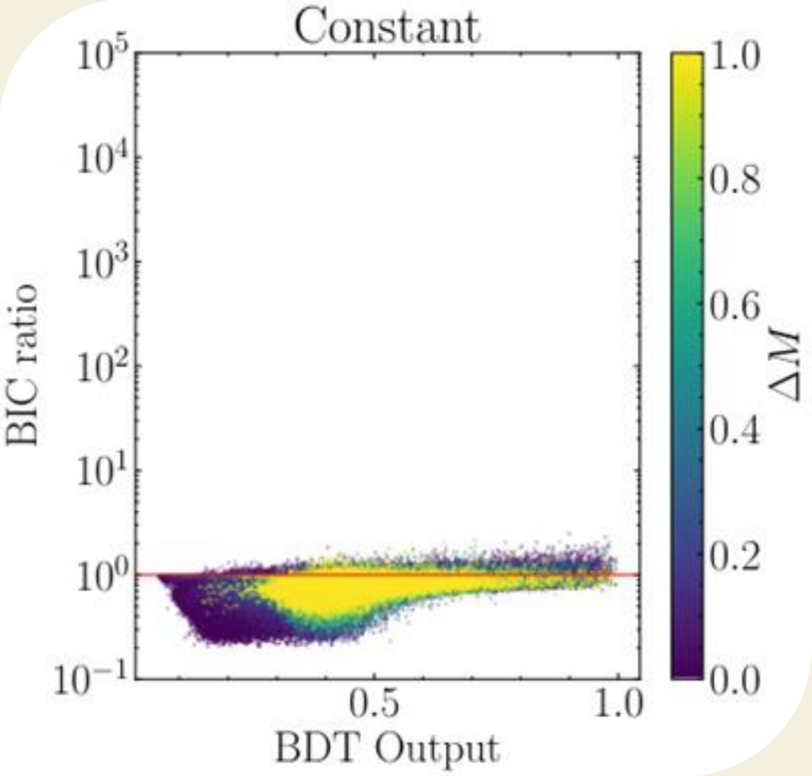
- 0 = Constant Class
- 1 = ML Class
- Bayesian Information Criterion (BIC):

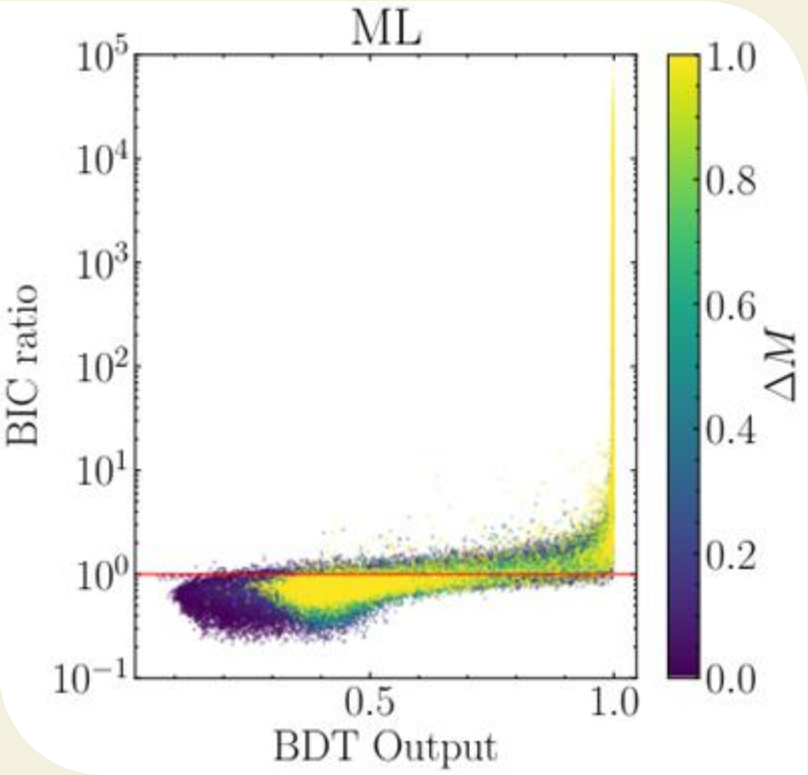
$$\mathrm{BIC}(\mathcal{M}) \;=\; k \ln n \;-\; 2 \ln \hat{L} = k \ln n + \chi^2$$

- Can compare the Constant and ML BICs for a given lightcurve using BIC ratio:

$$\text{BIC ratio} = \frac{\mathrm{BIC}(\mathcal{M}_{\mathrm{Const}})}{\mathrm{BIC}(\mathcal{M}_{\mathrm{ML}})} = \frac{\chi^2_{\mathrm{Const}} + \ln n}{\chi^2_{\mathrm{ML}} + 5 \ln n}$$

BDT and BIC Ratio as Classifiers





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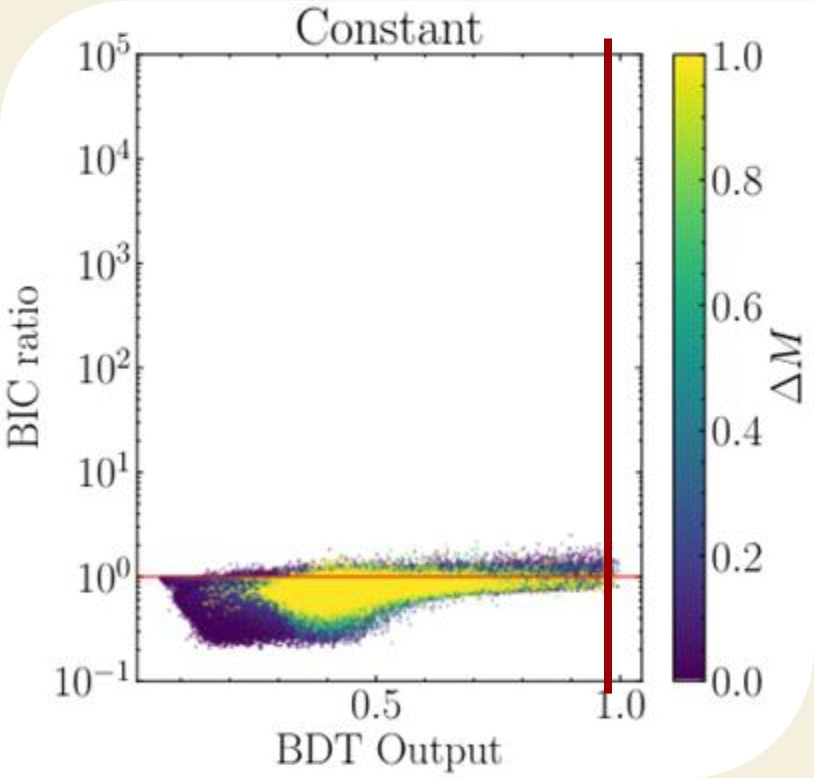

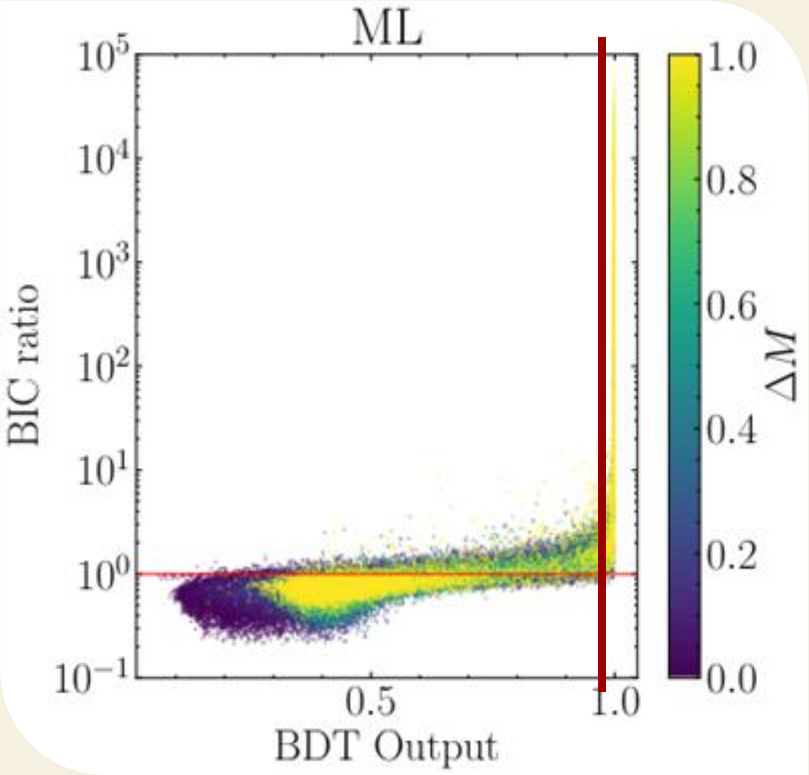

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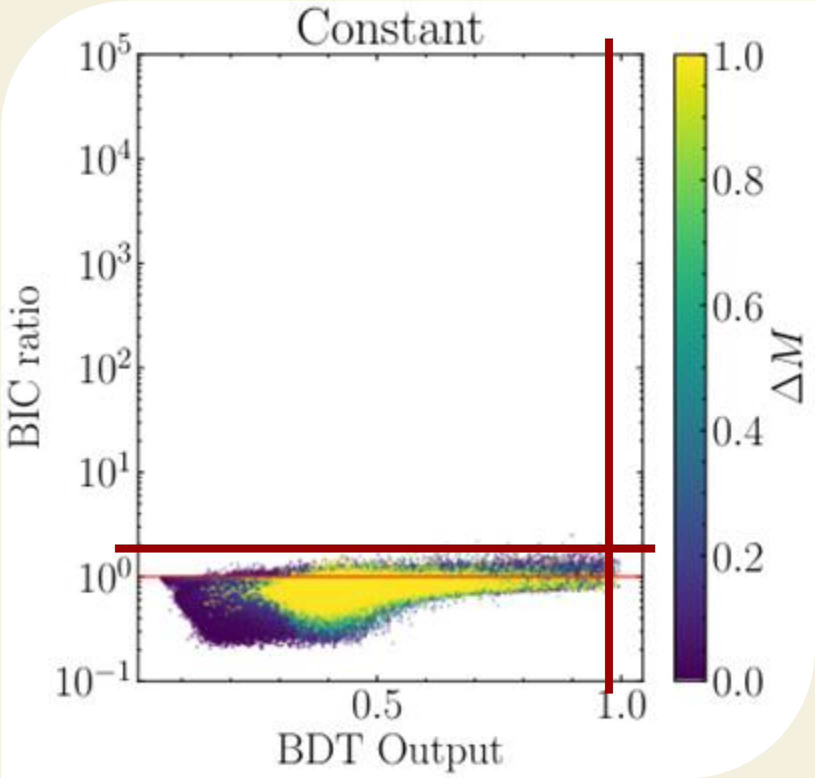
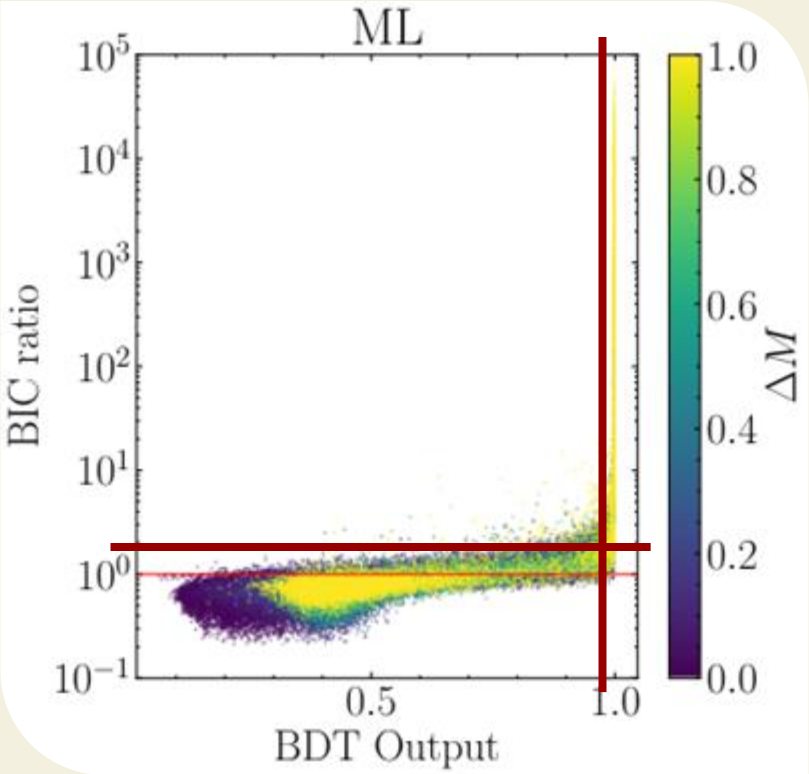




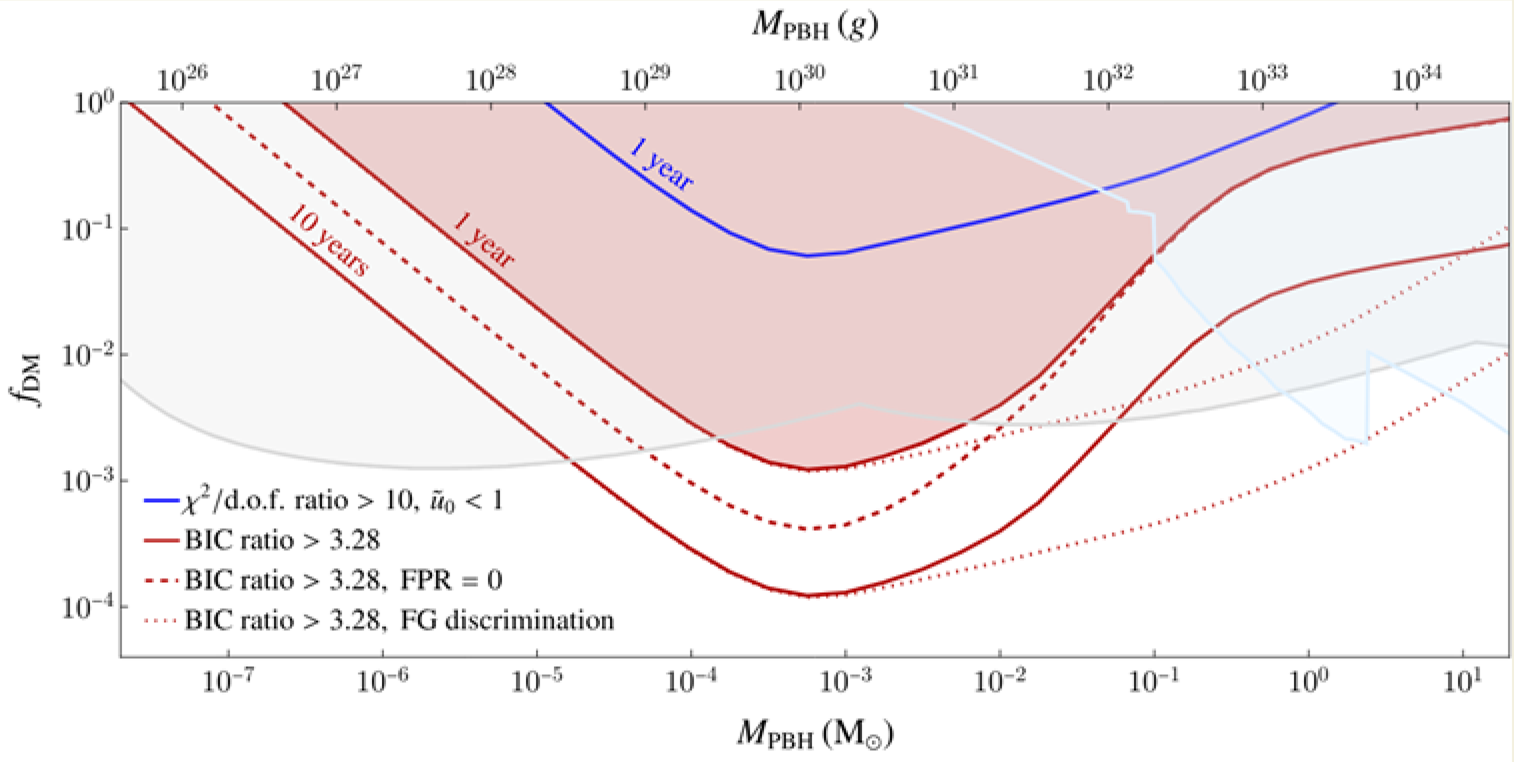
The Importance of False Positives

- Expect some amount of false positives to contaminate the data:
    - False Positive Rate (FPR) = N_{FP} / (N_{FP} + N_{TP})
- With ~10^6 light curves simulated, cannot predict an FPR of lower than ~10^{-6} per star per year (without extrapolation)
- Bad news for LSST – ~10^9 stars visited, so with this FPR we would expect ~10^3 false positives – completely drowning out the expected foreground (from our modelling ~10^2 foreground events expected per year)
- ***Therefore it is absolutely crucial to effectively control the false positive rate if we want to set novel constraints on PBHs using Rubin.***

Extrapolating to Lower FPR

cut	FPR	$\bar{\epsilon}$
BIC ratio > 3.28	10^{-7}	0.38
BDT > 0.999	10^{-7}	0.34
χ^2/d.o.f. ratio > 10	3.5×10^{-4}	0.30
χ^2/d.o.f. ratio > 10, $\tilde{u}_0 < 1$	1.1×10^{-4}	0.20

Projected Constraints on PBHs



Thank you for listening!

Any questions?

Backup Slides

Tail Fits

- Pareto Distribution:

$$f(x, b) = b/x^b$$

- Johnson S_B:

$$f(x, a, b) = (b/(x(1-x)))\phi(a + b\log(x/(1-x)))$$

where ϕ is the normal distribution probability distribution function.

Analytic Efficiency Function

$$\epsilon = \left(\left(\frac{t_{\mathrm{E}}}{t_0} \right)^{-1/t_r} + 1 \right)^{-1}$$

Calculating Constraints

$$\kappa = 2 \sum_{i=1}^{N_{\mathrm{bins}}} \left[N_i^{\mathrm{FG,eff}} - N_i^{\mathrm{SIG}} + N_i^{\mathrm{SIG}} \ln \frac{N_i^{\mathrm{SIG}}}{N_i^{\mathrm{FG,eff}}} \right]$$

- 90% CL found by locating (M_{PBH}, f_{DM}) for which $\boldsymbol{\kappa}$ = 4.61

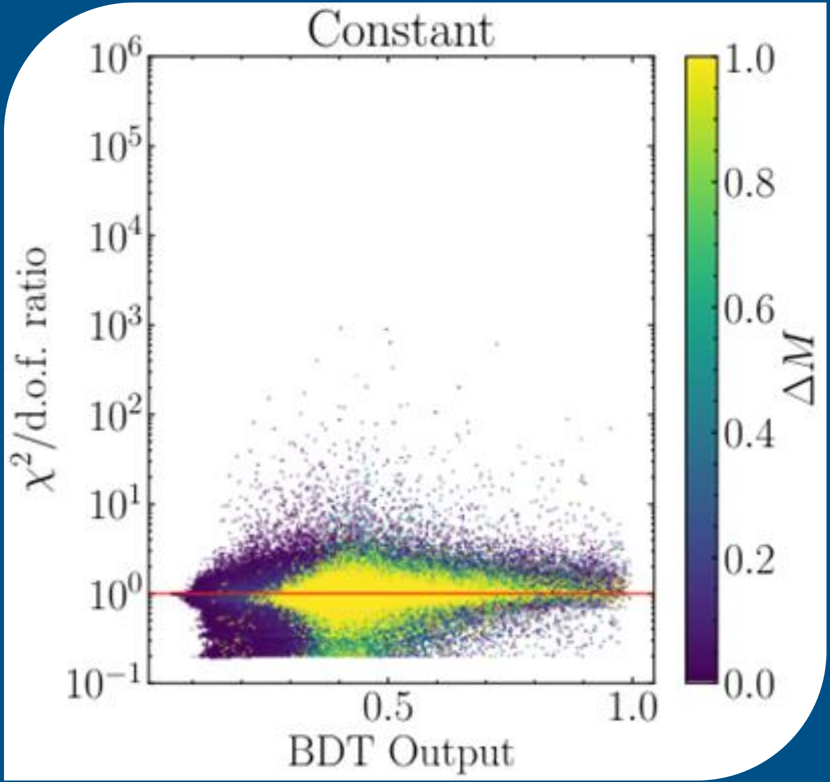
χ^2 Ratio

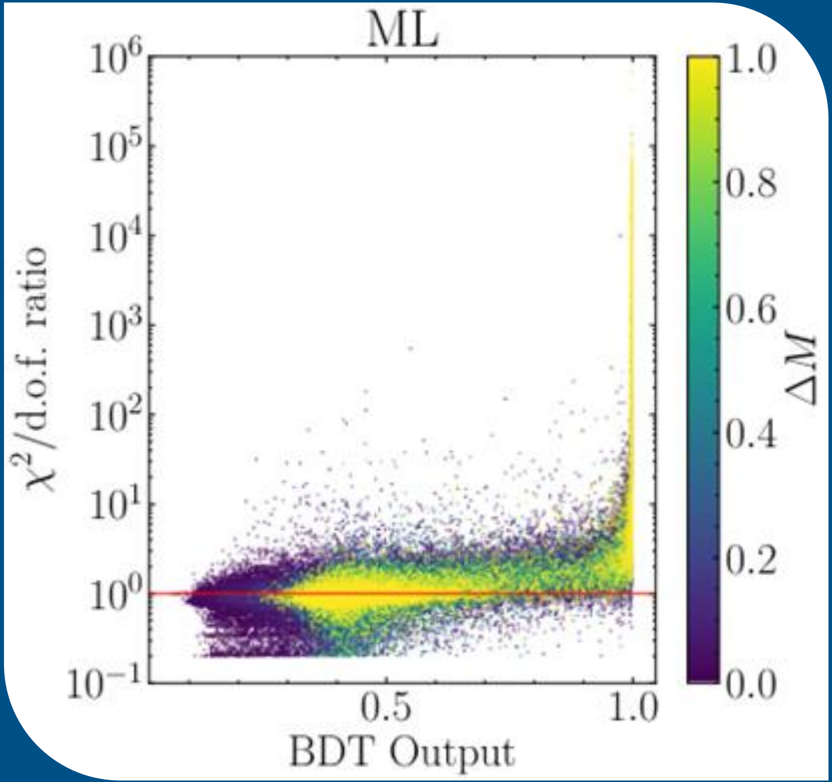
- Even for Constant class lightcurves, can often get low χ^2 values for ML fits by fitting to the noise
- Can compare the Constant and ML goodness-of-fits for a given lightcurve using the ratio of the reduced χ^2:

$$\chi^2/\text{d.o.f. ratio} \equiv \frac{\chi^2_{\text{Const}}/\nu_{\text{Const}}}{\chi^2_{\text{ML}}/\nu_{\text{ML}}}$$

  - $\nu_{\text{Const}} = n - 1$; $\nu_{\text{ML}} = n - 5$
  - Often get very large values for Constant lightcurves, suggesting ML model fits better than Constant model!

χ^2 Ratio

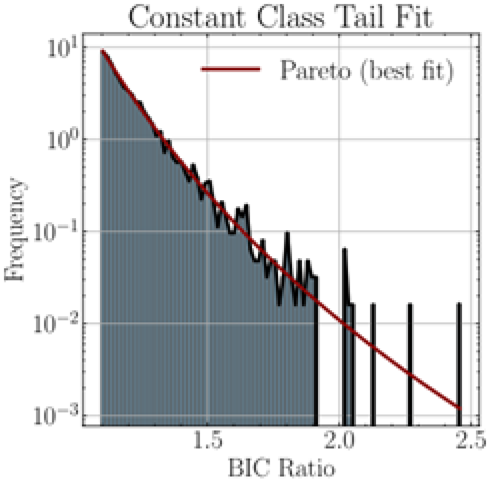

Constant
10^6
10^5
10^4
10^3
10^2
10^1
10^0
10^{-1}
χ^2/d.o.f. ratio
0.5
1.0
BDT Output
1.0
0.8
0.6
0.4
0.2
0.0
ΔM

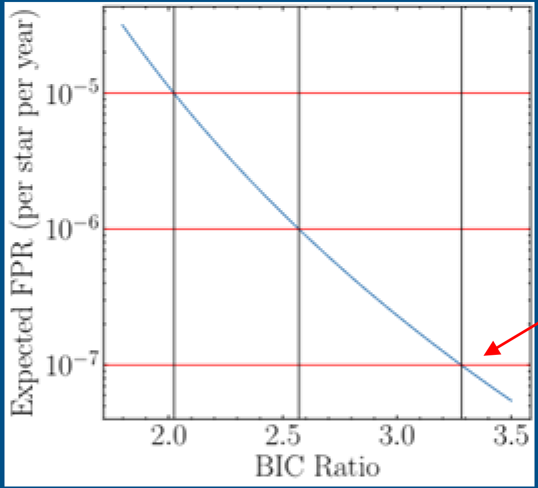

ML
10^6
10^5
10^4
10^3
10^2
10^1
10^0
10^{-1}
χ^2/d.o.f. ratio
0.5
1.0
BDT Output
1.0
0.8
0.6
0.4
0.2
0.0
ΔM

Extrapolating to Lower FPR

BIC Ratio

- To bring number of false positive events expected per year down to same level as foreground, need FPR ~ 10^{-7}
- Zooming into tail composed of top 1% of BIC ratios for Constant class, we find we can fit the tail well with a Pareto distribution using `distfit`:



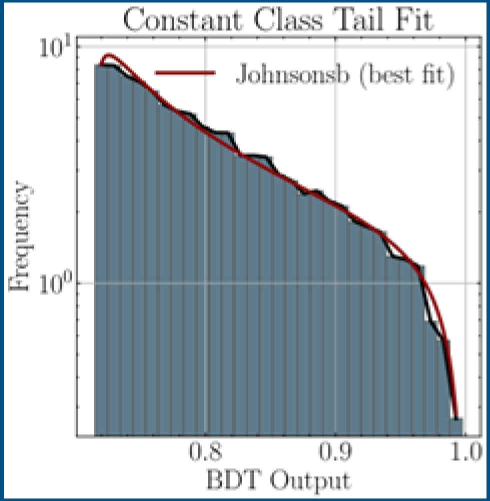


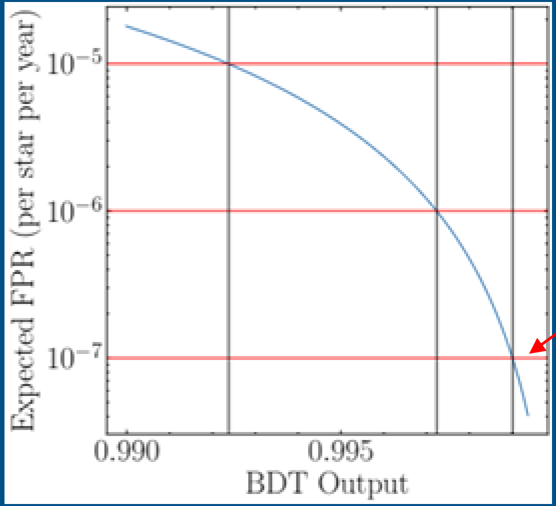
By extrapolation, a cut on the BIC ratio > 3.28 gives an expected FPR of 10^{-7}

Extrapolating to Lower FPR

BDT Output

- BDT output is bounded between 0 and 1, but can fit with a bounded distribution
- Zooming into tail composed of top 1% highest values of BDT, find the Johnson S_B to be a good fit using `distfit`:





A cut on BDT output > 0.999 gives an expected FPR of 10^{-7}

Effective ML Detection Efficiency

- Can define an effective efficiency per binned t_E as $\varepsilon = N_{>cuts}/N_{total}$
- We find an analytic function to fit the efficiency (solid line):

$$\epsilon = A\left(\frac{t_{\mathrm{E}}}{\mathrm{days}}\right)^{k} e^{\lambda(-t_{\mathrm{E}}/\mathrm{days})} + c$$

- This doesn't asymptote to 1 for large t_E as some other fits suggested in the literature do (dashed line)
- We use this efficiency and foreground estimates to calculate the number of expected point-like microlensing events and hence put constraints on PBHs