

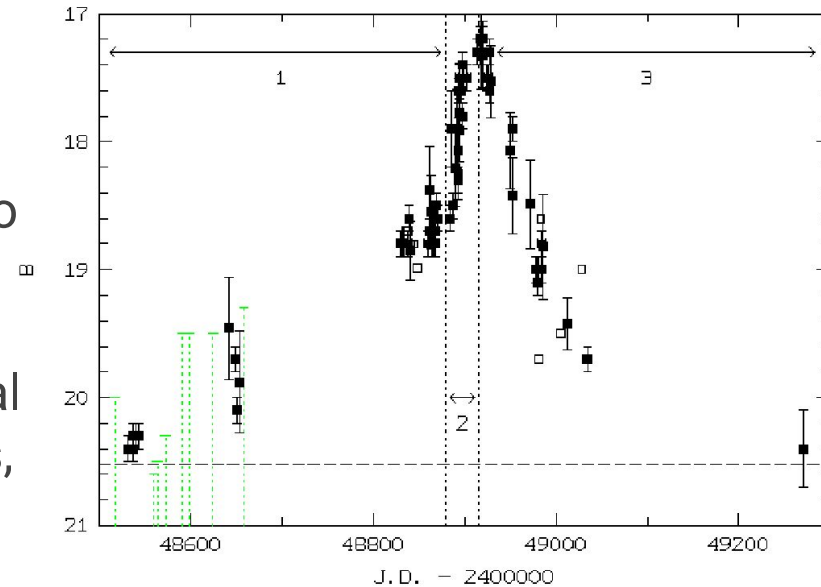
Using Gaussian Processes to detect AGN flares

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AGN flares

- Extreme variability of AGN
- Rare: $\sim 10^{-4}$ - 10^{-5} yr $^{-1}$ per AGN^[1]
- Timescales of several hundreds of days to many years^[2]
- Caused by accretion disk instabilities, tidal disruption events, variable accretion rates, supernovae, microlensing... or ?



[1] Lawrence, A. *et al* 2016 *MNRAS* **463** 296–331

[2] Graham, J. *et al* 2017 *MNRAS* **470** 4112–4132

What has been done before?

- Lawrence *et al* 2016 - 76 flare candidates in Pan-STARRS1^[1]:
 - Define a flare as brightening by > 1.5 mag/decade
- Graham *et al* 2017 - 51 flare candidates from over 900,000 known quasars^[2]:
 - De-trend light curves by subtracting Theil-Sen median
 - Then look for contiguous sets of points above zero (mini flare)
 - Define a flare as exceeding the median absolute deviation of these mini flares
 - Ignore flares with a duration < 300 days

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- **Amplitude selection**
- **Timescale selection**

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 - Define a flare as brightening by > 1.5 mag/decade
- Graham *et al* 2017 - 51 flare candidates from over 900,000 known quasars^[2]:
 - We want a statistical way to detect flares without having to assume an amplitude or timescale.
 - De-trend light curves by subtracting their 5-yr median
 - Then look for contiguous sets of points above zero (mini flare)
 - Ignore flares with a duration < 300 days
- Amplitude selection
- Timescale selection

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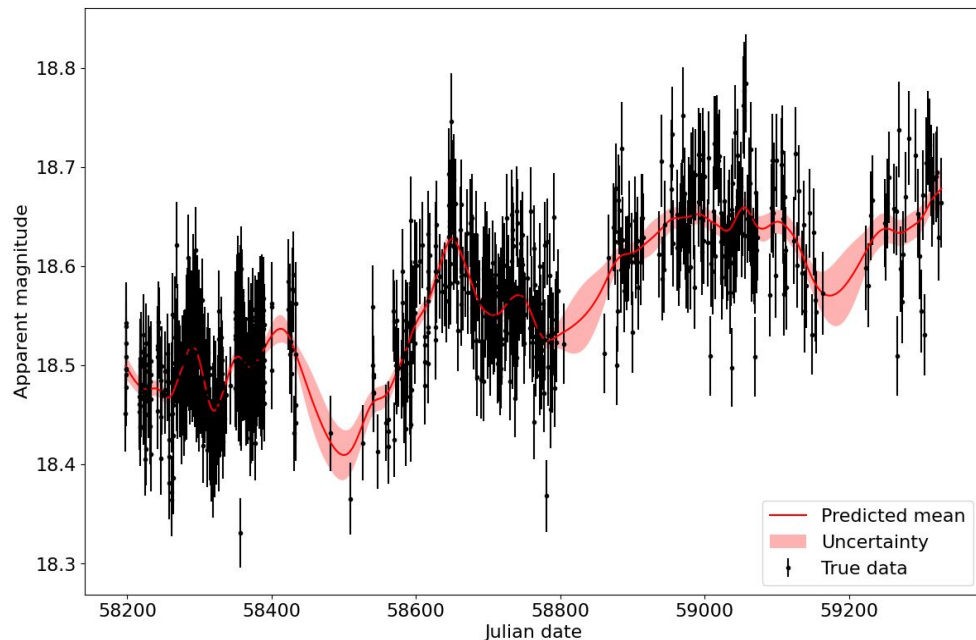
Our problem:

How do you detect a signal in data that is already intrinsically variable?

- We need a way of quantifying a significant departure from the baseline variability
- Must be statistically robust and impervious to outliers and poorly sampled data

Gaussian processes

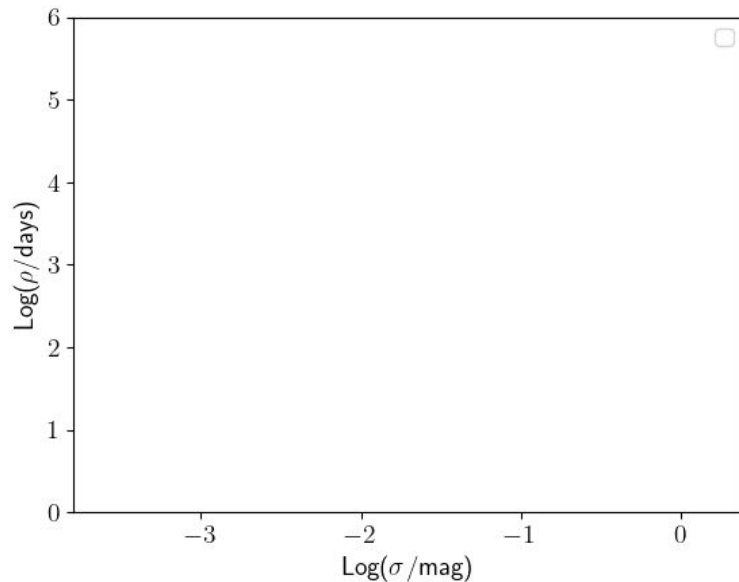
- Non-linear, non-parametric interpolation
- Informed by the sparsity of data
- Uses a kernel (covariance matrix) to describe the best-fit relationship between data points



GPs: A feasibility study

- A GP is a means of parameterising the covariance of data
- With this in mind, we might expect flares and non-flares to exist in different parts of parameter space
- We simulated 20,000 AGN light curves and injected 10,000 with a flare
- We ran a GP on these light curves with a Matérn 3/2 kernel (right)

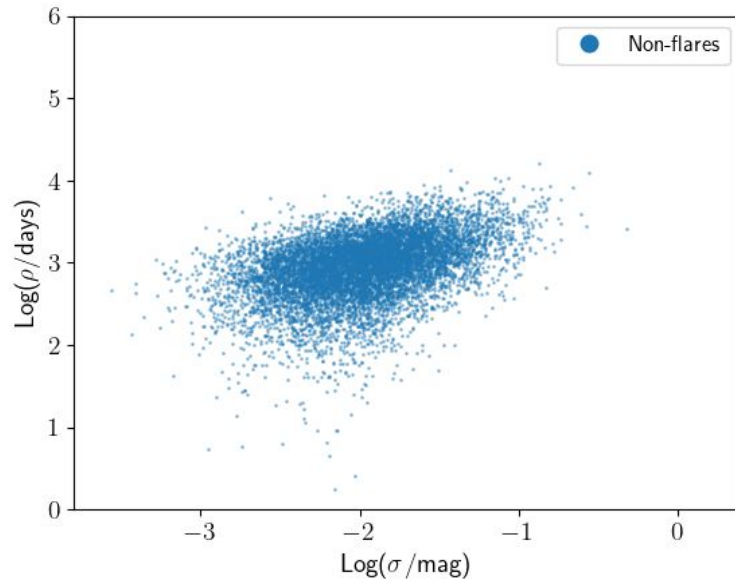
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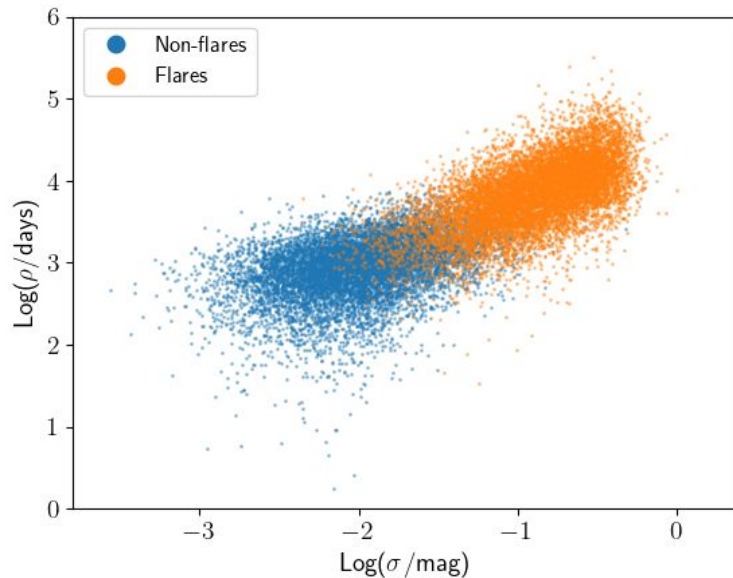
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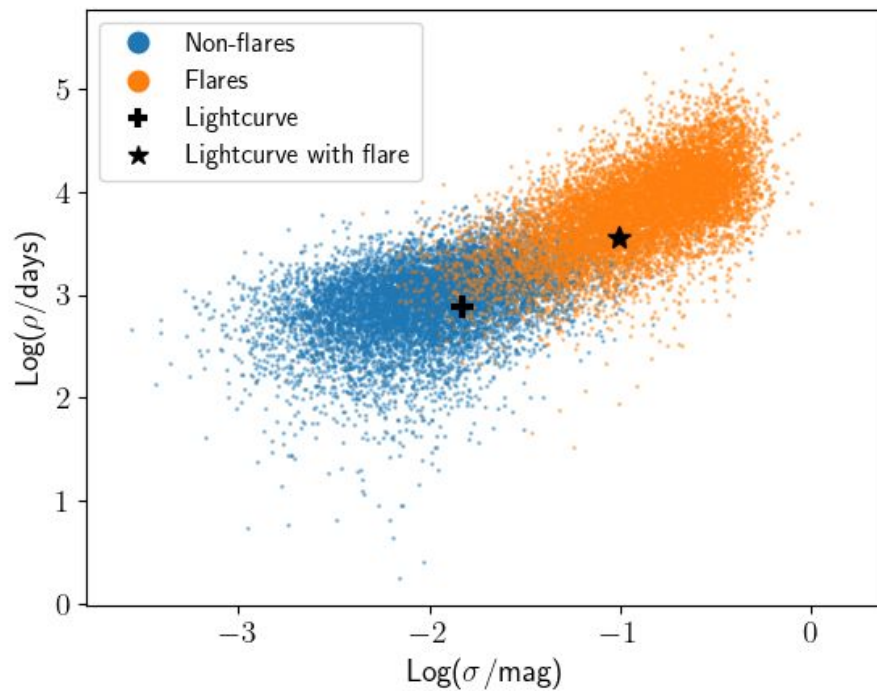
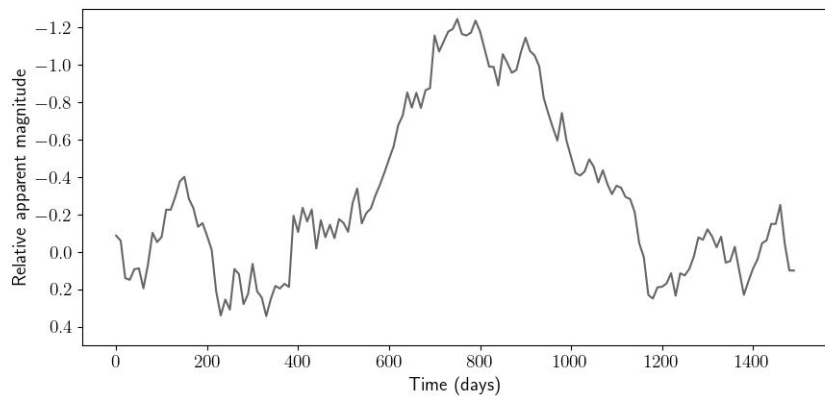
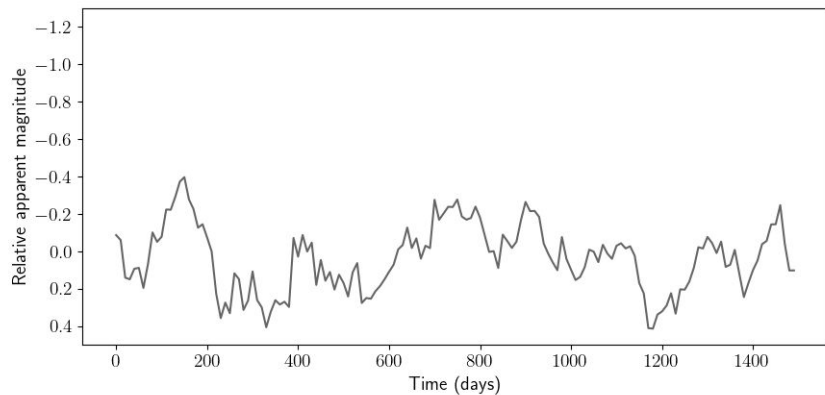
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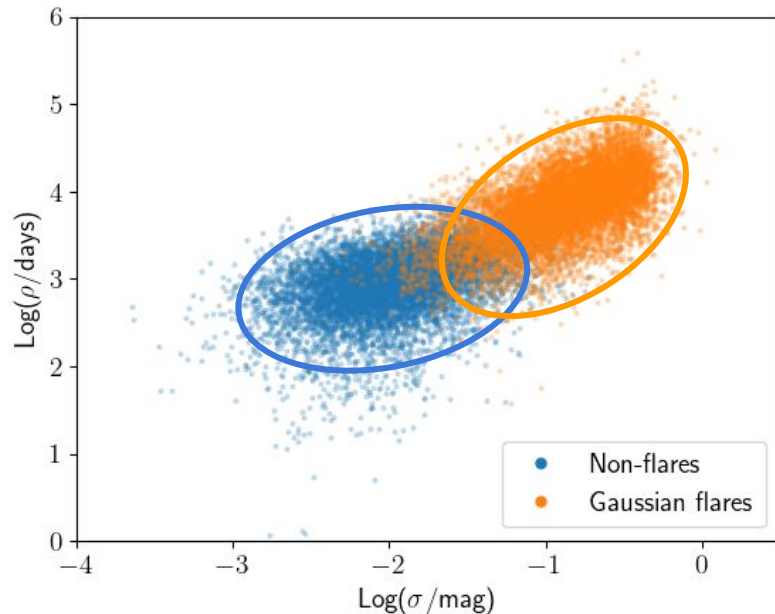
Some examples



McLaughlin & Mullaney (in prep)

Bayesian hypothesis testing

- Based on a light curve's hyperparameters, what is the probability that it contains a flare?
- Use prior probabilities and likelihoods from the GP
- Define a probability above which a light curve is flagged as a flare



McLaughlin & Mullaney (in prep)

Light curves

- Light curves sampled every 10 days, half without flares and half with injected flares
- Subsampled light curves
- Added outliers
- Real ZTF light curves, half injected with flares
- Real ZTF light curves - no flares added

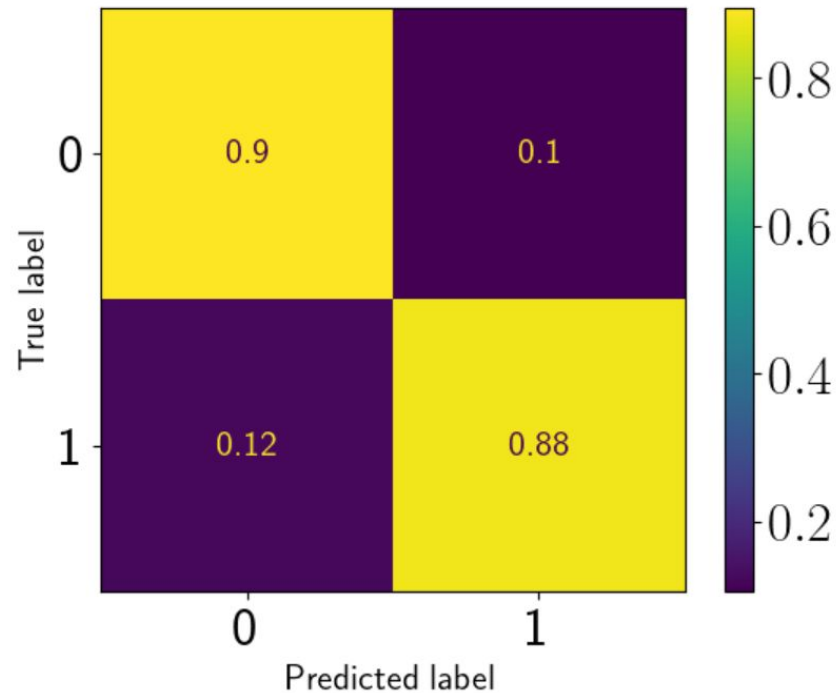
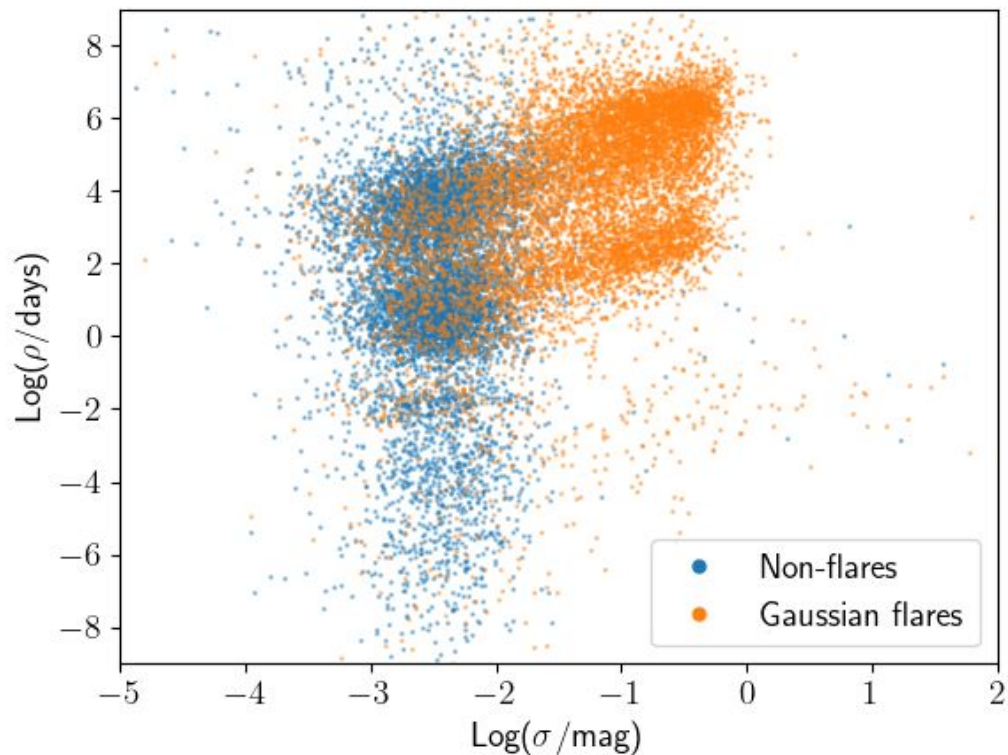


Simulated AGN light curves
(1D damped random walk)



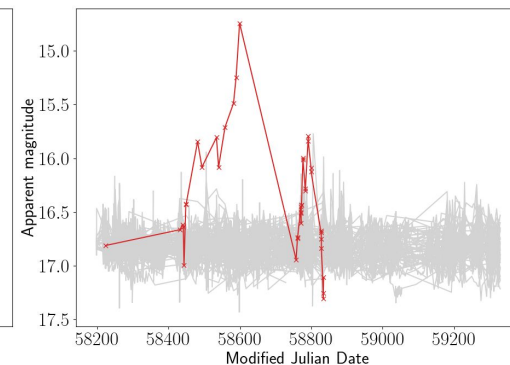
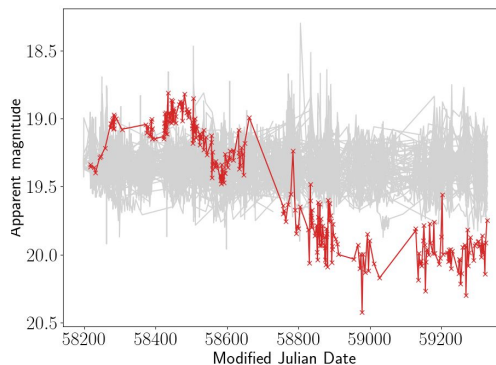
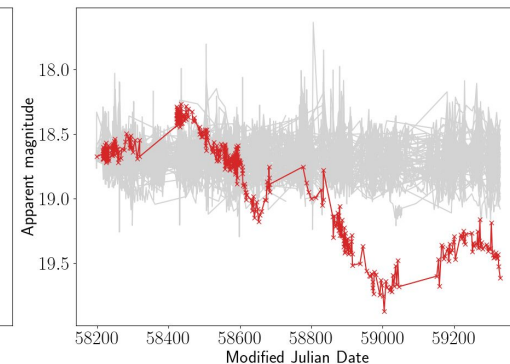
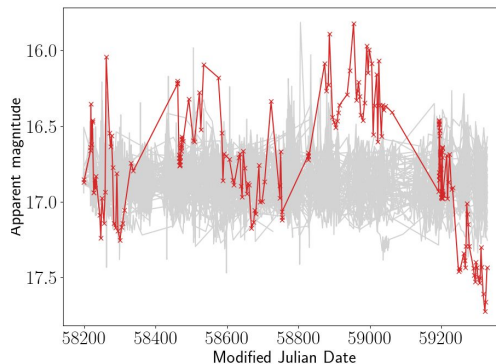
Real AGN light curves

Provisional results - retrieval rates



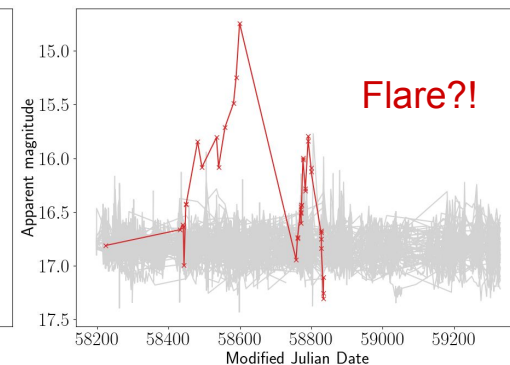
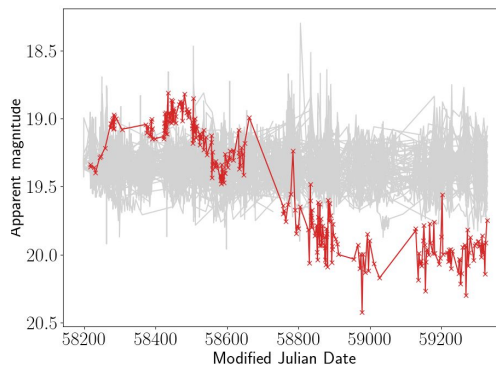
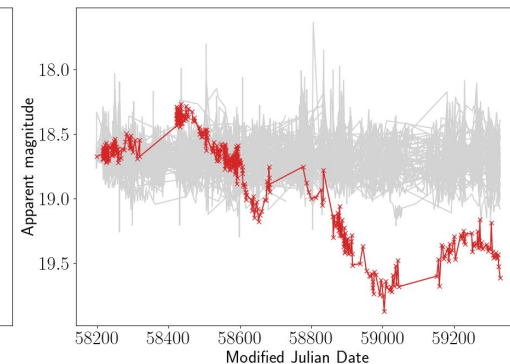
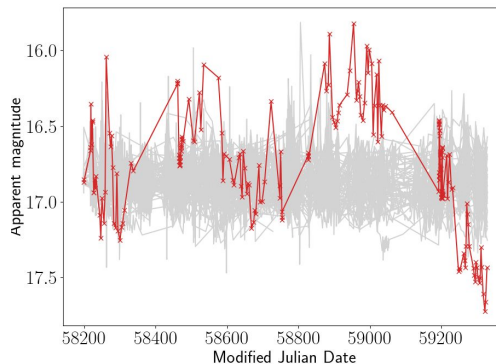
Provisional results - ZTF light curves

- The GP selected 55 out of 9035 spectroscopically selected ZTF light curves of Type 1 AGN as containing flares
- They show extreme variability when compared with a randomly selected sample of 100 ZTF light curves that were not flagged as flares



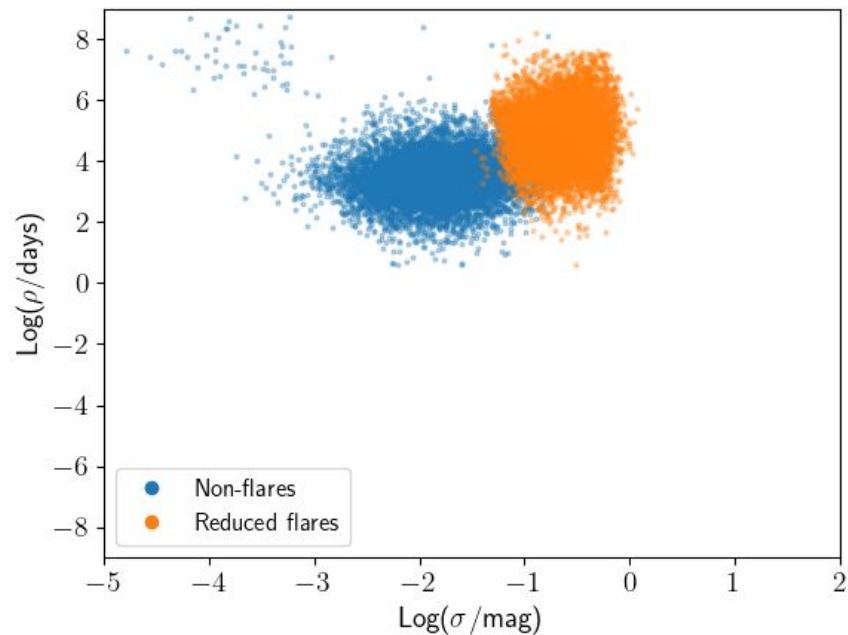
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What's next?

- The GP cannot tell you the location of the flare within the light curve
- Deep GPs or regime-switching models are possibilities
- If you can localise the flare, this approach is more effective



Summary

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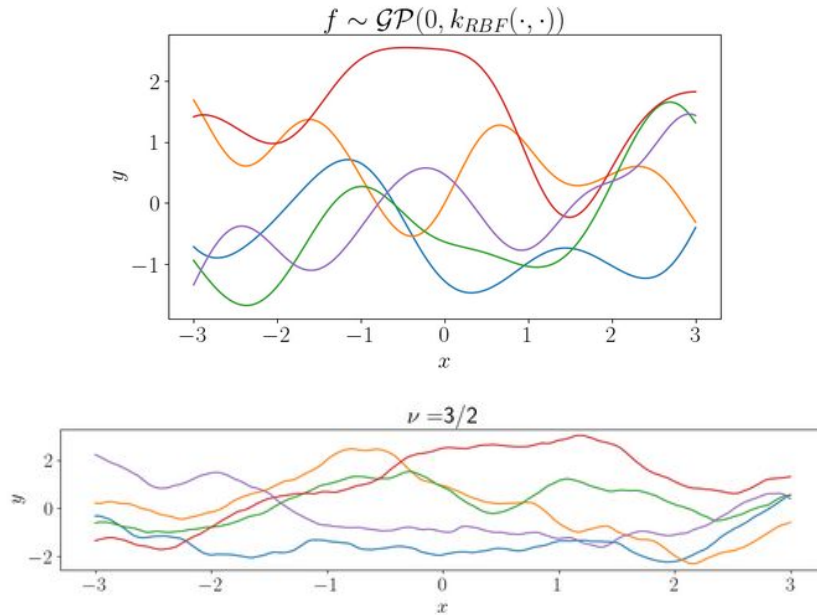
- Ultimate goal is a statistically robust means of identifying flares that is immune to anomalies & sampling
- We have shown that Gaussian Processes can classify flare and non-flare light curves in well-sampled simulated data, and real ZTF data with injected flares
- Regime-switching models or deep GPs may help to localise flares



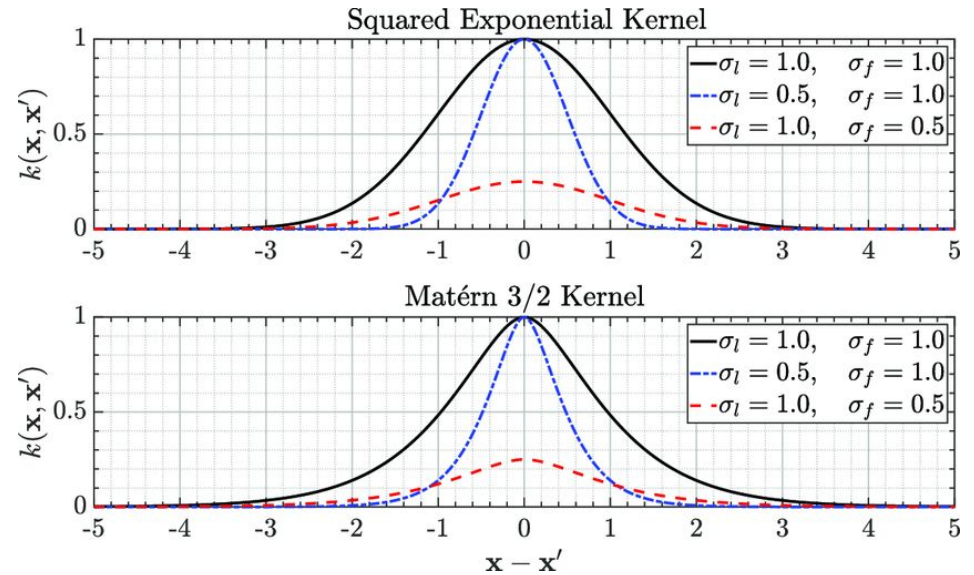
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Extra slides

Gaussian process kernels



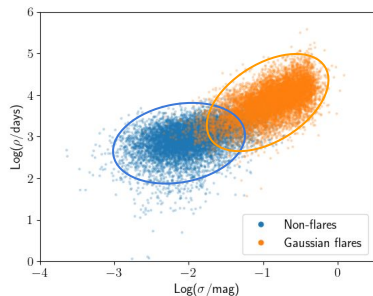
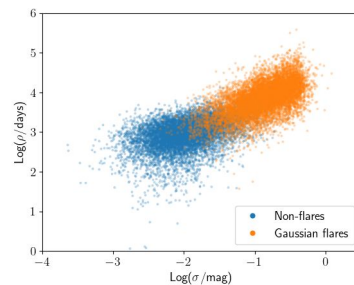
<https://andrewcharlesjones.github.io/journal/matern-kernels.html>



Florian M Heckmeier & Christian Breitsamter 2020 Meas. Sci. Technol. 31 125301

The steps broken down

Run flare and non-flare light curves through a GP and track their hyperparameters

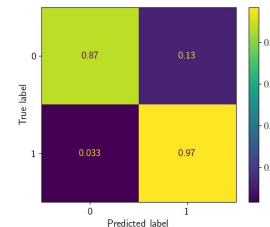


Use the hyperparameter distributions to define priors

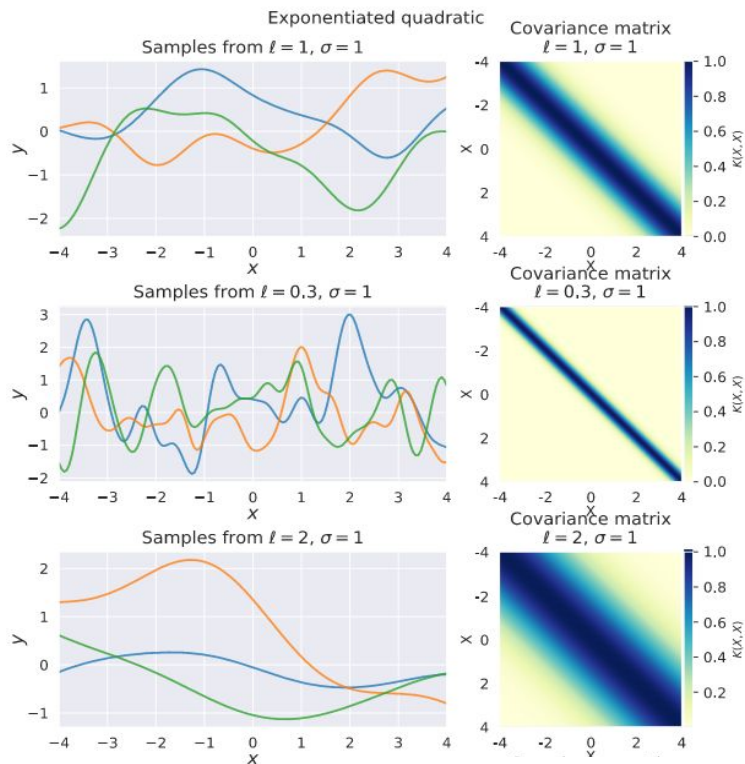
θ = "hyper prior":
1 (flare), 0 (not flare)

$$P(\sigma, \rho, \theta | y) \propto P(y | \sigma, \rho) \times P(\sigma, \rho | \theta) \times P(\theta)$$

Combine MCMC and Bayesian Hypothesis testing to calculate the probability of a given light curve containing a flare

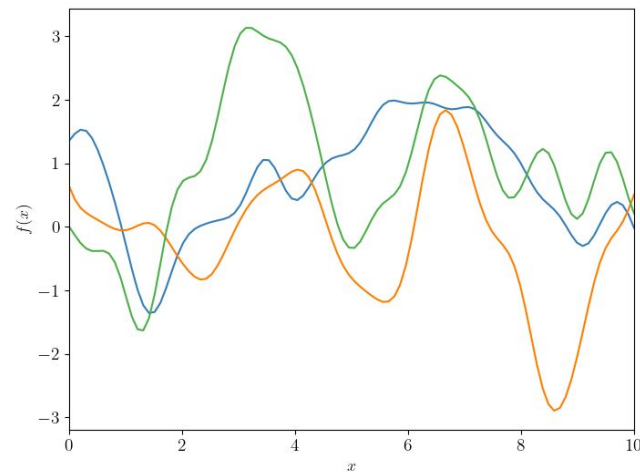


Gaussian process kernels (cont.)



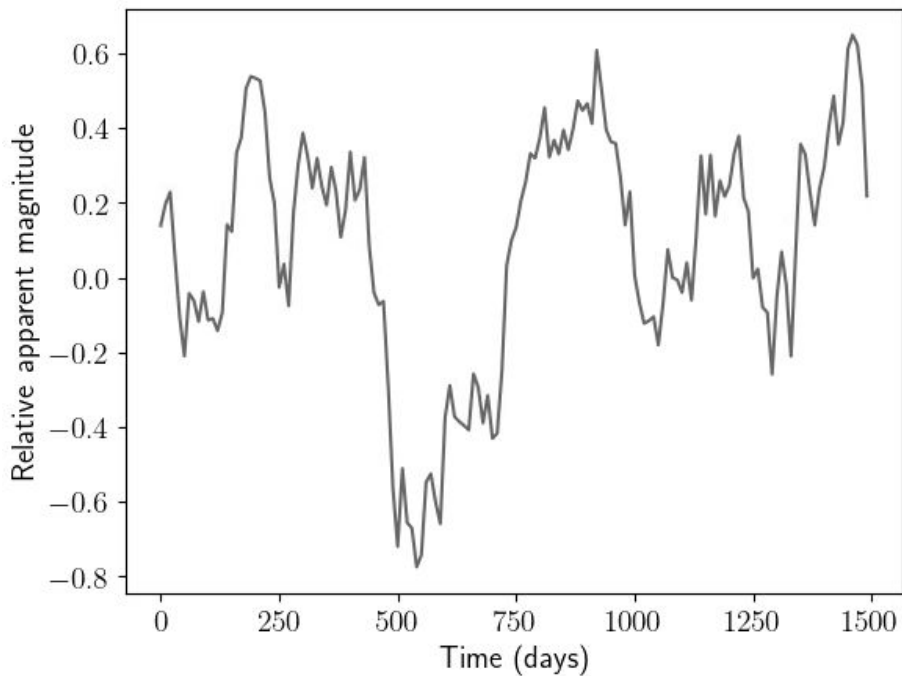
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Matérn 3/2 kernel

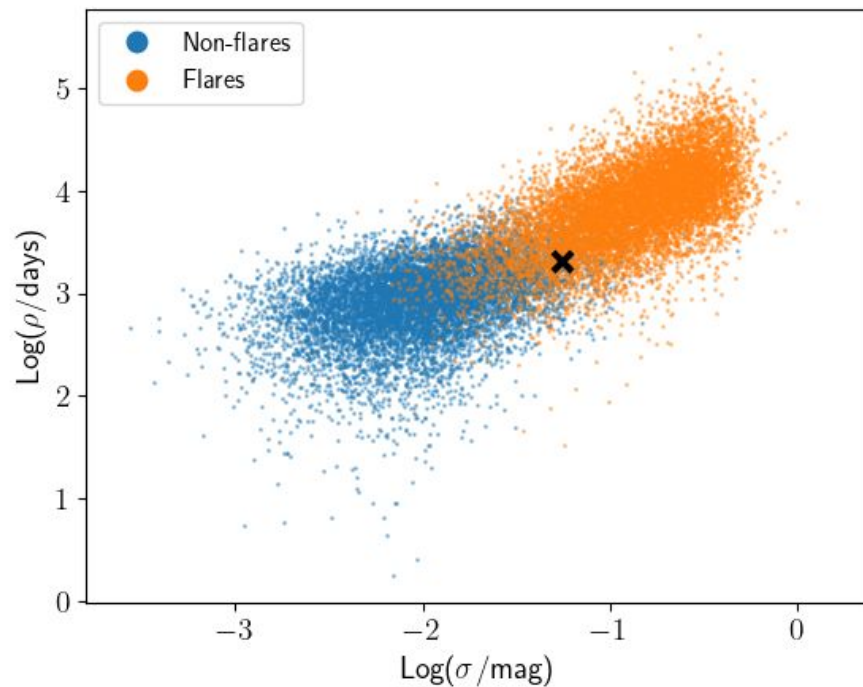


McLaughlin & Mullaney (in prep)

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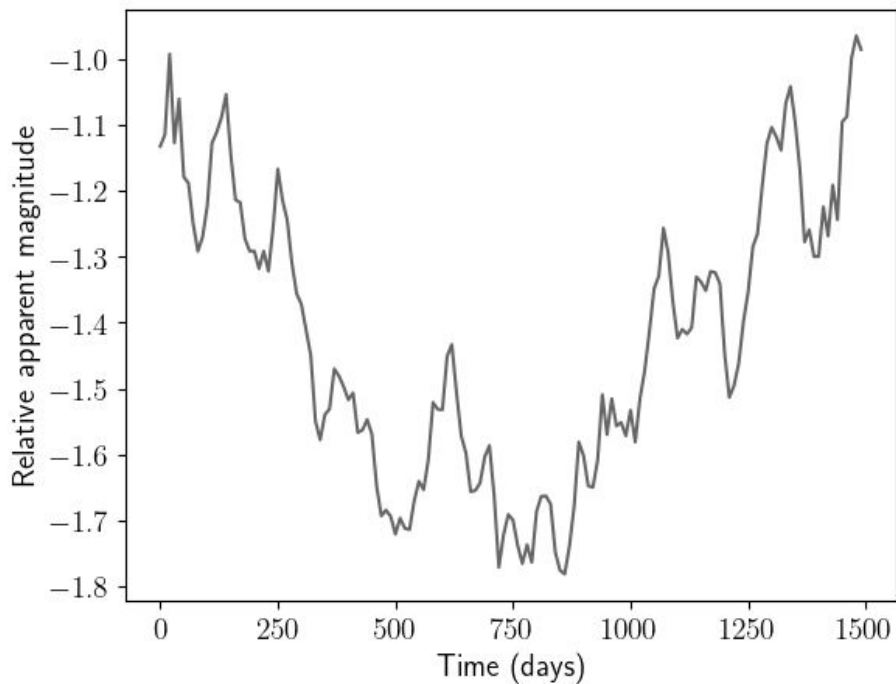


Simulated with a damped random walk

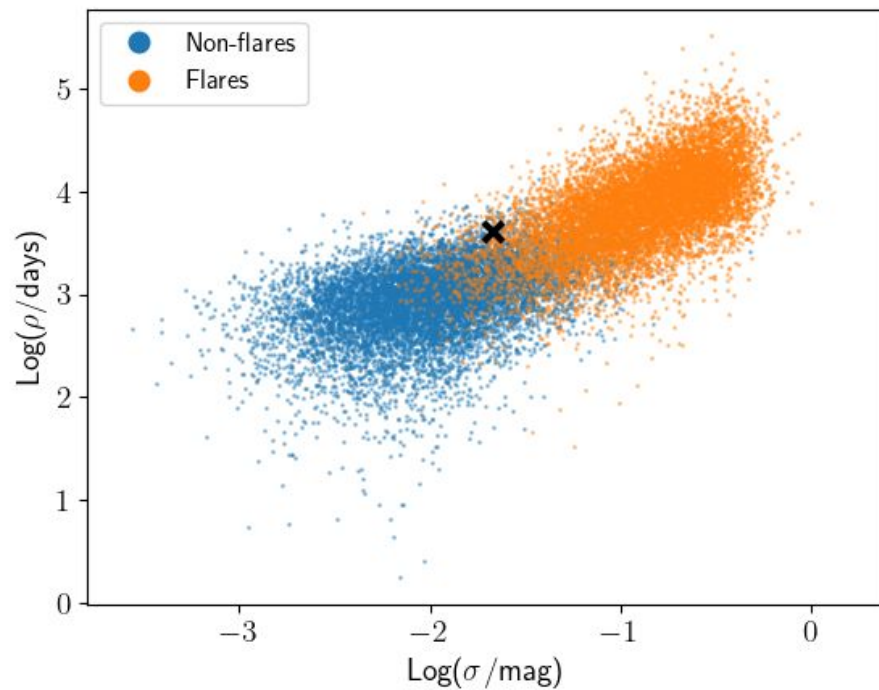


McLaughlin & Mullaney (in prep)

Some examples



Simulated with a damped random walk + injected 1.6 mag flare



McLaughlin & Mullaney (in prep)