# Gaussian Process Regression in Microlensing

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What is Gaussian Process (GP) Regression  
\n• 
$$
\mathcal{L} = \prod_i^N \frac{1}{\sqrt{2\pi \sigma_i^2}} e^{-\frac{(m-x_i)^2}{2\sigma_i^2}}
$$
,  $\ln \mathcal{L} = -\frac{N}{2} \ln 2\pi - \sum \ln \sigma - \frac{\chi^2}{2}$ ,  $\leftarrow$   $\frac{\text{``normal'' likelihood, often 'using }\chi^2 \text{ for the simplified 'objective function'}}$ 

assuming Gaussian-distributed noise and no time-dependent correlation.

• 
$$
F(t) = physics(t) + GP(t) + white noise
$$

For (single source) microlensing lightcurves,  $physics(t) = F<sub>s</sub>A + F<sub>B</sub>$ , where A is the magnification model based on the arrangement of the lens

• The GP allows for time-dependent error correlation through use of a covariance matrix  $(\Sigma)$ :

$$
\ln \mathcal{L} = -\frac{N}{2} \ln 2\pi - \ln \det \Sigma - \frac{r^T \Sigma^{-1} r}{2},
$$
   
 
$$
\begin{array}{|l|} \hline \text{Equivalent likelihood with} \\ \text{correlated errors;} \\ \text{reduces to the "normal" } \mathcal{L} \\ \text{when } \Sigma \text{ is diagonal.} \hline \end{array}
$$

where **r** is the residual vector,  $\Sigma_{nm} = \sigma_n^2 \delta_{nm} + \kappa(t_n,t_m)$ , and  $\kappa$  is the (physically motivated) GP kernel(s) that correlates the errors in the time-domain (the off-axis terms in the covariance matrix,  $\Sigma$ ).

# General Astrophysics Examples

- Gibson et al. (2012), Evans et al. (2015), Grunblatt et al. (2017) transit timing analysis.
- Brewer & Stello (2009), Barclay et al. (2015), Grunblatt, Howard & Haywood (2016), Czekala et al. (2017) used with radial velocity measurements.
- Used to model the background granulation noise in asteroseismic and helioseismic analyses (Harvey 1985; Huber at al. 2009; Michel et al. 2009; Kallinger et al. 2014; and others):

$$
\kappa(t_i, t_j) = S_0 \omega_0 e^{-\frac{1}{\sqrt{2}}\omega_0(t_i - t_j)} \cos\left(\frac{\omega_0(t_i - t_j)}{\sqrt{2}} - \frac{\pi}{4}\right)
$$

 $\mathcal L$  compute time scales with  $N^3$ ; limits usefulness to small data sets

Foreman-Mackey et al. (2017) introduces celerite: Computation time scales with  $N$ , exploiting kernels composed of complex exponentials

#### Variability in the source star (Li et al. 2019)

- Asteroseismology to determine source size and distance; which breaks the distance -distance degeneracy in the microlensing model.
- GP models are consistent with  $\chi^2$  models to  $\lesssim 3\sigma$ .
- Quasi-periodic kernel



#### Black Holes

- Events last multiple seasons
	- Blend star arrangements change due kinematics
- Physical sources of systematics includes, stellar variability, weather, sky conditions, etc.
- Golovich et al. (2022) used *celerite* for GP regression in the search for black holes in OGLE-III and -IV survey data

• 
$$
\Sigma_{ij} = \kappa_{SHO}(t_i, t_j) + \kappa_{\frac{M3}{2}}(t_i, t_j) + \left[K^2 \sigma^2 \delta_{ij}\right]
$$

• "[They] find that modeling the variability in the baseline removes a source of significant bias in individual events"



# Data Systematics (Spitzer events)

- A few flux units,  $\sim$  5 days
- Seasonal rotation of the camera and poorly defined neighboring star locations
- Are the strange kinematics solutions real? (Chung et al. 2019, Shvartzvald et al. 2019, 2017, Malpas et al. 2022).
- Are all the published mass and distances skewed towards not massive enough and too distant or are the Galactic-models and their inferences the problem?





# Physical Implications of using a GP with Binary-Lens Spitzer Data

- The GP hyperparameters are not independent of the parallax measurement.
- In general, inclusion of a GP does not change the parallax measurement much, but it does widen the the posteriors on the parallax parameters.
- Greater agreement between the physical determinations from Spitzer parallax and the inferences from galactic models is predominantly due to wider posterior posterior.
- Reestablished degenerate solutions that might otherwise have been ruled out.

Fixed

errors

 $S=1$ 

rescaling of





 $\diamond$  $O_{\mathcal{A}}$ 

 $\mu_{rel,N?}$  (mas yr $^{-1})$ 

 $\circ$ 

 $\mu_{rel, E?}$  (mas yr $^{-1})$ 

 $Q_{\rm d}$ 



 $s(AU)$ 

 $m_1(M_j)$ 

 $m_2(M_j)$ 

 $M(M_\odot)$ 

 $D_L(kpc)$ 



# GP with free rescaling of errors

### GP weaknesses

- Kernel choice; it's complicated
- Fits take longer to run
- Start-up cost
- Potential for degeneracies with the physical model
- May not be supported by the data.
- Introduces complexities for the modeler when multiple data sources are involved

e.g. Weakening of the baseline constraint between bands imposed by the expected color from color-color relations; The GP can "act" to undermine priors on the source color

# Roman Era Microlensing and GP Usage

- GP provides a means for marginalizing the affects of data systematics; e.g. from variable blend stars, poorly estimated error bars, and blend compositions changes due to kinematics.
- The Roman GBTDS will runs for 6 years and will have events spanning observing seasons on a similar scale to those seen in the Golovich et al. (2022) sample; use of GP may be computational plausible with efficient likelihood computation.
- A potential tool for synergy between the fields of asteroseismology and microlensing. GBTDS has an expected yield of  $\sim$ 10<sup>6</sup> detections of oscillations in stars (Gould et al. 2015).