Correlated noise in microlensing lightcurves

Michael Albrow Department of Physics and Astronomy University of Canterbury

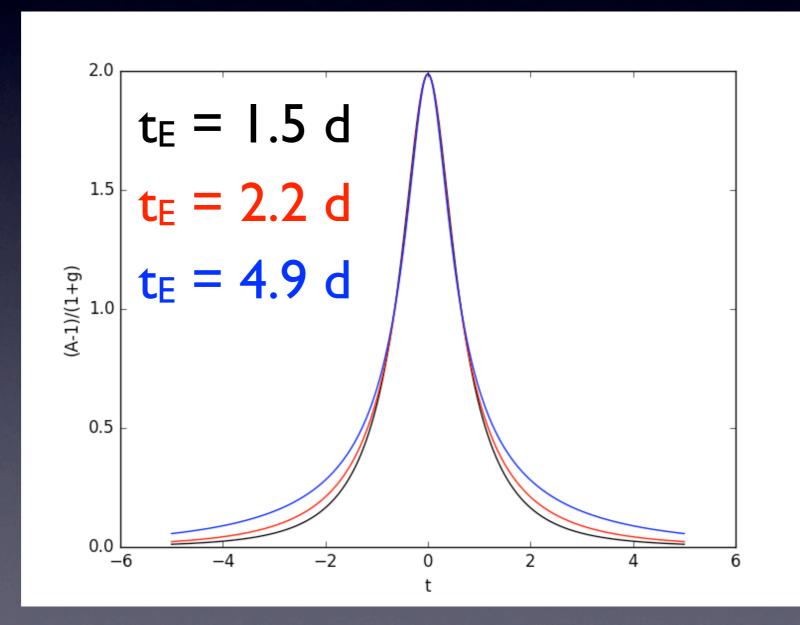
Motivation

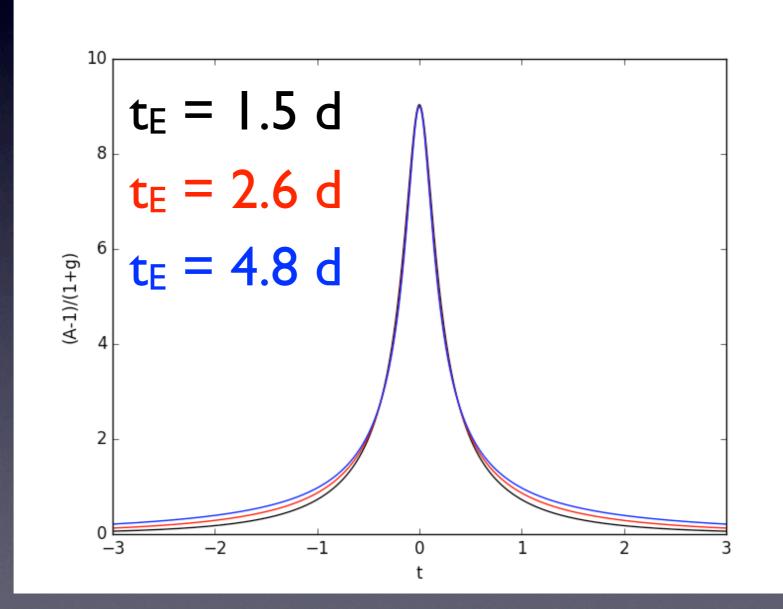
Can we detect free-floating planets with KMTNet?

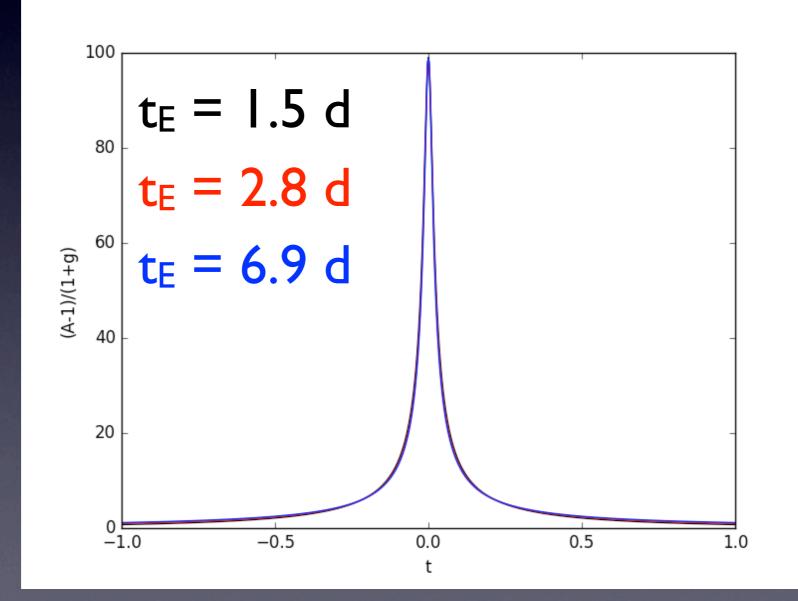


The problem

For simple PSPL lightcurves, there is a degeneracy between t_E and blending.



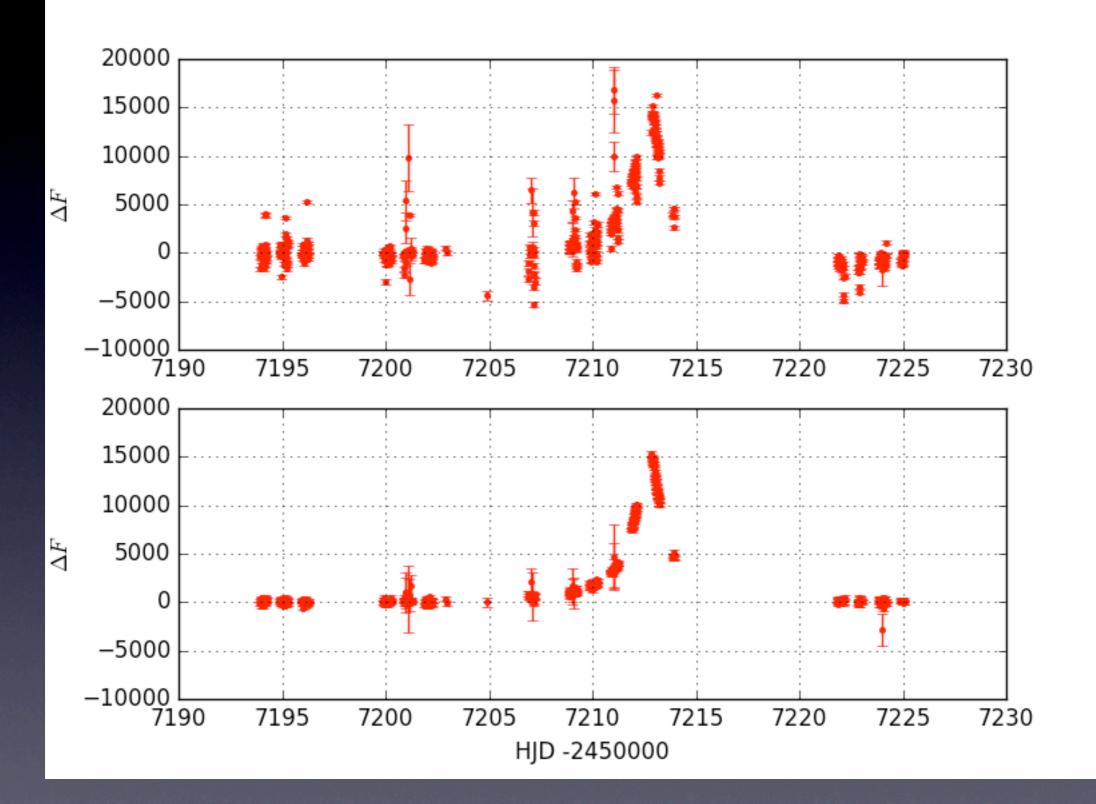


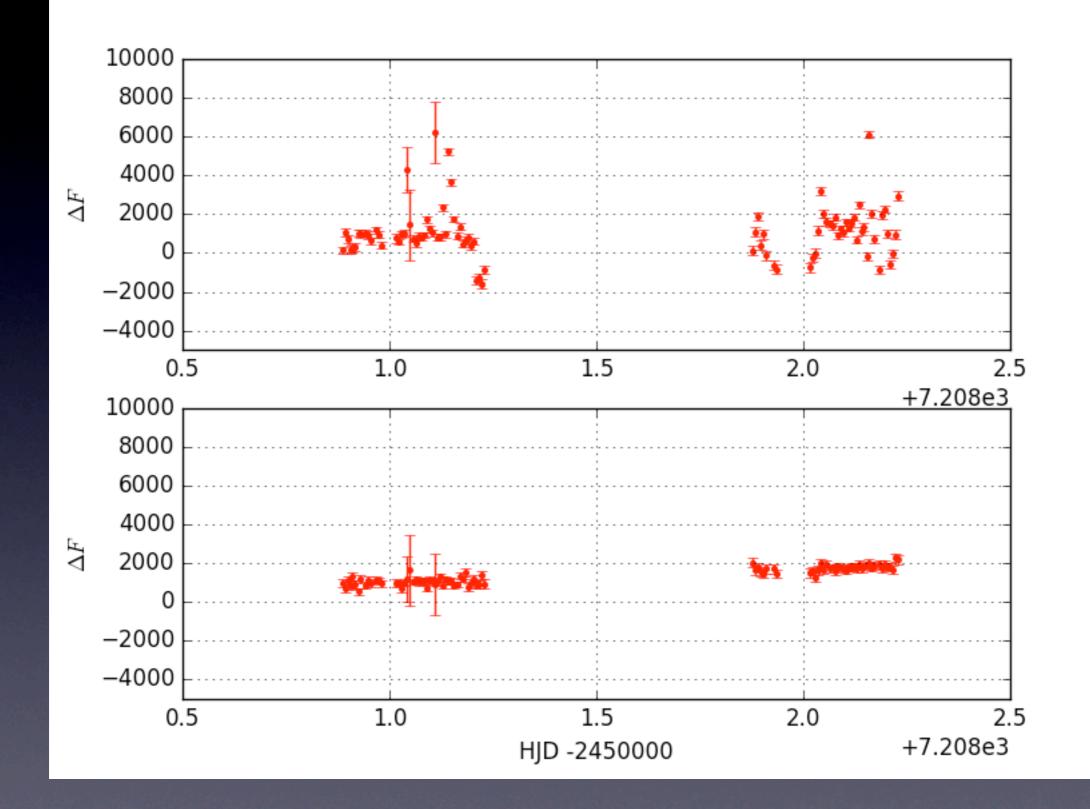


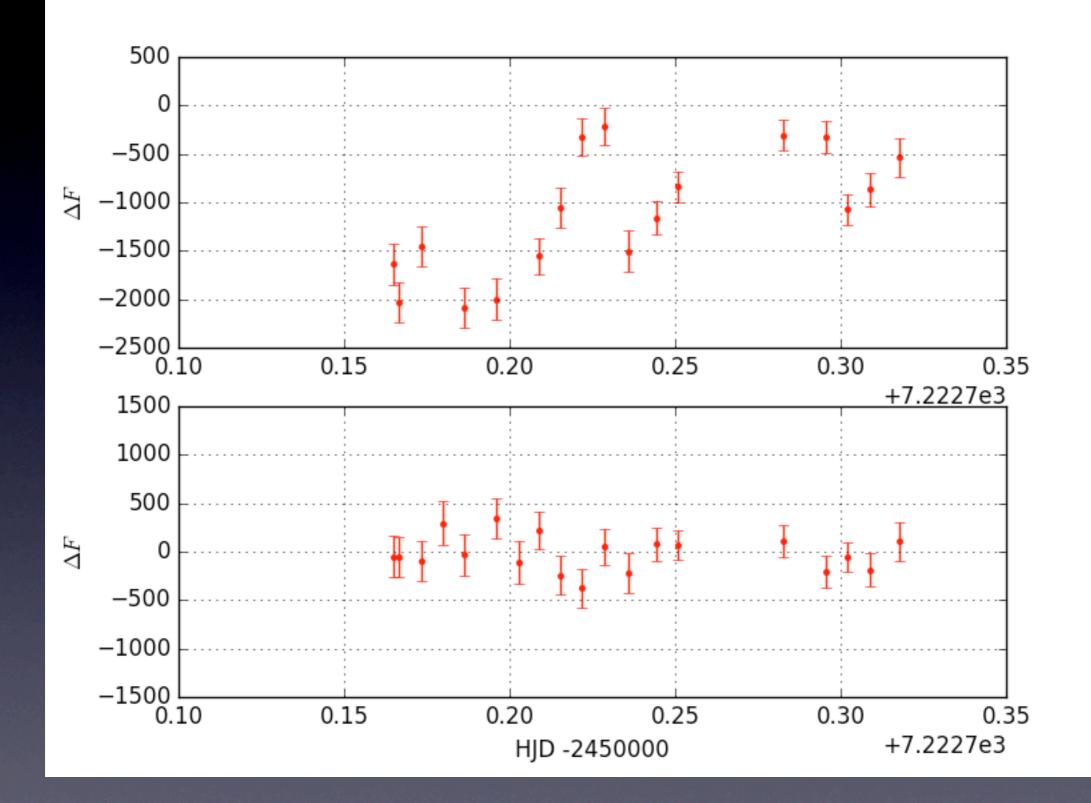
Correlated data

Ideally each measurement in a time series is independent, and normally distributed about its true value with a standard deviation equal to its quoted uncertainty.

This is rarely the case for real data.





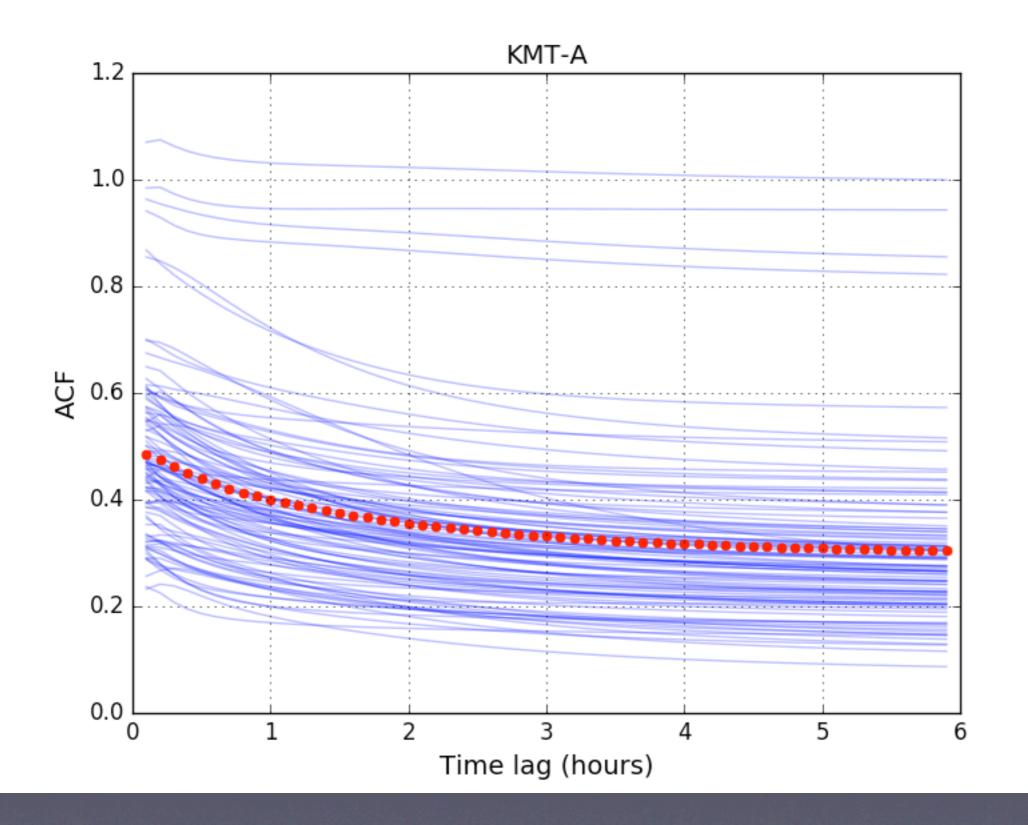


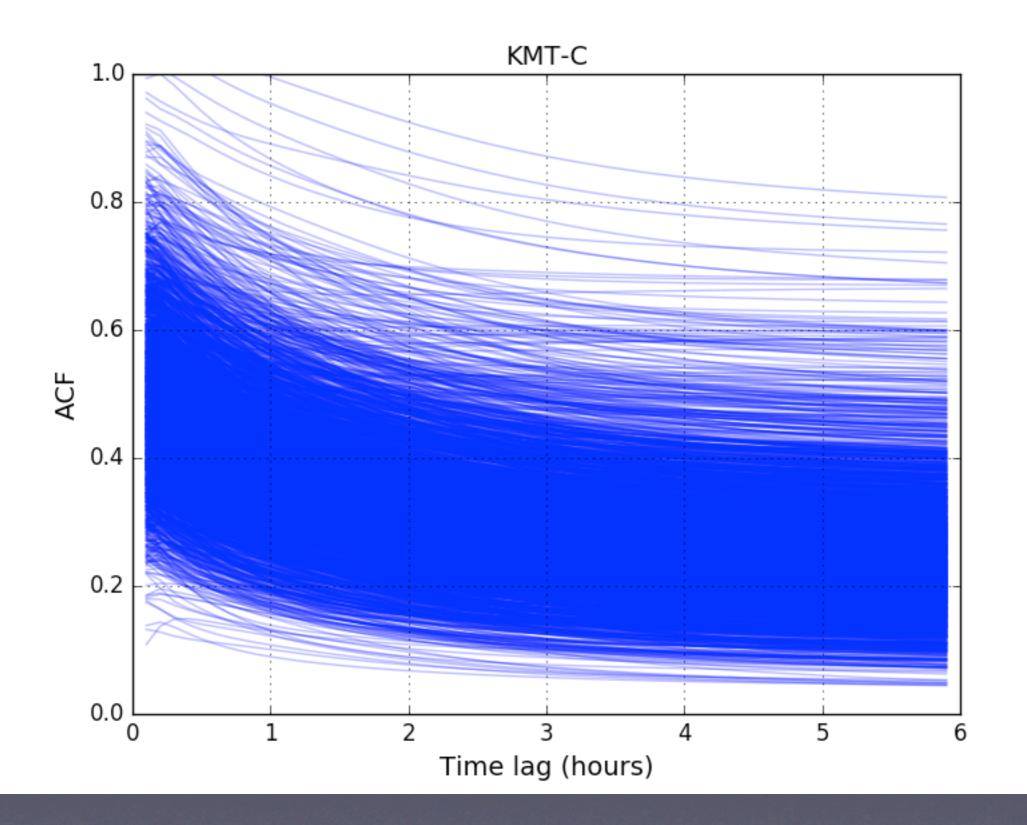
Correlated data

Of particular concern for microlensing analysis is a tendency for neighbouring data points to be correlated, not independent.

This can be due to slow changes in seeing, background illumination, airmass etc.

We can measure this correlation by examining the power spectrum or computing an autocorrelation function.





Models

Series of simulations of short-timescale microlensing events by injecting signals into real KMTNet data.

Models fitted to individual and combined data sets using MCMC (emcee package - Foreman-Mackey et al) for the non-linear parameters (initially just tE, u0, t0), with analytic solutions for the linear parameters at each step.

Fitting code available at: https://github.com/MichaelDAlbrow/SingleLensFitter

Detrending

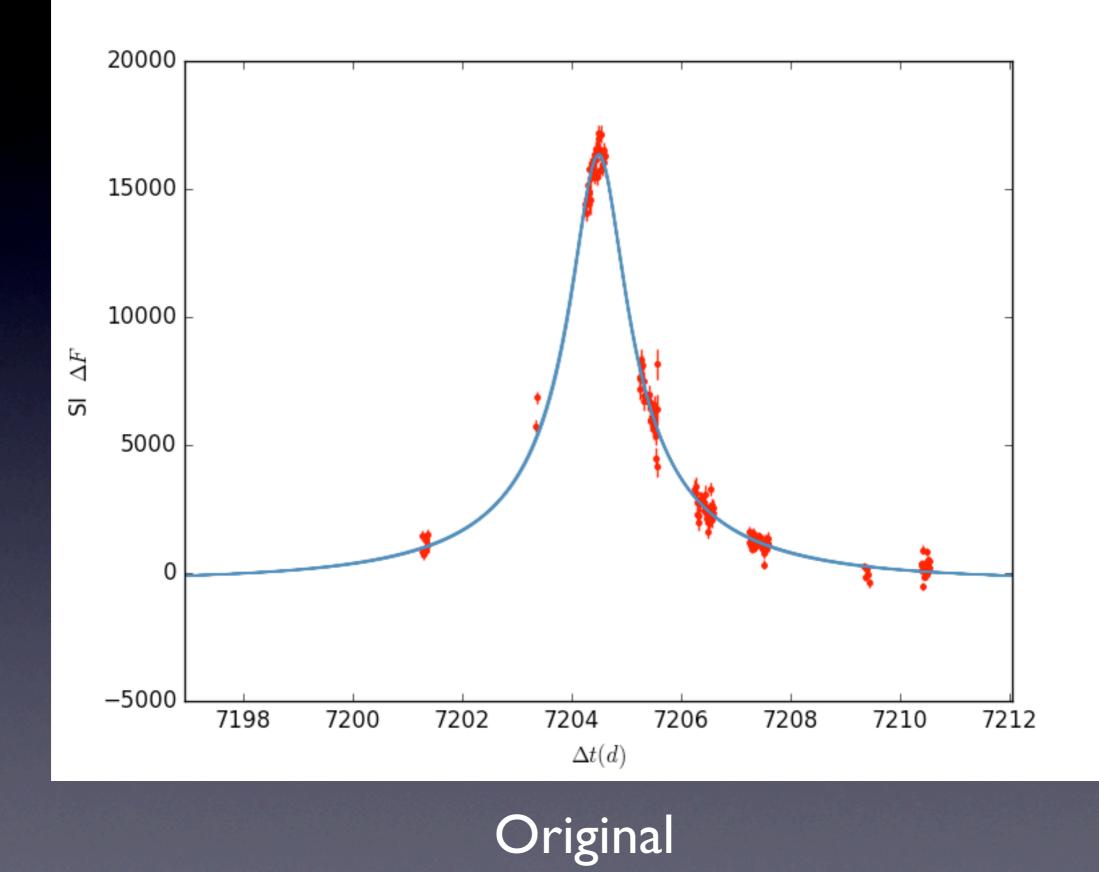
Fit and subtract a linear combination of functions that may be correlated with fluctuations in the data.

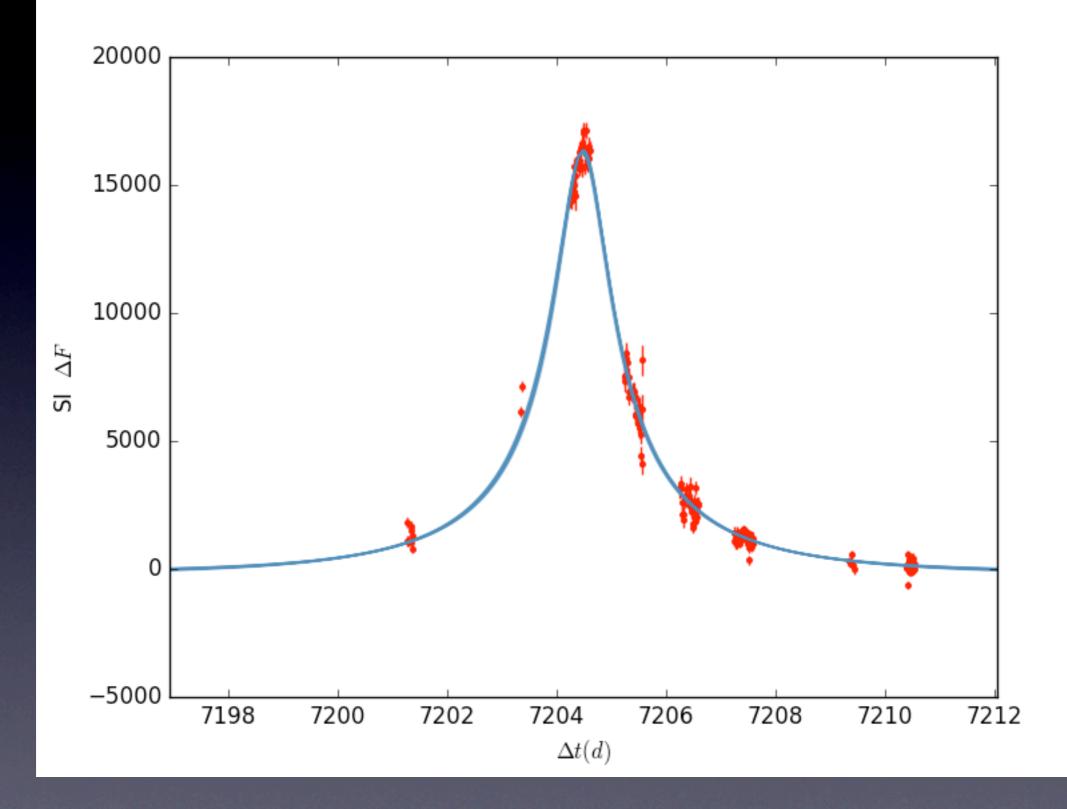
These functions may be physical parameters, e.g. seeing, background, airmass or eigenfunctions derived from an associated set of lightcurves (principal components).

Detrending

The detrending may be done in advance, but it is better to fit these linear functions at the same time as the microlensing parameters.

i.e. treat the functions the same way as the linear flux parameters.





With seeing & background correction.

Mixture model

Introduce a new non-linear parameter per data set that represents the probability that an individual data point is bad (drawn from a wide distribution).

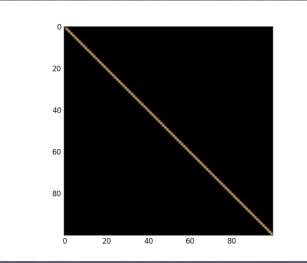
See: Hogg, Bovy & Lang 2010

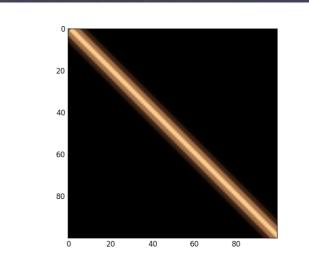
Gaussian process model

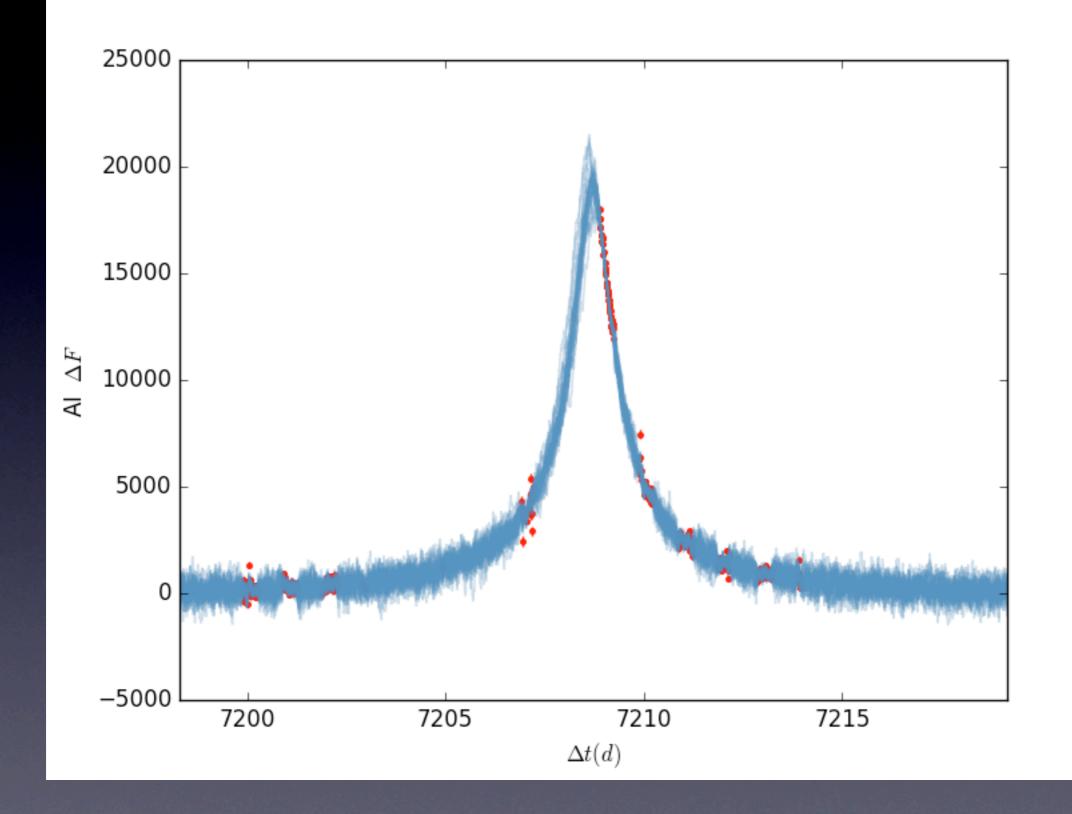
Drop the assumption that data points are independent, i.e. that the data covariance matrix is diagonal.

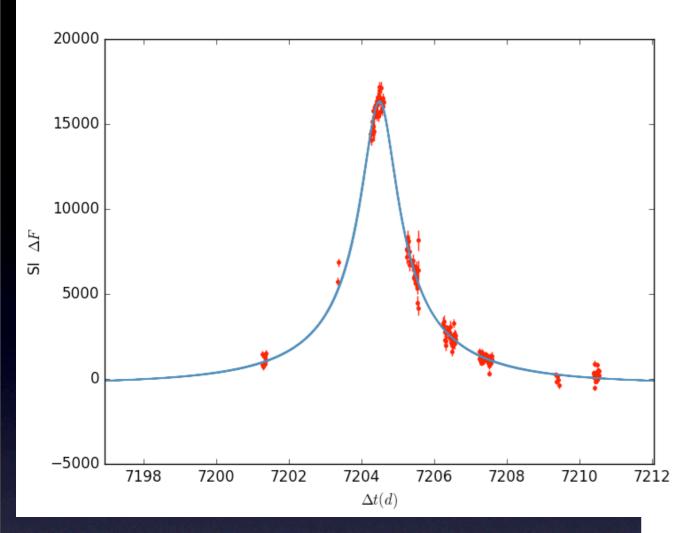
Instead, explicitly model the non-diagonal elements as a function of the time-difference between points.

See: Ambikasarin et al. 2014 george software package (Foreman-Mackey et al.)

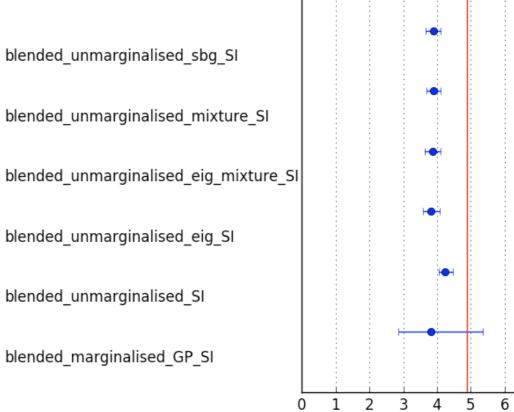














Results

If you have perfect data, you will get very good results, even if your time coverage is not great.

If you have real data, your error in t_E is likely to be many times greater than the formal uncertainty (marginalised over all other parameters, and where 'many' can mean a factor of 10 or 100).

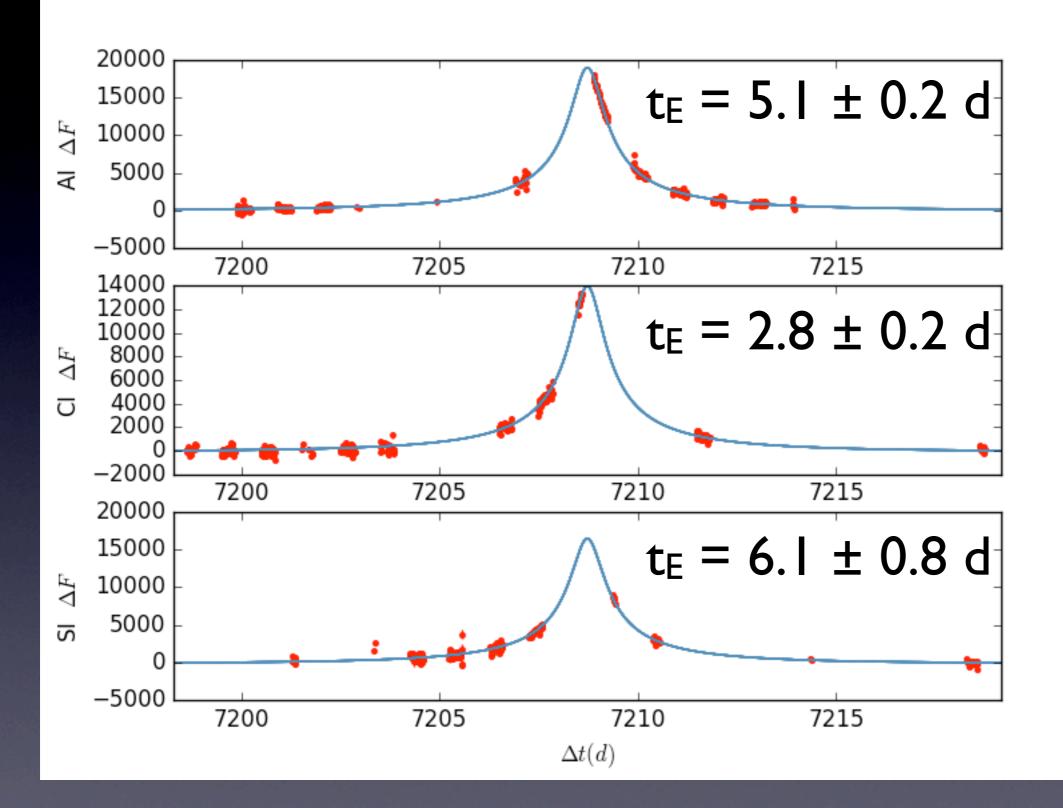
Results

Detrending sometimes helps.

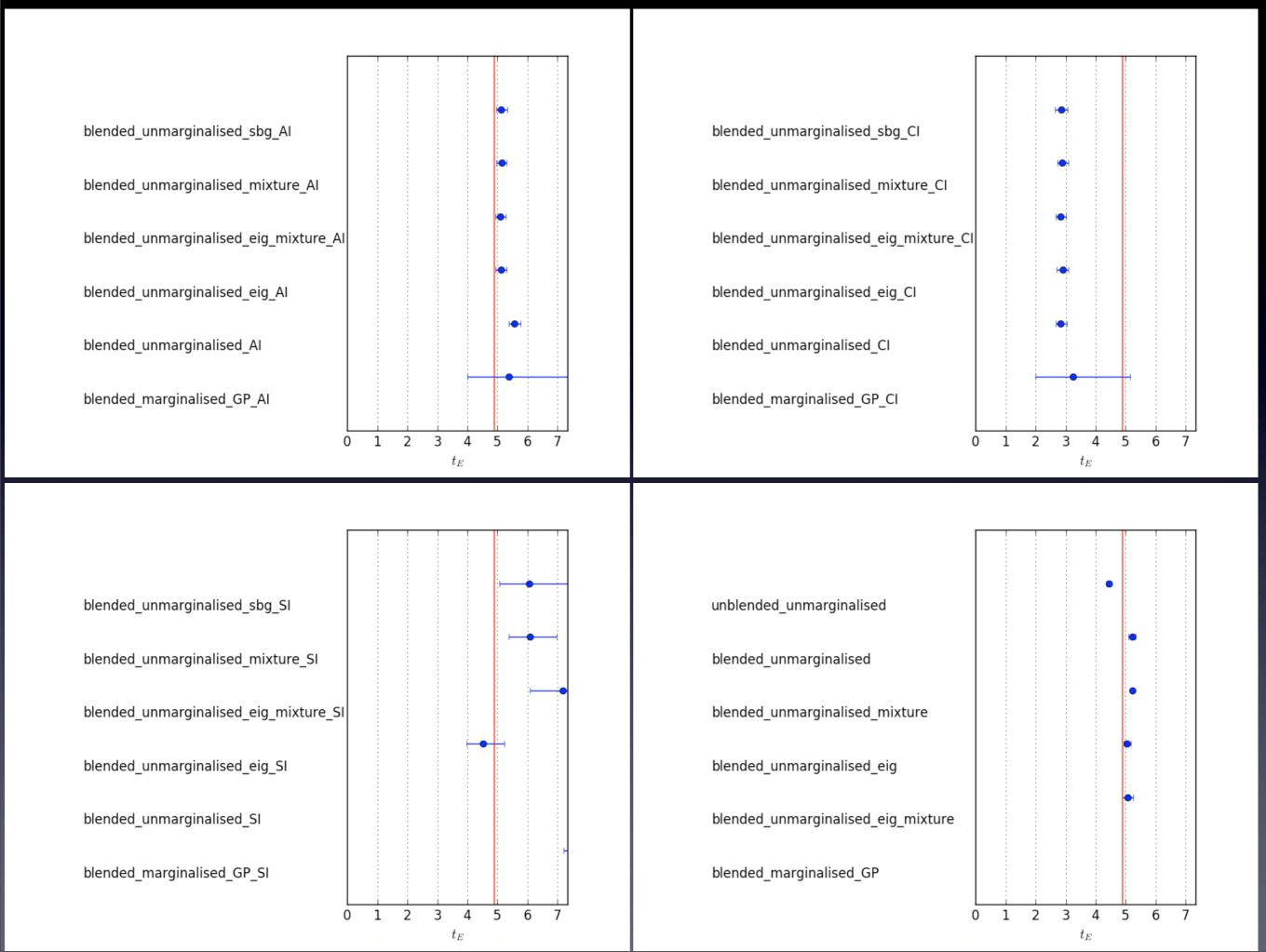
Mixture modelling has little effect if you have already removed obvious outliers from your data.

Gaussian process modelling does not improve the mean result much, but it gives realistic uncertainties for t_E .

true $t_E = 4.89$ d



combined fit $t_E = 5.2 \pm 0.1 d$



Results

To get an accurate result you need uncorrelated data that constrains both the wings and peak of an event.

If you have correlated data from a single site your results are likely to be "wrong". The degree of "wrongness" is non-trivial to establish.

Multi-site data seems to mitigate the effects of imperfect photometry and usually gives reasonable accuracy.

If you have a candidate free-floating planet:

Fit the lightcurve.

Establish a set of theoretical curves with different t_E and blending that are degenerate with your fit result.

Inject these curves into lightcurves of constant stars in your field.

Fit these simulations and determine how accurately you recover the injected parameters.