Near-infrared Hubble diagrams Type Ia Supernovae in the nearby universe

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The problem

Optical samples of SN Ia for cosmology have reached their limit to constrain the nature of the dark energy (DE) because of the systematic uncertainties.

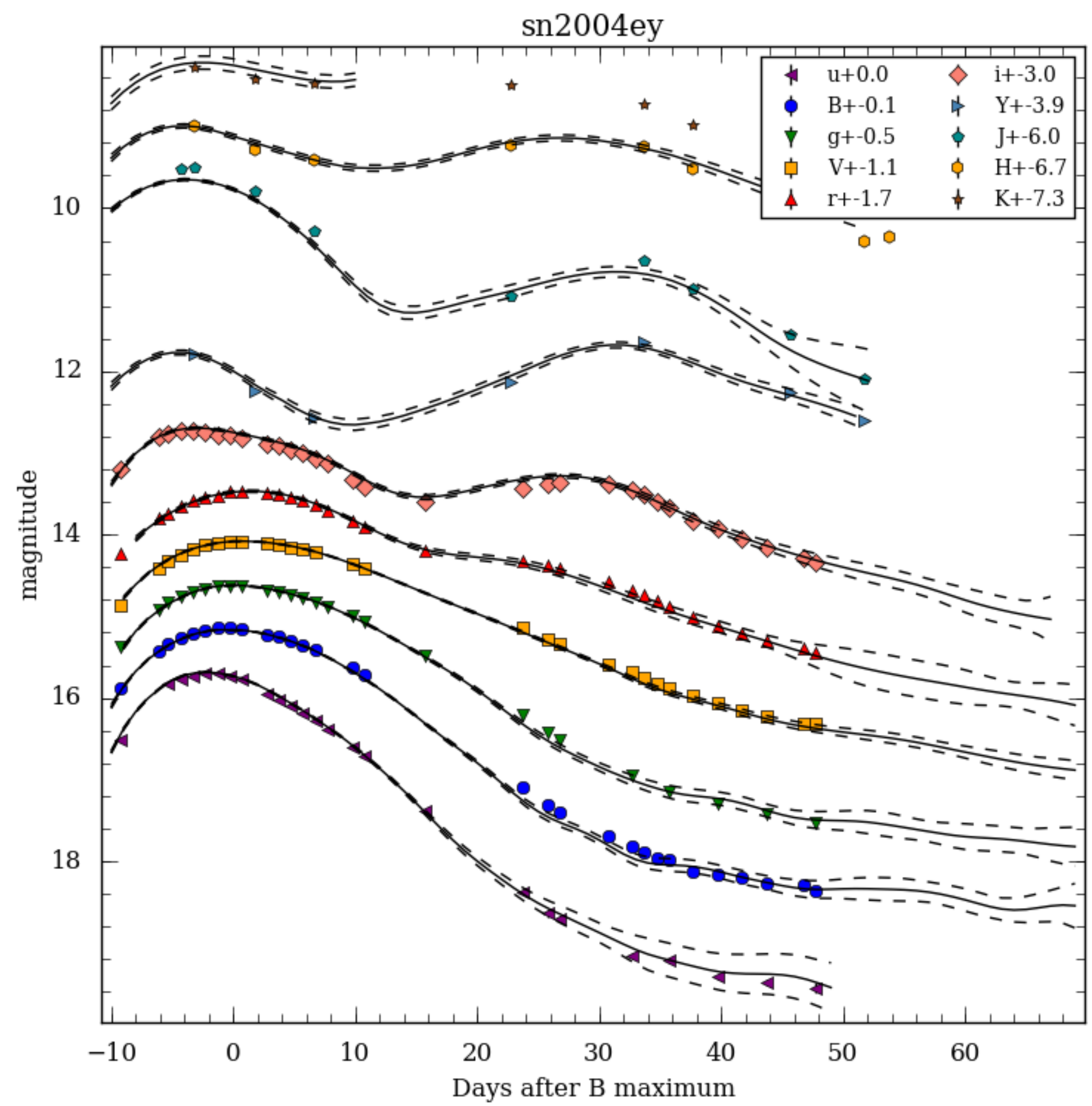
- More optical data *doesn't* mean better DE constraints.

- **Optical** light is **dimmed** and **reddened** by **dust** in the host galaxy, the Milky Way, and the extragalactic medium.

A solution: NIR observations!

- Near infrared (**NIR**) light is much **less sensitive to dust** than the optical wavelengths. Then the systematic uncertainty due to dust is reduced.

- SN Ia observed in **NIR** are much **more standard candles** than in optical wavelengths.

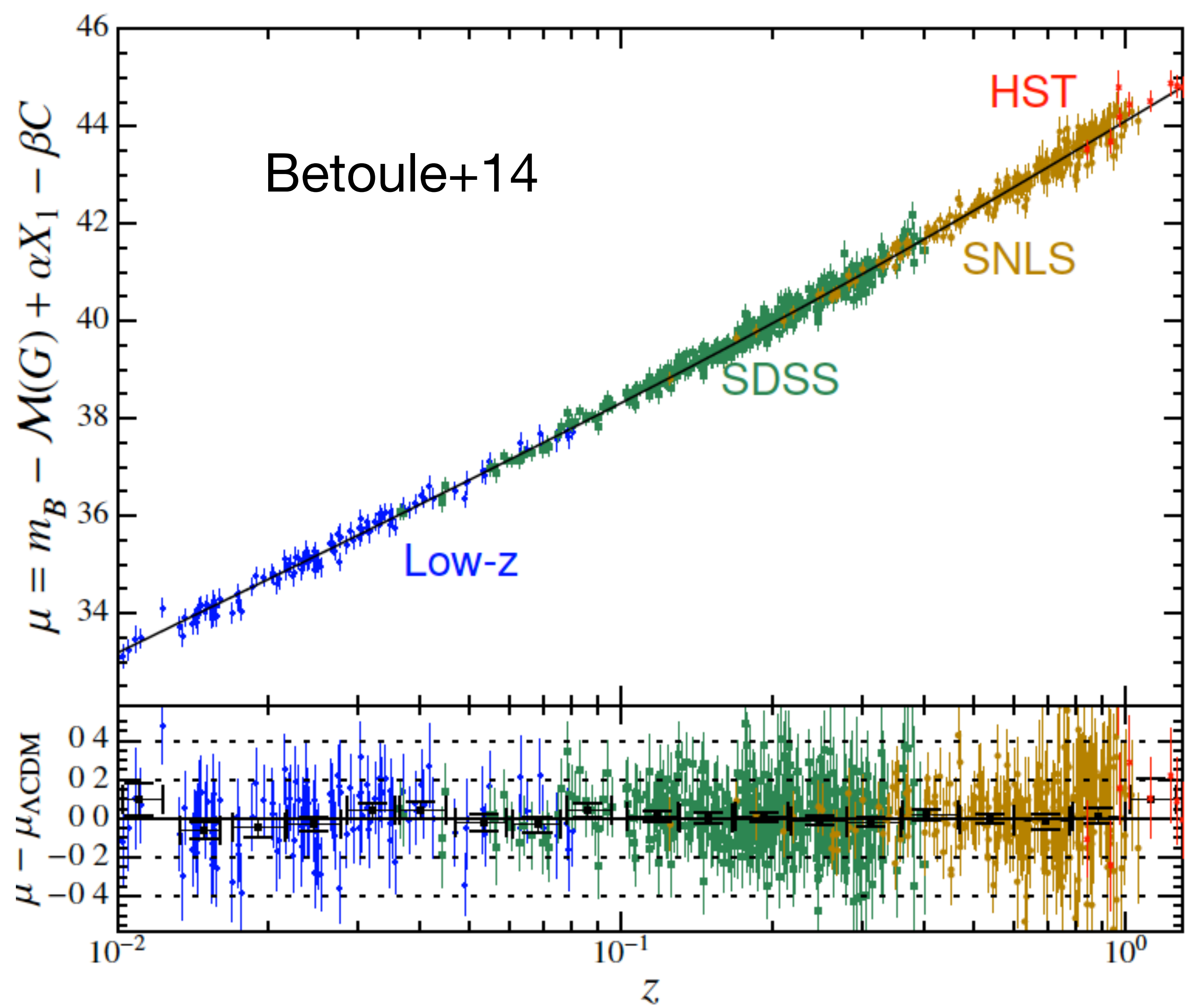


NIR SNIa Cosmology

- Low-redshift sample: CfA, CSP, PanSTARRS.

- High redshift sample:
  - **RAISIN** = “Tracers of cosmic expansion with **SN IA** in the **IR**”
  - WFIRST

Optical Hubble diagram



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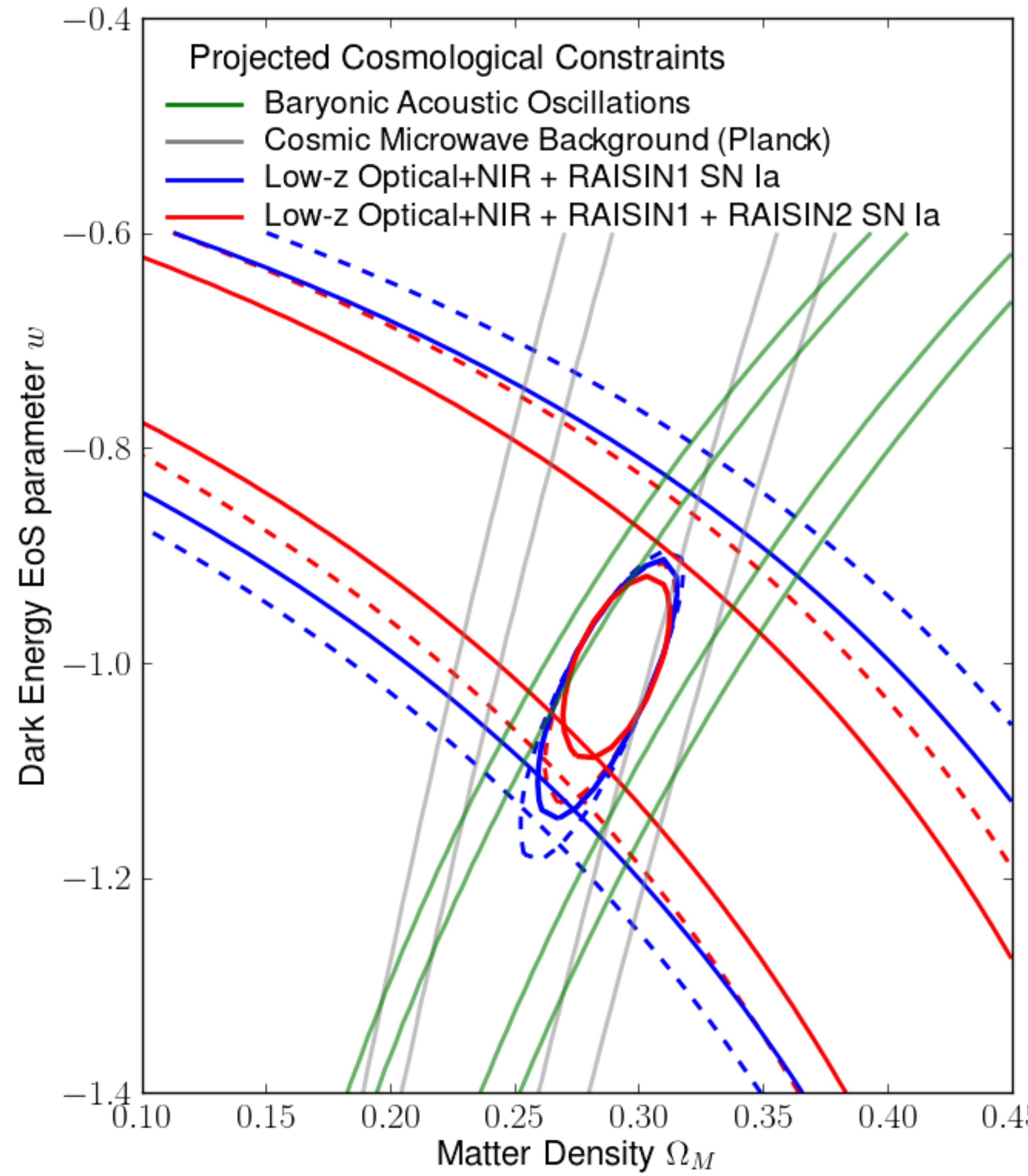
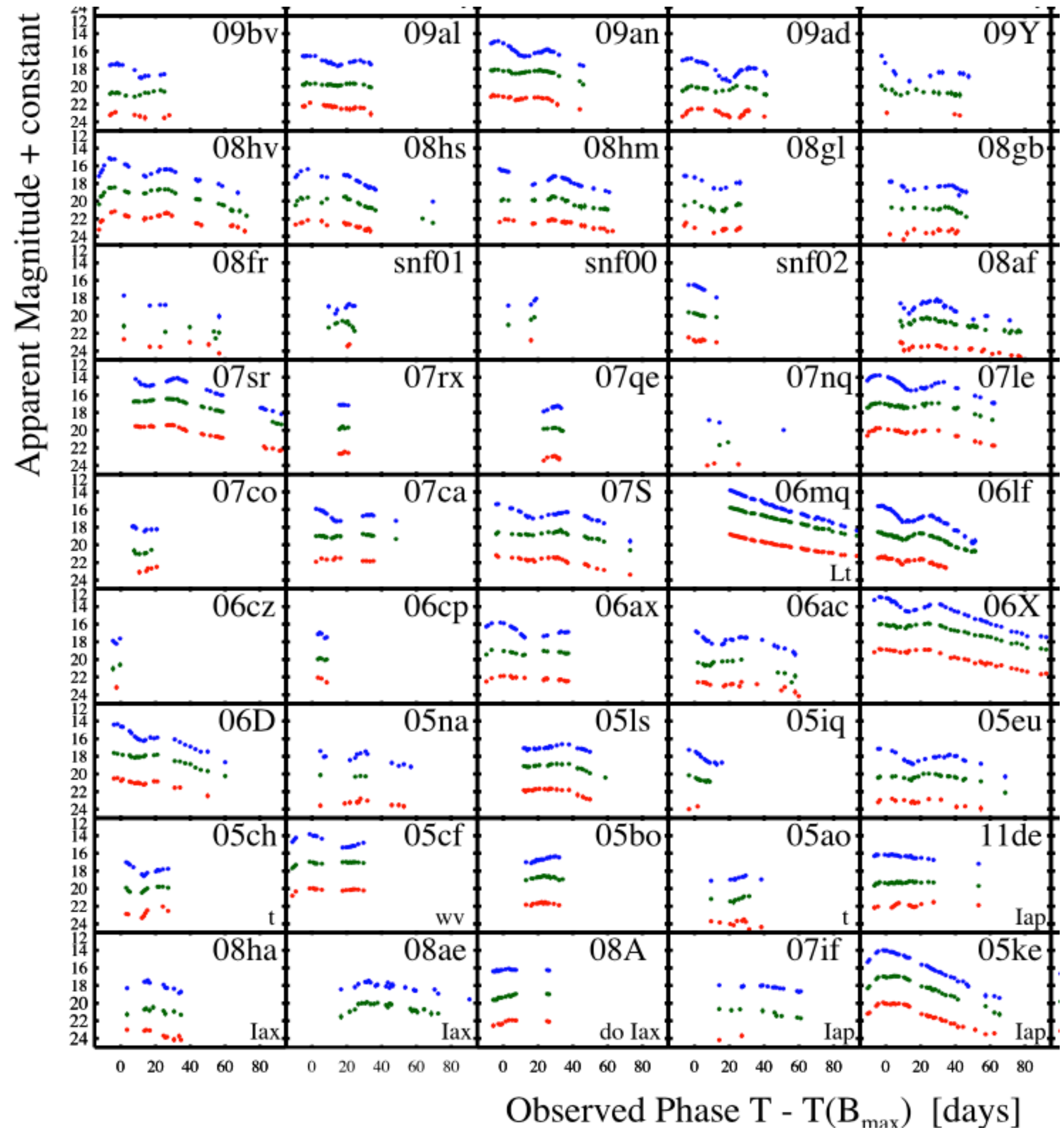


NIR Low-z data

Photometric time-series

Compiled by **Andrew Friedman** (UCSD)

- CfA, CSP, Krisciunas
- 154 SNe with optical + NIR (YJHK) light curves.



Friedman+2015

Goal

Infer the distance modulus of each SNIa from their near-infrared time-series data (aka, light curves)

Method

★ Construct NIR light-curve templates

- Gaussian-Processes regression

- Hierarchical Bayesian model

★ Fit the NIR light-curve template to the time series data

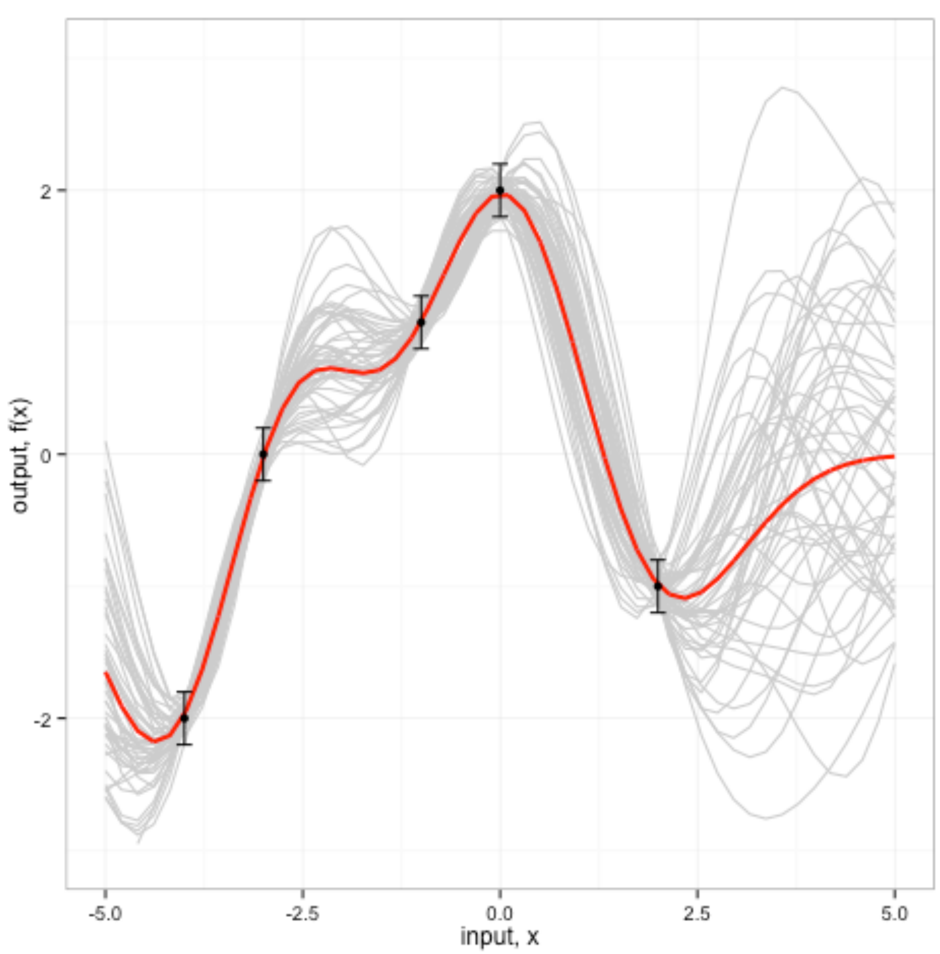
Gaussian Processes

Interpolating the time series using Gaussian Processes regression

$M_{\mathrm{r},s}(\mathbf{t}_s^*)$ = random functions that fit the time-series data.

$$M_{\mathrm{r},s}(\mathbf{t}_s^*)|M_{\mathrm{r},s}(\hat{\mathbf{t}}_s), \hat{\mathbf{t}}_s, \mathbf{t}_s^* \sim N[\bar{M}_{\mathrm{r},s}(\mathbf{t}_s^*), \mathrm{cov}(M_{\mathrm{r},s}(\mathbf{t}_s^*))]$$

$\bar{M}_{\mathrm{r},s}(\mathbf{t}_s^*)$ = ***most likely function*** that fits the time series.



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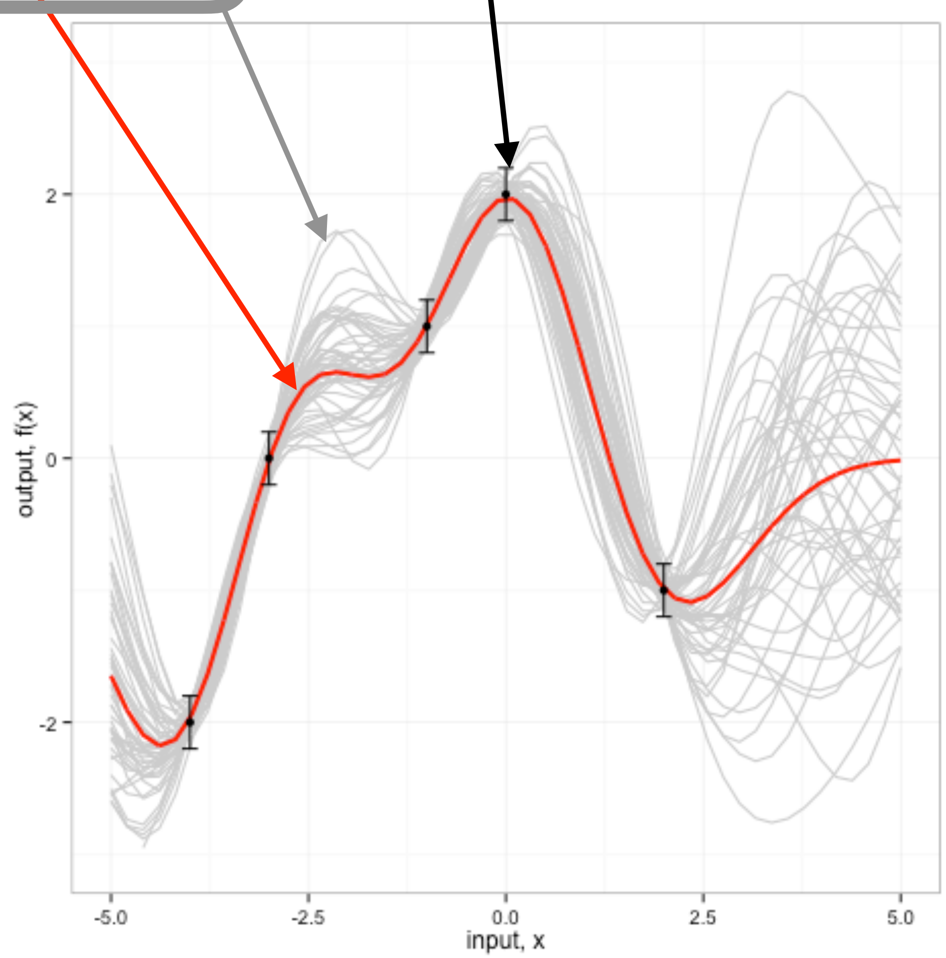

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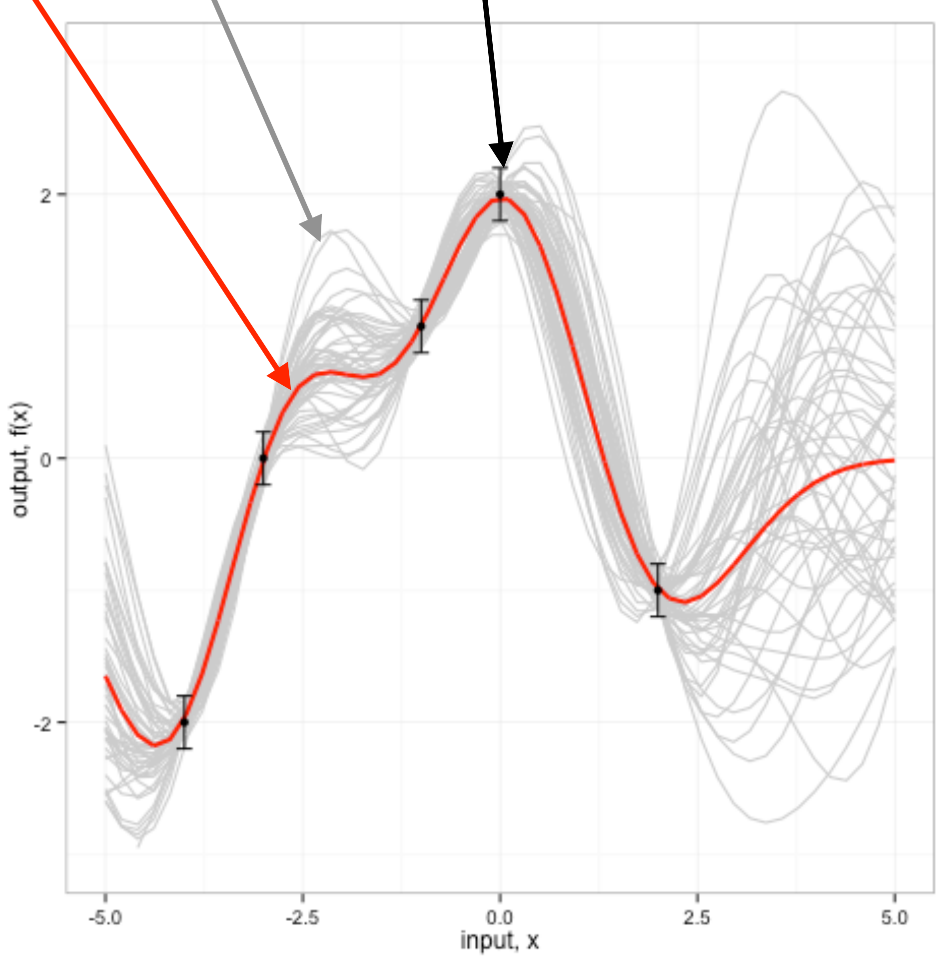

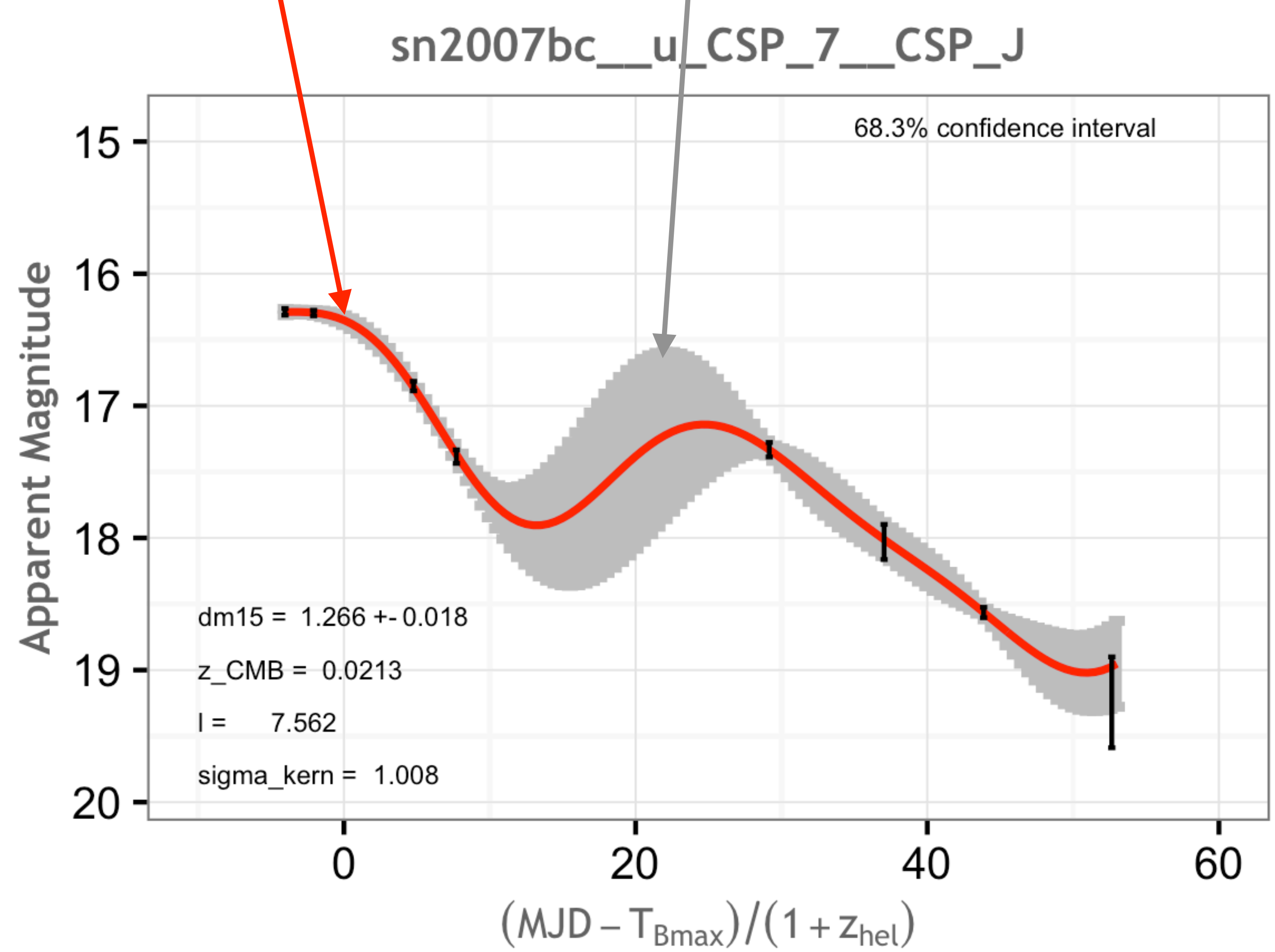

Gaussian Processes

Interpolating the time series using Gaussian Processes regression

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$\bar{M}_{\mathrm{r},s}(\mathbf{t}_s^*)$= ***most likely function*** that fits the time series.

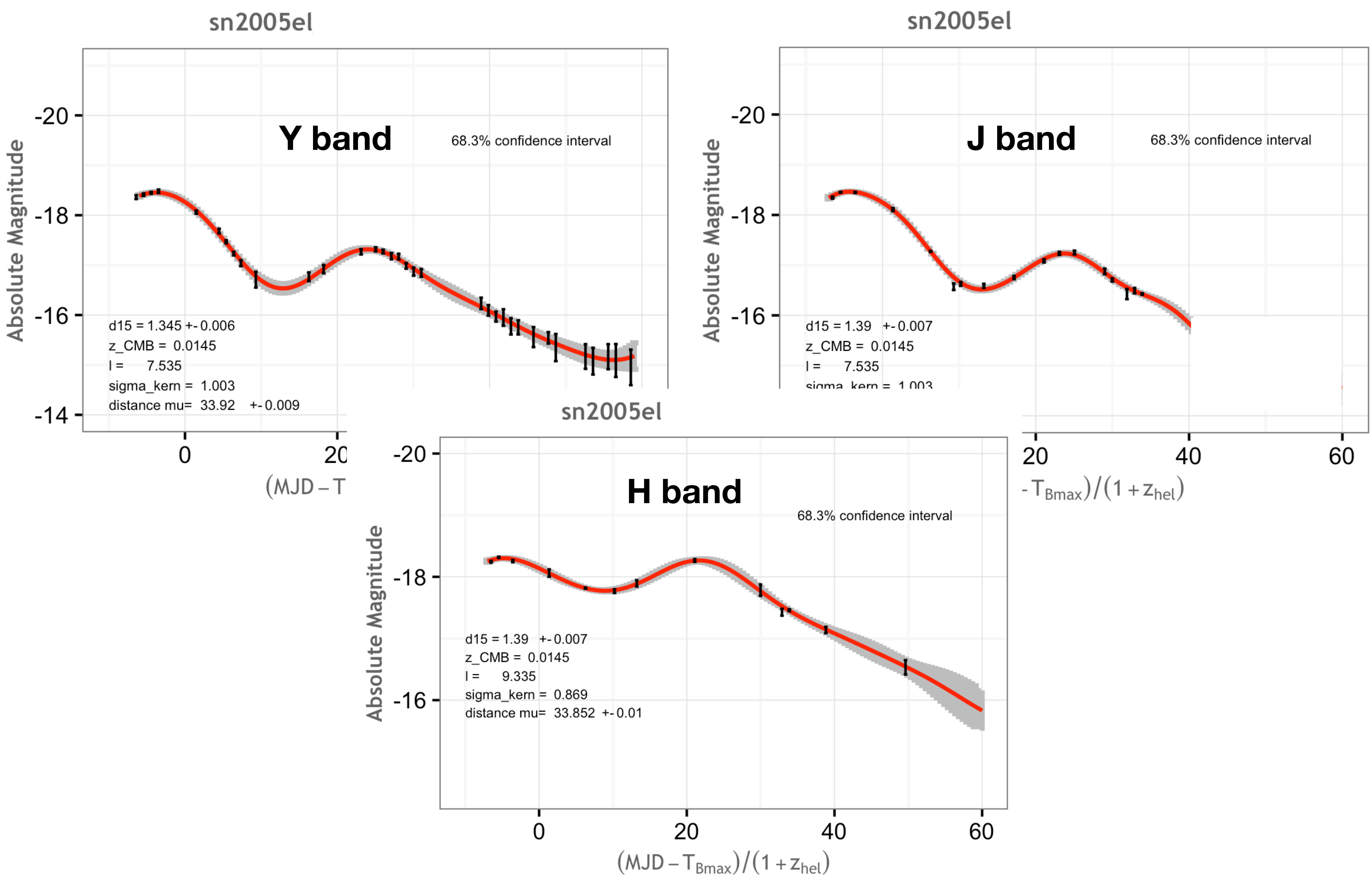
where the mean function and covariance matrix are:

- $\bar{\mathbf{M}}_{\mathrm{r},s}(\mathbf{t}_s^*) = K(\mathbf{t}_s^*, \hat{\mathbf{t}}_s) \cdot \left[K(\hat{\mathbf{t}}_s, \hat{\mathbf{t}}_s) + W(\hat{\mathbf{t}}_s, \hat{\mathbf{t}}_s)\right]^{-1} \cdot \mathbf{M}_{\mathrm{r},s}(\hat{\mathbf{t}}_s)$
- $\mathrm{cov}(\mathbf{M}_{\mathrm{r},s}(\mathbf{t}_s^*)) = K(\mathbf{t}_s^*, \mathbf{t}_s^*) - K(\mathbf{t}_s^*, \hat{\mathbf{t}}_s) \cdot \left[K(\hat{\mathbf{t}}_s, \hat{\mathbf{t}}_s) + W(\hat{\mathbf{t}}_s, \hat{\mathbf{t}}_s) + \sigma^2_{\mu\mathrm{pec},s} I_s \cdot I_s^\top\right]^{-1} \cdot K(\hat{\mathbf{t}}_s, \mathbf{t}_s^*)$

where

$$K(t,t') = \sigma_K^2 \exp\left[-\frac{(t-t')^2}{2l^2}\right], \quad \text{and} \quad W(\hat{t},\hat{t}') = \sigma_M^2 \delta_{tt'}.$$

Gaussian-Processes Interpolation examples



Bayesian Hierarchical model

Constructing the NIR light-curve templates

We assume that the $\tilde{M}_s(t_*)$ are drawn from a Gaussian distribution with mean $\mathcal{M}(t_*)$ and variance $\sigma^2_{\mathcal{M}}$:

$$p\left(\{\tilde{M}_s\}|\mathcal{M},\sigma_{\mathcal{M}}\right) = \prod_{s=1}^{N_{\mathrm{SN}}} N\left(\tilde{M}_s|\mathcal{M},\sigma^2_{\mathcal{M}}\right)$$

Template

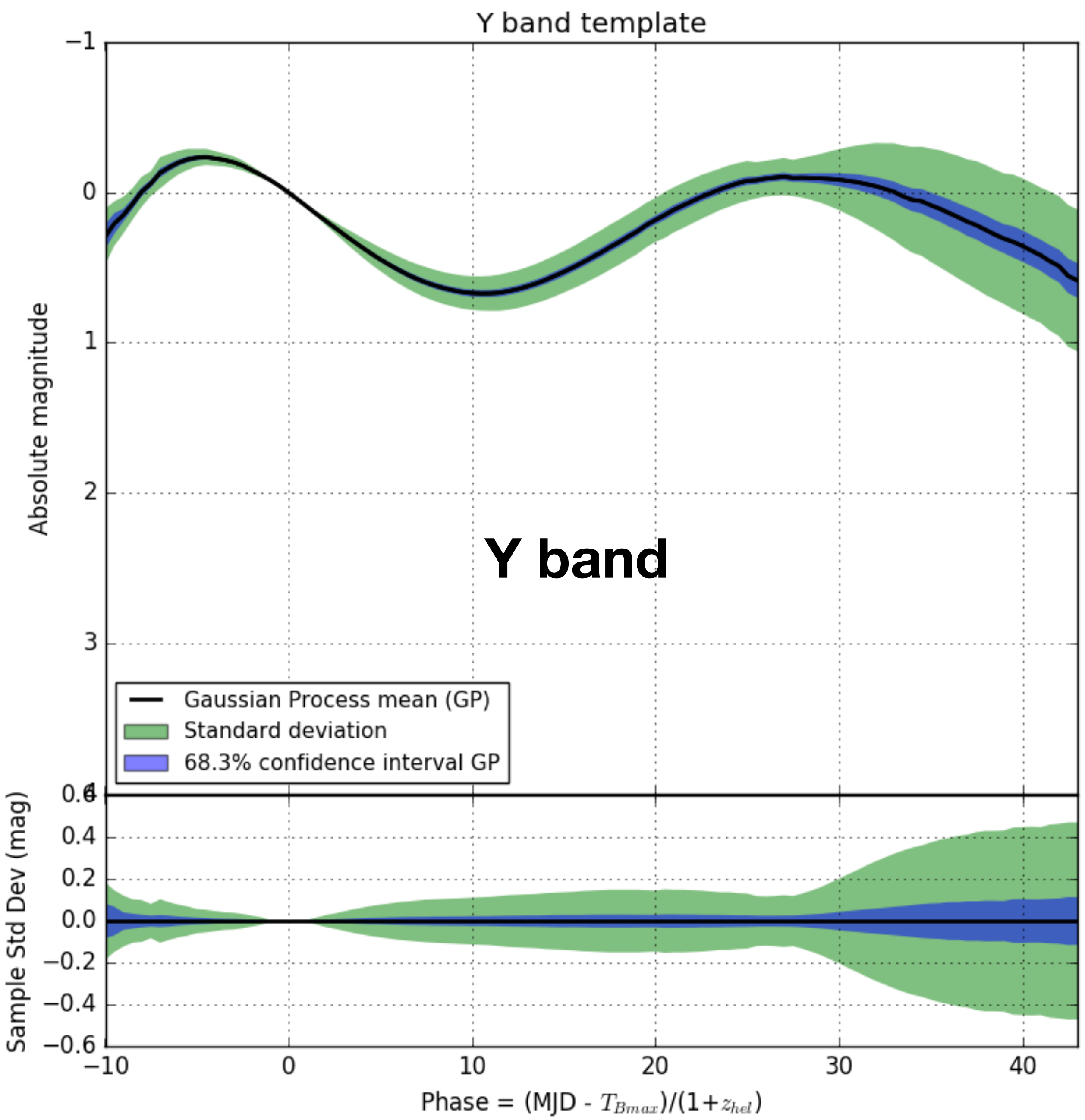
Joint posterior distribution:

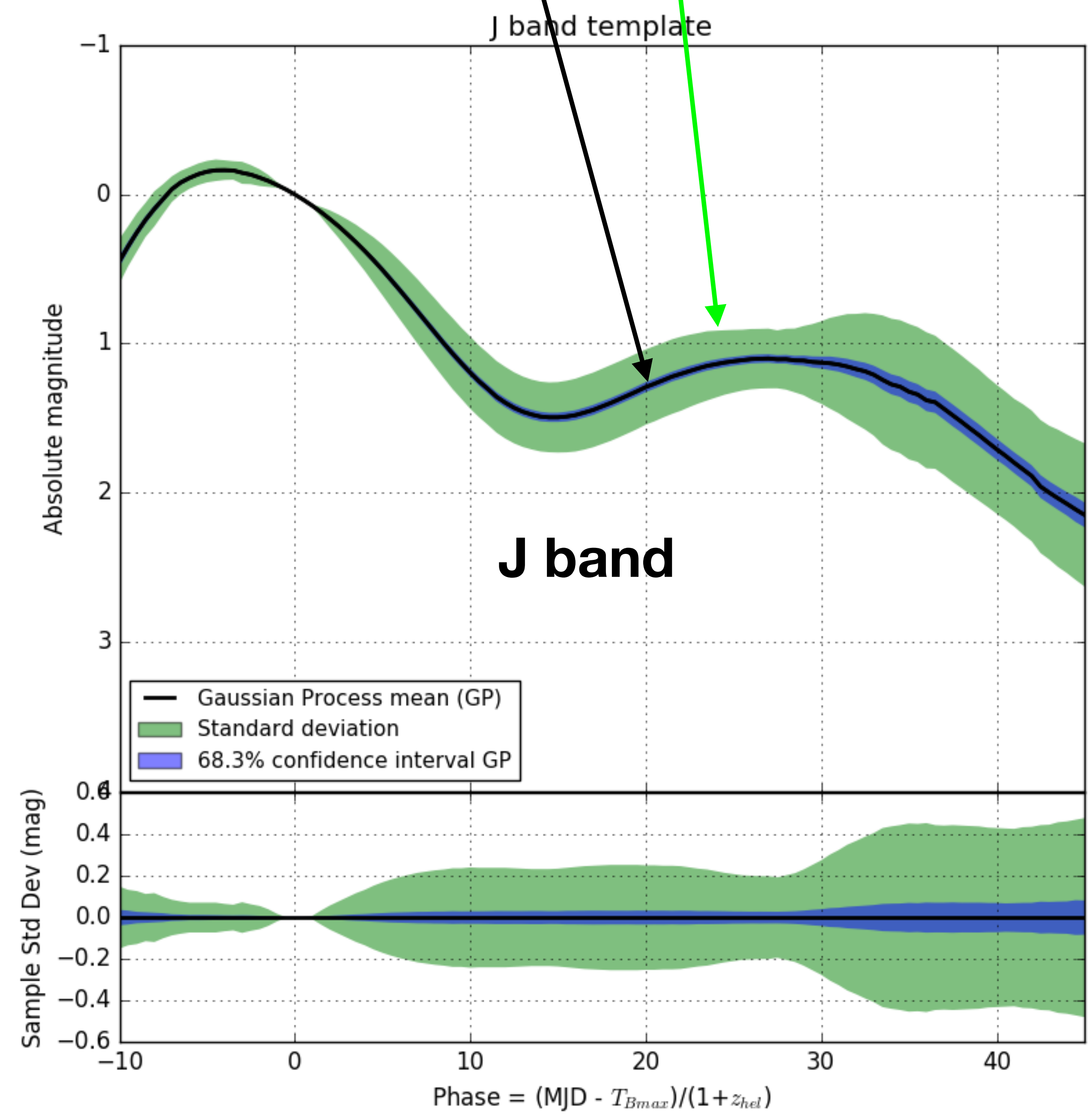
$$p\left(\{\tilde{M}_s\},\mathcal{M},\sigma_{\mathcal{M}}|\{\bar{M}_s,\sigma_{\bar{M},s}\}\right) \propto$$
$$p\left(\mathcal{M},\sigma_{\mathcal{M}}\right) \times p\left(\{\tilde{M}_s\}|\mathcal{M},\sigma_{\mathcal{M}}\right) p\left(\{\bar{M}_s\}|\{\tilde{M}_s\}\{\sigma_{\bar{M},s}\}\right).$$

NIR Low-z templates

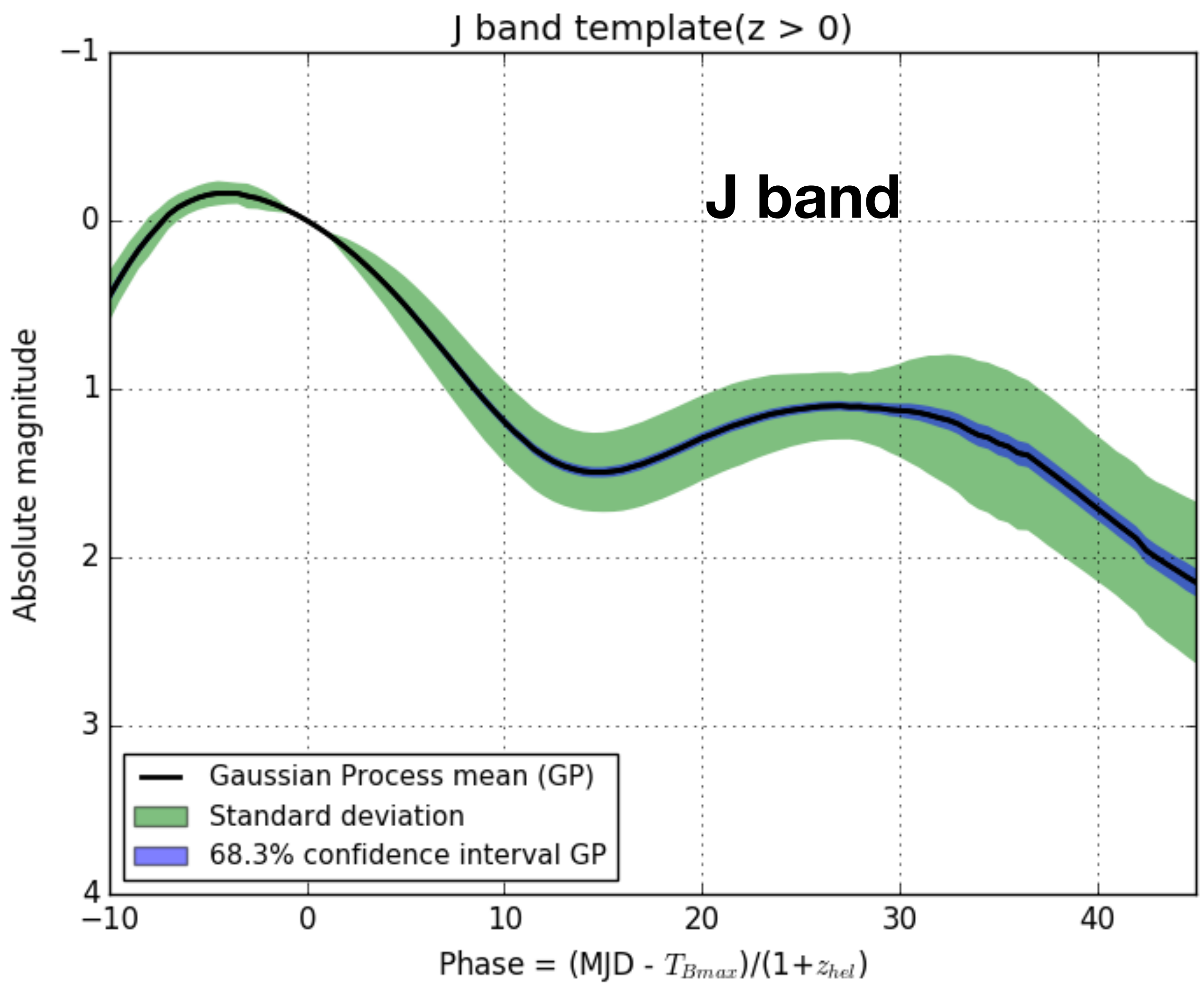
Hierarchical Bayesian model

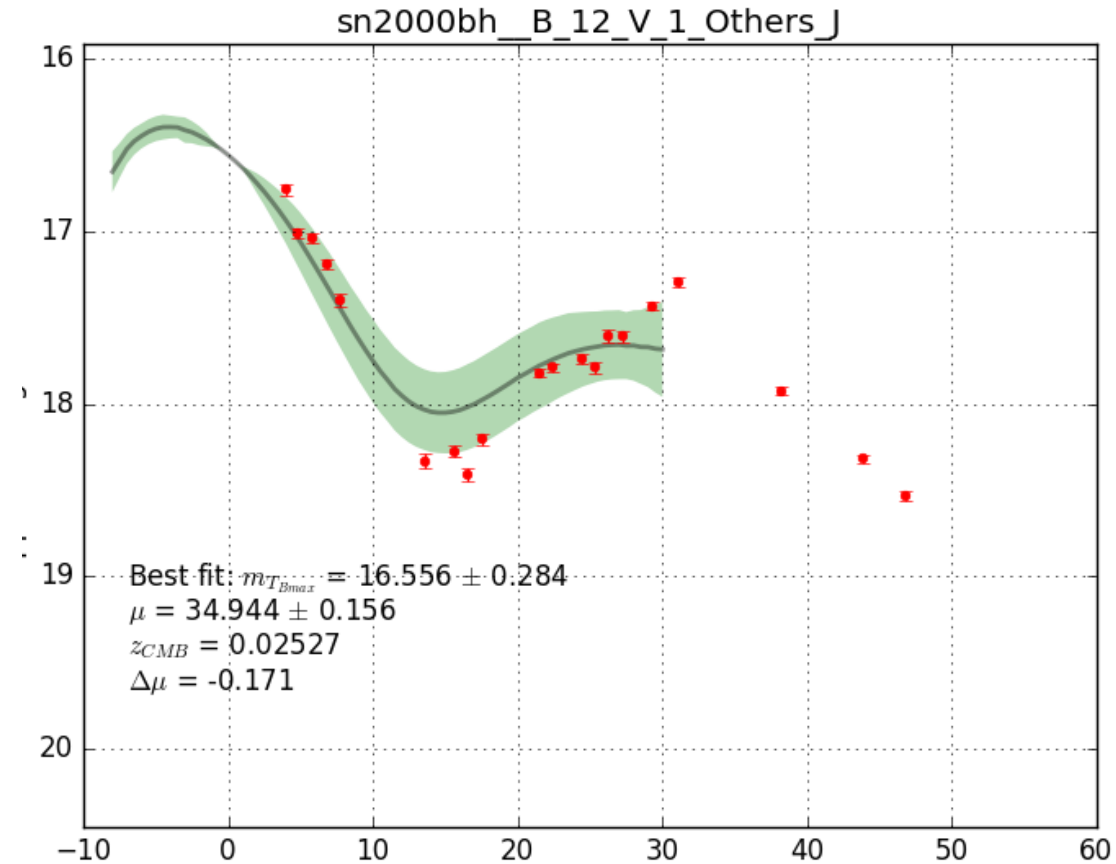
$$p\left(\{\tilde{M}_s\}|\mathcal{M},\sigma_{\mathcal{M}}\right) = \prod_{s=1}^{N_{\rm SN}} N\left(\tilde{M}_s|\mathcal{M},\sigma^2_{\mathcal{M}}\right)$$

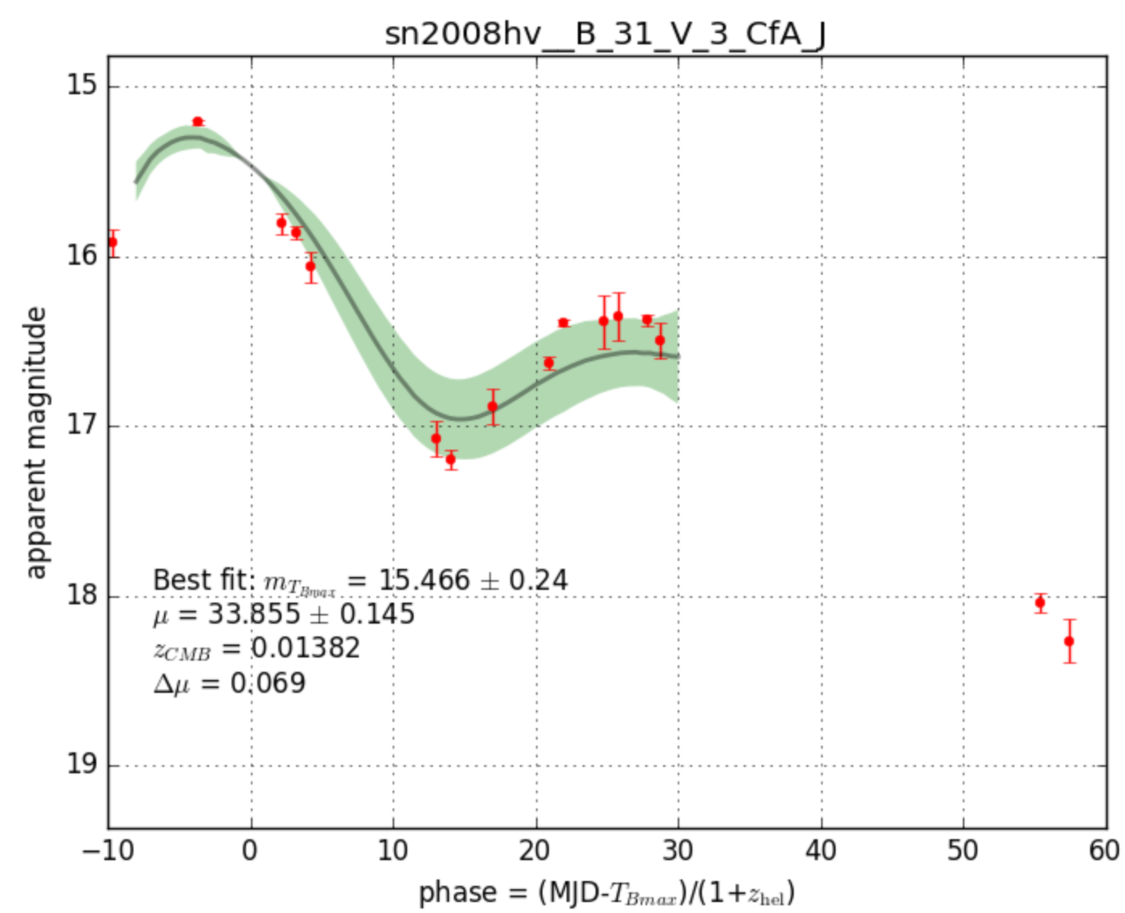




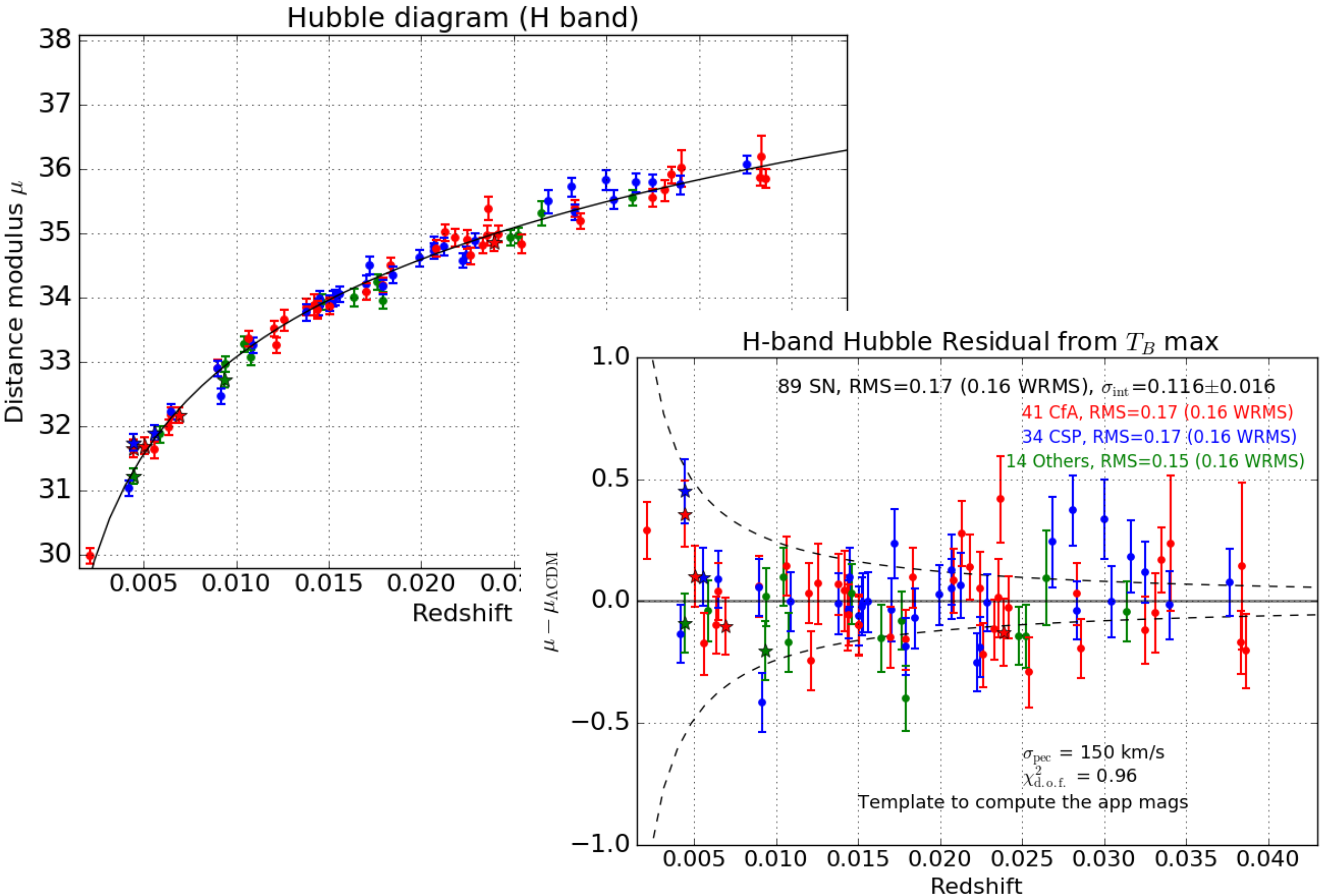
Fitting the time series with the template







NIR Low-z Hubble diagram



Summary

- Gaussian-Processes regression works great to infer the light curves from the time series data.

- Hierarchical Bayesian model is a power tool to infer global properties (our NIR light-curve templates) from a population (our time-series sample).

  - A full Hierarchical Bayesian analysis of NIR+Optical SNIa light curves: Mandel+09, Mandel+11.