

The purpose of MCMC is to
provide a fair sampling of some probability distribution

What does acceptance fraction of 0 or 1 mean?

(Integrated) Autocorrelation Time

Autocorrelation time The autocorrelation time is a direct measure of the number of evaluations of the posterior PDF required to produce independent samples of the target density. [GW10](#) show that the stretch-move algorithm has a significantly shorter autocorrelation time on several non-trivial densities. This means that fewer PDF computations

(Integrated) Autocorrelation Time

The autocovariance function of a time series $X(t)$ is

$$C_f(T) = \lim_{t \rightarrow \infty} \text{cov} [f(X(t+T)), f(X(t))]. \quad (11)$$

This measures the covariances between samples at a time lag T . The value of T where $C_f(T) \rightarrow 0$ measures the number of samples that must be taken in order to ensure independence. In particular, the relevant measure of sampler efficiency is the integrated autocorrelation time

$$\tau_f = \sum_{T=-\infty}^{\infty} \frac{C_f(T)}{C_f(0)} = 1 + 2 \sum_{T=1}^{\infty} \frac{C_f(T)}{C_f(0)}. \quad (12)$$

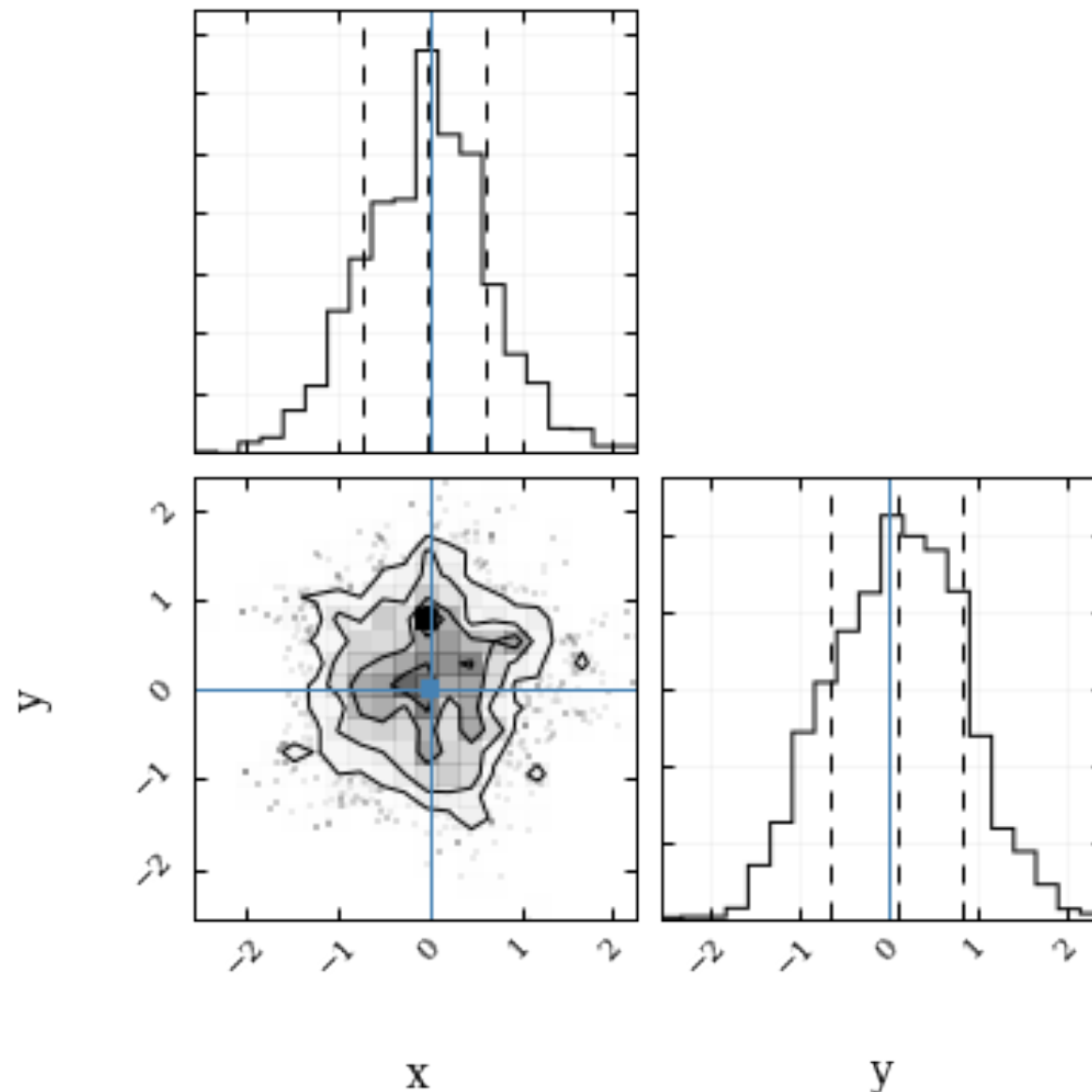
In practice, one can estimate $C_f(T)$ for a Markov chain of M samples as

$$C_f(T) \approx \frac{1}{M-T} \sum_{m=1}^{M-T} [f(X(T+m)) - \langle f \rangle] [f(X(m)) - \langle f \rangle]. \quad (13)$$

(Integrated) Autocorrelation Time

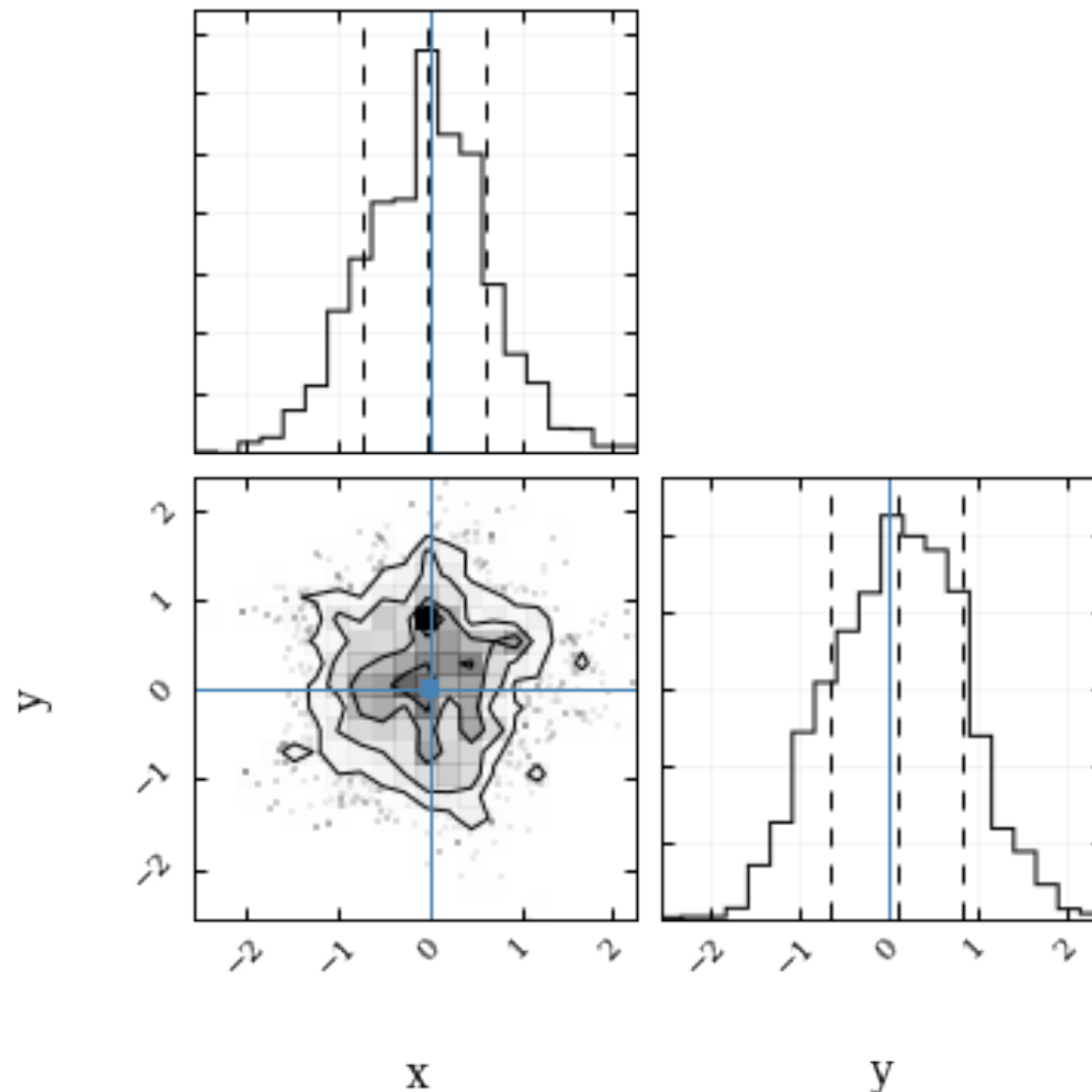
the $E_{p(\theta)}[q(\theta)]$ inside the sum is that estimator too. It is slightly off-topic here, but related to this, if you have a long chain of length K and with autocorrelation time τ and you thin the chain down to every τ th sample (instead of using all K samples), you will get just as good sampling-based estimates as if you had used all K samples.

Summary Statistics



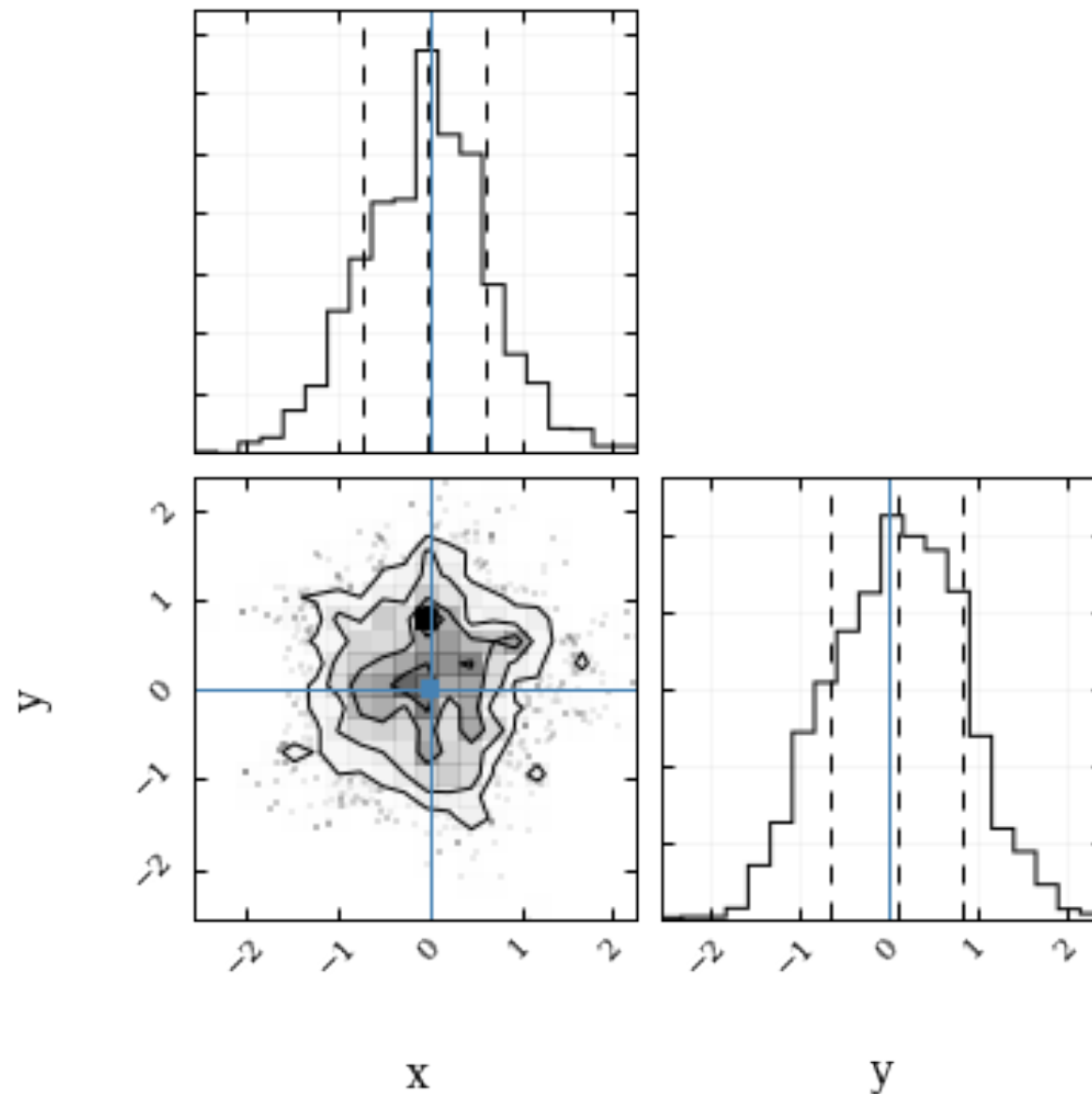
How to report the results of probabilistic inference?

Summary Statistics



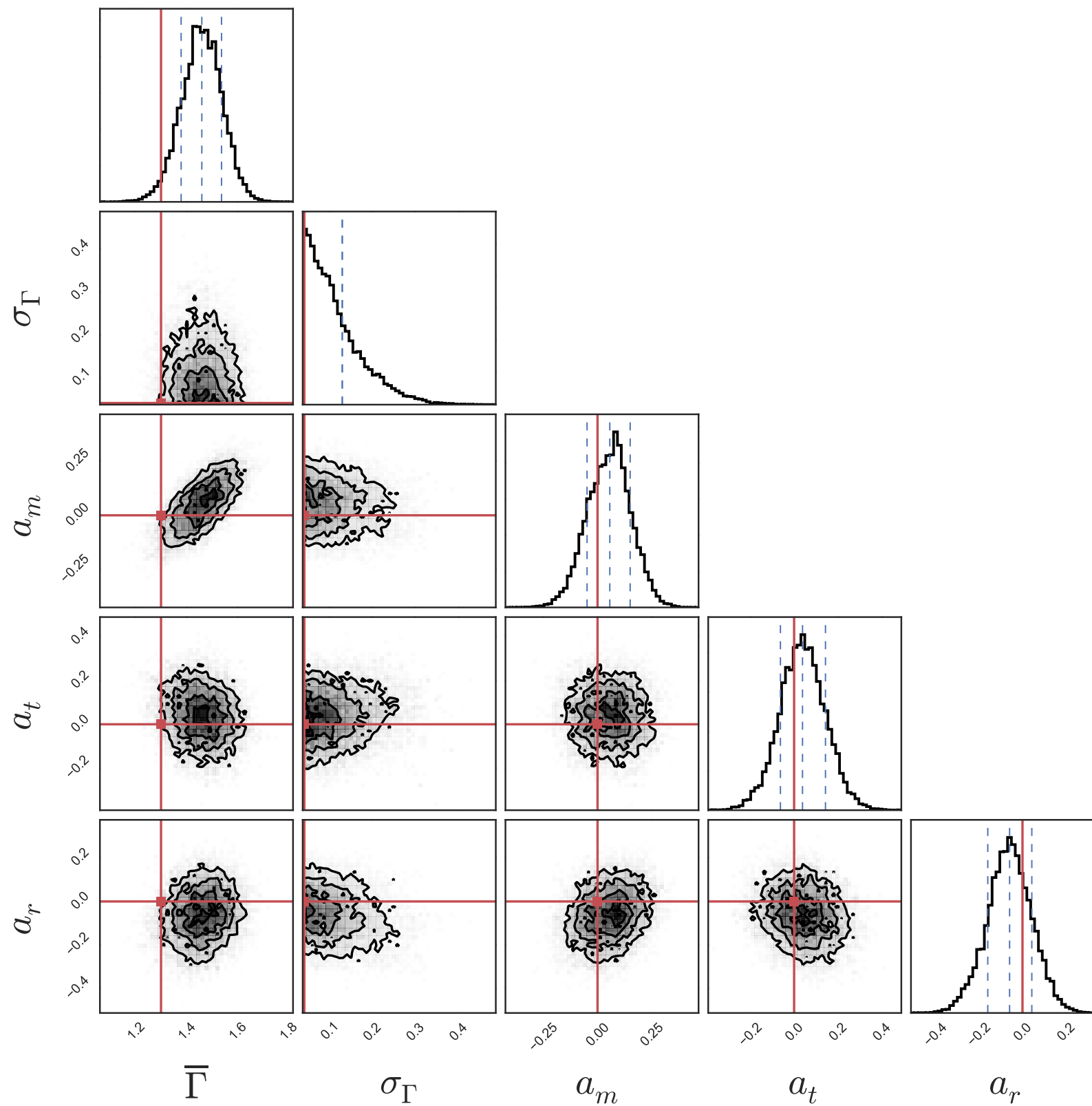
mean, median, mode,
percentiles,
HPD (highest probability density), ...

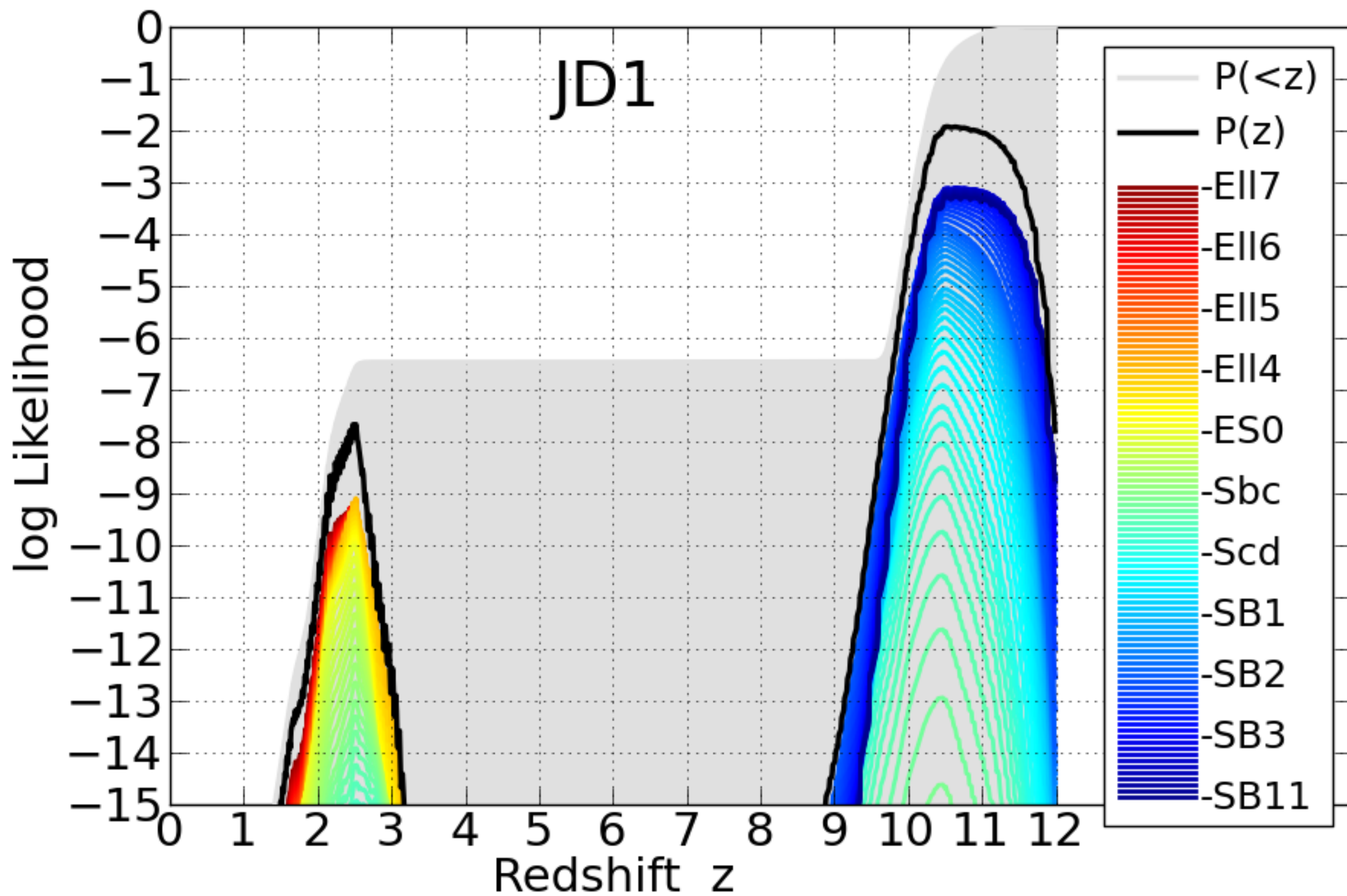
Summary Statistics

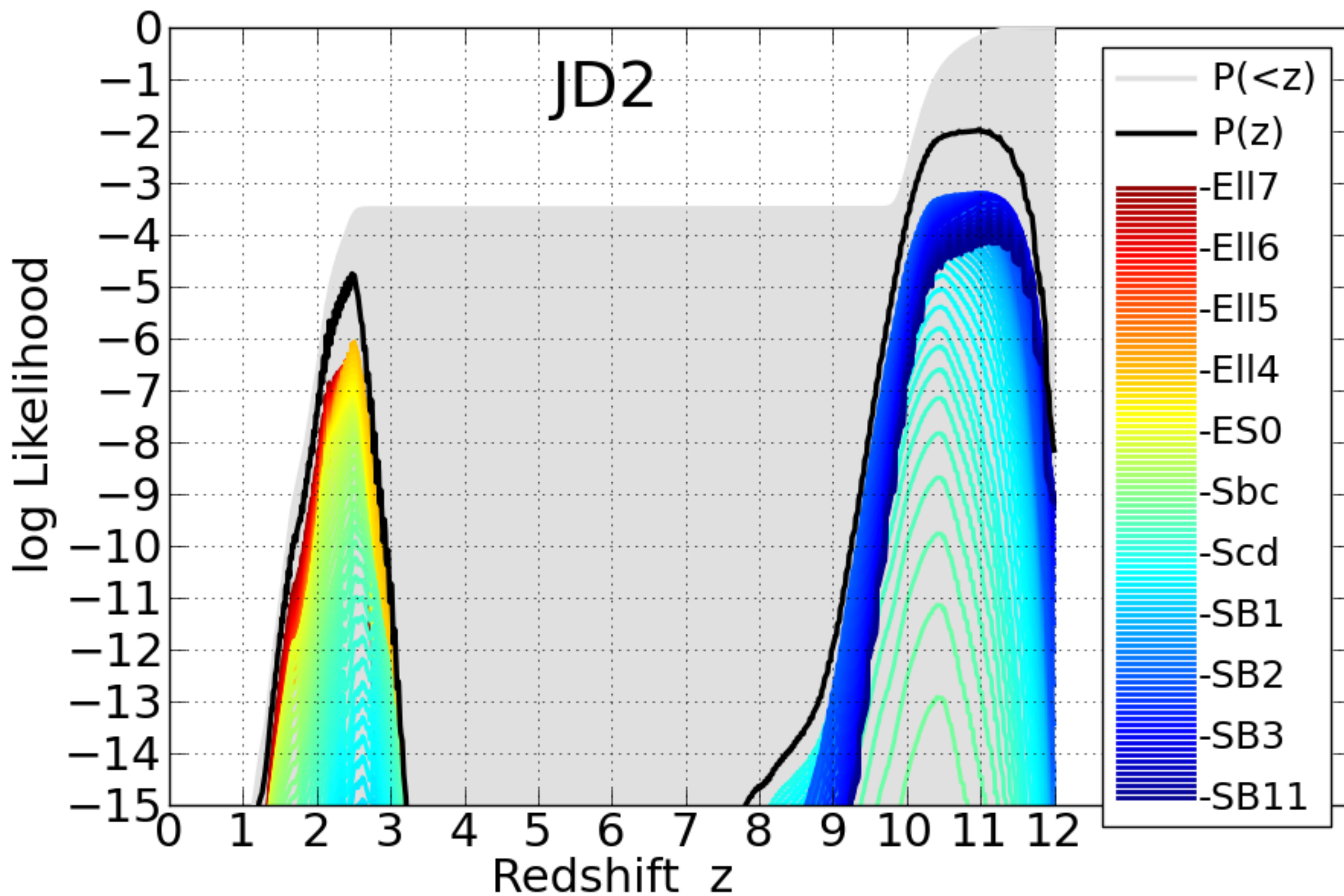


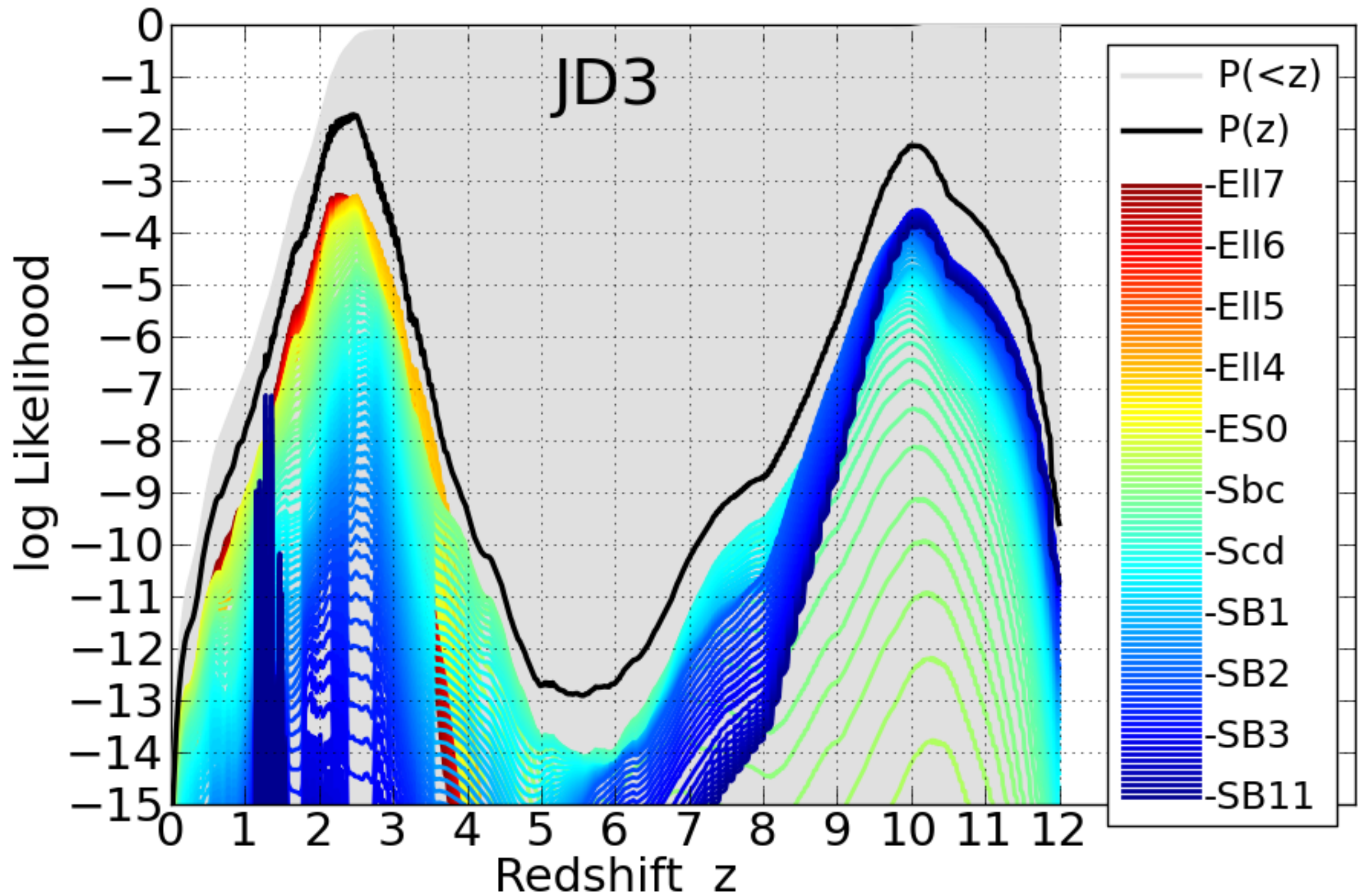
What do you report in the abstract?

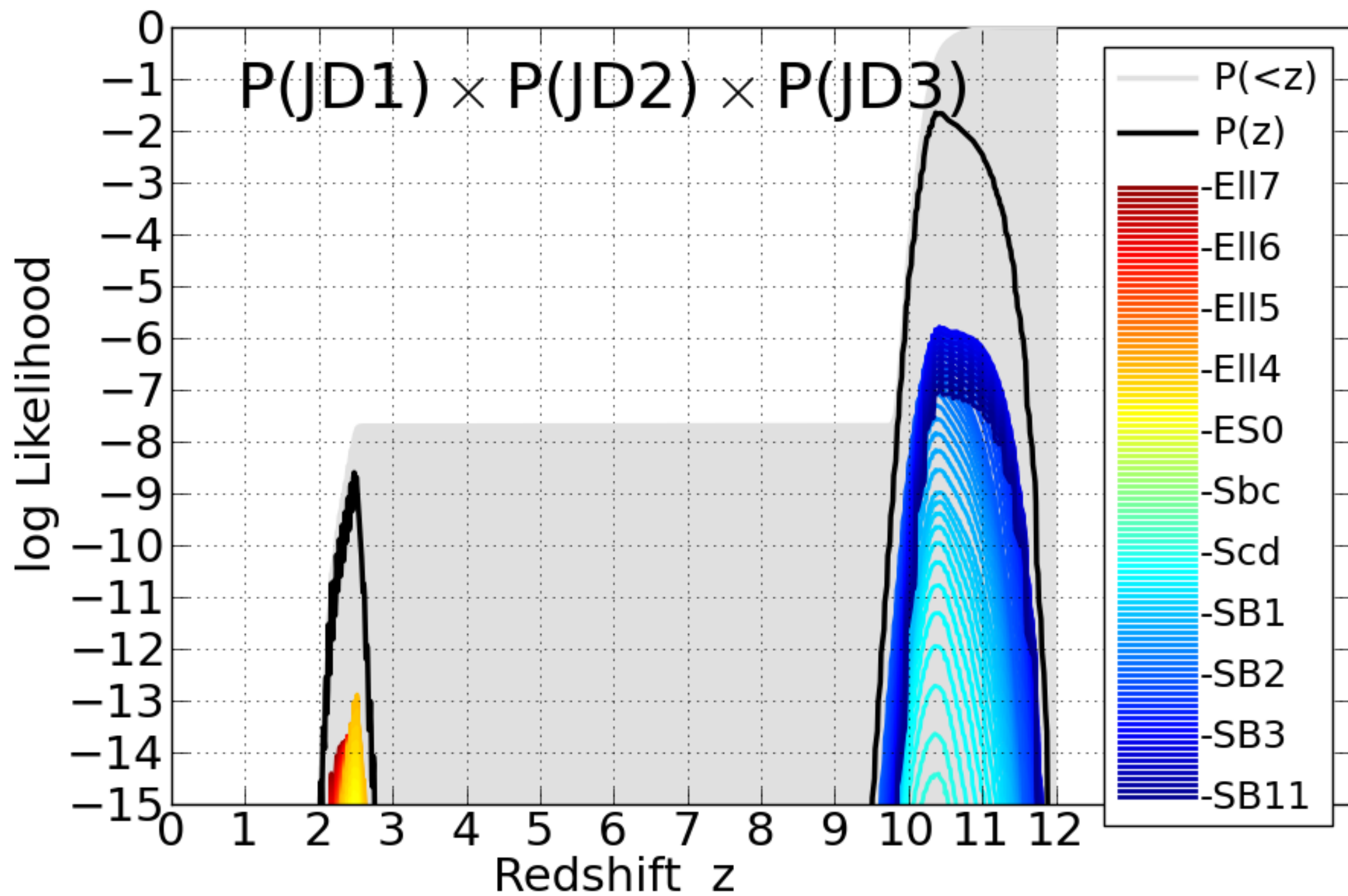
Summary Statistics











Hierarchical Modeling

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

Hierarchical Modeling

$$P(\theta) = \frac{P(\theta|\alpha)}{\int P(\theta|\alpha)d\theta} = P(\theta|\alpha)$$

Hierarchical Modeling

$$P(\theta|D) \propto P(D|\theta)P(\theta|\alpha)$$

Hierarchical Modeling

$$P(\alpha, \theta | D) \propto P(D | \theta) P(\theta | \alpha) P(\alpha)$$

Hierarchical Modeling

$$P(\alpha, \theta | D) \propto P(D | \theta) P(\theta | \alpha) P(\alpha)$$

D = set of fluxes for a star

Theta = Model for mass of star

alpha = Stellar IMF

Hierarchical Modeling

Let's say I don't care about the mass of the star(s),
but want to learn about the IMF

$$P(\alpha|D) \propto \left[\int P(D|\alpha, \theta) P(\theta|\alpha) d\theta \right] P(\alpha) = P(D|\alpha) P(\alpha)$$

The mass of the star is now a “nuisance parameter”.

Hierarchically estimate the IMF from SED of a star!