Notes for A. Pancoast et al. "GEOMETRIC AND DYNAMICAL MODELS OF REVERBERATION MAPPING DATA"

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1. Introduction

Reverberation mapping gives us a tool to learn about BH mass and BLR geometry/kinematics without having to spatially resolve the region. The method relies on the large time-variability of AGN luminosity, spanning timescales of days to years. The line emission strength is assumed to be proportional to the continuum emission strength, but with a time lag due to the light travel time from the central ionizing source to the BLR material. This lag time can be used to infer the BLR radius and the spectral line shape tells us about the velocity. A problem with the reverberation mapping method is that to get the BH mass we need the virial factor f which accounts for the BLR geometry/kinematics. This is usually found externally but we would rather want a direct model of BLR geometry/kinematics. The data required for reverberation mapping encode the geometry and kinematic information to some degree, depending upon the quality, in the form of the transfer function (or response function) that maps the continuum emission onto the line emission. The average lag used to estimate black hole mass is the first moment of the transfer function. Estimating the transfer function requires inverting a linear integral equation which can be done with regularized linear inversion, which allow for uncertainty estimation. Another method used in this paper is to compare reverberation mapping data directly with models of the broad line region, obtaining uncertainty estimates as well as allowing for model selection.

To be able to use this method there is a need to model the AGN continuum light curve. The continuum light curve seems to be described well by a DRW. It is possible to use Gaussian random processes to model the continuum light curve. In the case of this article an exponential covariance matrix.

2. Method

Bayesian inference is used to update the parameters and the likelihood function is given by a Gaussian, which is centered around the model predicted line flux timeseries

$$p(D|\theta) = \prod_{i=1}^{n} \frac{exp\left[-\frac{1}{2}\left(\frac{y_{i,line}-m_i(\theta)}{(\kappa\sigma_i)}\right)^2\right]}{(\kappa\sigma_i)\sqrt{2\pi}}$$

Where κ is a noise boost term to account for any uncertainty not in the errorbars like mean subtraction or flux calibration. MCMC MH and nested sampling is used to sample the posterior PDF for the model parameters.

mock flux lines are constructed to compare with the data through interpolation. To account for the uncertainty in interpolating between the data points the entire continuum function $f_c ont(t)$ is seen as an unknown parameter which should be inferred from the data. The prior distribution for this function is a Gaussian process, whose probability distribution is specified by a mean function $\mu(t)$ and covariance function (kernel) $C(t_1, t_2)$. The PDF for the function value will be a multivariate Gaussian for any set of finite times

$$p(\boldsymbol{f}|\mu, C) = \frac{1}{\sqrt{2\pi}^n det(\boldsymbol{C})} exp\left(-\frac{1}{2}(\boldsymbol{f}-\boldsymbol{\mu})^T \boldsymbol{C}^{-1}(\boldsymbol{f}-\boldsymbol{\mu})\right)$$

so μ is here the mean vector evaluated at the relevant time points and $\boldsymbol{C}$ is the covariance matrix evaluated at the relevant times. These two function are parameterized by the following hyperparameters: μ (the long-term mean), σ (the long-term standard deviation), τ (typical timescale of variations) and α (a smoothness parameter between 1 and 2), such that the mean function is a constant μ(t) = μ and the covariance function is

$$C(t_1, t_2) = \sigma^2 exp\left[-\left(\frac{|t_2 - t_1|}{\tau}\right)^{\alpha}\right]$$

f(t) is kept track of at 500 times reaching slightly out from both sides of the data range. The function f(t) can be parameterized by 500 variables with standard normal priors, which are converted to f(t) values by multiplication with the Cholesky decomposition of C. This gives the uncertainty while the interpolation between the 500 points is linear. values for the hyperparameters are from interpolation of the Lick AGN Monitoring Project continuum timeseries of Arp 151, one of the most variable AGN in the LAMP sample. The values used for the hyperparameters were μ = 75 (arbitrary units), σ = 30 (same units as μ), $\tau = 6 \times 106$ seconds and α = 1.5 (dimensionless).