Notes for Brandon C. Kelly et al. "ARE THE VARIATIONS IN QUASAR OPTICAL FLUX DRIVEN BY THERMAL FLUCTUATIONS?"

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1. Introduction

Many reasons for quasar variability were given but the RM showed changes in the emissions lines implying that the continuum variations are dominated by processes intrinsic to the accretion disk. If the optical/UV variations are intrinsic to the accretion disk, then thermal fluctuations appear to be a natural choice for driving the optical/UV variations, as the optical/UV emission is thought to be thermal emission from the accretion disk.

The idea is to model the optical light curve as a strocastic process (DRW) using three free parameters: a characteristic timescale, amplitude of short timescale variability, and the mean value of the light curve.

Due to the PSD slope of -2 a first order autoregressive function works to model the light curve because the slope together with the lack of any peaks in the power spectra, as well as the aperiodic and noisy appearance of quasar light curves, suggests that quasar light curves are stochastic or chaotic in nature. Since physical process in the accretion disk is continuous and because it allows for a way to handle irregular light curve sampling, The stochastic model is in continuous time so CAR(1). The relaxation time, τ, can be interpreted as the time required for the time series to become roughly uncorrelated, and σ can be interpreted as describing the variability of the time series on timescales short compared to τ. It is tempting to associate τ with a characteristic timescale, such as the time required for diffusion to smooth out local accretion rate perturbations, and σ to represent the variability resulting from local random deviations in the accretion disk structure, such as caused by turbulence and other random MHD effects. τ is on the order of the length of the light curve or longer.

The parameters for a CAR(1) process are commonly estimated by maximum likelihood directly from the observed time series. This is an advantage over nonparametric approaches, such as the discrete power spectrum or the structure function. The observed power spectrum and structure function can both suffer from windowing effects caused by the finite duration and sampling of the light curve, whereby power from high frequencies can leak to low frequencies (aliasing), and power at low frequencies can leak to high frequencies (e.g., red noise leak). MCMC is used to obtain the posterior probability distributions for the model parameters. It is shown how to calculate the likelihood for the model parameters and the priors on the parameters are uniform for b and σ. For τ it is noted that when data is regularily sampled the CAR(1) process becomes a AR(1) process with $\alpha_{AR} = e^{-\Delta t/\tau}$ Where Δt is the time sampling interval. This value gives the correlation between neighboring data points. Therefore, we consider it reasonable to assume that any value of α_{AR} is a priori likely, i.e., we do not assume anything a priori about the correlations between subsequent data points, and therefore we assume a uniform prior on α_{AR} from 0 to 1. This prior is noninformative in the sense that all of the information on α_{AR} comes from the data.

If the CAR(1) process provides a good model of the observed data, then the residuals should be uncorrelated and follow a normal distribution with mean 0 and variance 1. The goodness of fit can then be assessed by inspecting a plot of the residuals with time to ensure that they are uncorrelated, and by comparing a histogram of the residuals with the expected standard normal distribution.

Work with the log flux or apparent magnitude since the Gaussian white noise gives positive and negative values for the light curve while the flux is strictly positive. remember cosmological time dilation between rest and observed frame for the model parameters. assuming antisymmetric error does not help results.

The stochasticity of the solution underlies the fact that the physics are complex, not that the process is not deterministic.

The CAR(1) model is used because of its simplicity, and because it allows us to perform statistical inference without having our results biased by the irregular sampling, measurement errors, and finite span of the time series.The CAR(1) model is the simplest of stationary continuous autoregressive processes, and additional flexibility may be achieved through the addition of higher order derivatives.