The Bayesian Block Algorithm

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This presentation describes the Bayesian Block algorithm in the context of its application to analysis of time series data from the Fermi Gamma Ray Space Telescope. More generally this algorithm performs optimal segmentation analysis on sequential data in any mode, with arbitrary sampling and in the presence of gaps and exposure variations. A new procedure for correcting for backgrounds is also described.

I. INTRODUCTION

Much astrophysical information obtained the Fermi Gamma Ray Space Telescope arises from analysis of time series data. The Bayesian Blocks algorithm provides a useful time-domain tool with several areas of application in this regard:

Detection of transient events, such as Gamma Ray Bursts, and flares in active galactic nuclei and even the Crab Nebula. Characterization of these events by modeling the shape of the light curve. Yielding parameters from this characterization, such as rise and decay times, time scales of variability, and an index of variability. Identification of times over which the near constancy of the flux suggests good time intervals over which to carry out estimates of the energy spectrum.

All operations of Bayesian Blocks can be implemented with no limitation on sampling, time resolution or signal amplitude. Data gaps and variable exposure are easily accommodated. Other applications include data-adaptive histograms, multi-variate time series analysis and a novel approach to delay estimation in strong lensing events.

II. BACKGROUND CORRECTION

It is common to have two data streams from two regions of the sky and denoted (1) source + background and (2) background. The first includes the position of a known source, or that of a suspected possible new source. The second usually comprises a nearby region of the sky deemed to be relatively empty of sources. The goal is to effectively correct (1) for the presence of (2).

Effectively subtracting (2) from (1) is often attempted, but in many cases this cannot be done. The example considered here is the case of event data, that is both (1) and (2) consist of a sequence of time of detection of individual photons. A possible approach is to collect the events in a set of time bins common to both source and background, and then subtract the corresponding average rates. This operation degrades the time resolution and destroys information contained in the raw data.

The Bayesian Blocks algorithm for event data \cite{1} can be easily adapted to address this problem. The first step is to carry out a preliminary block analysis of the two data streams; call them $BB_{source+back}$ and $BB_{back}$. Then identify the pair of blocks (one from $BB_{source+back}$ and one from $BB_{back}$) within which each photon falls. Call the corresponding average block event rate $R_{source+back}$ and $R_{back}$. Then adjust the Voronoi-interval $\Delta t_j$ for photon $j$ from stream (1) according to

$$\Delta t_j \rightarrow \Delta t_j \frac{R_{source+back}}{R_{source+back} - R_{back}}$$

This has the effect of adjusting the local rate ascribed to each photon to what it would have been without the background (averaged according to this prescription).
III. THE PUBLISHED CODE

Details and principles are given in this reference [1]. This reference includes data files and code for implementing the Bayesian Blocks algorithm and reproducing the figures in the paper. Further updates or corrections to this material are developed they will be posted at [http://bayesianblocks.blogspot.com](http://bayesianblocks.blogspot.com).

In addition Jake Vanderplas’ related blog [3] nicely described the algorithmic approach of dynamic programming, with examples in the context of histograms. See also the posting at the Starship Asterisk discussion forum [2].

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