



Agís-González, B*1., Risaliti, G*2,8. & Miniutti, G*1.

tro de Astrobiología (CSIC/INTA); ESA P.O. Box: 78, E-28691, Villanueva de la Cañada, Madrid, Spain. "Harvard-Smithsonian Center for Astrophysics, 60 Garden St., Cambridge, MA 02138, USA.®INAF-Osservatorio Astrofisico di Arcetin Largo Enrico Fermi 5, I-50125 Frenze, Italy.

Introduction

The AGN spectra can be very complex, with multiple different models providing acceptable fits to the same data, meaning that spectral fitting alone cannot discern between alternative physical models. Principal component analysis (PCA) is a powerful tool for distinguishing different patterns of variability in AGN. It reduces the dimensionality of the data without loosing information and yields the directions that maximize the variance of the data. It works transforming a data as et where variables correlate among each other into a new coordinate system lies in the direction for which the distribution has the largest variance. This direction is known as the first principal component. The second principal component is orthogonal to the first one and is the axis along which the distribution has the next largest variance. The same is valid for a third component as on. In this way, the variability is summed up in as few principal components as possible. And these principal components can be linearly combined to reconstruct the initial data set.

Need for Simulations

Method

To carry out the PCA we must first divide the data or simulations into the

The advantage of this method is that it produces detailed spectra of each variable component in a model independent way. Calculating the RMS spectra can show the total variability as a function of energy, but cannot be used to determine how many variable components of the initial spectrum contribute to the variability.

But there is a s the interpretation of these variable components. As they need not to correspond to physical components, since there is no requirement for the true physical components to vary independently. Thus, a same principal component can be generated by more that one parameter or physical process varying. To solve this inconvenience and keep the independence from the models we turn to simulations. This technique was introduced by Koljonen et al. (2013) and it consists in creating simulated spectra based on physical models that are allowed to vary within given parameter ranges. Then, the PCA is applied to these spectra of models and produces the corresponding principal component. From these PCS, patterns from each spectral model can be detected. Then, they can be matched to the PCs found from the data for each source.

In energy. In order to maximize the spectral information we adapt the bin size so that the lower flux timesliced spectrum has at least 25 counts at high energies. The resulting components show the strength of the

Ine resulting components show the strength of the correlation between energy bins so a positive (or negative, the sign of the y axis is arbitrary) component shows that all bins vary equally, whereas a component that is positive at low energies and negative at high energies represents a pivoting effect.

servers on the resulting component spectra are obtained by a Monte-Carlo method, in which the observed photon counts binned in energy and time are perturbed by a random amount proporcional to a poisson photon noise following a normal distribution and the PCA redone on the perturbed data set. This process is repeated 50 times.



NGC 4051: Highest Flux Observation

relativistic reflection component found by P15

NGC 4051: Another Observation

We analyzed another observation of NGC 4051. As the results are equivalent to those found by P15, we decided to have a look to the 14 individual observations analysed by them.



NGC 4051: Lowest Flux Observation

These are the principal component from the greatest flux observation of NGC4051 analysed by P15. It is a observation around 40ks, so sliced in 4 small spectra. As it is a short time we only take into account the first PC as the second and the third one can be dominated by noise. The principal resultant components are again matched with the interpretation of a varying power law with a However, the lowest flux observation analysed by P15 shows another different first principal more the second matching of the suppressed at low energies and arises at high energies. These anges can be simulated from the greatest flux simulation simply dropping the flux of the fection component and adding a constant soft excess with a black body which suppresses, e variability at low energies. Besides, this constant soft excess is also suggested in the alysis carried out by Vaughan et al (2011).

