X-Ray Spectral Study of Supernova Remnants Using Unsupervised Deep Learning

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Abstract

Recent rapid development of deep learning algorithms, which can implicitly capture structures in high-dimensional data, opens a new chapter in astronomical data analysis. We report here a new implementation of deep learning techniques for X-ray analysis.

We apply variational autoencoder (VAE) using a deep neural network for spatio-spectral analysis of data obtained by *Chandra* X-ray Observatory from three type-Ia supernova remnants (SNRs); *Tycho*'s SNR, *Kepler*'s SNR, and SN 1006. VAE, which is one of the best-known generative models, is capable of extracting features from complex data. We established an unsupervised learning method combining VAE and Gaussian mixture model (GMM), where the dimensions of the observed spectral data are reduced by VAE, and clustering in the feature space is performed by GMM.

For X-ray data, Poisson statistics is appropriate because each bin in an X-ray spectrum represents a number of photons. As Ichinohe & Yamada (2019) shows for an ideal case, Poisson statistics is important for VAE training with such X-ray spectral dataset. We also newly implemented the data processes at the input and output of VAE in order to apply Poisson reconstruction loss for the training, and applied the model to observational X-ray spectral data of SNRs.

We found that some characteristic spatial structures can be automatically recognized by this method, which uses only spectral properties. As demonstrated with *Tycho*'s SNR in Chapter 5, the VAE extracts features using the relative intensities of lines as well as the properties of the continuum spectrum. We found that our method successfully reveals the characteristic spatial structures, e.g., the Fe knot in the south-east of the SNR, the layered structure in the north-western ejecta rim, and the synchrotron dominated filaments. Our unsupervised machine learning method automatically revealed spatial structures which have been discussed in the literature (see, e.g., Yamaguchi et al., 2017). This demonstration shows that our method is a powerful tool for data analysis that makes it possible to automatically exploit the rich information contained in data obtained by X-ray observations of SNRs. It may be possible to discover SNR physics (e.g., plasma evolution, interaction with ambient media, or cosmic-ray acceleration), and supernova explosion mechanism (e.g., nucleosynthesis, asymmetric explosion, or progenitor type), by post-training analysis using the results of machine learning.

In Chapter 6, the VAE extracts features using only spectral shape of *Kepler*'s SNR. We found that our method revealed the characteristic spatial structures, such as the synchrotron dominated forward shock, the layered structure in the northern rim, and the region interacting dense circumstellar medium (CSM). We also show the relation between the VAE latent space and the original data space, using the decoder to generate spectra from given latent parameters. For *Kepler*'s SNR, the VAE has extracted the latent axes corresponding to the relations of Fe and intermediate-mass element (IME) line blends, continuum emission, the N and O blends, and Fe L blend peak energy reflecting the electron temperature or plasma ionization state. VAE is capable of unveiling the meaning of the latent axes, and help us to understand the dimensionality reduction result.

We also applied our method to SN 1006 in Chapter 7. We found that the VAE have successfully captured some important physical features; the intensity and hardness of synchrotron emission, the line ratio of Si K α and S K α, and the emission lines of O, Ne, Mg. Furthermore, the 'dark belt', which is darker than the surrounding regions, was also represented in the latent variables using only spectral shape information. We also found that VAE has captured the feature of synchrotron emission and line emissions of O, Ne, Mg, and IMEs in the latent space.

For comparison, we also examined a method combining a manifold learning algorithm, t-SNE and a hierarchical clustering, where t-SNE embeds the observational dataset into two dimensional space, and hierarchical clustering is performed in the embedded space for the analysis of SN 1006. This method automatically found some spatial structures, such as synchrotron dominated forward shocks in the northeastern and southwestern of SN 1006. The t-SNE can be an alternative to VAE, if data dimension is not so large.

These results show that unsupervised machine learning can be useful for extracting characteristic spatial structures from spectral information in observational data (without detailed spectral analysis), which would reduce human-intensive preprocessing costs for understanding fine structures in diffuse astronomical objects, e.g., SNRs or galaxy clusters. Our method is also applicable to temporally variable data, i.e., light curves, because the training uses only spectral information. Furthermore, our method can also be applied to other energy bands. We conclude that our unsupervised method can be used to select regions to extract spectra for detailed analysis and help us make the best use of the large amount of spectral data currently available and arriving in the coming decades.