Detecting radio frequency interference in radio astronomy without seeing it

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1. Abstract

Radio Frequency Interference (RFI) is a growing concern for modern radio telescopes due to their increasing sensitivity and the proliferation of consumer electronics that depend on electromagnetic emissions. As a result, approaches for RFI detection and mitigation have become a necessity in modern radio observatories. Processing pipelines are employed in observatories that perform RFI detection and mitigation in a post correlation setting, using algorithms such as AO-Flagger [1] or more recently deep learning architectures such as UNET [2].

Currently, deep learning approaches to RFI detection have been based on supervised architectures [3], [4], [5], [6]. In this case, due to the unavailability of human-labelled datasets, supervised methods are trained and evaluated on simulated interference, or ground truth maps generated by heuristic methods such as the AO-Flagger. In effect, the generalisability of RFI detection algorithms is limited on out-of-distribution RFI samples that the algorithms have not yet been exposed to during training. In this work we propose a novel semi-supervised autoencoder-based detection approach to enforce generalisability of RFI detection by modelling time-frequency data that contains no interference.

Autoencoders (AE) can be used as RFI detectors when they learn to represent and reconstruct training samples without RFI. In this case, larger reconstruction errors should be expected on unseen samples that contain RFI than those which do not, thus enabling RFI detection. What is notable about this approach is that these models should learn the inverse of current supervised methods; i.e. the landscape of uncontaminated RF emissions, rather than being explicitly trained on interference alone. We further extend autoencoder-based RFI detection through the use of the NLN (Nearest Latent Neighbours) algorithm [7], which has been shown to yield performance increases in AEs in a novelty detection.

We evaluate our method on several standard classification-based metrics; the area under the receiving operator characteristics and precision recall curves as well as Jacquard index and F1-score. Furthermore, we use freely-available compressed LOFAR [8] data for the evaluation, using the AO-flagger based heuristic measure of ground-truth. Finally, we measure computation performance of our methods and compare the results of our work to the current state-of-the-art. Our preliminary results suggest that our autoencoder-based method requires significantly less data to achieve comparable performance to current state-of-the-art.

References

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