Dynamic Spectra Sequence Modelling with Transformers

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Introduction

- In the past, Breakthrough Listen has leveraged mostly Computer Vision-based techniques (e.g. Convolutional Autoencoders) to generate vector embeddings used to distinguish between some Radio Frequency Interference [1, 2]. However, most of these samples were still projected too closely in the embedding space to separate them from the main centroid [3].
- Motivated by the recent success of sequence models applied to SETI searches (e.g. [4]), along with the observation that dynamic spectra are inherently sequential, we find it valuable to apply sequence modelling techniques commonly used in the field of Natural Language Processing, such as the Transformer model [5].

Aims

- Due to its architecture, the Transformer has largely become the industry standard for dealing with sequence data, as they can capture positional and contextual relationships, and allow for parallel processing of data.
- The objective of this project is to train a Transformer using dynamic spectra, and compare its performance at downstream tasks to current models.

Data

- We've identified the Breakthrough Listen Kaggle dataset [6] as a suitable benchmark for our model's performance. These data are small regions of dynamic spectra, referred to as cadence snippets, generated using real observations from the Green Bank Telescope.
- Most of these snippets contain only Radio Frequency Interference, but certain snippets were injected with artificial signals using *setigen* [7] to emulate potential technosignature candidates.

Expected Outcomes

- While work is still ongoing, we expect to soon have a self-supervised model for converting dynamic spectra into vector embeddings, which we can then use to apply clustering and anomaly detection methods to help us search for and detect anomalous signals present in the data. We expect this model to outperform techniques that Breakthrough Listen currently uses, due to the reasons outlined above.

References

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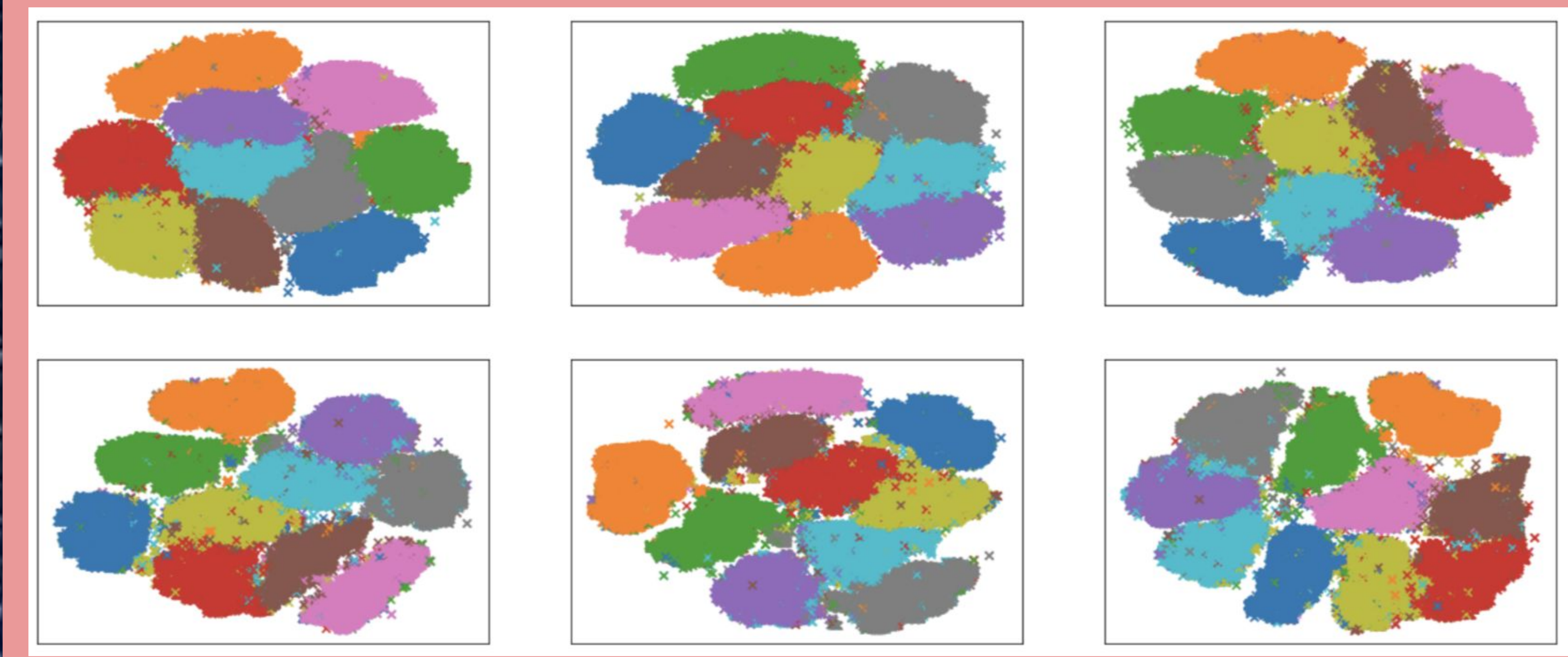

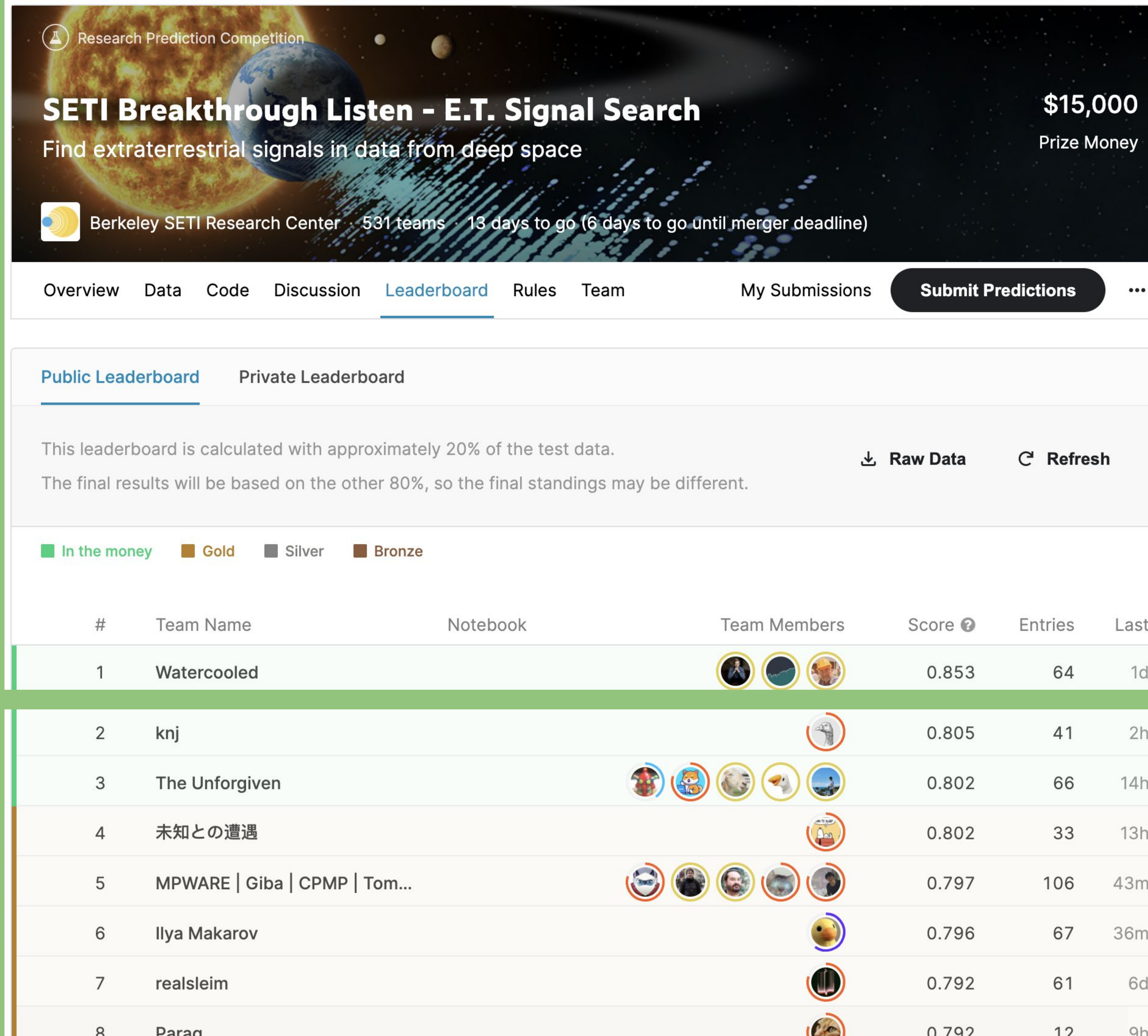

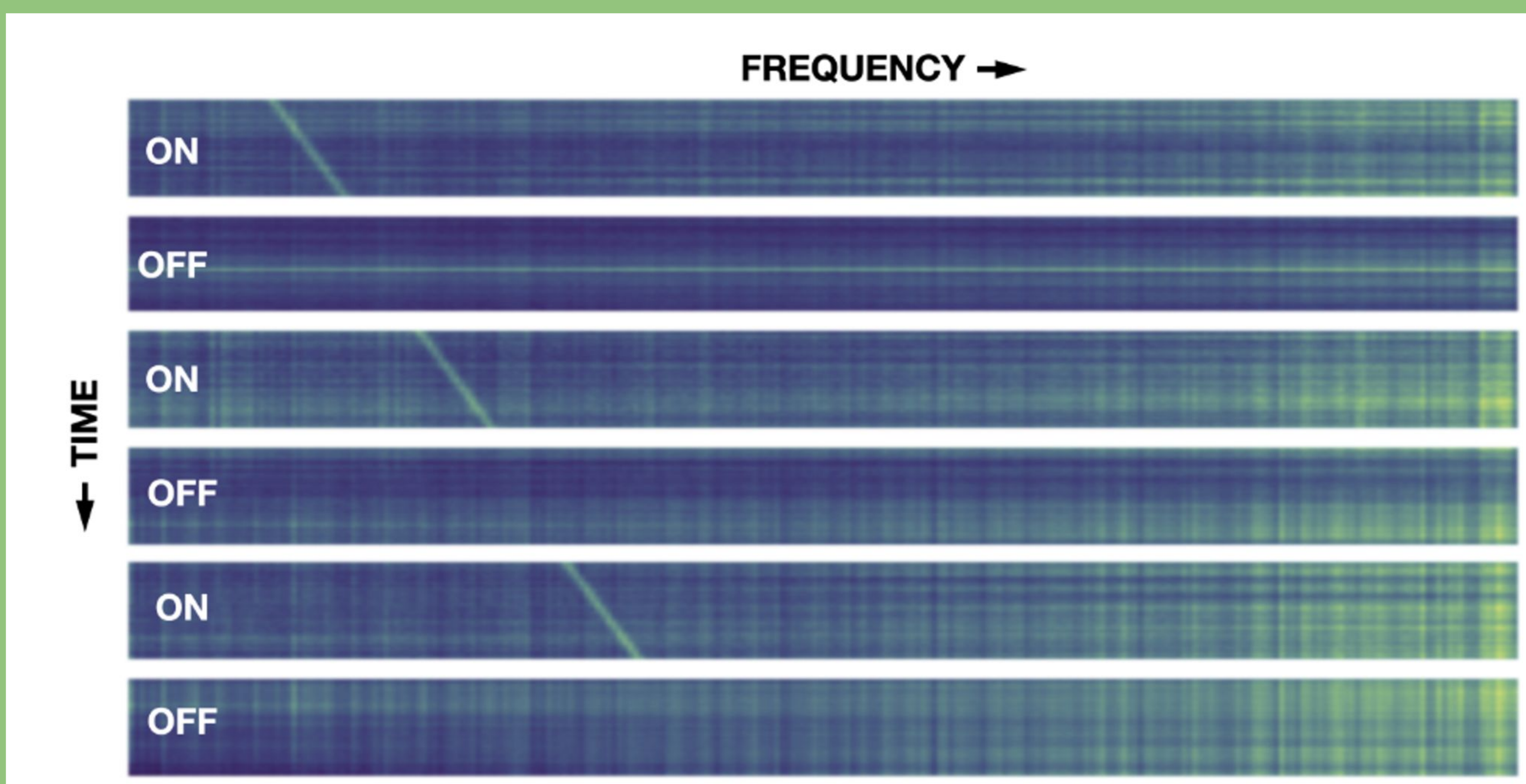

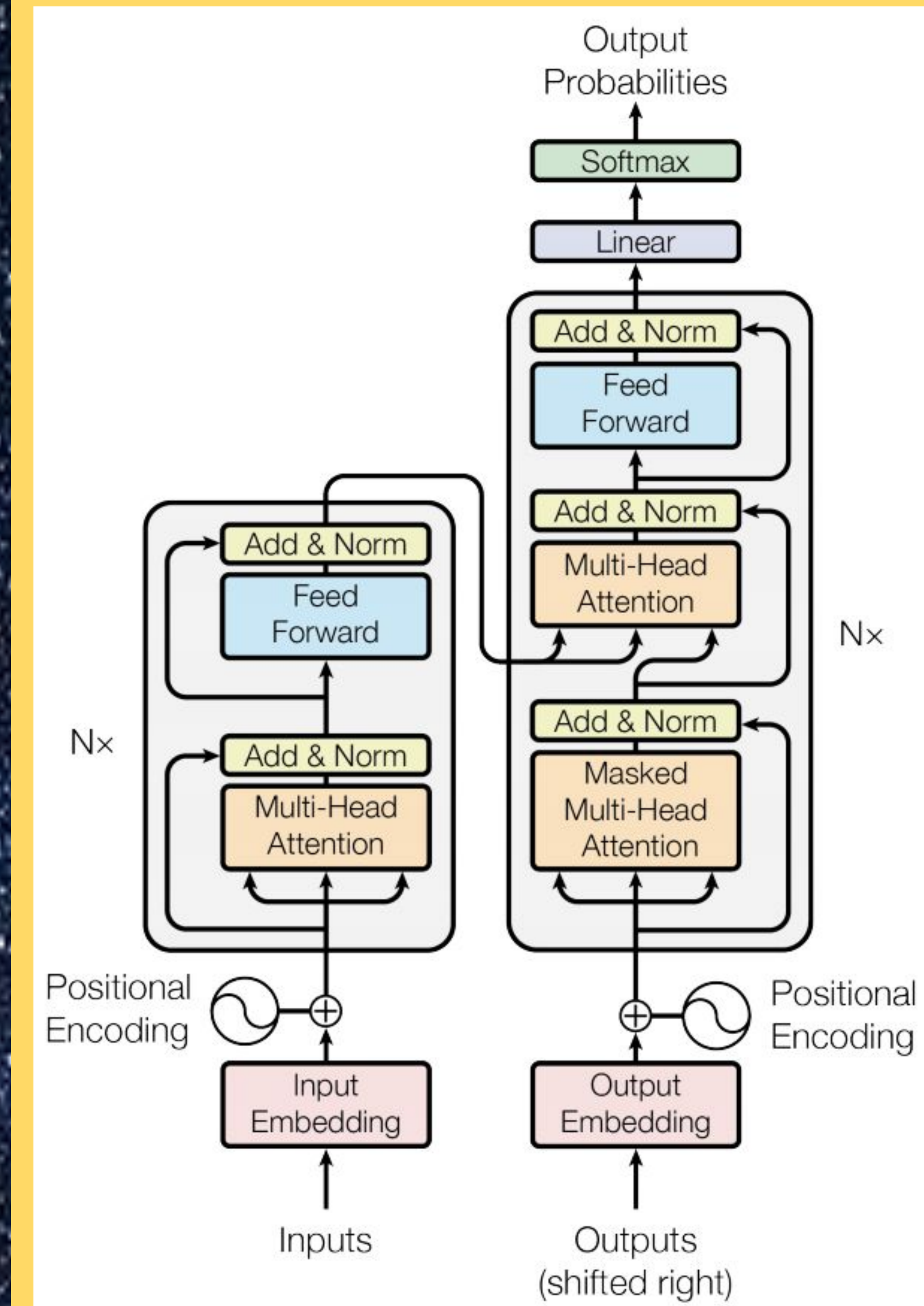

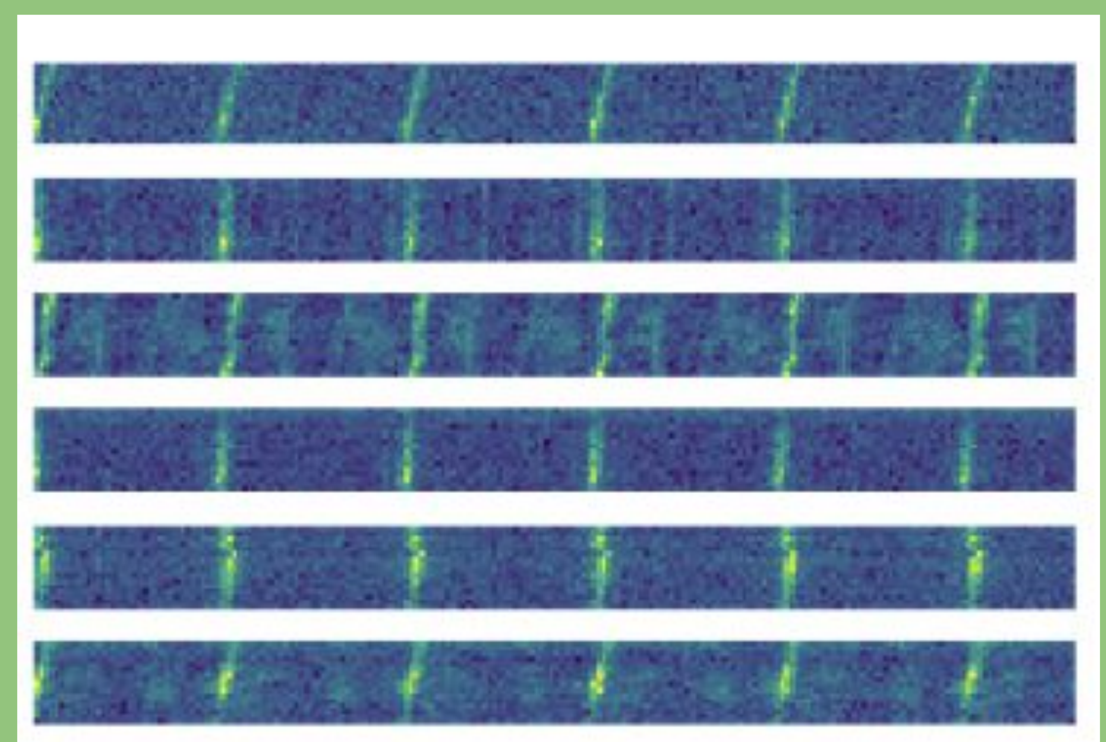

Acknowledgments

This work was made possible with financial support from the Breakthrough Prize Foundation, which funds the Breakthrough Initiatives, which manages Breakthrough Listen. We thank the Kaggle staff for their support with hosting the Breakthrough Listen Signal Search competition. The technical supervision provided by Steve Croft and Yuhong Chen was also greatly appreciated.