4^{th} *URSI AT-RASC, Gran Canaria, 19 – 24 May 2024*

Understanding Pathways for Collisionless Plasma Heating and Dissipation with Gaussian Process Regression

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1 Extended Abstract

Understanding collisionless heating and dissipation in plasma environments is a high priority goal relevant in heliophysics, geospace, astrophysics, and laboratory and fusion plasmas. Many theoretical tools to study plasmas are based on the idea of thermodynamic local-thermal-equilibrium, which inherently assumes the applicability of Maxwell-Boltzmann statistics in approximating the distribution of particle velocities in phase space.

The collisionless nature of many plasma environments enables the existence of non-Maxwellian distributions, which may be generated via nonthermal heating mechanisms: e.g. wave-particle interactions. Common non-Maxwellian features in distribution functions include secondary populations (beams) and suprathermals (halos and tails). The lack of collisions, and resulting non-Maxwellian features, inherently undermine the assumption of local-thermodynamic equilibrium.

A range of techniques are used to capture nonthermal features, e.g. beams and tails, in plasma distribution functions. However, the vast majority of these methods implement parametric models to effectively fit nonthermal features. We demonstrate that common parametric methods have difficulty capturing known sources of non-Maxwellianity that arise through wave-particle interactions. We argue that expanded use of machine learning interpolation and regression methods poses a novel opportunity to understand wave-particle driven interactions that result in heating and dissipation plasma systems outside of parametric estimations.

Here we outline the use of a non-parametric machine learning model, Gaussian process regression (GPR) in approximating phase space distribution functions from the Parker Solar Probe and Magnetospheric Multiscale (MMS) missions. GPR is a machine learning method used for functional interpolation. We demonstrate that GPR-modled VDFs perform significantly better in approximating observed VDFs over parametric fit functions. Furthermore, GPR provides distributions over multiple function values, enabling straightforawrd and intuitive error analysis.

Through application of GPR models to spacecraft distribution functions, we highlight advancements in understanding wave-particle interactions and their roles in plasma heating. The improved representation over parametric fitting allows for estimation of phase-space gradients of GPR-VDFs that can be implemented to understand wave-particle interactions within frameworks of quasilinear theory as well as plasma-dispersion solvers. These techniques allow for improved understanding of how wave-particle interactions act as pathways to turbulent dissipation. We discuss results from GPR-VDFs applied to PSP observations to understand the role of cylotron resonant interactions in coronal and solar heating. We furthermore apply these results to multipoint-measurements to highlight the use of GPR-VDFs in estimating empirical diffusion coefficients, enabling observation of turbulent plasma heating in the magnetosphere.