Application of Gaussian process regression techniques to experimental plasma profile fitting and model validation

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In order to move towards predictive plasma modelling, the models in question must undergo a process called *verification and validation* (V&V) to determine its range of applicability. However, with large complex non-linear systems such as a tokamak plasma device, the validation of any models representing such a system against experimental data becomes increasingly difficult [1] but no less important. *Gaussian process regression (GPR)* techniques combine linear regression with concepts from Bayesian inference to significantly reduce constraints associated with basis function selection. These properties make GPR well-suited for fitting experimentally measured tokamak plasma profiles [2], as it is not strictly limited by prescribed structure while retaining the profile smoothness and continuity required by most plasma models. An added advantage is that the GPR technique not only estimates the plasma profiles and its associated uncertainties, but can also estimate their derivatives and associated uncertainties with increased statistical rigour. This information can then be used to generate model inputs and facilitate sensitivity studies through the rigourous propagation of experimental errors [3]. Due to the generality of the algorithm, it also allows for large-scale data processing for validation of the neural network surrogate transport models [4] through fast integrated modelling frameworks [5].

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