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Connecting Physics Models and Diagnostic Data using Bayesian Graphical Models

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** See annex of F. Romanelli et al, "Overview of JET Results", (Proc. 22 nd IAEA Fusion Energy Conference, Geneva, Switzerland (2008)).*

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ABSTRACT.
With increasingly detailed physics questions to ask, and with more advanced diagnostics available, there is a strong case for trying to generalise the way analysis of diagnostic data, and connection to underlying physics models, is done in today's experiments. With current analysis chains, it is difficult, verging on impossible, to fully grasp the exact assumptions, hidden in different legacy codes, that goes into a full analysis of the main physics parameters in an experiment. We show that by using Bayesian probability theory as the underlying inference method, it is possible to generalise scientific analysis itself, and therefore build an effective and modular scientific inference software infrastructure. The Minerva framework [1,2] uses the concept of Bayesian graphical models [3] to model the full set of dependencies, functional and probabilistic, between physics assumptions and diagnostic raw data. Using a graph structure, large scale inference systems can be modularly built that optimally and automatically use data from multiple sensors. The framework, used at the JET, MAST, H1 and W7-X experiments, is exemplified by a number of JET applications, ranging from inference on the flux surface topology to profile inversions from multiple diagnostic systems.'

1. INTRODUCTION'

Probability theory in the Bayesian interpretation is often used as an alternative to standard least squares, or heuristic analysis methods to increase the understanding of how different types of uncertainties influence the inference of underlying physics parameters. What is not always emphasised, is the fully generic way in which this is actually done: a scientific inference problem, whether the width of a spectral line is measured, or a tomographic X-ray inversion is done, is always fully defined by the specification of two quantities: an assumption of the range and a priori likely values of the parameters of the model, and a probabilistic measure of the misfit between model and observations, which together form a joint probability distribution over observations and free parameters. This identity, through the joint probability distribution, of all types of inference problems, creates the possibility of a general data analysis software infrastructure. The Minerva framework [1,2], used for the analysis in this paper, is a generic scientific inference system where models are modularly built using Bayesian Graphical Models [3], through which complex networks of probabilistic dependencies can be handled effectively. Minerva allows the connection between physics models, parameterisations, nuisance parameters (such as calibration factors, instrument functions), experimental constraints (such as line of sight geometry), and observed raw data for different diagnostic systems to be fully specified in generic probabilistic graph structures. These can subsequently be analysed using standard inversion methods, such as linear and nonlinear optimizers, and different Markov Chain Monte Carlo (MCMC) samplers. Using graph models, the analysis of diagnostic data can be done with a high level of transparency and modularity, where physics models and diagnostics can be modularly replaced without changing legacy codes (fig.1). It also creates the possibility of optimal utilisation of data from multiple diagnostics, by combining different diagnostic observations for joint inference on common physics parameters, as done in [4-7]. parameters. Top figure shows the generative aspect of Minerva models; by sampling from an observation node, synthetic observations given the current state of the ancestors can be done, which can be used for experimental design etc. Bottom figure: the same model can be used for different types of inference on the free parameters, by storing actual observations at the observation nodes and dropping the graph in one of a number of generic inversion methods. Currently a range of nonlinear optimizers for finding Maximum Posterior (MAP) points, Markov Chain Monte Carlo (MCMC) samplers, and automatic graph linearisation can be applied.

APPLICATIONS

By developing stand-alone Minerva graph models for individual diagnostic systems, it is possible to do analysis with different combinations of those diagnostics under changing model assumptions. Figure 2a shows a direct inference, in this case without an imposed force balance assumption, on the JET flux surface topology using a Minerva graph that includes increasingly more diagnostic systems. The system also delivers the uncertainties of the inferred positions of flux surfaces for the different cases, using up to six diagnostic systems [6]. A force balance assumption can be built into the graph structure by adding nodes that implements a Grad-Shafranov force balance constraint [8]. For the latter case, it has been shown that small scale features can be resolved from the magnetic sensors alone (figure 2b), although the precise uncertainties are still under investigation. Figure 3 shows the results of ne and Te profile inversion using the JET core and edge LIDAR diagnostics, and an 8-channel interferometry system jointly, which have been fully remodelled and installed as Minerva graphs. The latter system delivers substantially higher resolution, also for the pedestal region, than any of the diagnostic systems used individually [7]. The generic architecture of Minerva allows graphs and models to be transferred between laboratories, and is also being applied at the MAST, H1 and W7-X experiments [9-10]. The successes so far of this approach seems to indicate that it could scale to include all main diagnostics of an experiment, which would then lead to a highly transparent and modular, centralised analysis system that would also deliver substantial improvements in accuracy and internal consistency of inferred physics parameters.

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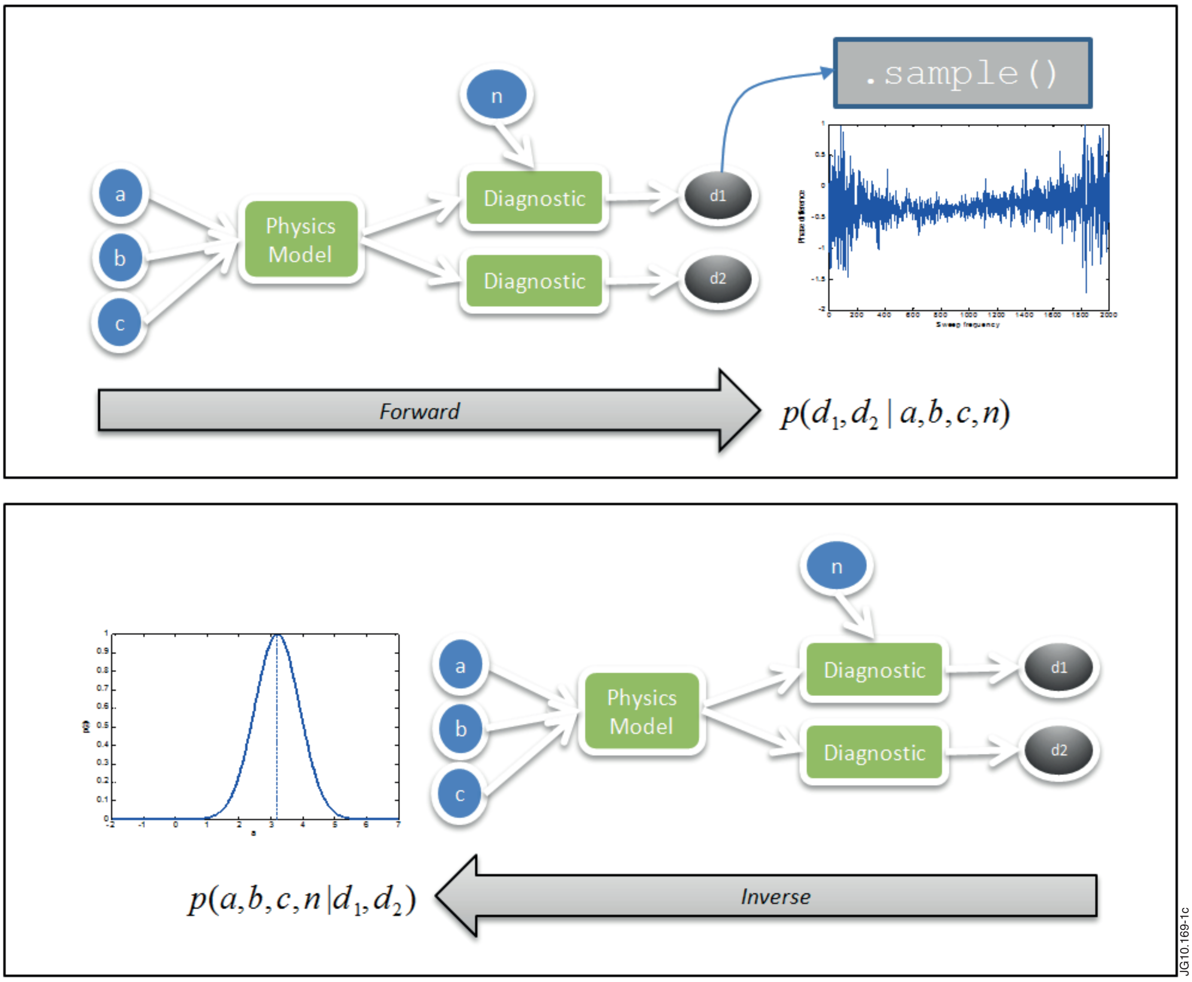

*Figure 1. Minerva Bayesian graph model for joint inference on a common physics model from data from two diagnostics. Blue ovals are free parameters (*n *is a diagnostic nuisance parameter), gray ovals observations. The graph defines the joint distribution* p(a,b,c,n,d1,d2) *which is proportional to the posterior distribution of the free parameters. Top figure shows the generative aspect of Minerva models; by sampling from an observation node, synthetic observations given the current state of the ancestors can be done, which can be used for experimental design etc. Bottom figure: the same model can be used for different types of inference on the free parameters, by storing actual observations at the observation nodes and dropping the graph in one of a number of generic inversion methods. Currently a range of nonlinear optimizers for finding Maximum Posterior (MAP) points, Markov Chain Monte Carlo (MCMC) samplers, and automatic graph linearisation can be applied.*

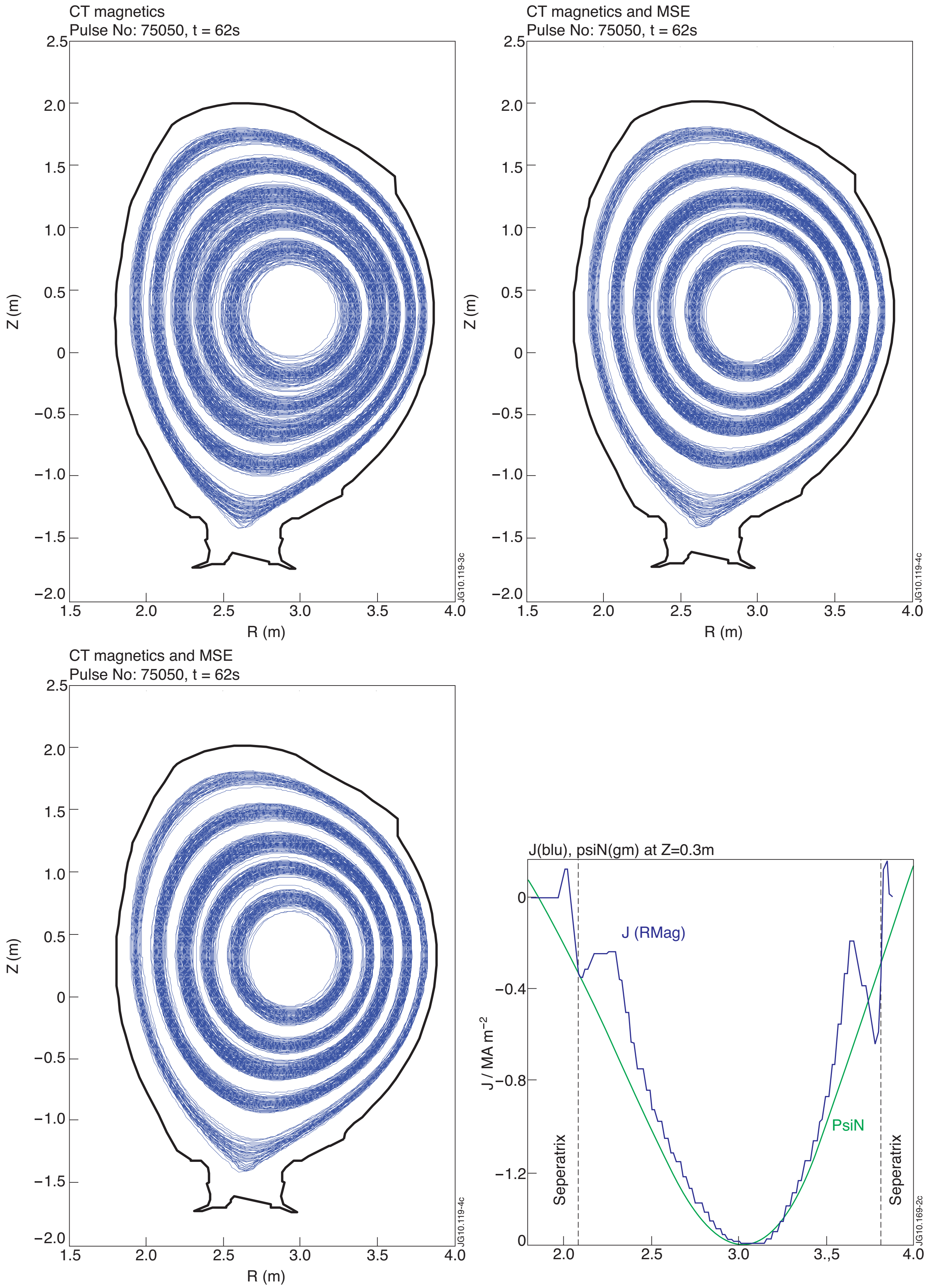

Figure 2: (a) Samples from posterior current distribution including progressively more diagnostics: (pickup coils, saddle coils and flux loops), (added MSE), (added interferometry and polarimetry), (b) toroidal current distribution using magnetics and an imposed force balance assumption.

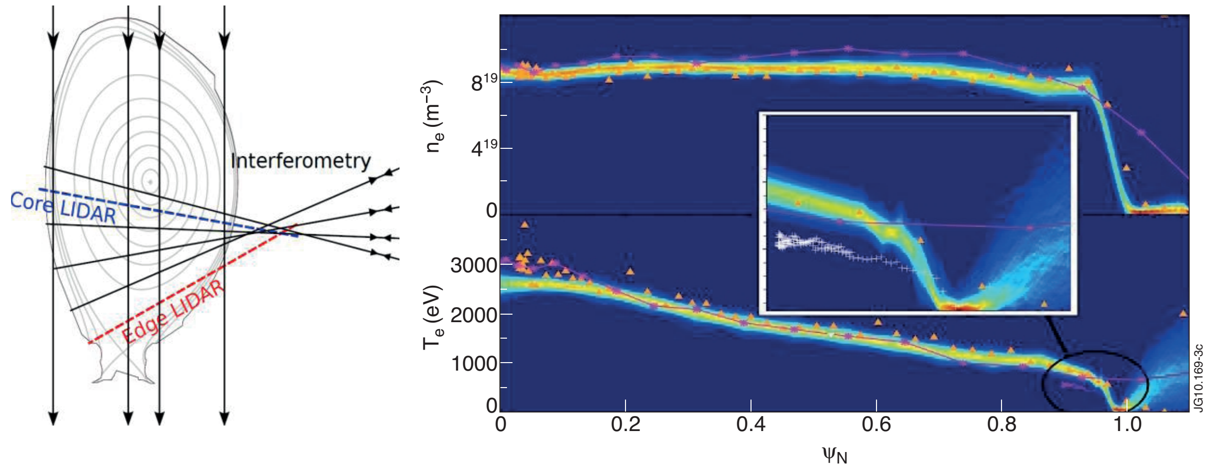

Figure 3: (a) Beam paths for the JET core and edge LIDAR systems. b) ne and Te profiles as a function of normalised poloidal flux comparing the joint inversion of the JET core LIDAR, edge LIDAR, and interferometry diagnostics (colored thick lines – red color is high posterior probability, blue low), edge LIDAR analysed on its own (violet), core LIDAR analysed on its own (white), and the independent high resolution Thomson scattering measurements (orange). [7]. JET Pulse No: 75656, t=19.13s