Fully Bayesian Forecasts with Neural Bayes Ratio Estimation (Poster #9, arXiv:2309.06942)

Thomas Gessey-Jones (tg400@cam.ac.uk) and Will Handley (wh260@cam.ac.uk)

Problem - Data Marginalized Forecasts for Bayesian Model Comparison are Typically Infeasible

Nested Sampling: Generally applicable but too slow to explore data space
Savage–Dickey forecasts: Restrictive assumptions and require nested models
Both require explicit likelihoods.

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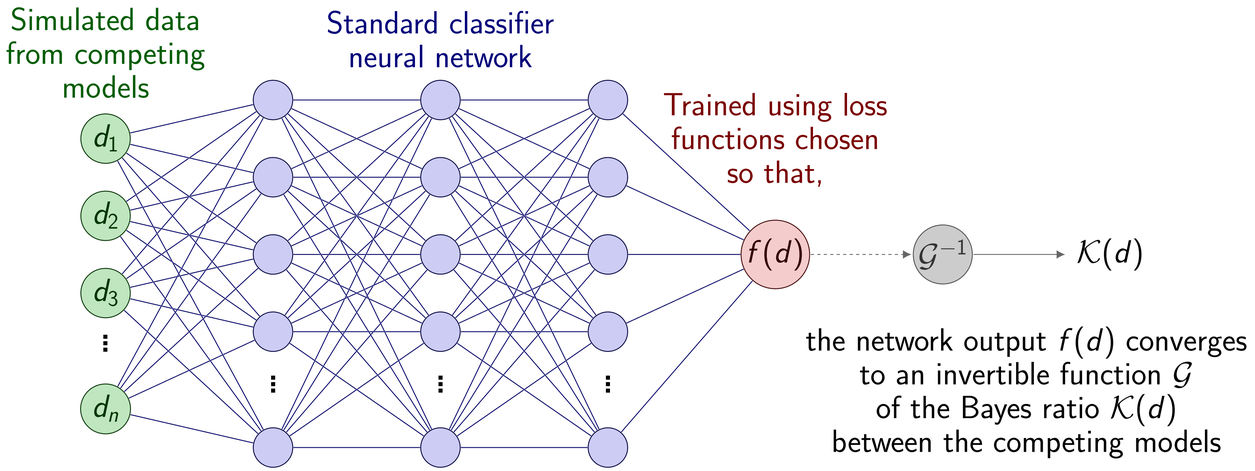
Solution - Neural Bayes Ratio Estimation (Evidence Network)



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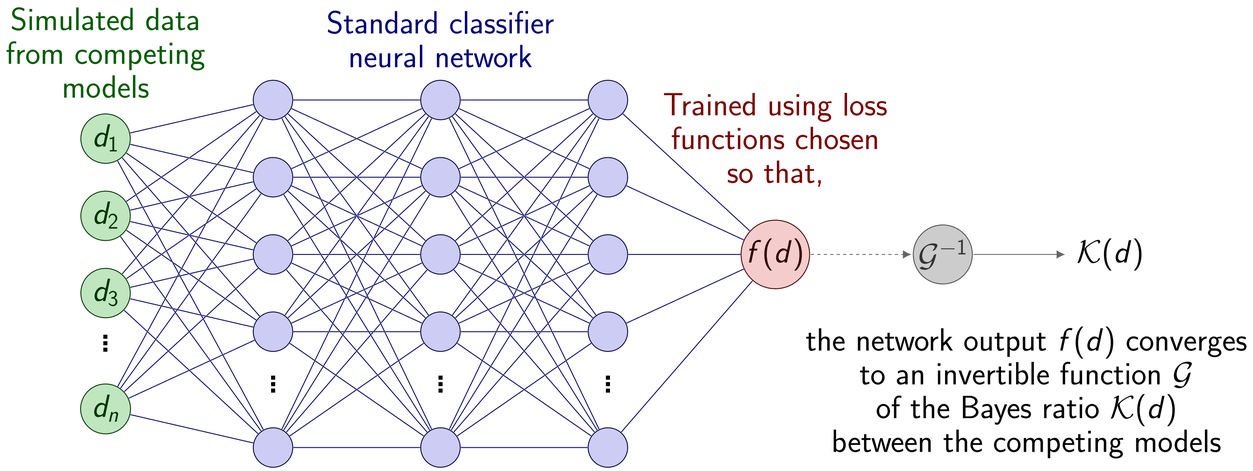
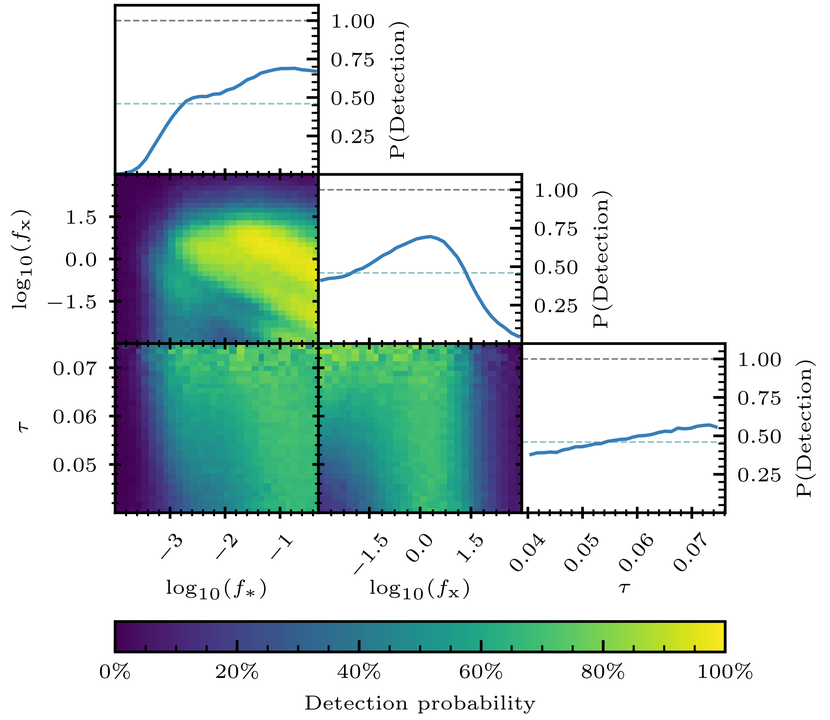


the network output $f(d)$ converges to an invertible function $\mathcal{G}$ of the Bayes ratio $\mathcal{K}(d)$ between the competing models

Example - Detecting the Global 21-cm Signal



Just 5.54 GPU hours to perform instead of the 45,000,000 CPU hours nested-sampling would have taken.