

# Bayesian Calibration of Computer Models with Modern Gaussian Process Emulators

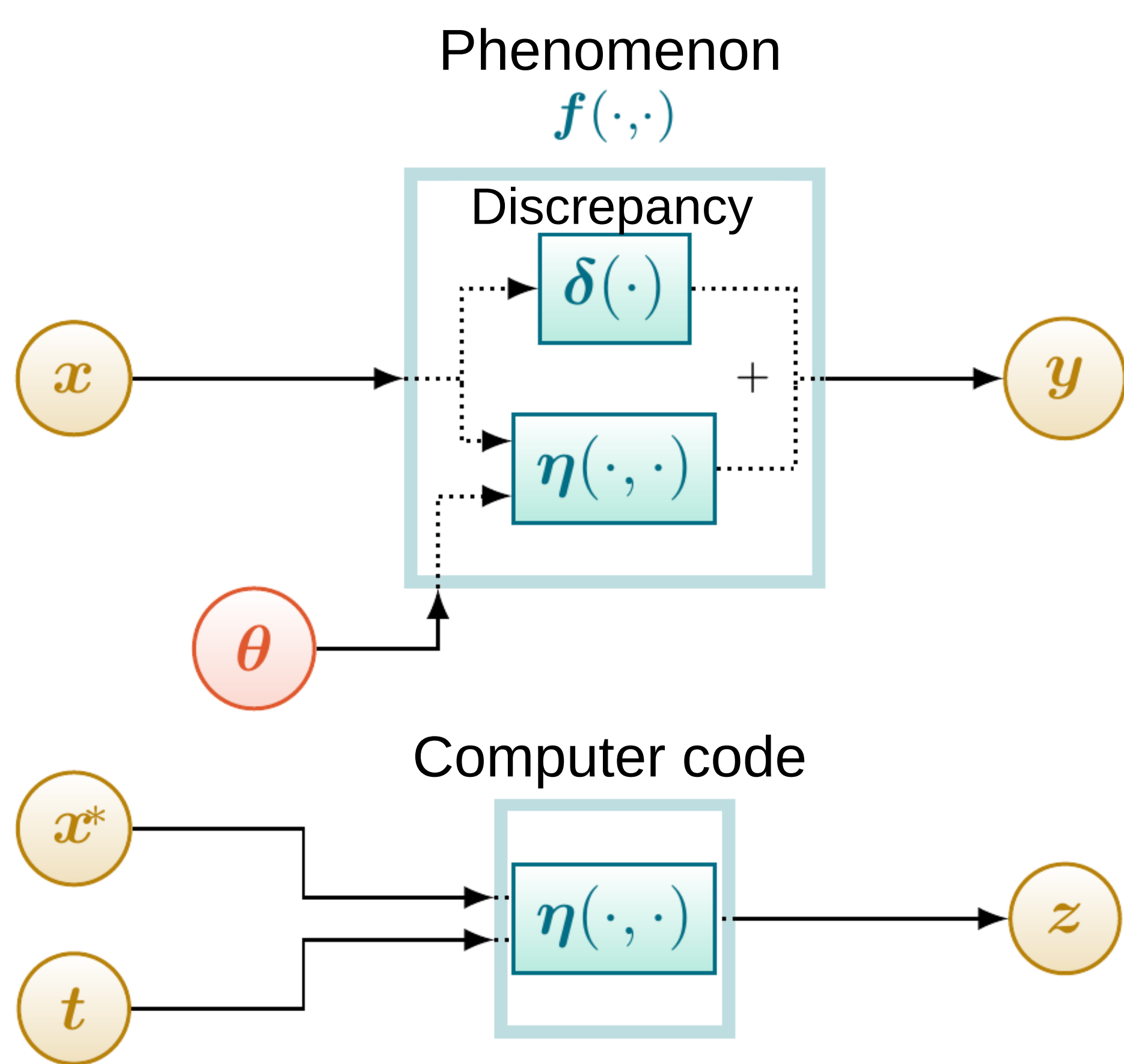
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## 1. Context

- Uncertainty analysis of a phenomenon  $f$
- Approximation by an expensive code  $\eta$
- Infer non-observable parameters  $\theta$
- Data: - real observations  $Y : p(\mathbf{y}_i | f(\mathbf{x}_i))$   
- computer runs  $Z : p(\mathbf{z}_j | \eta(\mathbf{x}_j, \mathbf{t}_j))$

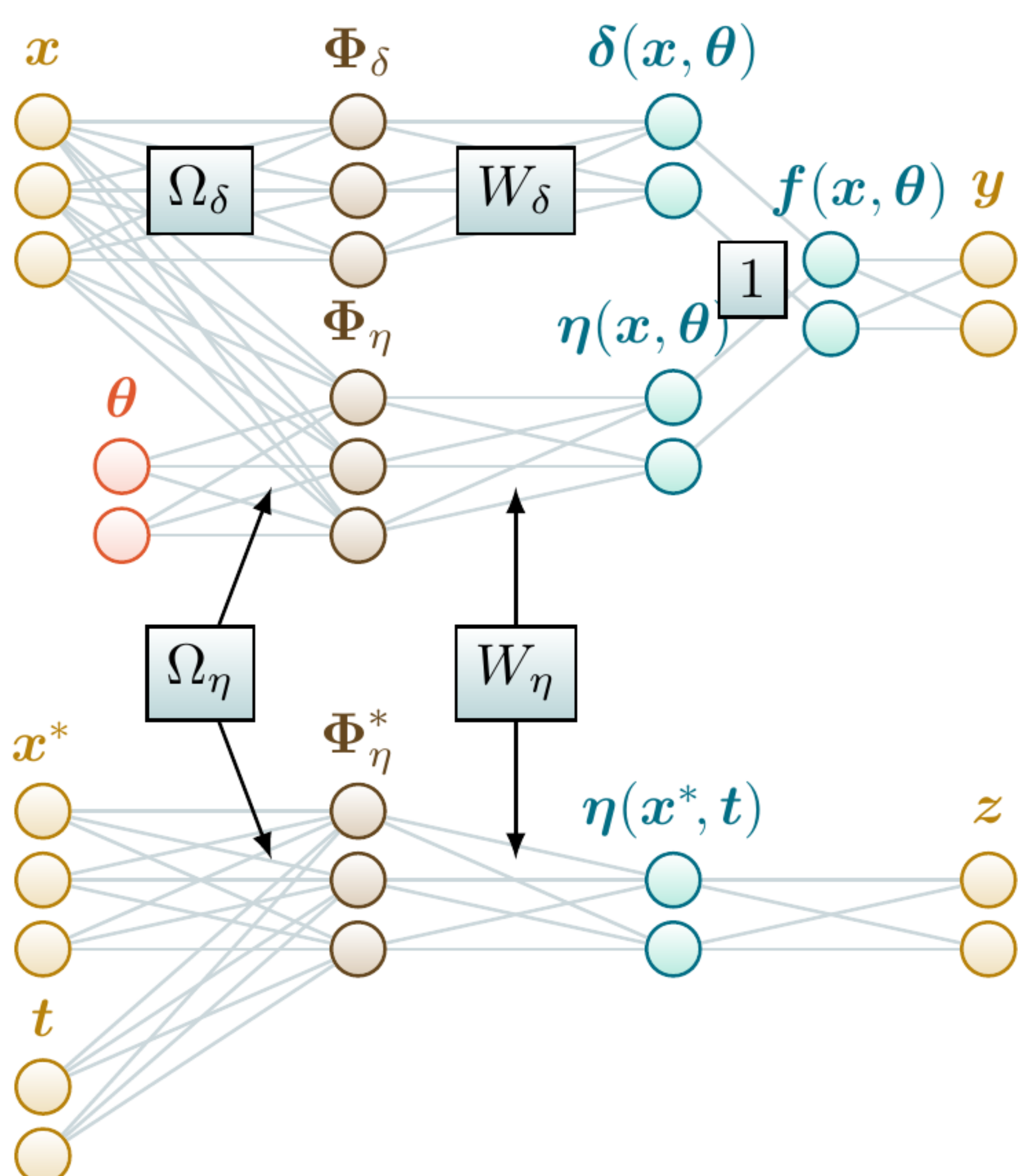
## 2. Framework



## 3. Random features approximation

$$\eta(\mathbf{x}, \theta) = \Phi_\eta(\Omega_\eta^{(1)}\mathbf{x} + \Omega_\eta^{(2)}\theta)^\top W_\eta$$

where  $\Phi_\eta$  is an element-wise activation function and  $W$  and  $\Omega$ 's are random matrices.



## 4. Variational inference

A tractable lower bound of the log-likelihood can be derived:

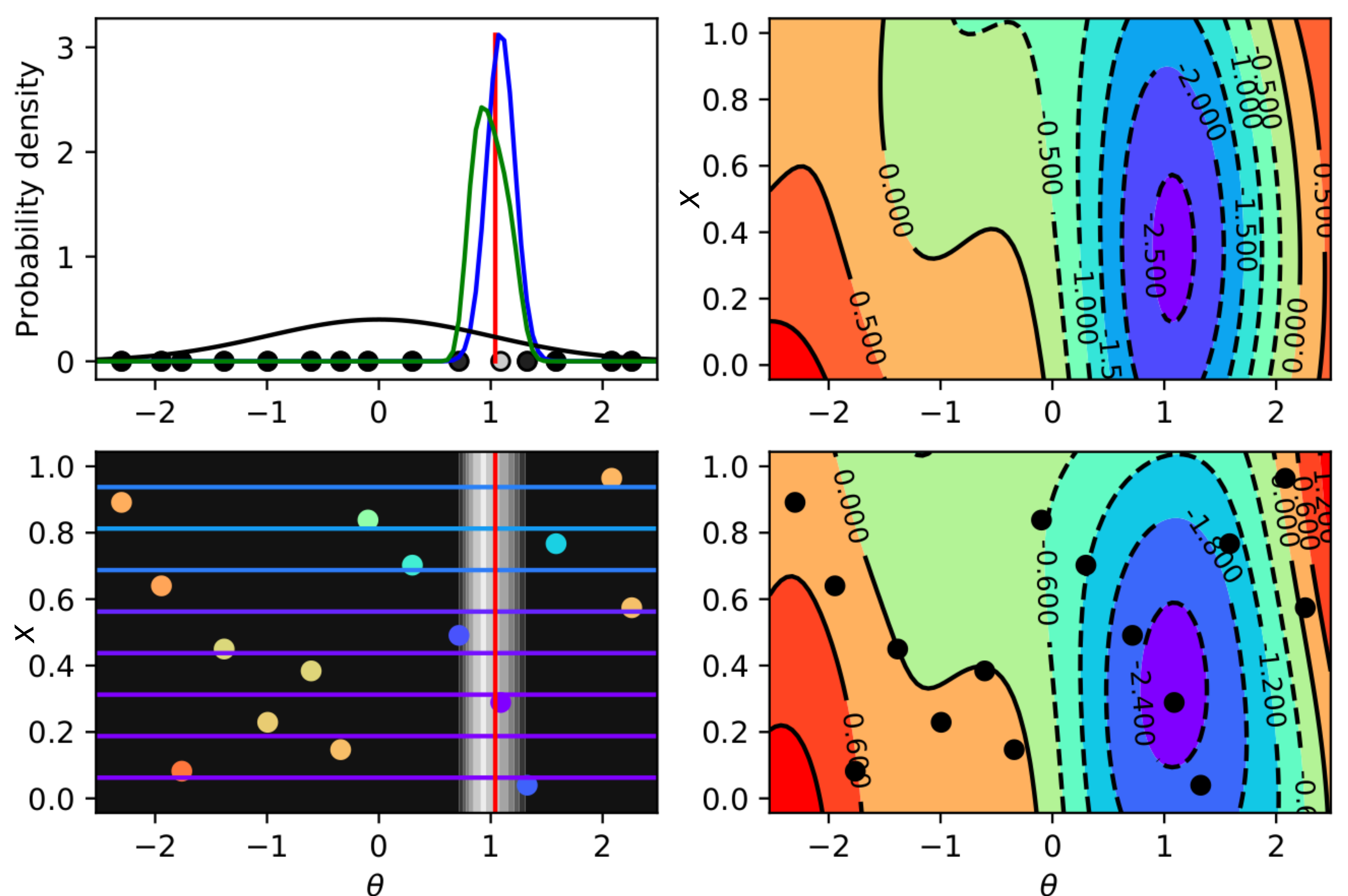
$$\mathcal{L} \geq \mathcal{E} - \text{KL},$$

- $\mathcal{E} = \mathbb{E}_{q(W, \theta)}(\ln(p(Y, Z | X, X^*, T, \psi, \Omega, W_\eta, W_\delta, \theta)))$
- $\text{KL} = D_{\text{KL}}(q(W_\eta, W_\delta, \theta) || p(W_\eta)p(W_\delta)p(\theta))$
- $q(W, \theta)$  approximate the posterior  $p(W_\eta, W_\delta, \theta | Y, Z, X, X^*, T, \Omega, \psi)$
- $\psi$  GP hyperparameters of  $\eta$  and  $\delta$

## 5. Numerical experiments

### 1. Simulated test case

- One variable inputs
- One calibration input
- 15 computer runs
- 8 observations
- Data is sampled from the prior distribution



### 2. Test case in life science

- One variable inputs
- 3 calibration input
- 200 computer runs
- 19 observations
- Data from measures of current through ion channels of cells

	$\times 10^3$	$L^2$	Projected	Variational	KOH	Robust
CPU time, s	0.02	3.79	0.32	3.25	0.36	
$L^2$ residuals	1.31	-	-	-	-	
MSE	-	3.19	2.05	5.21	2.06	

## 6. Conclusion

- Low-rank GP approximation
- Stochastic variational inference

Infer GPs and calibration input with sound quantification of uncertainty

→ Experiment shows a flexible framework for calibration.