

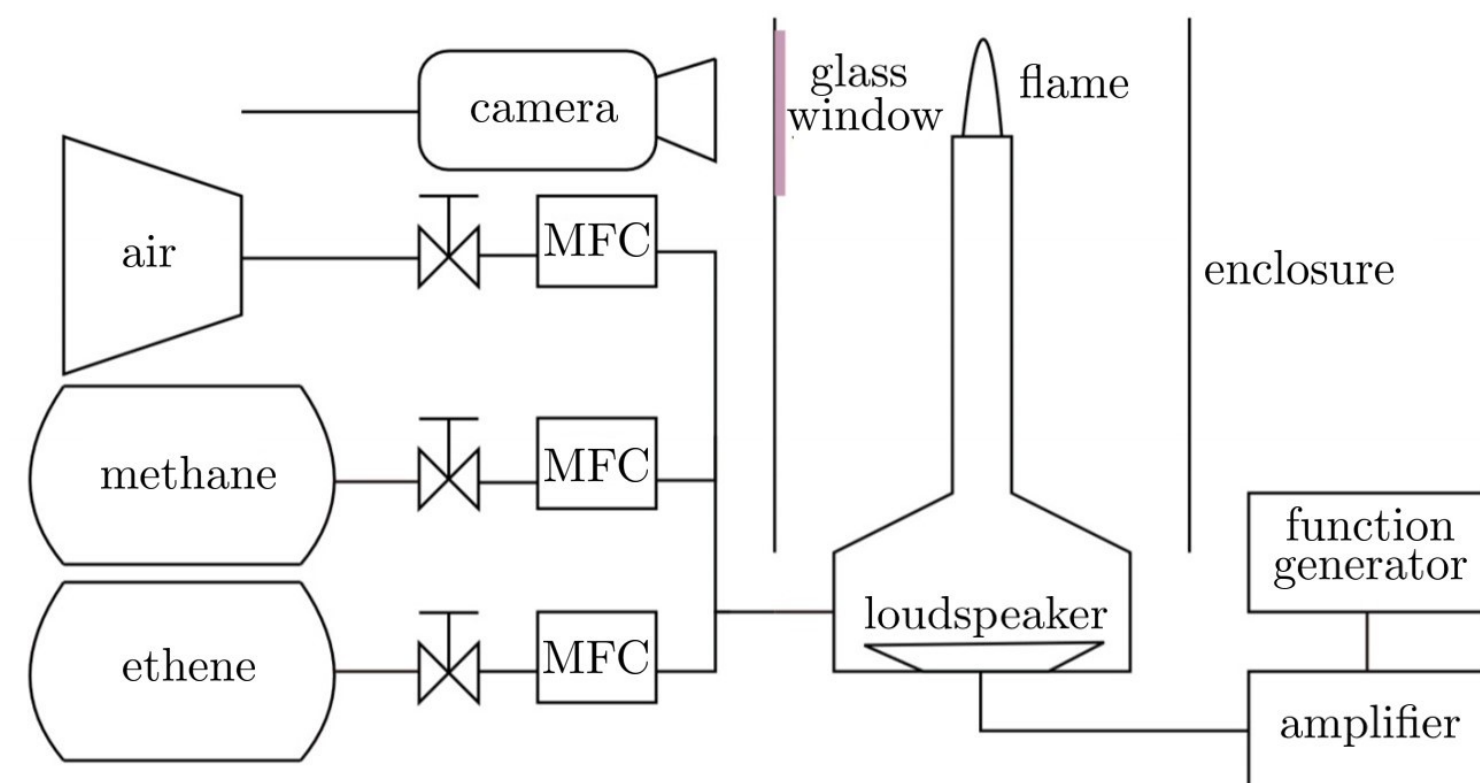


Online parameter inference for the simulation of a Bunsen flame using heteroscedastic Bayesian neural network ensembles

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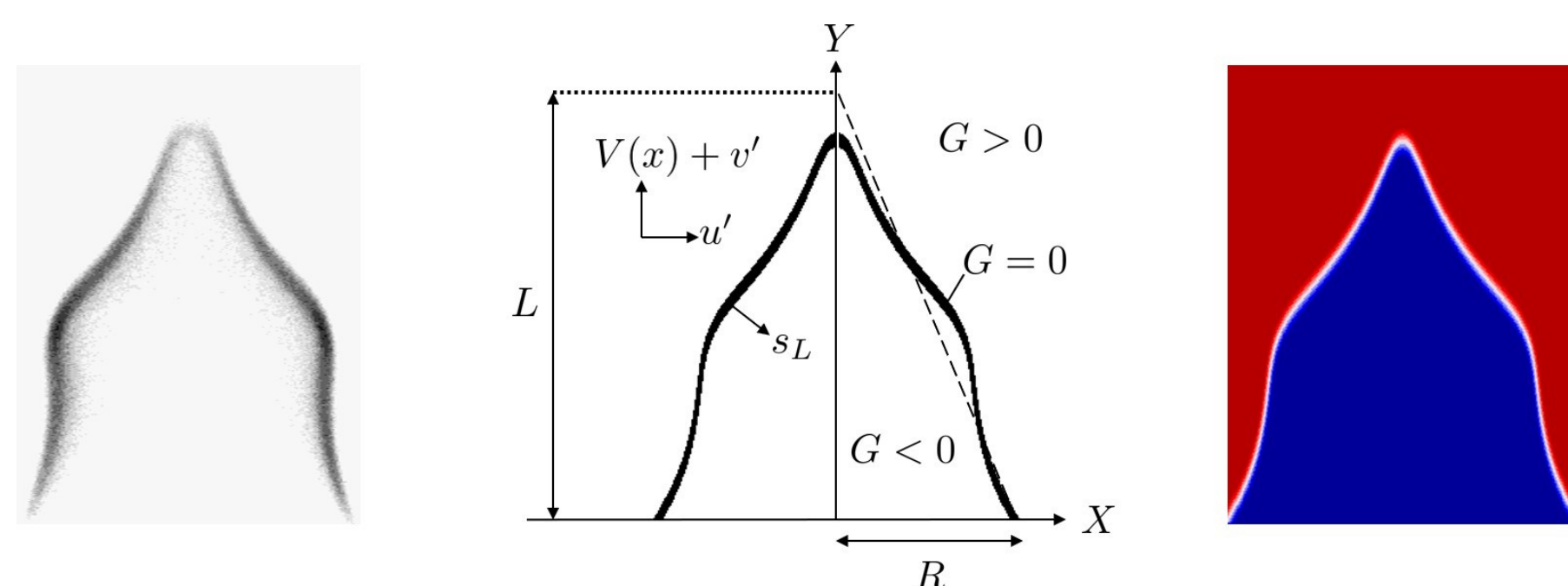
1. Introduction

- Task:
“Can we infer the parameters of the model from images of the flame?”
- This would allow us to **predict future behaviour** and calculate key quantities like the **heat release rate**



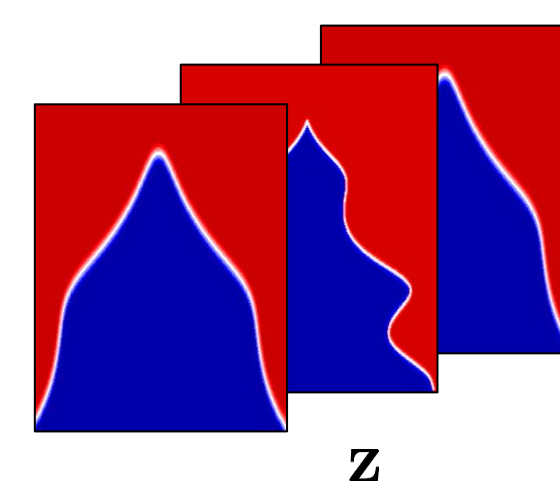
2. Flame model and simulator

- The flame is modelled as a thin boundary between reactants and products using the G-equation (Williams 1985)
- The **parameters of the model** include flame dimensions, perturbation speeds and frequencies



3. Bayesian neural network ensemble

- Training: learn the parameters from a **library of flame shapes** generated with the simulator

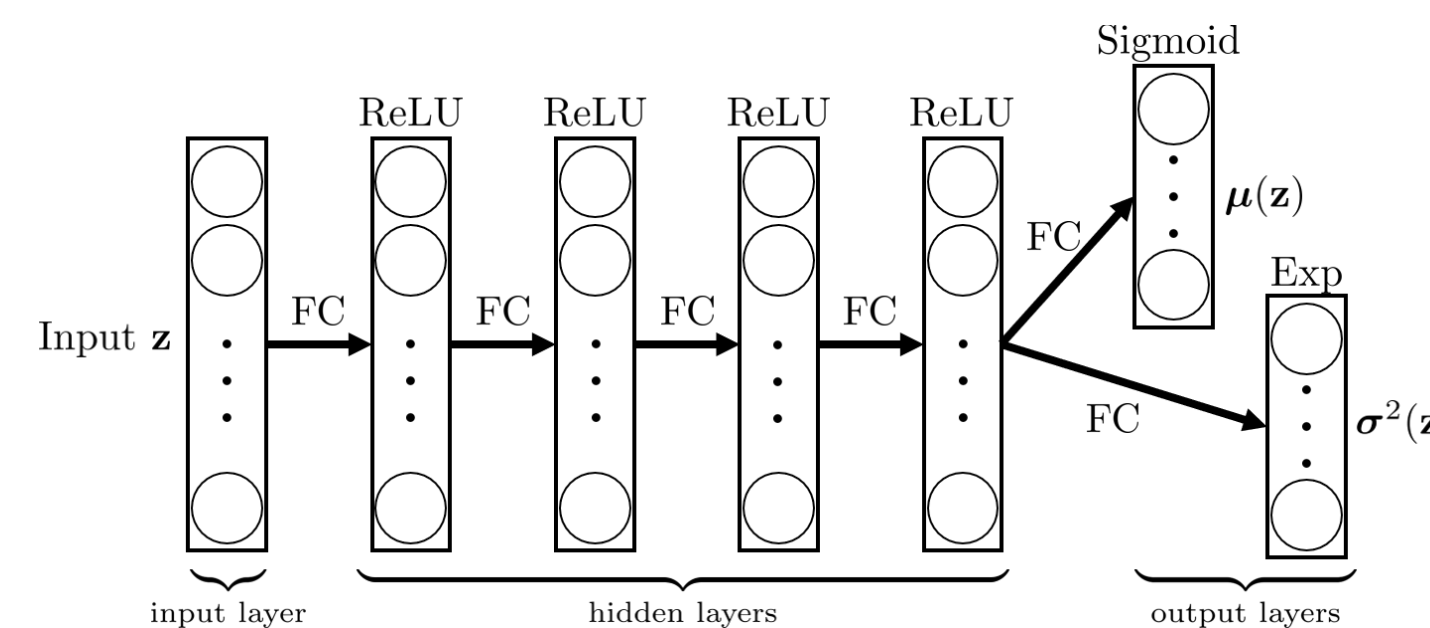


For known parameters, t
learn means and variances:
 $\mu_j(z), \sigma_j^2(z)$
assuming the parameters are
Gaussian distributed:
 $t \sim \mathcal{N}(t; \mu_j(z), \sigma_j^2(z))$

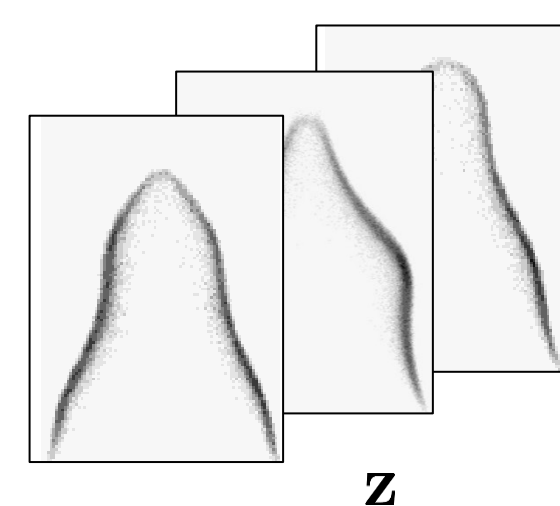
- Loss function: **maximise the Bayesian posterior** of the parameters given the flame shapes

$$\mathcal{L}_j = \underbrace{(\mu_j(z) - t)^T \Sigma_j(z)^{-1} (\mu_j(z) - t) + \log(|\Sigma_j(z)|)}_{\text{Gaussian likelihood}} + \underbrace{(\theta_j - \theta_{anc,j})^T \Sigma_{prior}^{-1} (\theta_j - \theta_{anc,j})}_{\text{anchored prior}}$$

- Neural network architecture (20 in the ensemble)

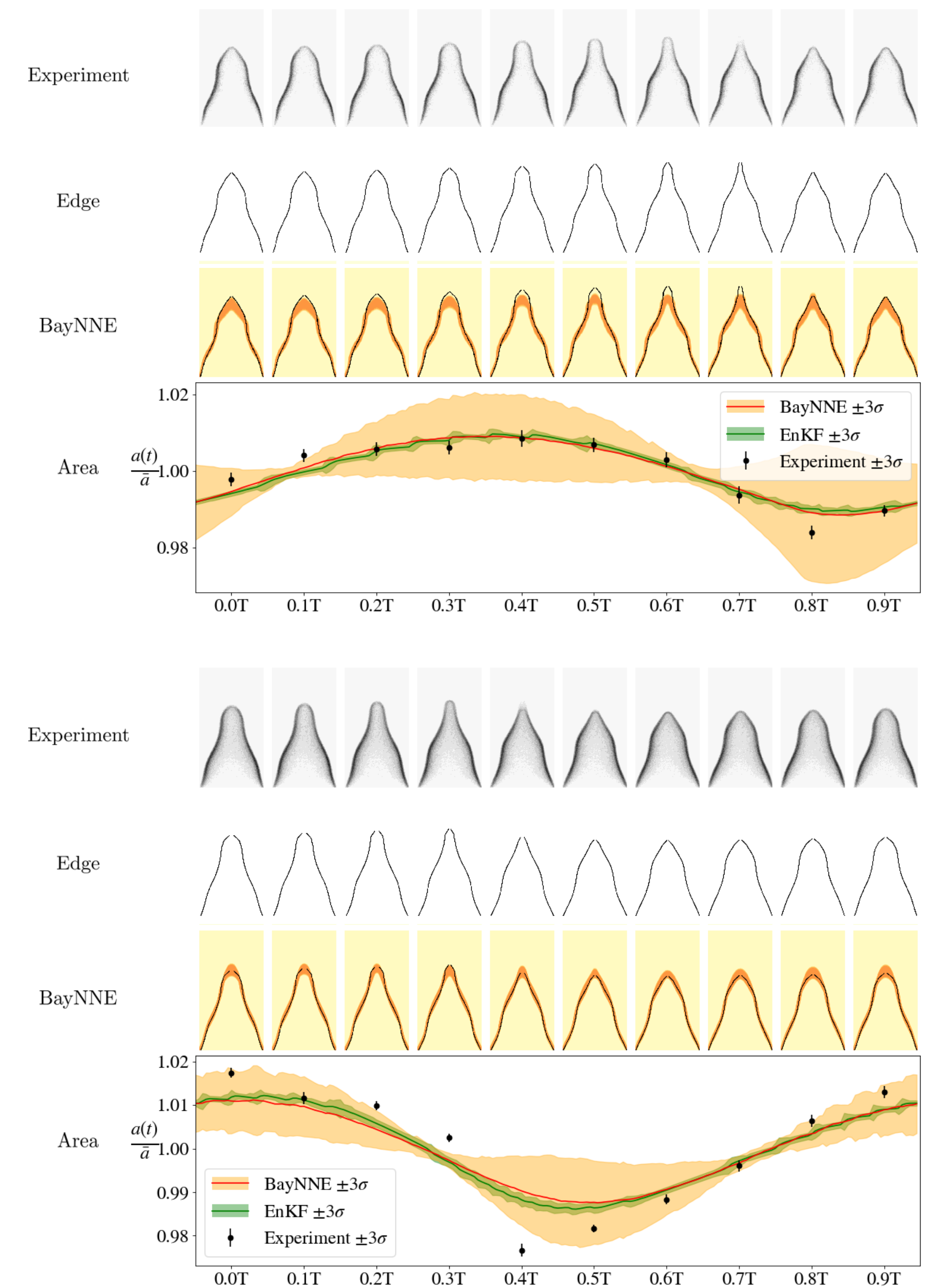


- Testing: infer the parameters from the experiments



$$\mu_j(z), \sigma_j^2(z)$$

4. Results



5. Summary

The BayNNE:

- is trained on a library of simulated flame shapes and tested on real data
- accurately infers parameters of the flame model orders of magnitude faster than the state-of-the-art**