

# Calibrated Physics-Informed Uncertainty Quantification



CNIS



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TLDR: Calibrated uncertainty quantification of neural PDE solvers using physics residual errors as non-conformity scores for data-free conformal prediction

# Motivation

Method: CP-PRE

CP-PRE provides bounds to a model's

adherence to the governing physics equations.

Performs conformal prediction using Physics

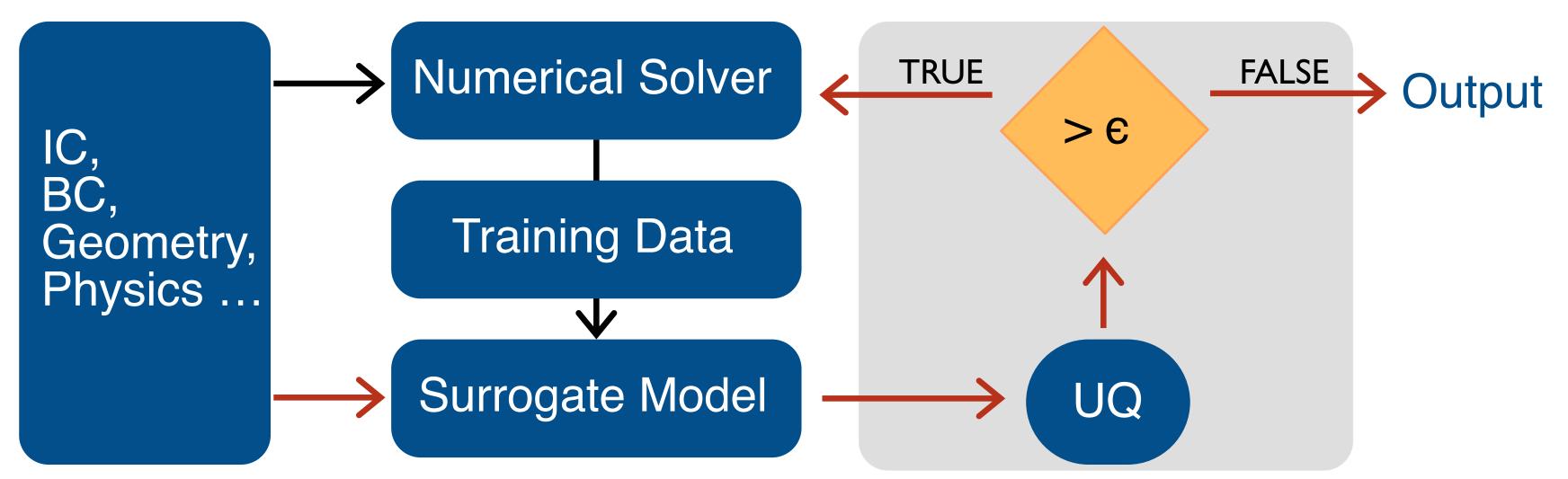
Residual Errors as a nonconformity score for

calibrated measures of physical misalignment.

The error bars are over the residual space

associated with the PDE, bounding the model's

violation of the conservation equations.



Surrogate models approximating PDE solutions need to be be made "actionable" using valid UQ methods

Physics Residual

Conformal

Prediction

**Physics Residual Error (PRE):** 

PDE residual estimated over the discretised

 $PRE = D(u) - b \sim 0$ 

D - Composite spatio-temporal differential

operator characterising the PDE

**u** - Prediction, **b** - External forcing

solution predicted by the surrogate model.

## Contributions

Novel UQ method for neural-PDE solvers that

- provides coverage guarantees
- is model-agnostic
- requires no calibration data
- is sampling Free
- provides physics-informed uncertainty bounds

#### Marginal Coverage

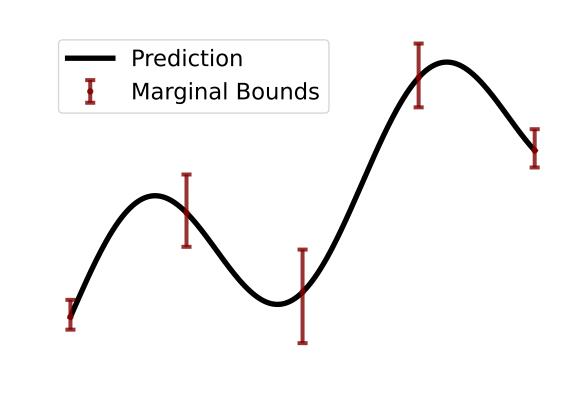
#### Cell-wise coverage

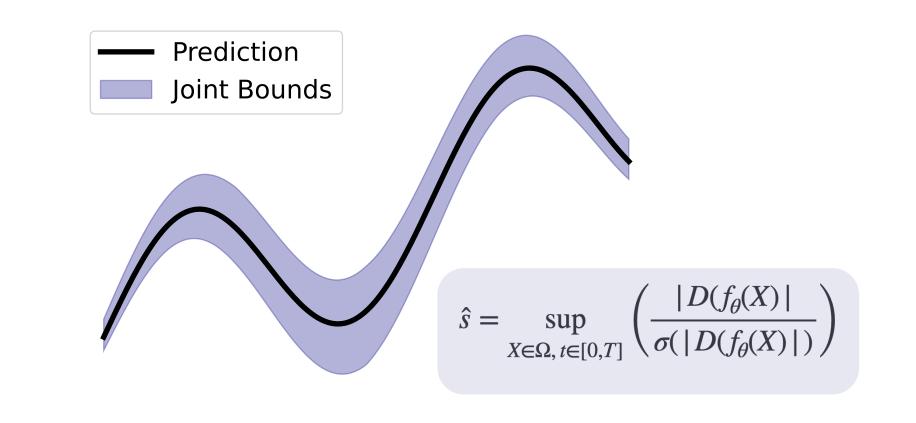
Identify erroneous regions within the spatio-temporal domain, tagging unphysical features within the domain by providing point-wise uncertainty.

#### Joint Coverage

#### Spatio-temporal coverage

Identifies erroneous predictions across the spatio-temporal domain, tagging unphysical predictions. Domain-wise confidence enables rejection of physically inconsistent predictions.





Method	Score Function	Prediction Set		
Absolute Error Residual (Traditional CP)	$\left(\left f_{\theta}(X_i) - Y_i\right \right)_{i=1}^n$	$f_{\theta}(X_{n+1}) \pm \hat{q}^{\alpha}$		
Physics Residual Error (Ours)	$\left(  D(f_{\theta}(X_i)) - 0  \right)_{i=1}^n$	$0\pm\hat{q}^{lpha}$		

### Experiments

#### **Navier-Stokes Equations**

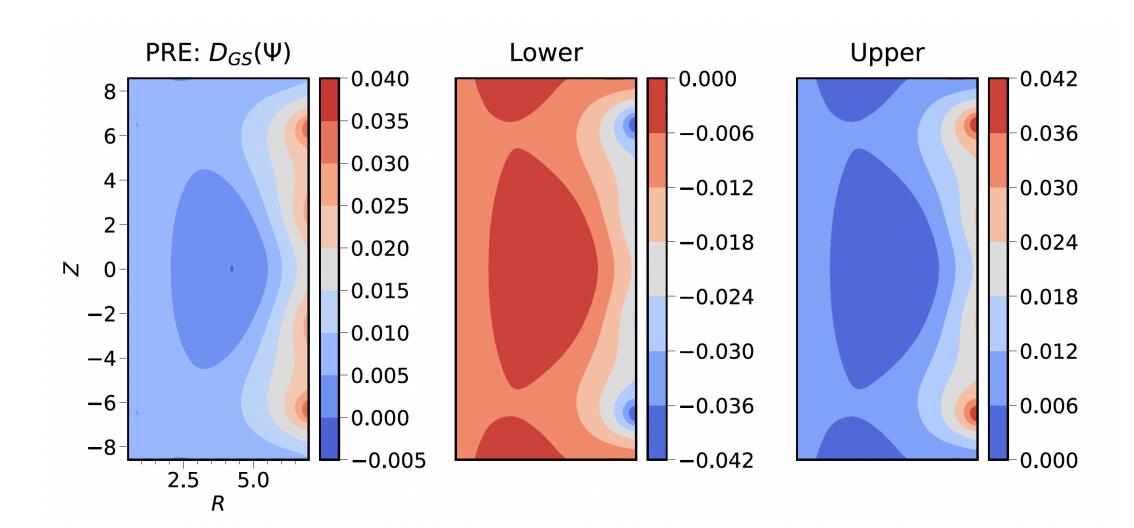
- Baseline comparison of our method against other methods of UQ for neural PDE surrogates modelling the incompressible Navier-Stokes equations.
- We obtain guaranteed coverage for both in-distribution and out-of-distribution evaluations while being the most computationally efficient.

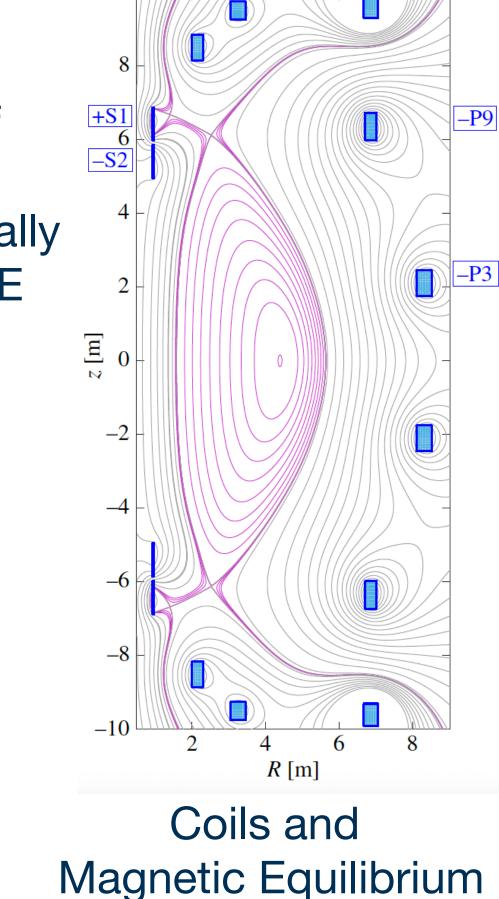
	in-distribution		out-of-distribution		Time	
UQ	MSE	Coverage (95%)	MSE	Coverage (95%)	Train (hr)	Eval (s)
Deterministic MC Dropout Deep Ensemble BNN SWA-G CP-AER CP-PRE (Ours)	$1.05e-04 \pm 6.91e-06$ $5.96e-04 \pm 2.30e-05$ $1.22e-04 \pm 3.95e-06$ $6.90e-03 \pm 1.31e-04$ $1.96e-04 \pm 1.15e-05$ $1.05e-04 \pm 6.58e-06$ $1.07e-04 \pm 5.18e-06$	82.21 ± 0.22 91.31 ± 0.08 89.91 ± 0.20 84.22 ± 2.37 <b>95.56 ± 0.40</b>	$3.67e-03 \pm 5.30e-05$ $4.30e-03 \pm 8.05e-05$ $3.67e-03 \pm 3.52e-05$ $6.95e-03 \pm 1.31e-04$ $3.63e-03 \pm 1.37e-04$ $3.66e-03 \pm 2.81e-05$ $3.70e-03 \pm 4.23e-05$	$44.05 \pm 0.26$ $30.74 \pm 0.19$ $85.19 \pm 0.23$ $31.00 \pm 2.85$ $95.54 \pm 0.15$	3:22 3:34 16:22 3:39 3:28 3:22 3:22	25 153 147 152 146 20026 <b>134</b>

#### Magnetic Equilibrium in a Fusion Reactor

#### **Grad-Shafranov Equation**

Position of field coils (blue rectangles) determines the quality of equilibrium (contour lines) in a fusion reactor. During the design phase, it is infeasible to solve the equilibrium equation numerically for a million iterations. Surrogate models equipped with CP-PRE provides an actionable model that allows us to explore the proposed design space with confidence.





PRE over the predicted equilibrium with the lower and upper bounds





Initial Condition





Marginal