



# 2025年度中国等离子体物理暑期学校

## 诊断数据智能分析

### ——数据融合及不确定性量化

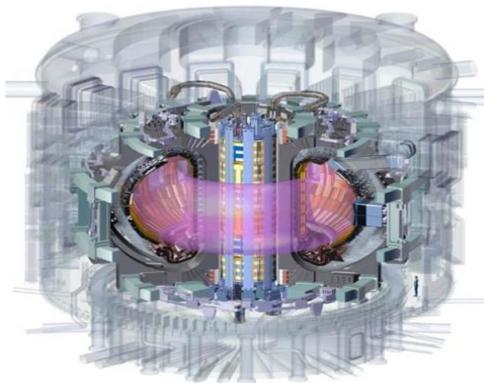
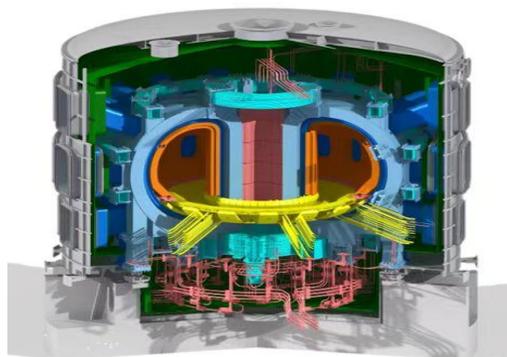
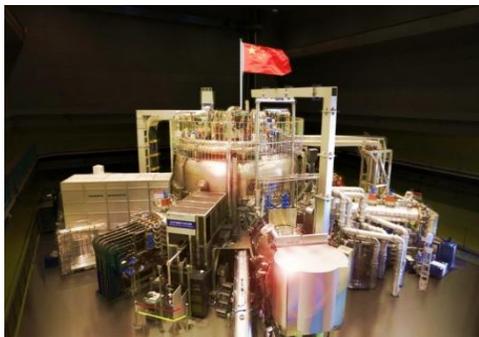
兰 婷

中国科学院合肥物质科学研究院等离子体物理研究所

2025年7月12日，安徽·合肥

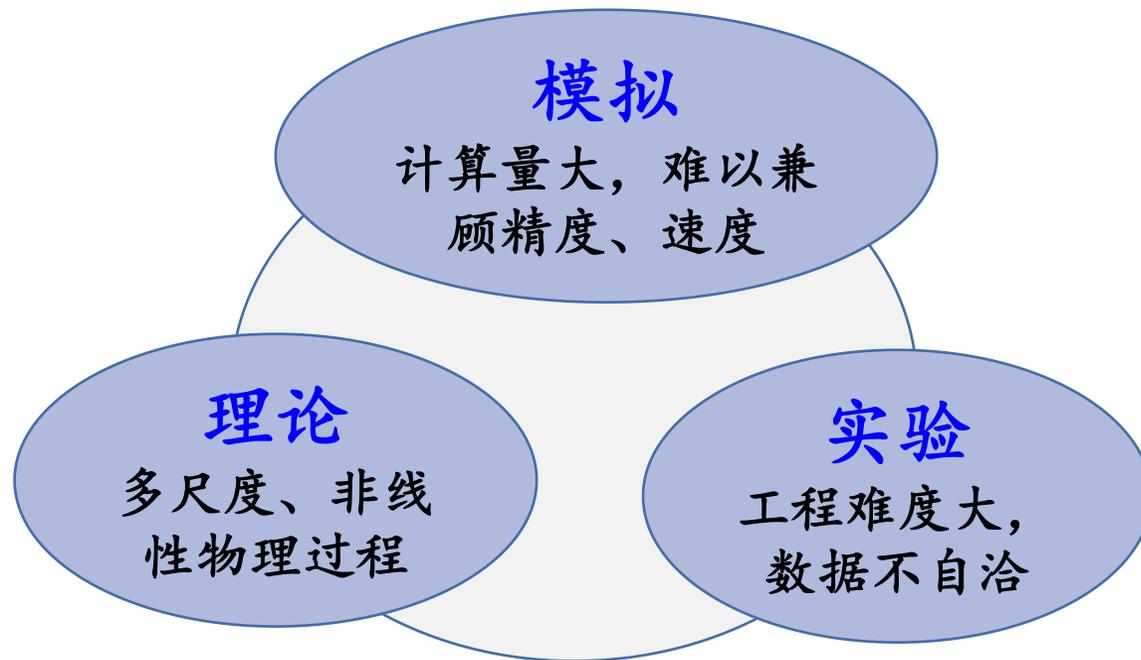


# AI4F—磁约束聚变研究新范式



引入AI技术，服务于未来聚变堆燃烧等离子体研究

燃烧等离子体环境：  
物理更复杂，  
计算量更大，  
数据不完备，  
关键物理过程难以理解，  
.....



# AI应用于聚变领域方方面面

## Publications

589

Total

From 1637 to 2024

## Citing Articles

3,311 Analyze

Total

2,932 Analyze

Without self-citations

## Times Cited

6,212

Total

4,154

Without self-citations

破坏性事件测控: Disruption、Vertical displacement、Fault detection

参数标定: Scaling、Operational regimes

反演: Reconstruction

代理模型: Fast modeling、Accelerated simulation、Real-time prediction

等离子体及装置控制: Plasma control、Device control、Safety factor control

模式识别: Retrieval、Pattern recognition

算法及流程优化: Optimization、Automatic analysis、

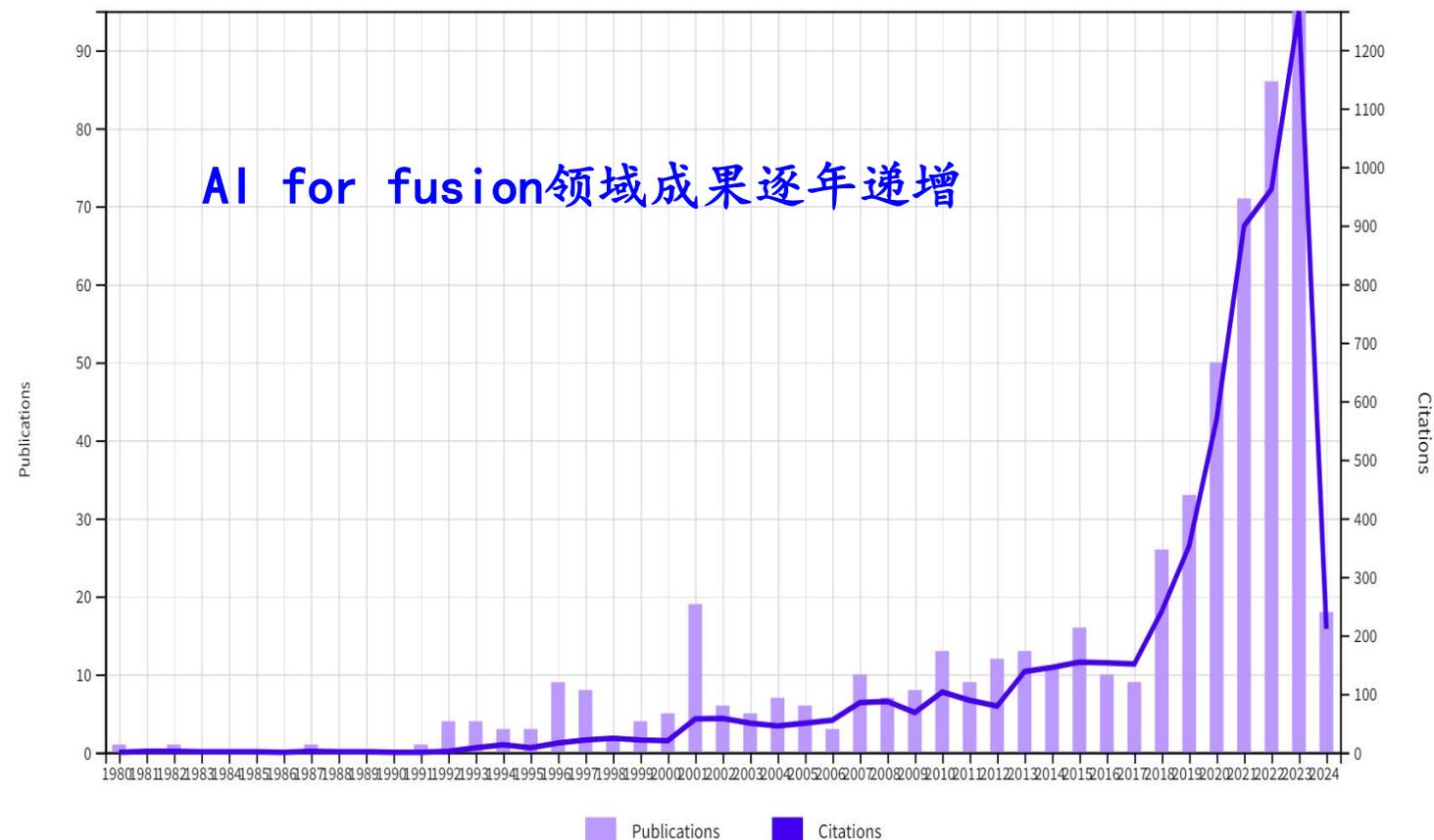
降噪、降维: Denoise、Dimensionality reduction

特征提取: Feature extractor

设计优化: Bayesian design

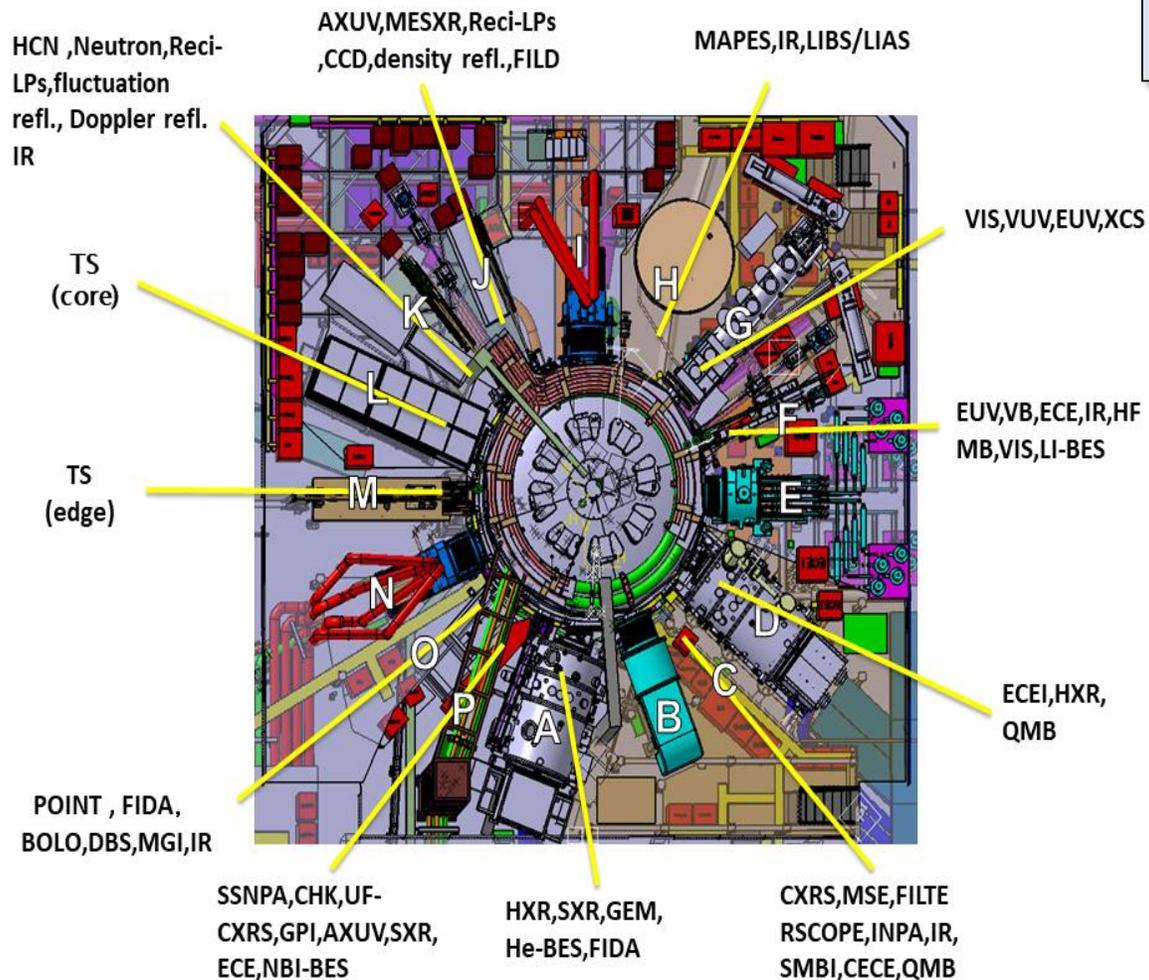
.....

AI for fusion领域成果逐年递增



# 诊断间数据不自洽

## EAST托卡马克诊断系统布局

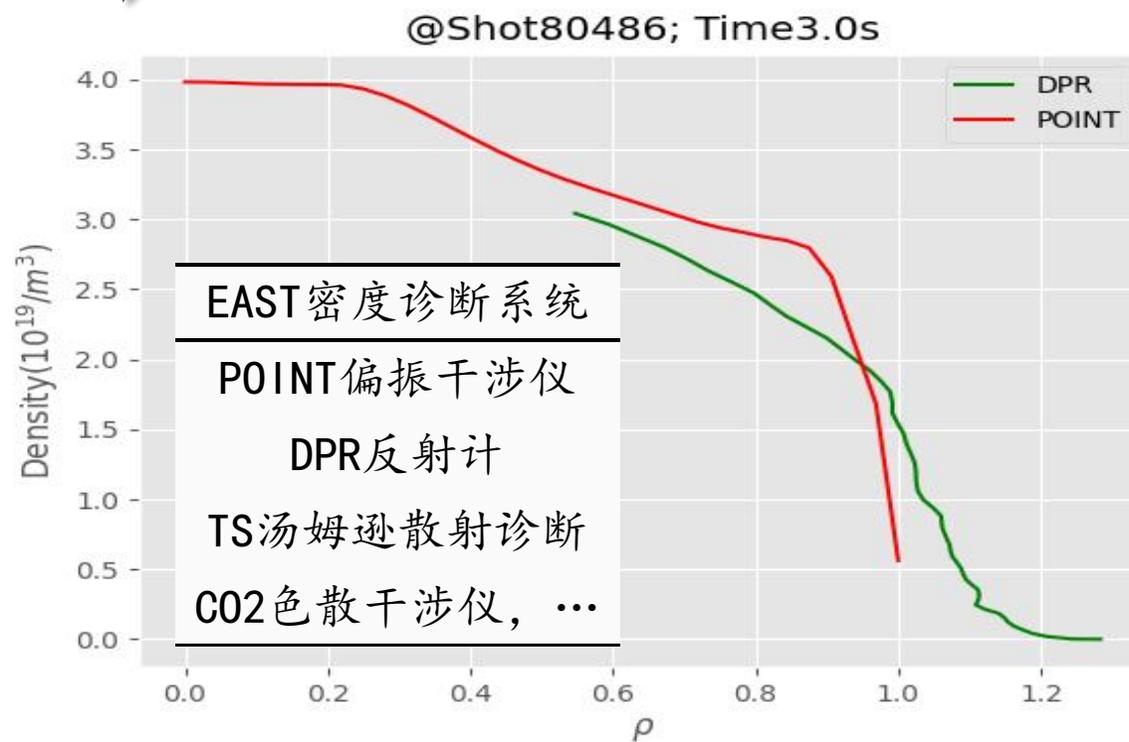


诊断间不自洽:

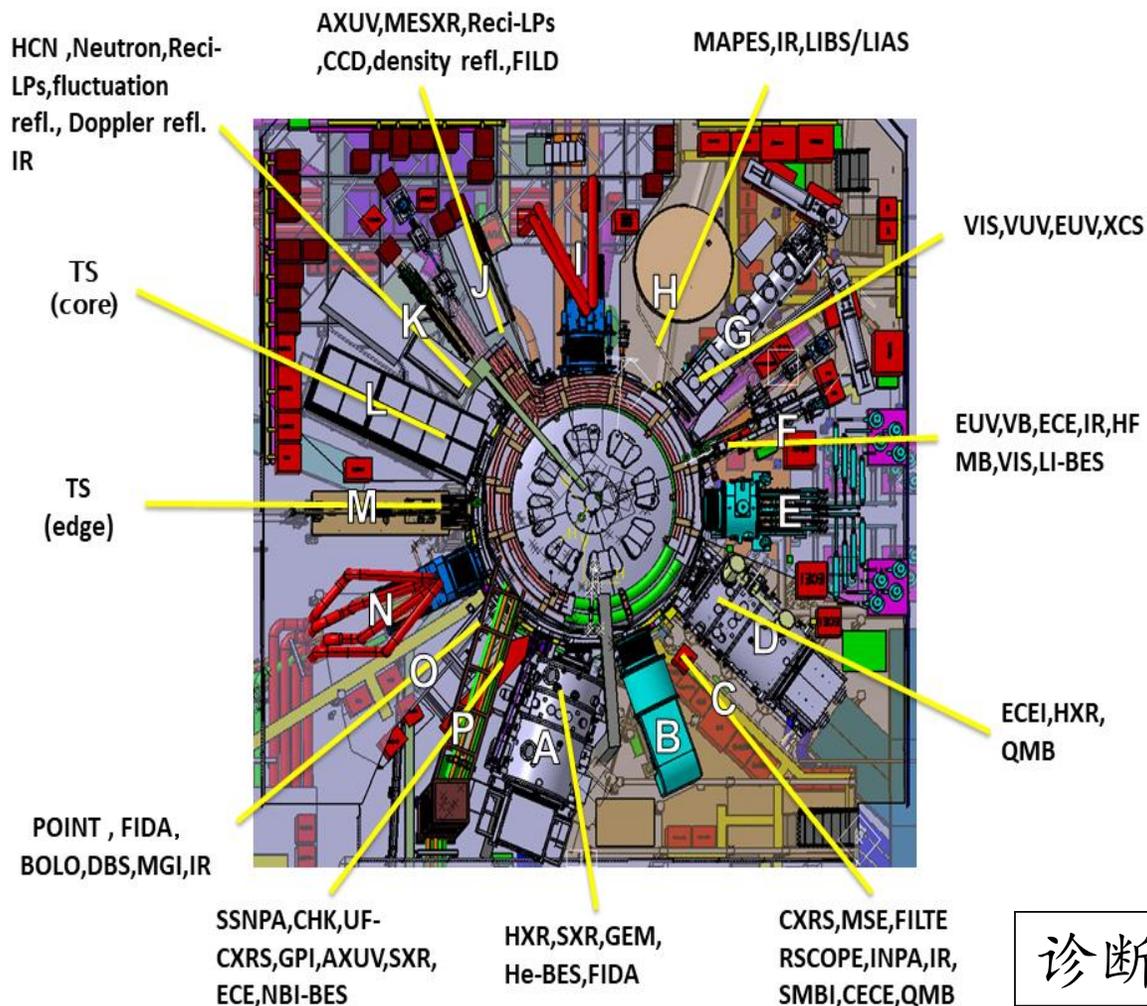
不同系统对同一物理量的测量不一致



给数据的理解和使用带来困难



# 测量不确定性导致诊断间数据不自洽



- 仪器及环境噪声干扰
- 实验数据统计波动
- 测量通道的空间稀疏性
- 测量及数据传输中的信息遗漏
- 数据处理模型的认识或方法误差

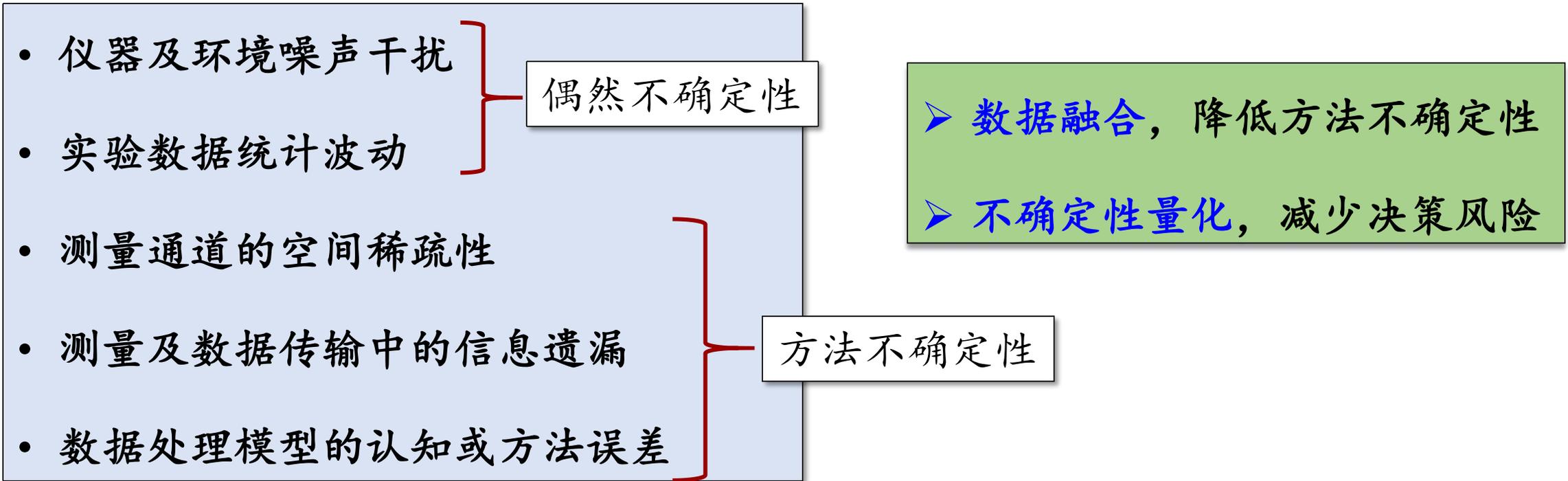


诊断间不自洽

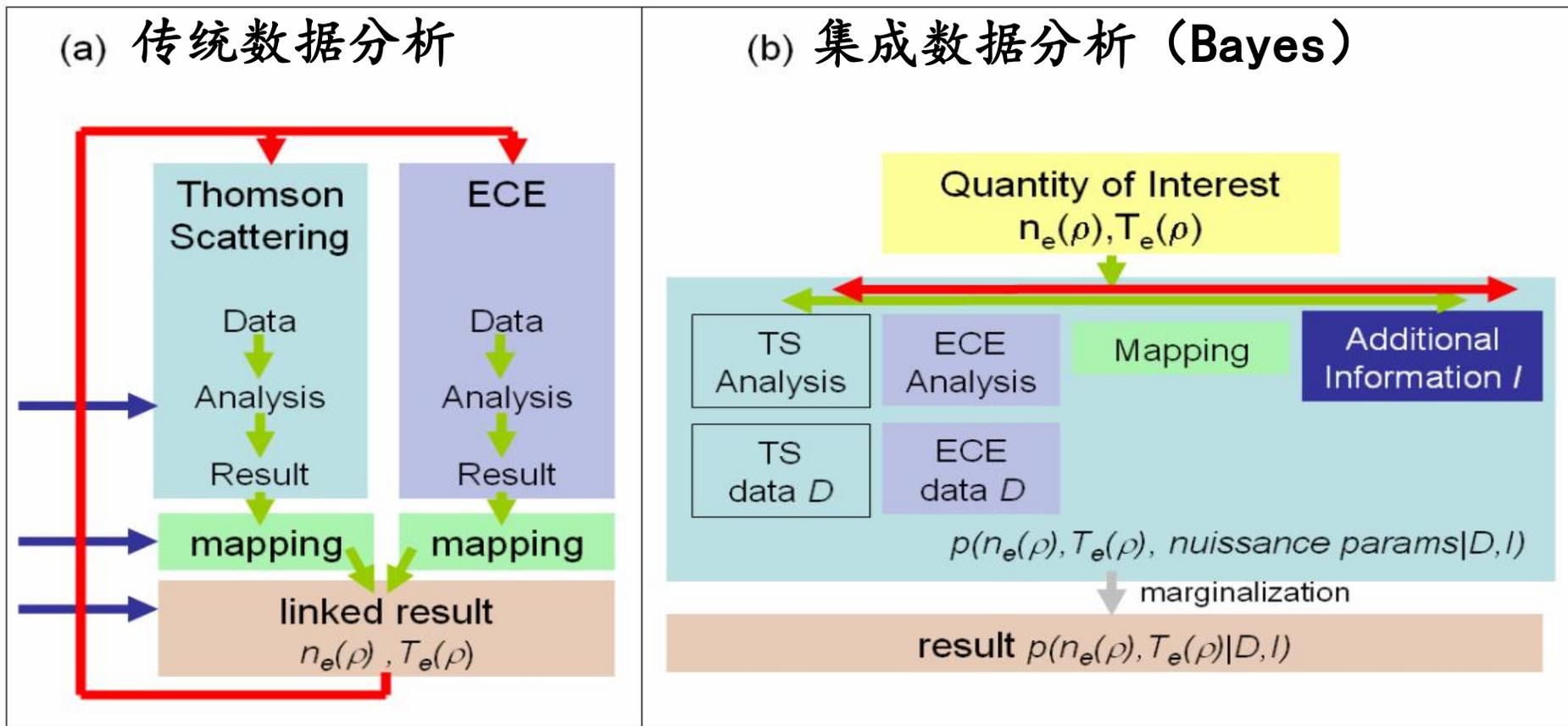


测量不确定性

# 数据融合及不确定性量化



# 基于贝叶斯推断的数据融合及不确定性量化



- data analysis
- Validation & cross checks
- additional information: physics, technical constraints ...

By R. Fischer

# 贝叶斯定理



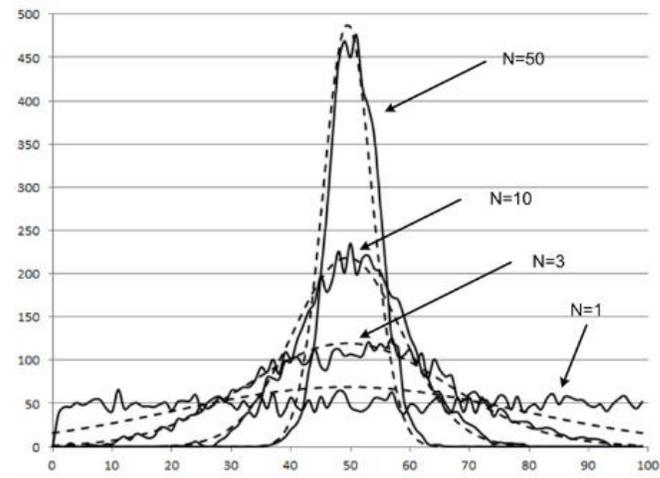
英国数学家贝叶斯

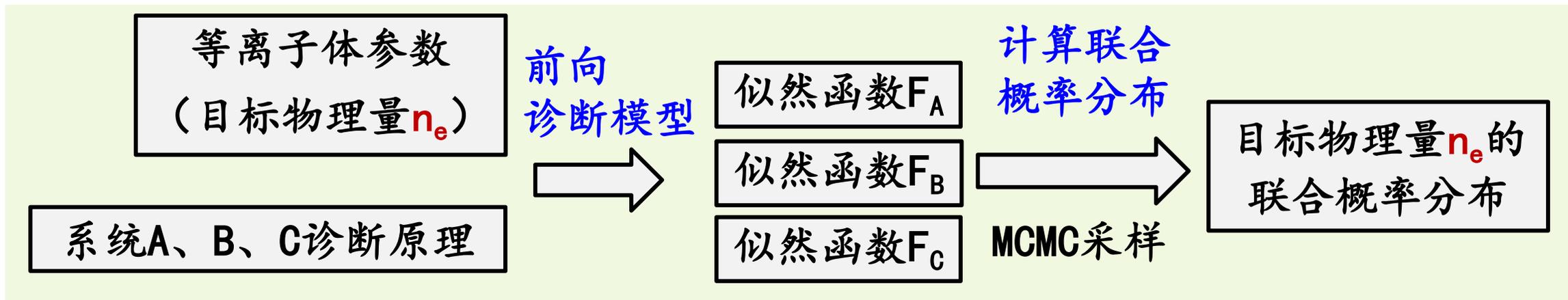
$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)}$$

后验概率
似然概率
先验概率

$$P(D|\theta) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(D - f(\theta))^2}{2\sigma^2}\right)$$

中心极限定理





贝叶斯原理

$$P(n_e|D) = \frac{P(D|n_e)P(n_e)}{P(D)}$$

数据

$$P(D|n_e) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(D - f(n_e))^2}{2\sigma^2}\right)$$

模型

$$P(n_e|D_{POINT}, D_{HCN}, D_{DPR}, D_{TS}, \dots) \propto$$

$$P(D_{POINT}|n_e)$$

$$\times P(D_{HCN}|n_e)$$

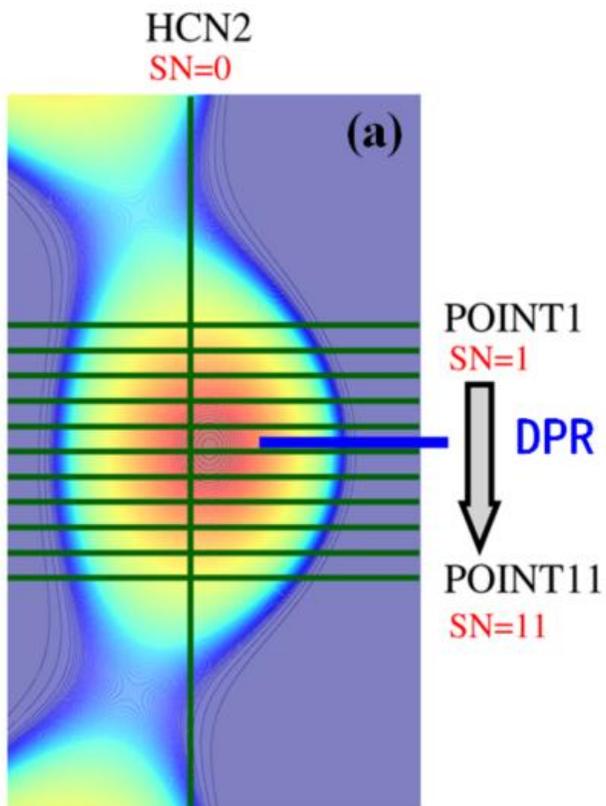
$$\times P(D_{DPR}|n_e)$$

$$\times P(D_{TS}|n_e, T_e)$$

$$\times \dots$$

# 前向诊断模型构建

## EFIT磁面+模拟等离子体参数分布+诊断原理



**POINT**

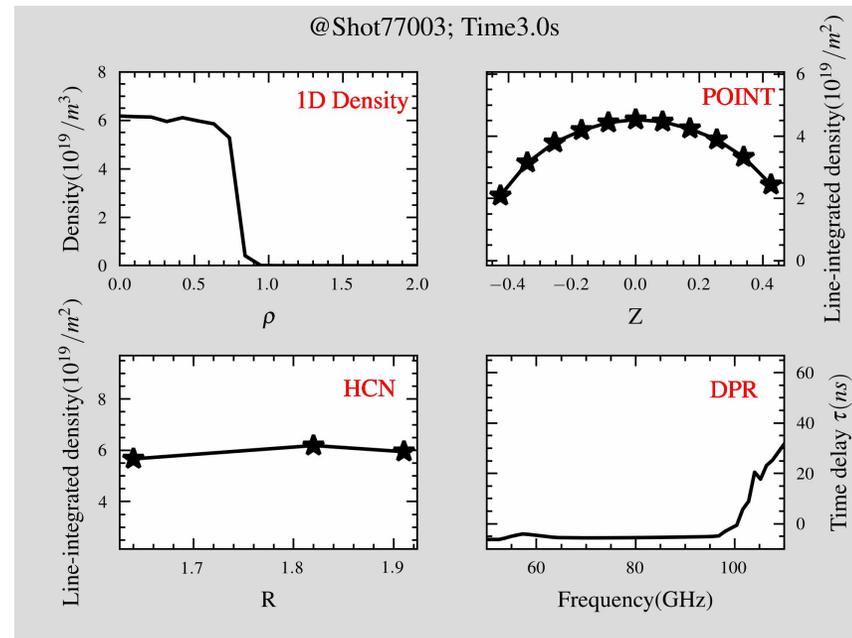
$$\begin{cases} \phi = \frac{\phi_L + \phi_R}{2} = C_1 \lambda \int n_e dL, \\ \alpha_F = \frac{\phi_L - \phi_R}{2} = C_2 \lambda^2 \int n_e B_{\parallel} dL, \end{cases}$$

$\omega = (\omega_{ce}^2/4 + \omega_{pe}^2)^{1/2} \pm \omega_{ce}/2.$

**DPR**

$$\tau_p = \tau_{plasma} - \tau_{wall} + \frac{2\Delta r_{vacuum}}{c}$$

## POINT、HCN、DPR模拟信号



$$n_e(r_{eff}) = \theta_1 \cdot 10^{20} m^{-3} \cdot \left[ \frac{1 - \theta_4 \cdot (r_{eff}^2 / a^2)}{1 + (r_{eff}^2 / (\theta_2 \cdot a)^2)^{\theta_3}} \right]$$

$\Theta_1$ : 最大密度

$\Theta_2$ : 梯度位置

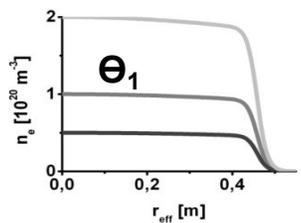
$\Theta_3$ : 边界陡峭程度

$\Theta_4$ : 平台倾斜程度

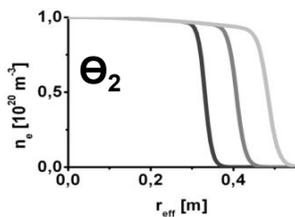
真实值:

$\Theta_1=5$       $\Theta_2=0.93$

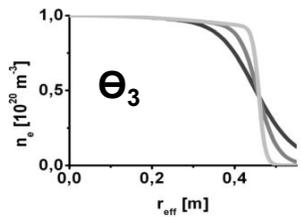
$\Theta_3=10$      $\Theta_4=0.18$



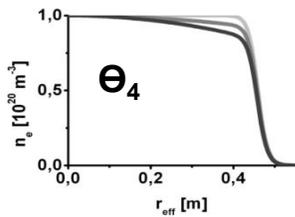
(a)



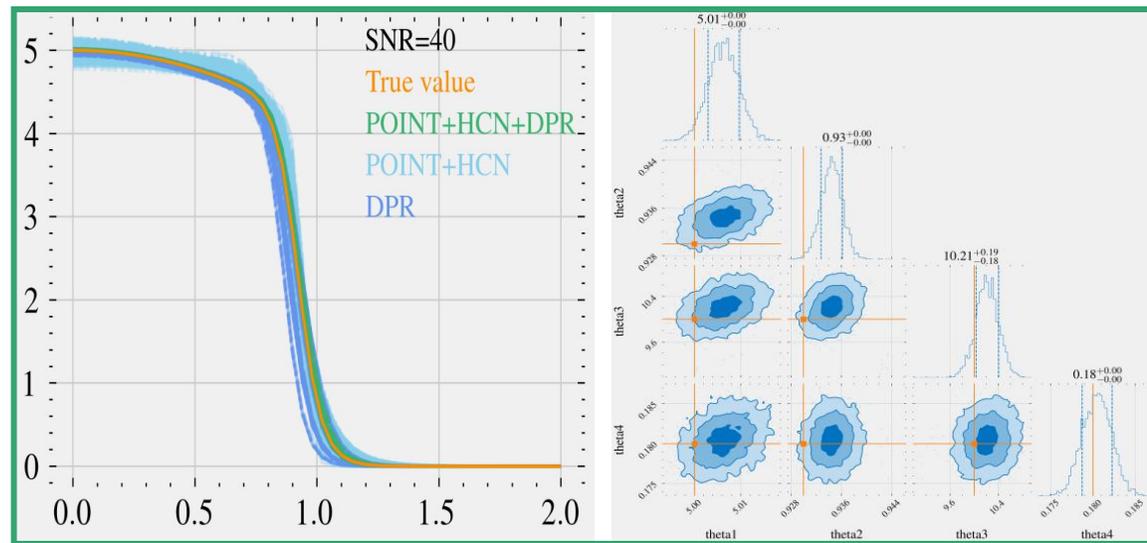
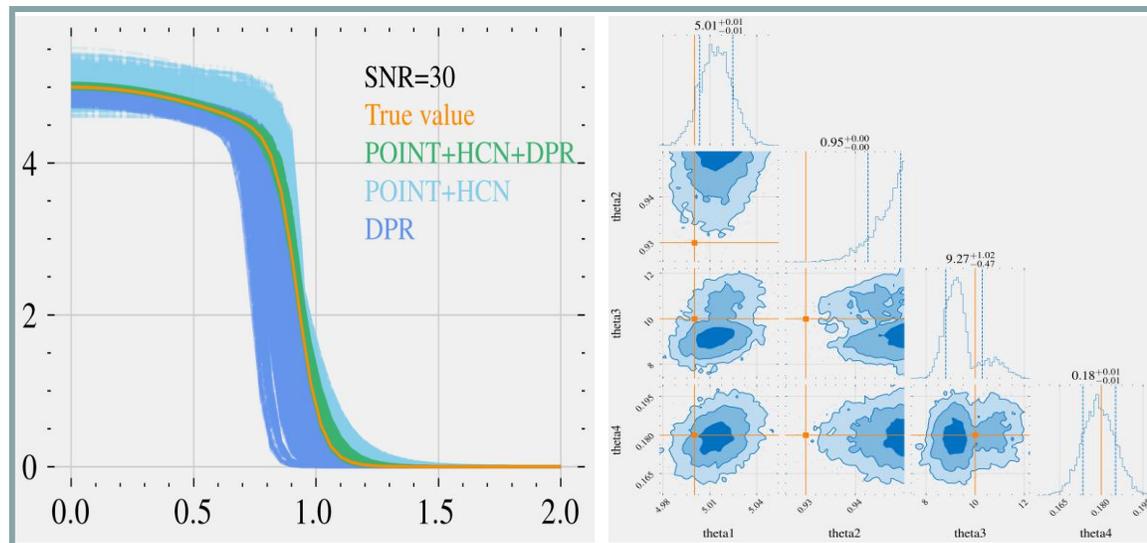
(b)



(c)

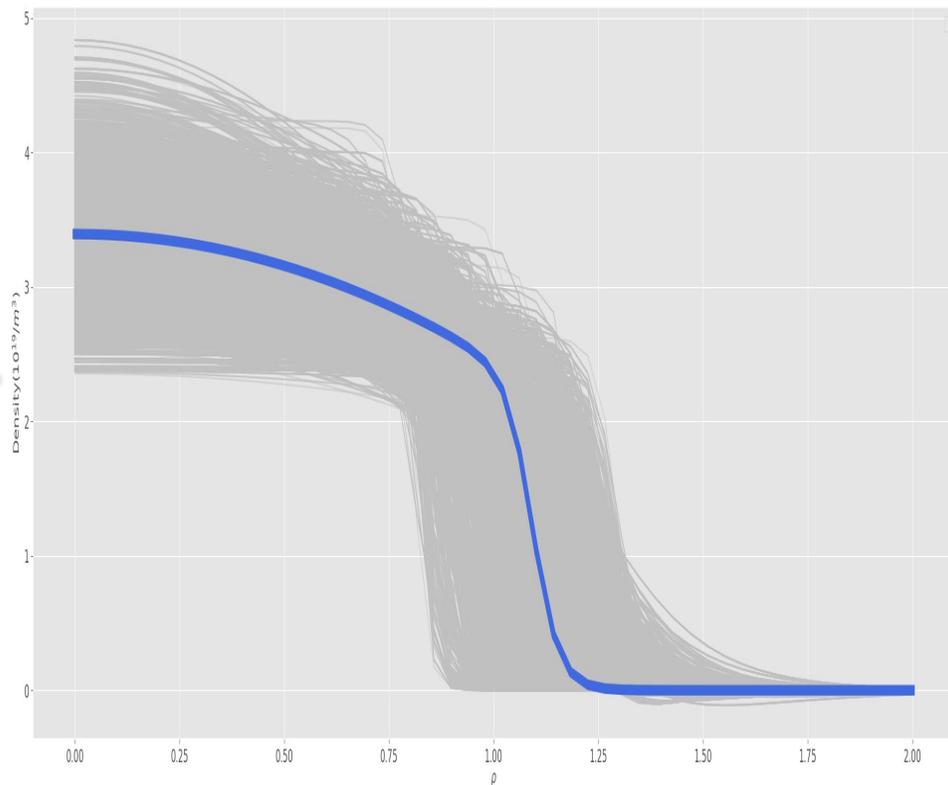
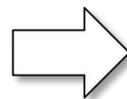
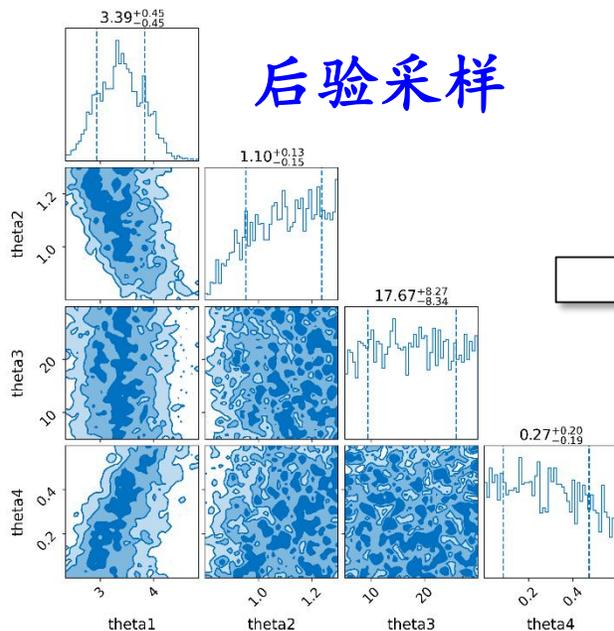
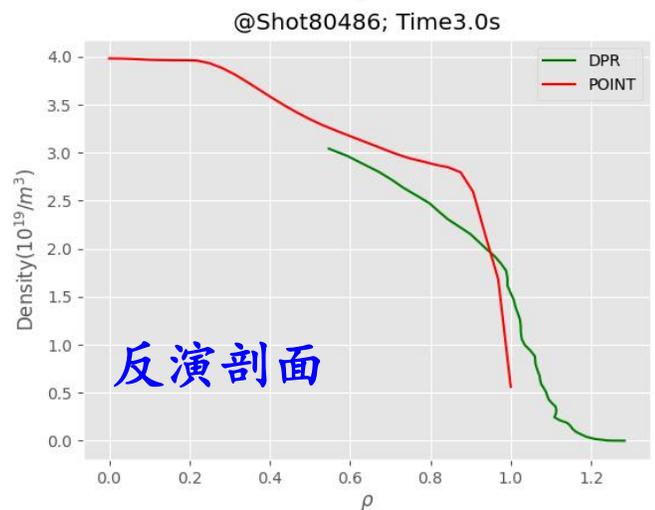
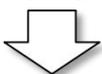
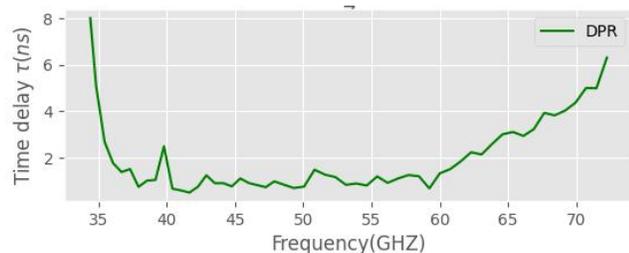
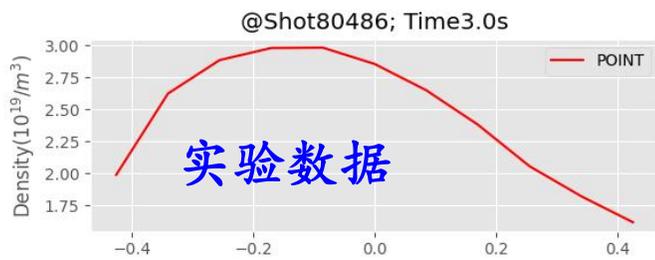


(d)



# 基于贝叶斯的POINT密度剖面反演

## 基于贝叶斯的POINT实验数据反演结果



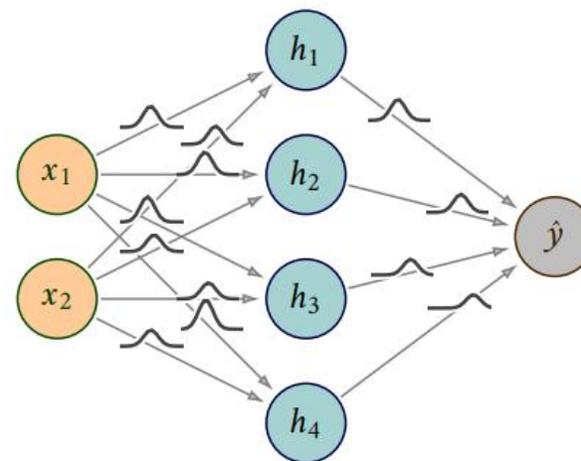
Bayesian	MC	(1) No need to change the model training process, (2) Low training complexity, (3) Easy to implement.	(1) Not very reliable for OoD data, (2) Needs multiple samplings during inference.
	MCMC	(1) Computationally more intensive compared to VI, (2) Asymptotically guarantees of producing exact samples.	(1) Very slow, (2) Fail to find poor convergence, (3) High MC error.
	VI	(1) Very fast (faster than MCMC), (2) Benefiting from stochastic optimization methods, (3) Suited to big datasets.	(1) Heavily depend on the starting point, (2) Very complicated calculations.
	BAL	(1) Able to learn from small amounts of data, (2) Able to add samples with high classification uncertainty to training.	(1) Lack of scalability to high-dimensional data, (2) Difficult to quantify loss functions.
	BBB	(1) Returning the posterior over the weights, (2) Allowing more complicated prior distributions.	(1) Requiring extra sweep over KL trade-off coefficients, (2) More parameters to train (approximately two times).
	VAE	(1) Easy to optimize its loss, (2) Mapping an input sample in the original data to latent factors.	(1) Collapse in latent space, (2) Difficult to interpret the code, (3) Low quality of the generated sample images.
Ensemble	DE	(1) Robust prediction, (2) Can be considered as base learners, (3) Limiting the dispensable sensitivity of particular training data, (4) Robust uncertainty estimates.	(1) More resource consuming, (2) Time consuming, (3) Weak performance on smaller problems.
	DEB or BDE	(1) Can perform better than DEs in OoD settings, (2) Emulating the analytic posterior predictive.	(1) Weaker than standard DEs in not detrimental confident predictions, (2) Lazy learning procedure.

表征不确定性:

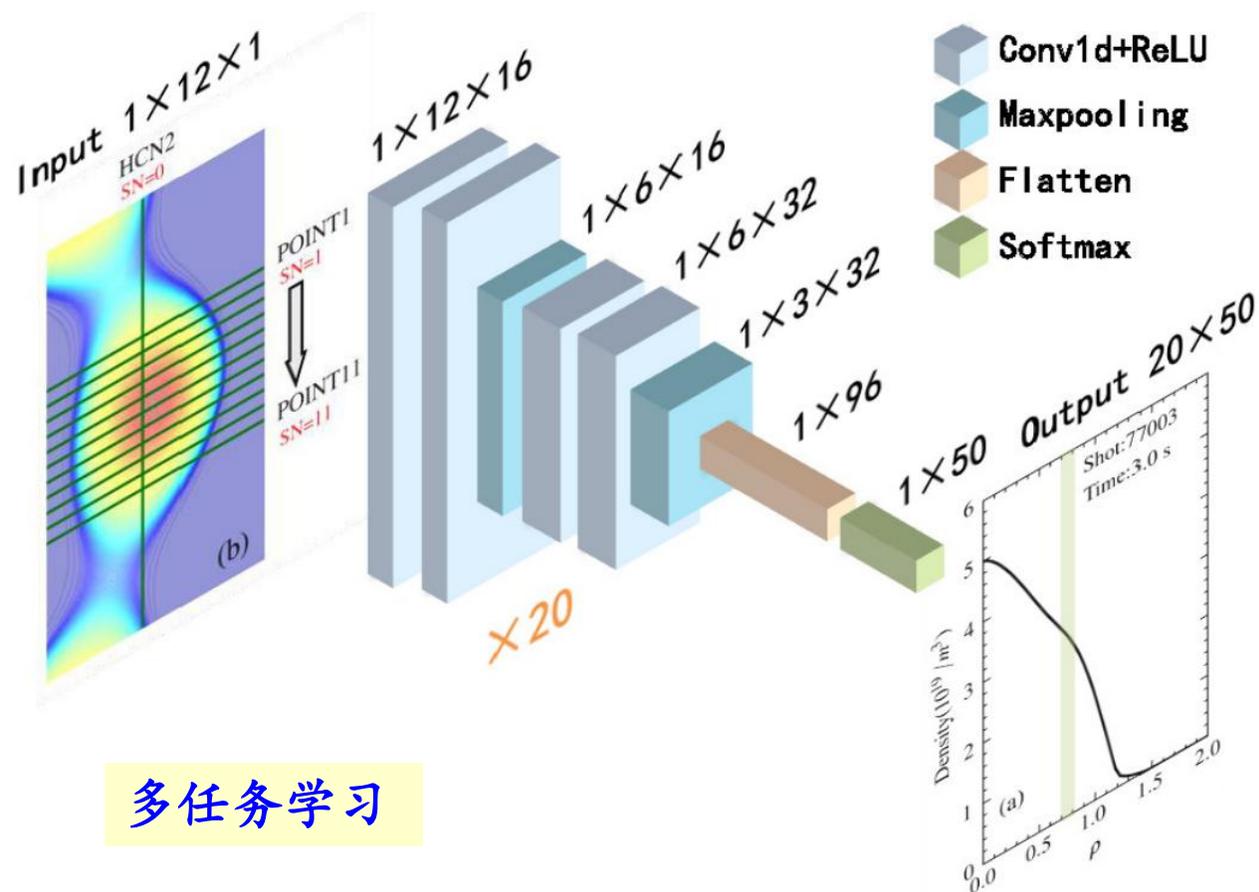
➤ 贝叶斯神经网络

➤ 深度集成网络

Bayesian Neural Network



# 基于CNN的POINT、HCN密度诊断数据融合



多任务学习

优点1:

➤ 不依赖于EFIT输入

可训练参数: 243240

优化器: adam

损失函数: MSE

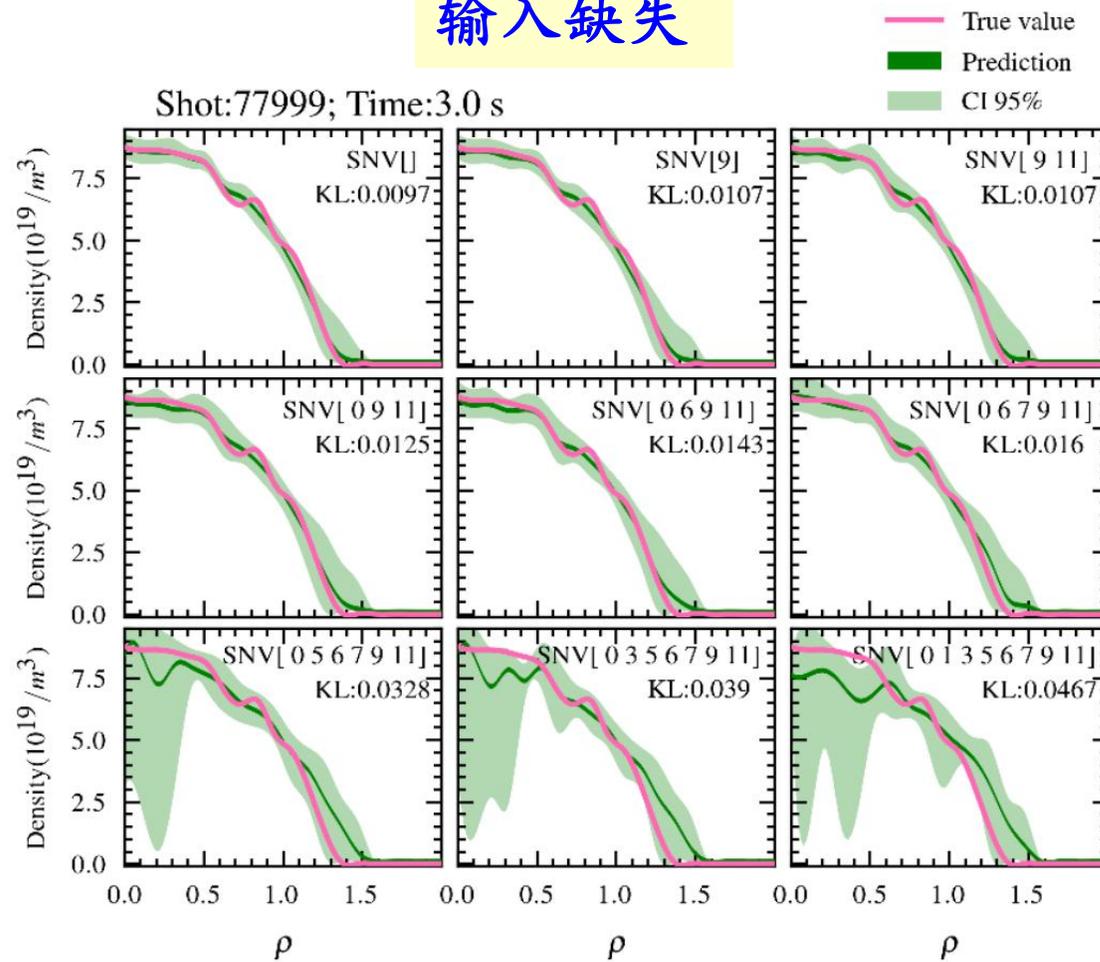
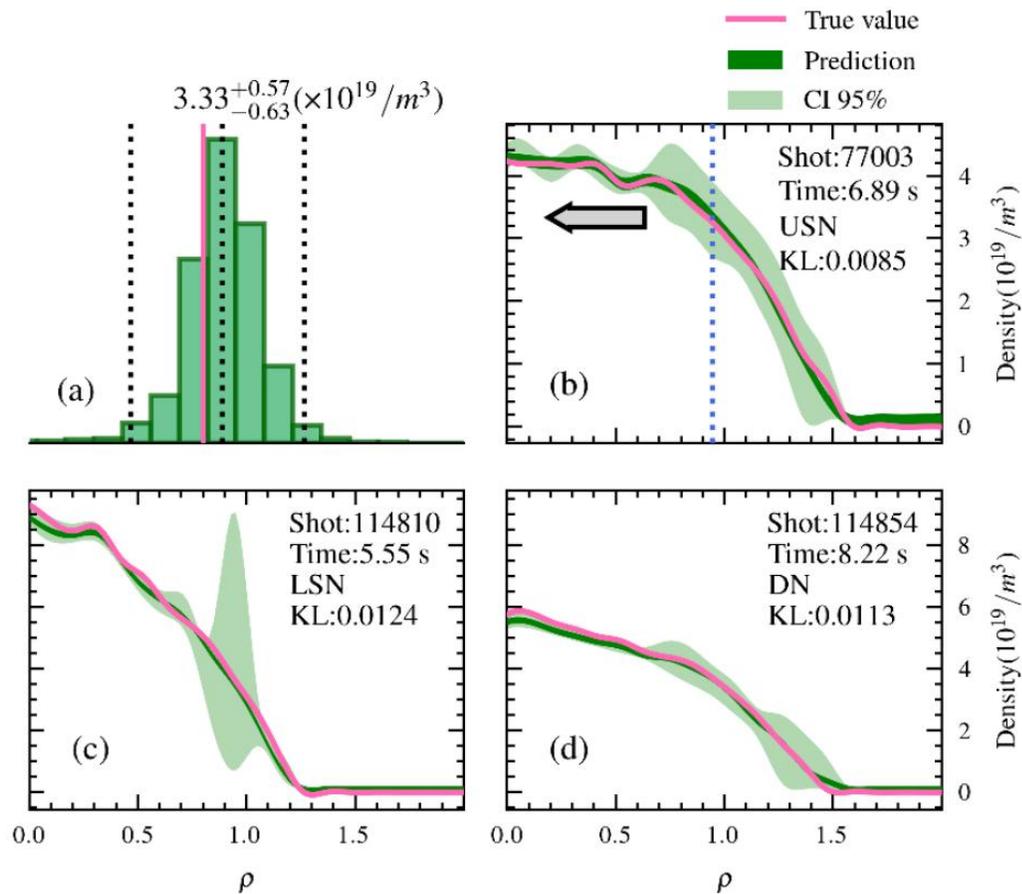
训练集比例: 0.8

服务器: Tesla V100 32GB GPUs

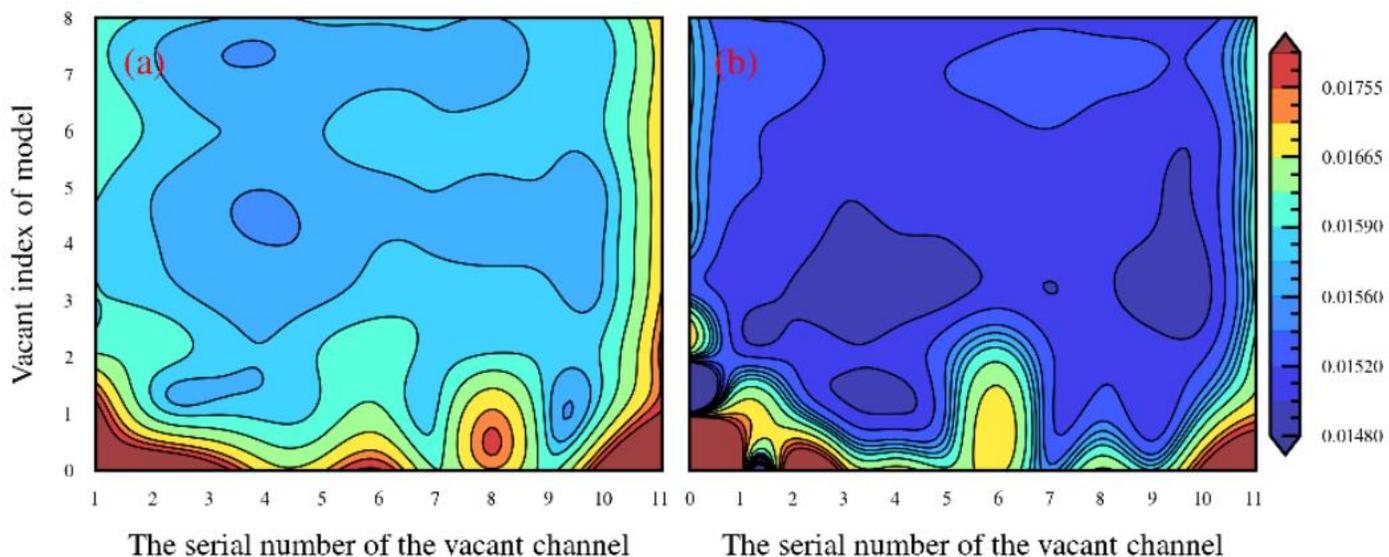
# 基于CNN的POINT、HCN密度诊断数据融合结果

输入完备

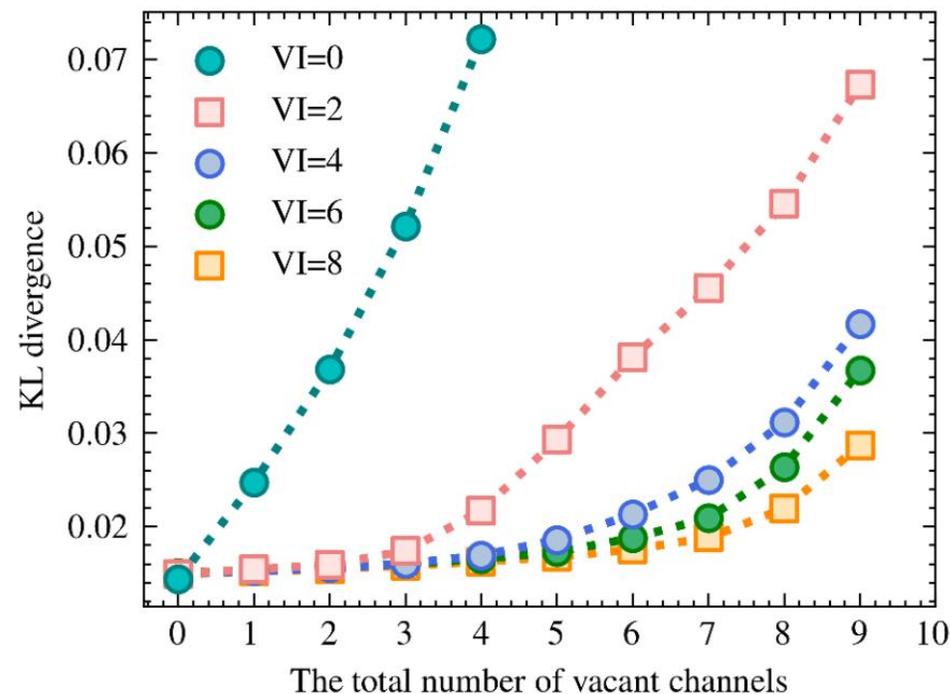
输入缺失



缺失1道



缺失多道



优点2:

➤对数据缺失具有鲁棒性

## 贝叶斯推断

### 优点:

- 自然的以概率方式描述各个物理量及测量的不确定性
- 方便融合多个诊断系统的数据

### 不足:

- 先验分布会显著影响后验分布结果
- 后验分布的采样过程耗时可能较长

VS

## 深度学习

### 优点:

- 降低融合模型带来的方法不确定性
- 更快给出判定结果, 可用于对数据处理时效性具有更高要求的场景

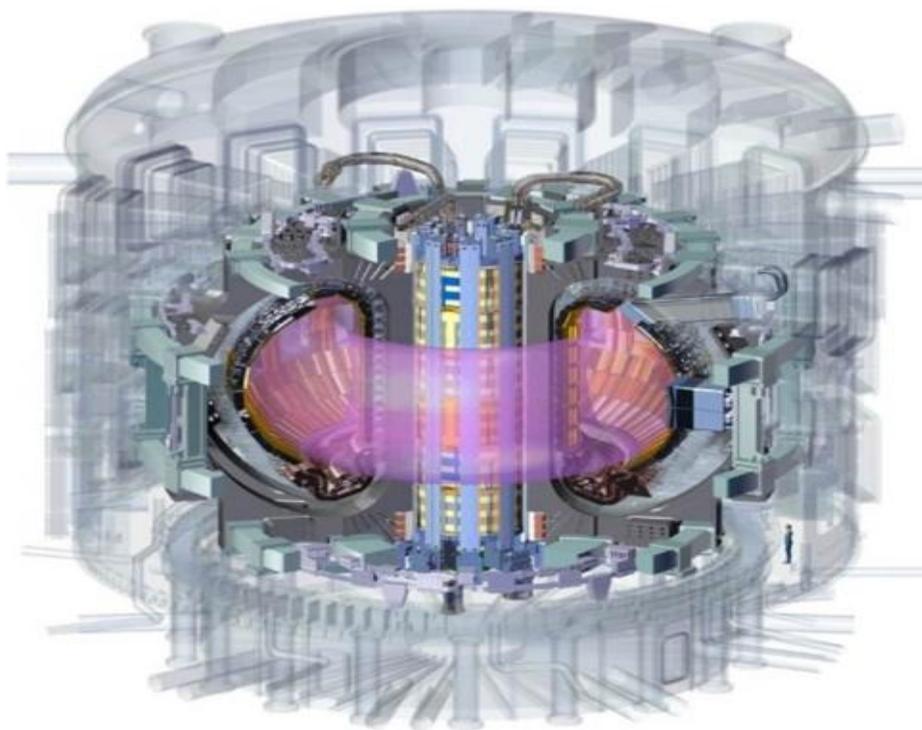
### 不足:

- 冗长的前期训练
- 需要设计融合策略, 融合诊断原理不同、数据属性不同、特征属性不同的多类诊断数据

# 数据清洗

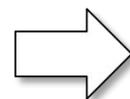
□ 数据清洗：将信噪比低或者无用数据准确识别出来，与信噪比高或者可用数据准确分类，提高数据可用度，可信度。

## AI赋能：自动识别和补全



### 复杂测量环境：

- 电磁干扰
- 机械振动
- 中子辐照

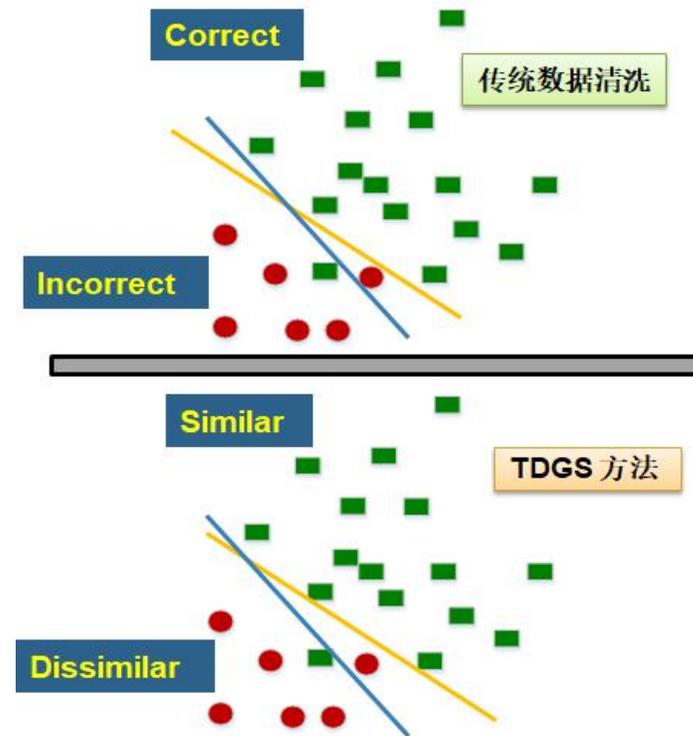
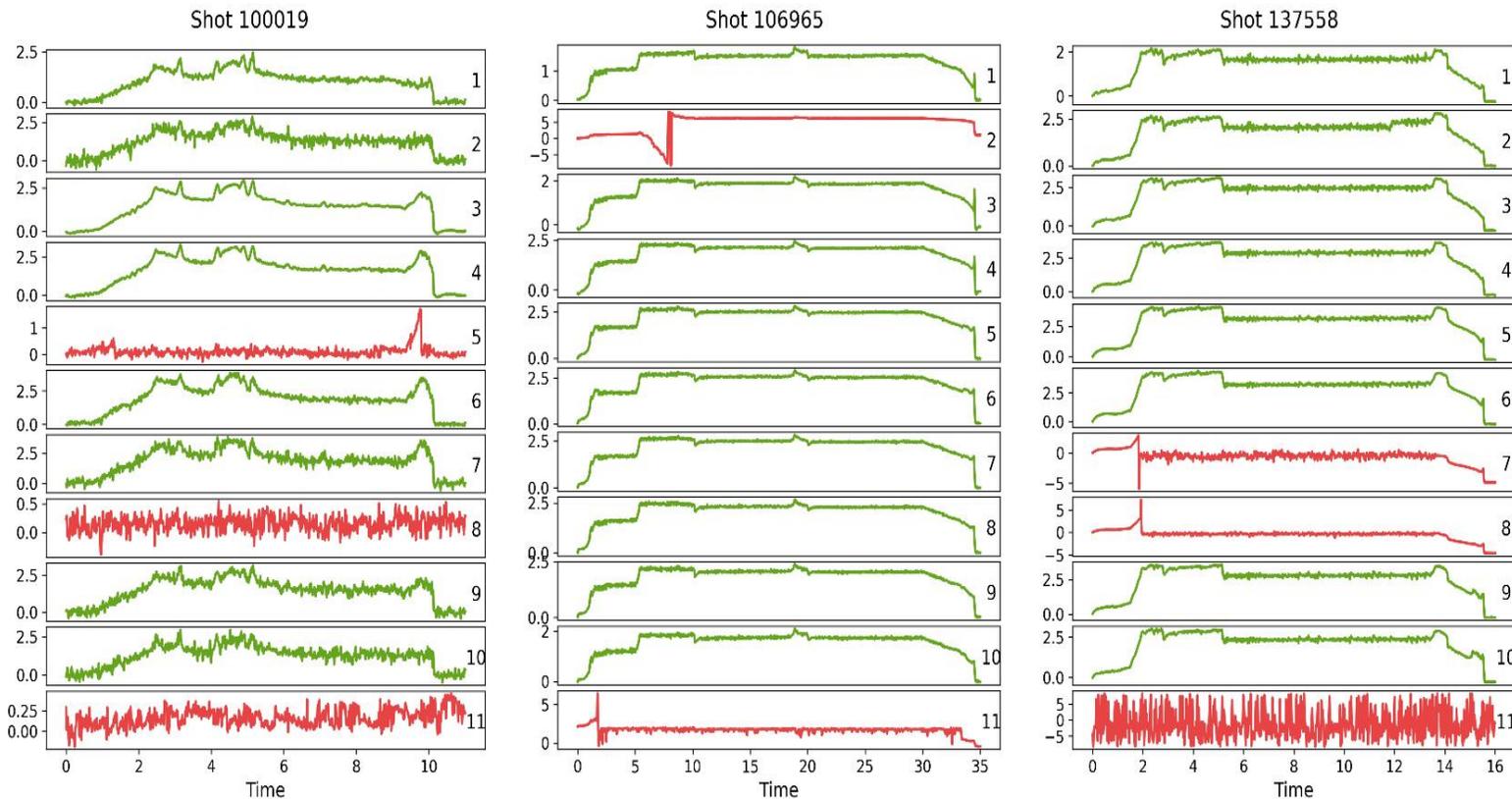


### 常见脏数据包括：

- 数据缺失
- 异常值
- 信噪比低
- 错误标注
- 时间错位

# EAST实时数据清洗

## EAST弦积分密度数据

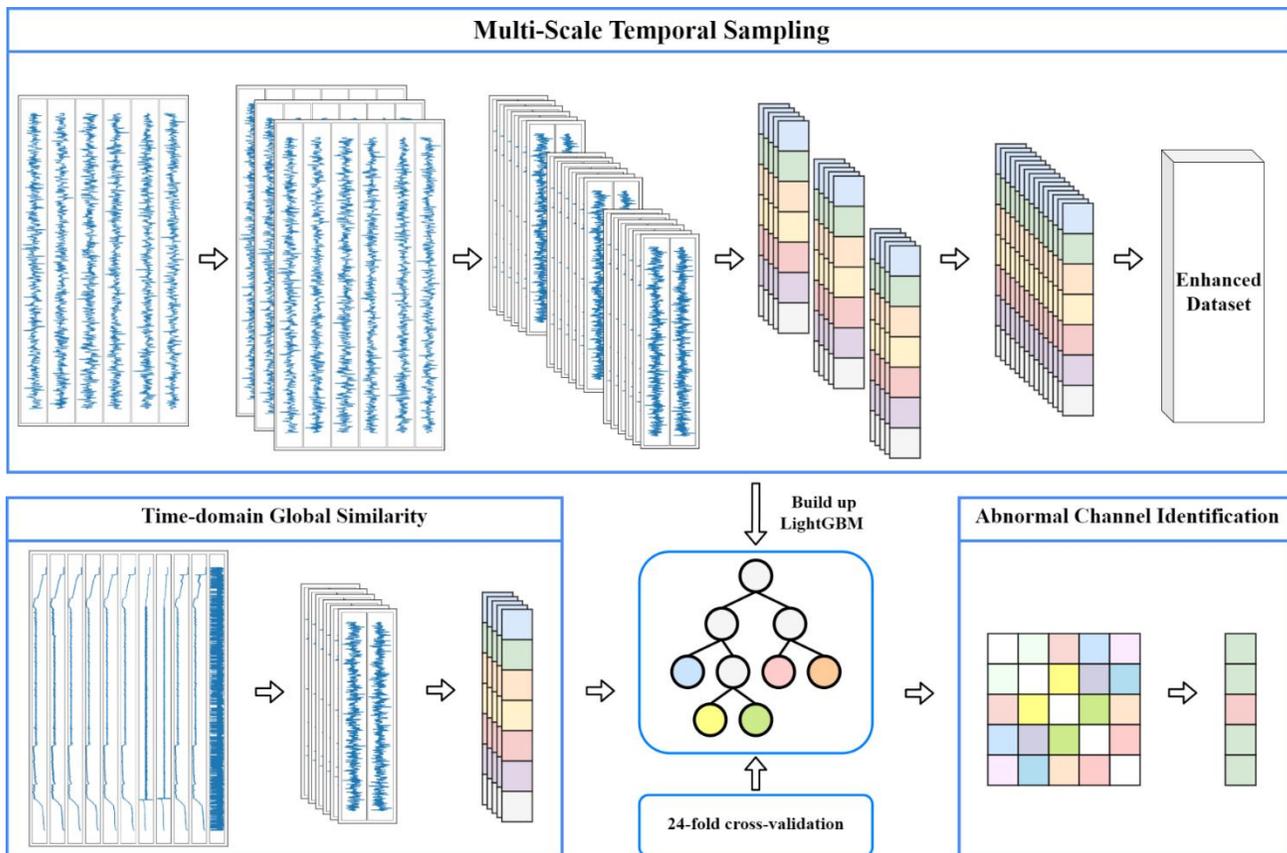


输入：整炮的数据； 输出：数据相似性

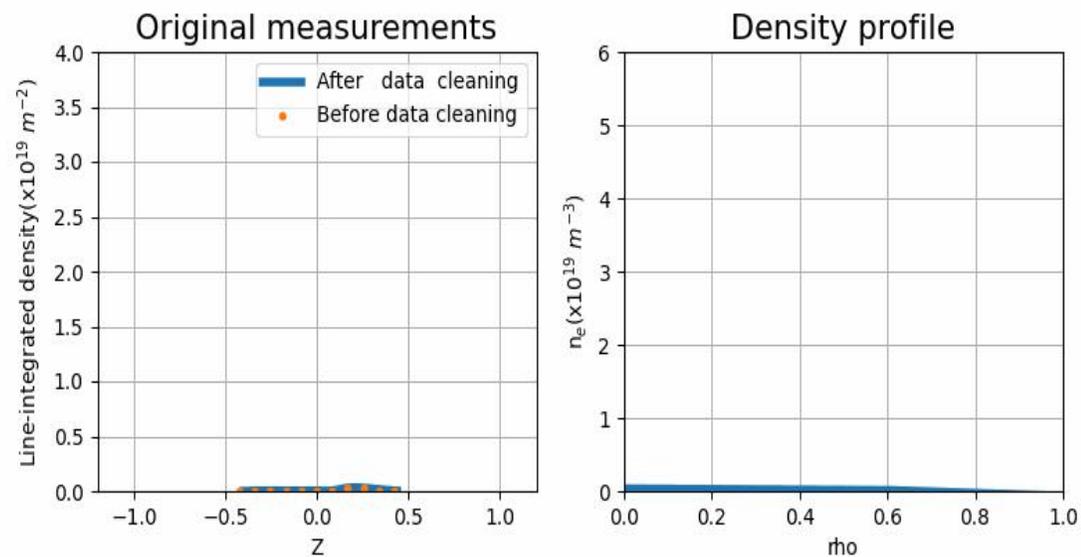
➔

数据正确性

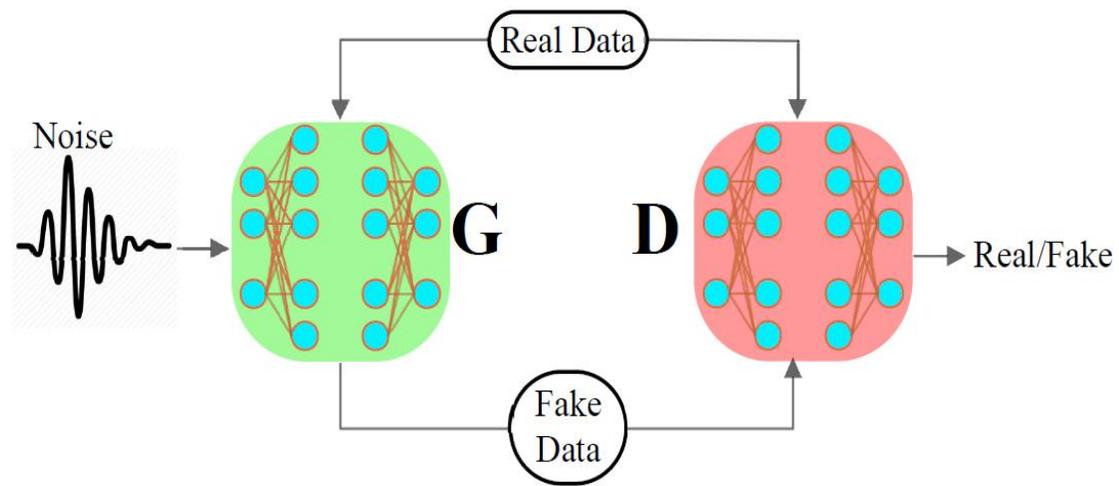
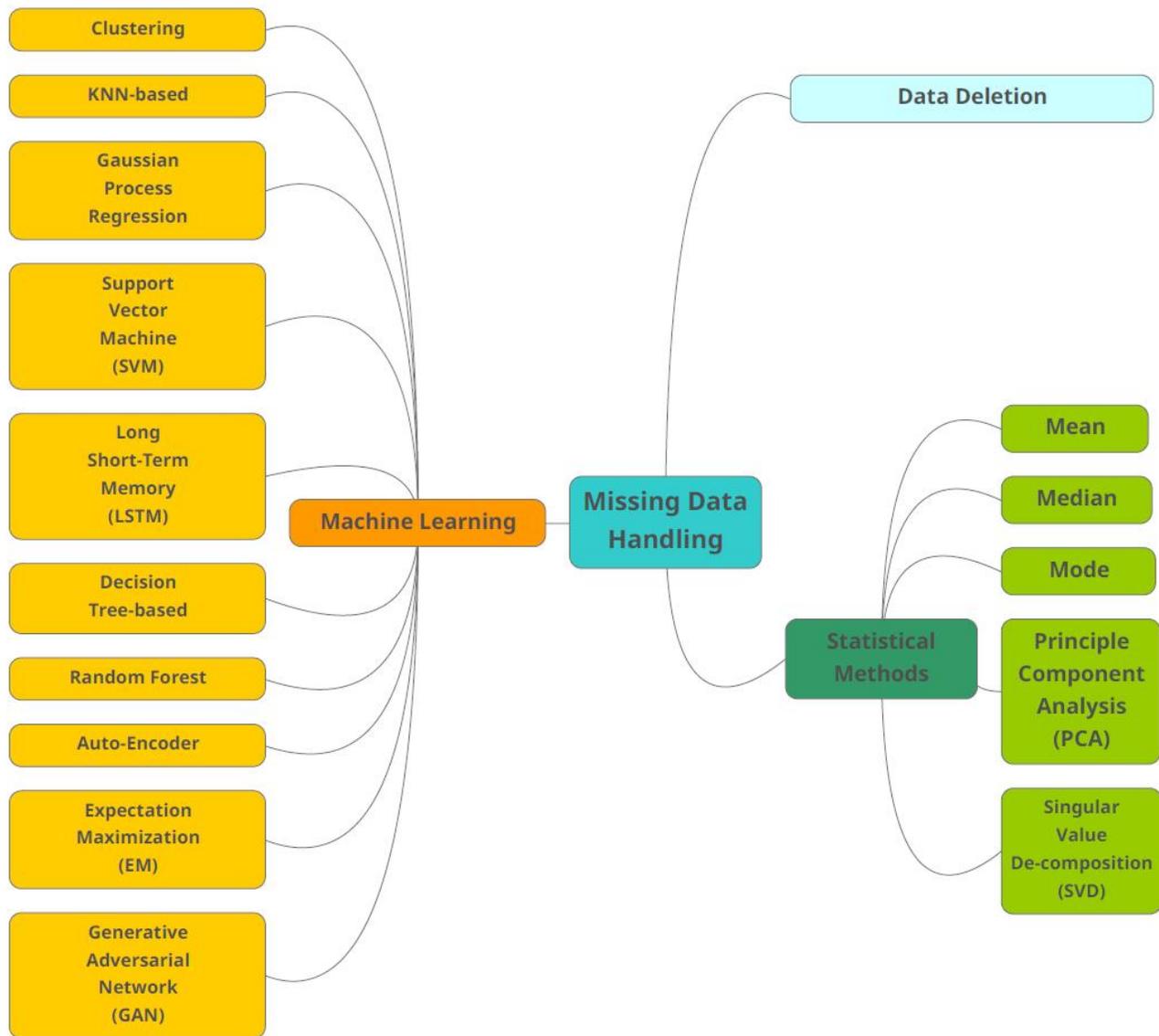
## RT-TDGS (Real-Time Time-domain Global Similarity) 方法



Results of 99997 @ -0.97 s.



# 数据补全



Shahbazian R. Information 13.12 (2022): 575.

# 验证、确认以及不确定性量化分析 (VVUQ)

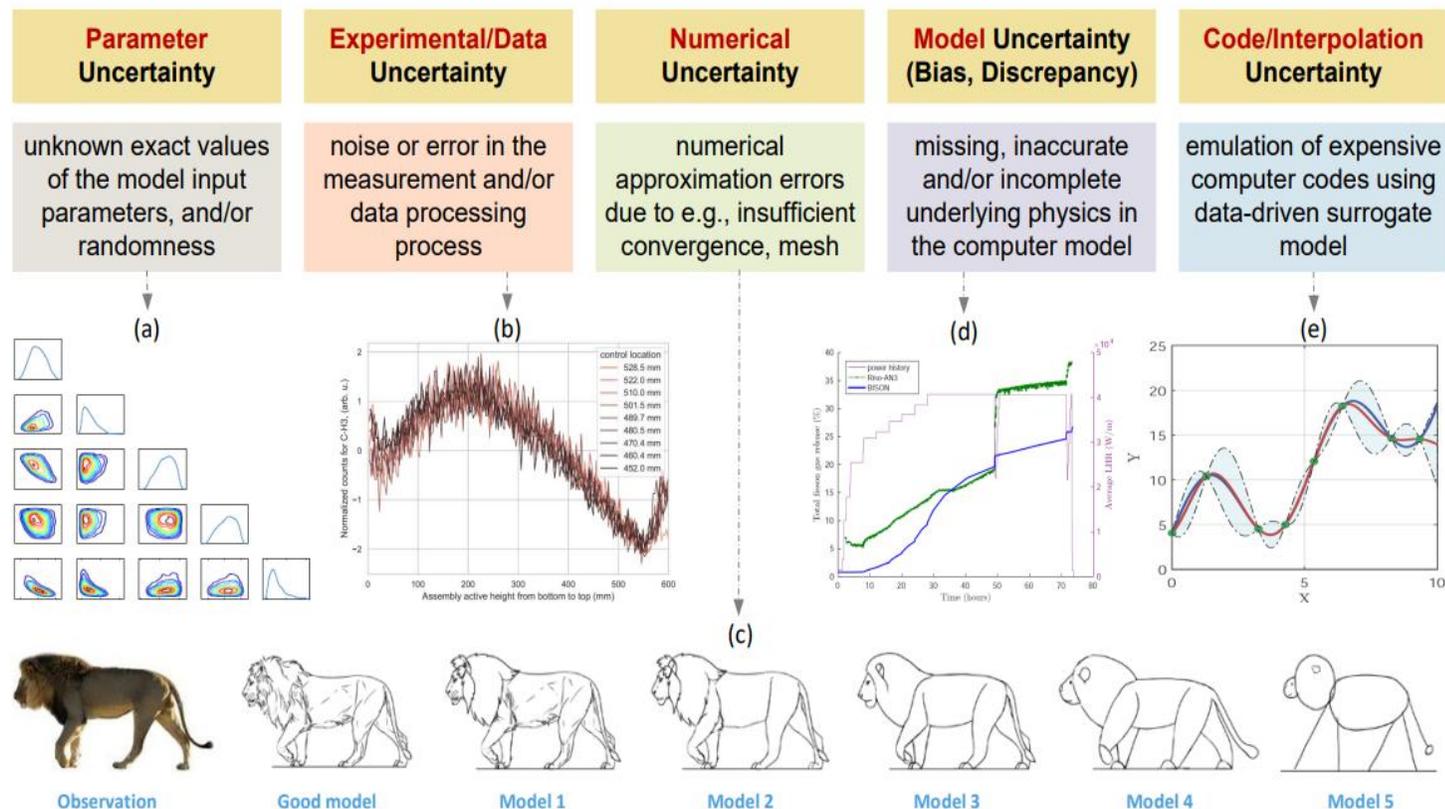
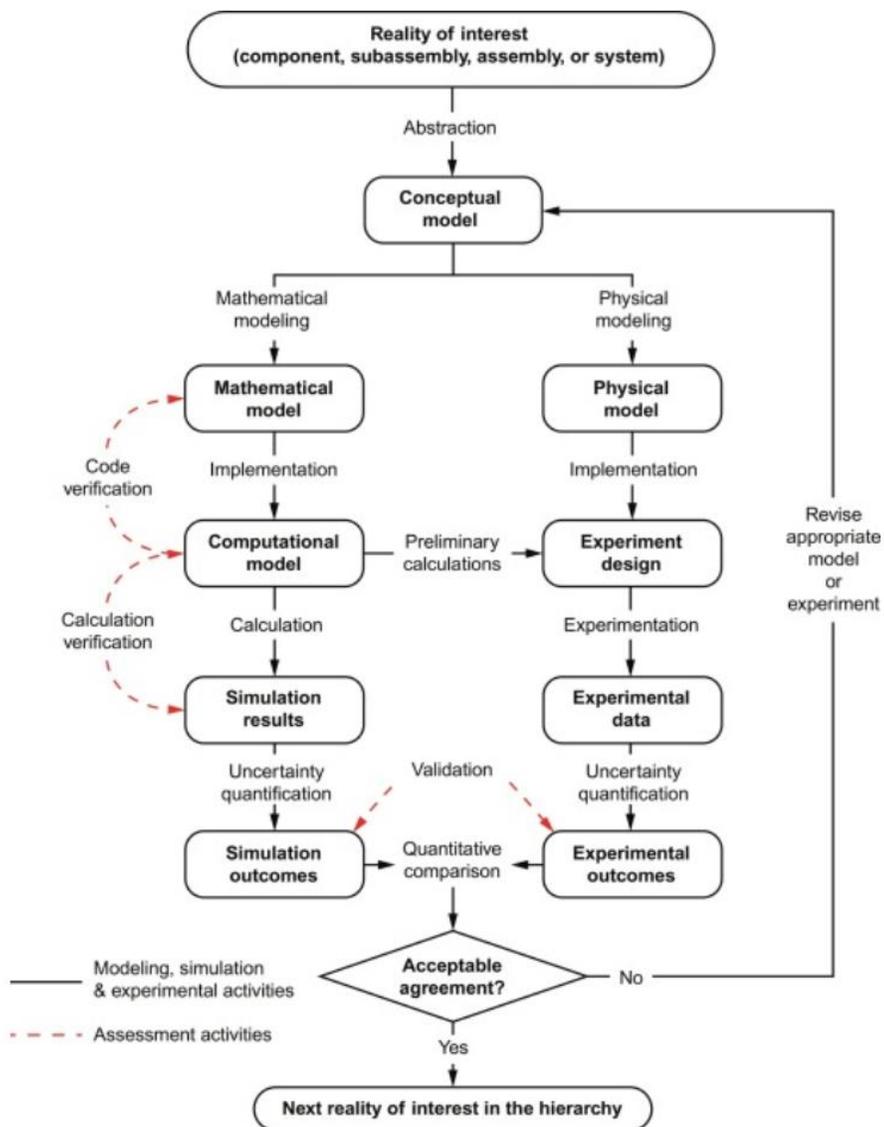


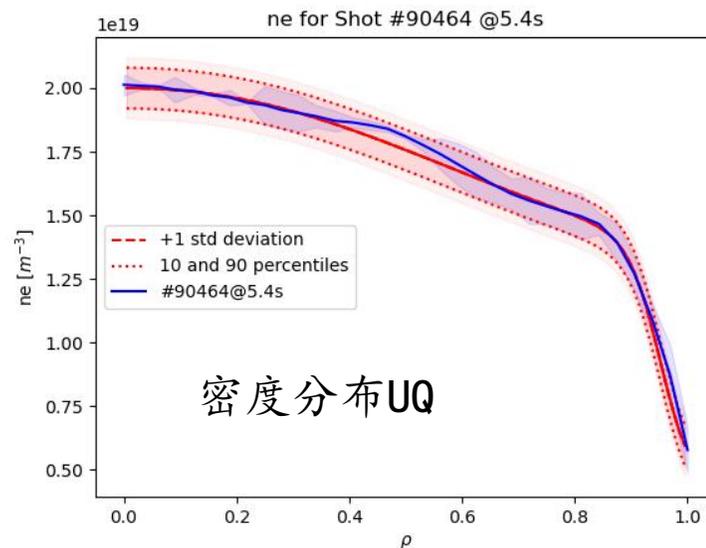
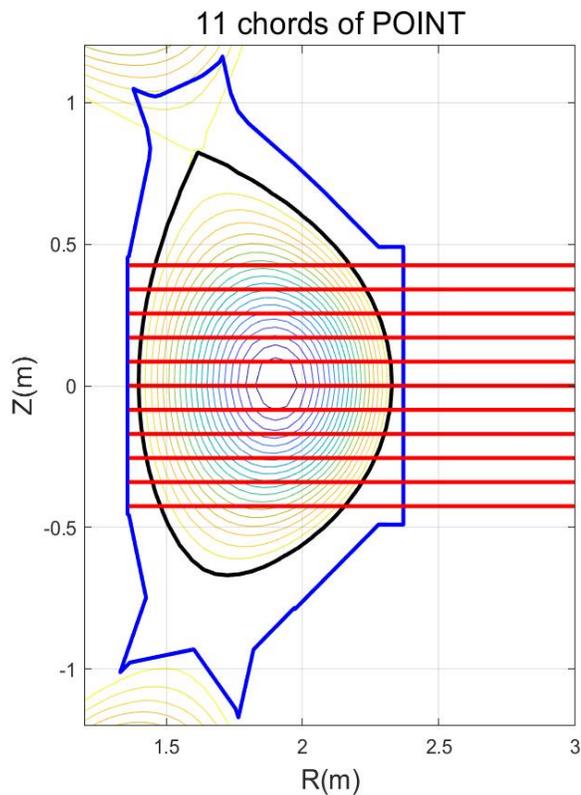
Figure 1: Illustration of uncertainty sources in physics-based M&S.

Wu, Xu. ArXiv:2503.17385 (2025).

# POINT 系统VVUQ

从POINT系统**诊断原理**（物理）、**工程设计**、原始及最终处理的**实验数据**、**理论模拟**数值（修正的双曲正切模型）对诊断进行认证、确认和不确定度（VVUQ）分析：

- 检验：通过代码三步检测进行代码质量评估，同时对代码功能进行检测，测试计算结果。
- 模型与实验结果确认：计算模拟结果与实验数据的置信度、相似度，确认模型的可用性。
- 量化：通过对系统原理、工程设计、实验环境、数据分析代码的评估，确认不确定度来源。



置信度: 99.5% (JS散度计算)。  
 相似度:  $\geq 97.5\%$  (芯部),  $82.5\%$  (边界)。  
 通过添加边界反射计数据, 边界不确定度可达90%以上  
 确认过程不确定度: 3.12%, 来自模拟。

**POINT系统不确定度: 6.17%**;  
 2.99%, 来自数据处理,  
 3.18%, 来自工程设计。

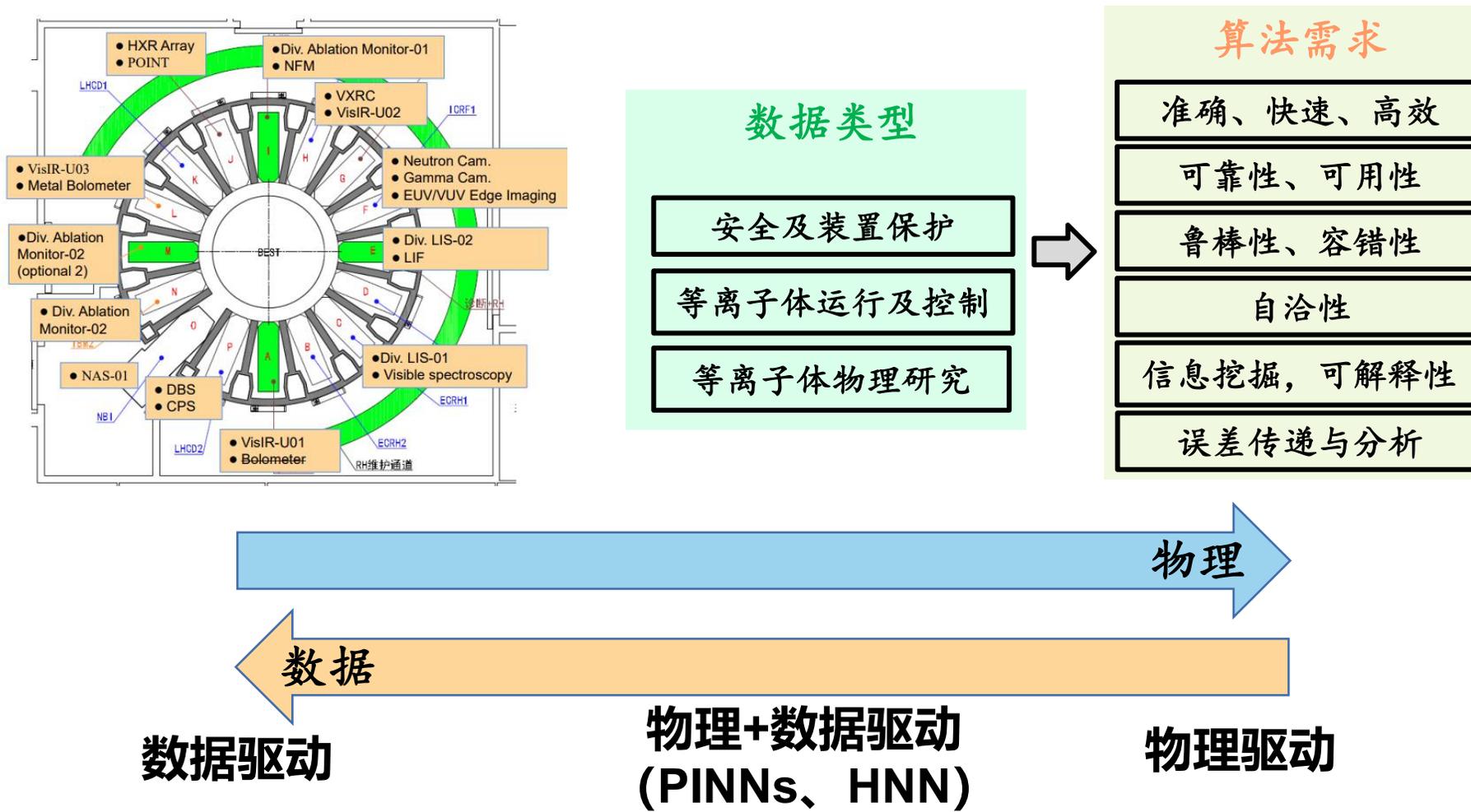
POINT系统现存不确定度:

不确定来源	振动	频率变化	折射效应	有限温度效应	样条插值
不确定度	1.0%	0.28%	0.4%	1.5%	2.99%

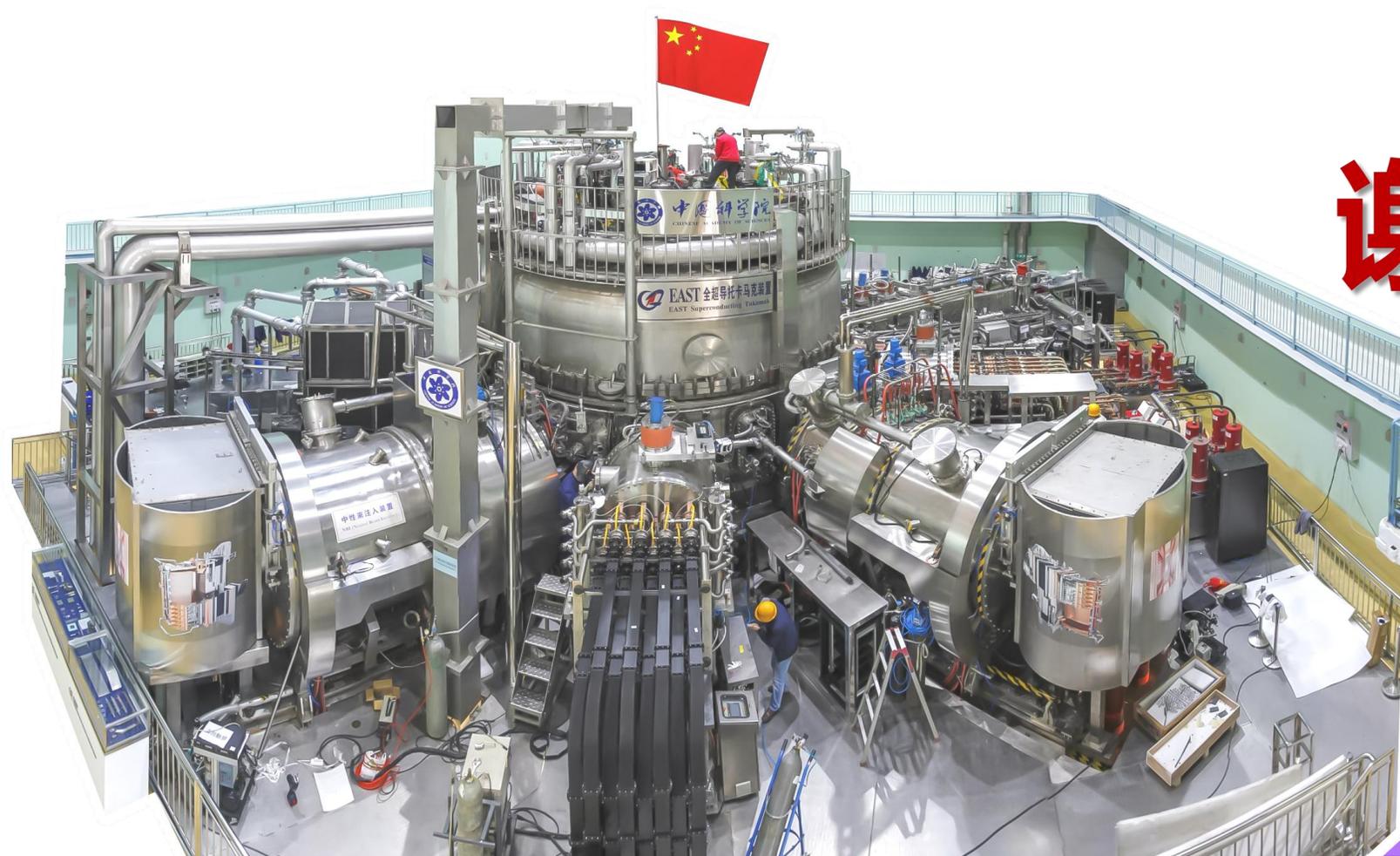
# 总结

- 测量不确定性给诊断可靠性和运行决策可靠性带来风险，可采用多诊断系统数据融合、不确定性量化来降低测量不确定性带来的风险。
- 贝叶斯推断及深度学习在准确性、处理速度、训练成本等方面各有优缺点，须根据聚变装置具体应用场景选择合适的数据融合方法。
- 各种融合方法对数据中的错误或者无效数据都比较敏感，有必要在数据融合前进行数据清洗。
- 通过VVUQ可量化实验、模拟不确定度，提高实验与模拟自洽性、可解释性。

# 聚变堆多模态诊断数据智能化挖掘



将物理规律与AI技术相结合, 提高AI模型泛化能力、增强对物理规律的理解



谢谢各位!

