FusionMAE: large-scale pretrained model to optimize and simplify diagnostic and control of fusion plasma

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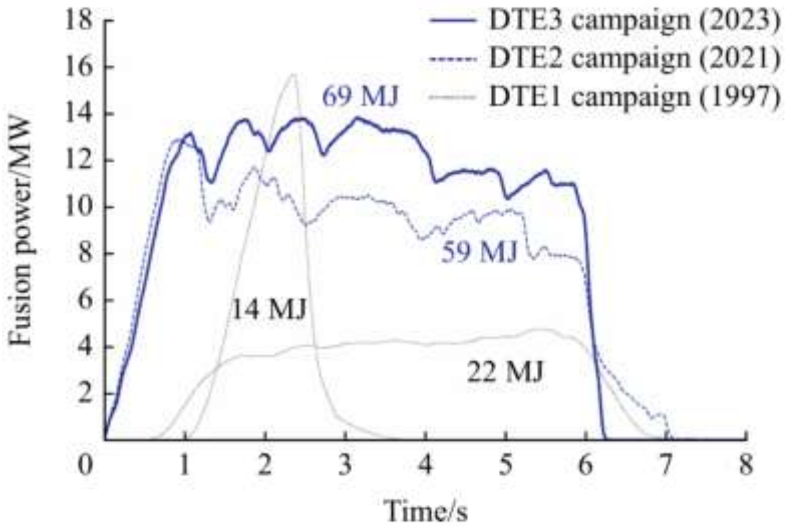
Outline

Background

- **The scientific feasibility of fusion energy has already been demonstrated.**
  - JET set a world record by producing 59 megajoules of fusion energy over a 5-second pulse.
- **However, the engineering feasibility of fusion continues to face significant challenges.**
  - ITER, one of the largest international scientific projects, involves collaboration among over 30 countries.
  - Its complexity is evident in various aspects, such as the integration of approximately 50 different plasma diagnostic systems and 70 sets of control actuators.

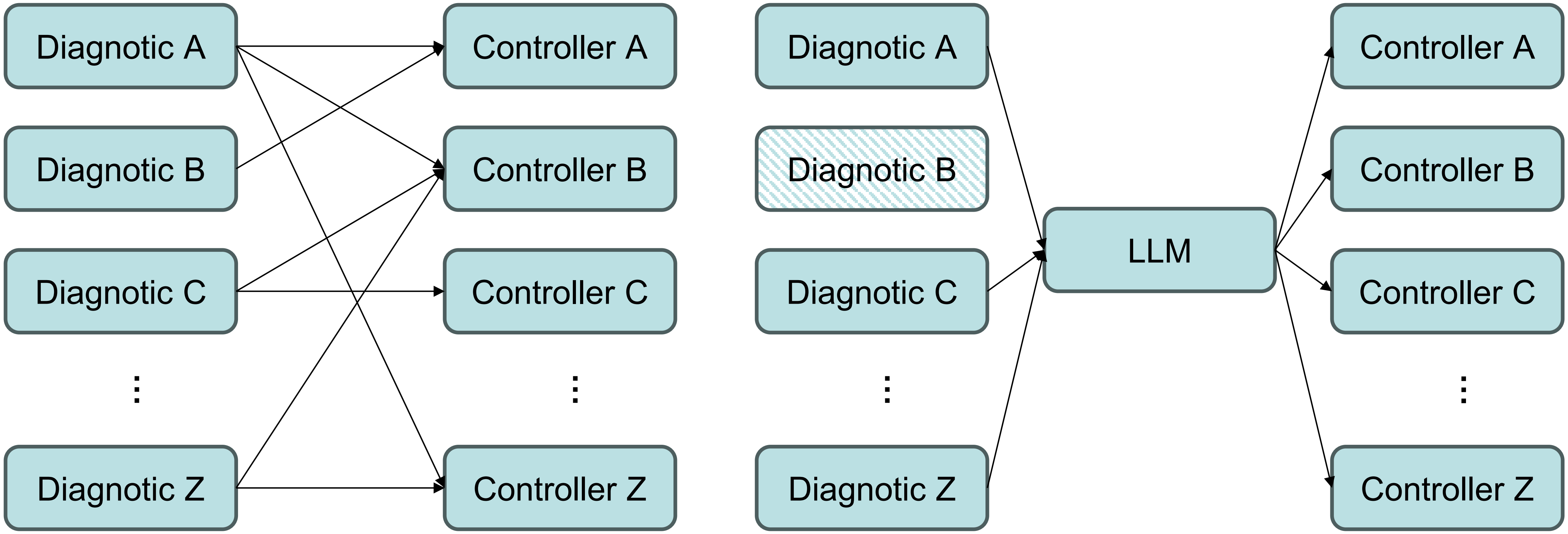


Fusion power obtained during JET DTE

The conceptual diagram of the ITER

Background

- Large language models (LLM) have become a key tool for tackling highly complex tasks.
- We have seen many successful AI4Fusion applications—yet all rely on small-model paradigms.
- Can we leverage LLM's paradigm to analyze fusion experimental data and simplify device design?



Outline

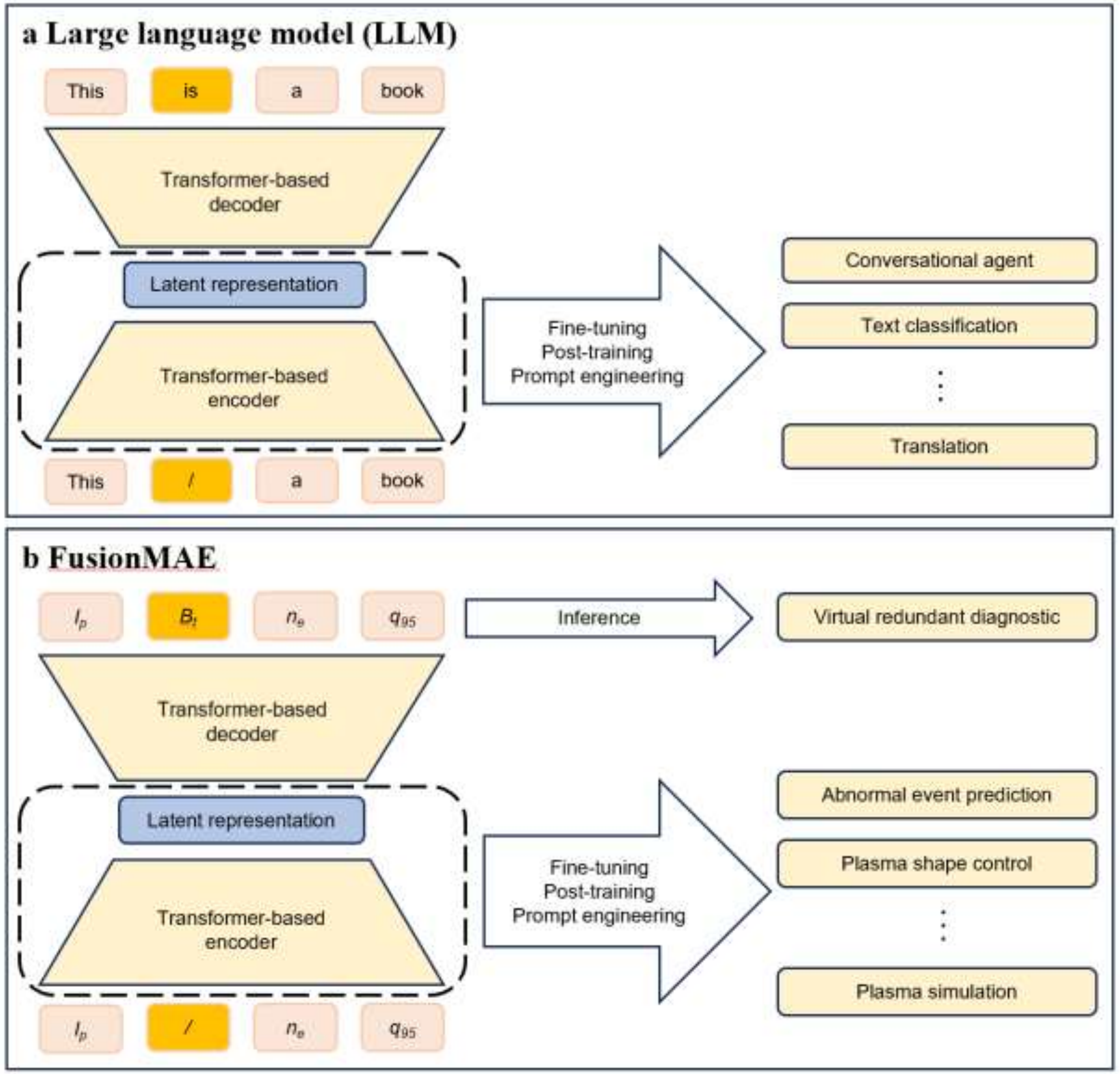
FusionMAE vs LLM

Large language model (LLM)

- Learn general knowledge and basic grammar by generative pre-training
- BERT is pretrained by filling masked words
- GPT is pretrained by predicting the next word
- LLM can be used in language downstream tasks and promote their performance

Fusion masked auto-encoder(FusionMAE)

- Learn basic plasma physics by filling missing diagnostic data
- FusionMAE itself can serve as virtual redundant diagnostic in future reactors
- FusionMAE can be used in fusion downstream tasks and promote their performance



Dataset of FusionMAE

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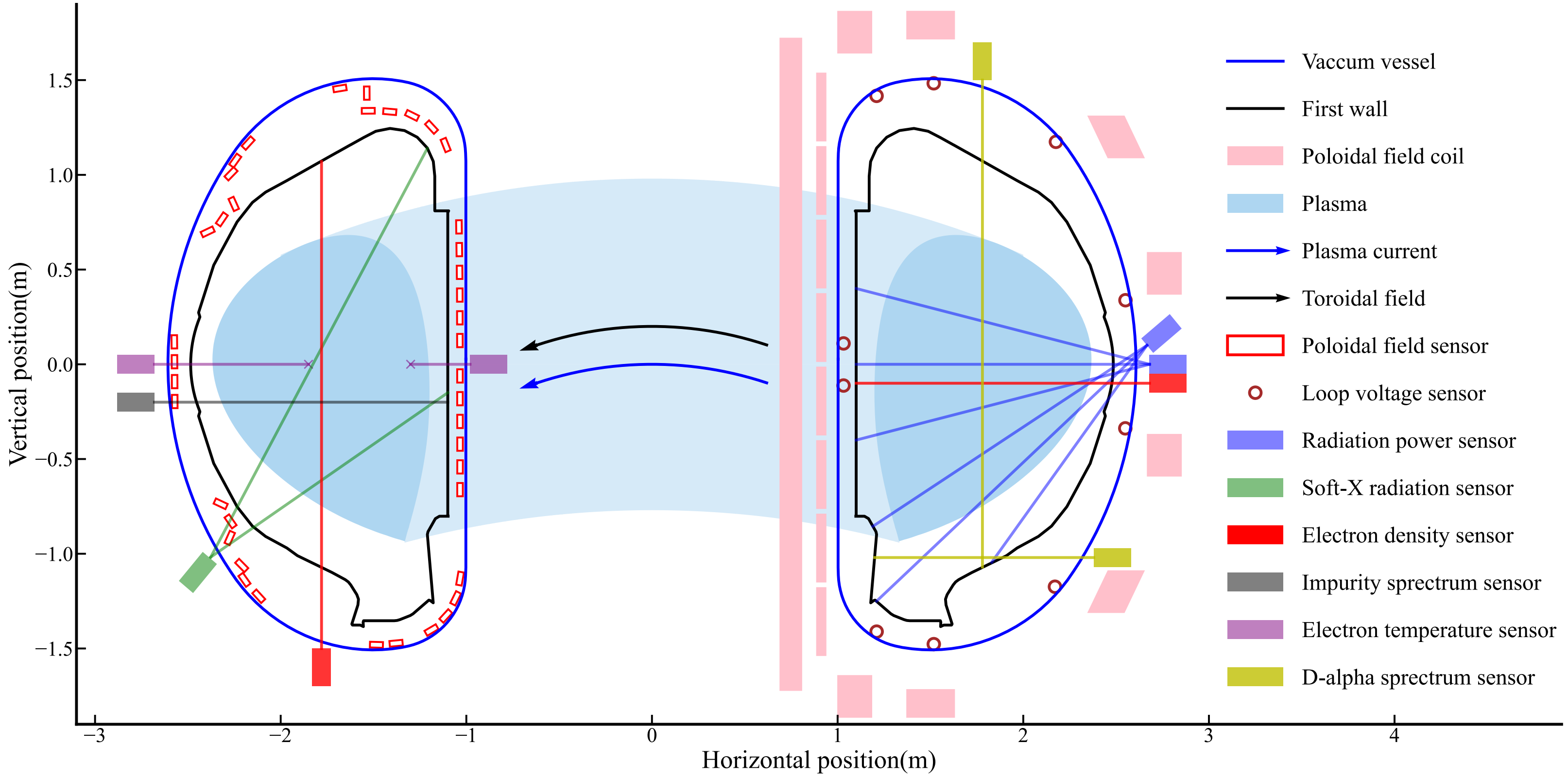
- 88 channels from 12s set of different diagnostic system in HL-3
- All the experimental data of HL-3 are used, 1950 valid shots for training and validation, 495 shots for testing



Channel name	Data health rate
I_p	100%
R	90.9%
Z	90.9%
a	90.9%
κ	90.9%
δ_u	90.9%
δ_l	90.9%
B_t	99.7%
B_p	99.8%
V_{loop}	100%
n_e	64.4%
T_e	57.3%
W_e	90.9%
P_{rad}	63.2%
SX	78.7%
D_α	74.3%
A_{MHD}	93.1%
A_{imp}	64.7%
β_N	90.9%
q_{95}	90.9%
l_i	90.9%
I_{PF}	99.9%
I_{CS}	99.9%
P_{NBI}	99.9%
P_{EC}	98.7%
P_{LH}	98.6%

Self-supervised pretraining

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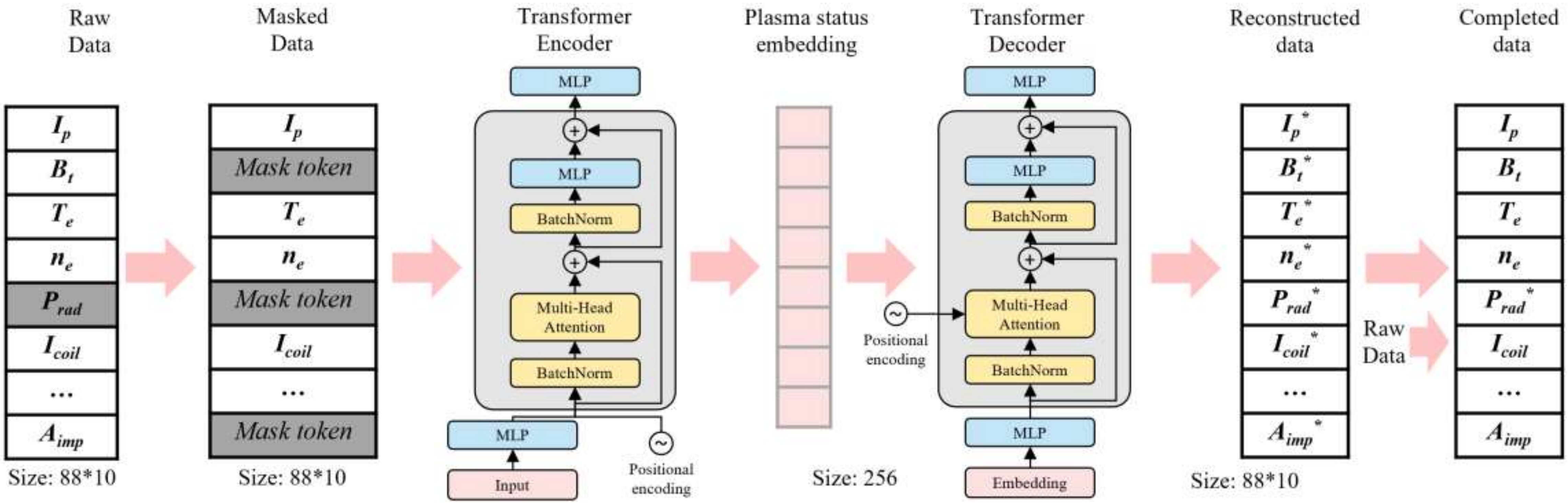
■ **Based on the classical Masked Auto-Encoder framework (Kaiming He, et al, 2021)**

- A 10ms window of diagnostic data is treated as one <token> (sample rate: 1kHz)
- Some diagnostic data are naturally invalid, they will be replaced by <mask token>
- Valid tokens are randomly masked at 25% ratio and used as training labels for FusionMAE



AE loss and MAE loss

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Two Mechanisms Drive Multi-Diagnostic Data Fusion

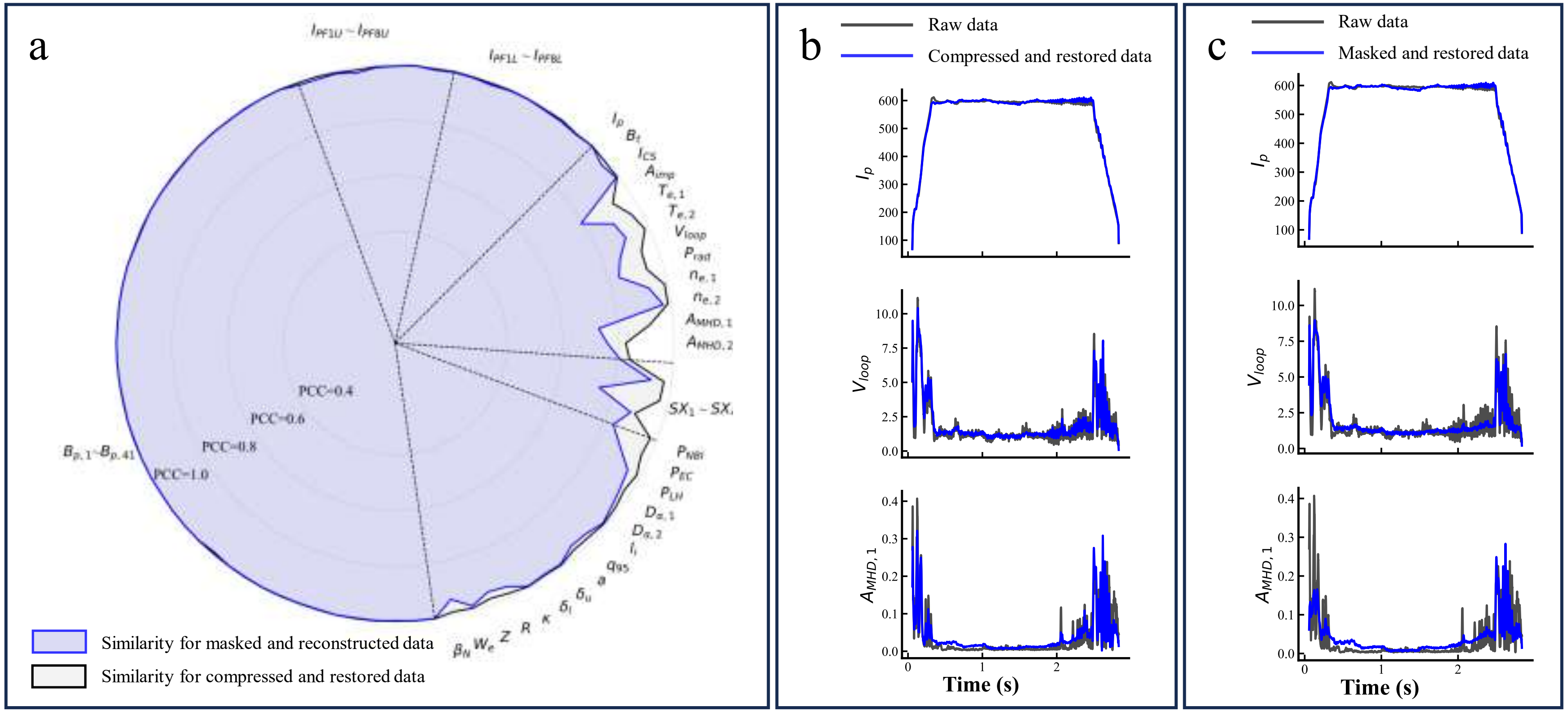
- **Compression**: Raw 88×10 matrices are compressed into 256-length vectors, forcing structured feature fusion to preserve reconstructability → **AE loss** between reconstructed data and unmasked data
- **Cross-Complementarity**: Partially masked data forces the network to recover missing values, learning inter-signal correlations→ **MAE loss** between reconstructed data and masked data

Training target

- min(0.2 * AE loss + MAE loss)

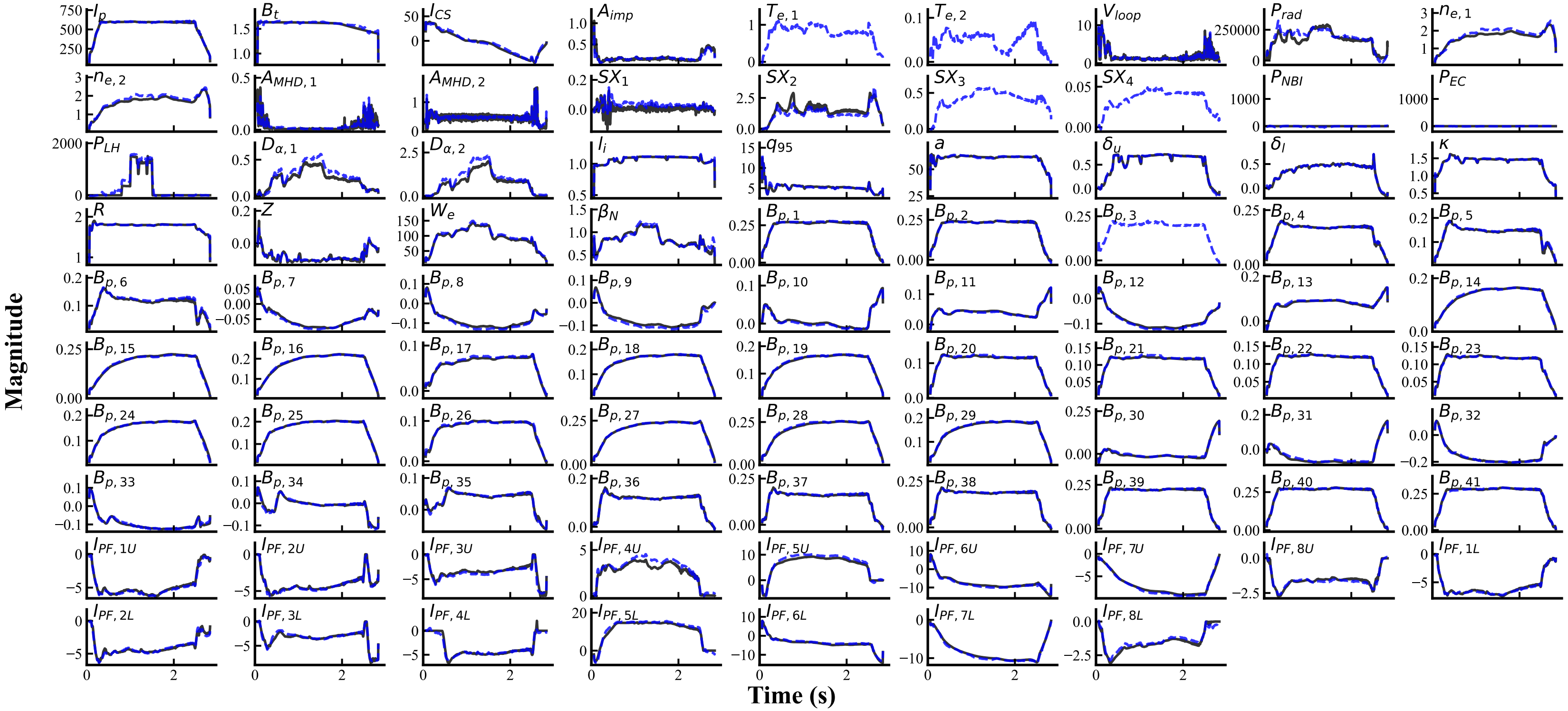
Model performance

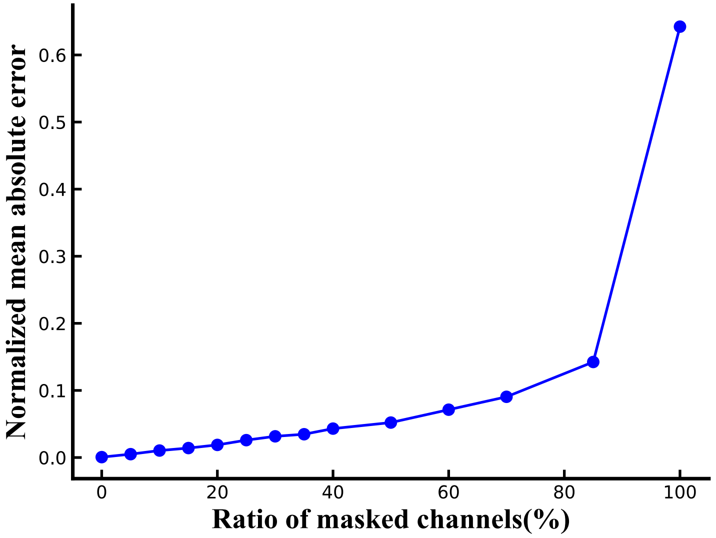
- AE similarity: 98.4%
- MAE similarity: 96.7%



AE loss and MAE loss

- **Fullfill all the missing data under randomly missing situations, unless the ratio of missing is too high**



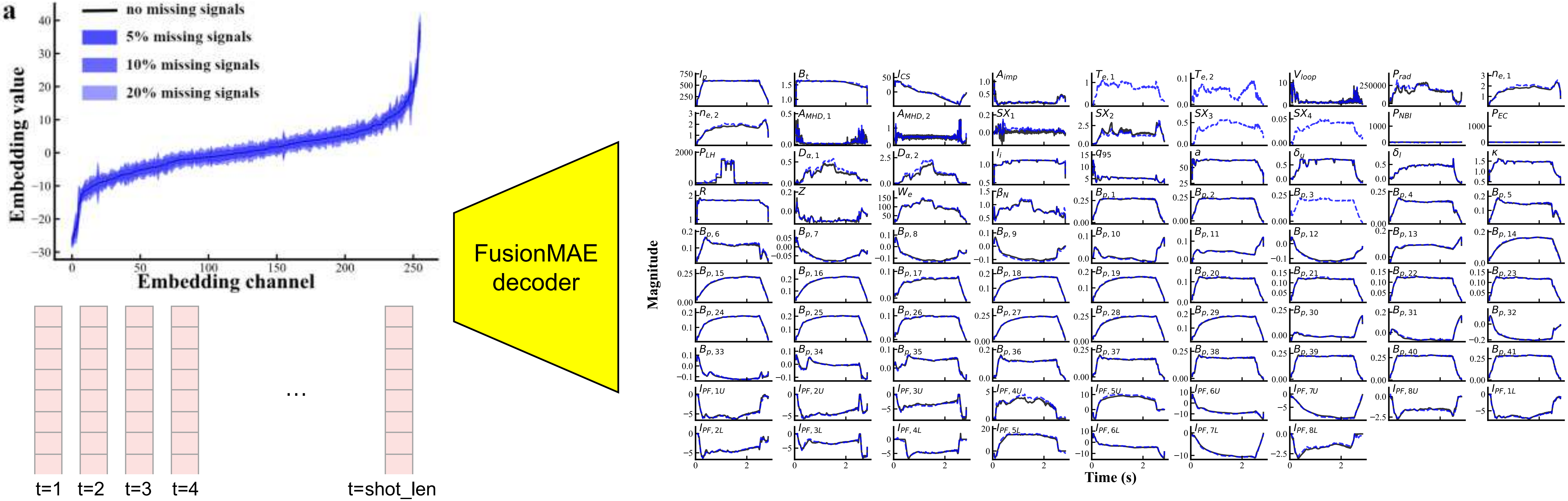


Outline

- Introduction
- FusionMAE: self-supervised pretraining model for fusion
- Plasma embedding given by FusionMAE
- Emergent capabilities of FusionMAE
- Summary

Self-consisted representation of plasma status

- All information are fused into a concrete vector: **plasma embedding**
- Different set of diagnostic generates similar plasma embedding. And less diagnostic brings more uncertainty for plasma embedding estimation

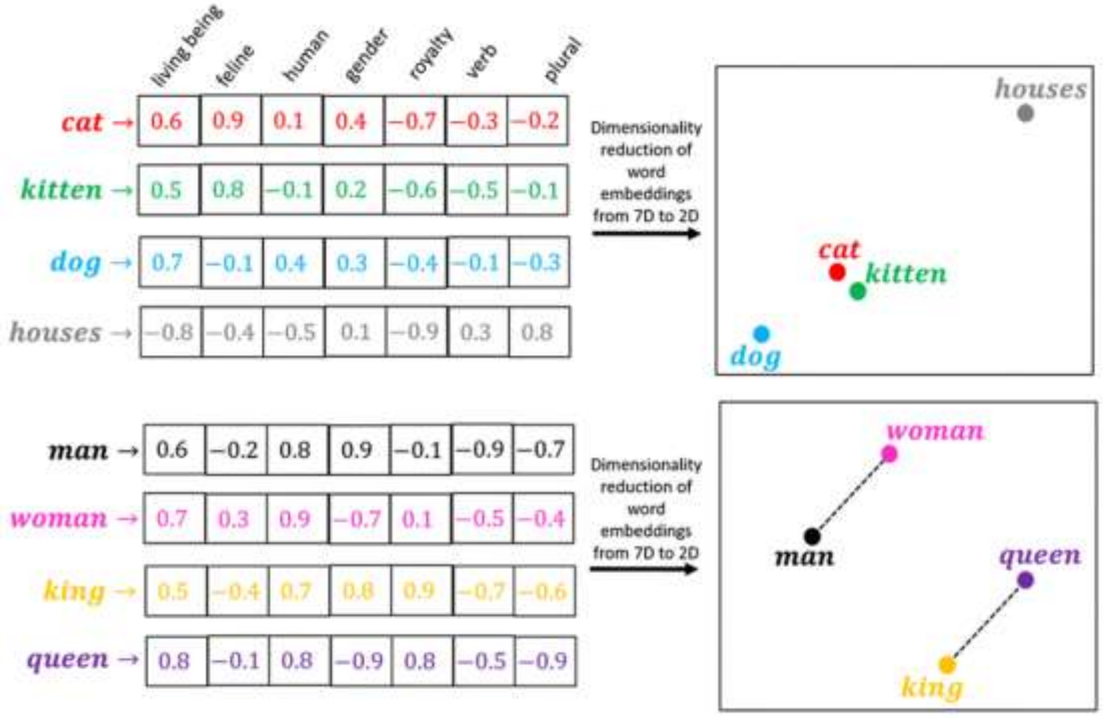


Plasma embedding

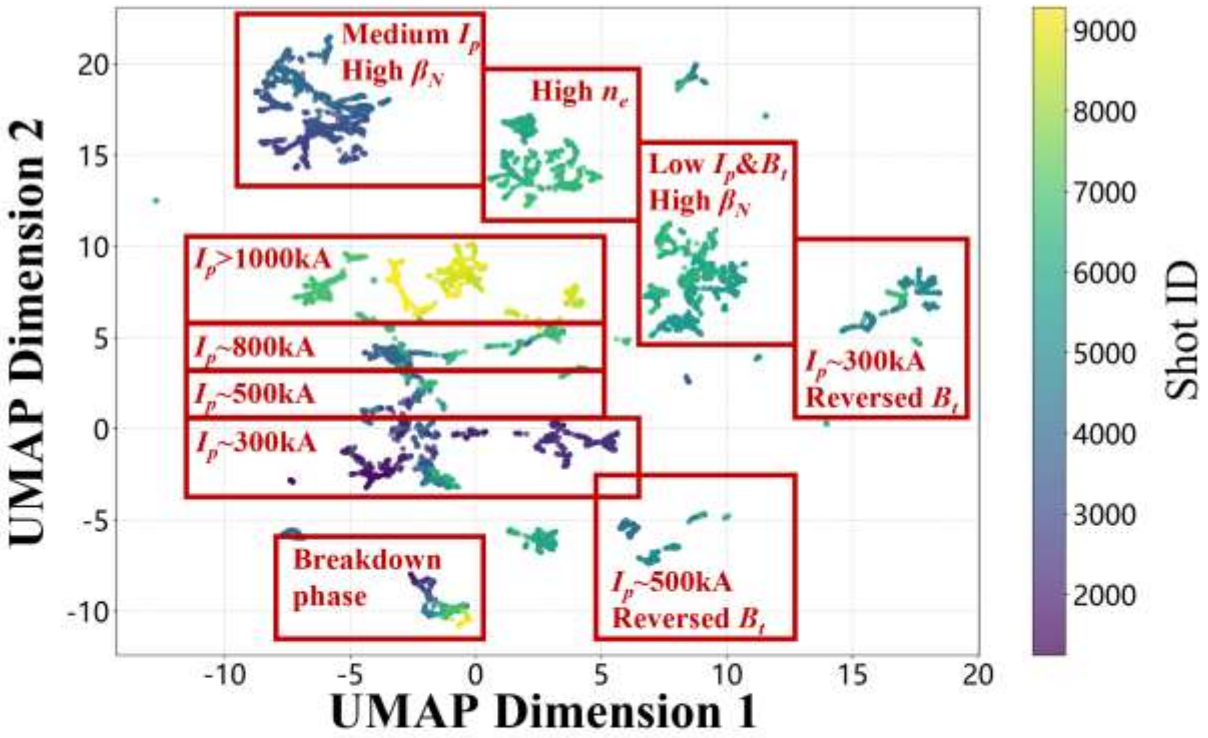
Plasma embedding vs word embedding

■ Plasma embedding exhibits vector space properties similar to word embeddings

- Plasmas with similar properties yield closely clustered embedding representations
- During training, all 88 signals are processed equivalently, yet the model autonomously identifies I_p, β_N, n_e, and B_t as key indicators for plasma "similarity"



Word embedding for LLM



HL-3 discharge embedding from FusionMAE

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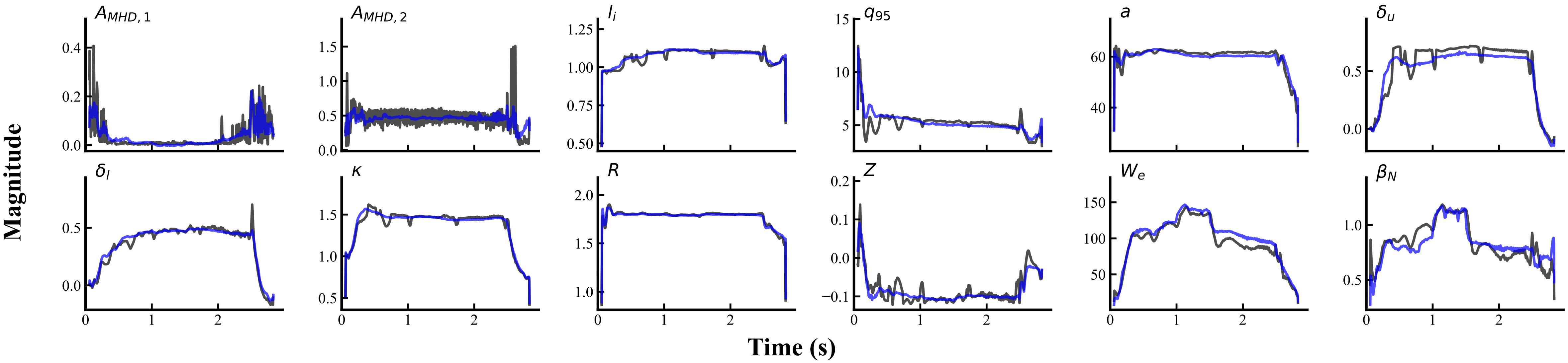
Automatic data analysis

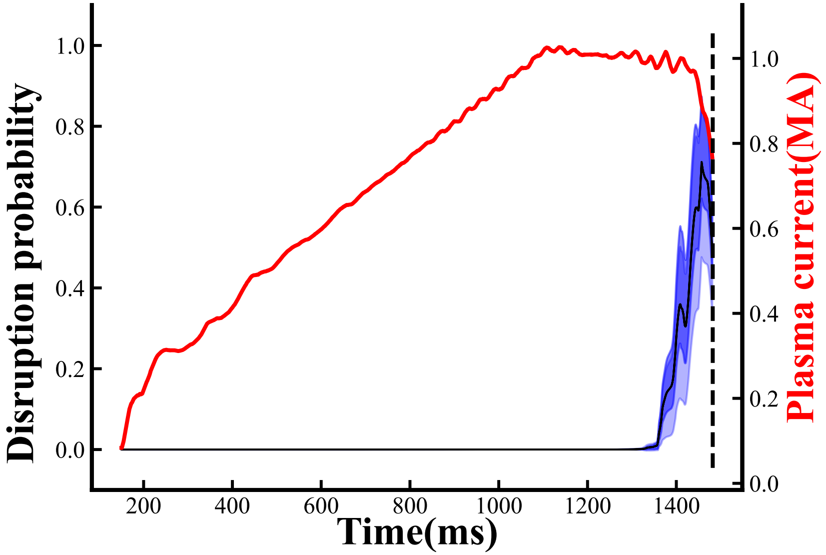
■ Automatic data analysis like by ‘restoring missing secondary data’

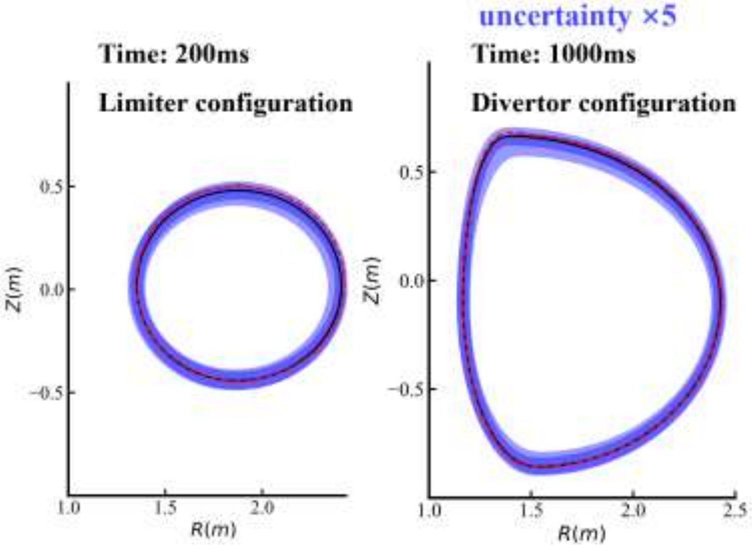
- Key secondary data (equilibrium, stored energy, MHD) across all 88 input channels are masked and restored by FusionMAE
- FusionMAE’ s output achieves high consistency with manual data analysis results
- The model has successfully learned the underlying principles of fusion data analysis

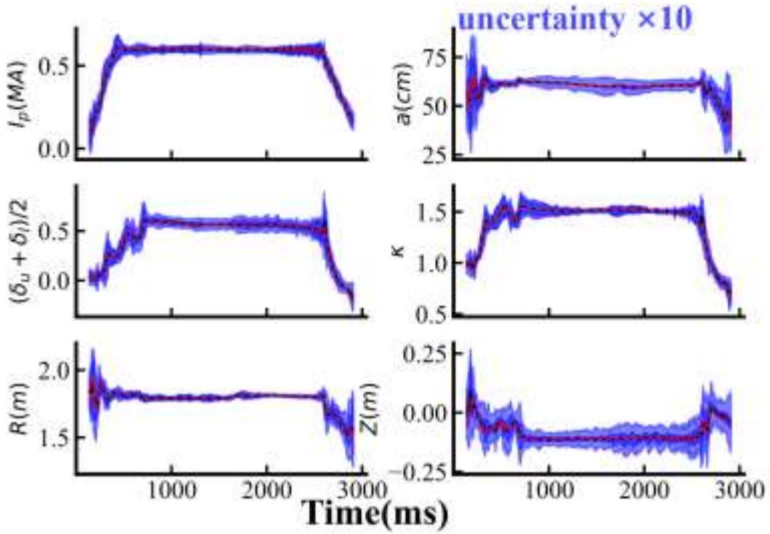


Benefit all downstream tasks

- **DPR: Disruption prediction** 83% ›› 91%
- **EFIT-NN: surrogate model for equilibrium fitting** 90% ›› 95%
- **PPR: data-driven plasma evolution prediction** 91% ›› 98%





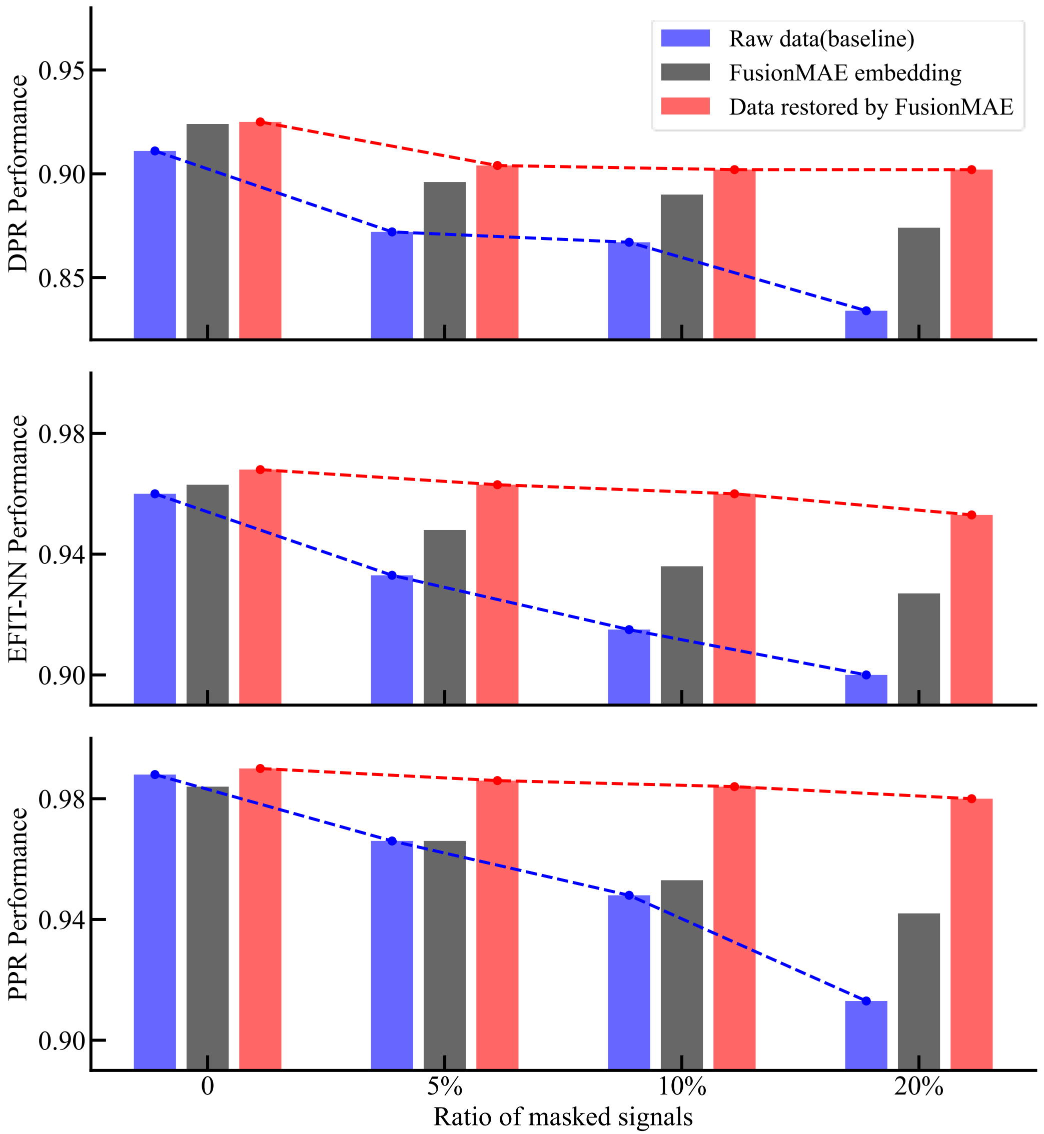


Robust control against missing signals

■ FusionMAE Maintains Downstream Task Performance with Missing Diagnostics

- Demonstrates robust performance even with partial diagnostic input
- Performance degradation is significantly slower compared to specialized small AI-models

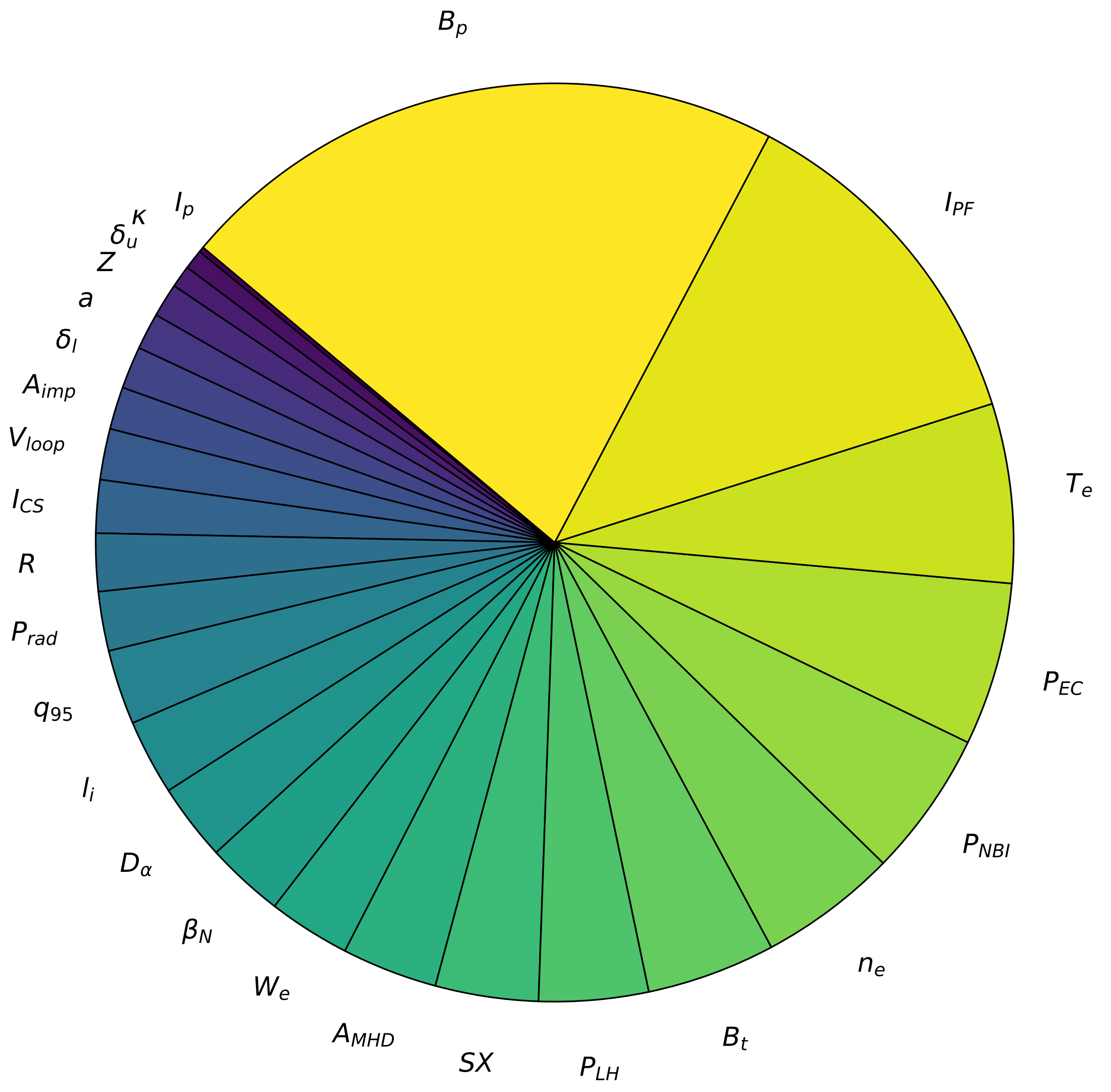
- **Blue:** specialized small AI-model trained on raw data
- **Gray:** FusionMAE encoder + several MLP layers
- **Red:** specialized small AI-model trained on data completed by FusionMAE



Diagnostic contribution analysis

- **Evaluating Diagnostic Contribution**
  - The contribution of a diagnostic channel is measured by its impact on the plasma state vector when removed
  - Significant change in the state vector indicates high importance of the diagnostic

$$contribution(i) = \frac{1 - PCC^*(i)}{\sum_{j=1}^{88}(1 - PCC^*(j))}$$



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FusionMAE: GPT1.5 for fusion

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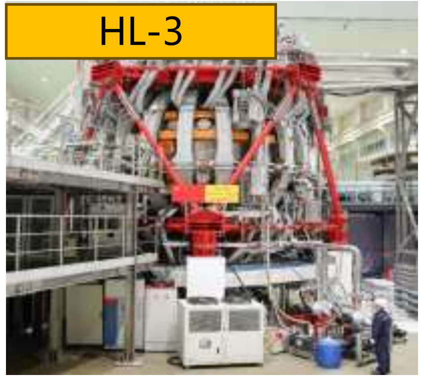
■ Innovative large-scale pretrained model for fusion data

- FusionMAE learns basic plasma physics by inferring missing signals across 88 diagnostic channels with 96.7% reliability
- The model exhibits emergent abilities akin to foundation models in HL-3:
  - ➢ Automated secondary data analysis
  - ➢ Unifying the interface between control and diagnosis in fusion device
  - ➢ Serving as a foundation model for diverse downstream control tasks
  - ➢ Holistic performance improvements across all supported task



■ Transformative Potential for Fusion Reactors

- Reduce the number of required diagnostics
- Achieve more compact designs and lower costs
- Benefit all AI4Fusion applications as a foundation model

More device!

Thank you for your attention