GyroSwin: 5D Surrogates for Gyrokinetic Plasma Turbulence Simulations

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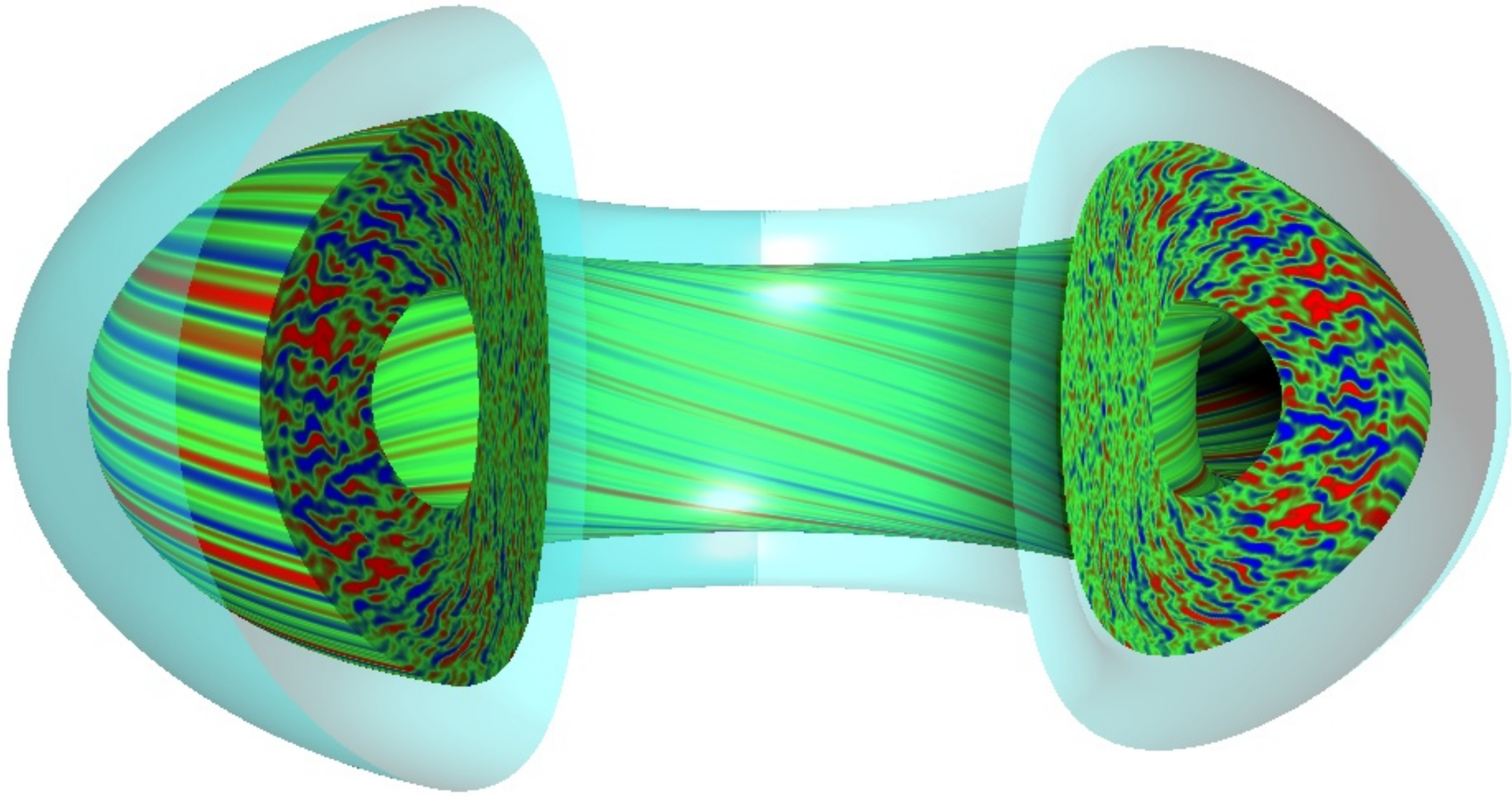
Plasma Turbulence

- Turbulence arises due to micro-instabilities in plasma (Francis F. Chen, 2016)
  - Leads to particle and energy transport (Romanelli et al. 2014)
  - Causes plasma to leak out of its magnetic cage => needs to be controlled!
  - To be able to control it, we first need to be able to simulate it!



Source: https://w3.pppl.gov/~hammett/viz/viz.html

Modeling Plasma Turbulence

- Described via nonlinear Gyrokinetic equations (Peeters et al. 2009)
  - Evolve a 5D (2x velocity, 3x spatial) distribution function over time
  - Numerically solving those equations can take months!
- Practitioners rely on reduced numerical solutions without nonlinear term (Bourdelle et al. 2007)

$$\underbrace{\frac{\partial f}{\partial t} + (v_{\parallel}\boldsymbol{b} + \boldsymbol{v}_D)\cdot\nabla f - \frac{\mu B}{m}\frac{\boldsymbol{B}\cdot\nabla B}{B^2}\frac{\partial f}{\partial v_{\parallel}}}_{\text{Linear}} + \underbrace{\boldsymbol{v}_{\chi}\cdot\nabla f}_{\text{Nonlinear}} = S$$

Motivation

- Quasilinear approximations (Bourdelle et al. 2007, Staebler et al. 2007)
  - Are based on linear simulations (3D) + saturation rules => not general (Giacomin et al. 2024)
  - Neglect nonlinear phenomena (zonal flows) => severely affect emerging turbulence

- Can we build a **scalable surrogate model** for 5D plasma turbulence modelling?

GyroSwin

- 5D local window attention (Liu et al. 2021)
- Multitask learning
    - 5D distribution function
    - 3D electrostatic potential fields
    - Scalar heat flux time trace
- Inductive Biases
    - Channelwise mode separation
    - Latent integral modules

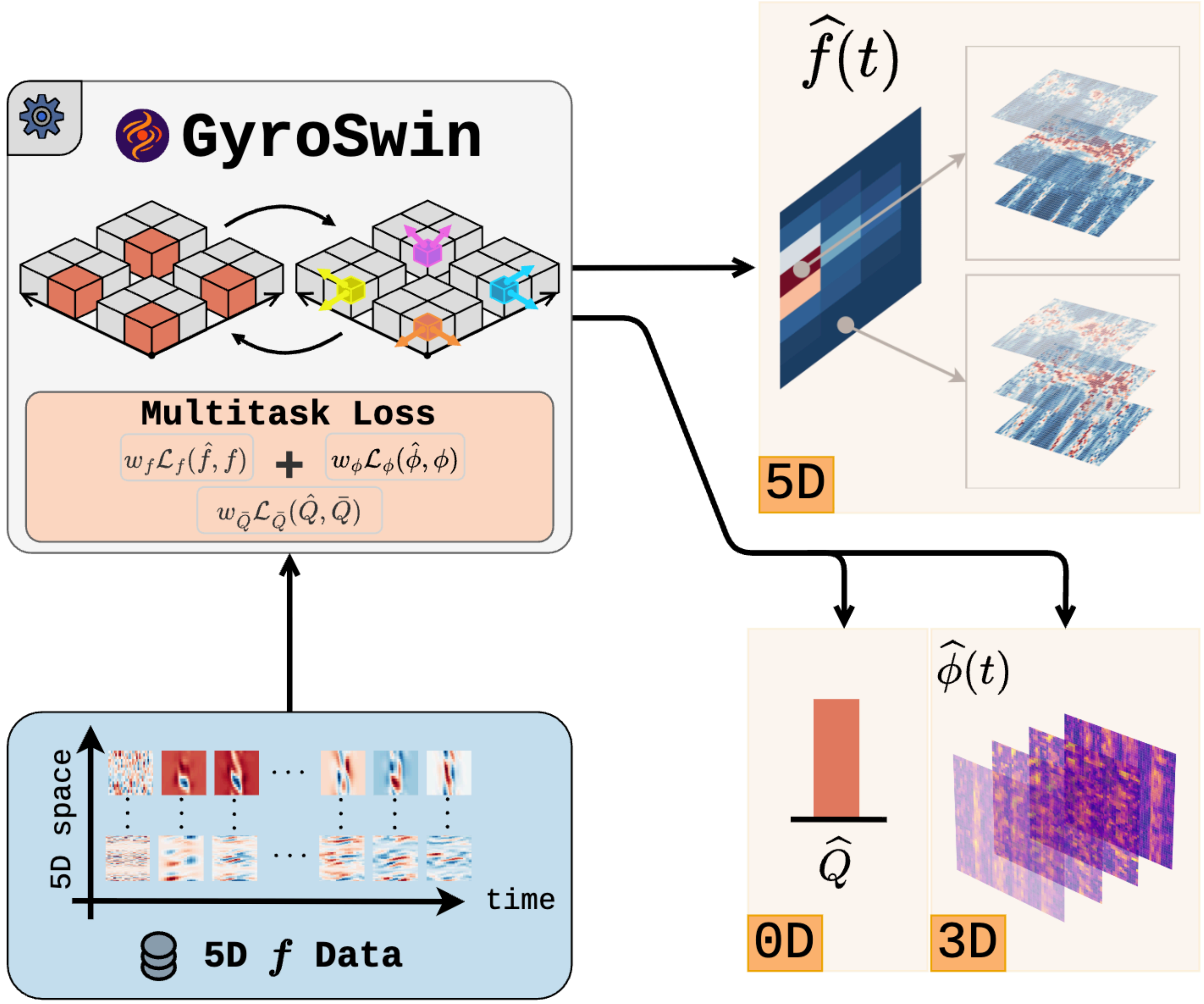


Figure: GyroSwin models the 5D distribution function of nonlinear gyrokinetics and incorporates integration blocks to predict 3D electrostatic potential fields and scalar heat flux.

Experiment design

- Data Generation using GKW [1]
  - Consider adiabatic electron approximation (resolution=32x8x16x85x32)
  - Generate 255 simulations (~6TB) with 4 operating parameters
  - Small training set (48 sims) for comparisons, large set (241 sims) for scaling experiments
  - Evaluate on 6 in-distribution (ID) and 5 out-of-distribution (OOD)

- Different surrogate approaches offer different capabilities:

Method	**Average Flux**	**Diagnostics**	**Zonal Flows**	**Turbulence**
Tabular Regressors, e.g., GPR, MLP	**1D→0D**	✗	✗	✗
SOTA Reduced Numerical modelling, e.g., QL	**3D→0D**	**3D→1D**	✗	✗
Neural Surrogates, e.g. GyroSwin (Ours)	**5D→0D**	**5D→1D**	**5D→1D**	**5D→5D**

Table: Comparison of different surrogate approaches by capabilities.

Turbulence modelling & average flux

Method	Input	f ID (↑)	f OOD (↑)	$\bar{Q}$ ID (↓)	$\bar{Q}$ OOD (↓)
SOTA Reduced Numerical modelling					
QL (Bourdelle et al., 2007)	3D	n/a	n/a	89.53 ± 11.76	95.22 ± 21.57
Classical Regression Techniques					
GPR (Hornsby et al., 2024)	0D	n/a	n/a	43.82 ± 10.84	59.28 ± 17.55
MLP	0D	n/a	n/a	50.50 ± 10.79	61.98 ± 18.41
Neural Surrogate Models (48 simulations)					
FNO (Li et al., 2021)	3D	9.33 ± 0.56	9.20 ± 0.58	119.88 ± 13.15	124.96 ± 23.27
PointNet (Qi et al., 2016)	5D	7.33 ± 0.21	7.40 ± 0.24	119.93 ± 13.15	125.05 ± 23.29
Transolver (Wu et al., 2024)	5D	9.83 ± 1.40	10.80 ± 1.46	119.93 ± 13.15	125.05 ± 23.28
ViT (Dosovitskiy et al., 2021)	5D	16.83 ± 1.49	19.20 ± 1.36	119.63 ± 13.13	125.13 ± 23.29
GyroSwin (Ours)	5D	26.50 ± 3.55	28.60 ± 8.82	67.68 ± 10.28	70.48 ± 17.21
Scaling GyroSwin to 241 simulations					
$\text{GyroSwin}_{\text{Small}}$ (Ours)	5D	98.00 ± 27.53	76.40 ± 17.60	23.72 ± 4.05	53.54 ± 18.10
$\text{GyroSwin}_{\text{Medium}}$ (Ours)	5D	94.17 ± 21.96	91.20 ± 18.61	37.24 ± 9.60	44.17 ± 17.68
$\text{GyroSwin}_{\text{Large}}$ (Ours)	5D	$\mathbf{110.33} \pm 19.74$	$\mathbf{111.80} \pm 23.86$	$\mathbf{18.35} \pm 1.56$	$\mathbf{26.43} \pm 9.49$

Table: Evaluation for 5D turbulence modelling and nonlinear heat flux prediction. We evaluate all methods across six ID and five OOD simulations. For Q we report RMSE of time-averaged predictions after an autoregressive rollout. For f we report correlation time for autoregressive rollouts with threshold τ = 0.1. Higher correlation time is better.

Conclusions

- GyroSwin is the first 5D neural surrogate for nonlinear Gyrokinetics

1. **Scalable**: Based on local window attention
2. **Efficiency**: Three orders of magnitude faster than nonlinear numerical code GKW
3. **Stable rollouts**: Trained on MSE on next time step. During inference model is rolled out for over 100 time steps without diverging.

neural-gyrokinetics

Paper

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