Cross-tokamak disruption prediction via domain adaptation and generalization

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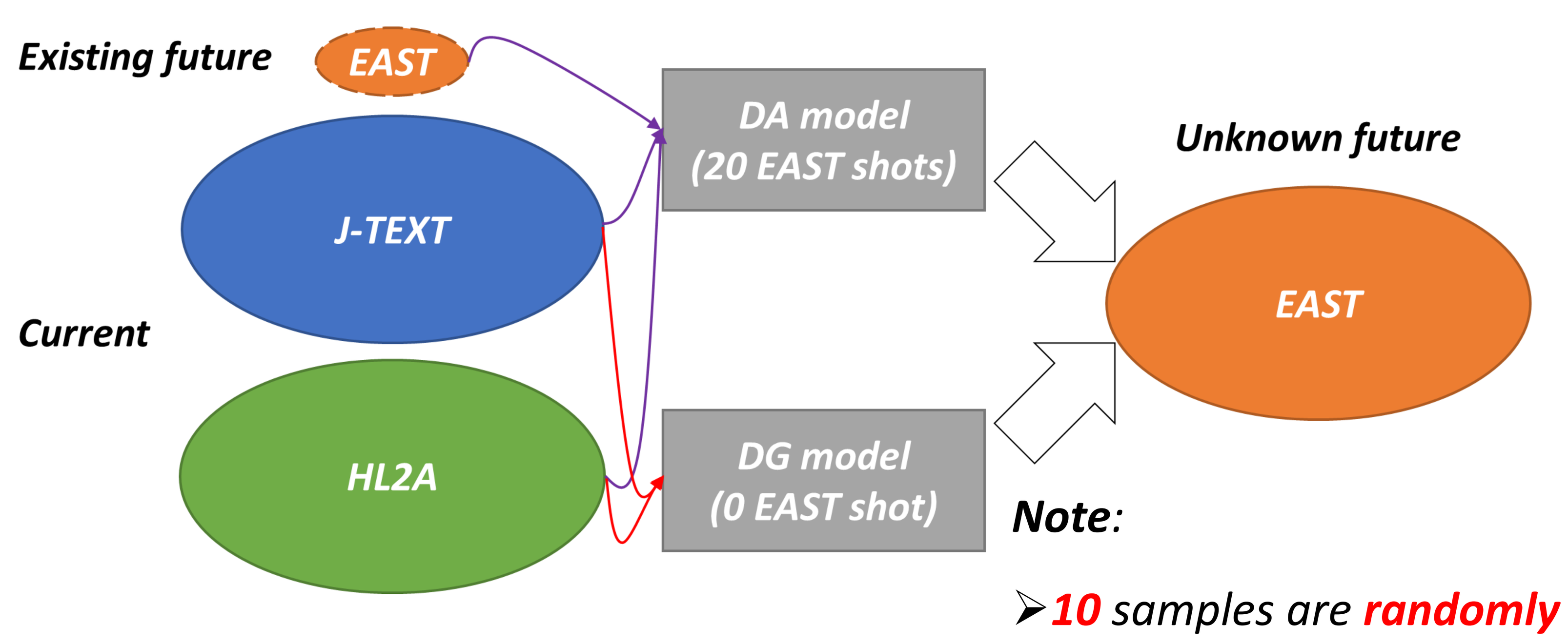
Introduction

- ***Unmitigated*** *disruptions at* ***high performance discharge*** *are unacceptable for future reactors.*
- *Future reactors are **NOT** able to provide **enough** data to train a predictor.*
- *Current tokamaks can bear disruptions, and have accumulated a large amount of data with **various disruption patterns**.*
- ***DA/DG*** *is a promising way to make full use of **knowledge from current tokamaks** and **reduce data** from the **target machine**, even **0 shot**.*

Dataset Description



	J-TEXT	HL2A	EAST
Training Set (DA/DG)	1021	474	20/0
Validation Set (DA/DG)	0/255	0/115	20/0
Test Set (DA/DG)	0	0	506

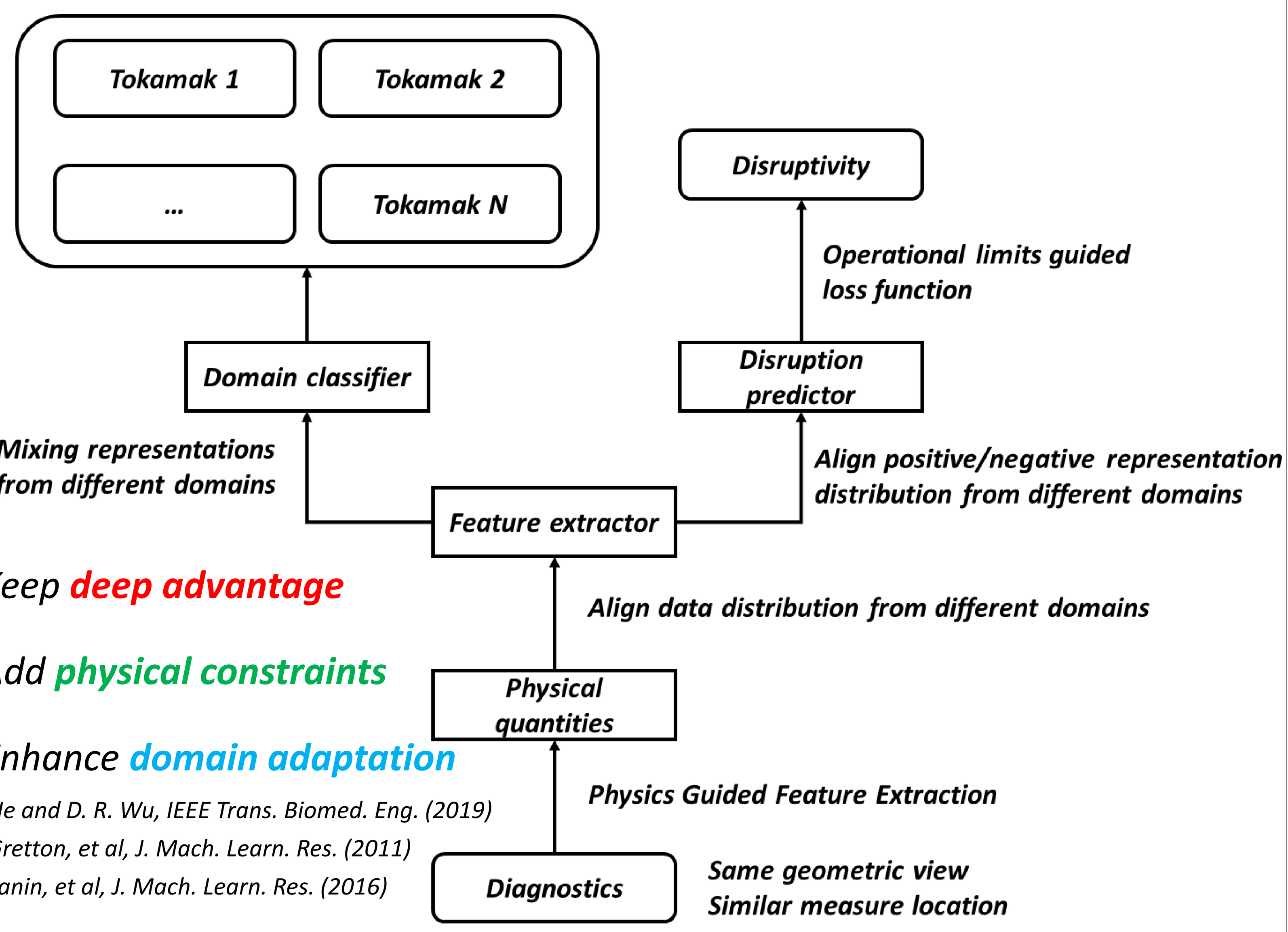
Note:

- ***10*** *samples are **randomly** selected from each shot at training.*
- ***EAST DA validation*** *use the rest samples from **the same** shots as training.*

Framework & Algorithms

Basic Idea: apply DA/DG algorithms to every stage throughout training

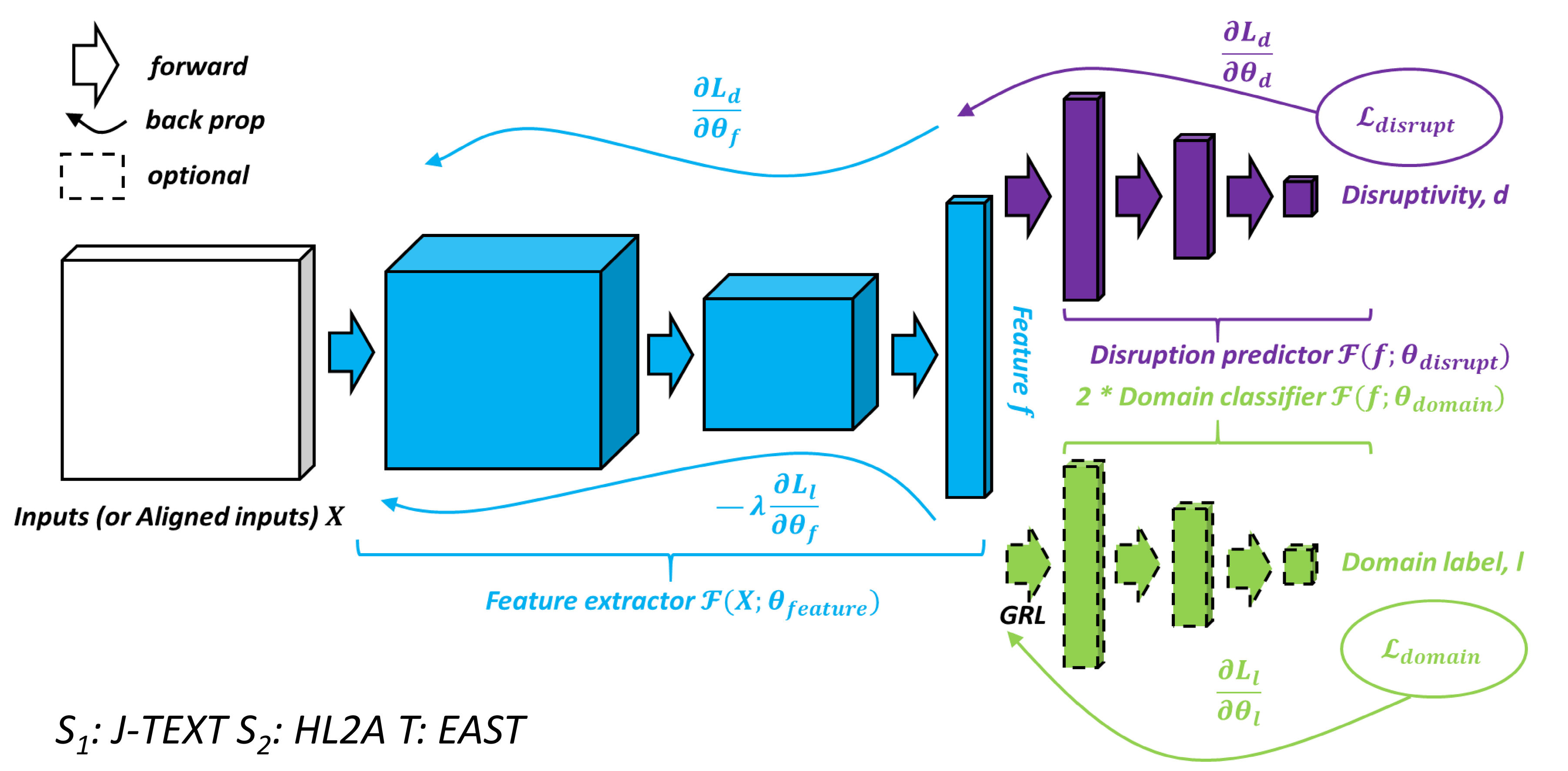
- *Diagnostics: Same geometric view and similar measure location*
- *Inputs: Euclidean Alignment (EA)[1]* $\widetilde{X}_i = \left(\frac{1}{n}\sum_{i=1}^{n} X_i X_i^T\right)^{-\frac{1}{2}} X_i$
- *Representations[2]:* $MMD(X,Y) = \left\|\frac{1}{n}\sum_{i=1}^{n}\phi(x_i) - \frac{1}{m}\sum_{j=1}^{m}\phi(y_j)\right\|_H^2$
- *Operational limits:* $-\frac{1}{N}\sum_{i=1}^{N}(l_i * \log(p(y_i)) + (1-l_i) * \log(1-p(y_i)))$
- *Confusing domains[3]: Domain Adversarial training*



- *Keep **deep advantage***
- *Add **physical constraints***
- *Enhance **domain adaptation***

[1] H. He and D. R. Wu, IEEE Trans. Biomed. Eng. (2019)
[2] A. Gretton, et al, J. Mach. Learn. Res. (2011)
[3] Y. Ganin, et al, J. Mach. Learn. Res. (2016)

Model structure, losses and training



S_1: J-TEXT S_2: HL2A T: EAST

Aligned inputs (optional): $\widetilde{X_{S_1}} = EA\,(X_{S_1}), \widetilde{X_{S_2}} = EA\,(X_{S_2}), \widetilde{X_T} = EA\,(X_T)$

$$\mathcal{L}_{disrupt} = \lambda_1\mathcal{L}_{BCE} + \lambda_2\mathcal{L}_{MMD} + \lambda_3\mathcal{L}_{limit}$$

$$\mathcal{L}_{domain}(DA\ case) = \frac{1}{2}(BCE_{S_1 v.s. T}BCE(p_{l1}, l_1) + BCE_{S_2 v.s. T}BCE(p_{l2}, l_2))$$

$$\mathcal{L}_{domain}(DG\ case) = BCE_{S_1 v.s. s_2}BCE(p_l, l)$$

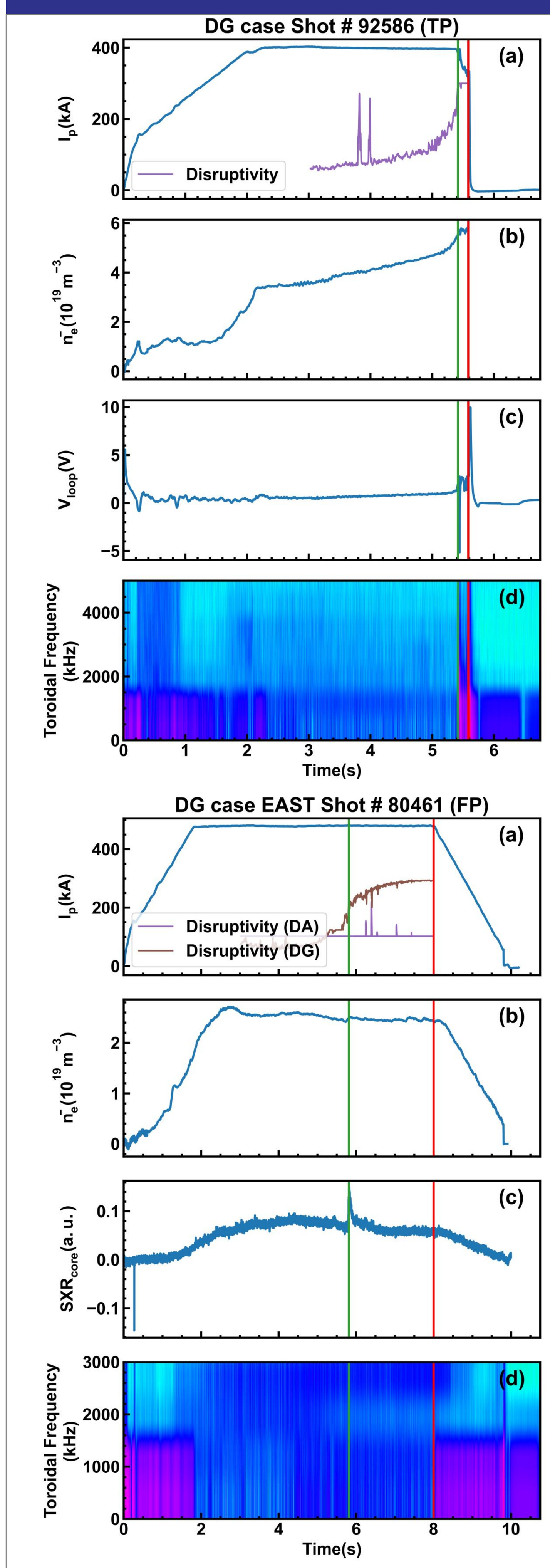
$$\mathcal{L}_{BCE} = BCE(p_d, d)$$

$$\mathcal{L}_{MMD}(DA\ case) = \frac{1}{4}\begin{pmatrix} MMD(f_{S_1,pos}, f_{T,pos}) + MMD(f_{S_2,pos}, f_{T,pos}) \\ +MMD(f_{S_1,neg}, f_{T,neg}) + MMD(f_{S_1,neg}, f_{T,neg}) \end{pmatrix}$$

$$\mathcal{L}_{MMD}(DG\ case) = \frac{1}{2}\left(MMD(f_{S_1,pos}, f_{S_2,pos}) + MMD(f_{S_1,neg}, f_{S_2,neg})\right)$$

$$\mathcal{L}_{limit} = -\frac{1}{N}\sum_{i=1}^{N}(limit_i * \log(p(d_i)) + (1-limit_i) * \log(1-p(d_i)))$$

Results



Cases	TPR	FPR	AUC
DA1 Mixing	65.05%	15.04%	0.7937
DA2 MMD	82.11%	20.89%	0.8492
DA3 DANN	82.63%	22.47%	**0.8724**
DA4 EA	83.68%	40.19%	0.8141
DA5 EA+MMD	81.05%	32.28%	0.7986
DA6 EA+DANN	81.58%	28.48%	0.8210

Cases (0 shot)	TPR	FPR	AUC
DG1 Mixing	60.00%	11.39%	0.8009
DG2 MMD	74.74%	25.95%	0.8115
DG3 DANN	**90.00%**	31.01%	**0.8343**

- *Both DA and DG cases perform **acceptable** on target domain (EAST/J-TEXT).*
- *Aligning inputs **CAN** diminish difference between domains, but disruption related **knowledge** will also be **abandoned**.*
- *It is the best to align at **representation** stage.*
- *Best DG case is able to predict **most** disruptions with **accurate** precursors.*
- *Most of the **False Positive** cases are due to **sensitivity** to instabilities.*
- *Utilizing **target** data may **reduce** **FPs**.*

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