Counter Data Paucity through Adversarial Invariance Encoding: A Case Study on Modeling Battery Thermal Runaway

Anika Tabassum, Srikanth Allu, Ramakrishnan Kannan, Nikhil Muralidhar

OAK RIDGE National Laboratory

STEVENS INSTITUTE of TECHNOLOGY
THE INNOVATION UNIVERSITY®

Code and Dataset: github.com/anikat1/battery-invariance-learning

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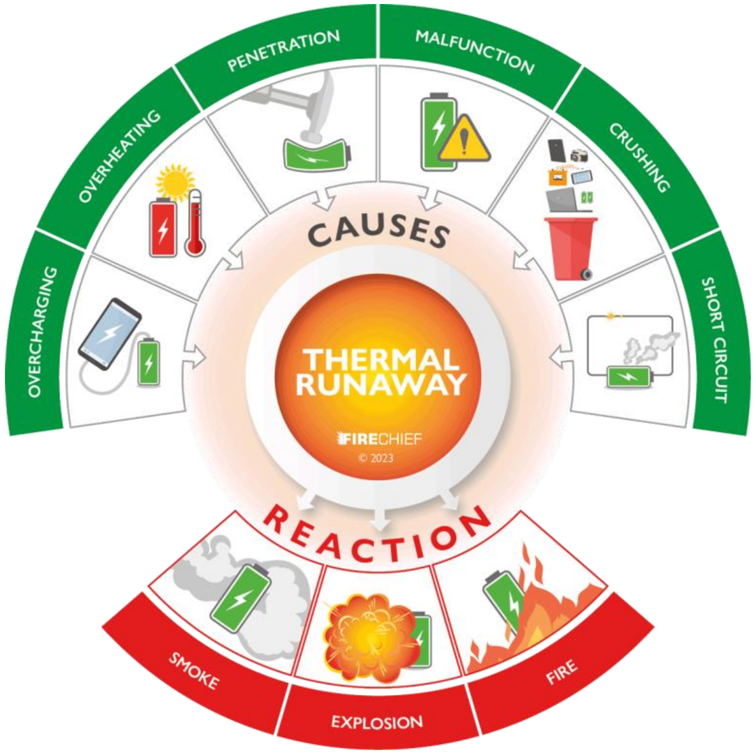
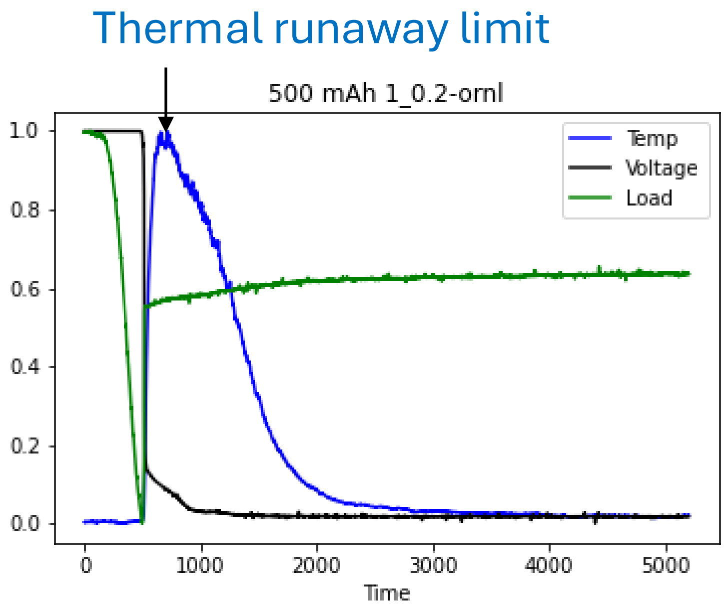
Battery Safety Modeling

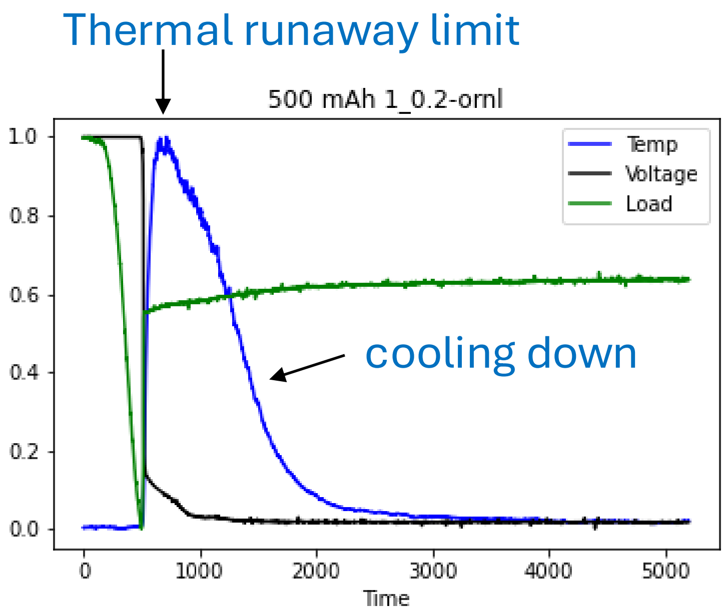
- The internal short circuit leading to thermal runaway must be mitigated under all conditions.
- Short circuit events pose a major safety risk for industry applications (e.g., EVs, laptops, mobiles).
- Understanding peak temperature and time is important preventing thermal runaway.

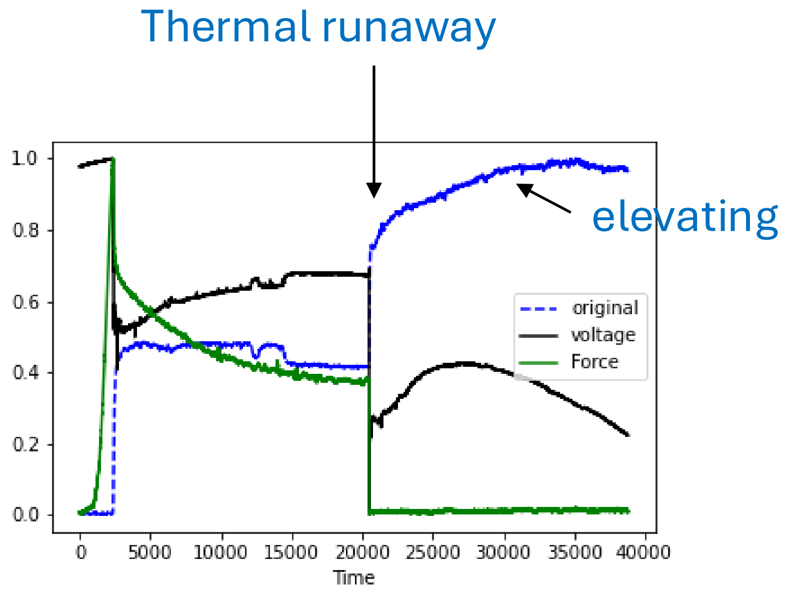




Thermal runaway event

- A short circuit condition in Li-ion batteries where:
  - sudden rise in temperature (T) for increased mechanical load
  - once reach its thermal limit can cool upto normal operating conditions
  - may continue to stay/elevated till load reduce or voltage increase





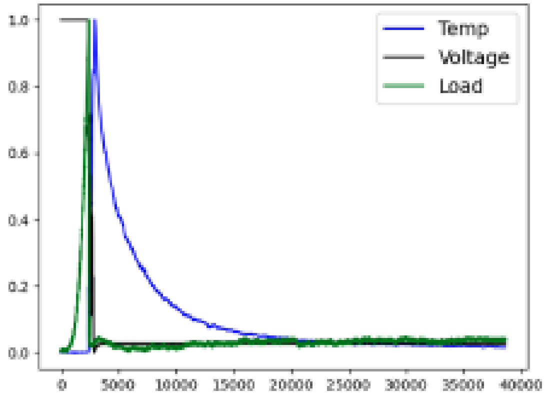
Showing different physics properties for different mechanical load conditions.

- How to have a model to adapt such contexts?

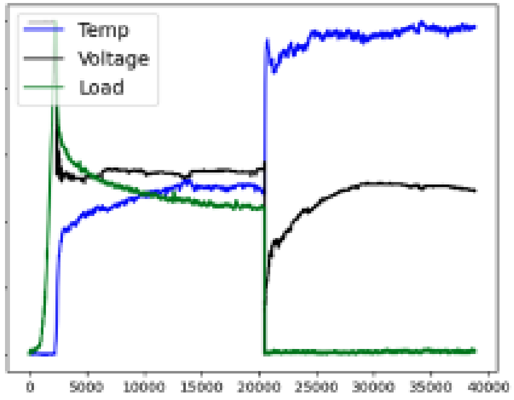
Challenges for Thermal Runaway Detection

- Temperature responses significantly vary among battery properties (materials, SoC, capacity)
- Thermal runaways are rare events (*destructive* data collection process)

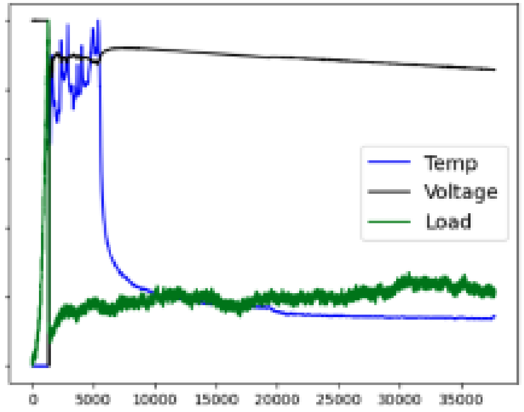
Temp. responses varying Material



(a) LCO

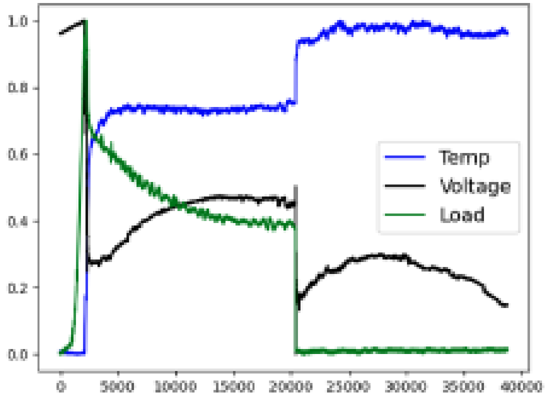


(b) LFP

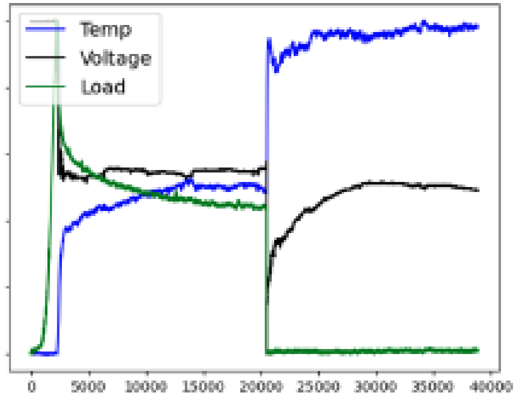


(c) NMC

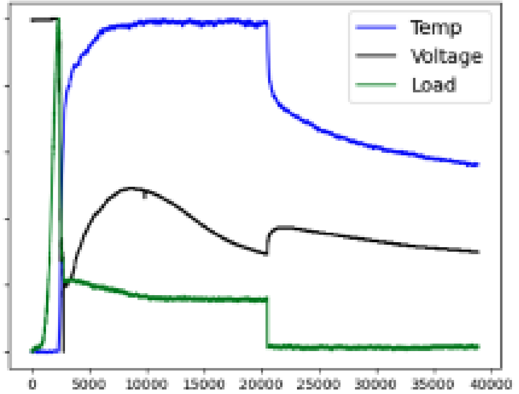
Temp. responses varying state-of-charge



(d) 50%



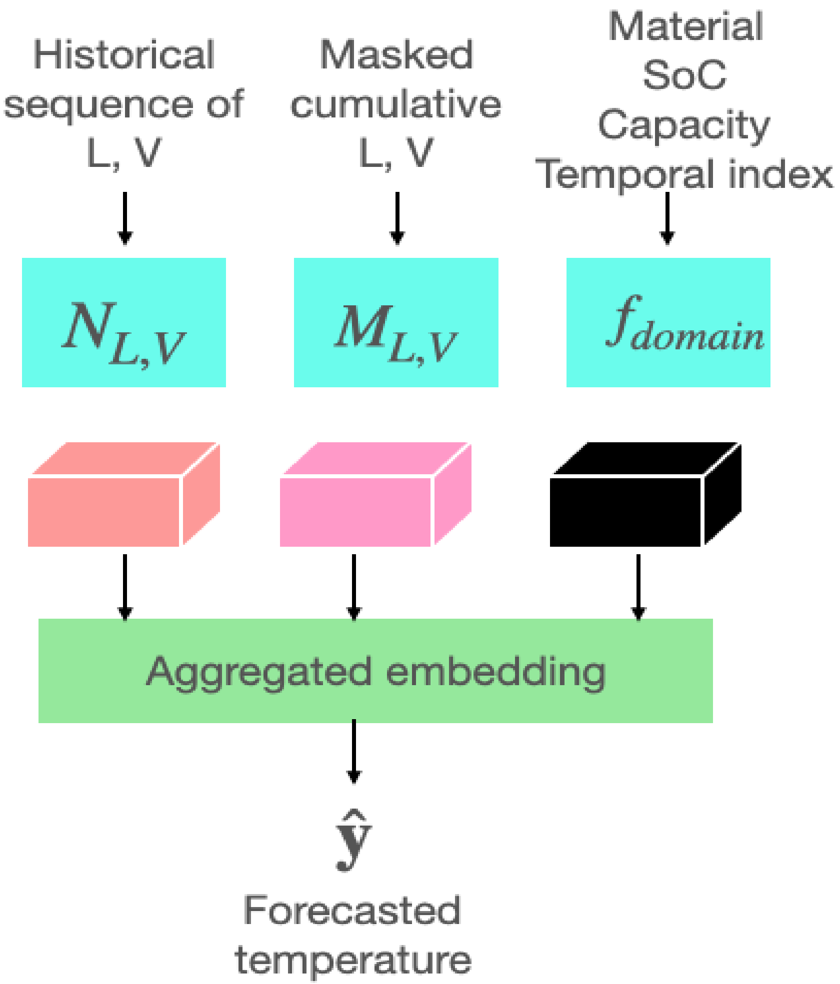
(e) 70%



(f) 90%

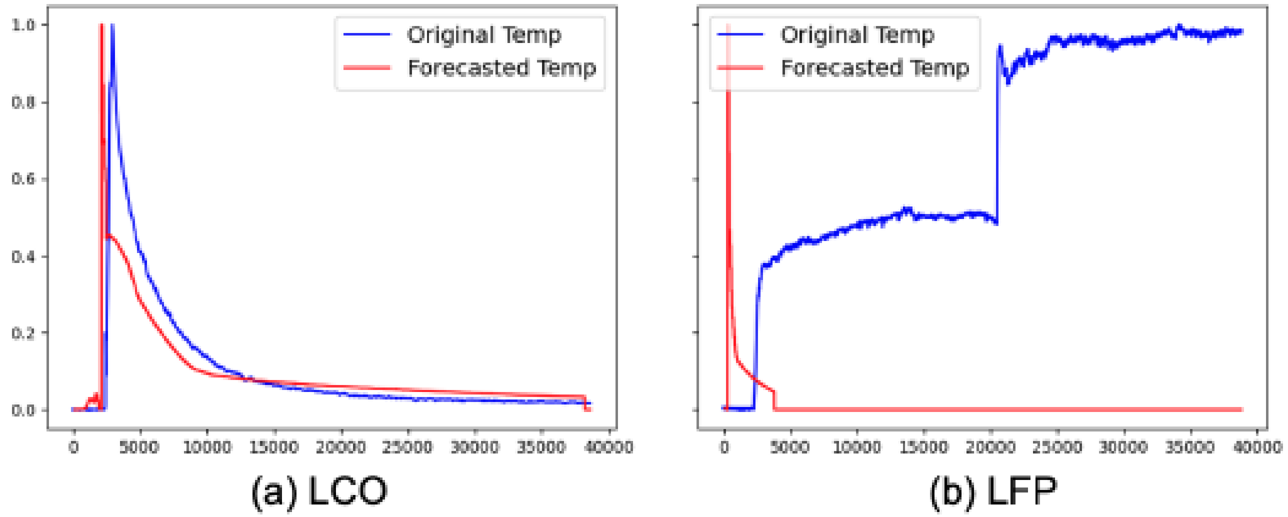
Challenges with DL Models

Generalization Technique 1: Incorporate Battery properties to the model

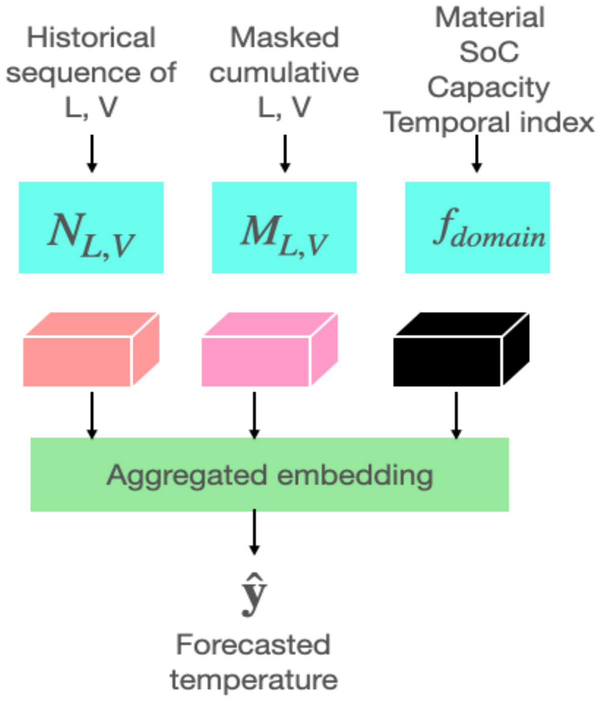


Generalization Technique: Incorporate Side Information

- Off the shelf ML models fails to generalize
  - physics properties
  - Battery properties (material, state-of-charge, capacity)

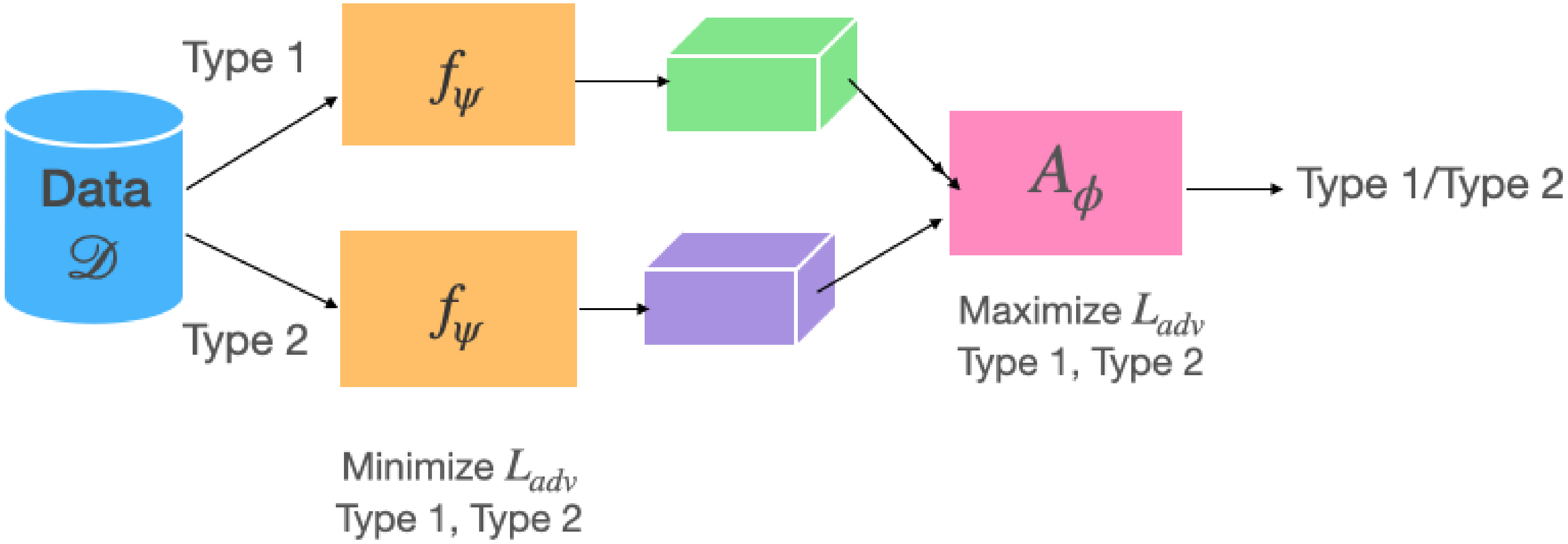


Forecast obtained by a sequential deep-learning model for two different materials



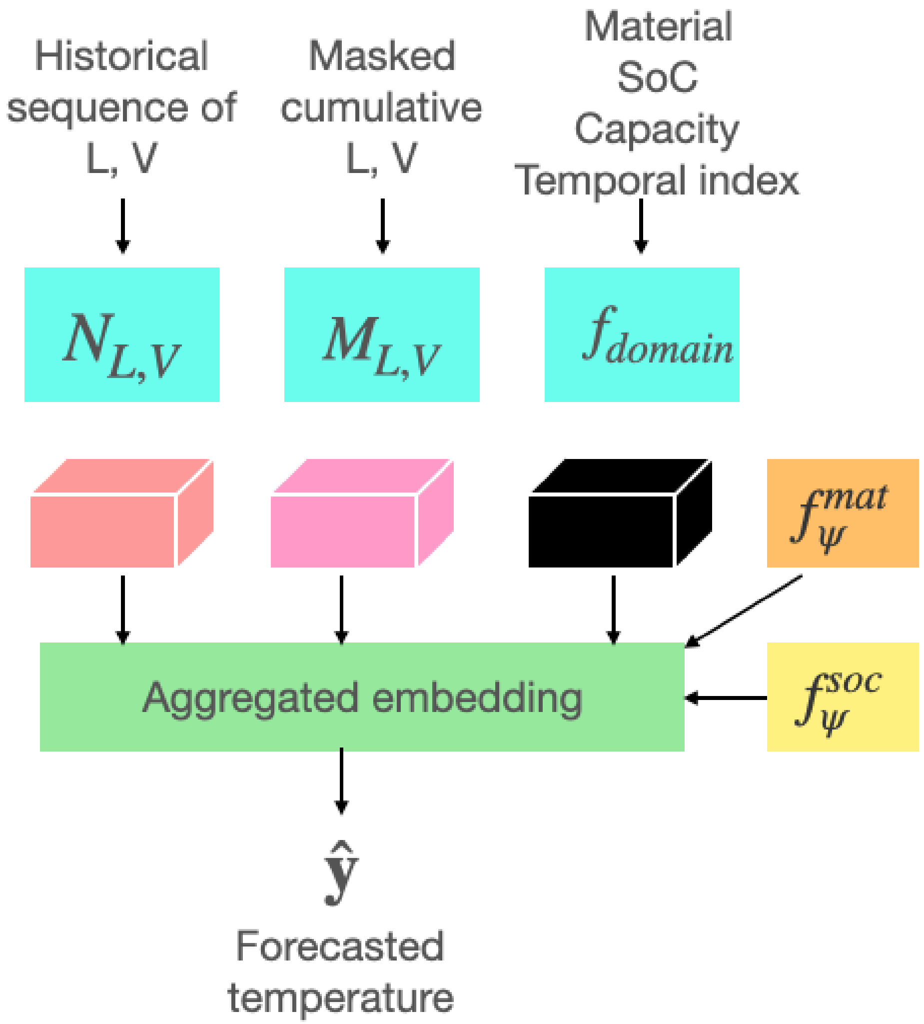
Invariant Encoding

Our goal: Marginalize distribution shifts in input across battery properties
- material, SoC, capacity



Predictor

- Incorporate the additional invariant features.
- How it is different from GAN models?
  - Unlike generator invariance will be trained twice:
    - adversarial for learning invariance
    - predictor for improving predictions

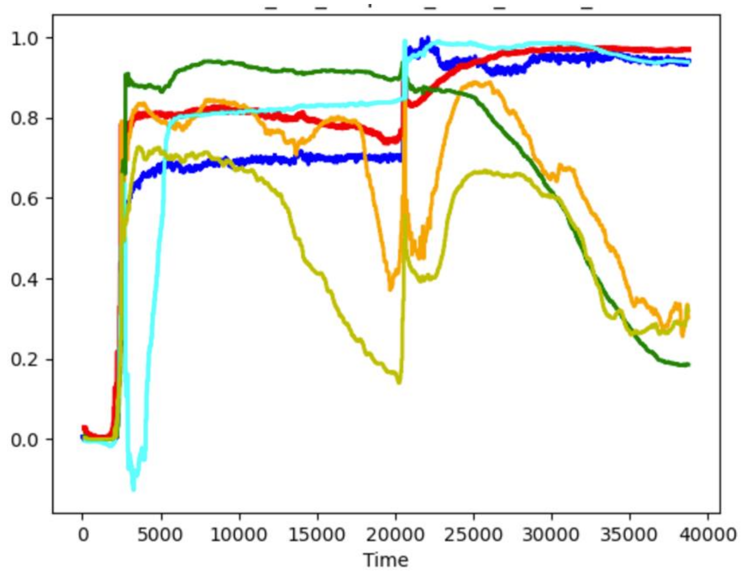


Can Invariance Generalize for Seen and Unseen Soc Context?

Case	Model	RMSE	MAPE	DTW	EM	Peak_m	Peak_t
Seen material seen SOC	LSTM	0.28	0.238	39.425	0.156	0.049	0.207
	NBeatsX	0.147	0.099	5.9	0.095	**0.013**	0.025
	Transformer	0.284	0.232	36.8	0.225	0.153	**0.254**
	AIDC (w/o adv)	0.202	0.148	26.715	0.106	0.062	0.026
	AIDC	**0.113**	**0.098**	**7.486**	**0.094**	**0.032***	0.16
Seen material unseen SOC	LSTM	0.253	0.2	30.94	0.143	0.072	0.29
	NBeatsX	0.434	0.289	46.962	0.242	0.056	0.133
	Transfomer	0.291	0.235	43.53	0.226	0.212	0.161
	AIDC (w/o adv)	0.302	0.241	39.611	0.194	0.0823	0.184
	AIDC	**0.156**	**0.111**	**8.164**	**0.108**	**0.061**	**0.099**
Unseen material seen SOC	LSTM	0.27	0.201	34.401	0.176	0.258	0.378
	NBeatsX	0.259	0.224	27.243	0.198	**0.057**	0.014
	Transformer	0.231	0.166	27.95	0.163	0.417	0.015
	AIDC (w/o adv)	0.26	0.190	18.766	0.183	0.323	0.014
	AIDC	**0.21**	**0.166**	**14.623**	**0.158**	0.204	**0.013**

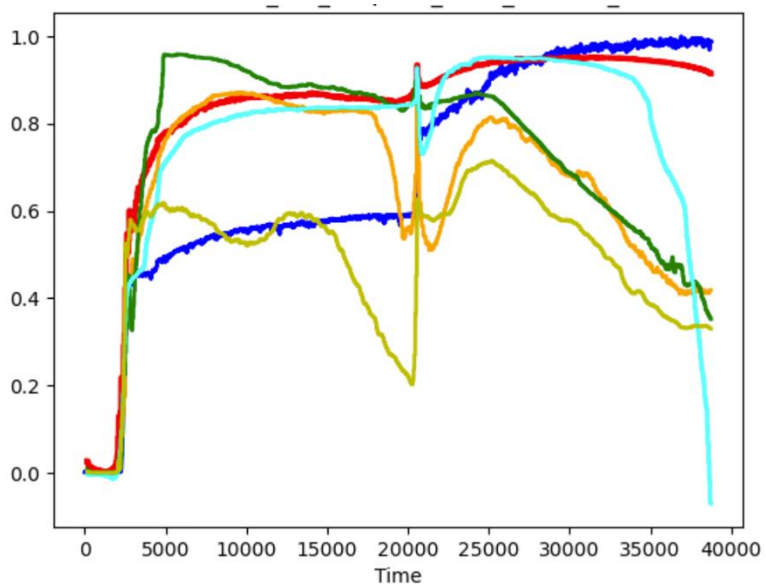
Does Invariance Generalize for Thermal Runaway Properties?

Seen material, seen SoC



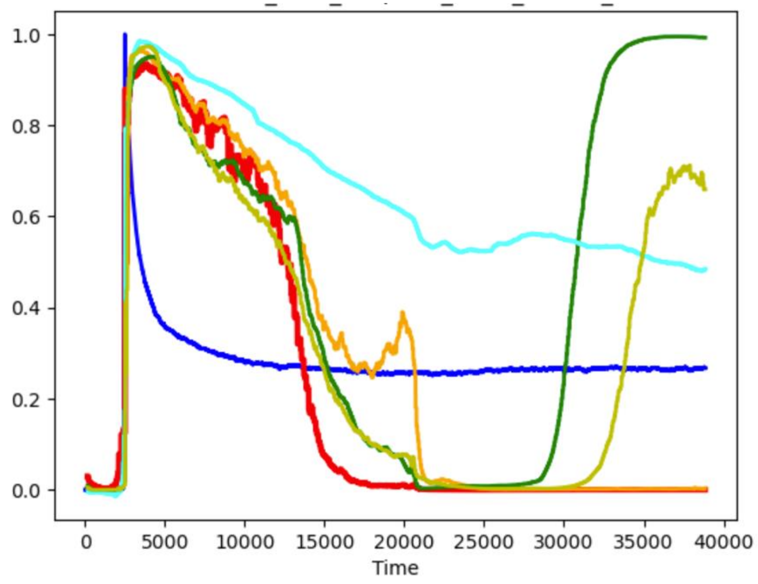
LFP, 70% SOC

Seen material, unseen SoC



LFP, 100% SOC

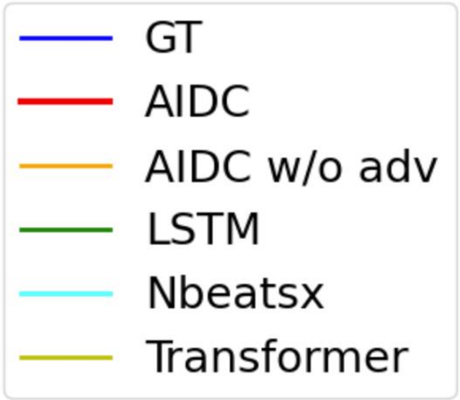
unseen material, seen SoC



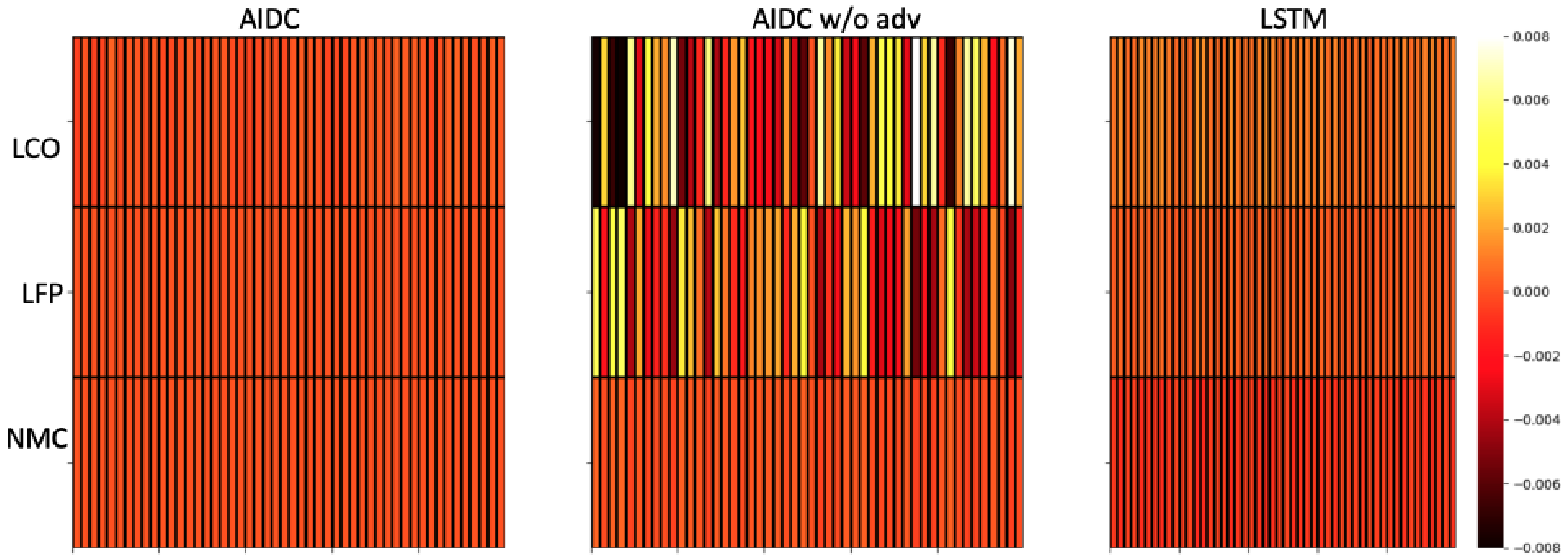
NMC, 50% SOC

Except our model, all other models fail to capture thermal runaway properties:

- having multiple peaks



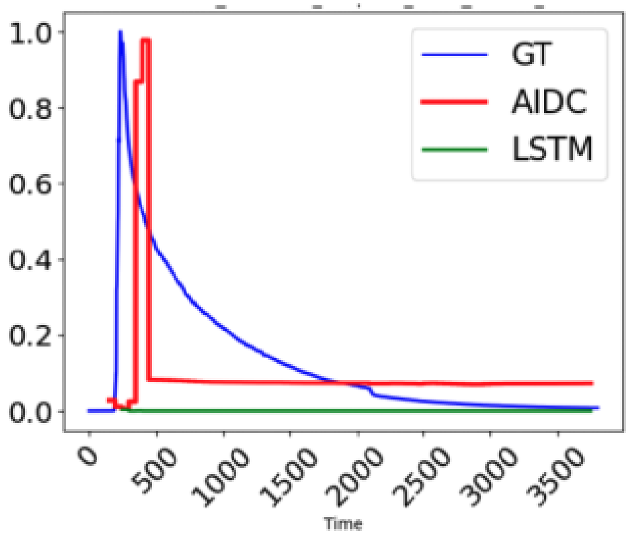
Does Our Invariant Model Actually Learn Invariance?



Heatmap plot of the gradients of our model, our model w/o adversarial training, and LSTM w.r.t. seen LCO, LFP, unseen NMC cathode material

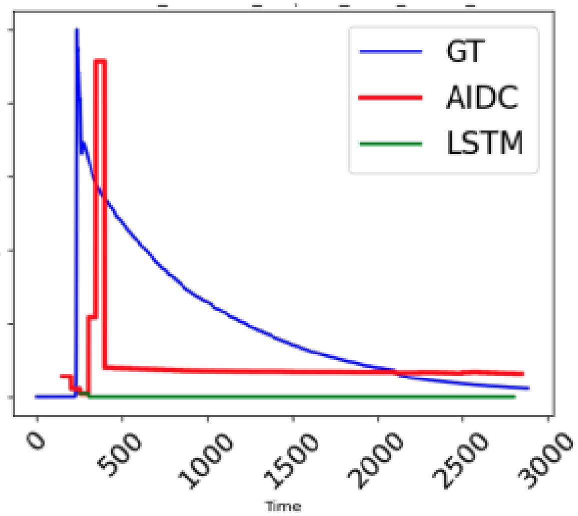
Our model is less sensitive across both seen and unseen material

Sensitivity Across Weak vs Strong Out-of-Distribution (OoD) Cases



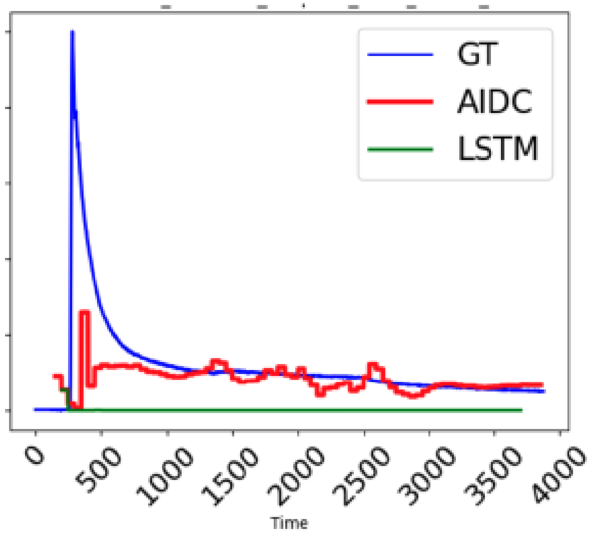
(a) LMO-LNO, 50% SOC

Weak OoD
unseen material
seen SoC)



(b) LMO-LNO, 75% SOC

Weak OoD
unseen material
unseen (in-distribution) SoC



(c) LMO-LNO, 30% SOC

Strong OoD
unseen material
unseen SoC

Plots of our model *AIDC* compared to LSTM for weak and strong out-of-distribution (OoD) data on a different experimental setting unseen during training.

LSTM completely fails to generalize or predict temperature peaks or thermal runaways for all OoD (flat green).

Key points and Observation

- Invariant encoding
  - generalize to unseen battery properties
  - shared learning across different battery properties
  - can aid in improving prediction performance by marginalizing distribution shifts across different domains

Thank you