Advancing AI for Energy Applications

EPRI Energy & Climate Research Seminar

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AI for energy systems: Recurring themes

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

AI for energy systems: Recurring themes

Distilling raw data into insights (emissions, solar panels, grid infrastructure)

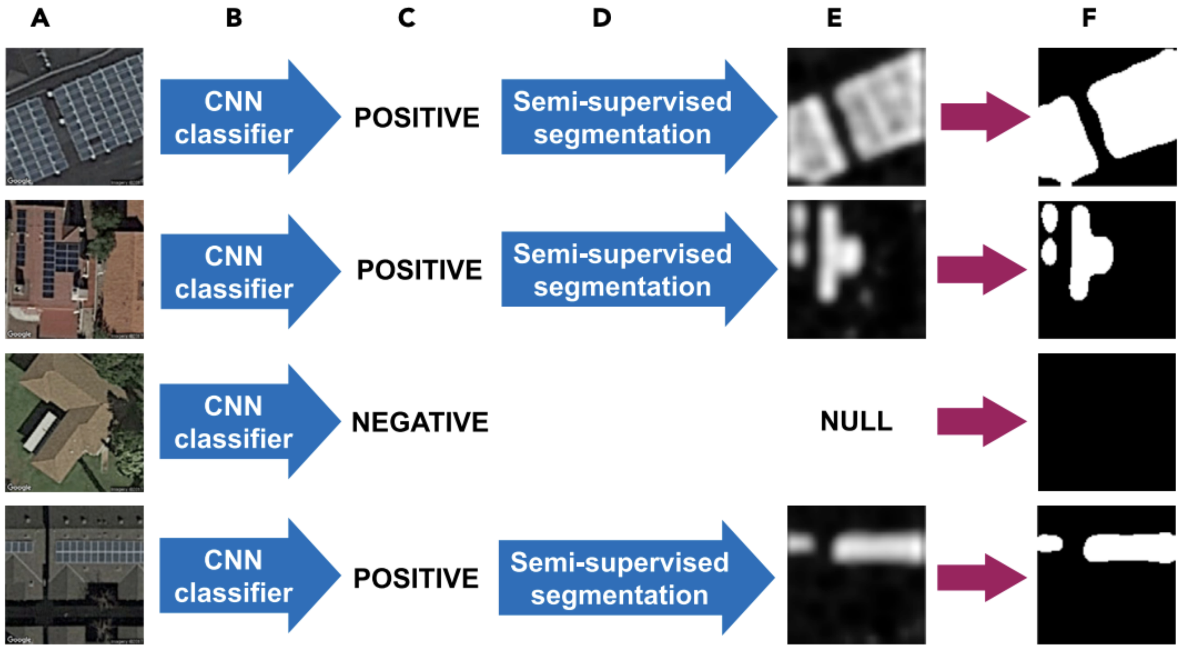

Figure source: Yu, Wang, Majumdar, Rajagopal (2018)

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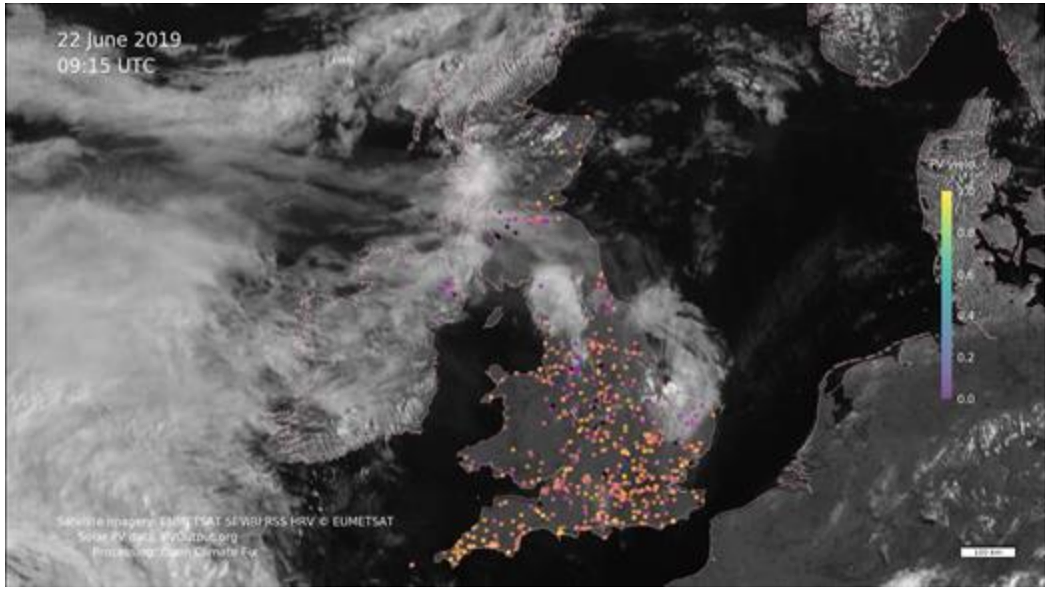

Image source: OCF

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Approximating time-intensive simulations (power dispatch, climate/weather)

power demand

AC optimal power flow

minimize **costs**

subject to **AC power flow**

device limits

dispatch

Figure source: Donti, Rolnick, Kolter (2021)

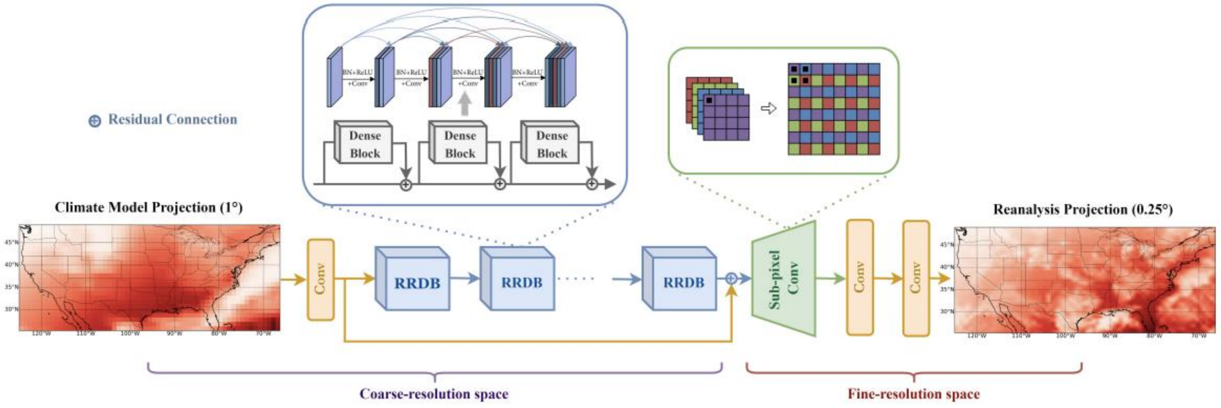

Figure source: Harilal, Hodge, Monteleoni, Subramanian (2022)

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Image source: L2RPN Challenge

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Image source: EPRI Journal (2019)

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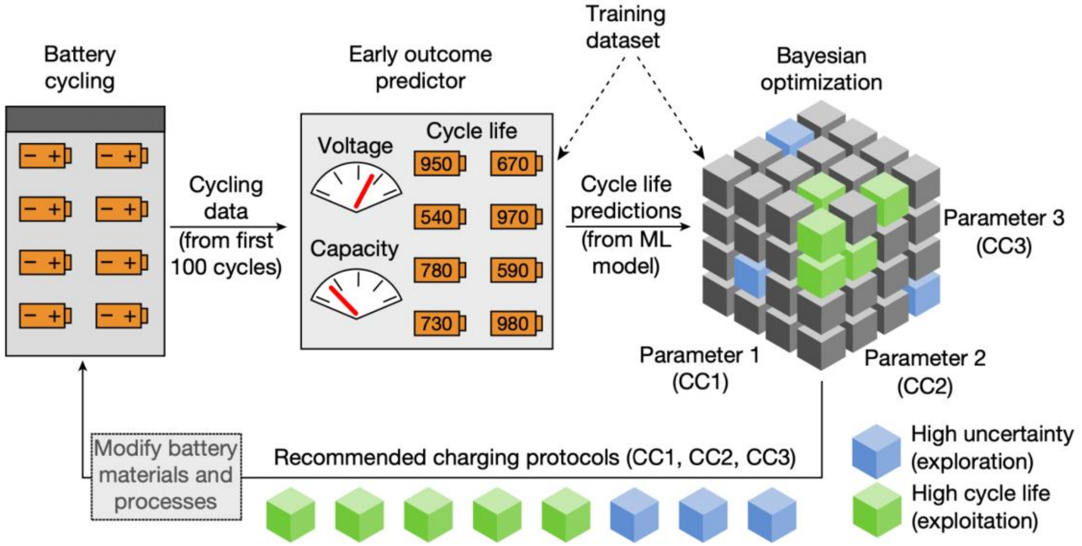

Figure source: Attia et al. (2020)

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Data management & scenario generation
(entity matching, time series generation)

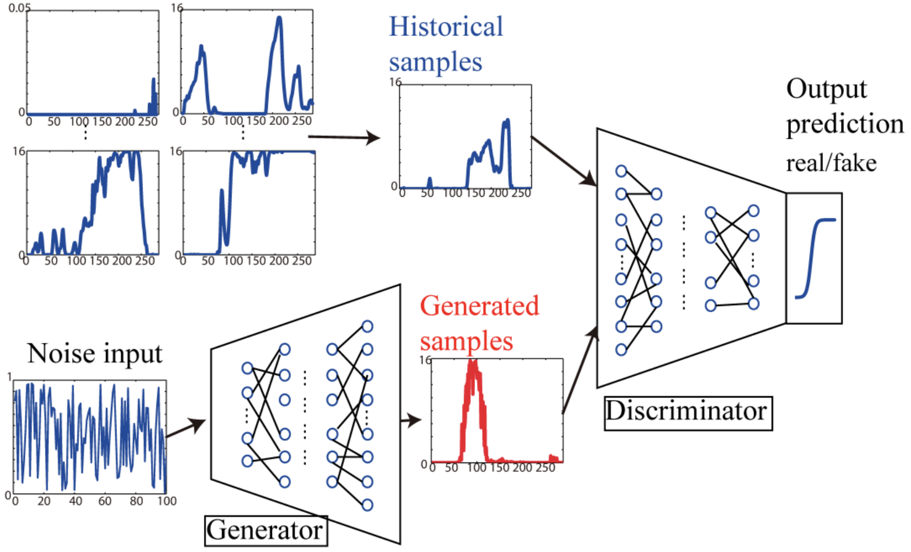

Image source: Chen, Wang, Kirschen, Zhang (2018)

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Requirements for AI in energy systems

Safety, robustness, and physical feasibility, due to nature of safety-critical systems

Interpretability and auditability, given (e.g.) regulation and public accountability

Speed, given large & dynamic nature of systems

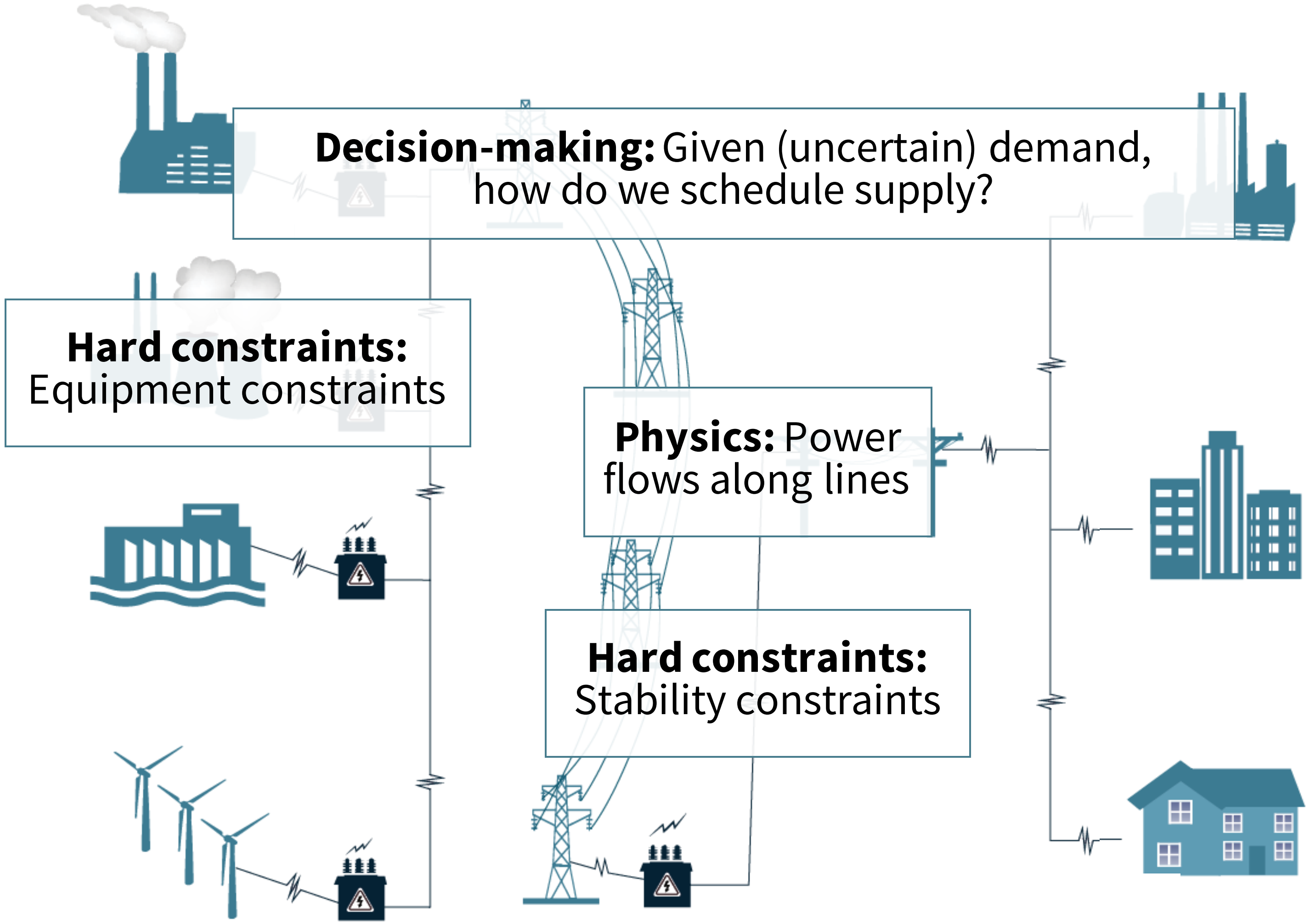
Privacy-preservation, esp. with consumer data

Hardware integration with sensors & control devices

Usability, accessibility, and data efficiency

Requires a diversity of methodological paradigms

Example: Bridging AI with optimization/control



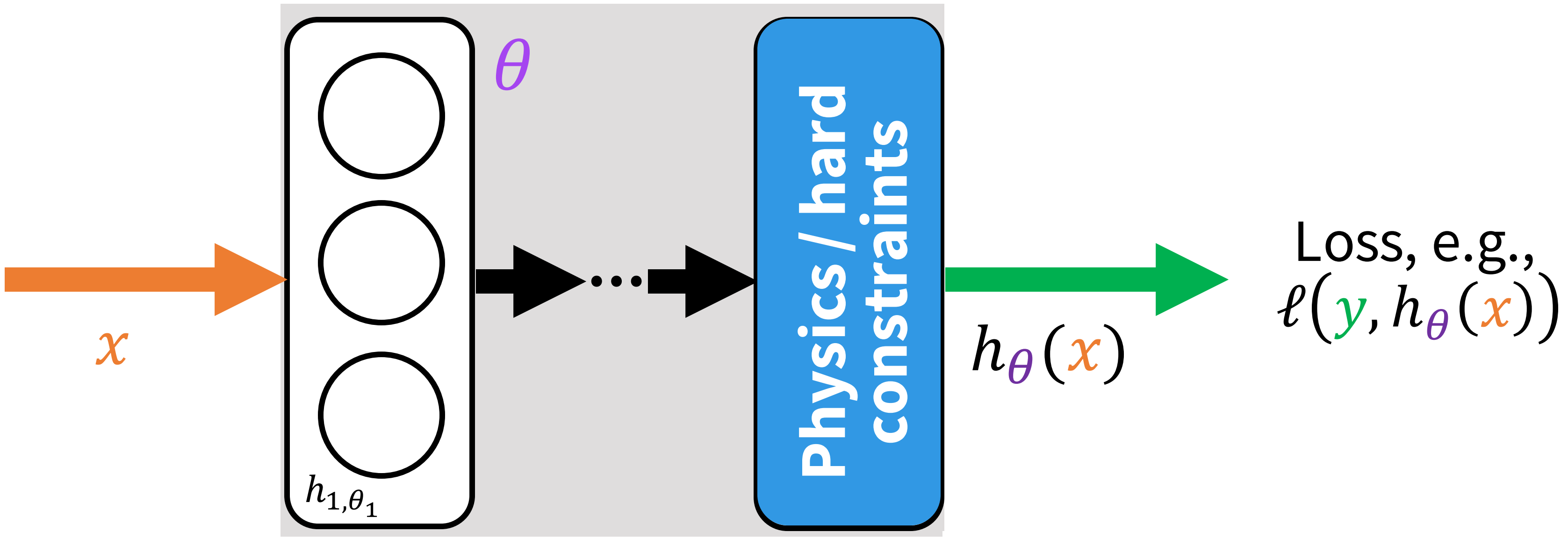
Trad. optimization & control
- Satisfies (many) constraints
- Struggles with speed / scale

Machine learning (ML)
- Fast and scalable
- Struggles with constraints

Figure adapted from: US Congressional Budget Office

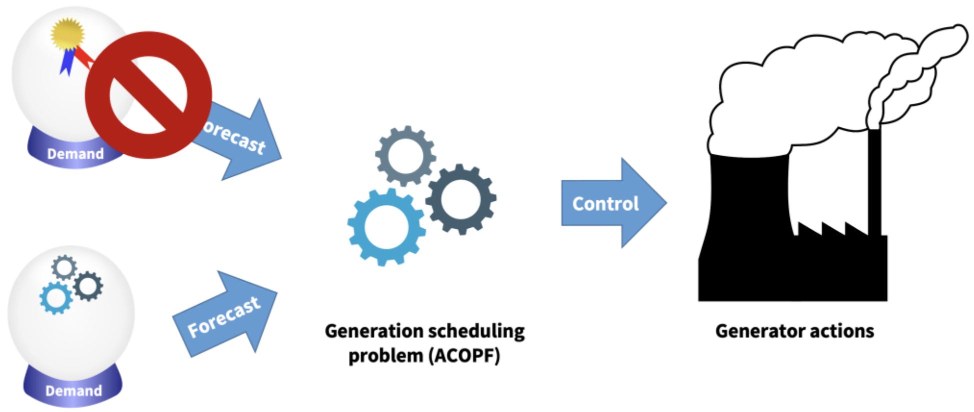
Optimization-in-the-loop ML

Framework for developing ML methods that incorporate knowledge of physics, hard constraints, or downstream decision-making procedures, via implicit layers



See also: Donti, Priya. *Bridging Deep Learning and Electric Power Systems*. Diss. Carnegie Mellon University, 2022.

Optimization-in-the-loop ML for power systems



Decision-cognizant forecasting of supply & demand

power demand

AC optimal power flow

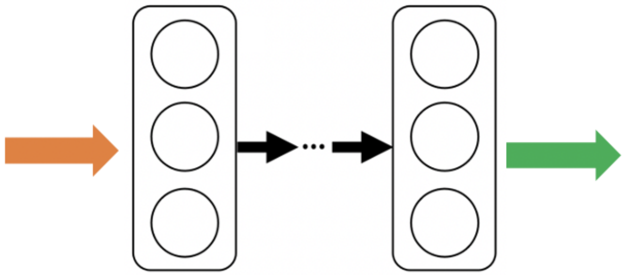
minimize **costs**

subject to **AC power flow**

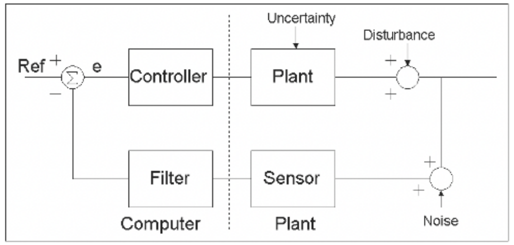
device limits

dispatch

Fast, feasible approximations to power systems optimization (ACOPF, SCOPF)



Deep RL



Robust control

Provably robust control via deep reinforcement learning

Many opportunities for innovation

Physics-informed ML & robust RL

Interpretable ML & uncertainty quantification

Generalization and causality

Energy efficient ML & TinyML

AutoML

….

Demands of different climate/energy domains must shape directions of AI innovation

		Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time-series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
Mitigation	**Electricity systems**									
	Enabling low-carbon electricity		•	•		•	•		•	•
	Reducing current-system impacts		•				•		•	•
	Ensuring global impact		•					•		•
	Transportation									
	Reducing transport activity		•				•		•	•
	Improving vehicle efficiency		•			•				
	Alternative fuels & electrification					•				•
	Modal shift	•	•				•		•	
	Buildings and cities									
	Optimizing buildings	•				•	•	•		
	Urban planning		•				•	•		•
	The future of cities				•			•	•	•
	Industry									
	Optimizing supply chains		•			•	•			
	Improving materials									•
	Production & energy		•	•		•				
	Farms & forests									
	Remote sensing of emissions		•							
	Precision agriculture		•			•	•			
	Monitoring peatlands		•							
	Managing forests		•			•	•			
	Carbon dioxide removal									
	Direct air capture									•
	Sequestering CO_2		•						•	•
Adaptation	**Climate prediction**									
	Uniting data, ML & climate science		•	•			•		•	
	Forecasting extreme events		•	•			•		•	
	Societal impacts									
	Ecology		•					•		
	Infrastructure					•	•		•	
	Social systems		•				•			•
	Crisis		•		•					
	Solar geoengineering									
	Understanding & improving aerosols						•		•	
	Engineering a control system					•			•	
	Modeling impacts						•		•	
Tools for Action	**Individual action**									
	Understanding personal footprint	•			•	•	•			
	Facilitating behavior change				•					•
	Collective decisions									
	Modeling social interactions			•		•				
	Informing policy	•	•		•				•	•
	Designing markets					•	•			•
	Education				•	•				
	Finance				•		•		•	

Figure: Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2022). Tackling climate change with machine learning. *ACM Computing Surveys (CSUR)*, *55*(2), 1-96.

Enablers for AI in energy systems

More openness in data, beyond only bilateral agreements and limited access

- Can include sharing of synthetic data

Simulators and test beds, with realistic/diverse scenarios and easy-to-use interfaces

- Includes digital twins, but also simpler frameworks (e.g., Grid2Op)
- Need for *progression pathways* from basic to advanced simulators/test beds

Evaluation metrics / benchmarks: What does it mean for a method to succeed (or fail)?

Modular, “open-source” software, enabling integration & evaluation of new methods

Translational research exchange: Enhanced collaboration between academia, national labs, and energy industry players (power system operators, utilities)

Note: None of these enablers are AI-specific!

AI and climate change

AI applications for climate action

Impacts from AI computation & hardware

AI's system-level impacts

AI applications that increase emissions

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Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 1-10.