Joint Institute for Strategic Energy Analysis

Decision Points and Practical Considerations for AI Projects VERGE '23

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Agenda

- What is NREL and what AI systems do we work on?
- Challenges and Practical Considerations for AI implementations: Questions, Decisions, Tips and Strategies
  - Challenges Arising from Input Data
    - Costs, Risks, Biases, Limitations
  - AI Trust Issues
    - Identifying and Mitigating Risks of AI misbehavior
  - AI System Costs, Trends and Trade-Offs
    - Energy, Compute, and Time

Green AI @ NREL

AI Researchers at NREL research and apply AI to address commercial, national, and global energy efficiency and renewable energy challenges.

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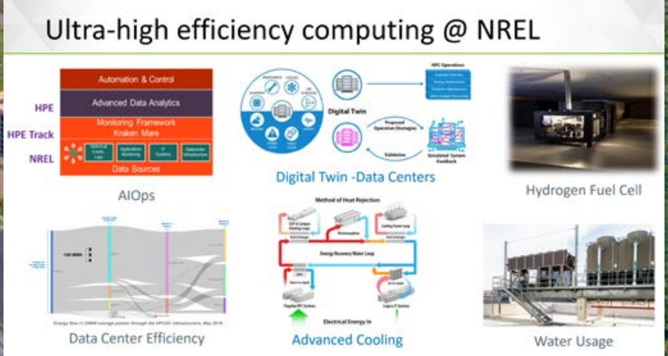

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- **AI for Energy-Efficient Computing**
  - **Grid-Integrated, Carbon-Aware Datacenters**
  - **Energy & carbon measurement, estimation, characterization**
  - **Energy-Efficient Algorithms**
    - **Deep Learning**
- **AI for Mobility Systems**
  - **Connected/autonomous vehicles, infrastructure**
  - **Energy-efficient transit systems**
- **AI for Energy Systems**
  - **Grid operations**
  - **Renewables**
  - **Storage**
  - **Cybersecurity**
- **AI for Materials**
  - **Materials Discovery**
  - **Battery Systems**
  - **Semiconductors & Photovoltaics**
- **AI for Building Systems**
  - **HVAC operations and coordination**
  - **Grid- and Mobility-Integrated Buildings**

Green AI @ NREL

Let's Advance the State-of-the-Art in AI-driven Efficiency and Decarbonization Together!

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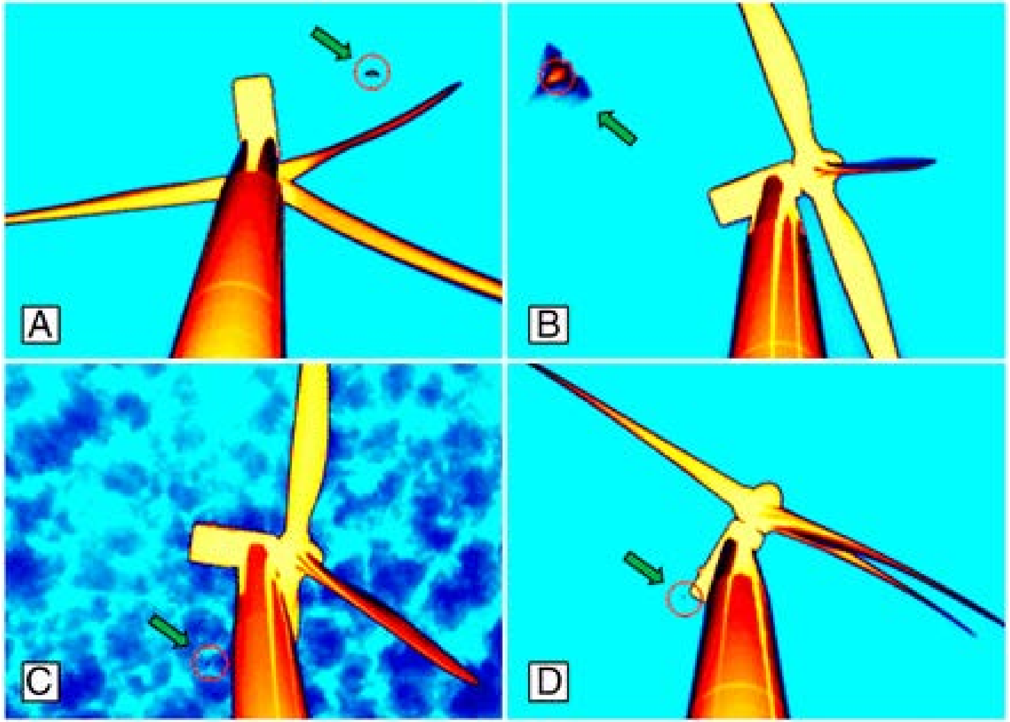
Data: Collection, Quantity, Quality

- What are the costs of collecting and cleaning the input data?
  - Monetary
  - Temporal
  - Privacy / Data Sharing
  - Storage & Retrieval
  - Collection Quality
- What limitations does the data impose on the system?
  - Performance Domain & Limitations
  - Performance Quality: How good of a job can we do with the data we have?
  - Are there biases inherent in the training and/or test datasets?
    - Are there DEI issues with the datasets? What can we do to mitigate these issues?
- What are the risks of dirty or malicious training data?
  - Could a bad actor inject 'poisoned' data to influence system behavior?

Detecting Bat and Bird Activity near Wind Turbines

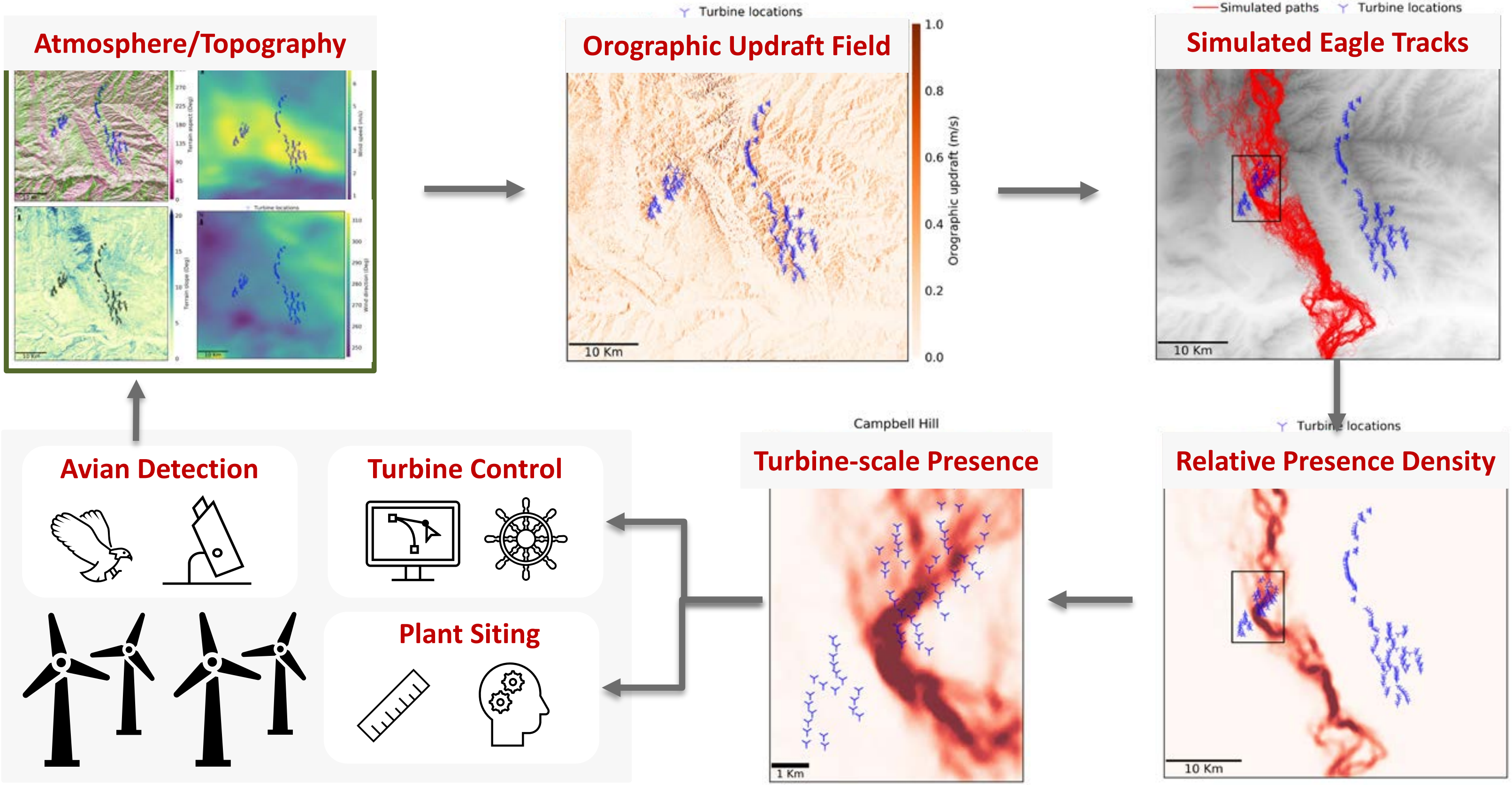
- Utilized
  - Thermal video cameras (1,304 hours)
  - Near-infrared video
  - Acoustic detectors
  - Radar (3-4 million animals detected)
- Bat behavior
  - Many bats passing close to WT stationary or slow-moving
  - Wind speed and blade rotation influenced behavior
  - Approach less frequently with fast spinning WT
- Bird behavior
  - Far out numbered bats (Radar)
  - Absence from video observations
  - Suggesting no interaction with WT



Bats at wind turbines, Paul. M. Cryan et al. Proceedings of the National Academy of Sciences Oct 2014, 111 (42) 15126 15131; DOI:10.1073/pnas.1406672111

Work led by John Yarbrough

Stochastic Soaring Raptor Simulator (SSRS)



Work led by Charles Tripp, Rimple Sandhu, Eliot Quon, Regis Thedin

AI Trustability

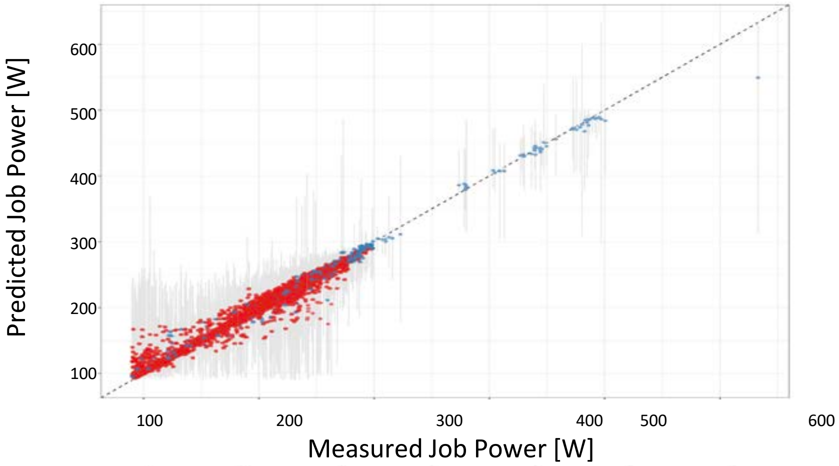
Consider the probability and consequences of “bad AI behavior”

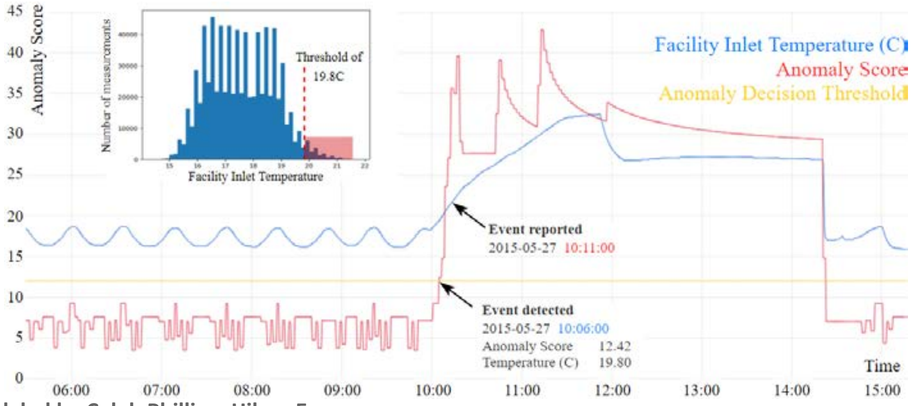
- Safety: Could this system waste money, break something, break a contract, break the law, injure someone?
- Business & Legal Risks
  - Data disclosure and security
  - Copyright Infringement
  - AI-Based Discrimination: Are there DEI challenges facing this system?
- Vulnerability to malicious actors
  - Data poisoning
- Out-of-sample behavior
  - How likely is the system to encounter untrained scenarios / inputs?
  - What might happen if the system does not behave as desired in these scenarios?
  - Are there feasible safeguards to mitigate these risks?
  - Are there ways of bolstering training data to cover system blind spots?

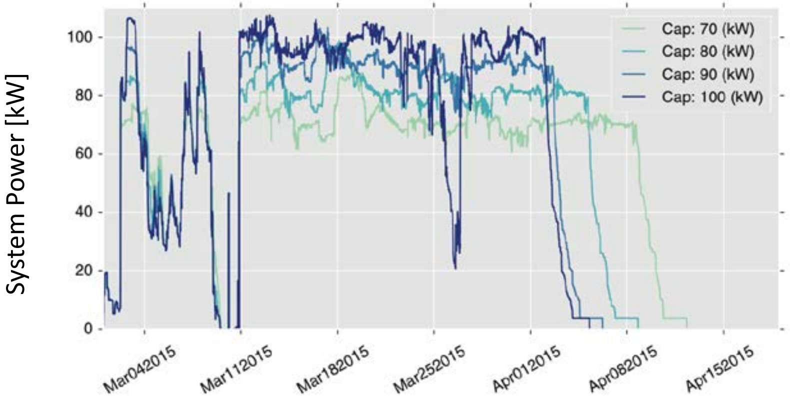
More Details: Baker et al. *Workshop Report on Basic Research Needs for Scientific Machine Learning: Core Technologies for Artificial Intelligence*. United States. https://doi.org/10.2172/1478744

Grid-Integrated, Carbon-Aware Computing

- Job Energy Prediction
- Energy, Cost, and Carbon-Aware Scheduling
- Anomaly detection
- Predictive maintenance
- Operational optimization (PUE)







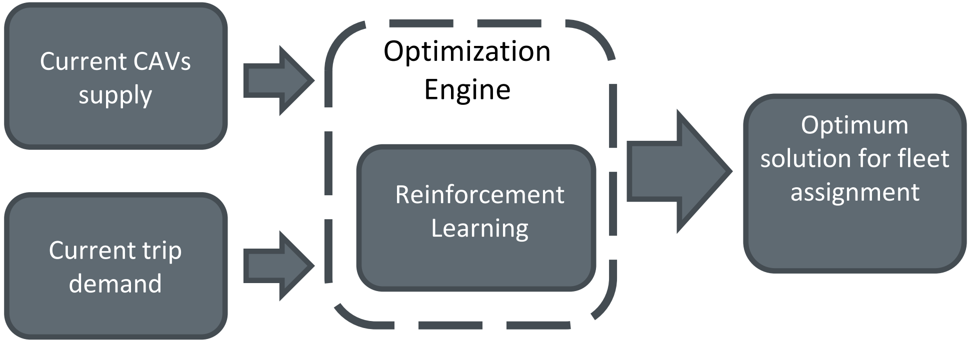
Work led by Caleb Phillips, Hilary Egan

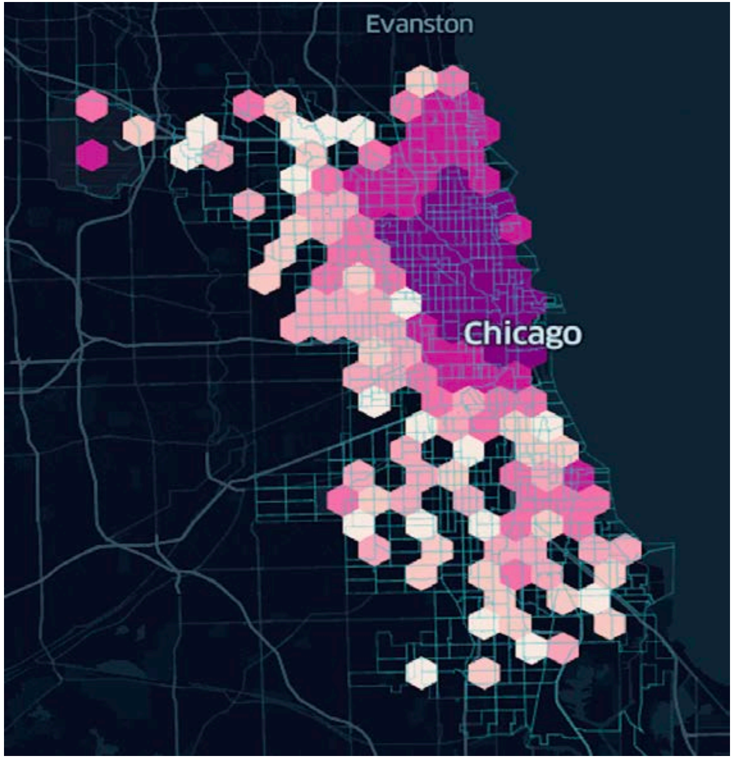
Mitigating AI Trust Issues

- Are there safeguards we can implement to constrain or manage system outputs?
  - Using known-good baseline systems to limit control outputs.
- Can we detect "bad behavior", or detect "dangerous outputs" before they cause a problem?
  - Anomaly detection systems
- Choosing a Level of Autonomy: What kind of oversight do we need to mitigate system risks?
  - High risk: use AI systems to advise and assist a human practitioner who is trained to understand and manage the limitations and failure modes of the system
  - Moderate risk: implement anomaly detection and human monitoring
  - Low risk: allow day-to-day autonomy but maintain a reasonable level of oversight, spot-checks, and validation
- Explainability: can we know why it did what it did?

Autonomous Vehicle Fleet Assignment

- Objective
  - Optimize fleet assignment under a variety of scenarios where all trips in the city are served by connected autonomous vehicle (CAVS) fleet
- Impacts
  - Reduce empty-passenger miles traveled
  - Save energy and operation cost

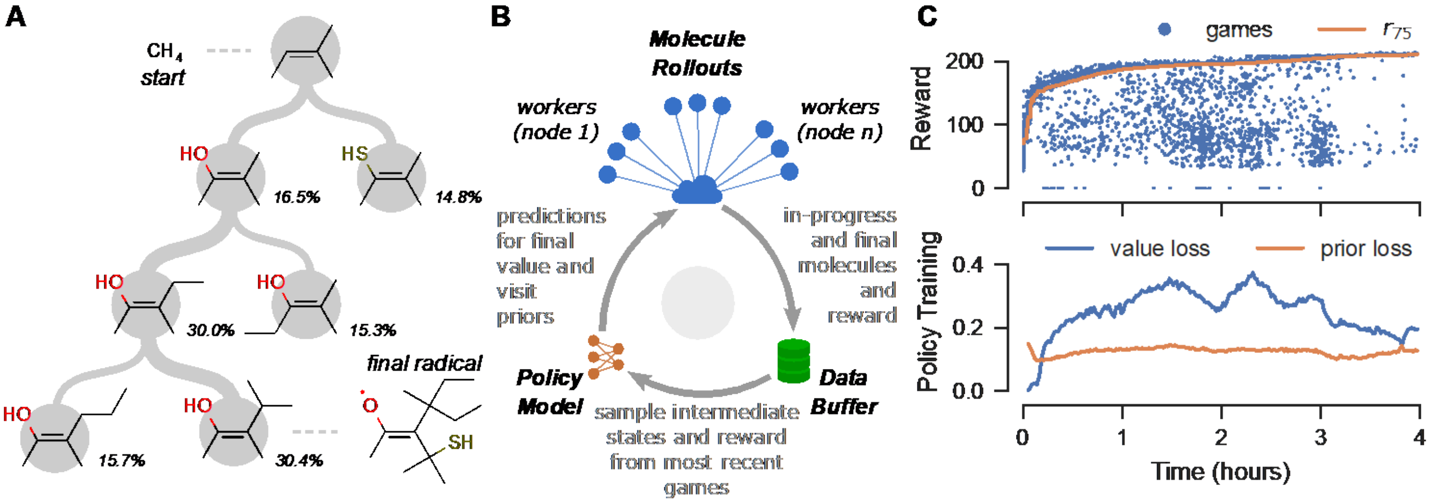




Work led by Dave Biagioni

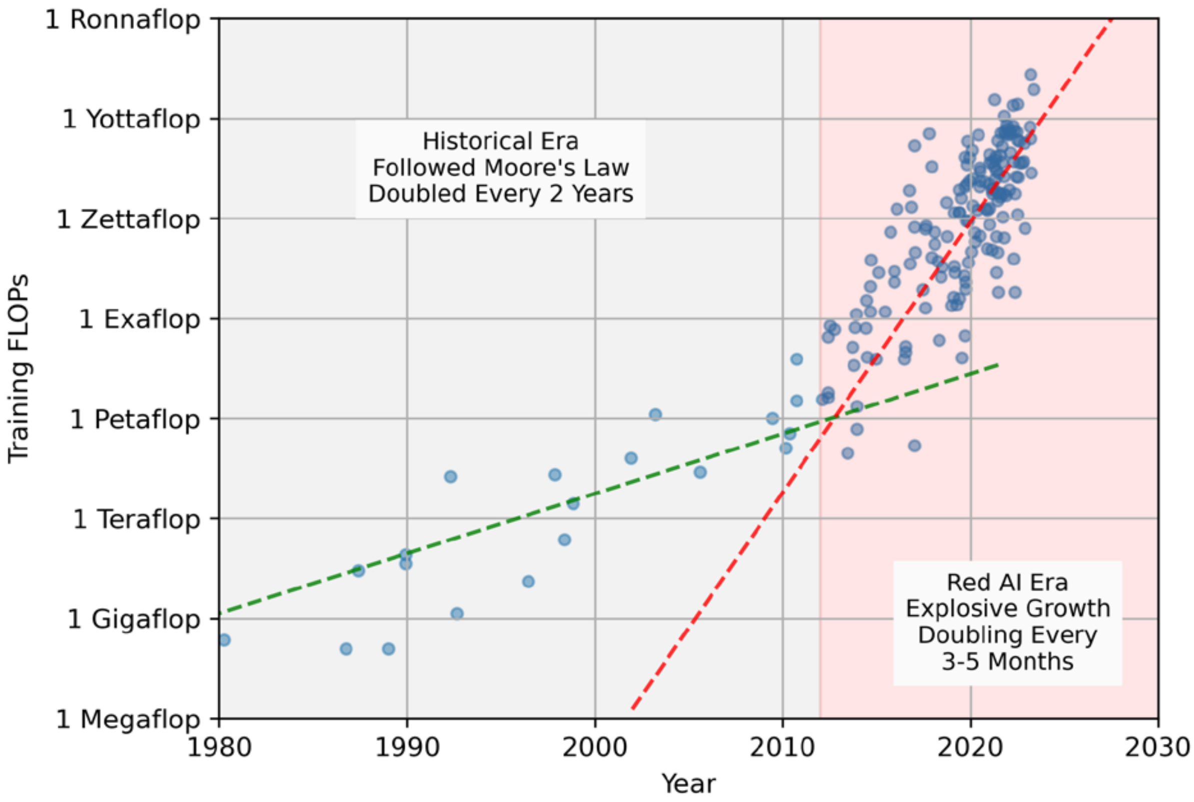
Materials Discovery

- AlphaZero Reinforcement Learning uses self-play to explore large action spaces and decouples rollouts from policy updates
- Inherently scalable design (demonstrated with thousands of TPUs), leveraging GPUs in both rollouts (policy evaluations) and policy training



Work led by Peter St. John

Red AI: Exploding Computational Costs



Historically the computational cost of AI grew with our computers.

But, in the last decade AI growth has far outstripped the growth in computing power.

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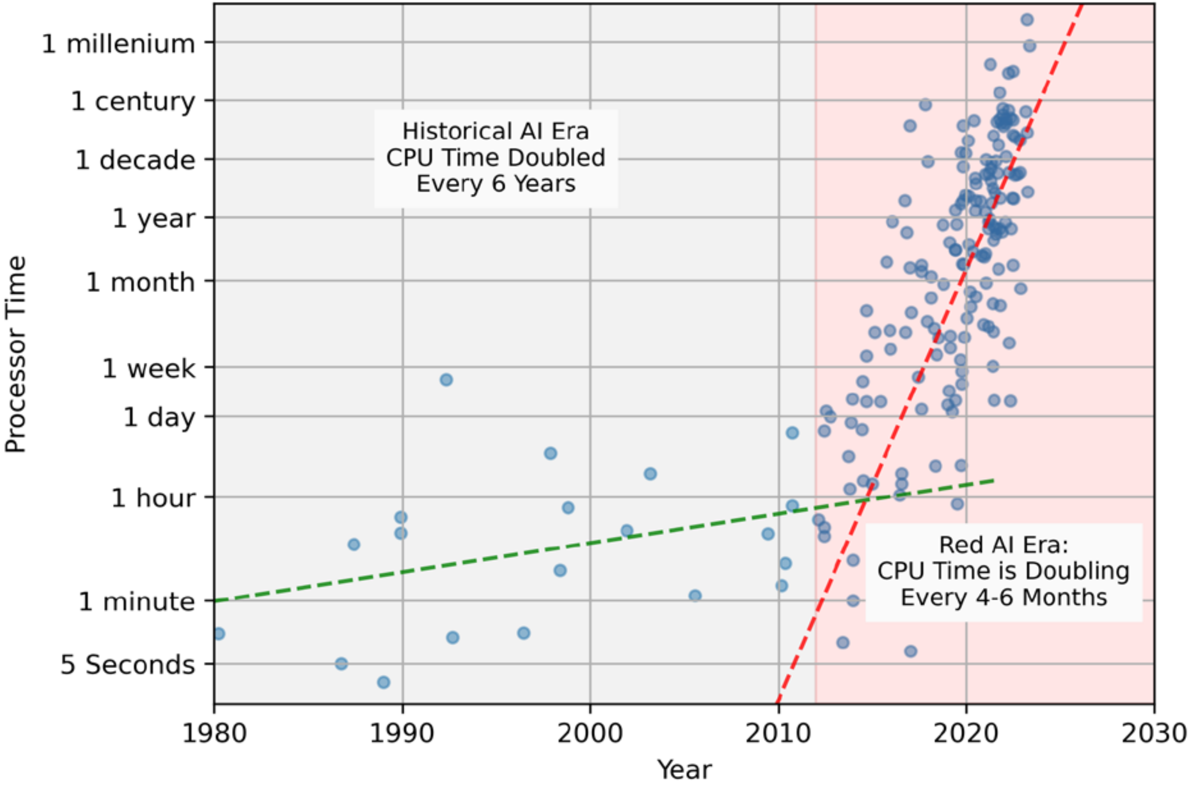
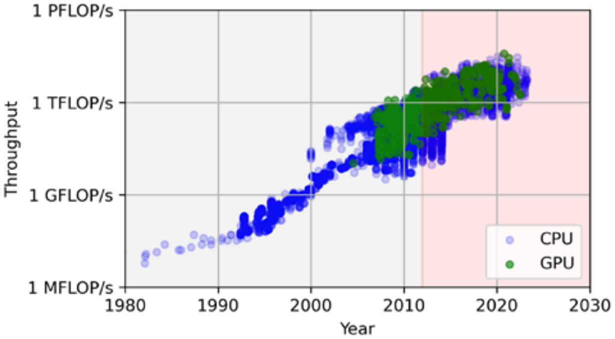
AI Compute Time Doubles Every 4-6 Months



Also growing rapidly:

- AI Compute Costs
- AI Data Requirements



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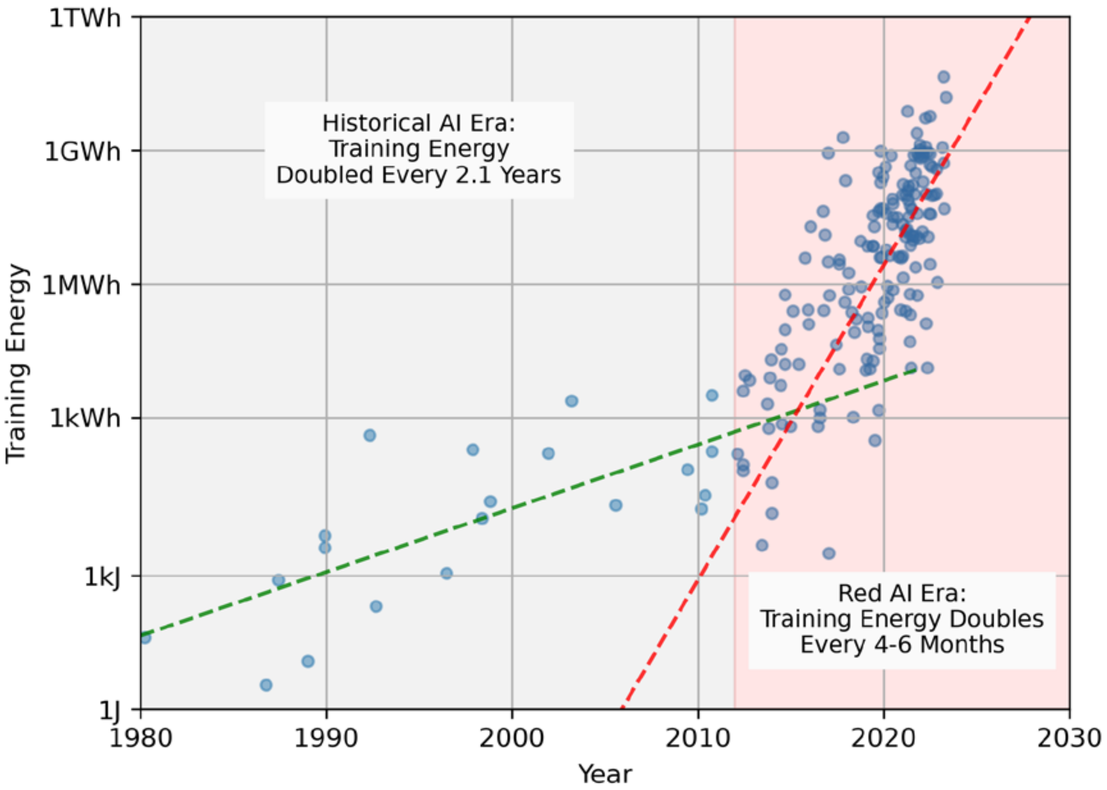
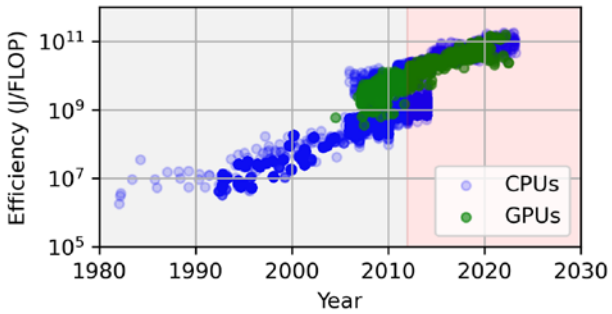
AI Energy Costs Double Every 4-6 Months



Also growing rapidly:

- Inference Energy
- AI Deployment
- Carbon Footprint



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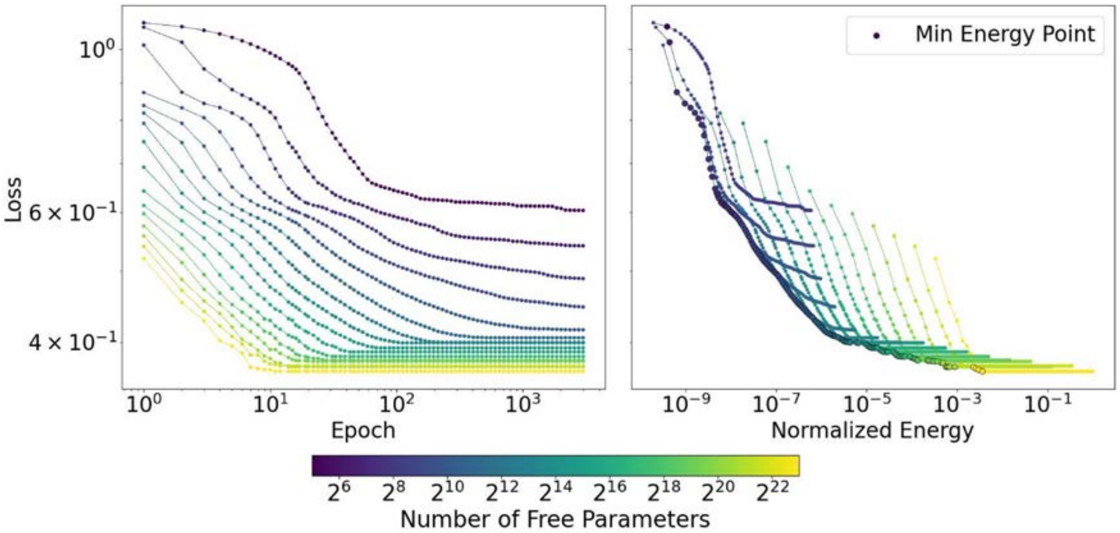
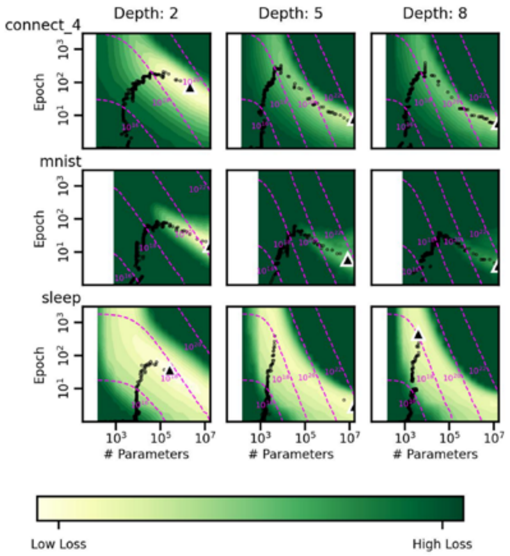
The AI Performance – Energy Trade-off





- Larger models can achieve higher performance but are substantially less efficient.
- Even for achieving lower performance targets.
- We are developing training methods that walk along the optimal frontier

Work led by Charles Tripp, Jordan Perr-Sauer

Thank you!

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