Developing a generative ML model for LAPD trend inference and profile prediction

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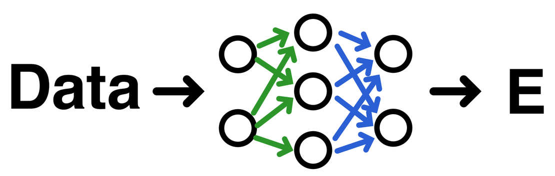
Learning a probability distribution over machine state and diagnostics for diagnostics reconstruction and trend inference

Energy based models (EBMs) define probability as:

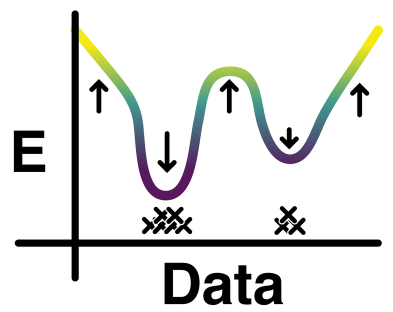
$$p(x) \sim e^{-\beta E(x)}$$

A neural network assigns energy value to input:

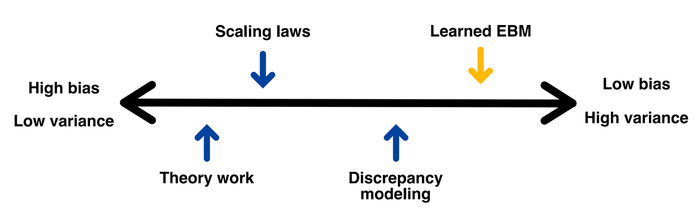


1 EBM basics

- Assigns an energy value to configurations of input variables — the model is generative
- Trained by pushing energy down on data, up on samples (contrastive divergence)
- **Learns the relationship between all input variables – predict anything from anything**
  - Conditional sampling is easy
  - Solution to inverse problems are built-in
  - Can fill in missing data
  - Energies are additive: can easily combine models

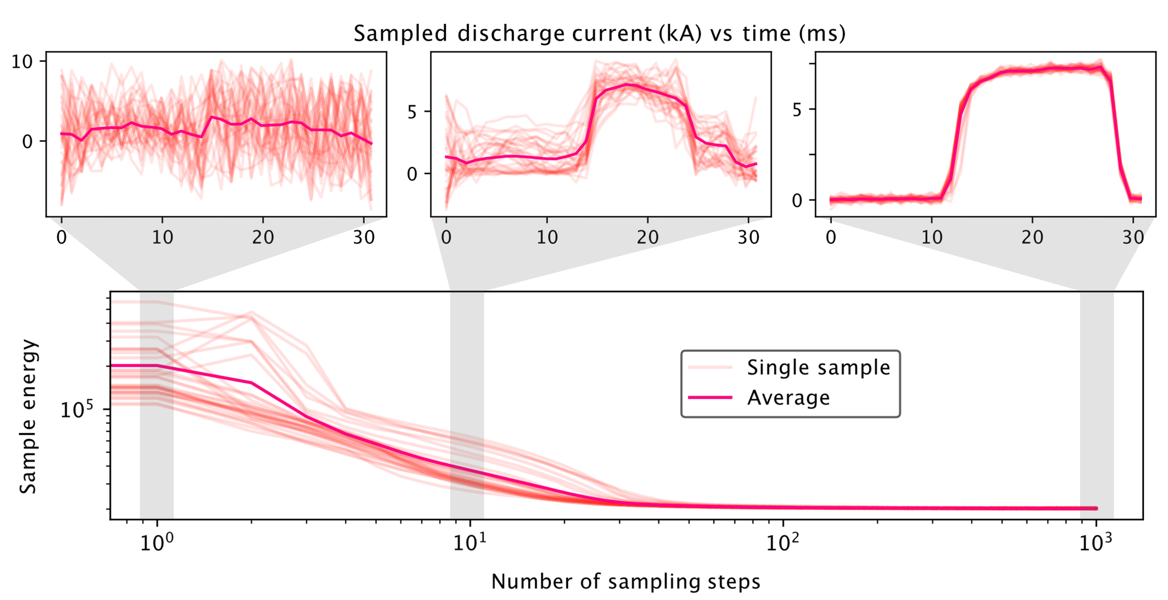


- In a high-variance (learned) approach:
  - All effects accounted for in prediction
  - Model has few preconceived notions



- These EBMs are trained using contrastive divergence
- Based on methodology outlined in:
  Du & Mordatch (2020) arXiv:1903.08689v6
  Nijkamp et al. (2019) arXiv:1903.12370
  Du et al. (2021) arXiv:2012.01316v4

Example: constrained EBM sampling



- The energy function is sampled iteratively from uniform noise
- Above: samples of discharge current constrained to 7.2 kA by **modifying the energy function** at 1, 10, and 1000 steps

The Large Plasma Device (LAPD) is **data-rich**

- many diagnostics
- **10m+ shots recorded**

2 LAPD data sources

Machine state information (MSI)

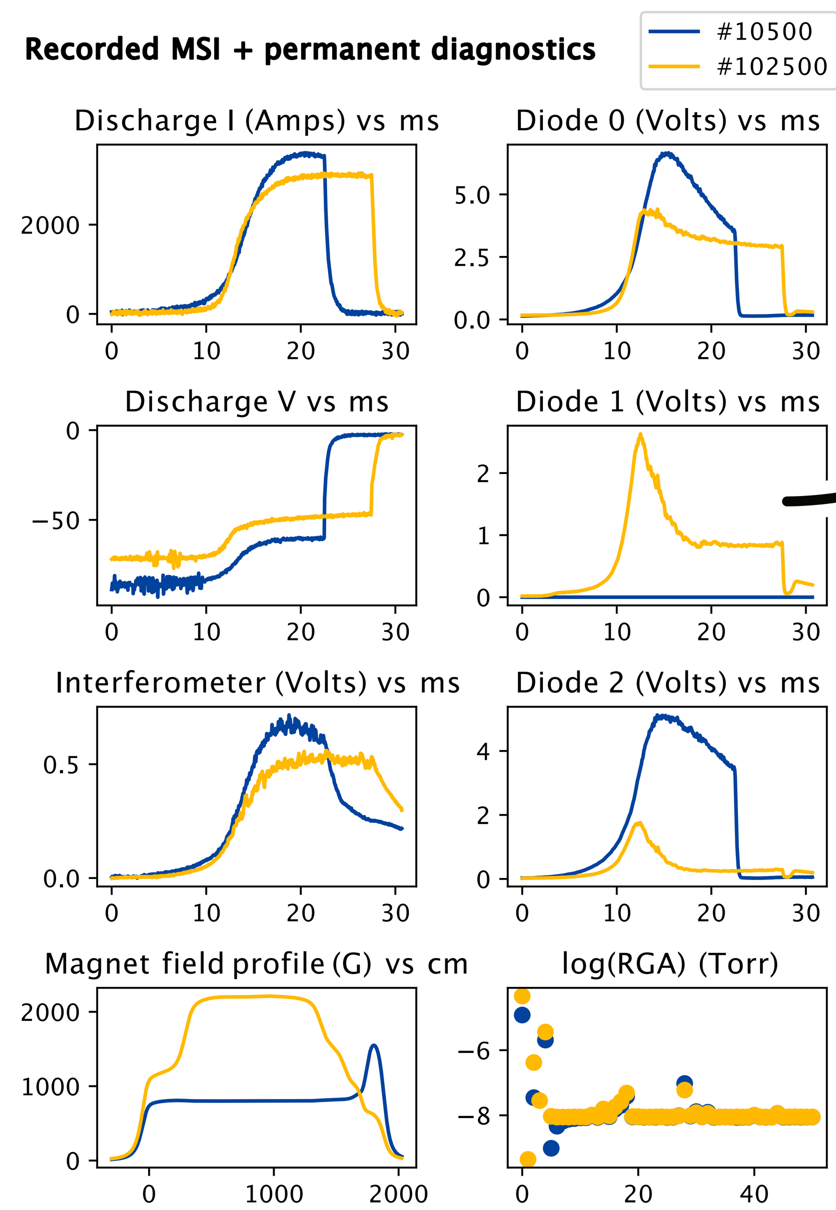
- Discharge current
- Discharge voltage
- Gas pressure
- RGA partial pressures
- Axial magnetic field

Fixed diagnostics

- Interferometers (x1)
- Visible light diodes (x5)
- Fast framing camera

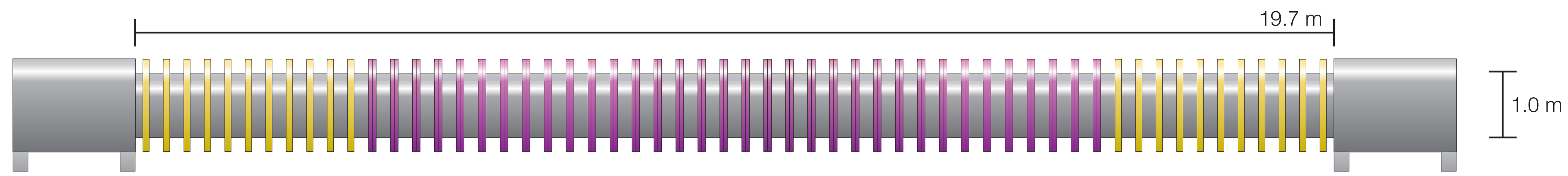
Probe diagnostics (mobile)

- Langmuir probes
  - Ion saturation current
  - Floating potential
  - Langmuir sweeps (Te)
- Hairpin resonator density measurements
- Magnetic fluctuations

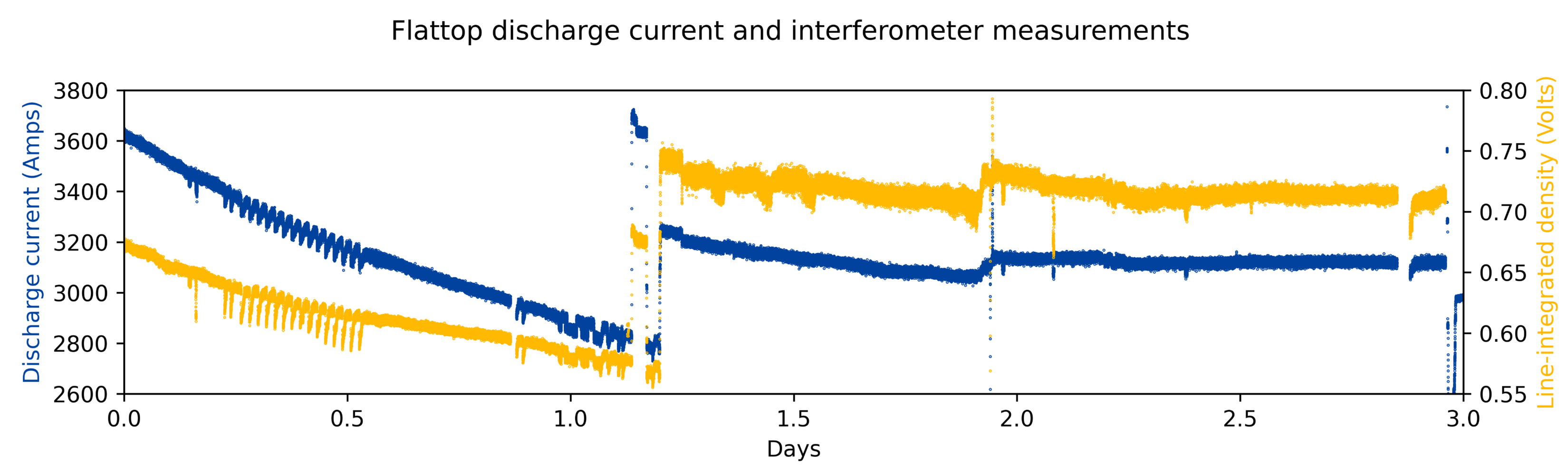


The Large Plasma Device (LAPD)

- 19.7m long, 1m diameter
- T_e ~ 5-10 eV
- n_e up to ~10^{13} cm^{-3}
- **1 Hz shot rate** – up to 31 million shots per year (have 10m+ shots recorded right now)
- Hundreds of diagnostics ports
- **Data-rich environment**



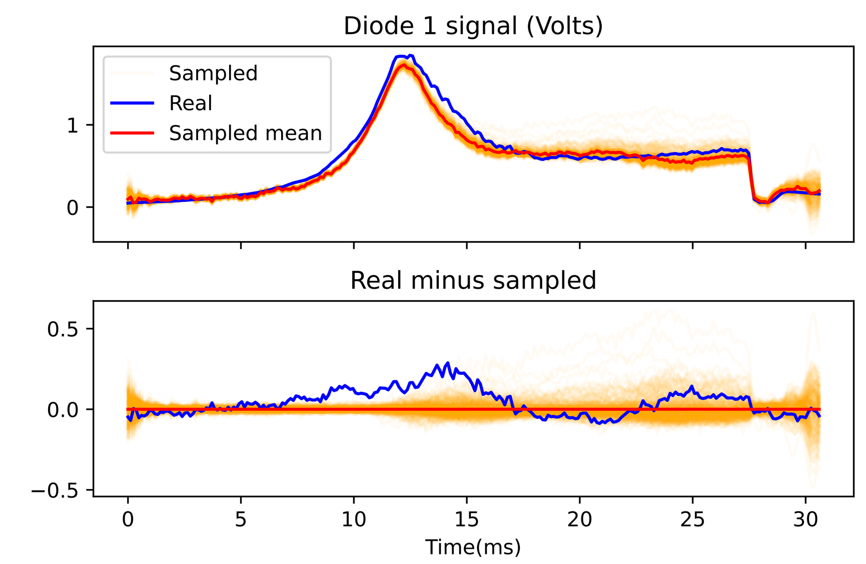
Long-timescale trends seen in data: EBMs could compensate



- **Changes in discharge current likely in-part caused by probe positions**
- Current assumption: plasmas do not change significantly shot-to-shot
  - **May be able to relax this assumption using ML**

Missing signals can be **reconstructed** via conditional sampling

3 Reconstructing signals



- Missing singles can be reconstructed based on what the model has seen before
- Reconstruct by freezing all other signals and varying the missing signal by moving along the energy surface
  - Sample from models: Langevin dynamics

$$\ddot{x} = -\nabla E(x) + \sqrt{T\mathcal{N}(0,1)}$$

Energy surface — Gaussian process

  - Conditionally sample: fill in missing data

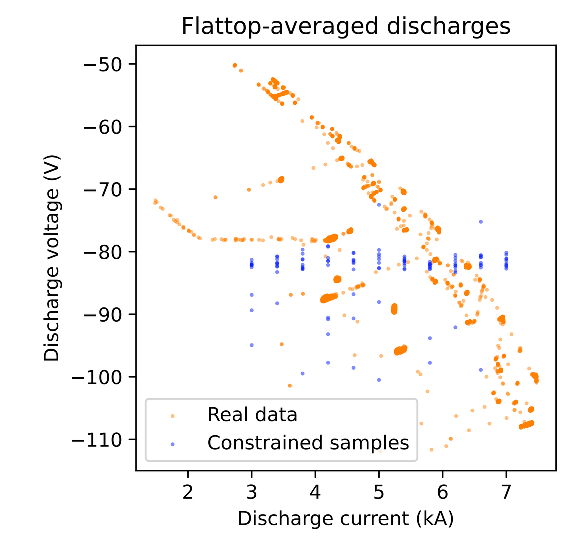
$$y \sim p(y \mid x)$$

Missing signal — Existing signals

Diagnostics contain information that is **difficult to exploit**

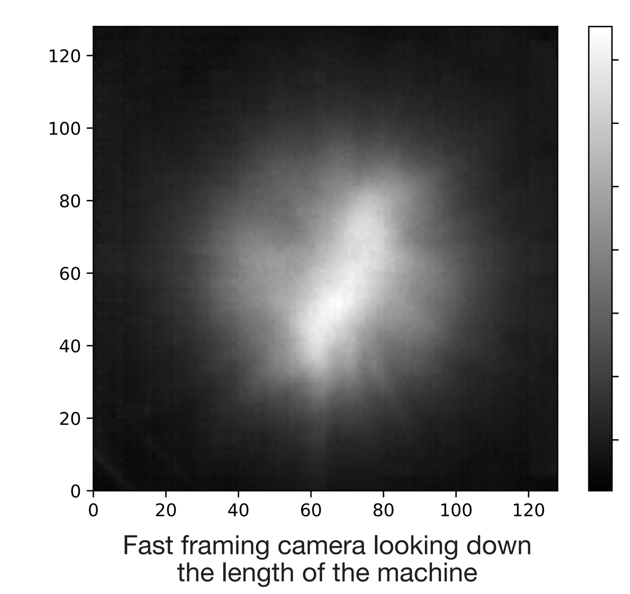
Learning trends permits **automated exploration**

4 Inferring trends



- EBMs can be used for trend discovery
  - Conditionally sample for any arbitrary set of parameters
  - Can isolate variables that would otherwise be very difficult to analyze
- Left: 11 discharges currents sampled between 3 and 7 kA
- Current model learns correlations inside diagnostic traces well, but not between different diagnostics
- Current model has capacity preferentially in individual diagnostic processing → may need to modify architecture

5 Towards profile prediction



Fast framing camera looking down the length of the machine

- Fast framing camera contains information on plasma cross-section
- **Goal:** learn correlation between probe signals and fast camera frames to predict profiles
- **Primary bottleneck:** preprocessing and sorting of disparate data runs and probe configurations
- Currently have over ~20,000 shots with probe and fast framing camera data (1,300 frames at 35,000 fps) spread over hundreds of different data runs

6 Summary

- Data pipeline was constructed for machine state information (MSI) and fixed diagnostics (an interferometer and diodes)
- Energy-based models (EBMs) learn a probability distribution by assigning an energy value to each input configuration
- **EBMs can be conditionally sampled to fill in missing signals**
- Data have been collected for EBM-based profile reconstruction

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