THRML-Powered RBM Demonstration

Training an RBM on binary bars and stripes data

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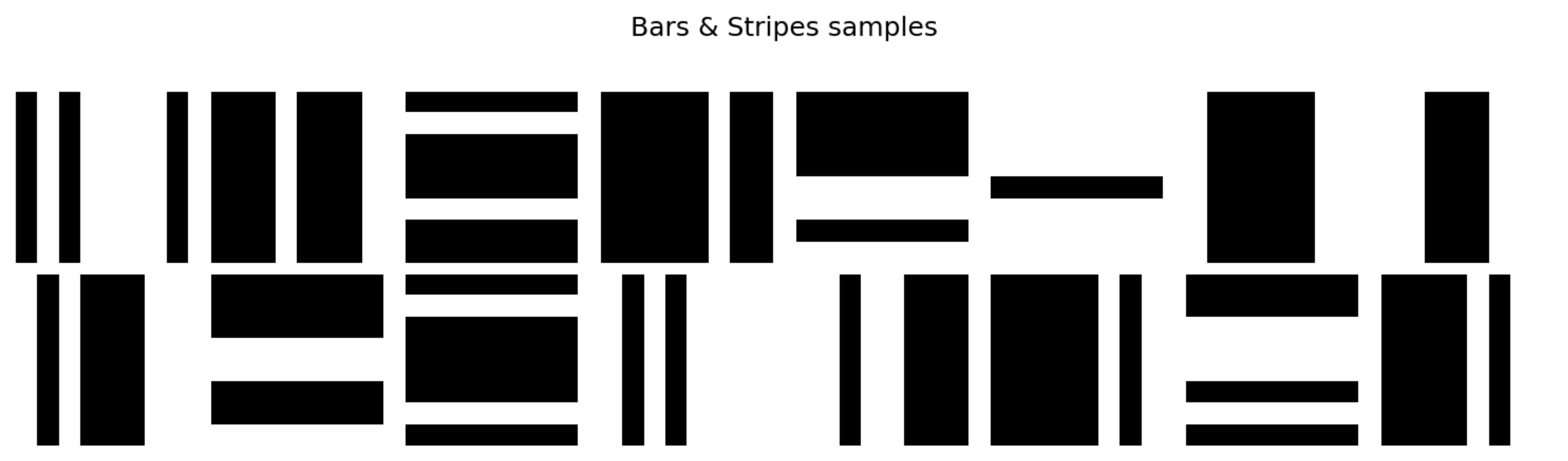
Overview

- Build a **Restricted Boltzmann Machine (RBM)** as an **Ising Energy-Based Model**
- Train it using **THRML's KL Gradient Estimator**
- Evaluate using:
  - 1-step **clamped reconstructions**
  - **THRML free-running sampling**
  - **Naive Python Gibbs sampling**
- Show how **THRML acts as a general Gibbs engine**
- Visualize learned filters and sampling results

Dataset: 8×8 Bars & Stripes

- Synthetic binary dataset used in EBM research
- Contains:
    - Horizontal bars
    - Vertical bars
    - Multiple bars per image
- Structured, multimodal, ideal for generative testing


Bars & Stripes samples

Training with THRML

THRML provides:

- **Block sampling** engine
- **KL divergence gradient estimator**
- **Factor graph representation**
- **Sampling schedules**
- Multi-chain sampling via `batch_shape`

We train RBM parameters:

- weights (W)
- visible biases (b_v), hidden biases (b_h)
- temperature parameter (\beta)

Our RBM/Ising energy function

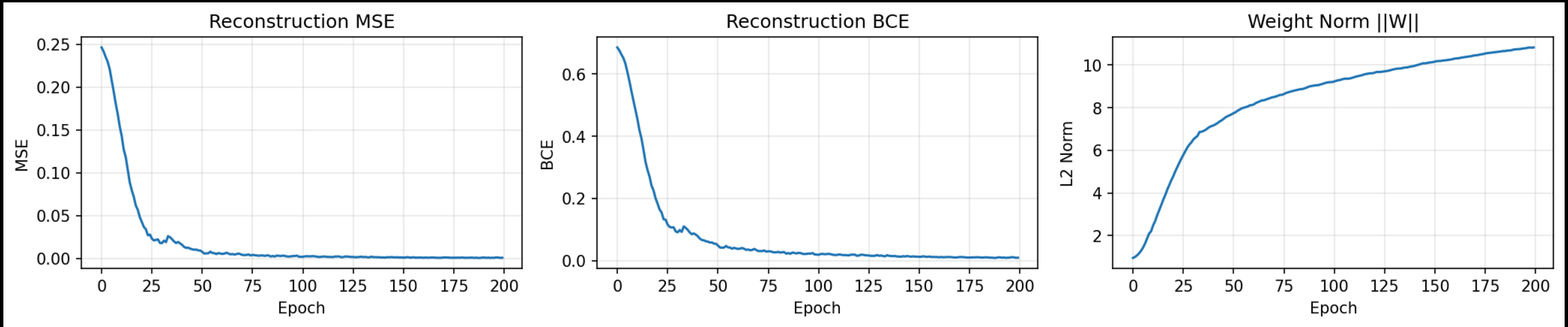
$$E(v,h) = -\beta \left[\sum_i b_i^{(v)} v_i + \sum_j b_j^{(h)} h_j + \sum_{i,j} W_{ij} v_i h_j \right]$$

directly taken from the Gibbs/Ising Hamiltonian, and each sum corresponds to a physical energy term

- 1st term, external field on visible spins
- 2nd term, external field on hidden spins
- Pairwise interaction energy

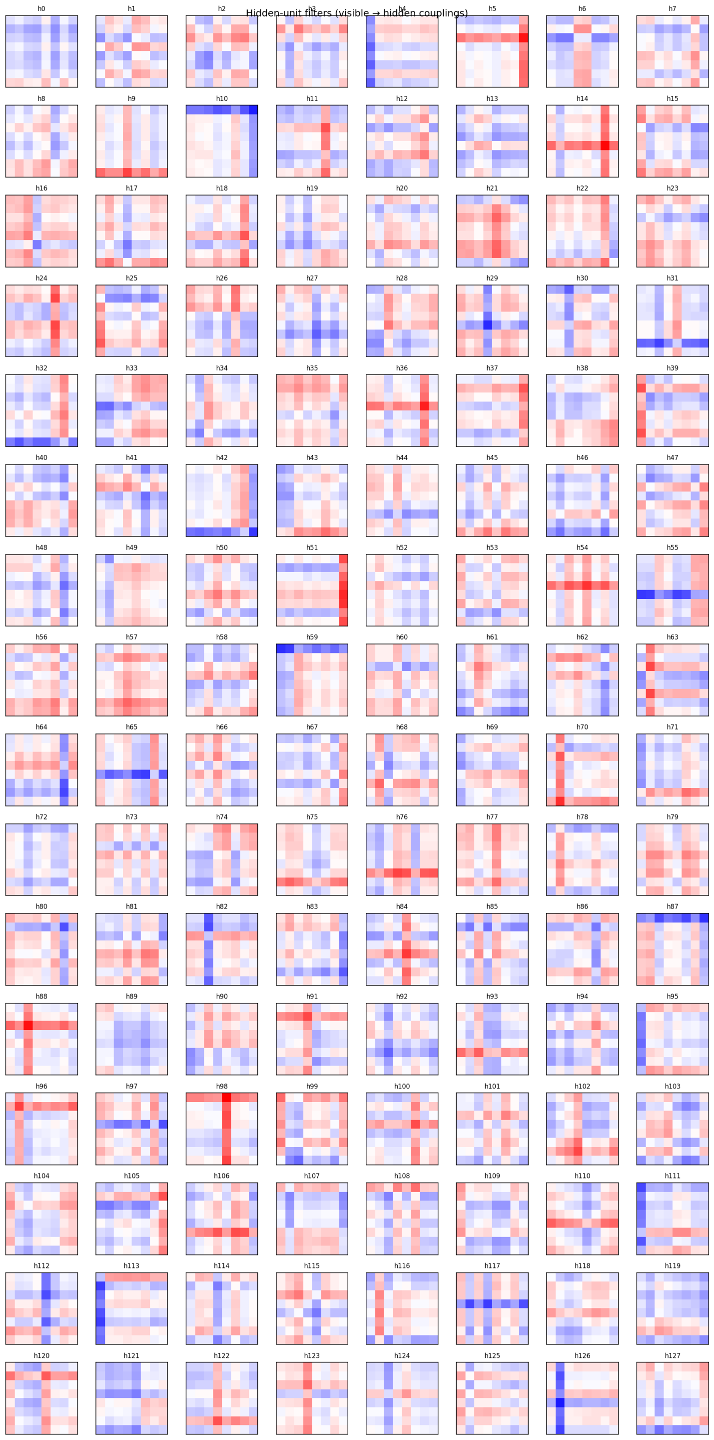
Training Curves

- **MSE** drops sharply → good reconstructions
- **BCE** approaches ~0 → near-perfect predictions
- Weight norm increases steadily → filters specialize


Reconstruction MSE
MSE
0.25
0.20
0.15
0.10
0.05
0.00
0
25
50
75
100
125
150
175
200
Epoch
Reconstruction BCE
BCE
0.6
0.4
0.2
0.0
Weight Norm ||W||
L2 Norm
10
8
6
4
2

Learned Hidden Unit Filters

- Each hidden unit learns a **feature detector**
- Filters resemble:
    - Vertical bars
    - Horizontal bars
    - Crossings
    - Composite stripe patterns
- RBM learns a **distributed encoding** of the dataset


Hidden-unit filters (visible → hidden couplings)
h0
h1
h2
h3
h4
h5
h6
h7
h8
h9
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h11
h12
h13
h14
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h125
h126
h127

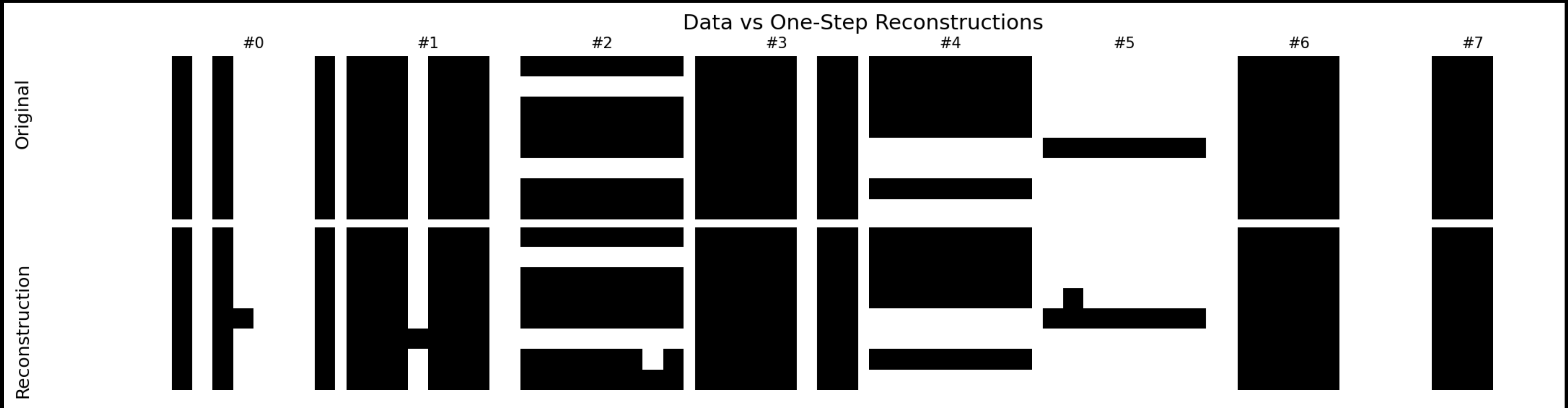
Clamped 1-Step Reconstructions

Process:

1. Clamp visibles to data
2. Sample (h \sim p(h|v))
3. Sample (v' \sim p(v|h))

Purpose:

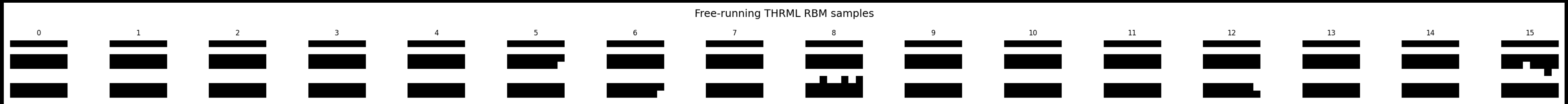
- Validate training
- Check encoder–decoder consistency
- Ensure stable attractor basins


Data vs One-Step Reconstructions
#0
#1
#2
#3
#4
#5
#6
#7
Original
Reconstruction

THRML Free-Running Sampling

- Start from random spins
- Run full Gibbs chain (no clamping)
- THRML explores the learned energy landscape
- Produces pure model samples

Shows true generative behavior of the RBM.


Free-running THRML RBM samples
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15

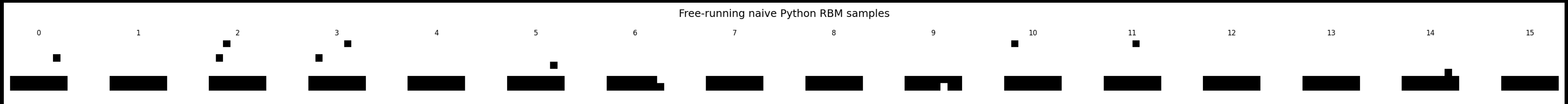
Naive Python Gibbs Sampling (Baseline)

Why?

- Validate correctness of THRML sampler
- Check if a hand-written sampler produces similar samples

Results:

- Python sampler produces Bars & Stripes
- Confirms correctness of learned energy landscape
- THRML behaves consistently with standard RBM sampling


Free-running naive Python RBM samples
0
1
2
3
4
5
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10
11
12
13
14
15

Why Three Sampling Modes?

1. Clamped Reconstructions

- ✓ Measure training quality
- ✓ Checks encoder/decoder mapping
- ✓ Local consistency

2. THRML Free-Running Sampling

- ✓ Explore full Boltzmann distribution
- ✓ Checks generative behavior
- ✓ Shows learned modes

3. Naive Gibbs Sampling

- ✓ Baseline sanity check
- ✓ Confirms THRML correctness
- ✓ Ensures consistent energy landscape

What We Learned

RBM Learning

- RBM trained via THRML achieves extremely low recon error
- Filters reflect dataset structure

Energy Landscape

- THRML free-running samples match Bars & Stripes
- Energy minima match dataset modes

Sampler Validation

- Python Gibbs sampler matches THRML outputs
- Confirms correctness of THRML's block sampler

THRML as a Gibbs Engine

Benefits

- Eliminates hand-written Gibbs loops
- Works for **arbitrary** factor graphs
- Supports multi-chain sampling
- Hardware-friendly (GPU/TPU acceleration)
- Clean integration with EBMs

Takeaway

THRML can serve as a **general-purpose thermodynamic sampling engine** for probabilistic models.

Conclusion

We successfully:

- Built a THRML-powered RBM
- Learned structured representations
- Generated high-quality samples
- Validated sampler correctness
- Demonstrated the feasibility of using THRML as a Gibbs engine

A strong foundation for larger EBMs and future thermodynamic computing systems.

Thank You

Questions?

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