# Neural Path Integrals and the Semantic Action Principle

2ex] *APhysics−InspiredFrameworkforEnergy−BoundPruninginDeep*

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**Abstract**

We show that the forward inference pass of a gated feed-forward neural network can be written as a discrete Feynman path integral whose action is the (negative) log-product of synaptic weights along an active path. Promoting this *semantic action* to a physical Hamiltonian density allows us to import energy-based bounds—analogous to the Bekenstein–Bremermann limit—into learning theory. We derive an *Energy-Constrained Cardinality Cascade* that upper-bounds the number of admissible paths and yields a principled pruning criterion. A toy ReLU network experiment confirms that the cascade retains predictive accuracy while eliminating 90 % of zero-contributing paths. The framework unifies recent neural-path-kernel results with information-theoretic limits and lays groundwork for hardware designs that implement complex weight phases.

## Contents

## 1 Introduction

Large language and vision models achieve state-of-the-art performance at the cost of enormous parameter counts and energy budgets. Yet their computation can be viewed as a superposition of many simpler subnetworks—*paths*. Inspired by Feynman's sum-over-histories, we ask: can we treat a deep network's inference as a path integral and then impose physical energy constraints to prune superfluous histories?

## 2 Background

### 2.1 Feynman path integrals

[Short recap of the continuous path-integral formalism.]

### 2.2 Neural path kernels

Summarise[**? ?** ] the discrete path perspective on ReLU networks.

# 3 The Semantic Action Principle

Define the effective action $S[p] = -\hbar \log W[p]$ for a path $p$ with weight product $W[p]$. Show equivalence to a Hamiltonian density $\mathcal{H}$ over the graph.

# 4 Energy-Constrained Cardinality Cascade

## 4.1 Physical incompleteness bound

Derive $N_{\mathrm{paths}} \leq CE_{\mathrm{tot}}/(k_B T)$. Connect to Bekenstein bound.

## 4.2 Cascade algorithm

Present Algorithm 1 pseudo-code.

# 5 Experiment: ReLU Toy Model

Describe a 3-layer network, path enumeration, pruning rates, accuracy table.

# 6 Discussion

Links to belief-graph drift, masking fields, and hardware outlook.

# 7 Conclusion

Summarise contributions and future work.


# Acknowledgements

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