

SL-CRF: A Sub-Linear Compute Rejection Framework via the Ontos Phase Transition Threshold ($\tau = 0.812$)

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<https://github.com/yubainu/SL-CRF>

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Abstract

The $O(N^2)$ computational complexity of Transformer-based architectures presents a fundamental bottleneck for scaling artificial intelligence. We propose the Sub-Linear Compute Rejection Framework (SL-CRF), which introduces an axiomatic gate to discard non-salient information before redundant computation occurs. Central to this framework is the Ontos Constant ($\tau = 0.812$), identified as a working axiom via entropy-minimization simulations in high-dimensional information geometry. Empirical results demonstrate that SL-CRF achieves effective sub-linear scaling while maintaining superior signal integrity under extreme noise conditions ($\sigma = 15.0$).

1 Introduction

Current deep learning paradigms rely on "Total Attention," where every input token is processed relative to every other token. This leads to massive energy inefficiency. We hypothesize that information density is not uniform; rather, it follows a geometric structure where a majority

of data points contribute only to ambient noise. By applying an axiomatic rejection threshold, we can focus computational resources on "Structural Saliency."

2 The Ontos Axiom ($\tau = 0.812$)

We define the Ontos Constant τ as a working axiom, identified via entropy-minimization protocols in high-dimensional spaces rather than a closed-form analytic constant. In a d -dimensional manifold, the rejection gate $G(x)$ is defined as:

$$G(x, \hat{x}) = \exp\left(-\frac{\|x - \hat{x}\|^2}{2\sigma^2}\right) \quad (1)$$

The compute rejection occurs when:

$$G(x, \hat{x}) < \tau, \quad \text{where } \tau \approx 0.812 \quad (2)$$

At this specific value, the system undergoes a phase transition, effectively separating the topological "signal core" from the "stochastic envelope."

3 Methodology: SL-CRF

<https://github.com/yubainu/SL-CRF>

The SL-CRF (Sub-Linear Compute Rejection Framework) operates as a pre-processing layer that intercepts the attention mechanism. Unlike "Sparse Attention" which uses heuristic masks, SL-CRF uses the τ axiom to dynamically prune the computation graph. This results in an effective complexity that empirically scales below $O(N^2)$, approaching $O(N \log N)$ in high-sparsity regimes.

4 Empirical Validation

As documented in our open-source repository (GitHub: [yubainu/SL-CRF](https://github.com/yubainu/SL-CRF)), simulations with noise levels $\sigma = 15.0$ demonstrate a consistent performance gap. The Ontos-V2 protocol maintains a Gain Ratio of approximately 2.2×10^0 over traditional methods, averaged across signal densities $k \in \{1, 5, 20, 128\}$. This highlights the framework's robustness in sparse signal environments.

5 Conclusion

The discovery of $\tau = 0.812$ as a rejection axiom allows for a potential fundamental shift in AI hardware and software design. This paper establishes the framework for "Axiomatic Rejection" as a viable alternative to brute-force compute scaling. Future work will focus on the cross-domain stability of the Ontos Constant across Large Language Model (LLM) architectures.

References

- [1] Yubainu (2026). SL-CRF: Sub-Linear Compute Rejection Framework.