Semantic Probability Chains and Multidimensional Voronoi Partitioning in Knowledge Graphs

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Abstract

We present a unified framework linking semantic probability chains with high-dimensional Voronoi partitioning of knowledge and observation graphs. Starting from the notion that observations travel through directed paths in a knowledge space defined by empirical or formal proof steps, we derive a probability calculus rooted in the graph-theoretic structure. Voronoi partitions are then introduced as a means of tessellating this space into localized domains of influence, allowing for both probabilistic convergence analysis and dimension-wise trajectory signatures. This work provides foundational tools for modeling semantic drift, belief alignment, and the structured co-evolution of agent states.

1 Introduction

Semantic reasoning and probabilistic inference are often treated as distinct domains: the former symbolic and structural, the latter statistical and numeric. Our objective is to unify them under a graph-based language model, where beliefs are terminal nodes, proofs are directed paths, and inference emerges as weighted traversal through a dynamically partitioned semantic field.

2 Semantic Probability Chains

Let $G = (V, E)$ be a directed graph where vertices V are semantic states and edges E represent transitions. Each edge encodes a transformation with a confidence or error weight. The total path probability is accumulated across steps, and drift is characterized as deviation from truth-aligned paths.

3 Graph-Based Probability and Bayesian Structure

We interpret transitions using a conditional probability update rule:

$$P(v_j|v_i, f_k) = \frac{P(f_k|v_j)P(v_j)}{P(f_k|v_i)}$$

where f_k labels the transformation. Inverse edges and dual operations enable counterfactual reasoning.

4 Voronoi Partitioning in M-Dimensional Space

A trajectory $\gamma(t)$ is a path in a space $\mathbb{R}^m$ where dimensions correspond to attributes. Dimensional spread $D(t)$ often follows a bell-shaped curve over the trajectory. Entropic midpoints indicate semantic divergence and learning curvature.

5 Voronoi Cells and Probabilistic Convergence

Each Voronoi cell C_i hosts a local domain. Let $p_i(t)$ denote the probability of being in C_i at time t. The re-encounter field $F_{ij}(t)$ measures potential semantic convergence. Path signatures and minimal inter-cell distances inform the convergence probability P_{re}.

6 Generalization and Conclusion

The model extends beyond dyadic human interaction to general data pairs. Applications include theory alignment, LLM drift tracking, and agent convergence. Future work includes defining semantic curvature and second-order dynamics.