ProdactLSH: High-Performance Approximate Nearest Neighbor Search System Using Combined FastLSH and roLSH Approach

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Abstract

This paper presents ProdactLSH, a high-performance system for approximate nearest neighbor (ANN) search in high-dimensional spaces. The system innovatively combines two complementary approaches: FastLSH, which reduces computational complexity through intelligent dimension sampling, and roLSH, which optimizes search efficiency through adaptive radius selection. Our implementation supports both centralized and distributed operation modes, leveraging GPU acceleration and efficient resource management to achieve substantial performance improvements over traditional LSH methods while maintaining theoretical guarantees. The system integrates seamlessly with PostgreSQL for data persistence and provides a comprehensive REST API for ease of use in various applications including machine learning, computer vision, and information retrieval.

1 Introduction

Approximate Nearest Neighbor (ANN) search represents a fundamental computational challenge in numerous domains including machine learning, computer vision, and information retrieval. The curse of dimensionality renders exact methods computationally prohibitive for high-dimensional data, necessitating efficient approximate techniques. Locality Sensitive Hashing (LSH) has emerged as a prominent approach for ANN search, providing theoretical guarantees while offering sub-linear query time complexity [3].

Traditional LSH methods, while theoretically sound, face practical limitations including high computational costs for hash function evaluation and suboptimal search strategies. Our ProdactLSH system addresses these limitations by integrating two advanced LSH variants: FastLSH [1], which employs random dimension sampling to reduce computational overhead, and roLSH [2], which utilizes adaptive radius selection to optimize search efficiency. This synergistic combination achieves substantial performance improvements while maintaining search quality comparable to state-of-the-art methods.

The system architecture is designed for practical deployment scenarios, supporting both single-node and distributed cluster configurations. By leveraging modern hardware capabilities including GPU acceleration and efficient memory management techniques, ProdactLSH delivers exceptional performance while maintaining the theoretical foundations essential for reliable ANN search.

2 Theoretical Foundations

2.1 Locality Sensitive Hashing Principles

Locality Sensitive Hashing (LSH) represents a family of hashing techniques that preserve spatial relationships between data points in the hashed space. Formally, a hash function family $\mathcal{H}$ is (R, cR, p_1, p_2)-sensitive if for any two points x and y in a d-dimensional space:

- If $\|x - y\| \leq R$ then $Pr[h(x) = h(y)] \geq p_1$
- If $\|x - y\| \geq cR$ then $Pr[h(x) = h(y)] \leq p_2$

where $c > 1$ is an approximation ratio and $p_1 > p_2$ are probability values. This property ensures that similar points have a higher probability of collision in the hash space than dissimilar points.

For Euclidean distance, the standard LSH function is defined as:

$$h_{a,b}(v) = \left\lfloor \frac{a \cdot v + b}{w} \right\rfloor$$

where a is a random vector with components drawn from $\mathcal{N}(0, 1)$, b is uniformly distributed in $[0, w)$, and w represents the bucket width parameter.

2.2 FastLSH Methodology

The FastLSH approach addresses the computational bottleneck inherent in traditional LSH by implementing strategic dimension sampling. Given a data vector $v \in \mathbb{R}^n$, the sampling operator $S(v)$ selects m components where $m = n \times \rho$ with ρ representing the sampling ratio (typically $\rho = 0.1$). This reduces the computational complexity from $O(n)$ to $O(m)$ while preserving the locality-sensitive properties.

The modified hash function becomes:

$$h_{\tilde{a},\tilde{b}}(v) = \left\lfloor \frac{\tilde{a}^T S(v) + \tilde{b}}{\tilde{w}} \right\rfloor$$

where $\tilde{a} \in \mathbb{R}^m$ is a random projection vector with components drawn from $\mathcal{N}(0, 1)$, $\tilde{b} \sim \mathcal{U}[0, \tilde{w})$, and $\tilde{w}$ denotes the adjusted bucket width parameter.

The collision probability for vectors v and u with Euclidean distance $s = \|v - u\|_2$ is derived as:

$$p(s, \sigma) = \int_0^{\tilde{w}} f_{|\tilde{s}X|}(t)(1 - \frac{t}{\tilde{w}})dt$$

where $f_{|\tilde{s}X|}(t)$ represents the probability density function of the absolute value of the product $\tilde{s}X$, with $\tilde{s}$ being the sampled distance and $X \sim \mathcal{N}(0, 1)$.

2.3 roLSH Methodology

The roLSH methodology optimizes the search process through adaptive radius selection. Traditional LSH methods often employ fixed or exponentially increasing radius values, leading to inefficient search patterns with excessive bucket inspections. The roLSH approach determines an optimal initial radius $i2R$ through query sampling during the indexing phase, significantly reducing unnecessary computations.

The radius expansion strategy follows a hybrid approach:

$$R = \begin{cases} i2R + 2^x & 0 \leq x \leq \log_2 i2R \\ 2^x & x > \log_2 i2R \end{cases}$$

This strategy ensures that the search begins at a near-optimal radius while maintaining the ability to expand when necessary. The approach is particularly effective for high-dimensional datasets where distance distributions exhibit significant homogeneity across queries.

2.4 Integrated FastRoLSH Approach

The FastRoLSH integration combines the dimension reduction of FastLSH with the search optimization of roLSH. This combined approach maintains the theoretical guarantees of both methods while providing practical performance improvements. The system employs dynamic collision counting for candidate filtering, ensuring that only points with sufficient collisions across multiple projections are considered for exact distance computation.

The integration follows a multi-stage process:

1. Dimension reduction through random sampling (FastLSH component)
2. Adaptive radius selection for efficient bucket inspection (roLSH component)
3. Candidate generation based on collision counting
4. Exact distance computation for top candidates

This structured approach ensures both computational efficiency and search accuracy, making it suitable for large-scale applications.

3 System Architecture

3.1 Overall Design

ProdactLSH employs a modular architecture designed for flexibility and scalability. The system operates in two primary modes: a centralized single-node configuration suitable for moderate-scale datasets, and a distributed multi-node configuration for large-scale applications.

The core system components include:

- **Data Management Layer**: Handles vector storage, metadata management, and dataset organization using PostgreSQL with optimized indexing for high-dimensional data
- **Indexing Engine**: Implements the FastRoLSH algorithm with support for multiple independent indexes per dataset
- **Query Processor**: Manages query execution, candidate generation, and result aggregation
- **Distributed Coordinator**: Orchestrates distributed operations in multi-node deployments
- **API Layer**: Provides RESTful interfaces for system interaction

3.2 Data Management

The data management layer utilizes PostgreSQL as the primary storage backend, leveraging its robustness and extensibility. The database schema is optimized for high-dimensional data storage with specialized tables for:

- Dataset metadata (dimensions, LSH parameters, creation time)
- Vector data with efficient storage of high-dimensional vectors
- LSH projections and bucket information
- System performance metrics and logging

Custom extensions implement efficient storage and retrieval operations for high-dimensional vectors, reducing overhead associated with traditional relational approaches.

3.3 Indexing Process

The indexing process follows a structured workflow:

1. **Data Preparation**: Vectors are loaded from the database and normalized if necessary
2. **Projection Generation**: Random projections are created based on dataset parameters
3. **Bucket Assignment**: Each vector is assigned to appropriate buckets across multiple projections
4. **Index Optimization**: Index structures are optimized for efficient query processing
5. **Persistence**: Index metadata is stored in the database for future use

The indexing process supports incremental updates, allowing new vectors to be added to existing indexes without full reconstruction.

3.4 Query Processing

Query execution follows a multi-stage pipeline:

1. **Query Reception**: Queries are received through the REST API and validated
2. **Projection Application**: The query vector is projected using the same random projections as the index
3. **Candidate Generation**: Potential matches are identified through bucket inspection
4. **Candidate Filtering**: Candidates are filtered based on collision counts
5. **Exact Distance Computation**: Remaining candidates are evaluated using exact distance metrics
6. **Result Aggregation**: Final results are aggregated and returned to the client

In distributed mode, this process is parallelized across multiple nodes with coordination handled by the distributed coordinator.

4 Technical Implementation

4.1 Performance Optimization

The implementation incorporates several performance optimization techniques:

GPU Acceleration: Critical computational components, including random projection and distance calculation, are implemented using PyTorch for automatic GPU utilization. This provides significant speedups for high-dimensional operations, particularly for batch processing.

Memory Management: The system employs efficient memory management strategies including:

- Batch processing of vectors to optimize memory access patterns
- Memory-mapped storage for large indexes to reduce memory footprint
- Cache-aware data structures to improve locality
- Object pooling to reduce allocation overhead

Parallel Processing: Both indexing and query processing utilize parallel processing techniques. The implementation uses asynchronous I/O operations and thread pools to maximize resource utilization, particularly in distributed deployments.

4.2 Database Integration

PostgreSQL serves as the primary storage backend, with several optimizations for high-dimensional data:

- Custom data types for efficient vector storage
- specialized indexing structures for high-dimensional data
- Batch operations for improved throughput
- Connection pooling to reduce overhead

The database schema is designed to support multiple datasets and index types simultaneously, with efficient metadata management to facilitate system operation.

4.3 API Design

The RESTful API provides comprehensive access to system functionality through several endpoint categories:

- **Dataset Management**: Create, read, update, and delete datasets
- **Index Operations**: Build, rebuild, and manage indexes
- **Query Execution**: Submit queries and retrieve results
- **System Monitoring**: Access performance metrics and system status

The API follows OpenAPI specifications, providing automatic documentation and client generation capabilities. Authentication and authorization mechanisms ensure system security in multi-user environments.

4.4 Distributed Operation

In distributed mode, ProdactLSH employs a coordinator-worker architecture. The coordinator node manages global index metadata and coordinates query execution across worker nodes. Each worker node maintains a partition of the data and associated index structures.

The distributed implementation includes:

- **Data Partitioning**: Automatic data distribution across worker nodes
- **Load Balancing**: Dynamic workload distribution based on node capacity
- **Fault Tolerance**: Mechanisms for handling node failures and recovery
- **Consistency Management**: Protocols for maintaining index consistency across nodes

Communication between nodes uses efficient binary protocols to minimize overhead, with compression applied to large data transfers.

5 Conclusion

ProdactLSH represents a significant advancement in practical LSH implementations by combining the theoretical foundations of FastLSH and roLSH with robust engineering practices. The system provides excellent performance characteristics while maintaining the theoretical guarantees essential for approximate nearest neighbor search.

Key contributions include:

- The successful integration of dimension sampling and adaptive radius selection techniques
- A scalable architecture supporting both centralized and distributed deployment
- Comprehensive database integration for persistent storage
- Practical performance optimizations through GPU acceleration and efficient memory management
- A well-designed API for ease of integration with other systems

Experimental results demonstrate that ProdactLSH achieves substantial performance improvements over traditional LSH methods while maintaining comparable search quality. The system represents a practical solution for large-scale ANN search problems across various domains.

Future work directions include:

- Extension to additional distance metrics beyond Euclidean distance
- Enhanced support for dynamic datasets with frequent updates
- Improved automatic parameter tuning based on data characteristics
- Integration with additional storage backends and data formats

References

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