## OAK

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#### **ACM Reference Format:**

#### ABSTRACT

Vector databases are growing in popularity as they become widely used in similarity search and RAG systems as part of ML workloads. At the same time, applications increasingly leverage mixed-modality data, requiring support for search over vector data such as images and text, and structured data such as metadata and keywords, simultaneously. Recent work in ACORN helps improve the feasibility of this hybrid search by providing a performant and predicateagnostic index built on Hierarchical Navigable Small Worlds (HNSW), a state-of-the-art graph based index for approximate nearest neighbor search (ANNS). However, ACORN does not take into consideration predicate access patterns, leaving room for performance improvent under certain modal workloads. To address this, we present OAK, a system for creating predicate subgraphs. To evaluate OAK, we compare OAK to ACORN on .... We show that OAK achieves improved performance ... Our code is available at: https: //github.com/breezykermo/oak.

# INTRODUCTION IMPLEMENTATION EVALUATION

DEEP1B [1] and SIFT1B [2] are datasets commonly used to test performance and accuracy for VectorDBs. Similarly, the big ANN benchmarks repository [3, 4] provides various datasets calibrated to four different classes of load: filtered (including metadata), out-of distribution (queries are significantly different in distribution than the database), sparse (vectors have a majority of zero values), and streaming (load includes insertion and deletion operations).

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