Rank Cover Trees for Nearest Neighbor Search

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SUMMARY

Virtually all known distance-based similarity search indexes make use of some form of numerical constraints (triangle inequality, additive distance bounds, ...) on similarity values for pruning and selection. The use of such numerical constraints, however, often leads to large variations in the numbers of objects examined in the execution of a query, making it difficult to control the execution costs. We introduce a probabilistic data structure for similarity search, the Rank Cover Tree (Rct), that entirely avoids the use of numerical constraints. All internal selections are made according to the ranks of the objects with respect to the query, allowing much tighter control on the overall execution costs. A rank-based probabilistic analysis shows that with very high probability, the Rct returns a correct query result in time that depends competitively on a measure of the intrinsic dimensionality of the data set.

IDEA OF SAMPLING

- We try to find items similar to a query object \mathbf{q} with respect to some data set $X \subseteq \Omega$.
- Suppose we found a similar point x with respect to a (small) subset X' ⊆ X, for example, by means of a sequential scan.
- We are likely to observe transitivity: an item
 y ∈ X \ X' which is similar to the item x is also similar to q.
- The probability of observing this kind of transitivity can be bounded!

K-Nearest Neighbor Search

- Maintain level-wise sets C_i covering the query results. Start with C_h containing the artificial root.
- *C_i* is constructed from the set *C_{i+1}* by keeping the *k_i* children of all elements in *C_{i+1}*, which are most similar to the query **q**.
- The set C_0 contains the query result.
- We choose k_i = ω · max{k/ ^h√|X|, 1}, where ω is a parameter allowing to trade-off between accuracy and query time.
- Our analysis shows: if ω is chosen greater than $\delta^{\log_{\Phi}(\sqrt{5}h)}h + \max\{h, e\sqrt[h]{|X|}\}\)$, then the approximation is free of error with very high probability.

MOTIVATION

Text, images, market data, biological data, scientific data, and many other forms of information are currently being accumulated in large data repositories at a rate that greatly outstrips our ability to analyze and to interpret. Together with this explosion of information, the demand for effective methods for searching, clustering, categorizing, summarizing and matching within data sets continues to grow. For such applications, solutions based on similarity search are among the earliest (and most effective) proposed in statistics, pattern recognition, and machine learning. The design and analysis of effective similarity search structures has consequently been the subject of intensive research for many decades.

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CONSTRUCTION

- For each item $\mathbf{x} \in X$, introduce \mathbf{x} into levels $0, \ldots, \lambda_{\mathbf{x}}$. For a tree of height $h, \lambda_{\mathbf{x}}$ follows a geometric distribution with $p = |X|^{-1/h}$.
- Build a partial Rct on the highest level by connecting items in that level to an artificial root.
- Connect the next level by using approximate

• The expansion rate δ measures intrinsic dimensionality.

RECALL RATES



CURSE OF DIMENSIONALITY

One can make the following observations with respect to very high-dimensional data:

- The performance of classical data structures for similarity search converges towards that of a sequential scan.
- Point-to-point distances become indistinguishable as they concentrate heavily around their mean value.
- Individual search paths within a similarity search data structure can no longer be effectively excluded from consideration.

nearest neighbors found in the partial Rст.
Well-formed with high probability.



Average Query Time [ms]



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