Indexing chemical fingerprints for efficient querying of molecular databases

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Overview

- Motivation
- Problem Statement
- Our Contribution
 - M-tree based index
 - Inverted Index
- Experiments and Results
- Conclusion

Motivation

 Fast database search is vital in drug discovery, where the aim is identifying chemical compounds with high similarity to known drugs.

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- ZINC database contains over 35 million purchasable compounds.

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- Exact Search?
 - Billions of dollars are spent for experiments on a single drug.
 - Not looking for approximation methods like Locally Sensitive Hashing.

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Figure: Fingerprint construction ¹

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Number of data points: 264016

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• But why index?

Problem Statement

Range Search Problem

Given a fingerprint, say 'f', a similarity measure 'sim', a threshold distance $'\theta'$ and a database of chemical compounds D, we find the subset $S \subset D$ of all fingerprints, such that:

$$S = \{g \mid g \in D, sim(f,g) < \theta\}$$
 (1)

Some more concepts/definitions

Tanimoto similarity

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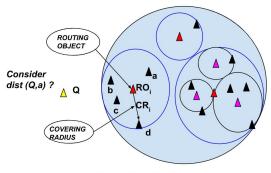
• Distance measure? Metric?

M-tree

- Routing objects
- Covering radius

M-tree

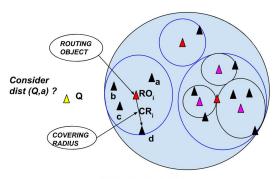
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M-TREE STRUCTURE

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M-TREE STRUCTURE

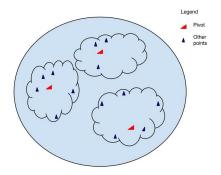
• Max: $|dist(Q, RO_i) + CR_i|$, Min: $|dist(Q, RO_i) - CR_i|$

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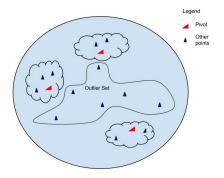
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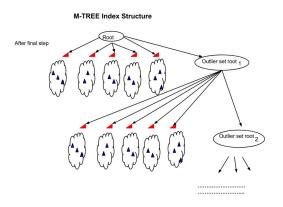


Indexing approach

• Repeat procedure on outlier set.

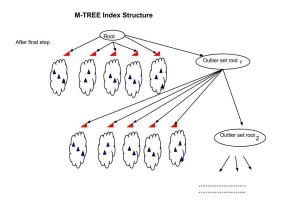
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• Termination?

Range Search

- Start from the root as pivot p
- Apply triangle inequality bounds to prune or include all points from sub-tree.
- If not, then go to the children of *p* and repeat the process with them as the new pivot, till we reach leaf.

Inverted Index

- High dimensionality and sparsity of chemical data are an impediment to our indexing process.
- Use of inverted index motivated by its use in text mining.

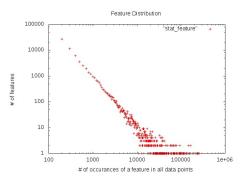
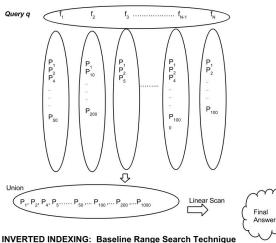
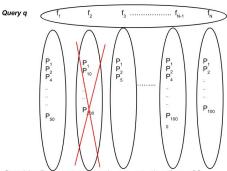


Figure : Distribution of data points against the features

Range Search



Pruning



Consider P_{200} , not present in any set other than of f_2 Maximum Similarity possible for such a point with the query?

$$1/(N_q - 1 + V_2)$$

Can we prune the set?

 $\begin{pmatrix} N_q - \text{number of features in query,} \\ V_2 - \text{minimum number of} \\ \text{features present in any point} \\ \text{containing } f_2 \end{pmatrix}$

Greedy Technique

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- If till the *i*th feature is considered, if j features (call it set *R*) have been pruned till now, we can prune the *i*th feature as well if the following holds.

$$\frac{j+1}{N_q-1+\min(V_i,\rho)}<1-t\tag{4}$$

where ρ is the minimum number of features present in any point containing atleast one of the features pruned until now i.e $\rho = \min_{k \in R} V_k$

Extension to non-binary fingerprints

Prune *i*th feature if:

$$\frac{\min(j_i, W_i)}{S_q - W_i - k_i + l_i + \max(k_i, V_i)} < 1 - t \tag{5}$$

Here j_i is the maximum feature value taken for the feature f_i , W_i is the i^{th} feature value of query q, S_q is the sum magnitude of the feature values of the query q, k_i is the is the minimum feature value taken for the feature f_i , l_i is the minimum sum of feature values for any point containing the feature f_i , t is the threshold similarity.

Experiments¹

- Datasets
 - PubChem Dataset (264016 compounds, 785985 features)
 - DUD Dataset (128374 compounds, 32198 features)
- Evaluations
 - Compared range search result with that of full database scan.
 - ullet Compared average run-times of range search with the state of the art Bit-bound technique 2

²**Source:** Swamidass, S Joshua and Baldi, Pierre. *Bounds and algorithms for fast exact searches of chemical fingerprints in linear and sublinear time.*

M-tree based index analysis

- Indexing time per compound on average increases linearly with data-set size as well as with size of pivot-set
- Outlier base limit size has no significant effect.

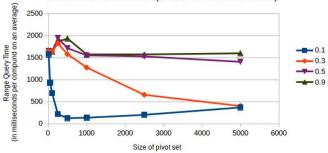
M-tree based index analysis...

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Range Search Query time using diffferent sizes of pivot set for a dataset of 100k size (for different threshold sizes)



Inverted index analysis

• Indexing time per compound on average is constant. Does not change with data-set size.

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- Indexing time per compound on average is constant. Does not change with data-set size.
- Pruning upto 50-100 features on average for low threshold distances.

Comparison

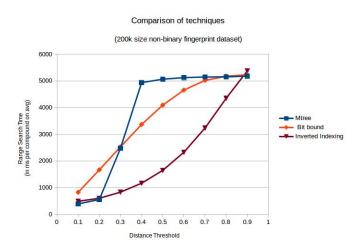


Figure : PubChem-n dataset

Comparison ...

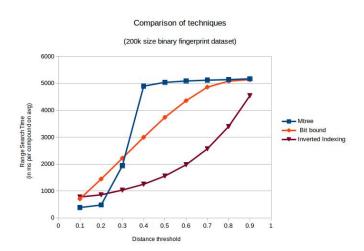


Figure : PubChem-b dataset

Comparison ...

Comparison of techniques **DUD** dataset 350 300 250 Range Search Time (in ms per compound on avg) Mtree 200 - Bit bound Inverted Indexing 150 100 50 0 0 0.1 0.2 0.3 0.5 0.8 0.9 0.6 0.7

Figure: DUD dataset

Distance Threshold

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- Proposed a novel Inverted Indexing technique which achieved 5-6 times speed-up over the Bit-Bound Technique.
- Showed the effectiveness of our techniques through comprehensive analysis on 2 real world datasets (both binary and non-binary).

Thank You!