Algorithms for Nearest Neighbors

State-of-the-Art

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Outline

Problem Statement
Applications
Data Models
Variations of the Computation Task
Overview of Algorithmic Techniques
Partitioning idea
Look-up idea
Embedding idea

3 Further Work

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Informal Problem Statement

Part I

What are nearest neighbors about?

Short overview of applications

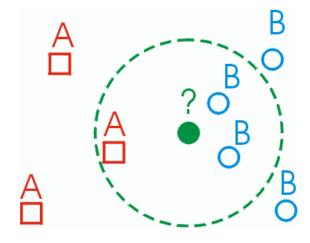
Variations of the problem

To preprocess a database of *n* objects so that given a query object, one can effectively determine its nearest neighbors in database

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First Application (1960s)

Nearest neighbors for classification:



Picture from http://cgm.cs.mcgill.ca/ soss/cs644/projects/perrier/Image25.gif

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Data Model

Formalization for nearest neighbors consists of:

- Representation format for objects
- Similarity function

Remark 1: Usually there is original and "reduced" representation for every object

Remark 2: Accuracy of NN-based classification, prediction or recommendations depends solely on a data model, no matter what specific exact NN algorithm we use.

Applications in Web Technologies

- Text classification (YaCa)
- Personalized news aggregation (Yandex Lenta)
- Recommendation systems (MoiKrug, Yandex Market)
- On-line advertisement distribution systems (Yandex Direct)
- Long queries in web search (Yandex Search)
- Content-similar pages, near-duplicates (Yandex Search)
- Semantic search

Variations of Data Model (1/3)

- Vector Model
 - Similarity: scalar product, cosine
- Set Model
 - Similarity: size of intersection
- String Model
 - Similarity: Hamming distance

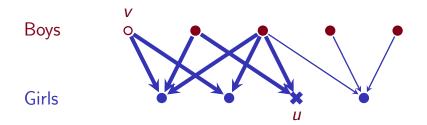
Variations of Data Model (2/3)

- Sparse Vector Model: query time should be in o(d)
 - Similarity: scalar product
- Small graphs
 - Similarity: structure/labels matching

More data models?

Variations of Data Model (3/3)

- New 3-step bipartite model
 - Similarity: number of 3-step paths



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Variations of the Computation Task

- Approximate nearest neighbors
- Multiple nearest neighbors
- Nearest assignment
- All over-threshold neighbor pairs
- Nearest neighbors in dynamically changing database: moving objects, deletes/inserts, changing similarity function

Part II Overview of Algorithmic Techniques

Partitioning, look-up and embedding-based approaches for **vector model**

New rare-point method (joint work with Hinrich Schütze)

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Linear Scan

What is the most obvious solution for nearest neighbors?

Answer:

compare query object with every object in database

Advantages:

No preprocessing Exact solution Works in any data model

Directions for improvement:

order of scanning, pruning

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KD-Trees

Preprocessing:

Build a *k*d-tree: for every internal node on level *I* we make partitioning based on the value of *I* mod *d*-th coordinate

Query processing:

Go down to the leaf corresponding to the the query point and compute the distance;

(Recursively) Go one step up, check whether the distance to the second branch is larger than that to current candidate neighbor if "yes" go up, else check this second branch

Voronoi diagrams

Voronoi diagram is a mapping transforming every point p in database to the polygon of points for which pis the nearest neighbor

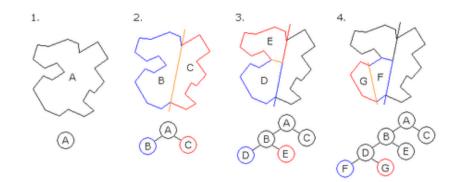


Can we generalize one-dimensional binary search?

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BSP-Trees

Generalization: BSP-tree allows to use any hyperplanes in tree construction



VP-Trees

Partitioning condition: d(p, x) <? rInner branch: $B(p, r(1 + \varepsilon))$ Outer branch: $R^d/B(p, r(1 - \delta))$

Search:

If d(p,q) < r go to inner branch If d(p,q) > r go to outer branch and return minimum between obtained result and d(p,q)

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Locality-Sensitive Hashing

Desired hash family \mathcal{H} :

- If $\|p-q\| \leq R$ then $\operatorname{Pr}_{\mathcal{H}}[h(p) = h(q)] \geq p_1$
- If $\|p-q\| \ge cR$ then $\mathscr{P}_{\mathcal{T}_{\mathcal{H}}}[h(p) = h(q)] \le p_2$

Preprocessing:

Choose at random several hash functions from \mathcal{H} Build inverted index for hash values of object in database

Query processing:

Retrieve all object that have at least one common hash value with query object; Perform linear scan on them

Inverted Index

How can we use sparseness of vectors in database?

Preprocessing:

For very coordinate store a list of all points in database with nonzero value on it

Query processing:

Retrieve all point that have at least one common nonzero component with the query point; Perform linear scan on them

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Rare-Point Method

Cheating: we will search only for neighbors that have at least one common rare feature with query object

Preprocessing:

For very rare feature store a list of all objects in database having it

Query processing:

Retrieve all point that have at least one common rare feature with the query object; Perform linear scan on them

Kleinberg Embedding-Based Approach

Preprocessing:

Choose at random linear transformation $A: R^d \rightarrow R^l, \qquad l \ll d$ Apply A to all points in database and make some tricky preprocessing for images

Query processing:

Compute A(q); Find its nearest neighbor in R';

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Directions for Applied Research

Attractive goals: NN-based recommendation system, NN-based ads distribution system

- Choose reasonable data model, add some assumptions about the nature of database and queries
- Find (theoretically) the best solutions in the resulting formalization
- Perform experimental analysis of obtained solutions
- Develop a prototype product

Part IV Further Work

Directions for Applied Research

Directions for Theoretical Research

Questions to Practitioners

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Directions for Theoretical Research

- Develop techniques for proving hardness of some computational problems with preprocessing. Find theoretical limits for some specific families of algorithms
- Extend classical NN algorithms to new data models and new task variations
- Develop theoretical analysis of existing heuristics. Average case complexity is particulary promising. Find subcases for which we can construct provably efficient solutions
- Compare NN-based approach with other methods for classification/recognition/prediction problems

Questions to Practitioners

- What is your experience in using nearest neighbors? What algorithm/data model are used? Do you face any scalability/accuracy problems? What is a bottleneck subproblem?
- Are you interested to apply NN approach in any of your future products?
- Give us benchmark data
- Give us names and contacts of potentially interested engineers

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Data structures and algorithms for nearest neighbor search in general metric spaces http://www.pnylab.com/pny/papers/vptree/vptree.ps

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Inverted files for text search engines

http://www.cs.mu.oz.au/~alistair/abstracts/zm06compsurv.html

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Links to nearest neighbors implementations

http://people.revoledu.com/kardi/tutorial/KNN/resources.html

Summary

- Nearest neighbors is one of the key algorithmic problems for web technologies
- Key ideas: look-up tables, partitioning techniques, embeddings
- Further work: from algorithms to prototype products, from heuristics to theory, from canonical problem to new data models and new search tasks

Thanks for your attention! Questions?

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