

# Novel Approaches to Nearest Neighbors

Random Walks. SEARCH Class.

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## Outline

- 1 Welcome to nearest neighbors!
- 2 Nearest Neighbors via Random Walks
- 3 Data Structure Complexity: SEARCH Class

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## Chapter I

# Welcome to Nearest Neighbors!

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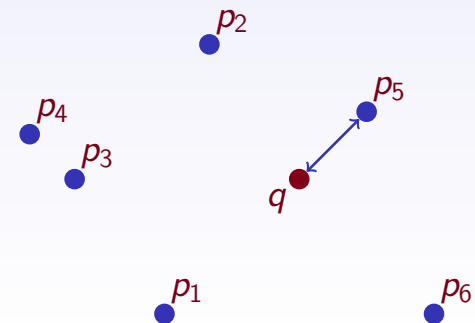
## Problem Statement

**Search space:** object domain  $\mathbb{U}$ , similarity function  $\sigma$

**Input:** database  $S = \{p_1, \dots, p_n\} \subseteq \mathbb{U}$

**Query:**  $q \in \mathbb{U}$

**Task:** find  $\operatorname{argmax} \sigma(p_i, q)$



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## Applications

# Content-based retrieval

Spelling correction Searching for similar  
DNA sequences Related pages web search

Concept matching

# kNN classification rule

Nearest-neighbor interpolation Near-duplicate  
detection Plagiarism detection

Computing co-occurrence similarity

Recommendation systems Personalized news  
aggregation Behavioral targeting

Maximum likelihood decoding MPEG  
compression

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## Brief History

1908 Voronoi diagram

1967 kNN classification rule by Cover and Hart

1973 Post-office problem posed by Knuth

1997 The paper by Kleinberg, beginning of provable  
upper/lower bounds

2006 Similarity Search book by Zezula, Amato,  
Dohnal and Batko

2008 First International Workshop on Similarity  
Search. Consider submitting!

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## Some Nearest Neighbor Solutions

Sphere Rectangle Tree Orchard's Algorithm LAESA

k-d-B tree Geometric near-neighbor access tree

Excluded middle vantage point forest.mvp-tree Fixed-height

fixed-queries tree AESA Vantage-point  
tree R\*-tree Burkhard-Keller tree BBD tree

Navigating Nets Voronoi tree Balanced aspect ratio tree Metric tree

vp<sup>s</sup>-tree M-tree Locality-Sensitive Hashing

SS-tree R-tree Spatial approximation tree Multi-vantage  
point tree Bisector tree mb-tree

# Generalized hyperplane tree

Hybrid tree Slim tree Spill Tree Fixed queries tree X-tree k-d  
tree Balltree Quadtree Octree Post-office tree

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## Part II

# Disorder Inequality

This section represents joint work with Navin Goyal and  
Hinrich Schütze

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## Concept of Disorder

Sort all objects in database  $S$  by their similarity to  $p$

Let  $\text{rank}_p(s)$  be position of object  $s$  in this list

**Disorder inequality** for some constant  $D$ :

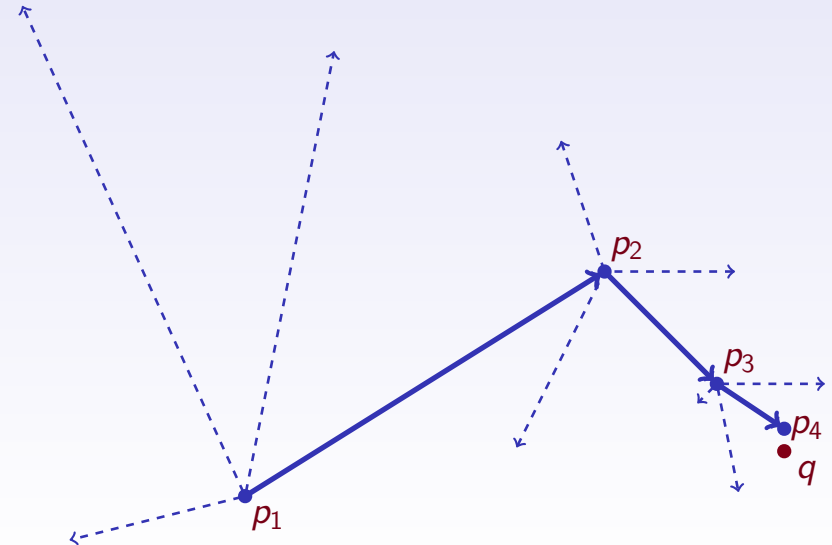
$$\forall p, r, s \in \{q\} \cup S : \quad \text{rank}_r(s) \leq D \cdot (\text{rank}_p(r) + \text{rank}_p(s))$$

Minimal  $D$  providing disorder inequality is called **disorder constant** of a given set

For “regular” sets in  $d$ -dimensional Euclidean space  $D \approx 2^{d-1}$

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## Ranwalk Informally (1/2)



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## Ranwalk Informally (2/2)

### Hierarchical greedy navigation:

- 1 Start at random city  $p_1$
- 2 Among all **airlines** choose the one going most closely to  $q$ , move there (say, to  $p_2$ )
- 3 Among all **railway routes** from  $p_2$  choose the one going most closely to  $q$ , move there ( $p_3$ )
- 4 Among all **bus routes** from  $p_3$  choose the one going most closely to  $q$ , move there ( $p_4$ )
- 5 Repeat this  $\log n$  times and return the final city

**Transport system:** for level  $k$  choose  $c$  random arcs to  $\frac{n}{2^k}$  neighborhood

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## Ranwalk Algorithm

### Preprocessing:

- For every point  $p$  in database we sort all other points by their similarity to  $p$

**Data structure:**  $n$  lists of  $n - 1$  points each.

### Query processing:

- 1 Step 0: choose a random point  $p_0$  in the database.
- 2 From  $k = 1$  to  $k = \log n$  do Step  $k$ : Choose  $D' := 3D(\log \log n + 1)$  random points from  $\min(n, \frac{3Dn}{2^k})$ -neighborhood of  $p_{k-1}$ . Compute similarities of these points w.r.t.  $q$  and set  $p_k$  to be the most similar one.
- 3 If  $\text{rank}_{p_{\log n}}(q) > D$  go to step 0, otherwise search the whole  $D^2$ -neighborhood of  $p_{\log n}$  and return the point most similar to  $q$  as the final answer.

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## Analysis of Ranwalk

### Theorem

Assume that database points together with query point  $S \cup \{q\}$  satisfy disorder inequality with constant  $D$ :

$$\text{rank}_x(y) \leq D(\text{rank}_z(x) + \text{rank}_z(y)).$$

Then Ranwalk algorithm always answers nearest neighbor queries correctly. It uses the following resources:

Preprocessing space:  $\mathcal{O}(n^2)$ .

Preprocessing time:  $\mathcal{O}(n^2 \log n)$ .

Expected query time:  $\mathcal{O}(D \log n \log \log n + D^2)$ .

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## Arwalk Algorithm

### Preprocessing:

- For every point  $p$  in database we sort all other points by their similarity to  $p$ . For every level number  $k$  from 1 to  $\log n$  we store pointers to  $D' = 3D(\log \log n + \log 1/\delta)$  random points within  $\min(n, \frac{3Dn}{2^k})$  most similar to  $p$  points.

### Query processing:

- 1 Step 0: choose a random point  $p_0$  in the database.
- 2 From  $k = 1$  to  $k = \log n$  do Step  $k$ : go by  $p_{k-1}$  pointers of level  $k$ . Compute similarities of these  $D'$  points to  $q$  and set  $p_k$  to be the most similar one.
- 3 Return  $p_{\log n}$ .

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## Analysis of Algorithm

### Theorem

Assume that database points together with query point  $S \cup \{q\}$  satisfy disorder inequality with constant  $D$ :

$$\text{rank}_x(y) \leq D(\text{rank}_z(x) + \text{rank}_z(y)).$$

Then for any probability of error  $\delta$  Arwalk algorithm answers nearest neighbor query within the following constraints:

Preprocessing space:  $\mathcal{O}(nD \log n(\log \log n + \log 1/\delta))$ .

Preprocessing time:  $\mathcal{O}(n^2 \log n)$ .

Query time:  $\mathcal{O}(D \log n(\log \log n + \log 1/\delta))$ .

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## Future of Disorder (1/2)

**Average disorder.** If disorder inequality does not hold for a small fraction of pairs, how should we modify our algorithm?

**Improving our algorithms.** Is it possible to combine advantages of Ranwalk and Arwalk? Does there exist a deterministic algorithm with sublinear search time utilizing small disorder assumption? E.g., can we use expanders for derandomization?

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## Future of Disorder (2/2)

**Disorder of random sets.** Compute disorder values for some modelling examples. For example, consider  $n$  random points on  $d$ -dimensional sphere

**Lower bounds.** Is it possible to prove lower bounds on preprocessing and query complexities in some “black-box” model of computation?

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## Inclusions with Preprocessing (1/2)

### Input

Family  $\mathcal{F}$  of subsets of  $U$

### Query task

Given a set  $f_{new} \subseteq U$  to decide whether  $\exists f \in \mathcal{F} : f_{new} \subseteq f$

### Constraints

Data storage after preprocessing  $poly(|\mathcal{F}| + |U|)$   
Time for query processing  $poly(|U|)$

**Open problem:** is there an algorithm satisfying given constraints?

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## Part III

## Data Structure Complexity: SEARCH Class

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## Inclusions with Preprocessing (2/2)

Reformulation in SAT style:

### Input

Formula  $\mathcal{F}$  in DNF with  $n$  variables

### Query task

Given an assignment  $x$  to evaluate  $\mathcal{F}(x)$

### Constraints

Data storage after preprocessing  $poly(|\mathcal{F}|)$   
Time for query processing  $poly(n)$

**Open problem:** is there an algorithm satisfying given constraints?

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## “NP Analogue” for Search Problems

Every problem in **SEARCH class** is characterized by poly-time computable Turing Machine  $M$ :

### Input

Strings  $x_1, \dots, x_n$ ,  $|x_i| = m$

### Query task

Given string  $y$  of length  $m$  to answer whether  $\exists i : M(x_i, y) = \text{yes}$

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## Tractable problems in SEARCH

### Input

Strings  $x_1, \dots, x_n$ ,  $|x_i| = m$

### Query task

Given string  $y$  of length  $m$  to answer whether  $\exists i : M(x_i, y) = \text{yes}$

### Tractable solution

Preprocessing in  $\text{poly}(m, n)$  space

Query processing in  $\text{poly}(m, \log n)$  time with RAM access to preprocessed database

Inclusions is in SEARCH. Is it tractable?

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## Complete problems in SEARCH (1/2)

**Program Search** problem:

### Input

Turing machines  $P_1, \dots, P_n$

### Query task

Given string  $y$  of length  $m$  to answer whether  $\exists i : P_i(y) = \text{yes}$  after at most  $m$  steps

**Open problem:** is Program Search tractable?

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## Complete problems in SEARCH (2/2)

**Parallel Run** problem:

### Input

$x_1, \dots, x_n$

### Query task

Given poly-time computable  $P$  to answer whether  $\exists i : P(x_i) = \text{yes}$

**Open problem:** is Parallel Run tractable?

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# NN Proofs?

## NN-proof system:

- Fix some family of basic statements about points in multidimensional space and some proof system
- Can we compute  $poly(|S|)$  statements about points of database  $S$  such that for any query  $q$  and any real nearest neighbor  $p_{NN} \in S$  there is a logarithmic-size proof from precomputed statements that indeed  $p_{NN}$  is nearest point in  $S$  to  $q$

Do such an NN proof system exist?

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# Highlights

- Random walk provide logarithmic nearest neighbor search for bounded disorder sets
- SEARCH class: is it tractable?
- Do NN proof systems exist?


Thanks for your attention! Questions?


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# References


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