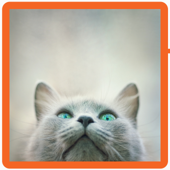
Neighbor-Sensitive Hashing

Yongjoo Park
Michael Cafarella
Barzan Mozafari

University of Michigan, Ann Arbor

k-Nearest Neighbors Problem (kNN)



query

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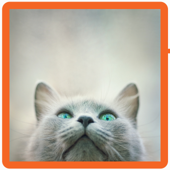

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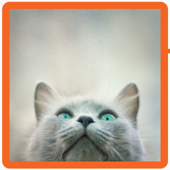

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What are the k most similar items?

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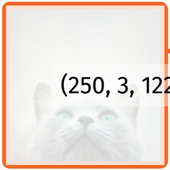

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(250, 3, 122, 130, 68, . . .)

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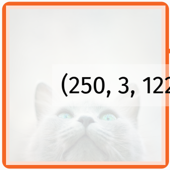


query

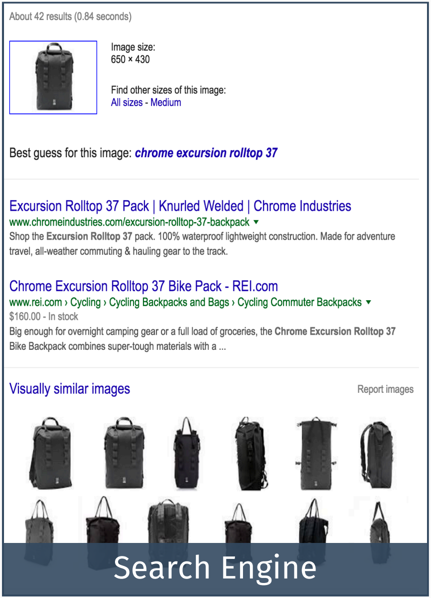
(250, 3, 122, 130, 68, . . .)

What are the k most similar items?

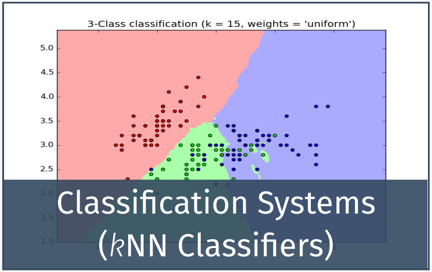
(109, 33, 92, 87, 161, . . .),
(50, 83, 22, 230, 98, . . .),
(2, 183, 59, 18, 178, . . .),
(221, 183, 259, 88, 112, . . .),
. . ..

database

kNN is Heart of Key Applications



Search Engine

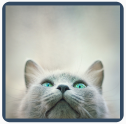


Classification Systems (kNN Classifiers)

Recommender Systems (Collaborative Filtering)

Naïve Approach to *k*NN

Naïve Approach: *linear search* with the original representations



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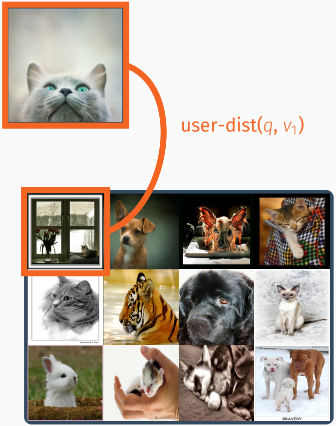

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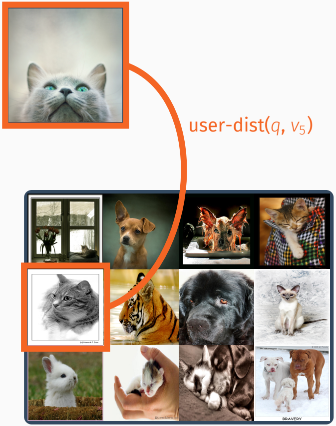

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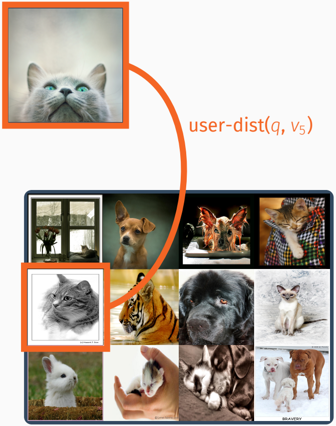

Pick the items with the k smallest user-defined distances

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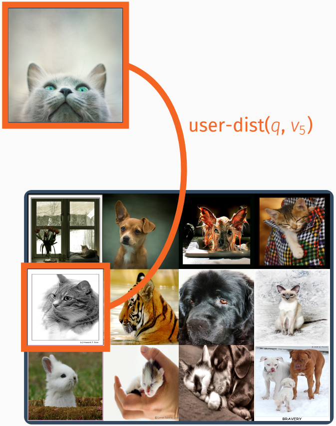

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Extremely slow

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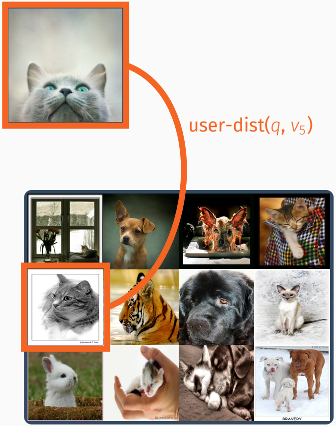


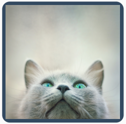
Pick the items with the k smallest user-defined distances

Extremely slow

Note: No known fast exact algorithms for *dense, high-dimensional* vectors

Locality-Sensitive Hashing for kNN

LSH: Use similarity-preserving hash functions



First proposed by [Datar et al., 2004] and [Charikar, 2002]

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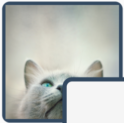

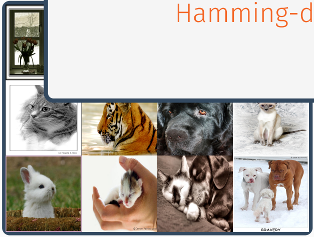

Let $h(\cdot)$ be a function that produces a hashcode. Then,

$$\text{Hamming-dist}(h(q), h(v_i)) \quad \propto \quad \text{user-dist}(q, v_i)$$

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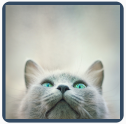

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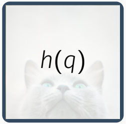
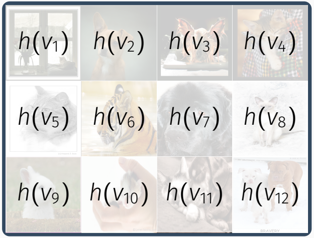


Hashed Query



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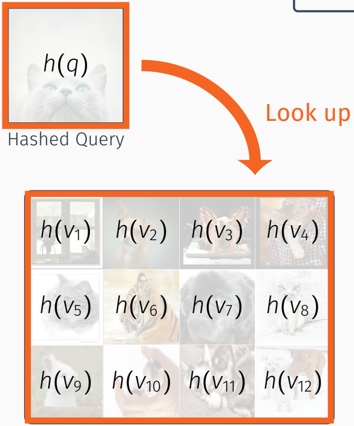

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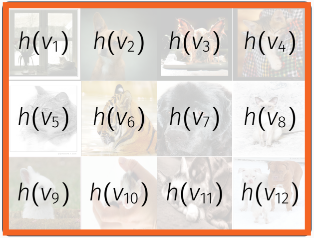

Hashed DB

hashcodes $\rightarrow$ lookup operations in a hash table $\rightarrow$ fast.

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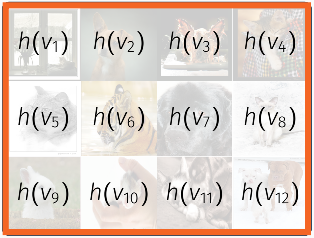

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Perfect hash functions may not exist, or extremely hard to find $\rightarrow$ approximate.

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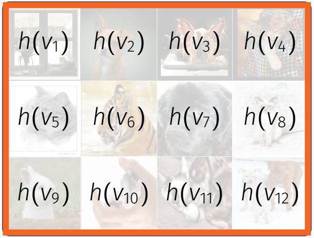

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Perfect hash functions may not exist, or extremely hard to find $\rightarrow$ approximate.

Note: Longer hashcode makes the searching slower.

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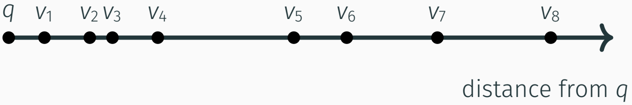
Hashcodes Generation for LSH

Suppose LSH generates hashcodes of length 4.



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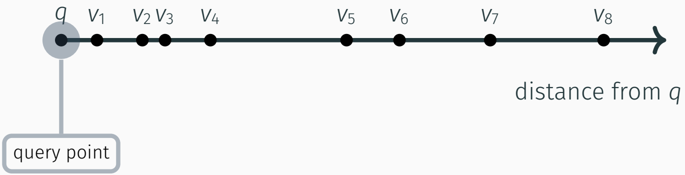

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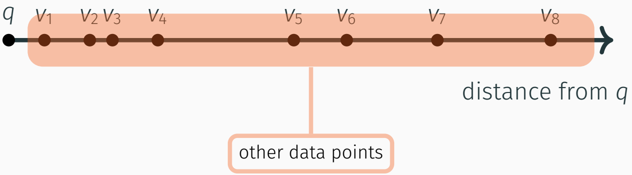

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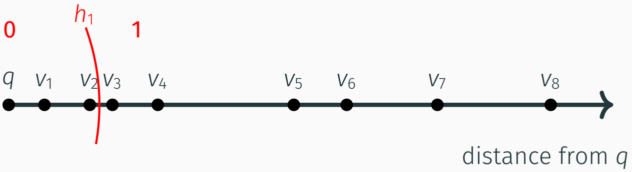

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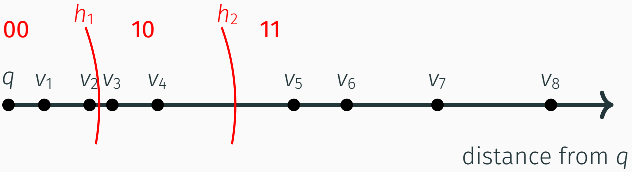

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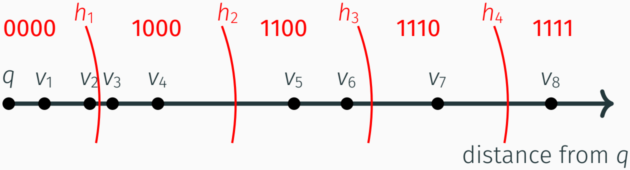

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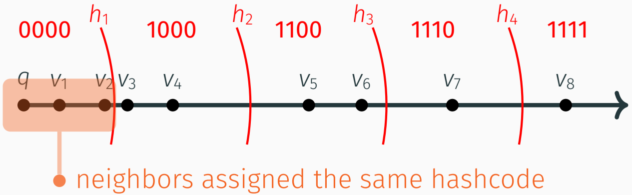

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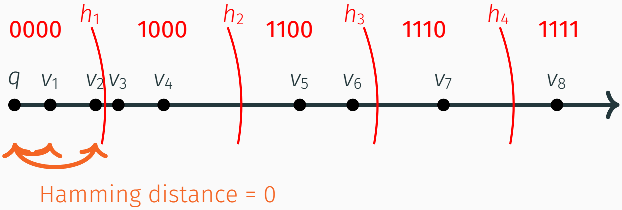

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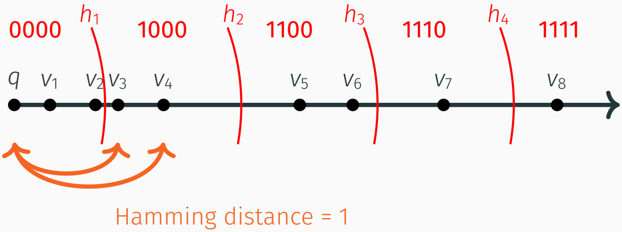

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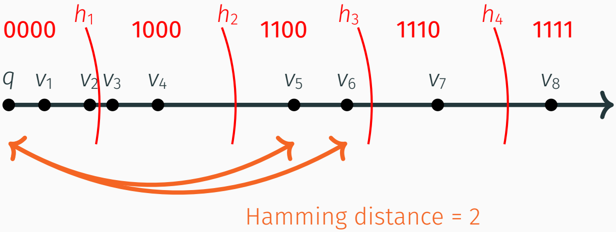

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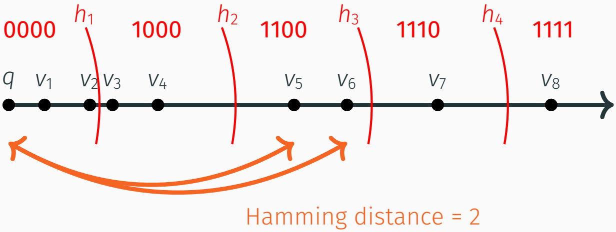

Hashcodes as a proxy

Hashcodes Generation for LSH

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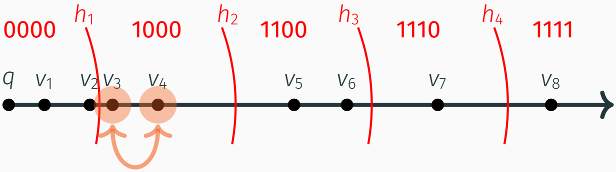

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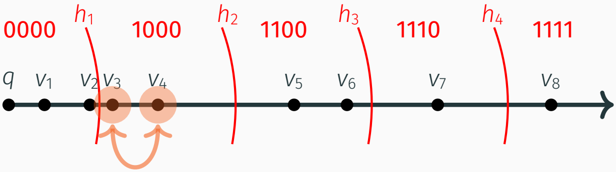

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$\rightarrow$ For 3-NN, approximate

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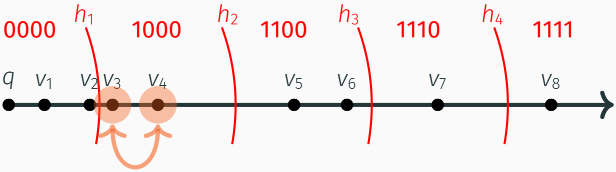

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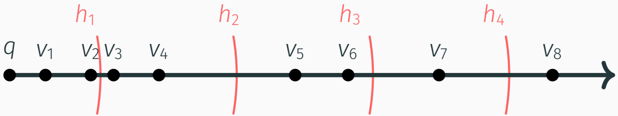
Motivation

A new scheme able to distinguish v_3 and v_4
based on their hashcodes?

Outline

Neighbor-Sensitive Hashing Intuition

We are interested in 3-NN. Hash functions by LSH.



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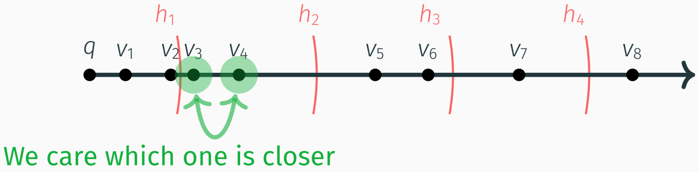

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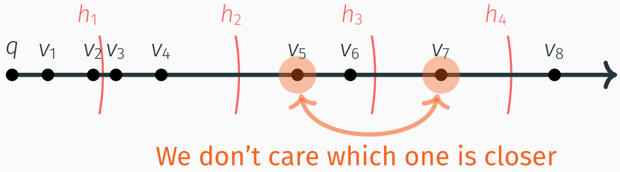

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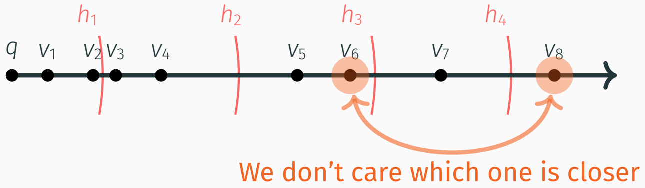

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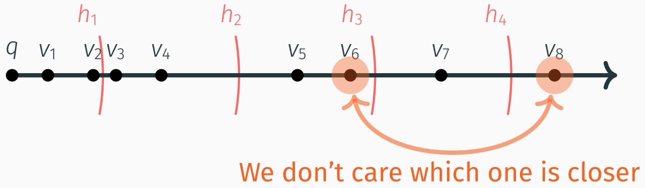

Observation: h_3 and h_4 are wasted (for 3-NN).

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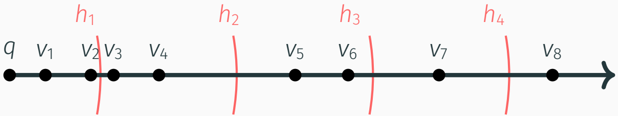


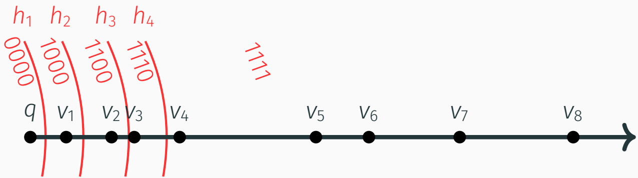
Observation: h_3 and h_4 are wasted (for 3-NN).

Our Idea

Generating hash functions **close to the query**
so that we can **better distinguish** the close items.

Neighbor-Sensitive Hashing Intuition (cont'd)

Suppose we could (somehow) generate hash functions in this way.



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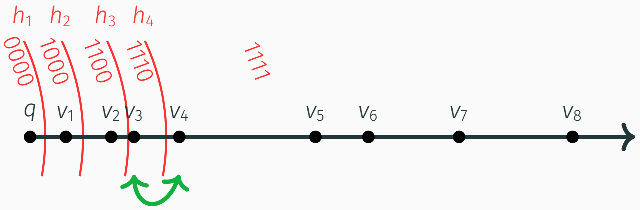

We could **distinguish v_3 and v_4** based on their hashcodes.
(thus, able to solve 3-NN accurately)

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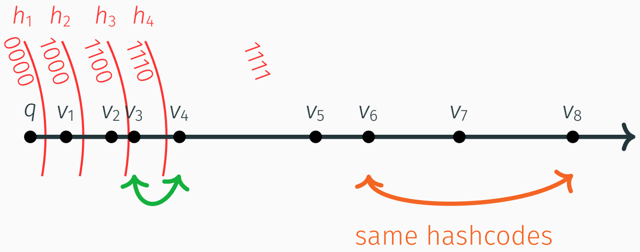

We could **distinguish v_3 and v_4** based on their hashcodes.
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Note: **Could not** distinguish v_6 and v_8 based on their hashcodes.

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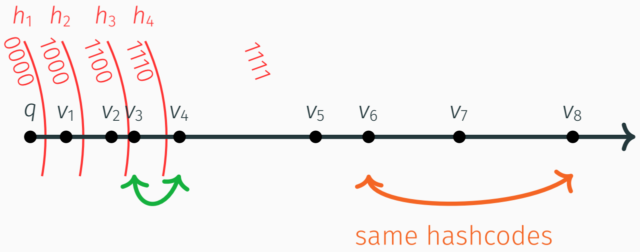

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Not an issue for 3-NN

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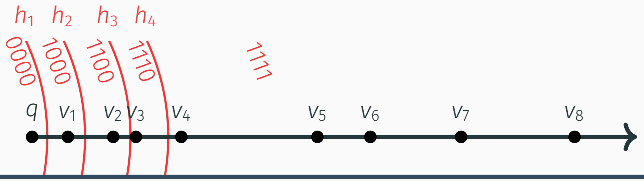

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Difference in NSH's Intuition:

A decade of existing work: small Hamming distance between close data items

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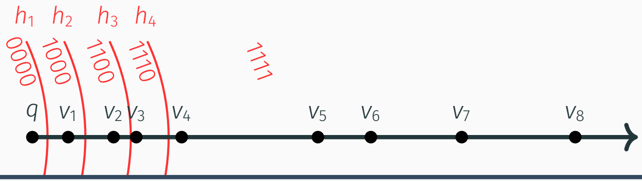

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NSH: larger Hamming distance between close items

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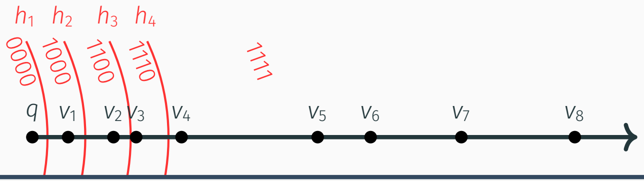

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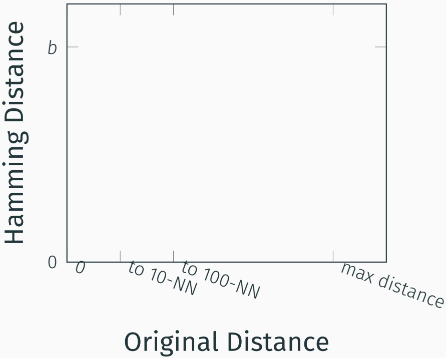
Seemingly **counter-intuitive**; however, our paper proves that larger Hamming distance leads to higher accuracy in general.

Important Difference between LSH and NSH



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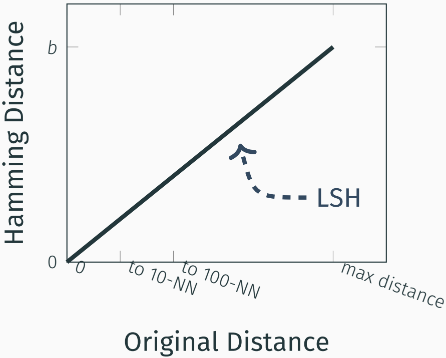

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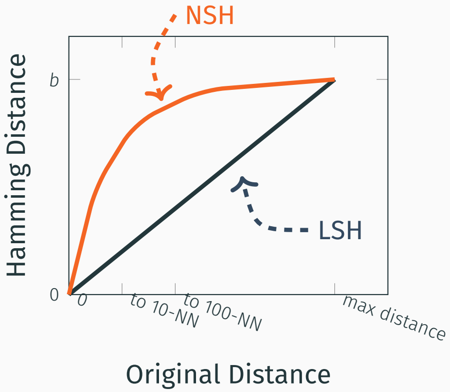

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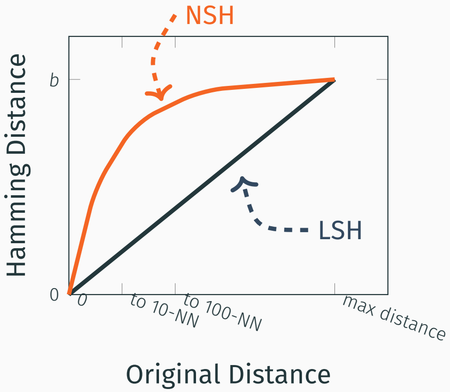
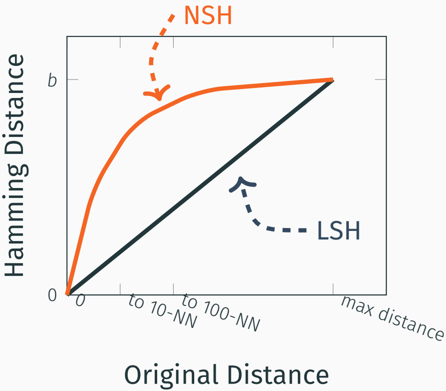


A larger slope indicates higher distinguishing-power based on hashcodes.

Important Difference between LSH and NSH



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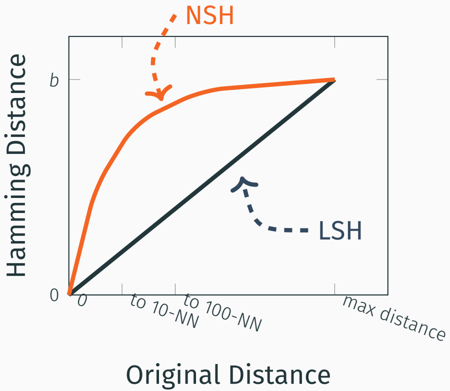

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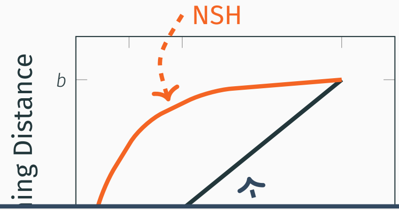

Key Challenge

How to enlarge the Hamming distances *selectively* for close data items?

Original Distance

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Outline

Neighbor-Sensitive Hashing Overview

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Transform data points to expand the space around the query.

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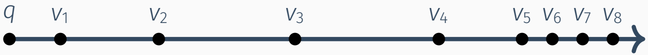

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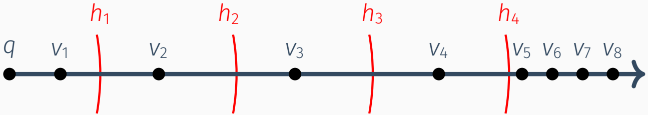

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Then, generate hash functions on this transformed space.

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Neighbor-Sensitive Hashing Overview

Key Questions

How can we expand the space around a query?

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Is it easier if we know the query *a priori* ?

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Neighbor-Sensitive Hashing Overview

Key Questions

How can we expand the space around a query?

Is it easier if we know the query *a priori* ?

How can we expand the space around an arbitrary query?

Then, generate hash functions on this transformed space.

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Neighbor-Sensitive Transformation

We expand the space around an *arbitrary query* using our proposed Neighbor-Sensitive Transformation (NST).

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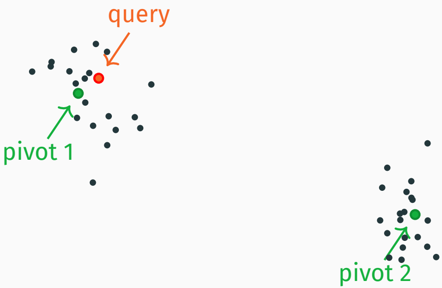

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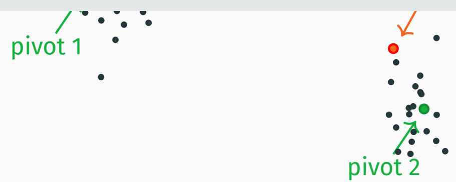
Our Formal Claim (Theorem 2)

Using NST with regular hash functions produces higher accuracy than LSH.



Big Picture: NSH Workflow

Offline Processing

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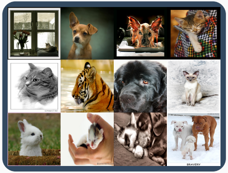

Original Database

Big Picture: NSH Workflow

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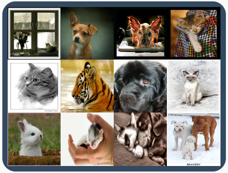

Original Database

NST →

Transformed DB

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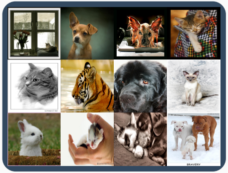

Original Database

NST → Transformed DB → hash → Hashed DB

Big Picture: NSH Workflow

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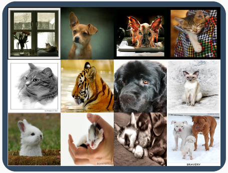

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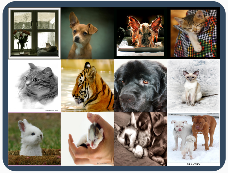

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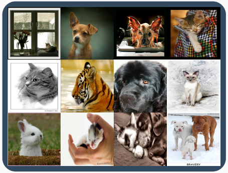

Original Database

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Online Processing

Original Query

NST → Transformed Query

Big Picture: NSH Workflow

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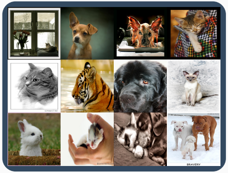

Original Database

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Online Processing

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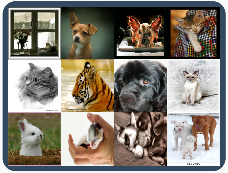


Original Database

NST → Transformed DB → hash → Hashed DB

Search

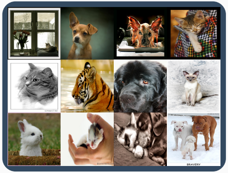
Online Processing

Original Query

NST → Transformed Query → hash → Hashed Query

Big Picture: NSH Workflow

Offline Processing



Original Database

NST →

Transformed DB

LSH Workflow

hash →

Hashed DB

Search ↑

Online Processing

Original Query

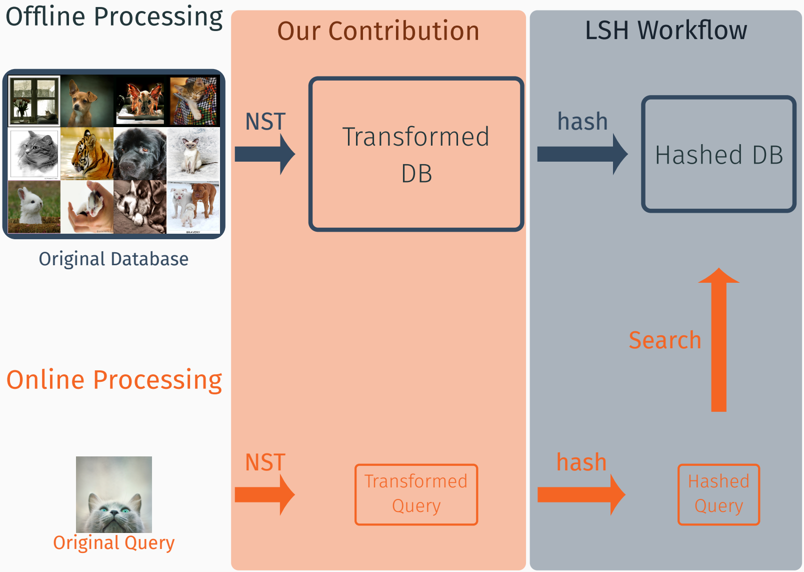
NST →

Transformed Query

hash →

Hashed Query

Big Picture: NSH Workflow



Neighbor-Sensitive Hashing Visualized

We visualized the hash functions
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Dataset: five 2D normal distributions, Generated 4 hash functions

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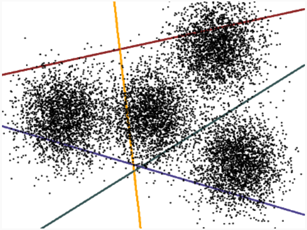

LSH

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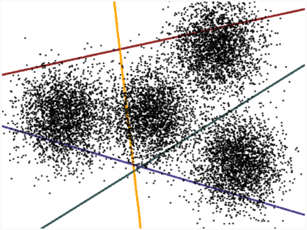

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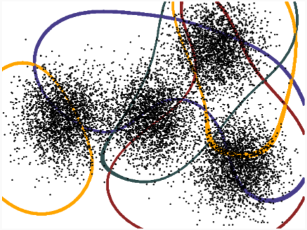

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Quality Metric

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1. MNIST: 69K hand-written digit images
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Neighbor-Sensitive Hashing Property

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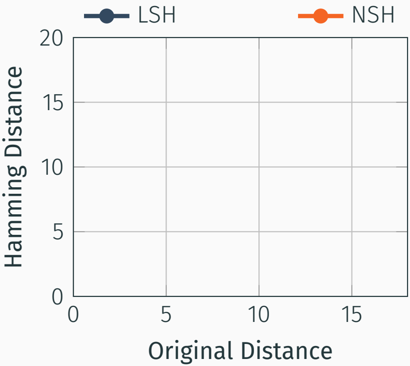

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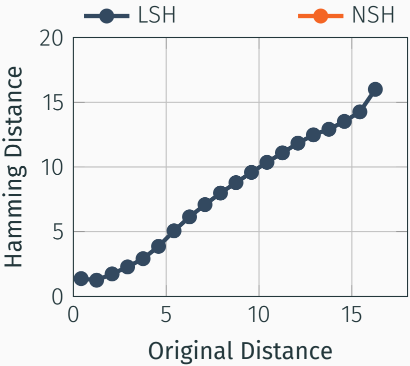

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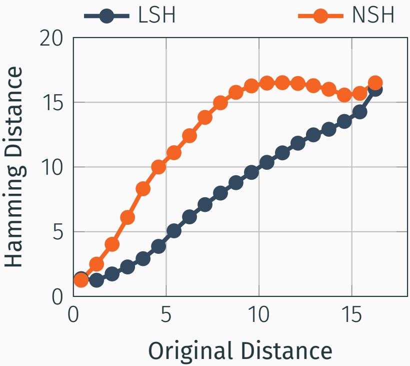

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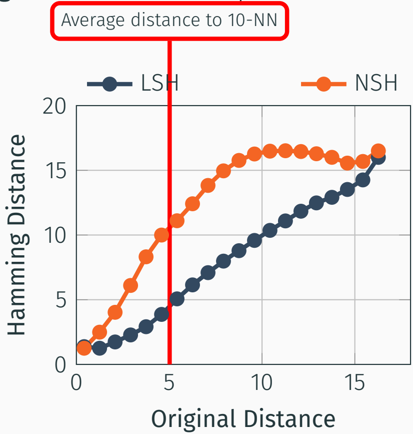

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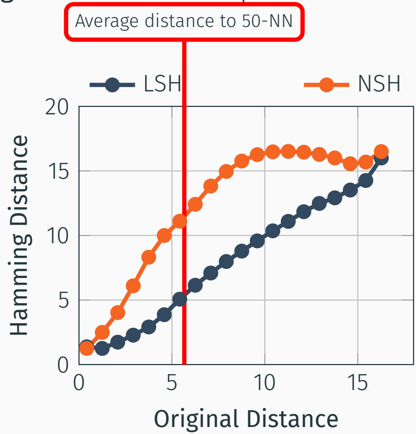

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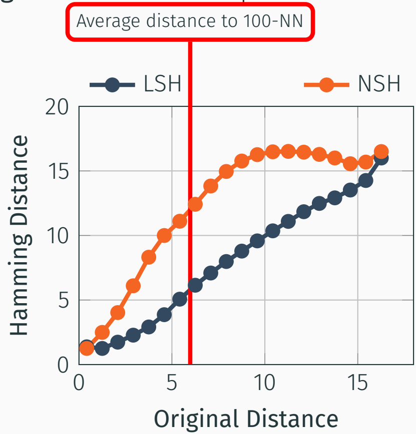

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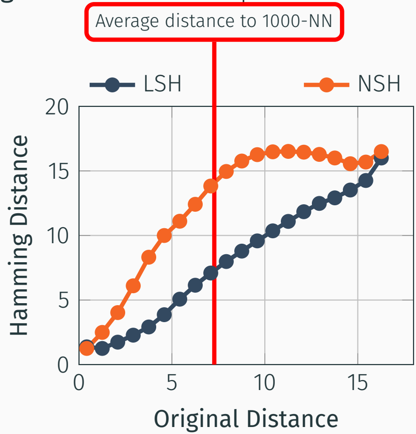

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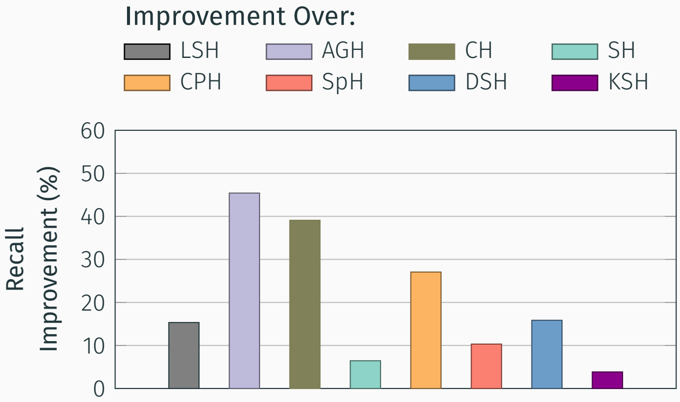
Recall Improvement for Fixed Hashcode Size

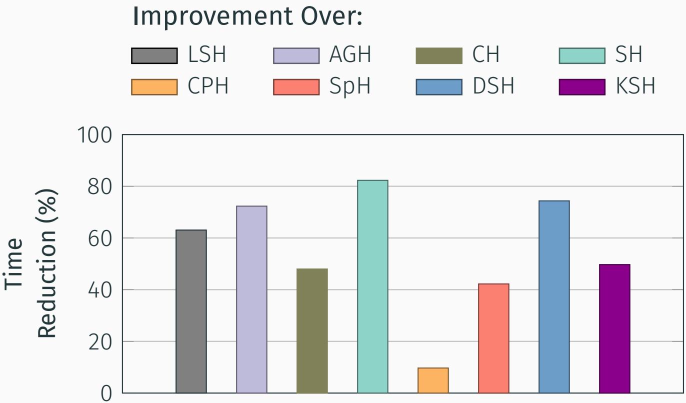
Compared search accuracy of 9 different methods (including NSH).



Dataset: TINY, Hashcode size: 64 bits

Time Reduction for Fixed Recall

Measured search time of 9 different methods (including NSH).



Dataset: SIFT, Hashcode size: 64 bits, Target recall: 50%

Offline Computation Time

Method	Hash Function Generation (sec)		Hashcode Generation (min)	
	32bit	64bit	32bit	64bit
LSH	0.38	0.29	22	23
SH	28	36	54	154
AGH	786	873	105	95
SpH	397	875	18	23
CH	483	599	265	266
CPH	34,371	63,398	85	105
DSH	3.14	1.48	24	23
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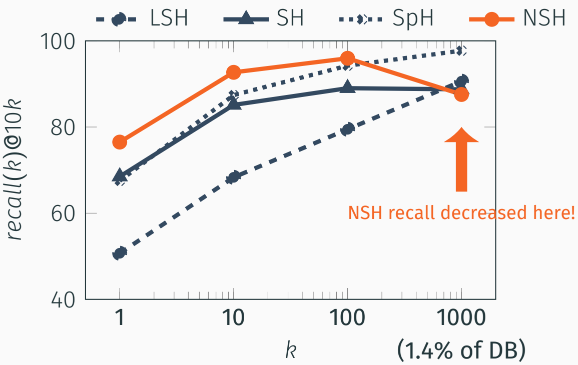
Our method was among the fastest.

Dataset: TINY

Neighbor-Sensitive Effect

NSH was more effective for relatively small k.



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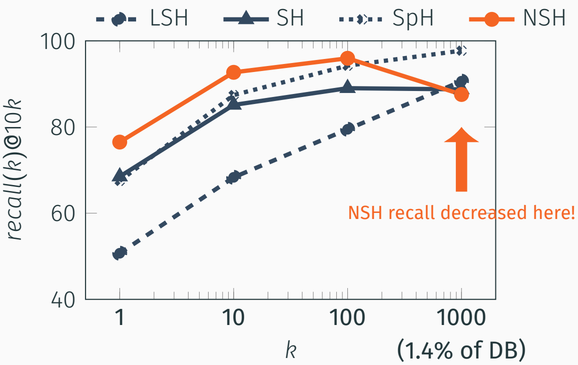

With a **bigger** dataset,
this “recall-dropping effect” was not observed.

Conclusion

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2. Based on the idea, we have proposed a novel hashing-based search method—Neighbor-Sensitive Hashing.

3. We have empirically demonstrated that our proposed method could achieve better kNN performance (faster or more accurate) compared to existing methods.

Thank You!

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The function $f(\cdot)$ qualifies for NST
if $f(\cdot)$ satisfies some technical requirements.
(please see our paper)

Backup: Neighbor-Sensitive Transformation

We expand the space around a query using
Neighbor-Sensitive Transformation.

A Neighbor-Sensitive Transformation (NST) is simply
a function of data points
(e.g., $f(v_1), f(v_2), \ldots$)

The function $f(\cdot)$ qualifies for NST
if $f(\cdot)$ satisfies some technical requirements.
(please see our paper)

Our Formal Claim (Theorem 2)

Using NST with regular hash functions produces
higher accuracy than LSH.

Backup: Neighbor-Sensitive Transformation (cont'd)

Let us assume a query q is known

Backup: Neighbor-Sensitive Transformation (cont'd)

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Then, the following function works as NST for q:

$$f_p(v) = \exp\left(-\frac{\|p - v\|^2}{\eta^2}\right)$$

where **pivot** p is a data point close to q.

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Then, the following function is NST for arbitrary q:

$$f(v) = (f_{p_1}(v), \ldots, f_{p_m}(v))$$

with multiple pivots $p_1, \ldots, p_m$.

Backup: Neighbor-Sensitive Transformation (cont'd)

Let us assume a query q is known

Then, the following function works as NST for q:

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We don't formally prove, but show empirically that this is NST for arbitrary queries.