Applying Hash-based Indexing in Text-based Information Retrieval

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Text-based Information Retrieval (TIR)

Motivation

Consider a set of documents D.

Term query—given a set of query terms:
Find all documents $D' \subset D$ containing the query terms.

➜ Implemented by well-known web search engines.
➜ Best practice: Index D using an inverted file.

Text-based Information Retrieval (TIR)

Motivation

Consider a set of documents D.

Document query—given a document d:
Find all documents $D' \subset D$ with a high similarity to d.

➜ Use cases: plagiarism analysis, query by example

www.**turing**.org.uk/ - 11k - Cached - Similar pages - Filter

➜ Naive approach: Compare d with each $d' \in D$.

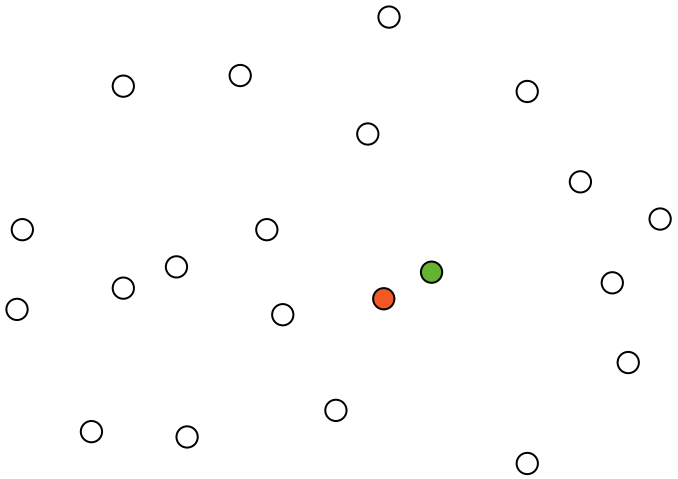
In detail:
Construct document models for D and d obtaining $\mathbf{D}$ and $\mathbf{d}$.
Employ a similarity function $\varphi : \mathbf{D} \times \mathbf{D} \rightarrow [0, 1]$.

Is it possible to be faster than the naive approach?

Background

Nearest Neighbour Search

Given a set $\mathbf{D}$ of m-dimensional points and a point $\mathbf{d}$:
Find the point $\mathbf{d}' \in \mathbf{D}$ which is nearest to $\mathbf{d}$.



Finding $\mathbf{d}'$ cannot be done better than in $\mathcal{O}(|\mathbf{D}|)$ time if m exceeds 10.

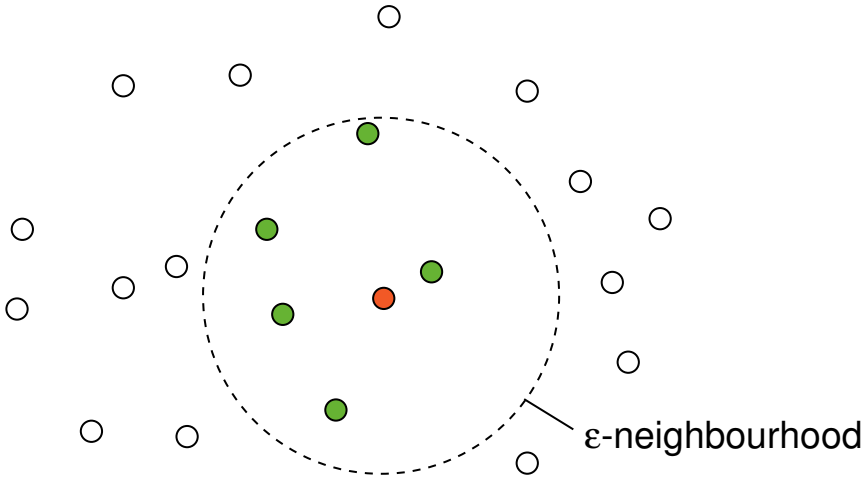
[Weber *et. al.* 1998]

In our case: $1.000 \ll m < 1.000.000$

Background

Approximate Nearest Neighbour Search

Given a set $\mathbf{D}$ of m-dimensional points and a point $\mathbf{d}$:
Find some points $\mathbf{D}' \subset \mathbf{D}$ from a certain ε-neighbourhood of $\mathbf{d}$.

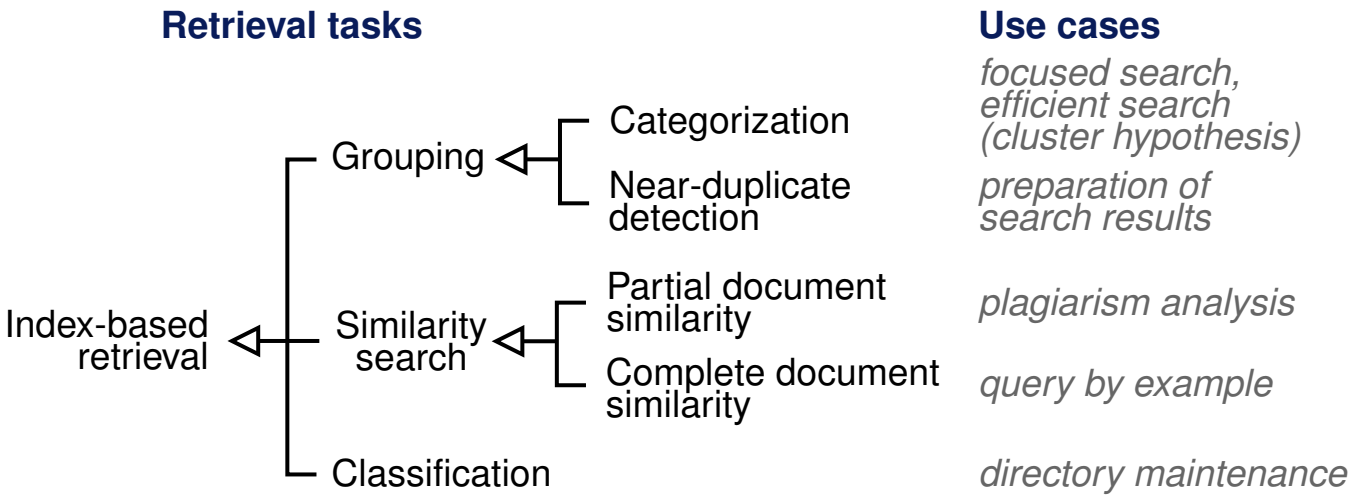


Finding $\mathbf{D}'$ can be done in $\mathcal{O}(1)$ time with high probabilty by means of hashing. [Indyk and Motwani 1998]

The dimensionality m does not affect the runtime of their algorithm.

Text-based Information Retrieval (TIR)

Nearest Neighbour Search



Approximate retrieval results are often acceptable.

Similarity Hashing

Introduction

With standard hash functions collisions occur accidentally.

In similarity hashing collisions shall occur purposefully where the purpose is “high similarity”.

Given a similarity function φ a hash function

$$h_\varphi : \mathbf{D} \rightarrow U \qquad \text{with } U \subset \mathbf{N}$$

resembles φ if it has the following property [Stein 2005]:

$$h_\varphi(\mathbf{d}) = h_\varphi(\mathbf{d}') \;\Rightarrow\; \varphi(\mathbf{d}, \mathbf{d}') \geq 1 - \varepsilon \qquad \text{with } \mathbf{d}, \mathbf{d}' \in \mathbf{D}, 0 < \varepsilon \ll 1$$

Similarity Hashing

Index Construction

Given a similarity hash function h_φ a hash index

$$\mu_h : \mathbf{D} \rightarrow \mathcal{D} \qquad \text{width } \mathcal{D} = \mathcal{P}(D)$$

is constructed using

- a hash table $\mathcal{T}$
- a standard hash function $h : U \rightarrow \{1, \ldots, |\mathcal{T}|\}$

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To *index* a set of documents D given their models $\mathbf{D}$,

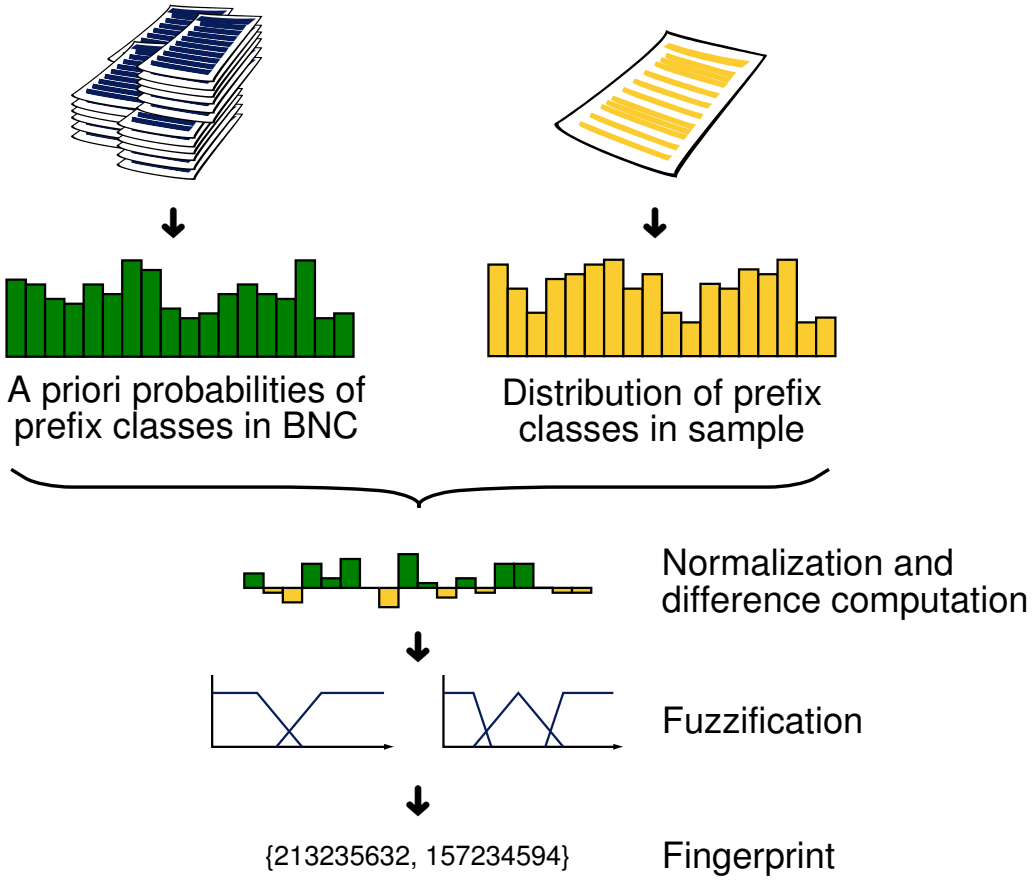
- compute for each $\mathbf{d} \in \mathbf{D}$ its hash value $h_\varphi(\mathbf{d})$
- store a reference to d in $\mathcal{T}$ at storage position $h(h_\varphi(\mathbf{d}))$

To *search* for documents similar to d given its model $\mathbf{d}$,

- return the bucket in $\mathcal{T}$ at storage position $h(h_\varphi(\mathbf{d}))$

Similarity Hash Functions

Fuzzy-Fingerprinting (FF) [Stein 2005]

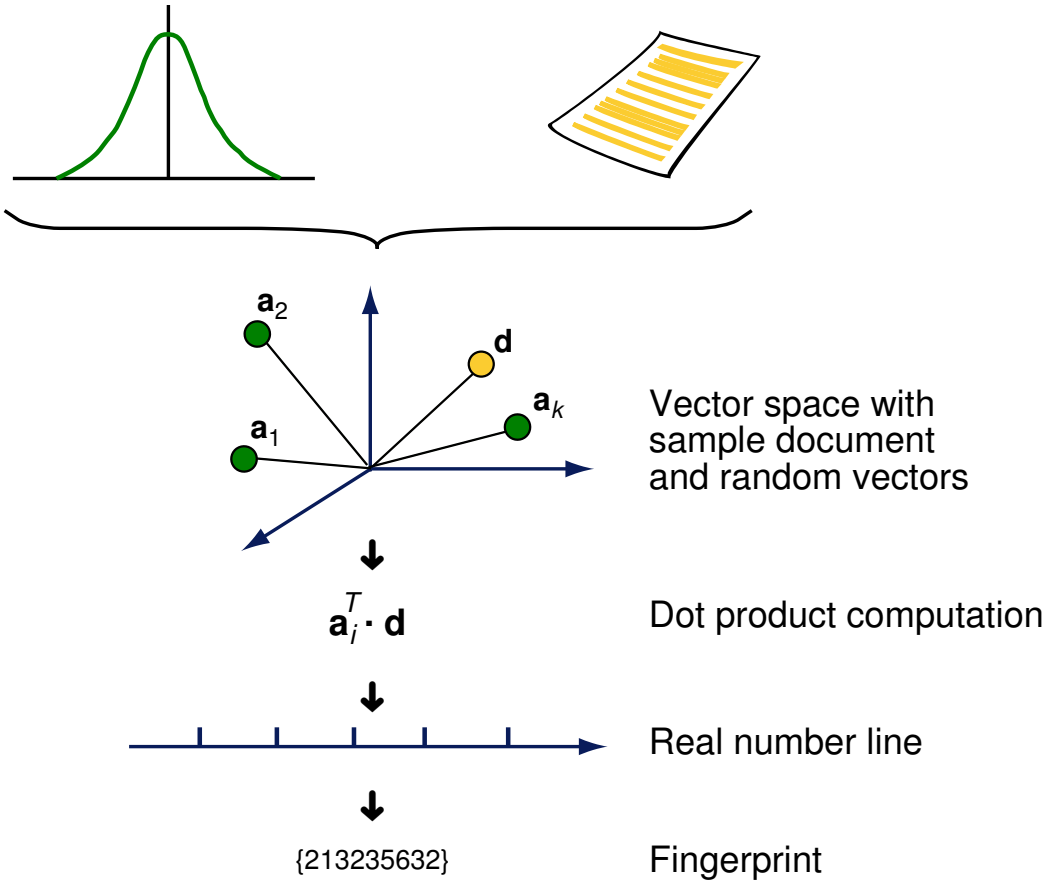


All words having the same prefix belong to the same prefix class.

Similarity Hash Functions

Locality-Sensitive Hashing (LSH)

[Indyk and Motwani 1998, Datar *et. al.* 2004]

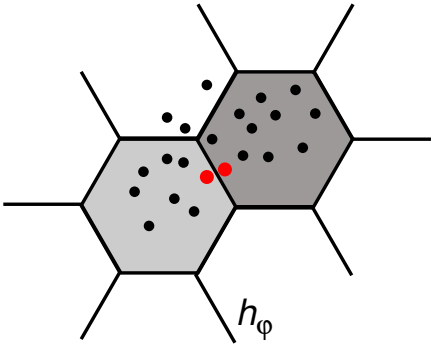


The results of the k dot products are summed.

Similarity Hash Functions

Adjusting Recall and Precision

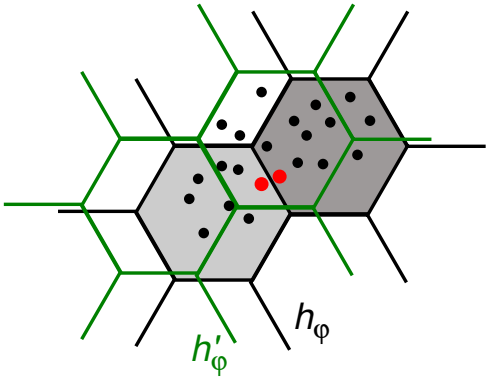
Recall:



Similarity Hash Functions

Adjusting Recall and Precision

Recall:



(FF) # fuzzy schemes.

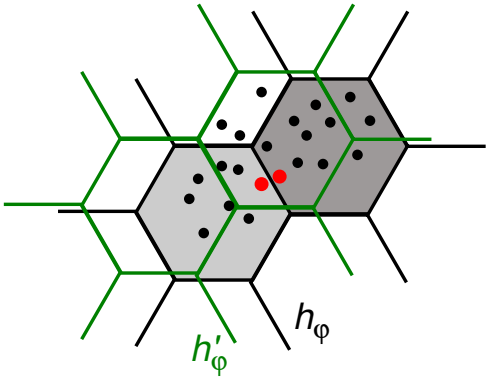
(LSH) # random vector sets.

A set of hash values per document is called fingerprint.

Similarity Hash Functions

Adjusting Recall and Precision

Recall:



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Precision:

(FF) # prefix classes or
intervals per fuzzy scheme.

(LSH) # random vectors.

Experimental Setting

Three test collections for three retrieval situations

1. Web results: 100.000 documents from a focused search.

➜ Documents as Web retrieval systems return them.

2. Plagiarism corpus: 3.000 documents with high similarity.

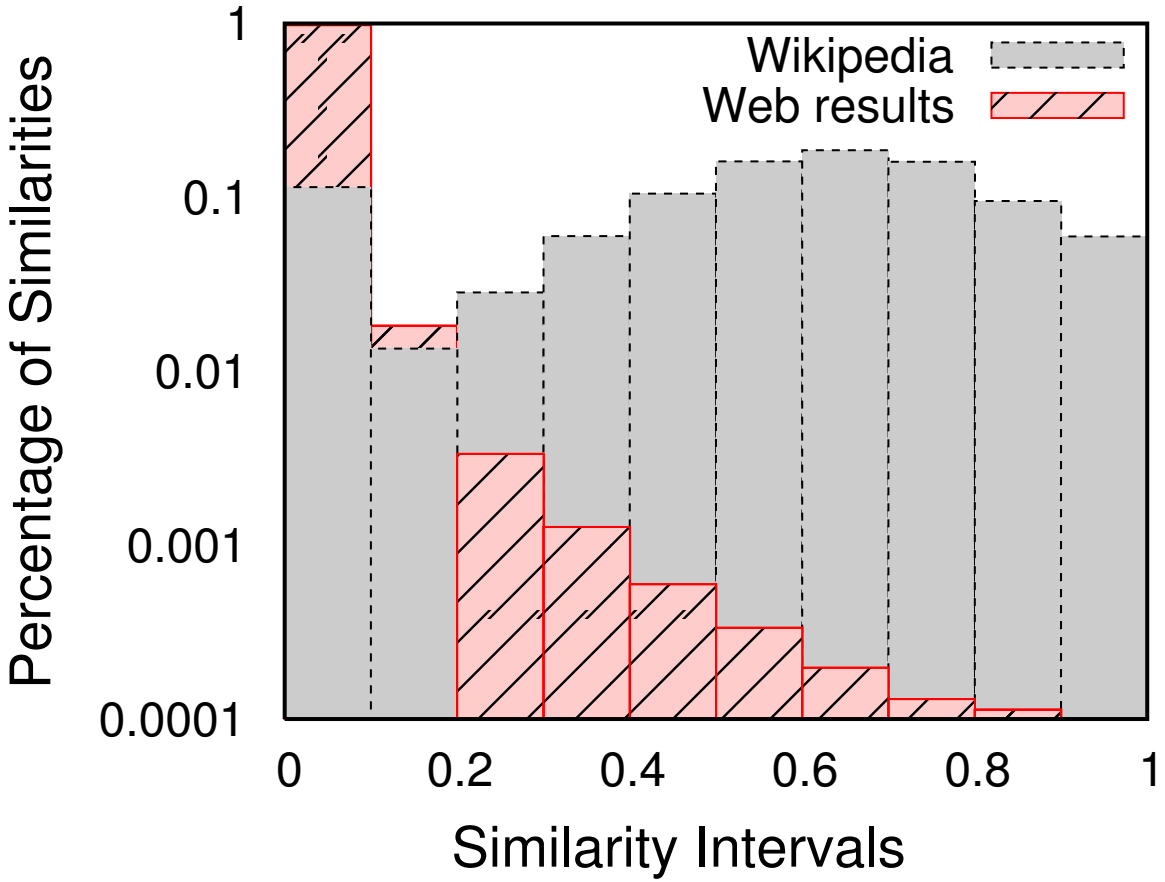
➜ Documents as they appear in plagiarism analysis.

3. Wikipedia Revision corpus: 6m documents, 80m revisions.

➜ Documents as they appear in social software, plagiarism analysis, and the Web.

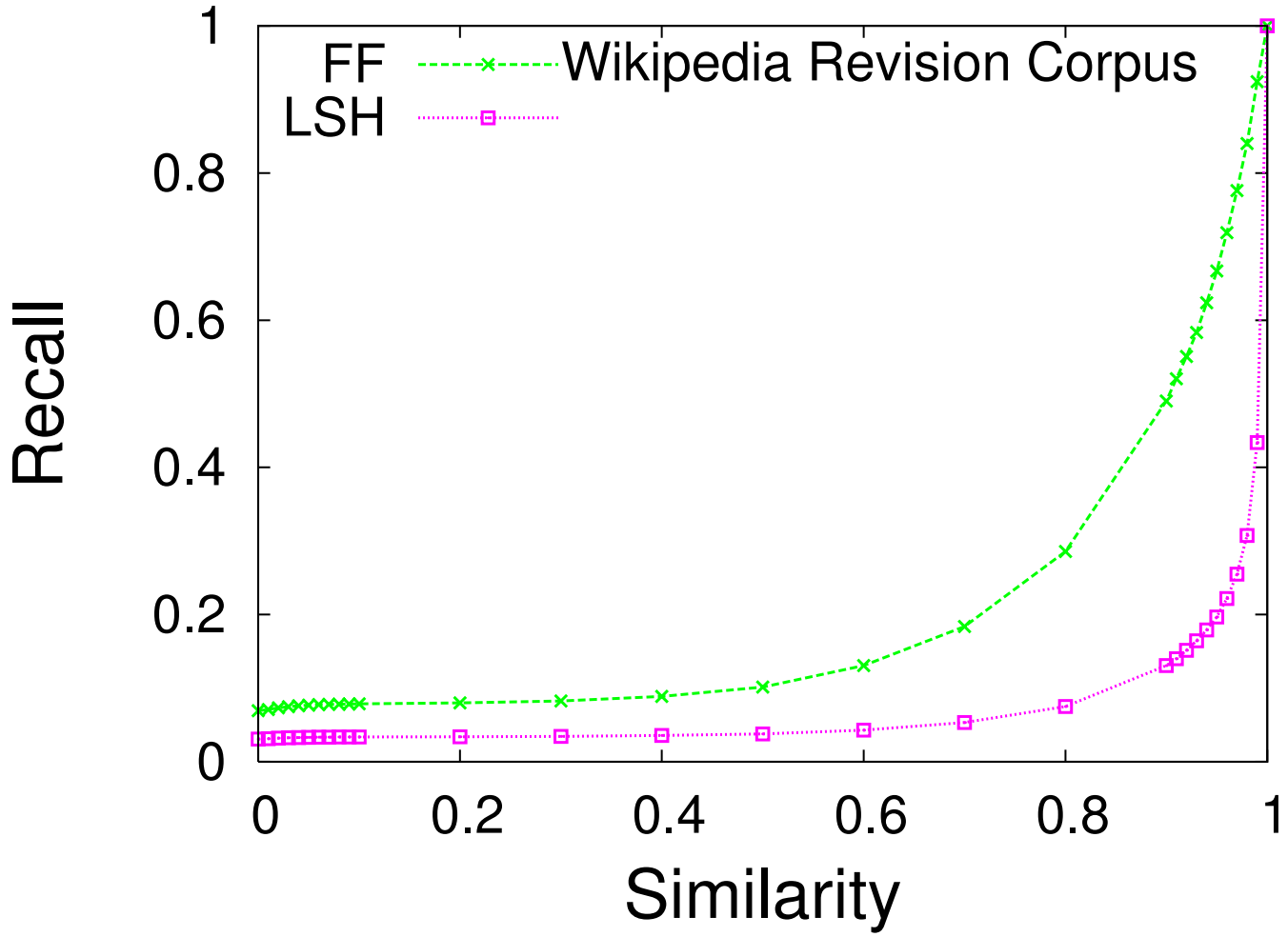
- first revision of each document used as query document d
- comparison with each of d's revisions
- comparison with d's immediate succeeding document

Experimental Setting



Precision and Recall were recorded for similarity thresholds ranging from 0 to 1.

Results



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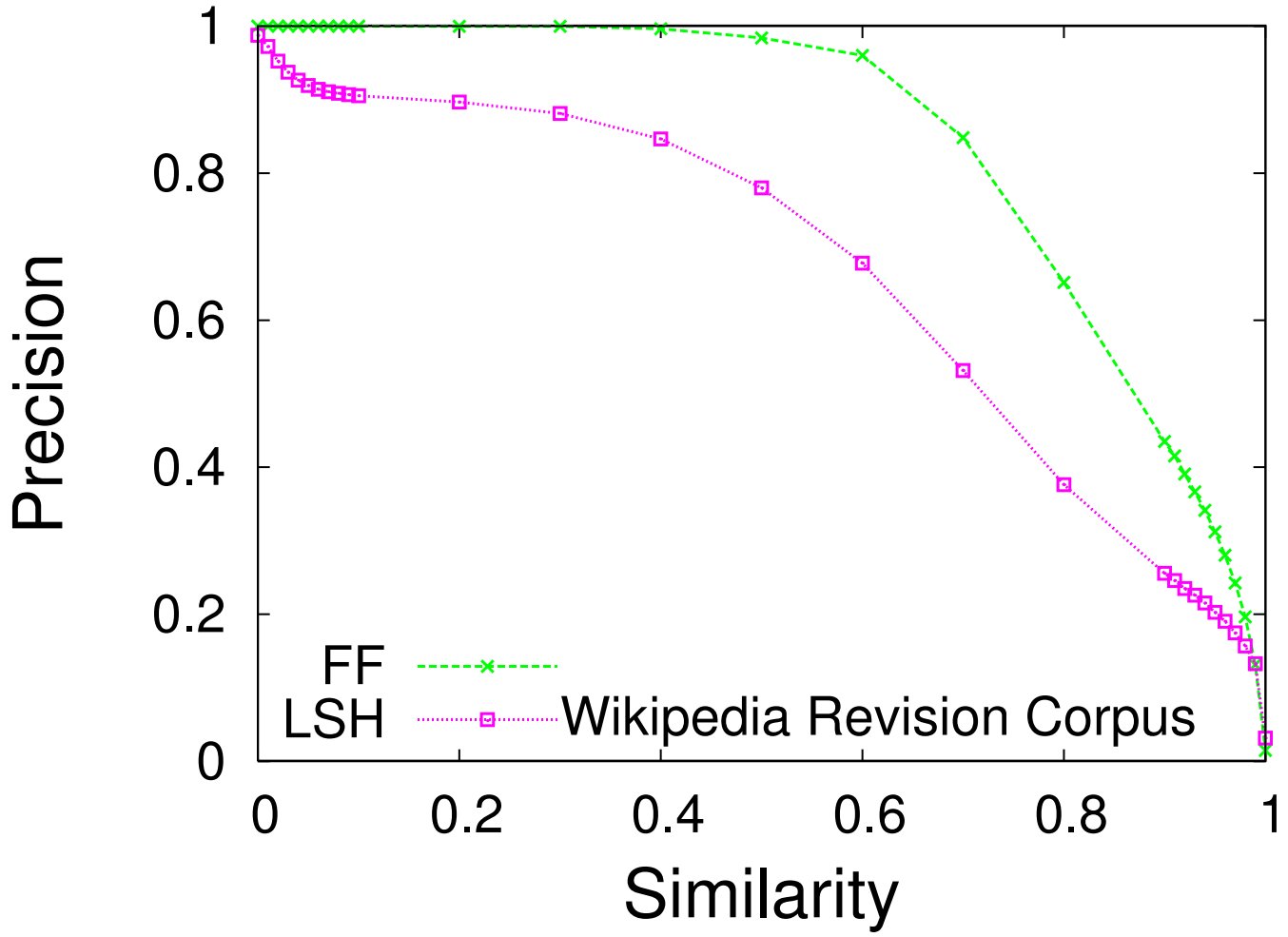

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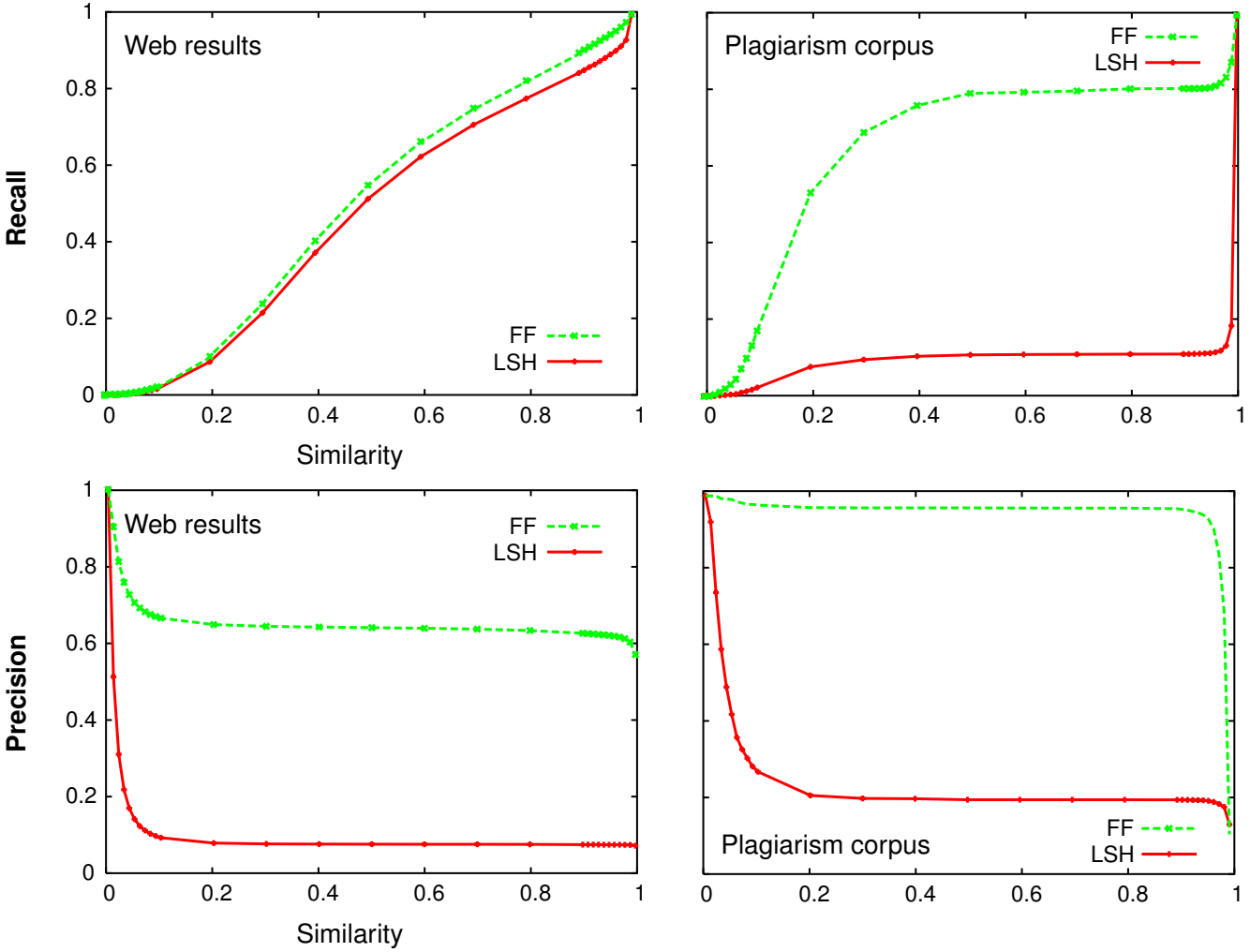

Summary

Similarity hashing may contribute to various retrieval tasks

Comparison of similarity hash functions:

- FF outperforms LSH in terms of Precision and Recall.
- FF constructs significantly smaller fingerprints.

Conclusions:

- ➜ Both hash-based indexing methods are applicable to TIR.
- ➜ The incorporation of domain knowledge significantly increases retrieval performance.

None of the hash-based indexing methods is limited to TIR.
The only prerequisite is a reasonable vector representation.

Thank you!