Information Retrieval

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Johns Hopkins University

Acknowledgments

These slides draw heavily from these excellent sources:

- Paul McNamee’s JSALT2018 tutorial:
  - https://www.clsp.jhu.edu/wp-content/uploads/sites/75/2018/06/2018-06-19-McNamee-JSALT-IR-Soup-to-Nuts.pdf
- Doug Oard’s Information Retrieval Systems course at UMD
  - http://users.umiacs.umd.edu/~oard/teaching/734/spring18/
- Christopher D. Manning, Prabhakar Raghavan, Hinrich Schütze, Introduction to Information Retrieval, Cambridge U. Press. 2008.
  - https://nlp.stanford.edu/IR-book/information-retrieval-book.html
- W. Bruce Croft, Donald Metzler, Trevor Strohman, Search Engines: Information Retrieval in Practice, Pearson, 2009
  - http://ciir.cs.umass.edu/irbook/

I never waste memory on things that can easily be stored and retrieved from elsewhere.

-- Albert Einstein

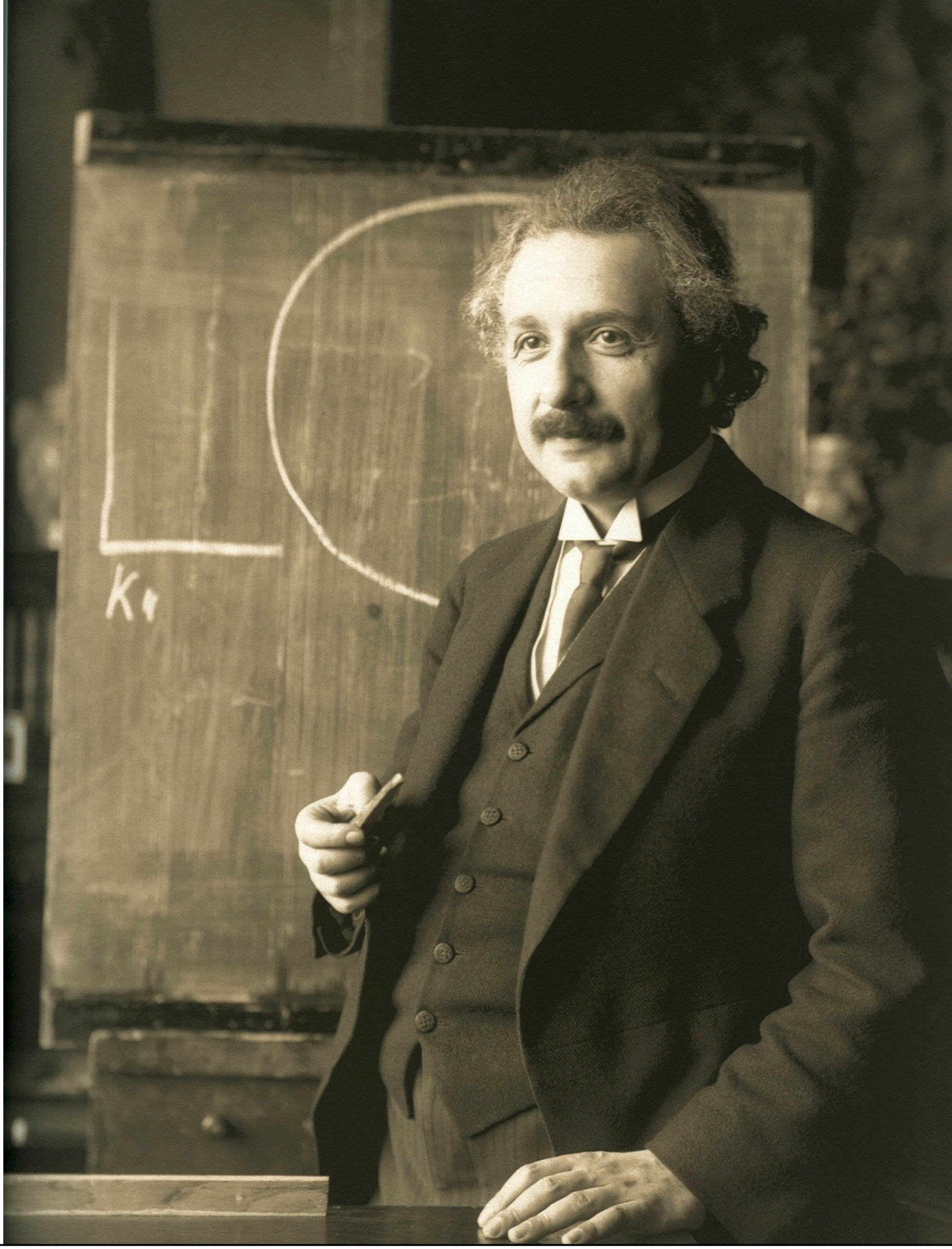


Image source: Einstein 1921 by F Schmutzer

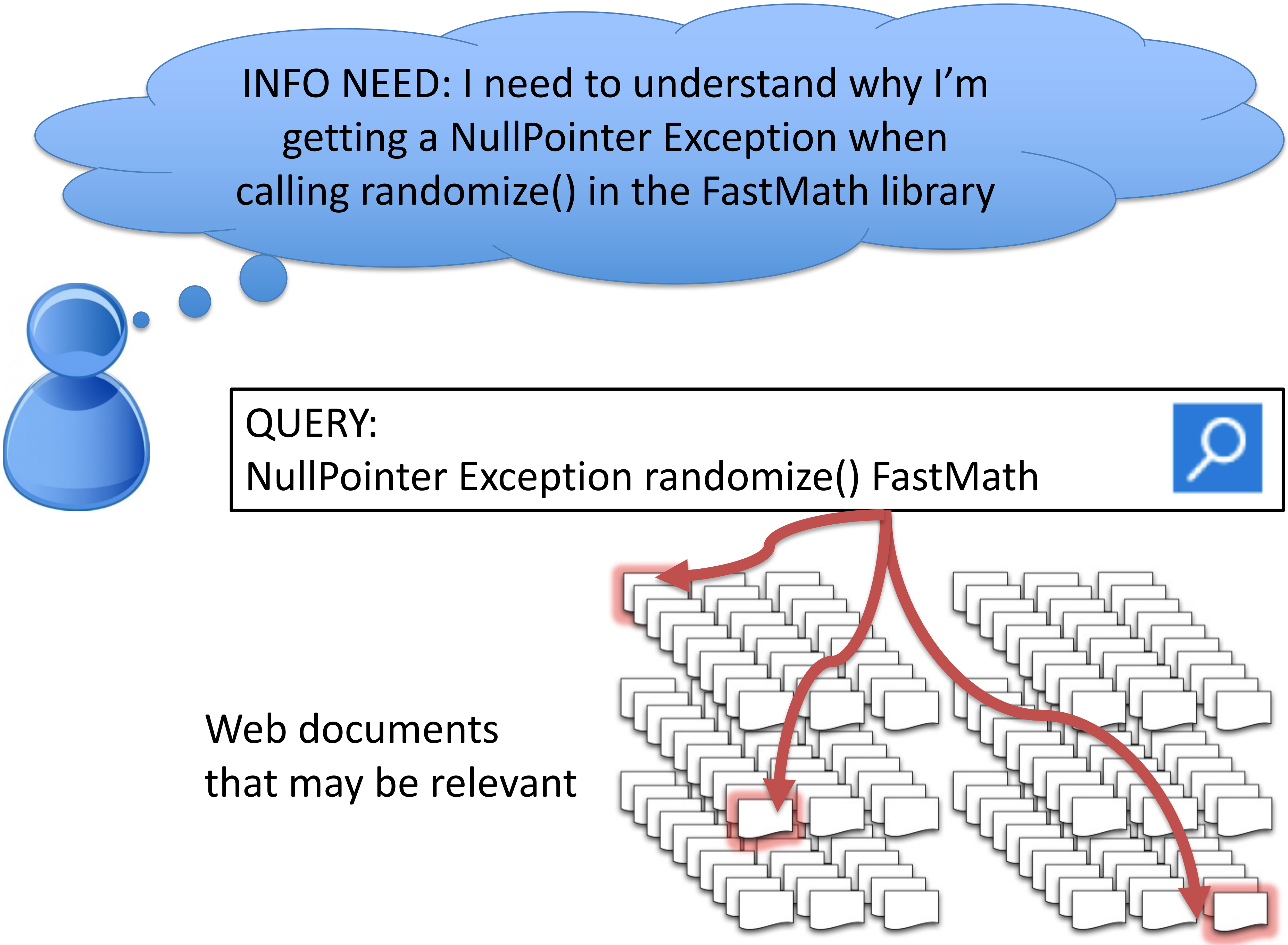
https://en.wikipedia.org/wiki/Albert_Einstein#/media/File:Einstein_1921_by_F_Schmutzer_-_restoration.jpg

What is Information Retrieval (IR)?

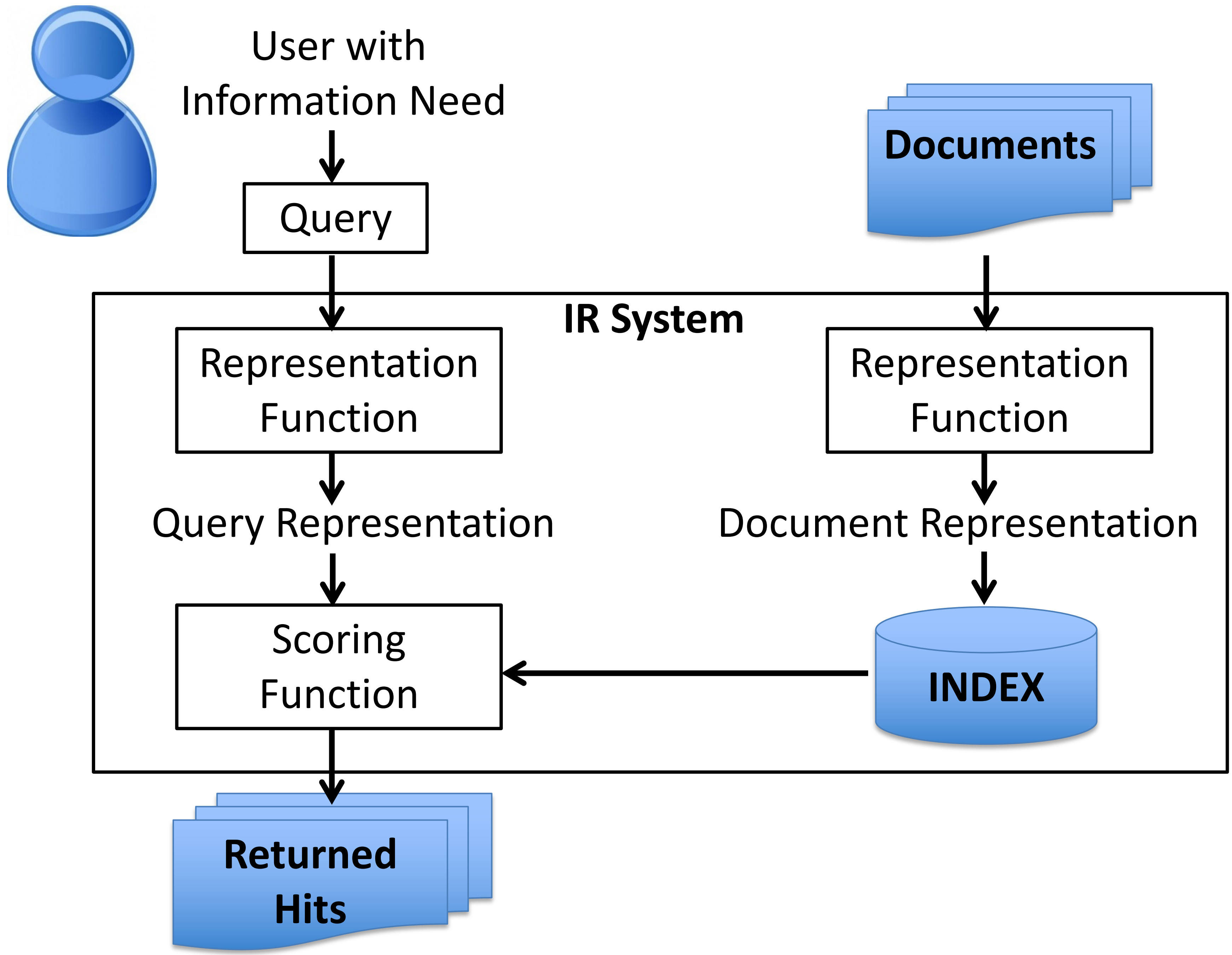
1. Information retrieval is a field concerned with the **structure, analysis, organization, storage, searching, & retrieval of information**.

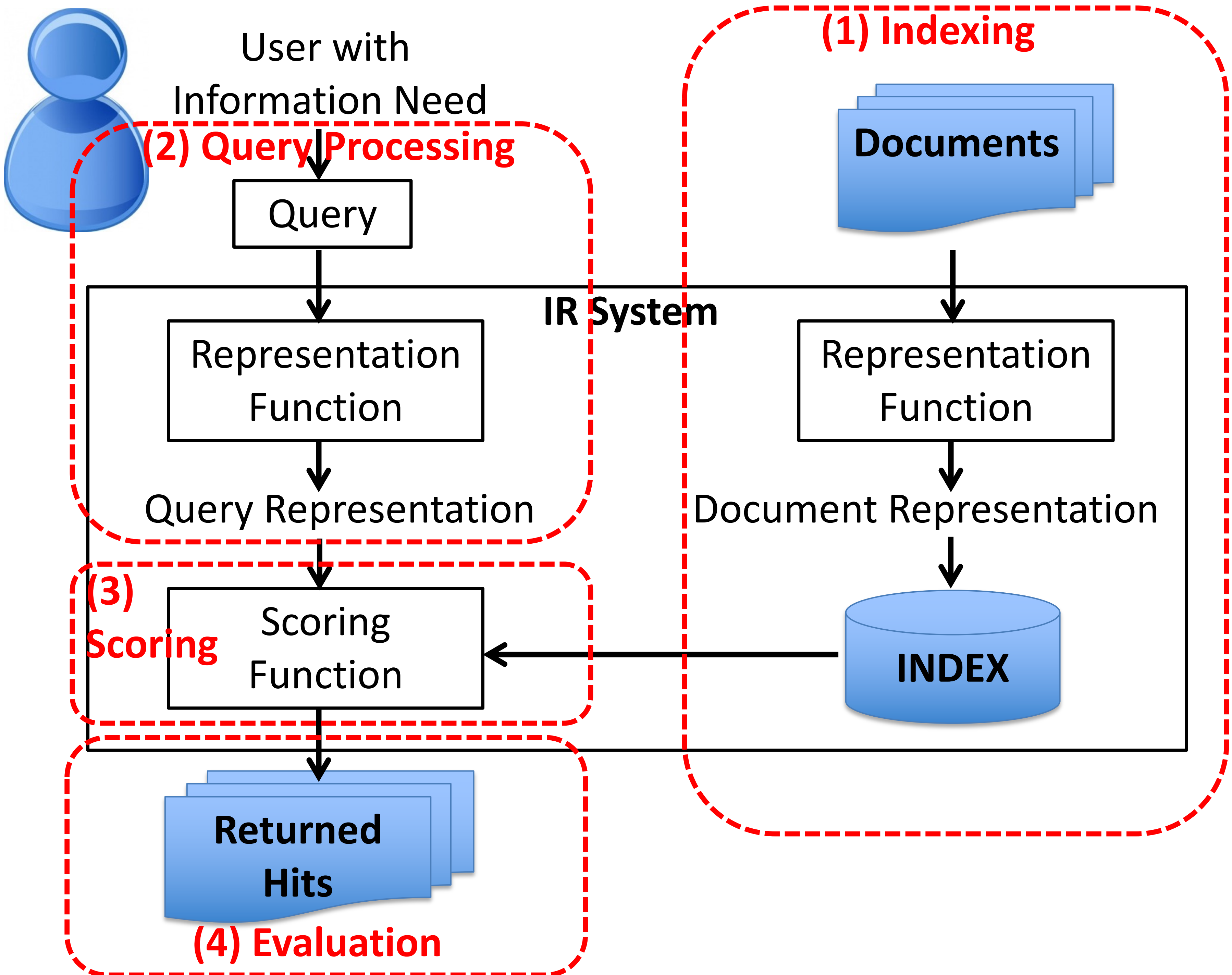
   (Gerard Salton, IR pioneer, 1968)

2. Information retrieval focuses on the efficient recall of information that **satisfies a user's information need**.


INFO NEED: I need to understand why I’m getting a NullPointer Exception when calling randomize() in the FastMath library
QUERY:
NullPointer Exception randomize() FastMath
Web documents that may be relevant

Structure of IR System


User with
Information Need
Query
Documents
IR System
Representation
Function
Representation
Function
Query Representation
Document Representation
Scoring
Function
INDEX
Returned
Hits


User with Information Need
(1) Indexing
Documents
(2) Query Processing
Query
IR System
Representation Function
Representation Function
Query Representation
Document Representation
(3) Scoring
Scoring Function
INDEX
Returned Hits
(4) Evaluation

Index vs Grep

- Say we have collection of Shakespeare plays
- We want to find all plays that contain:

QUERY:
Brutus AND Caesar AND NOT Calpurnia

- Grep: Start at 1st play, read everything and filter if criteria doesn't match (linear scan, 1M words)
- Index (a.k.a. Inverted Index): build index data structure off-line. Quick lookup at query-time.

These examples/figures are from: Manning, Raghavan, Schütze, Intro to Information Retrieval, CUP, 2008

The Shakespeare collection as Term-Document Incidence Matrix

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Antony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
...							

Matrix element (t,d) is:

1 if term t occurs in document d,

0 otherwise

These examples/figures are from: Manning, Raghavan, Schütze, Intro to Information Retrieval, CUP, 2008

The Shakespeare collection as Term-Document Incidence Matrix

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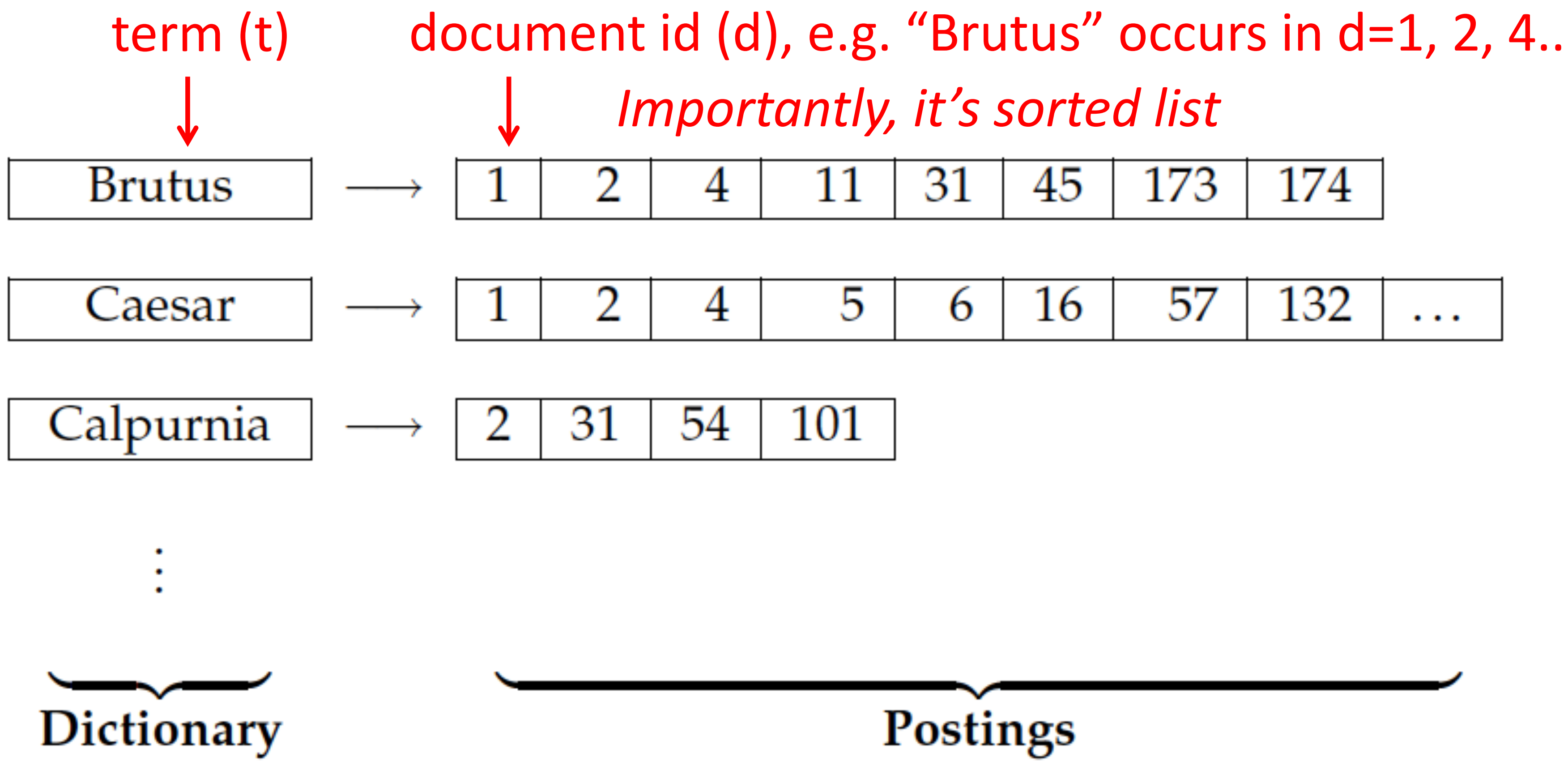
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
…							

QUERY:
Brutus AND Caesar AND NOT Calpurnia

Answer: "Antony and Cleopatra"(d=1), "Hamlet"(d=4)

These examples/figures are from: Manning, Raghavan, Schütze, Intro to Information Retrieval, CUP, 2008

Inverted Index Data Structure



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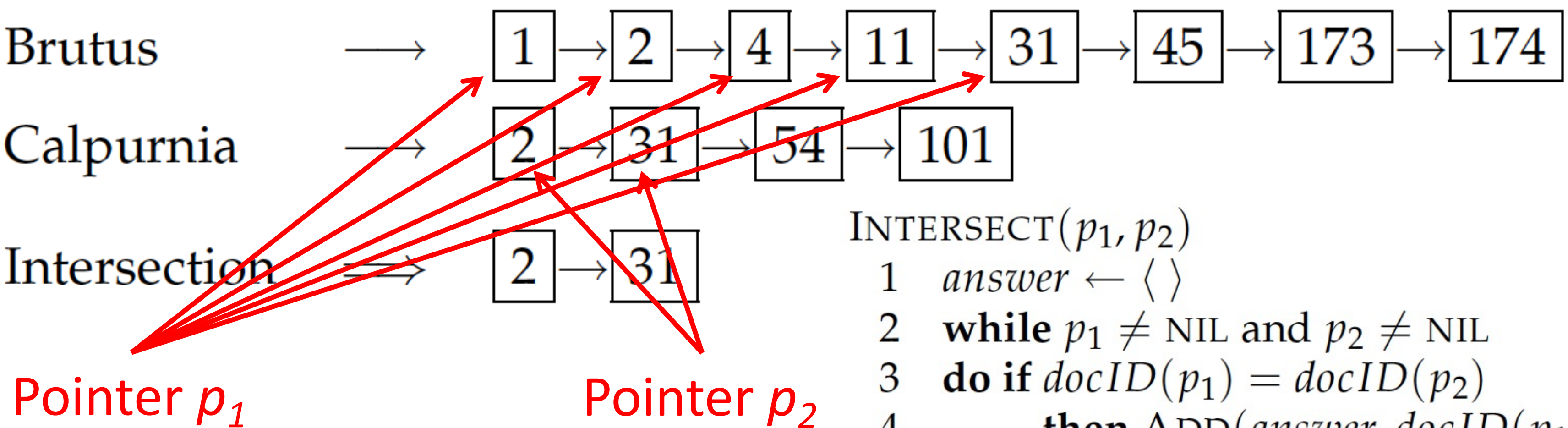
Efficient algorithm for List Intersection (for Boolean conjunctive “AND” operators)

QUERY:
Brutus AND Calpurnia



INTERSECT(p_1, p_2)
```
answer ← ⟨ ⟩
while p1 ≠ NIL and p2 ≠ NIL
do if docID(p1) = docID(p2)
      then ADD(answer, docID(p1))
           p1 ← next(p1)
           p2 ← next(p2)
      else if docID(p1) < docID(p2)
             then p1 ← next(p1)
             else p2 ← next(p2)
return answer
```

These examples/figures are from: Manning, Raghavan, Schütze, Intro to Information Retrieval, CUP, 2008

Time and Space Tradeoffs

- Time complexity at query-time:
  - Linear scan over postings
  - $O(L_1 + L_2)$ where L_t is length of posting for term t
  - vs. grep through all documents $O(N)$, $L << N$
- Time complexity at index-time:
  - $O(N)$ for one pass through collection
  - Additional issue: efficient adding/deleting documents
- Space complexity (example setup):
  - Dictionary: Hash/Trie in RAM
  - Postings: Array on disk

Quiz: How would you process these queries?

QUERY:
Brutus AND Caesar AND Calpurnia

QUERY:
Brutus AND (Caesar OR Calpurnia)

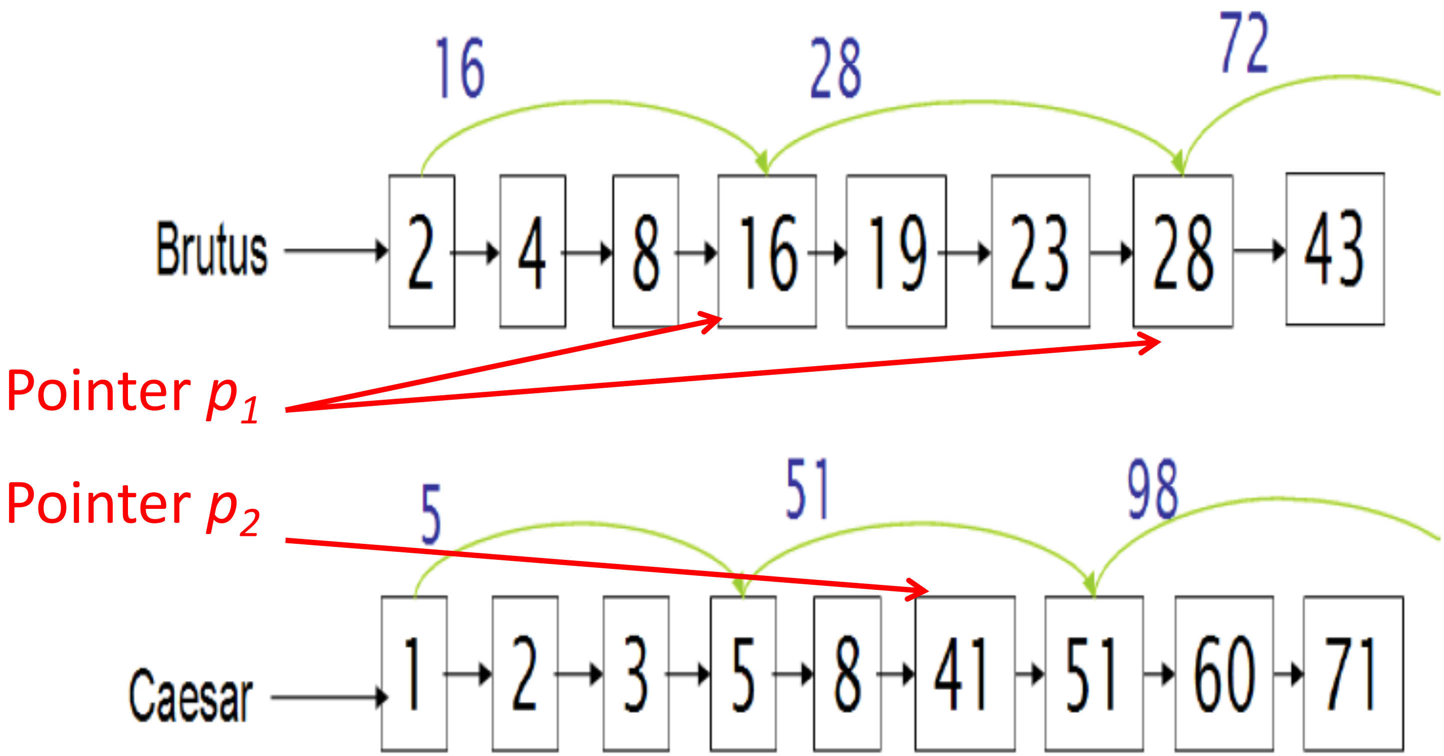
QUERY:
Brutus AND Caesar AND NOT Calpurnia

Brutus	⟶	1	2	4	11	31	45	173	174	
Caesar	⟶	1	2	4	5	6	16	57	132	…
Calpurnia	⟶	2	31	54	101					

Think: What terms to process first? How to handle OR, NOT?

Optional meta-data in inverted index

- Skip pointers: For faster intersection, but extra space



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Optional meta-data in inverted index

- Position of term in document: Enables phrasal queries

QUERY:
"to be or not to be"

to, 993427:

$\langle$ 1, 6: $\langle 7, 18, 33, 72, 86, 231 \rangle$;
2, 5: $\langle 1, 17, 74, 222, 255 \rangle$;
4, 5: $\langle 8, 16, 190, 429, 433 \rangle$;
5, 2: $\langle 363, 367 \rangle$;
7, 3: $\langle 13, 23, 191 \rangle$; ... $\rangle$

term (t)

document frequency

be, 178239:

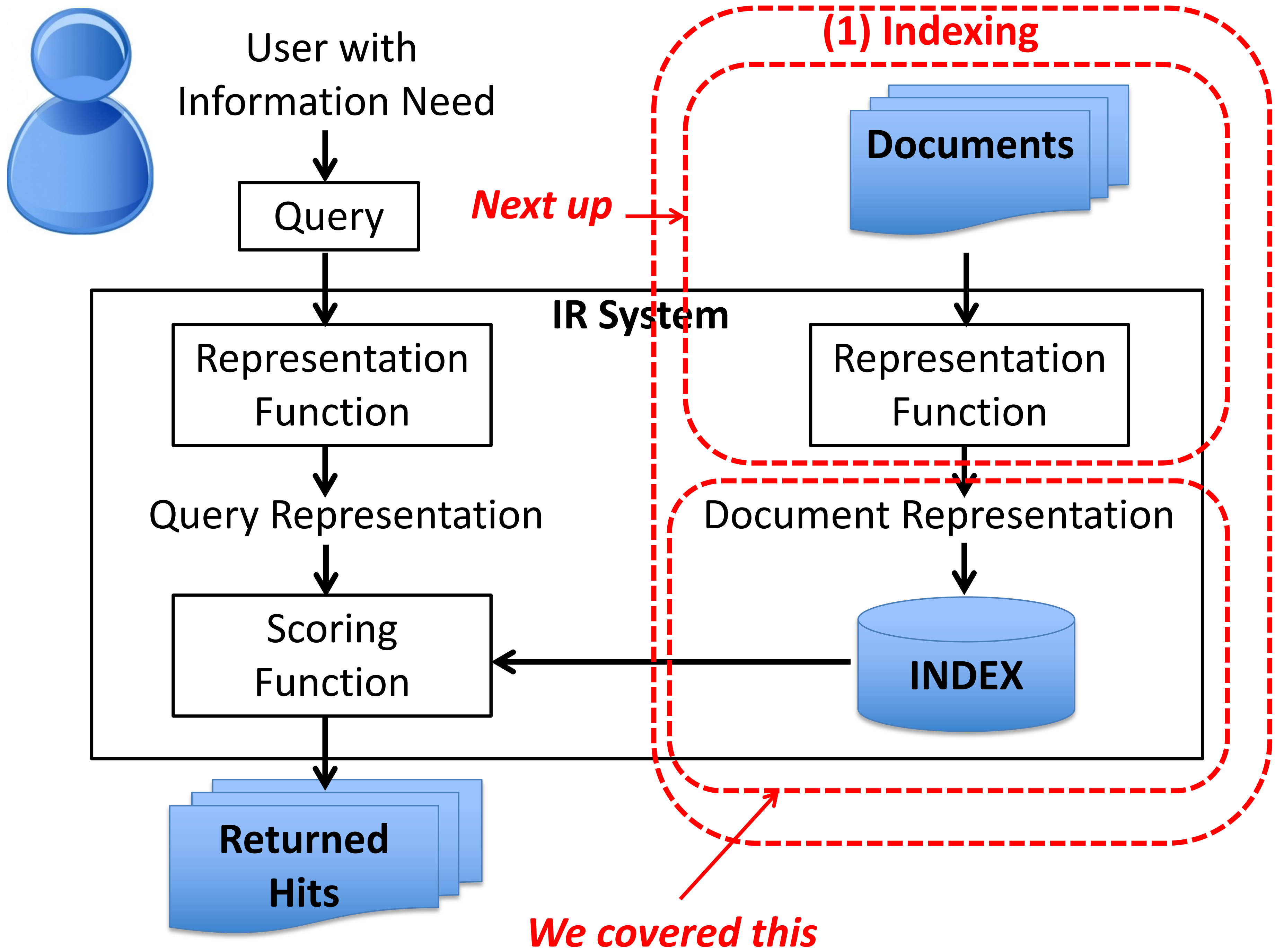
$\langle$ 1, 2: $\langle 17, 25 \rangle$;
4, 5: $\langle 17, 191, 291, 430, 434 \rangle$;
5, 3: $\langle 14, 19, 101 \rangle$; ... $\rangle$

term occurs in document d=4
with term frequency of 5,
at positions 17, 191, 291, 430, 434

Index construction and management

- Dynamic index
  - Searching Twitter vs. static document collection
- Distributed solutions
  - MapReduce, Hadoop, etc.
  - Fault tolerance
- Pre-computing components for score function

→ Many interesting technical challenges!



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(1) Indexing
Next up
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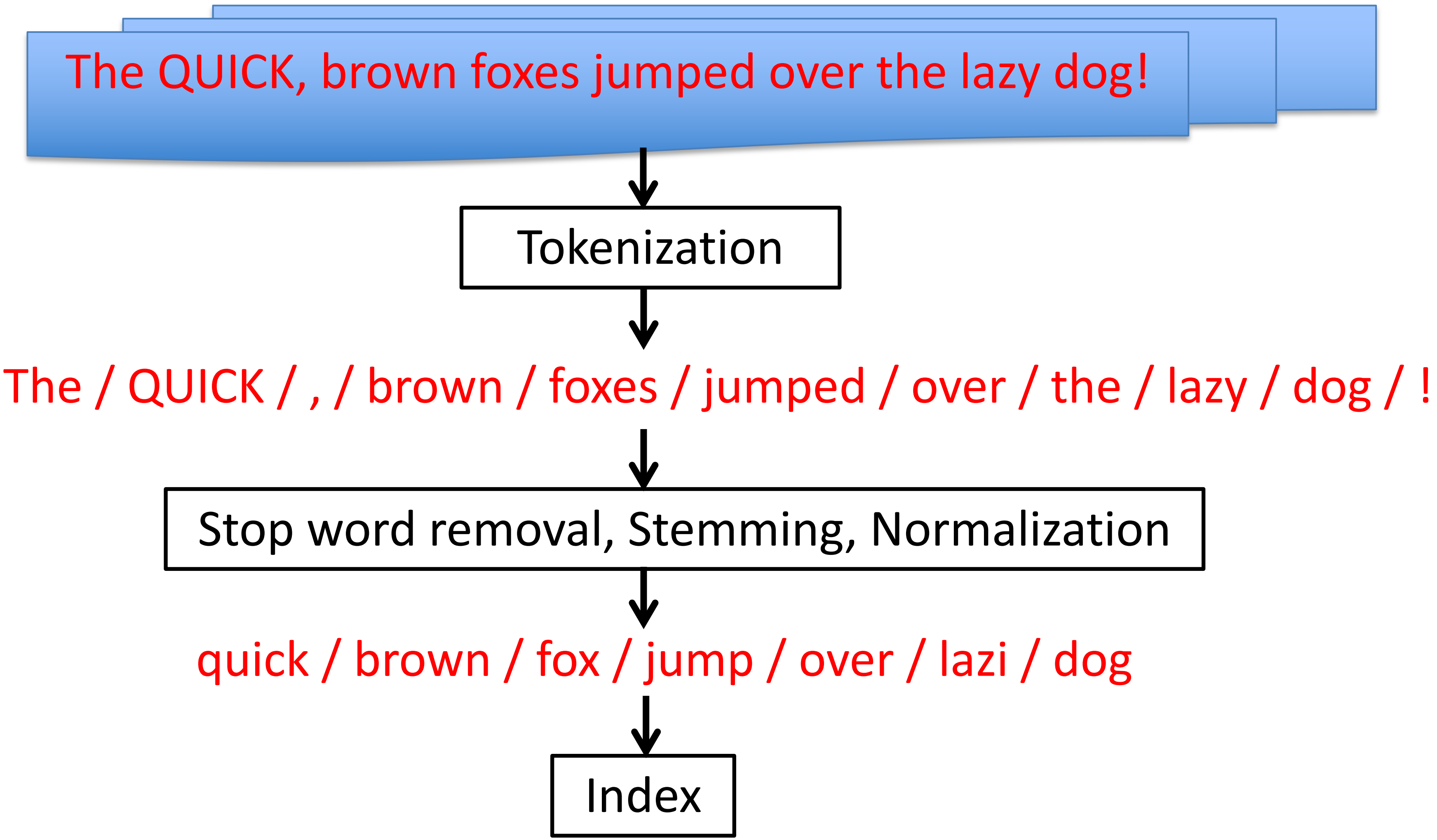
Document Representation
INDEX
We covered this

Representing a Document as a Bag-of-words (but what words?)



Issues in Document Representation

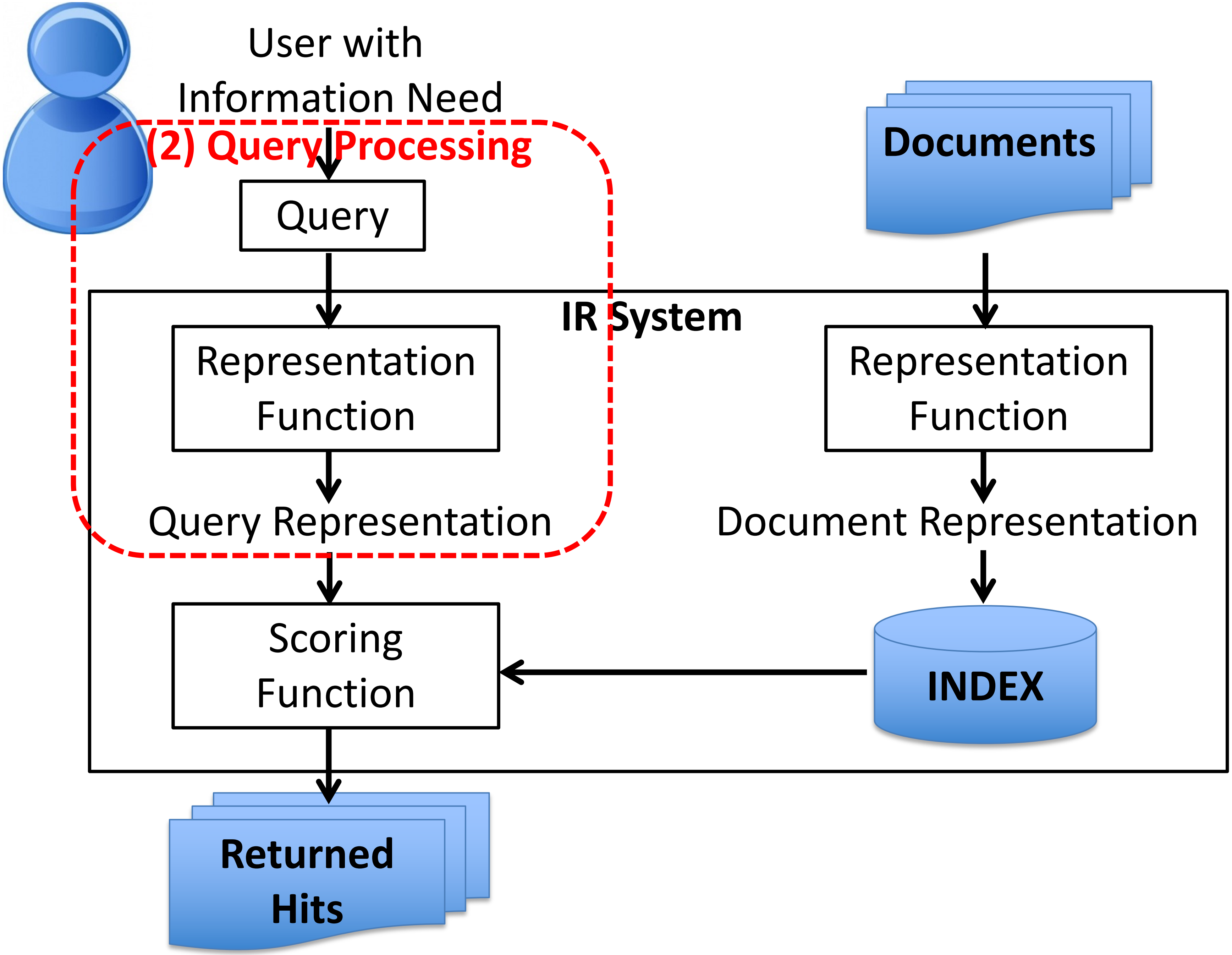
- Language-specific challenges
- Polysemy & Synonyms:
  - “bank” in multiple senses, represented the same?
  - “jet” and “airplane” should be same?
- Acronyms, Numbers, Document structure
- Morphology

aghnaaguq

aghnagh-	-~:(ng)u-	-$\sim_f$(g/t)u-	-q
woman-	-to.be.N-	-INTR.IND-	-3SG

‘*She is a woman*’

Central Siberian Yupik morphology example from E. Chen & L. Schartz, LREC 2018:
http://dowobeha.github.io/papers/lrec18.pdf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Query Representation

- Of course, the query string must go through the same tokenization, stop word removal and normalization process like the documents

- But we can do more, esp. for free-text queries
  - – to guess user's intent & information need

Keyword search vs. Conceptual search

- Keyword search / Boolean retrieval:

  BOOLEAN QUERY:
  Brutus AND Caesar AND NOT Calpurnia

  – Answer is exact, must satisfy these terms

- Conceptual search (or just “search” like Google)

  FREE-TEXT QUERY:
  Brutus assassinate Caesar reasons

  – Answer may not need to exactly match these terms
  – *Note this naming may not be standard*

Query Expansion for "conceptual" search

- Add terms to the query representation
  - Exploit knowledge base, WordNet, user query logs

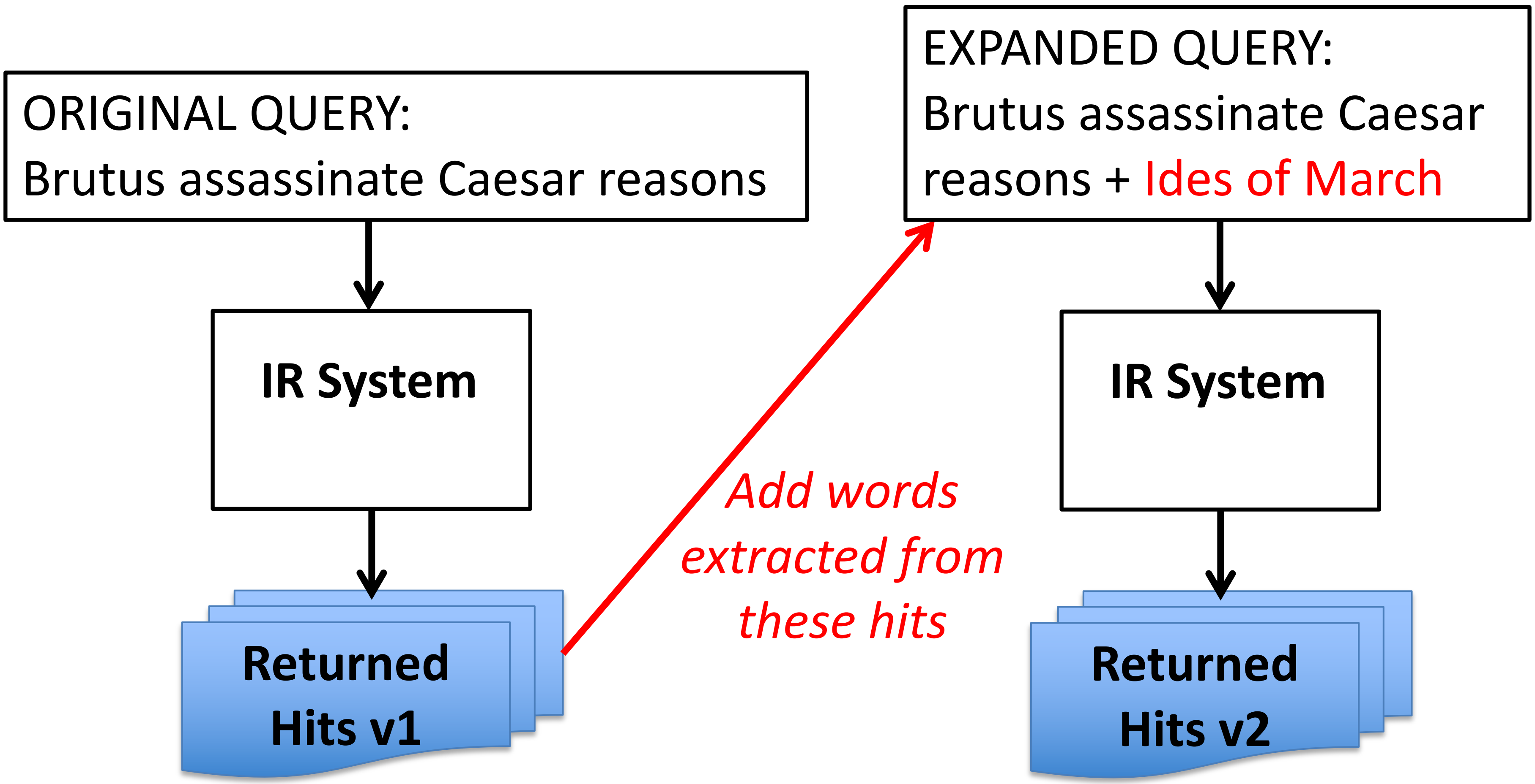
ORIGINAL FREE-TEXT QUERY:
Brutus assassinate Caesar reasons

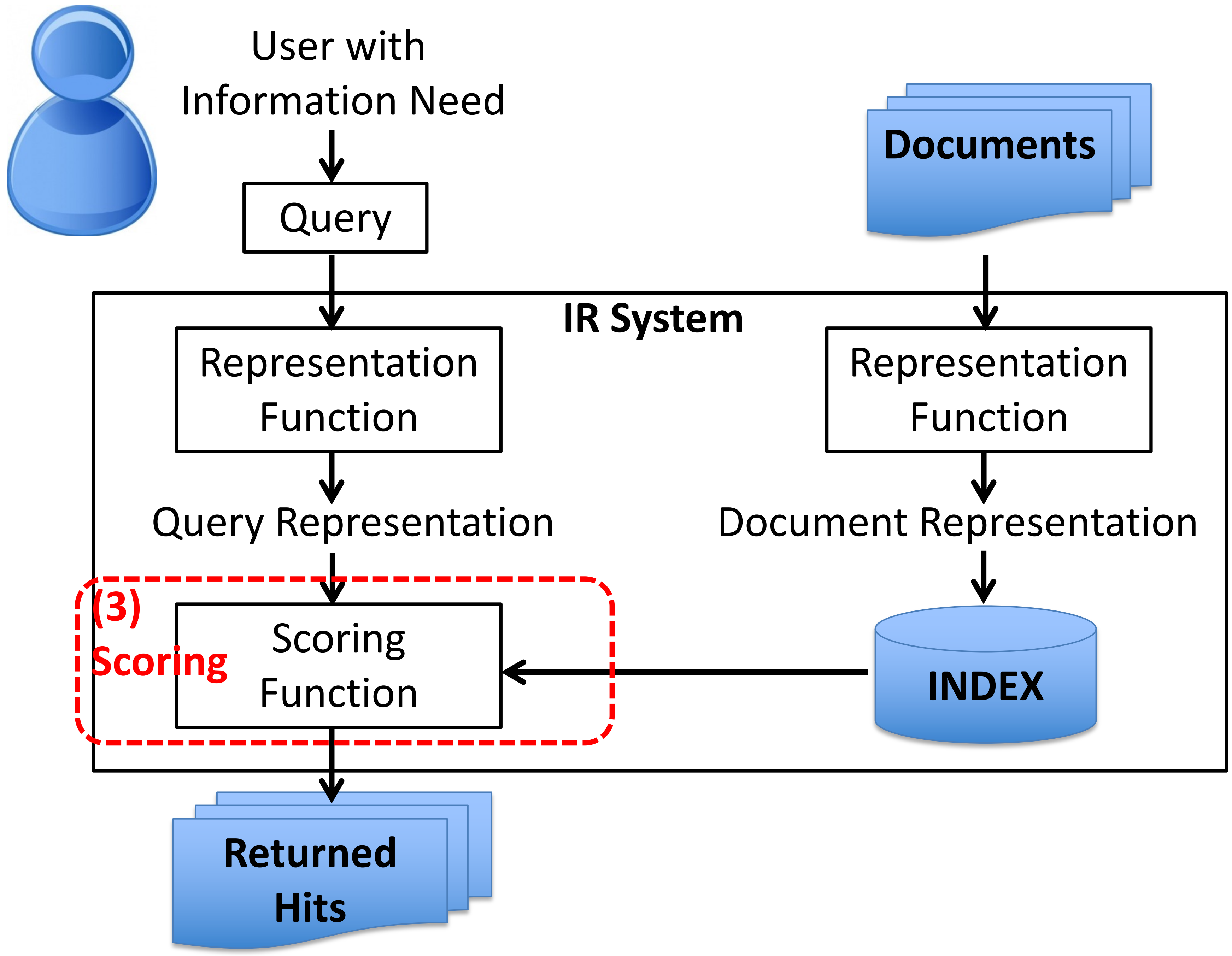
↓

EXPANDED QUERY:
Brutus assassinate kill Caesar reasons why

Pseudo-Relevance Feedback

- Query expansion by iterative search

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Motivation for scoring documents

- For keyword search, all documents returned should satisfy query, and are equally relevant
- For conceptual search:
  - May have too many returned documents
  - Relevance is a gradation

  → *Score* documents and return a *ranked list*

TF-IDF Scoring Function

- Given query *q* and document *d*

$$\text{TF-IDF}(q,d) = \sum_{t \in q} \mathrm{tf}_{t,d} \times \mathrm{idf}_t$$

terms t in q

Term frequency (raw count) of t in d

Inverse document frequency

$$\mathrm{idf}_t = \log \frac{N}{\mathrm{df}_t}$$

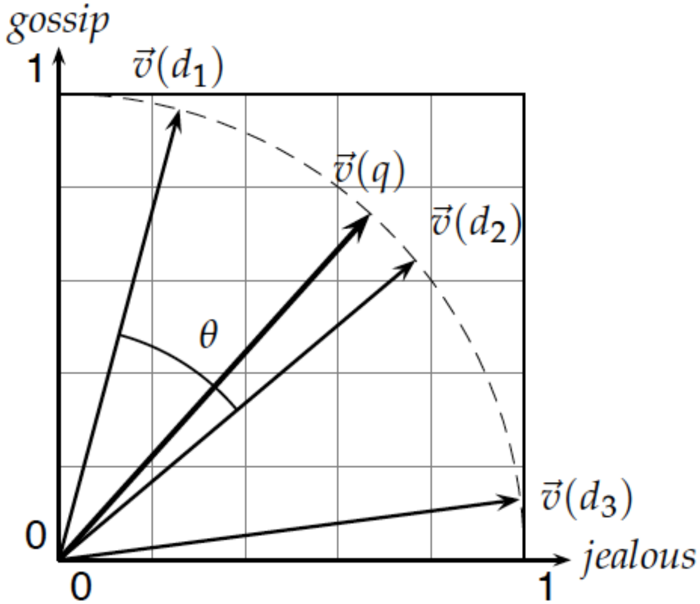
Total number of documents

Number of documents with >=1 occurrence of t

Vector-Space Model View

- View documents (d) & queries (q) each as vectors,
  - Each vector element represents a term
  - whose value is the TF-IDF of that term in d or q
- Score function can be viewed as e.g. Cosine Similarity between vectors

$$\text{score}(q,d) = \frac{\vec{V}(q)\cdot\vec{V}(d)}{|\vec{V}(q)||\vec{V}(d)|}$$



These examples/figures are from: Manning, Raghavan, Schütze, Intro to Information Retrieval, CUP, 2008

Alternative Scoring Functions: BM25

$$score(q,d) = \sum_{t \in q} \mathrm{idf}_\mathrm{t} \times \frac{\mathrm{tf}_{\mathrm{t,d}} \cdot (k_1 + 1)}{\mathrm{tf}_{\mathrm{t,d}} + k_1 \cdot (1 - b + b \cdot \frac{|D|}{avgdl})}$$

Query

Document

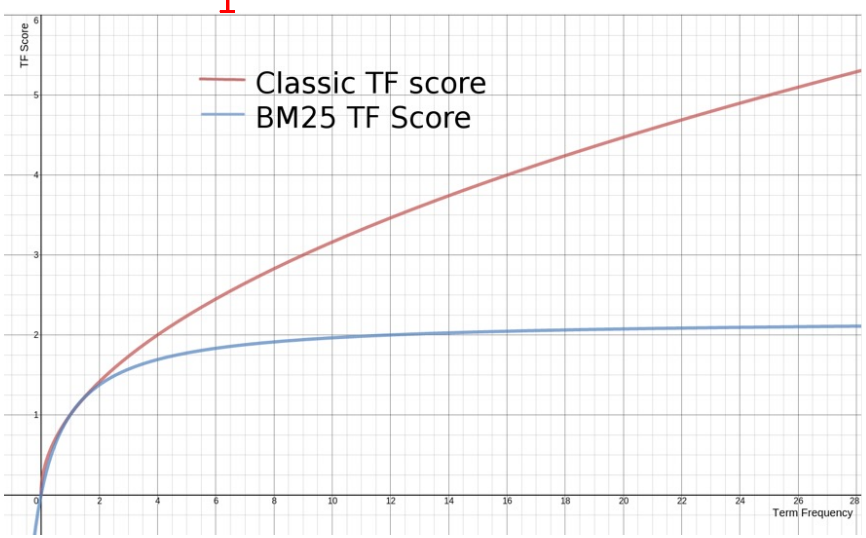
Inverse Document Frequency of query term

Frequency of query term in document

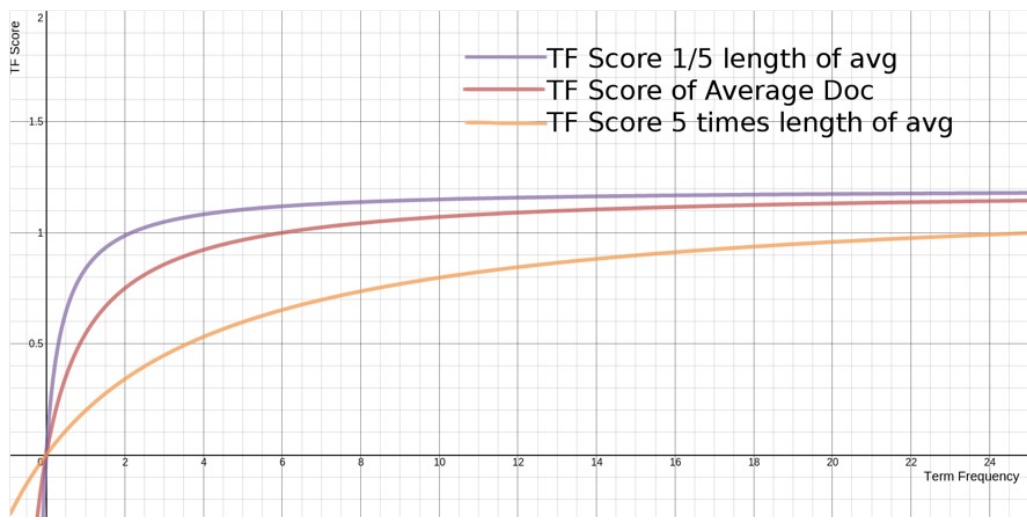
Document length ratio

Tunable Hyperparameters

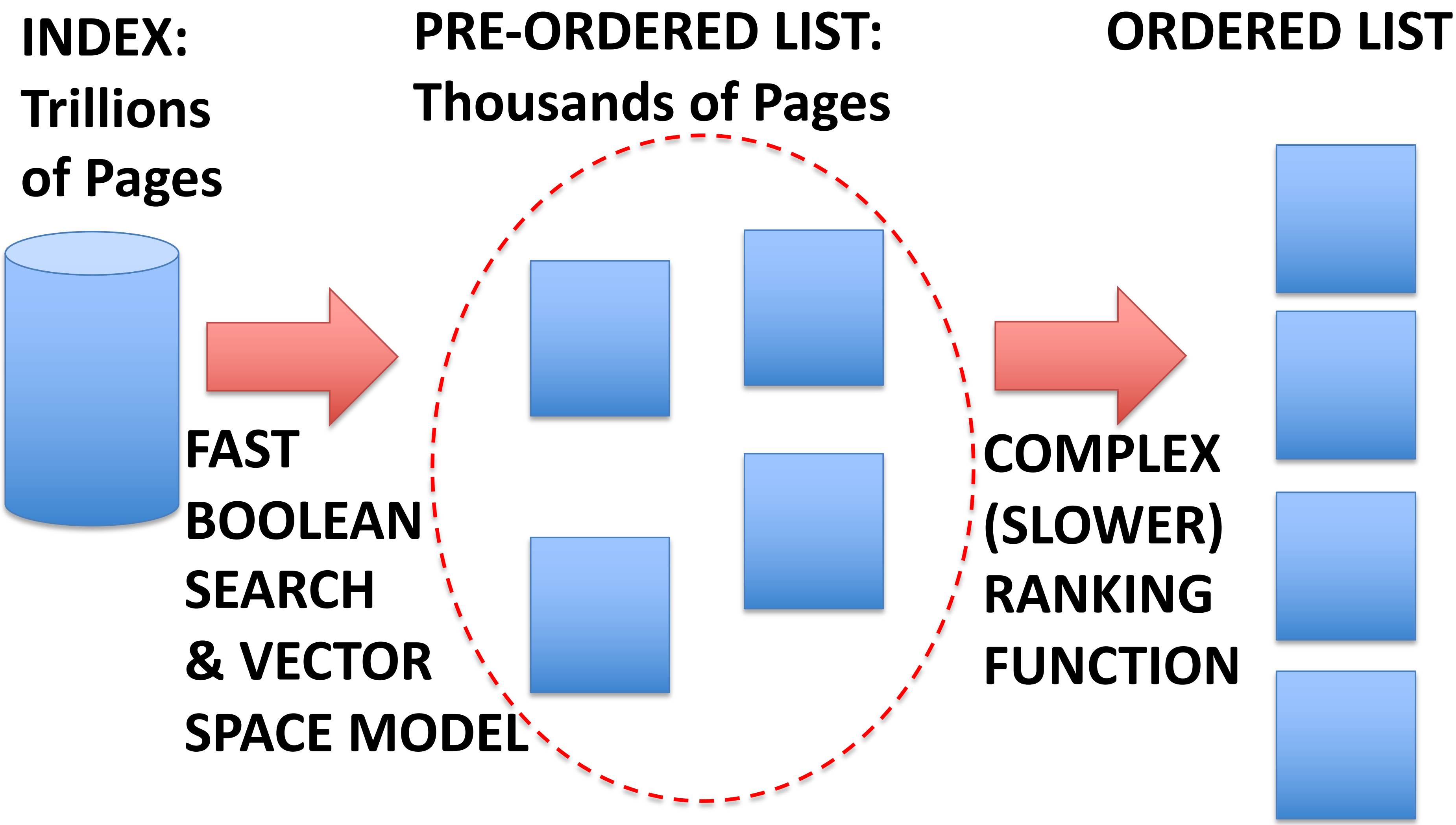
k_1: Saturation for tf



b: Document length bias



Two-Stage Scoring



Motivation of Two-Stage Scoring with ``Learning-to-Rank” methods

- Machine learning approach:
  - Enables more **features** (signal sources)
  - 1st stage aims for high Recall, 2nd stage aims for high Precision
- Useful features based on Query (q) and Document (d)
  - Various vector space model results, applied to text, URL, title
  - Click-through: e.g. How many times d is clicked given q vs. How many times d is skipped
  - Results after Query-expansion
- Useful features based on Document only (static)
  - Popularity of page: #Likes, #inlinks, Pagerank
  - Domain structure: main page or subpage

Example features

jhu cs courses 2016

Word match?

URL match?

Popular page?

Recently updated?

User intention match?

Not spam?

Clickthrough log?

Johns Hopkins University Computer Science | Facebook
https://www.facebook.com/compscijhu
Johns Hopkins University Computer Science, Baltimore. 407 likes · 5 talking about this. **Computer Science** at **Johns Hopkins University** (**CS@JHU**) is a...

600.318/418: Operating Systems - **Johns Hopkins University**
srl.**cs.jhu**.edu/**courses**/600.418/index.html
Computer science majors and graduate students will be admitted regardless of enrollment limits. ... This **course** provides an introduction to operating systems.

Department of **Computer Science | Course Information**
www.**cs.jhu**.edu/**course**-info
CS Course Catalog – complete list of departmental **courses** with descriptions. Note that not all **courses** are offered every year. **Course** Area Designators – a chart ...

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Problem Formulation

<u>1. Feature extraction</u>

<query, doc$_1$> → vector x_1

<query, doc$_2$> → vector x_2

<query, doc$_3$> → vector x_3

<u>2. Apply ranking function & sort</u>

$F(x_1) = 3$ → Rank 2

$F(x_2) = 1$ → Rank 3 (worst)

$F(x_3) = 4$ → Rank 1 (best)

<u>What function class for F()?</u>

Assume linear weights: $F(x_i) = w^T x_i$

Learn weights w that replicate ranking on training set

Training Set

Query 1	Labels for each query-doc pair
<query, doc_1> → vector x_1	$label(x_1) = 3$
<query, doc_2> → vector x_2	$label(x_2) = 1$
<query, doc_3> → vector x_3	$label(x_3) = 4$

Query 2	Labels for each query-doc pair
<query, doc_1> → vector x_1	$label(x_1) = 3$ (Very relevant)
<query, doc_2> → vector x_2	$label(x_2) = 2$ (Relevant)
<query, doc_3> → vector x_3	$label(x_3) = 1$ (Slightly relevant)
<query, doc_4> → vector x_4	$label(x_4) = 0$ (Irrelevant)

Where does the label come from?

- Human annotation
  - High quality, but expensive
- Click-through logs
  - Noisy, but cheap/abundant

Notation

query: $q^{(n)} \qquad n = 1, \ldots, N$

document for query n: $d_i^{(n)} \qquad i = 1, \ldots, I_n$

vector of D features per query-doc: $x_i^{(n)} \in \mathcal{R}^D$

label for each query-doc pair: $l_i^{(n)} \in \mathcal{Z}$

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Different training approaches

- How to optimize something on a set with a sort operation? Reduce to traditional regression/classification problems

Training Approach	Reduction
Point-wise	Document
Pair-wise	Two Documents
List-wise	All Documents per query

Point-wise Approach

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Find w that makes each F(x) equal to its label

Training Objective: $\sum_n \sum_i (F(x_i^{(n)}) - l_i^{(n)})^2$

Training Objective: $\sum_n \sum_i (F(x_i^{(n)}) - l_i^{(n)})^2$

$\rightarrow \sum_z (F(x_z) - l_z)^2$ where z ranges over all i, n

Solve with linear regression!

Pair-wise Approach

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Find w that gives every pair the correct ranking

Training Objective:

$$F(x_i^{(n)}) > F(x_j^{(n)}) \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

Training Objective:

$$F(x_i^{(n)}) > F(x_j^{(n)}) \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

$$\rightarrow F(x_i^{(n)}) - F(x_j^{(n)}) > 0 \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

$$\rightarrow w^T x_i^{(n)} - w^T x_j^{(n)} > 0 \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

$$\rightarrow w^T (x_i^{(n)} - x_j^{(n)}) > 0 \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

$$\rightarrow w^T (\delta_{ij}^{(n)}) > 0 \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

Solve with binary classification!

Make a new sample out of every pair

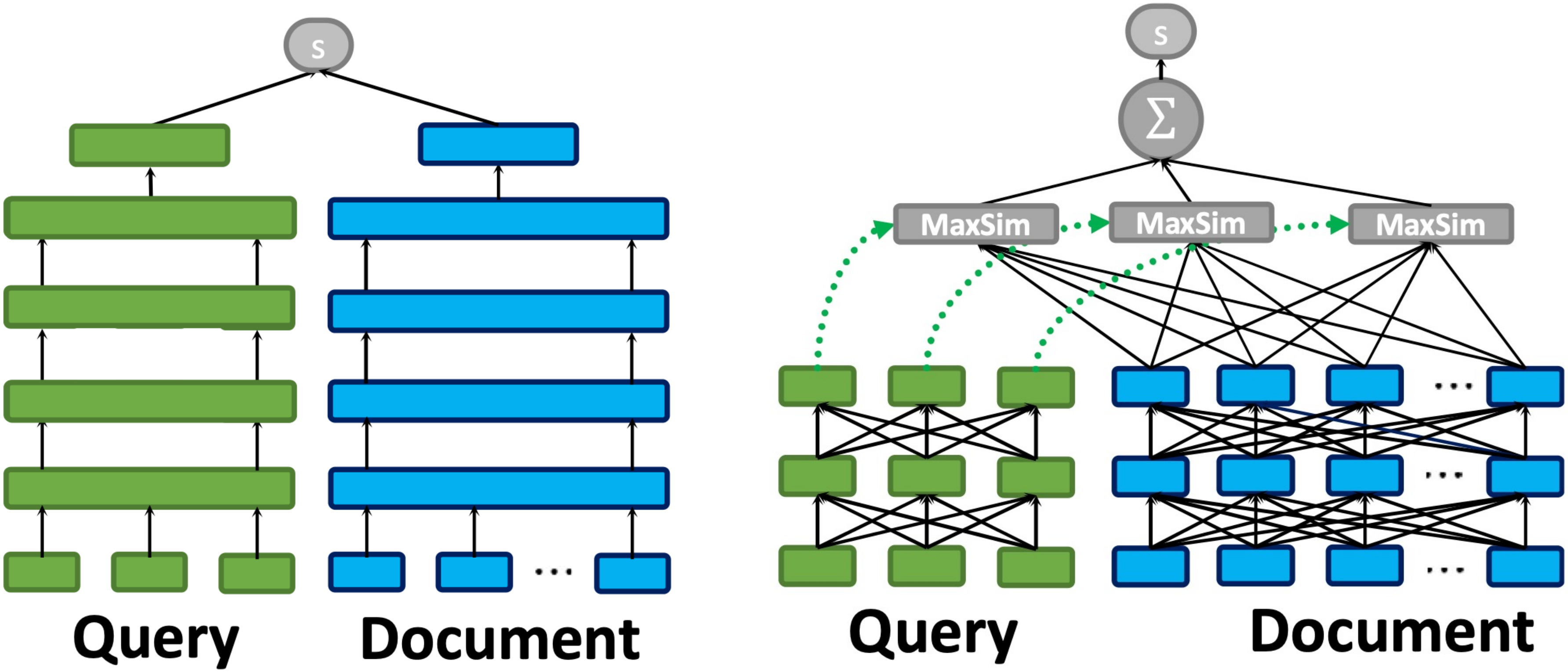
Give new label: Positive for i,j pairs

Negative for j,i pairs

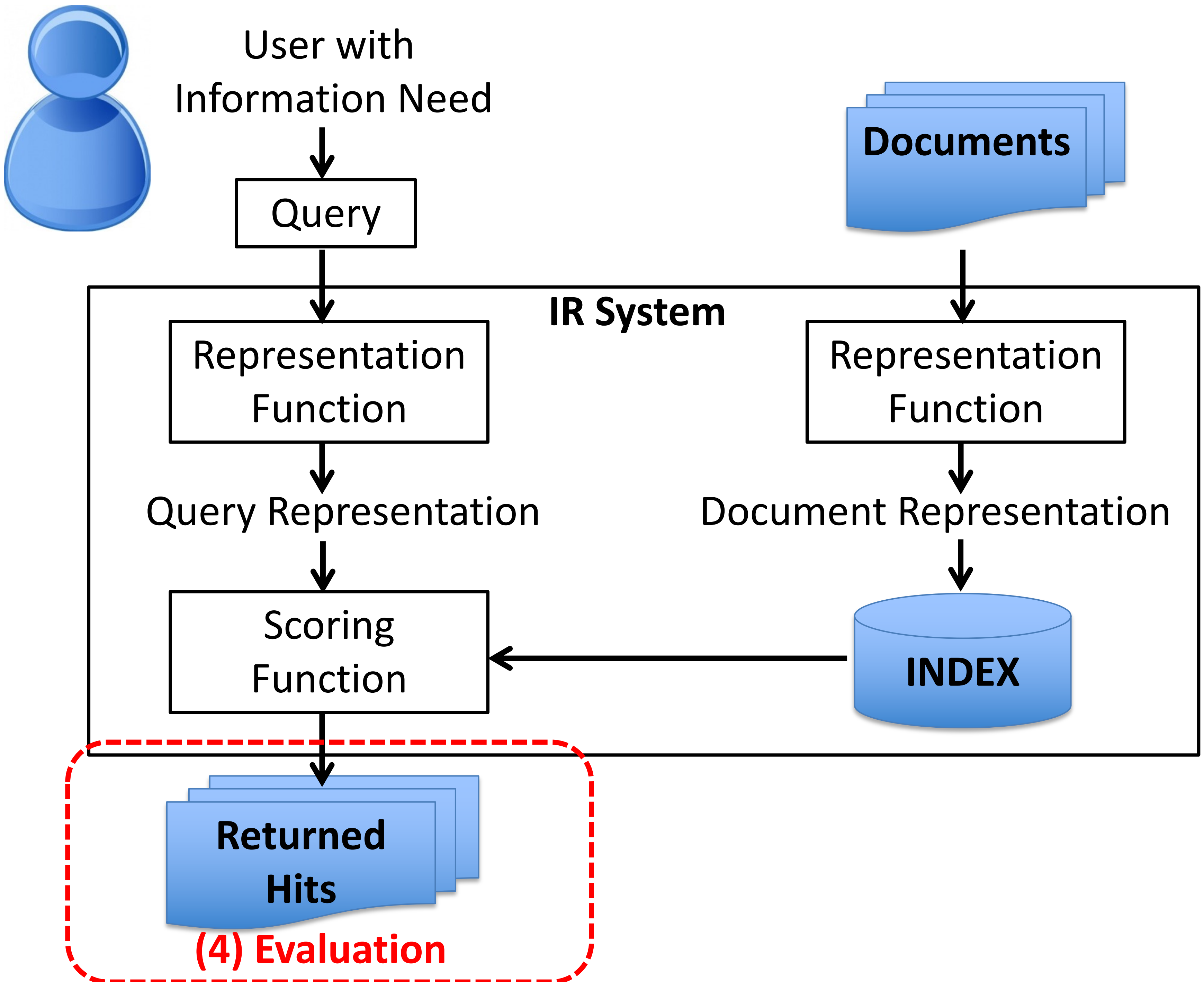
Disclaimer

- We’ve focused on very simple ranking functions (linear) for simplicity
- In practice, more complex functions (e.g. decision trees, neural nets) are common
- Some functions use “dense” word embeddings as opposed to “sparse” features described previously
- Recommend further reading:
  – Dawei Yin, et. al. “Ranking Relevance in Yahoo Search”, Proceedings of KDD2016
  – Omar Khattab & Matei Zaharia. “ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT”, SIGIR 2020

Embeddings & Neural Nets for Scoring



From: Khattab (SIGIR2020) https://arxiv.org/pdf/2004.12832.pdf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(4) Evaluation

Evaluation: How good/bad is my IR?

- Evaluation is important:
  - Compare two IR systems
  - Decide whether our IR is ready for deployment
  - Identify research challenges
- Two Ingredients for a trustworthy evaluation:
  - Answer Key
  - A Meaningful Metric: given query q, returned ranked list, and answer key, computes a number

Precision and Recall

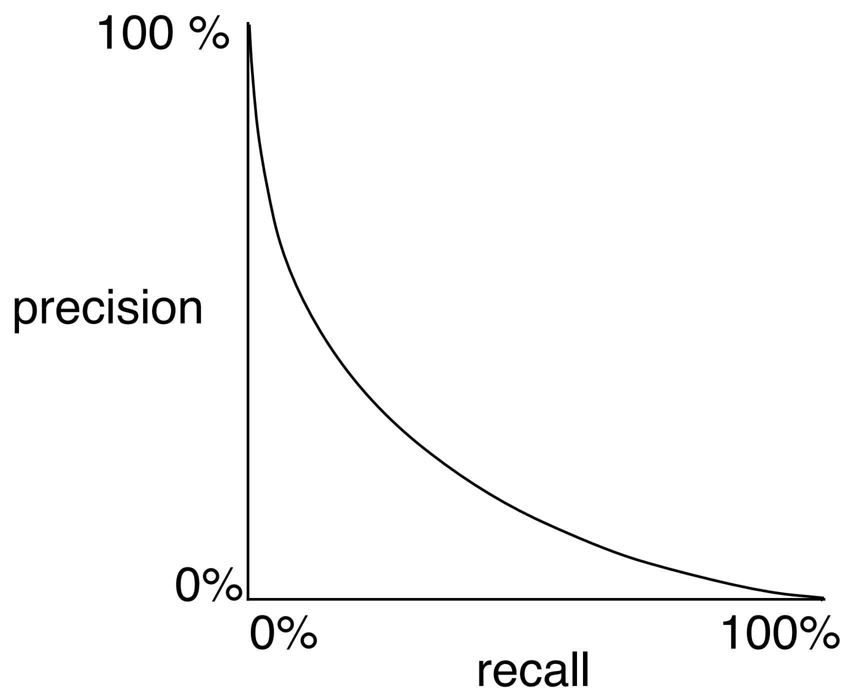
“Type one errors” “Errors of commission” “False positives”

	relevant	not relevant
retrieved	A	B
not retrieved	C	D

“Type two errors”
“Errors of omission”
“False negatives”

$$\text{precision} = \frac{A}{A + B}$$

$$\text{recall} = \frac{A}{A + C}$$



average precision = area under curve

From Paul McNamee’s JSALT 2018 tutorial slides

Issues with Precision and Recall

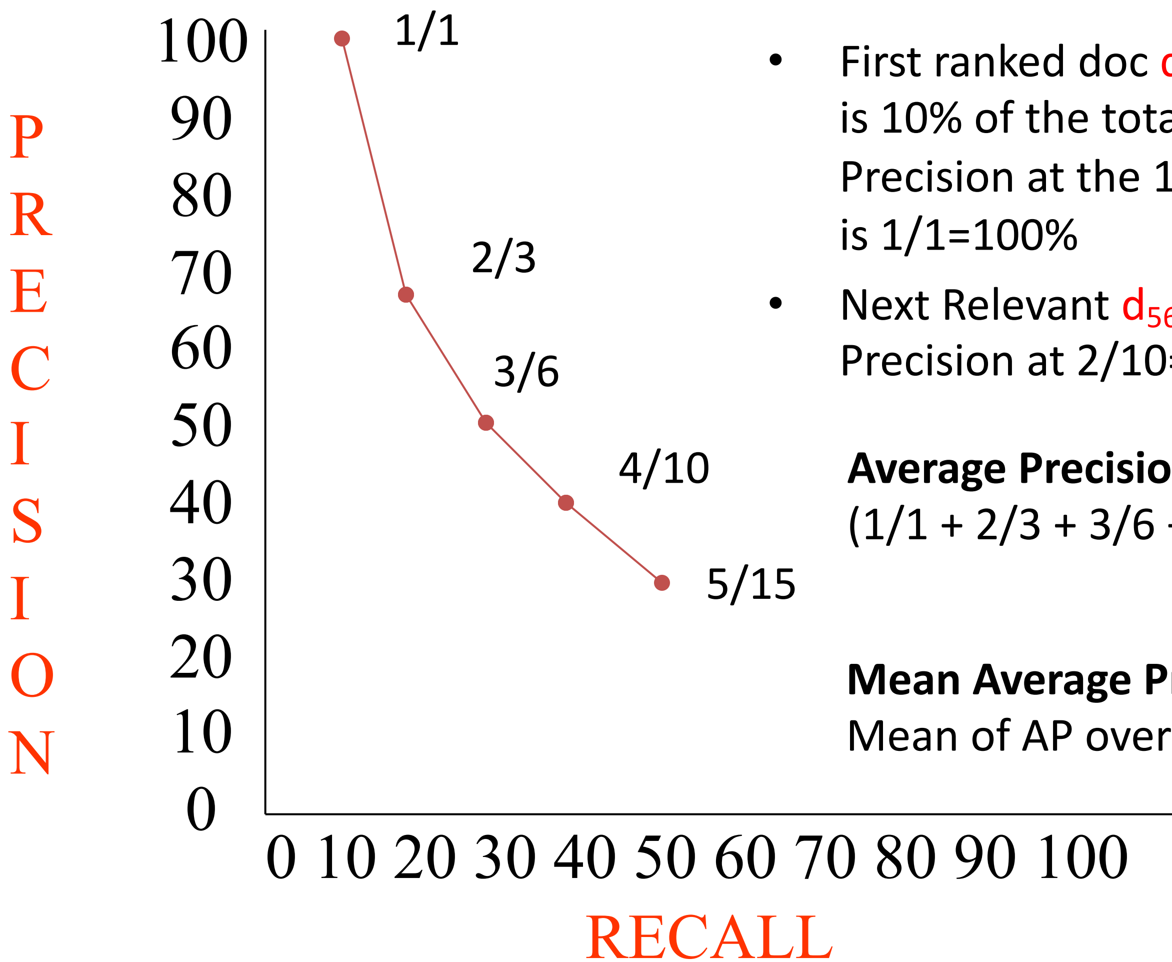
- We often don’t know true recall value
  - For large collection, impossible to have annotator read all documents to assess relevance of a query
- Focused on evaluating sets, rather than ranked lists

We’ll introduce Mean Average Precision (MAP) here. Note that IR evaluation is a deep field, worth another lecture by itself!

Example for 1 query: precision & recall at different positions in ranked list

10 relevant: $R_q=\{d_3,d_5,d_9,d_{25},d_{39},d_{44},d_{56},d_{71},d_{89},d_{123}\}$

Ranked List: d_{123}, d_{84}, d_{56}, d_6, d_8, d_9, d_{511}, d_{129}, d_{187}, d_{25}, d_{38m}, d_{48}, d_{250}, d_{113}, d_3

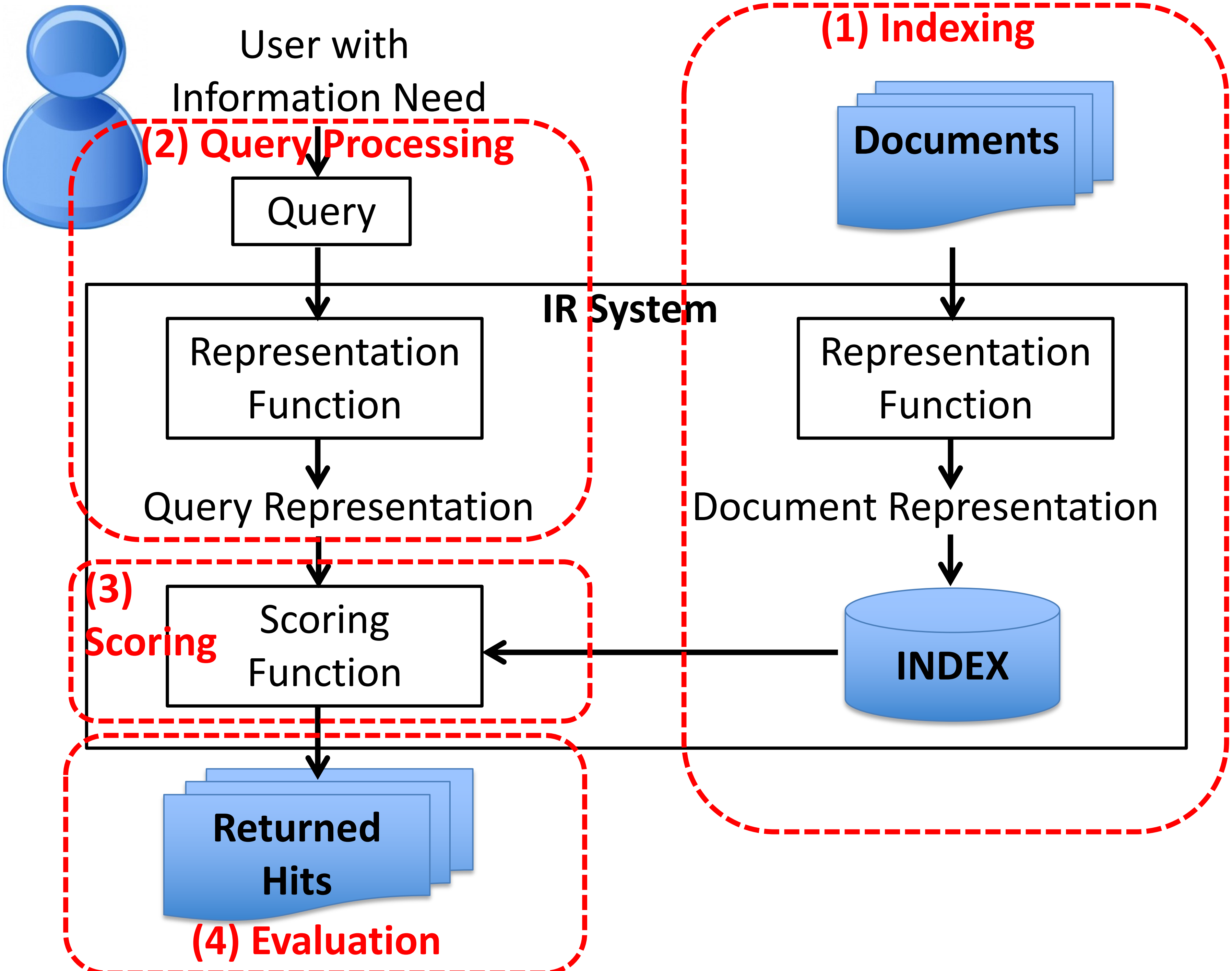


- First ranked doc d_{123} is relevant, which is 10% of the total relevant. Therefore Precision at the 1/10=10% Recall level is 1/1=100%
- Next Relevant d_{56} gives us 2/3=66% Precision at 2/10=20% recall level

Average Precision (AP):
(1/1 + 2/3 + 3/6 + 4/10 + 5/15) / 5 = 0.58

Mean Average Precision (MAP):
Mean of AP over multiple queries

From Paul McNamee's JSALT 2018 tutorial slides



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