Term Vocubular and Posting Lists [1]

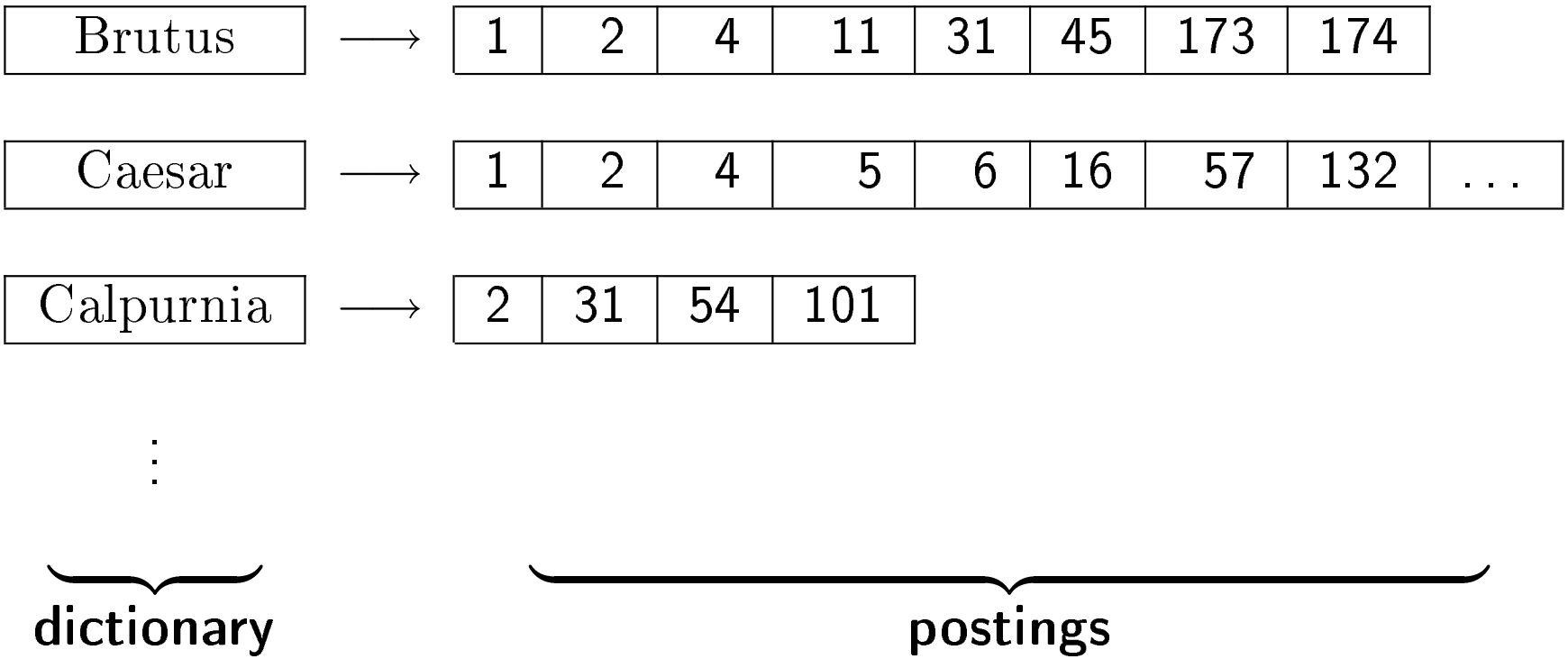
September, 2009

[1] Vorlage: Folien von M. Schütze

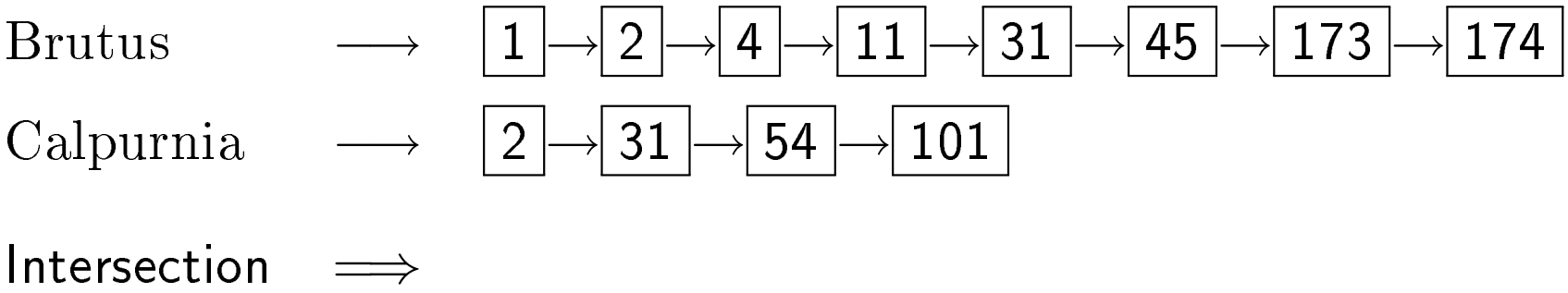
Outline

Inverted index

For each term t, we store a list of all documents that contain t.



Intersecting two postings lists



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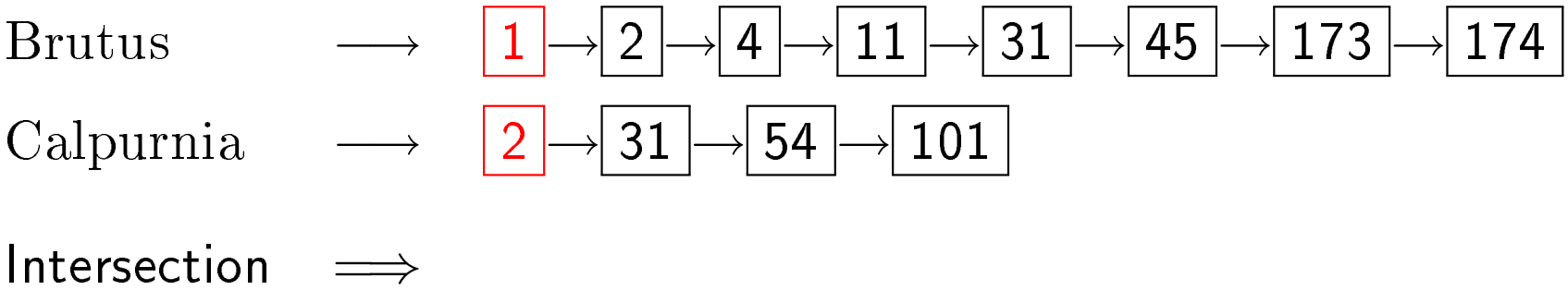

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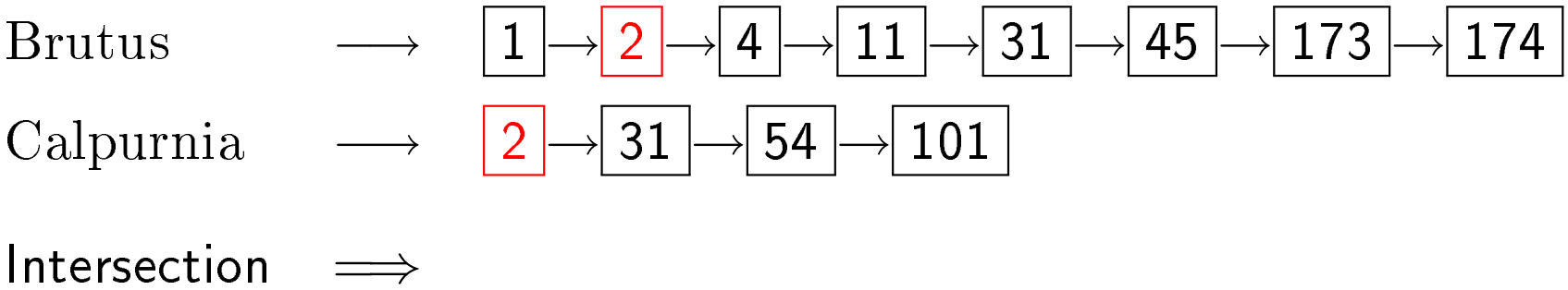

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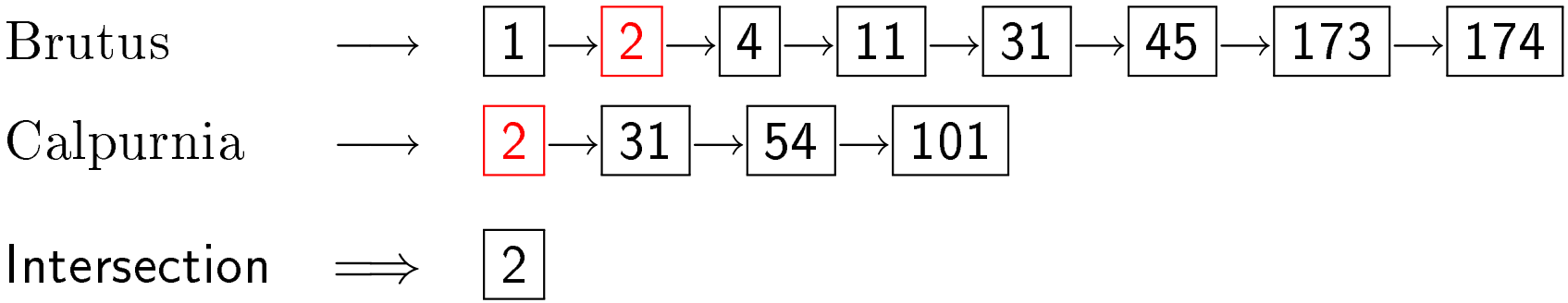

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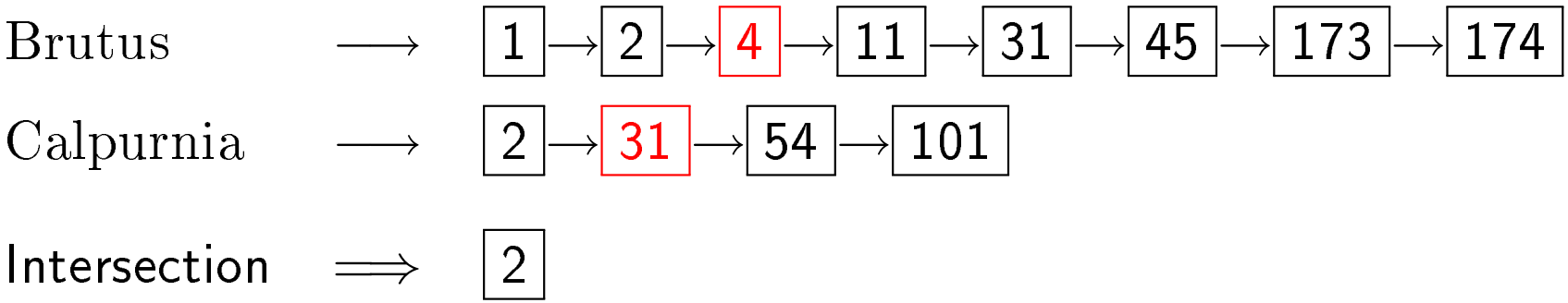

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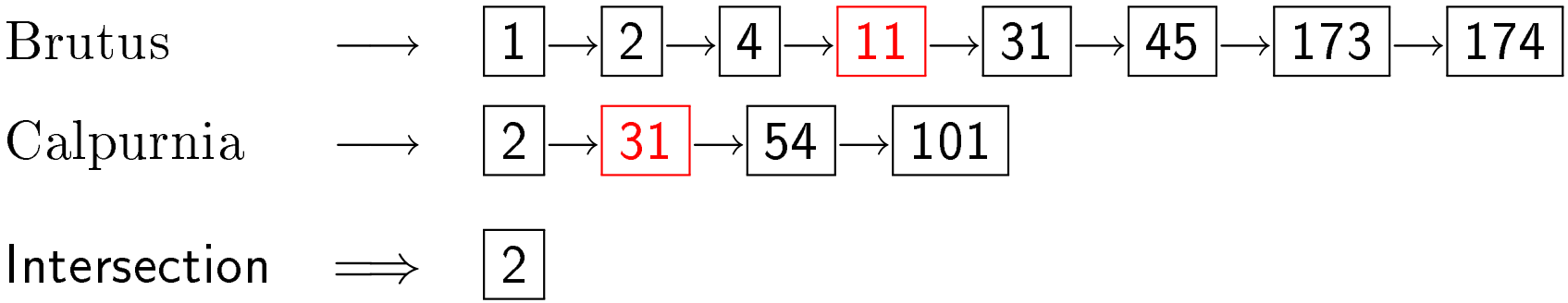

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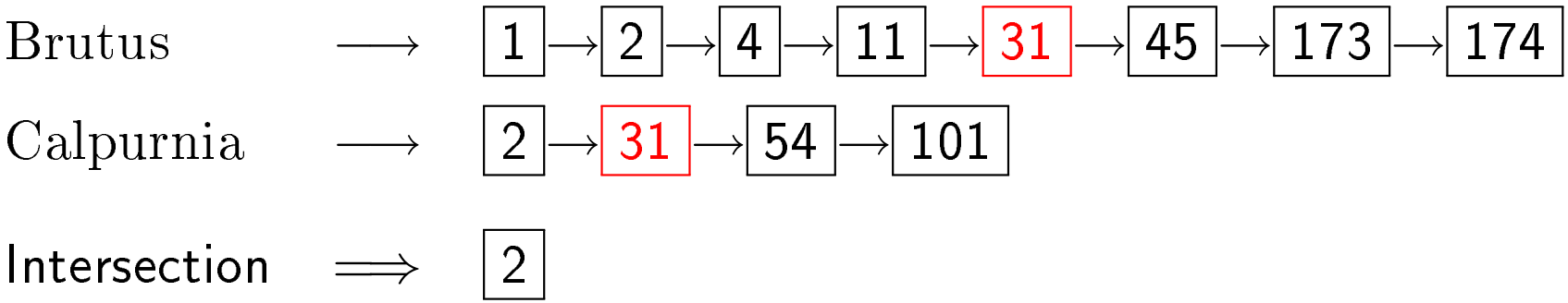

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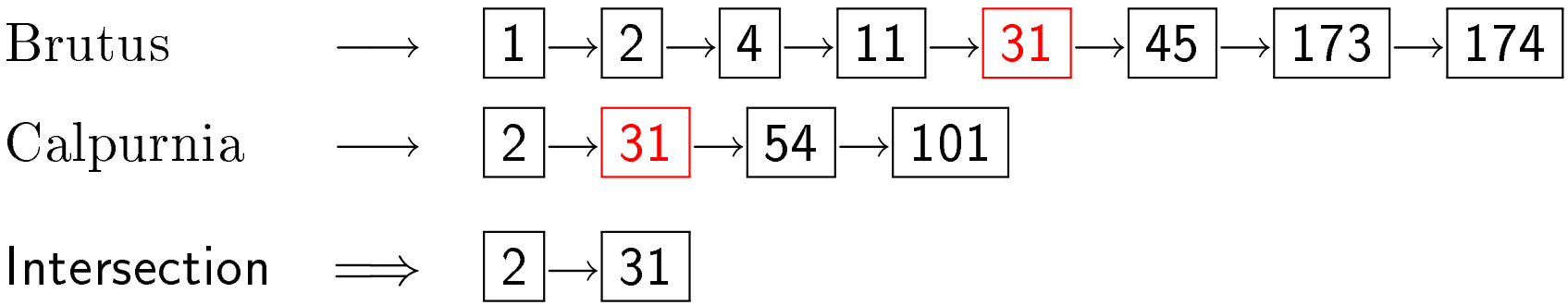

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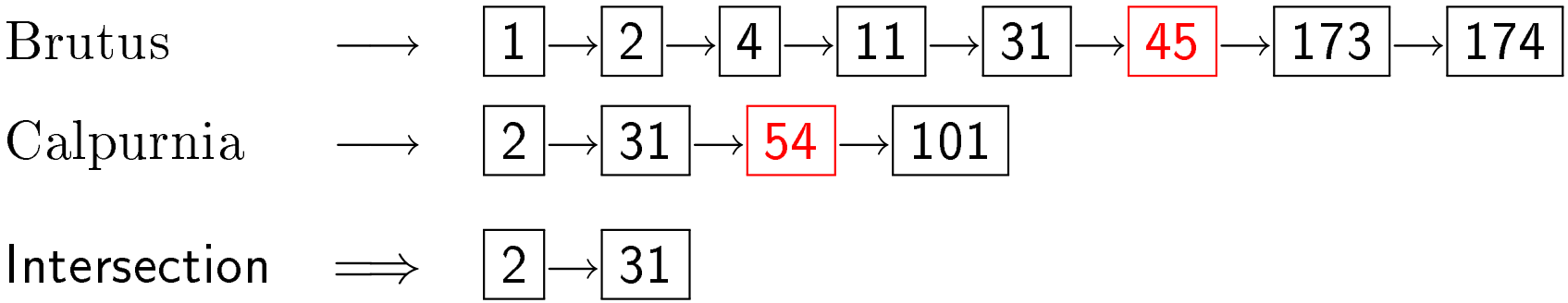

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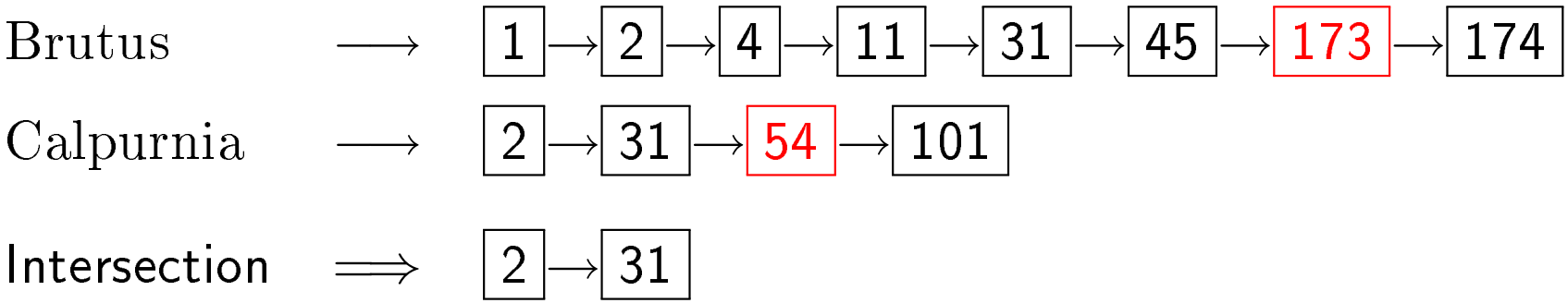

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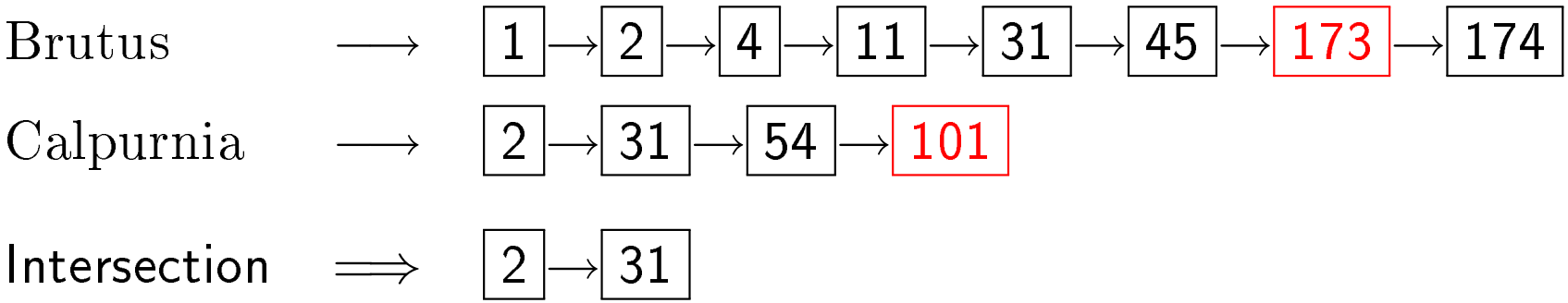

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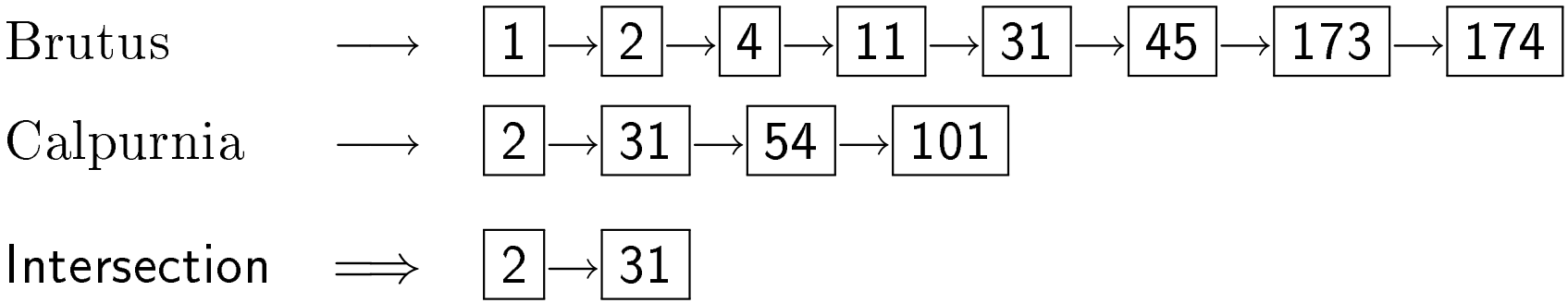

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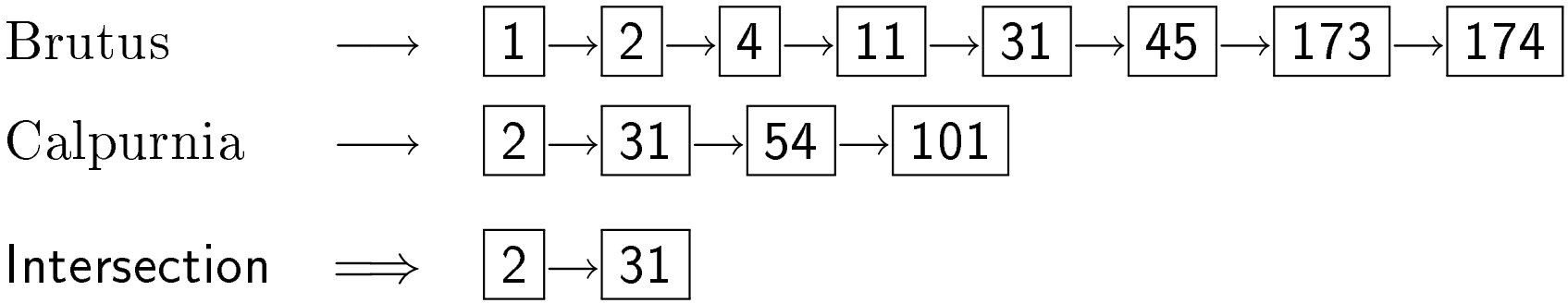

- Linear in the length of the postings lists.

Constructing the inverted index: Sort postings

term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
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i'	1
it	2
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killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
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  - We know what a term is.
- Both issues can be complex in reality.
- We'll look a little bit at what a document is.
- But mostly at terms: How do we define and process the vocabulary of terms of a collection?

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- Alternative: use heuristics

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- A group of files (ppt or latex in HTML)?

Terms

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- Token – An instance of a word or term occurring in a document.
- Type – The same as a term in most cases: an equivalence class of tokens.

Type/token distinction: Example

- In June, the dog likes to chase the cat in the barn.

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- In June, the dog likes to chase the cat in the barn.
- How many tokens? How many types?

Recall: Inverted index construction

- Input:

  Friends, Romans, countrymen. | So let it be with Caesar

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- Each token is a candidate for a postings entry.
- What are valid tokens to emit?

Why tokenization is difficult – even in English

Example: Mr. O'Neill thinks that the boys' stories about Chile's capital aren't amusing.

Tokenize this sentence

One word or two? (or several)

- Hewlett-Packard

One word or two? (or several)

- Hewlett-Packard
- State-of-the-art

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- cheap San Francisco-Los Angeles fares
- York University vs. New York University

Numbers

- 3/12/91

Numbers

- 3/12/91
- 12/3/91

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- 3/12/91
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- Mar 12, 1991

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- 3/12/91
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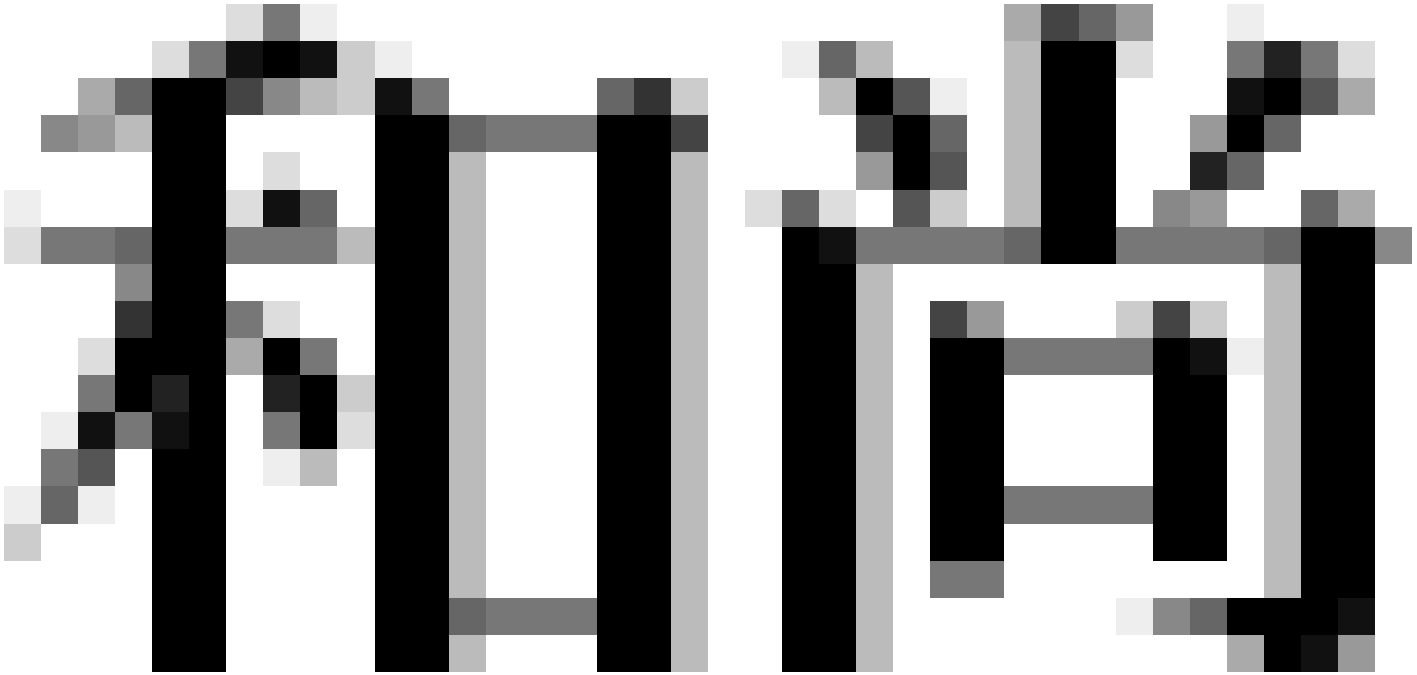
- Older IR systems may not index numbers, but generally it's a useful feature.

Chinese: No whitespace

莎拉波娃现在居住在美国东南部的佛罗里达。今年４月９日，莎拉波娃在美国第一大城市纽约度过了１８岁生日。生日派对上，莎拉波娃露出了甜美的微笑。

Ambiguous segmentation in Chinese



The two characters can be treated as one word meaning ‘monk’ or as a sequence of two words meaning ‘and’ and ‘still’.

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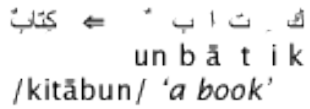
- Swedish, Finnish, Greek, Urdu, many other languages

Japanese

ノーベル平和賞を受賞したワンガリ・マータイさんが名誉会長を務めるＭＯＴＴＡＩＮＡＩキャンペーンの一環として、毎日新聞社とマガジンハウスは「私の、もったいない」を募集します。皆様が日ごろ「もったいない」と感じて実践していることや、それにまつわるエピソードを８００字以内の文章にまとめ、簡単な写真、イラスト、図などを添えて１０月２０日までにお送りください。大賞受賞者には、５０万円相当の旅行券とエコ製品２点の副賞が贈られます。

Arabic script



Arabic script: Bidirectionality

استقلت الجزائر في سنة 1962 بعد 132 عاما من الاحتلال الفرنسي.

← → ← → ← START

'Algeria achieved its independence in 1962 after 132 years of French occupation.'

Back to English

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- Why don't you want to put window, Window, windows, and Windows in the same equivalence class?

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- He got his PhD from MIT. $\rightarrow$ MIT $\neq$ mit

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- It's often best to lowercase everything since users will use lowercase regardless of correct capitalization.

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- Stop word elimination used to be standard in older IR systems.
- But you need stop words for phrase queries, e.g. "King of Denmark"
- Most web search engines index stop words.

More equivalence classing

- Soundex: IIR 3 (phonetic equivalence, Tchebyshev = Chebysheff)

More equivalence classing

- Soundex: IIR 3 (phonetic equivalence, Tchebyshev = Chebysheff)
- Thesauri: IIR 9 (semantic equivalence, car = automobile)

What does Google do?

- Stop words
- Normalization
- Tokenization
- Lowercasing
- Stemming
- Non-latin alphabets
- Umlauts
- Compounds
- Numbers

Lemmatization

- Reduce inflectional/variant forms to base form

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- Inflectional morphology (cutting → cut) vs. derivational morphology (destruction → destroy)

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- Example for derivational: automate, automatic, automation all reduce to automat

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  - replacement → replac
  - cement → cement
- Sample convention: Of the rules in a compound command, select the one that applies to the longest suffix.

Porter stemmer: A few rules

Rule			**Example**		
SSES	$\rightarrow$	SS	caresses	$\rightarrow$	caress
IES	$\rightarrow$	I	ponies	$\rightarrow$	poni
SS	$\rightarrow$	SS	caress	$\rightarrow$	caress
S	$\rightarrow$		cats	$\rightarrow$	cat

Three stemmers: A comparison

Sample text: Such an analysis can reveal features that are not easily visible from the variations in the individual genes and can lead to a picture of expression that is more biologically transparent and accessible to interpretation

Porter stemmer: such an analysi can reveal featur that ar not easili visibl from the variat in the individu gene and can lead to a pictur of express that is more biolog transpar and access to interpret

Lovins stemmer: such an analys can reve featur that ar not eas vis from th vari in th individu gen and can lead to a pictur of expres that is mor biolog transpar and acces to interpres

Paice stemmer: such an analys can rev feat that are not easy vis from the vary in the individ gen and can lead to a pict of express that is mor biolog transp and access to interpret

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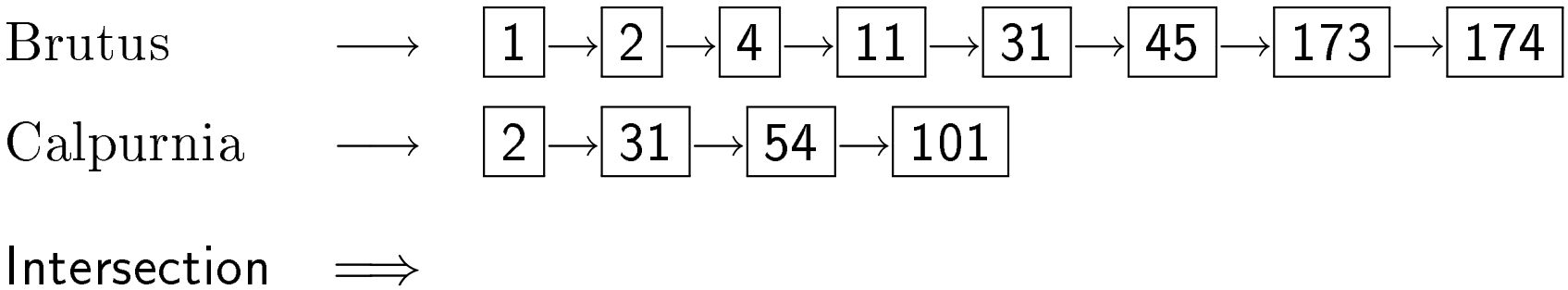
- Porter Stemmer equivalence class oper contains all of operate operating operates operation operative operatives operational.
- Queries where stemming hurts: “operational AND research”, “operating AND system”, “operative AND dentistry”

Interesting issues in your native language?

Outline

Recall basic intersection algorithm



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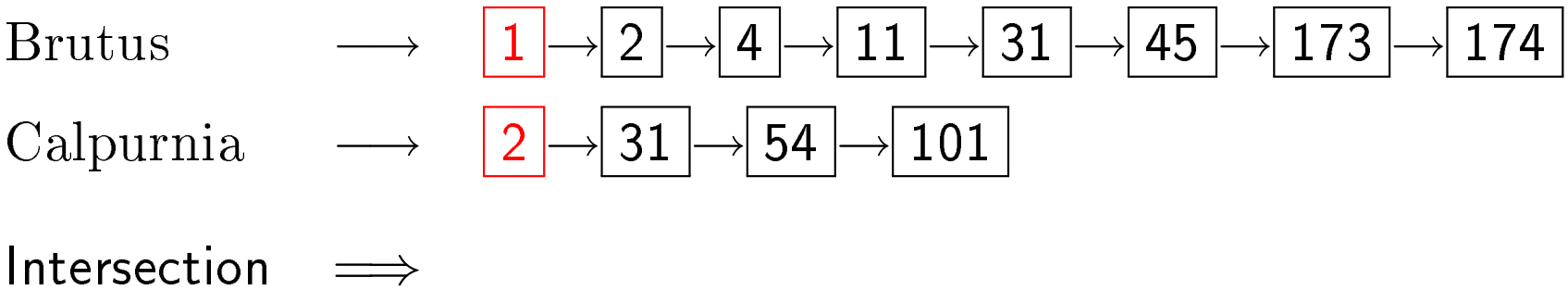

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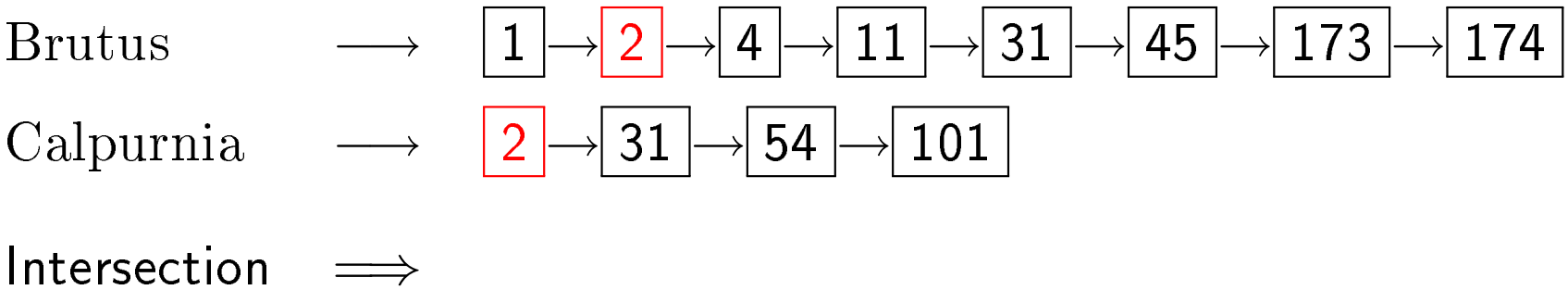

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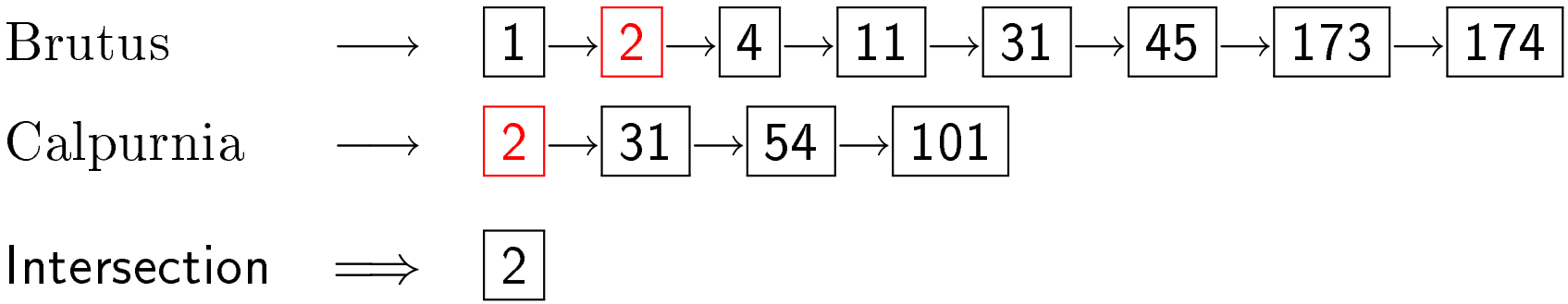

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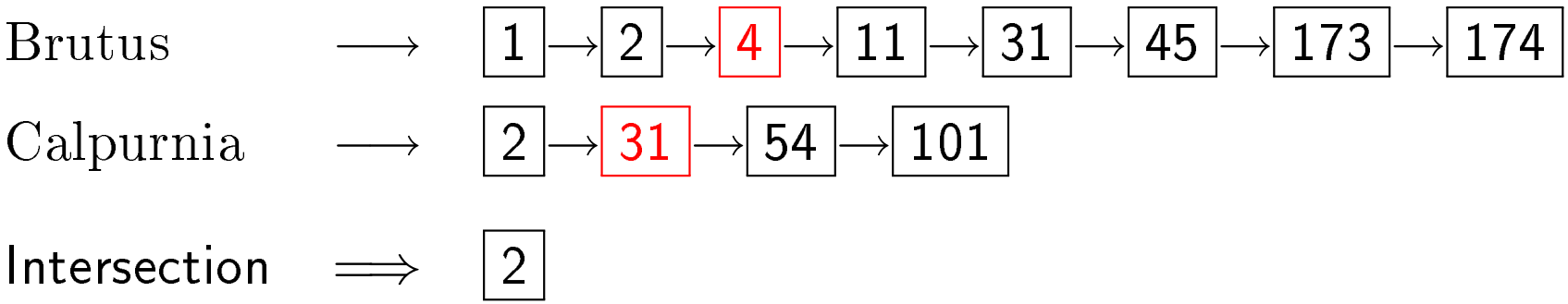

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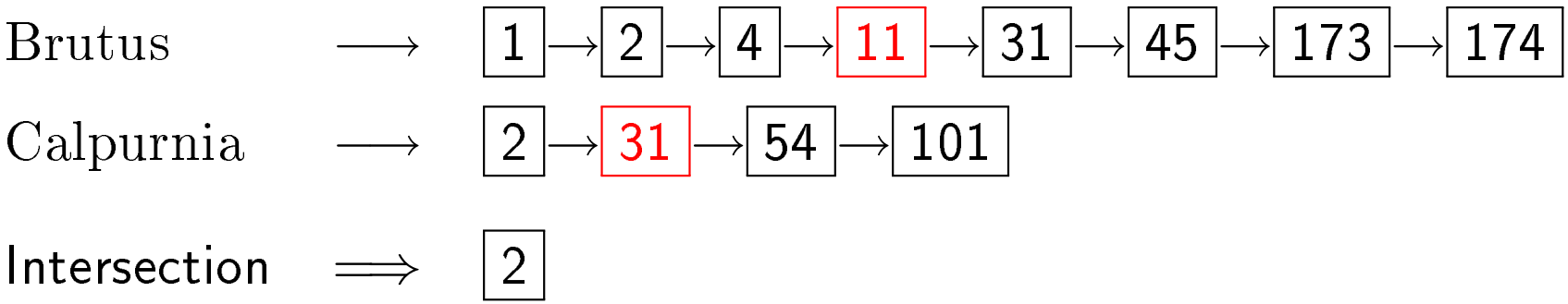

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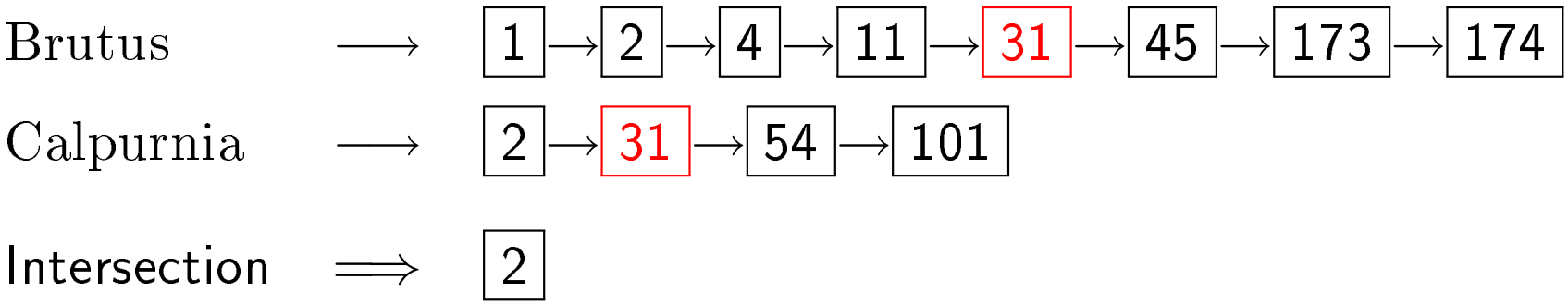

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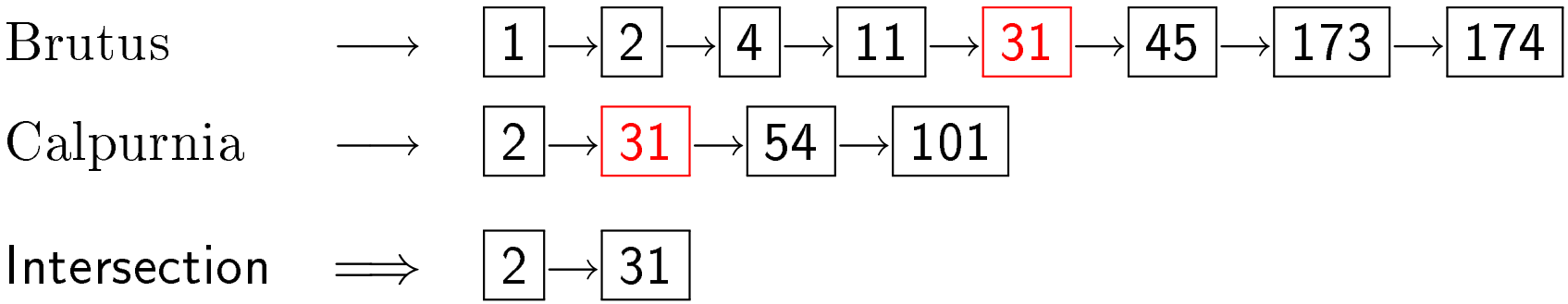

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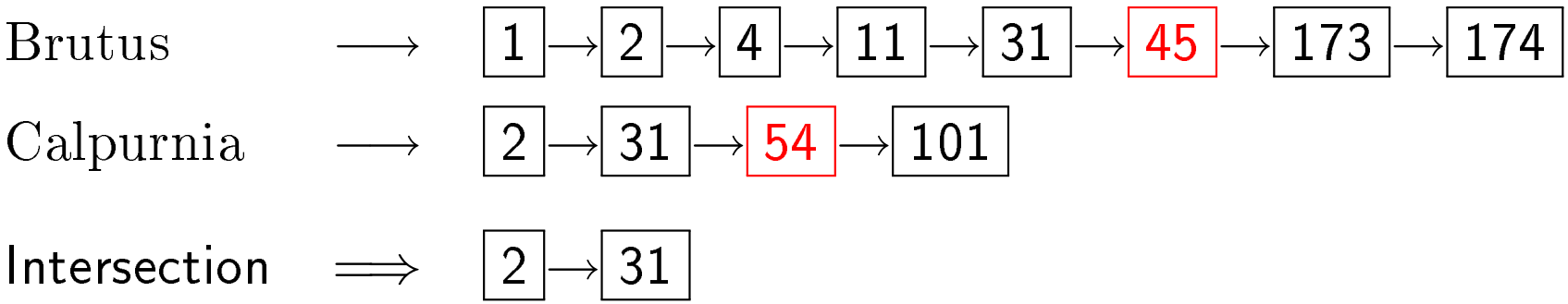

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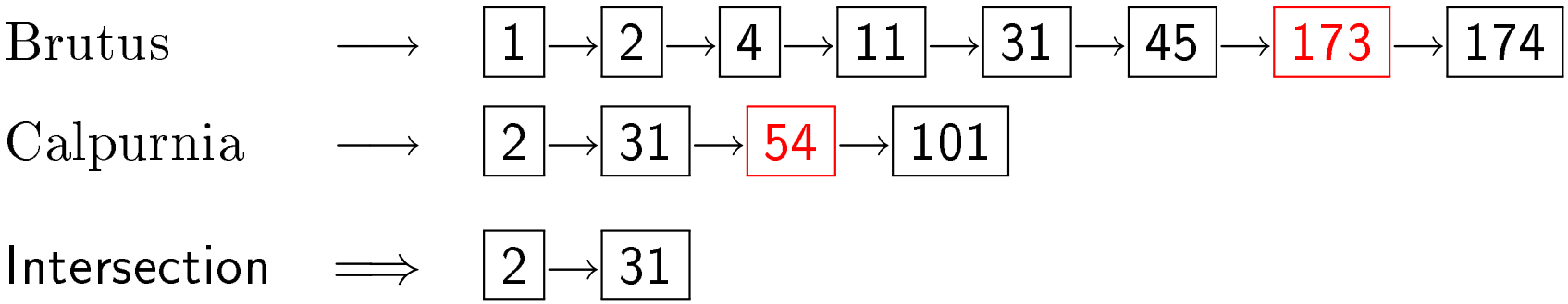

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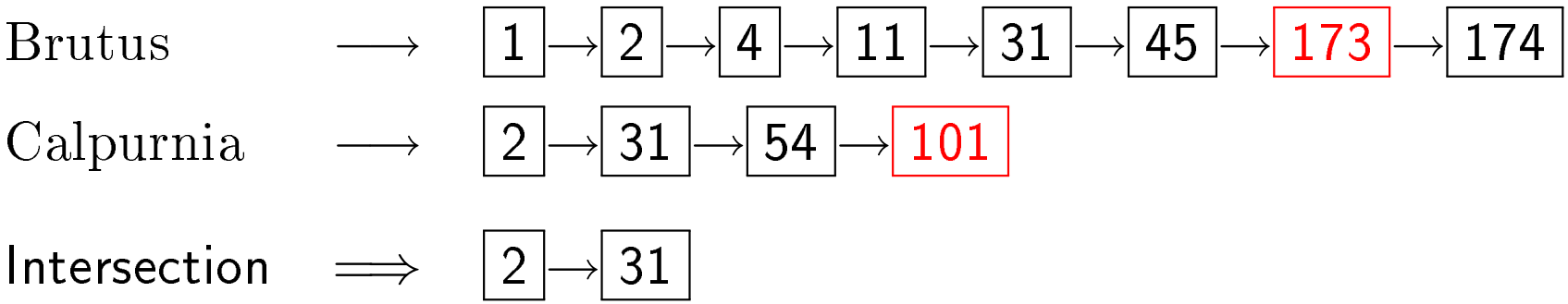

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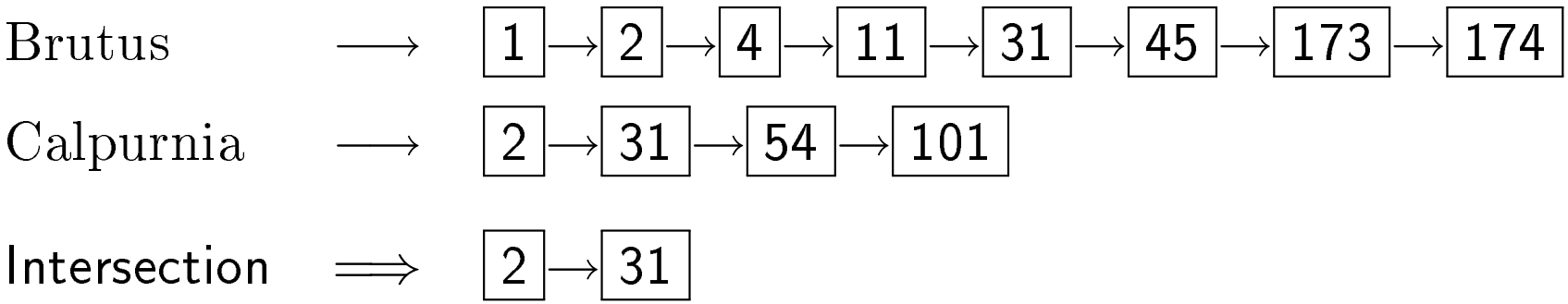

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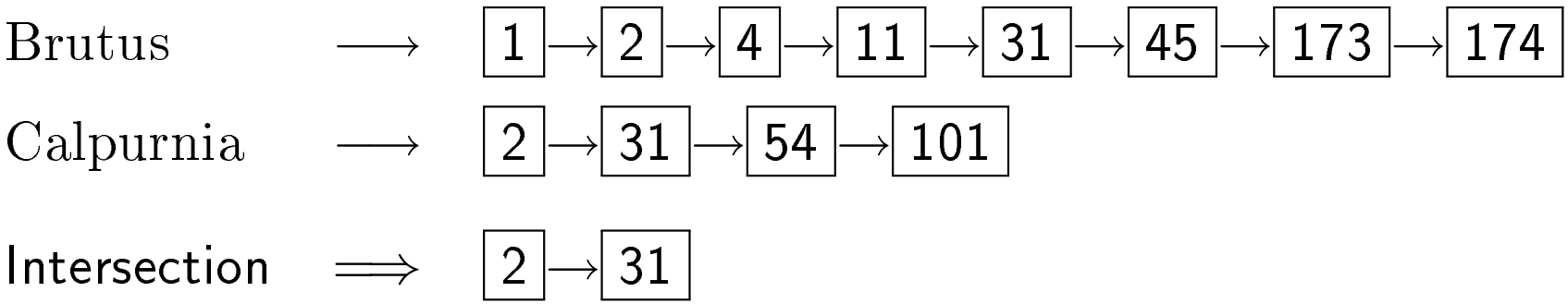

- Can we do better?

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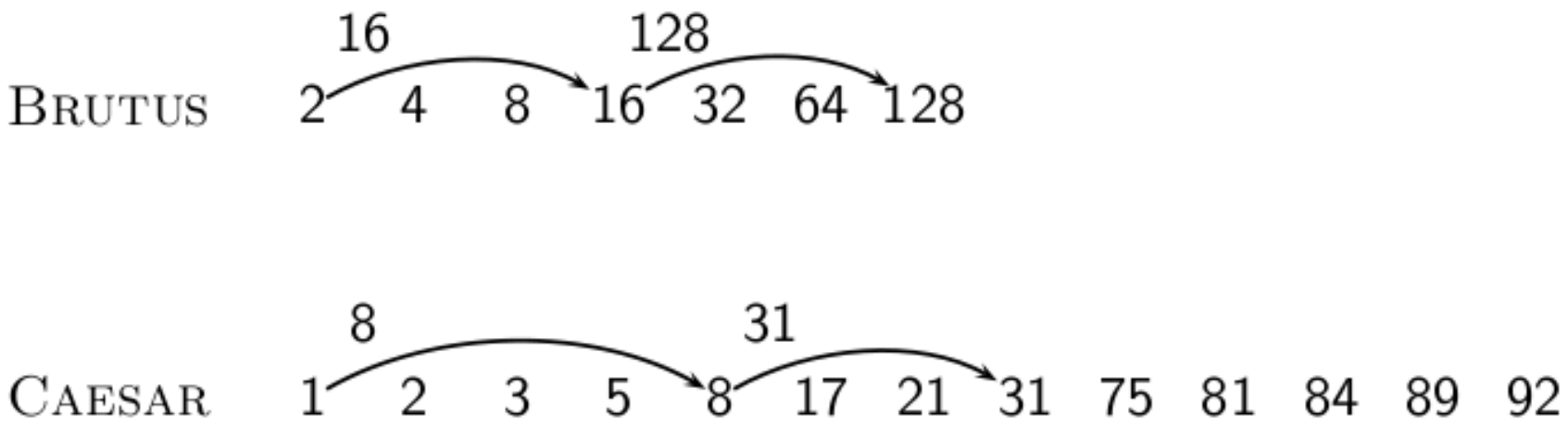
- How do we make sure results don't change?

Skip lists

Basic idea


16
128
BRUTUS
2 4 8 16 32 64 128
8
31
CAESAR
1 2 3 5 8 17 21 31 75 81 84 89 92

Intersecting with skip pointers

```
IntersectWithSkips(p1, p2)
 1  answer ← ⟨ ⟩
 2  while p1 ≠ NIL and p2 ≠ NIL
 3  do if docID(p1) = docID(p2)
 4        then Add(answer, docID(p1))
 5             p1 ← next(p1)
 6             p2 ← next(p2)
 7        else if docID(p1) < docID(p2)
 8                then if hasSkip(p1) and (docID(skip(p1)) ≤ docID(p2))
 9                     then p1 ← skip(p1)
10                     else p1 ← next(p1)
11                else if hasSkip(p2) and (docID(skip(p2)) ≤ docID(p1))
12                     then p2 ← skip(p2)
13                     else p2 ← next(p2)
14  return answer
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- More skips: Each skip pointer skips only a few items, but we can frequently use it.
- Fewer skips: Each skip pointer skips many items, but we can not use it very often.

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- Any ideas?

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- Example: $\underline{\text{to}_1\ \text{be}_2\ \text{or}_3\ \text{not}_4\ \text{to}_5\ \text{be}_6}$

to, 993427:
⟨ 1, 6: ⟨7, 18, 33, 72, 86, 231⟩;
2, 5: ⟨1, 17, 74, 222, 255⟩;
4, 5: ⟨8, 16, 190, 429, 433⟩;
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Document 4 is a match!

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- For example: *employment /3 place*
- Find all documents that contain employment and place within 3 words of each other.
- Employment agencies that place healthcare workers are seeing growth is a hit.
- Employment agencies that help place healthcare workers are seeing growth is not a hit.

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- This is important for dynamic summaries etc.

"Proximity" intersection

```
POSITIONALINTERSECT(p1, p2, k)
 1  answer ← ⟨ ⟩
 2  while p1 ≠ NIL and p2 ≠ NIL
 3  do if docID(p1) = docID(p2)
 4        then l ← ⟨ ⟩
 5             pp1 ← positions(p1)
 6             pp2 ← positions(p2)
 7             while pp1 ≠ NIL
 8             do while pp2 ≠ NIL
 9                do if |pos(pp1) − pos(pp2)| ≤ k
10                      then ADD(l, pos(pp2))
11                      else if pos(pp2) > pos(pp1)
12                              then break
13                   pp2 ← next(pp2)
14                while l ≠ ⟨ ⟩ and |l[0] − pos(pp1)| > k
15                do DELETE(l[0])
16                for each ps ∈ l
17                do ADD(answer, ⟨docID(p1), pos(pp1), ps⟩)
18                pp1 ← next(pp1)
19             p1 ← next(p1)
20             p2 ← next(p2)
21        else if docID(p1) < docID(p2)
22               then p1 ← next(p1)
23               else p2 ← next(p2)
24  return answer
```

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- Combination scheme: Include frequent biwords as vocabulary terms in the index. Do all other phrases by positional intersection.
- Williams et al. (2004) evaluate a more sophisticated mixed indexing scheme. Faster than a positional index, at a cost of 26% more space for index.

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- Why are they more expensive than regular Boolean queries?
- Can you demonstrate on Google that phrase queries are more expensive than Boolean queries?

Resources

- Chapter 2 of IIR

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