CS3245

Information Retrieval

10

Lecture 10:
Query Refinement
and XML IR

Live Q&A
https://pollev.com/jin

Last Time

Search engine evaluation

- Benchmark
  - Measures: Precision / Recall / F-measure, Precision-recall graph and single number summaries
  - Documents, queries and relevance judgments
    - Kappa Measure
- A/B Testing
  - Overall evaluation criterion (OEC)

Today

How to refine the query?

- Relevance Feedback
- Query Expansion

cat → cat kitten feline -dog

How to handled structured documents / queries?

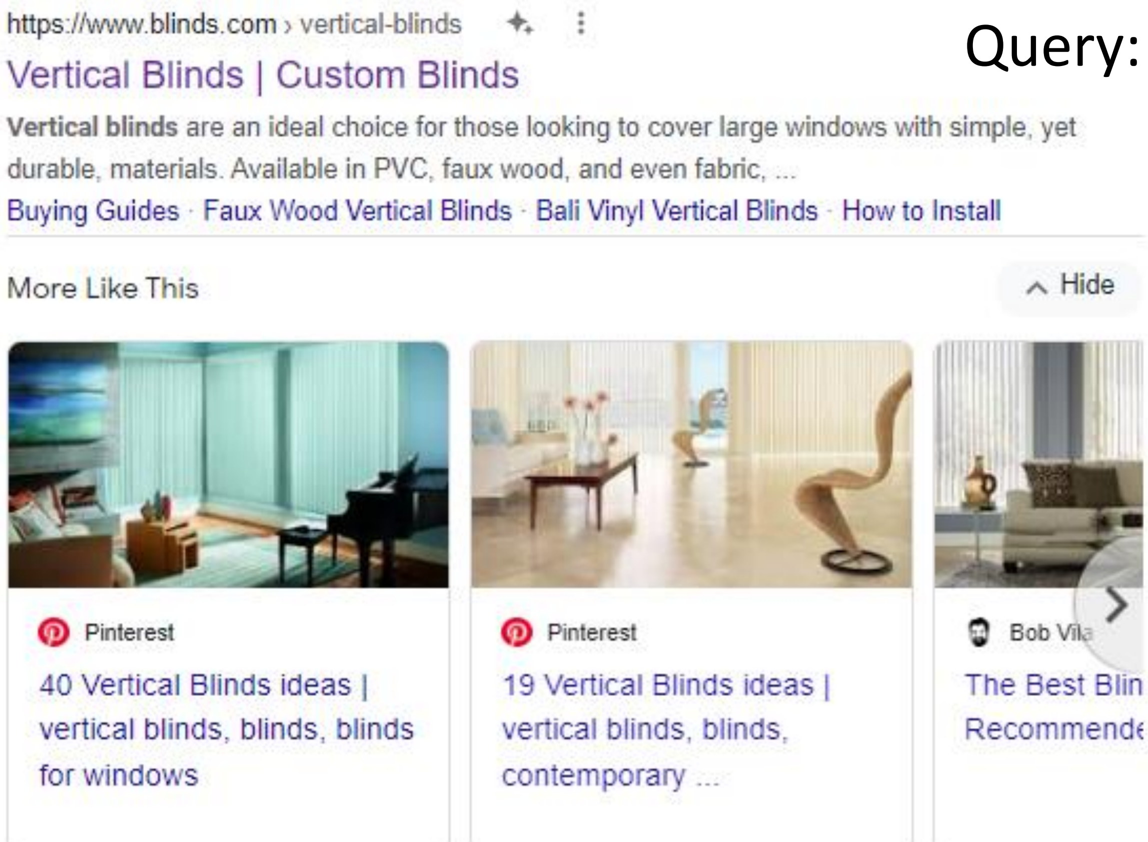
- XML Retrieval

```xml
<play>
    <author>Shakespeare</author>
    <act number="1">
        <scene number="vii">
            <verse>...</verse>
            <title>Macbeth's Castle</title>
        </scene>
    </act>
    <title>Macbeth</title>
</play>
```

RELEVANCE FEEDBACK

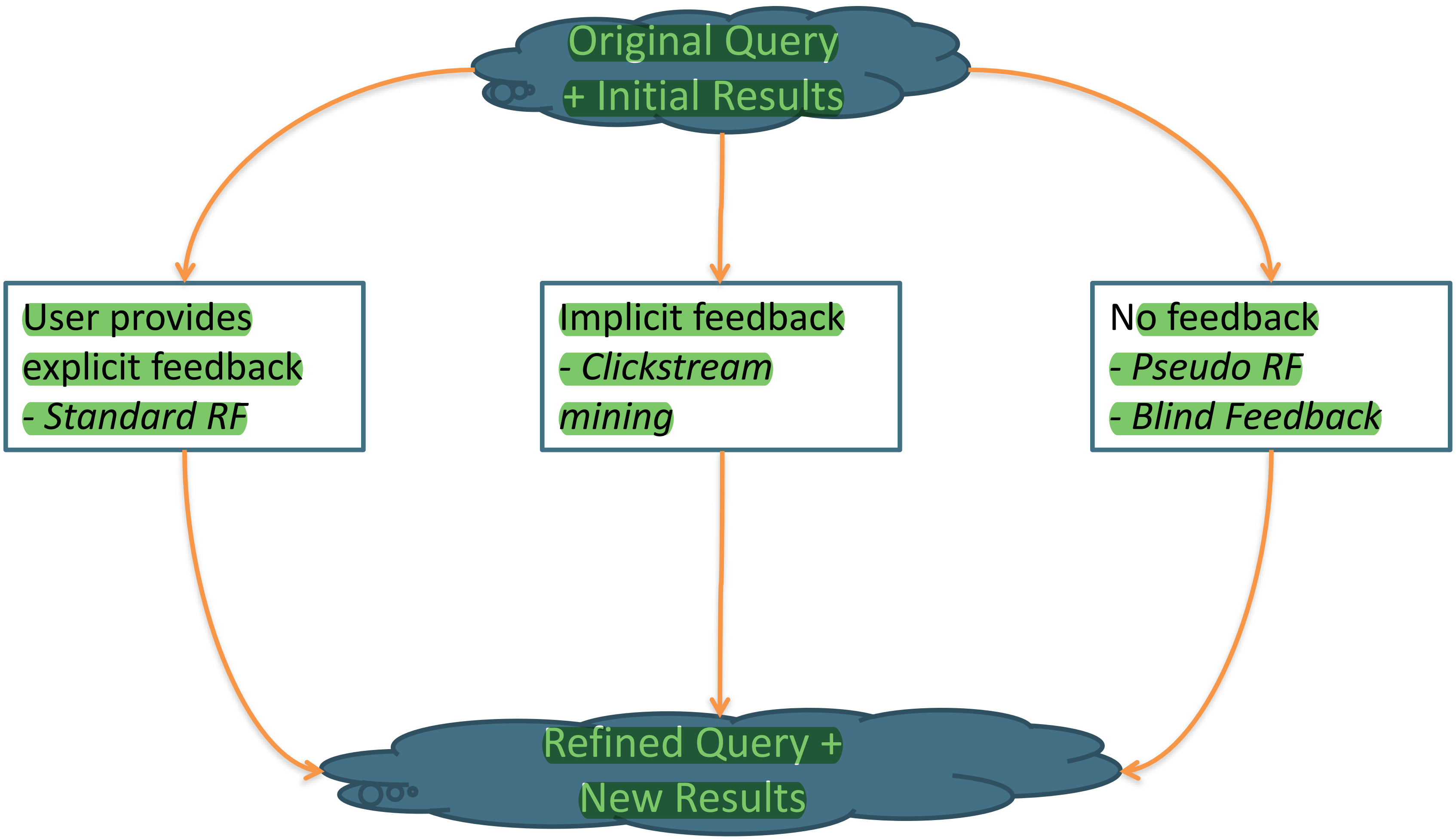
Relevance Feedback

Query: vertical blinds



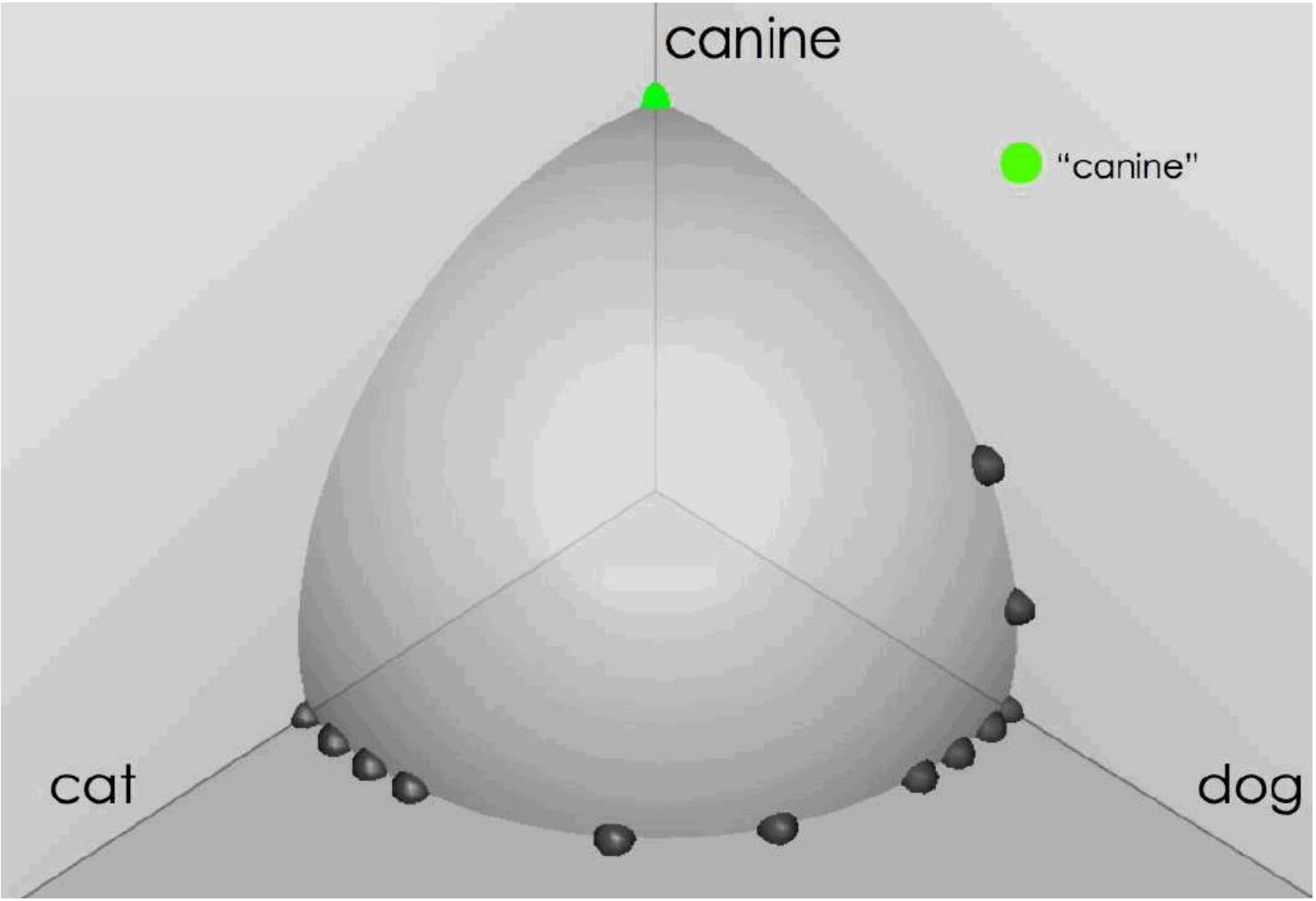
https://www.seroundtable.com/google-more-like-this-star-search-feature-34176.html

Relevance Feedback



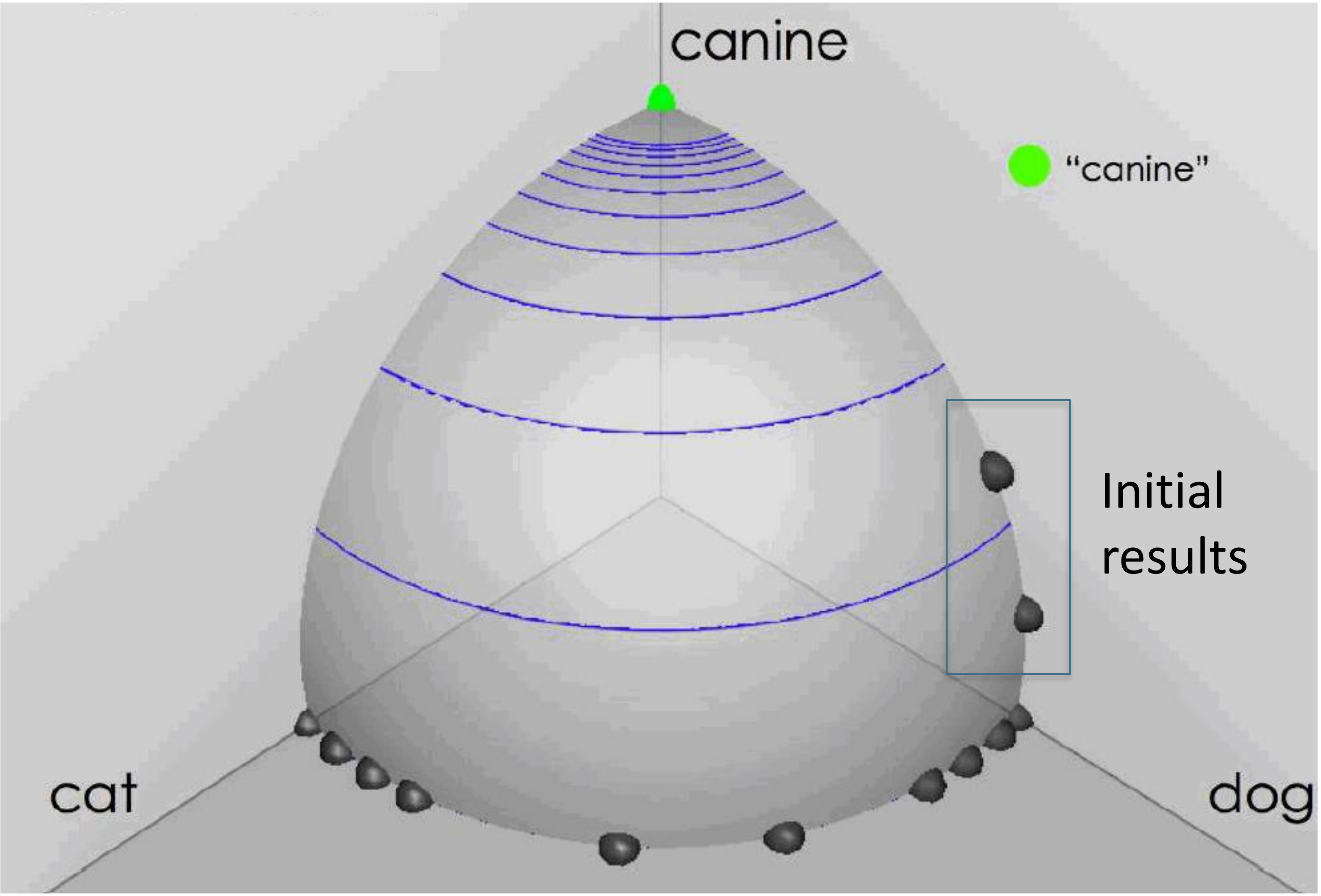
Initial results for query *canine*

source: Fernando Diaz



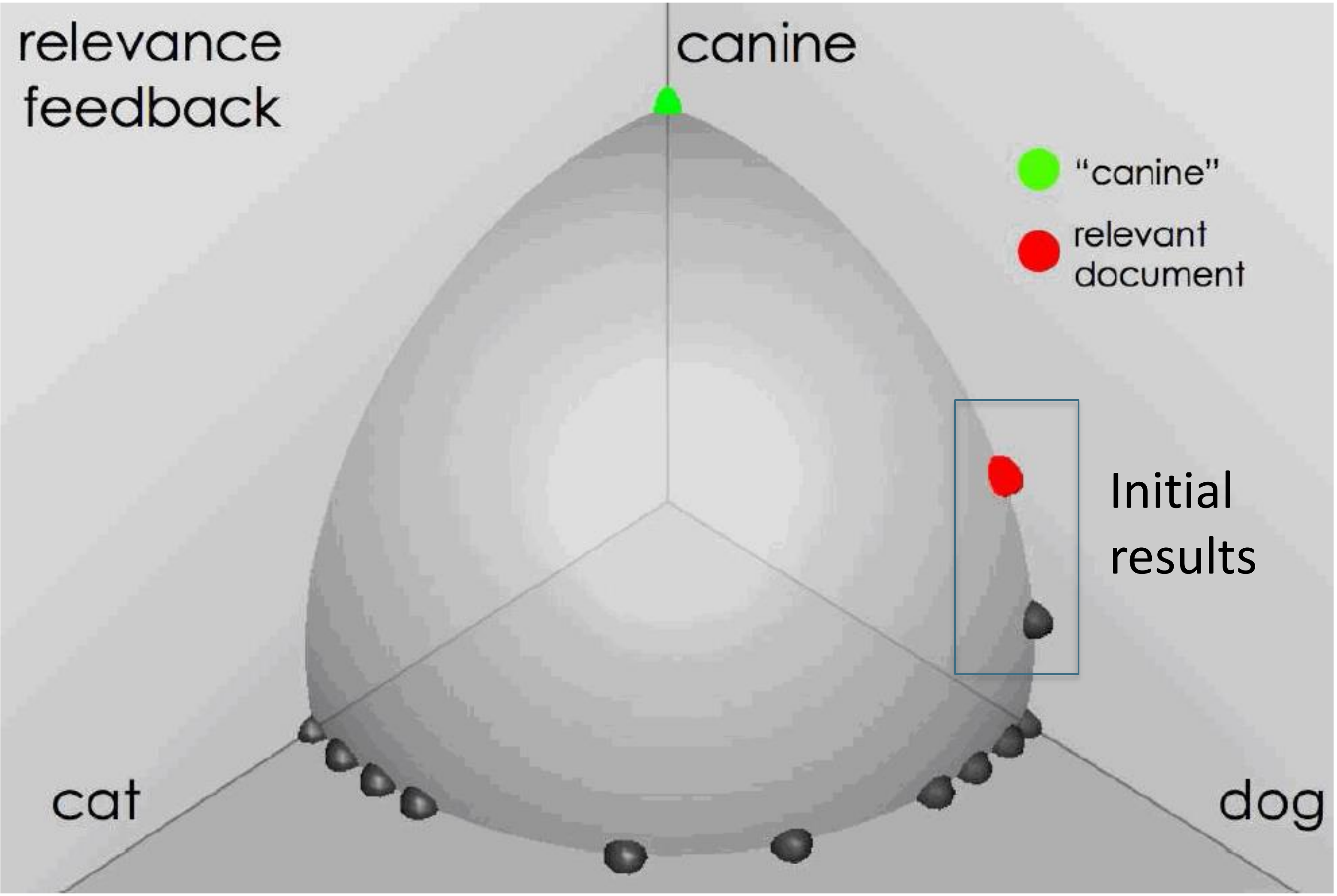
Initial results for query *canine*

source: Fernando Diaz



User feedback: Select what is relevant

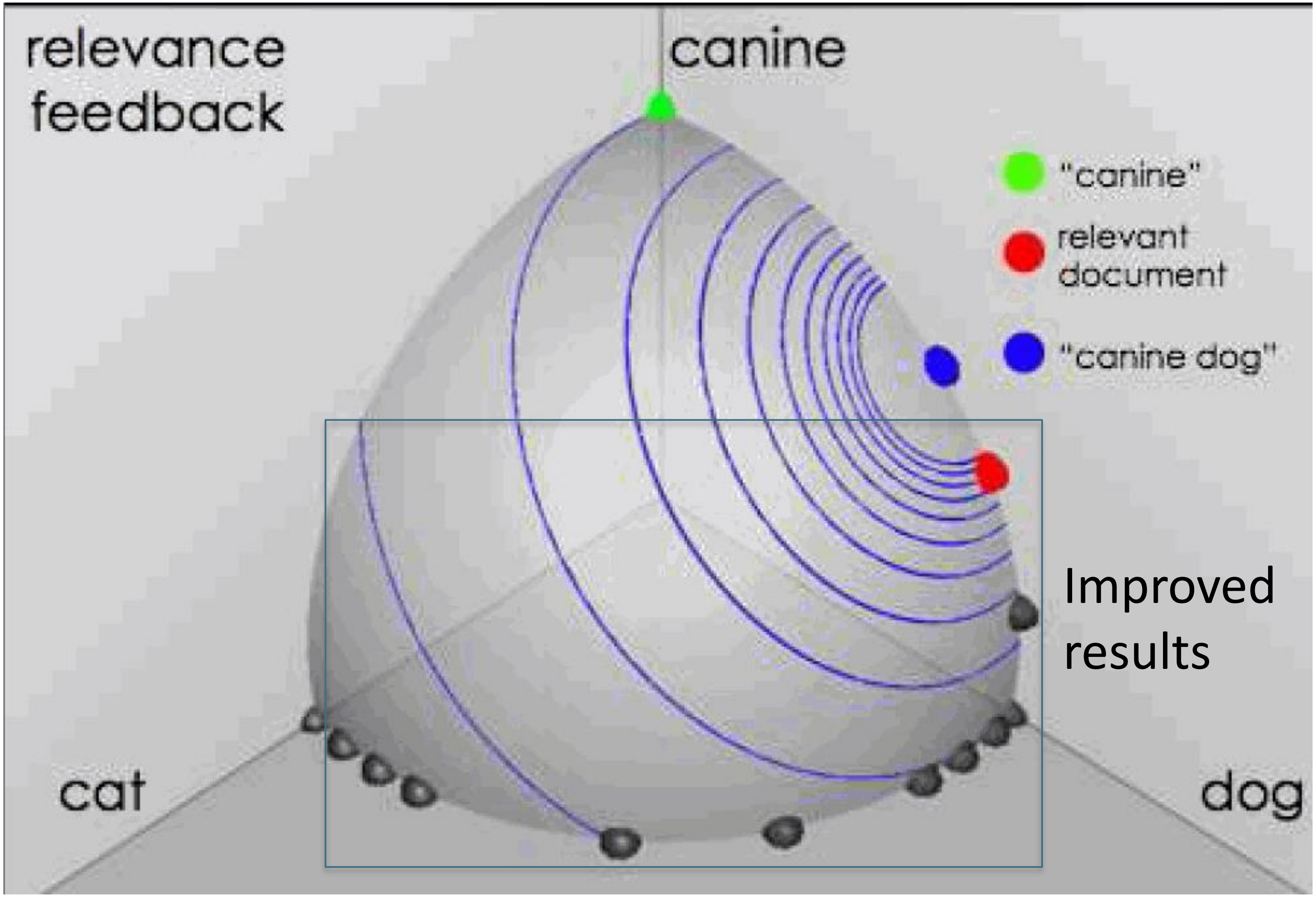
source: Fernando Diaz



Initial
results

Results after relevance feedback

source: Fernando Diaz



Initial query/results

Initial query: *New space satellite applications*

User marks relevant items

4.2 new	12.6 space
15.4 satellite	8.5 application

Original terms with initial weights

- \+ 1. 0.539, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer
- \+ 2. 0.533, 07/09/91, NASA Scratches Environment Gear From Satellite Plan
- – 3. 0.528, 04/04/90, Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes
- – 4. 0.526, 09/09/91, A NASA Satellite Project Accomplishes Incredible Feat: Staying Within Budget
- – 5. 0.525, 07/24/90, Scientist Who Exposed Global Warming Proposes Satellites for Climate
- – 6. 0.524, 08/22/90, Report Provides Support for the Critics Of Using Big Satellites to Study Climate
- – 7. 0.516, 04/13/87, Arianespace Receives Satellite Launch Pact From Telesat Canada
- \+ 8. 0.509, 12/02/87, Telecommunications Tale of Two Companies

Assume others as nonrelevant

Refined query after relevance feedback

2.074 new	15.10 space	Original terms with adjusted weights
30.81 satellite	5.660 application	
5.991 nasa	5.196 eos	New terms with weights
4.196 launch	3.972 aster	
3.516 instrument	3.446 arianespace	
3.004 bundespost	2.806 ss	
2.790 rocket	2.053 scientist	
2.003 broadcast	1.172 earth	
0.836 oil	0.646 measure	

Results for the expanded query

2 1. 0.513, 07/09/91, NASA Scratches Environment Gear From Satellite Plan
1 2. 0.500, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer
3. 0.493, 08/07/89, When the Pentagon Launches a Secret Satellite, Space Sleuths Do Some Spy Work of Their Own
4. 0.493, 07/31/89, NASA Uses 'Warm' Superconductors For Fast Circuit
8 5. 0.492, 12/02/87, Telecommunications Tale of Two Companies
6. 0.491, 07/09/91, Soviets May Adapt Parts of SS-20 Missile For Commercial Use
7. 0.490, 07/12/88, Gaping Gap: Pentagon Lags in Race To Match the Soviets In Rocket Launchers
8. 0.490, 06/14/90, Rescue of Satellite By Space Agency To Cost $90 Million

Original Positions of Marked Relevant Documents

How to refine a query?

- We have …
  - q_0 = *the initial query*
    - For retrieving some initial docs

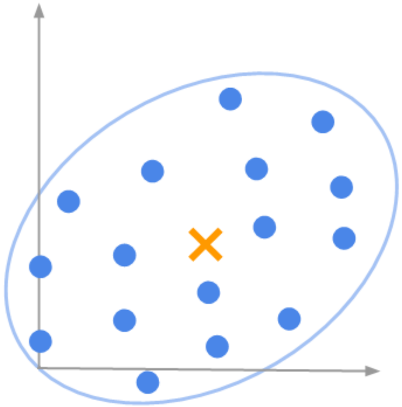
  - D_r = a (small) set of known relevant doc vectors
  - D_{nr} = a (small) set of known irrelevant doc vectors
    - From the relevant feedback on the initial docs

- We want to find …
  - q_m = the modified query

Centroid

- The center of mass of a set of documents.

$$\vec{\mu}(D) = \frac{1}{|D|} \sum_{d \in D} \vec{d}$$



  - |D| = the number of documents in the set.

- Example:
  - D = {d_1, d_2, d_3} with d_1 = (1, 2), d_2 = (3, 5), d_3 = (2, 2)
  - Centroid of D: ((1+3+2)/3, (2+5+2)/3) = (2, 3)

Rocchio (1971)

Popularized in the SMART system (Salton)

$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

Centroid of D_r *Centroid of D_{nr}*

- {α,β,γ} = weights (hand-chosen or set empirically)
  - Tradeoff α vs. β/γ: What if we have only a few judged documents?
  - Tradeoff β vs. γ: Which is more valuable?
- Term weights in the query vector can go negative
  - Set the weights to 0 or exclude documents which contain such terms

Evaluation of relevance feedback

Use q_m and compute precision recall graph

1. Assess on all documents in the collection
   - Spectacular improvements, but … it's cheating!

2. Use documents in residual collection (set of documents minus those assessed relevant)
   - Lower results but more realistic
   - Compare the relative performance instead

- Best: use two collections each with their own relevance assessments
  - q_0 and user feedback from first collection
  - q_m run on second collection and measured

When does RF work?

Empirically, a round of RF is often very useful. Two rounds is sometimes marginally useful.

The two assumptions should hold:

1. User's initial query at least partially works.

2. (Non)-relevant documents are similar.

Pseudo relevance feedback (PRF)

- Blind feedback automates the "manual" part of true RF, by assuming the top *k* is actually relevant.

- Algorithm:
  - Retrieve a ranked list of hits for the user’s query
  - Assume that the top *k* documents are relevant.
  - Do relevance feedback

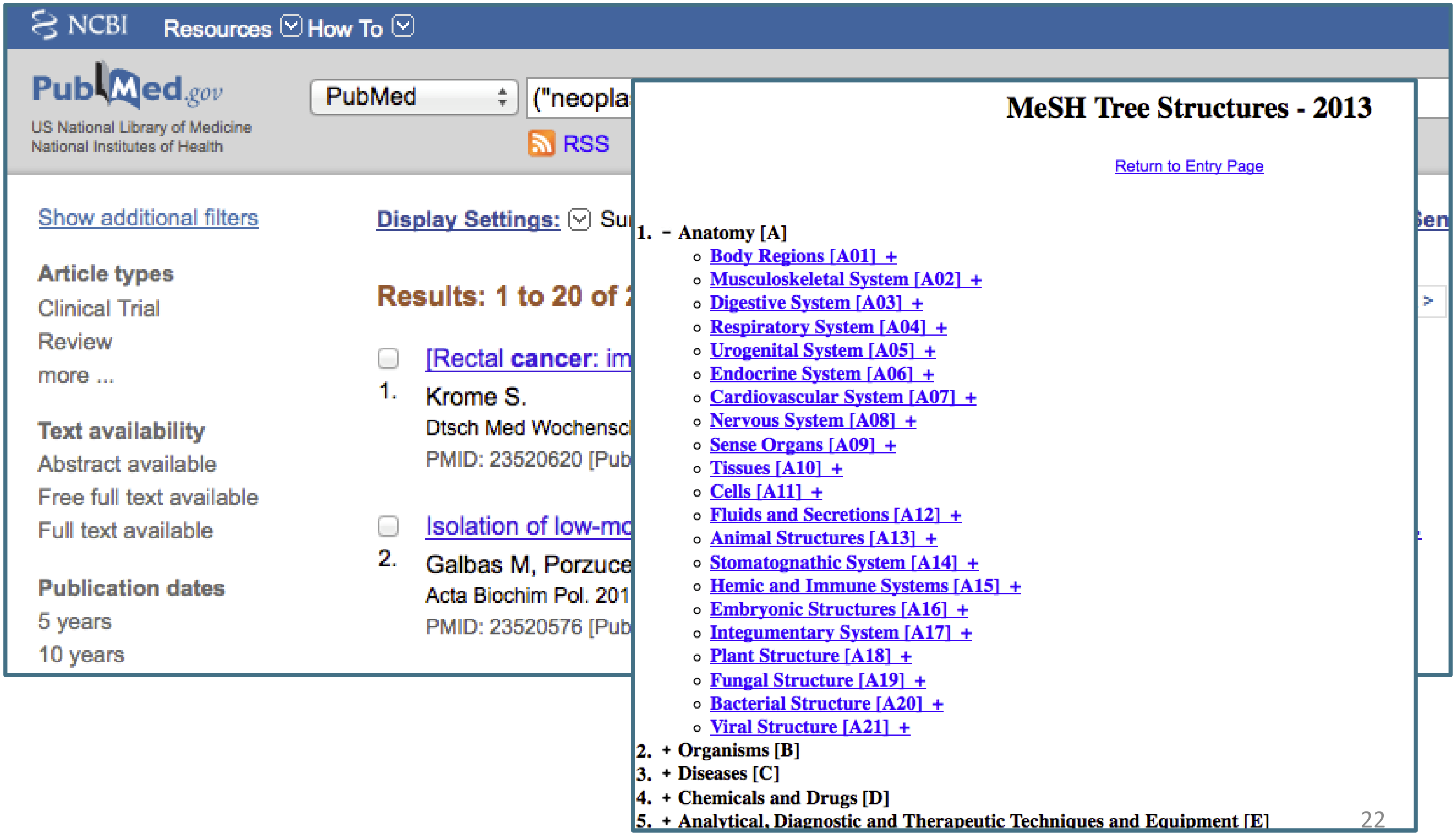
- Works very well on average
  - But can go horribly wrong for some queries
  - Several iterations can cause query drift

QUERY EXPANSION

Query Expansion

- For each query term, expand it with the related words of *t* from a thesaurus
  - The thesaurus can be **manually compiled** or **automatically generated**.
- Examples
  - feline → feline cat
    S: (adj) **feline** (of or relating to cats) *"feline fur"*
  - interest rate → interest rate fascinate evaluate
- Generally increases recall, but may decrease precision when terms are ambiguous.

Manually compiled thesauri: MeSH



Manually compiled thesaurii: [WordNet]

```
from nltk.corpus import wordnet as wn

wn.synsets("motorcar")
wn.synsets("car.n.01").lemma_names
```

WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: washing machine [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) washer, automatic washer, **washing machine** (a home appliance for washing clothes and linens automatically)
  - *direct hypernym* / ***inherited hypernym*** / *sister term*
    - S: (n) white goods (large electrical home appliances (refrigerators or washing machines etc.) that are typically finished in white enamel)
      - S: (n) home appliance, household appliance (an appliance that does a particular job in the home)
        - S: (n) appliance (durable goods for home or office use)
          - S: (n) durables, durable goods, consumer durables (consumer goods that are not destroyed by use)
            - S: (n) consumer goods (goods (as food or

Automatic Thesaurus Generation

You shall know a word by the company it keeps
– John R. Firth

- You can "harvest", "peel", "eat" and "prepare" apples and pears, so apples and pears must be similar
- Generate a thesaurus by analyzing the documents
- Assumption: distributional similarity
  - i.e., Two words are similar if they **co-occur / share same grammatical relations** with similar words.

Co-occurrences are more robust; grammatical relations are more accurate. Why?

Co-occurrence Thesaurus

In NLTK! ☺
Have a look!

A concordance permits us to see words in context. For example, we saw that
then inserting the relevant word in parentheses:

```
>>> text1.similar("monstrous")
Building word-context index...
subtly impalpable pitiable curious imperial perilous trustw
abundant untoward singular lamentable few maddens horrible
mystifying christian exasperate puzzled
>>> text2.similar("monstrous")
Building word-context index...
very exceedingly so heartily a great good amazingly as swe
remarkably extremely vast
>>>
```

Observe that we get different results for different texts. Austen uses this word

The term `common_contexts` allows us to examine just the contexts that are sh

```
>>> text2.common_contexts(["monstrous", "very"])
be_glad am_glad a_pretty is_pretty a_lucky
>>>
```

XML RETRIEVAL

Unstructured vs. Structured

Macbeth

Shakespeare

Act 1, Scene vii

Macbeth's Castle

…

```
<play>
    <author>Shakespeare</author>
    <act number="1">
        <scene number="vii">
            <verse>…</verse>
            <title>Macbeth's Castle</title>
        </scene>
    </act>
    <title>Macbeth</title>
</play>
```

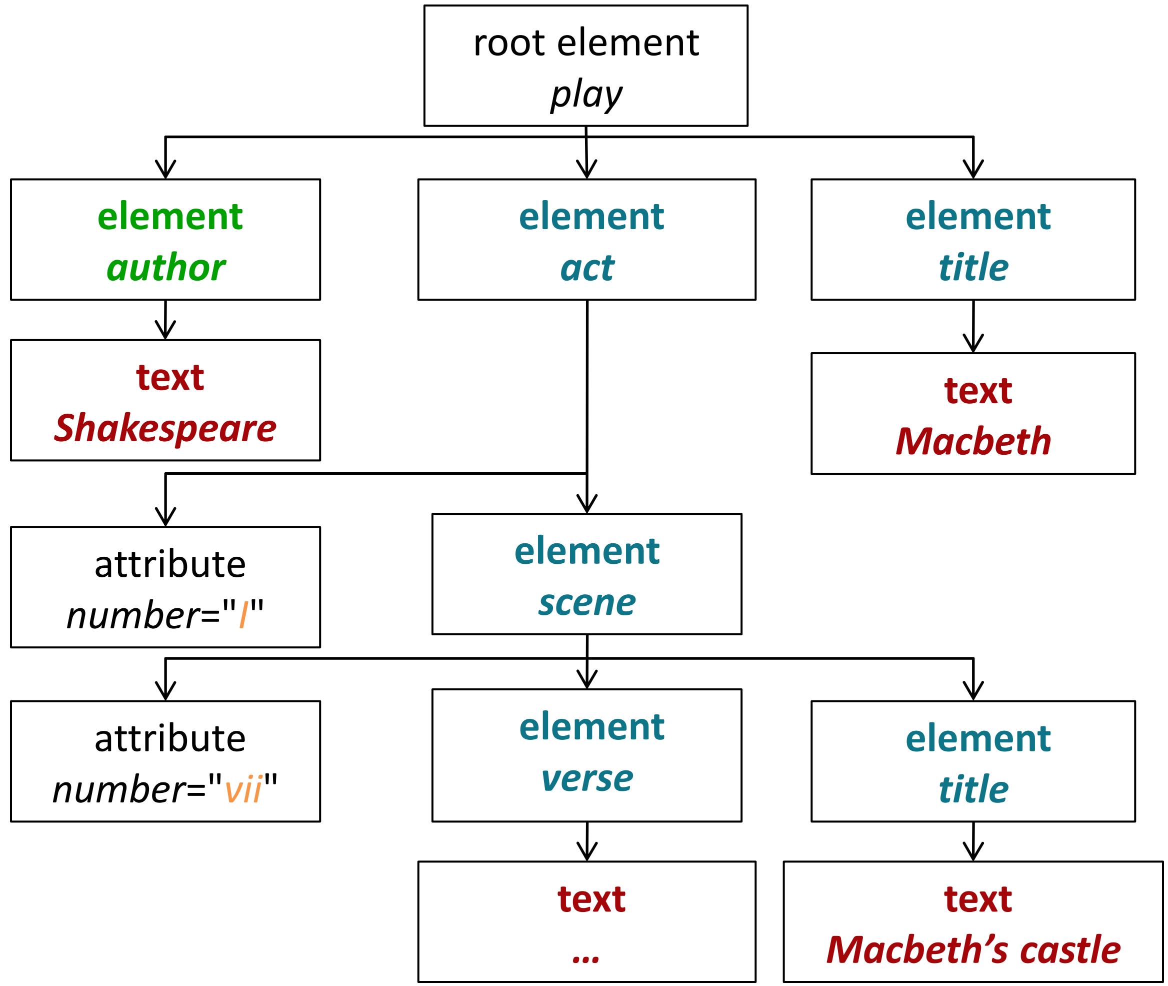
XML Document

Internal nodes encode **document structure** or **metadata**

An element can have one or more **attributes** and sub elements

Leaf nodes consist of text

Possible **queries** which match with **(part of)** this document:
Macbeth
scene/title#castle



Structured Retrieval

Applications of structured retrieval

Digital libraries, patent databases, blogs, tagged text with entities like persons and locations (named entity tagging)

Example

- Digital libraries: *give me a full-length article on fast fourier transforms*
- Patents: *give me patents whose claims mention RSA public key encryption and that cite US Patent 4,405,829*
- Entity-tagged text: *give me articles about sightseeing tours of the Vatican and the Coliseum*

Common Problems

- What is the unit of retrieval?
  - E.g., the whole document or a **component** of it.
- Do the users know about the structure of the documents well?
- How to rank the items in the result list?
- How to evaluate the retrieval performance?

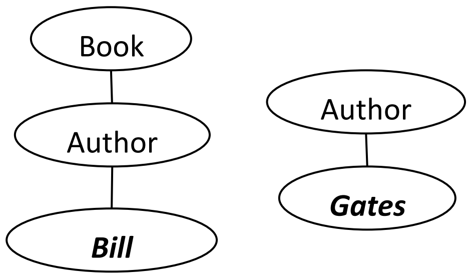
VECTOR SPACE MODEL FOR XML IR

Key idea: Structural terms

- An unstructured document / query
  - Consists of one or more terms
  - Is a vector in a high-dimensional space where each dimension corresponds to a term

Bill Gates

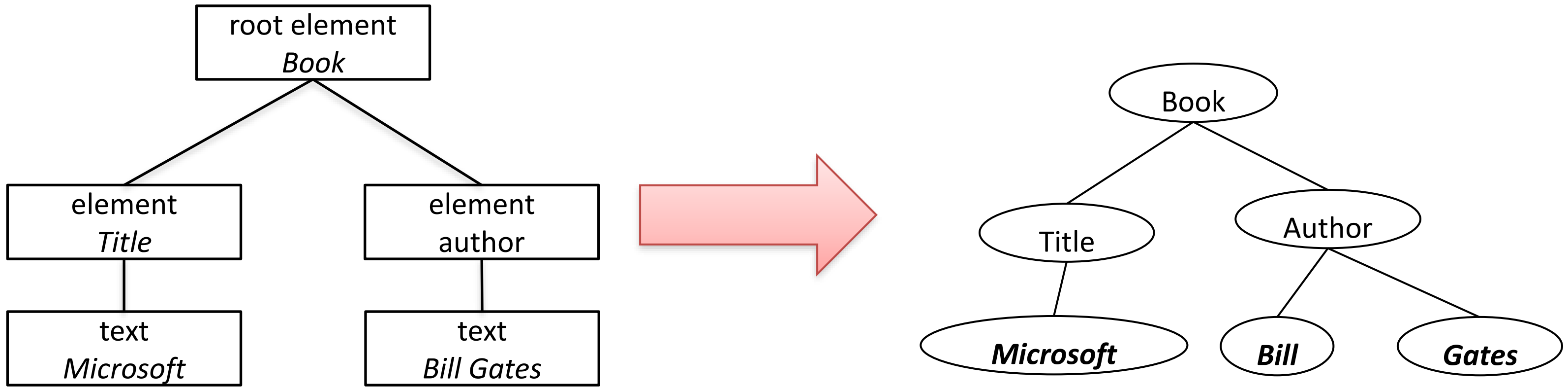
- A structured document / query
  - Consists of one or more structural terms
  - Is a vector in a high-dimensional space where each dimension corresponds to a structural term



A structural term <c, t> is a pair of XML-context c and vocabulary term t.

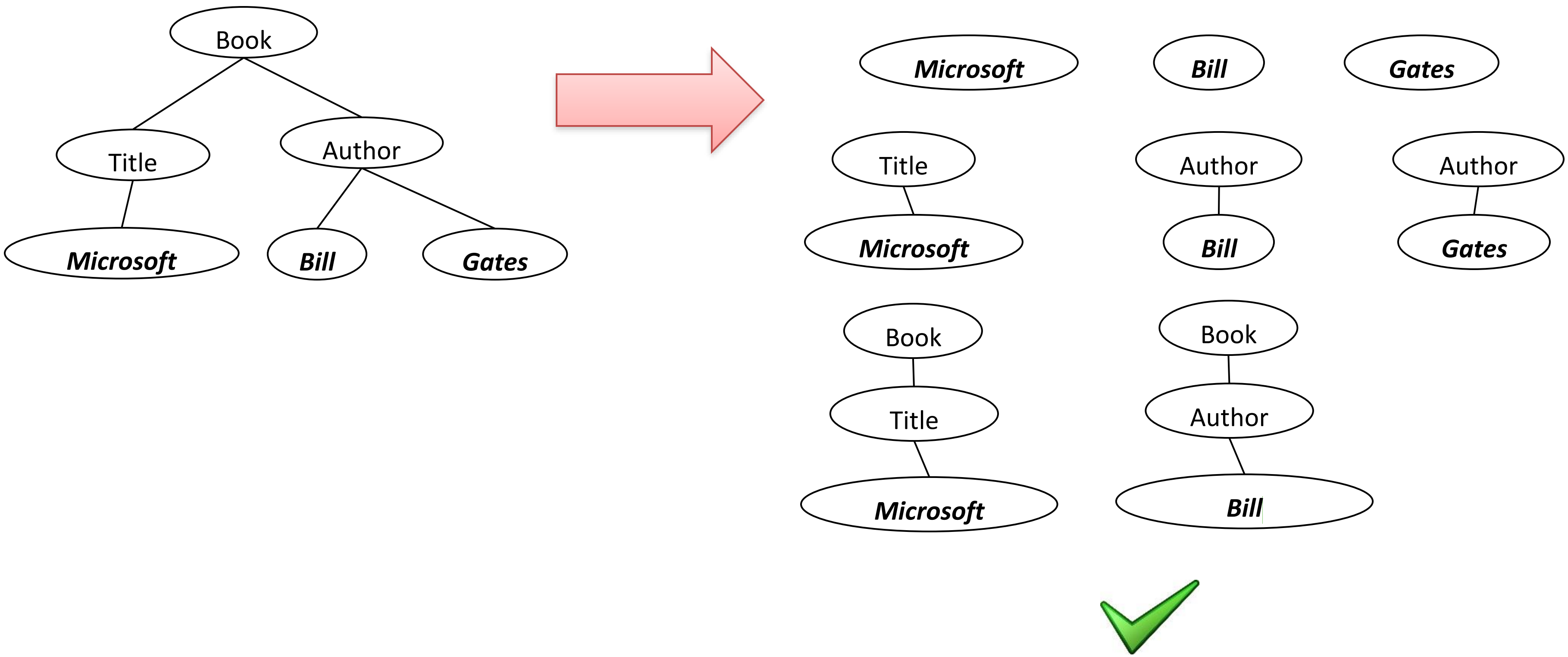
Structural terms extraction

- Step 1: Take each text node (leaf) and break it into multiple nodes, one for each word. E.g. split **Bill Gates** into **Bill** and **Gates**



Structural terms extraction

- Step 2: Extract all paths that end in a single vocabulary term as **structural terms**



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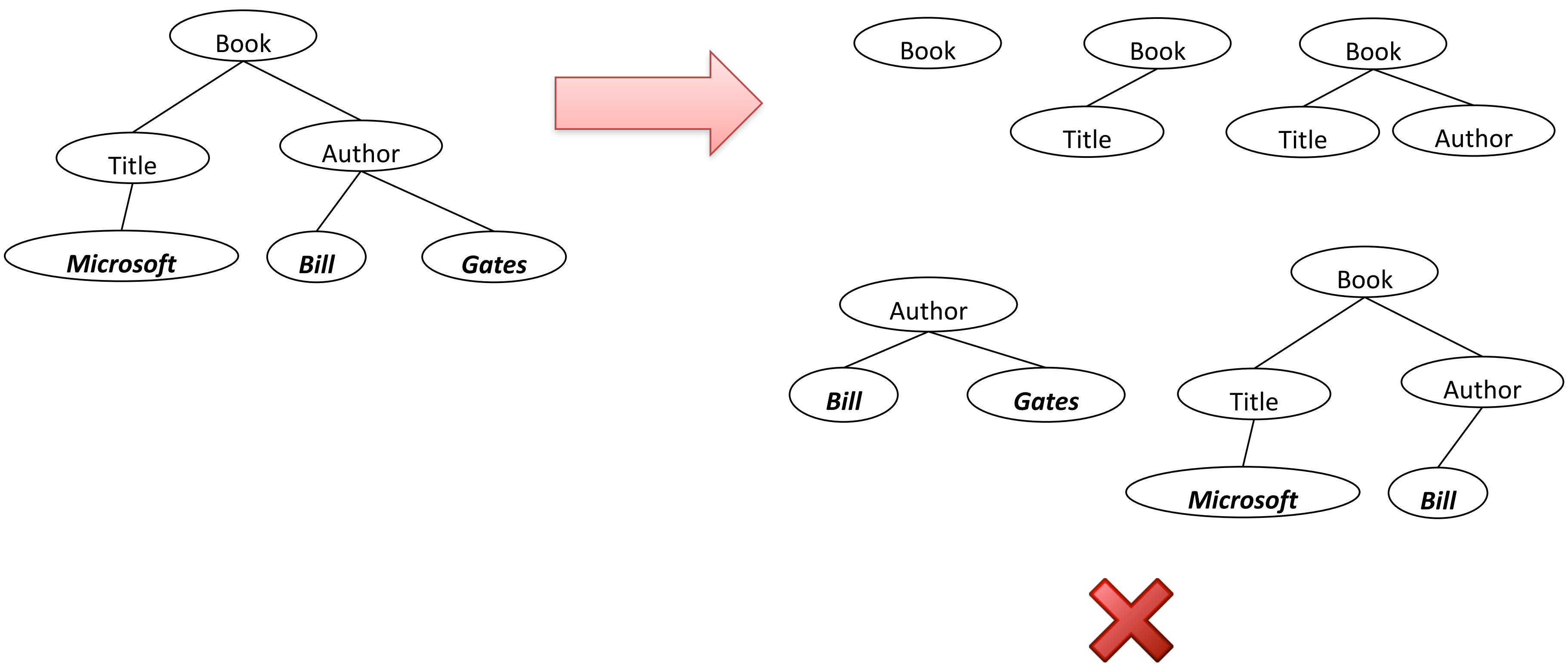
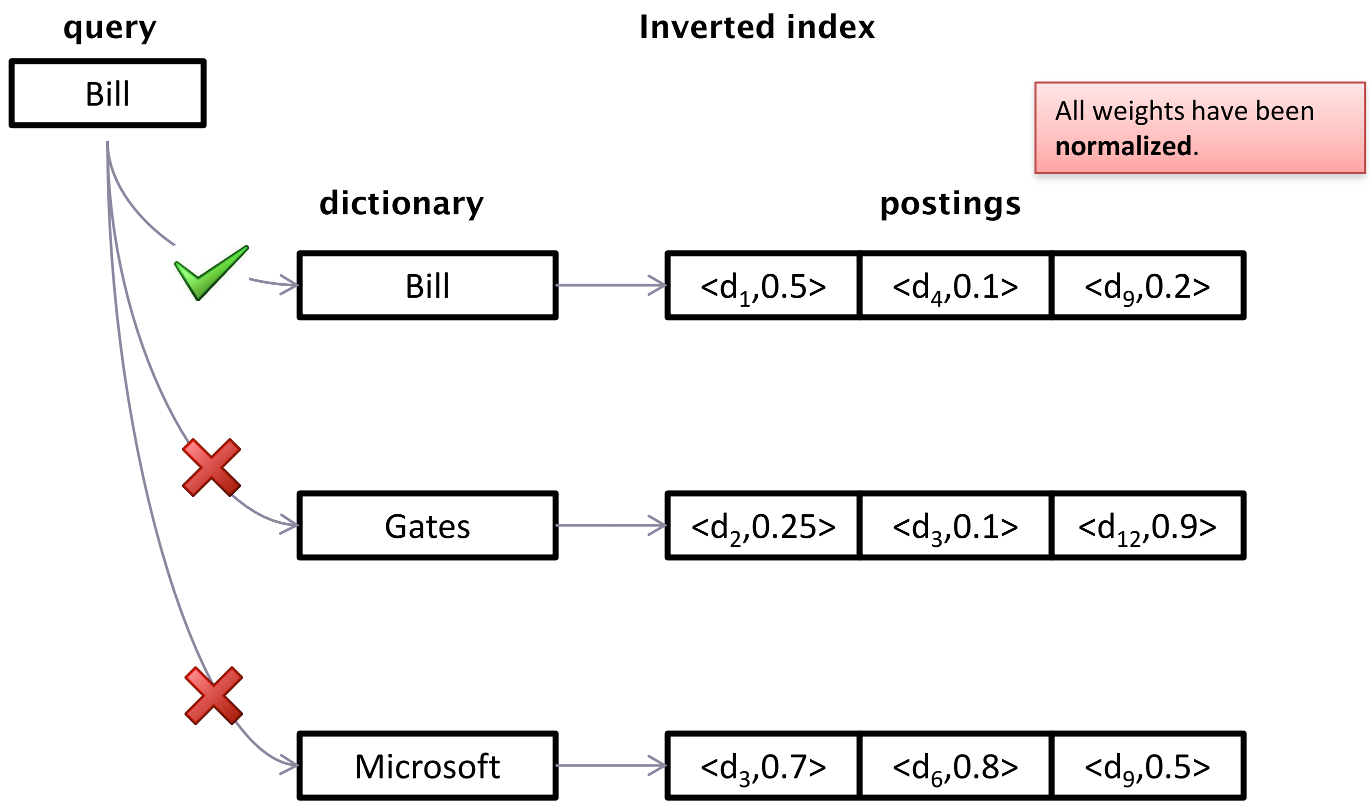


Recap: Cosine Similarity

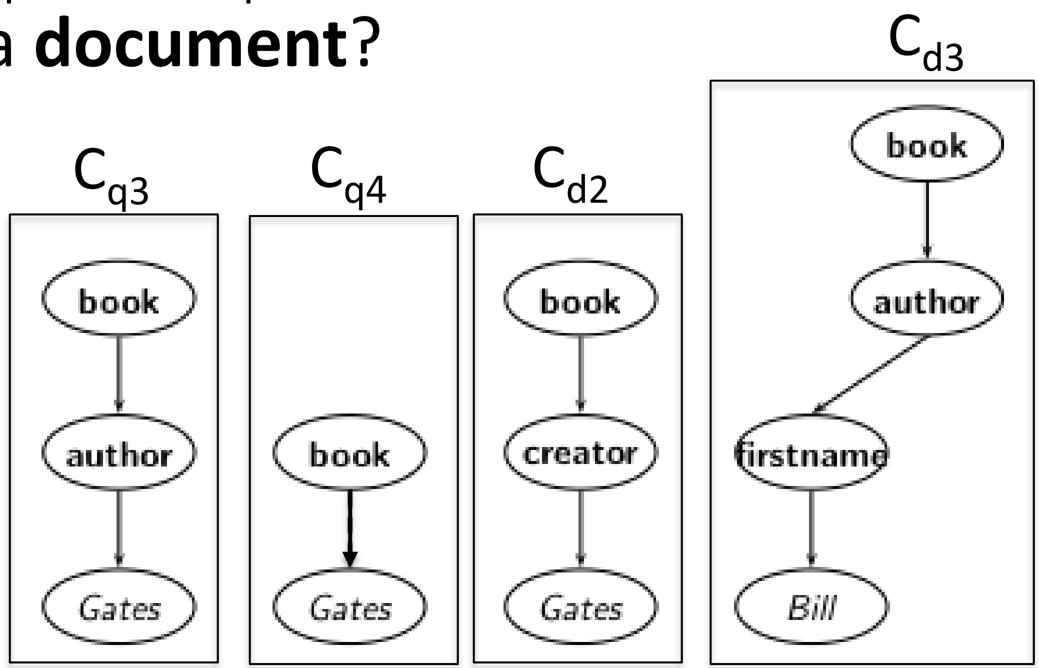


if w_q = 1.0, then score(d_9) += (1.0 x 0.2) = 0.2

Query Term Weight * Document Term Weight

Matching between structural terms

- Can C_{q3} and C_{q4} from a **query** match with C_{d2} and C_{d3} from a **document**?



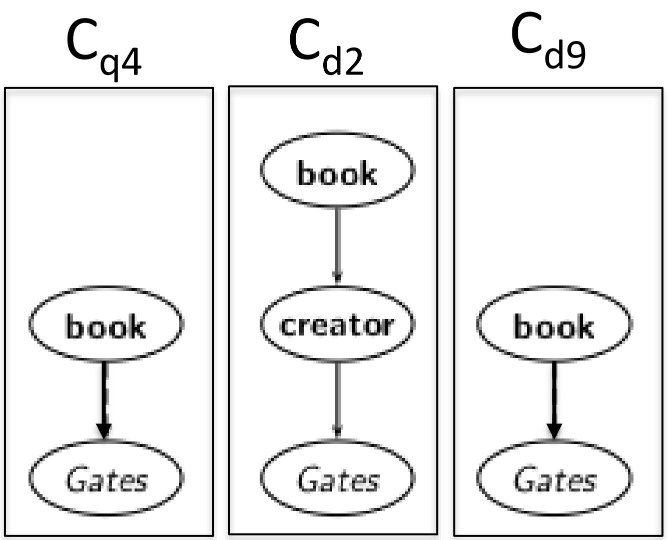
- c_q matches c_d **iff** we can transform c_q into c_d by inserting additional nodes.

Similarity between structural terms

- Context Resemblance:
  - A simple measure of the similarity of a structural term c_q in a query and a structural term c_d in a document

$$\mathrm{CR}(c_q, c_d) = \begin{cases} \frac{1+|c_q|}{1+|c_d|} & \text{if } c_q \text{ matches } c_d \\ 0 & \text{if } c_q \text{ does not match } c_d \end{cases}$$

  - $|c_q|$ and $|c_d|$ are the number of nodes in the terms, respectively.
  - Examples
    - $\mathrm{CR}(c_{q4}, c_{d2}) = (1 + 2) / (1 + 3) = 0.75$
    - $\mathrm{CR}(c_{q4}, c_{d9}) = 3 / 3 = 1$



SimNoMerge

- The final score for a document is computed as a variant of the cosine measure, which we call SimNoMerge.
- SimNoMerge(q, d) =

$$\sum_{c_k \in B} \sum_{c_l \in B} \underbrace{\mathrm{CR}(c_k, c_l)}_{\text{Context resemblance}} \sum_{t \in V} \underbrace{\mathrm{weight}(q, t, c_k)}_{\text{Query structural term weight}} \underbrace{\frac{\mathrm{weight}(d, t, c_l)}{\sqrt{\sum_{c \in B, t \in V} \mathrm{weight}^2(d, t, c)}}}_{\text{Normalized document structural term weight}}$$

- V is the vocabulary of non-structural terms
- B is the set of all XML contexts
- weight (q, t, c), weight(d, t, c) are the weights of term t in XML context c in query q and document d, resp. (standard weighting e.g. $\mathrm{idf}_t \times \mathrm{wf}_{t,d}$, where idf_t depends on which elements we use to compute df_t.)
- SimNoMerge (q, d) is not a true cosine measure since its value can be larger than 1.0.

SimNoMerge example

This example is slightly different from book

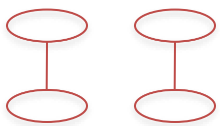
All weights have been **normalized**.

query

$\langle c_1,t\rangle$ e.g., author#Bill

Inverted index

dictionary **postings**



$CR(c_1,c_1) = 1.0$

$\langle c_1,t\rangle$ → $\langle d_1,0.5\rangle$ | $\langle d_4,0.1\rangle$ | $\langle d_9,0.2\rangle$

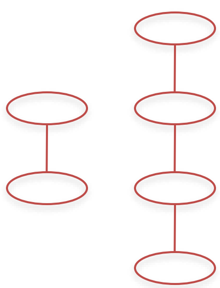
e.g., author#Bill

OK to ignore Query vs <c2, t> since CR = 0.0

$CR(c_1,c_2) = 0.0$

$\langle c_2,t\rangle$ → $\langle d_2,0.25\rangle$ | $\langle d_3,0.1\rangle$ | $\langle d_{12},0.9\rangle$

e.g., title#"Bill"



$CR(c_1,c_3) = 0.60$

$\langle c_3,t\rangle$ → $\langle d_3,0.7\rangle$ | $\langle d_6,0.8\rangle$ | $\langle d_9,0.5\rangle$

e.g., book/author/firstname#Bill

d_9 contains two structural terms $\langle c_1, t\rangle$ and $\langle c_3, t\rangle$.

Context Resemblance * Query Term Weight * Document Term Weight

if $w_q = 1.0$, then score(d_9) +=
$(1.0 \times 1.0 \text{ x } 0.2) + (0.6 \times 1.0 \text{ x } 0.5) = 0.5$

Query vs $\langle c_1,t\rangle$ Query vs $\langle c_3,t\rangle$

"No Merge" because each context is separately calculated

SimNoMerge algorithm

ScoreDocumentsWithSimNoMerge (q, *B*, *V*, *N*, *normalizer*)

$$
\begin{array}{l}
\textbf{for } n \leftarrow 1 \textbf{ to } N \\
\textbf{do } score[n] \leftarrow 0 \\
\textbf{for each } \langle c_q, t \rangle \in q \\
\textbf{do } w_q \leftarrow \textrm{WEIGHT}(q, t, c_q) \\
\quad \textbf{for each } c \in B \\
\quad \textbf{do if } \textrm{CR}(c_q, c) > 0 \\
\qquad \textbf{then } postings \leftarrow \textrm{GETPOSTINGS}(\langle c, t \rangle) \\
\qquad\quad \textbf{for each } posting \in postings \\
\qquad\quad \textbf{do } x \leftarrow \textrm{CR}(c_q, c) * w_q * weight(posting) \\
\qquad\qquad score[docID(posting)] += x \\
\textbf{for } n \leftarrow 1 \textbf{ to } N \\
\textbf{do } score[n] \leftarrow score[n] / normalizer[n] \\
\textbf{return } score
\end{array}
$$

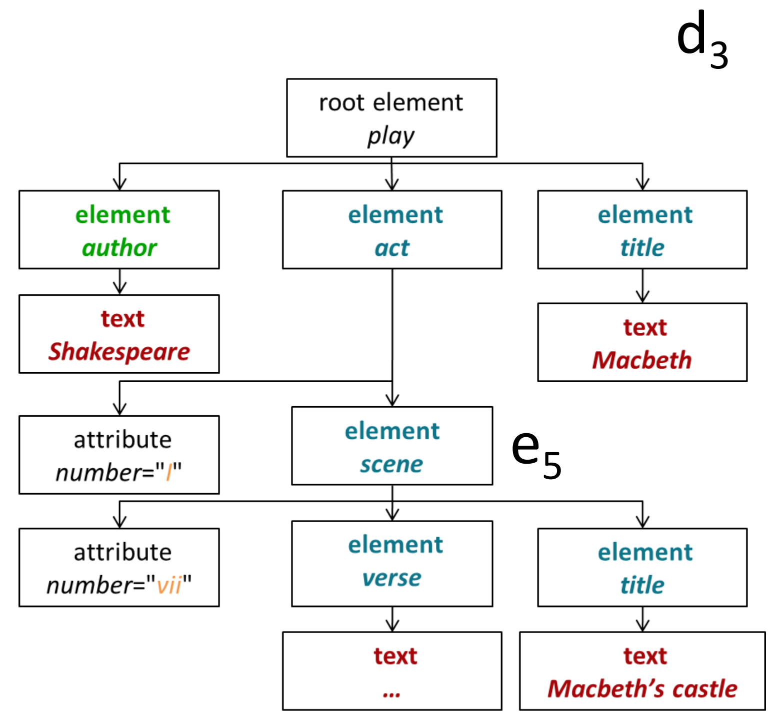
From document to component

- The same idea applies to indexing and retrieving components (i.e., elements) in XML documents.

- E.g.,
  - Element e_5 in d_3 can be indexed and retrieved by itself.

structural term dictionary → **component postings**

<c_3,t> → <d_3/e_5,0.7>



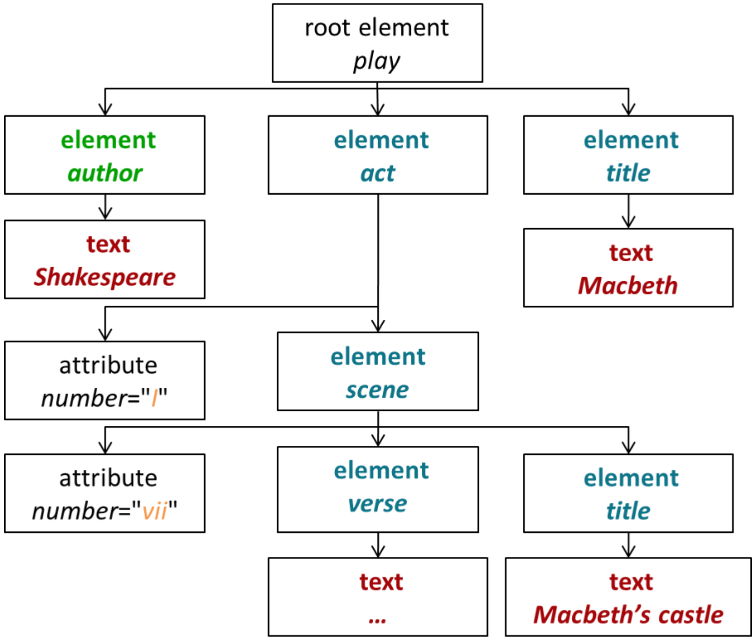
XML IR
EVALUATION

XML IR Evaluation

- Component-based
- Two aspects: **Component Coverage** + **Topical Relevance**.

Component coverage

Evaluates whether the element retrieved is "structurally" correct, i.e., neither too low nor too high in the tree.



Component Coverage

- Four cases:
  - Exact coverage (E)
    - The information sought is the main topic of the component and the component is a meaningful unit of information.
  - Too small (S)
    - The information sought is the main topic of the component, but the component is not a meaningful (self-contained) unit of information.
  - Too large (L)
    - The information sought is present in the component, but is not the main topic.
  - No coverage (N):
    - The information sought is not a topic of the component.

Topical Relevance

- Four levels:
  - Highly relevant (3)
  - Fairly relevant (2)
  - Marginally relevant (1)
  - Nonrelevant (0)

Combining the relevance dimensions

- A digit-letter code
  - E.g., **2S** is a fairly relevant component that is too small.
- 16 combinations in theory but many cannot occur.
  - E.g., a nonrelevant component cannot have exact coverage, so the combination **0E** is not possible.

INEX relevance assessments

- The relevance-coverage combinations are quantized as

$$\mathbf{Q}(rel, cov) = \begin{cases} 1.00 & \text{if} \quad (rel, cov) = 3E \\ 0.75 & \text{if} \quad (rel, cov) \in \{2E, 3L\} \\ 0.50 & \text{if} \quad (rel, cov) \in \{1E, 2L, 2S\} \\ 0.25 & \text{if} \quad (rel, cov) \in \{1S, 1L\} \\ 0.00 & \text{if} \quad (rel, cov) = 0N \end{cases}$$

- The number of relevant components in a retrieved set *A* of components can then be computed as:

$$\#(\text{relevant items retrieved}) = \sum_{c \in A} \mathbf{Q}(rel(c), cov(c))$$

- Example: If the 5 components retrieved are assessed as {3E, 3E, 0N, 1E, 1S}, the precision is (1 + 1 + 0 + 0.5 + 0.25) / 5 = 0.55

Summary

1. Query Refinement
   - Relevance Feedback – "Documents"
   - Query Expansion – "Terms"

2. XML IR and Evaluation
   - Structured or XML IR: effort to port unstructured IR know-how to structured
     (DB-like) data
   - Specialized applications such as patents and digital libraries

- Resources
  - IIR Ch 9/10
  - MG Ch. 4.7 and MIR Ch. 5.2 – 5.4
  - http://inex.is.informatik.uni-duisburg.de/