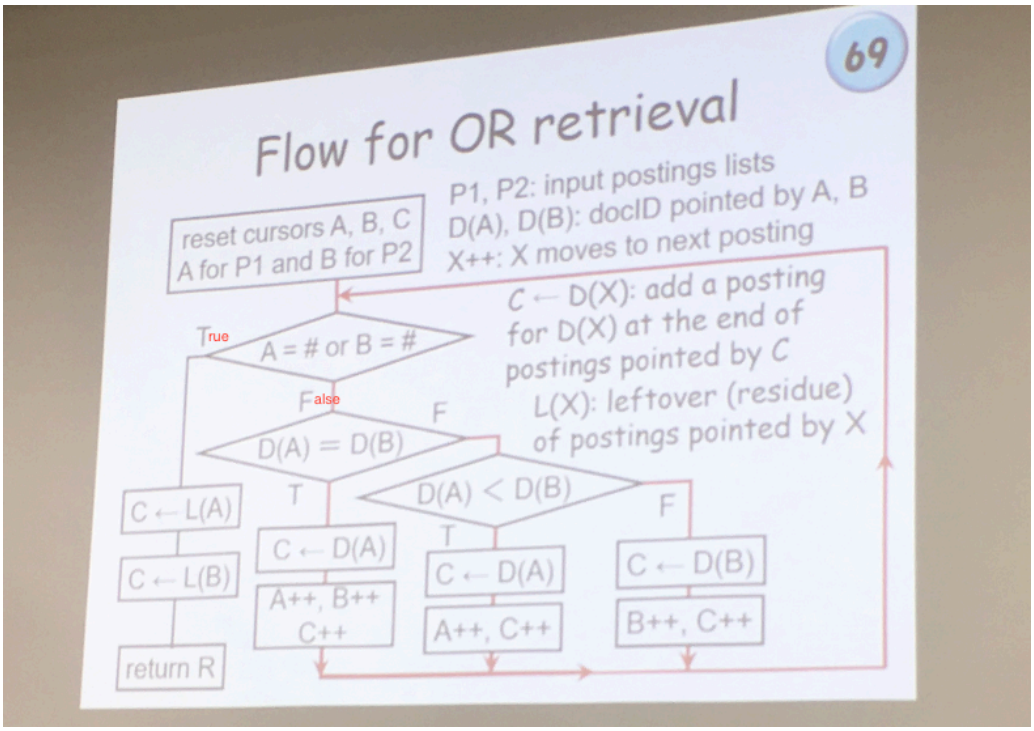
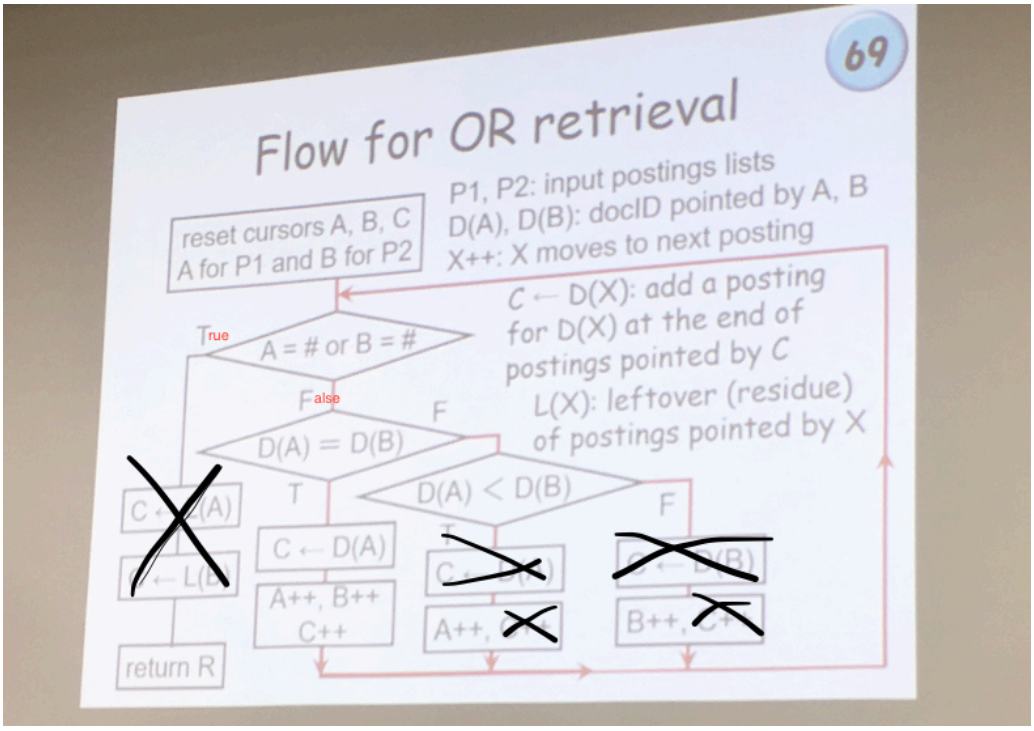
Day 6 & 7

Flow of OR retrieval



Exercise

- The flow in the previous slide (OR retrieval) was used to obtain a document set, R, in response to query S = T2 OR T4
    - T2 -> D1, D2, D5, D7, D9 -> #
    - T4 -> D1, D3, D5, D6, D7, D8 -> #
- Q1: identify how many times the condition D(A) = D(B) was evaluated in the flow?
  Ans: 7 times
- Q2: modify the OR flow to realize AND
  Ans:



Optimizing Boolean queries

- If query contains more than 2 terms, the order of operations is important
- Use operations involving AND operators and shorter postings lists as soon as possible to reduce the candidate documents
- Keeping unpromising candidates decreases efficiency

Boolean operation

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Boolean operation

+ OR	* AND	$\overline{\ }$ NOT

- Fill in blanks
- $0 + A = [A]$ $0 * A = [0]$ $1 + A = [1]$ $1 * A = [A]$
- $A + A = [A]$ $A * A = [A]$ $A + \overline{A} = [1]$ $A * \overline{A} = [0]$
- $A * (B + C) = ([A] * B) + (A * [C])$
- $\overline{A + B} = [\overline{A} * \overline{B}]$ $\overline{A * B} = [\overline{A} + \overline{B}]$
- Proof the following (may use above laws)

  [13] $A * (A + B) = A$

  [14] $(A + B) * (A + C) = A + B * C$

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Answer

[1] A [2] 0 [3] 1 [4] A [5] A [6] A [7] 1 [8] 0

[9] A [10] C [11] $\overline{A} * \overline{B}$ [12] $\overline{A} + \overline{B}$

[13] $A * (A + B)$

$= A * A + A * B = A * 1 + A * B$

$= A * (1 + B) = A * 1 = A$

[14] $(A + B) * (A + C)$

$= A * A + A * C + A * B + B * C$

$= A + A * C + A * B + B * C$

$= A * (1 + C + B) + B * C = A + B * C$

The number of comparisons for postings lists can substantially be reduced by preprocessing

Term weighting: background

- In the best match model, degree of relevance for each doc D wrt Q, R(D,Q) is calculated
- R(D,Q) is accumulation of the weight of each term in D wrt Q
- Here, we have a fundamental question
  - Which terms represent topic of document?
  - Equivalent to how we modeled a document?

  -> a set of words w/o certain properties
- The topic of document is reprensented by a set of words (aka “Bag of Words” or “BOW”)

Term weighting: issues

- Wish to give a different weight to each term, depending on the importance for retrieval
- **TF*IDF** was proposed around the 1960s and has been used and developed in the IR
  - TF (term frequency)
  - IDF (inverse document frequency)
- Whereas the rationale has not been clearly explained, TF*IDF (especially) IDF, has been popular methods for other communities where target object is represented a vector of features

TF (term frequency)

- In principle, the more frequently appear, the more being important
  - TF(D_i, Tk): Frequency of Tk in D_i
- In practice, a modification is recommended
  - (Ex1) long documents are more likely a large terms -> normalized by document length
  - (Ex2) the value in linearly proportion to the frequency is too sensitive to a small change of the frequency and thus is unstable -> take logarithm of TF to make the increase being saturated for a large frequency

IDF (inverse document frequency)

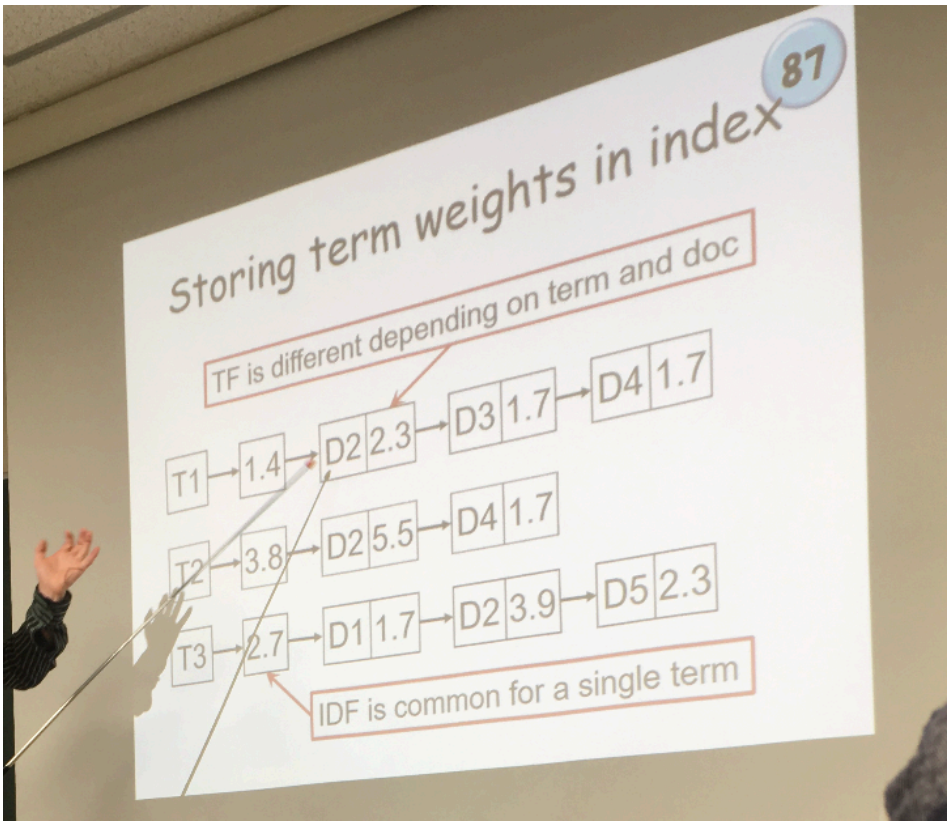
- in principle, terms that appear in a lot of documents is not associated with specificity
  - E.g. “the” is everywhere
- IDF for term T
  - N: # of documents in collection
  - DF(T): # of documents that contain T
  - **IDF(T) = log (N/DF(T) +1)**
  - +1 is to prevent IDF from being 0
- IDF is proper to each term, unlike TF

Why is IDF such a formula?

- Plausible explanation would be:
  - DF(T)/N is a probability that a randomly selected document D from the collection contains term T

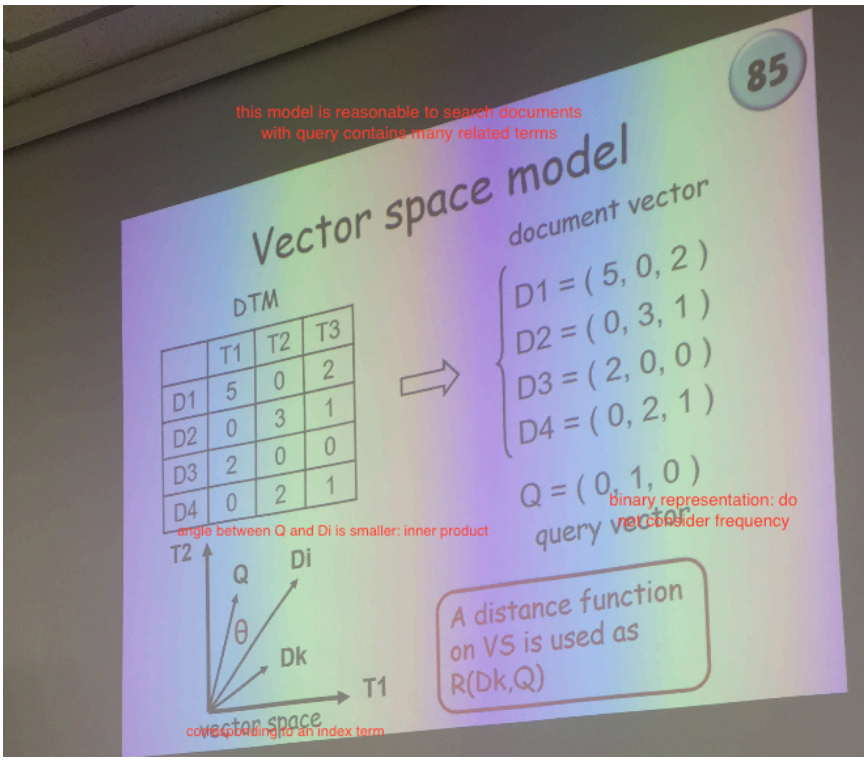
- The information content of the message “D contains T” is
  -log (DF(T)/N) = log (N/DF(T))
- IDF is usually effective whereas TF is rather harmful depending on the formula

Storing term weights in index
T1 -> 1.4 -> D1: 2.3 (TF is depending on term and doc)-> D3: 1.7 -> D4: 1.7
T2 -> 3.8 -> D2: 5.5 -> D4: 1.7
T3 -> 2.7 (IDF is common for a single term) -> D1: 1.7 -> D2: 3.9 -> D5 :2.3



Discussion
- Pros and Cons for the Boolean and Best match IR match

Vector space model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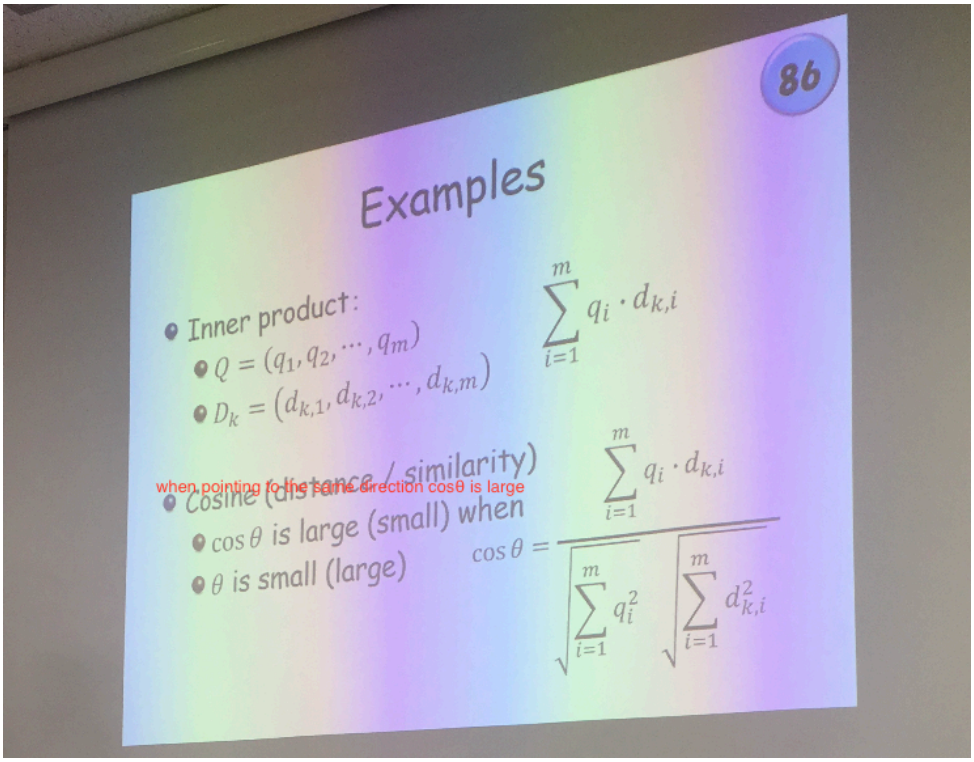
this model is reasonable to search documents
with query contains many related terms
Vector space model
document vector
DTM
T1 T2 T3
D1 5 0 2
D2 0 3 1
D3 2 0 0
D4 0 2 1
D1 = (5, 0, 2)
D2 = (0, 3, 1)
D3 = (2, 0, 0)
D4 = (0, 2, 1)
Q = (0, 1, 0)
query vector
binary representation: do not consider frequency
angle between Q and Di is smaller: inner product
T2
Q
Di
θ
Dk
T1
vector space
corresponding to an index term
A distance function
on VS is used as
R(Dk,Q)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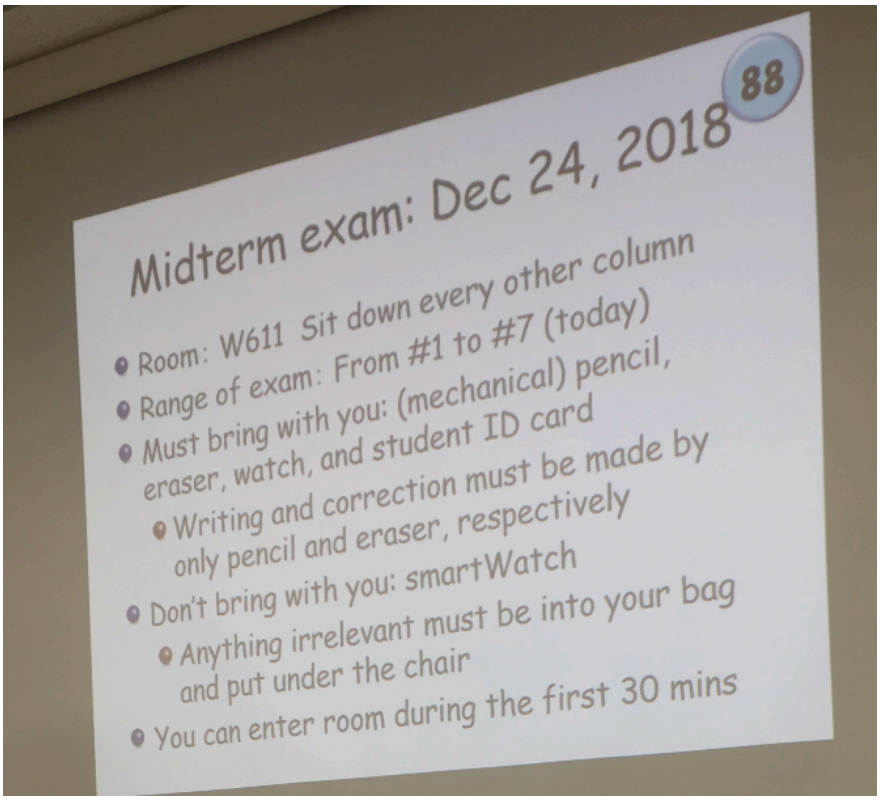
Examples
Inner product:
$Q = (q_1, q_2, \cdots, q_m)$
$D_k = (d_{k,1}, d_{k,2}, \cdots, d_{k,m})$
$\sum_{i=1}^{m} q_i \cdot d_{k,i}$
Cosine (distance / similarity)
when pointing to the same direction cosθ is large
$\cos\theta$ is large (small) when
θ is small (large)
$\cos\theta = \frac{\sum_{i=1}^{m} q_i \cdot d_{k,i}}{\sqrt{\sum_{i=1}^{m} q_i^2}\sqrt{\sum_{i=1}^{m} d_{k,i}^2}}$



https://nlp.stanford.edu/IR-book/essir2011/