Henry's awesome summary for comp6714 **16s2**.

Share ur course experience on this site: https://www.unsw.co/rango/category/comp6714

Tip for exam: Write down intermediate steps, so that we can give you partial marks even if the final answer is wrong.

Outline available, open it in Tools → Document outline.

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Ass1 spec:
https://drive.google.com/file/d/0B8nBg-44S4maTFV6cVA2U3NpLW8/view?usp=sharing
Ass2 spec:
https://drive.google.com/file/d/0B8nBg-44S4maejF4SW4yb3l6NlE/view?usp=sharing

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Log:
03/11/16 Compression
04/11/16 Tolerant Retrieval
05/11/16 Information retrieval
07/11/16 Vector Space Model
08/11/16 Evaluation
09/11/16 Probabilistic Model and Language Model (I am not confident about this part)
10/11/16 Web Search Basics and Link Analysis(done by anonymous hero)

Question: Is Spelling Correction not going to be examined?
See Tolerant Retrieval → 2 (spelling correction)

Finally. Thx everyone who contributes to this summary. didn't expect it at all :)

A. Boolean Model

1. **incidence vector**

   Term-document **incidence** -> bitwise operation:

	Doc1	D2	D3	D4	D5	D6
Term1	1	0	1	1	0	0

   So, Brutus, Caesar and Calpurnia (complemented) bitwise AND
   110100 AND 110111 AND 101111 = 100100

2. **semantics of the query model (AND/OR/NOT, and other operators, e.g., /k, /S)**

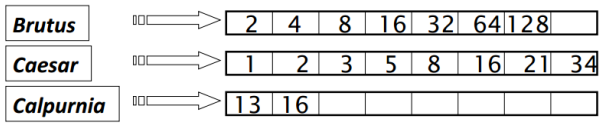
   Question(What's the meaning of semantics, difference with q4 below??)

   1) Views each document as a set of words
   2) Is precise: document matches condition or not.

   /k, /s see A.4

3. **inverted index, positional inverted index**

   The matrix above (in 1.) is space consuming, so we introduced
   1) Inverted index (dictionary and postings).

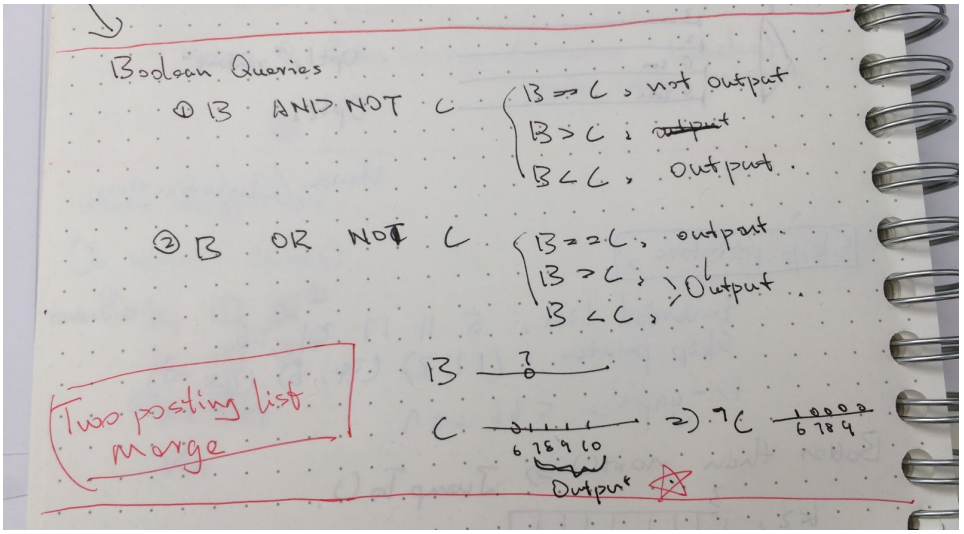
   

   2) positional inverted index:

   ```
   fools : 2: <1,17,74,222>;       4: <8,78,108,458>;       7: <3,13,23,193>;
   rush  : 2: <2,66,194,321,702>; 4: <9,69,149,429,569>;  7: <4,14,404>;
   in    : 2: <3,37,76,444,851>;   4: <10,20,110,470,500>; 7: <5,15,25,195>;
   ```

4. **query processing methods for basic and advanced boolean queries (including phrase query, queries with /S operator, etc.)**

   P33?
   P30 estimate??
   Merge of two postings simultaneously. **time complexity: O(x+y)**:
   AND/OR/NOT:

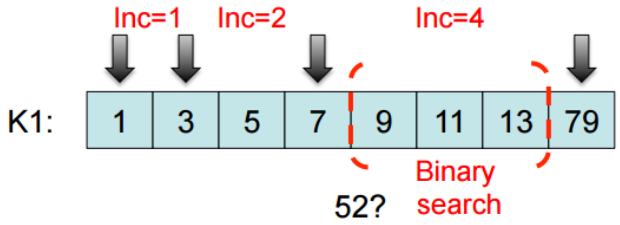
   

   /k means "within k words of":

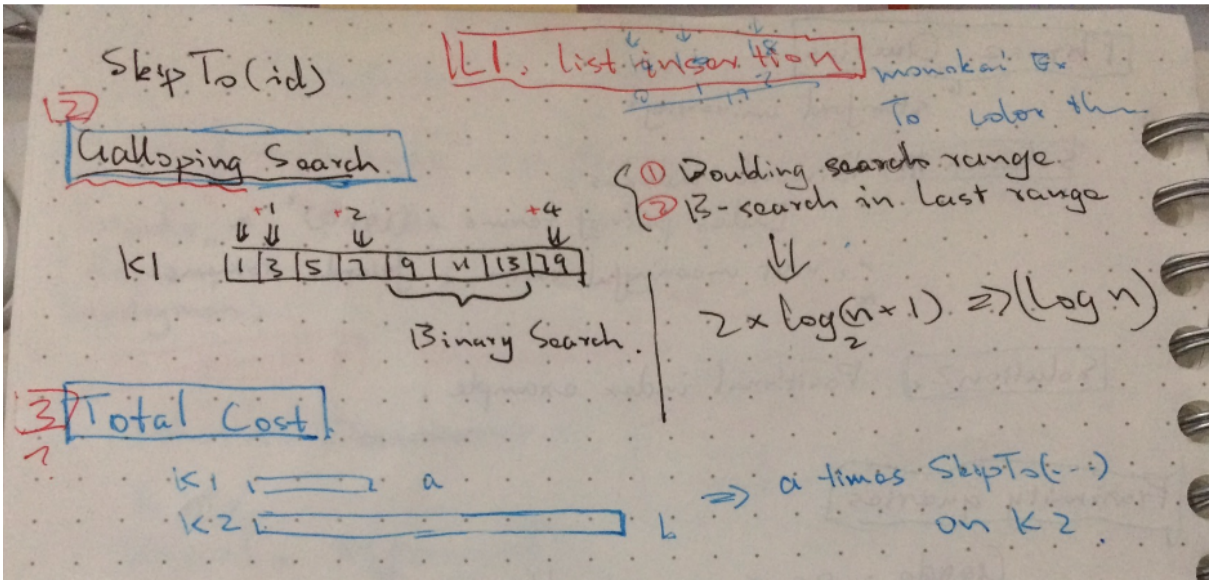
/S means “in same sentence”:
/P means “same paragraph”

The **Q3(2)** of ass1 and here are **two solutions**:
1) recording word id, sentence id and paragraph id as well as position id(but it’s space consuming).
2) including special tokens such as “end of word, end of sen, end of paragraph”,
This method is also known as the **extent list approach.**
During the query, once match or anyone encounter end we will move cursor to next begin(same position).

5. **query optimization methods (list merge order, skip pointers)**
   1) **list merge order:** start with the smallest set, same idea as **join** in database.
   2) **skip pointers: Galloping search**
   [Stage 1] Doubling the search range until you overshoot
   [Stage 2] Perform binary search in the last range
   So Total = 2 ⌈ log2 (n+1) ⌉ = **O(log2 n)/**



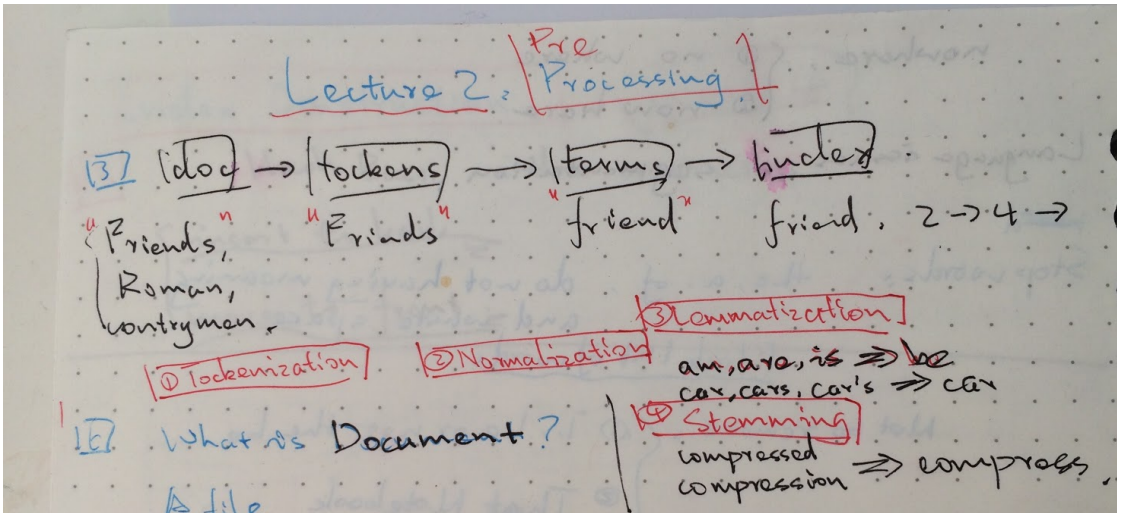
Optimization?? **// i guess these two are considered to be optimizations -hengji**



Not required: next-word index

B. Preprocessing

1. **typical preprocessing steps: tokenization, stopword removal, stemming/lemmatization**



How does stemming typically affect recall? Why?
Normalization increases recall but reduce precision

*** Difference of stemming and lemmatization:**
(re edited on 10/11/16 based on lecturer's slides)

Stemming: suggest crude ****affix chopping**(**Reduce terms to their "roots"**)**
E.g. [automate(s), automatic, automation] → automat

Typical rules in Porter

- *sses* → *ss*
- *ies* → *i*
- *ational* → *ate*
- *tional* → *tion*

Lemmatization: reduce **inflectional/variant** forms to **base form**
e.g. [am, are, is]→ be; [car, cars, car's] → car

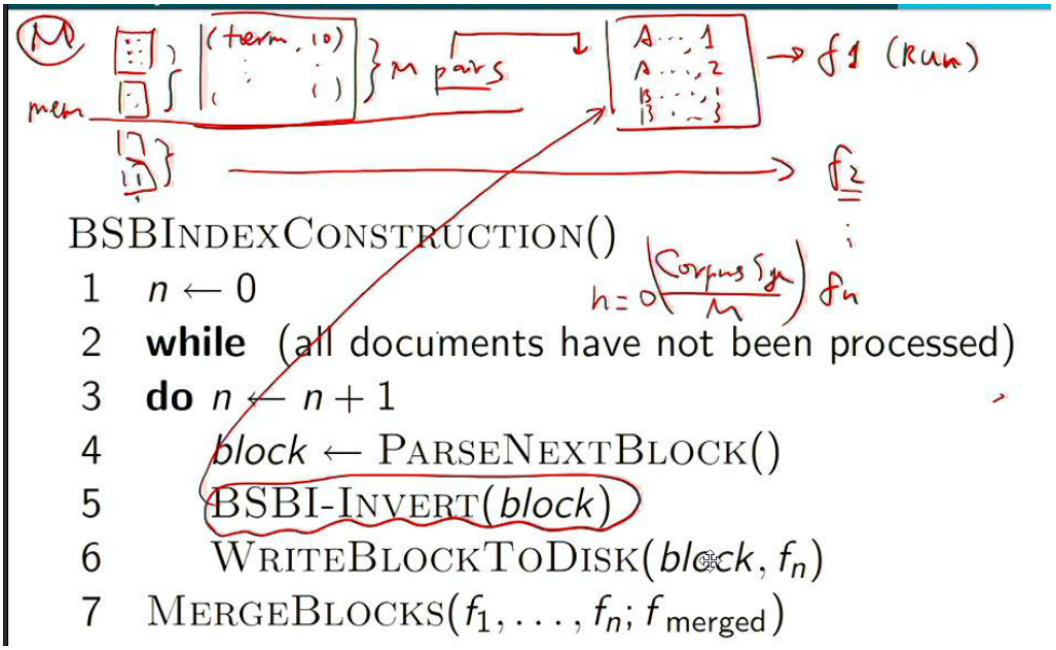
- *the boy's cars are different colors* → *the boy car be different color*
- Lemmatization implies doing "proper" reduction to dictionary headword form

2. Not required: details of the (Porter's) stemming algorithm.

C. Index Construction

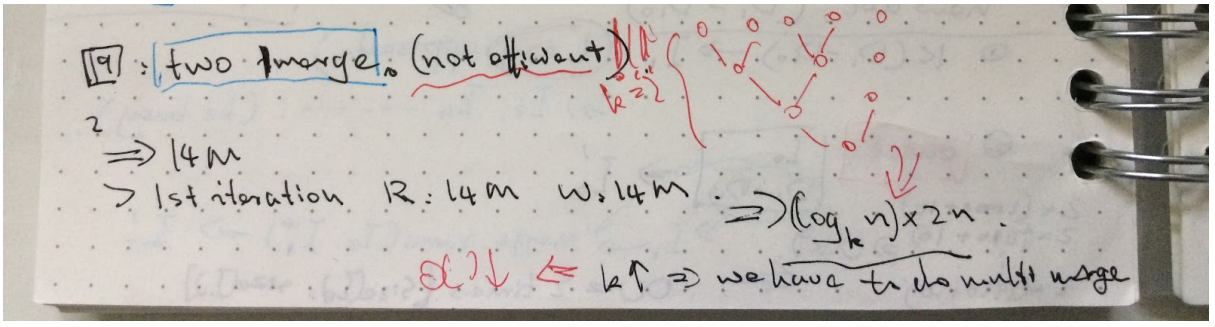
1. **Why we need dedicated algorithms to build the index?**
   Many design decisions in information retrieval are based on the **characteristics of hardware.**

2. **BSBI: Blocked sort-based indexing**
   Phase 1: Step 1 - step 4
   Step 1: all documents -> 10 blocks
   Step 2: read 2 blocks at one time
   Step 3: get m pairs and **sort them on the first column**(term id#), it's also the meaning of inverted
   Step 4: save them to file.
   Total number of files = Corpus size / by M(memory size)



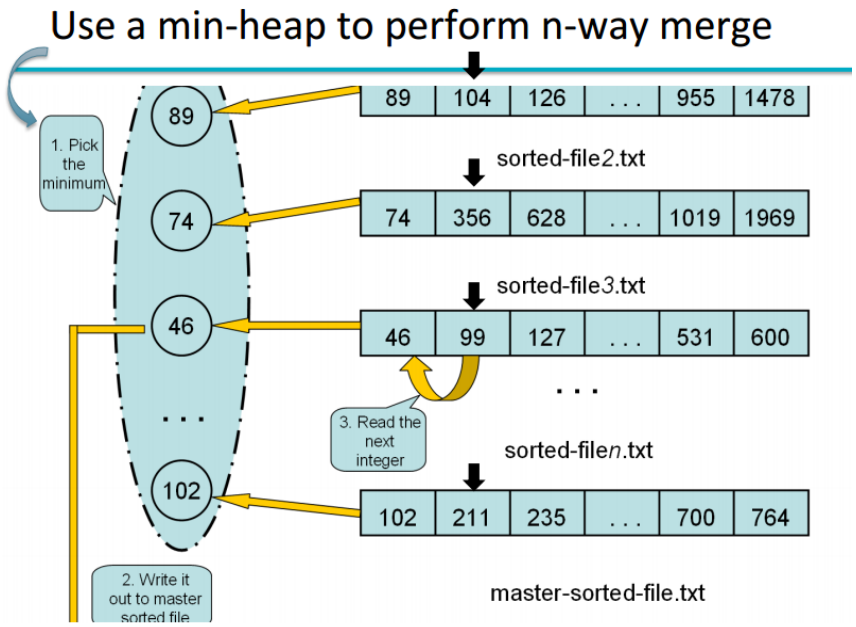
   Phase 2:
   Keep doing 2-way merge(OR)

   2-way merge is **not efficient**:



   Use a **min-heap** to perform **n-way merge:**

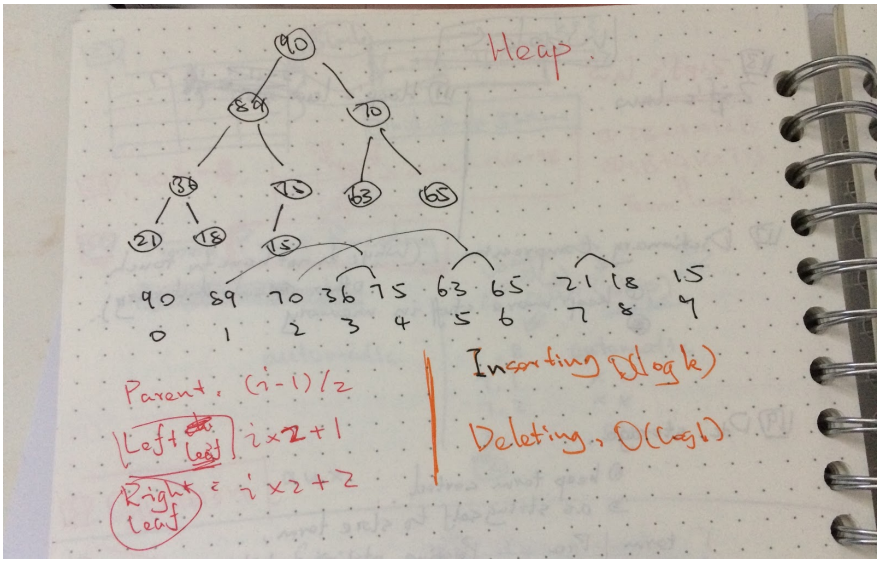
```
.. 3-way merge, initial page size = 2
.. Initial runs = [[15, 46], [19, 93], [64, 73], [33, 80], [26, 73], [22, 77], [27, 83], [7, 5
2], [12, 51], [7, 80], [19, 95], [36]]
.. New runs size = 4. Runs = [[15, 19, 46, 64, 73, 93], [22, 26, 33, 73, 77, 80], [7, 12, 27, 5
1, 52, 83], [7, 19, 36, 80, 95]]
.. New runs size = 2. Runs = [[7, 12, 15, 19, 22, 26, 27, 33, 46, 51, 52, 64, 73, 73, 77, 80, 8
3, 93], [7, 19, 36, 80, 95]]
.. New runs size = 1. Runs = [[7, 7, 12, 15, 19, 19, 22, 26, 27, 33, 36, 46, 51, 52, 64, 73, 73,
 77, 80, 80, 83, 93, 95]]
[7, 7, 12, 15, 19, 19, 22, 26, 27, 33, 36, 46, 51, 52, 64, 73, 73, 77, 80, 80, 83, 93, 95]
```



N-way merge time complexity analyse:In summary:
step 1: (finding the minimum element and delete it) is **O(log k),**
step 2: (inserting a new element from list) is **O(logk),** https://piazza.com/class/iqvpyd4946j42y?cid=14

As a result, the final cost of heap is **O(logk).**
Otherwise we have to scan the whole list to find the min element **O(k).**

How heap works:



3. **SPIMI: Single-pass in-memory indexing**
   Phase 1: Nothing special but **hash-based** algorithm, store hash instead of sorted indexes.
   Phase 2: Merging of blocks is similar to BSBI

```
4  do token ← next(token_stream)
5     if term(token) ∉ dictionary
6        then postings_list = AddToDictionary(dictionary, term(token))
7        else postings_list = GetPostingsList(dictionary, term(token))
8     if full(postings_list)
9        then postings_list = DoublePostingsList(dictionary, term(token))
10    AddToPostingsList(postings_list, docID(token))
11 sorted_terms ← SortTerms(dictionary)
12 WriteBlockToDisk(sorted_terms, dictionary, output_file)
```

Compression: there is free space in a page, and IO is the bottleneck.

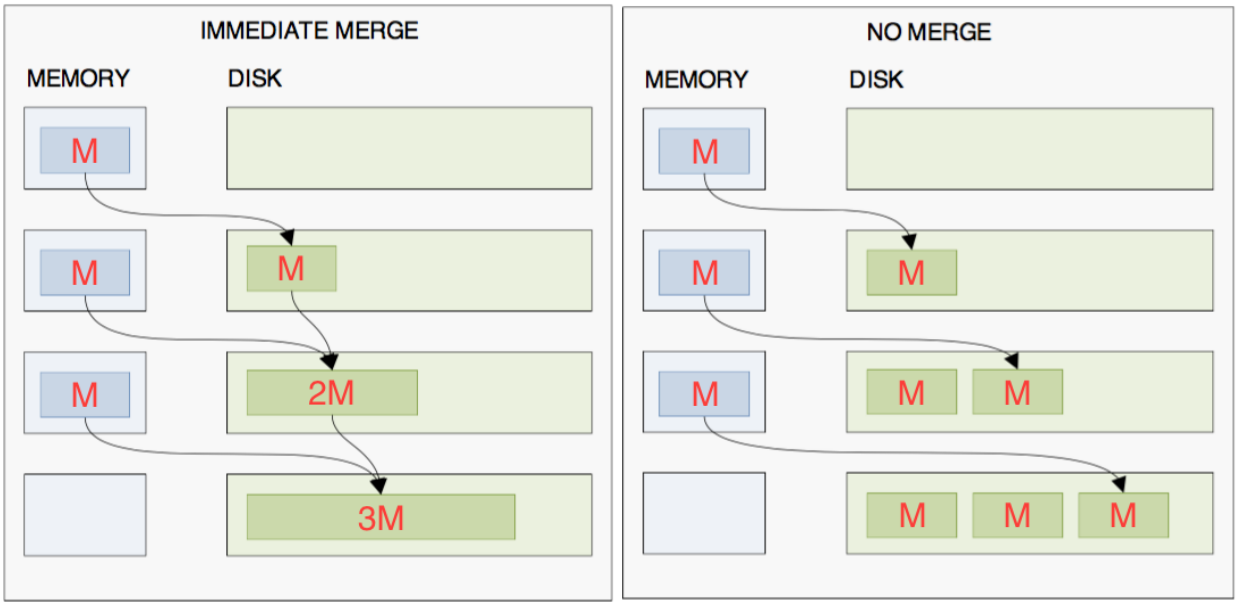
4. **Dynamic indexing: Immediate merge, no merge, logarithmic merge**

   Q4 of ass1:

   LAZY AND EAGER

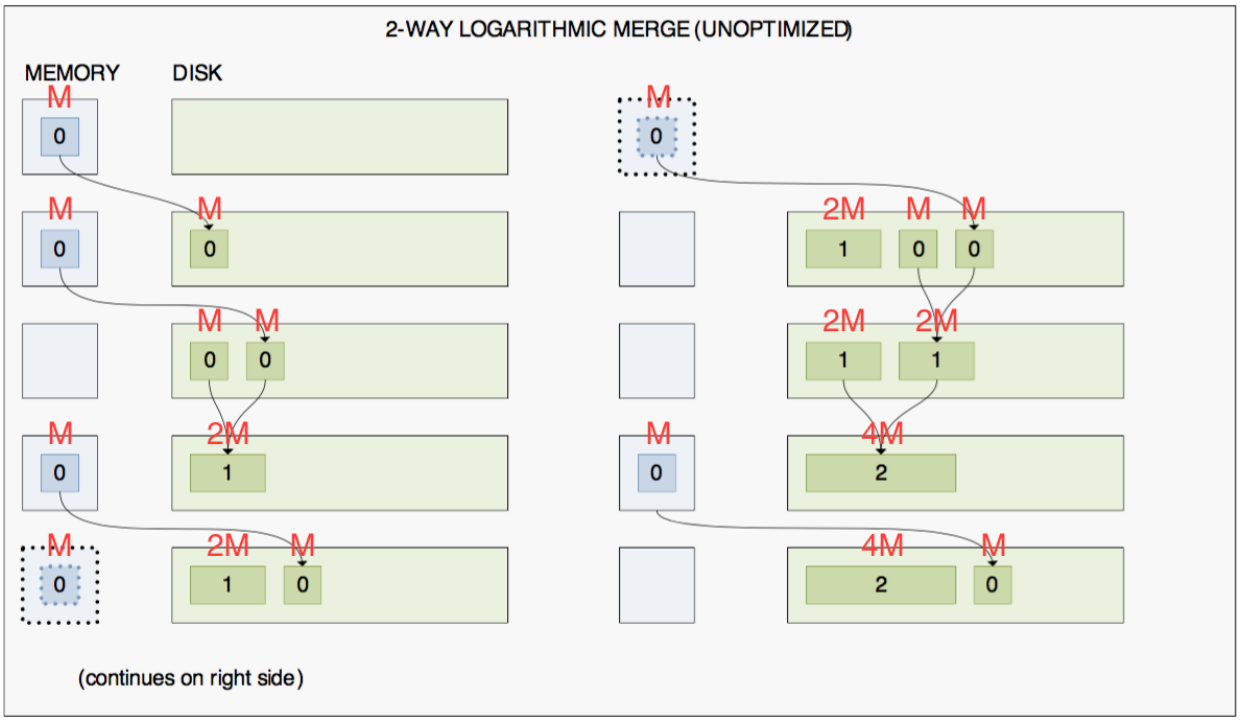
   Immediate merge. Always one sub-index.

   No merge. Let $n := \lceil \frac{|C|}{M} \rceil$. No merge will create n sub-indexes.

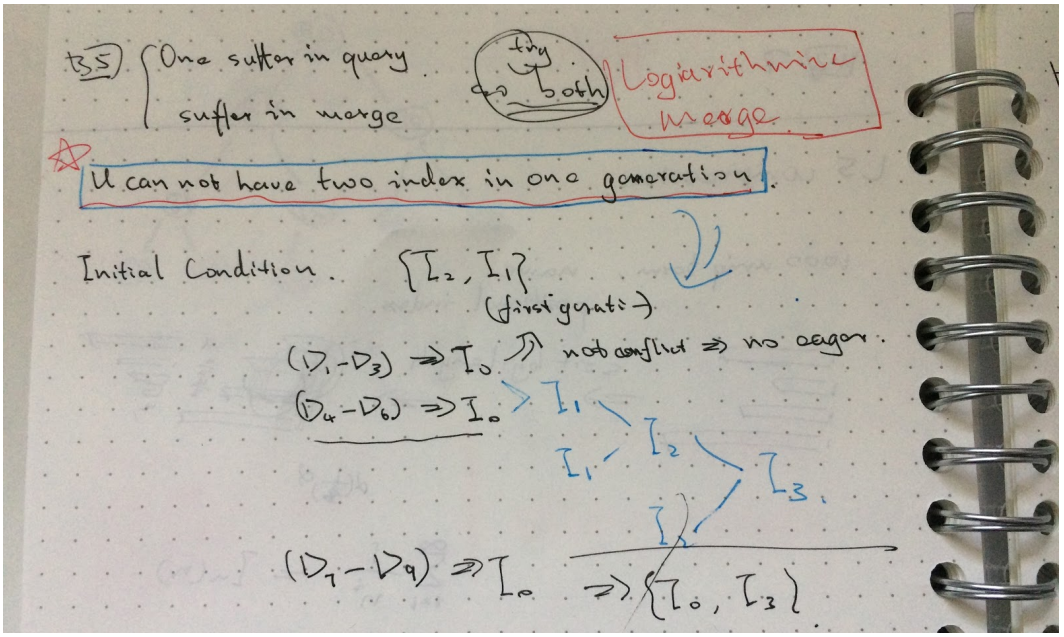


Logarithmic merge. Notice the 1-to-1 correspondence between the sub-indexes and the binary format of the number of sub-index created.

Therefore, the number of indexes is $f(n)$, where $f(n)$ gives the number of 1 in the binary representation of n. This is known as the *Hamming weight*[2]. Obviously, $f(n) = O(\log \lceil \frac{|C|}{M} \rceil)$.




```
>>> bin(1)
'0b1'
>>> bin(10)
'0b1010'
>>> bin(10).count('1')
2
```



D. Compression

1. **Why compression?**
   The speed of IO is always the bottleneck.
   1) Use less disk space → save money
   2) keep more stuff on memory → increase speed
   3) import from disk to memory, Premise: Decompression algorithms are fast.

2. **Heap's Laws and Zipf's Laws**
   1) Heap's Laws(growing at the square root size):
   Unique vocabulary vs total collection size in real documents
   - Heaps' law: $M = kT^b$
   - M is the size of the vocabulary, T is the number of tokens in the collection
   - Typical values: $30 \leq k \leq 100$ and $b \approx 0.5$
   - In a log-log plot of vocabulary size M vs. T, Heaps' law predicts a line with slope about ½

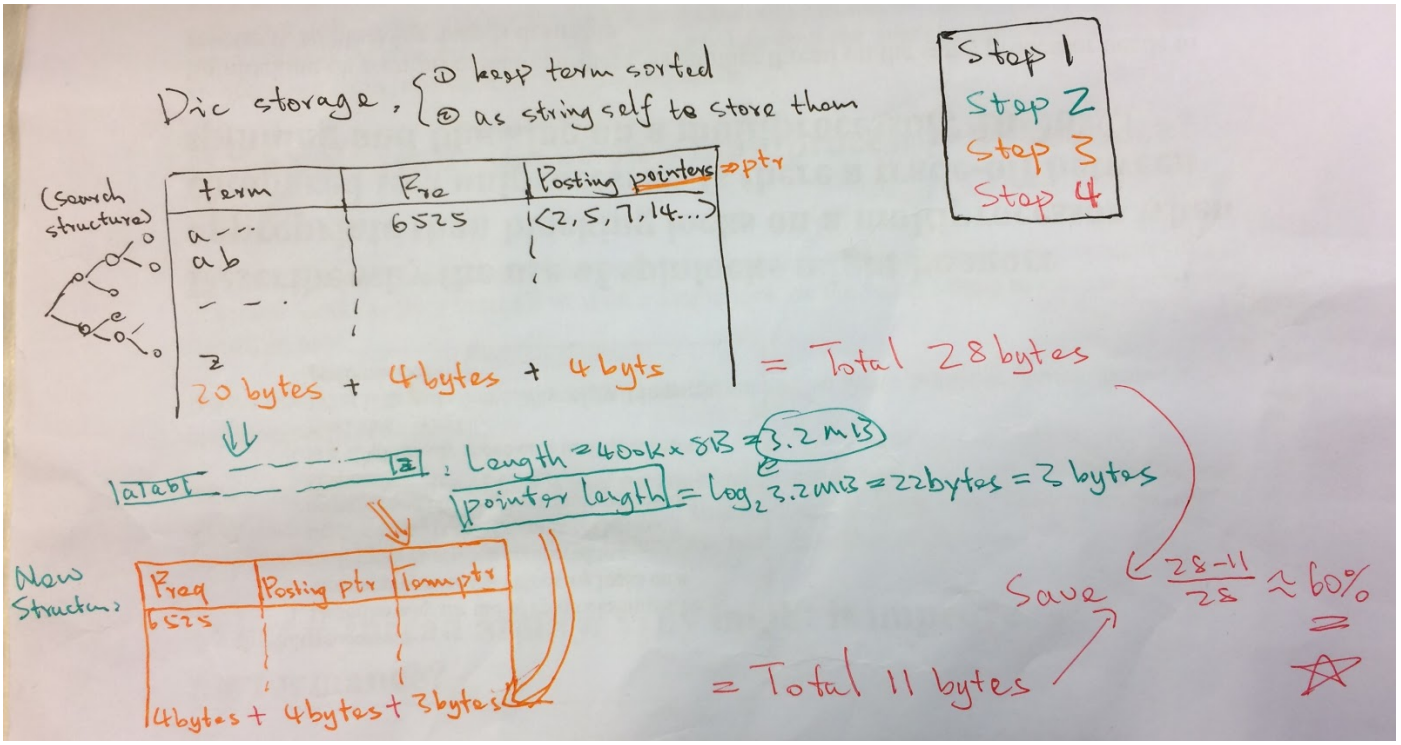
   Exercise:
   - Compute the vocabulary size M for this scenario:
     - Looking at a collection of web pages, you find that there are 3000 different terms in the first 10,000 tokens and 30,000 different terms in the first 1,000,000 tokens.
     - Assume a search engine indexes a total of 20,000,000,000 (2×10^{10}) pages, containing 200 tokens on average
     - What is the size of the vocabulary of the indexed collection as predicted by Heaps' law?

   Solution: k=30, so according to the formula, the size of vocabulary is 6*10^7.

   2) estimate the length of posting list
   If we sort the posting lists by size, the first is u, second is u/2, third is u/3
   Equivalent: $cf_i = K/i$ where K is a normalizing factor,
   so
   - $\log cf_i = \log K - \log i$
   - Linear relationship between $\log cf_i$ and $\log i$

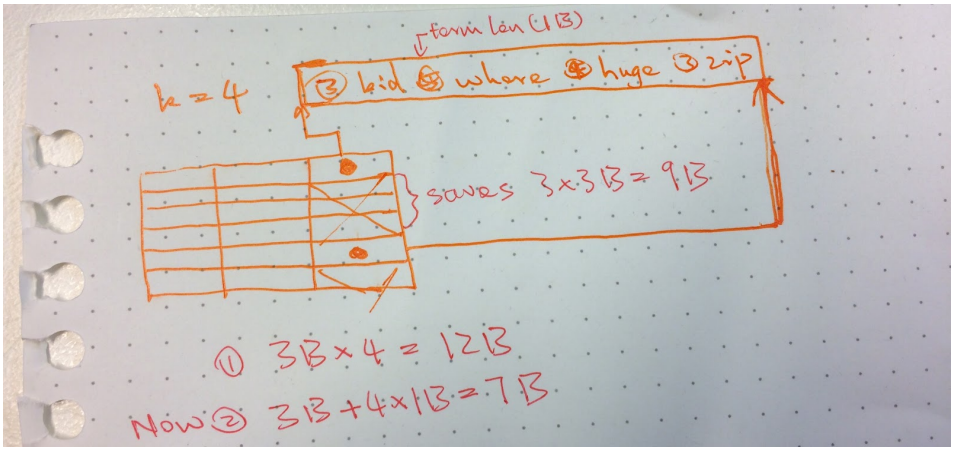
   Any **Exercise??**

3. Compression & organization of the dictionary



The graph above shows why **1) Dictionary-as-string** save up to **60% of dictionary space**.

2) Blocking: Store pointers to every kth term string
So for **each term ptr,** it saves(4 term positions → 1 block position) 3*3B, but also lost 4 bytes on **term lengths**.



3) Front coding: Sorted words commonly have long common prefix – store differences suffix only

- Complete front encoding
  - (prefix-len, suffix-len, suffix)
- Partial 3-in-4 front encoding
  - No encoding/compression for the first string in a block
  - Enables binary search

query aux

Assume previous string is "auto"

String	Complete Front Encoding	Partial 3-in-4 Front Encoding
8, automata	4, 4, mata	, 8, automata
8, automate	7, 1, e	7, 1, e
9, automatic	7, 2, ic	7, 2, ic
10, automation	8, 2, on	8, , on
aux	2,1,X	2,1,X

Why the last word's length is blank?
The length of the last string in the block can be inferred from the next block pointer. In compression, we try to squeeze out the last bit that is unnecessary.

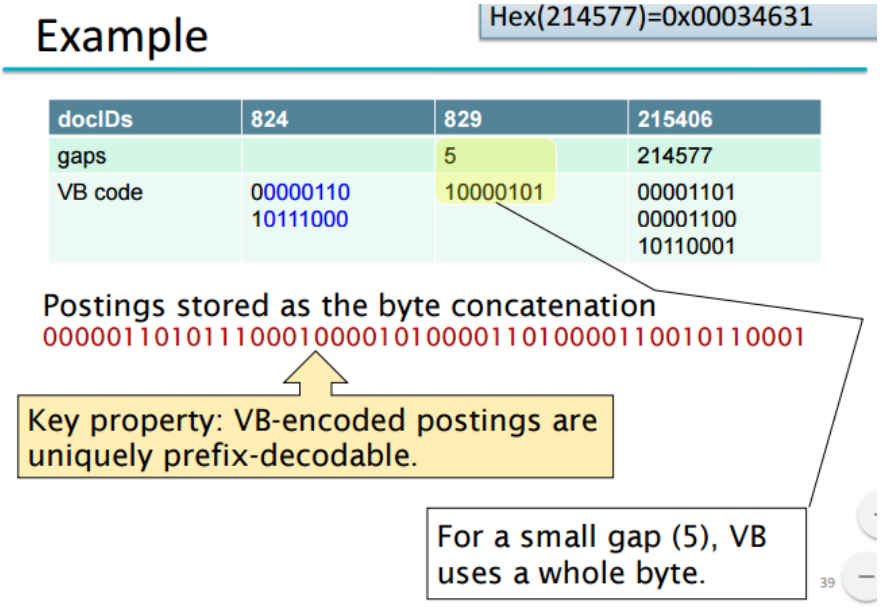
Advantage of **partial** front encoding: Skip in searching.
"Enable binary search" means that binary search can be used with partial front encoding, but *not* on the complete front encoding. This is because the former is used in conjunction with the block-based schemes, and **the first string of each block is stored as a plain string** (e.g., "automata") here. So **binary search** is possible to jump **to the right block** (and **then do sequential search within**). For complete front encoding, you have to decode all the strings before a string in question to get its plain content, hence not possible to do binary search.

Summary:
Fixed: 400K*(20B+4B+4B) = 11.2MB
1) dict: 400K*(4B+4B+3B) + 400K*8B(term average len) = 7.6MB
2) Block: 7.6MB - 400K/k*(3B*k-3B-k) = 7.1MB (k=4)
3) 5.9MB

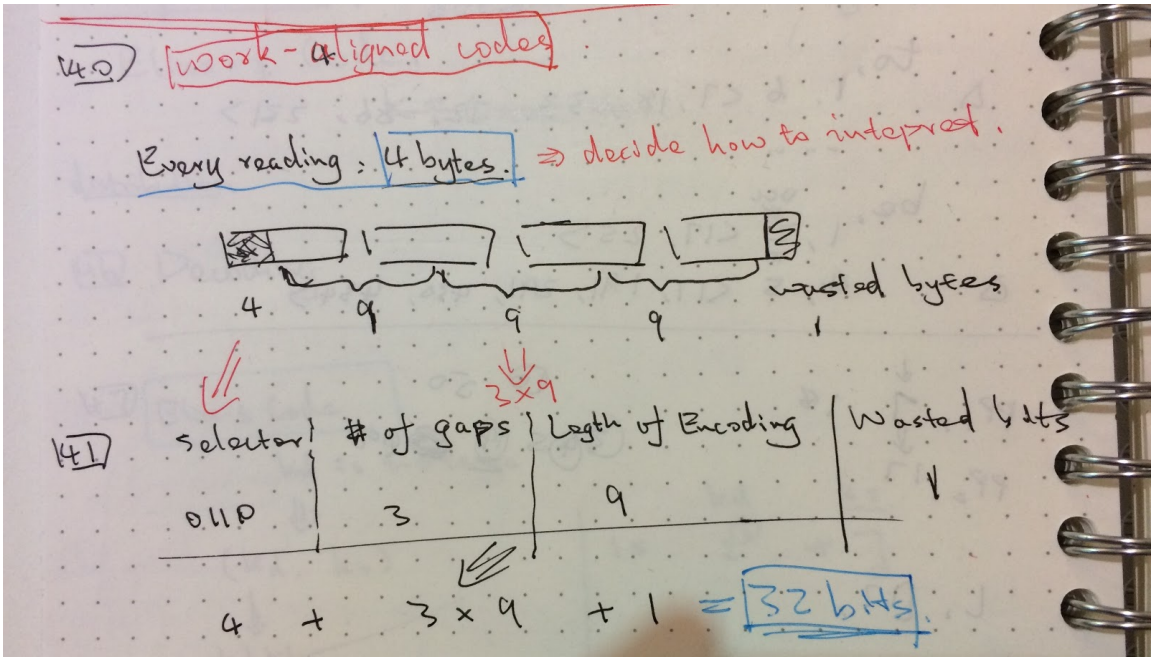
(question)P26 search impact….

4. **Compression & organization of the inverted index: byte vs bit aligned codes.**
Difference of byte and bit:
For byte aligned, *every* input must be encoded in bytes (i.e., canno9t be say 13 bits). The rest is bit-aligned.

1. VB(variable Byte) encoding
Continuation bit:
1: it's the last set
0: need to read next set



2. Word-aligned codes

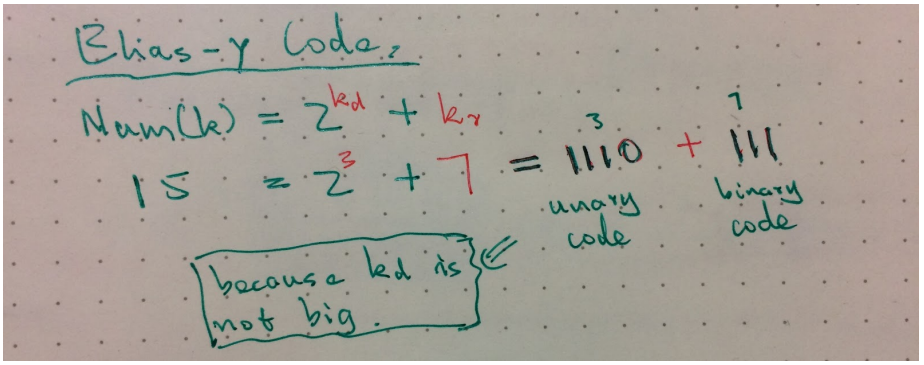


3. Unary Code

Unary = Represent n as n 1s with a final 0 e.g. 3 -> 1110.
Unary is very efficient for small numbers but expensive for large number.
Binary is more efficient for large numbers but can be ambiguous.

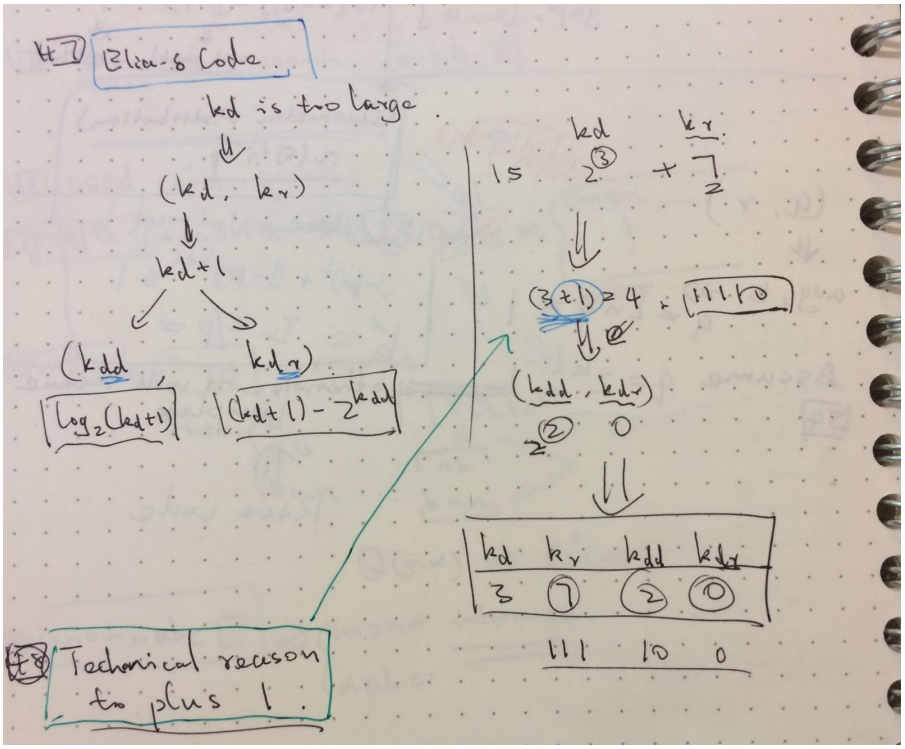
Elias-γ Code

K = concat(Kd, Kr) where Kd = ⌊log2 (K)⌋ in unary and Kr = K - 2^ ⌊log2 (K)⌋ in binary
E.g. 15; Kd = 3 -> 1110, Kr = 7 -> 111; 1110 111
γ Code uses 2 ⌊log2 (K)⌋ + 1 bits



Elias-δ Code

K = concat(Kdd, Kdr, Kr) where Kr = K - 2^ ⌊log2 (K)⌋ in binary and
Kdd = ⌊log2 (Kd + 1)⌋ in unary, Kdr = (Kd + 1) - 2 ^ ⌊log2 (Kd + 1)⌋ in binary

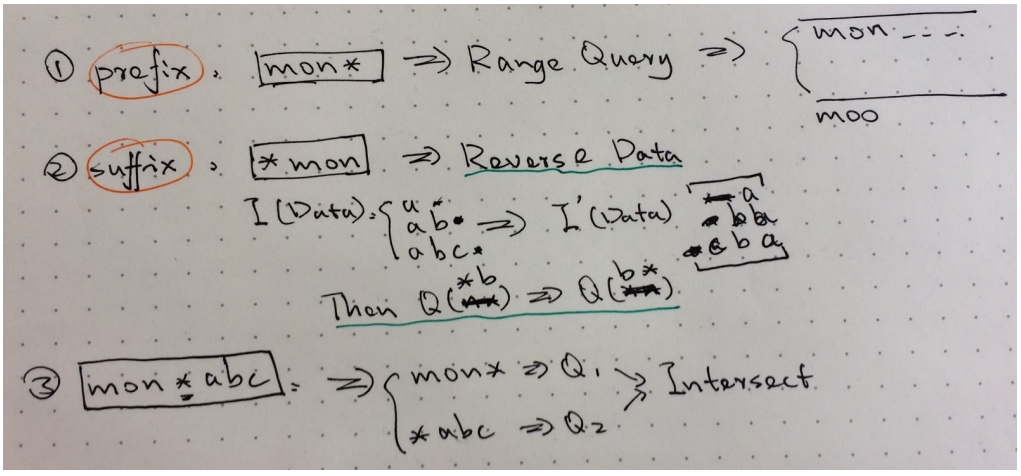


Not required: Simple, Details of the Golomb code, Google’s group varint encoding (the WSDM09 slides Pages 55–63)

E. Tolerant Retrieval

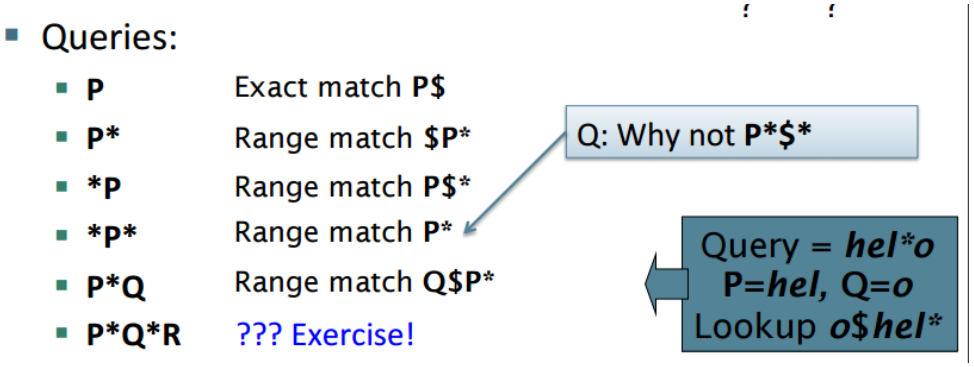
1. **Wildcard queries using a B-tree, a permuterm index, or a k-gram index.**
   1) Hash:
   Pro: fast(O(1))
   Cons: i. Hard to find variance, e.g. judgement/judgment
   ii. No prefix search
   iii. have to rehash when size increases.

   2) B-tree:
   Pro: Prefix search available
   Cons: i: Slow, balanced tree → O(log n)
   ii: Rebalancing binary trees is expensive
   // just to clarify, binary tree requires large balancing time, but B-tree does not require that much -hengji
   Handle wild-card queries:

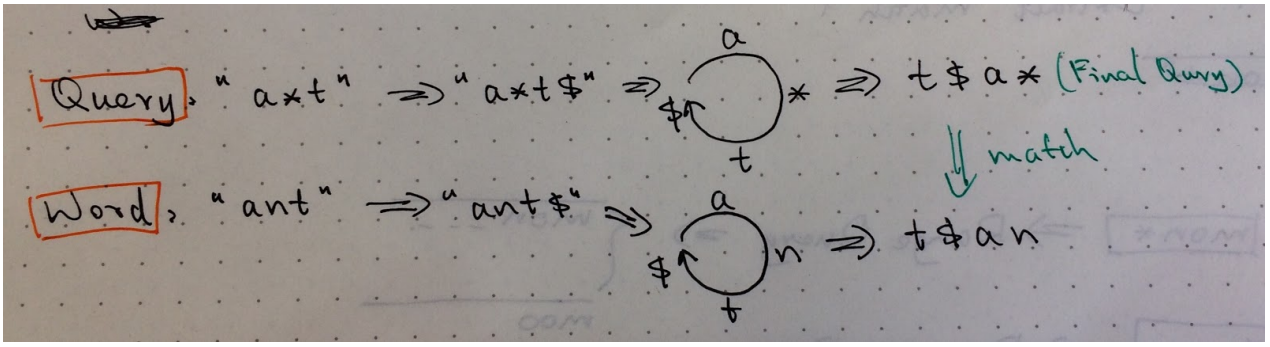


~~2.1) tier? Not required?~~

3) **permuterm index:**



How it works(understand it rather remember)?
Our final aim is to transfer all query to prefix query!



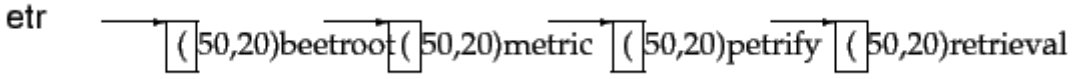
a) *P* → P(*)$(*) → P* **(Question: WHY: query is Public * means .+ instead of *+ ?)**

// can you rephrase the qu-estion? -hengji
b) P*Q*R: **(HOW)**
R$PQ*

Cons: simple but permuterm index can lead to a considerable blowup from the number of rotations per term

4) k-gram:
$ is a special word boundary symbol
1) "April" →"$April$"→ a,ap,pr,ri,il, l,i,is,s,t,th,he,e,$c,cr,ru, ue,el,le,es,st,t$, m,mo,on,nt,h
2) "mon*" → $m AND **mo** AND **on**
3) post-filtering: wrong result. e.g., "moon" is included.

(Q. How to store the index and how to do the query??) solved
The 3-gram **"etr"** would point to vocabulary terms such as metric and retrieval.



2. **Context-insensitive spelling correction: edit distance, Jaccard of n-grams. Context-sensitive spelling correction: Noisy channel model**
1) edit distance:

```
del[x,y]:    count(xy typed as x)
ins[x,y]:    count(x typed as xy)
sub[x,y]:    count(x typed as y)
trans[x,y]:  count(xy typed as yx)
```

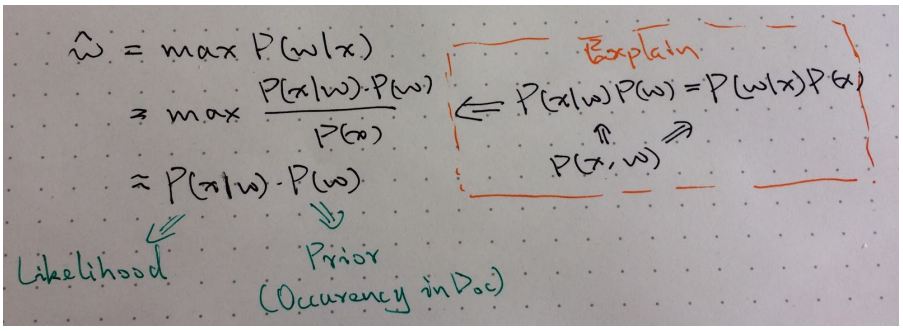
2) Jaccard of n-grams
https://www.cs.utah.edu/~jeffp/teaching/cs5140-S15/cs5140/L4-Jaccard+nGram.pdf
D1: I am Sam → [I am], [am Sam]
D2: Sam I am → [Sam I], [I am]
So JS(D1, D2) = 1/3

3) Context-sensitive spelling correction: Noisy channel model, My favourite part :)
(Only for non-word spelling error)
Main Steps:
a. Find a set of ***candidates(based on edit distance, e.g. distance == 1)***.
b. Score each word in the candidates based on the noisy **channel model.**

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|word)	P(word)	10^9*P(x|w)P(w)
actress	t	-	c|ct	.000117	.0000231	2.7
cress	-	a	a|#	.00000144	.000000544	.00078
caress	ca	ac	ac|ca	.00000164	.00000170	.0028
access	c	r	r|c	.000000209	.0000916	.019
across	**o**	**e**	**e|o**	**.0000093**	**.000299**	**2.8**
acres	-	s	es|e	.0000321	.0000318	1.0
acres	-	s	ss|s	.0000342	.0000318	1.0

Noisy channel model:

W: Hyposity(candidates)
X: Observation(wrong words)



Likelihood:

a. checking the confusion matrix

b.

```
BETA = 1.0

def score(err, beta = BETA):
    return exp(-beta * err)
```

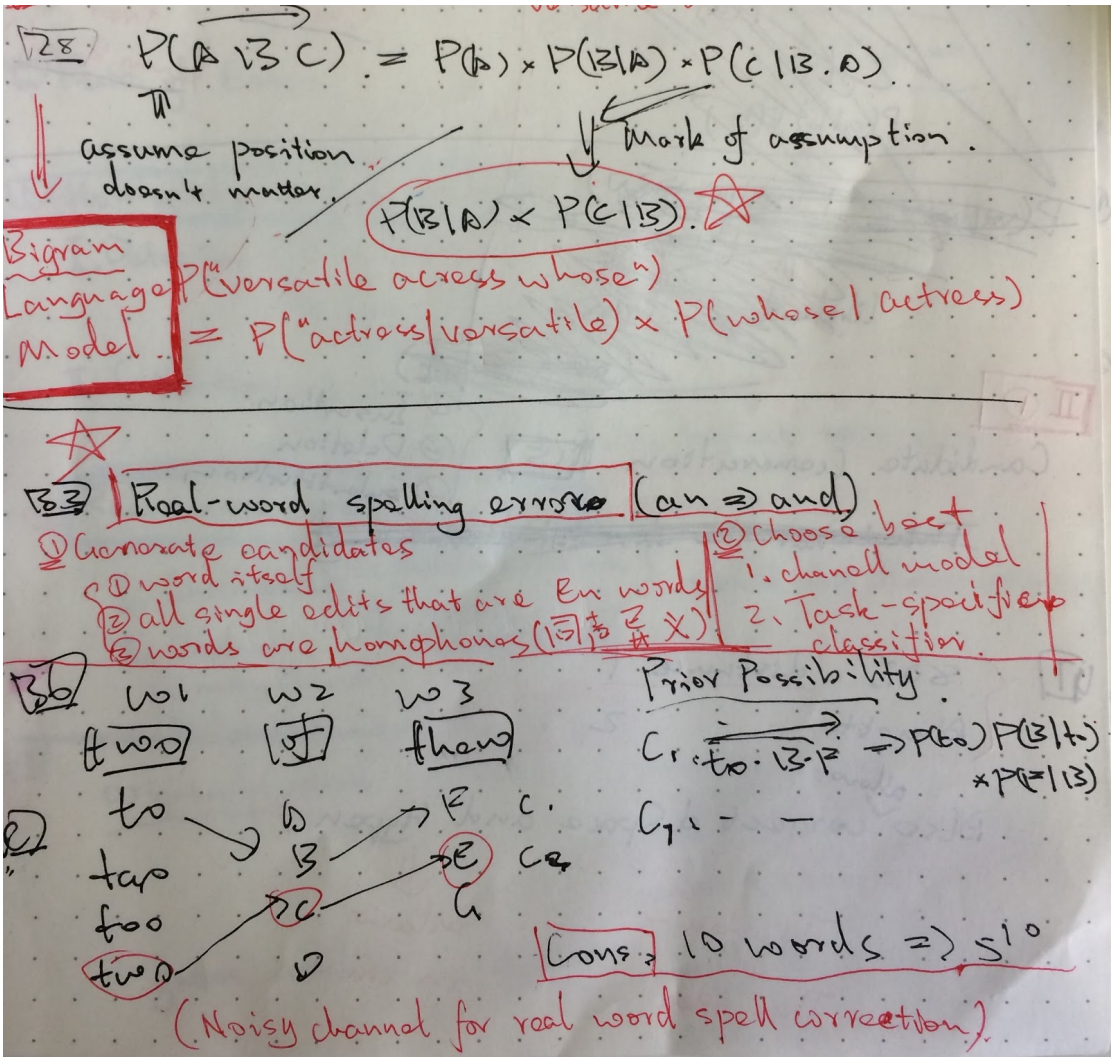
math.**exp**(x)
Return e**x.

Takes the context into consideration, also useful for real word spelling error.

Main idea of **bigram language model:**

$$P(ABC) = P(A)P(B \mid A)P(C \mid AB) = P(A)P(B \mid A)P(C \mid B)$$

The first $=$ is exact, due to the chain rule. The second $=$ holds as we use the bigram model which assumes $P(X \mid A, B, \ldots, W) = P(X \mid W)$



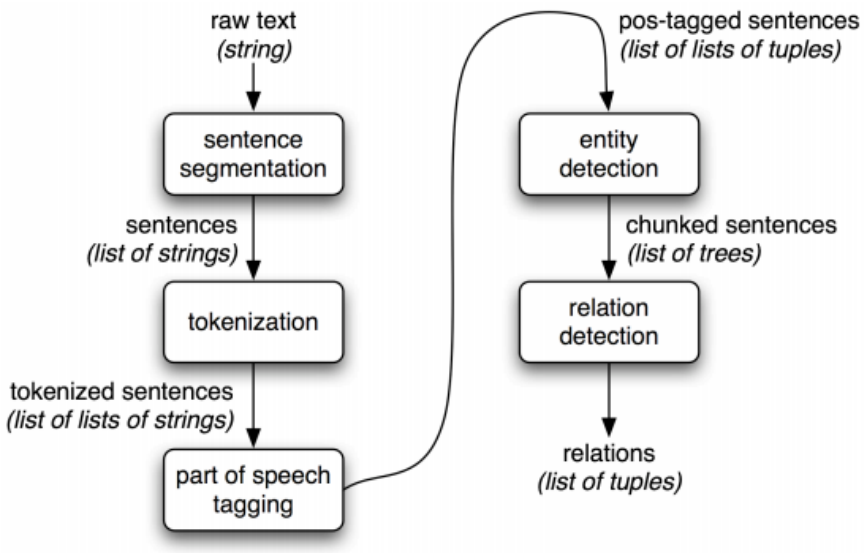
What is the channel probability for a correctly typed word?

Possibility of no error:

1 error in 20 words: P(“the”|”the”) = (20-1)/20

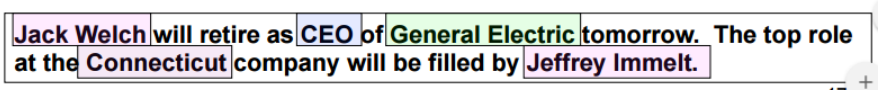
F. Information Extraction

1. Information extraction and its subtasks.
   Task: Filling slots in a database from unstructured text. [NAME, TITLE, ORGANIZATION**]**
   IE = Information extraction = segmentation + classification + association
   Subtasks:



2. Named entity recognition.
   Aim: identify all textual mentions of the named entities.
   Named entities: definite noun phrases that refer to specific types of individuals, such as organizations, persons, dates etc..

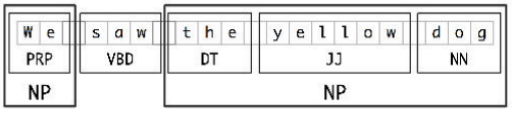
   - Can be broken down into two sub-tasks:
     1. identifying the boundaries of the NE (segmentation)
     2. identifying its type (classification)



   Method:
   Look up each word in an appropriate list of names.

   Ambiguity:
   1. Words have different meanings in different situation.
   2. Multi-word names like Stanford University.
   3. Name that contains other names: Henry's awesome note.
   Therefore, we need to be able to identify the beginning and end of multi-token sequencesà **chunking.**

   - Chunking useful for entity recognition
   - Segment and label multi-token sequences



   - Each of these larger boxes is called a chunk

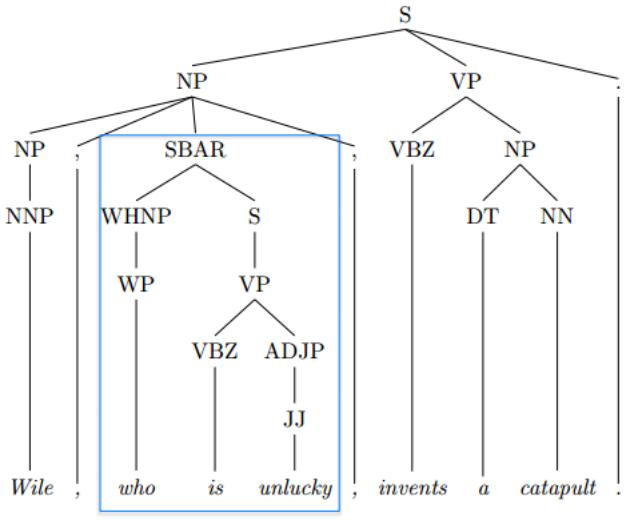
3. Pattern-based Relation Extraction: use of POS, and parsers

POS Tagging:

Word	POS	Chunk	EntityType
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	O

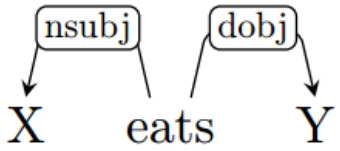
Parser(consider grammar):

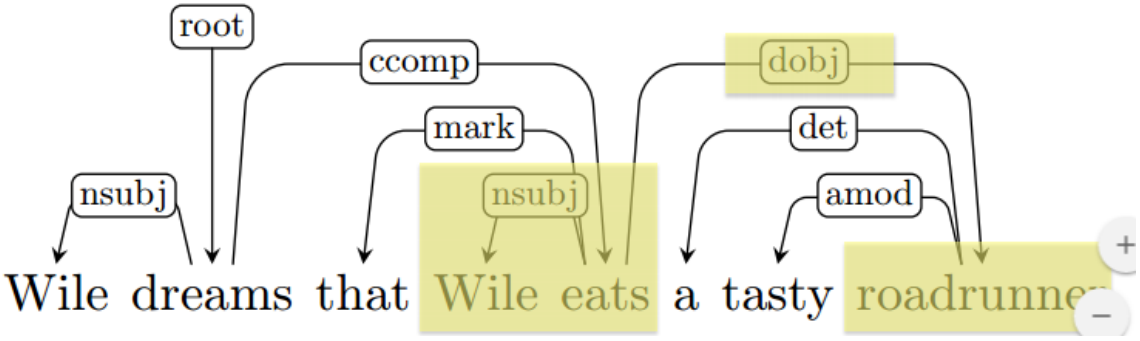
1. Constituent parse



This is just a sub-ordinate clause

2. Dependency parse





G. Vector Space Model

1. **What is/why ranked retrieval?**

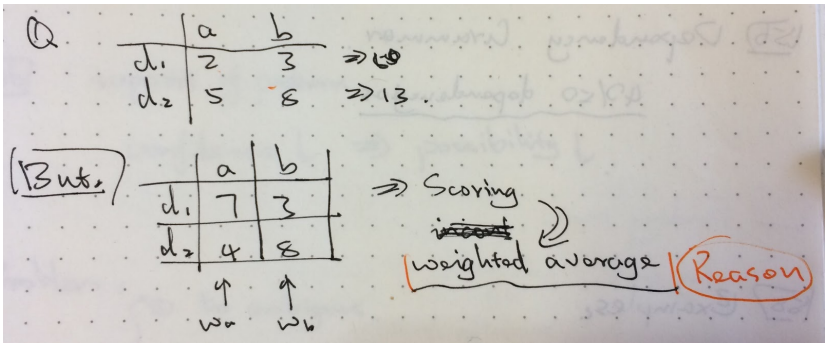
   1) What:

   returning an ordering of the top documents in the collection rather than the complete set

   2) Because:

   - Normal boolean search results in either too few (don't match) or too many results
   - Normal users cannot look through the whole returned docs

   3) The reason why we need weighted average:



2. **raw and normalized tf, idf**

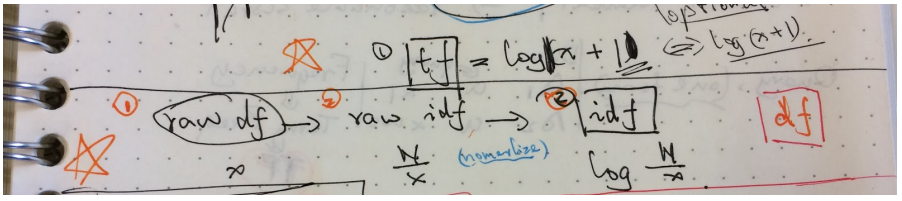
   1) tf (term frequency)

   $$Raw\ tf = tf_{t,d} = How\ many\ times\ term(t)\ occurs\ in\ doc(d)$$

   Then $tf = log(raw\ tf) + 1$ or $tf = log(raw\ tf + 1)$

   2) df (document frequency: How many documents that contain t**)**

   Raw df → raw idf → idf

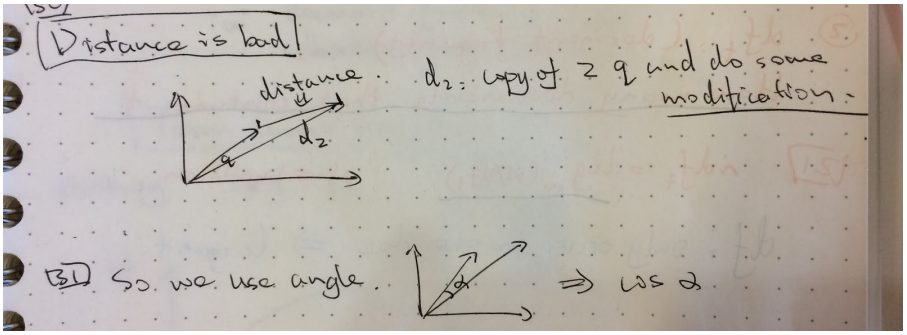


   1) + 2) → The final tf-idf weighting:

$$\text{Score}(q,d) = \sum_{t \in q \cap d} \text{tf.idf}_{t,d}$$

3. **cosine similarity**

   Because distance is a bad idea:



   My useful question about this part:
   https://piazza.com/class/iqvpyd4946j42y?cid=108

And Lab for this part(just do this lab and u will understand everything):
https://github.com/DBWangGroupUNSW/COMP6714/blob/master/L8%20-%20tf-idf.ipynb

Calculation of cosine of two vectors.

Step 1: Length normalization

Total length = $\|\vec{x}\|_2 = \sqrt{\sum_i x_i^2}$

Then get the normalized value by dividing this length.

```
import math
def l2_normalizer(vec):
    denom = np.sum([el**2 for el in vec])
    return [(el / math.sqrt(denom)) for el in vec]
```

Step 2: cosine(query,document)

Dot product Unit vectors

$$\cos(\vec{q},\vec{d}) = \frac{\vec{q}\bullet\vec{d}}{|\vec{q}||\vec{d}|} = \frac{\vec{q}}{|\vec{q}|}\bullet\frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2}\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

For example:

Normalized query vector: [0, 0, 0, 0.4, 0.1, 0.3, 0]

Normalized doc vector: [0, 0.1, 0, 0.1, 0.5, 0, 0]

$cos(q,\ d) = (0.4\ x\ 0.1 + 0.1\ x\ 0.5)\ /\ (1x1)$

4. **tf-idf variants (using SMART notation):**

Format is ddd.qqq for term frequency, document frequency, normalization coding structure in weighting formula of document and query e.g., lnc.ltc means documents use logarithm term freq, no idf weighting and cosine normalization while queries use logarithm tf, idf and cosine normalization

Term frequency		Document frequency		Normalization	
n (natural)	$tf_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(tf_{t,d})$	t (idf)	$\log \frac{N}{df_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+...+w_M^2}}$
a (augmented)	$0.5 + \frac{0.5\times tf_{t,d}}{\max_t(tf_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N-df_t}{df_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases}1 & \text{if } tf_{t,d} > 0\\ 0 & \text{otherwise}\end{cases}$			b (byte size)	$1/CharLength^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1+\log(tf_{t,d})}{1+\log(ave_{t\in d}(tf_{t,d}))}$				

We implement an equivalent form of the lnc.ltc model. Therefore, there is **no idf weighting on the query terms**, since it is already used in the document matrix.

Doc → [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]

Query → [0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1]

tf-idf example: lnc.ltc

Document: *car insurance auto insurance*
Query: *best car insurance*

Term	Query						Document				Prod
	tf-raw	tf-wt	df	idf	wt	n'lize	tf-raw	tf-wt	wt	n'lize	
auto	0	0	5000	2.3	0	0	1	1	1	0.52	0
best	1	1	50000	1.3	1.3	0.34	0	0	0	0	0
car	1	1	10000	2.0	2.0	0.52	1	1	1	0.52	0.27
insurance	1	1	1000	3.0	3.0	0.78	2	1.3	1.3	0.68	0.53

Exercise: what is *N*, the number of docs?

Doc length $=\sqrt{1^2+0^2+1^2+1.3^2} \approx 1.92$

Score = 0+0+0.27+0.53 = 0.8

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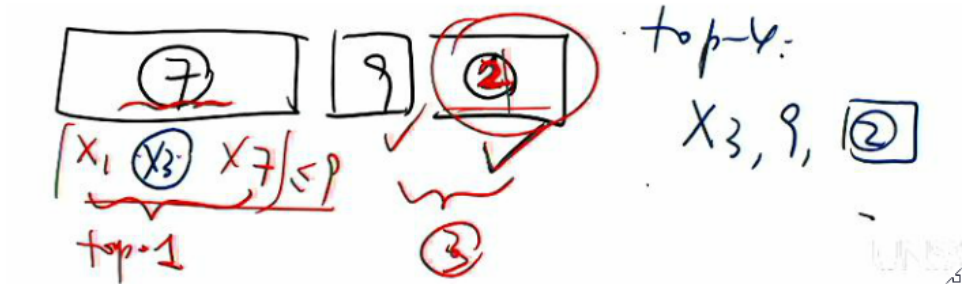
5. **Challenges of query**(add by myself):
   1) CANDIDATES → 80%(10 million doc) → get result of 8 million docs
   2) Query: $R(a \vee b \vee c)$, if c is a very common word → score a large number of docs → large df → small idf → small weight→ contribute to the final score is low
   3) inverted index is too large → to much I/O time

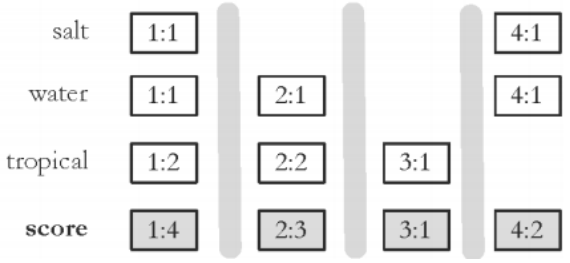
   See 8(4) for optimization.

6. **exact & approximate query optimization methods (heap-based top-k)**
   Get the top 7 numbers in [1, 2, 45, 23, 2, 12, 5, 2, 9, 6]
   1) min heap: n log K**o**
   2) if the entire array in memory: **quick select**

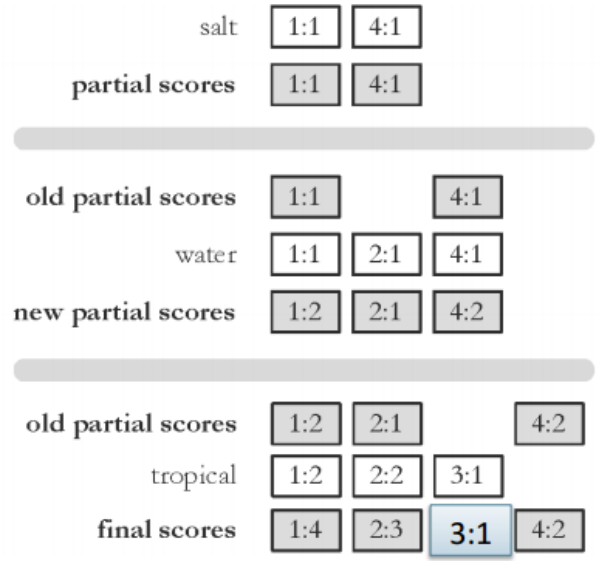


   Time complexity: n + KlogK(sorting)

7. basic query processing method: document-at-a-time vs term-at-a-time
   [4: 2] means this term occurs twice in the doc4.
   DAAT:



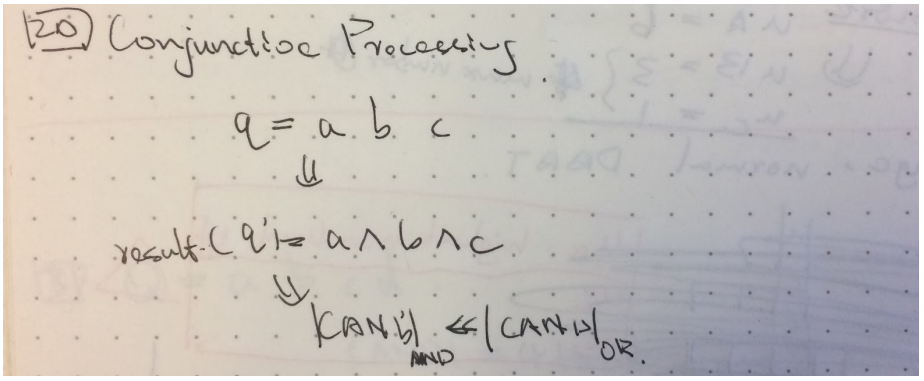
   TAAT:



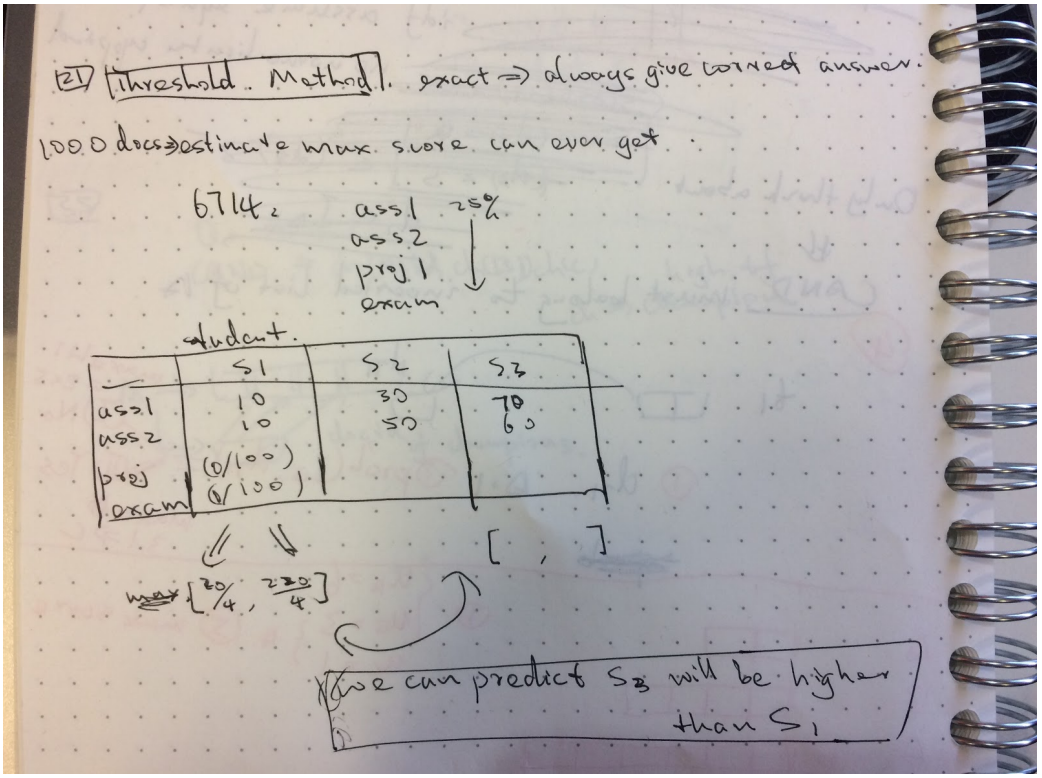
8. algorithm, MaxScore algorithm, etc.)

1) Conjunction method:

Requires the result document containing all the query terms (i.e., conjunctive Boolean queries)



2) Threshold Methods



3) Maxscore methods

Ass2 Q1

4) Index elimination(optimization)

Only consider docs containing any query terms

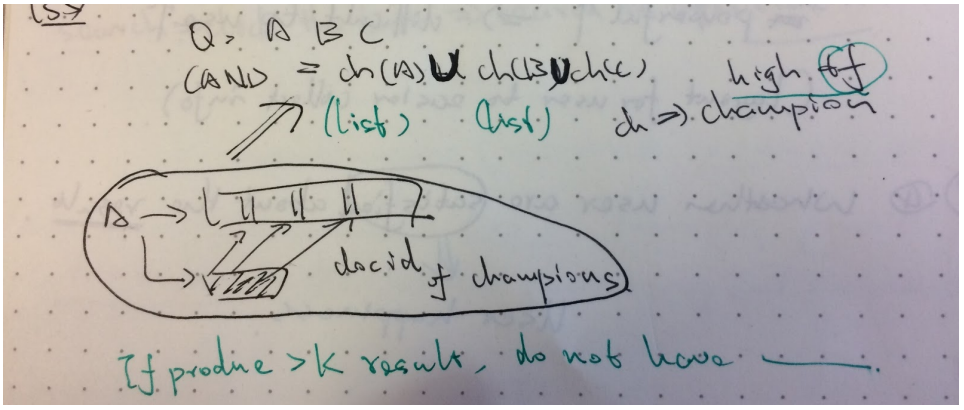
Only consider high-idf query terms

Only consider docs containing many query terms

Only consider docs containing any query terms

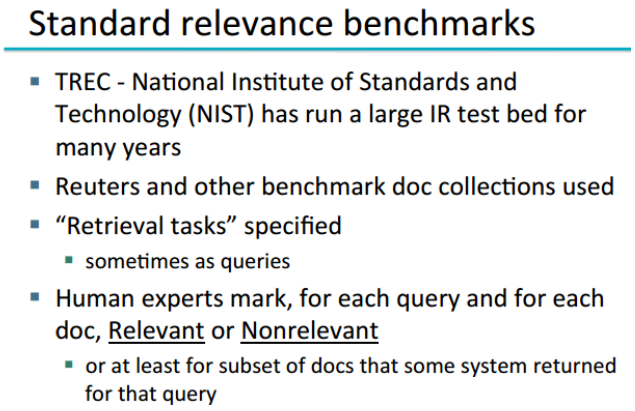
5) Champion lists

ch(A) means the top guys of documents that contain A.



H. Evaluation

1. Existing method to prepare for the benchmark dataset, queries, and ground truth
   1) benchmark dataset(correct answer):

   2) queries:

   3) ground truth((1)+(2)?):

2. Efficiency of a search engine(P4):
   1) index: Number of documents/hour
   2) How fast of search:
   Give 100ms then evaluate how many results returned
   3) Expressiveness of query language
   Ability to express complex information needs
   Speed on complex queries

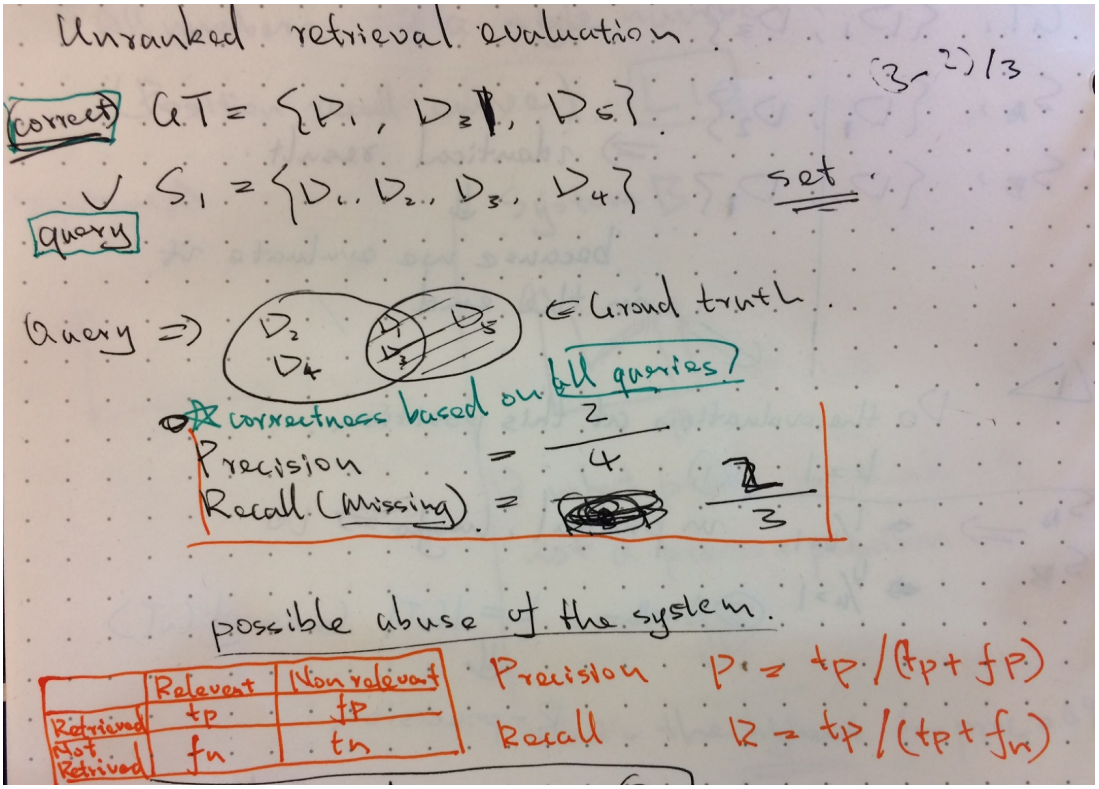
3. For unranked results: Precision, recall, F-measure

$$P = \frac{\#relevant\ doc\ in\ results}{\#total\ retrieved\ docs\ in\ query\ results}$$

$$R = \frac{\#relevant\ doc\ in\ results}{\#total\ relevant\ docs\ in\ system}$$

$$F = \frac{1}{\frac{\alpha}{P}+\frac{(1-\alpha)}{R}} = \frac{(\beta^2+1)PR}{\beta^2 P+R} = \frac{2PR}{(P+R)}$$

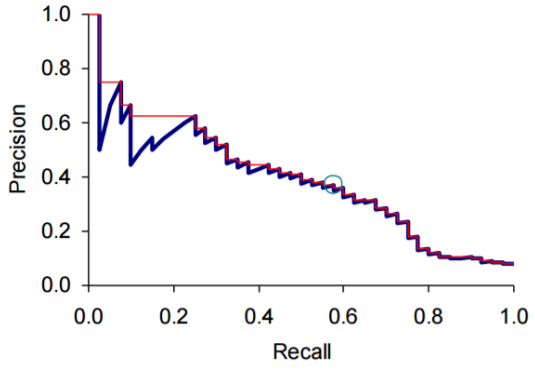
Balanced F1 measure is α=0.5, β=1



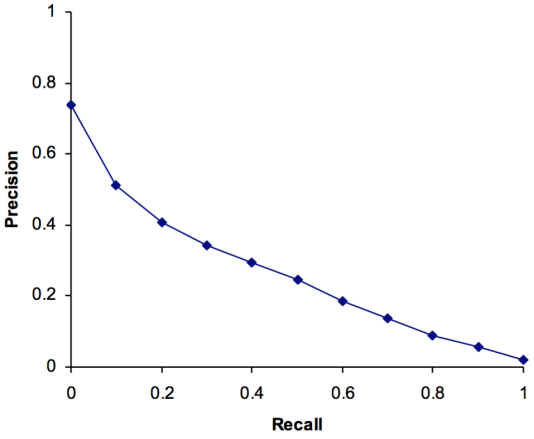
4. For ranked results: **precision-recall graph**, **11-point interpolated precision**, **MAP**, etc.

$$p_{interp}(r) = \max_{r' \geq r} p(r')$$

1) precision-recall graph(the red line is interpolated precision)



2) 11-point interpolated precision



how do you calculate this from the interpolations?? anyone?

It;s uninterpolated. I think/

just get the 11 points(1, 0.1, 0.2, … 0.9, 1.0) and connect them. but how to

calculate the value of precision? the plots are (0,~7.5)(0.1,~0.5)...

3) MAP and Kappa(is this required)

MAP - Ex result = **R R** N N N N N N **R** N **R** N N N **R** N N N N **R**,
total relevant doc = 8; $MAP = \frac{1}{8} \times \left(\frac{1}{1} + \frac{2}{2} + \frac{3}{9} + \frac{4}{11} + \frac{5}{15} + \frac{6}{20}\right)$

Kappa measure agreement between judges

$Kappa = \frac{[P(A)-P(E)]}{[1-P(E)]}$; A = all judges agree same point

Total = 400	**Judge 2: R**	**Judge 2: NR**
Judge 1: R	300	20
Judge 1: NR	10	70

$P(A) = \frac{300+70}{400} = 0.9250$; $P(NR) = \frac{10+70+20+70}{400+400} = 0.2125$

$P(R) = \frac{300+20+300+10}{400+400} = 0.7875$;

$P(E) = P(NR)^2 + P(R)^2 = (0.2125)^2 + (0.7875)^2 = 0.6653$

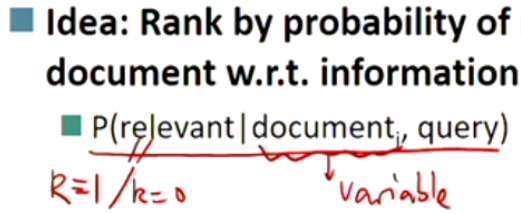
$Kappa = \frac{(0.9250-0.6653)}{(1-0.6653)} = 0.7759$;

Kappa > 0.8 = good agreement; 0.67 < Kappa < 0.8 = tentative

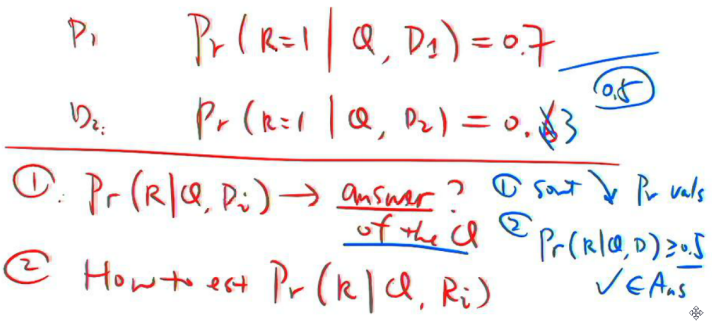
I. Probabilistic Model and Language Model

1. probability ranking principle (intuitively, how to rank documents and when to stop)
   (not sure about this part, headache about math)

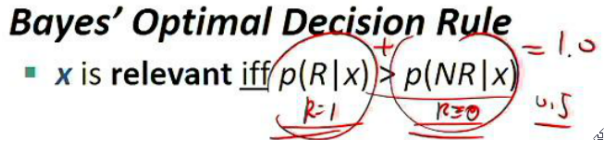
   1) We can use **this P** to present the possibility of how relevant the doc is, then sort them.

   2) Stop at >= 0.5 means only output D1(0.7) not D2(0.3).

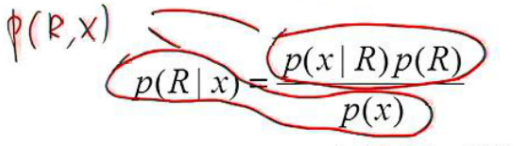
   

   3) 0.5 is because of:

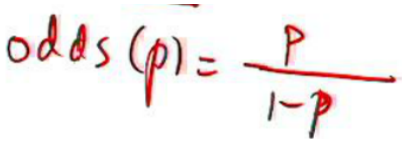
   

   4) The problem is **how do we estimate P(relevant | doc, query)**

   a.

   b. Odds:

   c. each document is a vector(only difference is that the x is either 1 or 0)
   (Then I was totally lost in this part….give up)

2. derivation of the ranking formula of the probabilistic model
   (check the echo video of w11(end) w12(start))

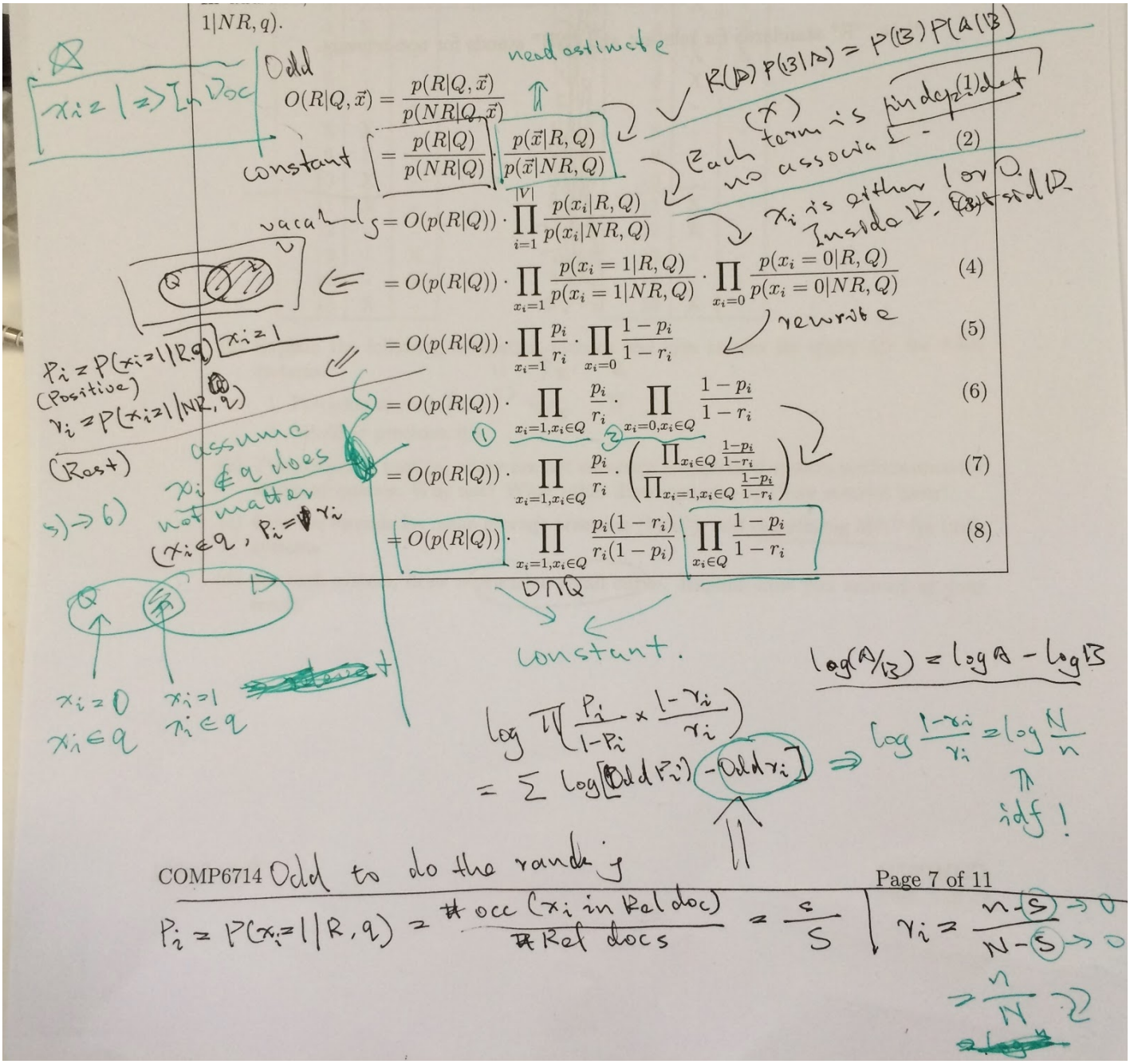
3. the BM25 method

$$RSV_d = \sum_{t \in Q} idf_t \cdot \frac{(k_1+1)tf_{t,d}}{k_1\left((1-b)+b\frac{L_d}{L_{ave}}\right)+tf_{t,d}} \cdot \frac{(k_3+1)tf_{t,Q}}{k_3+tf_{t,Q}}$$

4. **Query-likelihood unigram language model with Jelinek-Mercer smoothing.**

$$p(Q,d) = p(d)\prod_{t\in Q}\left((1-\lambda)p(t) + \lambda p(t|M_d)\right)$$

5. Binary independence model
   (check the echo video of w11(end) w12(start))



J. Web Search Basics and Link Analysis

1. Categorization of query types: **informational**, **navigational**, and **transactional**.

   From MRS08 p.432
   Informational queries seek general information on a broad topic, such as leukemia or Provence. There is typically not a single web page that contains all the information sought; indeed, users with informational queries typically try to assimilate information from multiple web pages.

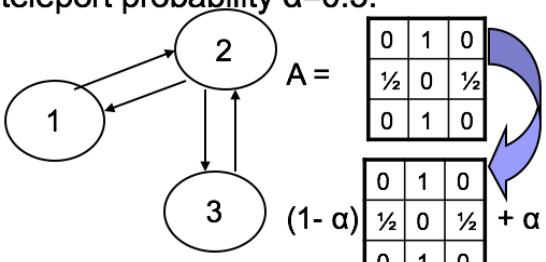
   Navigational queries seek the website or homepage of a single entity that the user has in mind, say Lufthansa airlines. In such cases, the user's expectation is that the very first search result should be the home page of Lufthansa. The user is not interested in a plethora of documents containing the term Lufthansa; for such a user, the best measure of user satisfaction is precision at 1.

   A **transactional query** is one that is a prelude to the user performing a transaction on the Web – such as purchasing a product, downloading a file or making a reservation. In such cases, the search engine should return results listing services that provide form interfaces for such transactions.

   Thx :)
   //no worries
   // lol

2. The pagerank algorithm and its variant (topic-specific, personalized pageranks)

   Exercise
   Consider a Web graph with three nodes 1, 2, and 3. The links are as follows: 1->2, 3->2, 2->1, 2->3. Write down the transition probability matrices P for the surfer's walk with teleporting, with the value of teleport probability α=0.5.



$$A = \begin{bmatrix} 0 & 1 & 0 \\ ½ & 0 & ½ \\ 0 & 1 & 0 \end{bmatrix}$$

$$(1-\alpha)\begin{bmatrix} 0 & 1 & 0 \\ ½ & 0 & ½ \\ 0 & 1 & 0 \end{bmatrix} + \alpha \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} = P = \begin{bmatrix} 1/6 & 2/3 & 1/6 \\ 5/12 & 1/6 & 5/12 \\ 1/6 & 2/3 & 1/6 \end{bmatrix}$$

   If surfer starts at state 1, $x0 = (1\ 0\ 0)$. If no given start state, $x0 = (1/3\ 1/3\ 1/3)$

$\vec{x}_0$	1	0	0
$\vec{x}_1$	1/6	2/3	1/6
$\vec{x}_2$	1/3	1/3	1/3
$\vec{x}_3$	1/4	1/2	1/4
$\vec{x}_4$	7/24	5/12	7/24
...	...	...	...
$\vec{x}$	5/18	4/9	5/18

<- steady state probability distribution

   // Thx for this clear example.

The main idea of **page ranking** of **Notebook L18**