Word or bigram for effective search with Asian languages ?

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Overview

- Which IR model performs the best?
- Are bigrams more effective than words?
- Pseudo-relevance feedback & failure
- Data fusion
- Bilingual and multilingual searches

Which IR model ?

Comparisons made using the English language corpus (rigid evaluation)

Using eleven search models:

- 2 probabilistic model
- 9 vector-space models

Analysis of differences obtained using a statistical test (5%, two-sided)

The best IR model

English	T	D	DN
Okapi	**0.3692**	0.3615	**0.4555**
I(*n*)L2	0.3591	0.3548	**0.4556**
Lnu-ltc	0.3562	0.3551	0.4185
dtu-dtn	0.3577	**0.3748**	0.3949
tf idf	0.2345	0.2522	0.3061

Which IR model ?

Okapi or *Deviation from randomness*

Relative improvement (prob. vs vector-space)

- +21% with T queries
- +14% with D queries

Okapi vs. *tf idf* model

- +53% with T queries
- +41% with D queries

Word or bigram?

In the Japanese or Chinese language, word boundaries are not explicitly marked.

Each sentence is automatically segmented using the *Chasen* (JA) or *Mandarin Tools* (ZH)

In Korean, words are decompounded using the *Hangul Analysis Module*

Word or bigram?

我不是中国人

Correct segmentation

我 不 是 中国人

Word or bigram?

我不是中国人

Bigrams generation

我不 不是 是中
中国 国人

Word or bigram (JA)?

Japanese	bigram T	word T	bigram DN	word DN
Okapi	0.2660	0.2655	**0.4079**	0.4002
PB2	0.2717	**0.2895**	0.3957	0.3925
tf idf	0.1292	0.1227	0.2302	0.1987

Word or bigram (ZH)?

Chinese	bigram T	word T	bigram DN	word DN
Okapi	0.2995	0.3230	0.3887	0.4135
PB2	0.3042	**0.3246**	0.3973	**0.4136**
tf idf	0.2130	0.1645	0.3138	0.2741

Word or bigram (KR)?

Korean	bigram T base	word T	word + decomp T
Okapi	0.3630	0.2245	0.3549
PB2	**0.3729**	0.2378	0.3659

Processing time / space

Bigram indexing is more complex

# of postings	11x for Chinese 3x for Japanese
Inverted file size	2x for Chinese 1.5x for Japanese
Building time	2x for Chinese 1.3 for Japanese

Processing time / space

When searching

N-gram querying can be 10 times slower [McNamee, CLEF 2005]

Similar for both Chinese & Japanese

Blind query expansion

Adding terms from the top-ranked documents usually improves MAP

But this method failed for Genomics TREC 2005!

We used

Rocchio's approach

our idf-based strategy

$w_j = \beta\, tf_{ij} + (\alpha/k)\, idf_j$

Blind query expansion

T queries	English word	Japane. word	Chinese word	Korean bigram
Okapi	0.3692	0.2655	0.3230	0.3630
Rocchio	0.4420	0.3523	**0.3788**	0.4346
IDFQE	**0.4476**	**0.3681**	0.3778	**0.4453**

But sometimes we fail!

Topic #45

<title> **population issue**, **hunger**

<desc> Find documents describing the **effects population issues** have on **hunger**.

But sometimes we fail!

Five relevant articles for Query #45

<HEADLINE> Readers Forum: What do you think about genetically modified (GM) food?

<HEADLINE> Editorial / Serious food for thought

<HEADLINE> Bangladeshi Population May Reach 210.8 Million in 50 Ye.

<HEADLINE> News Analysis: Major Trends in World Population Growth (1) by Gu Zhenqiu

<HEADLINE> 17 Sub-Saharan African Countries Facing Food Emergencies: FAO

But sometimes we fail!

English Query #45	T	D	DN
Okapi	0.0020	0.0017	0.0274
I(*n*)L2	0.0008	0.0007	0.0237
PB2	0.0031	0.0031	0.0531
tf idf	0.0001	0.0001	0.0011

Why we fail?

Query #45
<title> **population issue**, **hunger**
<desc> Find documents describing the effects **population issues** have on **hunger**.

populat -> df high (7,995)
issu -> df very high (44,209)
hung -> (df=3,036) but it does not appear in relevant items

Why we fail?

The context may be useful.
Query phrase may help … ”population issue”

The query phrase ”population issue” does not appear in the relevant documents.

Why we fail?

In the relevant articles, we may find

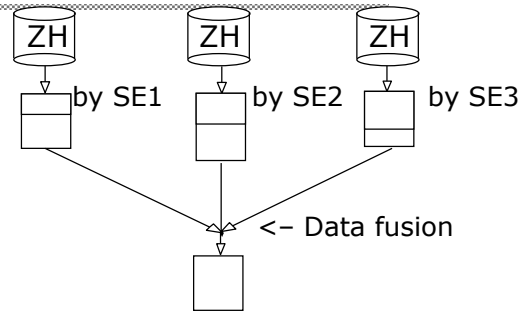
“food is expected to be a major issue in the next century”
”political issue”, ”food issues”
”issue of food security”, ”as a strategic issue”
”remain several unresolved issues.”

Why we fail? (2nd example)

Query #4
<title> the US Secretary of Defense, William Sebastian Cohen, Beijing

And the top-ranked documents, all non-relevant
1. <HEADLINE> U.S. Defense Secretary Arrives in China
2. <HEADLINE> Weekly Highlights of Diplomatic News
3. <HEADLINE> U.S. Secretary of Defence to Visit China
4. <HEADLINE> U.S. Defense Secretary Arrives in China
5. <HEADLINE> Highlights of Diplomatic News Today

Data Fusion



Data fusion

- Round-robin (baseline)
- Sum RSV (Fox et al., TREC-2)
- Normalize (divide by the max)
- Z-score
- Effective? In some cases, yes
  e.g., NLM at Genomics TREC-2005

Monolingual (data fusion)

best single	**ZH** T (3 SE) 0.3912	**JA** T (2 SE) 0.3681
Round-robin	0.3780	0.3639
SumRSV	**0.4121**	0.3637
Norm max	0.4062	0.3734
Z-score wt	0.4050	**0.3754**

Translation resources

- Machine-readable dictionaries (MRDs)
  - Babylon
  - Evdict
- Machine translation services (MT)
  - WorldLingo
  - BabelFish
- Parallel and/or comparable corpora
  (not used in this evaluation campaign)

Bilingual evaluation E->C/J/K

T	Chinese bigram	Japanese bigram	Korean bigram
Manual	0.2995	0.2660	0.3630
alphaWorks	0.1208	0.1855	0.2055
3 MTs	0.1317	0.1927	0.2396
3 MTS + PRF & Datafusion	0.2417	0.2631	0.3374

Bilingual evaluation (failure)

Missing translations of proper nouns (e.g., person, geographic, product name, …)

E.g., the three hardest topics (E->J)

Q#31 Fine dust particles, heart disease

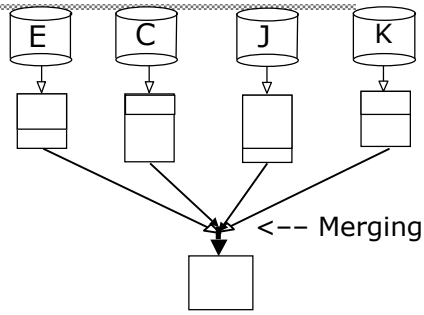
Q#35 Capital punishment, survey data

Q#28 Bubka, human bird, retirement

Multilingual IR

- Search on each language and merge the result lists (QT)

Merging problem



Multilingual IR

- Search on each language and merge the result lists (QT)
- Round-robin (baseline)
- Raw-score merging
- Normalize (by the max)
- Z-score

Multilingual evaluation

E -> CJKE	T (data fusion)	T (Okapi)
Round-robin	0.2244	0.2169
Raw-score	0.2165	**0.2332**
Norm max	0.2248	0.2102
Biased RR	0.2036	0.1965
Z-score	**0.2333**	0.2261

Test-collection NTCIR-5

	E	C	J	K
size	438 MB	1,100 MB	1,100 MB	312 MB
# doc.	**259,050**	**901,446**	858,400	220,374
# topic	49	50	47	50
mean rel. items	**62.7**	**37.7**	44.9	36.6

Conclusions (monolingual)

- The best IR model seems to be language-independent (Okapi, DFR)
- Pseudo-relevance feedback improves (IDFQE seems better than Rocchio - to be confirmed)
- Data fusion (not sure!)
- There is always hard topics

Conclusions (monolingual)

- Words or bigrams seem to present the same performance for JA & ZH (words slightly better for ZH)
- Bigrams seem the best approach for KR (to verify!)
- Processing space / time