Statistical-Based Approaches for Non-Segmenting Languages

Virach Sornlertlamvanich
Thai Computational Linguistics Laboratory (TCL), NICT
virach@tcllab.org

PACLING2005, Meisei University, Tokyo, Japan, 24-27 Aug, 2005

Outline

- Motivation
- Non-segmenting language
- Word extraction
- Dictionary-less search engine
- Language identification
- Term-based ontology Alignment

Motivation

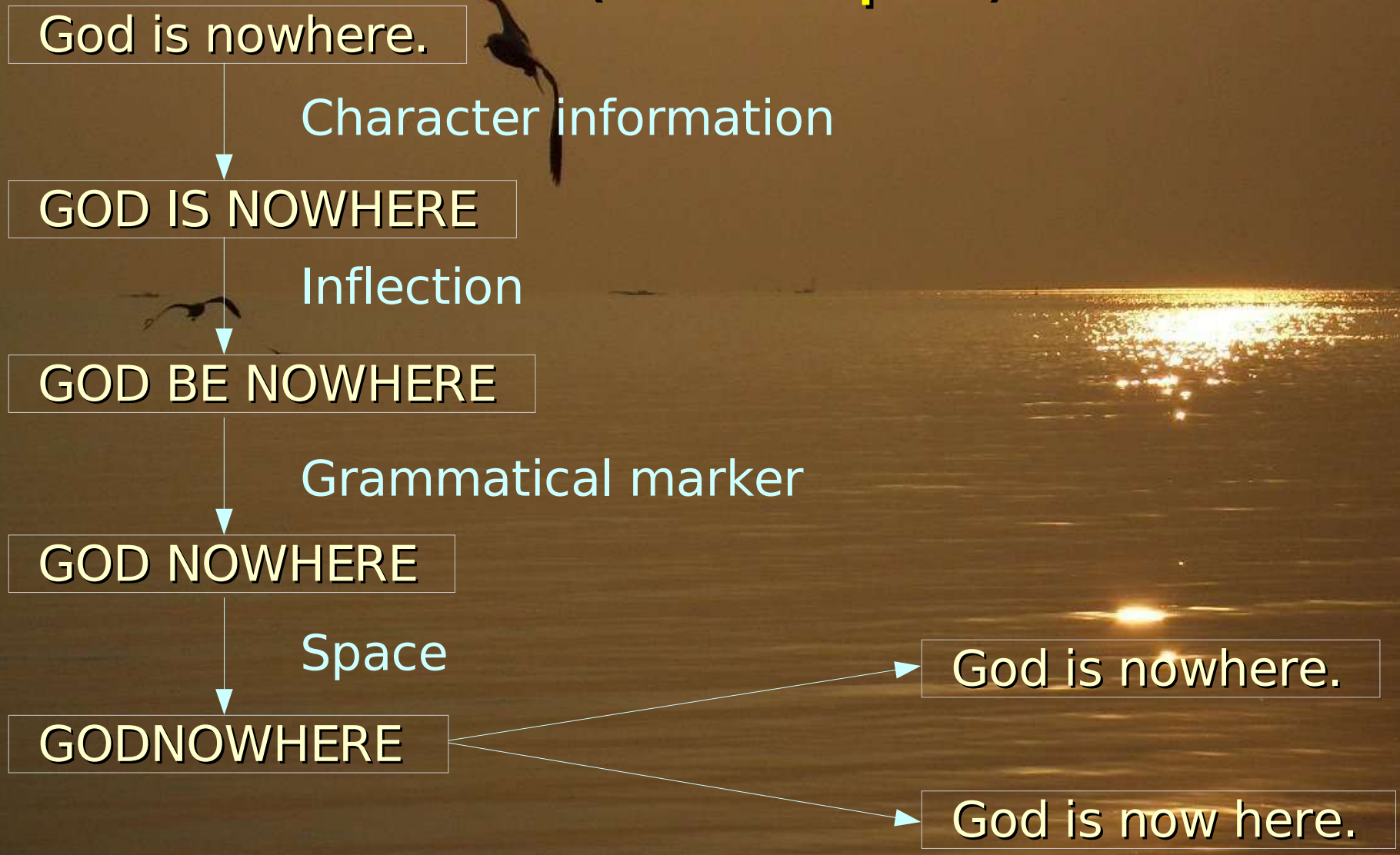
- Reliance on word segmentation
- Consistency in recognizing a word
- Updating the contemporary word list
- To establish an unified language processing

Thai Language as a Non-Segmenting Language

- No explicit word boudary marker e.g. capital letter, space character, punctuation mark, etc.
- No inflection
- No grammatical marker

How to determine word and sentence boundary?

Non-Segmenting Language (a sample)



Difficulty in Word Segmentation

- Ambiguity of being a word

แบบนอก	->	แบบ | นอก	<> แบ | บน | อก
มีที่นา	->	มี | ที่นา	<> มี | ที่ | นา
ขอบอกขอบใจ	->	ขอบอก | ขอบใจ	<> ขอ | บอก | ขอบใจ
ขนมอบกรอบ	->	ขนม | อบ | กรอบ	<> ขน | มอบ | กรอบ
ร้านข้าวซอยลำดวน	->	ร้าน | ข้าวซอย | ลำดวน	<> ร้าน | ข้าว | ซอย | ลำดวน

- Unknown word

นาตาลี	->	นา | ตา | ลี
อยุธยาอะลิอันซ์ซีพี	->	อยุธยา | อะลิอันซ์ | ซี | พี
กาลิเลโอ	->	กา | ลิเล | โอ

- Dictionary information i.e. POS, thesaurus

Word-Based Approach

- Word segmentation (accuracy for Thai)
  - Longest matching: 92%
  - Maximal matching: 93%
  - POS tri-gram: 96%
- Sentence segmentation (accuracy for Thai)
  - POS tri-gram: 84.57%
  - Feature-based approach (Winnow): 89.13%

Meaningful Bits

ADLTSUGKNOWLEDGEBWGZKTILA

ปร้จตเสีศฐาดึความรู้ษะภูกฮเศฉ

Term Candidate Extraction

- Virach Sornlertlamvanich et al. (COLING 2000) :
  - Automatic Corpus-Based Thai Word Extraction with the C4.5 Learning Algorithm
  - C4.5-trained decision tree for determining potential word boundary from MI, Entropy and some linguistic information
  - Capable of discovering new words in document without assistance from static dictionary

Mutual Information

$$Lm(xyz) = \frac{P(xyz)}{P(x)P(yz)}$$

$$Rm(xyz) = \frac{P(xyz)}{P(xy)P(z)}$$

x | y z

x y | z

where x is the leftmost character of string xyz
y is the middle substring of xyz
z is the rightmost character of string xyz
p( ) is the probability function.

High mutual information implies that xyz co-occurs more than expected by chance. If xyz is a word then its Lm and Rm must be high.

…Efunction… vs ...Function...

Entropy

$$LEnt(y) = -\sum P(xy/y) \cdot \log P(xy/y)$$

x | y

$$REnt(y) = -\sum P(yz/y) \cdot \log P(yz/y)$$

y | z

where A is the set of characters
x is the leftmost character of string xyz
y is the middle substring of xyz
z is the rightmost character of string xyz
p( ) is the probability function.

Entropy shows the variety of characters before and after a word.
If y is a word then its left and right entropy must be high.

...?function... vs ...?unction...

Other Features

- Frequency

  Words tend to be used more often than non word string sequences.

- Length

  Short strings are likely to happen by chance. The long and short strings should be treated differently.

- Functional Words

  Functional words are used mostly in phrases. They are useful to disambiguate words and phrases.

  Func(s) = 1 if s contains functional words.
  = 0 if otherwise.

Evaluation

Precision:	85%
Recall:	56%

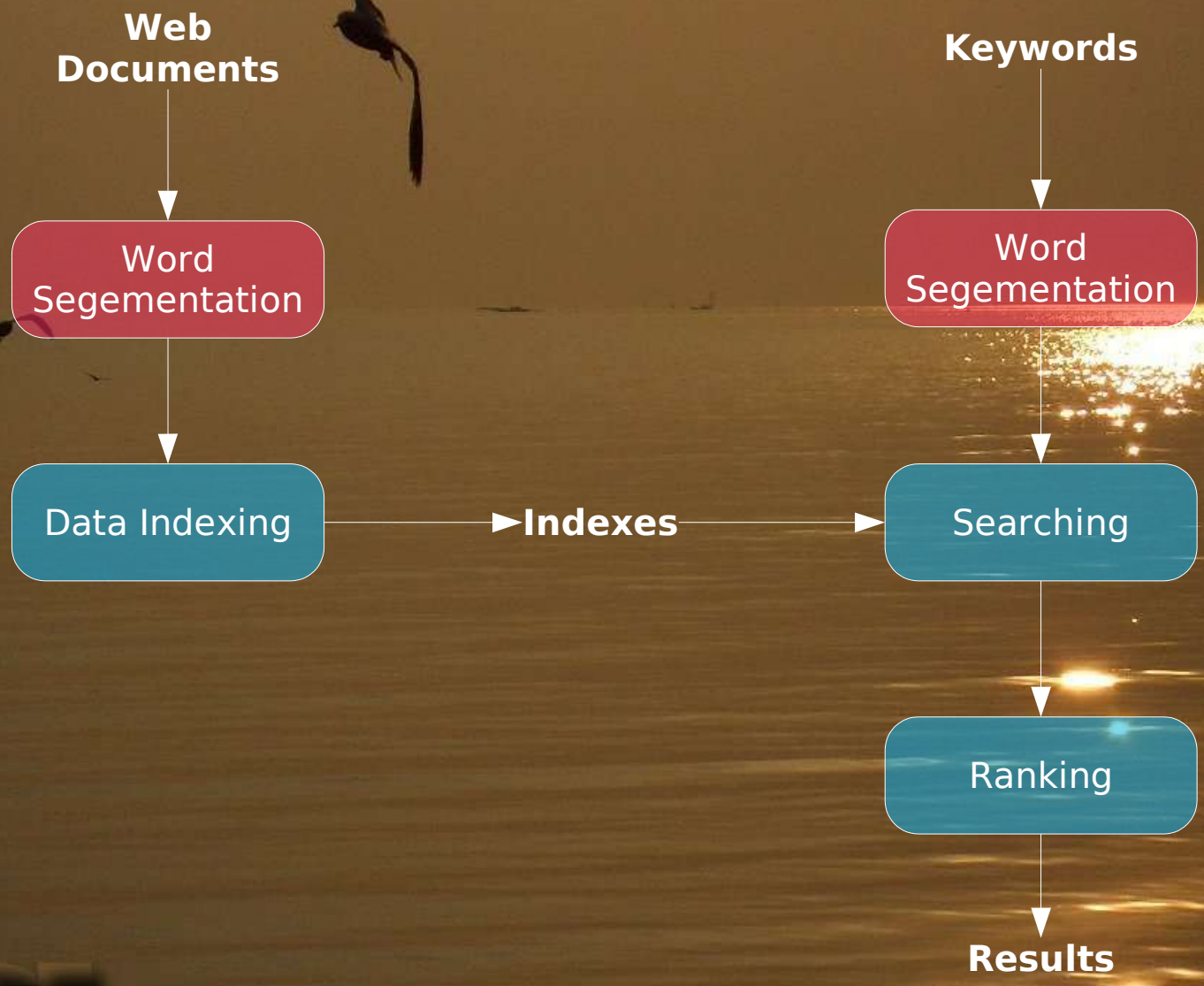
	Extracted words	Existing RID	Not existing in RID
Training set (2933)	1643	1028 (65.9%)	561 (34.1%)
Test set (2720)	1526	1046 (68.5%)	480 (31.5%)

RID : Royal Institute Dictionary
(30,000 words of Thai-Thai dictionary)

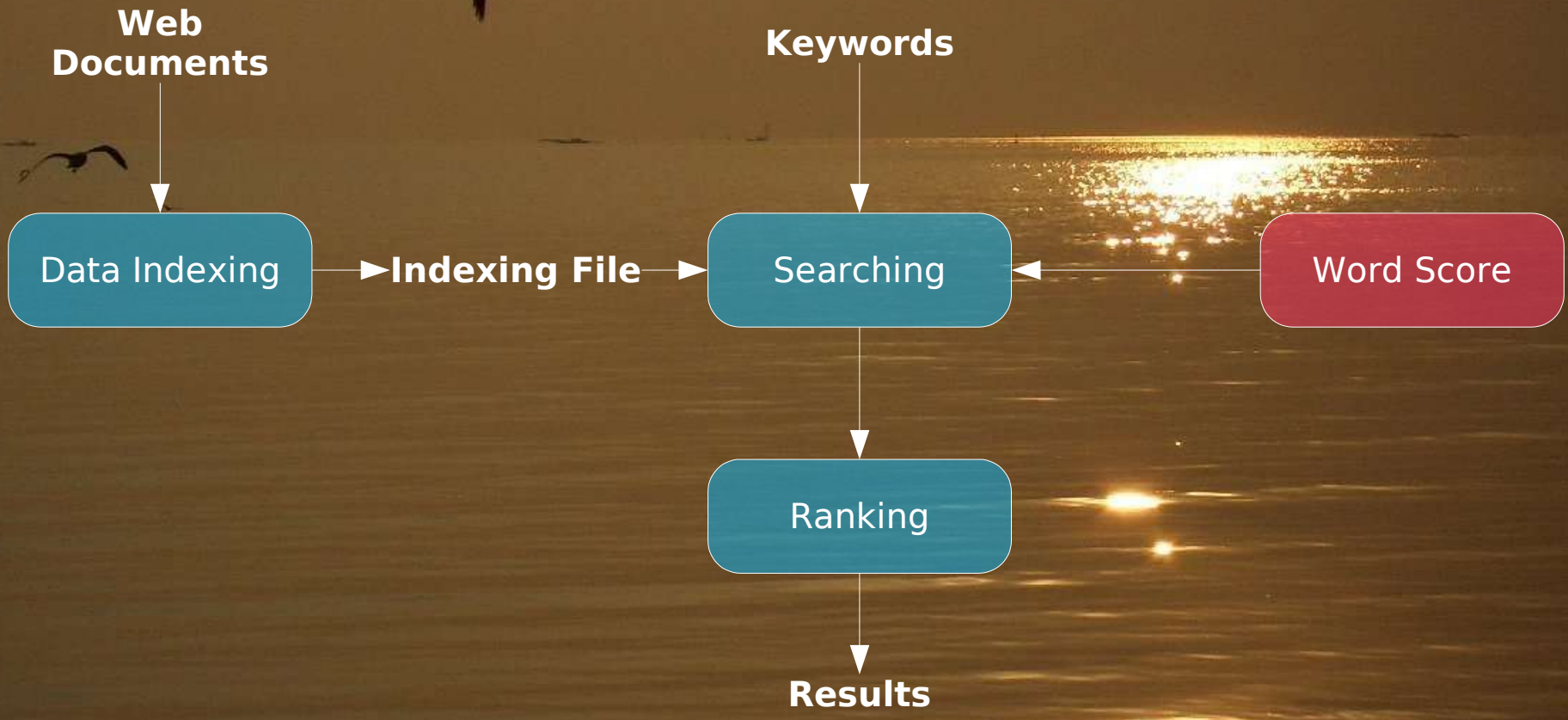
Dictionary-less Search Engine

- To overcome the limitation of vocabulary for making index
- To deal with the out-of-vocabulary problem
- To avoid the incomplete word segmentation result
- To avoid multiple search in case of phrase search
- To make it extensible for multi-lingual search

Dictionary-based Search Engine --Architecture--



Dictionary-less Search Engine --Architecture--



Dictionary-less Search Engine
--Word Score--

'xy' is the string in question, *'ab'* and *'cd'* are the contexts.

$$MI_L(abxy) = \frac{p(abxy)}{p(ab) \cdot p(xy)}$$

$$MI_R(xycd) = \frac{p(xycd)}{p(xy) \cdot p(cd)}$$

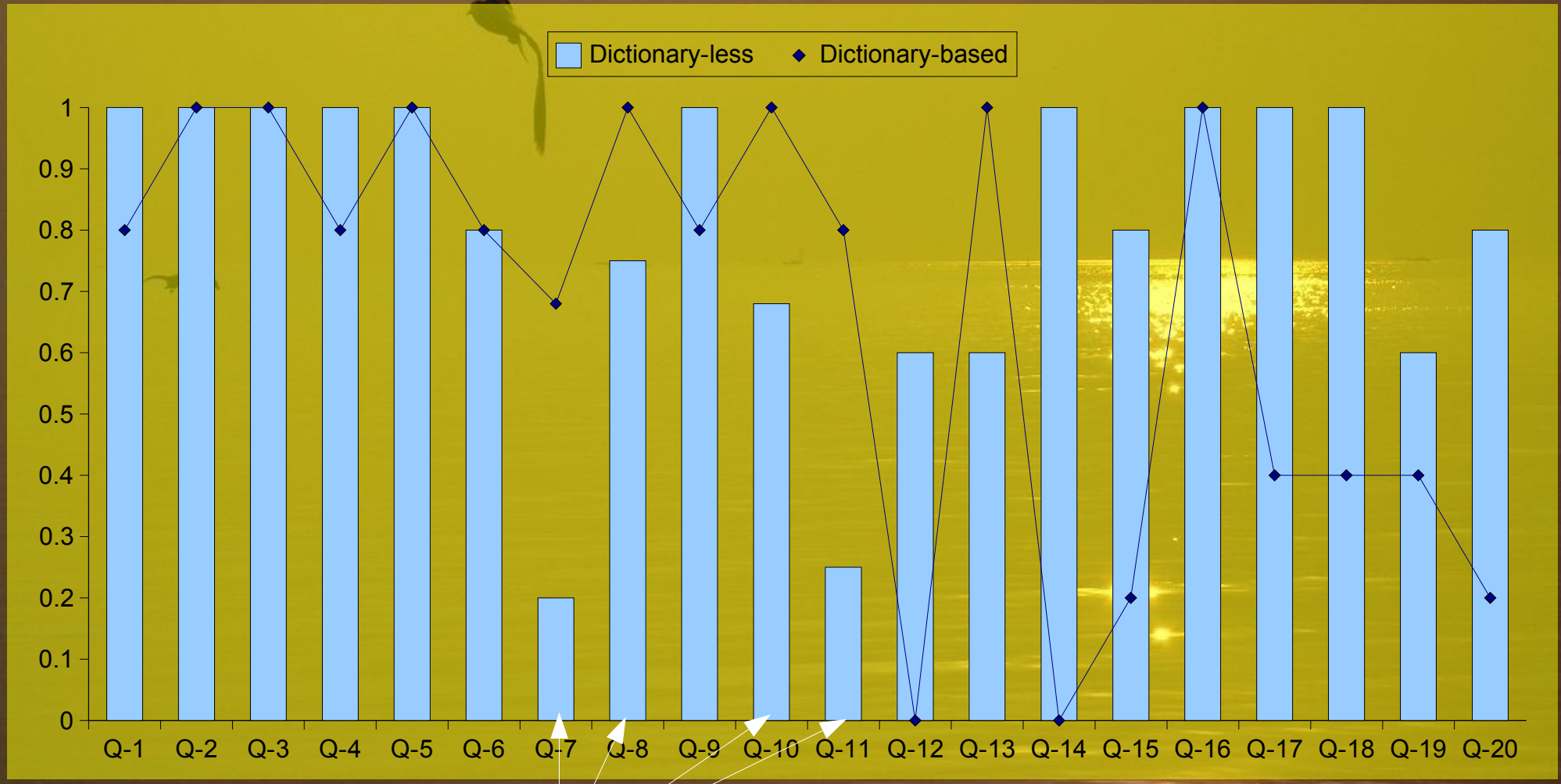
$$wscore_L(xy|ab) = 1 - norm(MI_L(abxy))$$

$$wscore_R(xy|cd) = 1 - norm(MI_R(xycd))$$

Dictionary-based VS Dictionary-less --Evaluation--

- Evaluate top 10 results of 20 queries by 5 evaluators
- Relevant if 3 out of 5 evaluators agree on each result
- Satisfaction on the result for each query is the evarage on the relevant

Dictionary-based VS Dictionary-less
--Evaluation--

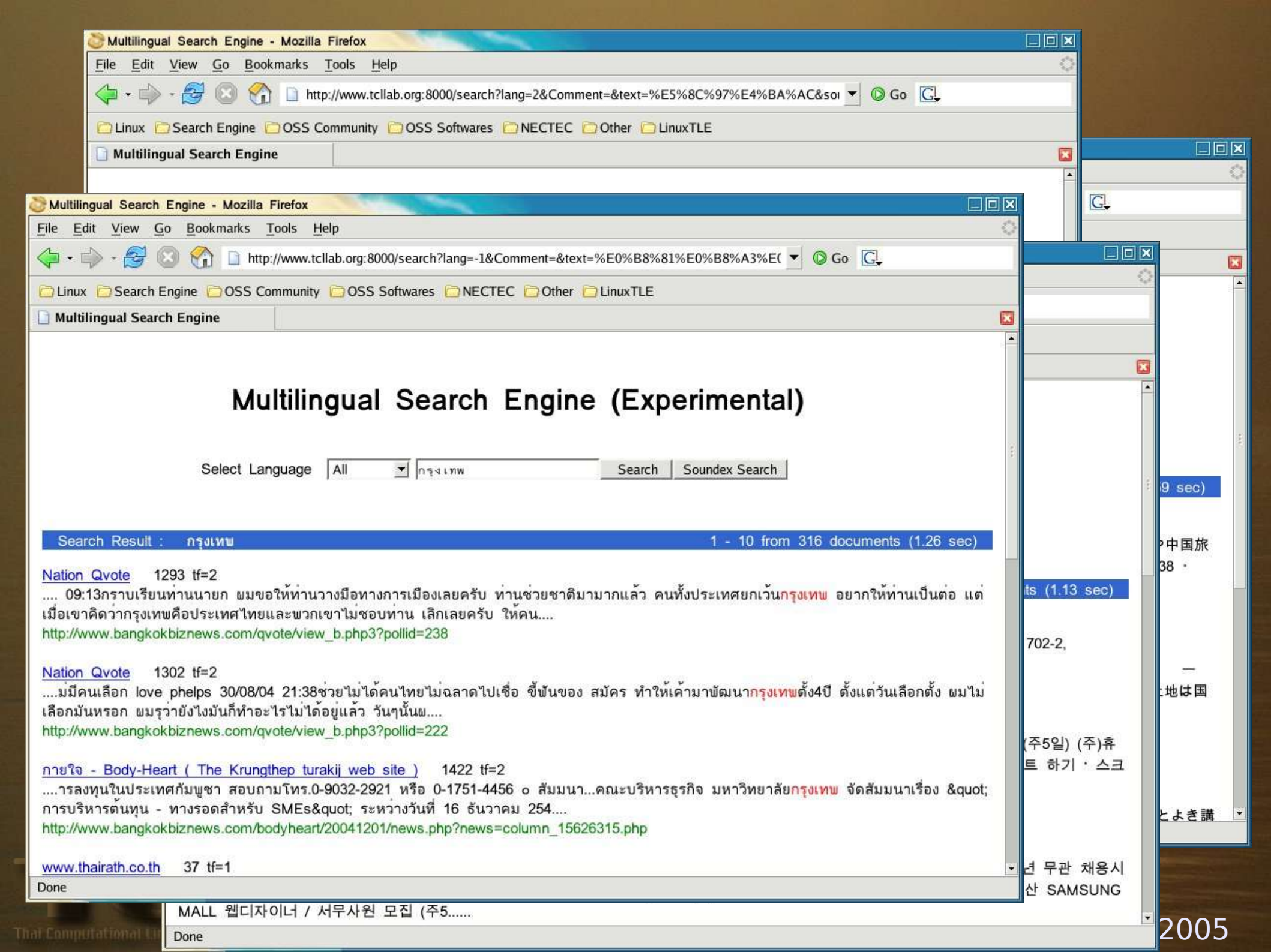


Inferior

Applying to Multi-Lingual Document Search

- 5853 articles from newspaper (65MB)

Language	Size (MB)
Thai	15.6
Chinese	28.1
Japanese	18.8
Korean	34.6
Total	**97.1**


Multilingual Search Engine - Mozilla Firefox
File Edit View Go Bookmarks Tools Help
http://www.tcllab.org:8000/search?lang=2&Comment=&text=%E5%8C%97%E4%BA%AC&so
Go
Linux Search Engine OSS Community OSS Softwares NECTEC Other LinuxTLE
Multilingual Search Engine
Multilingual Search Engine - Mozilla Firefox
File Edit View Go Bookmarks Tools Help
http://www.tcllab.org:8000/search?lang=-1&Comment=&text=%E0%B8%81%E0%B8%A3%E
Go
Linux Search Engine OSS Community OSS Softwares NECTEC Other LinuxTLE
Multilingual Search Engine
Multilingual Search Engine (Experimental)
Select Language All กรุงเทพ Search Soundex Search
Search Result : กรุงเทพ 1 - 10 from 316 documents (1.26 sec)
Nation Qvote 1293 tf=2
.... 09:13กราบเรียนท่านนายก ผมขอให้ท่านวางมือทางการเมืองเลยครับ ท่านช่วยชาติมามากแล้ว คนทั้งประเทศยกเว้นกรุงเทพ อยากให้ท่านเป็นต่อ แต่เมื่อเขาคิดว่ากรุงเทพคือประเทศไทยและพวกเขาไม่ชอบท่าน เลิกเลยครับ ให้คน....
http://www.bangkokbiznews.com/qvote/view_b.php3?pollid=238
Nation Qvote 1302 tf=2
....มีคนเลือก love phelps 30/08/04 21:38ช่วยไม่ได้คนไทยไม่ฉลาดไปเชื่อ ขี้ฟันของ สมัคร ทำให้เค้ามาพัฒนากรุงเทพตั้ง4ปี ตั้งแต่วันเลือกตั้ง ผมไม่เลือกมันหรอก ผมรู้ว่ายังไงมันก็ทำอะไรไม่ได้อยู่แล้ว วันๆนั้นผ....
http://www.bangkokbiznews.com/qvote/view_b.php3?pollid=222
กายใจ - Body-Heart (The Krungthep turakij web site) 1422 tf=2
....ารลงทุนในประเทศกัมพูชา สอบถามโทร.0-9032-2921 หรือ 0-1751-4456 o สัมมนา...คณะบริหารธุรกิจ มหาวิทยาลัยกรุงเทพ จัดสัมมนาเรื่อง " การบริหารต้นทุน - ทางรอดสำหรับ SMEs" ระหว่างวันที่ 16 ธันวาคม 254....
http://www.bangkokbiznews.com/bodyheart/20041201/news.php?news=column_15626315.php
www.thairath.co.th 37 tf=1
Done
MALL 웹디자이너 / 서무사원 모집 (주5.....
Done

Language Identification

- Identify the language of a given text based on String Kernels
- Advantages:
  - Identify the language from the text directly, regardless its coding system
  - Not require linguistic presuppositions about the data
  - Derive properties of n-gram language model
  - Apply to any kernel classifiers

String Kernels

- A kernel := the inner product function between two vectors,

$$K(x, y) = \langle \phi(x), \phi(y) \rangle$$

Explicit Mapping ($1 \leq r \leq 2$)

u = yzxxz, v = xyzxxxy

- By organizing all possible substrings in the lexicographic order, for substrings in Σ^1, we get:

Σ^1	$\phi_1(u)$	$\phi_1(v)$	$\phi_1(u)\cdot\phi_1(v)$
x	$2\lambda^1$	$4\lambda^1$	$8\lambda^2$
y	λ^1	$2\lambda^1$	$2\lambda^2$
z	$2\lambda^1$	λ^1	$2\lambda^2$

$$K_2(u,v)=8\lambda^2+2\lambda^2+2\lambda^2=12\lambda^2$$

Explicit Mapping ($1 \le r \le 2$)

u = yzxxz, v = xyzxxxy

- For substrings in Σ^2, we get:

Σ^2	$\phi_2(u)$	$\phi_2(v)$	$\phi_2(u)\cdot\phi_2(v)$
xx	λ^2	$2\lambda^2$	$2\lambda^4$
xy	0	$2\lambda^2$	0
xz	λ^2	0	0
yx	0	0	0
yy	0	0	0
yz	λ^2	λ^2	λ^4
zx	λ^2	λ^2	λ^4
zy	0	0	0
zz	0	0	0

$$K_2(u,v) = 2\lambda^4 + \lambda^4 + \lambda^4 = 4\lambda^4$$

$$K_r(u,v) = K_1(u,v) + K_2(u,v) = 12\lambda^2 + 4\lambda^4$$

Brute-Force Matching

1 2 3 4 5 6 7

v : x y z x x x y

u : y

y = λ^2

y z = $\lambda^2 \cdot \lambda^2$

y

y

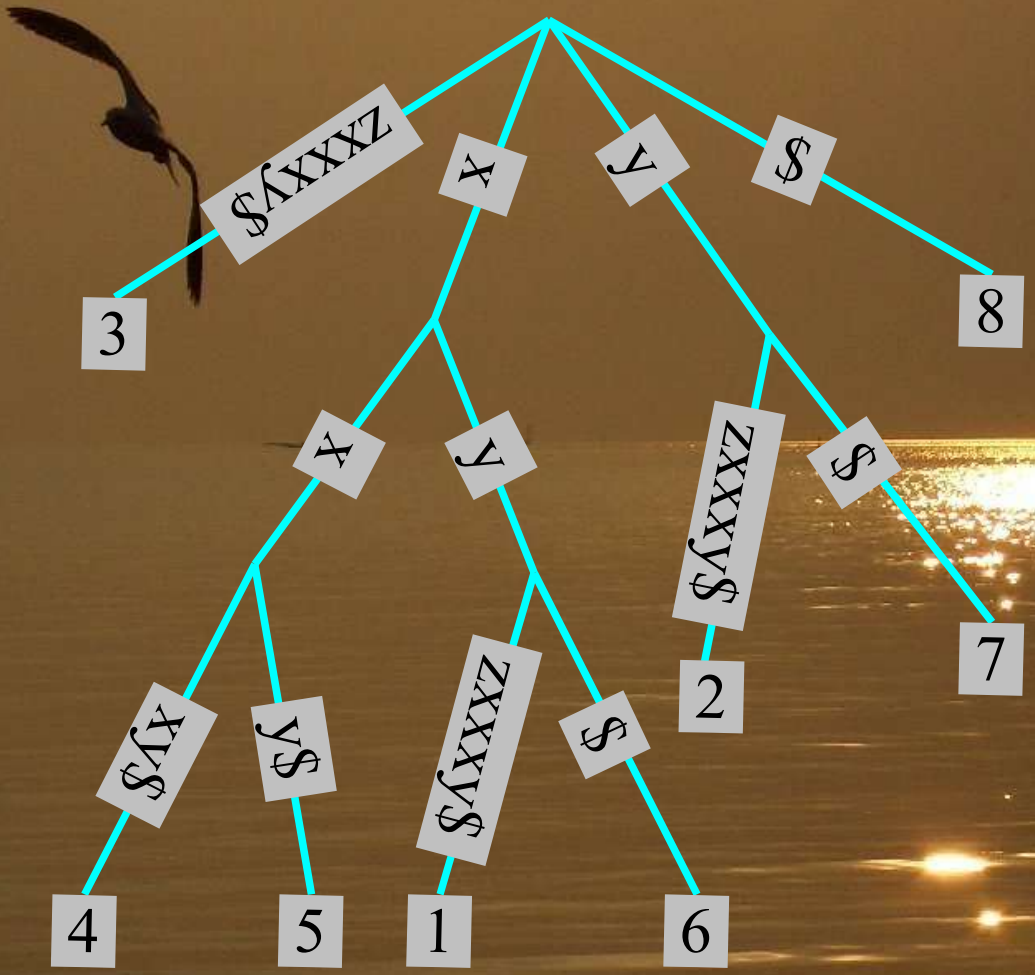
y

y

y = λ^2

The computational complexity is O(r|u||v|)

Faster Matching with Suffix Trees



Suffix tree for the string v = xyzxxxy$

The computational complexity is O(c|u|+|v|)

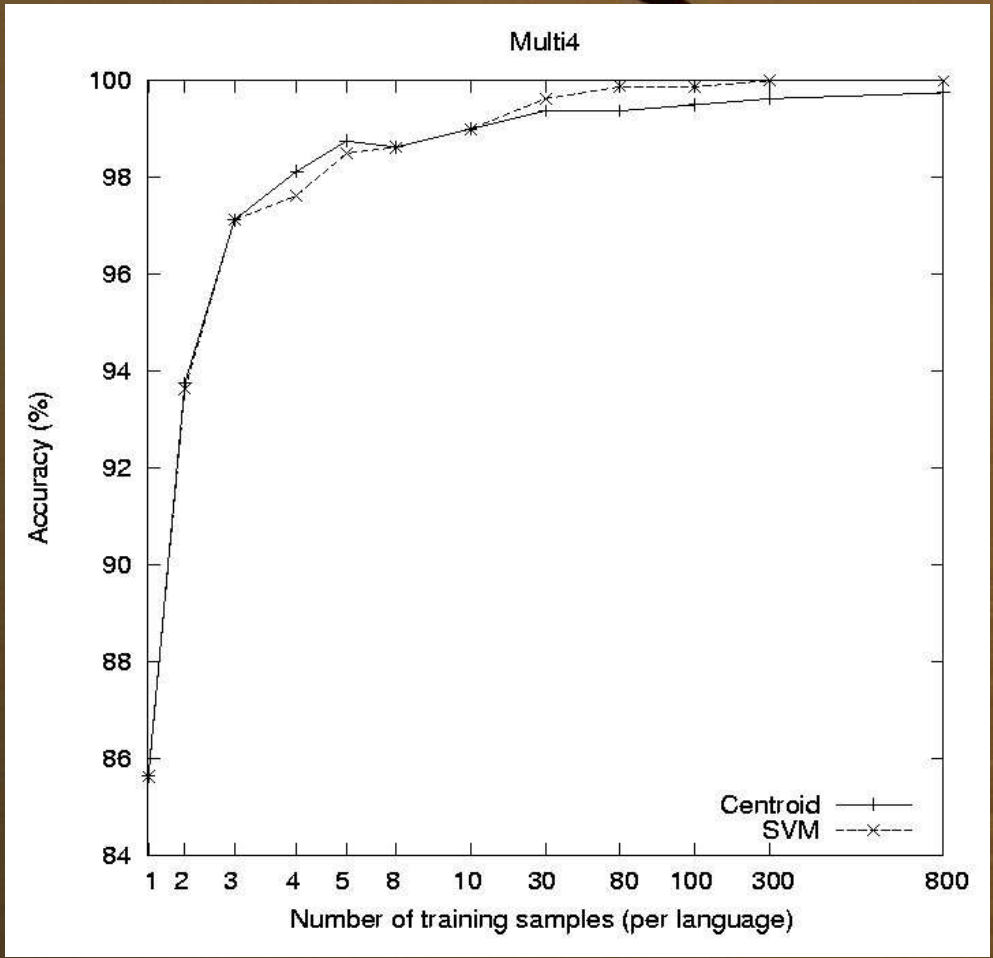
Language Identification --Training and Test Corpus--

- Centroid-based and SVM classification methods based on string kernel
- 5 fold cross validation
- 3 groups of 20 languages
  - Asian: Thai, Chinese, Japanese, Korean
  - Roman alphabet: English, French, Italian, Portuguese, Spanish, Swedish, German, Hungarian
  - Slavic family: Czech, Polish, Croatian, Slovak, Slovenian, Bulgarian, Russian, Greek

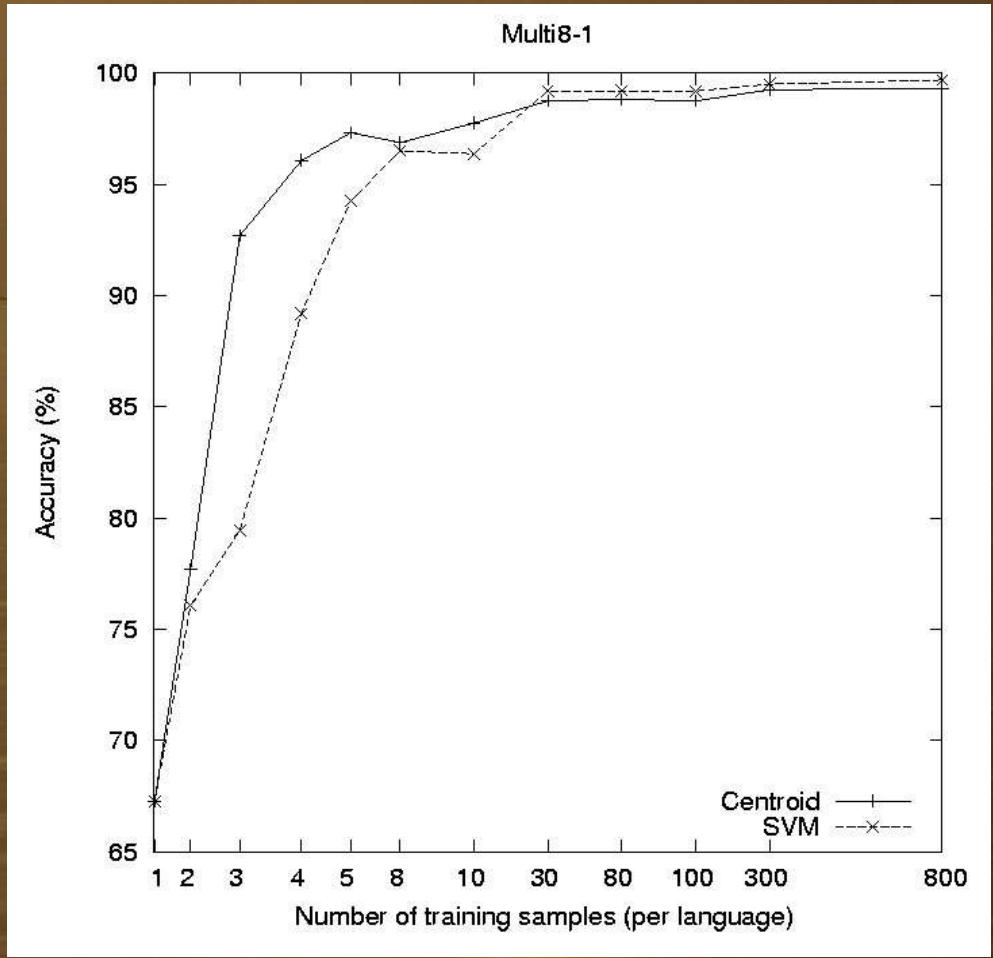
Language Identification --Training and Test Corpus--

	Language	Encoding	Size(KB)		Language	Encoding	Size(KB)
1	English	ISO-8859-1	474	11	Croatian	Windows-1250	207
2	French	ISO-8859-1	421	12	Slovak	Windows-1250	214
3	Italian	ISO-8859-1	202	13	Slovenian	Windows-1250	212
4	Portuguese	ISO-8859-1	257	14	Bulgarian	Windows-1251	200
5	Spanish	ISO-8859-1	213	15	Russian	Windows-1251	213
6	Swedish	ISO-8859-1	213	16	Greek	ISO-8859-7	279
7	German	ISO-8859-1	206	17	Thai	TIS-620	210
8	Hungarian	Windows-1250	206	18	Chinese	Big5	201
9	Czech	Windows-1250	295	19	Japanese	EUC-JP	416
10	Polish	Windows-1250	218	20	Korean	EUC-KR	204

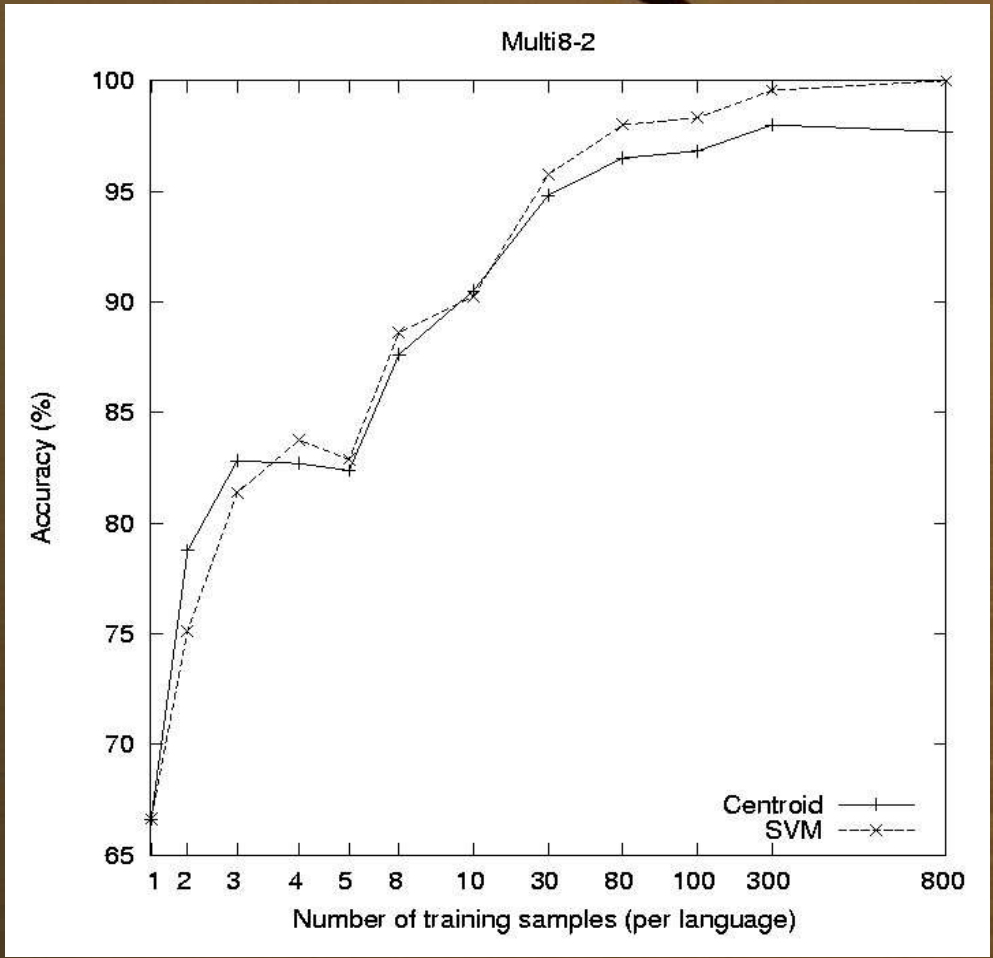
Asian Languages



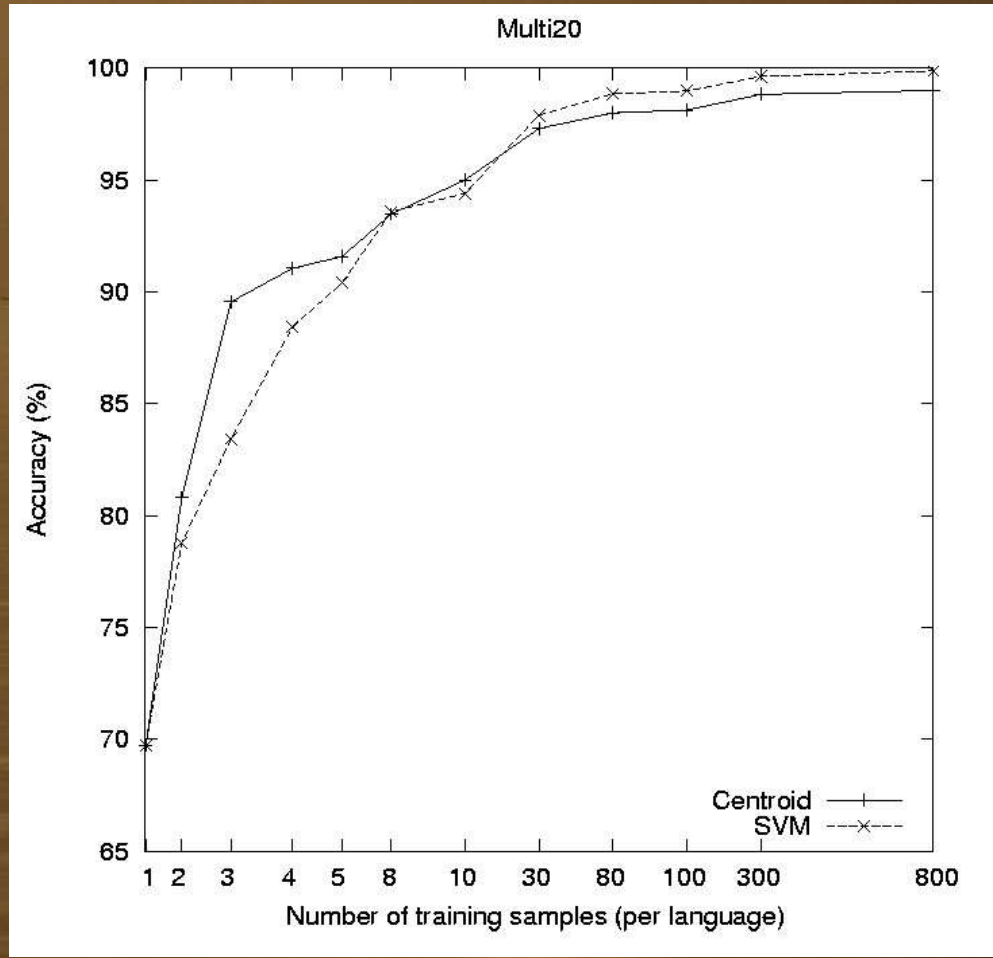
Roman Alphabet



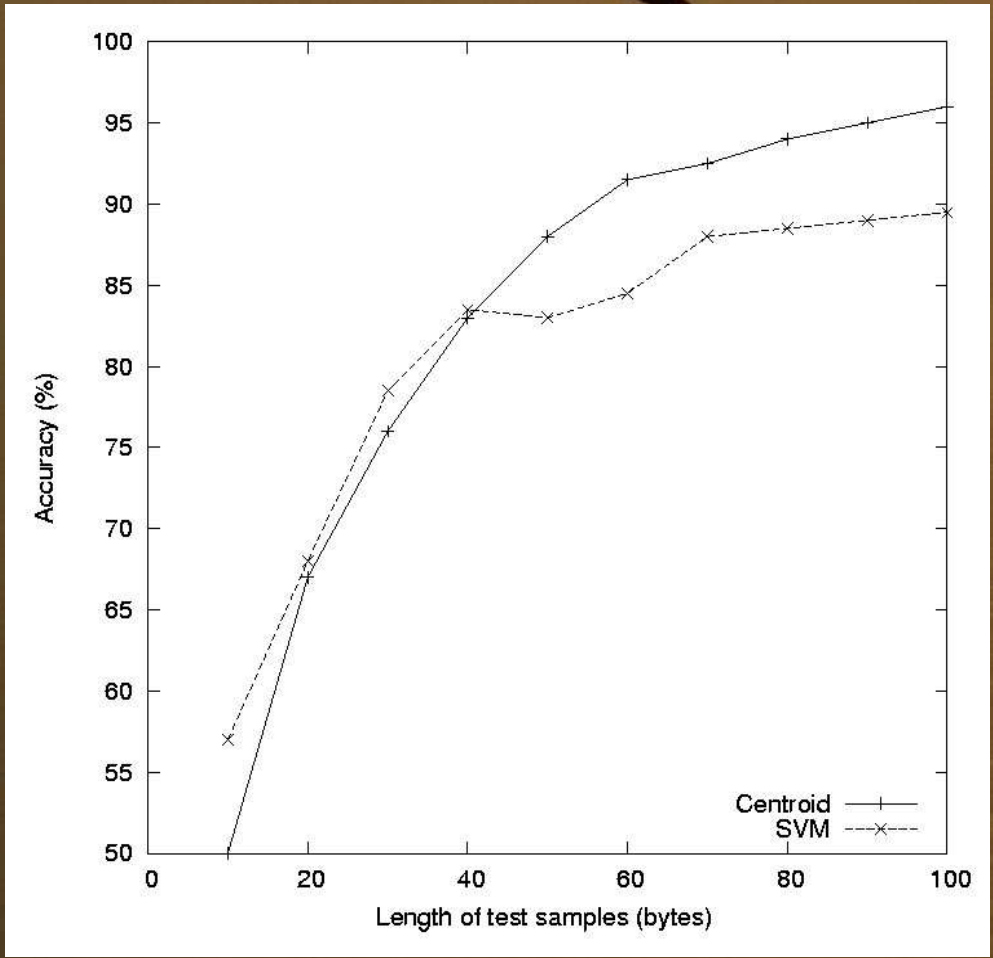
Slavic Family



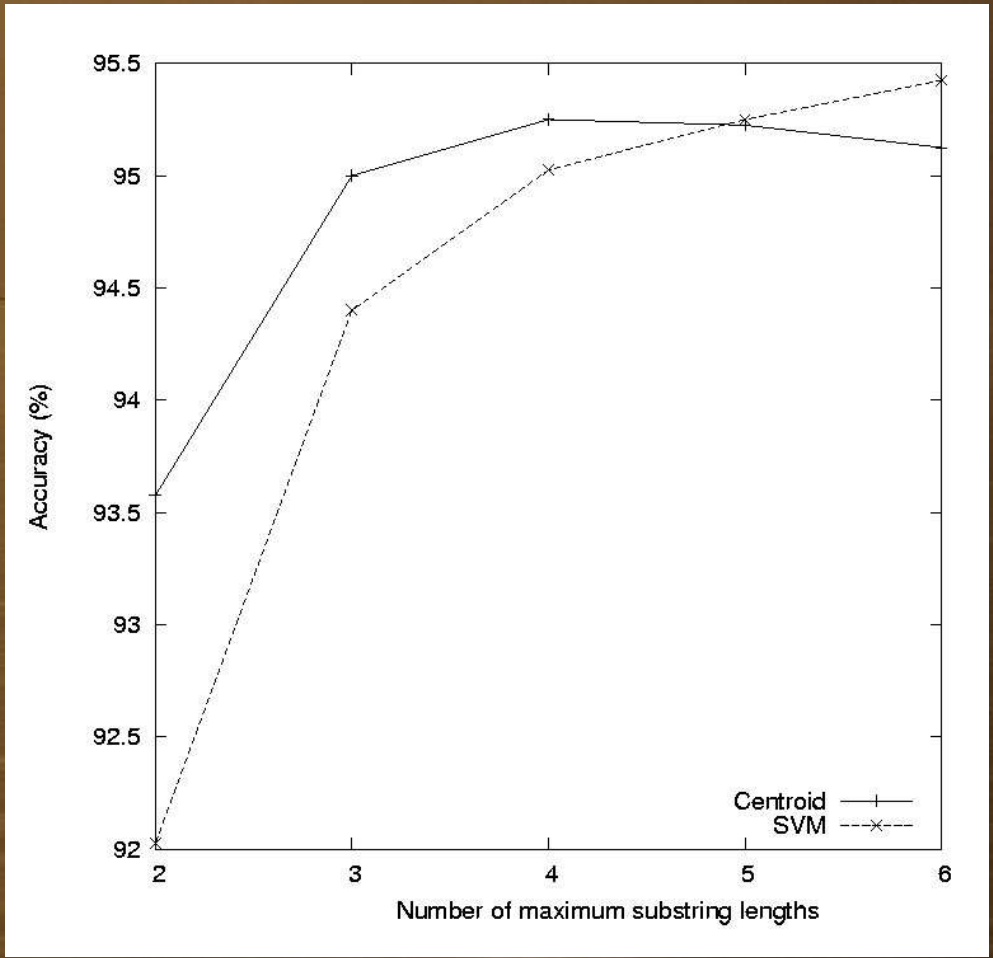
20 Languages



Length of Test Sample



Maximum Length of Substrings



Language Identification

- SVM shows its discrimimation power over Centroid based method under longer substrings, larger training set and test samples environment
- Both methods are good enough for discriminating the close language family
- Substrings can well represent the language in string kernels approach

Term-based Ontology Alignment

- Concept alignment between two ontologies that have different structures
- A study of the concept (semantic class) alignment between
  - EDR(Electronic Dictionary Research), and
  - MMT(Multilingual Machine Translation) concept dictionaries

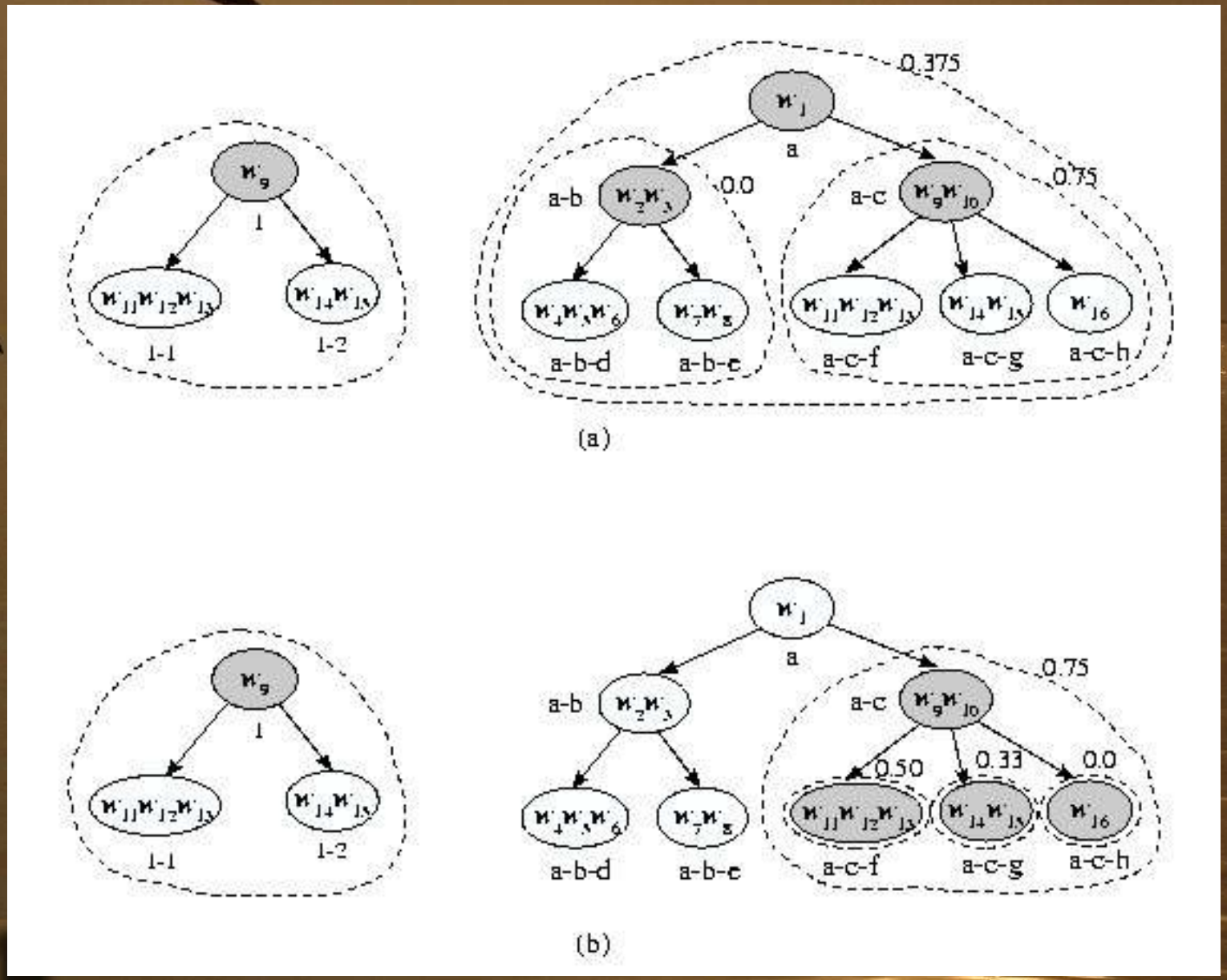
  based on similarity of term distribution

Extended Jaccard Similarity

- The degree of overlap between 2 concepts

$$JaccardSim(x_i, x_j) = \frac{x_i^T x_j}{\|x_i^2\| + \|x_j^2\| - x_i^T x_j}$$

Similarity of Source to Target Ontology



MMT and EDR Ontologies

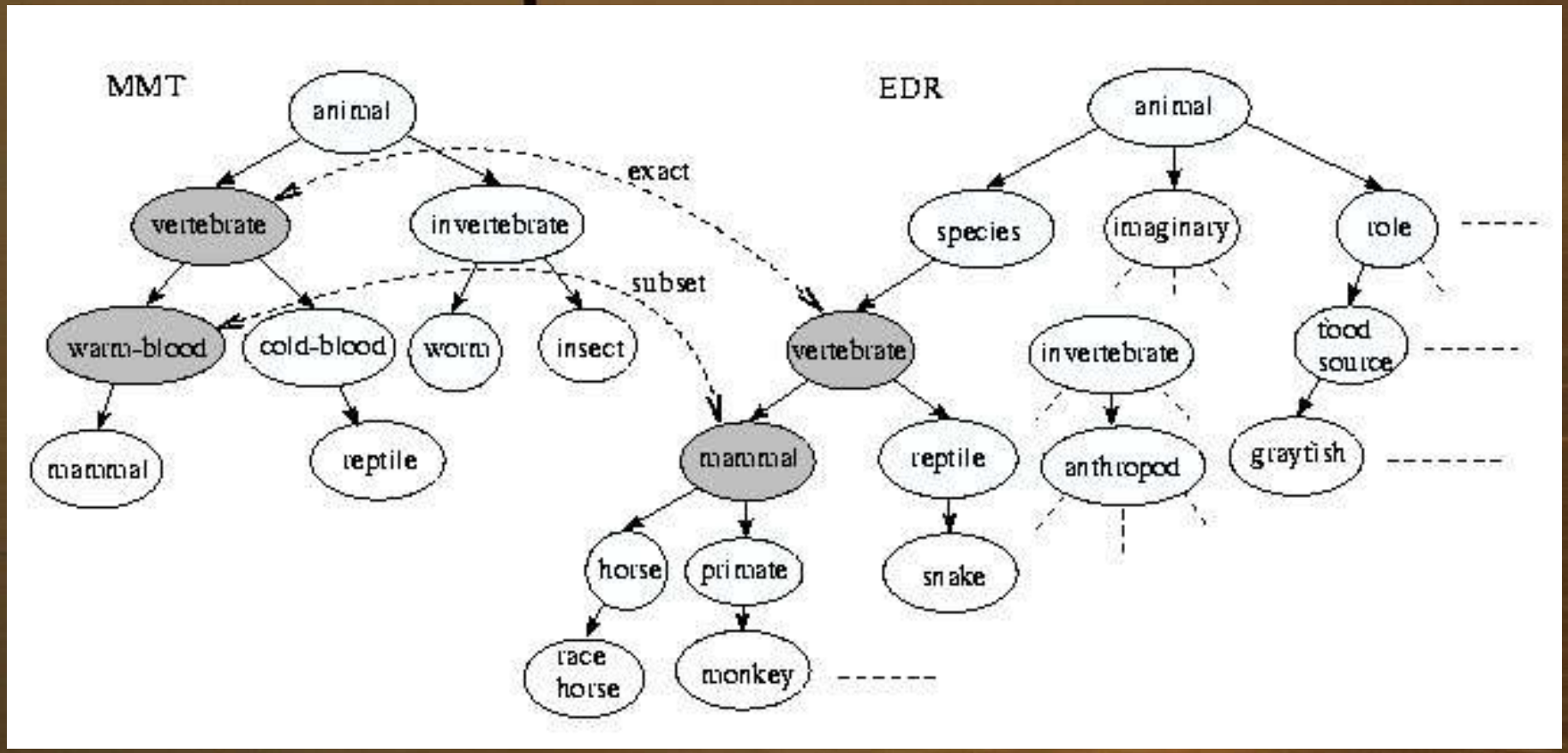
- EDR
  - 190,000 terms in EDR English word dictionary
  - 400,000 concepts in EDR concept dictionary
- MMT (Thai)
  - 60,000 terms in Thai word dictionary
  - 160 concepts in Thai concept dictionary

Experiment

- Experiment on 'animal' sub-tree
  - EDR contains 200 subconcepts, 7,600 words
  - MMT (Thai) contains 14 subconcepts, 400 words

Alignment of MMT to EDR Ontology

Exact or Subset-of



Concluding Remark

- Language independent consideration is required for multi-lingual text precessing
- Individual language has a unique bit sequence
- A term is a frequent use of a string

Credits

- Prapass Srichaivattana
  - Dictionary-less search engine
- Canasai Kruengkrai
  - Language identification
  - Term-based ontology alignment
- Shisanu Tongchim
  - Dictionary-less search engine
- Thatsanee Charoenporn
  - Term-based ontology alignment