Comparing the value of Latent Semantic Analysis on two English-to-Indonesian lexical mapping tasks

David Moeljadi

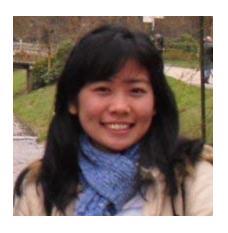
Nanyang Technological University
October 16, 2014

Outline

- The Authors
- The Experiments (general idea and results)
- The Details
 - Concept and word
 - Bilingual word mapping
 - Bilingual concept mapping
- Results and Discussion

The Authors

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Eliza Margaretha's undergraduate theses supervised by Ruli Manurung

The Experiments

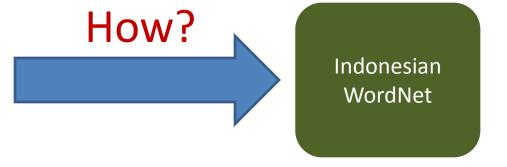
- General Idea -

English
WordNet
version 3.0

The Great
Dictionary of
the Indonesian
Language
(KBBI)

Parallel
EnglishIndonesian
corpus (news
article pairs)

Bilingual English-Indonesian dictionary



The Experiments

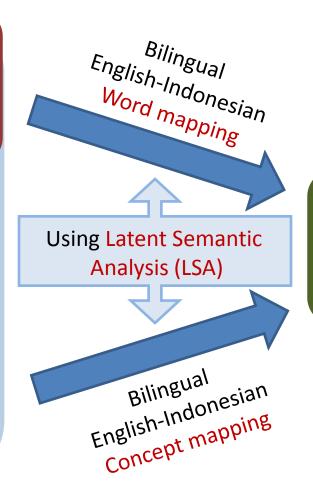
- General Idea -

English WordNet version 3.0

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Indonesian WordNet

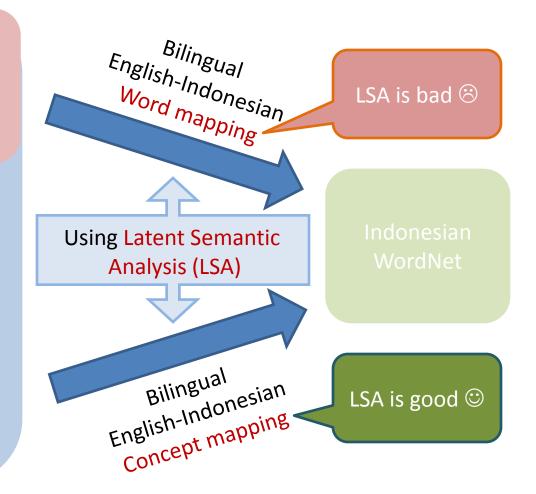
The Experiments

- Results -

English WordNet version 3.0 The Great
Dictionary of
the Indonesian
Language
(KBBI)

English-Indonesian corpus (news article pairs)

Bilingual English-Indonesian dictionary

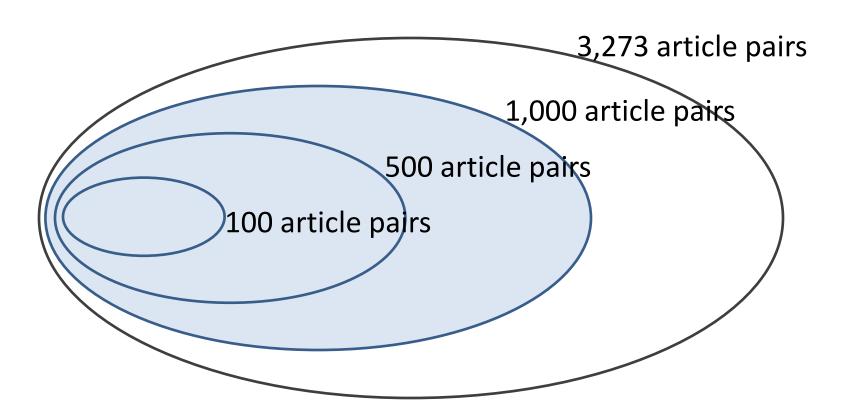


Concept and Word

```
Language Concept
                                      Word
Indonesian 00464894-n golf
                                00464894-n ♥ 'a game played on a large open course
                  0842027 with 9 or 18 holes';
English
                                                              golf
                  09213565-n
 08420278-n (20) bank, depository financial institution,
              banking concern, banking company
 a financial institution that accepts deposits and channels the money
 into lending activities
00015388-n ❖ 'a living organism characterized by
voluntary movement':
                 animal , hewan , sato , manusia , margasatwa , fauna , binatang
Indonesian
```

- The Corpus -

1. Define a collection of parallel article pairs



- Latent Semantic Analysis -

2. Set up a bilingual word-document matrix for LSA

ENG	Article 1E	Article 2E	•••	Article 100E
dog	5	0		0
the	10	15	•••	50
car	4	0	•••	7
IND	Article 1I	Article 2I		Article 100I
IND anjing	Article 1I 5	Article 2I 0		Article 100I
anjing	5	0		0

Each column is a pair of parallel articles

- Latent Semantic Analysis -

2. Set up a bilingual word-document matrix for LSA

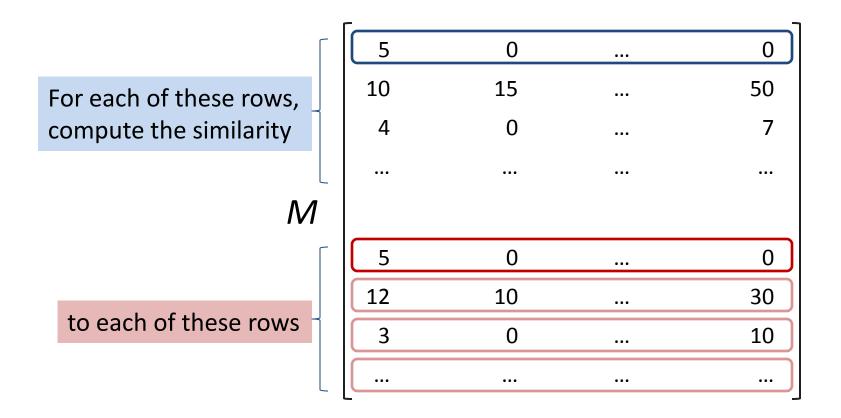
M_{E}	5 10 4	0 15 0		0 50 7
		•••	•••	
	_			_

$$M_I$$

$$\begin{bmatrix}
5 & 0 & \dots & 0 \\
12 & 10 & \dots & 30 \\
3 & 0 & \dots & 10 \\
\dots & \dots & \dots & \dots
\end{bmatrix}$$

- Latent Semantic Analysis -

2. Set up a bilingual word-document matrix for LSA



- Latent Semantic Analysis -

2. Set up a bilingual word-document matrix for LSA

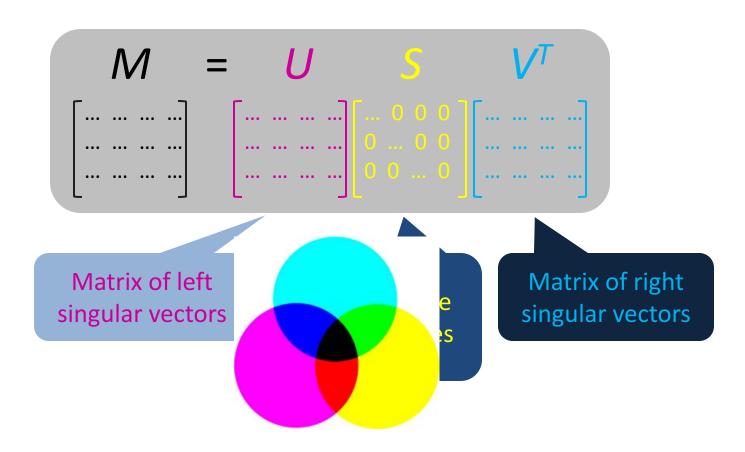
However, there are irrelevant information and noise need to be removed

M

5	0		0
10	15	•••	50
4	0	•••	7
•••	•••	•••	•••
	_		
5	0		0
12	10		30
3	0	•••	10
•••	•••	•••	•••

- Latent Semantic Analysis -

3. LSA: Compute SVD (Singular Value Decomposition)



- Latent Semantic Analysis -

3. LSA: Compute SVD (Singular Value Decomposition)



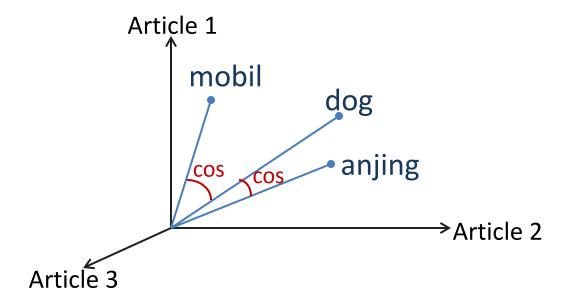
- Latent Semantic Analysis -
- 4. Compute the optimal reduced rank approximation (reducing dimensions of the matrix)
 - unearth implicit patterns of semantic concepts
 - the vectors representing English and Indonesian words that are closely related should have high similarity

	10%	25%	50%	100% (no reduction)
100 art.pairs	10	25	50	100
500 art.pairs	50	125	250	500
1000 art.pairs	100	250	500	1,000

- Latent Semantic Analysis -
- 4. Words are represented by row vectors in *U*, word similarity can be measured by computing row similarity in *US*.

```
M = U \qquad 5 \qquad V^{T}
\begin{bmatrix} \dots \dots \dots \dots \\ \dots \dots \dots \dots \end{bmatrix} \begin{bmatrix} \dots \dots \dots \dots \\ 0 \dots \dots \dots \end{bmatrix} \begin{bmatrix} \dots \dots \dots \dots \\ 0 \dots \dots \dots \end{bmatrix} \begin{bmatrix} \dots \dots \dots \dots \\ \dots \dots \dots \dots \end{bmatrix}
```

- Latent Semantic Analysis -
- 5. For a randomly chosen set of vectors representing English words, compute the *n* nearest vectors representing the *n* most similar Indonesian words using the cosine of the angle between two vectors



- Some Experiments -

6. Remove the stopwords from the matrix

English: the, a, of, in, by, for, ...

Indonesian: itu, sebuah, dari, di, oleh, untuk, ...

and do SVD again.

- 7. Apply two weighting schemes:
 - TF-IDF
 - Log-entropy and do SVD again.

- Some Experiments -

7. Apply TF-IDF

- term frequency-inverse document frequency
- TF: to measure how frequently a word occurs in a document

Number of word *w* in a document

Total number of words in a document

- IDF: to measure how important a word is in a corpus

log Total number of documents
Number of documents with word w in it

- can be used for stopwords filtering

- Some Experiments -

7. Apply TF-IDF (example)

	Article 1	Article 2	•••	Article 100
dog	5	0	0 0 0	0
the	10	15		50
car	4	0	* *	7
			•••	•••
Total	100	150		125

TF IDF

Number of word w in a document

Total number of words in a document

x log Total number of documents

Number of documents with word w in it

- Some Experiments -

7. Apply TF-IDF (example)

	Article 1	Article 2	•••	Article 100
dog	5	0	0 0 0	0
the	10	15		50
car	4	0	* *	7
			•••	•••
Total	100	150		125

TF IDF of dog
$$\frac{5}{100} \times \log \frac{100}{1} = 0.05 \times \log 100 = 0.05 \times 2 = 0.1$$

- Some Experiments -

7. Apply TF-IDF (example)

	Article 1	Article 2	•••	Article 100
dog	5	0	•••	0
the	10	15	•••	50
car	4	0		7
Total	100	150		125

TF-IDF of the in article 1
$$\frac{10}{100}$$
 x $\log \frac{100}{100}$ = 0.1 x $\log 1$ = 0.1 x 0 = 0
TF-IDF of car $\frac{4}{100}$ x $\log \frac{100}{2}$ = 0.04 x $\log 50$ = 0.04 x 1.7 = 0.07 in article 1 $\frac{7}{125}$ x $\log \frac{100}{2}$ = 0.06 x $\log 50$ = 0.06 x 1.7 = 0.09

- Some Experiments -

7. Apply TF-IDF and do SVD (example)

	Article 1	Article 2	•••	Article 100
dog	0.10	0.00	***	0.00
the	0.00	0.00	•••	0.00
car	0.07	0.00	# # # # # # # # # #	0.09

Stopwords filtering

- Some Experiments -

7. Apply TF-IDF and do SVD (example)

$$M = \begin{bmatrix} 0.10 & 0.00 & \dots & 0.00 \\ 0.07 & 0.00 & \dots & 0.09 \\ \dots & \dots & \dots & \dots \end{bmatrix}$$

$$M = U \qquad S \qquad V^{T}$$

$$\begin{bmatrix} \dots \dots \dots \dots \\ \dots \dots \dots \dots \end{bmatrix} \begin{bmatrix} \dots \dots \dots \dots \\ 0 \dots \dots \dots \end{bmatrix} \begin{bmatrix} \dots \dots \dots \dots \\ 0 \dots \dots \dots \end{bmatrix}$$

- Some Experiments -

7. Apply Log-entropy and do SVD

$$\log = \log(\mathrm{tf}_{ij} + 1)$$

entropy =
$$1 - \sum_{j} \frac{p_{ij} \log p_{ij}}{\log n}$$
, where $p_{ij} = \frac{\operatorname{tf}_{ij}}{\operatorname{gf}_{i}}$

 gf_i is the total number of times a word appears in a corpus, n is the number of documents in a corpus

After getting a new matrix from log-entropy, do SVD (same as in TF-IDF)

- Some Experiments -

8. Do mapping selection

Take the top 1, 10, 50, and 100 mappings based on similarity

film	0.814
filmnya	0.698
sutradara	0.684
garapan	0.581
perfi	\sim 54
pena GOOD 34	
kontroversiai	U.5 <mark>26</mark>
koboi	0.482
irasional	0.482
frase	0.482
(a)	

pembebanan	0.973
kijang	0.973
halmahera	0.973
alumina	0.973
terjadw D	.973
viskosit BA	ND .973
tabel	U.973
royalti	0.973
reklamasi	0.973
penyimpan	0.973
(b)	

The Most 10 Similar Indonesian Words for the English Words (a) Film and (b) Billion using 1,000 article pairs with 500-rank approximation and no weighting

- billion is not domain specific
- billion can
 sometimes be
 translated numerically
 instead of lexically
- lack of data: the collection is too small

- Some Experiments -
- Compute the precision and recall values for all experiments

$$P = \frac{\Sigma \text{ correct mappings (check with bilingual dictionary)}}{\Sigma \text{ total mappings found}}$$

$$R = \frac{\Sigma \text{ correct mappings (check with bilingual dictionary)}}{\Sigma \text{ total mappings in bilingual dictionary}}$$

- The Results -

1. As the collection size increases, the precision and recall values also increase

Collection Size	FREQ		LSA	
Conection Size	P	R	P	R
P_{100}	0.0668	0.1840	0.0346	0.1053
P_{500}	0.1301	0.2761	0.0974	0.2368
P_{1000}	0.1467	0.2857	0.1172	0.2603

2. The higher the rank approximation percentage, the better the mapping results

Rank Approximation	P	R
10%	0.0680	0.1727
25%	0.0845	0.2070
50%	0.0967	0.2226
100%	0.1009	0.2285

- The Results -

3. On account of the small size of the collection, stopwords may carry some semantic information

Stonwords	FREQ		LSA	
Stopwords	P	R	P	R
Contained	0.1108	0.2465	0.0840	0.2051
Removed	0.1138	0.2440	0.0822	0.1964

4. Weighting can improve the mappings (esp. Log-entropy)

Weighting Usego	FREQ		LSA	
Weighting Usage	P	R	P	R
No Weighting	0.1009	0.2285	0.0757	0.1948
Log-Entropy	0.1347	0.2753	0.1041	0.2274
TF-IDF	0.1013	0.2319	0.0694	0.1802

- The Results -

5. As the number of translation pairs selected increases, the precision value decreases and the possibility to find more pairs matching the pairs in bilingual dictionary (the recall value) increases

Mapping	FREQ R		LSA		
Selection			P	R	
Top 1	0.3758	0.1588	0.2380	0.0987	
Top 10	0.0567	0.2263	0.0434	0.1733	
Top 50	0.0163	0.2911	0.0133	0.2338	
Top 100	0.0094	0.3183	0.0081	0.2732	

Conclusion: FREQ baseline (basic vector space model)

is better than LSA

- Semantic Vectors for Concepts -
- Construct a set of textual context representing a concept c by including (1) the sublemma words,
 the gloss words, and (3) the example sentence words, which appear in the corpus.

WordNet Synset ID: 100319939, Words: chase, following, pursual, pursuit, Gloss: the act of pursuing in an effort to overtake or capture, Example: the culprit started to run and the cop took off in pursuit, Textual context set: {{following, chase}, {the, effort, of, to, or, capture, in, act, pursuing, an}, {the, off, took, to, run, in, culprit, started, and}}

- Semantic Vectors for Concepts -
- Construct a set of textual context representing a concept c by including (1) the sublemma words,
 the definition words, and (3) the example sentence words, which appear in the corpus.

KBBI ID: k39607 - Similarity: 0.804, Sublemma: mengejar, Definition: berlari untuk menyusul menangkap dsb memburu, Example: ia berusaha mengejar dan menangkap saya, Textual context set: {{mengejar}, {memburu, berlari, menangkap, untuk, menyusul}, {berusaha, dan, ia, mengejar, saya, menangkap}}

- Semantic Vectors for Concepts -

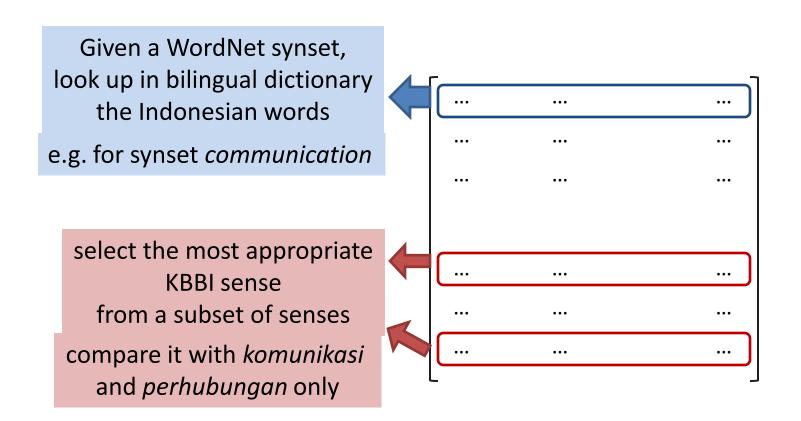
2. Compute the semantic vector of a concept, that is a weighted average of the semantic vectors of the words in the set Sublemma 60% Textual context set: {{following, chase}, Gloss {the, effort, of, to, or, capture, in, act, pursuing, an}, 30% Example {the, off, took, to, run, in, culprit, started, and}} 10% Sublemma Textual context set: {{mengejar}, 60% {memburu, berlari, menangkap, untuk, menyusul}, Definition {berusaha, dan, ia, mengejar, saya, menangkap}} 30% Example 10%

- Latent Semantic Analysis -
- 3. Use 1,000 article pairs and set up a bilingual conceptdocument matrix for LSA

ENG	Article 1E		Article 1000E
100319939		** *	
201277784		•••	

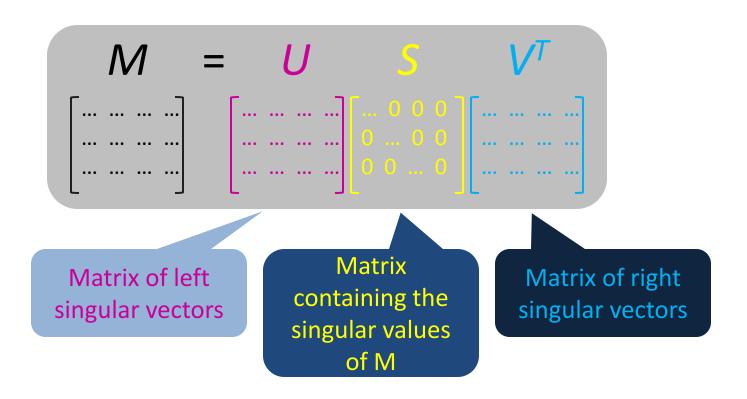
IND	Article 1I	•••	Article 1000I
k39607		•••	
k02421			•••

- Latent Semantic Analysis -
- 3. Set up a bilingual concept-document matrix for LSA



- Latent Semantic Analysis -

4. LSA: Compute SVD (Singular Value Decomposition)



- Latent Semantic Analysis -
- 5. Compute the optimal reduced rank approximation (reducing dimensions of the matrix)

	10%	25%	50%
1,000 art. pairs	100	250	500

6. Compute the level of agreement between the LSA-based mappings with human annotations (ongoing experiment to manually map WordNet synsets to KBBI senses)

- Check the results -
- 7. As a baseline, select three random suggested Indonesian word senses as a mapping for an English word sense

8. As another baseline, compare English concepts to their suggestion based on a full rank word-document matrix

9. Choose top 3 Indonesian concepts with the highest similarity values as the mapping results

- Results -

10. Compute the Fleiss kappa values

		Fleiss Kappa Values					
Judges	Synsets	Judges only	Judges + RNDM3	Judges + FREQ Top 3	Judges + LSA 10% Top3	Judges + LSA 25% Top3	Judges + LSA 50% Top3
≥ 2	144	0.4269	0.1318	0.1667	0.1544	0.1606	0.1620
≥ 3	24	0.4651	0.2197	0.2282	0.2334	0.2239	0.2185
≥ 4	8	0.5765	0.3103	0.2282	0.3615	0.3329	0.3329
≥ 5	4	0.4639	0.2900	0.2297	0.3359	0.3359	0.3359
Ave	rage	0.4831	0.2380	0.2132	0.2713	0.2633	0.2623

Results of Conc

LSA 10% is better than the randor frequency baseline (FREQ)

Rank Approximation	P	R
10%	0.0680	0.1727
25%	0.0845	0.2070
50%	0.0967	0.2226
100%	0.1009	0.2285

- LSA 10% is better than LSA 25% and LSA 50% (cf. the word mapping results)

- Mapping results -

WordNet Synset ID: 100319939, Words: chase, following, pursual, pursuit, Gloss: the act of pursuing in an effort to overtake or capture, Example: the culprit started to run and the cop took off in pursuit, Textual context set: {{following, chase}, {the, effort, of, to, or, capture, in, act, pursuing, an}, {the, off, took, to, run, in, culprit, started, and}}

KBBI ID: k39607
jar, Definition: be buru, Example: ia buru, Exampl

(a)

The textual context set for the synset is very small -> no sufficient context for LSA to choose the correct KBBI sense

The textual context sets both are fairly large -> provide sufficient context for LSA to choose the correct KBBI sense

WordNet synset ID: 201277784, Words: crease, furrow, wrinkle

Gloss: make wrinkled or creased, **Example**: furrow one's brow,

Textual context set: {{}, {or, make}, {s, one}}

KBBI ID: k02421 - Sin nition: jalinan peristiwa tertentu pautannya dapa atau waktu dan oleh hubungan kausal atau sebab-akibat, Example: (none), Textual context set: {{alur}, {oleh, dan, atau, jalinan, peristiwa, diwujudkan, efek, dapat, karya, hubungan, waktu, mencapai, untuk, tertentu}, {}}

(b)

Discussion

Initial intuition:

LSA is good for both word and concept mappings

Results:

- 1. LSA blurs the co-occurrence information/details
 - -> bad for word mapping
- 2. LSA is useful for revealing implicit semantic patterns
 - -> good for concept mapping

Reasons:

- The rank reduction in LSA perhaps blurs some details
- A problem of polysemous words for LSA

Suggestion:

Make a finer granularity of alignment (e.g. at a sentential level) for word mapping



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