Applying Latent Semantic Indexing in Frequent Itemset Mining for **Document Relation Discovery**

Thanaruk Theeramunkong¹, Kritsada Sriphaew^{1,2} (presenter) and Manabu Okumura²

¹School of Information and Computer Technology, Sirindhorn International Institute of Technology, THAILAND



²Precision and Intelligence Laboratory, Tokyo Institute of Technology, JAPAN



Outline

- What is our definition of document relation?
- Why we introduce LSI?
- How to evaluate the discovered relations?
- Results and Summary

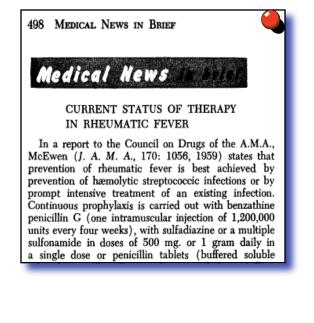


- In document network/graph area, a relation is introduced by edge or path between document nodes where an edge is introduced by hyperlink, author, citation, etc. [Kessler63, Garfield72, Small73, Chen99, An04]
- In IR and TM area, a relation is introduced by cosine similarity between query and the document vector or among two document vectors. respectively [Page98, Lawrence98, Baeza-Yates99, Theeramunkong04]

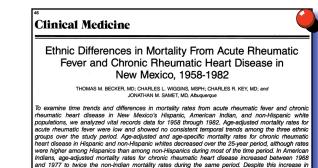


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- Usually, a relation is binary since it is introduced among only two documents
- Our approach: find document relations in which each relation introduce on n documents where n >= 2









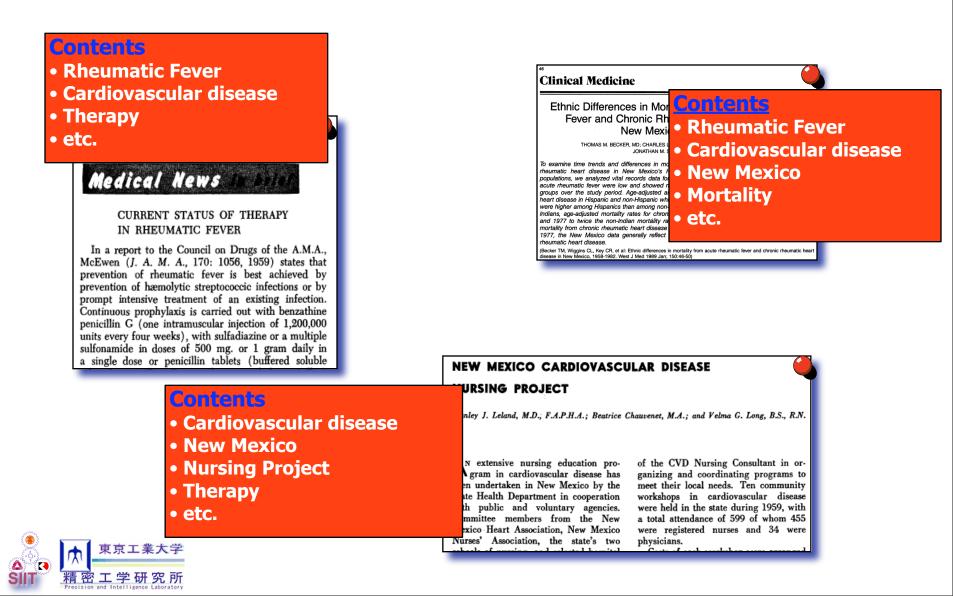
mortality from chronic rheumatic heart disease among New Mexico's American Indians from 1968 to 1977, Ihe New Mexico data generally reflect national trends of decreasing mortality from chronic rheumatic heart disease.

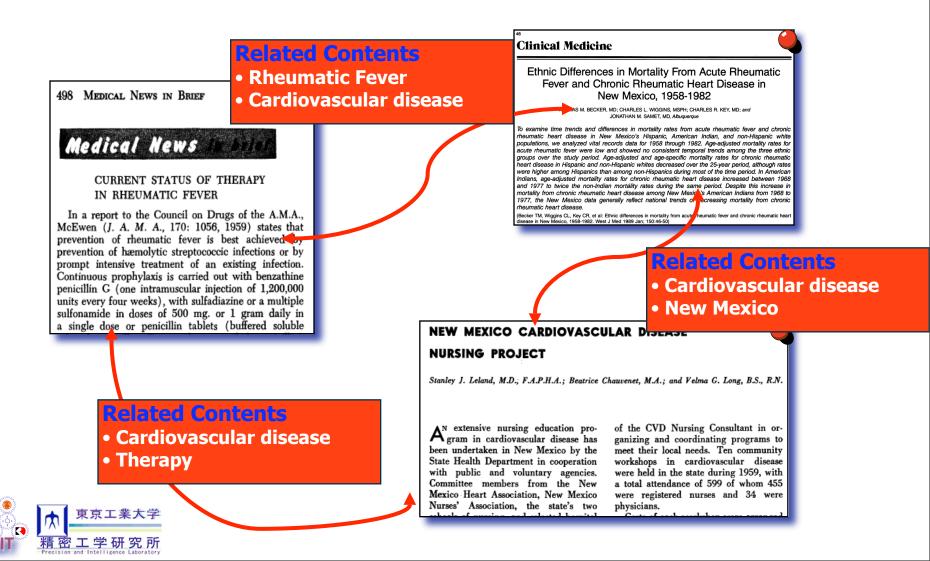
(Becker TM, Wiggins CL, Key CR, et al: Ethnic differences in mortality from acute rheumatic fever and chronic rheumatic heart disease in New Mexico, 1958-1982. West J Med 1989 Jan; 150:46-50)

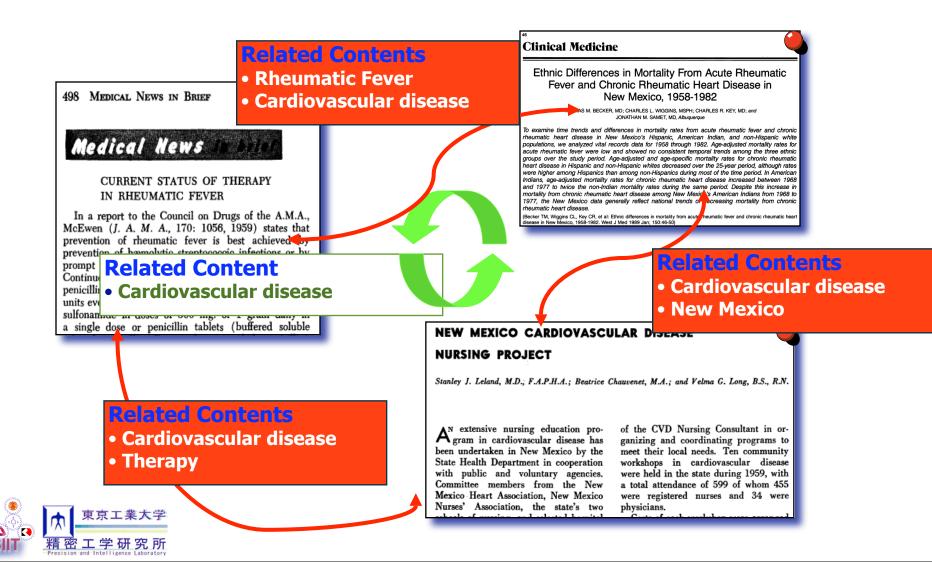
NEW MEXICO CARDIOVASCULAR DISEASE NURSING PROJECT

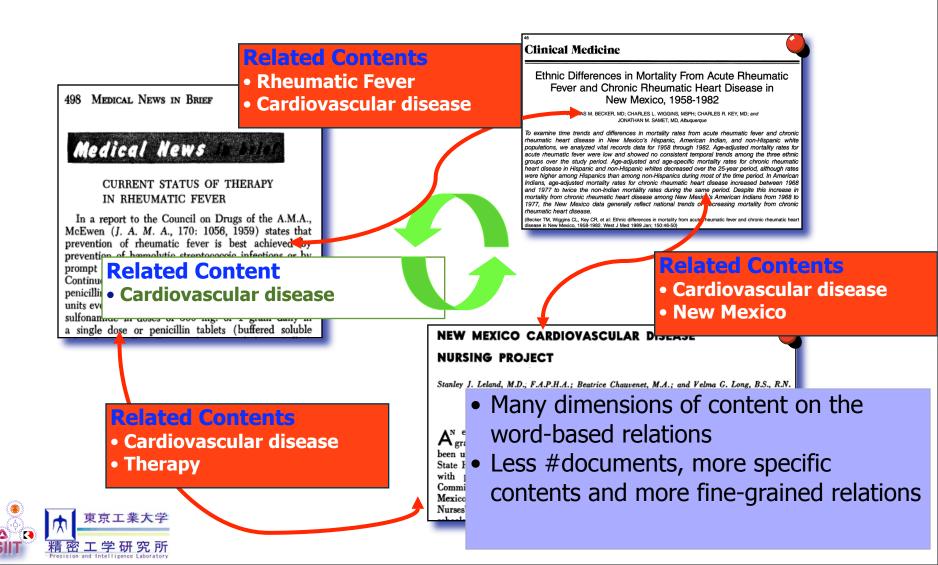
Stanley J. Leland, M.D., F.A.P.H.A.; Beatrice Chauvenet, M.A.; and Velma G. Long, B.S., R.N.

A^N extensive nursing education program in cardiovascular disease has been undertaken in New Mexico by the State Health Department in cooperation with public and voluntary agencies. Committee members from the New Mexico Heart Association, New Mexico Nurses' Association, the state's two of the CVD Nursing Consultant in organizing and coordinating programs to meet their local needs. Ten community workshops in cardiovascular disease were held in the state during 1959, with a total attendance of 599 of whom 455 were registered nurses and 34 were physicians.









Method for document relation discovery

Modified Frequent Itemset Mining [Sriphaew05, Sriphaew07]

Term	document					
Term	Α	В	С	D		
Data	4	1	4	2		
Mining	2	5	3	2		
Association	0	3	1	1		
Rule	0	4	1	1		
Technique	2	1	2	1		
Data Mining	2	0	1	1		
Association Rule	0	4	1	1		



Method for document relation discovery

Modified Frequent Itemset Mining [Sriphaew05, Sriphaew07]

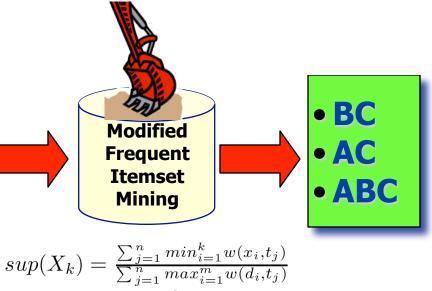
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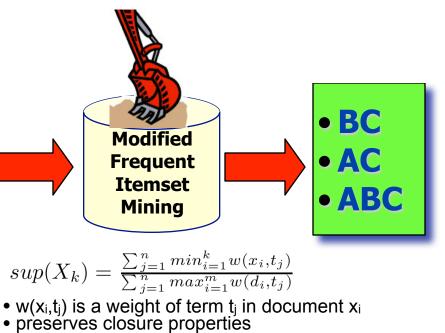
- w(x_i,t_j) is a weight of term t_j in document x_i
 preserves closure properties



Method for document relation discovery

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Why FIM?

- Possible to apply cosine similarity on every combination of document sets
- But our target is set of documents (involve more than two documents)
- Pruning strategy exists
- Several efficient algorithms



Problems of Document Representation

- Existing approach directly exploits words/terms in documents to discover relations using word co-occurrences and shared vocabularies.
- A relation on a set of documents may occur even if they do not share any common words or terms but their terms are semantically related.



Why we use LSI?

- We want some terms which are semantically related to existing terms in a document to have some weights while reducing meaningless terms (terms appear in small eigen vector)
- We still want to have term-document matrix where we can apply FIM to discover document relations, therefore, PCA which its input is covariance matrix is not our case.



Latent Semantic Indexing (LSI)

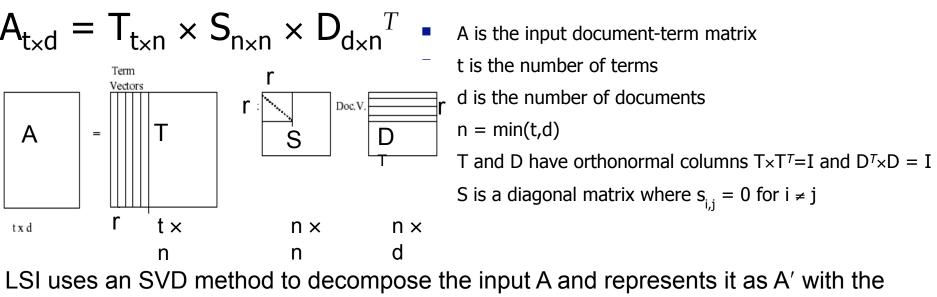
 $\mathbf{A}_{\mathsf{t} \times \mathsf{d}} = \mathbf{T}_{\mathsf{t} \times \mathsf{n}} \times \mathbf{S}_{\mathsf{n} \times \mathsf{n}} \times \mathbf{D}_{\mathsf{d} \times \mathsf{n}^T}$

- A is the input document-term matrix
- t is the number of terms
- d is the number of documents
- n = min(t,d)
- T and D have orthonormal columns $T \times T^{T} = I$ and $D^{T} \times D = I$
- S is a diagonal matrix where $s_{i,j} = 0$ for $i \neq j$

LSI uses an SVD method to decompose the input A and represents it as A' with the objective function: $\min || \mathbf{A} - \mathbf{A}' ||_2$



Latent Semantic Indexing (LSI)



LSI uses an SVD method to decompose the input A and represents it as A' with the objective function: $\min || A - A' ||_2$

In some cases, rank(A) = r where $r \le n$, the diagonal elements of S are $\sigma_1, \sigma_2, \dots, \sigma_n$ where $\sigma_i > 0$ for $1 \le i \le r$ and $\sigma_i = 0$ for $r < i \le n$

In this work, we get potential σ_i by using simple kappa statistics, i.e., relative accuracy of Ritz values acceptable as eigenvalue >= 1.00E-06



Proposed threshold δ

- Since some meaningless terms will have some wieghts after dimension reduction, therefore, we want to filter out those terms.
- We generate new document-term matrix A" where,

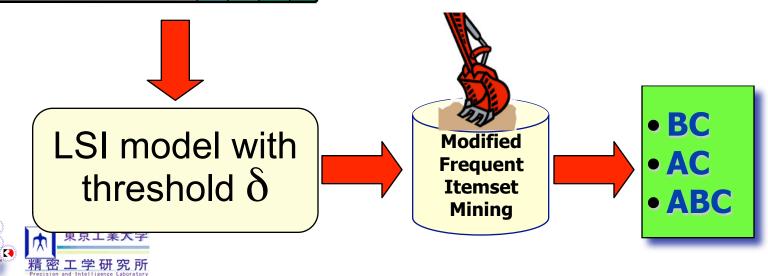
$$A''_{txd} = [a''_{ij}], 1 \le i \le t \text{ and } 1 \le j \le d$$
$$a''_{ij} = \begin{cases} a'_{ij}, if a'_{ij} \ge \delta \\ 0, otherwise \end{cases}$$



Objectives

Torm	d	document					
Term	Α	В	С	D			
Data	4	1	4	2			
Mining	2	5	3	2			
Association	0	3	1	1			
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- Study effects of different weighting, **tf** and **tf-idf** for new modified approach of FIM
- * Study effects of LSI with δ threshold and the quality of document relations



 $\dot{\Psi}$

Problems:

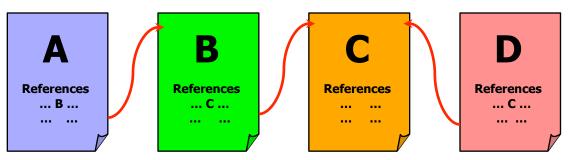
- Lack of corpus with correct answers
- Excessive time-consuming and labor-intensive task for human evaluation For example, we need to investigate ¹⁰⁰⁰⁰C₂≈ 50×10⁶ pairs if we want to construct a corpus with 10,000 documents

Solution Idea:

- Use other potential relation information as comparative criteria
- Trust knowledge for evaluation <u>citations</u> (or references) in research articles.
- Remark: our approach discovers word-based relations but we make comparison with the citation-based relations w/o using

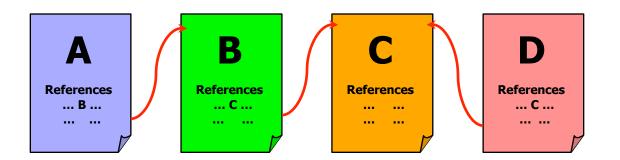
citation information for discovery



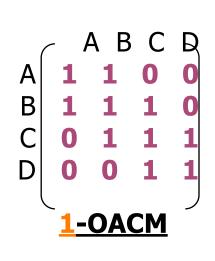


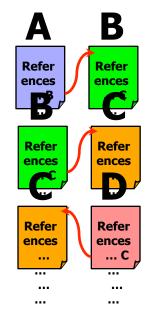
Formulating the evaluation criteria as an "Ordered Accumulative Citation Matrix" (OACM) using the citation information and the transitivity function



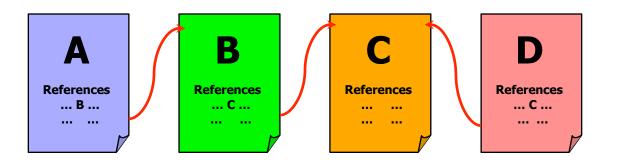


First Criteria:

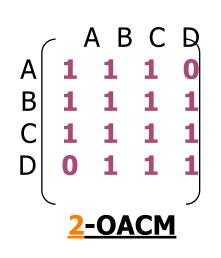


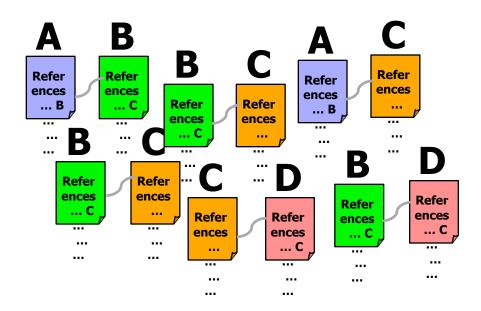




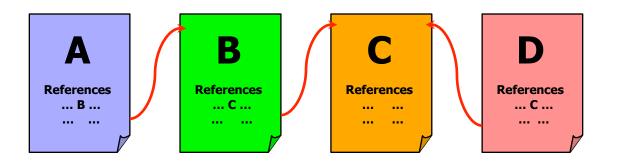


Second Criteria:

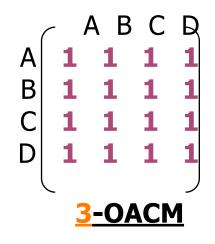


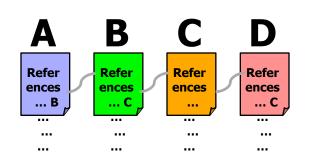






Third Criteria:





We stop at third criteria (3-OACM) since there is no significant difference after third criteria in our preliminary experiments

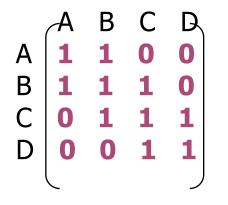


Proposed Scoring method: Counting the valid relations based on evaluation criteria

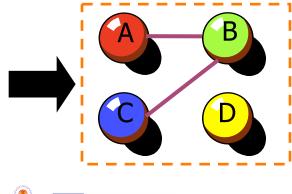


Proposed Scoring method: Counting the valid relations based on evaluation criteria

Evaluation Criteria: <u>1-OACM</u>



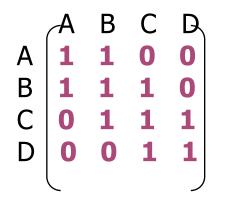
Based on 1-OACM



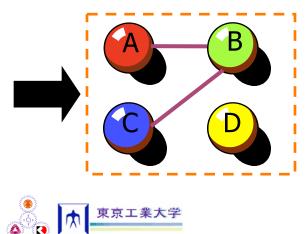


 Proposed Scoring method: Counting the valid relations based on evaluation criteria
 Discovered document relations

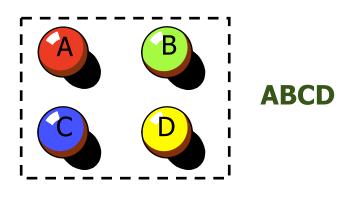
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Based on 1-OACM



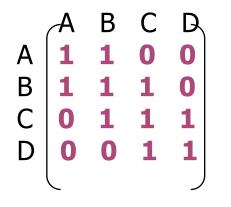
工学研究所



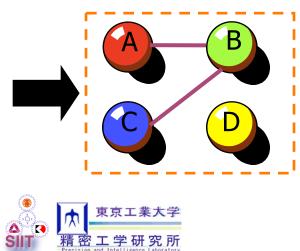
Validity of discovered relation ABCD based on 1-OACM = 2/3 = 0.67

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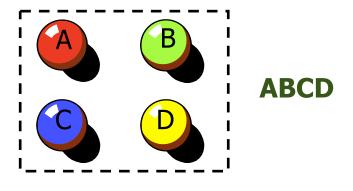


Based on 1-OACM



For all discovered set,

we use **weighted mean** of validity as evaluation measurement where the weight is given by the number of documents in each discovered relation.



Validity of discovered relation ABCD based on 1-OACM = 2/3 = 0.67

Dataset

Test Collection

- **10,817** scientific research articles*
- 3 classes: Hardware, Data, Computer
- Extract citation network to form evaluation criteria but exclude those texts from data
- Preprocessing: filtering stopwords, terms occur <3 times and bigram</p>



Experimental Results²²

N is Top-N rankings (by support) of discovered relations when either tf/tf-idf is used and LSI is applied with different δ thresholds

		1-OA	1-OACM		ACM	3-0A	ACM
Methods	N	tf	tfidf	tf	tfidf	tf	tfidf
	1000	14.29	25.00	85.71	100.00	100.00	100.00
	5000	37.59	38.03	87.23	95.77	95.62	97.18
w/o LSI	10000	18.22	38.97	58.94	87.66	87.13	93.81
	50000	6.16	16.24	35.91	60.52	75.68	94.05
	100000	4.37	14.36	31.22	55.83	74.49	93.08
	1000	41.51	42.86	90.57	85.71	94.34	91.43
	5000	23.80	25.90	66.47	67.94	84.01	83.76
$LSI_{\delta=0.5}$	10000	19.92	23.01	64.44	67.26	86.06	85.02
	50000	14.12	17.89	59.80	64.13	90.15	89.13
	100000	11.40	14.48	56.81	60.57	90.39	90.13

1. w/o LSI,

tfidf is better than tf

tfidf can help to find relations for direct use of words/terms

2. LSI case,

Applying LSI is better than w/o LSI

tf is better than tfidf is better than idf degrades the performance of LSI

Experimental Results²³

N is Top-N rankings (by support) of discovered relations when either tf/tf-idf is used and LSI is applied with different δ thresholds

		1-OACM		2-0/	ACM	3-0A	ACM
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	100000	11.40	14.48	56.81	60.57	90.39	90.13
	1000	47.14	44.15	90.00	80.32	95.71	85.64
	5000	25.95	28.28	69.09	70.86	85.98	85.72
$LSI_{\delta=0.7}$	10000	22.26	25.59	67.80	70.64	87.52	86.95
	50000	14.77	19.91	60.76	66.72	91.43	91.27
	100000	12.09	16.06	57.51	61.73	91.52	90.98
	1000	44.68	45.42	85.11	81.25	90.43	87.08
	5000	26.55	28.95	70.23	71.42	86.86	86.43
$LSI_{\delta=1.0}$	10000	23.67	27.85	69.27	72.66	88.54	89.15
	50000	15.27	19.79	61.05	66.58	91.75	91.29
	100000	12.53	16.45	57.35	62.03	91.67	91.90



Experimental Results²³

N is Top-N rankings (by support) of discovered relations when either tf/tf-idf is used and LSI is applied with different δ thresholds

			~		~				
		1-0A		2-0/		3-04		1.	δ threshold
Methods	N	tf	tfidf	tf	tfidf	tf	tfidf	ļ	There is a suitable threshold to
	1000	14.29	25.00	85.71		100.00			
	5000	37.59	38.03	87.23		95.62	97.18		achieve highest validity
w/o LSI	10000	18.22	38.97	58.94	87.66	87.13			LSI helps to discover direct citati
	50000	6.16	16.24	35.91	60.52	75.68	94.05		
	100000	4.37	14.36	31.22	55.83	74.49			more than indirect citations (we le
	1000	41.51	42.86	90.57	85.71	94.34			method to
Tat	5000	23.80	25.90	66.47	67.94	84.01	83.76		optimize δ threshold as future work)
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	50000	14.12	17.89	59.80		90.15	89.13		
	100000	11.40	14.48	56.81	60.57	90.39		2	LSI case & OACM,
	1000	47.14	44.15	90.00		95.71	85.64		-
	5000	25.95	28.28	69.09		85.98	85.72		1-OACM
$LSI_{\delta=0.7}$	10000	22.26	25.59	67.80		87.52	86.95		Higher δ is better than Lower δ
	50000	14.77	19.91	60.76		91.43	91.27		-
	100000	12.09	16.06	57.51	61.73	91.52	90.98	1	2-,3-OACMs
	1000	44.68	45.42	85.11	81.25	90.43			Lower δ is better than Higher δ
	5000	26.55	28.95	70.23	71.42	86.86	86.43		U
$LSI_{\delta=1.0}$	10000	23.67	27.85	69.27	72.66	88.54	89.15		LSI helps to discover direct citati
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Conclusions

- This work presents new approach to discover document relations using FIM and applying LSI for improving good document representation
- The quality of discovered document relations from our word-based approach can be relatively compared with ones from citation network. Those relations may be not the same kind of relations, but they shows good relation between those two kinds of document relations
- LSI is helpful to discover meaningful document relations especially the relations that is identical to **direct citations** whereas we still have indirect citations in the top ranks of discovered relations



Discussions and Future Works

- Some weak points of this work:
 - Testing on one corpus since it is difficult to construct large enough data of this kind.
 - Starting research for a new problem of document relation discovery where each relation composes of two or more documents. Therefore, there is no other method addressed the same problem with us. Although we can modify other existing methods for this task, we just want to sketch up the solution and fulfill all necessary processes for document relations especially the evaluation concept
- Low validity does not mean bad relations but it is not coincident with citation relations. Our method performs well in detect jeopardize articles and some novel relations which is not introduced by citations
- Exploring other term weighting and dimension reduction approaches





