

Comparing Frame Membership to WordNet-based Similarity and Distributional Similarity

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Agenda

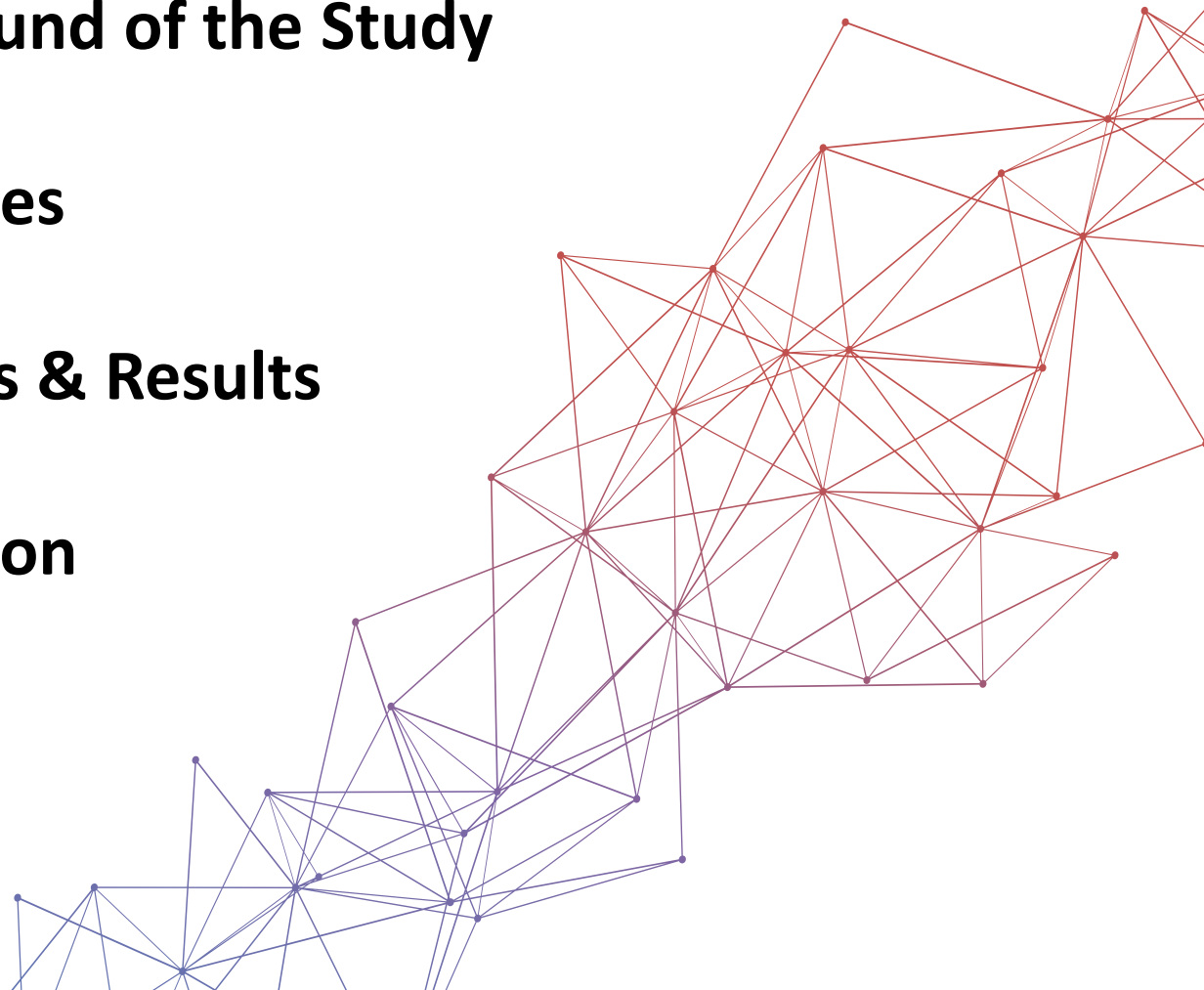
Talking points for this presentation

Background of the Study

Objectives

Methods & Results

Conclusion



BACKGROUND

Frame Membership

- A frame is “a schematic representation of a situation involving various participants, props and other conceptual roles, each of which is a frame element (FE)”.
- Each frame contains a number of Lexical Units (LUs) which are evokers of this frame.
- Frame co-membership refers to LUs evoking the same frame, sharing the same FEs and displaying the same perspective of the experiential knowledge.
- However, co-LUs may belong to different POS and fail to be categorized by a single lexical semantic relation. Manual annotation of corpus-based examples is the prerequisite of frame co-membership.
- FrameNet is a language resource which contains 13669 LUs and 1224 Frames.

WordNet-based Similarity

- WordNet is database grouping word senses in Synonymy Sets (Synsets).
- It also documents other lexical semantic relations such as hypernym-hyponym, sister terms and meronym-holonym, etc., unlike co-LUs in FN.
- Word senses in the same synset always belong to the same POS unlike co-LUs in FN.
- Similarity measures based on WN either depend mainly on measuring length of the shortest path between two concepts or comparing the information content of two concepts whether reflected in the gloss of the synset or in the probability of a random word to belong to a concept.

Distributional Similarity

- Distributional semantics explores word forms, not word senses and it adopts a statistical approach to meaning representation.
- Main hypothesis: similar words tend to occur in similar contexts.
- It obtains information from large corpora through investigating second order co-occurrences (words occurring with the same words).
- Several tools are developed to measure the distributional similarity among words. This study uses Sketch Engine's distributional similarity tool which unifies the POS.

Previous work used two or three of these approaches together to

1. *Automate the development and expansion of FN through the use of distributional methods* (Faralli et al., 2018; Toth, 2018),
2. *Enrich FN through WN synsets* (Fellbaum & Baker, 2008; Laparra et al., 2010; Tonelli & Pighin, 2009) or
3. *Identify LUs automatically through combining distributional and WN-based similarity measures* (Pennacchiott et al., 2008).



FN

- Detailed valence information about LUs
- Precision of manual annotation
- Limited lexical coverage
- Difficulty of reflecting the relations between LUs numerically.

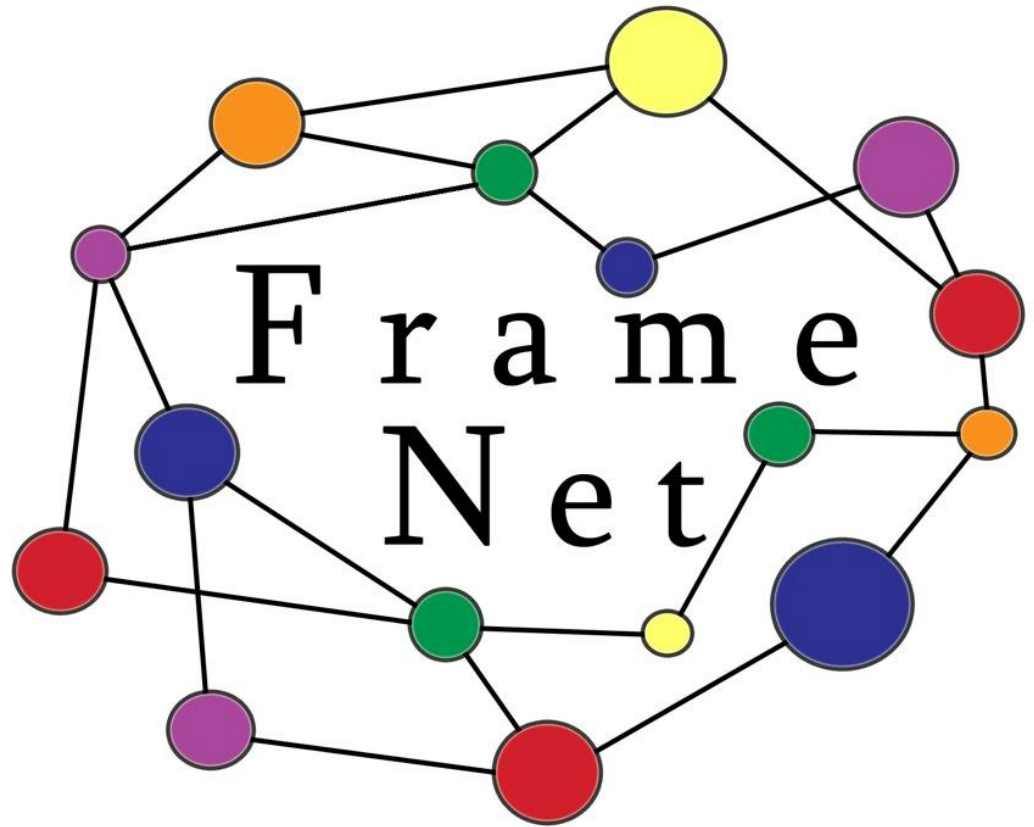
WN

- Extensive lexical coverage
- Fine granularity of senses
- Limited syntactic information
- Conventional lexical semantic relations which can be reflected numerically.

D.S

- Statistically evident relation
- No manual effort
- Retrieves fuzzy set of words
- No theoretical relation can interpret this similarity relation.

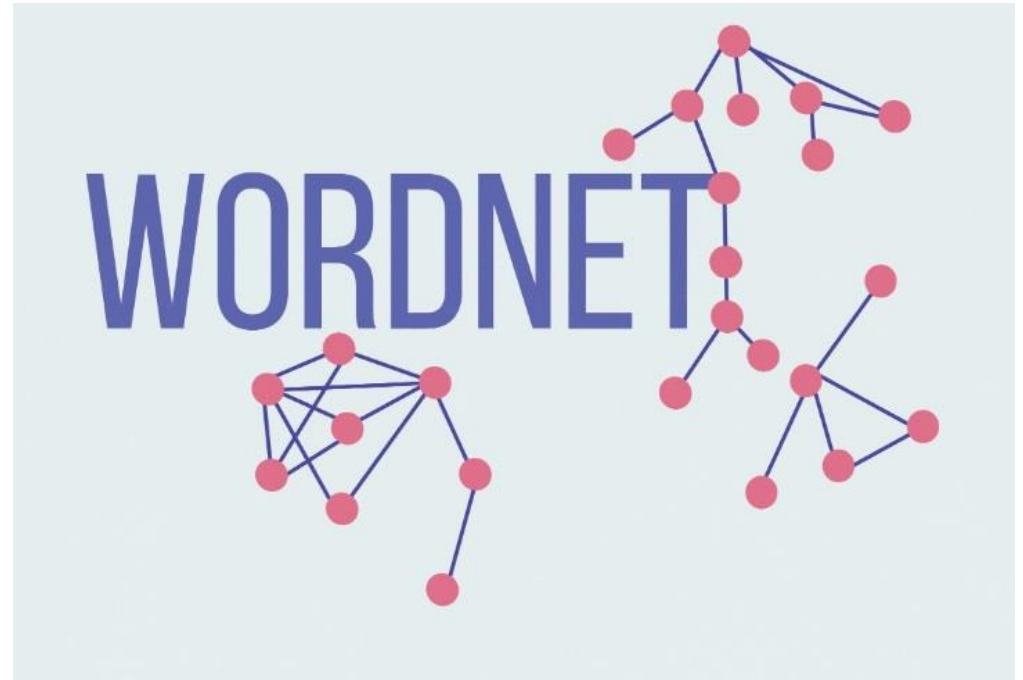
Objectives



The presentation aims at

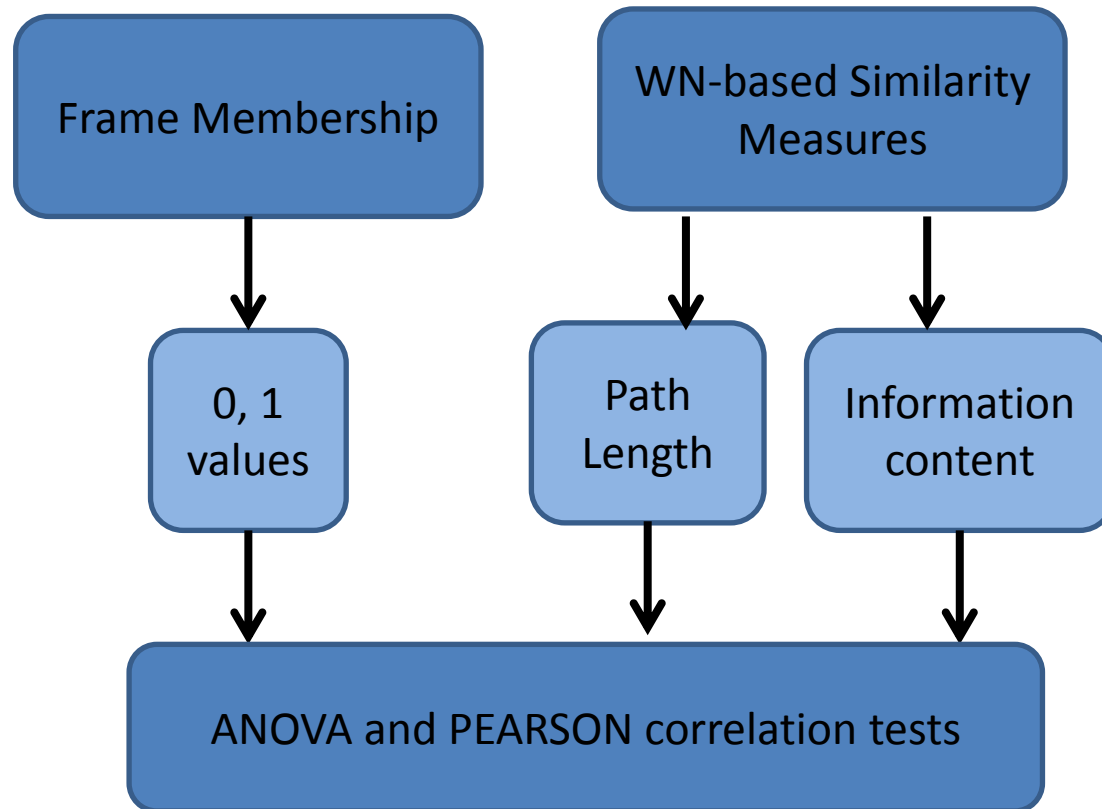
- Comparing FN membership to WN-based measures of similarity
- Suggesting a distribution-based method for the automatic induction of LUs

Method & Results



Experiment 1

Comparing FN membership to WN-based measures of similarity



	FN	Lesk	ICH	Resnik	WUP	Path	JCN	HSO	Vector	LIN
FN	1	0.2775	0.3808	0.6857	0.3987	0.3208	0.3333	0.5088	0.8496	0.5000
Lesk		1	0.3161	0.4270	0.2816	0.2414	0.1747	0.3285	0.5106	0.3390
ICH			1	0.7709	0.9710	0.9830	0.5242	0.6360	0.6415	0.8898
Resnik				1	0.7856	0.7079	0.5252	0.7300	0.6957	0.8286
WUP					1	0.9558	0.3872	0.5128	0.5197	0.9027
Path						1	0.5719	0.6398	0.6343	0.8842
JCN							1	0.9350	0.8496	0.5247
HSO								1	0.9441	0.6514
Vector									1	0.6465
LIN										1



- **Patwardhan (2003) VECTOR:** calculates cosine similarity between WN concepts which are represented through vectors retrieved from a corpus of WN glosses ($>0:1$), (same or different POS), (distributional relations)

Suggested SimScore: 0.6107

- **Resnik (1995) RES:** measures the IC of $c1$ and $c2$, based on the concept's generality of specificity (i.e., the probability of a random word to belong to the concept) and the IC of Least Common Subsumer (LCS) between $c1$ and $c2$ ($0:\infty$ values), (same POS), (*is-a* relation)

Suggested SimScore: 4.6135

- **Hirst and St-Onge (1998) HSO:** measures lexical chains whether horizontal or hierarchical between two concepts ($0:16$), (same or different POS), (all WN relations)

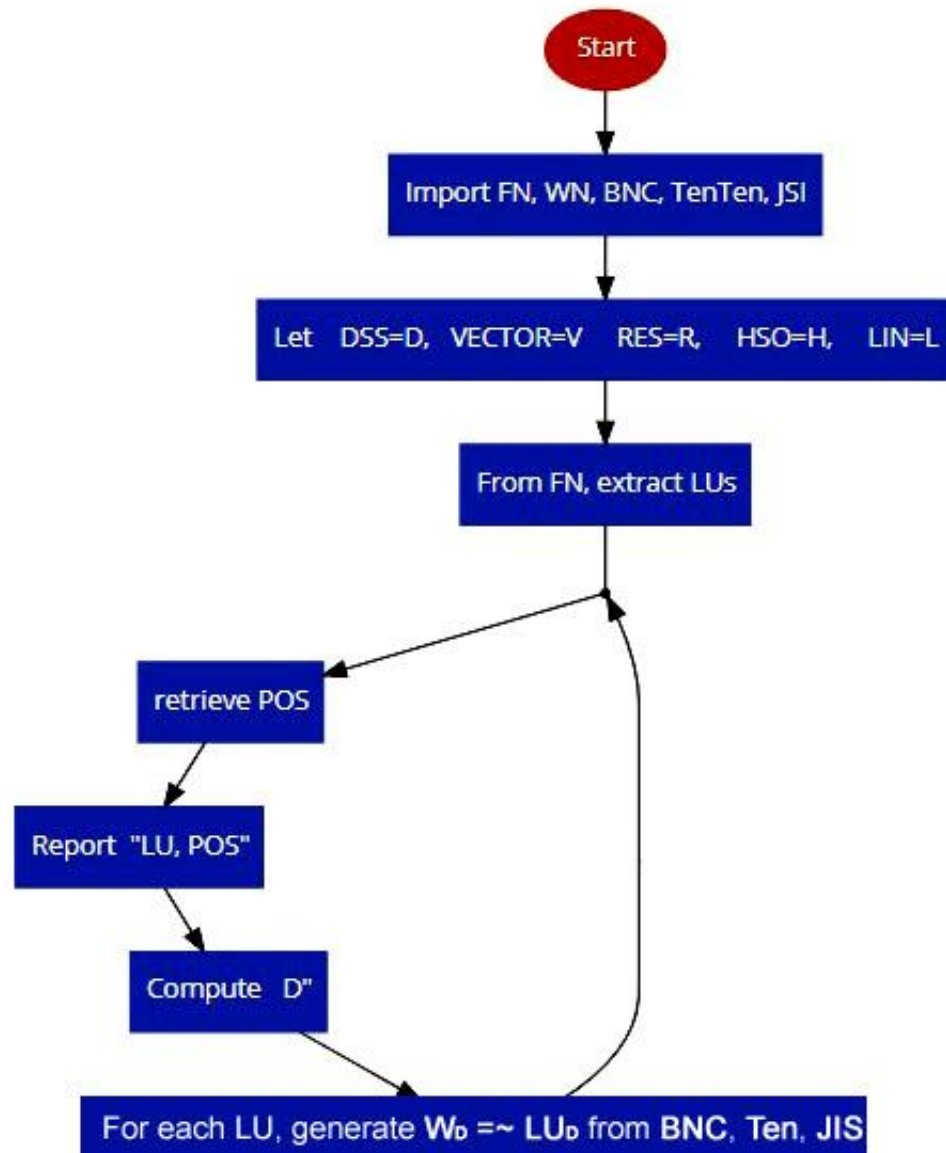
Suggested SimScore: 5

- **Lin (1998) LIN:** measures the IC of $c1$ and $c2$ and the IC of Least Common Subsumer (LCS) of $c1$ and $c2$ ($0:1$ values), (same POS), (*is-a* relation)

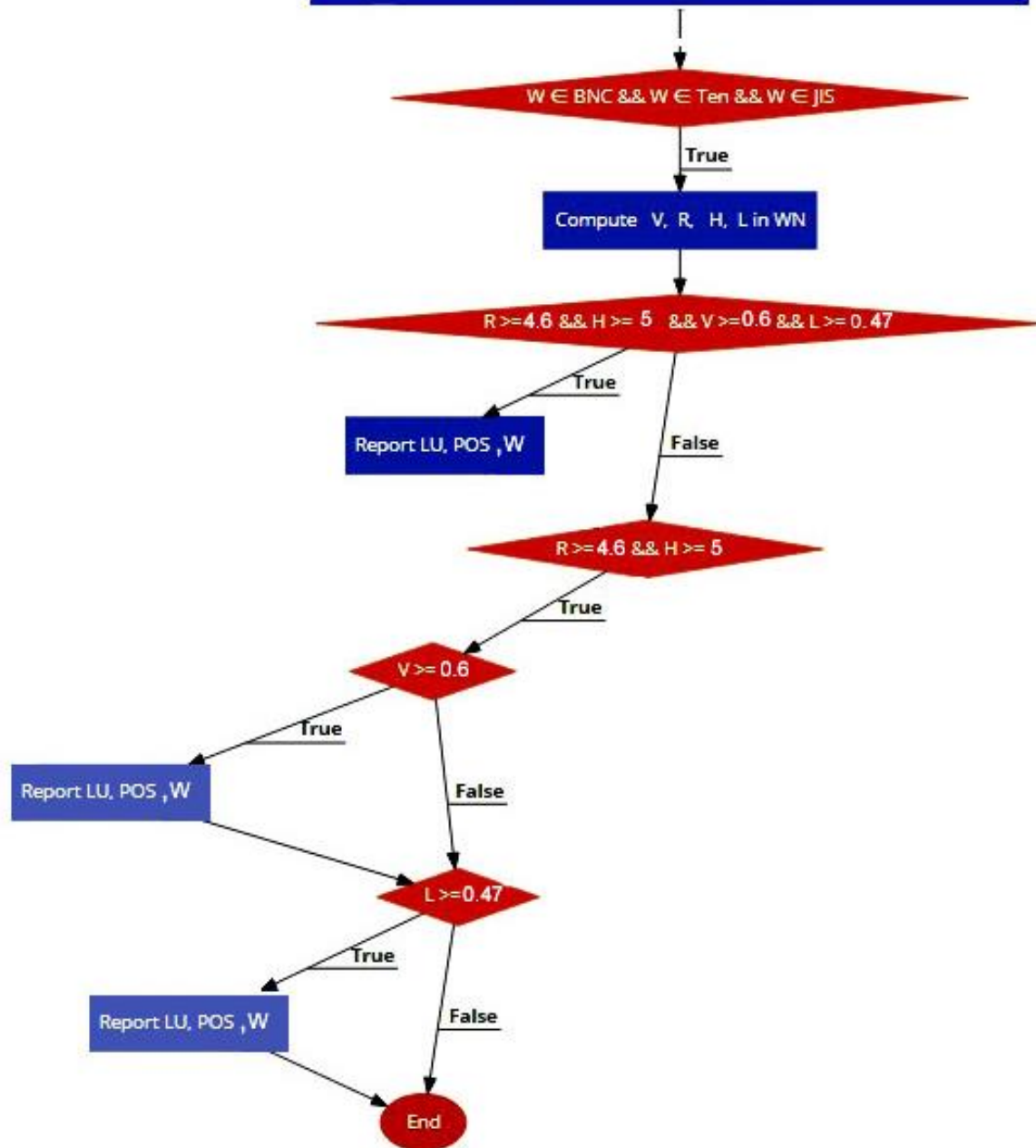
Suggested SimScore: 0.4786

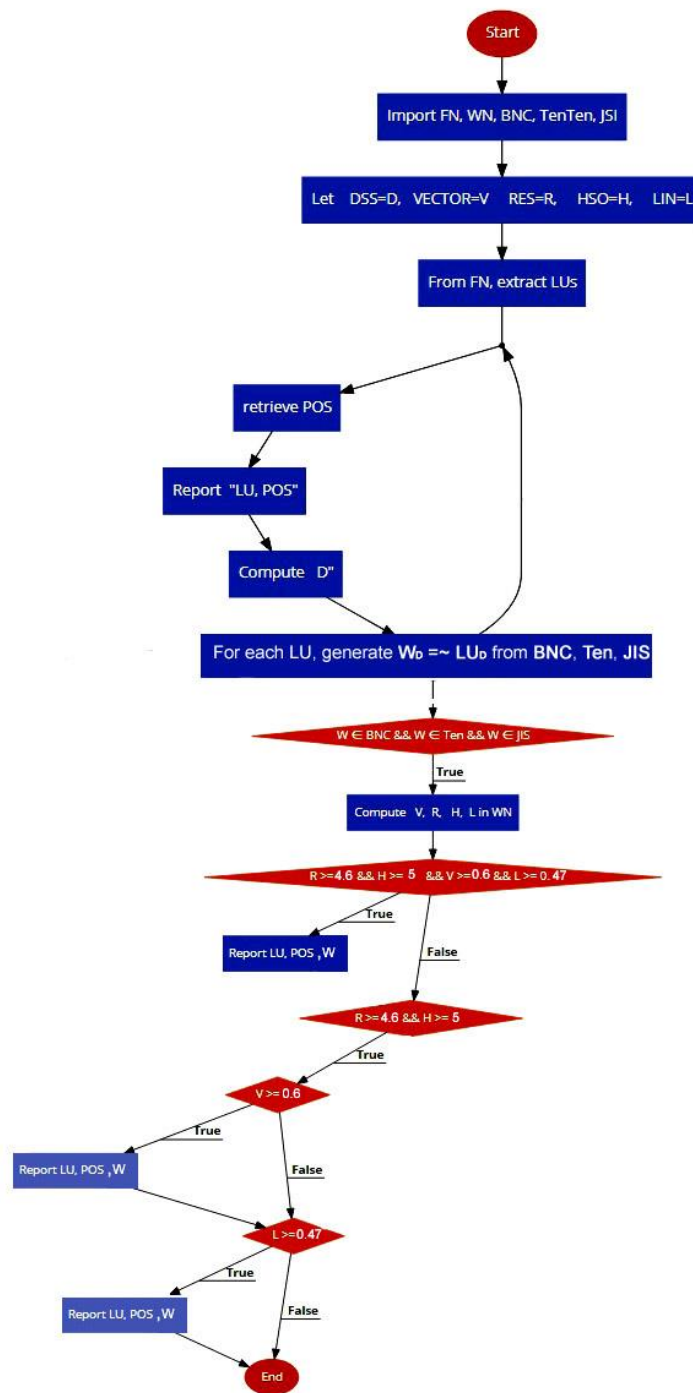
Experiment 2

Distribution-based method for the automatic induction of LUs



For each LU, generate $W_0 \sim LU_0$ from BNC, Ten, JIS





- Unifying the POS in Rychly's and Kilgarrieff's (2007) distributional algorithm helped in minimizing the effect of polysemy.
- The BNC retrieved the lowest similarity scores and the least common words among the studied corpora which affected the overall recall.
- The implementation of WN-based similarity measures enhanced the precision of the distributionally retrieved results but decreased the recall.



Sample of compatible pairs

Word Pair	D.S	FN	Vector 0.6107	Resnik 4.6135	HSO 5	Lin 0.4786
<i>abduct – kidnap</i>	0.565	1	1	10.3728	16	1
Assail- attack	0.451	1	1	7.5011	16	1
Help– assist	0.527	1	1	6.8313	16	1
<i>Spend- donate</i>	0.447	0	0.1462	0	0	0
<i>Crime- behavior</i>	0.473	0	0.1736	3.3826	3	0.4347
<i>Accept- recognize</i>	0.512	0	0.65	0.2222	0	0

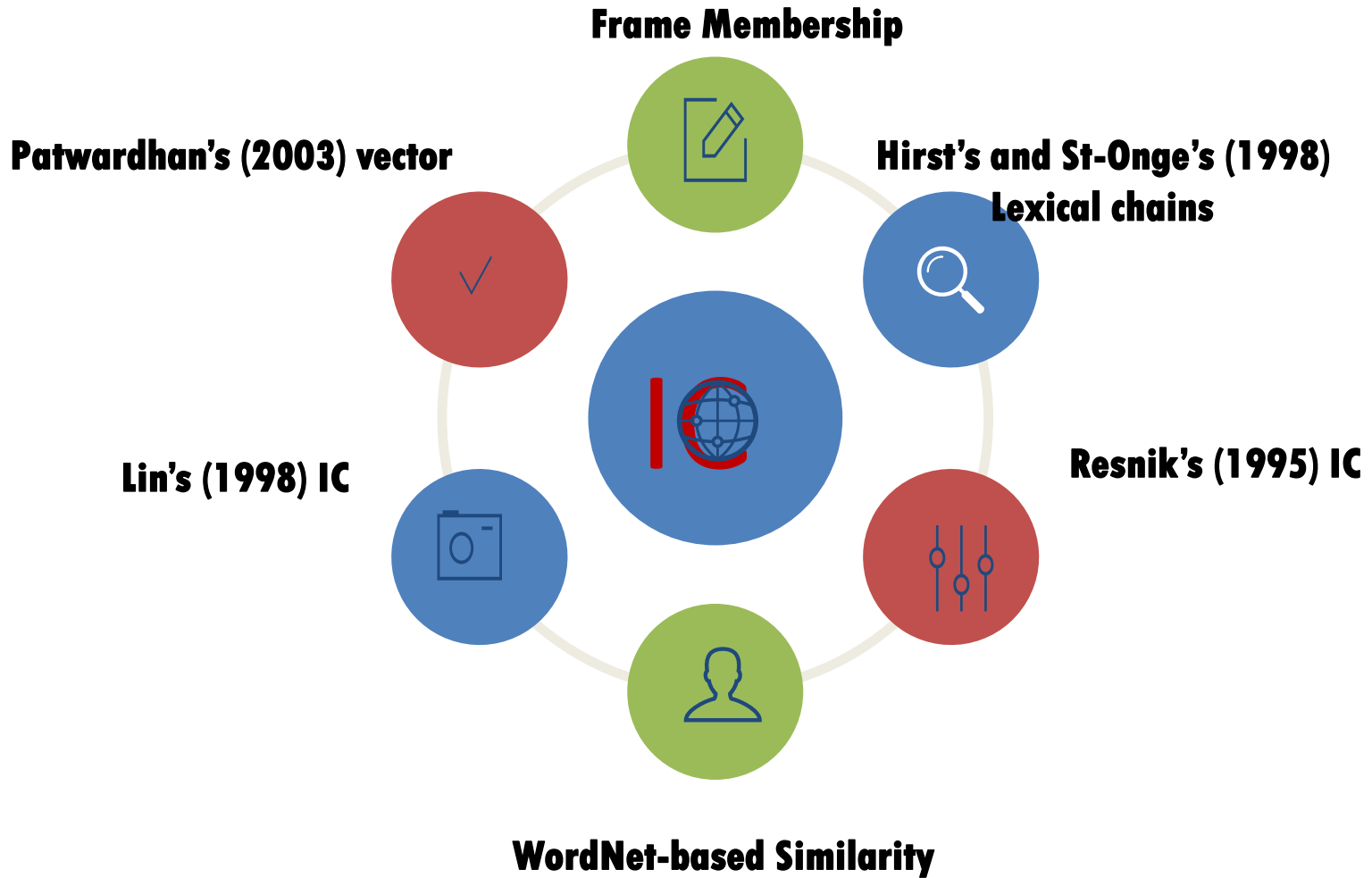
Sample of new LUs

Automatically induced LU	Original LU in FN	Vector 0.6107	Resnik 4.6135	HSO 5	Lin 0.4786
Support (n)	Help	0.5716	6.8313	6	0.9567
Misdemeanor (n)	violation	1	9.8198	16	1
Smuggle (v)	Trade	0.3247	8.1041	6	0.8772
Misspend (v)	Waste	0.6229	6.8663	16	0
Language (n)	Speech	1	8.8754	16	1
Introduce (v)	Present	1	8.2526	16	1

Conclusion

- FN membership correlated with some WN-based similarity measures, despite the gradable versus binary values and the inapplicability of some measures on co-LUs
- The use of several corpora including the BNC (the primary corpus of FN) enhanced the precision of the distributional similarity results, although it reduced the recall
- Patwardhan's (2003) vector, Resnik's (1995) IC, Hirst's and St-Onge's (1998) lexical chain and Lin's (1998) IC measures improved the precision of the distributional-based induction of Lus.

Summary



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https://framenet.icsi.berkeley.edu/fndrupal/framenet_search

<https://wordnet.princeton.edu/>

<https://www.sketchengine.eu/>

THANK YOU!

Comments and suggestions

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