Introduction					Results	
Creating gold-standard training sets can be		Relation	KWS	CDS	EDS	
prohibilitively expensive for tasks such as KBC.		age	500	0	0	
Commonly, researchers use <b>weak</b> or <b>distant</b>		parents	413	128	782	
supervision techniques to more cheaply produce		spouse	1533	346	403	
large training sets. This work analyzes three such		siblings	773	43	325	
approaches for producing so called silver-standard		foundBy	148	239	2207	
examples.		countryHQ	21	168	1715	
Central Question	<b>Number of Examples</b> Across each person relation KWS tends to outperforms despite using only 5%					
Which weak supervision techniques provide the best basis for learning accurate models and scale appropriately with the KBP task?	documents. One relation, <i>age</i> , could not be mapp to any known db, yielding 0 DS examples. EDS utilizes more seed entries from db than CDS.					
Methods Division						
Weak Supervision Approaches	Pipeline	; 	<u> </u>			
Distant Supervision refers to an external database as a source of seed examples [1] (NELL, Wikipedia Infoboxes, and Freebase).		Train corpus		Features Stanford NLP fact	ts	
• <i>Corpus Distant Supervision</i> ( <b>CDS</b> ) - map external db entries to sentences in a corpus native to the test		Training Labels		RDN Boost		
domain (e.g., TAC KBP newswire articles). Emphasizes matching learned models to test space.	Weak	Sold anno	otations	Learned models	5 ← Features	
• <i>External-Text Distant Supervision</i> ( <b>EDS</b> )- map db entries to sentences in an external text (Wikipedia	Extern databas	al ses Knowledge rules		p(y x)	Test corpus	
articles). Emphasizes utilization of seed examples.	To evalua	ate, we traine	ed Relatio	onal Depe	endency Ne	
<ul> <li>Knowledge-Based Weak Supervision (KWS) -</li> </ul>	works (R	(DN) [4] usin	g trainin	g example	es from eac	
encode "world knowledge" of domain experts [2]		DS, and KWS	0			
e.g., in FOL rules. Apply rules (via MLNs) to corpus		vas used for t				
to generate positive training examples.	We considered 6 TAC KBP relations (see results) re					
enerate positive training examples.		g persons and				
Weight KWS Rul	e (MLN Cla		0			
1.0 $entityType(a, "PER"), entityType(b, "NUM"), nextWord(a, c), word(c, ","), nextWord(c, b) \rightarrow age(a, b)$						
0.8 $entityType(a, "PER"), entityType(b, "PER"), nextLemma(a, "mother") \rightarrow parents(a, b)$						
0.6 $entityType(a, "PER"), entityType(b, "PER"), lemmaBetween(a, b, "husband") \rightarrow spouse(a, b)$						
1.0 $entityType(a, "ORG"), entityType(b, "PER"), prevPrevLemma(b, "found"), prevLemma(b, "by") \rightarrow foundedBy(a, b)$						

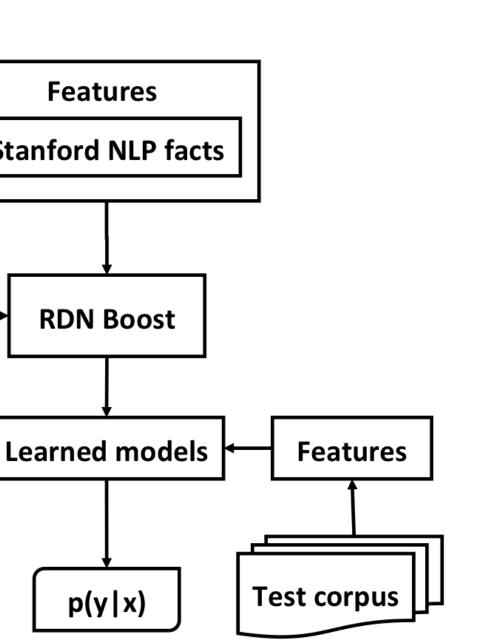
# A Comparison of Weak Supervision Methods for KBC A. Soni<sup>1</sup>, D. Viswanathan<sup>2</sup>, N. Pachaiyappan<sup>2</sup>, S. Natarajan<sup>2</sup> <sup>1</sup>Swarthmore College, <sup>2</sup>Indiana University

## s and Discussion

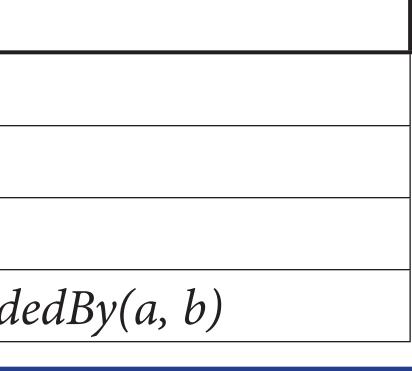
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Relation	KWS	CDS	EDS
parents	0.68	0.62	0.49
spouse	0.81	0.46	0.53
siblings	0.69	0.52	0.58
foundBy	0.60	0.72	0.63
countryHQ	0.58	0.69	0.69

Area Under ROC Curve RDN models trained usation, ing each of the three training sets. Results are across 5 runs. KWS outperforms across all person relations, but struggles with organizations where rules are more difficult to encode. Gold examples help KWS equal DS in *countryHQ* relation.



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Knowledge-based WS is viable alternative/complement to the popular distant supervision approaches can produce more examples and better models requires good (formalisible) world knowledge Distant supervision techniques • scale better with larger corpus • yield fewer results; require existing db can utilize external texts if (native) training data is unavailable We acknowledge Deep Exploration and Filtering of Text Program under the Air Force Research Laboratory (AFRL) prime contract and FA8750-12-2-0039 References [1] M. Mintz, S. Bills, R. Snow, and D. Jurafsky. 2009. Distant supervision for relation extraction without labeled data. [2] S. Natarajan, J. Picado, T. Khot, K. Kersting, C. Re, and J. Shavlik. 2014. Effectively creating weakly labeled training examples via approximate domain knowledge. [3] F. Niu, C. Re', A. Doan, and J. W. Shavlik. 2011. Tuffy: Scaling up statistical inference in Markov logic networks using an RDBMS. [4] S. Natarajan, T. Khot, K. Kersting, B. Gutmann, and J. Shavlik. 2010. Boosting relational dependency networks.

## Conclusions