Unsupervised Word Sense Disambiguation Yarowsky (1995)

Introduction

- <u>Word Sense Disambiguation</u>: Word Sense Disambiguation (WSD) is the process of identifying the sense of a polysemic word.
- <u>Polysemic word</u>: *Clear* (to brighten? unclutter?...)
- <u>Aim</u>: To use an unsupervised algorithm for WSD that will rival supervised techniques.
- <u>Why</u>: Supervised techniques require hand/human annotation; therefore are time-consuming.

Background

- Premise: Exploits two properties of human language
- One sense per collocation and One sense per discourse
- One sense per collocation: Nearby words give strong (and consistent) clues to the sense of the target word
- One sense per discourse: The sense of the target word is consistent within any given document

One sense per discourse

- Gale, Church and Yarowsky(1992): Words strongly exhibit only one sense in a given discourse/ document.
- Does not use this as a hard constraint. If local evidence is stronger, it can be overridden.

One sense per collocation

- Collocation: Words appearing in the same location.
 Has not considered idiomatic sense etc..
- Yarowsky(1993) observed and quantified that words exhibit one sense in a given collocation.
- Strongest with adjacent collocations, and weakens with distance. Strong with words in a predicateargument relationship, content words.
- Properties are highly reliable, therefore useful for WSD

One sense per collocation

- Yarowsky(1994): Supervised algorithm based on the 'One sense per collocation' property
- Training procedure: Calculates the probability *Pr(Sense | Collocation)*, and orders them by log likelihood ratio:

 $Log \frac{Pr(Sense_a \mid Collocation)}{Pr(Sense_b \mid Collocation)}$

- Integrates evidence sources (POS, inflected forms..) with positional relationships (trigram sequences, predicate argument association..) using a decision list algorithm
- **sense different from collocation!

- <u>Seed collocations</u>: Accurately represent SenseA and SenseB of a word.
- For example: Present noun sense: day(SenseA) OR gift (SenseB).
- Words occur not only in collocations that indicate sense, but multiple such collocations.
- For example: For Present, 'time' and 'day' are both collocations that could indicate the same sense (day).
- Demonstrated on 7538 instances of plant, a polysemous word in an untagged corpus.

- Given a large corpus, identify all polysemous words
- Store contexts as lines in an untagged training set.



- For each sense of the word, identify a small number of training samples representative of that sense.
- How: Dictionary definitions, Single collocate for each class (such as taken from *WordNet*)
- For example: *life* and *manufacturing* are used as seed collocations for two major senses of a plant.
- The remaining examples (85-98%) constitute untagged residual.



Figure 1: Sample Initial State

A = SENSE-A training example B = SENSE-B training example ? = currently unclassified training example Life = Set of training examples containing the collocation "life".

 Train the classification algorithm on SenseA/ SenseB seed sets - Yarowsky(1994).

Initial decision list for plant (abbreviated)							
LogL	Collocation	Sense					
8.10	plant life	$\Rightarrow \overline{A}$					
7.58	manufacturing plant	⇒ B					
7.39	life (within $\pm 2-10$ words)	\Rightarrow A					
7.20	manufacturing (in $\pm 2-10$ words)	⇒ B					
6.27	animal (within $\pm 2-10$ words)	\Rightarrow A					
4.70	equipment (within $\pm 2-10$ words)	\Rightarrow B					
4.39	employee (within $\pm 2-10$ words)	⇒ B					
4.30	assembly plant	⇒ B					
4.10	plant closure	\Rightarrow B					
3.52	plant species	\Rightarrow A					
3.48	automate (within $\pm 2-10$ words)	⇒ B					
3.45	microscopic plant	\Rightarrow A					
		1					

- Apply the resulting classifier to the entire sample set.
- <u>Threshold</u>: Words in the residuals that are tagged as SenseA or Sense B with probability above a certain threshold can be added to the growing seed sets.

• <u>Result</u>: Newly learned collocations that are reliably indicative as the previous trained seed sets.

- Step 3c: Optionally, use the one sense per discourse constraint.
- If several instances of a polysemous word have been tagged SenseA, then the tag can extend to all examples in the discourse
- Step 3d: Repeat Step 3 iteratively.
- The training set will continue to grow, and the residual will diminish.

- Stop when the training parameters are held constant.
- Most training examples will show multiple collocations indicative of the same sense.
- The one sense per discourse property can also be utilized here, for error correction.

- The classification procedure learned can be applied to new data
- Can be used to annotate the untagged corpus with sense tags and probabilities.

- Original seed words may not remain on top of the list for the final classification.
- They may be displaced by more broadly applicable collocations

Final decision list for plant (abbreviated)							
LogL	Collocation	Sense					
10.12	plant growth	⇒ A					
9.68	car (within $\pm k$ words)	⇒ B					
9.64	plant height	⇒ A					
9.61	union (within $\pm k$ words)	\Rightarrow B					
9.54	equipment (within $\pm k$ words)	⇒ B					
9.51	assembly plant	⇒ B					
9.50	nuclear plant	⇒ B					
9.31	flower (within $\pm k$ words)	⇒ A					
9.24	job (within $\pm k$ words)	⇒ B					
9.03	fruit (within $\pm k$ words)	⇒ A					
9.02	plant species	⇒ A					

Evaluation

- 460 million word corpus consisting of news articles, scientific abstracts, spoken transcripts.
- Using 2 seed collocations overall gives the best accuracy for words (avg 90.6%)
- Dictionary definitions as seeds increase accuracy
- OSPD one sense per discourse constraint

Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	· · · · · · · · · · · · · · · · · · ·		%		Seed Training Options		(7) + OSPD			
		Samp.	Major	Supvsd	Two	Dict.	Top	End	Each	Schütze
Word	Senses	Size	Sense	Algrtm	Words	Defn.	Colls.	only	Iter.	Algrthm
plant	living/factory	7538	53.1	97.7	97.1	97.3	97.6	98.3	98.6	92
space	volume/outer	5745	50.7	93.9	89.1	92.3	93.5	93.3	93.6	90
tank	vehicle/container	11420	58.2	97.1	94.2	94.6	95.8	96.1	96.5	95
motion	legal/physical	11968	57.5	98.0	93.5	97.4	97.4	97.8	97.9	92
bass	fish/music	1859	56.1	97.8	96.6	97.2	97.7	98.5	98.8	-
palm	tree/hand	1572	74.9	96.5	93.9	94.7	95.8	95.5	95.9	-
poach	steal/boil	585	84.6	97.1	96.6	97.2	97.7	98.4	98.5	-
axes	grid/tools	1344	71.8	95.5	94.0	94.3	94.7	96.8	97.0	-
duty	tax/obligation	1280	50.0	93.7	90.4	92.1	93.2	93.9	94.1	-
drug	medicine/narcotic	1380	50.0	93.0	90.4	91.4	92.6	93.3	93.9	-
sake	benefit/drink	407	82.8	96.3	59.6	95.8	96.1	96.1	97.5] -
crane	bird/machine	2145	78.0	96.6	92.3	93.6	94.2	95.4	95.5	-
AVG		3936	63.9	96.1	90.6	94.8	95.5	96.1	96.5	92.2

Summary

- An unsupervised algorithm that can accurately disambiguate words in a large untagged corpus.
- Avoids hand-tagging data.
- Self correcting; hence exhibiting strengths of supervised approaches.
- Operates on the assumption that human language has one sense per collocation and one sense per discourse.

Thank you!

