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# Unsupervised Word Sense Disambiguation Rivaling Supervised Methods

David Yarowsky (1995)

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## Definitions

**Sense Disambiguation** - is the problem of determining which "sense" (meaning) of a word is activated using the word in a particular context

**Collocation** – two or more words that tend to appear frequently together

**Discourse** – any document or a piece of writing

**Accuracy** – how often a target word (that appeared multiple times) contains one sense (the majority sense) in a document

**Applicability** – how often a target word appears more than once in a discourse

**Polysemous** – words having multiple meanings

**Seed collocations** – initial main/major collocations of a word in a discourse

## Background

- **Word sense disambiguation had been a major problem in NLP for over forty years (early 1990s)**
- **Major problem was “sense” vagueness**
- **Gale, Church, and Yarowsky (1992) utilized parallel text such as Canadian Hansards**
- **Decision list based on Supervised algorithm (Yarowsky, 1994)**

## Main Ideas

- **Unsupervised algorithm that can disambiguate word senses in a large untagged corpus**
- **Avoid tedious and time-consuming hand-tagging data training**
- **Two properties of human language/algorithm constraints:**
  - 1. One sense per collocation**
  - 2. One sense per discourse**

## One sense per discourse

- words tend to exhibit only one sense in a given discourse (Gale, Church, and Yarowsky)
- tested on a set of 37,232 examples, hand-tagged over 3 years

**The one-sense-per-discourse hypothesis:**

Word	Senses	Accuracy	Applicblty
plant	living/factory	99.8 %	72.8 %
tank	vehicle/contr	99.6 %	50.5 %
poach	steal/boil	100.0 %	44.4 %
palm	tree/hand	99.8 %	38.5 %
axes	grid/tools	100.0 %	35.5 %
sake	benefit/drink	100.0 %	33.7 %
bass	fish/music	100.0 %	58.8 %
space	volume/outer	99.2 %	67.7 %
motion	legal/physical	99.9 %	49.8 %
crane	bird/machine	100.0 %	49.1 %
<b>Average</b>		<b>99.8 %</b>	<b>50.1 %</b>

## **One sense per collocation**

- **observed and quantified by Yarowsky (1993)**
- **strongest for immediately adjacent collocations and weakens with distance**
- **stronger with content words than function words**
- **reliability of 97% for adjacent content words**
- **Four types of collocation:**
  1. **the word which collocates with the target word appears in a left window of 2-10 words relatively to the target word**
  2. **it is the previous word**
  3. **it is the next word**
  4. **it appears in a right window of 2-10 words**

The algorithm was illustrated by the disambiguation of 7538 instances of polysemous words:

**STEP 1:** Identify all the polysemous words in a large corpus, storing their contexts as lines in the original (untagged) training set

Sense	Training Examples (Keyword in Context)
?	... company said the <i>plant</i> is still operating
?	Although thousands of <i>plant</i> and animal species
?	... zonal distribution of <i>plant</i> life . ...
?	... to strain microscopic <i>plant</i> life from the ...
?	vinyl chloride monomer <i>plant</i> , which is ...
?	and Golgi apparatus of <i>plant</i> and animal cells
?	... computer disk drive <i>plant</i> located in ...
?	... divide life into <i>plant</i> and animal kingdom
?	... close-up studies of <i>plant</i> life and natural
?	... Nissan car and truck <i>plant</i> in Japan is ...
?	... keep a manufacturing <i>plant</i> profitable without
?	... molecules found in <i>plant</i> and animal tissue
?	... union responses to <i>plant</i> closures . ...
?	... animal rather than <i>plant</i> tissues can be
?	... many dangers to <i>plant</i> and animal life
?	company manufacturing <i>plant</i> is in Orlando ...
?	... growth of aquatic <i>plant</i> life in water ...
?	automated manufacturing <i>plant</i> in Fremont ,
?	... Animal and <i>plant</i> life are delicately
?	discovered at a St. Louis <i>plant</i> manufacturing
?	computer manufacturing <i>plant</i> and adjacent ...
?	... the proliferation of <i>plant</i> and animal life
?	... ..



## Step 2

- For each possible sense of the word, group a small number of training examples that showcase the sense
- Done by identifying a small number of seed collocations representative of each sense then tagging all training examples containing the seed collocates with the seed's sense label
- The words “life” and “manufacturing” are used as seed collocates for the example shown
- “?” represents untagged residual
- Resulted in 82 examples of living plants (1%), 106 examples of manufacturing (1%), and 7350 residual/unsure (98%)

Sense	Training Examples (Keyword in Context)
A	used to strain microscopic <i>plant</i> life from the ...
A	... zonal distribution of <i>plant</i> life . ...
A	close-up studies of <i>plant</i> life and natural ...
A	too rapid growth of aquatic <i>plant</i> life in water ...
A	... the proliferation of <i>plant</i> and animal life ...
A	establishment phase of the <i>plant</i> virus life cycle ...
A	... that divide life into <i>plant</i> and animal kingdom
A	... many dangers to <i>plant</i> and animal life ...
A	mammals . Animal and <i>plant</i> life are delicately
A	beds too salty to support <i>plant</i> life . River ...
A	heavy seas, damage , and <i>plant</i> life growing on ...
A	... ..
?	... vinyl chloride monomer <i>plant</i> , which is ...
?	... molecules found in <i>plant</i> and animal tissue
?	... Nissan car and truck <i>plant</i> in Japan is ...
?	... and Golgi apparatus of <i>plant</i> and animal cells ...
?	... union responses to <i>plant</i> closures . ...
?	... ..
?	... ..
?	... cell types found in the <i>plant</i> kingdom are ...
?	... company said the <i>plant</i> is still operating ...
?	... Although thousands of <i>plant</i> and animal species
?	... animal rather than <i>plant</i> tissues can be ...
?	... computer disk drive <i>plant</i> located in ...
?	... ..
B	automated manufacturing <i>plant</i> in Fremont ...
B	... vast manufacturing <i>plant</i> and distribution ...
B	chemical manufacturing <i>plant</i> , producing viscose
B	... keep a manufacturing <i>plant</i> profitable without
B	computer manufacturing <i>plant</i> and adjacent ...
B	discovered at a St. Louis <i>plant</i> manufacturing
B	... copper manufacturing <i>plant</i> found that they
B	copper wire manufacturing <i>plant</i> , for example ...
B	's cement manufacturing <i>plant</i> in Alpena ...
B	polystyrene manufacturing <i>plant</i> at its Dow ...
B	company manufacturing <i>plant</i> is in Orlando ...

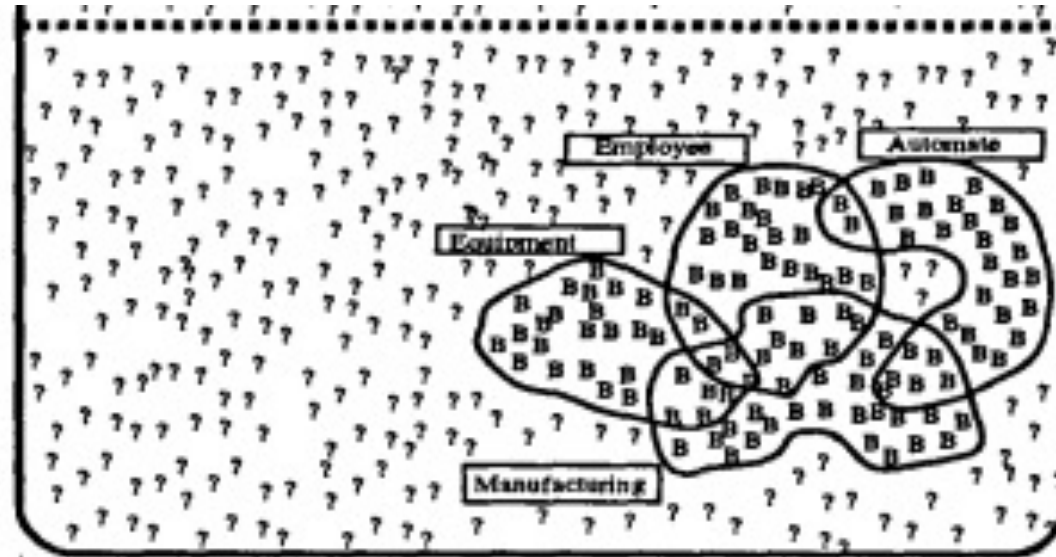
## STEP 3:

- train the supervised classification algorithm on the Sense A/ Sense B seed sets
- devise a decision list by identifying other collocations that reliably partition the seed training data, ranked by the purity of the distribution
- the purity of distribution is computed for each collocation  $x$  and sense  $A$  as the log-likelihood ratio for that sense given that collocation:  $\log \frac{P(\text{sense}-A \mid \text{collocation}-x)}{P(\text{sense}-B \mid \text{collocation}-x)}$ , then apply smoothing to avoid 0 values

LogL	Collocation	Sense
8.10	<i>plant life</i>	⇒ A
7.58	<i>manufacturing plant</i>	⇒ B
7.39	<i>life (within ±2-10 words)</i>	⇒ A
7.20	<i>manufacturing (in ±2-10 words)</i>	⇒ B
6.27	<i>animal (within ±2-10 words)</i>	⇒ A
4.70	<i>equipment (within ±2-10 words)</i>	⇒ B
4.39	<i>employee (within ±2-10 words)</i>	⇒ B
4.30	<i>assembly plant</i>	⇒ B
4.10	<i>plant closure</i>	⇒ B
3.52	<i>plant species</i>	⇒ A
3.48	<i>automate (within ±2-10 words)</i>	⇒ B
3.45	<i>microscopic plant</i>	⇒ A
	...	

## STEP 3 (cont.):

- Apply the resulting classifier to the whole data set
- Classify the residual/tagged “?” as sense A or sense B with a probability above a certain threshold
- Results in an augmented collocation sets

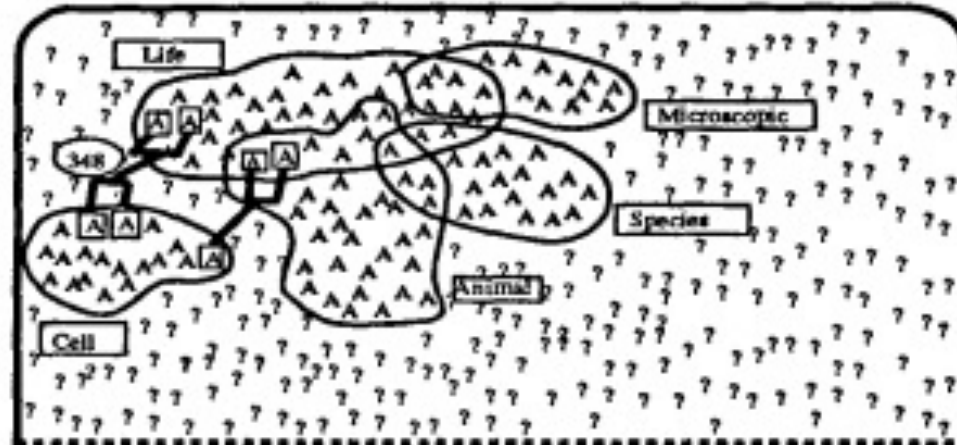


## STEP 3 (cont.):

- following the one sense per discourse principle, label previously untagged contexts:

Change in tag	Disc. Numb.	Training Examples (from same discourse)
A → A	724	... the existence of <i>plant</i> and animal life ...
A → A	724	... classified as either <i>plant</i> or animal ...
? → A	724	Although bacterial and <i>plant</i> cells are enclosed
A → A	348	... the life of the <i>plant</i> , producing stem
A → A	348	... an aspect of <i>plant</i> life, for example
? → A	348	... tissues; because <i>plant</i> egg cells have
? → A	348	photosynthesis, and so <i>plant</i> growth is attuned

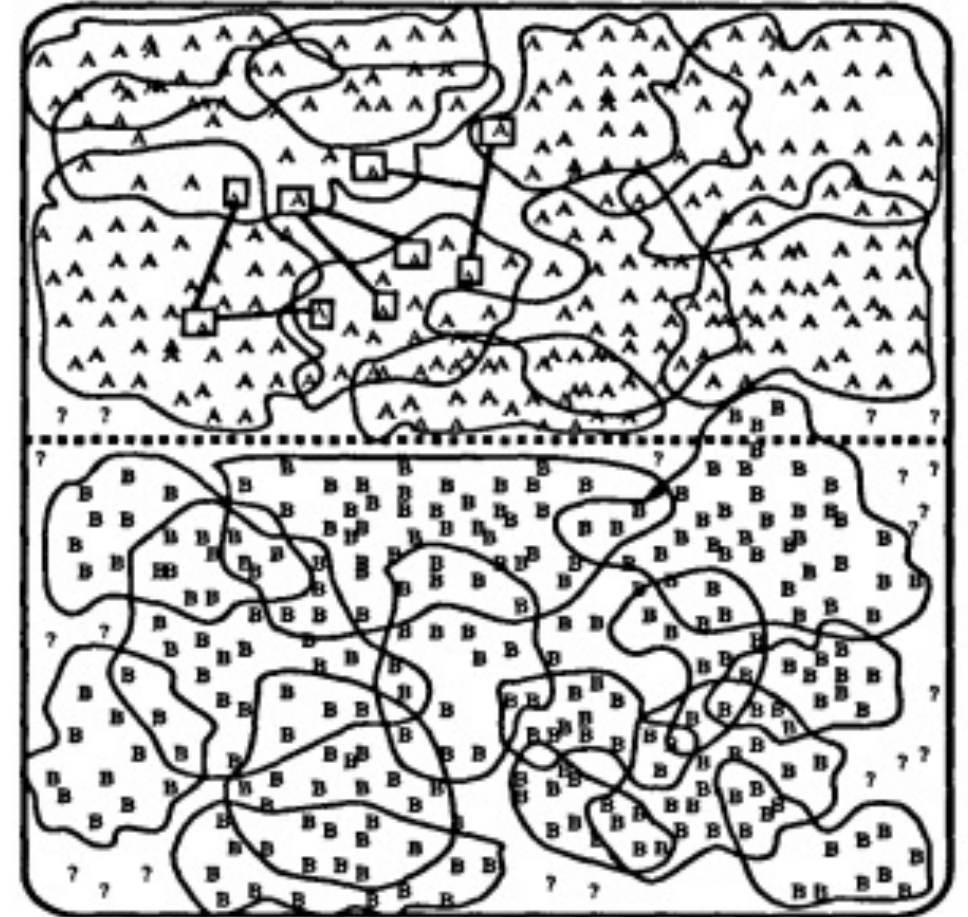
- may lead to new collocations that might be related to already identified collocations



- repeat Step 3 iteratively

## STEP 4:

- algorithm converges on a stable residual set
- resolves conflicts by using only the single most reliable piece of evidence, not a combination of related collocations



## STEP 5:

- original untagged corpus is then tagged with sense labels and probabilities
- the new model can now be applied to new data
- notice that the original seeds are replaced

Initial decision list for <i>plant</i> (abbreviated)		
LogL	Collocation	Sense
8.10	<i>plant</i> life	⇒ A
7.58	manufacturing <i>plant</i>	⇒ B
7.39	life (within ±2-10 words)	⇒ A
7.20	manufacturing (in ±2-10 words)	⇒ B
6.27	animal (within ±2-10 words)	⇒ A
4.70	equipment (within ±2-10 words)	⇒ B
4.39	employee (within ±2-10 words)	⇒ B
4.30	assembly <i>plant</i>	⇒ B
4.10	<i>plant</i> closure	⇒ B
3.52	<i>plant</i> species	⇒ A
3.48	automate (within ±2-10 words)	⇒ B
3.45	microscopic <i>plant</i>	⇒ A
	...	



Final decision list for <i>plant</i> (abbreviated)		
LogL	Collocation	Sense
10.12	<i>plant</i> growth	⇒ A
9.68	car (within ± <i>k</i> words)	⇒ B
9.64	<i>plant</i> height	⇒ A
9.61	union (within ± <i>k</i> words)	⇒ B
9.54	equipment (within ± <i>k</i> words)	⇒ B
9.51	assembly <i>plant</i>	⇒ B
9.50	nuclear <i>plant</i>	⇒ B
9.31	flower (within ± <i>k</i> words)	⇒ A
9.24	job (within ± <i>k</i> words)	⇒ B
9.03	fruit (within ± <i>k</i> words)	⇒ A
9.02	<i>plant</i> species	⇒ A
...	...	

## Example:

...”the loss of animal and *plant* species through extinction...”

**Based on the final decision list, the collocation “plant species” has a LogL value of 9.02, which means it refers to sense-A which is life or living plant**

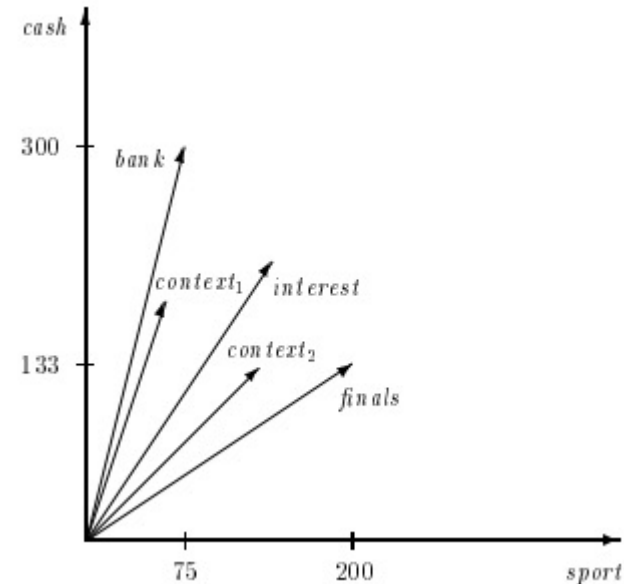
- **Words used were randomly selected from previous literature (Yarowski) like drug = drogue/medicament**
- **Schultze's 1992 disambiguation experiments (tank, space, motion, and plant)**
- **460 million word corpus containing news articles, scientific abstracts, spoken transcripts, and novels**



## Schutze's "Dimension of Meaning" Paper (1992):

- unsupervised algorithm, trained on a New York Times corpus
- represented the semantics of words and contexts as vectors
- applied SVD to reduce dimensionality

	<i>bank</i>	<i>interest</i>	<i>finals</i>
<i>cash</i>	300	210	133
<i>sport</i>	75	140	200



## Results

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Word	Senses	Samp. Size	% Major Sense	Supvsd Algrtm	Seed Training Options			(7) + OSPD		Schütze Algrtm
					Two Words	Dict. Defn.	Top Colls.	End only	Each Iter.	
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

## Seed Training Options

1. Two words: hand-tagged like “plant life” and “manufacturing plant”
  - easy to implement but not so robust
2. Dictionary definitions: find significantly frequent words w.r.t the most reliable collocational relationships (decision list)
3. Top collocates label salient corpus collocates


**Definitions**  
Definitions from [Oxford Languages](#)

See definitions in:

All Biology Civil Engineering Mechanics Intelligence Horticulture

*noun*  
noun: **plant**; plural noun: **plants**

1. a living organism of the kind exemplified by trees, shrubs, herbs, grasses, ferns, and mosses, typically growing in a permanent site, absorbing water and inorganic substances through its roots, and synthesizing nutrients in its leaves by photosynthesis using the green pigment chlorophyll.  
**Similar:** herb flower vegetable shrub weed greenery flora



- a small plant, as distinct from a shrub or tree.  
"garden plants"
2. a place where an industrial or manufacturing process takes place.  
"the company has 30 plants in Mexico"  
**Similar:** factory works foundry mill workshop shop yard
- machinery used in an industrial or manufacturing process.  
"inadequate investment in new plant"  
**Similar:** machinery machines equipment apparatus appliances gear
3. a person placed in a group as a spy or informer.  
"we thought he was a CIA plant spreading disinformation"  
**Similar:** spy informant informer undercover agent secret agent agent
- a thing put among someone's belongings to incriminate or compromise them.  
"he insisted that the cocaine in the glove compartment was a plant"

*verb*

## One Sense Per Discourse constraint

- Instead of treating tokens of target word independently, we assume (put bias) that they likely exhibit the same sense
- Error correction in step 4
- Example: “[discourse is plant life]...sell plants especially locally grown ones...”

## Conclusions

- **Utilized one sense per discourse and one sense per collocation properties of language**
- **Outperformed Schultze's unsupervised algorithm (96.7% to 92.2%) on 4 words**
- **Achieved relatively same performance as Supervised model (95.5% to 96.1%)**
- **Shown better results with one sense per discourse restraint (96.5% to 96.1%)**
- **The model successfully shown improvement from supervised word-sense disambiguation's tedious hand-tagging**

## Final Thoughts/Discussions

- **Were One-sense-per-collocations and one-sense-per-discourse fair assumptions/properties?**
- **What about small corpus?**



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