

# Unsupervised Methods for NLP WSD

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## 1 Introduction - Unsupervised NLP

- The Competition - Supervised Methods
- Colleagues - Human Knowledge
- Unsupervised Learning

## 2 Word Sense Disambiguation (WSD)

- Unsupervised Labeling
- Bayesian Sense Induction

## 3 Work in Progress - Aspect & Sentiment in Reviews

## 4 Conclusion

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Supervised methods are used for many NLP tasks (parsing, relation extraction, WSD)

Why?

- + high accuracy with sufficient annotation
- + full collection of powerful and easy-to-use tools (e.g., SVM, kNN, Maximum Entropy)

## Why not?

- annotation is expensive
- doesn't transfer well between domains and tasks
- is it a good model for human learning?
  - do humans perform singular-value decomposition?
  - discriminative rather than generative
  - concepts come from the annotation rather than the data

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Many “unsupervised” approaches make use of manually compiled knowledge bases.

- Dictionaries
- Thesauri
- FrameNet
- PropBank



## WordNet senses for *bank*:

- |   |                       |     |                   |
|---|-----------------------|-----|-------------------|
| 1 | river bank            | ... |                   |
| 2 | financial institution | 9   | bank building     |
| 3 | bank of earth         | 10  | a flight maneuver |

- lack of coverage
- no domain/task specificity
- over representation of marginal cases
- based on a specific theory

- Linguistic Theory
- Psychology
- Neurology
- Formal Logic

*“Whenever I fire a linguist our system performance improves”*

- Fred Jelinek

Why? (see *“Some Of My Best Friends Are Linguists”* - Fred Jelinek)

- strict models do not allow for “grey” areas
- attempts to cover rare cases leads to excessive complexity
- models do not scale to practical cases

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# Unsupervised Learning

Unsupervised techniques offer many tools and insights:

- EM
  - classification / generalization
- Automatic Alignment
  - corpus statistics
  - information theory
- Bayesian Models, LDA
  - probabilistic view
  - minimal assumptions

We can still benefit from:

- insights and tools from supervised learning
- careful use of knowledge bases
- aspects of scientific theory

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# Outline

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# Good Senses Make Good Neighbors:

## Exploiting Distributional Similarity for Unsupervised WSD

Brody and Lapata (2008)

## Supervised WSD

- Most accurate WSD systems to date are supervised.
- Rely on sense-labeled training data to train standard classifiers.
  - Acquiring sufficient labeled data is very expensive.
  - Limits the use in new domains and languages.
  - Makes supervised WSD unfeasible for many applications.

## Unsupervised WSD

- + Independent of labeled data.
- + Most promising solution for large-scale use.
- Much less accurate than supervised methods.

## The Idea: Automatic Labeling

- go directly to the data
- replace manual annotation
- retain use of supervised classifiers

## Synonyms from a Lexical Resource (Leacock et al., 1998; Mihalcea, 2002)

- Obtain synonymous / related words for each sense.
- Search a large corpus / web for the synonyms.
- Find good sense indicators from the retrieved contexts.

## WordNet senses for the word “sense”:

- 1 A general conscious **awareness**.  
(e.g., *a sense of security*)
- 2 The **meaning** of a word.  
(e.g., *The dictionary gave several senses for the word*)
- 3 Sound practical **judgment**.  
(e.g., *I can't see the sense in doing it now*)
- 4 A natural appreciation or **ability**.  
(e.g., *keen musical sense*).

## Semantic Neighbors from WordNet

- **Neighbors of *awareness*:** [sentienc](#) , sensation, sensitivity, sensitiveness, sensibility, modality, module, knowingness, ...
- **Neighbors of *meaning*:** [signified](#) , acceptation, signification, significance, meaning, import, symbolization, symbolisation,...
- **Neighbors of *judgment*:** [gumption](#) , logic, sagacity, judgment, judgement, discernment, prudence, judiciousness, eye, ...
- **Neighbors of *ability*:** hold, grasp, appreciation

- few exact synonyms
- many related words
- neighbors are not “substitutable”
- neighbors are themselves polysemous

## Monosemous Semantic Neighbors

- **Neighbors of *awareness*:** cognisance, self-awareness
  - **Neighbors of *meaning*:** signified, signification, nuance, moral, intention
- 
- greatly reduced number of neighbors
  - no monosemous neighbors for last two senses
  - neighbors may be rare

## Distributional Neighbors

- Extension of McCarthy et al. (2004).
- Based on distributional similarity - words are related if used in similar contexts.
- Uses semantic similarity to associate neighbors with senses.

## Method Advantages

- + relates directly to context cues
- + domain specific
- + polysemy restricted by similarity



## Distributional Neighbors

- **Neighbors of *awareness*:** awareness, feeling, instinct, enthusiasm, sensation, vision, tradition, consciousness, anger, panic, loyalty
  - **Neighbors of *meaning*:** emotion, belief, meaning, manner, necessity, tension, motivation
- 
- No neighbors for last two senses.
  - Not prevalent in the corpus (corroborated by the test data).

# Associating Neighbors and Senses

Neighbors from a lexical resource are already associated.

Distributional neighbors are not.

- Use semantic similarity on the knowledge base.  
(WordNet::Similarity – Pedersen et al. 2004)
- Choose target sense most similar to *any* sense of the neighbor.

- 1 Acquire “neighbors” - words related to (a sense of) the target
- 2 Extract instances of neighbors from a large corpus
- 3 Label instances with associated sense
- 4 Use labeled data to train supervised classifier

“... an attempt to state the **meaning** of a word”

becomes

“... an attempt to state the **sense** (s#2) of a word.”

## Corpus

### The British National Corpus (BNC)

- cross-section of 20th century, written & spoken, British English.
- 100 million words

## Evaluation

### Nouns from Senseval 2 & 3 lexical samples

- instances from BNC
- coarse-grain senses

	# Words	Ambiguity	1st Sense
SE-2	25	3.28	65.96%
SE-3	20	4.35	60.90%

## Distributional Neighbors

- dependency based (Lin, 1998)
- co-occurrence based (InfoMap)

## Classifiers

Evaluated on a variety of classifiers, from different paradigms:

- SVM - multi-class bound-constrained SVC (Hsu and Lin, 2001)
- Maximum Entropy (Megam, Daumé III 2004)
- Label Propagation (SemiL, Zhu and Ghahramani 2002)

- McCarthy et al - predominant sense detection
- Lesk - overlap between context and dictionary definition

# Results

Senseval 2	AllWN	MonoWN	Depend	Manual
SVM	48.12%	53.29%	64.38%	72.52%
MaxEnt	40.93%	52.11%	62.32%	71.91%
LP	42.67%	49.54%	63.32%	69.28%
McCarthy	59.98%			
Lesk	48.12%			

Senseval 3	AllWN	MonoWN	Depend	Manual
SVM	53.16%	46.32%	57.47%	71.22%
MaxEnt	49.67%	44.85%	57.35%	71.75%
LP	47.41%	43.60%	60.60%	67.57%
McCarthy	57.14%			
Lesk	48.66%			

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# Conclusions

- statistics + knowledge-base is better than just knowledge-base
- surpasses state-of-the-art unsupervised methods
- utility similar to supervised framework  
better classifier → better scores

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# Bayesian Sense Induction

Brody and Lapata (2009)

*“ ... we find that word sense disambiguation does not yield significantly better translation quality than the statistical machine translation system alone.”*

– Carpuat and Wu (2005)

*“ ... missing correct matches because of incorrect sense resolution has a much more deleterious effect on retrieval performance than does making spurious matches.”*

– Voorhees (1993)

# Why?

*“ Major barriers to building a high-performing word sense disambiguation system include the difficulty of labeling data for this task and of predicting **fine-grained sense distinctions**. These issues stem partly from the fact that **the task is being treated in isolation from possible uses** of automatically disambiguated data.”*

– Vickrey et al. (2005)

*“ ... one of the main problems in word sense disambiguation lies upstream, in the very sense lists used by systems. **Conventional dictionaries are not suited to this task**; they usually contain definitions that are too general ... and there is no guarantee that they reflect the exact content of the particular textbase being queried ... ”*

– Véronis (2004)

## Sense Induction / Discrimination

- Detects natural distinctions in the data.
- Independent of any dictionary.
- Distinctions suit the relevant domain and task.



# Clustering Approach

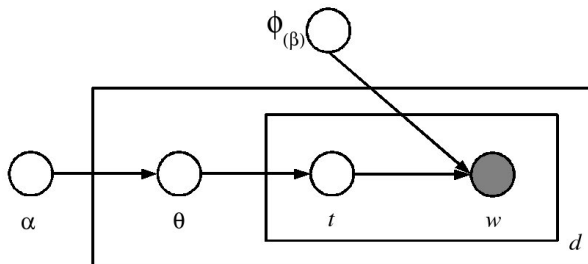
## Common Approach : standard clustering task

- Does not take into account the linguistic nature of the data.
- Does not lend itself to easy integration.

## Our Approach : probabilistic generative model

- + Generative aspect suits linguistic data
- + Probabilistic nature makes for easy integration  
(via mixture or product models)

# LDA for Document Classification (Blei et al., 2003)



# LDA for Document Classification (Blei et al., 2003)

The William Randolph Hearst Foundation will give \$1.25 million to Lincoln Center , Metropolitan Opera Co. , New York Philharmonic and Juilliard School . “Our board felt that we had a real opportunity to make a mark on the future of the performing arts with these grants an act every bit as important as our traditional areas of support in health, medical research , education and the social services ,” Hearst Foundation President Randolph A. Hearst said Monday in announcing the grants . Lincoln Center’s share will be \$200,000 for its new building , which will house young artists and provide new public facilities . The Metropolitan Opera Co. and New York Philharmonic will receive \$400,000 each. The Juilliard School , where music and the performing arts are taught , will get \$250,000 . The Hearst Foundation , a leading supporter of the Lincoln Center Consolidated Corporate Fund , will make its usual annual \$100,000 donation, too.

# LDA for Document Classification (Blei et al., 2003)

“Arts”

“Budgets”

“Children”

“Education”

NEW  
FILM  
SHOW  
MUSIC  
MOVIE  
PLAY  
MUSICAL  
BEST  
ACTOR  
FIRST  
YORK  
OPERA  
THEATER  
ACTRESS  
LOVE

MILLION  
TAX  
PROGRAM  
BUDGET  
BILLION  
FEDERAL  
YEAR  
SPENDING  
NEW  
STATE  
PLAN  
MONEY  
PROGRAMS  
GOVERNMENT  
CONGRESS

CHILDREN  
WOMEN  
PEOPLE  
CHILD  
YEARS  
FAMILIES  
WORK  
PARENTS  
SAYS  
FAMILY  
WELFARE  
MEN  
PERCENT  
CARE  
LIFE

SCHOOL  
STUDENTS  
SCHOOLS  
EDUCATION  
TEACHERS  
HIGH  
PUBLIC  
TEACHER  
BENNETT  
MANIGAT  
NAMPHY  
STATE  
PRESIDENT  
ELEMENTARY  
HAITI

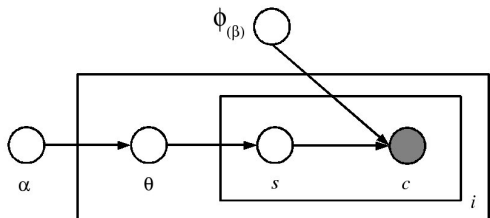
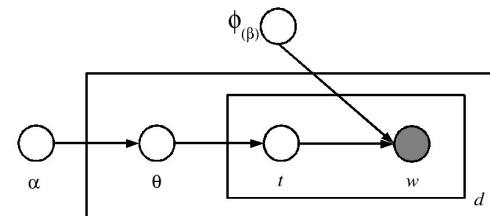
# Previous LDA Approaches to WSD

- Supervised - use LDA-derived topics instead of Bag-of-Words. (Cai et al., 2007)
- Unsupervised - integrate distributional similarity approach with LDA. (Boyd-Graber and Blei, 2007)

## Problems in Previous Approaches

- Treat topics as domain labels.
- Use as an aid in disambiguation.

# Adapting Classic LDA

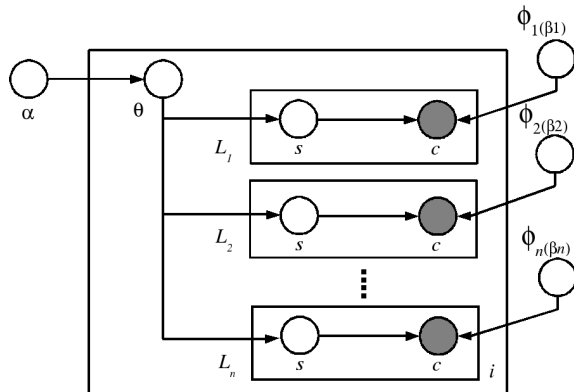


- one model per word
- immediate context instead of whole document
- context elements replace words
- small number of senses (<10)

# Multiple Information Sources

- Original LDA model deals with one input layer - words.
- Many classification problems use several sources of information.
- This is common practice in WSD (domain features, local context, syntactic features).
- We extended our model to deal with multiple layers:  
 $\pm 10$  word window (10w),  $\pm 5$  word window (5w),  
collocations (1w), word bigrams (ng), part-of-speech  
bigrams (pg), dependency relations (dep)

# Layered LDA





## Semeval Sense Discrimination Task (Agirre and Soroa, 2007)

Provided a standardized framework for evaluation of unsupervised sense discrimination systems.

- evaluation dataset
- automated system for mapping to gold-standard
- standardized evaluation metrics

## Evaluation Dataset - Semeval (Agirre et al., 2007)

- 35 nouns from the lexical sample.
- Text from the Penn Treebank II. The Treebank data is a collection of articles from first half of the 1989 Wall Street Journal.

## In-Domain

Wall Street Journal (WSJ) corpus.

- news with a business and financial perspective
- all articles 1987-89 and 1994 - 740k instances

## OntoNotes Sense Definitions for *drug*:

- **Sense 1** Medicines. A substance that affects the body in some legal, usually-beneficial way. Does not apply to narcotics.
- **Sense 2** Narcotics. A substance, usually illegal, that causes bodily pleasure or some other reaction. Has a very negative connotation.

**“Enforcement”**

U.S.  
administration  
federal  
against  
war  
dealer  
government  
official  
enforcement  
testing  
charge  
trafficker  
money  
president  
abuse  
program  
law

**“Treatment”**

patient  
people  
problem  
doctor  
company  
abuse  
aid  
user  
test  
prescription  
cost  
year  
alcohol  
effect  
addict  
treatment  
Dr.

**“Industry”**

company  
million  
sale  
maker  
stock  
inc.  
market  
product  
co.  
U.S.  
sterling  
prescription  
drug  
generic  
analyst  
industry  
pharmaceutical

**“Research”**

administration  
food  
company  
approval  
fda  
patient  
test  
market  
U.S.  
approve  
treat  
aid  
study  
product  
treatment  
develop  
receive

## OntoNotes Sense Definitions for *power*:

- **Sense 1** An ability to control or influence.
- **Sense 2** Entity that possesses ability to control or influence.
- **Sense 3** Exerted physical force.
- **Sense 4** A mathematical measurement.

**“Production”****“World Politics”****“Financial”****“National Politics”**

plant  
company  
computer  
nuclear  
electric  
system  
year  
U.S.  
utility  
price  
line  
market  
industry

party  
government  
political  
military  
president  
economic  
U.S.  
people  
world  
soviet  
country  
struggle  
election

plant  
co.  
nuclear  
million  
unit  
utility  
electric  
company  
light  
corp.  
power  
share  
inc.

bank  
president  
congress  
state  
government  
security  
federal  
executive  
company  
court  
law  
veto  
authority

# Layer Experiments

## Single Layer

Layer	F-Score
10w	<b>86.9%</b>
5w	86.8%
1w	84.6%
ng	83.6%
pg	82.5%
dep	82.2%
MFS	80.9%

## Remove One

Layer	Diff.	F-Score
-10w	-0.2%	83.1%
-5w	-0.3%	83.0%
-1w	-0.3%	83.0%
-ng	-0.3%	83.0%
-pg	-0.6%	82.7%
-dep	<b>+1.4%</b>	84.7%
All	—	83.3%

## Combinations

Layer	F-Score
<b>10w+5w</b>	<b>87.3%</b>
5w+pg	83.9%
1w+ng	83.2%
10w+pg	83.3%
1w+pg	84.5%
10w+pg+dep	82.2%
MFS	80.9%

## Scores on Semeval

System	F-Score
<b>LDA-IN</b>	<b>87.3%</b>
I2R	86.8%
UMND2	84.5%
MFS	80.9%

- LDA system significantly outperforms the MFS baseline
- better performance than highest-scoring system in Semeval
- induced senses match the domain



## The Problem:

- traditional WSD uses unsuitable sense inventories

## Our Solution:

- a generative, probabilistic model for sense induction
- achieves state-of-the-art results on the induction task
- induced senses match the target domain

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# Online Reviews

What we have:

- overall score
- details in free-form text



ASUS Eee PC 1005HA-PU1X-BK 10.1-Inch Black Netbook - 10.5 Hour Battery Life  
Other products by [ASUS](#)  
[★ ★ ★ ★ ★](#) (2) [Get customer reviews](#) | [View about this product](#)

Color Name:

Track: [Click for price](#)

List Price: \$399.99  
Price: [See price in cart](#) [Add to cart](#) [Add to wish list](#)  
This item ships for **FREE** with Super Saver Shipping. [Details](#)

**In Stock.**  
Ships from and sold by Amazon.com.

Want it delivered Monday, October 27? Order it in the next 17 hours and 38 minutes, and choose **One-Day Shipping** at checkout. [Details](#)  
[22 new](#) [Used from \\$338.00](#)

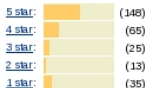
What we want:

- overall score
- summary of details:

Aspect	Score
Weight	80% Pos
Keyboard	50% Pos
Wireless	30% Pos
Battery	70% Pos

## Customer Reviews

286 Reviews



**Average Customer Review**

[★★★★☆](#) (286 customer reviews)

# Why Unsupervised?

- manual annotation is not feasible
- aspects are unpredictable
- varying ways of expressing sentiment
- spelling errors and typos are an issue for lexicons

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- Unsupervised methods
  - + don't require annotation
  - + fit themselves to the task and data
  - + cognitively interesting/plausible
  - are less accurate
  - require more thought

# Conclusions

- Unsupervised methods *can* be used to achieve good results
- We can harness supervised tools and knowledge resources
- Inducing classes from the data itself is a huge advantage

# Thank You!



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