# Building Large-Scale Ontology by Learning from Text 

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## What is an Ontology?

- A set of concepts
- Relations between concepts
- Inference rules among the relations


## Unsupervised Learning from Text

## Concepts

A court ruled Friday that an egg
producer who kept his 2,000 hens in small cages was not guilty of "The verdict is, as alleged by animal rights activists. quoted as saying by the national NTB news agency atter his acquittal

The National Society for the Prevention of Cruelty to Animal claimed that by keeping hens in small cages, Wettre violated national legislation to allow animals' natural development and But th竍 cage space in which to live. NSPCA chairman Toralf Met
The society was ordered pay " $\$ 15,00$ in <TEXT> society was ordered pay $\$ 15,600$ in court costs. </DOC>
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<BYLINE>By JONATHAN KELSO Bji</HEAD
<BYLINE>By JONATHAN KELLOGG</BYLINE
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Strategists for Jack Kemp's presidential
campaign say George Bush's poor showing in lowa, coupled with Kemp s ough-talking ads against Bob Dole, could put Kemp in the George Bush's poor showing in lowa, coupled with running for the Republican nomination.
Before last Monday's lowa caucuses, Kemp had been on a roll in New Hampshire, using an effective advertising campaign and the support.

\{N561 infringement, encroachment, violation\},
\{N85 failure, refusal, inability\},
\{N192 price, rate, amount \},
\{N289 policy, decision, stance\},

## Unsupervised Learning from Text

## Relational Templates

producer who Friday that an egg
cruelty to animals, as alleged by animal rights activists. "The verdict is a great relief. It would have been too much to be found guilty of cruelty to my 2,000 hens," Karl Wettre was
quoted as saying by the national NTB news agency after his
The National Society for the Prevention of Cruelty to Animal claimed that by keeping hens in small cages, Wettre violated national legislation to allow animals' natural development and But the stipulating court found that Wettre observed Norwegian regulations cage space in which to louve.
NSPCA chairman Toralf Met
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<TEXT society was ordered pay $\$ 15,600$ in court costs.
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campaign say Geoorge Bush's poor showing in lowa, coupled with Kemp's tough-talking ads against Bob Dole, could put Kemp in the campaign say George Bush's poor showing in lowa, coupled with Kemp's tough-talking ads against Bob Dole, could put Kemp in the running for the Republican nomination Before last Monday's lowa caucuses, Kemp had been on a roll in New Hampshire, using an effective advertising campaign and the support.
\{N728 refugee, immigrant, migrant\}, \{N271 company, industry, business \}, \{N549 he, I, they \}, ...

## complained to

\{N98 clergy, priest, cleric\}, \{N76 government, authority, administration\}, ...

## about

\{N561 infringement, encroachment, violation\},
\{N85 failure, refusal, inability\}, ...

## Unsupervised Learning from Text

## Inference Rules

<DOC>
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AET>
producer who kept his 2,000 hens in small cages was not guilty of
cruelty to animals, as alleged by animal rights activists.
The verdict is a great relief. It would have been too much to be found guilty of cruelty to my 2,000 hens," Karl Wettre was
quoted as saying by the national NTB news agency after his acquittal.
The National Society for the Prevention of Cruelty to Animals
claimed that by keeping hens in small cages, Weltre violated Claimed that by keeping hens in smal' cages, Wettre violated
national legislation to allow animals' natural development and behavior.
But the court found that Wettre observed Norwegian regulations stipulating that a hen should have at least 112 square inches of cage space in which to live.
disappointed but not surroisedveit was quoted as saying: " "'m
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<BYLINE>By JONATHAN KELLOGG<<BYLINE>
<BYLINE>Associated Press Writer</BYLINE>
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```
X complained to Y about Z }
X filed a complain about Z with/to Y
X reported Z to Y
a complaint from X about Z
X pleaded with Y
X protested Z
X objected to Z
X decried Z
\(X\) is concerned about \(Z\),
```


## Outline

- Distributional Word Similarity
- Acquisition of Paraphrases
- Clustering By Committee (CBC)
- Relationship to MEANING
- Summary


## Distributional Hypothesis

- Words that appear in similar contexts have similar meanings [Harris 69].
- Example: duty vs. responsibility
-V:from:N absolve 4, back down 1, ban 1, bring 2, Charter 1, come back 2, detach 1 , discharge 3 , dismiss $1 / 1$, disqualify 1 , distance 1 , distract $1 / 2$, ease 1 , escape 1 , excuse $6 / 1$, exempt 3 , express 1 , flinch 1 , free $2 / 1$, get away 1 , grow 1 , hide $1 / 1$, present 1 , reassign 3 , release $6 / 2$, relieve 1 , remove $17 / 3$, resign 2 , retire 10 , retreat $1 / 1$, return 11 , return home 1 , run 1 , save 1 , separate 1 , shield 1 , shrink 2 , sign off 1 , slip away 1 , step 1 , step down 2 , suspect 1 , suspend 13 , sway 1 , take time off $1 / 1$, transfer 1 , vary 1
- Demo


## Synonyms vs Antonyms (1)

- Example indicators of incompatibility
- from X to Y
- either X or Y
- Search results on Alta Vista

| adversary NEAR ally | 2469 | adversary NEAR opponent | 2797 |
| :--- | :--- | :--- | :--- |
| "from adversary to ally" | 8 | "from adversary to opponent" | 0 |
| "from ally to adversary" | 19 | "from opponent to adversary" | 0 |
| "either adversary or ally" | 1 | "either adversary or opponent" | 0 |
| "either ally or adversary" 2 | "either opponent or adversary" | 0 |  |

## Synonyms vs Antonyms (2)

- Use bilingual dictionaries
- Obtain potential synonym from other sources unrelated to word distributional.
- Words with same translation in another language are potentially synonyms.
- Examples
- failure $\rightarrow$ échec, fault $\rightarrow$ échec
- path $\rightarrow$ chemin, thread $\rightarrow$ chemin
- Intersect them with distributionally similar words


## Evaluation

- Data
- 80 synonyms and 80 antonyms from the Webster's Collegiate Thesaurus that are also top-50 distributionally similar words of each other
- Evaluation task: retrieve synonyms
- Results

Method
Pattern-based
Bilingual Dictionaries

Precision Recall
$86.4 \quad 95.0$
$93.9 \quad 39.2$

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## Motivations: Query/Text Mismatch

- Suppose a user asks
- What does Peugeot manufacture?
- Document may contain:
- Peugeot is a French car maker;
- Peugeot builds cars;
- Peugeot's production of cars;
- Peugeot unveils a new compact sedan;
- Peugeot's line of minivans;
- Peugeot's car factory;


## Paraphrase: Similar Expressions

- A generalization of similar words.
- Extended Distributional Hypothesis
- Two expressions are similar if they tend to occur in similar contexts.
- What is an expression?
- A subtree of a parse tree?
- A local (one level) tree: X sold Y to Z?
- A path in a parse tree
- a binary relationship between two words (nouns) ${ }_{13}$


## Paths in Parse Trees


$\mathrm{N}:$ from: $\mathrm{V}<$ buy $>\mathrm{V}$ :obj: $\mathrm{N}>$ sheep $>\mathrm{N}: n n: \mathrm{N}$
X: Comstock
Y: bighorn

## Constraints on Paths

- A path must have at least two links
- A path must begin and end with a noun
- A path must not cross boundaries of finite clauses or adverbial clauses
- All internal links must be frequent
- OK: N:from:V<buy>V:obj:N>stock>N:nn:N
- NOT: N:from:V<buy>V:obj:N>sheep>N:nn:N


## Similarity between Paths

" $X$ finds a solution to $Y$ "
SlotX
commission
committee
committee
government
government he
I
legislator sheriff

Slot Y
strike civil war
crisis
crisis
problem
problem
situation
budget deficit dispute
" $X$ solves $Y$ "
SlotX
committee
clout
government
he
she
petition
researcher
resistance
sheriff

SlotY
problem crisis
problem mystery problem woe
mystery crime murder

Path similarity is the geometric average of the slot similarities 2003-6-20

## Experimental Data

- ACQUAINT Data Set (3 GB)
- Used in TREC Question-Answering Track
- Contents: AP Newswire, New York Times, Xinghua News (in English)
- Paths extracted:
- 290 M paths ( 113 M unique).
- 183 K paths with frequency counts greater than 50 and total mutual information greater than 300 .
- Demo


## Limitations

- Synonym vs. Antonym
- Like other distribution-based learning algorithms, synonyms and antonyms are distributionally indistinguishable.
- Indistinguishable roles
- When multiple roles of a relations come from the same domain, these roles are indistinguishable.
- X causes Y


## Related Work in Paraphrase Acquisition from Corpus

- From parallel translations of the same novel.
- Regina Barzilay and Kathleen R. McKeown. (ACL 2001)
- From news stories about the same event.
- Yusuke Shinyama, Satoshi Sekine, Kiyoshi Sudo and Ralph Grishman. (HLT 2002)
- The documents have to be paraphrases
- Such data sets are very small.


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## CBC: A Motivating Example

| ___ appellate court | campaign in |
| :---: | :---: |
| __ capital | governor of __ |
| ___ driver's license | illegal in |
| __outlaws sth. | primary in ___ |
| __'s sales tax | senator for |
| _-s airport | archloishop of |
| __'s busimess district | fily to |
| -'s mayor | mayor off |
| __'s sulbway | outskints of |

NexgiMíork<br>Messoimgiton<br>Chalifdania<br>Texasylvania<br>Florrilda Carolina<br>Ahizzoisa<br>Heasgichusetts<br>Nexasersey<br>North Carolina<br>Iowa<br>Virginia<br>Michigan<br>Massachusetts<br>New Hampshire Missouri<br>Pennsylvania

## Clustering By Committee (CBC)

- Most clustering algorithms treat each data element as a single point in the feature space.
- Natural language words are often mixture of several points (senses).
- Solution:
- Define a recruiting committee for each cluster which consists of monosemous words only.


## Algorithm

- Phase 1: find top similar words
- Compute each element's top- $k$ most similar elements
- Phase 2: construct committees
- Find tight clusters among top-k similar words of each given word and use them as candidates for committees.
- Phase 3: create clusters using the committees
- Similar to K-means


## Phase 2: Construct Committees

- Goal: construct committees that
- form tight clusters (high intra-cluster similarity)
- dissimilar from other committees (low intercluster similarity)
- cover the whole space
- Method: Find clusters in the top-similar words of every given words


## Candidate Committees



California
_Georgia 0.17 TEXAS 0.13 FLORIDA 0.23 California 0.21
South Carolina 0.21
Texas
Georgia 0.17 ARIZONA 0.14
| FLORIDA 0.21
Texas 0.23
California 0.19
Florida
__North Carolina 0.14

Georgia 0.22

## A Committee and its Features

|  | -V:from:N |  | -N:in:N |  |
| :--- | :---: | :---: | :---: | :---: |
|  | arrive | 9.93 | embassy | 9.45 |
| Committee: | fly | 9.76 | U.S. Embassy 8.79 |  |
| New Delhi | return | 7.00 | meeting | 8.72 |
| Cairo | take off | 6.95 | ambassador | 8.54 |
| travel | 6.05 | summit | 8.45 |  |
| Islamabad | t-:to:N |  | -N:gen:N |  |
| Jakarta | fly | 9.67 | airport | 9.04 |
| Manila | evacuate | 7.85 | Chinatown | 6.78 |
| Amman | send | 7.12 | district | 6.73 |
| Seoul | head | 6.15 | street | 6.41 |
|  | -A:subj:N |  | -N:mod:A |  |
|  | keen | 5.50 | downtown | 8.76 |
|  | ready | 4.99 | capital | 7.91 |
|  | responsible | 3.64 | central | 7.16 |

## Phase 3: Construct Clusters

- For each word
- Find its most similar cluster and place the word in the cluster
- Remove the overlapping features between the word and the cluster
- Find the next most similar cluster to the residue features
- A word can belong to different clusters
- Each corresponds to one of its senses.
$\stackrel{\text { Demo }}{\square}$


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## Relationship to MEANING?

- Automatic vs Manual/Semiautomatic Construction of Lexical Knowledge Bases
- Evaluation of Lexical Resources
- Selectional Preference


## WordNet is GREAT, but...

- People are very poor at recall
- There are many rare senses
- almost anything is a person: company, fish, dog, shrimp, ......
- Poor coverage of proper names
- Nike is a Greek diety


## Sample Comparison with WordNet

1 handgun, revolver, shotgun, pistol, rifle, machine gun, sawedoff shotgun, submachine gun, gun, automatic pistol, automatic rifle, firearm, carbine, ammunition, magnum, cartridge, automatic, stopwatch
236 whitefly, pest, aphid, fruit fly, termite, mosquito, cockroach, flea, beetle, killer bee, maggot, predator, mite, houseplant, cricket
471 supervision, discipline, oversight, control, governance, decision making, jurisdiction
706 blend, mix, mixture, combination, juxtaposition, combine, amalgam, sprinkle, synthesis, hybrid, melange
941 employee, client, patient, applicant, tenant, individual, participant, renter, volunteer, recipient, caller, internee, enrollee, giver

## Evaluation of Lexical Resources

- Comparison with "Gold Standard"
- WordNet
- BBI
- Roget's Thesaurus
- Embedded Evaluation: using the resource in an application.
- Information retrieval
- Machine translation
- Language modeling


## Color Cluster vs. WordNet

pink, red, turquoise, blue, purple, green, yellow, beige, orange, taupe, color, white, lavender, fuchsia, brown, gray, black, mauve, royal blue, violet, chartreuse, deep red, teal, dark red, aqua, gold, burgundy, lilac, crimson, black and white, garnet, coral, grey, silver, ivory, olive green, cobalt blue, scarlet, tan, amber, cream, rose, indigo, light brown, maroon, uniform, reddish brown, peach, navy blue, plum, nectarine, mulberry, flower, tone, blond, khaki, plaid

## Selectional Preference

- Generalization from:
- drink: beer 151 , water 101 , alcohol 72 , coffee 71 , it 62, wine 61 , lot 45 , milk 28 , alcoholic beverage 25 , what 24 , tea 22 , glass 22 , more 20 , champagne 19 , rubbing alcohol 17, bottle 17, ...
- to:
- drink: \{N541 coffee, tea, soft drink\} 1289, \{N550 whisky, whiskey, cognac \} 690, \{N592 vinegar, lemon juice, olive oil\} 673, \{N1358 himself, themselves, myself\} 380, \{N3 LOT, bit, some\} 298, \{N792 container, bottle, jar\} 203, \{N1336 Bud Light, Budweiser, Pepsi\} 135, \{N949 liqueur, Grand Marnier, brandy \} 126, ....


## Expectation Maximization

- Generative Model
- Generate a class for a given context
- The class generates the word

$$
P(c \mid w)=\frac{P(c, w)}{P(w)}=\frac{P(c) P(w \mid c)}{\sum_{c^{\prime}} P\left(c^{\prime}\right) P\left(w \mid c^{\prime}\right)}
$$

- Problem?
- The EM model doesn't learn!
- Solution: learn multiple preferences at the same time.


## Summary

- Distinguishing Antonyms from Synonyms
- Paraphrase Acquisition
- Based on extended distributional hypothesis
- www.cs.ualberta.ca/~lindek/demos/paraphrase.htm
- Clustering by Committee
- www.cs.ualberta.ca/~lindek/demos/wordcluster.htm
- Relationship to MEANING
- CYC in a day?


## Clustering Similar Paths

N:obj:V<cure>V:subj:N
N :for: $\mathrm{N}<$ treatment>N:subj:N
N :obj:V<treat>V:subj:N
N:of:N<variety<N:obj:V<treat>V:subj:N
N :for: $\mathrm{N}<$ treatment $>\mathrm{N}: n \mathrm{n}: \mathrm{N}$
N :for:V<prescribe>V:obj:N
N:obj:V<cure>V:with:N
N :obj:V<diagnose>V:subj:N
N :for: $\mathrm{N}<$ therapy $>\mathrm{N}$ :nn: N
N :obj:V<treat>V:with:N
N :with:N<patient<N:obj:V<treat>V:subj:N
N :for: $\mathrm{V}<$ treat $>\mathrm{V}$ :subj:N
N :with: $\mathrm{N}<$ people<N:obj:V<help>V:subj:N
N :for: $\mathrm{V}<$ prescribe $>\mathrm{V}$ :subj: N
N :with: $\mathrm{N}<$ people $<\mathrm{N}$ :obj:V<treat $>\mathrm{V}$ :subj:N
N :obj:V<cure>V:by:N
2003-6-20

