

SemLink - Linking PropBank, VerbNet, FrameNet

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Semlink: Overview

- WordNet, OntoNotes Groupings, PropBank
- VerbNet
 - Verbs grouped in hierarchical classes
 - Explicitly described class properties
- FrameNet
- Links among lexical resources
 - PropBank, FrameNet, WordNet, OntoNotes groupings
- Automatic Semantic Role Labeling with PropBank/Verbnets

WordNet – Princeton

(Miller 1985, Fellbaum 1998)

On-line lexical reference (dictionary)

- Nouns, verbs, adjectives, and adverbs grouped into synonym sets
- Other relations include hypernyms (ISA), antonyms, meronyms
- Typical top nodes - 5 out of 25
 - (*act, action, activity*)
 - (*animal, fauna*)
 - (*artifact*)
 - (*attribute, property*)
 - (*body, corpus*)

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WordNet – Princeton – *leave, n.4, v.14*

(Miller 1985, Fellbaum 1998)

- Limitations as a computational lexicon
 - Contains little syntactic information
 - No explicit lists of participants
 - Sense distinctions very fine-grained,
 - Definitions often vague
- Causes problems with creating training data for supervised Machine Learning – SENSEVAL2
 - Verbs > 16 senses (including *call*)
 - Inter-annotator Agreement ITA 71%,
 - Automatic Word Sense Disambiguation, WSD 64%

Dang & Palmer, SIGLEX02

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Creation of coarse-grained resources

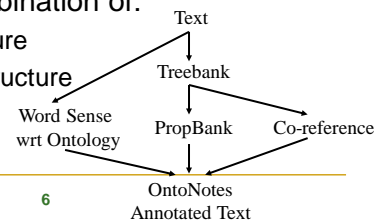
- Unsupervised clustering using rules (Mihalcea & Moldovan, 2001)
- Clustering by mapping WN senses to ODE (Navigli, 2006).
- OntoNotes - Manually grouping WN senses and annotating a corpus (Hovy et al., 2006)
- Supervised clustering WN senses using OntoNotes and another set of manually tagged data (Snow et al., 2007) .

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OntoNotes Goal: Modeling Shallow Semantics DARPA-GALE

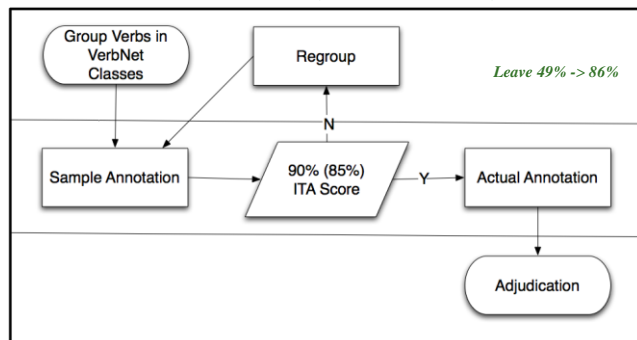
- AGILE Team: BBN, Colorado, ISI, Penn
- Skeletal representation of literal meaning
- Synergistic combination of:
 - Syntactic structure
 - Propositional structure
 - Word sense
 - Coreference



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Empirical Validation – Human Judges the 90% solution (1700 verbs)



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Groupings Methodology – Human Judges (w/ Dang and Fellbaum)

- Double blind groupings, adjudication
- Syntactic Criteria (VerbNet was useful)
 - Distinct subcategorization frames
 - *call him an idiot*
 - *call him a taxi*
 - Recognizable alternations – regular sense extensions:
 - *play an instrument*
 - *play a song*
 - *play a melody on an instrument*

SIGLEX01, SIGLEX02, JNLE07, Duffield, et. al., CogSci 2007

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Groupings Methodology (cont.)

- Semantic Criteria
 - Differences in semantic classes of arguments
 - Abstract/concrete, human/animal, animate/inanimate, different instrument types,....
 - Differences in the number and type of arguments
 - Often reflected in subcategorization frames
 - *John left the room.*
 - *I left my pearls to my daughter-in-law in my will.*
 - Differences in entailments
 - Change of prior entity or creation of a new entity?
 - Differences in types of events
 - Abstract/concrete/mental/emotional/....
 - Specialized subject domains

WordNet: - call, 28 senses, 9 groups



OntoNotes Status

- More than 2,500 verbs grouped
- Average ITA per verbs = 89%
- http://verbs.colorado.edu/html_groupings/
- More than 150,000 instances annotated
- WSJ, Brown, ECTB, EBN, EBC, WebText
- Training and Testing
- *How do the groupings connect to PropBank?*

Frames File Example: *expect*

Roles:

Agent_{ARG0}: expecter
Theme_{ARG1}: thing expected

Example: Transitive, active:

Portfolio managers expect further declines in interest rates.

Agent: *Portfolio managers*
REL: *expect*
Theme: *further declines in interest rates*

Where we are now - DETAILS

- DARPA-GALE, OntoNotes 5.0
 - BBN, Brandeis, Colorado, Penn
 - Multilayer structure: NE, TB, PB, WS, Coref
 - Three languages: English, Arabic, Chinese
 - Several Genres (@ ≥ 200K): NW, BN, BC, WT
 - Close to 2M words @ language (less PB for Arabic)
 - Parallel data, E/C, E/A
 - PropBank frame coverage for rare verbs
 - Recent PropBank extensions

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Included in OntoNotes 5.1: Extensions to PropBank

- Original annotation coverage:
 - PropBank: verbs; past participle adjectival modifiers
 - NomBank: relational and eventive nouns.
- Substantial gap – trying to bridge
 - light verbs, other predicative adjectives, eventive nouns

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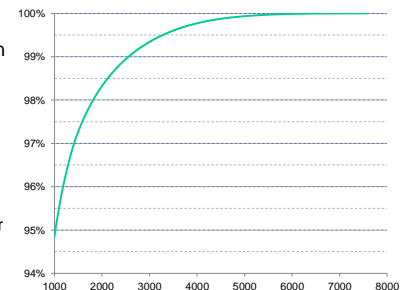
English Noun and LVC annotation

- Example Noun: *Decision*
 - Roleset: Arg0: decider, Arg1: decision...
 - "...[your_{ARG0}] [decision_{REL}]
[to say look I don't want to go through this
anymore_{ARG1}]"
- Example within an LVC: *Make a decision*
 - "...[the President_{ARG0}] [made_{REL-LVB}]
the [fundamentally correct_{ARGM-ADJ}]
[decision_{REL}] [to get on offense_{ARG1}]"

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PropBank Verb Frames Coverage

- The set of verbs is open
- But the distribution is highly skewed
- For English, the 1000 most frequent lemmas cover 95% of the verbs in running text.
 - Graphs show counts over English Web data containing 150 M verbs.



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Verb Frames Coverage By Language

Language	Projected Final Count	Estimated Coverage in Running Text
English	5,100	99%
Chinese	18,200*	96%
Arabic	5,250*	99%

* This covers all the verbs and most of the predicative adjectives/nouns in ATB, and CTB

How do the PropBank verb frames relate to Word Senses?

Answer requires more explanation about OntoNotes senses

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Word Senses in PropBank

- Orders to ignore word sense not feasible for 700+ verbs
 - Mary left the room
 - Mary left her daughter-in-law her pearls in her will

Frameset **leave.01** "move away from":

Arg0: entity leaving

Arg1: place left

Frameset **leave.02** "give":

Arg0: giver

Arg1: thing given

Arg2: beneficiary

How do these relate to word senses in other resources?

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Sense Hierarchy

(Palmer, et al, SNLU04 - NAACL04, NLE07, Chen, et. al, NAACL06)

- PropBank Framesets – ITA >90%
 - coarse grained distinctions
 - 20 Senseval2 verbs w/ > 1 Frameset
 - Maxent WSD system, 73.5% baseline, 90%

- Sense Groups (Senseval-2) - ITA 82%
 - Intermediate level
 - (includes Levin classes) – 71.7%

Tagging w/groups, ITA 90%, 200@hr, Taggers - 86.9% Semeval07

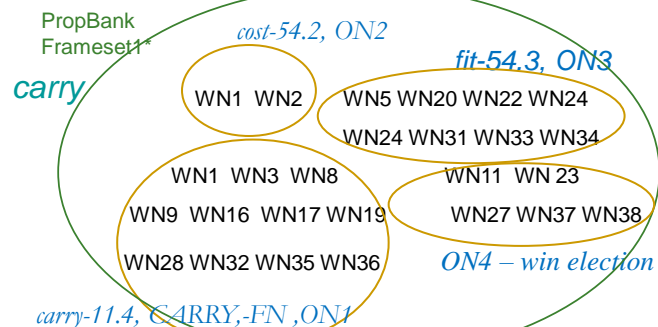
- WordNet – ITA 73%
 - fine grained distinctions, 64%

Chen, Dligach & Palmer, ICSC 2007
Dligach & Palmer, ACL-11, - 88%

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SEMLINK-PropBank, VerbNet, FrameNet, WordNet, OntoNotes Groupings



*ON5-ON11 carry oneself, carried away/out/off, carry to term

Limitations to PropBank

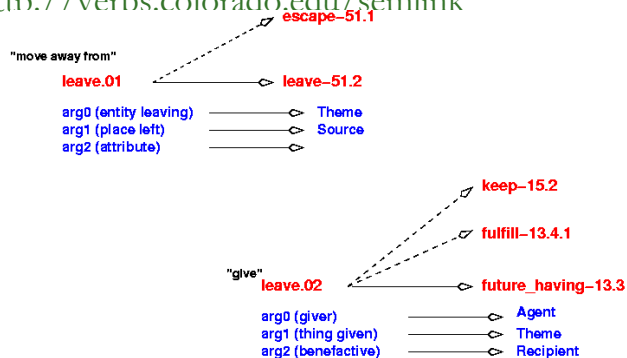
- WSJ too domain specific,
 - Additional Brown corpus annotation & GALE data
 - FrameNet has selected instances from BNC
- Args2-4 seriously overloaded, poor performance
 - VerbNet and FrameNet both provide more fine-grained role labels

VerbNet – based on Levin, B.,93

- Class entries: *Kipper, et. al., LRE08*
 - Capture generalizations about verb behavior
 - Organized hierarchically
 - Members have common semantic elements, semantic roles, syntactic frames, predicates
- Verb entries:
 - Refer to a set of classes (different senses)
 - each class member linked to WN synset(s), ON groupings, PB frame files, FrameNet frames,

Mapping from PB to VerbNet

<http://verbs.colorado.edu/semlink>



FrameNet: *Telling.inform*

Time	In 2002,
Speaker	the U.S. State Department
Target	INFORMED
Addressee	North Korea
Message	that the U.S. was aware of this program , and regards it as a violation of Pyongyang's nonproliferation commitments

Mapping from PropBank to VerbNet (similar mapping for PB-FrameNet)

Frameset id = <i>leave.02</i>	Sense = <i>give</i>	VerbNet class = <i>future-having 13.3</i>
Arg0	Giver	Agent/Donor*
Arg1	Thing given	Theme
Arg2	Benefactive	Recipient

*FrameNet Label

Baker, Fillmore, & Lowe, COLING/ACL-98
Fillmore & Baker, WordNetWKSHP, 2001

PropBank/VerbNet/FrameNet

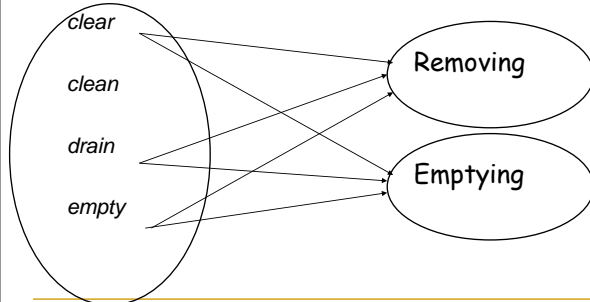
- Complementary
- Redundancy is harmless, may even be useful
- PropBank provides the best training data
- VerbNet provides the clearest links between syntax and semantics
- FrameNet provides the richest semantics
- Together they give us the most comprehensive coverage
- So.... We're also mapping VerbNet to FrameNet

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Mapping Issues (2)

VerbNet verbs mapped to FrameNet

- VerbNet clear-10.3
- FrameNet Classes



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Mapping Issues (3)

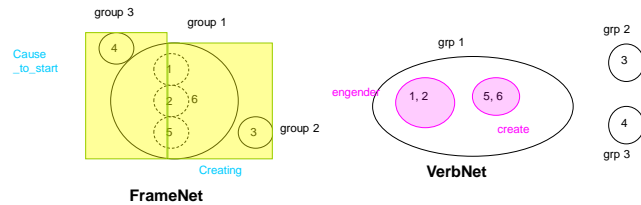
VerbNet verbs mapped to FrameNet

<p>VN Class: put 9.1</p> <p>Members: <i>arrange*</i>, <i>immerse</i>, <i>lodge</i>, <i>mount</i>, <i>sling**</i></p> <p>Thematic roles:</p> <ul style="list-style-type: none"> • agent (+animate) • theme (+concrete) • destination (+loc, -region) <p>Frames:</p> <ul style="list-style-type: none"> • ... <p><small>*different sense ** not in FrameNet</small></p>	<p>FrameNet frame: place</p> <p>Frame Elements:</p> <ul style="list-style-type: none"> • Agent • Cause • Theme • Goal <p>Examples:</p> <ul style="list-style-type: none"> • ...
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Class formation Issues: *create*

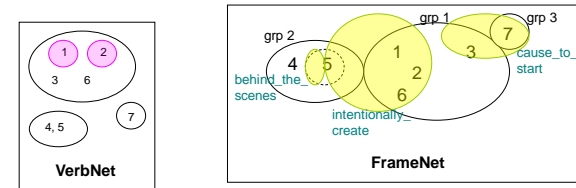
Susan Brown



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Class formation Issues: *produce*

Susan Brown

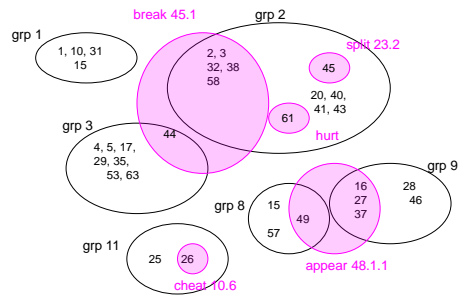


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Class formation Issues: *break*/Verbnet

Susan Brown

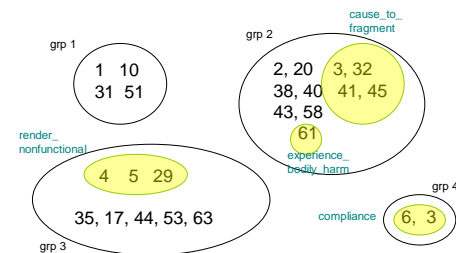
WN44 – the skin broke
 WN49 – the simple vowels broke in
 many Germanic languages



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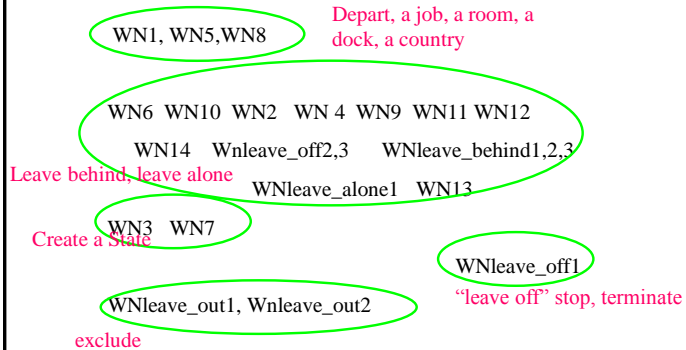
Class Formation Issues: *break*/FrameNet

Susan Brown

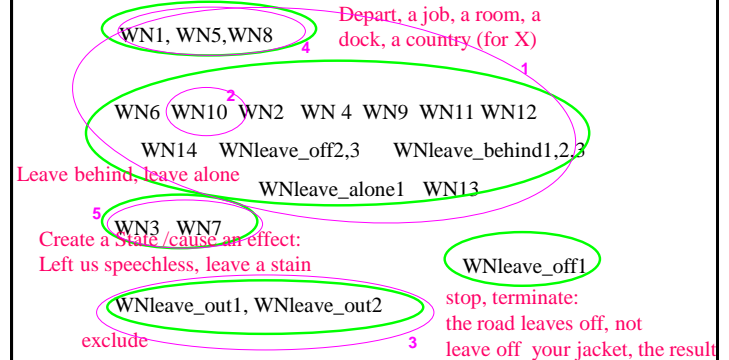


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WordNet: - leave, 14 senses, grouped



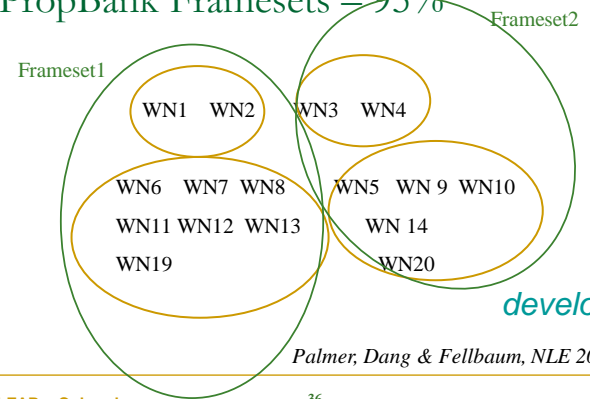
WordNet: - leave, 14 senses, groups, PB



Leave behind, leave alone...

- **John left his keys at the restaurant.**
*We left behind all our cares during our vacation.
 They were told to leave off their coats.
 Leave the young fawn alone.*
- **Leave the nature park just as you found it.**
*I left my shoes on when I entered their house.
 When she put away the food she left out the pie.
 Let's leave enough time to visit the museum.*
- **He'll leave the decision to his wife.**
*When he died he left the farm to his wife.
 I'm leaving our telephone and address with you.*

Overlap between Groups and PropBank Framesets – 95%



Palmer, Dang & Fellbaum, NLE 2007

Broader coverage still needed

- Only 78% of PropBank verbs included in VN
- Most classes focused on verbs with NP and PP complements
- Neglected verbs that take adverbial, adjectival, and sentential complements

SEMLINK

- Extended VerbNet: 5,391 senses (91% PB)
 - Type-type mapping PB/VN, VN/FN
 - (100+ new classes from (Korhonen and Briscoe, 2004; Korhonen and Ryant, 2005))
 - Semi-automatic mapping of WSJ PropBank instances to VerbNet classes and thematic roles, hand-corrected. (now FrameNet also)
 - VerbNet class tagging as automatic WSD
- Brown, Dligach, Palmer, IWCS 2011*
- Run SRL, map Arg2 to VerbNet roles, Brown performance improves

38 Yi, Loper, Palmer, NAACL07

Summary

- Reviewed available lexical resources
 - WordNet, Groupings, PropBank, VerbNet, FrameNet
- We need a whole that is greater than the sum of the parts – Semlink
- Greater coverage, greater richness, increased training data over more genres, opportunities for generalizations

Lexical resources can provide

- Generalizations about subcat frames & roles
- Backoff classes for OOV items for portability
- Semantic similarities/"types" for verbs
- Event type hierarchies for inferencing
- Need to be unified and empirically validated and extended: Semlink+
 - VN & FN need PB like coverage, and techniques for automatic domain adaptation - **Lexlink**
- **Hybrid lexicons – symbolic and statistical lexical entries?**

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