Goals – Ex. Answering Questions

- Similar concepts
  - Where are the grape arbors located?
  - Every path from back door to yard was covered by a grape-arbor, and every yard had fruit trees.
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/Verbnet
- Applications
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)
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*
Creation of coarse-grained resources

- Unsupervised clustering using rules (Mihalcea & Moldovan, 2001)
- Clustering by mapping WN senses to OED (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)
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

Diagram:

- Text
  - Treebank
    - Word Sense wrt Ontology
    - PropBank
      - OntoNotes
        - Annotated Text
      - Co-reference
Empirical Validation – Human Judges
the 90% solution (1700 verbs)

Group Verbs in VerbNet Classes

Regroup

Sample Annotation

90% (85%) ITA Score

Actual Annotation

N

Y

Adjudication

Leave 49% -> 86%
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
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
OntoNotes Status

- More than 2,000 verbs grouped
- Average ITA per verbs = 89%
- [http://verbs.colorado.edu/html_groupings/](http://verbs.colorado.edu/html_groupings/)
- More than 150,000 instances annotated for 1700 verbs
- WSJ, Brown, ECTB, EBN, EBC
- Training and Testing
- *How do the groupings connect to PropBank?*
Analysts have been expecting a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.
**Lexical Resource - Frames Files: give**

Roles:

- **Arg0:** giver
- **Arg1:** thing given
- **Arg2:** entity given to

Example: double object

*The executives gave the chefs a standing ovation.*

- **Arg0:** *The executives*
- **REL:** *gave*
- **Arg2:** *the chefs*
- **Arg1:** *a standing ovation*
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?*
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%

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

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

Chen, Dligach & Palmer, ICSC 2007
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: Basis in Theory

- Verb class hierarchy: 3100 verbs, 47 top level classes, 193
- “Behavior of a verb . . . is to a large extent determined by its meaning” (p. 1)
  - Amanda hacked the wood with an ax.
  - Amanda hacked at the wood with an ax.
  - Craig notched the wood with an ax.
  - *Craig notched at the wood with an ax.
- Can we move from syntactic behavior back to semantics?
Limitations to Levin Classes

- Coverage of only half of the verbs (types) in the Penn Treebank (1M words, WSJ)
- Usually only one or two basic senses are covered for each verb
- Confusing sets of alternations
  - Different classes have almost identical “syntactic signatures”
  - or worse, contradictory signatures

*Dang, Kipper & Palmer, ACL98*
VerbNet – Karin Kipper Schuler

Class entries:
- Capture generalizations about verb behavior
- Organized hierarchically
- Members have common semantic elements, semantic roles and syntactic frames

Verb entries:
- Refer to a set of classes (different senses)
- each class member linked to WN synset(s) and FrameNet frames
Hacking and Notching

- Same thematic roles:
  - Agent, Patient, Instrument

- Some shared syntactic frames,
  - e.g. Basic Transitive (Agent V Patient)

- Different Semantic predicates
VerbNet Semantic Predicates

- **Hack: cut-21.1**
  
  cause(Agent, E)  
  manner(during(E), Motion, Agent)  
  contact(during(E), ?Instrument, Patient)  
  degradation_material_integrity(result(E), Patient)

- **Notch: carve-21.2**
  
  cause(Agent, E)  
  contact(during(E), ?Instrument, Patient)  
  degradation_material_integrity(result(E), Patient)  
  physical_form(result(E), Form, Patient)
### VerbNet example – *Pour-9.5*

**Members:** 3, **Frames:** 5

- **Dribble** (FN 11; WN 1, 2)
- **Drift** (FN 11; WN 1, 2)
- **Pour** (FN 11; WN 1, 3, 4)
- **Slop** (WN 1)
- **Slosh** (WN 3)

**Roles:**
- **Agent:** [+animate]
- **Theme:** [+substance | [+concrete & +plural]]
- **Location:** [+location & -region]
- **Source:** [+location & -region]

**Frames**
VerbNet *Pour-9.5* (cont.)

<table>
<thead>
<tr>
<th>EXAMPLE</th>
<th>SYNTAX</th>
<th>SEMANTICS</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Tumara poured water into the bowl.&quot;</td>
<td>AGENT V THEME {{PATH &amp; -DEST_DIR}} LOCATION</td>
<td>MOTION(diring(E), THEME) NOT(PREP(start(E), THEME, LOCATION)) PREP(E, THEME, LOCATION) CAUSE(Agent, E)</td>
</tr>
<tr>
<td>&quot;Tumara poured water here.&quot;</td>
<td>AGENT V THEME LOCATION {{ADV_LOC}}</td>
<td>MOTION(diring(E), THEME) NOT(PREP(start(E), THEME, LOCATION)) PREP(E, THEME, LOCATION) CAUSE(Agent, E)</td>
</tr>
<tr>
<td>&quot;Water poured onto the plants.&quot;</td>
<td>THEME V {{PATH &amp; -DEST_DIR}} LOCATION</td>
<td>MOTION(diring(E), THEME) NOT(PREP(start(E), THEME, LOCATION)) PREP(E, THEME, LOCATION) CAUSE(Agent, E)</td>
</tr>
<tr>
<td>&quot;Maria poured water from the bowl into the cup.&quot;</td>
<td>AGENT V THEME {{SRC}} SOURCE {{-DEST_CONF}} LOCATION</td>
<td>NOT(PREP(start(E), THEME, LOCATION)) PREP(E, THEME, SOURCE) PREP(E, THEME, LOCATION) CAUSE(Agent, E)</td>
</tr>
<tr>
<td>&quot;Water poured from the bowl into the cup.&quot;</td>
<td>THEME V {{SRC}} SOURCE {{-DEST_CONF}} LOCATION</td>
<td>NOT(PREP(start(E), THEME, LOCATION)) PREP(E, THEME, SOURCE) PREP(E, THEME, LOCATION) CAUSE(Agent, E)</td>
</tr>
</tbody>
</table>
EXAMPLE: *Tamara poured water into the bowl.*

SYNTAX: AGENT V THEME LOCATION

SEMANTICS
- \text{CAUSE(AGENT,E)}
- \text{MOTION(DURING(E), THEME)},
- \text{NOT(PREP(START(E), THEME, LOCATION))},
- \text{PREP(E, THEME, LOCATION)}
Hidden Axioms  REVEALED!

- EXAMPLE:  *Tamara poured water into the bowl.*

- SYNTAX:  **AGENT V THEME LOCATION**

- SEMANTICS

- POUR.  \textit{pour}^{9.5} \textit{(AGENT, THEME LOCATION)} \rightarrow
  \begin{align*}
  \text{CAUSE(AGENT,E),} \\
  \text{MOTION(DURING(E), THEME),} \\
  \text{NOT(PREP(START(E), THEME, LOCATION)),} \\
  \text{PREP(E, THEME, LOCATION).}
  \end{align*}
VerbNet – *cover fill*-9.8

- **WordNet Senses:** ..., cover(1,2, 22, 26),..., staff(1),

- **Thematic Roles:** Agent [+animate]
  Theme [+concrete],
  Destination [+location, +region]

- **Frames with Semantic Roles**
  "The employees staffed the store"
  "The grape arbors covered every path"

  Theme V Destination

  location(E, Theme, Destination)
  location(E, grape_arbor, path)
VerbNet as a useful NLP resource

- Semantic role labeling
- Inferences

While many of the weapons used by the insurgency are leftovers from the Iran-Iraq war, Iran is still providing deadly weapons such as EFPs - or Explosively Formed Projectiles -.

provide(Agent, Theme, Recipient)
VerbNet as a useful NLP resource

- Semantic role labeling
- Inferences

While many of the weapons used by the insurgency are leftovers from the Iran-Iraq war, Iran is still providing deadly weapons such as EFPs -LRB- or Explosively Formed Projectiles -RRB-.

\[ \text{provide}(\text{Iran, weapons, ?Recipient}) \rightarrow \]
\[ \text{cause}(\text{Iran, E}) \]
\[ \text{has\_possession}(\text{start(E), Iran, weapons}) \]
\[ \text{has\_possession}(\text{end(E), ?Recipient, weapons}) \]
\[ \text{transfer}(\text{during(E), weapons}) \]
Mapping from PB to VerbNet

http://verbs.colorado.edu/semblink
FrameNet: Telling. *inform*

<table>
<thead>
<tr>
<th>Time</th>
<th>In 2002,</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speaker</td>
<td>the U.S. State Department</td>
</tr>
<tr>
<td>Target</td>
<td>INFORMED</td>
</tr>
<tr>
<td>Addressee</td>
<td>North Korea</td>
</tr>
<tr>
<td>Message</td>
<td>that the U.S. was aware of this program, and regards it as a violation of Pyongyang's nonproliferation commitments</td>
</tr>
</tbody>
</table>
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
### Mapping from PropBank to VerbNet
(similar mapping for PB-FrameNet)

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

*FrameNet Label

Baker, Fillmore, & Lowe, COLING/ACL-98
Fillmore & Baker, WordNetWKSHP, 2001
Mapping Issues (2)
VerbNet verbs mapped to FrameNet

- **VerbNet clear-10.3**
  - clear
  - clean
  - drain
  - empty

- **FrameNet Classes**
  - Removing
  - Emptying
**Mapping Issues (3)**

**VerbNet verbs mapped to FrameNet**

**VN Class: put 9.1**

- **Members:** arrange*, immerse, lodge, mount, sling**

- **Thematic roles:**
  - agent (+animate)
  - theme (+concrete)
  - destination (+loc, -region)

**Frames:**

- ...

*different sense

**FrameNet frame: place**

- **Frame Elements:**
  - Agent
  - Cause
  - Theme
  - Goal

- **Examples:**

  - ...

**not in FrameNet**
Class formation Issues: *create*

Susan Brown

FrameNet

VerbNet
Class formation Issues: *produce*

Susan Brown

VerbNet

FrameNet

1          2
3        6
4, 5
7

1             3
2
6
4     5
214x552
grp 2
grp 1
grp 3

4 5
behind_the
scenes

1 2 6

intentionally_create

7
cause_to_start
Class formation Issues: *break*/Verbnet

Susan Brown

WN44 – *the skin broke*
WN49 – *the simple vowels broke in many Germanic languages*
Class Formation Issues: break/FrameNet

Susan Brown

grp 1
1 10
31 51

grp 2
2, 20
38, 40
43, 58
3, 32
41, 45
61

grp 3
4 5 29
35, 17, 44, 53, 63

grp 4
6, 3

render_nonfunctional

cause_to_fragment

experience_bodily_harm

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

PropBank Frameset1*

carry

carry-11.4, CARRY,-FN ,ON1

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

cost-54.2, ON2

fit-54.3, ON3

ON4 – win election

Palmer, Dang & Fellbaum, NLE 2
WordNet: - leave, 14 senses, grouped

- WN1, WN5, WN8
  Depart, a job, a room, a dock, a country

- WN6, WN10, WN2, WN4, WN9, WN11, WN12
  - WN14, Wnleave_off2,3, WNleave_behind1,2,3
  - WNleave_alone1, WN13
  Leave behind, leave alone

- WN3, WN7
  Create a State

- WNleave_out1, Wnleave_out2
  "leave off" stop, terminate

- WNleave_off1
  exclude
WordNet: - leave, 14 senses, groups, PB

- Depart, a job, a room, a dock, a country (for X)
- Leave behind, leave alone
- Create a State /cause an effect: Left us speechless, leave a stain
- Exclude
- Stop, terminate: the road leaves off, not leave off your jacket, the result...
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%

Frameset 1
- WN1
- WN2
- WN6
- WN7
- WN8
- WN11
- WN12
- WN13
- WN19

Frameset 2
- WN3
- WN4
- WN5
- WN9
- WN10
- WN14
- WN20

develop

Palmer, Dang & Fellbaum, NLE 2007
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%

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  fine grained distinctions, 64%

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

Chen, Dligach & Palmer, ICSC 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
Extended VerbNet 5,391 lexemes

- (100+ new classes from (Korhonen and Briscoe, 2004; Korhonen and Ryant, 2005))
- now covers 91% of PropBank tokens. Kipper, et. al., LREC-04, LREC-06, LREJ-08, NAACL09 Tutorial

Semi-automatic mapping of PropBank instances to VerbNet classes and thematic roles, hand-corrected. (now FrameNet)

VerbNet class tagging as automatic WSD

Run SRL, map Arg2 to VerbNet roles, Brown performance improves

Yi, Loper, Palmer, NAACL07
Can SemLink improve Generalization?

- SRL Performance improved from 77% to 88%
  Automatic parses, 81% F, Brown corpus, 68%
- Overloaded Arg2-Arg5
  - PB: verb-by-verb
  - VerbNet: same thematic roles across verbs
- Example
  - Rudolph Agnew, …, was named [ARG2 {Predicate} a nonexecutive director of this British industrial conglomerate.]
  - …the latest results appear in today’s New England Journal of Medicine, a forum likely to bring new attention [ARG2 {Destination} to the problem.]
- Use VerbNet as a bridge to merge PB and FN and expand the Size and Variety of the Training
Arg1 groupings; (Total count 59710)

<table>
<thead>
<tr>
<th>Group1 (53.11%)</th>
<th>Group2 (23.04%)</th>
<th>Group3 (16%)</th>
<th>Group4 (4.67%)</th>
<th>Group5 (.20%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theme; Theme1; Theme2; Predicate; Stimulus; Attribute</td>
<td>Topic</td>
<td>Patient; Product; Patient1; Patient2</td>
<td>Agent; Actor2; Cause; Experiencer</td>
<td>Asset</td>
</tr>
</tbody>
</table>
**Arg2 groupings; (Total count 11068)**

<table>
<thead>
<tr>
<th>Group1 (43.93%)</th>
<th>Group2 (14.74%)</th>
<th>Group3 (32.13%)</th>
<th>Group4 (6.81%)</th>
<th>Group5 (2.39%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recipient; Destination; Location; Source; Material; Beneficiary</td>
<td>Extent; Asset</td>
<td>Predicate; Attribute; Theme; Theme2; Theme1; Topic</td>
<td>Patient2; Product</td>
<td>Instrument; Actor2; Cause; Experiencer</td>
</tr>
</tbody>
</table>
Process

- Retrain the SRL tagger
  - Original:
    - Arg[0-5,A,M]
  - ARG1 Grouping: (similar for Arg2)
    - Arg[0,2-5,A,M] Arg1-Group[1-6]

- Evaluation on both WSJ and Brown

- More Coarse-grained or Fine-grained?
  - more specific: data more coherent, but more sparse
  - more general: consistency across verbs even for new domains?
# SRL Performance (WSJ/BROWN)

Loper, Yi, Palmer, SIGSEEM07, Yi, Loper, Palmer, NAACL07

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Recall</th>
<th>F-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arg1-Original</td>
<td>89.24</td>
<td>77.32</td>
<td>82.85</td>
</tr>
<tr>
<td>Arg1-Mapped</td>
<td>90.00</td>
<td>76.35</td>
<td>82.61</td>
</tr>
<tr>
<td>Arg2-Original</td>
<td>73.04</td>
<td>57.44</td>
<td>64.31</td>
</tr>
<tr>
<td>Arg2-Mapped</td>
<td>84.11</td>
<td>60.55</td>
<td>70.41</td>
</tr>
<tr>
<td>Arg1-Original</td>
<td>86.01</td>
<td>71.46</td>
<td>78.07</td>
</tr>
<tr>
<td>Arg1-Mapped</td>
<td>88.24</td>
<td>71.15</td>
<td>78.78</td>
</tr>
<tr>
<td>Arg2-Original</td>
<td>66.74</td>
<td>52.22</td>
<td>58.59</td>
</tr>
<tr>
<td>Arg2-Mapped</td>
<td>81.45</td>
<td>58.45</td>
<td>68.06</td>
</tr>
</tbody>
</table>
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
Need more feedback - and you can give it to us

- On VerbNet classifications
- On FrameNet classifications
- On OntoNotes groupings vs WN vs PB
- On usefulness of the distinctions made by all of the above
Acknowledgments

We gratefully acknowledge the support of the National Science Foundation Grants for Consistent Criteria for Word Sense Disambiguation and Robust Semantic Parsing, and DARPA-GALE via a subcontract from BBN.