Beyond Shallow Semantics

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Language is infinitely flexible

- New usages of old words –
  - *Talk to the hand*....
    *because I’m not listening.*
  - *She blinked the snow off of her eyelashes*...
  - *If you don’t know who starred in “Ides of March” just “wiki” it.*
  - ..... 

- How can we help the computer adapt to this flexibility?
Cautionary note

- There will never be enough data, and the data will never have all the examples
- Existing lexical resources, data annotation frameworks, etc., will always have gaps and be inadequate
Outline

- Current capabilities
- What we can “almost” do, and how to get there – next steps.
- Where we would like to head long-term.
- Contributions and limitations of lexical resources with respect to this process.
- How can we overcome the limitations?
The county coroner says he urged Saint Rita's to move its patients.
The county coroner says he urged Saint Rita's to move its patients.
Where we are now – shallow semantics

- Syntactic Structure – parse trees, Treebanks
- Semantic types – nominal entities [Person, Location, Organization], NE tagging
- Semantic roles – Agents, PropBanks
- Sense distinctions – *call me a taxi, call me an idiot*, WordNet, OntoNotes groups
- Coreference – *[county coroner: he]*
Syntactic structure

POS TAGS: DET NOUN VERB PREP DET NOUN

The cat sat on the mat.

PARSES – TREEBANK

Also, SEMANTIC ROLES, SENSE TAGS, REFERENCES, …
POS TAGS: DET NOUN VERB PREP DET NOUN

The cat sat on the mat.

PARSES – TREEBANK

SEMANTIC ROLES – PROPBANK
Predicates and Semantic Roles

- For each predicate in a sentence
- Assign labels to sentence elements specifying role relative to the predicate

  - Who did What to Whom, When, Where, Why, How, etc.
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
Included in OntoNotes 5.0 (4.99): 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
Example Noun: *Decision*

- Roleset: Arg0: decider, Arg1: decision…

  “…[your$_{\text{ARG0}}$] [decision$_{\text{REL}}$]
  [to say look I don't want to go through this anymore$_{\text{ARG1}}$]”

Example within an LVC: *Make a decision*

  “…[the President$_{\text{ARG0}}$] [made$_{\text{REL-LVB}}$]
  the [fundamentally correct$_{\text{ARGM-ADJ}}$]
  [decision$_{\text{REL}}$] [to get on offense$_{\text{ARG1}}$]”
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.
## Verb Frames Coverage By Language

<table>
<thead>
<tr>
<th>Language</th>
<th>Projected Final Count</th>
<th>Estimated Coverage in Running Text</th>
</tr>
</thead>
<tbody>
<tr>
<td>English</td>
<td>5,100</td>
<td>99%</td>
</tr>
<tr>
<td>Chinese</td>
<td>18,200*</td>
<td>96%</td>
</tr>
<tr>
<td>Arabic</td>
<td>5,250*</td>
<td>99%</td>
</tr>
</tbody>
</table>

* 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
WordNet: - call, 28 senses, 9 groups

- Loud cry: WN5, WN16, WN12
- Label: WN3, WN19
- Challenge: WN18, WN27
- Phone/radio: WN2, WN13
- WN28
- WN17, WN11
- WN24,

- Bird or animal cry: WN15, WN26
- Request: WN4, WN7, WN8, WN9
- Call a loan/bond: WN20, WN25
- Visit: WN6, WN23
- Bid: WN10, WN14, WN21,
Empirical Validation – Human Judges

1. Group Verbs in VerbNet Classes
2. Sample Annotation
3. 90% (85%) ITA Score
4. Actual Annotation
5. Adjudication

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- **Regroup**
- **N**
- **Y**

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OntoNotes Status for Sense Tags

- More than 2,500 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
- WSJ, Brown, ECTB, EBN, EBC, WebText
- Training and Testing data sets
SEMLINK-PropBank, VerbNet, FrameNet, WordNet, OntoNotes

Palmer, Dang & Fellbaum, NLE 2007

PropBank Frameset1*

carry

cost-54.2, ON2

WN1 WN2

fit-54.3, ON3

WN5 WN20 WN22 WN24

WN24 WN31 WN33 WN34

WN11 WN 23

WN27 WN37 WN38

ON4 – win election

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

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

- Sense Groups (Senseval-2/OntoNotes) - ITA 89%
  Intermediate level
  (includes Verbnet/some FrameNet) – SVM, 88+%  
  Dligach & Palmer, ACL2011

- WordNet – ITA 73%
  fine grained distinctions, 64%
Colorado WSD approach

- Supervised ML with rich linguistic features
  - Bag of words, topics, subj/obj/pp, semantics
- Dynamic Dependency Neighbors for WSD, Dligach & Palmer, ACL08, IJSC08, NAACL-HLT SRW09, ACL11
  - Better performance than NE + WN hypernyms
  - Based on subject/object dependencies from gigaword, “neighbors” have similar relations
These were some of the pieces

- We’ve reviewed
  - PropBanking coverage
  - Sense tagging approach
- And mentioned
  - Treebanking
  - Coreference annotation

- Now let’s put them together…
The county coroner says he urged Saint Rita's to move its patients.
The county coroner says he urged Saint Rita's *PRO* to move its patients.

ARGO: PER: county coroner

ARG1: PB: urge.01

ARG0: PER: he

ARG1: ORG: Saint Rita's

ARG2: PB: move.01

ARG0: PRO

ARG1: PER: its patients

move-v.1: change position
move-v.2: intentionally act, decide
move-v.3: affect, impress
move-v.4: change residence or employment
move-v.5: sell, dispose of
move-v.6: socially or professionally interact
move-v.7: make intrusive advances on
Basis for

- Recognizing Textual Entailment
  - Sammons, et al., ACL10

- Question Answering
  - Zapirain, et al, NAACL10

- Experiments in semantics-based statistical machine translation
  - NSF grant w/ Kevin Knight

- Not complete
  - Gaps (Prepositional phrases, noun modifiers, etc)
  - Connections between sentences - PDTB
Next steps

The county coroner says he urged Saint Rita's to move its patients. The eventual devastation threatened their lives.

Did the flooding endanger the Saint Rita's patients?

Question Answering, Machine Translation, Information Extraction,
Next Steps

Types of Inference

- Recovering implicit arguments
- Detecting semantic similarity
  - Synonyms, paraphrases (semantic equivalence), meronyms, semantic class memberships, etc.
- Recovering implicit relations
Did the flooding (caused by Katrina) endanger the Saint Rita’s patients?
Next steps

The county coroner says he urged Saint Rita's to move its patients. The eventual devastation threatened their lives.

- Did the flooding endanger the Saint Rita’s patients?
- Detecting semantic similarities
Next steps

The county coroner says he urged Saint Rita's to move its patients. The eventual devastation threatened their lives.

- Did the flooding endanger the Saint Rita’s patients?
- Detecting semantic similarities
The county coroner says he urged Saint Rita's to move its patients. The eventual *devastation* threatened their lives.

- Did the *flooding* endanger the Saint Rita’s patients?
- Detecting semantic similarities
- Recovering implicit arguments

What role do lexical resources play?
VerbNet – based on Levin, B., 93

Class entries:
- 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,
VerbNet: \textit{send-11.1} \ (Members: 11, Frames: 5) \ includes “\textit{ship}”

- **Roles**
  - Agent [+animate | +organization]
  - Theme [+concrete]
  - Source [+location]
  - Destination [+animate | [+location & -region]]

- **Syntactic Frame:** NP V NP PP.\texttt{destination}
  - example \ "Nora sent the book to London."
  - syntax \ Agent V Theme \{to\} Destination
  - semantics \ motion(during(E), Theme)\n  \quad location(end(E), Theme, Destination)\n  \quad cause(Agent, E)
VerbNet can also provide inferences

- Every path from back door to yard was covered by a grape-arbor, and every yard had fruit trees.
- Where are the grape arbors located?
VerbNet – *cover, fill*-9.8 class

- **Members**: fill, …, cover,…, staff, …. 

- **Thematic Roles**: Agent  
  Theme  
  Destination  

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

  Theme V Destination

  \[
  \text{location}(E, \text{Theme}, \text{Destination}) \\
  \text{location}(E, \text{grape\_arbor}, \text{path})
  \]
Extended VerbNet: 5,391 lexemes (91% PB)
Type-type mapping PB/VN, VN/FN
Semi-automatic mapping of WSJ PropBank instances to VerbNet classes and thematic roles, hand-corrected. (now FrameNet also)
VerbNet class tagging as automatic WSD

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

Brown, Dligach, Palmer, IWCS 2011

Yi, Loper, Palmer, NAACL07
Lexical resources can provide

- Useful generalizations about subcat frames
  - FrameNet and PropBank would also provide subcat information, and WordNet has some.

- Useful generalizations about semantic roles that lead to more coherent and consistent training data.
  - Arg2 results: ↑ 6% WSJ, ↑ 10% Brown corpus

- Backoff classes for OOV items for portability

- Event type hierarchies for inferencing

- Can they help with our example?

*Yi, Loper, Palmer, NAACL07*
Next steps

The county coroner says he urged Saint Rita's to move its patients.
The eventual devastation threatened their lives.

- Did the flooding endanger the Saint Rita’s patients?

- Detecting semantic similarities

- Recovering implicit arguments
Recovering Implicit Arguments
[Palmer, et. al., 1986, Gerber & Chai, 2010]

\[ \text{Arg0 The two companies} \] \[ \text{REL1 produce} \] \[ \text{Arg1 market pulp, containerboard and white paper} \]. The goods could be manufactured closer to customers, saving \[ \text{REL2 shipping} \] costs.

- Used VerbNet for subcategorization frames
Implicit arguments

**SYNTAX**  
Agent V Theme {to} Destination

\[ \text{AGENT} \text{ shipped} \ \text{THEME} \ \text{to} \ \text{DESTINATION} \]

**SEMANTICS**

- \text{CAUSE(AGENT, E)}
- \text{MOTION(DURING(E), THEME),}
- \text{LOCATION(END(E), THEME, DESTINATION),}
Implicit arguments instantiated using coreference

- [AGENT] shipped [THEME] to [DESTINATION]
- [Companies] shipped [goods] to [customers].

SEMANTICS
- CAUSE(Companies, E)
- MOTION(DURING(E), goods),
- LOCATION(END(E), goods, customers),

Can annotate, semi-automatically!
Implicit Arguments –

- Use argument type plus coreference to instantiate X

- The eventual devastation of X threatened their lives.

- Did the flooding of X endanger the Saint Rita’s patients?
The county coroner says he urged Saint Rita's to move its patients. The eventual **devastation** threatened their lives.

- *Did the flooding endanger the Saint Rita’s patients?*
- Detecting semantic similarities
- Recovering implicit arguments
Semantic similarities

- [threaten, endanger]
  - WordNet synsets

- [endanger, “put in danger”]
  - PropBank light verb construction annotation
  - Noun predicates, preposition predicates*

  *Ken Litkowski working with FrameNet

- [devastation, flooding???]?
  - Sense tagging, lexical resources?
Semantic similarities, cont.

- [devastation, flooding]
- **WordNet, sense 3 out of 5**
  - \( S: (n) \text{devastation, desolation} \) (an event that results in total destruction)
  - Ruin \( \rightarrow \) destruction \( \rightarrow \) ending
WordNet, *flood*, verb

- (v) *deluge*, *flood*, *inundate*, *swamp* (fill quickly beyond capacity; as with a liquid) "the basement was inundated after the storm"; "The images flooded his mind"  
  - *fill* → *change*

- **S:** (v) *flood* (cover with liquid, usually water) "The swollen river flooded the village"; "The broken vein had flooded blood in her eyes"  
  - *cover* → *touch*

- **S:** (v) *flood*, *oversupply*, *glut* (supply with an excess of)  
  "flood the market with tennis shoes"; "Glut the country with cheap imports from the Orient"  

- **S:** (v) *flood* (become filled to overflowing) "Our basement flooded during the heavy rains"  
  - *fill* → *change*
No help from WordNet, PropBank, VerbNet, FrameNet

- WordNet, sense 3 out of 5
  - \textit{S:} (n) \textit{devastation}, desolation (an event that results in total destruction) \hspace{1cm} Ruin $\rightarrow$ destruction $\rightarrow$ ending
  - \textit{VerbNet, destroy.44, FrameNet, Destroying}

- WordNet, sense 1 out of 4
  - (v) \textit{deluge, flood, inundate, swamp} (fill quickly beyond capacity; as with a liquid) "the basement was inundated after the storm"; "The images flooded his mind"
  - \textit{VerbNet, fill 9.8, FrameNet, Filling}
More help from the data?

- The flooding caused by Katrina was devastating.

- Google: \([\text{flooding, devastation}]\),
  - almost 7M hits

- Google: \([\text{flooding, devastation, Katrina}]\)
  - 1.5M hits

- Clearly related

- Massive flooding of cities/buildings (man made habitats) can be devastating
Current Colorado approach

- Inducing semantic similarity sets from aligned parallel PropBanks *Wu, Choi, Palmer, AMTA10, SSST 11*
  - Start with Giza++, use GS or automatic PB structures to validate and extend alignments
  - Aligned predicates form similarity sets
  - Attempting to project a Chinese VerbNet
- *Could use some help!*
Another type of Implicit Relation
Example from Daniel Marcu, GALE Wrap-up Mtg

- Between Munich and LA you need less than 11 hours by plane.

- You can fly to Los Angeles from Munchen in no more than eleven hours.

- From Munich to Los Angeles, it does not take more than eleven hours by plane.
Recovering Implicit Relations

- TO FLY
  [Between Munich and LA_{ARGM-ADV}]
  [you_{ARG0}]
  [need_{REL} [less than 11 hours by plane_{ARG1}]].

- TO FLY
  [elided verb] [From Munich_{ARGM-DIR}]
  [to Los Angeles_{ARGM-GOL}]
  [it] does [not_{ARGM-NEG} [take_{REL-2.take10}]
  [more than eleven hours by plane_{ARG1}].

CUES: “caused_motion construction” and “plane”
Constructions allow us to

- Recognize a path prepositional phrase, and that it necessarily goes with a “MOTION” event – Caused-motion constructions
  - *John sneezed the tissue off the table.*
  - *Mary blinked the snow off of her eyelashes.*

- If we detect a MOTION event we can associate the *plane* with it as a vehicle

- Just the *plane* itself can suggest a motion event…
Constructions

- Have a semantics of their own that is recognizable and generalizable
- Are very productive
- Are instrumental in “extending” senses to new usages
- Crucial to handling these new usages

*Bonial, et. al., Incorporating Coercive Constructions into a Verb Lexicon, RELMS, 2011 (ACL Workshop)*
We are adding Constructions to VerbNet

- Individual entries for resultative construction, caused_motion construction, etc.
- Links to classes that include the construction as a core frame + verb_based frequencies
- Links to classes that can be coerced to include the construction + verb_based frequencies
- The approach is very, very data-driven
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
  - Flooding can cause devastation?

Need to be unified and empirically validated and extended: Semlink+

- VN & FN need PB like coverage, and techniques for automatic domain adaptation
Do we have to choose?

- Lexical resources?

OR

- Distributional approaches?
A possible long term Goal - A new generation of hybrid resources that

- Are empirically based
- Can automatically add new entries and extend and enrich current ones
- That include useful probabilities for syntactic frames, semantic types of arguments, similarities to other entries
- Rely on tested algorithms for mappings to other resources
Call to Arms –

Bring out the ML algorithms!

- Tons of data, can be automatically annotated
- Techniques for distributional compositional semantics can also be applied to building hybrid lexical/distributional resources; resources can include disco reps
- Goal – self-improving, empirically-based lexicons that can be grounded in knowledge representations for use in inferencing
- *Let’s work together*
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