CS 4650/7650
Shallow Semantics

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The Roadmap

- **Compositional semantics**
  assemble the meaning of a sentence from its components
- **Shallow semantics**
  identify the key predicates and arguments in sentences
- **Lexical semantics**
  vector-space models for the meaning of individual words

Compositional semantics: pros and cons

"Full" compositional semantics requires representations at least as expressive as first-order logic.

- Machine learning approaches have improved robustness. ☺
- Recent work has driven down the requirements for manually-created resources. ☺
- But coverage is still limited to narrow domains like travel and geography. ☹

Shallow semantics trades expressiveness for robustness and broader coverage.

Outline

Shallow semantics

PropBank

FrameNet

Abstract Meaning Representation

Shallow semantics

- Consider these four sentences:
  - Yesterday, Kristina hit Scott with a baseball
  - Scott was hit by Kristina yesterday with a baseball
  - Yesterday, Scott was hit with a baseball by Kristina
  - Kristina hit Scott with a baseball yesterday

Shallow semantics

- Consider these four sentences:
  - Yesterday, Kristina hit Scott with a baseball
  - Scott was hit by Kristina yesterday with a baseball
  - Yesterday, Scott was hit with a baseball by Kristina
  - Kristina hit Scott with a baseball yesterday
- The *roles* in each sentence are filled by the same text.
  - Hitter: Kristina
  - Person hit: Scott
  - Instrument of hitting: with a baseball
  - Time of hitting: yesterday

Deep roles

The event semantics representation for the sentence Scott was hit by Kristina yesterday (and all of the other examples) is:

$$\exists e, x, y \; \mathit{Hitting}(e) \wedge \mathit{Hitter}(e, \mathit{Kristina}) \wedge \mathit{PersonHit}(e, \mathit{Scott}) \\ \wedge \mathit{TimeOfHitting}(e, \mathit{Yesterday})$$

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- *Hitter*, *PersonHit*, and *TimeOfHitting* are roles.
- We use these specific roles because of the **predicate verb** hit.
- Roles that relate to a specific predicate are called "deep roles."

Thematic roles

- Without knowing more about deep roles like *Hitter*, we cannot do much inference.
- Building classifiers for every role would be a lot of work.
- Consider Scott was paid by Kristina yesterday.
- Scott, Kristina and yesterday have similar thematic functions in each sentence.

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- Building classifiers for every role would be a lot of work.
- Consider Scott was paid by Kristina yesterday.
- Scott, Kristina and yesterday have similar thematic functions in each sentence.

Thematic roles attempt to capture the similarity between *Payer* and *Hitter*, and between *PersonHit* and *PersonPaid*.

- Thematic roles date to Panini (7th-4th century BCE!)
- Modern formulation due to Fillmore (1968) and Gruber (1965)

Some typical thematic roles

AGENT	The volitional causer **The waiter** spilled the soup
EXPERIENCER	The experiencer The soup gave **all three of us** a headache.
FORCE	The non-volitional causer **The wind** blew my soup off the table.
THEME	The participant most directly affected The wind blew my **my soup** off the table.
RESULT	The end product The cook has prepared **a cold duck soup**.
CONTENT	The proposition or content of a propositional event The waiter assured me that **the soup is vegetarian**.
INSTRUMENT	An instrument used in an event It's hard to eat soup **with chopsticks**.
BENEFICIARY	The beneficiary The waiter brought **me** some soup.
SOURCE	Th origin of the object of a transfer event The stack of canned soup comes **from Pittsburgh**.
GOAL	The destination of the object of a transfer event He brought the bowl of soup **to our table**.

Case frames

- Different verbs take different thematic roles as arguments.
- The possible arguments for a verb is the **case frame** or **thematic grid**. For example, for break:
  - AGENT: Subject, THEME: Object
    John broke the window.
  - AGENT: Subject, THEME: Object, INSTRUMENT: PP (with)
    John broke the window with a rock.
  - INSTRUMENT: Subject, THEME: Object
    The rock broke the window.
  - THEME: Subject
    The window broke.
- When two verbs have similar case frames, this is a clue that they might be semantically related:
  (e.g., break, shatter, smash).

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  - *Enabling instruments* cannot:
    1. Shelly ate the pizza with the fork.
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  - *Enabling instruments* cannot:
    1. Shelly ate the pizza with the fork.
    2. *The fork ate the pizza.
- Thematic roles are bundles of semantic properties, but it's not clear how many properties are necessary.
  - For example, AGENTS are usually animate, volitional, sentient, and causal...
  - ...but any of these properties may be missing occasionally.

Key ideas of shallow semantics

- Predicate-argument semantics rather than first-order logic
- **Roles** are types of arguments.
  - Deep roles are predicate-specific.
  - Thematic roles are more general, but are hard to pin down.
  - Next we'll discuss semantic resources which address this issue.

Outline

PropBank

In the Proposition Bank (**PropBank**), roles are verb-specific, with some sharing:

- Arg0: proto-agent (has agent-like properties)
- Arg1: proto-patient (has patient-like properties)
- Arg2... ArgN: verb-specific
- 13 universal adjunct-like arguments: temporal, manner, location, cause, negation, ...

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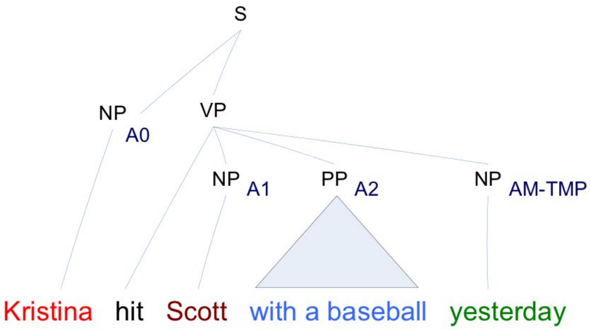
PropBank contains two main resources:

- a set of labeled sentences, built on the Penn TreeBank
- a set of "Frame Files" describing each verbal predicate

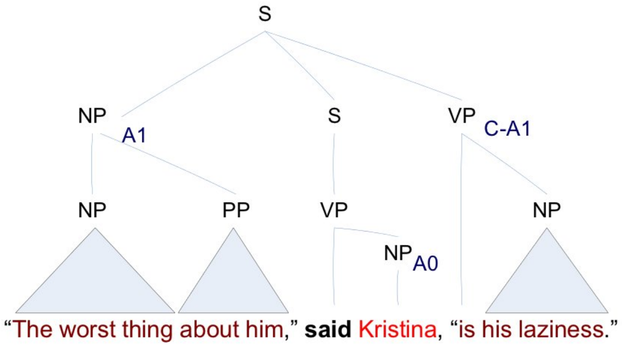
`http://verbs.colorado.edu/propbank/framesets-english/scratch-v.html`

Example PropBank annotations



[$_{\text{A0}}$ *Kristina*] ***hit*** [$_{\text{A1}}$ *Scott*] [$_{\text{A2}}$ *with a baseball*] [$_{\text{AM-TMP}}$ *yesterday*].

Example PropBank annotations



[$_{A1}$ *The worst thing about him*] ***said*** [$_{A0}$ *Kristina*] [$_{C\text{-}A1}$ *is his laziness*].

The PropBank corpus

- Last release: March 4, 2005
  - Verb Lexicon: 3,324 frame files
  - Annotation: 113,000 propositions
- PropBank has been used as the standard dataset for shared tasks on semantic role labeling (SRL)

Related corpora

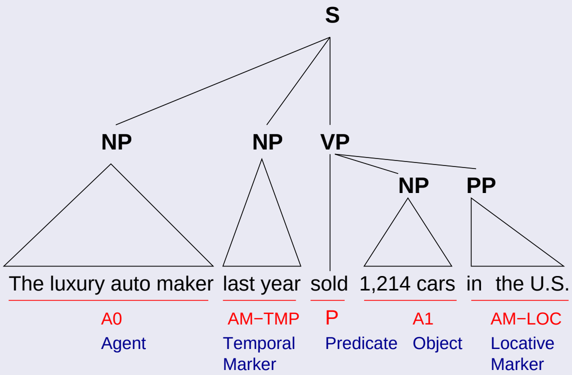
- Chinese PropBank
  - Adds a semantic layer to Chinese TreeBank
  - `http://www.cis.upenn.edu/~chinese/cpb/`
- NomBank
  - Focuses on arguments that co-occur with nouns in PropBank
  - [$_{A0}$ Her] [$_{REL}$ gift] of [$_{A1}$ a book] [$_{A2}$ to John]

Semantic role labeling

- Semantic role labeling (SRL) is the task of assigning semantic labels to spans of text.
- Labels describe the role of the phrase with respect to the *predicate verb*.
- In practice, usually PropBank labels, e.g. Arg0

Semantic Role Labeling: The Problem

SRL $\stackrel{def}{=}$ detecting basic event structures such as *who* did *what* to *whom*, *when* and *where* [**IE** point of view]



Continuation and Reference arguments

Arguments can be discontinuous.

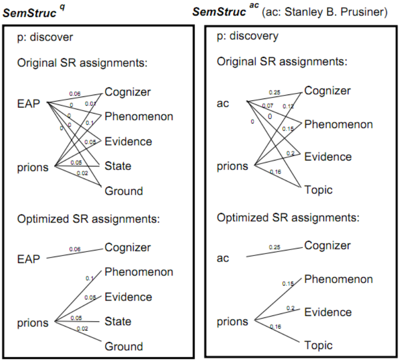
- [The pearls]$_{a1}$, [she]$_{a0}$ [said]$_{v}$, [are fake]$_{C-a1}$.

Pronouns can reference arguments defined elsewhere.

- [The pearls]$_{a0}$ [that]$_{R-a0}$ [are]$_{v}$ [fake]$_{a1}$.

Question answering

- Shen and Lapata (2007) use semantic roles to align questions against the content of factual sentences.
- Example:
  - Q: Who discovered prions?
  - S: 1997: Stanley B. Prusiner, United States, discovery of prions...



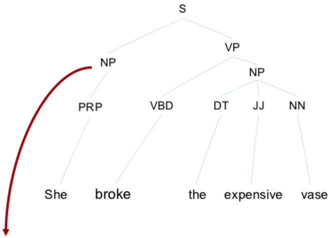
Subtasks

- **Identification**: determine which substrings are arguments
  - $[_{arg}$ Kristina$]$ **hit** $[_{arg}$ Scott$]$ $[_{arg}$ with a baseball$]$ $[_{\varnothing}$ again$]$
  - In principle this is hard: lots of possible substrings.
  - In practice, parsing helps a lot. In PropBank,
    - 96% of arguments are a gold parse tree constituent
    - 90% of arguments are a (Charniak) parse tree constituent
    - Simple rules can recover the remaining arguments.
- **Classification**: determine the label for each argument substring
  - $[_{A0}$ Kristina$]$ **hit** $[_{A1}$ Scott$]$ $[_{A2}$ with a baseball$]$ $[_{\varnothing}$ again$]$

Basic features: Gildea and Jurafsky, 2002

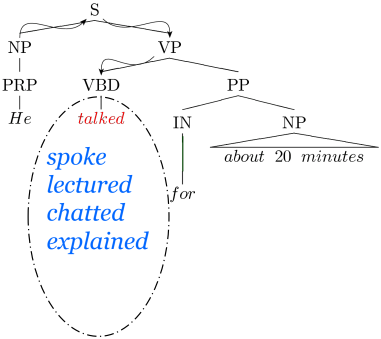
- Key early work
  - Future systems use these features as a baseline

- Constituent Independent
  - Target predicate (lemma)
  - Voice
  - Subcategorization
- Constituent Specific
  - Path
  - Position (*left*, *right*)
  - Phrase Type
  - Governing Category (*S* or *VP*)
  - Head Word



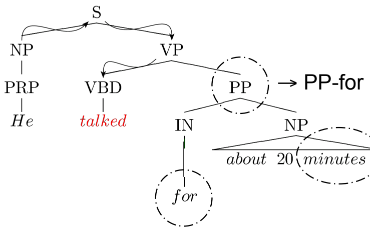
Target	*broke*
Voice	*active*
Subcategorization	$VP \rightarrow VBD\ NP$
Path	$VBD{\uparrow}VP{\uparrow}S{\downarrow}NP$
Position	*left*
Phrase Type	*NP*
Gov Cat	*S*
Head Word	*She*

Predicate cluster, automatic or WordNet

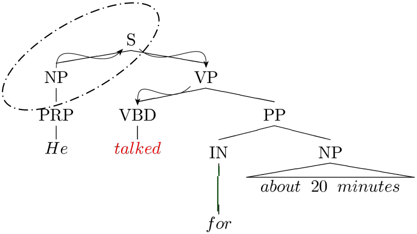


Slide from Sameer Pradhan

Noun Head and POS of PP

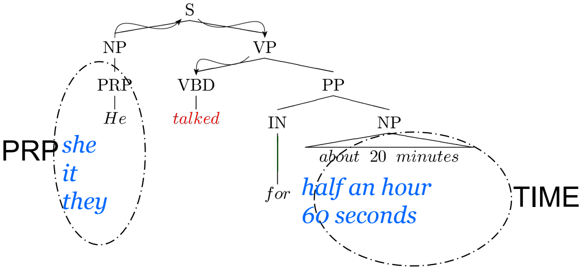


Partial Path

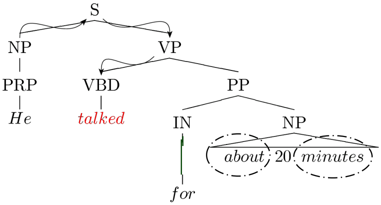


Named Entities and Head Word POS

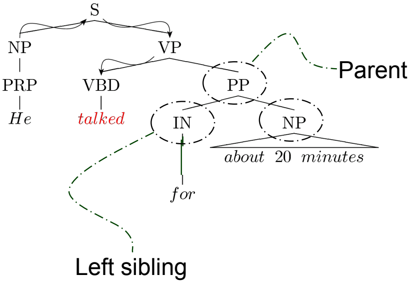
[Surdeanu et al., 2003]



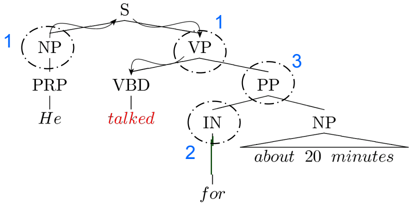
First and Last Word and POS



Parent and Sibling features



Constituent tree distance



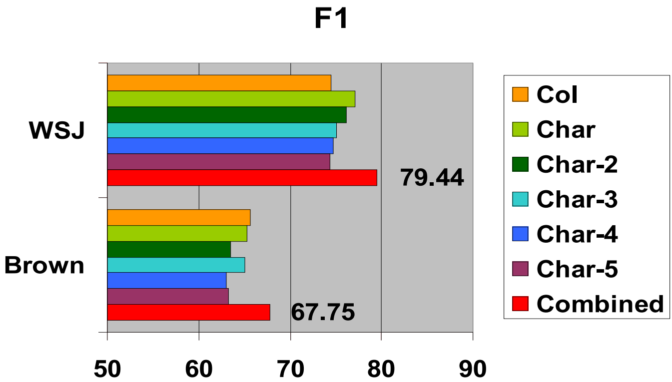
Combining local and global scoring

- Individual labels may each be good, but they may not fit together well.
- Global scoring checks the **overall** labeling. Some approaches:
  - Local scoring, then **re-rank** (Gildea and Jurafsky 2002, Toutanova et al 2005)
  - **Joint probability model** with some independence assumptions (e.g., TreeCRF of Blunsom et al 2004)
  - Do exact search for best local model satisfying **global constraints** (Punyakanok et al, 2004)

Global constraints for SRL

- Many of the global criteria can be viewed as constraints:
  - Arguments may not overlap.
  - No argument type may appear twice.
  - Arguments do not overlap the predicate.
- Only some constraints can be built into a dynamic program.
- Instead, solve as a constrained optimization problem using Integer Linear Programming (ILP). (see notes)

Generalized Inference – ILP (Koomen et al., 2005; Punyakanok et al., 2008)



- Inference with many parsers improves results ~ 2.6 F_1 points
- Best results at CoNLL-2005 shared task (Carreras & Màrquez, 2005)

Open Issues for SRL

SRL degrades badly when moved to new domains.

- From WSJ $\rightarrow$ Brown test corpus:
  F-measure decreases from 80% to 70%.
- Mainly due to role classification (Pradhan et al, 2008).
- SRL is high in the "food chain"
  - SRL consumes the output of many other NLP systems.
  - If POS tagging, parsing, or WSD get worse, then SRL will too.
- Lexical semantics is more domain-specific than syntax?

Open Issues for SRL

SRL depends on parsing, and may cascade parsing errors.
Can we do parsing and SRL jointly?

- K-best parses (Sutton and McCallum 2005)
- Parse sampling (Finkel et al 2006)
- Synchronouns dependency parsing for syntax and semantics (Gesmundo et al 2009)

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Supervised SRL requires expensive resources.
What about unsupervised learning?

- split-merge clustering to identify verb alternations (Lang and Lapata 2010, 2011)
- non-parametric Bayesian model of predicates and roles (Titov and Klementiev 2012)

Outline

Shallow semantics

PropBank

FrameNet

Abstract Meaning Representation

FrameNet

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  - [$_{A1}$ The price of bananas] increased [$_{A2}$ 5%].
  - [$_{A1}$ The price of bananas] rose [$_{A2}$ 5%].
  - There has been a [$_{A2}$ 5%] rise [$_{A1}$ in the price of bananas].

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  - [$_{A1}$ The price of bananas] increased [$_{A2}$ 5%].
  - [$_{A1}$ The price of bananas] rose [$_{A2}$ 5%].
  - There has been a [$_{A2}$ 5%] rise [$_{A1}$ in the price of bananas].
- First two sentences involve different verbs;
  second sentence conveys same semantics with a noun.
- Nonetheless, meaning is the same. FrameNet captures this.

FrameNet versus PropBank

FRAMENET ANNOTATION:

[$_{\text{Buyer}}$ Chuck] *bought* [$_{\text{Goods}}$ a car] [$_{\text{Seller}}$ from Jerry] [$_{\text{Payment}}$ for \$1000].

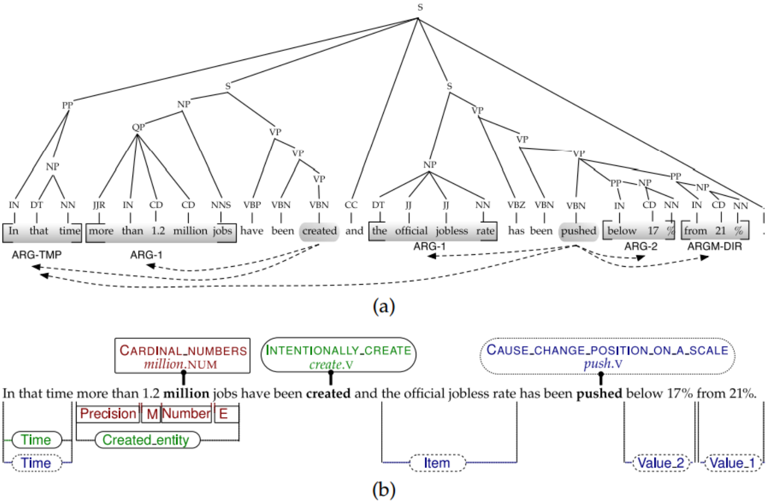
[$_{\text{Seller}}$ Jerry] *sold* [$_{\text{Goods}}$ a car] [$_{\text{Buyer}}$ to Chuck] [$_{\text{Payment}}$ for \$1000].

PROPBANK ANNOTATION:

[$_{\text{Arg0}}$ Chuck] *bought* [$_{\text{Arg1}}$ a car] [$_{\text{Arg2}}$ from Jerry] [$_{\text{Arg3}}$ for \$1000].

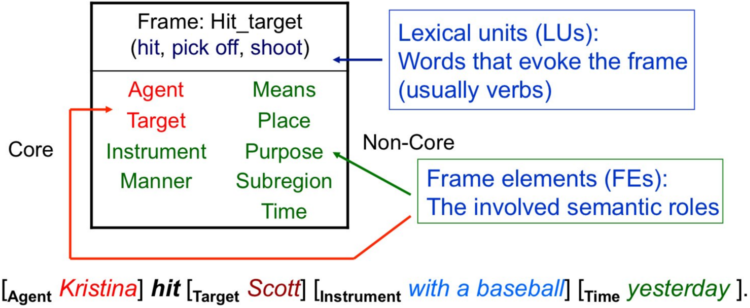
[$_{\text{Arg0}}$ Jerry] *sold* [$_{\text{Arg1}}$ a car] [$_{\text{Arg2}}$ to Chuck] [$_{\text{Arg3}}$ for \$1000].

FrameNet versus PropBank

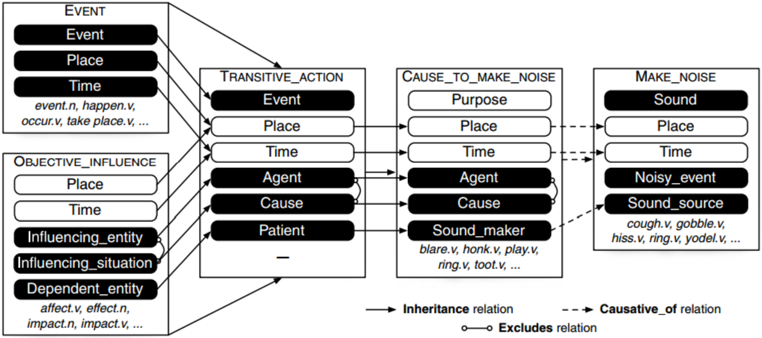


FrameNet

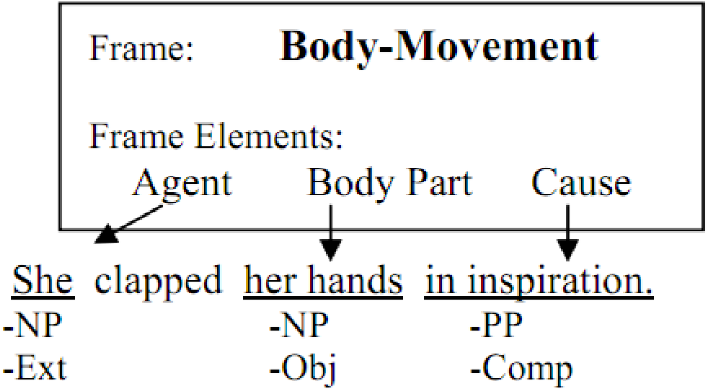
A Frame defines a set of *lexical units* and a set of *frame elements*:



FrameNet inheritance

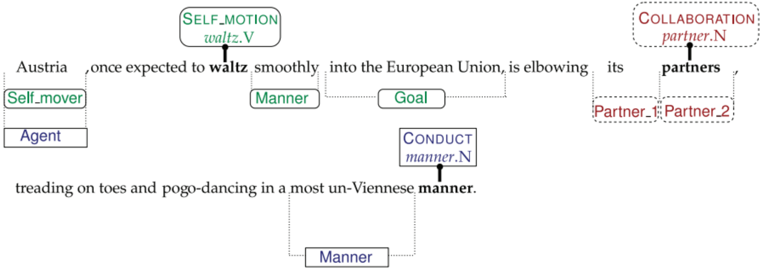


FrameNet annotation



(figure from Fleischman et al, 2003)

Framenet annotation



(Das et al., 2014)

The FrameNet corpus

- https://framenet.icsi.berkeley.edu/fndrupal/about
- As of 2012:
  - 1,000 semantic frames
  - 10K lexical units
  - 170K manually annotated sentences
  - still ongoing...
- Unlike PropBank,
  - not based on TreeBank parses
  - example sentences are chosen by hand

FrameNet parsing

Das et al., 2014

- Identify **targets**, which are tokens that evoke frames
  Rule-based approach gives F-measure of 79.2%
- Classify targets into **frames**
  Log-linear model gives F-measure of 61% for exact matches
- Identify **arguments** with a constrained log-linear model
  Beam-search decoding gives F-measure of approx 50%

Outline

Abstract meaning representation

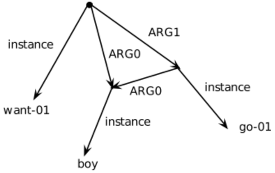
LOGIC format:

$\exists$ w, b, g:
instance(w, want-01) $\wedge$ instance(g, go-01) $\wedge$
instance(b, boy) $\wedge$ arg0(w, b) $\wedge$
arg1(w, g) $\wedge$ arg0(g, b)

AMR format (based on PENMAN):

```
(w / want-01
   :arg0 (b / boy)
   :arg1 (g / go-01
            :arg0 b))
```

GRAPH format:



Properties of AMR

- PropBank frame argument
- "General" semantic relations
- Quantities and dates