L114 Lexical Semantics

Session 5: The Semantics of Verbs

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Lexical relations between verbs

Verbs can be

- **synonyms**, e.g., *pass away–die*
- **hyponyms**, e.g., *walk–move*
- **meronyms**, e.g., *wash – soak, scrub, wring out, (dry).* [rare]
- **opposites**
    - **indirect converses** such as *bequeath–inherit*; *give–receive*
    - **reversives** such as *enter–leave*, *mount–dismount*

Overall, lexical relationships between verbs are weak and unsystematic in comparison to those in operation between nouns.

Hyponymy vs Entailment

X is a verbal **hyponym** of Y if the following test frame succeeds:

Test frame *"To X is necessarily to Y"*

To murder someone is necessarily to kill them.
To strangle someone is necessarily to kill them.

Entailment: a causal relationship between propositions, which includes and goes beyond hyponymy.

He killed the bee – The bee died.
He snored – He was sleeping.

Troponymy

Troponymy: subtype of hyponymy; manner of an action.
(Cruse (1979) calls this property **verbal taxonymy**.)

Test frame: *"To X is a way of Y-ing"*

To strangle/?murder somebody is a way of killing.
To crawl/?travel is a way of moving.

Thus, *strangle* is a troponym of *kill*. *murder* is not a troponym of *kill*, but of *commit a crime*.

WordNet distinguishes four types of lexical relations between verbs: hyponymy, troponymy, entailment, meronymy. Few instances in comparison to nouns.

NLP methods for finding verb similarities

Verbs with similar semantics tend to ...

- have similar **subcategorisation** behaviour → cluster verbs by their subcategorisation patterns; e.g., Schulte (2006); Sun and Korhonen (2009)
- have similar **selectional restrictions** → determine the difference between two verbs' selectional restrictions; e.g., Resnik (1995)
- have similar **thematic roles**, i.e., participants in the actions they denote → perform semantic role labelling, e.g., Gildea and Jurafsky (2002)
- undergo the same **diathesis alternations**. → manually classify verbs (Levin 1993)

Linguistic Selection

A selector imposes semantic constraints on its selectees.

Head–complement construction

I have been waiting for hours. (for-PP argument)

I have been waiting for the bus. (for-PP argument)

Selector: verb, Selectee: arguments

Head–modifier constructions

graceful degradation

Selector: modifier, Selectee: head

Verb–subject constructions

The water froze within seconds.

Selector: verb, Selectee: subject (most linguists would agree)

Selectional restrictions

Selectional restrictions: Violation of selector's presuppositions results in paradox or incongruity.

- This cannot be resolved by replacement with synonym
- But it can be resolved by replacement with near hypernym (in the case of paradox).

? *my male aunt* – paradox; resolvable (*relation*).
? *the cat barked* – paradox; resolvable (*animal*).
? *a lustful affix* – incongruity; unresolvable (except by *thing*).

. . . vs collocational restrictions

Collocational restrictions: Violation of selector's presuppositions results in inappropriateness; resolvable by replacement with synonym.

? *The aspidistra kicked the bucket* – resolvable (*died*).

	unblemished	spotless	flawless	immaculate	impeccable
performance					
argument					
complexion					
behaviour					
kitchen					
record					
reputation					
taste					
order					
credentials					

. . . vs collocational restrictions

Collocational restrictions are highly **unpredictable.**

	unblemished	spotless	flawless	immaculate	impeccable
performance	-	-	X	X	X
argument	-	-	X	-	?
complexion	?	?	X	-	-
behaviour	-	-	-	-	X
kitchen	-	X	-	X	-
record	X	X	X	?	X
reputation	?	X	-	?	-
taste	-	-	X	?	X
order	-	-	-	X	X
credentials	-	-	-	-	X

Quantifying selectional preferences: Resnik 1995

- **Selectional preference strength $S_R(v)$ of verb v:** the degree of selectiveness of a predicate about the semantic class of its arguments; expressed in bits of information.
- Semantic classes c are WordNet synsets
- $S_R(v)$ is based on difference in distribution between
  - $P(c)$ – likelihood of direct object of falling into semantic class c
  - $P(c|v)$ – likelihood of direct object of falling into semantic class c if associated with verb v
- Use KL divergence to determine $S_R(v) = D(P(c|v)||P(c))$:

$$S_R(v) = \sum_c P(c|v) log \frac{P(c|v)}{P(c)}$$

Resnik (1995), ctd

- Selectional association between a verb and a class (synset) is the **relative** contribution to the overall selectionality of the verb

$$A_R(v,c) = \frac{1}{S_R(v)} P(c|v) log \frac{P(c|v)}{P(c)}$$

Example result:

Verb	Dir. Obj. (preferred)	Assoc	Dir Obj. (dispreferred)	Assoc
read	WRITING	6.80	ACTIVITY	-0.20
write	WRITING	7.26	COMMERCE	0
see	ENTITY	5.79	METHOD	-0.01

- The Resnik algorithm can be used to perform WSD.

Diathesis alternation; Levin (1993)

Definition

Systematic variations in the expression of arguments, sometimes accompanied by changes in meaning (Levin, 1993)

Famous example:

Dative alternation

- Doris gives flowers to the headmistress.
- Doris gives the headmistress flowers.

This pattern is meaning-preserving and covers several semantic classes:

- verbs of "future having": *advance, allocate, offer, owe, lend*
- verbs of "sending": *forward, hand, mail*
- verbs of "throwing": *kick, pass, throw*

Example: "gullying"

The sailors gullied the whales.

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Whales gully easily.

- Has your hypothesis changed?
- We observe a strong correlation between syntactic behaviour and semantic class.

Other diathesis alternations

- *John loaded the truck with hay.*
- *John loaded hay on the truck.*

Semantic difference?
Other verbs following this pattern? (*spray? fill? pour? dump? cover?* (this is called the locative alternation.)

- *John cuts the bread.*
- *The bread cuts nicely. (middle)*
- *John cut Mary's arm/Mary on the arm (bodypart possessor ascension)*
- *John cut at the bread (conative)*

Other verbs following this pattern?

An Example

Diathesis Alternation	*touch*	*hit*	*cut*	*break*
conative		⊗	⊗	
bodypart possessor ascension	⊗	⊗	⊗	
middle			⊗	⊗
	pat, stroke, tickle	*bash, kick, pound, tap, whack*	*hack, saw, scratch, slash*	*crack, rip, scat-ter, snap*

Alternations and Semantic Dimensions

- Bodypart Possessor Ascension Alernation is sensitive to contact — separating out *break* as a non-contact verb (pure change of state)
- Conative Alternation is sensitive to both motion and contact — separating out *touch* as a verb of contact (non-change of state)
- Middle Altenation is sensitive to change of state — identifying hit as non-change-of-state (contact by motion verb), whereas cut is a verb of "cause of change of state by moving sth int contact with entity that changes state"

Levin's (1993) Verb Classification

- Based on 79 diathesis alternations
- Covers 3200 verbs in 48 main classes (191 subdivided ones)
- *break* class contains: *break*, *chip*, *crack*, *crash*, *crush*, *fracture*, *rip*, *shatter*, *smash*, *snap*, *splinter*, *split* and *tear*.
- Diathesis alternations are difficult to detect automatically
- But: we can use the fact that similar alternations result in similar SCF (subcategorisation frames).

Verb clustering with subcategorisation frames and selectional restrictions

- Sun and Korhonen: Improving Verb Clustering with Automatically Acquired Selectional Preferences. EMNLP 2009.
- Use spectral clustering algorithm and many features
- Evaluation:
  - Standard Test set 1 (TS1): 15 course- and fine-grained Levin classes, 10-15 verbs per class; 205 verbs
  - Test set 2 (TS2): 17 fine-grained Levin classes with 12 members each, resulting in 204 verbs
- Use all occurrences of verb (up to 10,000 occurrences) from corpora
- But: verbs with fewer than 40 occurrences discarded
- Better results than previous literature (unsupervised); 0.58 F-measure (previously 0.31) on T1; 0.80 F-measure on T2

Sun and Korhonen's Features

- Collocation (CO): 4 words immediately preceeding and following lemmatised verb. Remove stop words, keep 600 most frequent words.
- Prepositional preference (PP): type and frequency of prepositions in direct object relation
- Lexical Preference (LP): type and frequency of nouns and prepositions in subject, object, indirect object relation (these relations are called grammatical relations or GR)
- Subcategorisation frames (SCF): and relative frequencies with verbs
- Selectional Preferences: 20 clusters (of 200 nouns) used instead of LP
- Tense of verb
- Discard SCFs and GRs with frequencies lower than 40 or occurring with 4 or fewer different verbs

Frame Semantics

- Due to Fillmore (1976);
- a frame describes a prototypical situation;
- it is evoked by a frame evoking element (FEE);
- it can have several frame elements (semantic roles).

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APPLY_HEAT

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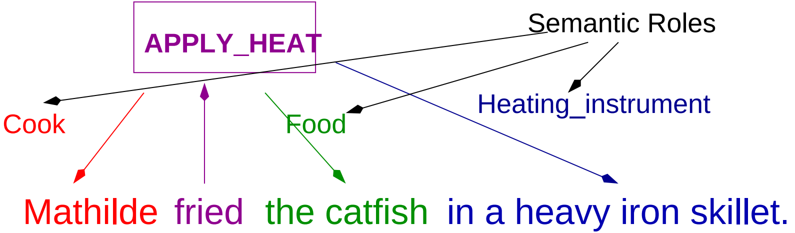
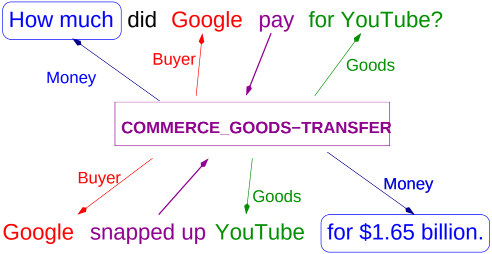


Frame Semantics

Properties of Frame Semantics

- Provides a shallow semantic analysis (no modality, scope);
- generalizes well across languages;
- can benefit various NLP tasks (IR, QA).



Types of thematic roles

- Verb-specific frames and domain-specific roles:
  - kiss — Kisser – Kissee
  - From-Airport, To-Airport, Departure-Time
- Only two roles: Proto-Agent, Proto-Patient
- Mid-level: AGENT, EXPERIENCER, INSTRUMENT, OBJECT, SOURCE, GOAL, LOCATION, TIME, and PATH (Fillmore, 1971).
- Granularity in FrameNet is situated between mid-level and verb-specific.

FrameNet Corpus

FrameNet is a corpus with frame semantics markup:

- uses a tagset of 76 semantic roles (frame elements) from 12 general semantic domains (body, cognition, communication);
- consists of a sample of sentences from the BNC annotated with frame elements;
- 49,013 sentences and 99,232 frame elements in total;
- this includes 927 verbs, 339 nouns, 175 adjectives.

The sentences in the corpus were not chosen from the BNC at random; rather representative usages were selected.

Some FrameNet Examples for RISK

- She **risked** her life on the ascent of K2.
- You would not really want to **risk** annoying her.

Agent/Protagonist, BadOutcome, Asset, Action

She risked **one of her elaborate disguises** when she went out that day

- . . . because she had been hidden in that hotel room for long enough.
- . . . because she suspected they already had a photo of her in it.

RISK in FrameNet

DARING	an **Agent** performs an **Action** which can harm the Agent and which is considered imprudent.	*to hazard, to risk, to chance, to dare, to venture, to take a risk...*
RUN_RISK	**Protagonist** is exposed to a dangerous situation, which may result in a **BadOutcome** or the loss of an **Asset**. There is no implication of intentionality on behalf of the Protagonist.	*the risk, the danger, to run a risk, the peril, endangered...*
RISKY_SITUATION	a **Situation** is likely to result in a (non-mentioned) harmful event befalling an **Asset**	*the risk, dangerous, (un)safe, threat, danger...*
BEING_AT_RISK	An **Asset** is exposed to or otherwise liable to be affected by a **HarmfulEvent**, which may occur as **DangerousEntity**.	*secure, security, safe, risk...*

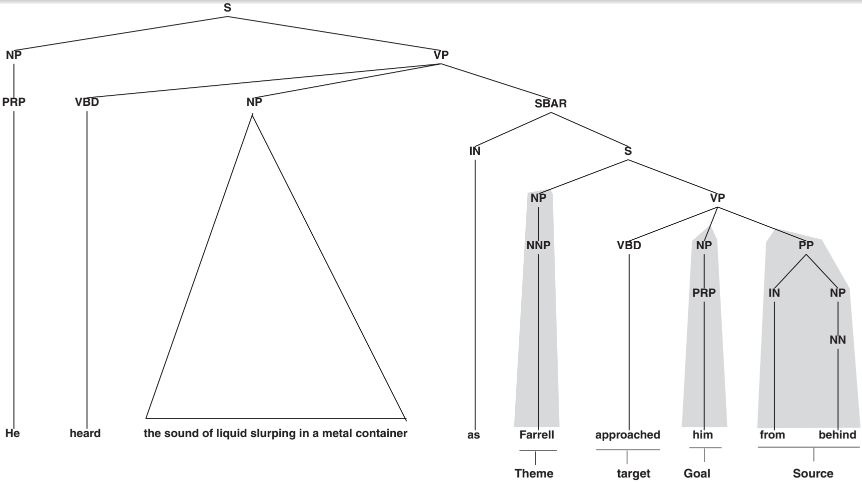
Semantic Role Labelling

Gildea and Jurafsky (2002):

1. Parse the training corpus using Collin's parser;
2. Match frame elements to constituents;
3. Extract features from the parse tree;
4. Train probabilistic model on the features.

The start and end word of each parsed constituent is found and matched against a frame element with the same start and end. No match is possible in 13% of the cases (parsing errors).

Matching


S
NP
VP
PRP
VBD
NP
SBAR
IN
S
NP
VP
NNP
VBD
NP
PP
PRP
IN
NP
NN
He
heard
the sound of liquid slurping in a metal container
as
Farrell
approached
him
from
behind
Theme
target
Goal
Source

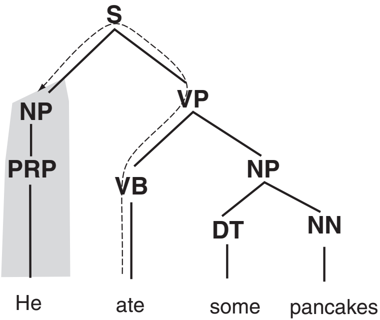
Features

Assume the sentences are parsed, then the following features can be extracted for role labeling:

- **Phrase Type:** syntactic type of the phrase expressing the semantic role (e.g., NP, VP, S);
- **Governing Category:** syntactic type of the phrase governing the semantic role (NP, VP); distinguishes subject-NPs from object-NPs;
- **Parse Tree Path:** path through the parse tree from the target word to the phrase expressing the grammatical role;
- **Position:** whether the constituent occurs before or after the predicate; useful for incorrect parses;
- **Voice:** active or passive; use heuristics to identify passives;
- **Head Word:** the lexical head of the constituent.

Features

Path from target *ate* to frame element *He*: VB↑VP↑S↓NP



"If there is an underlying AGENT, it becomes the syntactic subject (Fillmore, 1968)"

Paths and Grammatical Roles

Freq.	Path	Description
14.2%	VB↑VP↓PP	PP argument or adjunct
11.8	VB↑VP↑S↓NP	subject
10.1	VB↑VP↓NP	object
7.9	VB↑VP↑VP↑S↓NP	subject of embedded VP
4.1	VB↑VP↓ADVP	adverbial adjunct
3.0	NN↑NP↑NP↓PP	prepos. complement of noun
1.7	VB↑VP↓PRT	adverbial particle
1.6	VB↑VP↑VP↑VP↑S↓NP	subject of embedded VP
14.2		no matching parse constituent
31.4		other

Probabilistic Model

Divide the FrameNet corpus into:

- 10% test set;
- 10% development set;
- 80% training set;

Relatively small training set: average number of sentences per target word is 34, number of sentences per frame is 732.

Probabilistic Model

Build a classifier by combining conditional distributions of the features. Compute the distribution from the training data, e.g.:

$$P(r|pt,t) = \frac{\#(r,pt,t)}{\#(pt,t)} \quad (1)$$

r	semantic role
pt	phrase type
gov	governing category
pos	position
$voice$	voice
h	head word
t	target word (predicate)

Evaluation

Measure the performance of a distribution using the following metrics:

- **Coverage:** percentage of the test data for which the conditioning event has been seen in the training data.
- **Accuracy:** percentage of covered test data for which the correct role is predicted.
- **Performance:** product of coverage and accuracy.

Baseline: always choose most probable role for each target word (40.9%)

Evaluation

Distribution	Coverage	Accuracy	Performance
$P(r\|t)$	100	40.9	40.9
$P(r\|pt, t)$	92.5	60.1	55.6
$P(r\|pt, gov, t)$	92.0	66.6	61.3
$P(r\|pt, pos, voice)$	98.8	57.1	56.4
$P(r\|pt, pos, voice, t)$	90.8	70.1	63.7
$P(r\|h)$	80.3	73.6	59.1
$P(r\|h, t)$	56.0	86.6	48.5
$P(r\|h, pt, t)$	50.1	87.4	43.8

Results

- Final system performance 80.4, using head word, phrase type, target word, path and voice.
- But there are 3 features modelling grammatical function – which is best (pos, path, gov)?
- Voice is beneficial only if at least one of these 3 is used.
- If we don't have voice, position is best (79.9%).
- Position + voice instead of either path or governing category is equivalent;
- Head words are very accurate indicators of a constituent's semantic role; $P(r|h,t)$ can only be evaluated on 56.0% of the date, but was 86.7% correct.

Generalising Lexical Statistics

Head words are good predictors of semantic role, but data is sparse. This can be overcome using:

- **Clustering:** find words that are similar to head words that do not occur in the training data; increases performance to 85%;
- **WordNet:** if a word is not in the training data, use its hypernym in WordNet; percolate co-occurrence counts up the WordNet hierarchy (problem: multiple hierarchies and multiple word senses); increases accuracy to 84.3%;
- **Bootstrapping:** label unannotated data with the automatic system, use the resulting data as training data; increases accuracy to 83.2%.

Summary

- Semantic role labeling means identifying the constituents (frame elements) that participate in a prototypical situation (frame) and labeling them with their roles.
- This provides a shallow semantic analysis that can benefit various NLP tasks;
- FrameNet is a corpus/dictionary marked up with semantic roles;
- A simple probabilistic model combining lexical and syntactic features performs well on the task.
- The model interpolates distributions or performs backoff;
- Similar features can be used for identifying frame elements;
- In both models, lexical statistics are sparse, which can be addressed with clustering, WordNet, or bootstrapping.

Reading

- **Sun and Korhonen (2009)**. EMNLP
- **Gildea and Jurafsky (2002)**. Automatic Labeling of Semantic Roles. *Computational Linguistics*.
- **Fillmore and Atkins (1992)**. Towards a frame-based lexicon: The semantics of RISK and its neighbors. In Lehrer, A and E. Kittay (Eds.) *Frames, Fields, and Contrast: New Essays in Semantics and Lexical Organization.* Hillsdale: Lawrence Erlbaum Associates, 75-102.

Background Reading

- Jurafsky and Martin, chapters 19.4, 20.4.2 (selectional restrictions) and 20.9 (frames)
- Allan, Frames, Fields and Semantic components – chapter 8 of book "Natural Language Semantics".
- Cruse, 2.2 (arguments) 14.4.4 (thematic roles)