Language Technology
http://cs.lth.se/edan20/
Chapter 15: Lexical Semantics

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Words and Meaning

Referred to as lexical semantics:

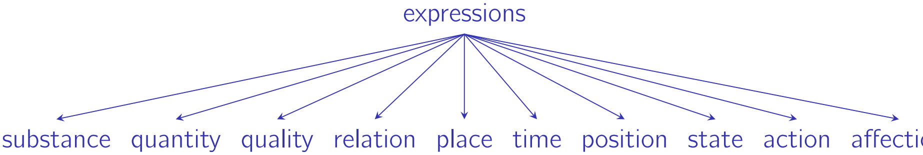
- Classes of words: If it is hot, can it be cold?
- Definition What is a meal? What is table?
- Reasoning: The meal is on the table. Is it cold?

Categories of Words

Expressions, which are in no way composite, signify substance, quantity, quality, relation, place, time, position, state, action, or affection. To sketch my meaning roughly, examples of substance are 'man' or 'the horse', of quantity, such terms as 'two cubits long' or 'three cubits long', of quality, such attributes as 'white', 'grammatical'. 'Double', 'half', 'greater', fall under the category of relation; 'in the market place', 'in the Lyceum', under that of place; 'yesterday', 'last year', under that of time. 'Lying', 'sitting', are terms indicating position, 'shod', 'armed', state; 'to lance', 'to cauterize', action; 'to be lanced', 'to be cauterized', affection.

Aristotle, Categories, IV. (trans. E. M. Edghill)

Representation of Categories



Classes

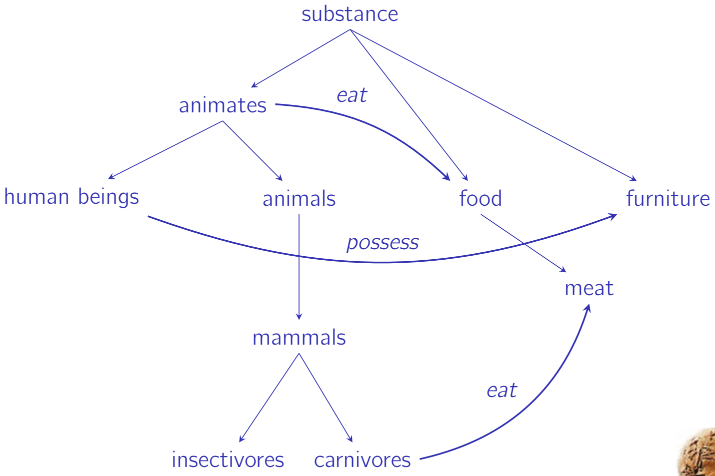
- Synonymy/Antonymy
- Polysemy
- Hyponyms/Hypernyms `is_a(tree, plant), life form, entity`
- Meronyms/Holonyms `part_of(leg, table)`
- Grammatical cases: [$_{\textit{nominative}}$ *I*] *broke* [$_{\textit{accusative}}$ *the window*] [$_{\textit{ablative}}$ *with a hammer*]
- Semantic cases: [$_{\textit{actor}}$ *I*] *broke* [$_{\textit{object}}$ *the window*] [$_{\textit{instrument}}$ *with a hammer*]
- Case ambiguity (*The window broke*/ *I broke the window*)

Lexical Database

```
%% is_a(?Word, ?Hypernym)
is_a(hedgehog, insectivore).
is_a(cat, feline).
is_a(feline, carnivore).
is_a(insectivore, mammal).
is_a(carnivore, mammal).
is_a(mammal, animal).
is_a(animal, animate_being).

hypernym(X, Y) :- is_a(X, Y).
hypernym(X, Y) :- is_a(X, Z), hypernym(Z, Y).
```

Semantic Networks



An Example: WordNet

Nouns	hyponyms/hypernyms synonyms/antonyms meronyms
Adjectives	synonyms/antonyms relational fraternal –> brother
Verbs	Semantic domains (body function, change, communication, perception, contact, motion, creation, possession, competition, emotion, cognition, social interaction, weather) Synonymy, Antonymy: (rise/fall, ascent/descent, live/die) "Entailment": succeed/try, snore/sleep

Semantics and Reasoning

The caterpillar ate the hedgehog.

Representation:

$$\exists(X, Y), caterpillar(X) \wedge hedgehog(Y) \wedge ate(X, Y).$$

Reasoning (inference):
It is untrue because the query:

```
?- predator(X, hedgehog)
X = foxes, eagles, car drivers, ...
```

but no caterpillar.

Lexicons

Words are ambiguous: A same form may have more than one entry and sense.

The *Oxford Advanced Learner's Dictionary* (OLAD) lists five entries for *bank*:

1. *noun*, raised ground
2. *verb*, turn
3. *noun*, organization
4. *verb*, place money
5. *noun*, row or series

and five senses for the first entry.

Definitions

Short texts describing a word:

- A **genus** or superclass using a hypernym.
- Specific attributes to differentiate it from other members of the superclass. This part of the definition is called the *differentia specifica*.

bank (1.1): **a land** sloping up along each side of a canal or a river.

hedgehog: **a small animal** with stiff spines covering its back.

waiter: **a person** employed to serve customers at their table in a restaurant, etc.

Significance of the Sense

<table>
<tr><th>French</th><th>German</th><th>Danish</th></tr>
<tr><td>arbre</td><td>Baum</td><td rowspan="2">Træ</td></tr>
<tr><td rowspan="2">bois</td><td>Holz</td></tr>
<tr><td rowspan="2">Wald</td><td rowspan="2">Skov</td></tr>
<tr><td>forêt</td></tr>
</table>

<table>
<tr><th>French</th><th>Welsh</th></tr>
<tr><td rowspan="2">vert</td><td>gwyrdd</td></tr>
<tr><td rowspan="4">glas</td></tr>
<tr><td rowspan="2">bleu</td></tr>
<tr></tr>
<tr><td rowspan="2">gris</td></tr>
<tr><td rowspan="2">llwyd</td></tr>
<tr><td>brun</td></tr>
</table>

Sense Tagging Using the Oxford Advanced Learner's Dictionary (OALD)

Sentence: *The patron ordered a meal*

Words	Definitions	Sense
The patron	**Correct sense:** A customer of a shop, restaurant, theater	**1.2**
	Alternate sense: A person who gives money or support to a person, an organization, a cause or an activity	**1.1**
ordered	**Correct sense:** To request somebody to bring food, drink, etc in a hotel, restaurant etc.	**2.3**
	Alternate senses: To give an order to somebody	**2.1**
	To request somebody to supply or make goods, etc.	**2.2**
	To put something in order	**2.4**
a meal	**Correct sense:** The food eaten on such occasion	**1.2**
	Alternate sense: An occasion where food is eaten	**1.1**

Identifying Senses

Semantic tagging looks like POS tagging: it assumes the sense of a word depends on its context.

> *We analyze the interaction between* **bank** *and market finance in a model where bankers gather information through monitoring...*

Statistical techniques optimize a sequence of semantic tags.
The context C of word w is defined as:

$$w_{-m}, w_{-m+1}, ..., w_{-1}, w, w_1, ..., w_{m-1}, w_m.$$

If w has n senses, $s_1..s_n$, the optimal sense given C is defined as:

$$\hat{s} = \underset{s_i, 1 \leq i \leq n}{\arg\max} P(s_i|C).$$

Using Bayes' rule, we have:

$$\begin{aligned}
\hat{s} &= \underset{s_i, 1 \leq i \leq n}{\arg\max} P(s_i)P(C|s_i), \\
&= \underset{s_i, 1 \leq i \leq n}{\arg\max} P(s_i)P(w_{-m}, w_{-m+1}, ..., w_{-1}, w_1, ..., w_{m-1}, w_m|s_i).
\end{aligned}$$

Naïve Bayes

The Naïve Bayes classifier uses the bag-of-word approach.
We replace

$$P(w_{-m}, w_{-m+1}, ..., w_{-1}, w_1, ..., w_{m-1}, w_m | s_i)$$

with the product of probabilities:

$$\prod_{j=-m, j\neq 0}^{m} P(w_j | s_i).$$

SemCor is a sense-annotated corpus for English.
Semisupervised and unsupervised algorithms

Beyond Words: Predicates and Arguments

Dictionaries store information about how words combine with other words to form larger structures.

This information is called valence (cf. valence in chemistry)

In the *Oxford Advanced Learner's Dictionary*, **tell**, sense 1, has the valence patterns:

tell something (to somebody) / tell somebody (something)

as in:

- *I told a lie to him*
- *I told him a lie*

Both have the same predicate–argument representation:

`tell.01(Speaker: I, Utterance: a lie, Hearer: him)`

Case Grammar

Verbs have semantic cases (or semantic roles):

- An Agent – Instigator of the action (typically animate)
- An Instrument – Cause of the event or object in causing the event (typically animate)
- A Dative – Entity affected by the action (typically animate)
- A Factitive – Object or being resulting from the event
- A Locative – Place of the event
- A Source – Place from which something moves,
- A Goal – Place to which something moves,
- A Beneficiary – Being on whose behalf the event occurred (typically animate)
- A Time – Time at which the event occurred
- An Object – Entity that is acted upon or that changes, the most general case.

Case Grammar: An Example

```
open(Object, {Agent}, {Instrument})
```

The door opened	Object = *door*
John opened the door	Object = *door* and Agent = *John*
The wind opened the door	Object = *door* and Agent = *wind*
John opened the door with a chisel	Object = *door*, Agent = *John*, and Instrument = *chisel*

Parsing with Cases

The waiter brought the meal to the patron

Identify the verb **bring** and apply constraints:

Case	**Type**		**Value**
Agentive	Animate	(Obligatory)	*The waiter*
Objective (or theme)		(Obligatory)	*the meal*
Dative	Animate	(Optional)	*the patron*
Time		(Obligatory)	past

FrameNet

In 1968, Fillmore wrote an oft cited paper on case grammars.

Later, he started the FrameNet project:

`http://framenet.icsi.berkeley.edu/`

Framenet is an extensive lexical database itemizing the case (or frame) properties of English verbs.

In FrameNet, Fillmore no longer uses universal cases but a set of frames – predicate argument structures – where each frame is specific to a class of words.

The *Impact* Frame

Impact:

bang.v, bump.v, clang.v, clunk.v, collide.v, collision.n, crash.v, crash.n, crunch.v, glancing.a, graze.v, hit.v, hit.n, impact.v, impact.n, plop.v, plough.v, plunk.v, run.v, slam.v, slap.v, smack.v, smash.v, strike.v, thud.v, thump.v

Frame elements:

cause, force, impactee, impactor, impactors, manner, place, result, speed, sub_location, time.

The *Revenge* Frame

15 lexical units (verb, nouns, adjectives):

avenge.v, avenger.n, get back (at).v, get_even.v, retaliate.v, retaliation.n, retribution.n, retributive.a, retributory.a, revenge.n, revenge.v, revengeful.a, revenger.n, vengeance.n, vengeful.a, and vindictive.a.

Five frame elements (FE):

Avenger, Punishment, Offender, Injury, and Injured_party.

The lexical unit in a sentence is called the target.

Annotation

1. [$_{<\mathit{Avenger}>}$ His brothers] **avenged** [$_{<\mathit{Injured\_party}>}$ him].
2. With this, [$_{<\mathit{Avenger}>}$ El Cid] at once **avenged** [$_{<\mathit{Injury}>}$ the death of his son].
3. [$_{<\mathit{Avenger}>}$ Hook] tries to **avenge** [$_{<\mathit{Injured\_party}>}$ himself] [$_{<\mathit{Offender}>}$ on Peter Pan] [$_{<\mathit{Punishment}>}$ by becoming a second and better father].

FrameNet uses three annotation levels: Frame elements, Phrase types (categories), and grammatical functions.

GFs are specific to the target's part-of-speech (i.e. verbs, adjectives, prepositions, and nouns).

For the verbs, three GFs: Subject (Ext), Object (Obj), Complement (Dep), and Modifier (Mod), i.e. modifying adverbs ended by $-$*ly* or indicating manner

The Valence Pattern

Sent. 1	*avenge*	FE	Avenger	Injured_party		
		PT	NP	NP		
		GF	Ext	Object		
Sent. 2	*avenge*	FE	Avenger	Injury		
		PT	NP	NP		
		GF	Ext	Obj		
Sent. 3	*avenge*	FE	Avenger	Injured_party	Offender	Punishmen
		PT	NP	NP	PP	PPing
		GF	Ext	Obj	Comp	Comp

Automatic Frame-semantic Analysis (Johansson, 2008)

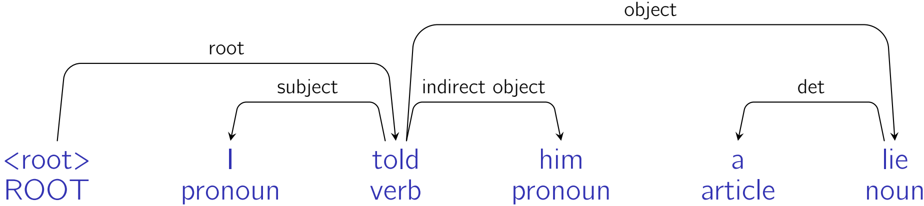
Given a sentence:

I **told** *him a lie*

and a target word – **tell** –, find the semantic arguments.

In Propbank, the possible arguments of **tell.01** are *speaker* (Arg0), *utterance* (Arg1), and *hearer* (Arg2)

Input: a syntax tree:



Classification of Semantic Arguments (Johansson, 2008)

Two steps:

- Find the arguments,
- Determine the role (name) of each argument

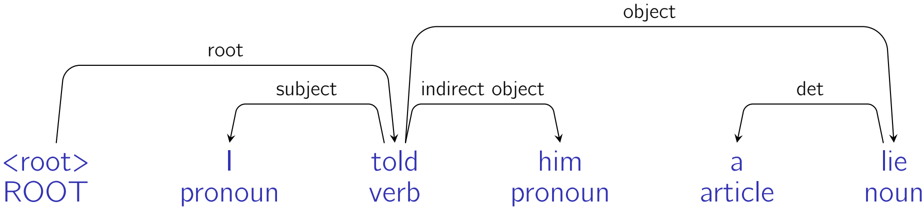
The identification of semantic arguments can be modeled as a statistical classification problem.

What features are useful for this task? Examples:

- Grammatical function: subject, object, ...
- Voice: *I told a lie* / *I was told a lie*
- Semantic classes: *I told him* / *the note told him*
- Semantic class usually not available: use word instead

Feature Extraction (Johansson, 2008)

Given a dependency tree:



We select the three dependents of *told* and we extract features to determine if it is a semantic argument and its name.

Word	**Grammatical function**	**Voice**	**Argument**
I	Subject	Active	*speaker* (Arg0)
him	Indirect object	Active	*hearer* (Arg2)
lie	Direct object	Active	*utterance* (Arg1)

Propbank

Semantic analysis often uses Propbank instead of Framenet because of Propbank's larger annotated corpus

CoNLL 2008 and 2009 used Propbank for their evaluation of semantic parsers.

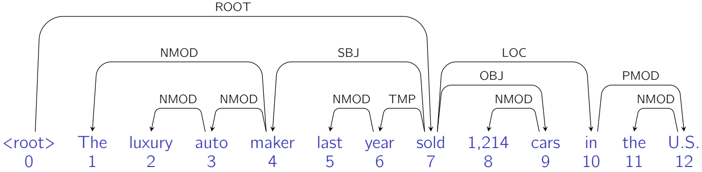
CoNLL annotation format of the sentence:

The luxury auto maker last year sold 1,214 cars in the U.S.

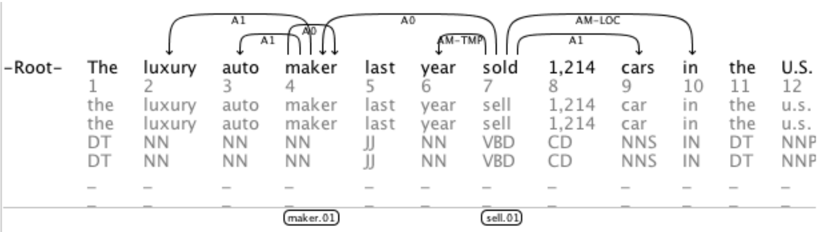
ID	Form	Lemma	POS	Feats	Head	Deprel	FillPred	Sense	APred1	APred2
1	The	the	DT	_	4	NMOD	_	_	_	_
2	luxury	luxury	NN	_	3	NMOD	_	_	A1	_
3	auto	auto	NN	_	4	NMOD	_	_	A1	_
4	maker	maker	NN	_	7	SBJ	Y	maker.01	A0	A0
5	last	last	JJ	_	6	NMOD	_	_	_	_
6	year	year	NN	_	7	TMP	_	_	_	AM-TMP
7	sold	sell	VBD	_	0	ROOT	Y	sell.01	_	_
8	1,214	1,214	CD	_	9	NMOD	_	_	_	_
9	cars	car	NNS	_	7	OBJ	_	_	_	A1
10	in	in	IN	_	7	LOC	_	_	_	AM-LOC
11	the	the	DT	_	12	NMOD	_	_	_	_
12	U.S.	u.s.	NNP	_	10	PMOD	_	_	_	_

Visualizing Dependencies

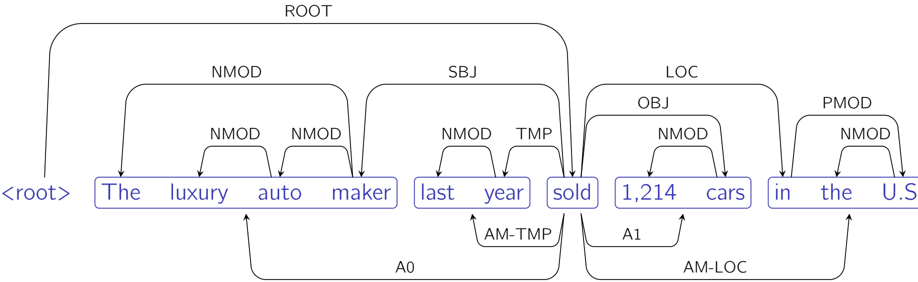
Syntactic dependencies:



Semantic dependencies (predicate–argument structures):



Alternative Visualization



	The	luxury	auto	maker	last	year	sold	1,214	cars	in	the	U.S.
maker.01		A1		A0								
sell.01	A0				AM-TMP			A1		AM-LOC		

The Real Annotation

The participants are given the predicted values up to the semantic columns so that they can focus on the semantic step.

For the sentence:

The luxury auto maker last year sold 1,214 cars in the U.S.

The input is in bold.

ID	**Form**	Lemma	**PLemma**	POS	**PPOS**	Feats	**PFeats**	Head	**PHead**	Deprel	**PDeprel**	FillPred	Sense	APred1	APred2
1	The	the	the	DT	DT	_	_	4	4	NMOD	NMOD	_	_	_	_
2	luxury	luxury	luxury	NN	NN	_	_	3	3	NMOD	NMOD	_	_	A1	_
3	auto	auto	auto	NN	NN	_	_	4	4	NMOD	NMOD	_	_	A1	_
4	maker	maker	maker	NN	NN	_	_	7	7	SBJ	SBJ	Y	maker.01	A0	A0
5	last	last	last	JJ	JJ	_	_	6	6	NMOD	NMOD	_	_	_	_
6	year	year	year	NN	NN	_	_	7	7	TMP	TMP	_	_	_	AM-TMP
7	sold	sell	sell	VBD	VBD	_	_	0	0	ROOT	ROOT	Y	sell.01	_	_
8	1,214	1,214	1,214	CD	CD	_	_	9	9	NMOD	NMOD	_	_	_	_
9	cars	car	car	NNS	NNS	_	_	7	7	OBJ	OBJ	_	_	_	A1
10	in	in	in	IN	IN	_	_	7	7	LOC	LOC	_	_	_	AM-LOC
11	the	the	the	DT	DT	_	_	12	12	NMOD	NMOD	_	_	_	_
12	U.S.	u.s.	u.s.	NNP	NNP	_	_	10	10	PMOD	PMOD	_	_	_	_

Parsing Pipeline

Input sentence

The luxury auto maker last year sold 1,214 cars in the U.S.

↓ **Predicate identification**

The luxury auto **maker** last year **sold** 1,214 cars in the U.S.

maker.?? sell.??

↓ **Predicate sense disambiguation**

The luxury auto **maker** last year **sold** 1,214 cars in the U.S.

maker.01 sell.01

↓ **Argument identification**

The luxury auto <u>maker</u> last <u>year</u> **sold** 1,214 <u>cars</u> <u>in</u> the U.S.

sell.01

↓ **Argument labeling**

The luxury auto <u>maker</u> last <u>year</u> **sold** 1,214 <u>cars</u> <u>in</u> the U.S.

sell.01

A0 AM-TMP A1 AM-LOC

Semantic Parsing As a Tagging Operation

We can also apply a technique similar to that in chunking (Zhou and Xu, 2015):
Starting from the segments:

	The	luxury	auto	maker	last	year	sold	1,214	cars	in	the	U.S.
maker.01		A1		A0								
sell.01	A0				AM-TMP			A1		AM-LOC		

We annotate the arguments with the IOB2 tagset (Begin, Inside, Outside):

	The	luxury	auto	maker	last	year	sold	1,214	cars	in	the	U.S.
maker.01	O	B-ARG1	I-ARG1	B-ARG0	O	O	O	O	O	O	O	O
sell.01	B-ARG0	I-ARG0	I-ARG0	I-ARG0	B-TMP	I-TMP	B-V	B-ARG1	I-ARG1	B-LOC	I-LOC	I-LOC

Semantic Parsing as a Tagging Operation (II)

The annotated corpus:

	The	luxury	auto	maker	last	year	sold	1,214	cars	in	the	U.S.
maker.01	O	B-ARG1	I-ARG1	B-ARG0	O	O	O	O	O	O	O	O
sell.01	B-ARG0	I-ARG0	I-ARG0	I-ARG0	B-TMP	I-TMP	B-V	B-ARG1	I-ARG1	B-LOC	I-LOC	I-LOC

Collecting the features from Zhou and Xu (2015):

1. The input is the word sequence and the output is the tag sequence: sequence-to-sequence learning;
2. The features are similar to those used for chunking:
   - The current word;
   - The predicate (from a previous detection);
   - The predicate context (three words centered on the predicate);
   - if the current word is in the predicate context;
3. The process is repeated as many times as there are predicates in the sentence.

Semantic Parsing as a Tagging Operation (III)

The annotated corpus:

	The	luxury	auto	maker	last	year	sold	1,214	cars	in	the	U.S.
maker.01	O	B-ARG1	I-ARG1	B-ARG0	O	O	O	O	O	O	O	O
sell.01	B-ARG0	I-ARG0	I-ARG0	I-ARG0	B-TMP	I-TMP	B-V	B-ARG1	I-ARG1	B-LOC	I-LOC	I-LOC

$$\mathbf{X} = \begin{bmatrix} \text{The} & \text{sell.01} & \text{year sold 1,214} & 0 \\ \text{luxury} & \text{sell.01} & \text{year sold 1,214} & 0 \\ \text{auto} & \text{sell.01} & \text{year sold 1,214} & 0 \\ \text{maker} & \text{sell.01} & \text{year sold 1,214} & 0 \\ \ldots & \ldots & \ldots & \ldots \\ \text{The} & \text{maker.01} & \text{auto maker last} & 0 \\ \text{luxury} & \text{maker.01} & \text{auto maker last} & 0 \\ \text{luxury} & \text{maker.01} & \text{auto maker last} & 0 \\ \text{auto} & \text{maker.01} & \text{auto maker last} & 1 \\ \ldots & \ldots & \ldots & \ldots \end{bmatrix} ; \mathbf{y} = \begin{bmatrix} \text{B-ARG0} \\ \text{I-ARG0} \\ \text{I-ARG0} \\ \text{I-ARG0} \\ \ldots \\ \text{O} \\ \text{B-ARG1} \\ \text{I-ARG1} \\ \text{B-ARG0} \\ \ldots \end{bmatrix}$$

EVAR

EVAR is a German project that aims at providing information on trains

- noun
  - concrete
    - thing
      - transport
    - location
    - animate
      - human
      - beast
  - abstract
    - worth
    - classifying
    - time

EVAR's Case Grammar

1. fahren1.1 (*The train is going from Hamburg to Munich*)
   - Instrument: noun group (nominative), Transport, obligatory
   - Source: prepositional group (Origin), Location, optional
   - Goal: prepositional group (Direction), Location, optional
2. fahren1.2 (*I am going by train from Hamburg to Munich*)
   - Agent: noun group (nominative), Animate, obligatory
   - Instrument: prepositional group (prep = mit), Transport, optional
   - Source: prepositional group (Origin), Location, optional
   - Goal: prepositional group (Direction), Location, optional
3. Abfahrt1.1 (*The departure of the train at Hamburg for Munich*)
   - Object: noun group (genitive), Transport, optional
   - Location: prepositional group (Place), Location, optional
   - Time: prepositional group (Moment), Time, optional

Application: Carsim

Identify the events (actions) and the semantic relations related to car accidents.

In Framenet, the **Impact** class consists of 38 verbs or nouns with the roles: **Impactor**, **Impactee**, **Impactees**

[*<Impactor>* The rock] **HIT** [*<Impactee>* the sand] with a thump

Source: `http://framenet.icsi.berkeley.edu/`

In Carsim:

[*ACTOR* En personbil] **körde** [*TIME* vid femtiden] [*TIME* på torsdagseftermiddagen] in [*VICTIM* i ett radhus] [*LOC* i ett äldreboende] [*LOC* på Alvägen] [*LOC* i Enebyberg] [*LOC* norr om Stockholm].