

Construction Detection in a Conventional NLP Pipeline

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Frame-semantic parsing
identifies the words that evoke frames
and the argument spans for those frames.

FrameNet

(Ruppenhofer et al.,
2016)



One domain that epitomizes the problem is causal language.

This **opens the way for** broader regulation. (Multi-word expr.)

For markets **to** work, banks **can't** expect bailouts. (Complex)

Judy's comments were **so** offensive **that** I left. (Complex)

These flavors complex**ify** the taste of the fruit. (Morphological)

There are some powerful CxG-based NLP tools, but none can yet robustly parse, e.g., the NYT.

Fluid Construction Grammar

Applying
 the-cxn (cxn 0.50) show attributes

?the-word \oplus ?the-word

in comprehension

status: cxn-applied

source structure: transient structure

\oplus root

applied construction: the-cxn (cxn 0.50) show attributes

?the-word \oplus ?the-word

resulting structure: transient structure

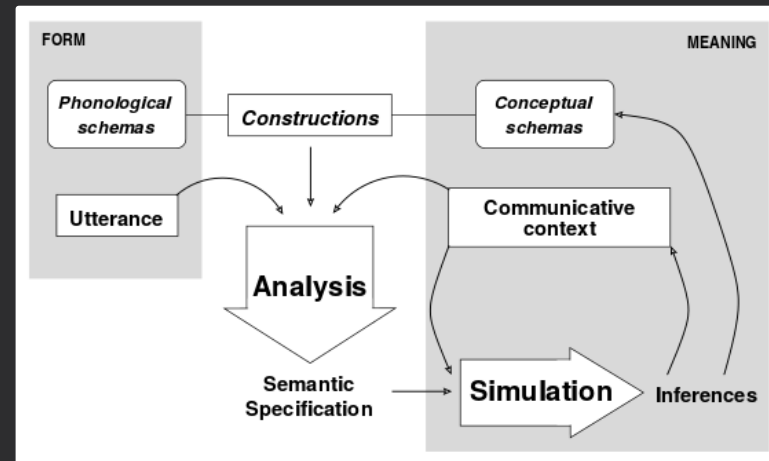
root

\oplus the-3

resulting bindings: ((?the-word . the-3))

meaning: (unique ?x-88)

Embodied Construction Grammar



Sign-Based Construction Grammar

(39) **Initial-that-Clause Construction:**

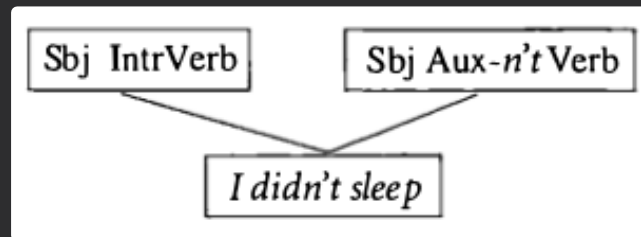
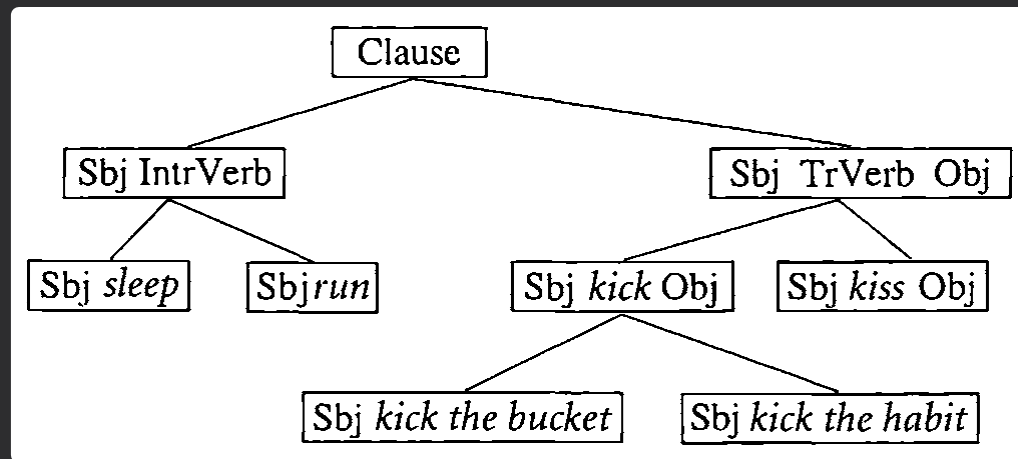
init-that-cl \Rightarrow

$$\left[\begin{array}{l} \text{MTR} \left[\begin{array}{l} \text{SYN} \left[\begin{array}{l} \text{CATEGORY} \left[\begin{array}{l} \text{verb} \\ \text{VFORM } \textit{finite} \end{array} \right] \\ \text{INV } - \\ \text{IC } + \end{array} \right] \\ \text{VALENCE } \langle \rangle \\ \text{GAP } \langle \rangle \end{array} \right] \\ \text{DTRS} \left\langle \left[\begin{array}{l} \text{SYN } \text{CP} \left[\textit{that} \right] \\ \text{SEM } X_p \end{array} \right], \mathbf{H} \left[\begin{array}{l} \text{SYN} \left[\begin{array}{l} \text{VALENCE } \langle \rangle \\ \text{GAP } \left\langle \left[\begin{array}{l} \text{SYN } \text{NP} \\ \text{SEM } X_p \end{array} \right], \dots \right\rangle \right] \end{array} \right] \end{array} \right. \end{array} \right]$$

An intermediate step:
apply the key insights of CxG
on top of conventional NLP.

1. Morphemes, words, MWEs, and grammar are all on the **same spectrum of linguistic forms**.
2. **Any aspect or combination** of those forms is equally capable of being mapped to meanings.

Full CxG theory entails
a detailed hierarchy and complex interactions:
“constructions all the way down.”



The “constructions on top” approach

Tagging causative frames

Construction recognition

POS tagging, syntactic parsing

Tokenization

The “**constructions on top**” approach represents low-hanging fruit for CxG in NLP and lays the groundwork for further uptake.

Constructional
analysis



Tagging causative frames

Construction recognition

POS tagging, syntactic parsing

Tokenization

Today's talk:

1. The “constructions on top” approach
2. The BECauSE corpus of causal language
3. Causeway: a simple system for tagging causal constructions
4. Lessons learned

FrameNet currently represents
a relatively small number
of non-lexical constructions.

The crane could buckle **due to** the heat .
└EFFECT┘ CAUSATION └CAUSE┘

This **opens the way for** broader regulation .
└POTENTIAL_HINDRANCE┘ PREVENTING_OR_LETTING └EVENT┘

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For markets **to** work, banks **can't** expect bailouts.

???

The FrameNet Constructicon project has begun to fill this gap.

{Motion verb [Verb] [PossNP] }

Name	<i>verb-way</i>
M	Verb, evokes the <code>Motion</code> frame. Requires at least one <code>SOURCE</code> , <code>PATH</code> , or <code>GOAL</code> -related argument.
D1	A verb with at least an <code>ACTOR</code> argument; any other arguments are suppressed and existentially interpreted.
D2	An NP, headed by <i>way</i> and with a possessive pronoun coindexed to D1's external argument; able to be modified by <code>ACTOR</code> -modifying or <code>PATH</code> -modifying expressions.
Interpretation	the meaning of D1 (the verb) is incorporated into the <code>Motion</code> frame as a <code>MANNER</code> or <code>MEANS</code> of motion. This is clear in many cases but the distinction is not always clear.

The FrameNet Construction project has begun to fill this gap.

Layer	C	o	n	s	t	a	n	c	e	s	q	u	e	e	d	h	e	r	w	a	y	d	o	w	n	t	h	e	p	l	a	t	f	o	r	m								
CE	T	h	e	m	e					T	r	a	n	s	i	t	i		W	a	y	_	e	x	p	P	a	t	h															
CE																		T	h	e																								
GF	E	x	t																							D	e	p																
PT	N	P								V	P	f	i	n				N	P							P	P																	
CEE																		C	E	E																								
CstrPT										V	P	f	i	n																														
GovX																																												

Way_means - CE	Way_means - CE	Way_means - GF	Way_means - PT	Way_means - CEE	Way_means
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Direction <F8>		▼	Path <F5>		▼
Goal <F7>		▼	Source <F6>		▼
Intransitive_mean...		▼	Theme <F1>		▼
Manner <F9>		▼	Transitive_means...		▼
Means <F10>		▼	Way_expression <...		▼
Modifier <M>		▼			

Causal language:
a clause or phrase in which
one event, state, action, or entity
is **explicitly presented**
as promoting or hindering
another

Connective:

construction-evoking element
indicating a causal relationship

John killed the dog **because**
it was threatening his chickens.

John **prevented** the dog **from**
eating his chickens.

Ice cream consumption **causes** drowning.

She must have met him before, **because**
she recognized him yesterday.

}
Not “truly”
causal

Connective: arbitrarily complex
construction-evoking element
indicating a causal relationship

For markets **to** work,
banks **can't** expect bailouts.

This **opens the way for** broader regulation.

We have annotated a small corpus with this scheme.

Bank of **E**ffects and **C**auses **S**tated **E**xplicitly (**BE****C**au**SE**):

	Documents	Sentences	Causality annotations
New York Times Washington section (Sandhaus, 2014)	59	2004	529
Penn Treebank WSJ	47	1542	330
2014 NLP Unshared Task in Polilnformatics (Smith et al., 2014)	1	615	240
Total	107	4161	1099

Constructional phenomena are frequent in the corpus.

16% of contiguous connective types...

62% of non-contiguous connective types...

Up to 20% of annotated instances...

...can't be represented as FN lexical units.

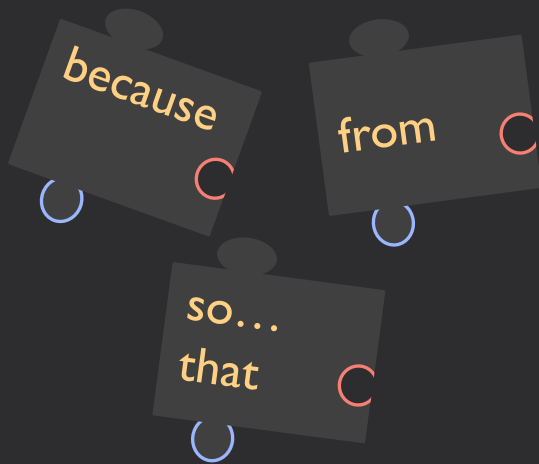
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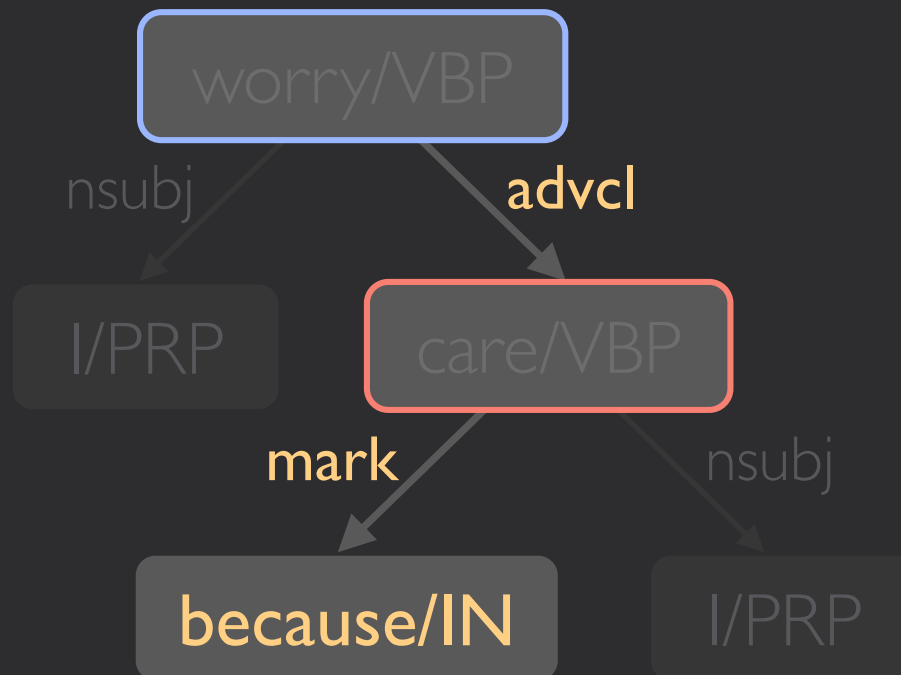
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I. Pattern-based connective discovery



I nearly died **from** worry.
You could have called me
from your hotel.

Syntax-based connective discovery:
each construction is treated as
a partially-fixed parse tree fragment.



I worry because I care.

1. Pattern-based connective discovery
(tentative)



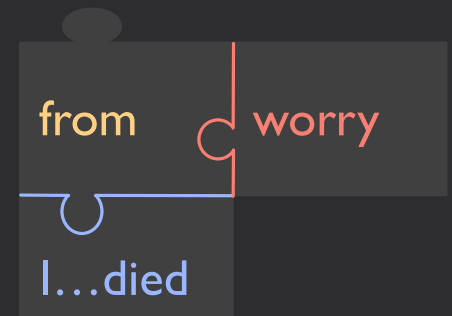
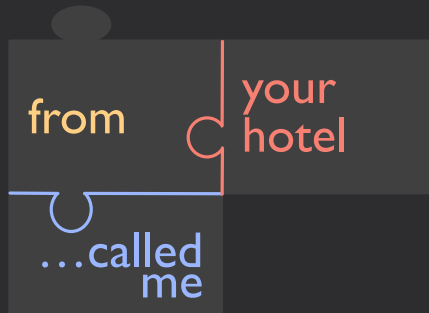
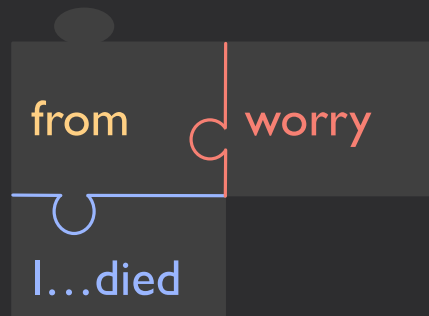
2. Argument identification
(tentative)



3. Statistical classifier to filter results



I nearly died **from** worry.
You could have called me **from** your hotel.



4. Remove duplicate connectives

Our results show the techniques are viable,
but further work is needed.

Pipeline [stages]	Connectives			Causes			Effects		
	P	R	F _I	S _C	H _C	J _C	S _E	H _E	J _E
Causeway [1-2]	7.3	71.9	13.2	65.0	84.3	39.3	30.4	63.0	30.7
Causeway [1-2] + MFS	40.1	37.9	38.6	71.0	87.6	42.0	34.3	64.4	31.9
Causeway [1-2] + MFS + 3b	60.9	36.2	45.1	75.1	92.3	42.9	40.7	75.2	35.8
Causeway [1-3]	51.9	47.6	49.4	68.7	86.9	39.9	38.0	72.5	34.1
Causeway [1-3] + MFS	57.7	47.4	51.8	67.1	84.4	39.0	37.7	70.7	33.4
Baseline	88.4	21.4	33.8	74.1	94.7	43.7	48.4	83.3	38.4
+ Causeway (full)	59.6	51.9	55.2	67.7	85.8	39.5	39.5	73.1	34.2

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Lesson 1:

Constructions are hard to individuate.

too sweet to eat

too sweet for me to eat

sweet enough to eat

sweet enough for me to eat

sweet enough that I can eat it

so sweet that I can't eat it

so sweet I can't eat it

Lesson 1:

Constructions are hard to individuate.

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→ sweet enough to eat

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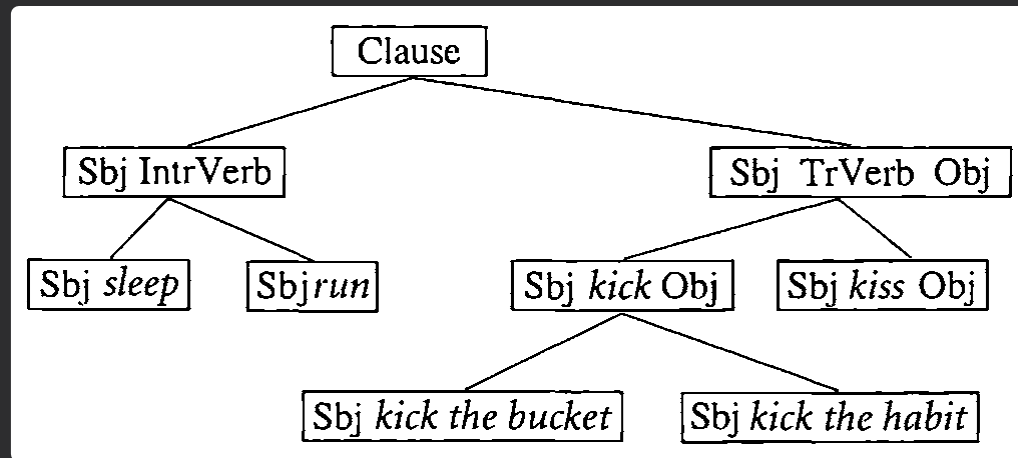
- too sweet to eat
- too sweet **for me to** eat
- sweet enough to eat
- sweet enough **for me to** eat
- sweet enough **that** I can eat it
- so** sweet **that** I can't eat it
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Lesson 1:

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- too sweet **to** eat
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The usual answer:
construct a hierarchy
to “capture the generalization.”



...but when does a product of constructions
become its own construction?

“As a result?”

For “constructions on top,”
decide where to draw the lines
for computational convenience.

Lesson 2:

Constructions can simultaneously carry multiple semantic relations.

My head was hurting, but taking a drink **made** it feel much better.

My head was hurting, but **after** I took a drink (Temporal)
it felt much better.

If you touch it, it will fall over. (Hypothetical)

These reports **create** (Inception/
a perception of higher risk. termination)

Contributions:

1. The “constructions on top” approach
2. The BECauSE corpus of causal language
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