Unifying Broad-Coverage Lexical Resources and Logical Reasoning

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Questions

- What properties should meaning representations have in order to facilitate inference?
- What kind of information should lexical resources encode to facilitate inference?
- What kinds of inferential relations are essential for textual inference?
- How is ambiguity and underspecification factored in, e.g. of scope, word senses, anaphora, factored in?
- Can we have ‘robust inference’? Does the notion even make sense?

The team

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Moving beyond shallow semantics

We need to move beyond shallow semantic parsing to deeper semantic analysis of text;

Understanding sentences requires more than identifying events and participants and giving them semantic role labels;

It is essential to recognize temporal sequencing within the event and any changes in state that might have occurred.

Many fighters have fled to the south through Syrian army lines.

Theme

VerbNet class:
Escape-51.1

Trajectory

Many fighters have fled to the south through Syrian army lines.

has_location(e1, Theme, ?Initial_Location)
motion(ë2, Theme, Trajectory)
has_location(e3, Theme, ?Destination)

VerbNet class:
Escape-51.1

Theme

Trajectory

Many fighters have fled to the south through Syrian army lines.

has_location(e1, Theme, ?Initial_Location)
motion(ë2, Theme, Trajectory)
has_location(e3, Theme, ?Destination)

Theme

VerbNet class:
Escape-51.1

Trajectory

Many fighters have fled to the south through Syrian army lines.

has_location(e1, Many fighters, ?Initial_Location)
motion(ë2, Many fighters, to the south through…)
has_location(e3, Many fighters, ?Destination)

implicit arguments

Agent

VerbNet class:
Concealment-16

Destination

Some have hidden near Damascus.

visible(e1, Agent)
do(e2, Agent)
¬visible(e3, Agent)
location(e3, Agent, Destination)
cause(e2, e3)

VerbNet class:
Concealment-16

Agent

Destination

Some have hidden near Damascus.

visible(e1, Some fighters)
do(e2, Some fighters)
¬visible(e3, Some fighters)
location(e3, Some fighters, near Damascus)
cause(e2, e3)

Our Goal: A Whole that Is Greater than the Sum of Its Parts

Computational Language and EducAtion Research
C L E A R

Bring resources and theories together to enable not just better extraction of events and participants from text, but deeper semantic analysis and clearer linking of events and participants across sentences and documents.

- VerbNet: comprehensive verb resource; generalizations across related verbs; predicate argument structure;
- Generative Lexicon: best known for semantic components (qualia) of nouns, but compelling theory of contextual meaning arising from the interaction of noun and verb meaning; more recently, event decomposition
- REO: event-focused ontology

Outline

- Improve our ability to identify a verb's VerbNet class (state-of-art WSD)
- Improve VerbNet semantic role labeling (state-of-art SRL)
- Enrich VerbNet semantic representations (nuanced temporal and causal sequencing, arguments with selectional preferences, verb-specific features)
- Link to relevant ontologies and other resources (REO, Corelex, BSO)

VerbNet overview

Domain-independent verb lexicon

Verbs grouped into hierarchical classes
- Semantic similarities
- Shared syntactic alternations

Explicitly described class properties
- Thematic roles involved in the predicate-argument structure
- Selectional preferences for those roles
- Syntactic frames
- Semantic representations

Run-51.3.2

Members

- AMBLE (FN 1; WN 1; G 1)
- AMBULATE (WN 1; G 1)
- BACKPACK (WN 1)
- BOLT (FN 1, 2, 3, 4; WN 4; G 1)
- BOUND (FN 1; WN 1; G 1)
- BREEZE
- BUSTLE (WN 1)
- GOOSE_STEP (WN 1)
- HIKE (FN 1; WN 2; G 1)
- HITCHHIKE (WN 1)
- HOPSCOTCH
- JOUNCE
- LIMP (FN 1; WN 1, 2)
- LOLLOP (WN 1)

Roles

- Agent [+animate]
- Theme [+animate | +machine]
- Location [+concrete]

Frames

NP V

EXAMPLE	"The horse jumped."
SYNTAX	Theme V
SEMANTICS	MOTION(DURING(E), Theme)

NP V PP.location

EXAMPLE	"The horse jumped over the fence."
SYNTAX	Theme V {{+spatial}} Location
SEMANTICS	MOTION(DURING(E), Theme) Prep(E, Theme, Location)

VerbNet widely used

Linking lexical resources to ontologies (Brown et al., 2017)

Semantic role labeling tasks (Shi and Mihalcea, 2005)

Word sense disambiguation for verbs (Abend et al., 2008; Brown et al., 2011; Kawahara and Palmer, 2014; Palmer et al., 2018)

Inference-enabling tasks (Giuglea and Moschitti, 2006; Loper et al., 2007; Zaenen et al., 2008; Kawahara and Palmer, 2014)

Verb sense disambiguation

JAMES GUNG

Class members are verb senses
Example: *draw*

VerbNet Class	**Example**	**Ontonotes Sense**	**Wordnet Senses**
Carry-11.4	*She drew the cart into the barn.*	1	1, 20, 27
Lure-59.3	*They drew him into the conspiracy.*	2	16, 24, 26
Remove-10.1	*The nurse drew blood.*	3	5, 7, 9, 13, 14, 17
Split-23.2	*She drew away from the crowd.*	4	12
Scribble-25.2	*He drew the symbols over the door.*	6	3, 6, 19
Create-26.4	*She drew him a picture.*	6	6, 8, 19

Verb Sense Disambiguation – James Gung

ClearWSD: Classifier-per-verb word sense disambiguation system for VerbNet classes

Rich semantic feature set using knowledge resources and word representation techniques

State-of-the-art accuracy on two benchmark datasets

https://github.com/jgung/ClearWSD/tree/master/src/main/java/edu/colorado/clear/wsd/ontonotes

Martha Palmer, James Gung, Claire Bonial, Jinho Choi, Orin Hargraves, Derek Palmer, Kevin Stowe, The Pitfalls of Shortcuts: Tales from the word sense tagging trenches, (2018) *Essays in Lexical Semantics and Computational Lexicography - In Honor of Adam Kilgarriff*. M. Diab, A. Villavicencio, M. Apidianaki, V. Kordoni, A. Korhonen, P. Nakov, M. Stevenson (editors). Springer series Text, Speech and Language Technology. Springer

Results

System	Accuracy
Kawahara & Palmer 2014	0.9716
Our System	**0.9803**

System comparison on Semlink 1.2.2c

System	Accuracy
Brown et al. 2011	0.8867
Croce et al. 2012	0.8672
Our System	**0.9160**

System comparison on Semlink 1.1

VerbNet semantic role labeling

JAMES GUNG

VerbNet Semantic Role Labeling

Automatically find the participants in an event and identify the role they play - Helpful on its own; essential building block for deeper representations of a text's meaning

Theme   Trajectory

Many fighters have fled to the south through Syrian army lines.

has_location(e1, Theme, ?Initial_Location)
motion(ë2, Theme, Trajectory)
has_location(e3, Theme, ?Destination)

Verb-specific features

SUSAN W. BROWN, GHAZALEH KAZEMINEJAD

Adding verb-specific features

VerbNet classes generalize across verbs with similar semantics and syntactic patterns

Useful for

- event linking within and across documents
- inferences about novel words that fit a class's pattern
- highlighting essential semantic components

However, classes can often be subdivided based on additional semantic features of the verbs

- selectional restrictions on a thematic role
- directionality of motion
- manner of an action
- change of value on a scale
- affect of a participant

Calibratable-change-of-state

Increase (e.g., *build, soar, grow, jump*)

Decrease (e.g., *fall, drop, plunge*)

Fluctuate (e.g., *swing, seesaw, fluctuate*)

The price of oil soared to $50 a barrel.
has_val(e1, Patient, Initial_State)
change_value(e2, direction, ?Extent, Attribute, Patient)
has_val(e3, Patient, Result)

Revising VerbNet semantic representations

VerbNet semantic representations

Each class contains semantic representations compatible with all the members and syntactic frames of the class

Representations make use of semantic predicates:

- **motion**
- **perceive**
- **cause**

Reference semantic role participants and an event variable E.

Some of these are meant to describe the participants during various stages of the event evoked by the syntactic frame.

Assumptions

The arguments of each predicate are represented using the semantic roles for the class;

Participants mentioned in the syntax as well as those not expressed are accounted for in the semantics;

OLD - Temporal sequencing is indicated with the second-order predicates start, during, and end;

Semantically coherent classes

Semantic representations capture generalizations about the semantic behavior of the class member as a group;

For some classes (e.g., Battle-36.4), verbs are semantically coherent, battle, skirmish, war ;

Sparta warred with Athens.
NP V PP
Agent V with Co-Agent
social interaction(during(E), Agent, Co-Agent)
conflict(during(E), Agent, Co-Agent)
possible contact(during(E), Agent, Co-Agent)
manner(Hostile, Agent)

Impetus for change

Zaenen et al. (2008) show VerbNet is unable to support some temporal and spatial inferencing tasks;

From The diplomat left Bhagdad you can't infer The diplomat was in Bhagdad;

For several motion classes, End(E) was given but not Start(E);

Some classes involving change of location of participants (e.g., gather, mix) did not include a motion predicate at all.

Efforts to use VerbNet in human-computer interaction found that an enriched event representation would facilitate the interaction between the language parsing and the planning components of the system (Narayan-Chen et al., 2017);

Impetus for change

Attempts to use VerbNet in robotics show the need for:

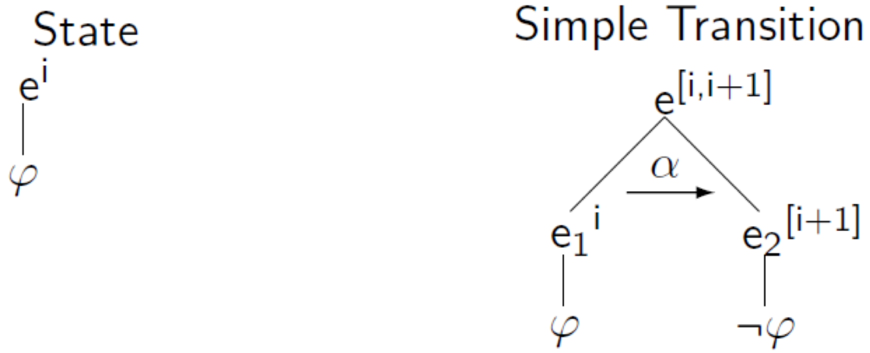
a 1st-order representation;

more specific event causal relation, instead of cause(Agent,E);

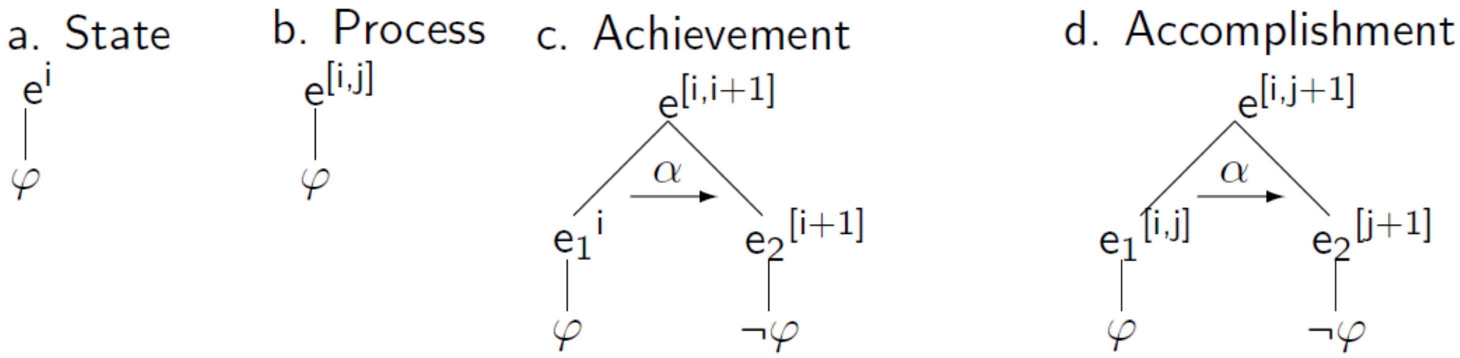
more explicit temporal relations, over reifed events rather than functional expressions over the matrix event, E.

Generative Lexicon event structure

Two Primitive Event Types



Derived Vendler Event Types



VerbNet with GL event structure

Elimination of tripartite division of temporal span of the event, i.e., Start, During, End;

Subevents introduced as 1st-order quantified individuals, e1; e2; : : :;

Temporal (Allen-like) relations can be employed for verb-class specific semantics:

before(e2; e3)

meets(e2; e3)

while(e2; e3)

Causation is an event-relation: cause(e1; e2)

More fighters fled across Syrian lines.

NEW VERBNET
has location(e1, Theme, ?Initial Location)
motion(e2, Theme, Trajectory)
has location(e3, Theme, ?Destination)

Ongoing revision

Major theoretical work has been completed.

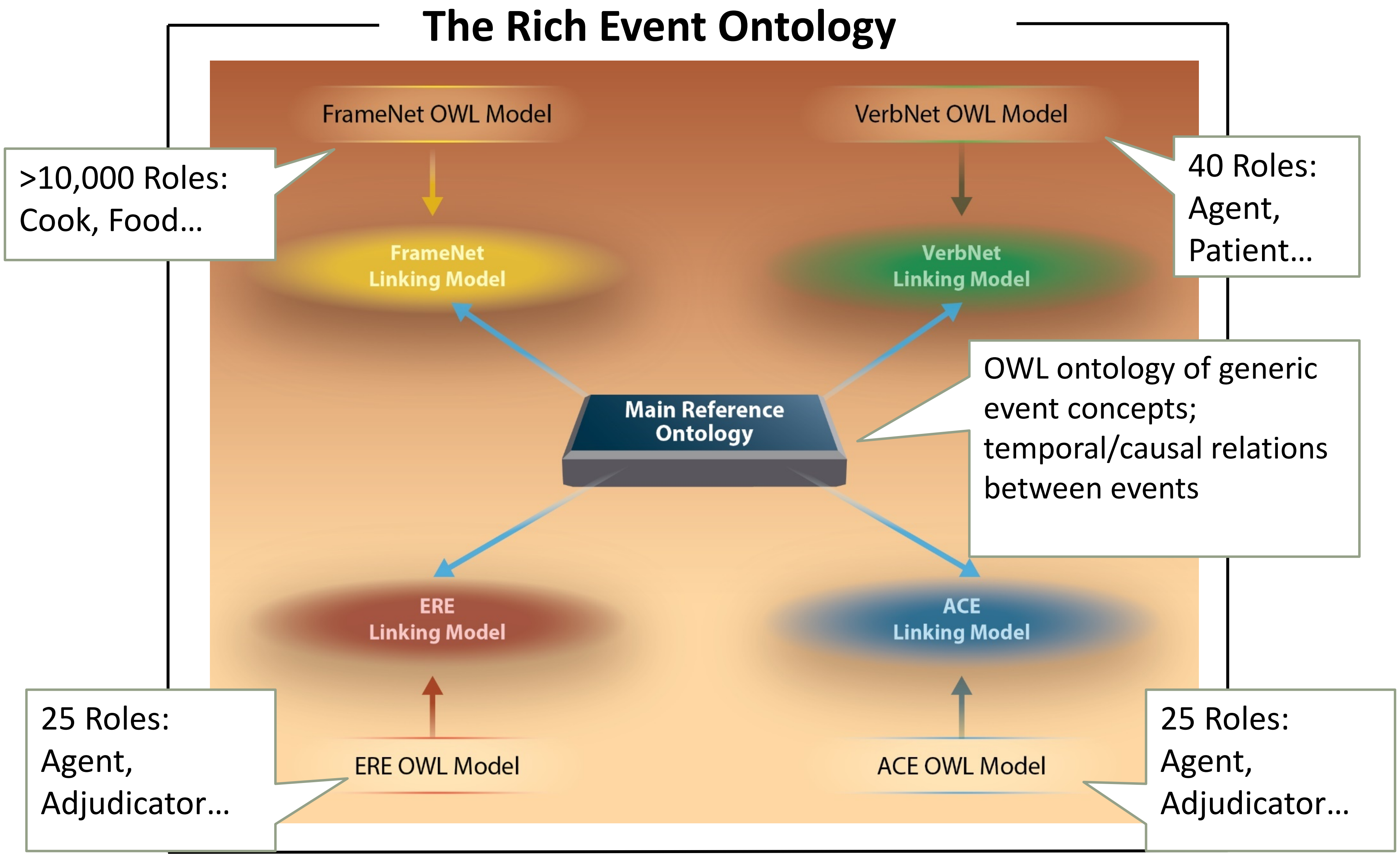
Generic representations for all basic VerbNet frame types have been created.

- change of location
- change of state
- change of possession
- states
- processes

Changes have been made automatically to 65 classes and manually checked for 41.

Future work includes semantics for verbs of creation, perception, and experience.

REO: Set of Ontologies



VerbNet Syntactic Frames and Dependency Parses

SARAH MOELLER

Mapping to Dependency Tags

Adjust-26.9

He adapted himself to waking up early.

NP V NP S_ING

nsubj root dobj advcl

Admire-31.2

Carol loved him writing novels

NP V NP S_ING

nsubj root dobj xcomp

Guo and Moeller 2017

Why not replace VN sytax with UD tags?

UD tag **mark**

- “that” complementizer,
- “whether” complementizer, or
- infinitival complement.

Use **mark** in VerbNet?

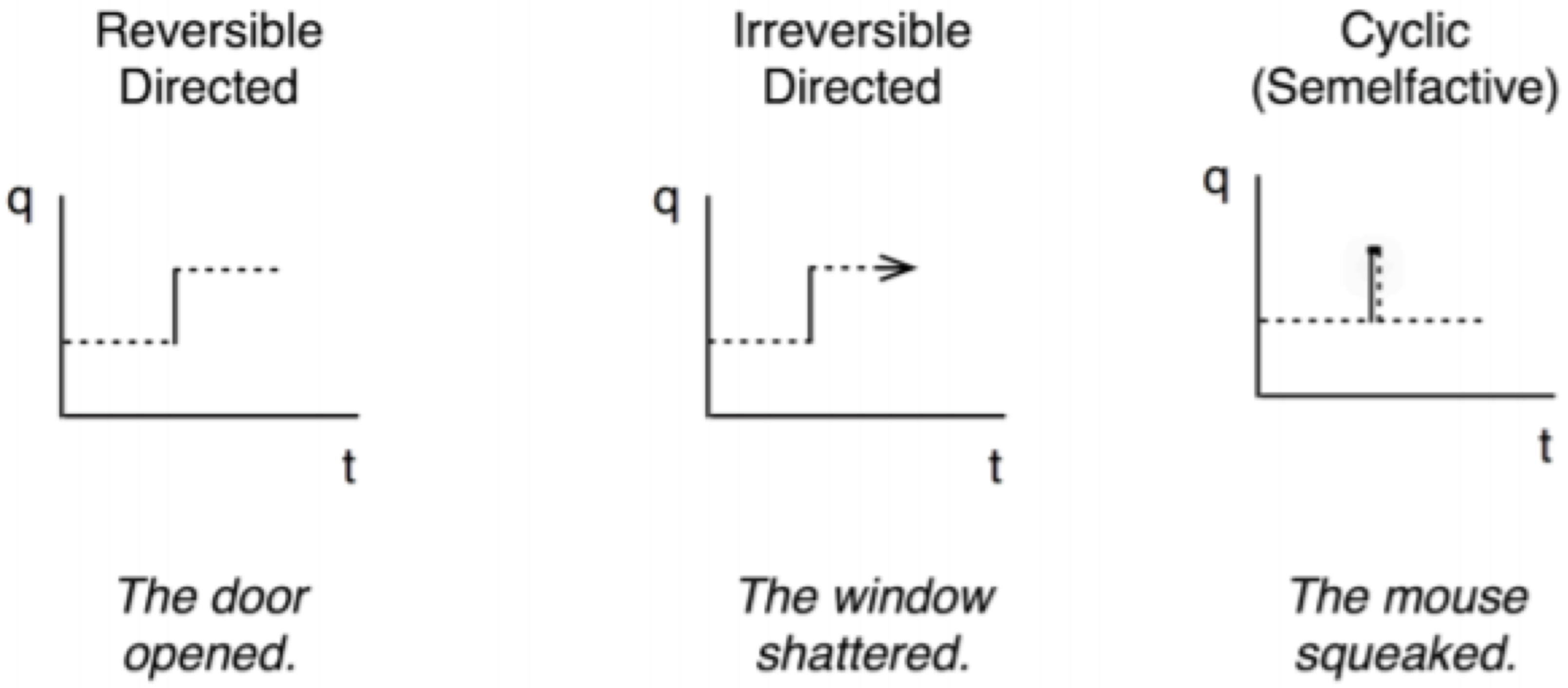
- that S
- whether S
- S_inf

mark S

We would lose information.

Future Work

Link VerbNet frames to Bill Croft's force dynamic representations



William Croft

Yet more work . . .

Collaborate with an end user to evaluate the new GL-VN representations in an application, such as Human-Robot interaction, IE, RTE and revise as needed.

Provide a public domain, downloadable Semantic Role Labeling system that automatically produces accurate VerbNet-based semantic representations of sentences.

Richer Event Descriptions (RED)

Moving from Light ERE to Rich ERE

- Increasingly rich event relations

RED Event Coref

- similar to LDC/CMU event nuggets/hoppers
- Adds event/subevent, set/member, bridging,

RED also adds event relations:

- Narrative containers, temporal and causal relations, aspectual and reporting events
- All events, not just ERE types, more IRREALIS

More coarse-grained than RPI

Temporal & Causal ordering

"Saucedo said that guerrillas in one car <u>opened fire</u> on police <u>standing</u> guard, while a second car <u>carrying</u> 88 pounds (40 kgs) of dynamite <u>parked</u> in front of the building, and a third car <u>rushed</u> the attackers away

- guarding BEFORE/OVERLAP firing
- X CONTAINS [firing, parking, rushing]
- firing BEFORE parking
- parking BEFORE rushed

Narrative Containers

Pustejovsky & Stubbs, 2011

Don't mark the relations between EVENTs.

Instead, put EVENTs in temporal buckets and relate the buckets

Event Relations and Features

BEFORE and OVERLAP
- Cause
- Precondition

CONTAINS
- Subevent

COREF has
- Identity
- Set/Member
- Part/Whole
- Bridging

MODALITY
- Actual
- Generic
- Hypothetical
- Uncertain/Hedged

POLARITY
- Positive
- Negative

Event Mention ITA

		IAA (ann-ann)	Kappa (ann-ann)
Event	DocTimeRel	0.86	0.74
	Polarity	0.99	0.83
	Modality	0.94	0.72
	Span Agreement	0.87 (0.79 in THYME)	
Entity	Polarity	0.999	0.40
	Modality	0.98	0.54
	Span Agreement	0.91 (0.87 in THYME)	

Event Relation ITA

Given agreement that there is a Relation

	F1
All Event Types	.78
Relations w/out subtypes	.90
CONTAIN vs. SUBEVENT	.87
CAUSE VS. Not CAUSE	.78
CAUSE vs. PRECONDITION	.64

Agreement on having a Relation is .58 F1