AMR/UMR as a basis for Knowledge Grounding/Situated Grounding

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Computational Language and EducAtion Research
C L E A R

Outline

- Background on GL-VN: a synchronization of the Generative Lexicon and VerbNet
- GL-AMR – adding a layer of inference to AMR
- More on Quantification
- Decorating the tree – mapping AMR/UMR to Wikidata
- AMR/UMR applications

GL-VerbNet as a basis for Logical Inference

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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.

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

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;

Outline

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

VerbNet goals

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 (Indig, et. al. 2016, Brown et al., 2017)

Semantic role labeling tasks (Shi and Mihalcea, 2005, Gung & Palmer, 2021)

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)

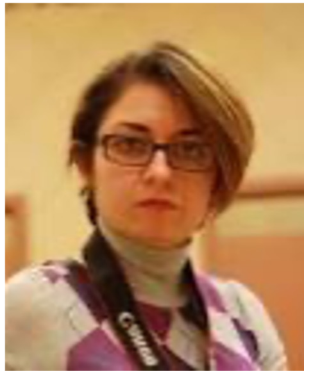
Story generation (Martin et al., AAAI-2018; Tambwekar, P, et. al, IJCAI 2019; Ammanabrolu, P., et. al., AAAI-2020)

VerbNet – 2023: Generative Lexicon/VerbNet Synchronizes semantics w/ GL dynamic event structure

- *Brown, S., Bonn, J., Kazeminejad, G., Zaenen, A., Pustejovsky, J., Palmer, M., Semantic Representations for NLP using VerbNet and the Generative Lexicon.*
- *Kazeminejad, G., Palmer, M., Brown, S., & Pustejovsky, J., Componential analysis of English verbs. Front Artif Intell. 2022*

- *Stowe, K., et. al., SemLink 2.0, IWCS, 2021*
- *Gung & Palmer, VerbNet Semantic Parsing, IWCS, 2021*



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VerbNet semantic representations

Class-based semantic representations

Representations make use of semantic predicates:

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

Reference semantic role participants and an event variable E.

Describe participants during various stages of the event evoked by the syntactic frame.

Class-based Assumptions

The arguments as semantic roles;

Explicit AND implicit arguments included

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

NEW – Temporal sequencing uses event variable E and subevent variables e_1, e_2 … e_n

Semantically coherent classes

Class-based semantic representations

For some classes (e.g., Battle-36.4), verbs are semantically coherent (e.g., *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 (cont.)

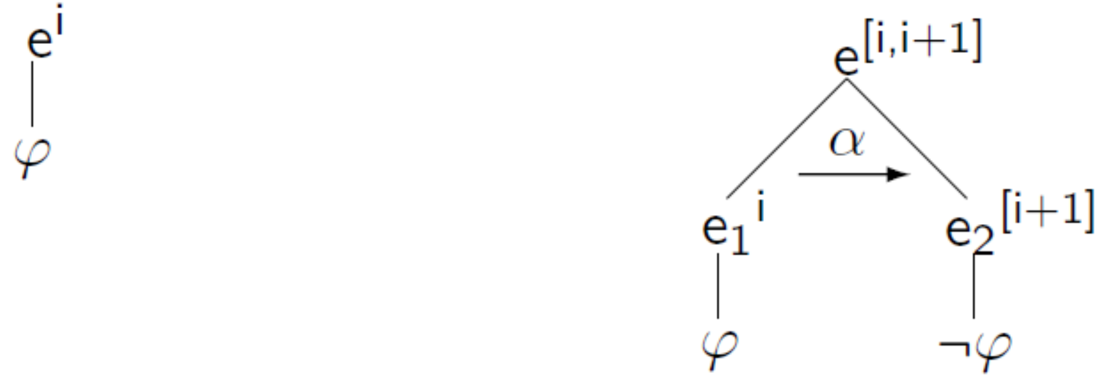
Attempts to use VerbNet in robotics showed the need for:

- 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 dynamic event structure

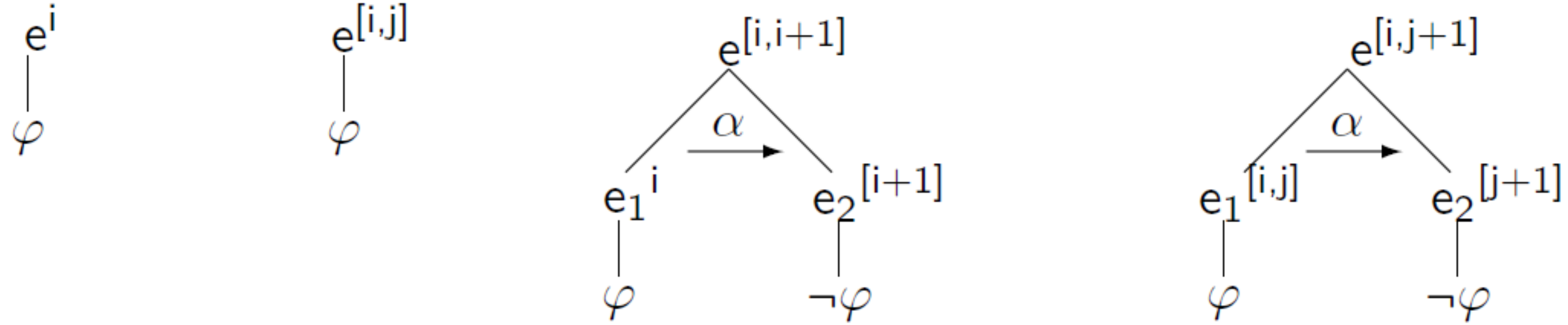
Two Primitive Event Types

State | Simple Transition



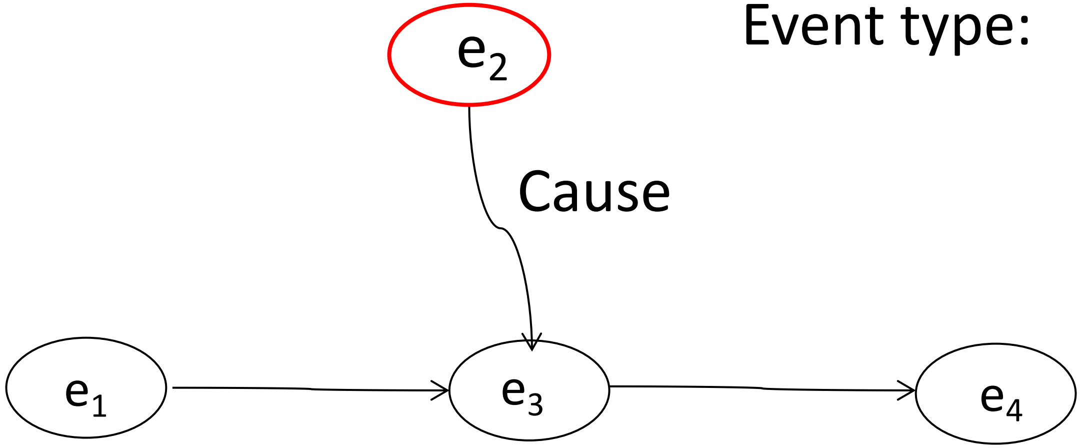
Derived Vendler Event Types

a. State | b. Process | c. Achievement | d. Accomplishment



GL-VN: “Change” event structure

Event type: Change of location
Change of State
Change of Possession



Initial_Location	Trajectory	Destination
Initial_State	Transition	Result
Source	Transfer	Recipient

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)

VerbNet class:
run-51.3.2-2-1

Theme

Destination

Trajectory

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

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

VerbNet class:
run-51.3.2-2-1

Theme

Destination

Trajectory

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

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

VerbNet class:
run-51.3.2-2-1

Theme Destination Trajectory

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

has_location(e1, Many fighters, ?Initial_Location)
¬**has_location**(e1, Theme, **to the south**)
motion(ë2, Many fighters, through Syrian…)
¬**has_location**(e3, Theme, ?Initial_Location)
has_location(e3, Many fighters, **to the south**)

implicit argument

VerbNet class:
Concealment-16

Agent

Destination

Some have hidden near Damascus.

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

Agent

VerbNet class:
Concealment-16

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)

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)

Sentence 1: Destination = Sentence2: Destination

Revision complete – Susan Brown, Julia Bonn

Stage 1 - Major theoretical revisions

Generic representations for all basic VerbNet frame types created.

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

Changes made automatically to 130 classes and manually checked.

Stage 2 - Semantics for verbs of creation, perception, experience, etc. completed. (additional 122 classes)

Status of completed revisions, 6746 verbs

Change of location	48 classes
Change of state	61 classes
Change of possession	16 classes
Transfer information	22 classes
States	39 classes
Business/organization	7 classes
Substance emission	5 classes
Total gold-standard classes.	198 classes, + 124 classes = 322 out of 329
	~4,500 verb senses
Automatically processed	130 classes ~2,200 verb senses

Verb-specific features

GHAZALEH KAZEMINEJAD

Kazeminejad, et. al., Frontiers in Artificial Intelligence: Language and Computation, in press

Adding verb-specific features

VerbNet classes can be quite heterogenous

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*)

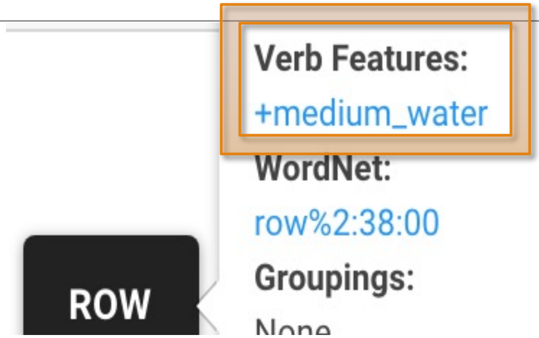
Decrease (e.g., *fall, drop, plunge*)

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

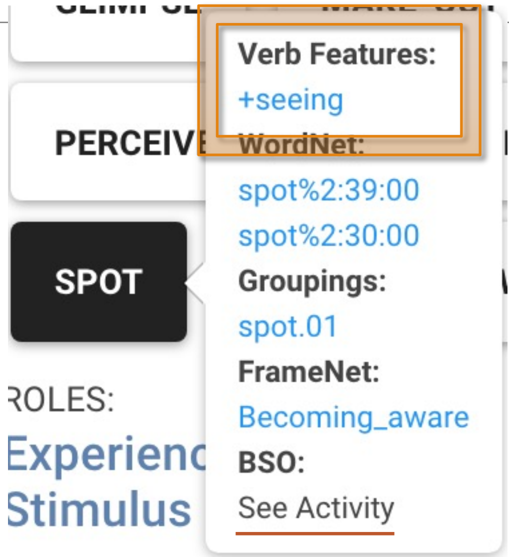
The price of oil soared to $50 a barrel.
has_val(e1, Patient, Initial_State)
change_value(e2, direction, ?Extent, Attribute, Patient)
has_val(e3, Patient, Result)

Verb Specific Features

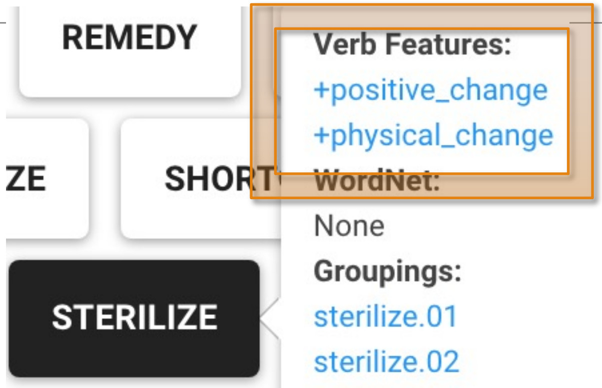
drive-11.5



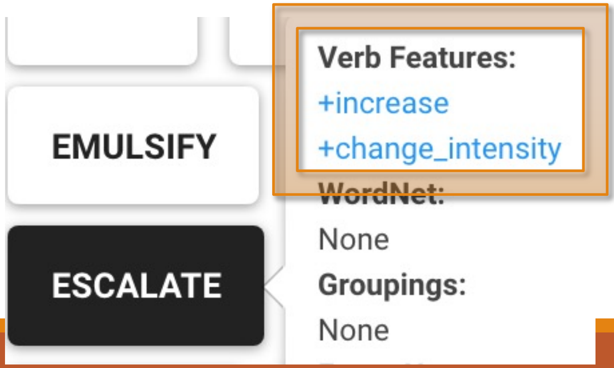
sight-30.2



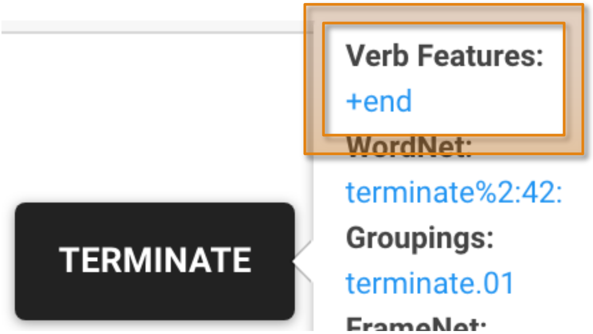
remedy-45.7



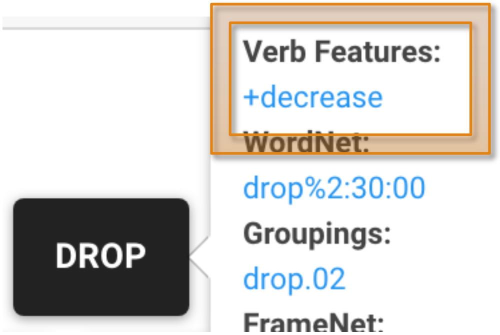
other_cos-45.4



terminus-47.9



calibratable_cos-45.6.1



Universal Verb Index

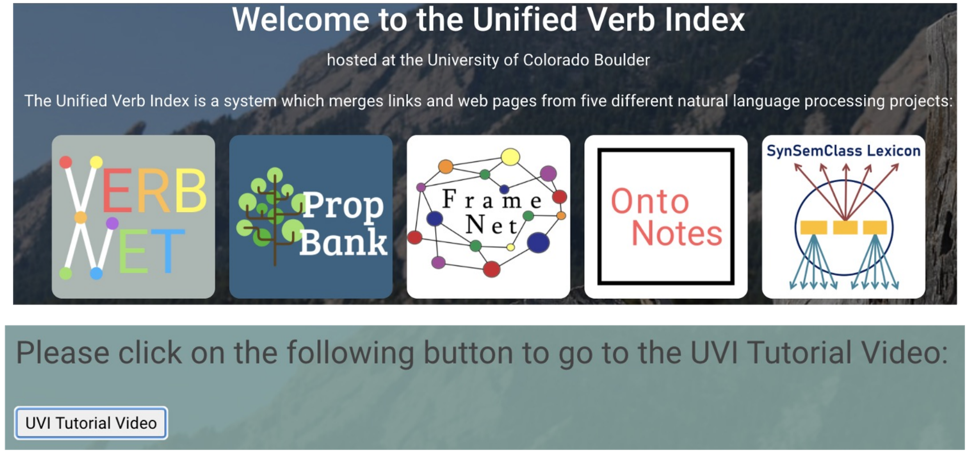
AKHILESH APPALA

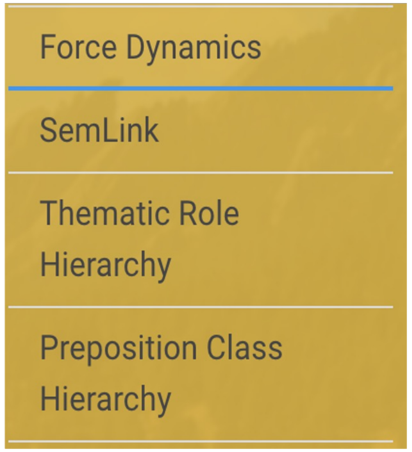
(ALSO LEO KIM, KEVIN STOWE, PRAJNYA SATISH, PIYUSH MISHRA & LAN SANG)

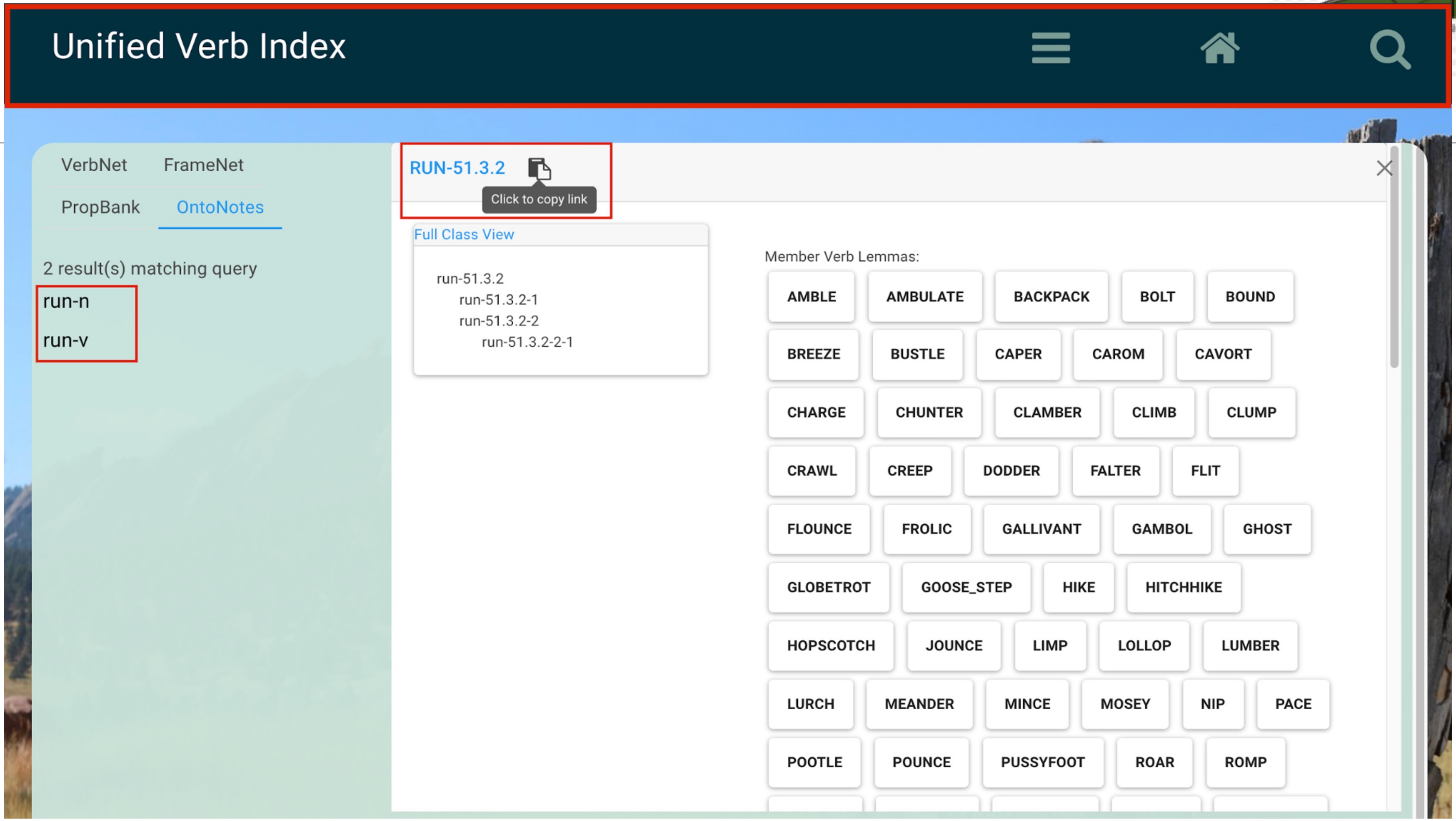
UVI – Universal Verb Index

Unified Verb Index – Web Interface to VerbNet, FrameNet, WordNet, Event Force Dynamics

A tutorial video on the NLP Applications page

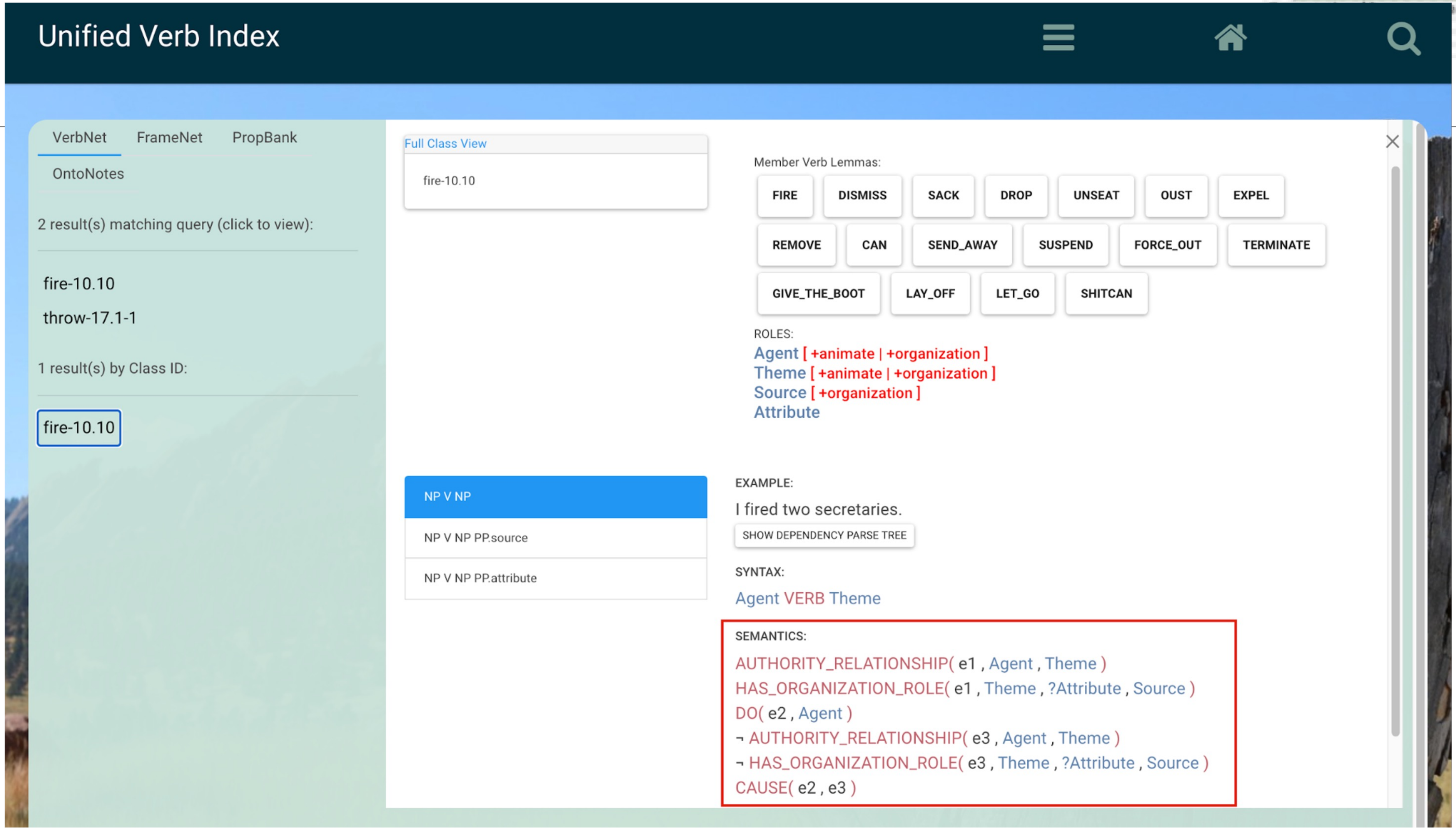






Unified Verb Index
VerbNet
FrameNet
PropBank
OntoNotes
2 result(s) matching query
run-n
run-v
RUN-51.3.2
Click to copy link
Full Class View
run-51.3.2
run-51.3.2-1
run-51.3.2-2
run-51.3.2-2-1
Member Verb Lemmas:
AMBLE
AMBULATE
BACKPACK
BOLT
BOUND
BREEZE
BUSTLE
CAPER
CAROM
CAVORT
CHARGE
CHUNTER
CLAMBER
CLIMB
CLUMP
CRAWL
CREEP
DODDER
FALTER
FLIT
FLOUNCE
FROLIC
GALLIVANT
GAMBOL
GHOST
GLOBETROT
GOOSE_STEP
HIKE
HITCHHIKE
HOPSCOTCH
JOUNCE
LIMP
LOLLOP
LUMBER
LURCH
MEANDER
MINCE
MOSEY
NIP
PACE
POOTLE
POUNCE
PUSSYFOOT
ROAR
ROMP

Fire-10.10



Unified Verb Index
VerbNet
FrameNet
PropBank
OntoNotes
2 result(s) matching query (click to view):
fire-10.10
throw-17.1-1
1 result(s) by Class ID:
fire-10.10
Full Class View
fire-10.10
NP V NP
NP V NP PP.source
NP V NP PP.attribute
Member Verb Lemmas:
FIRE
DISMISS
SACK
DROP
UNSEAT
OUST
EXPEL
REMOVE
CAN
SEND_AWAY
SUSPEND
FORCE_OUT
TERMINATE
GIVE_THE_BOOT
LAY_OFF
LET_GO
SHITCAN
ROLES:
Agent [+animate | +organization]
Theme [+animate | +organization]
Source [+organization]
Attribute
EXAMPLE:
I fired two secretaries.
SHOW DEPENDENCY PARSE TREE
SYNTAX:
Agent VERB Theme
SEMANTICS:
AUTHORITY_RELATIONSHIP(e1 , Agent , Theme)
HAS_ORGANIZATION_ROLE(e1 , Theme , ?Attribute , Source)
DO(e2 , Agent)
¬ AUTHORITY_RELATIONSHIP(e3 , Agent , Theme)
¬ HAS_ORGANIZATION_ROLE(e3 , Theme , ?Attribute , Source)
CAUSE(e2 , e3)

Verb Sense Disambiguation & Semantic Role Labeling

JAMES GUNG & MARTHA PALMER

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

VSD results - Multi-task Learning (SRL + VSD)

System	WSJ	Brown
ClearWSD	$97.0_{\pm 0}$	$89.3_{\pm 0}$
Baseline	$97.3_{\pm 0.1}$	$90.7_{\pm 0}$
SRL + VSD	$\mathbf{97.7}^{\star\star}{}_{\pm 0.1}$	$91.3_{\pm 0.4}$
SRL | VSD	$97.6^{\star\star}{}_{\pm 0.1}$	$91.3_{\pm 0}$

Table 4: VerbNet classification (sense disambiguation) accuracy on SemLink.

Gung & Palmer, IWCS 2021

VerbNet Parser

Identifies correct VerbNet class for a verb in a textual context

Identifies main participants in a sentence

Labels them w/ appropriate thematic roles

Inserts participants into semantic representation

Demo at http://verbnet-semantic-parser.appspot.com/

SRL Results
Same system (Bert-based)

System	PropBank WSJ	Brown	VerbNet WSJ	Brown
Zapirain et al. (2008)	$78.9_{\pm 0.9}$	–	$77.0_{\pm 0.9}$	$62.9_{\pm 1.0}$
Baseline	$88.5_{\pm 0.1}$	$82.4_{\pm 0.5}$	$87.4_{\pm 0.2}$	$80.1_{\pm 0.4}$
SRL + VSD	$88.2_{\pm 0.2}$	$82.8^{\star}_{\pm 0.6}$	$87.3_{\pm 0.1}$	$80.0_{\pm 0.7}$
SRL | VSD	$88.3_{\pm 0.2}$	$82.2_{\pm 0.4}$	$87.4_{\pm 0.2}$	$80.6^{\star\star}_{\pm 0.4}$
PREDICTED CLASS	$88.3_{\pm 0.1}$	$81.2_{\pm 0.6}$	$87.6^{\star\star}_{\pm 0.1}$	$80.9^{\star\star}_{\pm 0.6}$
ALL CLASSES	$\mathbf{88.6}^{\star}_{\pm 0.3}$	$82.3_{\pm 0.5}$	$\mathbf{87.6}^{\star\star}_{\pm 0.2}$	$\mathbf{81.1}^{\star\star}_{\pm 0.6}$
GOLD CLASS	$\mathbf{88.7}^{\star\star}_{\pm 0.0}$	$\mathbf{82.8}^{\star}_{\pm 0.2}$	$\mathbf{88.2}^{\star\star}_{\pm 0.2}$	$\mathbf{83.0}^{\star\star}_{\pm 0.9}$

VerbNet Semantic Role Labeling

Find the participants & identify roles they play; essential building block for deeper representations of meaning

VerbNet class:

run-51.3.2-2-1

Theme | Destination | Trajectory

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

has_location(e1, Theme, ?Initial_Location)

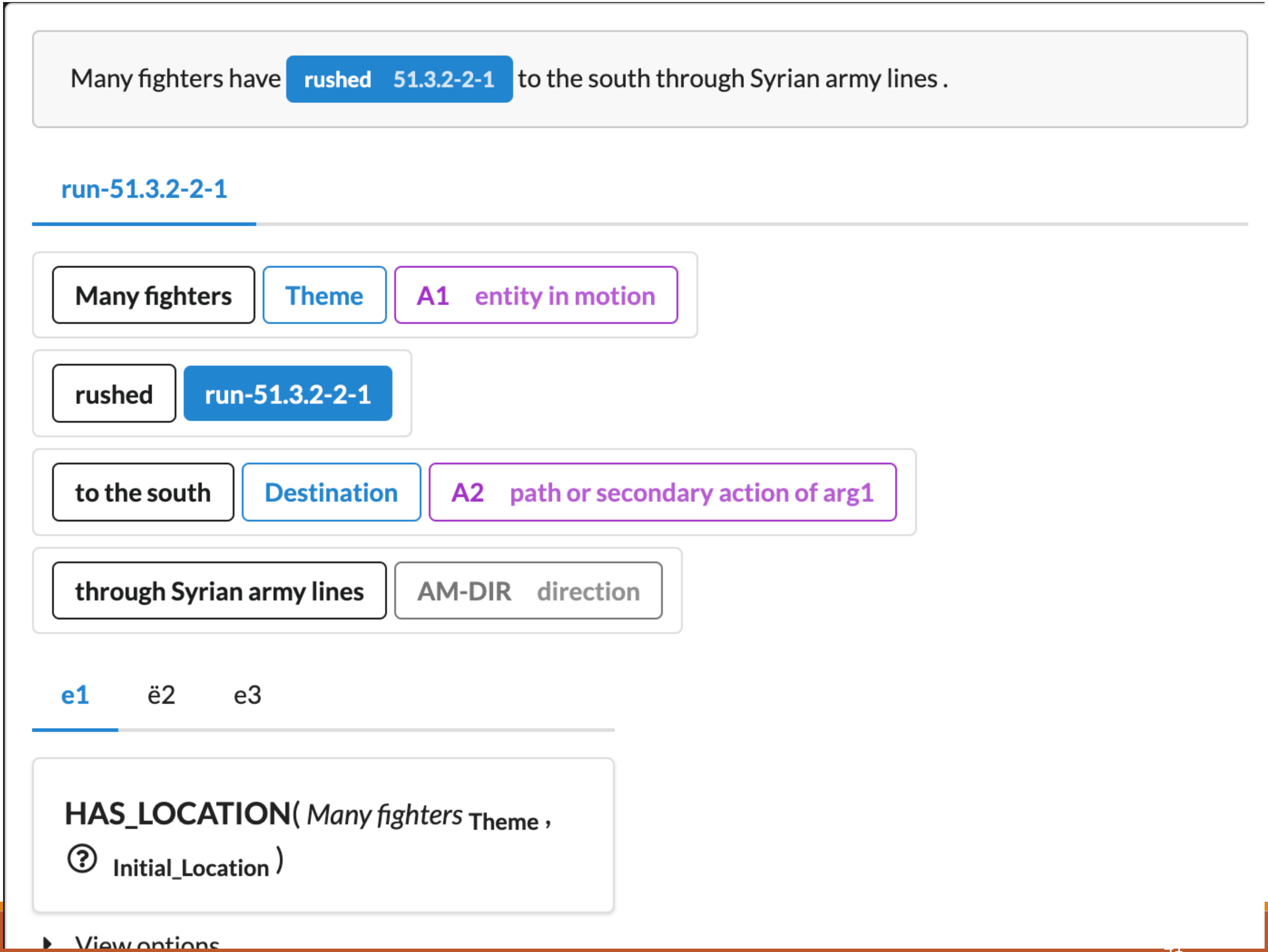
¬ **has_location**(e3, Theme, ?Destination)

motion(ë2, Theme, Trajectory)

¬**has_location**(e3, Theme, ?Initial_Location)

has_location(e3, Theme, ?Destination)

VerbNet Parser Output



e1 ë2 e3

MOTION(*Many fighters* **Theme** , ? **Trajectory**)

¬HAS_LOCATION(*Many fighters* **Theme** , ? **Initial_Location**)

e1 ë2 e3

HAS_LOCATION(*Many fighters* **Theme** , *to the south* **Destination**)

VerbNet Parser Output