Semantic parsers

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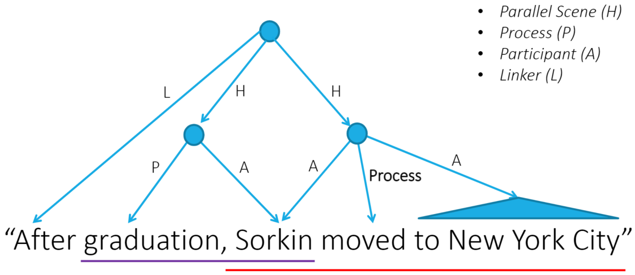
UCCA Abend and Rappoport (2013)

Universal Conceptual Cognitive Annotation (UCCA)

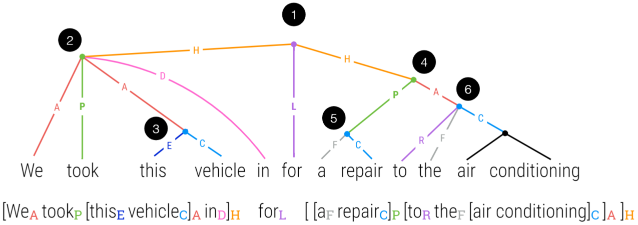
UCCA aims to to meet two goals

- Portability
  - The same set of categories can be applied accross different languages
- Stability
  - similar semantic structure is given to literal translations

UCCA scenes


L
H
H
P
A
A
Process
A
"After graduation, Sorkin moved to New York City"
Parallel Scene (H)
Process (P)
Participant (A)
Linker (L)

UCCA Foundational Layer



- Based on tokenized text
- Subset of tokens form units
- Units nest within larger units via edges labeled with categories
- At the top level, passage is segmented into units with Parallel Scenes (H) and (L)inkers

UCCA FL categories

Unit type:	**Superparallel unit**	**Scene unit**	**Sub-scene unit**	**Lexical unit**
Required elements	Parallel Scene (H)	Process xor State	Center	Token(s)
Optional elements	Linker	Participant (A), Adverbial (D), Time, Ground	{Elaborator, Quantity} xor Connector (N)	
	Function, Relator			
Legal parentage	root, A, E, C	A, E, C, H	any but F, R, root	any category

Secondary categories:
UNAnalyzable may be combined with any category in the table on a lexical unit;
Coordinated Main Relation (CMR) may occur with P or S

UCCA parsing

Three recent shared tasks

- SemEval 2019 shared task on UCCA parsing in English, French, German
- CoNLL 2019 and 2020 shared tasks on Cross-framework and Cross-Lingual Meaning Representation Parsing

Number of parsers available

- TUPA: Transition-based, multi-framework parser that serves as a baseline
- HLT@SUDA: won the SemEval task

UCCA applications

- Evaluation of text2text systems:
  - Semantic measure for Grammatical Error Correction
  - Semantic measure for (structural) text simplification
  - Human evaluation guided by semantic structure for MT
- Text simplification:
  - Text simplification using UCCA-based rules for preprocessing improves results
  - UCCA-guided simplification can also support MT in some settings
- UCCA-based machine translation and relation extraction

UCCA

- Abstracts away from much syntactic variation
- Demonstrated applicability to a number of languages
- Corpora and parsers available for a number of languages
- Already showing utility in evaluation of text2text systems and applications such as sentence simplification

UCCA extensions

- UCCA is a multi-layered structure
- The basic layer (the foundational layer) has a relatively flat structure
- Additional layers can capture semantic phenomena

Semantic roles

[Antoinette$_A$ drew$_P$ [a sheep]$_A$ [for the princess]$_A$ [in the desert]$_A$]

- FL does not distinguish Participants' roles
  - E.g., AGENT, THEME, CIRCUMSTANCE, PURPOSE, ...
- Expressed by various linguistic markers:
  - Word order [Mary$_A$ saw John$_A$] vs [John$_A$ saw Mary$_A$]
  - Case [**Er** sah [**den** Fuchs]] vs [**Ihn** sah [**der** Fuchs]]
  - Prepositions [The conquest [**of** Britain] [**by** the Romans]]

Semantic roles

- Several existing frameworks for role annotation: FrameNet, VerbNet, PropBank
- They chose SNACS for its independence of any one language or lexicon: https://arxiv.org/abs/1704.02134, https://aclanthology.org/P18-1018.pdf
  - 50 hierarchical categories
  - Designed to disambiguate prepositions and case

UCCA resources

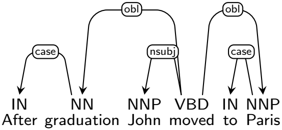
corpus	train/trial sentences	train/trial tokens	dev sentences	dev tokens	test sentences	test tokens	total passages	total sentences	total tokens
English-Wiki	4,113	124,935	514	17,784	515	15,854	367	5,142	158,573
English-20K	0	0	0	0	492	12,574	154	492	12,574
French-20K	15	618	238	6,374	239	5,962	154	492	12,954
German-20K	5,211	119,872	651	12,334	652	12,325	367	6,514	144,531

Table 2: Data splits of the corpora used for the shared task.

- Good coverage on multiple languages
- Shared tasks (SemEval, CoNLL)
- Multi layered, already connects to ontology
- Available parsers (e.g. tupa), not that resource hungry
- Tutorials at big conferences such as COLING
- But didn't really seen anything from them since 2020 (no commit, fresh models, etc..)
- Domain dependence wasn't really measured

Dependency parsing

Universal Dependency parsing



Universal dependency graph (UD)

- Syntactic UD parsing has seen great advances recently
- The UD project: https://universaldependencies.org/
- open community effort with over 300 contributors producing nearly 200 treebanks in over 100 languages
- Same format for all languages
- Active community, great models and industry ready parsers (stanza, spacy)
- Good for basically all domains (never had issues in legal, techical, medical domain for us)

Semantic Dependency Parsing

- Semantic analysis cannot be limited to tree structures
- E.g. node will often be the argument of multiple predicates
- Task 18 at SemEval 2015, Broad-Coverage Semantic Dependency Parsing (SDP 2015)
- Direct analysis of Who did What to Whom?
- SDP target representations aim to be task- and domain-independent.
- node re-entrancies, partial connectivity, higher degree of non-projectivity

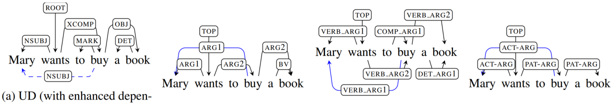
Data and languages

- Resources for English, Czech and Chinese
- Wall Street Journal (WSJ) and Brown segments of the Penn Treebank (PTB; Marcus et al., 1993) for English
- Around 30 000 sentences for English, Czech and Chinese

Representations

- DM: DELPH-IN MRS-Derived Bi-Lexical Dependencies
- PAS: Enju Predicate Argument Structures
- PSD: Prague Semantic Dependencies

Representations



(a) UD (with enhanced dependencies dashed) (b) DM (c) PAS (d) PSD

Figure 1: Comparison between syntactic and semantic dependency schemes

- PSD appearing linguistically most fine-grained
- PAS showing the smallest label inventory
- DM recognizes mwe-s better

Parsers

- Good easy to use parsers: https://github.com/yzhangcs/parser
- Good papers about the parsing: https://aclanthology.org/P18-2077.pdf
- Not many papers since 2018

AMR

AMR Banarescu et al. (2013)

- Abstract Meaning Representation (AMR) Annotation Release 3.0 (2020): https://catalog.ldc.upenn.edu/LDC2020T02
- AMR utilizes PropBank frames, non-core semantic roles, within-sentence coreference, named entity annotation, modality, negation, questions, quantities, and temporal expressions.
- Especially good for disambiguation:
  - run.01 , operate, proceed, operate
  - run.02 , walk quickly, a course or contest, run/jog

AMR

```
# ::id sdl_0002.1 ::date 2013-07-02T03:00:13 ::annotator SDL-AMR-09 ::preferred
# ::snt Rockstrom said that when rich countries increase their consumption , they also accelerate the expl
# with the result that they emit more greenhouse gases .
# ::save-date Thu Jul 11, 2013 ::file sdl_0002_1.txt
(s / say-01
        :ARG0 (p / person :wiki "Johan_Rockstrom"
            :name (n / name :op1 "Rockstrom"))
        :ARG1 (a / accelerate-01
            :ARG0 (c / country
                    :mod (r / rich))
            :ARG1 (e / exploit-01
                    :ARG0 c
                    :ARG1 (r2 / resource
                        :mod (n2 / nation)
                        :poss (w / world)))
            :mod (a2 / also)
            :time (i / increase-01
                    :ARG0 c
                    :ARG1 (c2 / consume-01
                        :ARG0 c))
            :ARG0-of (c3 / cause-01
                    :ARG1 (e2 / emit-01
                        :ARG0 c
                        :ARG1 (g / gas
                                :mod (g2 / greenhouse)
                                :mod (m / more))))))
```

AMR data

Dataset	Training	Dev	Test	Totals
BOLT DF MT	1061	133	133	1327
Broadcast conversation	214	0	0	214
Weblog and WSJ	0	100	100	200
BOLT DF English	7379	210	229	7818
DEFT DF English	32915	0	0	32915
Aesop fables	49	0	0	49
Guidelines AMRs	970	0	0	970
LORELEI	4441	354	527	5322
2009 Open MT	204	0	0	204
Proxy reports	6603	826	823	8252
Weblog	866	0	0	866
Wikipedia	192	0	0	192
Xinhua MT	741	99	86	926
Totals	55635	1722	1898	59255

AMR models

- Parse (StoG) model_parse_xfm_bart_large gives an 83.7 SMATCH score with LDC2020T02.
- Generation (GtoS) generate_t5wtense gives a 54 BLEU with tense tags or 44 BLEU with untagged LDC2020T02.
- Parsing 100 sentences on CPU (i5-8400) took 20 minutes (20 seconds to parse ud)

Graphbrain

Graphbrain

Semantic Hypergraph (SH) model

- Well-known semantic parsers (UCCA, AMR) usually take advantage of Deep Learning models
- Graphbrain combines symbolic and ML approaches
- The work was performed in the context of a computational social science (CSS) research team
- It is a formal language representation
- They define a parser with
  - modern NLP ML based building blocks
  - and random forest classifier
  - simple search tree to parse NL to SH

From natural language to SH

- It is a hard task to annotate enough data to train a NL-SH parser
- Better infer SH from grammatically-enriched representation - UD
- Two staged approach
  - **alpha-stage**: a classifier that assigns a type to each token in a given sentence.
  - **beta-stage**: is a search tree-based algorithm that recursively applies rules to build SH from sequence of atoms
- ML only in alpha-stage, a trivial classification problem

alpha-stage

With the usage of spaCy:

- Segmentation
- Tokenization
- POS tags
- Dependency labels
- NER
- Generate features for each token
- spaCy model: ”*en_core_web_lg*”

Data

- fiction books
- non-fiction books
- news
- scientific articles
- Wikipedia articles
- Selected randomly 60 sentences from each (300 sentences)
- 6936 tokens in full for classification
- They were annotated manually for classification
- Trained a random-forest classifier

Features

- Initial feature set from dependency features - 33 features total
- Feature selection algorithm - Iterative ablation procedure
- The final feature set contained 5 feature: F5 = TAG, DEP, HDEP, HPOS, POS_AFTER
- Accuracy around 95%

beta-stage

- This stage transforms the sequence of atoms into a semantic hyperedge
- It follows the alpha-stage
- A bottom up process:
  - Aggregates the deeper structure into a more complex one
  - Recursively combines hyperedges into a final, well-formed hyperedge

Final SH

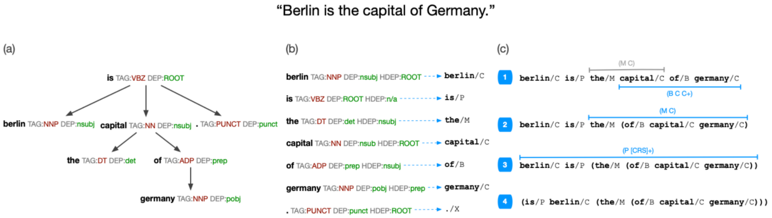


Figure 2: **(a)** Dependency parse tree with dependency labels (green) and fine grained part-of-speech tags (red). **(b)** α-stage classification of atom types. **(c)** β-stage structuring of sentence by iterative application of the patterns from table 2. A non-selected pattern is greyed-out.

SH concepts

Code	Type	Purpose	Example	Atom	Non-atom
C	concept	Define atomic concepts	apple/C	×	×
P	predicate	Build relations	(is/P berlin/C nice/C)	×	×
M	modifier	Modify a concept, predicate, modifier, trigger	(red/M shoes/C)	×	×
B	builder	Build concepts from concepts	(of/B capital/C germany/C)	×	
T	trigger	Build specifications	(in/T 1994/C)	×	
J	conjunction	Define sequences of concepts or relations	(and/J meat/C potatoes/C)	×	
R	relation	Express facts, statements, questions, orders,...	(is/P berlin/C nice/C)		×
S	specifier	Relation specification (e.g. condition, time,...)	(in/T 1976/C)		×

Table 1: Hyperedge types with use purposes and examples. Connector types are emphasized with a gray background. The rightmost columns specify whether this type may be encountered in atomic or non-atomic hyperedges.

Final SH results

Category	**Correct**	**Defect**	**Wrong**	**Total**	**Mean relative defect size**
Non-fiction	87 (.87)	8 (.08)	5 (.05)	100	.188
Wikipedia	81 (.81)	12 (.12)	7 (.07)	100	.190
News	77 (.77)	16 (.16)	7 (.07)	100	.147
Fiction	79 (.79)	5 (.05)	16 (.16)	100	.140
Science	71 (.71)	19 (.19)	10 (.10)	100	.290
All	**395 (.79)**	**60 (.12)**	**45 (.09)**	**500**	**.206**

Table 4: Global NL to SH parser evaluation.

Summary

- Lots of explainability in SH
- Only in English, but mapping to another language is not resource hungry (only annotated 300 sentences for English)
- The pattern language is very convenient and easy to use for IE tasks!!
- Very easy to manipulate the graphs with their own tools
- Recently held a seminar about the topic at the university: https://nlp.ec.tuwien.ac.at/seminar/

4lang

Background - 4lang

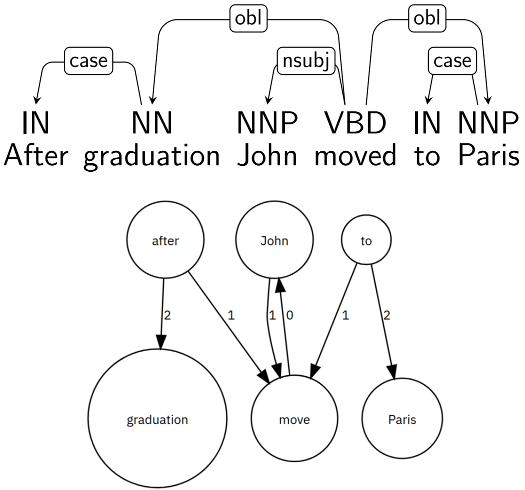


Figure 1: 4lang graph and UD parse of sentence "After graduation John moved to Paris"

4lang

Dependency	Edge
advcl advmod amod nmod nummod obl:npmod	$w_1 \xrightarrow{0} w_2$
nsubj csubj	$w_1 \underset{0}{\overset{1}{\rightleftharpoons}} w_2$
obj ccomp xcomp	$w_1 \xrightarrow{2} w_2$
appos	$w_1 \underset{0}{\overset{0}{\rightleftharpoons}} w_2$
nmod:poss	$w_2 \xleftarrow{1} \texttt{HAS} \xrightarrow{2} w_1$
nmod:npmod	$w_1 \xleftarrow{1} \texttt{NPMOD} \xrightarrow{2} w_2$
nmod:tmod obl:tmod	$w_1 \xleftarrow{1} \texttt{AT} \xrightarrow{2} w_2$
$w_1 \xrightarrow{\text{obl}} w_2 \xrightarrow{\text{case}} w_3$	$w_1 \xleftarrow{1} w_3 \xrightarrow{2} w_2$
$w_1 \xrightarrow{\text{acl:relcl}} w_2 \xrightarrow{\text{nsubj}} w_3$	$w_1 \xrightarrow{0} w_2$

Table 1: Mapping from UD relations to 4lang subgraphs.

4lang results

- 4lang is a set of rules from UD to semantic representation
- Used in multiple projects
- BRISE (Building Regulations Information for Submission Envolvement)[1] [2] is a smart city project of the City of Vienna
- Paper about the construction of semantic graphs for the task and rule-based classification in Recski et al. (2021)
- Lexical inference: Kovács et al. (2022)
- Offensive text detection Gémes and Recski (2021); Gémes et al. (2021)

[1] https://www.uia-initiative.eu/en/uia-cities/vienna-call4
[2] https://digitales.wien.gv.at/site/projekt/brisevienna/

A plus: Graphical Knowledge Representation (GKR)

- http://gkrparser.nlitoolkit.de/
- https://github.com/kkalouli/GKR_semantic_parser

Abend, O. and Rappoport, A. (2013). Universal Conceptual Cognitive Annotation (UCCA). In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 228–238, Sofia, Bulgaria. Association for Computational Linguistics.

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Gémes, K., Kovács, A., Reichel, M., and Recski, G. (2021). Offensive text detection on English Twitter with deep learning models and rule-based systems. to appear in FIRE 2021: Forum for Information Retrieval Evaluation.

Gémes, K. and Recski, G. (2021). TUW-Inf at GermEval2021: Rule-based and hybrid methods for detecting toxic, engaging, and fact-claiming comments. In *Proceedings of the GermEval 2021 Workshop on the Identification of Toxic, Engaging, and Fact-Claiming Comments*, pages 69–75, Heinrich Heine University Düsseldorf, Germany.

Kovács, Á., Gémes, K., Kornai, A., and Recski, G. (2022). Explainable lexical entailment with semantic graphs. *Natural Language Engineering*, page 1–24.

Recski, G., Lellmann, B., Kovács, A., and Hanbury, A. (2021). Explainable rule extraction via semantic graphs. In *Proceedings of the Fifth Workshop on Automated Semantic Analysis of Information in Legal Text (ASAIL 2021)*, pages 24–35, São Paulo, Brazil. CEUR Workshop Proceedings.