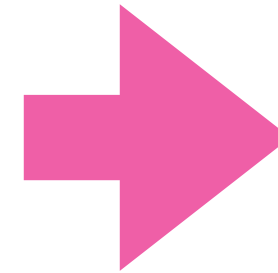
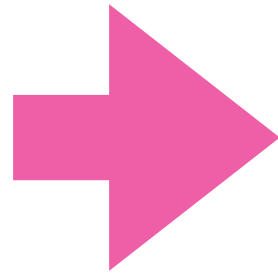
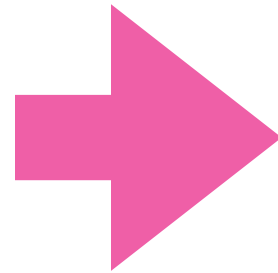
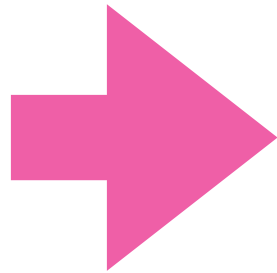


Semantic pipeline

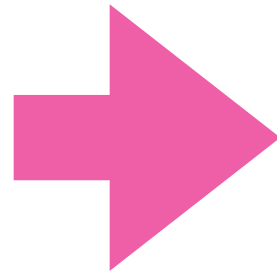
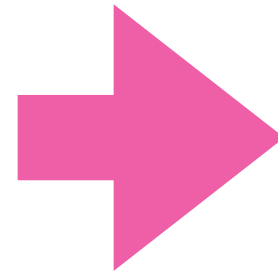
Adam Kovacs

High-level pipeline

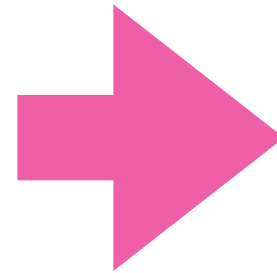
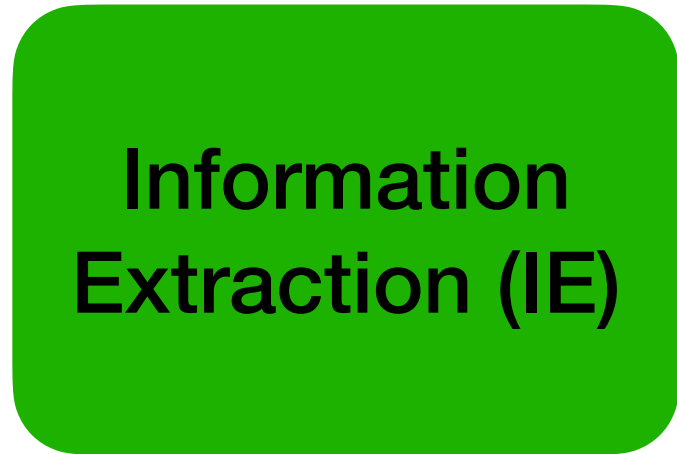
Raw text



Semantic
level



Extraction
level



Structured data

Preprocessing steps

Functions:

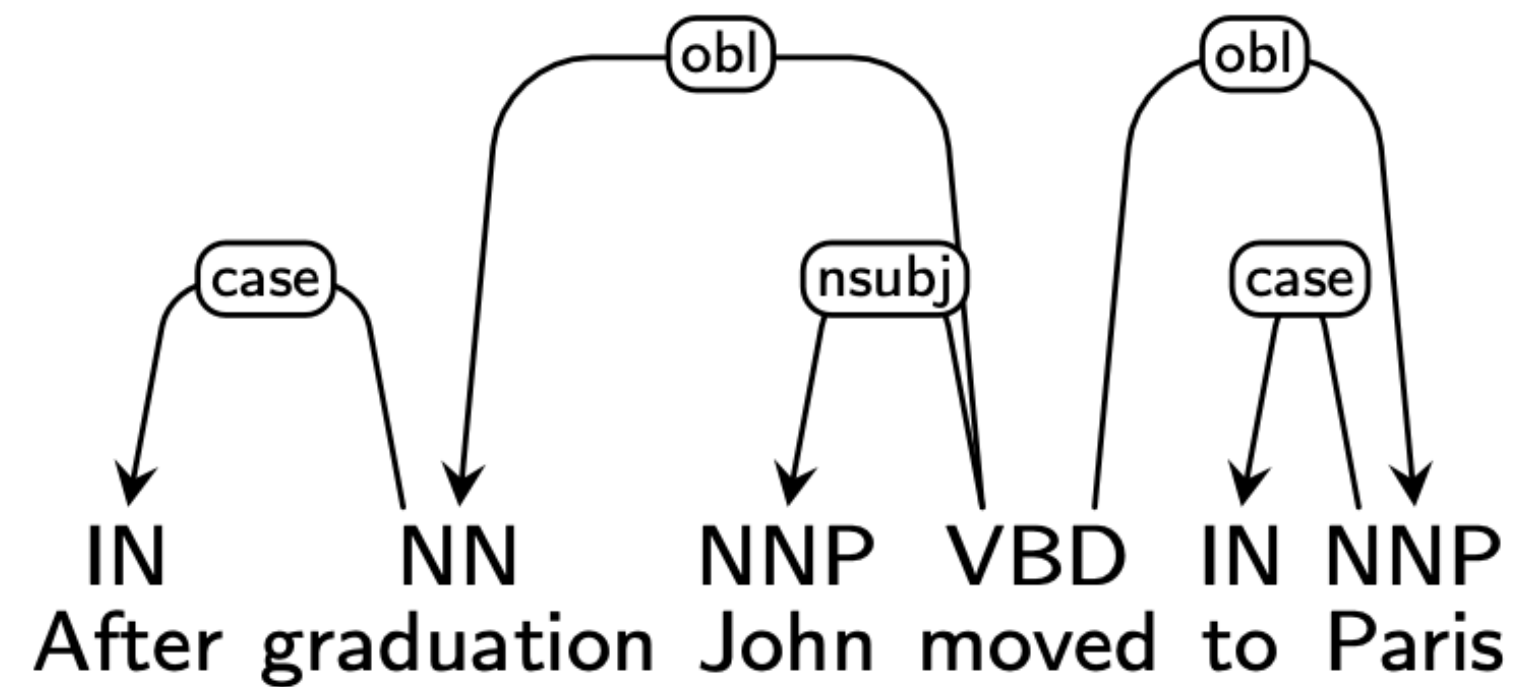
- Using the **spaCy** [1] module
 - Very fast
 - Production ready
 - Open-source
 - Tailored pipelines [2]
- **Pipeline** approach
 - Sentence segmentation
 - Tokenization
 - Lemmatization
 - NP chunking
 - Punctuation, stopwords

Coreference Resolution

- **Coreferree** [1] is a spaCy pipeline, supports SOTA models in coreference tasks
- Open-source
- Both between sentences and within sentence:

Although **he** was very busy with **his** work, **Peter** had had enough of it. **He** **and his wife** decided they needed a holiday. **They** travelled to **Spain** because **they** loved the **country** very much.

Universal Dependency Parsing (UD)



Universal dependency graph (UD)

- Open-community effort
- Treebanks for 100+ languages
- Same format for all of the languages
- **spaCy** parser
- Coverage for various domains (legal, medical, technical, etc..)
- Well-established

Entity Recognition (NER)

- Available pipelines for more than 20+ languages
- Available named entities in the models:
 - CARDINAL, DATE, EVENT, FAC, GPE, LANGUAGE, LAW, LOC, MONEY, NORP, ORDINAL, ORG, PERCENT, PERSON, PRODUCT, QUANTITY, TIME, WORK_OF_ART
- Can train spaCy model directly if there is available gold, annotated data
- Or use a few-shot learning approach: Concise-concept
- Use NLTK nombank for nominalization: [1]

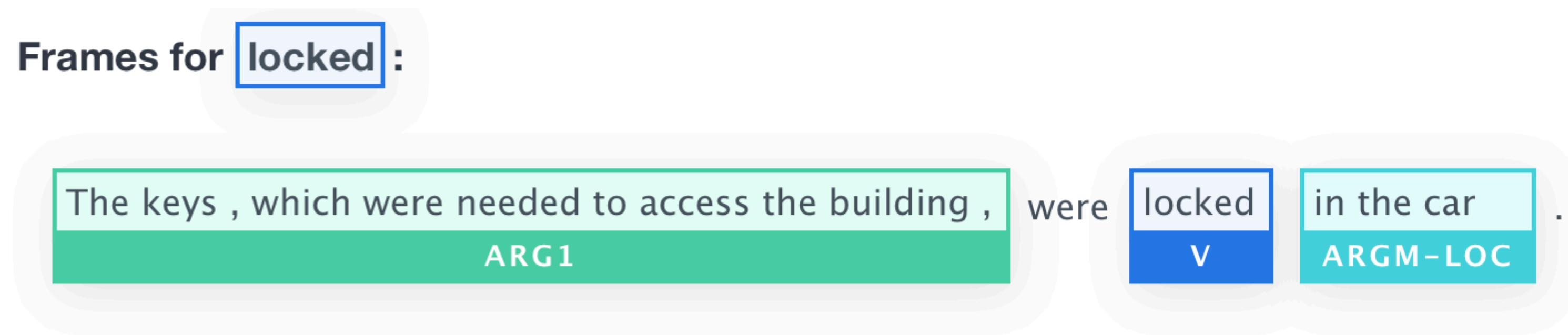
Entity linking

- spaCy entity linking to **Wikipedia, Wikidata**: [\[1\]](#), [\[2\]](#); **Dbpedia spotlight**: [\[3\]](#)
- Or external package [\[3\]](#)
- Interesting paper in the topic: *“Named Entity Recognition for Entity Linking: What Works and What’s Next”*
- Example: “Google LLC is an American multinational technology company.”
- Output: `[('Google LLC', 'http://dbpedia.org/resource/Google', '0.9999999999999999005'), ('American', 'http://dbpedia.org/resource/United_States', '0.9861264878996763')]`

Entity linking

- **VerbAtlas** SRL parser (later) links to frames in PropBank
 - “The quick brown fox jumps over the lazy dog.” - Frame: jump.03
 - “Roleset id: **jump.03** , physically or metaphorically leap, physical motion, “
- VerbNet semantic parser: <https://github.com/jgung/verbnet-parser>
 - Links to 329 verb classes

Semantic Role Labeling (SRL)



lock.01: attach, fastening, secured with a lock,

- **VerbAtlas** [1] : is a hand-crafted lexical-semantic resource whose goal is to bring together all verbal synsets from **BabelNet** into semantically-coherent frames.
- Both API and offline models (pretrained) are available, paper: [2]
- The semantic roles are fixed

Semantic roles in VerbAtlas

AGENT	ASSET	ATTRIBUTE	BENEFICIARY
CAUSE	CO_AGENT	CO_PATIENT	CO_THEME
DESTINATION	EXPERIENCER	EXTENT	GOAL
IDIOM	INSTRUMENT	LOCATION	MATERIAL
PATIENT	PRODUCT	PURPOSE	RECIPIENT
RESULT	SOURCE	STIMULUS	THEME
TIME	TOPIC	VALUE	

VerbNet: Cluster verbs

- Parser to disambiguate verbs into VerbNet categories: <https://github.com/jgung/verbnet-parser>

The screenshot displays the 'VerbNet Parser' web application. At the top, the title 'VerbNet Parser' is shown in white on a dark background. Below the title is a text input field containing the sentence 'My dog jumped over the fence.' and a blue button labeled 'Try it out!'. The results section shows the sentence with the verb 'jumped' highlighted in a blue box and labeled '51.3.2-2-1'. Below this, the category 'run-51.3.2-2-1' is listed. The parse tree is visualized with three levels of boxes: the top level contains 'My dog', 'Agent', and 'A0'; the middle level contains 'jumped' and 'run-51.3.2-2-1'; and the bottom level contains 'over the fence', 'Trajectory', and 'AM-DIR direction'.

VerbNet Parser

My dog jumped over the fence. Try it out!

My dog jumped 51.3.2-2-1 over the fence .

run-51.3.2-2-1

My dog Agent A0

jumped run-51.3.2-2-1

over the fence Trajectory AM-DIR direction

Go To COMMENTS

run-51.3.2

Members: 97, Frames: 5

Post COMMENT

CLASS HIERARCHY
RUN-51.3.2*
RUN-51.3.2-1
RUN-51.3.2-2
RUN-51.3.2-2-1

MEMBERS

AMBLE (FN 1; WN 1; G 1)	GOOSE_STEP (WN 1)	SCUD (WN 1)	STUMP (WN 2; G 2)
AMBULATE (WN 1; G 1)	HIKE (FN 1; WN 2; G 1)	SCURRY (FN 1; WN 1)	SWAG (WN 2; G 2)
BACKPACK (WN 1)	HITCHHIKE (WN 1)	SCUTTER	SWAGGER (FN 1; WN 1)
BOLT (FN 1, 2, 3, 4; WN 4; G 1)	HOPSCOTCH	SCUTTLE (FN 1; WN 1; G 2)	SWAN
BOUND (FN 1; WN 1; G 1)	JOUNCE	SEESAW	SWERVE
BREEZE	LIMP (FN 1; WN 1, 2)	SHAMBLE (WN 1)	TEAR (WN 3; G 2)
BUSTLE (WN 1)	LOLLOP (WN 1)	SHUFFLE (FN 1, 2; WN 1; G 1)	TIPTOE (FN 1; WN 1)
CAPER (WN 1)	LUMBER (FN 1; WN 1)	SIDLE (FN 1; WN 1, 2)	TODDLE (FN 1; WN 1)
CAROM (WN 1, 2)	LURCH (FN 1; WN 1, 2, 3; G 1, 2)	SKEDADDLE (WN 1)	TOIL
CAVORT (WN 1)	MEANDER (FN 1; WN 1)	SKID	TOOTLE
CHARGE (FN 1; WN 1, 4; G 5)	MINCE (FN 1; WN 2; G 2)	SKULK (FN 1; WN 3)	TOTTER (FN 1; WN 1, 2, 3)
CHUNTER	MOSEY (FN 1; WN 1)	SLEEPWALK (FN 1; WN 1)	TREAD (WN 2; G 1)
CLAMBER (FN 1; WN 1; G 1)	NIP	SLINK (FN 1; WN 1)	TROOP (FN 1; WN 2)
CLIMB (FN 1, 2, 3; WN 1, 2; G 1, 3)	PACE (WN 1, 2)	SLITHER (FN 1; WN 1)	TRUNDLE (FN 1; WN 1)
CLUMP (FN 1; WN 3; G 3)	POOTLE	SLOG (FN 1; WN 2)	WADDLE (FN 1; WN 1)
CRAWL (FN 1; WN 1; G 1)	POUNCE (WN 1)	SLOUCH (WN 2)	WEAVE (FN 1, 2)
CREEP (FN 1; WN 1, 2; G 1)	PUSSYFOOT	SOMERSAULT (WN 1)	WEND
DODDER (WN 1)	REPAIR (WN 3; G 2)	SPRING (WN 1; G 2)	WHIZ

Semantic parsers

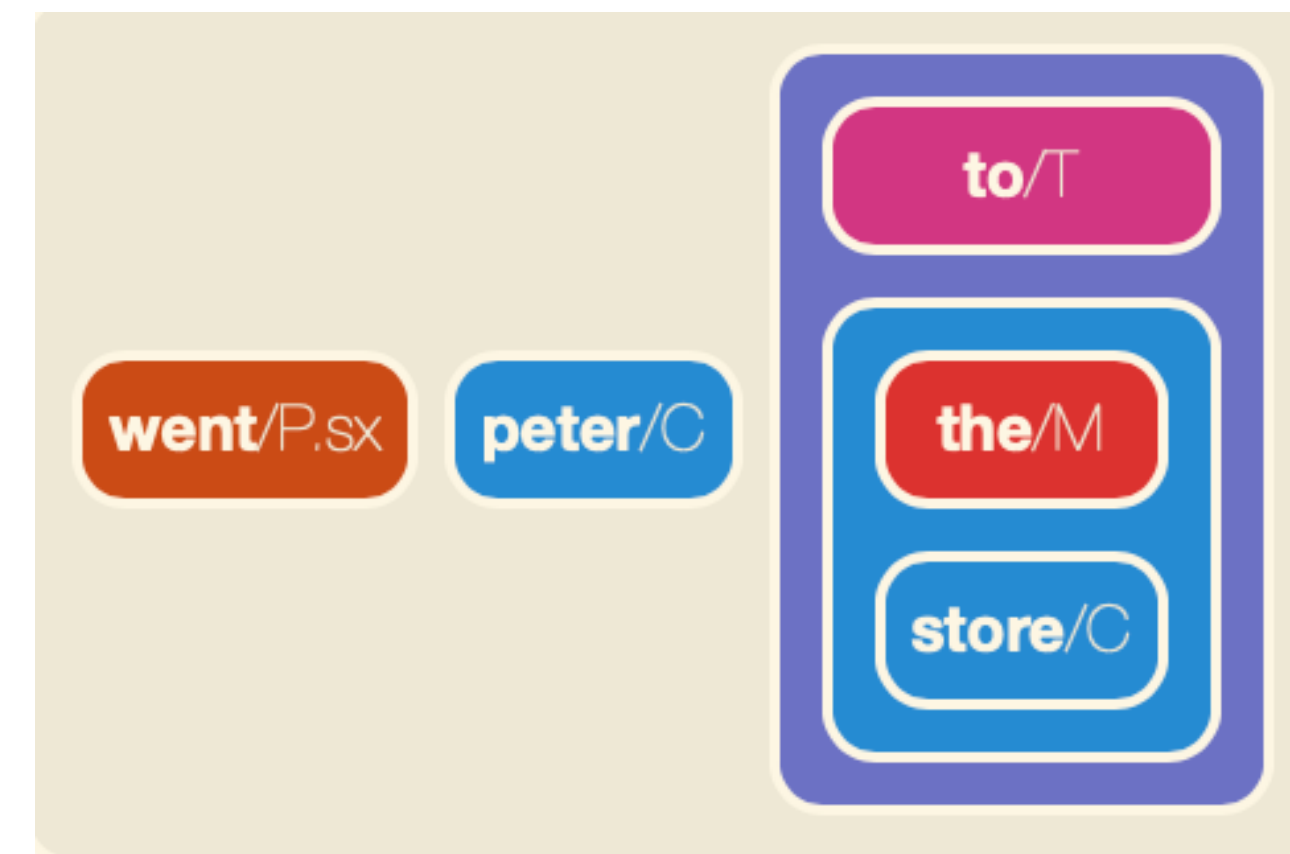
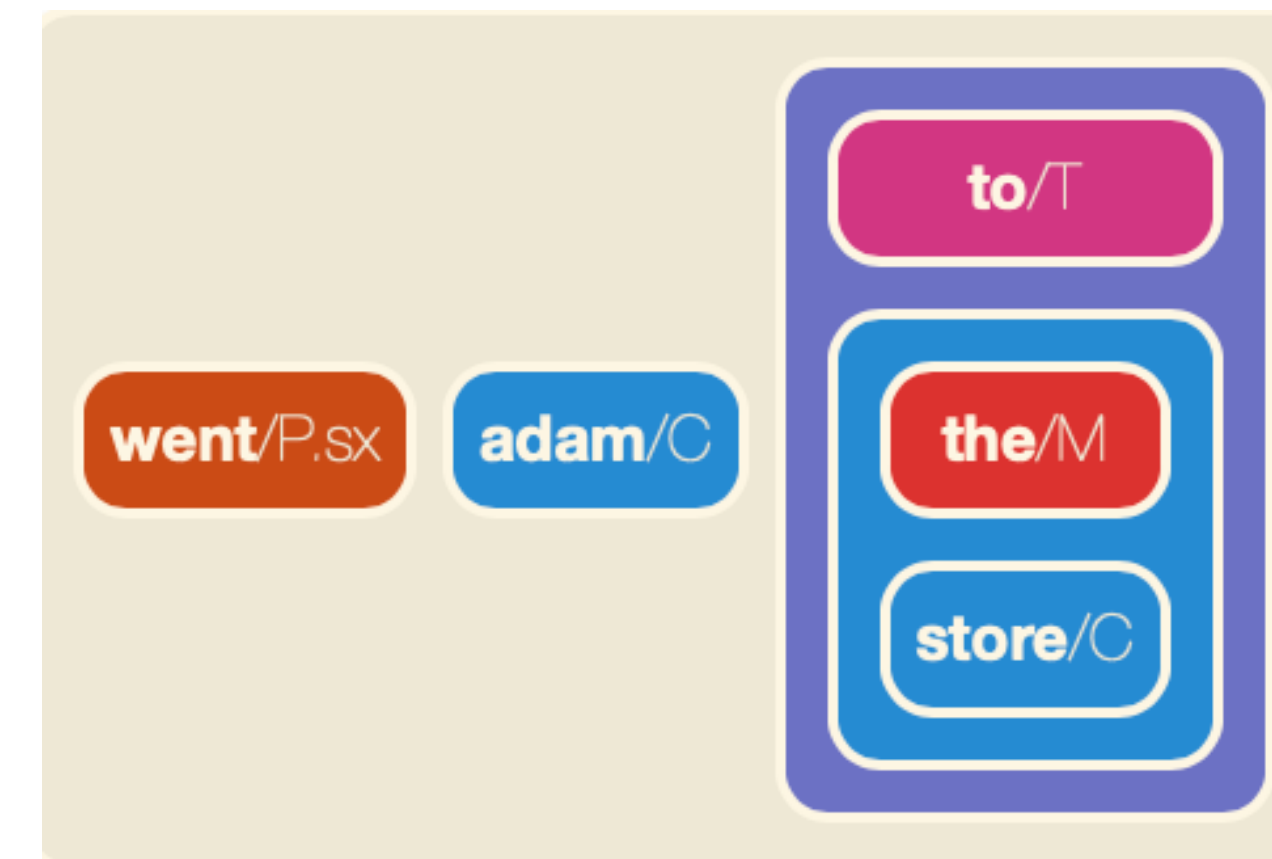
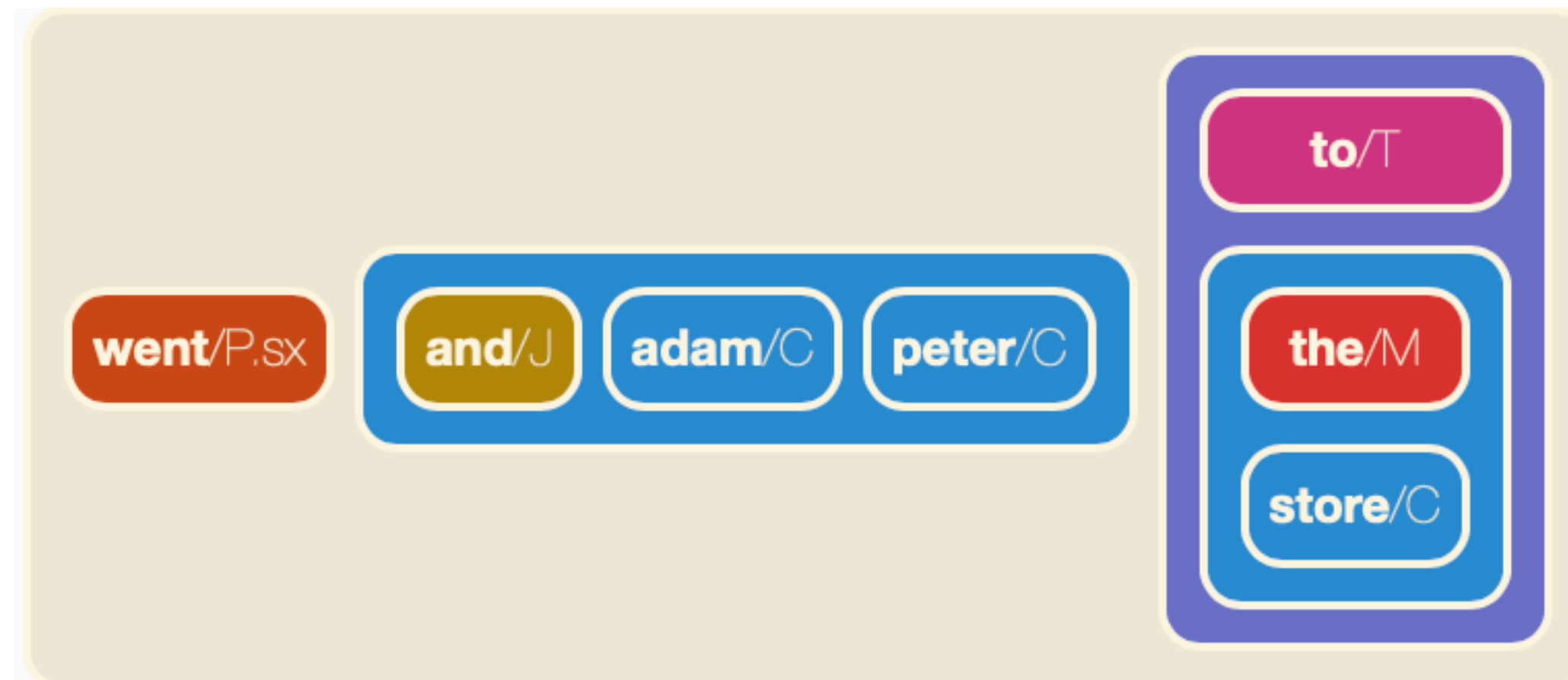
- Linking my previous presentations:
 - Possible choices for evaluation: https://github.com/adaamko/presentations/blob/main/semantic_parsers/parsers.ipynb
 - Analysis of semantic parsers: https://github.com/adaamko/presentations/blob/main/semantic_parsers/parsers.pdf
 - Evaluation of semantic parsers: https://github.com/adaamko/presentations/blob/main/semantic_parsers/semantic_parsing.pdf

Semantic parsers

- To summarize, useful resources:
 - **AMR** - mainly for English; takes lots of resources to parse; open-source parser; can handle lots of semantic phenomena
 - **UCCA** - multi and cross-lingual; less-resource hungry;
 - **Semantic Dependency Parsing (SDP)** - similar to SRL but tries to parse the whole structure of the sentence not just verbs and arguments; multi-lingual parsers are available
 - **GraphBrain** - only English; converts UD graphs into a more semantic format; very good pattern language and repository; easy to extend with new functionalities

Handling conjunctions

- Multiple graph formalisms can handle that (e.g. AMR, GraphBrain):



Handling Semantic Relationships

- Called **Relation Extraction (RE)** in NLP
 - Relation extraction (RE) is the task of extracting semantic relationship between entities from a text
 - Usually between two or more entities; Semantic categories (e.g. Destination, Component, Employed by, Founded by, etc..)
- Curated list on Github: [\[1\]](#)
- **Semeval** task: [\[2\]](#)
 - Cause-Effect, Instrument-Agency, Product-Producer, Content-Container, Entity-Origin, Entity-Destination, Component-Whole, Member-Collection, Message-Topic
- **Component-Whole:** my apartment has a large kitchen
- **Member-Collection:** there are many trees in the forest
- **Entity-Destination:** the boy went to bed

TACRED dataset

- TACRED is a large-scale relation extraction dataset with
- 106,264 examples built over newswire and web text
- Examples in TACRED cover 41 relation types or are labeled as no_relation if no defined relation is held.
- Example relations: *'org:founded_by', 'no_relation', 'per:identity', 'org:alternate_names', 'per:children', 'per:origin', 'per:countries_of_residence', 'per:employee_of', 'per:title', 'org:city_of_branch', 'per:religion', 'per:age', etc..*

RE parsers

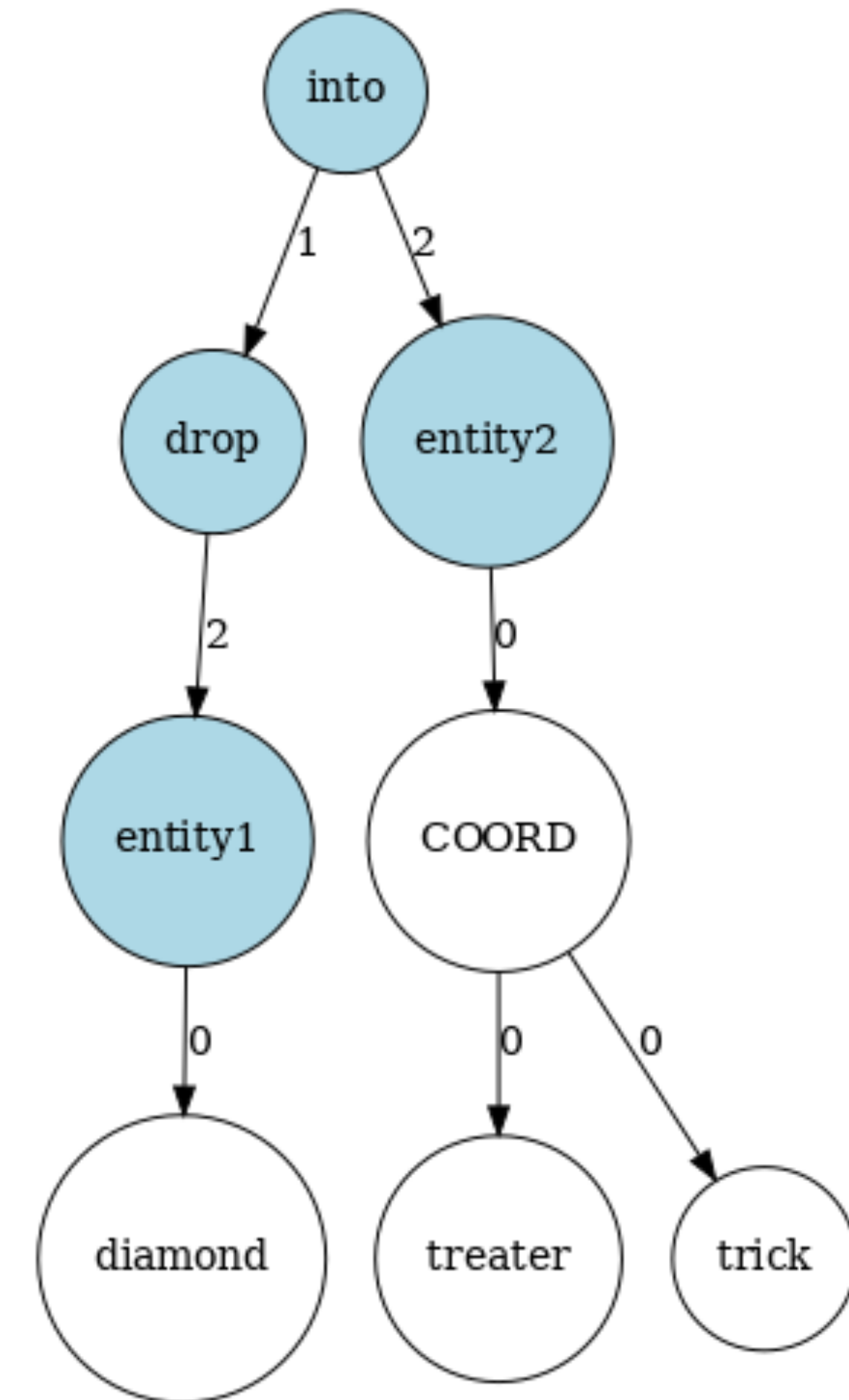
- **REBEL**: seq2seq model that simplifies Relation Extraction (EMNLP 2021).
[\[Github\]](#)
- **OpenNRE** [\[Github\]](#): Open-Source Package for Neural Relation Extraction (NRE)

Other relations

- Verb clustering: based on VerbNet
- NP chunking: built in component in spaCy
- Attribution: GraphBrain

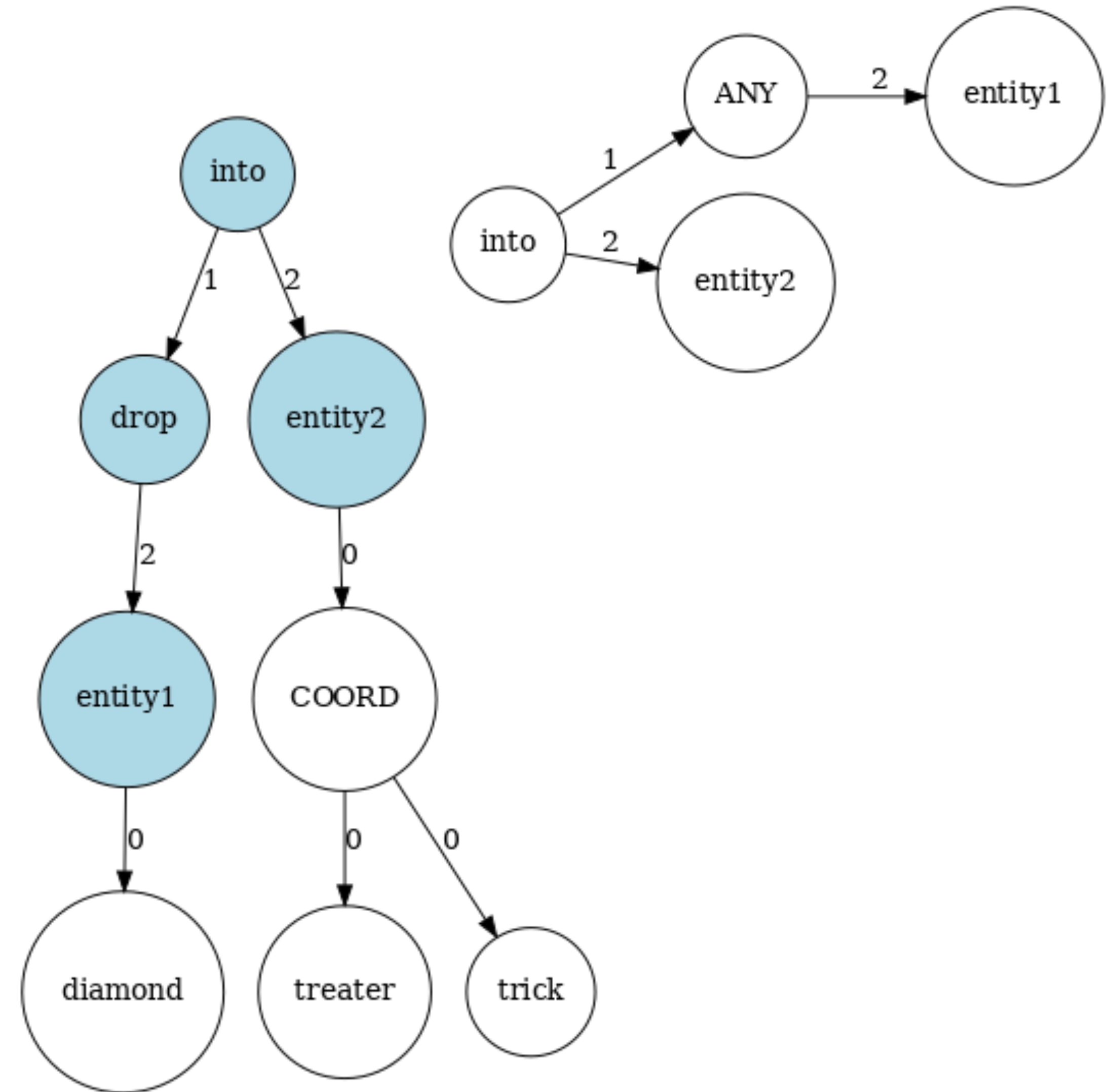
Case-study for RE

- The diamond **ring** was dropped into a trick-or-treater's **bag**.
- Method:
 - Parse text into a 4lang graph
 - Use POTATO and the Semeval training data to discover rules for the Entity-Destination label
 - Details in our paper



Case-study for RE

- The diamond **ring** was dropped into a trick-or-treater's **bag**.
- Method:
 - $(u_1 / \text{into} :2 (u_2 / \text{entity2}) :1 (u_3 / .* :2 (u_4 / \text{entity1})))$
- ```
(u_1 / into
:2 (u_2 / entity2)
:1 (u_3 / misplace|invest|drop|import|transport|
 fetch|pack|insert|pour|implant|remove|
 leak|add|dump|release|stuff
:2 (u_4 / entity1)))
```
- This pattern now matches 138 true positives and only 1 false positive, achieving 99.3% precision on the training dataset. On the validation data the same pattern achieves 95.6% precision and 21.9% recall.



# Suggested pipeline

