A Uniform Meaning Representation for NLP Systems

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University of Colorado & Brandeis University

ESSLLI 2023

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TRUTH EVEN UNTO ITS INNERMOST PARTS Brandeis אמת

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CLEAR

What should be in a Meaning Representation?

Current meaning representations

- Existing meaning representations vary in their focus and perspective
  - Formal semantic representations are aimed at supporting *logical inference* & focus on the proper representation of quantification, negation, tense, and modality (e.g., Minimal Recursion Semantics (MRS) and Discourse Representation Theory (DRT).
  - Lexical semantic representations focus on the proper representation of core predicate-argument structures, word sense, named entities and relations between them, & coreference (e.g., Tectogrammatical Representation (TR), AMR).
- The semantic ontologies they reference also differ a great deal. For example, MRS doesn't have a classification of named entities at all, while AMR has over 100 types of named entities

Can we have the best of both worlds?

Uniform Meaning Representations

UMR Course Outline

- 7/8: Lexical semantic representations: PropBank & AMR, and motivation for Uniform Meaning Representations
- 8/8: UMR Mechanisms for Quantification and Discourse Anaphora
- 9/8: Annotation in UMR for Multiple Languages
- 10/8: Extensions of AMR/UMR for Multimodal Communication and Situated Grounding
- 11/8: AMR/UMR for Knowledge Grounding and Logical Inference

Motivation: From Sentences to Propositions

Who did what to whom, when, where and how?

Powell met Zhu Rongji

Powell and Zhu Rongji met

Powell met with Zhu Rongji

Powell and Zhu Rongji had a meeting

. . .

battle

wrestle

join

debate

consult

Proposition: meet(Powell, Zhu Rongji)

meet(Somebody1, Somebody2)

When Powell met Zhu Rongji on Thursday they discussed the return of the spy plane.

meet(Powell, Zhu) discuss([Powell, Zhu], return(X, plane))

Capturing semantic roles

SUBJ

- *Tim broke [the laser pointer.]*

SUBJ

- *[The windows] were broken by the hurricane.*

SUBJ

- *[The vase] broke into pieces when it toppled over.*

Capturing semantic roles

Breaker

- *Tim broke [the laser pointer.]*

Thing broken

- *[The windows] were broken by the hurricane.*

Thing broken

- *[The vase] broke into pieces when it toppled over.*

Linguistic Background and Resources

- Semantic Roles
- Fillmore – Cases
  - Useful generalizations, fewer sense distinctions,
- Dowty – Proto-typical Agents and Patients
  - A bag of “agentive” entailments
  - **PropBank**
- Levin – Verb classes based on syntax
  - Syntax reflects semantics – **VerbNet - Friday**
- Back to Fillmore and **FrameNet - Friday**

Linguistic Background: Case Theory,

Charles J. Fillmore, The Case for Case, 1967

- Case relations occur in deep-structure
  - Surface-structure cases (nominative, accusative) are derived

- A sentence is a verb + one or more NPs
  - Each NP has a deep-structure case
    - *A(gentive)*
    - *I(nstrumental)*
    - *D(ative) - recipient*
    - *F(actitive) – result*
    - *L(ocative)*
    - *O(bjective) – affected object, theme*

  - Subject is no more important than Object
    - Subject/Object are surface structure

Case Theory Benefits - Generalizations

- Fewer tokens
  - Fewer verb senses
  - E.g. *cook/bake* [__O(A)] covers
    - *Mother is cooking the potatoes*
    - *The potatoes are cooking.*
    - *Mother is cooking.*
- Fewer types
  - "Different" verbs may be the same semantically, but with different subject selection preferences
  - E.g. *like* and *please* are both [__O+D]

- Great, let's do it!

Oops, problems with Cases/Thematic Roles

- How many and what are they?

- Fragmentation: 4 Agent subtypes? (Cruse, 1973)
  - *The sun melted the ice./This clothes dryer doesn't dry clothes well*

- Ambiguity: Andrews (1985)
  - Argument/adjunct distinctions – Extent?
  - *The kitten licked my fingers.* – Patient or Theme?

Oops, problems with Cases/Thematic Roles (cont.)

- Θ-Criterion (GB Theory): each NP of predicate in lexicon assigned unique θ-role (Chomsky 1981).

[$_{\text{Agent (or Source)}}$ Esau] sold [$_{\text{Theme}}$ his birthright]
[$_{\text{Goal}}$ to Jacob] for a <u>bowl of porridge</u>.

[$_{\text{Goal}}$ Esau] sold <u>his birthright</u>
[$_{\text{Source}}$ to Jacob] for a [$_{\text{Theme}}$ bowl of porridge].

Jackendoff

Thematic Proto-Roles and Argument Selection,

David Dowty, 1991

- Role definitions have to be determined verb by verb, and with respect to the other roles

- Event-dependent Proto-roles introduced
  - Proto-Agent
  - Proto-Patient

- Prototypes based on shared entailments

Proto-Agent- the *mother*

- Properties
  - Volitional involvement in event or state
  - Sentience (and/or perception)
  - Causes an event or change of state in another participant
  - Movement (relative to position of another participant)
  - (exists independently of event named)

Proto-Patient – *the potatoes/cake*

- Properties:
  - Undergoes change of state
  - Incremental theme
  - Causally affected by another participant
  - Stationary relative to movement of another participant
  - (does not exist independently of the event, or at all)

Argument Selection Principle

- For 2 or 3 place predicates
- Based on empirical count (total # of entailments for each role).
  - Greatest number of Proto-Agent entailments → Subject;
  - greatest number of Proto-Patient entailments → Direct Object.
- Alternation predicted if number of entailments for each role similar (non-discreteness). Ex. *frighten/fear*

[Mother AGENT] cooked the potatoes.

[The potatoes PATIENT] cooked.

PropBank Semantic Roles = Dowty's Proto-roles

- PropBank Frame for *break*:

  Frameset **break.01** "break, cause to not be whole":

  Arg0: breaker

  Arg1: thing broken

  Arg2: instrument

  Arg3: pieces

- Why numbered arguments?
  - Lack of consensus concerning semantic role labels
  - Numbers correspond to verb-specific labels
  - Arg0 – Proto-Agent, and Arg1 – Proto-Patient, (Dowty, 1991)
  - Args 2-5 are highly variable and overloaded – poorer performance

Why do we need Frameset ID's?

PropBank Frames Files: return.01, come back

Roles:

- Arg1: entity in motion
- Arg2: extent
- Arg3: start point
- Arg4: end point
- Arg5: medium

Example: *Their return to black townships across the country.*

- Arg1: *Their*
- REL: *return*
- Arg4: *to black townships across the country.*

Why do we need Frameset ID's?

PropBank Frames Files: return.02, give back

Roles:

Arg0: giver
Arg1: thing given
Arg2: entity given to

Example: *Fans politely return foul balls to stadium ushers.*

Arg0:	*fans*
REL:	*return*
Arg1:	foul balls
Arg2:	*to stadium ushers*

PropBank seeks to provide consistent argument labels across different syntactic realizations

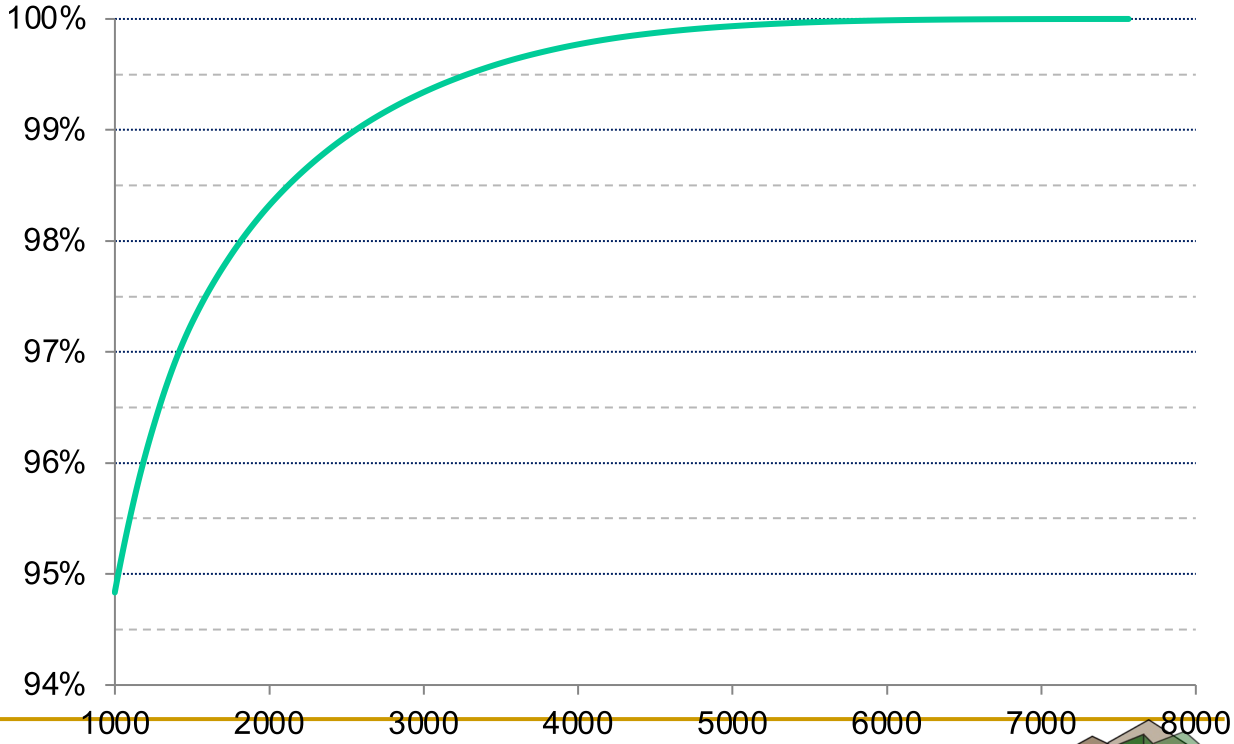
- Uuuuuusually…
  - Arg0 = agent, experiencer
  - Arg1 = patient, theme
  - Arg2 = benefactive / instrument / attribute / end state
  - Arg3 = start point / benefactive / instrument / attribute
  - Arg4 = end point

PropBank seeks to assign functional tags to all modifiers or adjuncts to the verb

- Variety of ArgM's:
  - TMP - when? *yesterday, 5pm on Saturday, recently*
  - LOC - where? *in the living room, on the newspaper*
  - DIR - where to/from? *down, from Antartica*
  - MNR - how? *quickly, with much enthusiasm*
  - PRP/CAU -why? *because … , so that …*
  - REC - himself, themselves, each other
  - GOL - end point of motion, transfer verbs? *To the floor, to Judy*
  - ADV - hodge-podge, miscellaneous, "nothing-fits!"
  - PRD - this argument refers to or modifies another: *…ate the meat raw*

PropBank Verb Frames Coverage*

- The set of verbs is open
- But the distribution is highly skewed
- For English, the 1000 most frequent lemmas cover 95% of the verbs in running text.
  - Graphs show counts over English Web data containing 150 M verbs.



*Thanks to Lance Ramshaw at BBN-Raytheon

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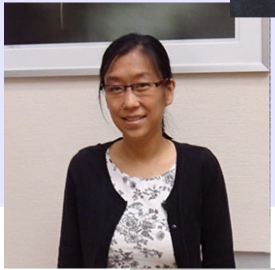
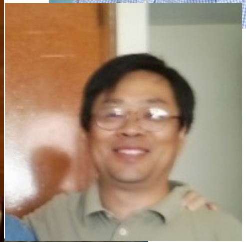
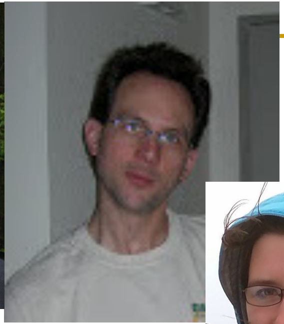
PropBank Language Experts





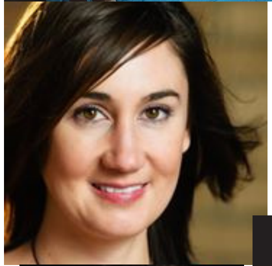


中文 (Chinese)
Wei-Te Chen, Nianwen Xue, Fei Xia, Shumin Wu, Zhibiao Wu

ENGLISH
Olga Babko-Malaya, Jena Hwang, Karin Kipper, Paul Kingsbury, Skatje Myers, Tim O'Gorman, Claire Bonial, Hoa Dang, Dan Gildea. James, Gung, Sameer Pradhan





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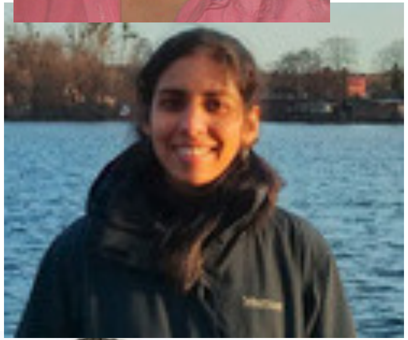
PropBank Language Experts

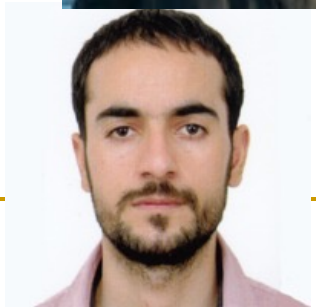
(Arabic) عربی

Aous Mansouri,
Maha Foster,
Ahmed Elsayed,
Mohammed Aitmoulay,
James Babani



한국어 (Korean)

Jinho Choi,
Na-rae Han,
Chunghye Han,



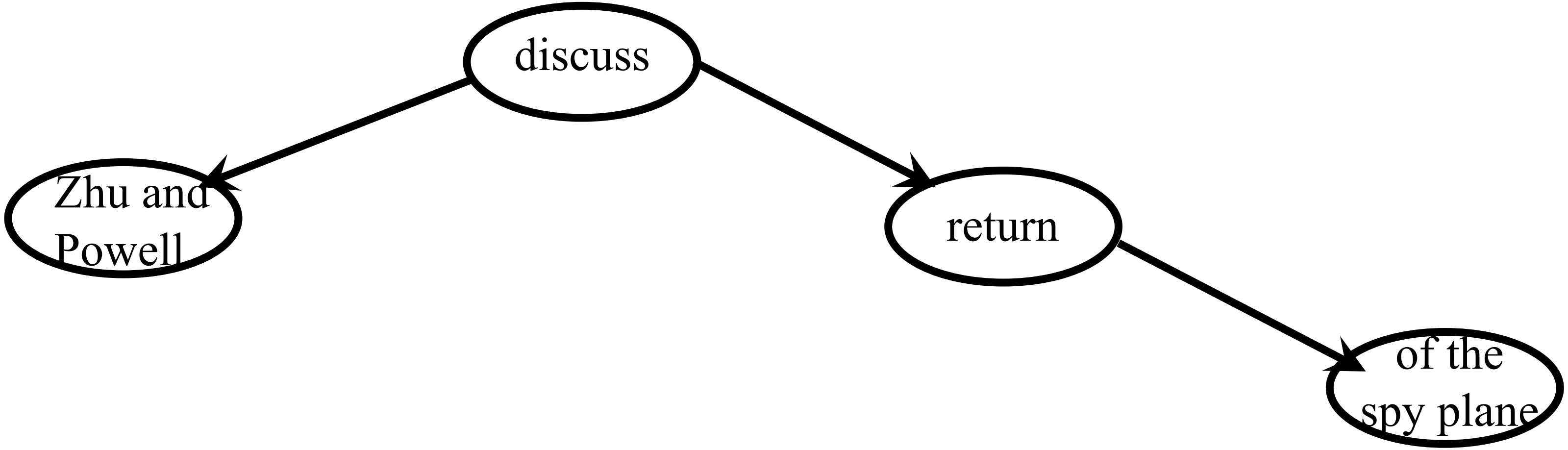
हिंदी (Hindi) and (Urdu) اردو

Bhuvana Narasimhan,
Ashwini Vaidya, Archna Bhatia, Riyaz Bhat,

A proposition as a tree

Zhu and Powell discussed the return of the spy plane

discuss([Powell, Zhu], return(X, plane))



PropBank Frame File - *11,436 framesets*

*Kingsbury & Palmer, LREC 2002 – Pradhan et. al., *SEM 2022,*

discuss.01 - talk about

Aliases: discussion (n.), discuss (v.), have_discussion (l.)

- **Roles:**

  ARG0: *discussant*

  ARG1: *topic*

  ARG2: *conversation partner, if explicit*

Valency Lexicon

Zhu and Powell discussed the return of the spy plane

discuss.01

ARG0: Zhu and Powell

ARG1: return.01

Arg1: of the spy plane

Zhu and Powell discussed the return of the spy plane

discuss.01

ARG0: Zhu and Powell

ARG1: return.01

Arg1: of the spy plane

discuss([Powell, Zhu], return(X, plane))

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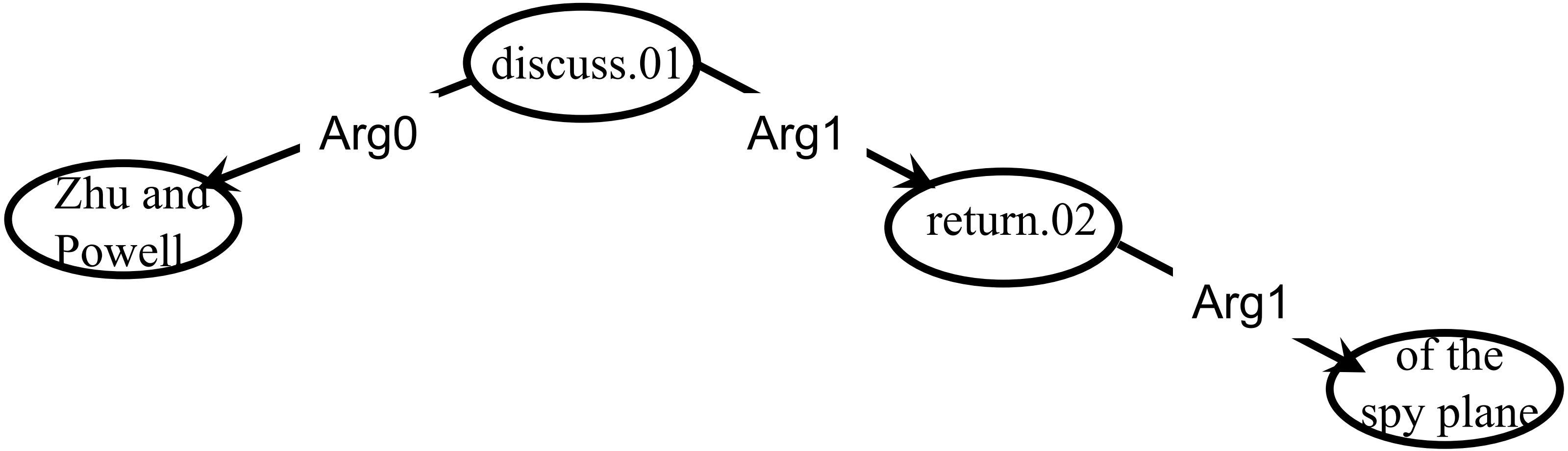

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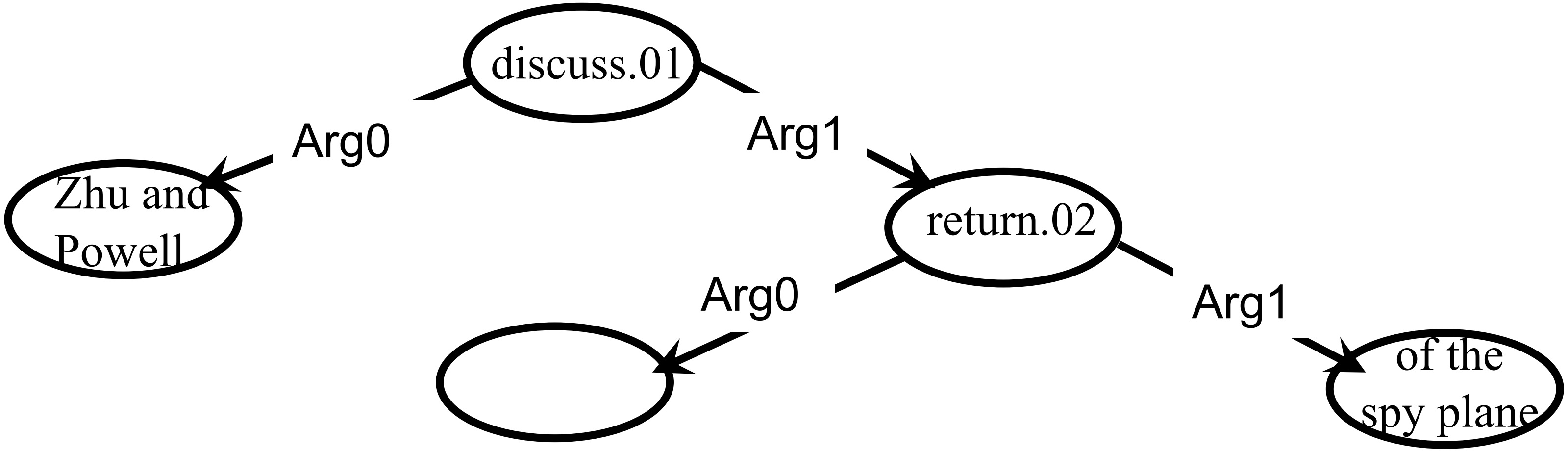

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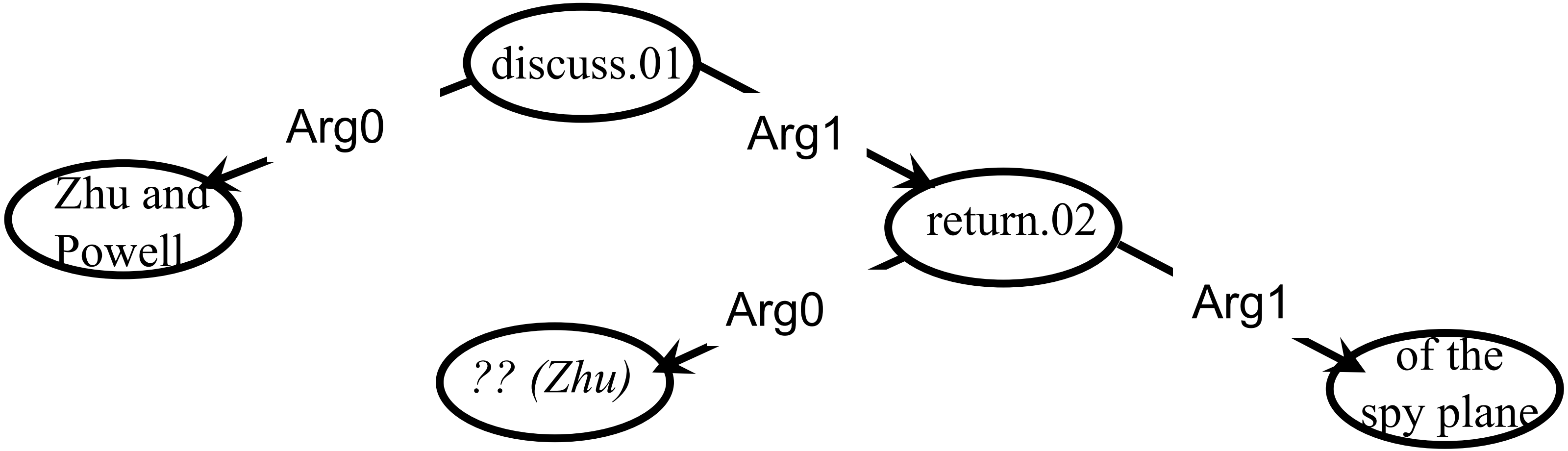

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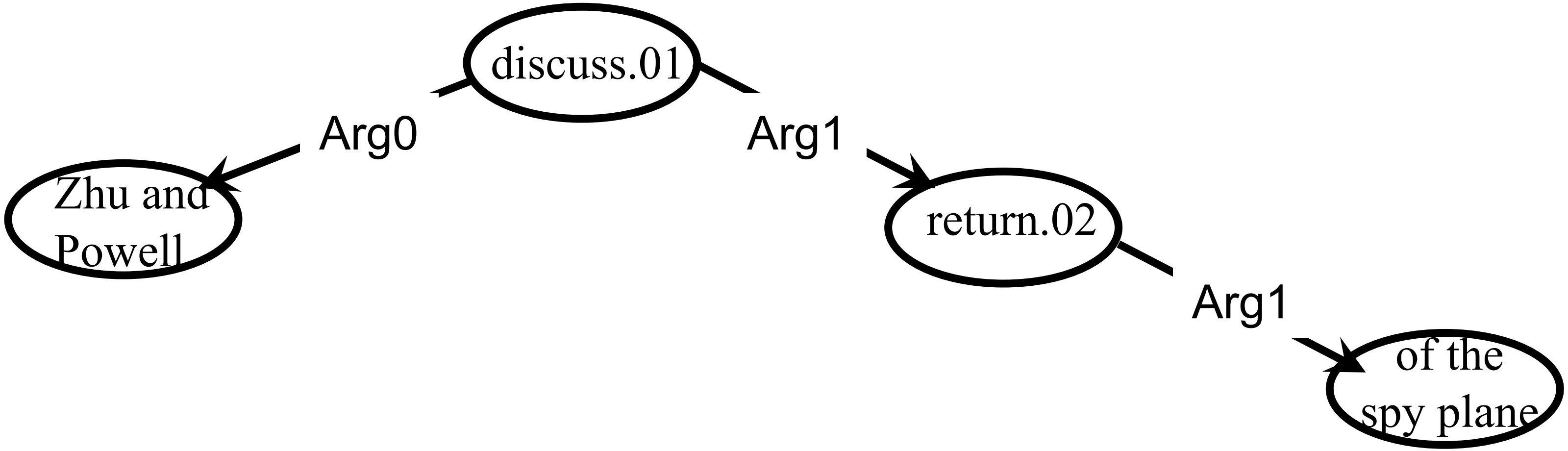

Proposition Bank

- Hand annotated predicate argument structures for Penn Treebank
  - Standoff XML, points directly to syntactic parse tree nodes, 1M words
  - Doubly annotated and adjudicated
  - *(Kingsbury & Palmer, 2002, Palmer, Gildea, Xue, 2004, …).*
- Based on PropBank Frame Files
  - English valency lexicon: ~4K verb entries (2004) → ~11K v,n, adj, prep (2022)
  - Core arguments – Arg0-Arg5
  - ArgM's for modifiers and adjuncts

Proposition Bank

Palmer, Gildea, Kingsbury, 2004
Palmer, Gildea, Xue, 2010,

- Annotated PropBank Corpora
  - English 2M+, Chinese 1M+, Arabic .5M, Hindi/Urdu .6K, Korean
- Semlink
  - mappings between OntoNotes, PropBank, VerbNet, FrameNet
- IBM, UPB 2.0 Universal Proposition Banks for Multilingual Semantic Role Labeling

Ishan
Jindal

Linguistic Annotation Collaboration

- UFAL, Charles University, Prague
  - SynSemClass
  - Event-type Ontology in Multiple Languages (w/ links ON, VN, FN, etc.)
  - Czech, English, German, Spanish





Zdeňka Urešová

Jan Hajic

Eva Hajicová

Abstract Meaning Representation (AMR)

Banarescu, et. al., LAW 2013

- NSF Funding (2009-2016)
  - STAGES - Statistical Translation And GEneration using Semantics
  - Colorado (PI), ISI, Rochester, Brandeis, Columbia

- DARPA DEFT funding (2012-2017)
  - USC-ISI, Colorado, LDC, CMU
  - First guidelines released April 24, 2012
  - LDC releases, recent one is 60K sentences with AMR’s, subset translated into Spanish, German, …

An Abstract Meaning Representation as a graph

Zhu and Powell discussed the return of the spy plane

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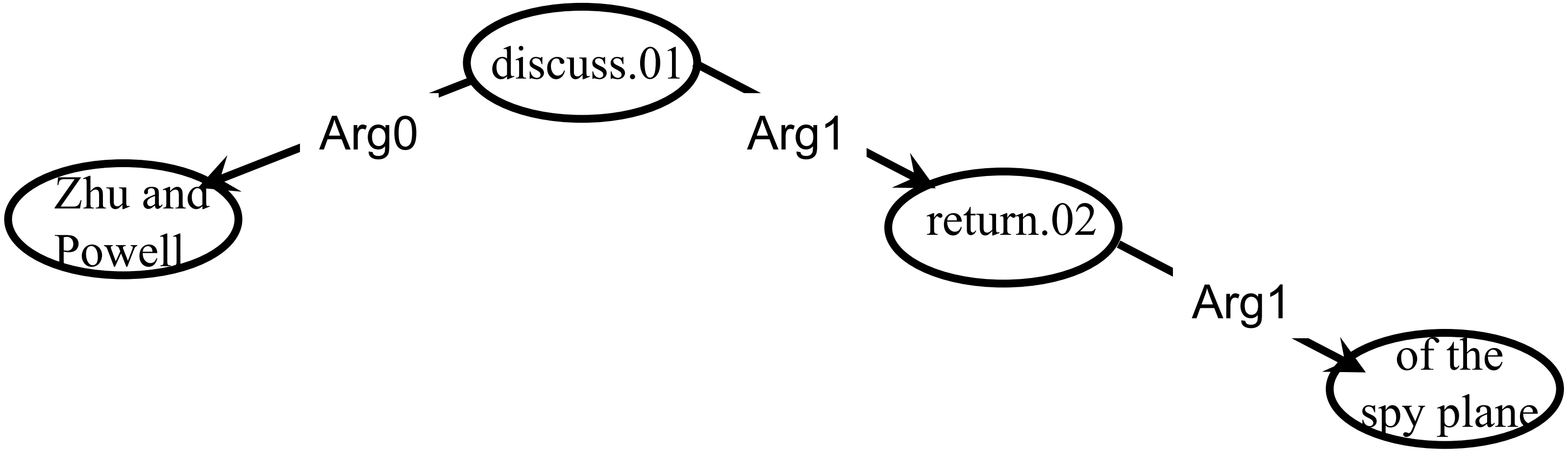

An Abstract Meaning Representation as a graph

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discuss([Zhu, Powell], return(X, plane))

AMR drops:

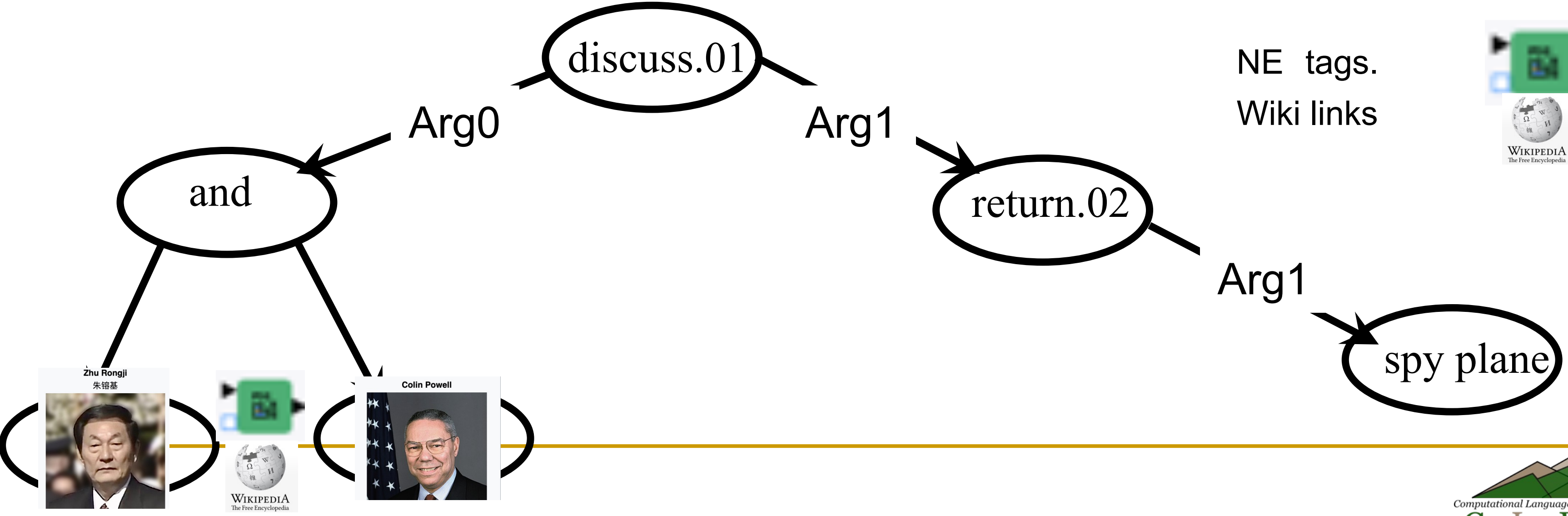
Determiners

Function words

adds:

NE tags.

Wiki links



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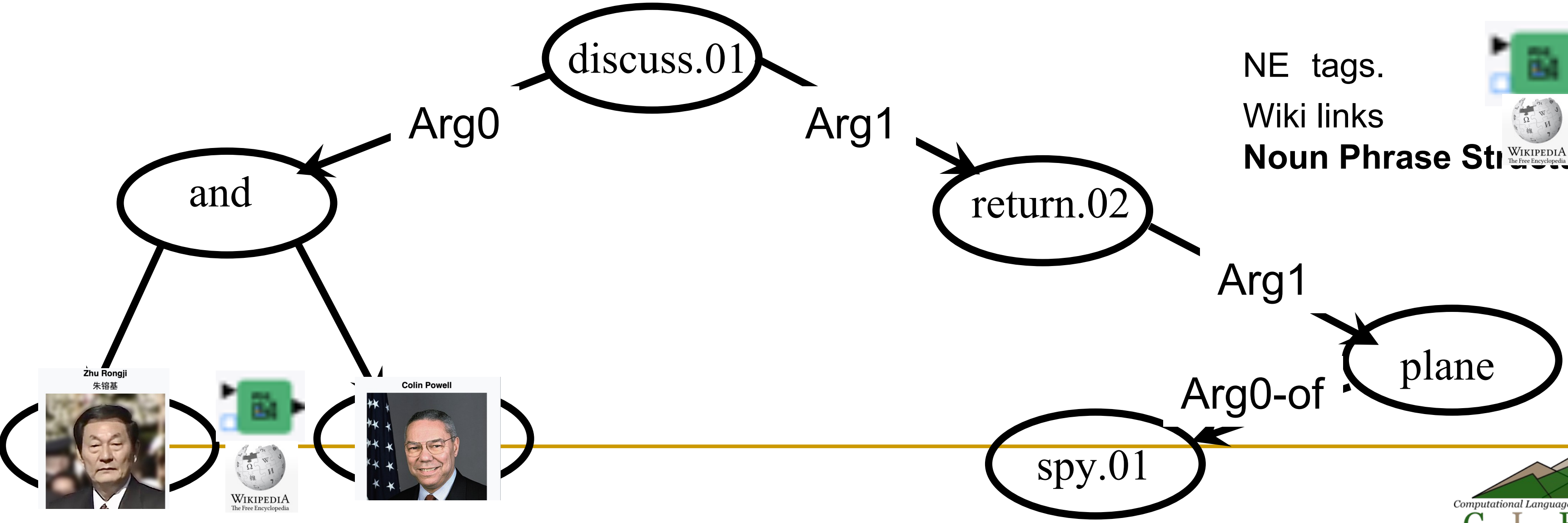
Noun Phrase Structure



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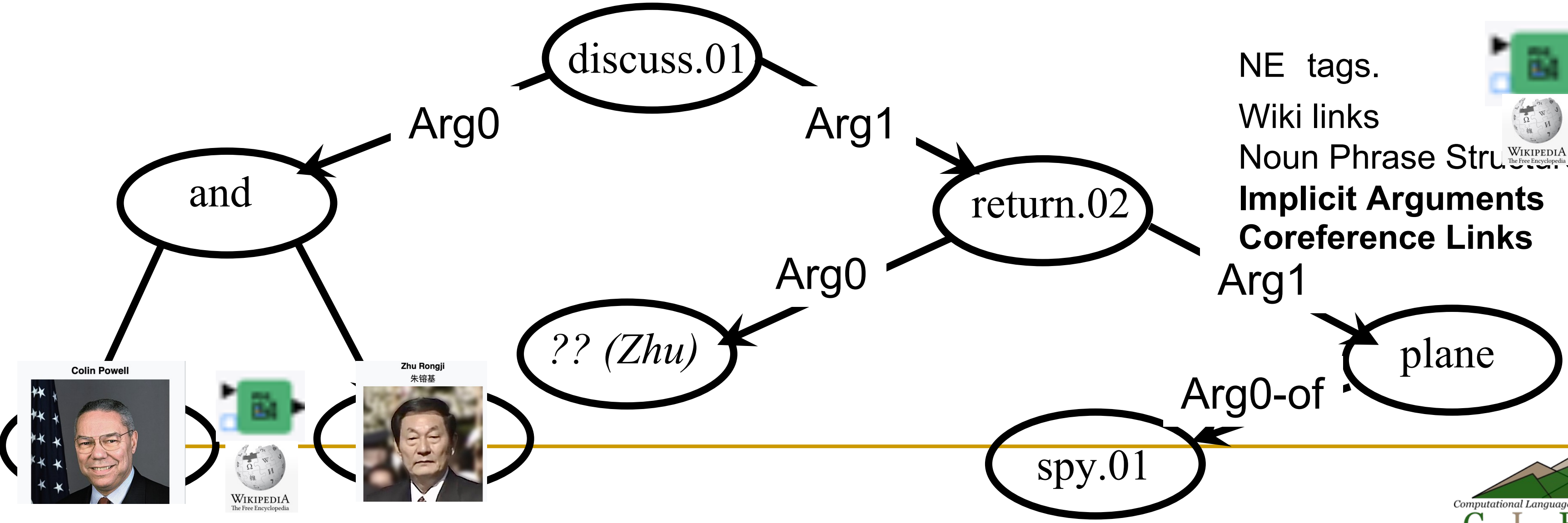

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Implicit Arguments
Coreference Links

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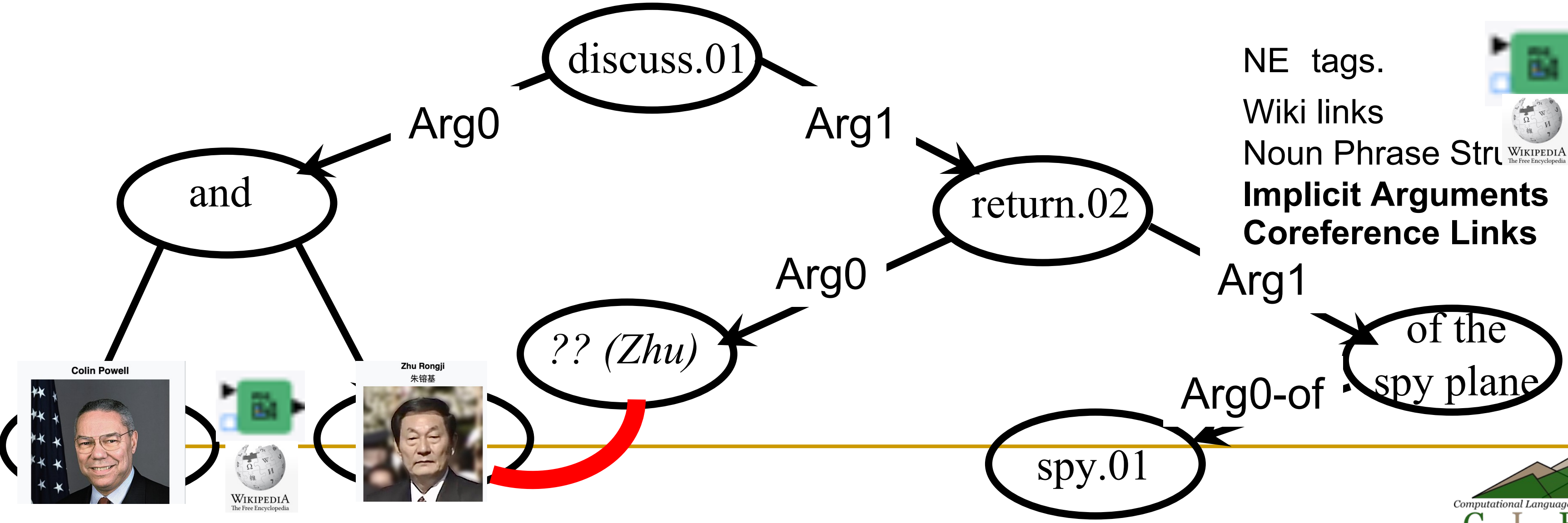

Actual AMR (w/out wiki links)

```
(d / discuss-01
      :ARG0 (a / and
            :op1 (p / person :name (n / name :op1 "Zhu"))
            :op2 (p2 / person :name (n2 / name :op1 "Powell")))
      :ARG1 (r / return-01
            :ARG1 (p3 / plane
                  :purpose (s / spy-01))))
```


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    :ARG1 (r / return-01
        :ARG0 (p / implicit-giver
        :ARG1 (p3 / plane
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```

Multi-sentence AMRs – situating w/re context

- Add information about which words refer to the same thing, how events relate to each other on a timeline, chains of cause and effect between events, and other kinds of rich information needed for understanding.
- Focus here on referring expressions, inter-sentential coreference

Tim O'Gorman, et. al., AMR Beyond the Sentence: the Multi-sentence AMR corpus, COLING 2018

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AMRs are

- A more abstract labeled ***semantic*** dependency tree
  - w/out function words
  - many nouns/adjectives have predicate-argument structures as well as verbs
  - NE's with wiki links
  - abstract discourse relations
  - partial interpretation of modality and negation
  - "some" implicit arguments/relations **& links to VN, FN, ON**

AMRs are

- A more abstract labeled ***semantic*** dependency tree
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  - NE’s with wiki links
  - abstract discourse relations
  - partial interpretation of modality and negation
  - “some” implicit arguments/relations **& links to VN, FN, ON**
  - **AND equivalence relations for coreference – make it a graph (directed acyclic graph).**

Coreference links, causal and temporal relations link individual sentence AMRs

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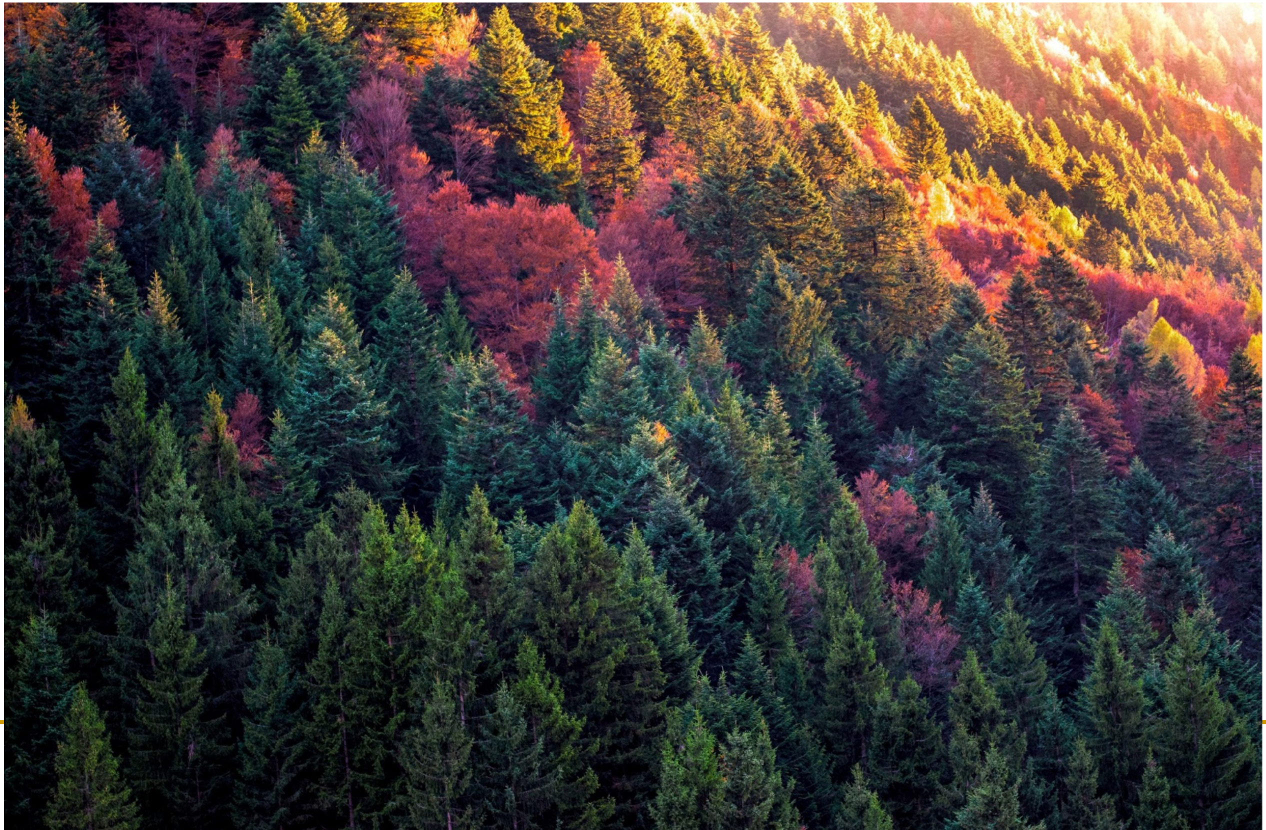
Until a document becomes a forest,



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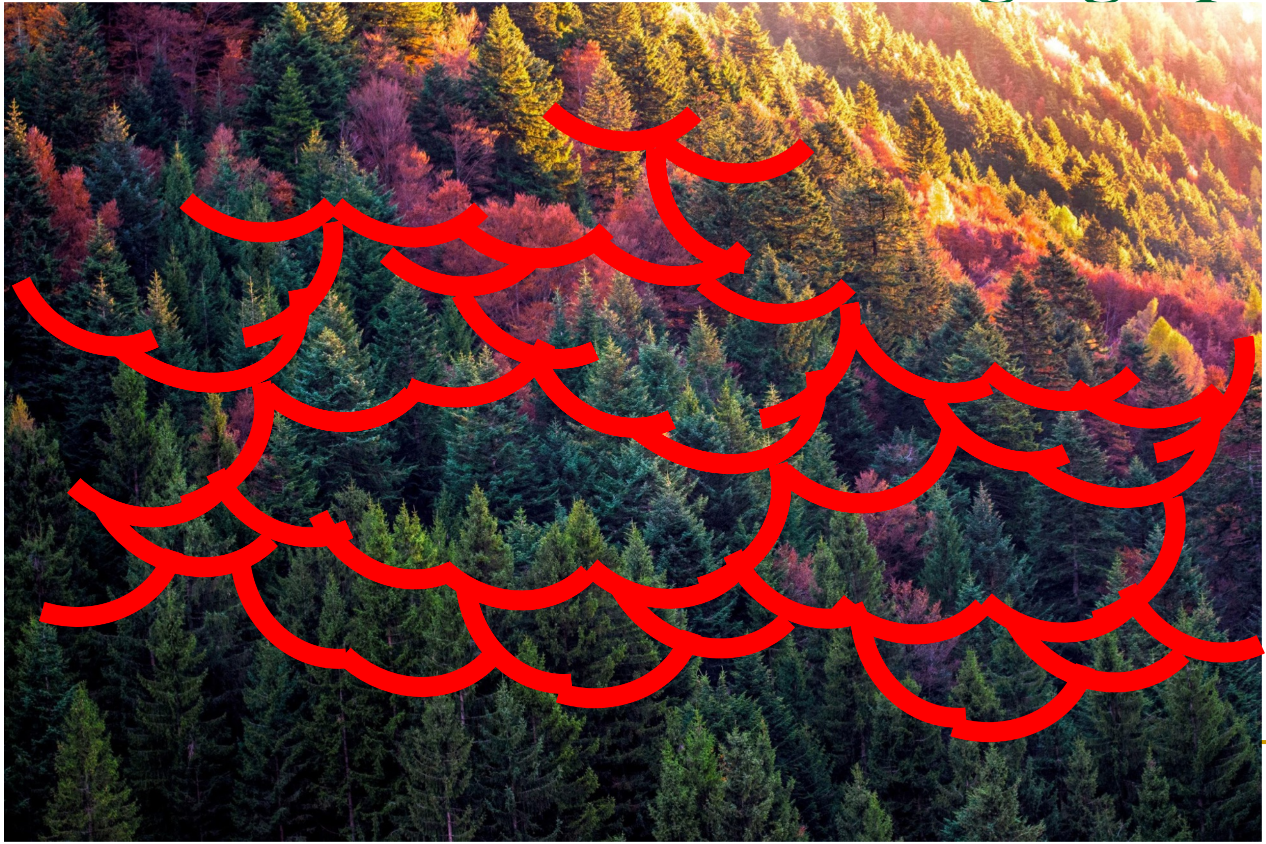
And the forest becomes a rich, connected knowledge graph, e.g.,



a Semantic Net!

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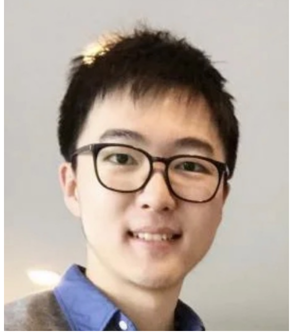
Training data supporting…medical histories, tracking WMD's, patent searches, etc.

- **Information Extraction**
- Text editing
- Text summary / evaluation
- Question and answering
- Machine Translation evaluation

- Dialogues, especially Human-Computer Interactions, are still a wild frontier….

Guergana Savova

Jim Martin



Jon Cai

National Institutes of Health

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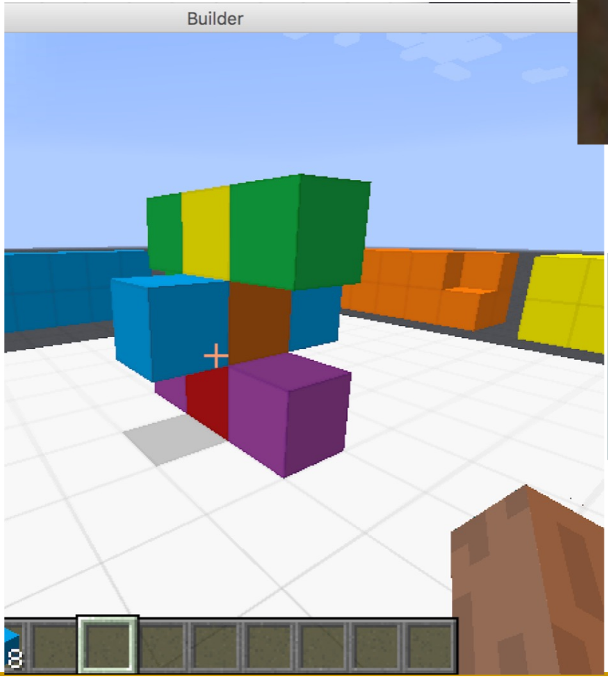
Minecraft Dialogue & AMR's –

Anjali Narayan-Chen, Prashant Jayannavar and Julia Hockenmaier
Collaborative Dialogue in Minecraft, ACL 2019

- Architect and Builder discuss building project, often a specific object
- Builder actions = sentences
- **Julia Bonn &**
  Kristin Wright-Bettner

provide 25K AMR's for everything (Instructions and actions) to allow for implicit arguments and coreference chains



Julia Hockenmaier

Anjali Narayan-Chen

Spatial Relation Rolesets and Ontology – Julia Bonn

Julia Bonn, Martha Palmer, Jon Cai, Kristin Wright-Bettner (2020) Spatial AMR: Expanded Spatial Annotation in the Context of a Grounded Minecraft Corpus, (LREC 2020)).

- 191 new/updated rolesets
  - ***new prepositional/adverbial relations***
  - + verbs, nouns, adjectives, MWEs
  - 20 new semantic/pragmatic role types
- Mapping to
  - Hobbs axiomatizations
  - VoxML, ISO-Space (Pustejovsky)

Kokel, H., et. al., demo paper, ICAPS2021,2021.

Dan, S., et. al., LREC 2020

iSAT – Institute for Student-AI Teaming

In our vision, AI is viewed as a **social, collaborative partner** that helps both students and teachers work and learn more effectively, engagingly, and equitably

NSF Institute for AI and Education

Actual AMR (w/out wiki links)

```
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            :ARG0 (p / implicit-giver
            :ARG1 (p3 / plane
                  :purpose (s / spy-01))))
```

Actual AMR (w/out wiki links)

ENGLISH!

```
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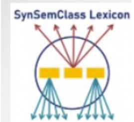
    :ARG1 (r / return-01
        :ARG0 (p / implicit-giver
        :ARG1 (p3 / plane
            :purpose (s / spy-01))))
```

How do we cover thousands of languages?

- Several languages already have valency lexicons
  - Chinese, Arabic, Hindi/Urdu, Korean PropBanks, ….
  - Czech Tectogrammatical SynSemClass , https://ufal.mff.cuni.cz/synsemclass



  - VerbNets, FrameNets: Spanish, Basque, Catalan, Portuguese, Japanese, …
  - Linguistic valency lexicons: Arapaho, Lakota, Turkish, Farsi, Japanese, …
- Can AMR be applied universally to build language specific AMRs?

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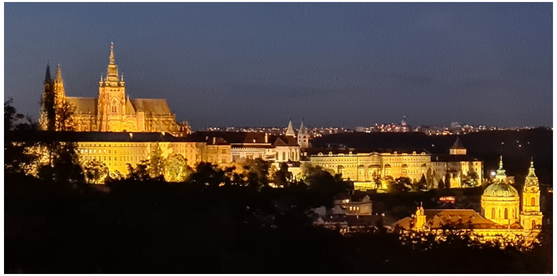
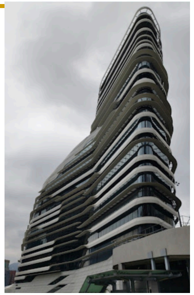
Uniform Meaning Representations

Designing Meaning Representation Workshops, ACL2019, COLING 2020

- Current NSF project *(CCRI UMR2 just started, + Alexis Palmer)*
  - Brandeis (Nianwen Xue & James Pustejovsky) *DMR1, DMR2*
  - Colorado (Martha Palmer, Jim Martin, Andy Cowell) *DMR1, DMR2, DMR3*
  - U of New Mexico (Bill Croft) *DMR1, DMR2, DMR3*
- Ensure adequate coverage for multiple languages, especially low resource languages – requires *adapting* AMR
  - e.g., Arapaho, Kukama, English, Chinese, Hindi, Arabic, Spanish, Sanapaná, Hua, Czech
- ADD: **Tense, Aspect, Modality, Logical form** so that UMR can better match formal semantic representations (MRS,DRT)

The whole team!

- Joint work with Julia Bonn, Daniel Chen, Jayeol Chun, Lukas Denk, Kenneth Lai, Sara Moeller, Skatje Myers, Jens Van Gysel, Meagan Vigus, Jiarui Yao, Jin Zhao, Tim O’Gorman, Andy Cowell, William Croft, Chu-Ren Huang, Jan Hajič, Jim Martin, Stephan Oepen, Martha Palmer, James Pustejovsky, Rosa Vallejos, Nianwen Xue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UP vs UMR

- Universal PropBank was developed by IBM, primarily with translation
  - Practical and efficient, produces consistent representations for all languages
  - Projects English frames to parallel sentences in 23 languages
  - BUT - May obscure language specific semantic nuances

- Uniform Meaning Representation
  - Richer than PropBank alone
  - Captures language specific characteristics while preserving
  - consistency
  - BUT - Producing sufficient hand annotated data is SLOW

- Comparisons of UP/UMR will teach us a lot about
  differences between languages

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C L E A R

Executive Summary

- Uniform Meaning Representations, provide a lightweight, flexible, *cross-linguistically general* format for capturing
  - Figurative language
  - Implicit arguments
  - Temporal and causal relations
  - Rich spatial configurations
  - Logical form
  - Tense, Aspect and Modality
- Both within and across sentences

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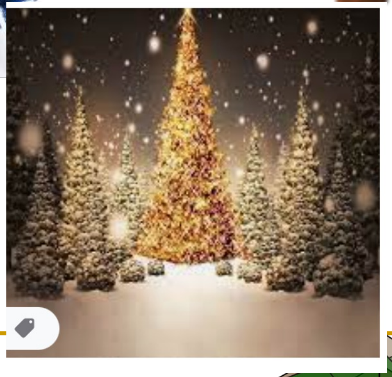

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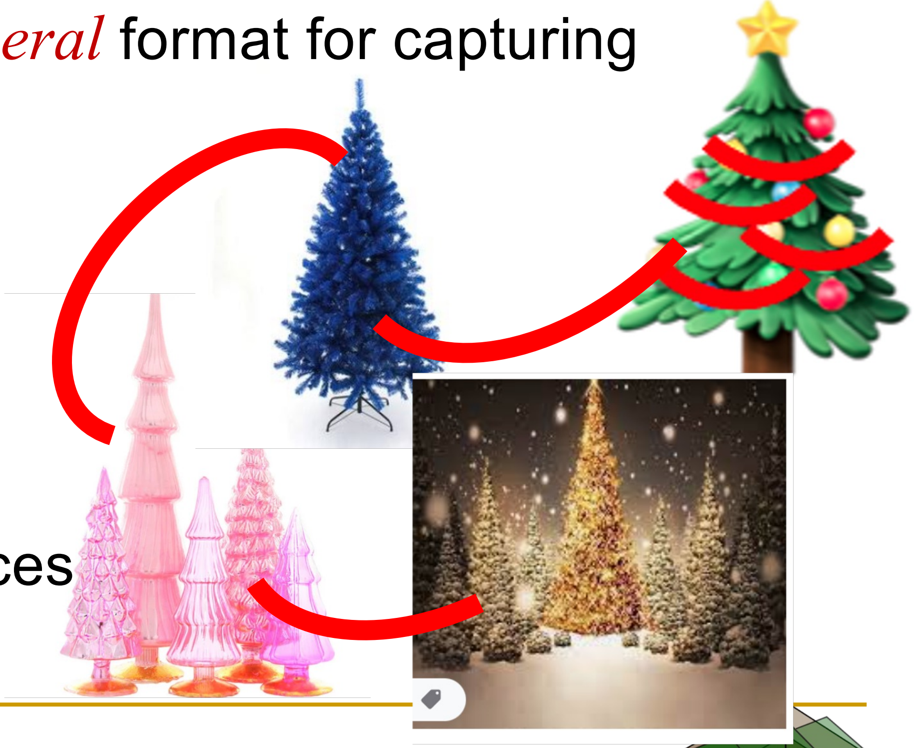

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