Meaning Representations for Natural Languages: Design, Models and Applications

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1 Brief 2-sentence description

This tutorial reviews the design of common meaning representations, SoTA models for predicting meaning representations, and the applications of meaning representations in a wide range of downstream NLP tasks and real-world applications. Reporting by a diverse team of NLP researchers from academia and industry with extensive experience in designing, building and using meaning representations, our tutorial has three components: (1) an introduction to common meaning representations, including basic concepts and design challenges; (2) a review of SoTA methods on building models for meaning representations; and (3) an overview of applications of meaning representations in downstream NLP tasks and real-world applications.

2 Longer 2-paragraph description

While deep learning methods have led to many breakthroughs in practical natural language applications, and in particular, large language models (LLMs) have demonstrated an impressive capability of generating coherent and fluent texts, there is still a sense among many NLP researchers that there is a long way to go before we can develop systems that can actually "understand" human language and explain the decisions they make. Indeed, "understanding" natural language entails many different human-like capabilities, and they include but are not limited to the ability to track entities in a text, understand the relations between these entities, track events and their participants described in a text, understand how events unfold in time, and distinguish events that have actually happened from events that are planned or intended, are uncertain, or did not happen at all. A critical step in achieving natural language understanding is to parse text into meaning representations that have the necessary meaning "ingredients" that help us achieve these capabilities. Such meaning representations can also potentially be used to evaluate the compositional generalization capacity of deep learning models.

There has been a growing body of research devoted to the design, annotation, and parsing of meaning representations in recent years. In this tutorial, we review the design of common meaning representations, SoTA models for predicting meaning representations, and the applications of meaning representations in a wide range of downstream NLP tasks and real-world applications. Reporting by a diverse team of NLP researchers from academia and industry with extensive experience in designing, building and using meaning representations, our tutorial has three components: (1) an introduction to common meaning representations, including basic concepts and design challenges; (2) a review of SoTA methods on building models for parsing text into meaning representations; and (3) an overview of applications of meaning representations in downstream NLP tasks and real-world applications. We will also present qualitative comparisons of common meaning representations and a quantitative study on how their differences impact model performance. Finally, we will share best practices in choosing the right meaning representation for downstream tasks and real-world applications.

3 Motivation

This tutorial aims to introduce the AI community to an emerging NLP area that has the potential of creating linguistic resources and building computational models that provide critical components for interpretable and controllable NLP systems. While large language models have shown remarkable ability to generate fluent and mostly coherent text, the blackbox nature of these models makes it difficult to know where to tweak these models to fix errors or at least anticipate errors if they can't easily be fixed. For instance, LLMs are known to halluci-

nate and generate factually incorrect answers when prompted as there is no mechanism in these models to constrain them to only provide factually correct answers. Addressing this issue requires that, first of all, the models have access to a body of verifiable facts, and then when generating answers to prompts or queries, do not alter them materially to make the answers factually incorrect. Interpretability and controllability in AI systems are critical in high-stake application scenarios such as the health domain where AI systems are used as medical assistants.

In the past few decades there has been a steady accumulation of semantically annotated resources that are increasingly richer in representation. As these resources become available, steady progress has been made in developing computational models that can automatically parse unstructured text into these semantic representations with increasing accuracy. These models have reached a level of accuracy that makes them useful in practical applications. For example, these models have been used in information extraction, where entities and relations are extracted from unstructured text. It is now conceivable that these models can be used to extract verifiable facts at scale to build controllable and interpretable systems that can output factually correct answers. These rich semantic representations are also needed in human-robot interaction (HRI) systems to facilitate on-the-fly grounding so that the robot can establish connections with its surroundings and interact with them in a meaningful way. These meaning representations are easily translated into logical representations to support logical reasoning that LLMs often struggle with, or they can be used to develop NLP systems for low-resource languages where there is insufficient data to train LLMs, but the richness in semantic representation can to some extent make up for the lack of quantity. This tutorial will provide an overview of these semantic representations, the computational models that are trained on them, as well as the practical applications built with these representations. We will also delve into future directions for this line of research and examine how these meaning representations might be used to build interpretable and controllable applications, used in human-robot interaction scenarios, and low-resource settings.

4 Tutorial Overview

4.1 Background

In this tutorial, we primarily discuss one thread of meaning representations encompassing the Proposition Bank (PropBank) (Palmer et al., 2005), Abstract Meaning Representations (AMR) (Banarescu et al., 2013) as well as Uniform Meaning Representations (UMR) (Gysel et al., 2021), a recent extension to AMR. We will discuss the representations themselves, as well as the latest semantic role labeling (SRL) and AMR parsing techniques using these representations, and overview applications of these meaning representations to practical natural language applications.

These approaches all share the use of the predicate-specific semantic roles defined in the Proposition Bank (PropBank) (Palmer et al., 2005). We will seek to provide attendees with good intuitions about the behavior and advantages of how such predicate-specific roles work across these different meaning representations. We will also contextualize how such an approach to semantics compares to other approaches such as FrameNet (Baker et al., 1998).

Next we discuss Abstract Meaning Representation (AMR), which can be viewed as an extension of PropBank to handle wide-coverage sentence representation. Whereas PropBank is annotated on a predicate-by-predicate basis and predicates can be viewed as independent, AMR adopts PropBank-style semantic roles but also connects the different predicates in a sentence in a single-rooted directed acyclic graph. AMR captures the essential predicate-argument structure of a sentence that is applicable to a variety of applications.

Finally we discuss recent attempt to extend AMR to increase coverage beyond the sentence, to add additional semantic phenomena, and to increase cross-linguistic applicability. We discuss these extensions with a focus on the new Uniform Meaning Representation (UMR), which extends AMR to add coverage of *Aspect*, *Scope*, *Person* and *Number* annotation to the sentence level representation, adds a document-level representation that captures temporal and modal dependencies as well as coreference relations that can go beyond sentence boundaries, and which defines conventions for AMR-style annotation of languages without existing PropBank lexicons.

In this tutorial we will provide an in-depth discussion of these meaning representations. When

doing so, we will also discuss how they are similar to or different from other meaning representations such as semantic dependencies (Oepen et al., 2015), Minimal Recursion Semantics (MRS) (Copestake et al., 2005), Discourse Representation Theory (DRT) (Kamp and Reyle, 2013; Bos et al., 2017) , and UCCA (Abend and Rappoport, 2013).

The increasing availability of meaning representation datasets such as PropBank as well as significant advances in modeling techniques have led to increased interest and progress in computational models for meaning representation parsers. In this tutorial, we will discuss models for SRL and AMR tasks. We will start with the traditional SRL models that rely heavily on syntactic feature templates (Xue and Palmer, 2004; Pradhan et al., 2005; Zhao et al., 2009; Akbik and Li, 2016), go on to advanced neural SRL models (He et al., 2017, 2018), and include more recent work (Marcheggiani and Titov, 2020; Fei et al., 2021a,b; Zhang et al., 2022). For AMR parsing, we will cover early approaches and SoTA methods for graph-based methods (Flanigan et al., 2014; Foland and Martin, 2017; Lyu and Titov, 2018; Cai and Lam, 2019; Zhang et al., 2019b; Zhou et al., 2020), transition-based methods (Wang et al., 2015; Wang and Xue, 2017; Ballesteros and Al-Onaizan, 2017; Fernandez Astudillo et al., 2020; Zhou et al., 2021), grammar-based methods (Peng et al., 2015; Artzi et al., 2015; Chen et al., 2018) sequence-to-sequence methods (Konstas et al., 2017; Xu et al., 2020), and other methods (Pust et al., 2015; Welch et al., 2018; Lindemann et al., 2020; Cai and Lam, 2020; Lee et al., 2020; Lam et al., 2021). We will also discuss whole-document AMR parsing (Anikina et al., 2020; Fu et al., 2021).

There is a wide range of NLP tasks that leverage meaning representations as an effective way to infuse knowledge into their models for better performance and interpretability. For instance, SRL has been widely used to build better models for open information extraction (Christensen et al., 2010; Solawetz and Larson, 2021) and event extraction (Zhang et al., 2020a, 2021), opinion mining (Marasović and Frank, 2018; Zhang et al., 2019a), machine translation (Bastings et al., 2017), natural language inference (Zhang et al., 2020b; Liu et al., 2022), and reading comprehension (Guo et al., 2020). Similarly, AMR has been adopted for a variety of downstream NLP tasks such as information extraction (Pan et al., 2015; Garg et al., 2016; Rao et al., 2017), summarization (Liu et al., 2015; Liao et al., 2018), machine translation (Song et al., 2019; Nguyen et al., 2021), question answering (Sachan and Xing, 2016; Mitra and Baral, 2016; Kapanipathi et al., 2021), and dialog systems (Bonial et al., 2020; Bai et al., 2021). With the increasing availability of high-quality meaning representation parsers, we also see increasing adoption of meaning representation in wide-range of real-world applications, from an enterprise-grade contract understanding system (Agarwal et al., 2021) to customizable targeted sentiment analysis.

4.2 Outline of the tutorial

The proposed tutorial is organized as follows:

I. Introduction (15 minutes). This section provides a high-level overview of the evolution of common meaning representation, discussing key concepts, unique challenges and examples of applications.

II. Common Meaning Representations (150 minutes) This section provides an in-depth review of three common meaning representation – PropBank, Abstract Meaning Representation, and Uniform Meaning Representation. It also provides a brief overview of other common meaning representations and a comparison between these meaning representations. Concretely, we will organize this section as follows:

- **PropBank**
  - An intuitive introduction of Propbank-style semantic roles
  - Defining predicate-specific semantic roles in frame files
  - Semantic roles for complicated predicates
  - Relation of propbank-style semantic roles to FrameNet and VerbNet semantic roles
- **Abstract Meaning Representation (AMR)** This section discusses different aspects of AMR, and covers how AMR represents word senses, semantic roles, named entity types, date entity types, and relations.
  - Format and basics
  - Some details and design decisions
  - Multi-sentence AMRs
  - Relation to other formalisms
- **Uniform Meaning Representation (UMR)** This section overviews Uniform Meaning Representations, and discusses how UMR builds on AMR and extends it to cross-lingual settings.

    - Sentence-level representations of UMR: aspect, person, number, and quantification scope
    - Document-level representations: temporal and modal dependencies, coreference
    - Cross-lingual applicability of UMR.
    - UMR-Writer: tool for annotating UMRs
- **Other Related Meaning Representations** This section provides a brief overview of other common meaning representations such as MRS, Tectogammatical Representation used in the Prague Dependency Treebanks (PDT), etc.
    - Discourse Representa1on Structures (annotations in Groening Meaning Bank and Parallel Meaning Bank)
    - Minimal Recursion Semantics
    - Universal Conceptual Cognitive Annotation
    - Prague Semantic Dependencies (Tectogrammatical annotation of syntax and semantics in the PDT-style treebanks)
- **Comparison of Meaning Representations** This section presents a qualitative comparison of the three meaning representations on their commonalities and differences.
    - Alignment to text / compositionality
    - Logical and executable forms
    - Lexicon and ontology differences
    - Task-specific representations
    - Discourse-level representations
- **Building Meaning Representation Datasets** This section discusses the general approaches, challenges, and emerging trend in building datasets for meaning representations.

III. Modeling Meaning Representation (100 minutes) This section discusses computational models for SRL and AMR parsing, from early approaches to current end-to-end SoTA methods.

- Semantic role labeling
- AMR parsing
- AMR generation

IV. Applying Meaning Representation (75 minutes) This section shares applications of the meaning representations for a wide range of tasks from information extraction to question answering. This section also discusses how the differences in these meaning representations impact the choice of which one(s) to use for which downstream tasks.

- Applications of Meaning Representations
- Case Studies

V. Open Questions and Future work (15 minutes) The final section concludes the tutorial by raising several open research questions in this space (e.g., creating datasets for training and evaluation at scale) and ways we as a community might work forward on these issues.

5 Proposed length of the tutorial

We are proposing a full-day tutorial to cover in depth on the design, modeling, and application of meaning representations.

6 Target audience, prerequisites, and objectives

This tutorial welcomes all stakeholders in the AI community, including AI researchers, domain-specific practitioners, and students. Our tutorial presumes no prior knowledge on the core concepts of meaning representation. However, a basic understanding of NLP, machine learning (especially, deep learning) concepts may be helpful. We intend to introduce the necessary concepts related to meaning representation during the introductory section of the tutorial.

In this tutorial, attendees will

- Develop fluency in core concepts of common meaning representations, state-of-the-art models for producing these meaning representations, and potential use cases.
- Gain insights into the practical benefits and challenges around leveraging meaning representations for downstream applications.
- Discuss and reflect on open questions related to meaning representations.

7 Ethics Statement

Infusing meaning representations into NLP models are shown to be effective in injecting knowledge into such models. As such, meaning representations allow deep understanding of languages and identify more nuanced instances of ethics concerns (e.g. biases). Furthermore, meaning representations allow the building of fully interpretable yet effective models. We hope that this tutorial helps

the audience to develop a deeper appreciation for such topics and equips them with powerful tools to mitigate recent concerns that have arisen with NLP models with regard to explainability and bias.

8 Background and Qualification of Presenters

8.1 Diversity of the team

This tutorial is to be given a team of researchers from seven different institutions across academia and industry, both junior instructors (including 1 assistant professor, 1 advanced PhD student, and 2 junior industry researchers) and researchers with extensive experience in academic and corporate research settings. The team includes creators, modelers, and users of common meaning representations. The team also has a good gender balance (two female and five male instructors).

8.2 Names, affiliations, homepages and contact details of all presenters

Julia Bonn

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8.3 Short biographies of all presenters

Julia Bonn is an advanced PhD student in Linguistics and Cognitive Science at the University of Colorado, Boulder. During her last 14 years as a Senior Research Assistant at CLEAR, she has been a long term contributor to PropBank and the PropBank Roleset Lexicon, Verbnet, AMR, and UMR. She is also the developer of SpatialAMR, an extension to AMR annotation for fine-grained, multimodal annotation of spatially-rich corpora. Her research interests center on bringing multimodality and pragmatics into cross-lingual meaning representations, and development of lexical resources for these applications with a special focus on how such resources can be designed to better serve polysynthetic languages.

Jan Hajič is the director of the large research infrastructure for Language Resources, Digital Humanities and Arts LINDAT/CLARIAH-CZ, which is part of the EU's CLARIN, DARIAH and EHRI networks. He is also the vice-director of the Institute of Formal and Applied Linguistics at Charles University, Prague, Czech Republic. His interests span morphology and part-of-speech tagging of inflective languages, machine translation, deep language understanding, and the application of statistical machine learning in NLP. He also has an extensive experience in building language resources for multiple languages with rich linguistic annotation. His work experience includes both industrial research (IBM Research Yorktown Heights, NY, USA, in 1991-1993) and academia (Charles University in Prague, Czech Republic and Johns Hopkins University, Baltimore, MD, USA, 1999-2000, adjunct position at University of Colorado, USA, 2017-2025). He has published more than 200 conference and journal papers, a book and book chapters, encyclopedia and handbook entries. He regularly teaches both regular courses as well as tutorials and lectures at various international training schools. He has been the PI or Co-PI of numerous international as well as large national grants and projects (EU and NSF). He is the chair of the Executive Board of META-NET, European research network in Language Technology, as well as a member of several other international boards and committees.

Jeffrey Flanigan is an Assistant Professor in the Computer Science and Engineering Department at University of California Santa Cruz. His research includessemantic parsing and generation, question answering, and using semantic representations in downstream applications such as summarization and machine translation. Previously he has given a tutorial in AMR at NAACL 2015, and a tutorial on Meaning Representations at EMNLP 2022. He has served as a senior area chair for CoNNL in 2022.

Tim O'Gorman is a Senior Research Scientist at Thorn. He was involved in AMR 2.0 and 3.0 annotations, the Multi-sentence AMR corpus, and updates to PropBank. He co-organized the CoNLL'19 and '20 Meaning Representation Parsing shared task. His interests are in the extensions of meaning representations to cross-sentence phenomena.

Ishan Jindal is a Staff Research Scientist with IBM Research - Almaden. He got his PhD degree in Electrical Engineering from Wayne State University, Michigan. His research interest lies at the intersection of Machine Learning (Deep Learning) and Natural Language Processing (NLP), with a particular focus on multilingual shallow semantic parsing and model analysis for enterprise use cases and their applications in various NLP downstream applications. His work has been published in top-tier conferences including ICASSP, EMNLP, NAACL, ICDM, ISIT, Big Data, and LREC. He has served as an area chair PC member in many conferences (e.g., ACL, EMNLP, NAACL, EACL, and AAAI) and journals (e.g., TNNLS and TACL).

Yunyao Li is the Head of Machine Learning at Apple Knowledge Platform. She was a Distinguished Research Staff Member and Senior Research Manager with IBM Research. She is particularly known for her work in scalable NLP, enterprise search, and database usability. She was an IBM Master Inventor. Her technical contributions have been recognized by prestigious awards on a regular basis, such as IBM Corporate Technical Award (2022), IBM Outstanding Research Achievement Awards (2021, 2020, 2019), ISWC Best Demo Award (2020), and YWCA's Tribute to Women Award (2019), among others. She is a member of inaugural New Voices Program of the American National Academies and represented US young scientists at World Laureates Forum Young Scientists Forum in 2019. Regularly organizes conferences, workshops, and panels at top AI conferences and served on prestigious program committees, editorial board and review panels. She is an ACM Distinguished Member and an elected member of the North American Chapter of the Association for Computational Linguistics (NAACL) Executive Board (2023-2024).

Nianwen Xue is a Professor in the Computer Science Department and the Language & Linguistics Program at Brandeis University. His core research interests include developing linguistic corpora annotated with syntactic, semantic, and discourse structures, as well as machine learning approaches to syntactic, semantic and discourse parsing. He is an action editor for Computational Linguistics. and currently serves on the editorial boards of Language Resources and Evaluation (LRE). He also served as the editor-in-chief of the ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP) from 2016 to 2019, and and has frequently served as area chairs for ACL, EMNLP, and COLING. He is the program co-chair of the 2024 Joint International Conference on Computational Linguistics, Language Resources

and Evaluation.

8.4 Background in the tutorial area: A list of publications/presentations

[EACL'2023] Jindal, Ishan, Alexandre Rademaker, Khoi-Nguyen Tran, Huaiyu Zhu, Hiroshi Kanayama, Marina Danilevsky, and Yunyao Li. "PriMeSRL-Eval: A Practical Quality Metric for Semantic Role Labeling Systems Evaluation." arXiv preprint arXiv:2210.06408 (2022).

[TLT'2023] Bonn, Julia, Skatje Myers, Jens EL Van Gysel, Lukas Denk, Meagan Vigus, Jin Zhao, Andrew Cowell, William Croft, Jan Hajič, James H. Martin, Alexis Palmer, Martha Palmer, James Pustejovsky, Zdenka Urešová, Rosa Vallejos, Nianwen Xue. "Mapping AMR to UMR: Resources for Adapting Existing Corpora for Cross-Lingual Compatibility." In Proceedings of the 21st International Workshop on Treebanks and Linguistic Theories (TLT, GURT/SyntaxFest 2023), pp. 74-95. 2023.

[NAACL'2022] Li Zhang, Ishan Jindal, and Yunyao Li. "Label definitions improve semantic role labeling." In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 5613-5620. 2022.

[LREC'2022] Ishan Jindal, Alexandre Rademaker, Michał Ulewicz, Ha Linh, Huyen Nguyen, Khoi-Nguyen Tran, Huaiyu Zhu, and Yunyao Li. "Universal proposition bank 2.0." In Proceedings of the Thirteenth Language Resources and Evaluation Conference, pp. 1700-1711. 2022.

[EMNLP'2022] Ishan Jindal, Yunyao Li, Siddhartha Brahma, and Huaiyu Zhu. "CLAR: A Cross-Lingual Argument Regularizer for Semantic Role Labeling." In Findings of the Association for Computational Linguistics: EMNLP 2020, pp. 3113-3125. 2020.

[ACL'2022] Tahira Naseem, Austin Blodgett, Sadhana Kumaravel, Tim O'Gorman, Young-Suk Lee, Jeffrey Flanigan, Ramón Astudillo, Radu Florian, Salim Roukos, and Nathan Schneider. 2022. DocAMR: Multi-Sentence AMR Representation and Evaluation. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3496–3505, Seattle, United States.

[ACL'2021] Yao, Jiarui, Haoling Qiu, Jin Zhao, Bonan Min, and Nianwen Xue. "Factuality assessment as modal dependency parsing." In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pp. 1540-1550. 2021.

[EMNLP'2021] Zhao, Jin, Nianwen Xue, Jens Van Gysel, and Jinho D. Choi. "UMR-Writer: A Web Application for Annotating Uniform Meaning Representations." In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pp. 160-167. 2021.

[ACL'2021] Yao, Jiarui, Haoling Qiu, Jin Zhao, Bonan Min, and Nianwen Xue. "Factuality assessment as modal dependency parsing." In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pp. 1540-1550. 2021.

[DMR'2021] Li, Zi, and Nianwen Xue. "Parsing meaning representations: Is easier always better?." In Proceedings of the first international workshop on designing meaning representations. 2019.

[KI'2021] Jens E. L. Van Gysel, Meagan Vigus, Jayeol Chun, Kenneth Lai, Sarah Moeller, Jiarui Yao, Tim O'Gorman, Andrew Cowell, William Croft, Chu-Ren Huang, Jan Hajič, James H. Martin, Stephan Oepen, Martha Palmer, James Pustejovsky, Rosa Vallejos, and Nianwen Xue. "Designing a uniform meaning representation for natural language processing." KI-Künstliche Intelligenz 35, no. 3-4 (2021): 343-360.

[ACL'2021] Du, Wenchao, and Jeffrey Flanigan. "Avoiding Overlap in Data Augmentation for AMR-to-Text Generation." In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pp. 1043-1048. 2021.

[EMNLP'2020] Yao, Jiarui, Haoling Qiu, Bonan Min, and Nianwen Xue. "Annotating temporal dependency graphs via crowdsourcing." In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 5368-5380. 2020.

[ACL'2018] Wang, Chuan, Bin Li, and Nianwen Xue. "Transition-based Chinese AMR parsing." In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies,

Volume 2 (Short Papers), pp. 247-252. 2018.

[NAACL'2018] Fei Liu, Jeffrey Flanigan, Sam Thomson, Norman Sadeh, and Noah A. Smith. 2015. Toward Abstractive Summarization Using Semantic Representations. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1077–1086, Denver, Colorado.

[NAACL'2016] Flanigan, Jeffrey, Chris Dyer, Noah A. Smith, and Jaime G. Carbonell. "Generation from abstract meaning representation using tree transducers." In Proceedings of the 2016 conference of the north american chapter of the association for computational linguistics: Human language technologies, pp. 731-739. 2016.

[ACL'2015] Wang, Chuan, Nianwen Xue, and Sameer Pradhan. "Boosting transition-based AMR parsing with refined actions and auxiliary analyzers." In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pp. 857-862. 2015.

[NAACL'2015] Wang, Chuan, Nianwen Xue, and Sameer Pradhan. "A transition-based algorithm for AMR parsing." In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 366-375. 2015.

[ACL'2014] Flanigan, Jeffrey, Sam Thomson, Jaime G. Carbonell, Chris Dyer, and Noah A. Smith. "A discriminative graph-based parser for the abstract meaning representation." In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 1426-1436. 2014.

8.5 Previous tutorials: citation to an available example of work in the area

[EMNLP'2022 Tutorial] Jeffrey Flanigan, Ishan Jindal, Yunyao Li, Tim O'Gorman, Martha Palmer, Nianwen Xue. "Meaning Representations for Natural Languages: Design, Models and Applications."

[LREC'2022 Tutorial] Jens Van Gysel, Meagan Vigus, Jin Zhao, Nianwen Xue. "Uniform Meaning Representation, a Cross-lingual Annotation Framework."

[WWW'2022 Tutorial] Linfei Wu, Hugo Chen, Yunyao Li, Ji Heng, and Bang Liu. "Deep Learning on Graphs for Natural Language Processing."

[AAAI'2022 Tutorial] Linfei Wu, Hugo Chen, Yunyao Li, Ji Heng, and Bang Liu. "Deep Learning on Graphs for Natural Language Processing."

[IJCAI'2021 Tutorial] Linfei Wu, Hugo Chen, Yunyao Li, Ji Heng, and Bang Liu. "Deep Learning on Graphs for Natural Language Processing."

[KDD'2021 Tutorial] Marina Danilevsky, Shipi Dhanorkar, Yunyao Li, Lucian Popa, Kun Qian, and Anbang Xu. "Explainability for Natural Language Processing."

[KDD'2021 Tutorial] Linfei Wu, Hugo Chen, Yunyao Li, Ji Heng, and Bang Liu. "Deep Learning on Graphs for Natural Language Processing."

[NAACL-HLT'2021 Tutorial] Linfei Wu, Hugo Chen, Yunyao Li, and Ji Heng. "Deep Learning on Graphs for Natural Language Processing."

[KDD'2019 KDD Hands-on Tutorial] Huaiyu Zhu, Yunyao Li, Laura Chiticariu, Sanjana Sahayaraj, Teruki Tauchi. "Declarative Text Understanding with SystemT."

[SIGMOD'2017 Tutorial] Yunyao Li and Davood Rafiei. "Natural Language Data Management and Interfaces: Recent Development and Open Challenges."

[EMNLP'2015 Tutorial]Laura Chiticariu, Yunyao Li and Frederick Reiss. "Transparent Machine Learning for Information Extraction: State-of-the-Art and the Future."

[NAACL'2015 Tutorial] Nathan Schneider, Jeffrey Flanigan and Tim O'Gorman. "The Logic of AMR: Practical, Unified, Graph-Based Sentence Semantics for NLP."

[VLDB"2014 Tutorial] Yunyao Li, Ziyang Liu, and Huaiyu Zhu. "Enterprise Search in the Big Data Era: Recent Developments and Open Challenges."

[SIGMOD'2010 Tutorial] Laura Chiticariu, Yunyao Li, Sriram Raghavan, Frederick Reiss. "Enterprise Information Extraction: Recent Developments and Open Challenges."

[RANLP'2005 Tutorial] Jan Hajič, Zdeňka Urešová. "The Prague Dependency Treebank and Valency Annotation."

[ACL'2004 Tutorial] Collin Baker, Jan Hajič, Martha Palmer, Manfred Pinkal. "Beyond Syntax: Predicates, Arguments, Valency Frames and Linguistic Annotation."

8.6 Evidence of teaching experience

Julia Bonn teaches guest lectures on semantic annotation and symbolic meaning representations in

Linguistics and Computer Science at CU Boulder.

Prof. Jan Hajič teaches regular undergraduate and graduate courses in Computational Linguistics and Natural Language Processing at Charles University since 1996. He has taught regular courses also at Johns Hopkins University (WSE, Baltimore, MD) in 1999-2000, UCB in Boulder, CO in the summer semester in 2019 and at a number of summer and winter schools in the past 25 years, plus invited talks and seminars at various universities and companies, including, e.g., University of Edinburgh and Google. He has also supervised numerous Masters' and Ph.D. students both in the Czech Republic and in the U.S.

Prof. Jeffrey Flanigan has taught 10 undergraduate and graduate courses on a wide range of topics in natural language processing, including courses offered in the NLP Master's program at UC Santa Cruz. He has given tutorials on meaning representations, parsing and applications at NAACL 2015 and EMNLP 2022, and many talks at conferences and workshops in NLP.

Dr. Tim O'Gorman has worked as a teaching assistant in the Univerity of Colorado Boulder and has provided guest lectures in computational semantics topics for multiple universities. He has given two prior conference tutorials on this topic, at NAACL 2015 and EMNLP 2022.

Dr. Ishan Jindal has given guest lectures at UCSC, IEEE SEM conference, and a conference tutorial at EMNLP 2022. He also has rich experience as a teaching assistant at Wayne state and was recognized as an Outstanding Teaching Assistant for the year 2017.

Dr. Yunyao Li has developed and co-taught several graduate-level courses on NLP at top universities world-wide, including University of Washington, University of California - Santa Cruz, UIUC, University of Maryland - Baltimore County, and University of Oregon. She also has developed and co-taught 2 MOOC courses on NLP (25,000+ enrollment). She regularly gives talks and guest lectures at conferences, universities, and workshops. She gives many tutorials at top conferences, such as Explainability for NLP (AACL'20, KDD'21), Deep Learning on Graphs for NLP (NAACL'21, KDD'21, IJCAI'21), and Meaning Representation (EMNLP'22), among many others.

Professor Nianwen Xue has taught many courses in the past 14 years, and these include Advanced Machine Learning Methods in Natural Language Processing, Information Extraction, Graduate Seminars on Machine Translation and Dialogue Systems, Linguistic Annotation for Machine Learning, Programming for Linguistics. He has given tutorials on meaning representation design, parsing, and application at LREC'2022 and EMNLP'2022. In addition, he has regularly given invited talks at various universities and summer schools.

8.7 Evidence of scholarship in AI/computer science

Julia Bonn's peer-reviewed publications include more than 10 at top AI/NLP conferences such as ACL (*SEM, DMR) and LREC, top AI journals such as Frontiers in AI, and a book chapter (Google Scholar citations: 206, h-index 7).

Prof. Jeffrey Flanigan has published more than 15 peer-reviewed publications that include papers at top AI/NLP conferences such as ACL, NAACL, and EMNLP (Google Scholar citations: 2273, h-index 10). He is an expert in semantic parsing, generation, question answering, and machine translation.

Prof. Jan Hajič has published 200 peer-reviewed publications in the area of Computational Linguistics and Natural Language Processing, mostly at conferences or in journals, a book on computational morphology, several book chapters and encyclopedia entries (Google Scholar citations: 12828, h-index 47). He is an expert on building, preserving and using language resources, machine translation, syntax, semantics and computational lexicons.

Dr. Ishan Jindal has published more than 15 peer-reviewed publications that include papers at top AI/NLP conferences such as NAACL, EMNLP, ICASSP, and LREC, and a book chapter (Google Scholar citations: 470, h-index 8). He is an expert on applying deep learning techniques to multilingual shallow semantic parsing.

Dr. Tim O'Gorman has 25 works in the ACL anthology, including first-author papers in EMNLP, COLING and LREC (Google Scholar citations: 664, h-index: 14). He is an expert in the design and annotation of semantic representations.

Dr. Yunyao Li has published more than 80 peer-reviewed publications at top AI/NLP conferences and journals such as IJCAI, AAAI, KDD, ACL, EMNLP, among others (Google Scholar citations: 4227, h-index 29). She is an expert on scalable natural language processing, enterprise search, and database usability. She is an ACM Distinguished

Member as a recognition for her significant contributions to computing.

Prof. Nianwen Xue has published more than 110 peer-reviewed publications that include papers at top AI/NLP conferences such as IJCAI, ACL, NAACL, EMNLP, and COLING, articles in top NLP journals such as Computational Linguistics, Natural Language Engineering, and Journal of Language and Evaluation, as well as books and book chapters (Google Scholar citations: 9492, h-index 43). He is an expert on syntactic, semantic, and discourse representation and parsing.

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